ISSN 1009-3095 Journal of Zhejiang University SCIENCE V.3, No.5, P.543-548, Nov.-Dec., 2002
http://www.periodicals.com.cn; http://www.zju.edu.cn/English
http://www.zjupress.com; http://lib.zju.edu.cn/eindex.htm; jzu_s@mail.hz.zj.cn

A method for predicting in-cylinder compound combustion emissions

SU Shi-chuan(苏石川)†, YAN Zhao-da(严兆大), YUAN Guang-jie(元广杰)
CAO Yun-hua (曹韵华), ZHOU Chong-guang(周重光)

(*The Institute Power Machinery and Vehicular Engineering, Zhejiang University, Hangzhou 310027, China*)

†E-mail: ssczju@hotmail.com

Received Oct. 8, 2001; revision accepted Jan. 20, 2002

Abstract: This paper presents a method using a large steady-state engine operation data matrix to provide necessary information for successfully training a predictive network, while at the same time eliminating errors produced by the dispersive effects of the emissions measurement system. The steady-state training conditions of compound fuel allow for the correlation of time-averaged in-cylinder combustion variables to the engine-out NO_x and HC emissions. The error back-propagation neural network (EBP) is then capable of learning the relationships between these variables and the measured gaseous emissions, and then interpolating between steady-state points in the matrix. This method for NO_x and HC has been proved highly successful.

Key words: Back-propagation neural network (EBP), Compound fuel, Emissions, Prediction
Document code: A **CLC number:** TK421$^+$.5

INTRODUCTION

Internal combustion engines (ICE) have been subjected to emission control techniques since pollutant emission regulations are becoming more and more stringent. The trend towards lower allowable emissions levels appears to be continuing with particular emphasis on diesels. How to reduce the emissions of diesel engines is the key of their development in the future. In the last decades, strenuous efforts were made to reduce diesel engine emissions. Especially, the compound fuel (ethanol-diesel) engine was made to reduce emissions and its all-around effect on the atmosphere is remarkable.

Neural network architectures have gained popularity in recent years due to their excellent recognition and prediction capabilities (Widrow et al., 1990). Emissions formation in ICE is very complex, but the neural network training does not need the detailed knowledge of the combustion kinetics available only to research laboratories with extremely expensive and intrusive equipments.

This study aims to prove that detailed knowledge of the emissions from a compound fuel (ethanol-diesel) engine can be easily obtained through the application of neural networks using information from readily available engine sensors and established methods such as in-cylinder pressure measurement using flush-mounted pressure transducers.

NEURAL NETWORK ARCHITECTURE AND ITS APPLICATION

There are many different types of neural network architectures based on different targeted results (Raina, 1994). This study shall focus on a feed forward network. Specifically, it will focus on a subset of feed forward networks called Error Back-Propagation (EBP) networks.

Neural Network Architectures

In the typical neural networks (Horink et al., 1989), the information from the first layer, the input x, is multiplied by a weight w corresponding to each neuron and distinct for each link to the hidden layer, and then summed to provide an intermediate value. This value is then sent through a non-linear activation function to act as the hidden layer variable (Nelles, 1997). The hidden layer is likewise multiplied, summed and fed through an activation function to provide the values of the output (Widrow et al., 1990). Thus the two layers are written as:

$$a_j = \sum_{i=1}^{d} w_{ji}x_i + w_{j0} \quad \text{and} \quad z_j = g(a_j)$$

$$bb_k = \sum_{j=1}^{m} w_{kj}z_j + w_{k0} \quad \text{and} \quad y_k = g'(b_k)$$

where d and m represent the number of neurons in the input and hidden layers respectively. The terms with the 0 in the subscript representing offset biases or thresholds used for better differentiation between classes. For some networks, the classes are large; but for the EBP, there are many according to the dimensional levels of the data set. The term g represents the activation function that can be based on a logistic or hyperbolic tangent function or any other non-linear function between the values of -1 and 1 (Haykin, 1994).

Once the network has been initialized through random weight seeding (all w in the equations above), the process of training begins. For EBP networks, this involves comparing the actual measured output values to those predicted by the network (y_k) and then correcting the weights in all layers accordingly to improve the prediction. After one pass through the network, output values are compared to actual values to produce an error value.

Fig. 1 is the Neural Module network architecture. The first architecture was a straight 3 layer EBP with a hyperbolic tangent activation function in the hidden layer and a linear activation function for the output layer. The second architecture employed a second hidden layer in parallel to the first. This second layer uses a different activation function in an attempt to find patterns in the data not uncovered by the first. The activation functions for these hidden layers in the second architecture were the Gaussian and Gaussian complement while the output activation function remained linear. Finally, the last architecture added a third hidden layer. This setup was basically the same as the second with the third hidden layer using a hyperbolic tangent activation function. Each of the gaseous emissions (NO_x, HC) predictions was trained with the three networks.

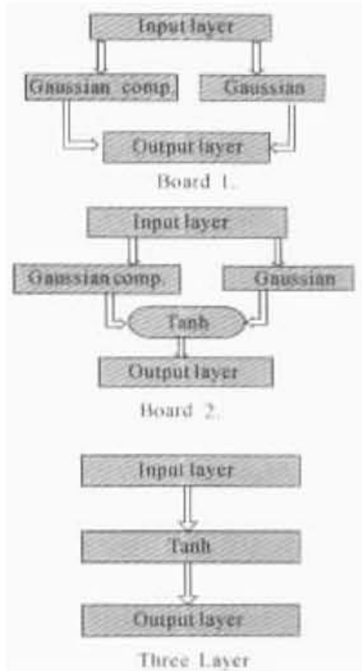

Fig. 1 The three different neural module network architecture

EXPERIMENTAL SETUP

Generally, the most informative signal readily available from an ICE comes from the in-cylinder pressure profile (Atkinson et al., 1998). Since this signal reflects the actual conditions of the engine operation, it can potentially provide a plethora of pertinent information concerning the characteristics and overall behavior of an engine. The main drawbacks to gathering this information are the invasive nature of the required sensor and the relative lack of robustness of most of such sensors. Therefore widespread adoption of the in-cylinder pressure transducer for engine control and diagnostics has not yet occurred. As a research tool, these drawbacks can be negligible as compared to the usefulness of the information provided. For this study, the pressure transducers were flush mounted in cylinders "3". The TDC position of cylinder "1" was then determined using standard methods with motoring traces recorded for closer analysis.

One selected DI diesel engine using compound fuel (ethanol-diesel) provided the data for this study. Fig. 2 and Fig. 3 are the typical pressure profile and heat release profile at 2000 r/min. And Fig. 4 shows the relationship between speed and power of this diesel engine. The data were acquired for network training purposes. For each dataset point, the engine was brought to the appropriate speed and power and allowed to reach steady state in order to prevent transience in operating conditions and to provide steady emissions production. The experiment setup is shown in Fig 5. Here the Engine Control Box consists of the dilution tunnel system, exhaust system and analyzers.

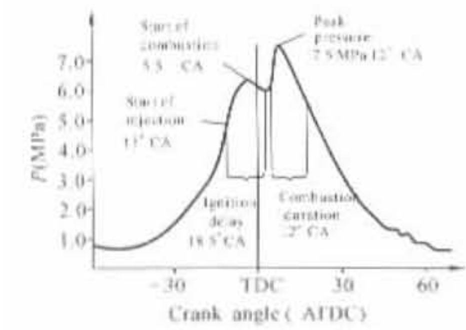

Fig. 2 In-cylinder pressure parameters taken from a (ethanol + diesel) engine 2000 r/min, 35.9 kW

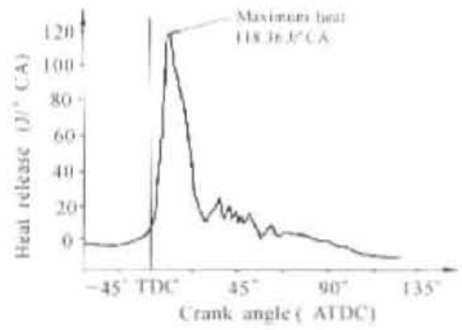

Fig. 3 Typical heat release from an (ethanol + diesel) engine, 2000 r/min

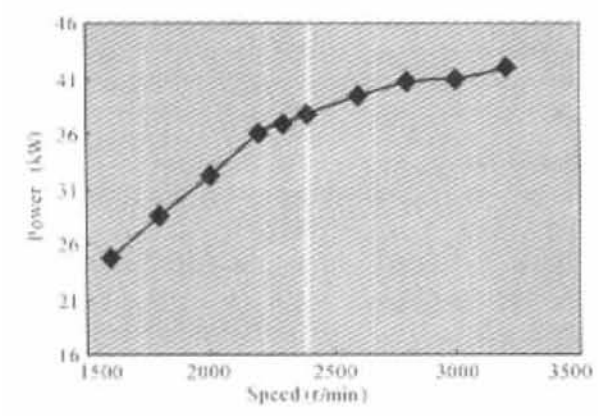

Fig. 4 Speed and power map for the (ethanol + diesel) engine

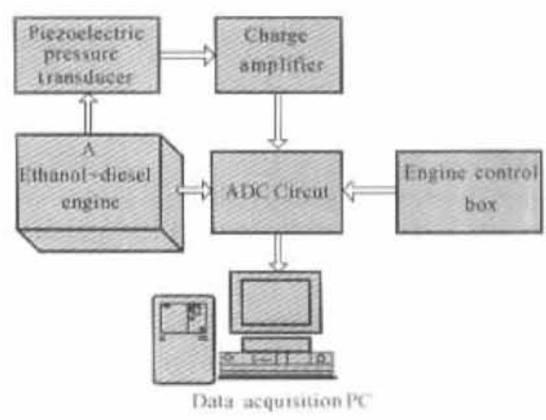

Fig. 5 Schematic of emissions measurement system for an (ethanol + diesel) engine

Once all the parameters had achieved a steady-state condition, data acquisition was initiated. After a set number of revolutions, another trigger initiated the acquisition using an ADC board. With the pressure signals from two cylinders and the top dead center (TDC) phasing signal being recorded (Watanabe et al., 1996), the ADC was capable of acquiring complete pressure histories for 64 combustion events.

Neural network selection and training

Each combustion event was analyzed and confirmed using the phasing signal after TDC. The combustion related parameters (Table 1) were taken from the pressure curves. The meaning of each parameter is shown in the Appendix. All these varibles affect the engine torgue, the specific fuel consumption and the emissions (Hafner et al., 2000). Each test point provided the 64 combustion events. All parameters were averaged for each test point and the result used to represent that point on the test matrix. Theoret-

Table 1 Variable Combinations for network inputs

Emission gas	Input variables
NO_x	PPV, CD, IMEP, ID, MBR, MHR, MP
HC	PPV, LPP, CD, ID, MHR, MP

ical considerations were given to the selection of the inputs that were to be used for training. Some inputs were chosen for their representation as direct measures of the formation rates of the gaseous emissions while others, although possessing a linear relationship with the emissions, were only loosely related to the formation rates. For instance, the peak pressure is a more or less direct measure of the in-cylinder temperatures and thus the NO_x formation rate, while the IMEP, because it reflects the amount of work being done, indicates the amount of fuel being combusted and gives a more general indication of the NO_x formed.

Hydrocarbon formation in the diesel engine is heavily influenced by the amount of oxygen available and the rate of combustion of the fuel injected. For the latter reason, MHR, combustion duration, and the peak pressure were chosen as inputs to the training networks. A misfire condition or a delayed start of combustion could be measured by a low value for the maximum heat release rate as compared to more normally high values associated with good combustion. Similarly, a very long or abnormal short combustion duration could indicate poor performance, especially in combination with the peak pressure. In either case, complete combustion is questionable and the hydrocarbon emissions should show the effect accordingly. The phasing of the pressure and volume of the cylinder have an effect on combustion and hence the location of peak pressure; and the ignition delay may indicate the combustion quality. Finally, the direct measures of possible hydrocarbon formation were considered. Since post oxidation of the fuel heavily influences the amount of hydrocarbons escaping down the exhaust pipe.

Neural Module supplies the option of applying multiple regression analysis to a dataset in order to return the statistical indicator R^2, which is defined as: $R^2 = 1 - \frac{SSE}{SS_{YY}}$, where SSE(Sum of Squares of Errors) $= \sum(y - \hat{y})$ and $SS_{YY} = \sum(y - \bar{y})^2$, where y is the actual value, $\hat{y}$ is the predicted value of y and $\bar{y}$ is the mean values of all the y's. An R^2 value was determined for both the training set and the test set data. A good network should give high results (approaching to 1.0) for both sets. These results were analyzed for the best R^2 value averaged between the test set and training set; the corresponding inputs, number of hidden-layer nodes, and architecture were recorded. Typically, the R^2 values reached a relative maximum for a given number of nodes in the hidden layer. The reason for the hidden node sweep is that there is no general theory governing the correct number of nodes necessary for good neural network prediction.

Training Results

In order to demonstrate whether variables derived from pressure profiles were more or less efficient for use in a neural network, sixty-four, thirty-two, sixteen, eight, and four pressure points taken from set intervals from the average pressure trace from each speed and power are used as input. The results of Neural Network Training are shown in Table 2.

Table 2 Network results from sets of pressure points from sampled average pressure

	Sample pressure trace				In-cylinder pressure variables			
Inputs number	Hidden neurons	R^2 test set	R^2 train set	R^2 average	Hidden neurons	R^2 test set	R^2 train set	R^2 average
NO_x								
64	40	0.9932	0.9864	0.9966				
32	20	0.9875	0.9925	0.9900				
16	16	0.9772	0.9862	0.9817				
8	12	0.9695	0.9861	0.9778				
4	10	0.9742	0.9912	0.9827	20	0.9927	0.9954	0.9941
HC								
64	40	0.9965	0.9926	0.9613				
32	20	0.9924	0.9945	0.9935				
16	16	0.9886	0.9789	0.9838				
8	12	0.9913	0.9945	0.9929				
4	10	0.9892	0.9869	0.9881	15	0.9980	0.9960	0.9975

NO_x AND HC PREDICTION RESULTS

Figs. 6, 7, 8, 9, 10 and 11 compares the network prediction results and the actual test results in different ethanol ratio from 20% to 40% at the full load state respectively. The average relative errors of HC and NO_x between predictive and actual values are 5.11%, 3.11%, 4.86%, 6.71%, 3.59%, and 6.57% respectively. That is, the predictive results and trend are in good agreement with the actual test results.

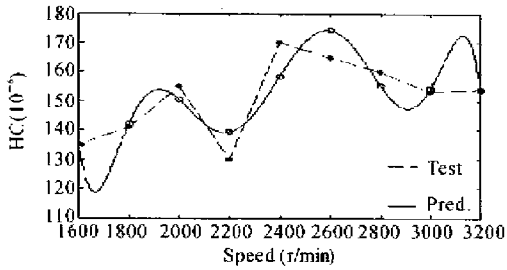

Fig. 6 HC prediction result (20% ethanol)

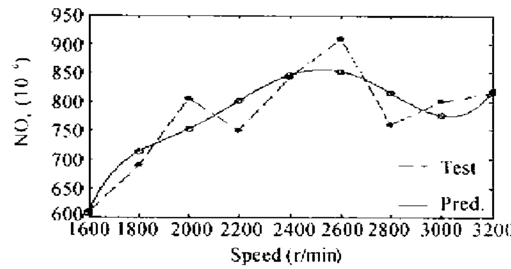

Fig. 7 NO_x prediction result (20% ethanol)

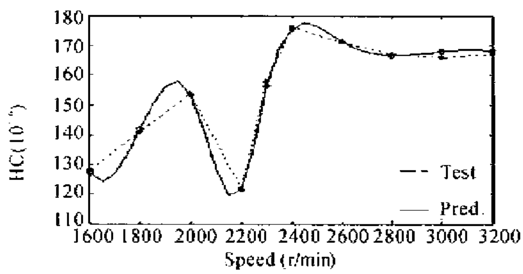

Fig. 8 HC prediction result (30% ethanol)

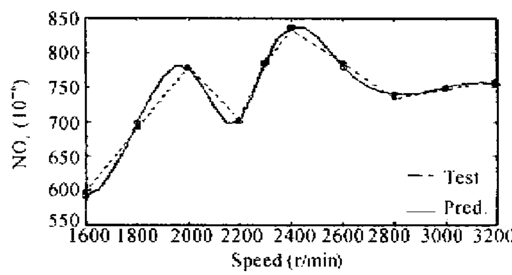

Fig. 9 NO_x prediction result (30% ethanol)

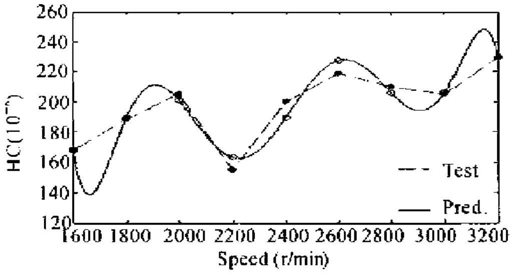

Fig. 10 HC prediction result (40% ethanol)

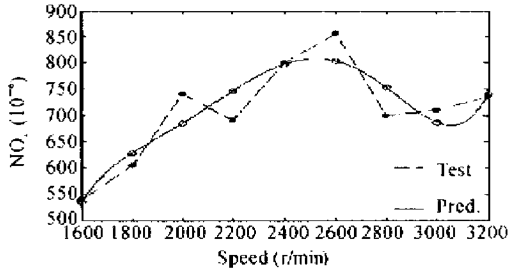

Fig. 11 NO_x prediction result (40% ethanol)

CONCLUSIONS

1. The successful prediction of the NO_x and HC by using EBP networks demonstrates the validity of the theory proposed in this paper.

2. The in-cylinder pressure information taken during steady-state operation of engine could be used successfully in the neural network to predict in cylinder NO_x and HC emissions levels. Since emissions formation is a complex function

of the in-cylinder combustion processes, these processes can be interpreted through the thoughtful use of in-cylinder pressure. The variables calculated from in-cylinder pressure have high correlation to the levels of the gaseous emissions generated. This study proved that these variables are well suited to neural network applications to predict NO_x and HC emissions levels produced by an engine.

3. This system may be as a foundation for real-time engines-out emissions sensing and prediction.

References

Atkinson, C., Long, T., Hanzevack, E. 1998. Virtual sensing: an emissions prediction system for on-board diagnostics and engine control. *SAE Paper* 980516.

Hafner, M., SchuK ler, M., Nelles, O., Isermann, R., 2000. Fast neural networks for diesel engine control design. *Control Engineering Practice* **8**: 1211 - 1221.

Haykin, S., 1994. Neural Networks: AComprehensive Foundation. Macmillan College Publishing Company, Inc., Englewood Cliffs, New Jercy.

Hornik, K., Stinchcombe, M., White, H., 1989, Neural networks. *Int. J. Control*, **2**: 359.

Nelles, O., 1997. Orthonormal basis functions for nonlinear system identification with local linear model trees (LOLIMOT). Proceedings of the 11th IFAC Symposium on System Identification (SYSID). Fukuoka, Japan, p. 667 - 672.

Raina, P., 1994. Comparison of learning and generalization capabilities of the Kak and the backpropagation algorithms. *Information Sciences*, **81**: 261 - 274.

Watanabe, S., Machida, K., Iijima, K., Tomisawa, N., 1996. A sophisticated engine control system using combustion pressure detection. *SAE Paper*: 960042.

Widrow, B., Lehr, M. A., 1990. 30 years of adaptive neural networks: Perception, Madaline, and Back propagation, *Proceedings of IEEE*, **78**(9): 1415 - 1442.

Yuan, G. J., 2000. Test Study the Performance of Emissions of Compound fuel Combustion in Diesel Engine. Thesis Requirement for the Degree of Master of Engineering, Zhejiang University.

Appendix

Combustion derived parameters

Parameter abbreviation	Explanation
PPV	Peak Pressure Value
IMEP	Indicated Mean Effective Pressure
LPP	Location of Peak Pressure
ID	Ignition Delay
CD	Combustion Duration
MBR	Maximum Burn Rate
MP	Maximum Power
MHR	Maximum Heat Release