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인공 신경망을 이용한 프리피스톤 리니어 엔진의 연구

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The Research About Free Piston Linear Engine with Artificial Neural Network

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Abstract >> Free piston linear engine (FPLE) is a promising concept being explored in the mid-20th century. On the other hand, Arficial neural networks (ANNs) are non-linear computer algorithms and can model the behavior of complicated non-linear processes. Some researchers already studied this method to predict internal combustion engine characteristics. However, no investigation to predict the performance of a FPLE using ANN approach appears to have been published in the literature to date. In this study, the ability of an artificial neural network model, using a back propagation learning algorithm has been used to predict the in-cylinder pressure, frequency, maximum stroke length of a free piston linear engine. It is advised that, well-trained neural network models can provide fast and consistent results, making it an easy-to-use tool in preliminary studies for such thermal engineering problems.

Key words : Free piston(프리피스톤), Linear engine(리니어 엔진), Artificial neural network(인공 신경망), Spark timing(불꽃점화)

Nomenclature

ANNs : artificial neural network
FPLE : free piston linear engine
MAPE : mean absolute percentage error
R : correlation coefficient

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1. Introduction

Nowadays, there is no hesitation that, conventional engine technology has been eminently successful in producing power by converting the reciprocating motion of the piston into rotary motion of the crankshaft with the help of connecting rod. But people are looking for unconventional engine technology. Because, problems related to a rapid increase of harmful exhaust emissions due to the burning of fossil fuel in case of hydrocarbon based power generation have become a confabulation issue all over the world. In addition, a third of total friction losses in conventional engine happen due to the presence of additional moving parts like crankshaft, connecting rod, bearing etc. Multifarious alternative engine configurations have been recommended with an intention of flourishing the fuel efficiency and lowering the exhaust emissions. Investigation on free piston engine has been commenced since mid-20th century[1], after the first proposal of the free piston type engine technology. Special features offered by free piston engine technology are the simplicity in mechanical shape, lower level of friction loss, and extraordinary operational flexibility. As there is no crankshaft in the free piston engine, it allows the piston to move freely inside the cylinder. Therefore, variable compression ratio with respect to the different load conditions is possible, which is an additional advantage offered by FPLE.

A number of studies have shown that FPLE also suitable for multi-fuel as well as homogeneous charge compression ignition operation[2]. One more advantage of FPLE is the very low peak temperature in combustion stroke, which can predict near to ground level of NOx production.

Testing the engine under the all thinkable operating conditions is time consuming and costly. As a substitute, by using Artificial Neural Networks (ANNs), the performance of a FPLE engine can be easily modeled for a decent prediction. The main difference between conventional modeling approach and ANNs is, its ability to know about the system without having enough knowledge of the process relationship. This new modelling approach can be applied to estimate preferred output parameters when enough empirical data are available.

The purpose of this paper is to look over the performance of a FPLE by using ANNs. In order to do that, experiments have been executed on a FPLE for a carefully chosen range of spark timing delay values. After that, experimental data have been gathered in order to train and test the ANN model for predicting the maximum stroke length, frequency and cylinder pressure of the engine.

2. Experimental Analysis

In this study, a two stroke dual piston type free piston engine has been used. A linear generator works as a starting motor in order to start the engine by delivering an initial, electrically powered stroke, so that the very

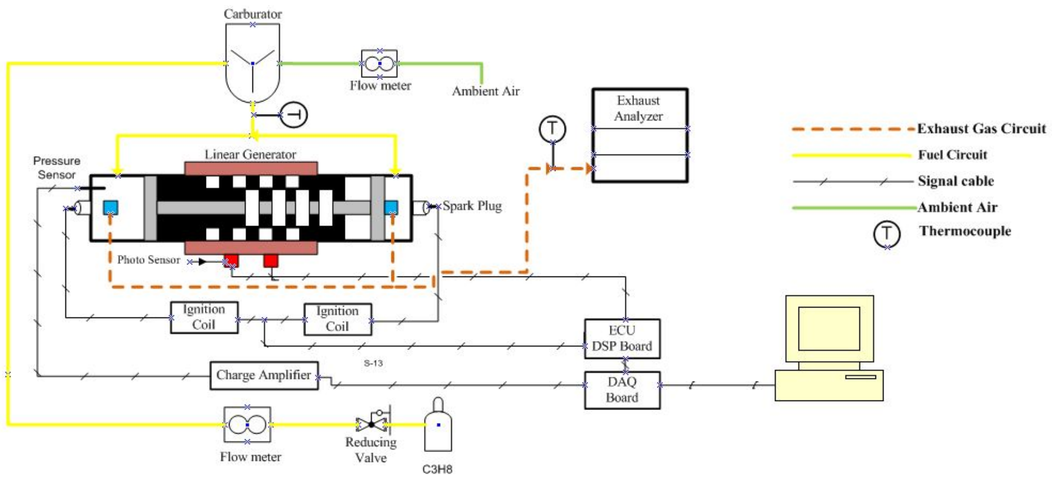


Fig. 1 Schematic diagram of the experimental setup

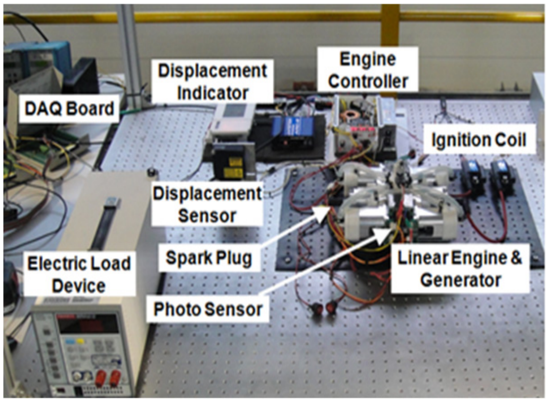


Fig. 2 A photograph of experimental setup

Table 1 Experimental conditions

Equivalence ratio, Ø	1.0
Input calories value, Qin [KJ/s]	5.88
Air flow rate [L/min]	90
Electric load [R]	30Ω
Intake temperature [K]	298.5
Fuel type	Propane
Spark timing delay [mm]	4.02, 5.03, 6.80, 8.95

first detection of the translator to the photo sensor (Sharp; GP1S092HCPIF) can be made easily. This is necessary for the first combustion because, sparking occurs only when the photo sensor interrupted by the translator and then a digital signal from the sensor was delivered to the ECU. Later, if combustion takes place, motoring mode and firing mode overlapped temporarily. After some short cycles, the linear generator was used as a conventional generator to generate the AC, and the linear generator was no longer used as a starting motor[3]. Fig. 1 and Fig. 2 are showing the schematic and apparatus view of the experimental setup and Table 1 shows the experimental conditions.

In this experiment, the spark timing delay is adjusted by the ECU. When the translator combined with piston is reciprocated, a 5 V signal is generated immediately after a thin plate stuck on the translator is detected by the

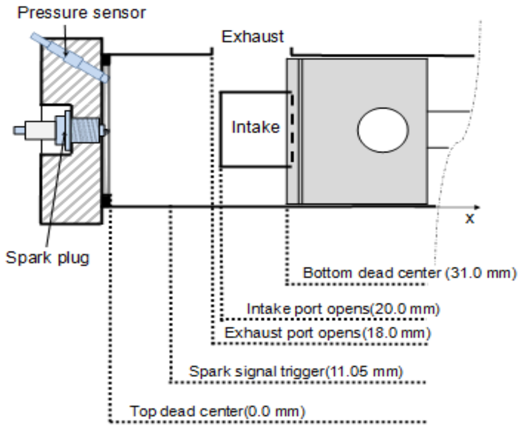


Fig. 3 Definition of spark timing

photo sensors. This signal is sent to ECU to define the spark timing delay. In cylinder pressure was measured by using a pressure sensor (Kistler-6025C); an optical displacement sensor (KAIS Co. ; KL3A-N1) has been used to detect the position of the translator in real time. All the data obtained from any sensor were saved as a text file through the DAQ board. Fig. 3 shows the definition of spark timing.

3. Theoretical Analysis

3.1 Artificial neural network

Neural-networks are non-linear computer algorithms and can model the behavior of complicated non-linear processes. ANNs do not need an explicit formulation of physical relationships for the concerned problem[4]. The main component of a neural network is the neuron. Basically, a biological neuron receives inputs from definite sources, merge them through their own way, and act upon a generally non-linear operation on the results, and presents them as the output. According to Haykin[5] a neural network is a massively parallel distributed processor that has a natural propensity for storing experimental knowledge and making it useful.

There are different learning algorithms used in training the ANNs. A popular algorithm is the back-propagation algorithm, which has different variants. Standard back-propagation is a gradient descent algorithm. It is very difficult to know which training algorithm will be the fastest for a given problem. ANN with back-propagation algorithm learns by changing the weights and these changes are stored as knowledge. Error during the learning is called as root-mean-squared (RMS) and defined as follows:

$$RMS=\left((1/p)\sum_j |t_j - o_j|^2\right)^{1/2} \tag{1}$$

Where, p is the number of points in the data set, t is the network target and o is the desired output.

3.2 Modeling with ANN

After gathering data from test runs an ANN model for FPLE has been developed. This technique is useful especially when one deals with parameters required time and sophisticated instrument. The spark timing delay has been used as an input layer component, while the maximum stroke length, frequency and cylinder pressure were used separately as output layer components of the ANNs. Fig. 4 shows the single hidden layer ANN architecture that has been used. The performance of an ANN is influenced by some features of the network such as the number of hidden layers and the number of nodes in each hidden layer[6]. By trail and error with different ANN configuration, the network was decided to consist of one hidden layer with eight neurons. Later, by using three layer feed-forward ANN output parameters were predicted. Utilizing standard back-propagation algorithm[7,8], the

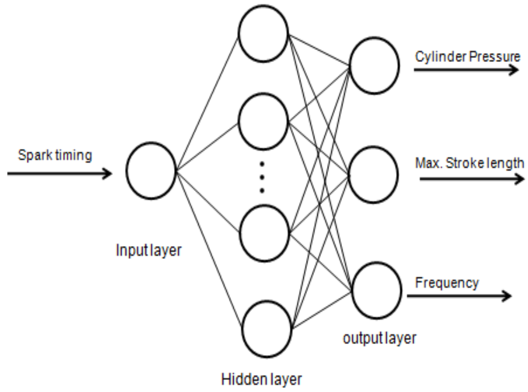


Fig. 4 Multi layer neural network for predicting engine performance

input vectors and the corresponding target vectors from the training set were used for training the network. The training procedure adjusted the weighting coefficients using Levenberg-Mar-quardt algorithm[7,8]. At every presentation, the output of the network compared with the predicted output, and an error was measured. By using back propagation those errors, are then sent to ANN and used for adjusting the weights such that the error decreases with each iteration. As a consequence, a function between input and output variables have been approximated via training procedure. Then, the input vectors from the test data set were presented to the trained network and the output parameters predicted by the network were compared with the experimental ones for the performance measurement. The back propagation algorithm was solved by using computer code and measuring the network performance was implemented under the MATLAB environment.

4. Results and Discussion

The aim of using the Artificial Neural Network (ANN) model considered as a practical approach is to test the ability to predict the engine performance of a FPLE.

Table 2 Input and output samples

Input parameter	Output parameters		
Spark timing	Cylinder pressure [KPa]	Max. Stroke length [mm]	Frequency [Hz]
4.02	3910.1	29.41	52.84
5.03	5663.0	30.76	57.31
6.80	4487.5	30.70	57.01
8.95	4547.4	27.94	55.13

After gathering data from test runs an ANN model for FPLE has been developed. A feed forward network with one hidden layer has been used. Initially, five neurons in the hidden layer have been used for all the performance. Then, the number of neurons has been increased. It is found that, the optimum number of neurons in the hidden layer is different for different performance. To have a more precise investigation into the model, a regression analysis of outputs and desired targets was performed as shown in Fig. 4. Selected sample data sets as shown in Table 2 have been used for training and testing the network. Statistical method, MAPE and correlation coefficient (R) were used for comparison in the precise analysis which is shown in Table 3.

The evaluation between ANN predicted and experimental values for different performance shown in Fig. 5.

ANN results for cylinder pressure represented in Fig. 5(a), where, correlation coefficient and MAPE were 0.9873 and 1.83% respectively. Fig. 5(b) and 5(c) stands for maximum stroke length and frequency respectively.

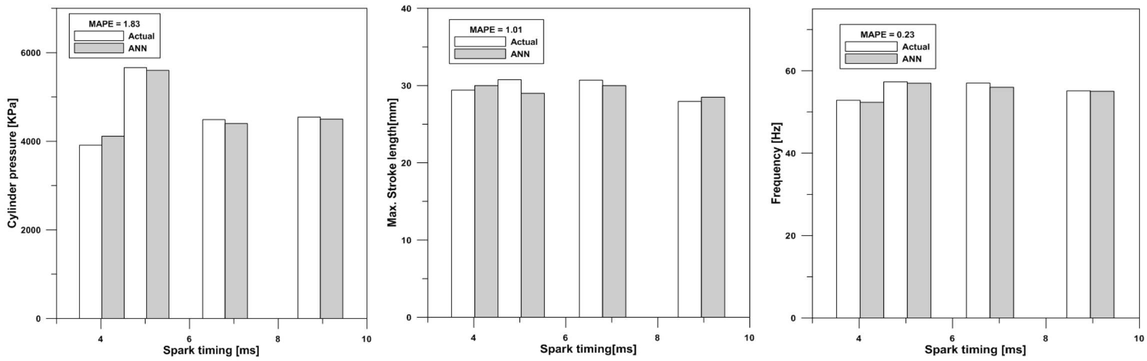
5. Conclusion

The aim of this paper has been to show the possibility of using the Artificial Neural Network(ANN) for the prediction of engine performance of a FPLE.

The result showed that, the training algorithm was sufficient enough for the prediction of this system. Scaled conjugate gradient (SCG) method with different transfer function has been studied in this paper for this combined model and best result was found with 8 neurons and the mean absolute percentage error was

Table 3 Performance analysis for algorithm and different transfer function

Performance	Training algorithm	Transfer function	Number of Neurons	R	MAPE
Cylinder pressure	SCG	Logsig	15	0.9873	1.83
Max. Stroke length.	SCG	Tansig	12	0.9984	1.01
Frequency	SCG	Tansig	8	0.999	0.23



(a) (b) (c)

Fig. 5 The ANN prediction versus experimental values for (a) cylinder pressure, (b) maximum stroke length, (c) frequency limited to 0.23-1.83%; which shows a good agreement between the predicted and experimental values.

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