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Research Article

Simulating the Diesel Engine Vibration with Fuzzy Neural Network

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Abstract: This study is conducted in order to evaluate the models of artificial intelligence in predicting the level of diesel vibrations. In this study, the Artificial Neural Network (ANN) and the Adaptive Neuro Fuzzy Inference System (ANFIS) are used in order to simulate the vibration of the whole diesel engine. Vibration in the gasoline or diesel engines has been investigated according to numerous aspects so far. Noise and vibration, which occurs in the engine due to the combustion process, can make direct effects on the users. This is particularly true in the engines with large compression ratios and engines in which the combustion pressure increases rapidly. Results indicate that the vibration of Diesel engines can be predicted with reasonable accuracy by applying the smart models. The results of predicting the Artificial Neural Network are partially better than the Adaptive neuro fuzzy inference system.

Keywords: Diesel engine, fuzzy neural network, simulation, vibration

INTRODUCTION

Conducting the practical research on the engine vibration and performance is complex, time-consuming and expensive for Engine Manufacturers Association (EMA). Therefore, a mathematical model is used for predicting the various engine performance and vibration, but the accuracy of results may not always be satisfactory (Yusaf *et al*., 2010). The Artificial Neural Network (ANN) is an alternative to the mathematical model; the neural networks are the non-linear computer algorithms which can model the behavior of complex non-linear processes; they have no need for the explicit formulation of relevant parameters (Bolan *et al*., 2013). Numerous researchers have used the Artificial Neural Networks in various engineering levels. Artificial Neural Network Analysis is used in analyzing and predicting the performance and vibration of diesel engines (Massie, 2001). Artificial Neural Networks are the computational models composed of neurons which are applied for complex functions. A neural network system has three layers, input, hidden and output layers. The input layer contains all the input parameters. Then the information of input layer is processed by the hidden layer. The hidden and output layers usually have an active function (Talal *et al*., 2010). The training stage is an important stage in preparing a neural network and it introduces the inputs with proper outputs to the network. Networks weights (BIAS AND WEIGHTS) are initially chosen randomly and optimized by the training network. Therefore, the weights will have the meaningful information after training (whereas they are random before training and have no meaning) and the network will try to produce a desired output. While reaching a satisfactory level of performance for the network, the training is stopped and the network uses these weights for decision making; in other words, these weights represent the memory and knowledge of network (Oguz *et al*., 2010). Intelligent neural networks have the higher ability to simulate the unknown variable based on the limited diversity of input and incomplete or even with-the-error data. The lack of need to determine a specific function for expressing the relationship between the input and output data is among the advantages of intelligent neural network. Moreover, these networks are able to extract the maximum information from the available data (Tokar and Markus, 2000). Artificial Neural Network (ANN) is one of the computational methods which seeks to provide a map between the input space (input layer) and optimal space (output layer) by the aid of learning process and using the simple processors, called neuron and through identifying the inherent relations among the data (Khanna, 1990). The Artificial Neural Network seeks to design the same structure as the biological structure of human brain and body network. Hidden layer (s) processes the information received from the input layer and make it available for the output layer. Training is a process, which ultimately leads to learning and each network is trained with receiving the example of training. Network learning is done when the weights relating the layers, are changed in a way that the difference between the predicted and measured values is acceptable (Caudill, 1987). Trained neural network can be used for predicting the outputs proportional to the new data set. Khanna (1990) and

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Dayhoff (1990) have introduced the high speed of processing and flexibility against the unwanted errors from the features of trained neural network. At the training stage, first the calculations are done from the network input towards the output and then the calculated error values are extended to the previous layers. The calculation is first performed layer by layer and the output of each layer will be the input of next layer. The structure of a neural network is recognized by determining the number of layers, number of neurons in each layer, stimulatory function (controller of output for each neuron), training method, algorithm of modifying the weights and type of model. By calculating the training error by the network, its amount is compared with the optimal amount and the training error is calculated and the learning algorithm begins to optimize the relevant error. If the training error is less than the pre-determined training error, the learning process will be ended. Caudill (1987) Adaptive Neuro Fuzzy Inference System (ANFIS) uses the neural network and fuzzy logic algorithms in order to design the non-linear mapping between the input and output spaces. This system is much powerful than the linguistic power of fuzzy system with numerical power of a neural network in modeling the complex processes (Nourani and Salehi, 2008). Adaptive neuro fuzzy inference system is a 5-layer network consisting of nodes and bows connecting the node. The first layer contains the input data with the membership degree which is determined by the user. All modeling operation is done in second to fourth layers. The last layer is the network output and has the objective to minimize the output difference obtained from the network and actual output (Harun *et al*., 2012). The appropriate structure of ANFIS is selected proportional to the input data, membership degree and laws and functions of output member ship degree. At the training stage, the input values become closer to the true values through modifying the parameters of membership degree based on the acceptable error rate (Yusaf *et al*., 2010). There are two techniques including the Grid partitioning and Sub-clustering methods for using the ANFIS. The way of determining the fuzzy membership function is the major difference between these two methods. In the clustering method, the influence range is among the properties of implementing the mentioned method which is determined by the user and usually varies between zero and one. The numbers, above the influence range, are less applied despite the high speed of running the program ANFIS and due to the higher computational error (Yuanwang *et al*., 2002).The main objective of this study is to investigate simulation model of Artificial Neural Network (ANN) and Adaptive Neural Inference System (ANFIS) in order to simulate the vibrations of diesel engine based on the minimal available data. The obtained results of this study can be used for the Engine Manufacturers Association (EMA) in developing the appropriate assessment method and conducting the practical research on the performance of diesel engines.

LITERATURE REVIEW

Numerous studies have been conducted in the field of using the fuzzy neural simulations. Ettefagh *et al*. (2008) they investigated the knock in spark ignition engines (gasoline) by the vibration analysis (velocity) of cylinder block and providing the parametric modeling approach. The results also indicate that the proposed method is able to show the knock by the simple software with the small sampling frequency which leads to the reduced computational time and software costs. Bolan *et al*. (2013) developed a model for identifying the incomplete fuel consumption according to the general parameters in the diesel engines by using the fuzzy neural network. The results of their research paved a new way for detecting an incomplete fuel in the engines. Geng and Cheng (2005) investigated the internal phenomenon of piston knock in the Reciprocating Engine according to the engine mechanics. The induced vibration response was created through the stroke according to the non-linear model for simulation. It was done according to the results, obtained from this simulation and for measuring and extracting the messages of induction strokes inside the diesel engine cylinder. Several studies have been also conducted by using the intelligent neural networks for modeling the behavior of internal combustion engines by the researchers in this regard. Oguz *et al*. (2010) applied the artificial neural network in the field of internal combustion engines in order to predict the power of diesel engine with biodiesel fuel. Andrew *et al*. (2007) have proved that the torsional vibrations (velocity) indicate the motor systems in some of the phenomena and they are not common in the vibrations. These effects result from the geometry of engine reciprocating mechanism and are detected by the analysis of cognitive and dynamic movement. The results indicate that the vibrations are also influenced by the friction between the cylinder and piston. Furthermore, Ghobadian *et al*. (2008) applied this method and fuzzy logic model in order to analyze the Diesel Engine Performance and Exhaust Emission and also Parlak *et al*. (2005) used it in order to predict the specific fuel consumption and exhaust temperature of engine. Kesgin (2003) also utilized the artificial neural network technique in combination with other meta-heuristic approaches in order to optimize the efficiency and NO_x emission.

RESEARCH METHODOLOGY

In this study, the Multilayer Perceptrons (MLP) is used with Feed Forward Back-Propagation (FFBP) method. This perceptron is simple, but it has higher application because of accurate absorption. Different threshold functions such as sigmoid (log sig), logarithmic (tan sig) and linear (purelin) and the training rules with monitoring such as train lm rule (Levenberg-Marquardt), traincsg and traingdx are used and their results are compared with each other in order to determine the best structure for predicting the engine root mean square velocity. To build such a network, the target program was developed in MATLAB software. The accelerometer AC102-1A, manufactured by CTC Company, was used in order to collect the front and rear signals of engine vibration signals. This accelerometer measured the frequencies of 0.5 to more than 15000 Hz very precisely. The convertor box was applied in order to connect the accelerometers and the encoder and sending their signal to the Raster-to-Vector converter. This box includes three interface circuits for each accelerometer and a circuit for launching the encoder. The output signals of convertor box are connected to the Raster-to-Vector converter D/A^2 (Advantech, USB-4711A) by using the relevant cable and finally the data was transferred to the USB of computer. Three accelerometers were connected to the box. In this study, 6-cylinder Perkins engine model 1006-6 is used with the compression ratio 16:1 and maximum power 110 Horse Power (HP) at 2200 rpm. This engine has been installed on the single differential tractor 399 MF which is produced by Tabriz Tractor Manufacturing Company. In this study, the frequency of sampling the accelerometer 1 was adjusted on 50 KHz, Accelerometer 2 on 40 KHz and frequency of sampling for each encoder outputs adjusted on 10 KHz. Connecting axes of accelerometers were along with the vertical direction, along with the tractor movement (longitudinal) and perpendicular to these two directions (lateral). The time of taking the data for each test was considered a minute. Furthermore, handheld computer was used for data entry. SPSS Software was used for the statistical analysis and SAS Software for estimating the significant test of effects of different levels on the vibration data, etc. MATLAB Software was used for data taking and processing the signals and LAB VIEW Software for converting the time signal into the Frequency signal (FFT), calculating the root mean square velocity and so on. The number of input layer neurons is equal to the number of independent variables (4 numbers) and the number of output neurons is equal to the number of dependent variables (1 number). The number of layers and neurons of the middle layer is determined through the trial and error method and by considering the minimum root of Mean Square Error (MSE) and the maximum coefficient of determination (R^2). The best topology of network is also determined by considering those variables.

DISCUSSION

Vibration data was collected for two conditions of "before repair engine" and "after repair engine" in cold weather. In the case of after repair, all filters including the air filters, fuel filters, oil filter and also the engine oil were changed. Figure 1 shows a part of signal domain of velocity in the front of tractor engine in cold weather. This signal is as the result of the fuel B 20 Rpm in the engine revolution 1200 rpm, vertical and in 0.5 sec.

Figure 1 show the time of engine combustion. Complete working period of this engine includes 6 combustions which occur in 4-2-6-3-5-1 cylinders, respectively. As shown in the figure, the working period is started from the pause point at the top of the cylinder 1and ended in the pause point at the top of the cylinder 4. At the complete period of this engine, the crankshaft has two revolutions and also three combustions occur in each engine revolution. Figure 2 shows the diagram of signal frequency domain of Fig. 1 at 1200 rpm. This diagram is obtained by using a Fast Fourier Transform of time domain signal.

As shown in the power spectrum diagram Fig. 2, the velocity peaks occur at frequencies of 60, 120 and 933 Hz, respectively. For engine revolution 1200 rpm, the combustion number is equal to 3 (number of combustion in each revolution) multiplied by 20

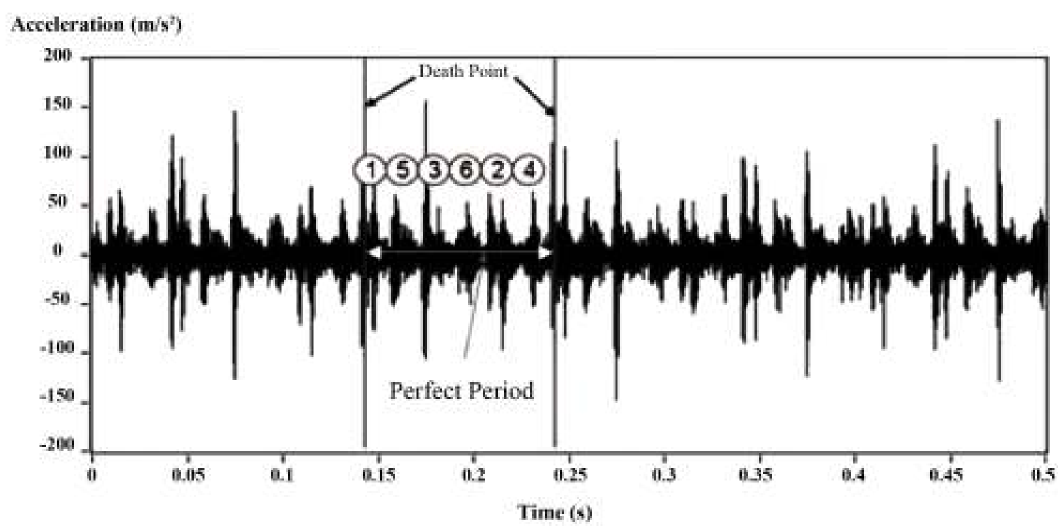

Fig. 1: Filtered signal of velocity time domain in front of engine in cold weather

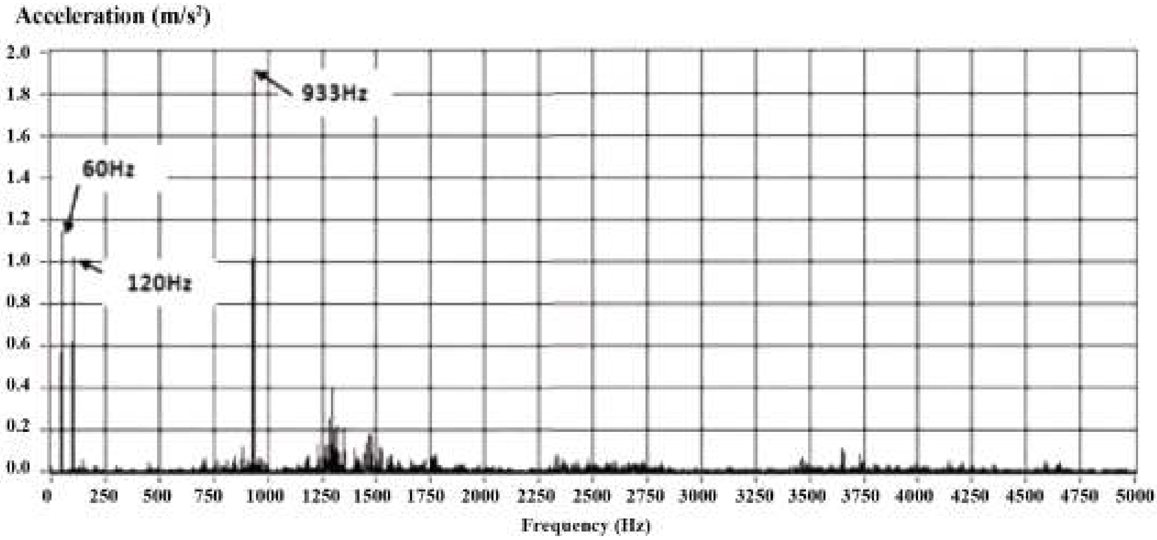

Fig. 2: Frequency domain signal in front of engine in the engine revolution equal to 1200 rpm

(revolution per second) which is 60 times/sec; and this number can be seen in the frequency diagram of Fig. 2 in the first velocity peak. Therefore, the frequency 60 Hz is related to the frequency of engine combustion. The next peak occurs in the frequency 120 Hz and is related to the frequency of stroke by the smoke and air valves and is exactly twice the frequency of engine combustion. The number of these valves is two for each cylinder, thus (60×2 = 120 Hz). No accurate viewpoint can be provided for the frequency 933 Hz.

The root mean square velocity was used in order to compare the velocity in engine revolutions (seven revolutions) in addition for different fuel blends (9 fuel blends). Five replicates were considered for each treatment. Equation (1) was applied by using the time-domain signal in order to calculate the root mean square velocity:

$$a_{RMS} = \sqrt{\frac{1}{N}\sum_{k=1}^{N} a_k^2} \quad (1)$$

where,

a_{RMS} = The root mean square velocity (m/sec^2)

a_k = k value of velocity from the signal of time domain

N = The total number of velocity values (N = 80000) in 1.6 sec

The effect of engine revolution on vibration rate: The values of root mean square velocity were obtained by the Eq. (1) for all engine revolutions and fuel blends. The effect of engine revolution different levels on the root mean square velocity was investigated in a factorial experiment in the form of Completely Randomized Design (CRD) and the means were studied

Table 1: The analysis of variance of root mean square velocity based on the engine revolution

Sources of change	Degrees of freedom	Before-repair engine	After-repair engine
Revolution	6	9231.620*	6371.110*
Fuel	8	9.280*	19.520*
Revolution×fuel	48	1.273*	1.716*
Error	252	0.064	0.043

*: Significant at probable level 5%

by using Duncan's comparison test at the probable level 5%. Table 1 shows the analysis of variance of root mean square velocity based on the engine revolution and fuel type in two conditions of before-repair and after- repair-engine at the probable level 5%.

According to Table 1, the analysis of variance of main effect of engine revolution and fuel type is significant at the level 5% in all tested conditions. Given the significance of interaction, the mean comparison was only performed for the treated components (engine revolution × Fuel type). Comparison of mean velocity in various revolutions and fuels was done in before-repair condition by Duncan method at significant level 5%. The results showed that the root mean square velocity is significantly increased in front of the engine by enhanced revolution. The comparison of velocity values for each fuel blend at any level indicates that the vibration is increased significantly for all fuel blends in all engine revolutions from 1000 to 2200 rpm. Figure 3 shows that the process of increasing the vibration from 1000 to 2200 rpm is steady and linear for all fuels. At 1600 rpm, the slope is increased and the vibration is suddenly increased in all fuels from 1800 to 2000 rpm and it is due to the sudden increase in power and torque of engine at 2000 rpm. After this revolution, the process of increased vibration goes back to the previous state. This phenomenon can be observed from the slope of diagrams in the Fig. 3. The mean increased vibration

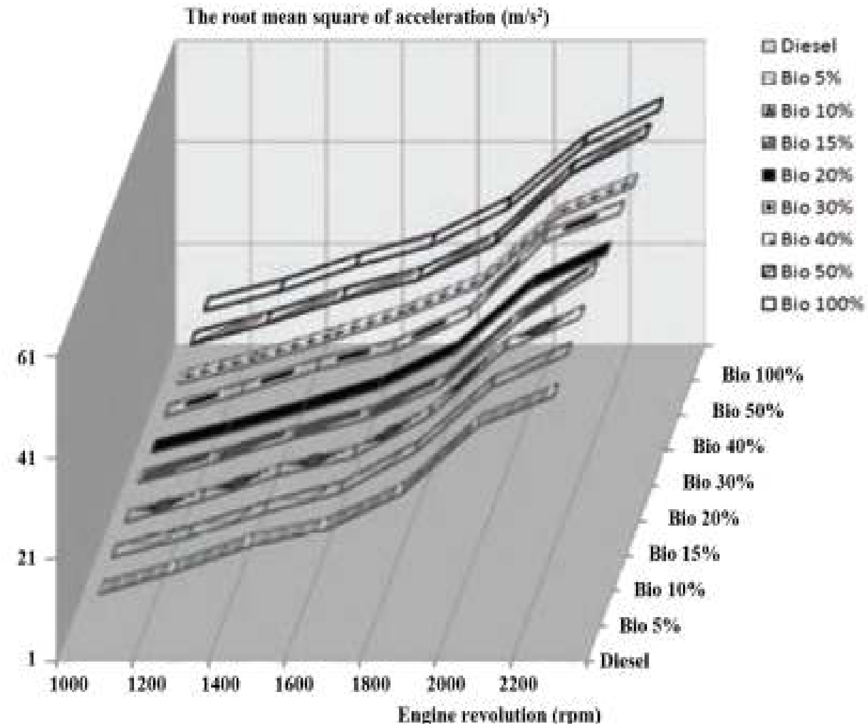

Fig. 3: Diagram of velocity in terms of engine for all fuel blends

for all fuels from 1000 to 2200 rpm is equal to 4.02, 4.73, 3.95, 7.07, 13.17 (from the revolution 1800 to 2000 rpm) and 6.86 m/sec^2, respectively.

Comparison of vibration before and after-repair engine: As the results indicated, the engine vibrations are highly dependent on its maintenance. Replacing the air and fuel filters and engine lubricating oil is an important factor in reducing the engine vibrations. Enough air in the combustion chamber of cylinder causes that the fuel combustion to be occurred completely. The gas lever is pressed greatly because of the insufficient air in the engine to achieve the desired engine revolution. This increases the fuel consumption and thereby increases the amount of vibration. Thus, replacing the air filter can reduce the fuel consumption and causes the combustion to be done completely in the engine. Changing the engine lubrication oil is another important factor in reducing the vibration in this engine. This reduces the friction between the parts such as the crankshaft bearings, cylinder, piston and other components. As the result, the vibration is greatly reduced. These results were obtained in similar studies such as Andrew *et al*. (2007), Geng and Cheng (2005) and Haddad and Pillen (1973). In after-repair engine condition, all filters including the air, fuel and oil filters were replaced. Furthermore, the engine oil was completely changed. The vibration was significantly reduced after repairing the engine compared to before-repair condition. The mean reduction at engine revolution from 1000 to 2200 rpm is equal to 2.74, 3.07, 4.32, 4.67, 4.21, 13.11 and 13.31 m/sec^2, respectively and the greatest reduction is observed in the revolutions from 2000 and 2200 rpm. In general, the experiments showed that the amount of vibration is reduced about 12% after repairing the engine.

Comparing the simulation results obtained from the neural network and data of experiments: The root mean square velocity is done in order to compare the obtained results of vibration data and the results of neural network of linear fitness (regression) among the dependent variables. Figure 4 shows the regression analysis for verification test of velocity data, respectively (This diagram is drawn only by considering 10% of test model data). The amount of coefficient of determination (R^2) for root mean square velocity is equal to 0.984 of the mean square error and negligible for these variables.

To compare the results obtained from the experiments (original data) with the results predicted with the aid of neural network and realize the network performance in predicting the engine vibration, the error is calculated between two sets of data and displayed in Fig. 5. In this figure, only the results of 10% of test models are compared and its error is calculated with the aid of network with the structure 4-30-30-1 which is already noted. As shown in the figure, there is a good consistency between the data of root mean square velocity and the neural network and the error rate in most of the models is approximately near zero. Comparison of results, obtained from the neural

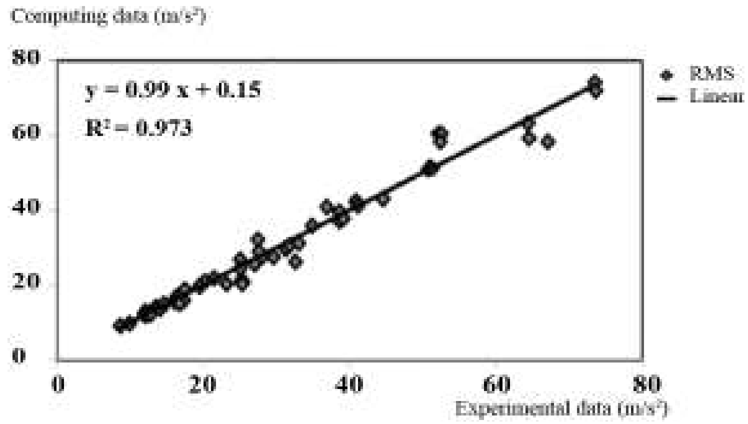

Fig. 4: Comparing the amount of root mean square velocity and the results predicted with experimental data

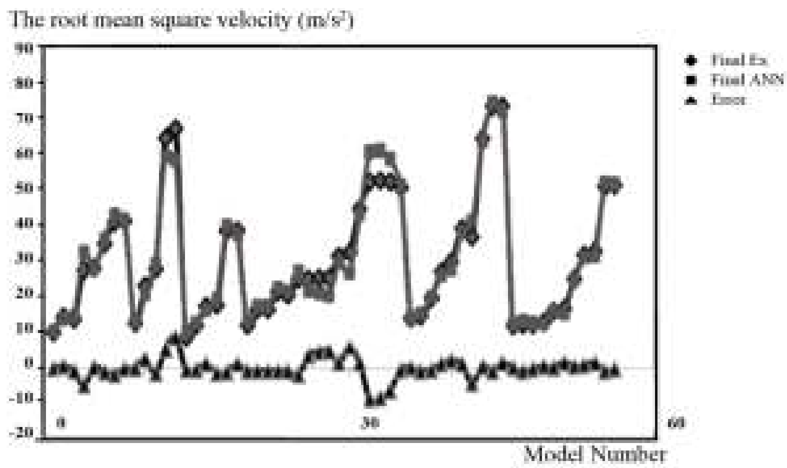

Fig. 5: Comparing experimental data with the results predicted with the aid of neural network

network simulation, with the results, obtained from the test, indicates that the neural networks are the powerful tools for simulating the vibration in the engine. Similar results have been obtained in several studies on the engine. In the research on the diesel-natural gas composite engine and in comparing the experimental and simulated data, the neural network was able to simulate and predict the engine performance as well as the emissions (Haddad and Pillen, 1973).

CONCLUSION

Given the importance of reduced vibrations in the automotive industry and existence of numerous problems in recording this parameter and the success of intelligent models in predicting the complex parameters, it is essential to use the intelligent neural models such as ANN and ANFIS in predicting the vibration parameter. The results of this study also indicate that both ANN and ANFIS methods have the ability to simulate the engine vibrations in diesel vehicles. High level of coefficients of determination and low error of RMSE and MPE confirm the reliability of results. Furthermore, according to the obtained results, the statistical amounts of mean percentage error and coefficient of determination in the artificial neural network method has been better than implementing the Adaptive Neuro Fuzzy Inference System (ANFIS) approximately for all engines. On this basis, the artificial neural network can be applied as a new approach for modeling the vibrations in diesel engines. The combination of this approach with the algorithms can be used as a powerful technique to optimize the control parameters used in control systems of vehicles, although using these methods requires quicker response time to the changes in engine functional conditions; however, the emission of vehicle noise and vibration can be reduced significantly by reinforcing these systems.

REFERENCES

Andrew, L.G., C.H. Dianne and J.S. Brian, 2007. The effect of piston friction on the torsional natural frequency of a reciprocating engine. Mech. Syst. Signal Pr., 21(7): 2833-2837.

Bolan, L., Z. Changlu, Z. Fujun, C. Tao and S. Jianyun, 2013. Misfire detection of a turbocharged diesel engine by using artificial neural networks. Appl. Therm. Eng., 55(1-2): 26-32.

Caudill, M., 1987. Neural networks primer, Part I. AI Expert, pp: 46-52.

Dayhoff, J.E., 1990. Neural Network Principles. Prentice Hall International, USA.

Ettefagh, M.M., M.H. Sadeghi, V. Pirouzpanah and H. Arjmandi Tash, 2008. Knock detection in spark ignition engines by vibration analysis of cylinder block: A parametric modeling approach. Mech. Syst. Signal Pr., 22(6): 1495-1514.

Geng, Z. and J. Cheng, 2005. Investigation into piston-slap-induced vibration for engine condition simulation and monitoring. J. Sound Vib., 282(3-5): 735-751.

Ghobadian, B., H. Rahimi, A.M. Nikbakht, G. Najafi and T.F. Yusaf, 2008. Diesel engine performance and exhaust emission analysis using waste cooking biodiesel fuel with an artificial neural network. Renew. Energ., 34: 976-982.

Haddad, S.D. and H.L. Pillen, 1973. Piston slap as a source of noise and vibration in diesel engines. J. Sound Vib., 34(2): 249-260.

Harun, M.I., N. Hoon Kiat, W.Q. Cheen and G. Suyin, 2012. Artificial neural networks modeling of engine-out responses for a light-duty diesel engine fuelled with biodiesel blends. Appl. Energ., 92: 769-777.

Kesgin, U., 2003. Genetic algorithm and artificial neural network for engine optimisation of efficiency and NOx emission. Fuel, 83: 885-895.

Khanna, T., 1990. Foundations of Neural Networks. Addison-Wesley, New York.

Massie, D.D., 2001. Neural-network fundamentals for scientists and engineers. ECOS 01, Istanbul, Turkey, pp: 123.

Nourani, V. and K. Salehi, 2008. Fourth National Congress on Civil Engineering. University of Tehran.

Oguz, H., I. Sarıtas and H. Emre Baydan, 2010. Prediction of diesel engine performance using biofuels with artificial neural network. Expert Syst. Appl., 37(9): 6579-6586.

Parlak, A., Y. Islamoglu, H. Yasar and A. Egrisogut, 2005. Application of artificial neural network to predict specific fuel consumption and exhaust temperature for a diesel engine. Appl. Therm. Eng., 26: 824-828.

Talal, F.Y., D.R. Buttsworth, H.S. Khalid and B.F. Yousif, 2010. CNG-diesel engine performance and exhaust emission analysis with the aid of artificial neural network. Appl. Energ., 87(5): 1661-1669.

Tokar, A.S. and M. Markus, 2000. Precipitation-runoff modeling using artificial neural networks and conceptual models. J. Hydrol. Eng., 5: 156-161.

Yuanwang, D., Z. Meilin, X. Dong and C. Xiaobei, 2002. An analysis for effect of cetane number on exhaust different from the existing tests cycles. Fuel, 81(15): 1963-1970.

Yusaf, T.F., D.R. Buttsworth, K.H. Saleh and B.F. Yousif, 2010. CNG-diesel engine performance and exhaust emission analysis with the aid of artificial neural network. Appl. Energ., 87(5): 1661-1669.