Journal of Zhejiang University SCIENCE
ISSN 1009-3095
http://www.zju.edu.cn/jzus
E-mail: jzus@zju.edu.cn

Study of CNG/diesel dual fuel engine's emissions by means of RBF neural network*

LIU Zhen-tao (刘震涛)†, FEI Shao-mei (费少梅)

(*College of Mechanical and Energy Engineering, Zhejiang University, Hangzhou 310027, China*)

†E-mail: liuzt@zju.edu.cn

Received Oct. 8, 2003; revision accepted Dec. 18, 2003

Abstract: Great efforts have been made to resolve the serious environmental pollution and inevitable declining of energy resources. A review of Chinese fuel reserves and engine technology showed that compressed natural gas (CNG)/diesel dual fuel engine (DFE) was one of the best solutions for the above problems at present. In order to study and improve the emission performance of CNG/diesel DFE, an emission model for DFE based on radial basis function (RBF) neural network was developed which was a black-box input-output training data model not require priori knowledge. The RBF centers and the connected weights could be selected automatically according to the distribution of the training data in input-output space and the given approximating error. Studies showed that the predicted results accorded well with the experimental data over a large range of operating conditions from low load to high load. The developed emissions model based on the RBF neural network could be used to successfully predict and optimize the emissions performance of DFE. And the effect of the DFE main performance parameters, such as rotation speed, load, pilot quantity and injection timing, were also predicted by means of this model. In resumé, an emission prediction model for CNG/diesel DFE based on RBF neural network was built for analyzing the effect of the main performance parameters on the CO, NO_x emissions of DFE. The predicted results agreed quite well with the traditional emissions model, which indicated that the model had certain application value, although it still has some limitations, because of its high dependence on the quantity of the experimental sample data.

Key words: Dual fuel engine, Emission performance, RBF neural network
Document code: A **CLC number:** TK421.24

INTRODUCTION

The serious environmental pollution and the energy crisis all over the world has caused the development of the lower pollution and lower energy consumption automobile to become major research goal. An engine using compressed natural gas (CNG) as fuel has outstanding advantages of higher efficiency and lower pollution. The CNG/diesel DFE for the city bus could also obviously reduce the pollution of the city air, especially for the big cities. So the research on the combustion process of DFE, especially the emissions performance, was very important and valuable (Liu, 2000; Yan *et al*., 2003; Fei *et al*., 2003).

In general, the combustion process and mechanism of the engine involved the physico-chemical synthesize process (Yan and Kriam, 1992). Due to their complexity and instantaneity, there was no suitable analytic function to describe the combustion process, especially for the DFE. In this paper a new emissions model based on radial basis function (RBF) neural network is proposed for the CNG/diesel DFE.

* Project (No. 50106014) supported by the National Natural Science Foundation of China

THEORY OF THE RBF NEURAL NETWORK

Structure of RBF neural network

The neural network, especially RBF neural network has become popularity in recent years due to its excellent recognition and prediction capabilities. Radial basis function $\boldsymbol{\Phi}(\cdot)$ was the basis of RBF neural network, and usually was a nonlinear radial symmetrical function (Zhou *et al.*, 2001; Korres *et al.*, 2002; Ilkivová *et al.*, 2002; Kaoru *et al.*, 2003). The Gauss function is the core function of the radial basis function; and has two vector parameters $\boldsymbol{X}$ and $\boldsymbol{C}$; with $\boldsymbol{X}$ being the independent variable vector of the function, and $\boldsymbol{C}$ being the core of the radial basis function. $\boldsymbol{X}$–$\boldsymbol{C}$ forms an ellipse with $\boldsymbol{C}$ being the center and $\boldsymbol{\Phi}(\boldsymbol{X}-\boldsymbol{C})$ being the radius function of the ellipse. The neural network using RBF as neurons function is called RBF neural network.

RBF neural network includes three layers, the first layer is the input layer whose elements conform to the quantity of the input parameters; the second layer is the hidden layer consisting of many radial basis function neurons; the hidden layer nodes are calculated from the Euclidean distance between the center and the network input vectors and then the results are passed on to the radial basis functions; the last layer is the output layer made up of common linear neurons. The RBF neural network structure is shown in Fig.1 (Omatu and Khalid, 1996).

This model has $\boldsymbol{R}$ input and $\boldsymbol{P}$ output, with the relationship between the input and output in this model being as follows (Omatu and Khalid, 1996):

$$f_j(x) = \sum_{i=1}^{M} w_{ij}\boldsymbol{\Phi}(\| \boldsymbol{X} - \boldsymbol{C}_i \|) \qquad (1)$$

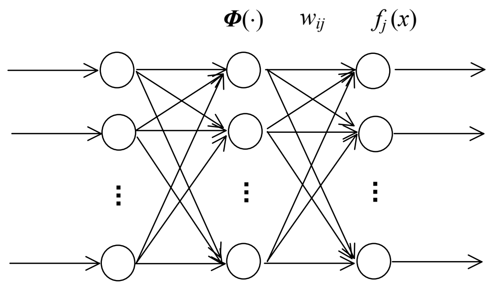

Fig.1 Structure of RBF neural network

where $\boldsymbol{X}$–input vector; $\boldsymbol{C}_i$ – the center of RBF neural network, a constant vector with the same dimension as $\boldsymbol{X}$; $\boldsymbol{R}$–the dimension of the input vector; M–neurons number of the hidden layer; $\boldsymbol{\Phi}(\cdot)$–radial basis function; $\| \boldsymbol{X} - \boldsymbol{C}_i \|$–Euclidean distance between $\boldsymbol{X}$ and $\boldsymbol{C}_i$; j–output node, j=1,2,…,P; w_{ij}–the weight value which connected the i hidden node with the j output node.

Operational principle of RBF neural network

The network structure is shown in Fig.1; where input vector $\boldsymbol{X}=[a_1, a_2, \ldots, a_N]$, ideal output y_j (j=1,2, …,P), the actual output $\hat{y}_j$ and the weight value of the output layer w_{ij} can be obtained by the RBF neural network which has $\boldsymbol{R}$ as input, M hidden nodes and $\boldsymbol{P}$ output. Choosing Gauss function $\boldsymbol{\Phi}(x)=\exp(-\lambda x^2)$, $\lambda=3$ as radial basis function, the actual output $\hat{y}_j$ is calculated by the following formula:

$$\begin{aligned} \hat{y}_j &= \sum_{i=1}^{M} w_{ij}\boldsymbol{\Phi}(\| \boldsymbol{X} - \boldsymbol{C}_i \|) \\ &= \sum_{i=1}^{M} w_{ij}\exp(-\lambda \| \boldsymbol{X} - \boldsymbol{C}_i \|^2) \end{aligned} \qquad (2)$$

Then, the weight value w_{ij} is adjusted to satisfy the following formula, from which the final result of the RBF neural network can be obtained.

$$\begin{aligned} E &= \sum_{j=1}^{P} (y_j - \hat{y}_j)^2 \\ &= \sum_{j=1}^{P} \left(y_j - \sum_{i=1}^{M} w_{ij}\boldsymbol{\Phi}(\| \boldsymbol{X} - \boldsymbol{C}_i \|) \right)^2 \le E_0 \end{aligned} \qquad (3)$$

DEVELOPMENT OF THE EMISSIONS MODEL BASED ON RBF NEURAL NETWORK

Development of the model

Because of the limited experiment units, the quantity of the HC part of CH_4 could not be obtained, so the model only included the CO, NO_x emission. The structure of the model is shown in Fig.1. The relationship between the input and output in this model was as follows:

$$(\mathrm{CO}, \mathrm{NO}_x) = \Phi(n, G_g, G_m, \theta) \qquad (4)$$

where (CO, NO_x)–the quantity of CO, NO_x emissions ($\times 10^{-6}$); n–rotation speed (r/min) varying from 794 r/min to 2814 r/min; G_g–quantity of natural gas (butterfly valve open %) varying from 15 % to 85 %; G_m–pilot (kg/h) varying from 1.1 kg/h to 4.8 kg/h; θ–injection timing (°CA) varying from 15 °CA to 20 °CA.

The input layer nodes' number was chosen to be the same as that of the input parameters, R=4, the output layer nodes' number which was the same as that of the output parameters, P=2, and E_0 was set to 0.15%. The training data were obtained from the test, and the specifications of the test engine are given in Table 1. There were 100 groups experimental data over the operation conditions from light load and low rotate speed to heavy load and high rotate speed using for training the RBF neural network, and 20 group test data over the large range operation conditions using for verifying the model. After training the network using the experimental data, the sum-squared error could reach up to predicted 0.15% precise after about 15000 cycles, the convergence of the weights was shown in Fig.2. And the hidden layer nodes' number M also confirmed, where the hidden layer nodes' number was 11.

Table 1 Specifications of the test engine

Type	6108
$D\times S$	108 mm×125 mm
Capacity	6.87 L
Compression ratio	16
Injection timing	18 °CA ± 2 °CA
Rated power/rotation speed	112 kW/2800 r/min

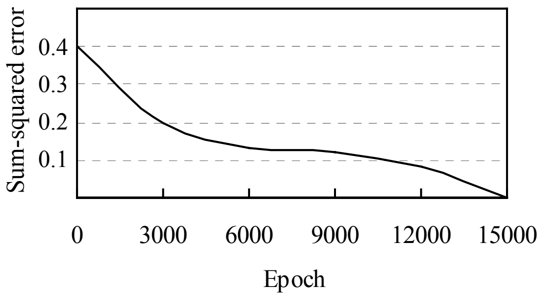

Fig.2 Convergence of the weights

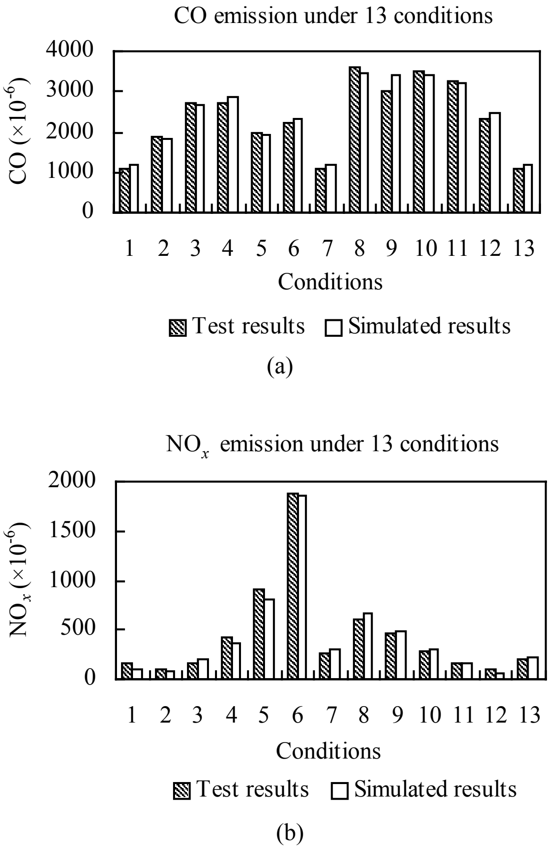

Fig.3 Comparison of simulated results with test results
(a) CO emission; (b) NO_x emission

Verification of the model

The model was also verified on a dual fuel engine with specifications: $D\times S$=108 mm×125 mm, rated power/rotation speed=112 kW/2800 r/min. Fig.3 showing that the simulated results and test results for CO, NO_x emissions under 13 operating conditions were in good agreement indicated that the model can be used to predict the CO, NO_x emissions of DFE.

PREDICTION OF CO, NO_x EMISSIONS BY MEANS OF THE MODEL

The purpose for developing this model was to use it to predict the CO, NO_x emissions of the DFE. The following were the effects of several main operating parameters variation on the CO, NO_x emissions by means of the model.

Effect of rotate speed

Fig.4 on variation of CO, NO_x emissions with rotate speed under certain conditions (G_m=2.5 kg/h, θ=18 °CA, G_g=25%) shows that CO emission increased with increase of rotate speed. This occurred as with shortening of combustion time, CO could not be oxidated completely by increasing rotate speed. However, the NO_x emission was decreased with increasing rotate speed. This was due to the early decrease in heat output and the reduction in the cylinder due to the increase of rotate speed. Therefore the time and temperature of the nitrogen in it was shortened and lowered, so the NO_x emission was reduced.

Effect of CNG quantity

The effect of the CNG quantity on the CO and NO_x emissions are shown in Fig.5 under certain condition (n=2800 r/min, G_m=2.5 kg/h, θ=18 °CA). The effect of the CNG quantity had the same effect as that engine load, so here the engine load is used to show the effect of the CNG quantity. Increasing CNG quantity increased the quantity of heat output and the maximum temperature in the cylinder. Therefore, the combustion process finished adequately, so the CO emission was reduced and the NO_x emission was increased.

Effect of pilot

Fig.6 on the effect of pilot quantity on CO, NO_x emissions under light load condition (n=1700 r/min, G_g=25%, θ=18 °CA) shows that variation of the NO_x emission was not obvious even increasing quantity of pilot, but that the CO emission was reduced, because the quantity of natural gas in the cylinder was little under light load, so even the quantity of pilot, the early heat output and the increase in the maximum temperature in the cylinder, varied the NO_x emission little; but the CO emission was reduced due to the intense oxidation of NO_x.

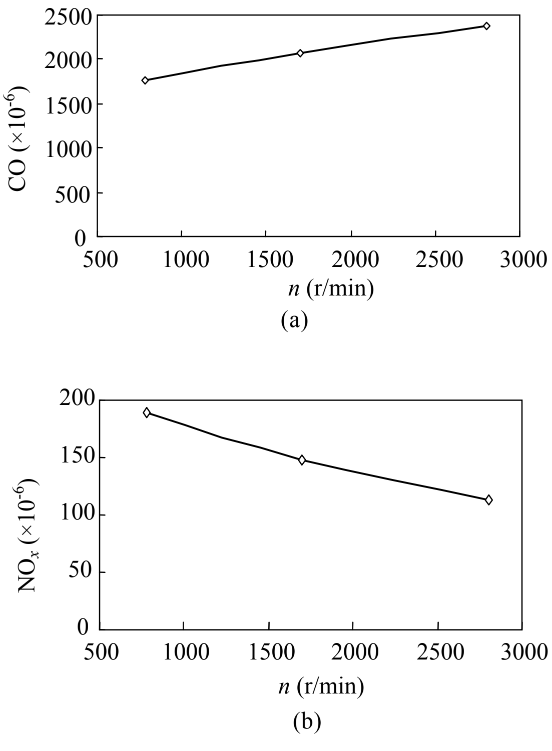

Fig.4 Effect of rotate speed on (a) CO emission and (b) NO_x emission

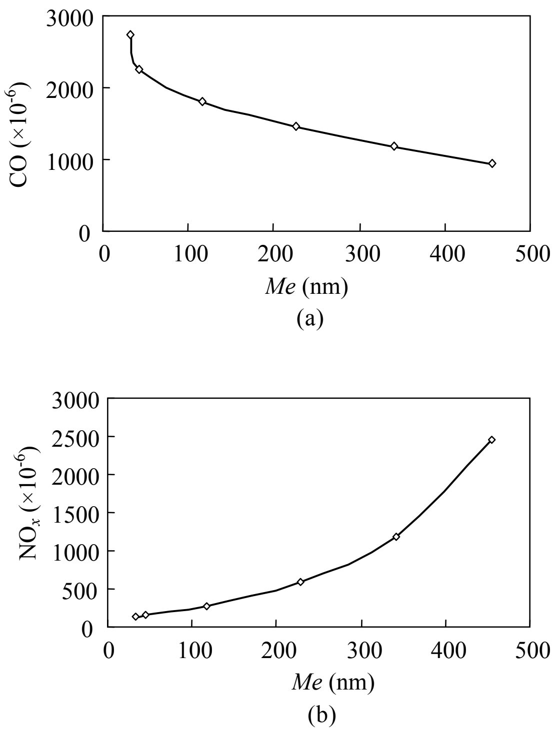

Fig.5 Effect of G_g on (a) CO emission and (b) NO_x emission

Fig.7 on the effect of pilot quantity on CO, NO_x emissions under heavy load (n=1700 r/min, G_g=75%, θ=18 °CA) shows that the CO emission was less than that under light load but that the NO_x emission was much higher than that under light load. With increase in the quantity of pilot and the natural gas in the cylinder, the CO emission was reduced and the NO_x emission was increased due to the increasing of the ignition energy and the gross heat output.

Effect of injection timing

Fig.8 on the effect of injection timing on the CO, NO_x emissions under light load (n=1700 r/min, G_g=25%, G_m=2.5 kg/h) shows that with increasing of injection timing, the CO emission and NO_x emission were not monotonously increased or reduced. It meant that there was optimal injection timing for the lowest CO, NO_x emissions under light load. The same results could be seen in Fig.9 under heavy load condition (n=1700 r/min, G_g=85%, G_m=2.5 kg/h). Simulated results (Fig.8 and Fig.9) showed 16 °CA was the optimal injection timing in this DFE.

CONCLUSION

1. An emission prediction model for CNG/ diesel dual fuel engine based on RBF neural network was built for analyzing the effect of the main parameters on the CO, NO_x emissions of DFE. The simulated results agreeing quite well with the traditional emissions model indicates that the model has certain application value.

2. Verification of the model also proved that the simulated results showed good agreement with the test data. Therefore the model can be proposed as theoretical foundation for predicting the performance and emissions. In practice the model can be used as an important method for improving and optimizing parameters of the DFE.

3. The model still has limitations, because it is highly dependent on the number of the experimental sample data.

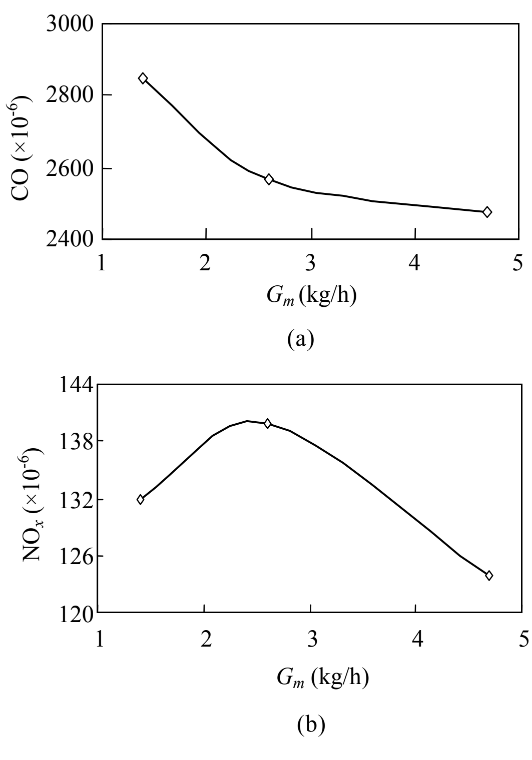

Fig.6 Effect of quantity of pilot under light load on (a) CO emission and (b) NO_x emission

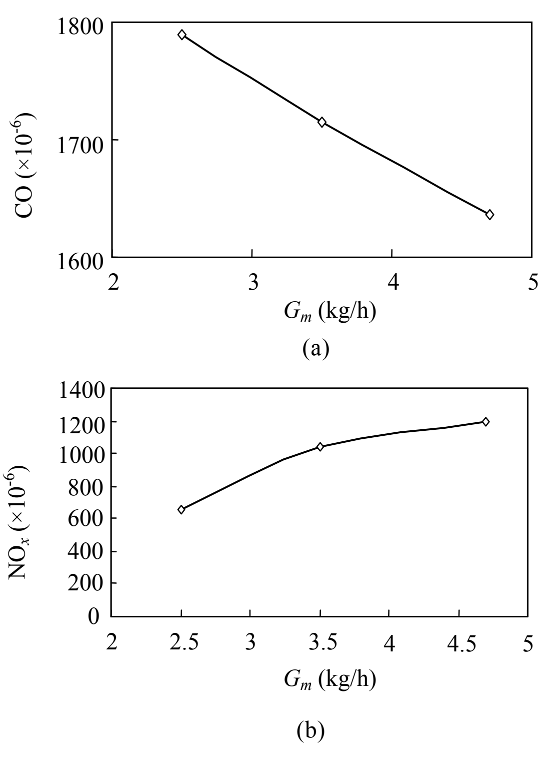

Fig.7 Effect of quantity of pilot under heavy load on (a) CO emission and (b) NO_x emission

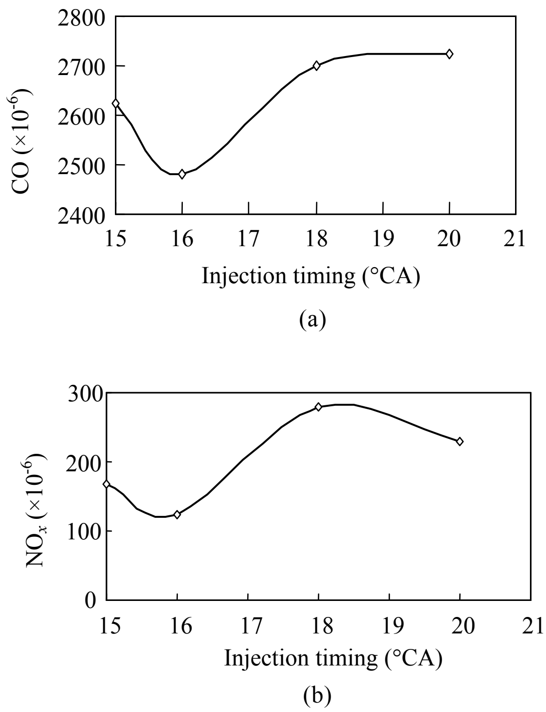

Fig.8 Effect of injection timing under light load on (a) CO emission and (b) NO$_x$ emission

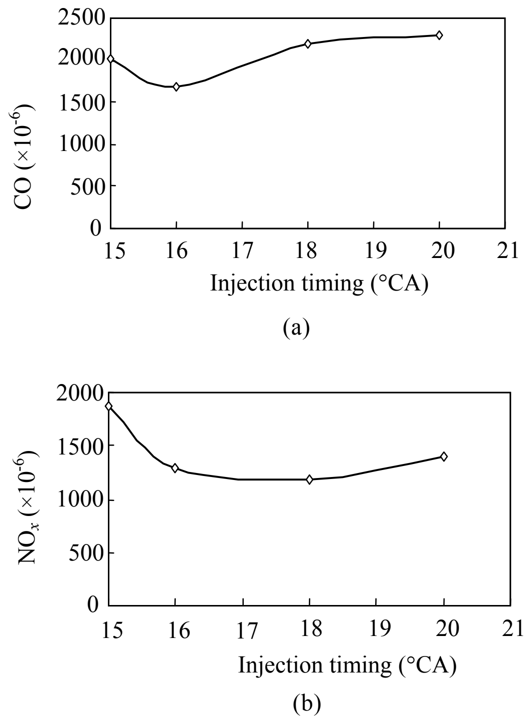

Fig.9 Effect of injection timing under heavy load on (a) CO emission and (b) NO$_x$ emission

References

Fei, S.M., Liu, Z.T., Yan, Z.D., 2003. Knock prediction for dual fuel engines by using a simplified combustion model. *Journal of Zhejiang University SCIENCE*, **4**(5):591-594.

Ilkivová, M.R., Ilkiá, B.R., Neuschl, T., 2002. Comparison of a linear and nonlinear approach to engine misfire detection. *Control Engineering Practice*, **10**:1141-1146.

Kaoru, I., Youji, I., Hajime, M., 2003. Image restoration using the RBF network with variable regularization parameters. *Neurocomputing*, **50**:177-191.

Korres, D.M., Anastopoulos, G., Lois, E., Alexandridis, A., Sarimveis, H., Bafas, D., 2002. A neural network approach to the prediction of diesel fuel lubricity. *Fuel*, **81**:1243-1250.

Liu, Z.T., 2000. A Study of Combustion and Control Model of Natural Gas-Diesel Fuel Engine by Means of Neural Network. Ph.D thesis, Zhejiang University (in Chinese).

Omatu, S., Khalid, M., 1996. Neuro-control and its Applications. Springer-Verlag, London.

Yan, Z.D., Kriam, G.A., 1992. A predictive model for dual fuel D. I diesel engine performance and emission. *ASME*, **27**:33-39.

Yan, Z.D., Zhou, C.G., SU, S.C., Liu, Z.T., Wang, X.Z., 2003. Application of neural network in the study of combustion rate of natural gas/diesel dual fuel engine. *Journal of Zhejiang University SCIENCE*, **4**(2):170-174.

Zhou, B., Tan, D.M., Wei, D.Y., 2001. Prediction of the Emissions from internal combustion engine using a neural network. *CSICE*, **4**(2):361-364.