

A Wavelet Neural Network Method to Determine Diesel Engine Piston Heat Transfer Boundary Conditions

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ABSTRACT

This paper presents a method of calculating temperature field of the piston by using a wavelet neural network (WNN) to identify the unknown boundary conditions. Because of the complexity of the heat transfer and limitations of experimental conditions of heat transfer analysis of the piston in a diesel engine, boundary conditions of the piston temperature field were usually obtained empirically, and thus the result itself was uncertain. By employing the capability of resolution analysis from a wavelet neural network, the method obtains improved boundary heat transfer coefficients with a limited number of measured temperatures. Using FEA software iteratively, results show the proposed wavelet neural network analysis method improves the prediction of unknown boundary conditions and temperature distribution consistent with the experimental data with an acceptable error.

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INTRODUCTION

The piston is one of the main components heated in a diesel engine. It contacts directly with high temperature gases, and bears the alternative heat load and mechanical load. It works under the conditions of high temperature, high pressure and high speed. Therefore, it is of great importance to calculate the temperature field of the piston accurately for its optimized design when thermal stress and heat distortion of the piston were taken into account [1]. However, the values of temperature at limited points can only be measured during the calculation of the temperature field of a piston due to uneven heat, too large of a temperature gradient, the piston structural restriction and experimental conditions. Since the 1970's, computer science and technology have advanced rapidly and hence heat conduction problems were generally solved by using numerical methods such as the finite element method [2,3], the finite difference method [4], the boundary element method [5], sequential method [6], etc. The key of numerical simulation is how to obtain boundary conditions close to the real values. Based on the approaching ability of WNN, this paper studies the determination of multi-region heat transfer coefficients and the calculation of the temperature field of a heated piston under third class boundary conditions.

Recent years witnessed the rapid development of artificial neural network technology which has been recently adopted to predict the performance of various thermal systems [7, 8].

Artificial neural networks are artificial intelligence systems which mimic the biological processes of a human brain. It uses non-linear processing units to simulate the functions of biological neurons and variable connection strength among processing units to mimic the synaptic behavior of the human brain. These processing units connect together in a certain form to form a network which shows features of high dimensionality, self-organizing fussiness, and self-learning capabilities [9]. Therefore, it can be applied to solve the inverse heat conduction problems by training the network with multiple samples of temperature distribution data which is obtained from forward heat conduction problems [10]. As a result, the actual network outputs can approximate the target values closely by adjusting the weights of the individual nodes.

The thought of this paper is: first perform a forward analysis using a numerical method such as the finite element method, then an inverse heat conduction problem model is established via a three-layered WNN from which the results of the forward analysis are taken as the input and output of the WNN and training the WNN. The fully trained neural network then is used to predict an unknown output under the conditions of a group of specified inputs.

1. THE WNN AND THE NETWORK MODEL EMPLOYED

WNN is a neural network that transmits signals forward and receives feedback from the deviation in a reversed way at the same time. Because wavelet transform has good ability of time-frequency localization, it is able to focus on the arbitrary details in terms of time field and frequency field, by adjusting the shift factor and scale factor of the wavelet basis function. Therefore, we can select wavelet basis function as the transfer function for nodes of hidden layer, revise network weights constantly, and obtain outputs that approach expectations. The topological structure of WNN is shown in [Figure 1](#).

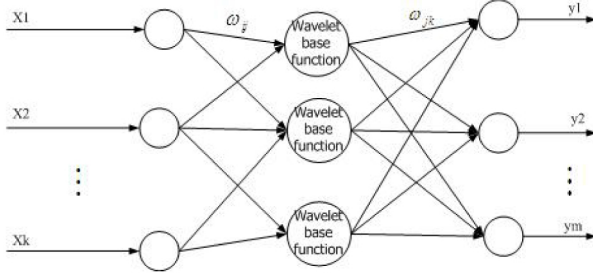


Figure 1. The WNN topological structure.

In [Figure 1](#), $x_1, x_2, \dots, x_k$ are inputs of the WNN, $y_1, y_2, \dots, y_m$ are expected outputs of the WNN, ω_{ij} and ω_{jk} are weights of the WNN. When the signal sequence of input is x_i ($i = 1, 2, \dots, k$), the calculating formula of outputs for hidden layer is:

$$h(j) = h_j \left[\sum_{i=1}^k \omega_{ij} x_i - b_j / a_j \right] \quad j = 1, 2, \dots, l \quad (1)$$

Where, $h(j)$ is output of the j 'st node of hidden layer; ω_{ij} is connection weight between input layer and hidden layer; b_j is shift factor of the wavelet basis function h_j ; a_j is scale factor of the wavelet basis function h_j ; h_j is wavelet basis function and l is number of hidden nodes. The calculation formula of the WNN is:

$$y(k) = \sum_{j=1}^m \omega_{jk} h(j) \quad k = 1, 2, \dots, m \quad (2)$$

Where, ω_{jk} is a connection weights between input layer and hidden layer; $h(i)$ is the output of the i 'st node of hidden layer, m is the number of nodes of output layer. The WNN revises the weights of network and the parameters of wavelet basis function via a gradient revise method, and the revising process is shown as follows.

(1). Computing the predicted errors of the network:

$$e = \sum_{k=1}^m y_n(k) - y(k) \quad (3)$$

Where, $y_n(k)$ is the expected output, $y(k)$ he predicted output of the wavelet neural network.

(2). Revising the weights of the WNN and coefficients of wavelet basis function according to the predicted error.

$$\omega_{n,k}^{(i+1)} = \omega_{n,k}^i + \Delta \omega_{n,k}^{(i+1)} \quad (4)$$

$$a_k^{(i+1)} = a_k^i + \Delta a_k^{(i+1)} \quad (5)$$

$$b_k^{(i+1)} = b_k^i + \Delta b_k^{(i+1)} \quad (6)$$

Where, $\Delta \omega_{n,k}^{(i+1)}$, $\Delta a_k^{(i+1)}$, $\Delta b_k^{(i+1)}$ are obtained respectively from network predicted errors, and

$$\Delta \omega_{n,k}^{(i+1)} = -\eta \partial e / \partial \omega_{n,k}^{(i)} \quad (7)$$

$$\Delta a_k^{(i+1)} = -\eta \partial e / \partial a_k^{(i)} \quad (8)$$

$$\Delta b_k^{(i+1)} = -\eta \partial e / \partial b_k^{(i)} \quad (9)$$

Where, η is the learning rate [11].

2. EXAMPLE ANALYSIS OF THE PISTON HEAT TRANSFER

2.1. Mechanism and Implementation Steps of the Piston Heat Transfer

Heat transfer process in the cylinder of the diesel engine can be divided into three steps: First, combustion takes place in the cylinder and heat energy is released; second, convective heat transfer takes place between the gas in the cylinder and the solid firmware (cylinder cover, the cylinder body and piston group - cylinder sleeve), followed by heat conduction through the piston body and the cylinder walls; and last, cooling through coolant (cyclic cooling water, lube). The poor working environment of the piston makes cooling especially important. Cooling process of piston is described as follows: The heat energy obtained from fuel gas flows from the piston head to the piston ring then to cylinder sleeve and is finally cooled down by cooling water in the cylinder sleeve.

In the calculation of the temperature field for the heat transfer conduction through the piston body, the key is how to determine the heat transfer coefficient of each region. Hardness plug temperature-measuring method [12-13] can only measure the temperature of a finite number of points. However, by this method, as mentioned above, we are able to seek the optimal boundary conditions through the WNN

Table 1. Average temperature of the piston different parts

Position	Temperature (°C)	Position	Temperature (°C)
Combustion chamber vertex	355	Combustion chamber throat and mouth	350
Combustion chamber bottom	277	Piston top internal/external	350/340
The second ring shore	220	Firepower shore	325
Piston skirt central	117	Piston skirt upper	167
Piston back	290	Piston skirt lower	108

structure according to some measured data, and then get the temperature field distribution of a piston.

In the process of obtaining heat transfer boundary, we need a large amount of data. In order to obtain a large number data to train the network, we can use finite element analysis software-ANSYS to do the simulation. The implement steps are as follows:

Step 1: Build up the model according to the dimensions of the piston and parameters of the material from which it was built. Calculate and save the corresponding temperature of each measuring point in hardness plug temperature-measuring method under the conditions of the fixation of the heat transfer temperature for the borders of each region, and the variation of heat transfer coefficients from different groups.

Step 2: Train the network for 100 times. The training is based on the input and output data of the neural network which comes from temperatures of each measuring point and the corresponding heat transfer coefficients of each region, respectively.

Step 3: Input the measured temperature data to the trained network, and predict the heat transfer coefficients of each region from the trained network.

Step 4: Calculate the temperature of measuring points under the heat transfer coefficients by ANSYS software and analyze its results.

2.2. Obtaining Thermal Boundary Conditions

The data obtained from the bench experiment using hardness plug temperature-measuring method in a certain type of diesel engine are listed as follows:

- Internal average temperature of the combustion chamber is 873.24°C, which is the average of data obtained from the AVL calibration graph;
- Distal temperature of the cooling water is about 94°C, which is measured from the bench experiment;
- The oil temperature of cooling tube is about 117°C;
- The air temperature in the crankcase is about 108°C;

The distribution of the measured points in the hardness plug temperature-measuring method is shown in [Figure 2\(a\)](#) and [Figure 2\(b\)](#), and the measured results are shown in [Table 1](#), which are the average of measured data.

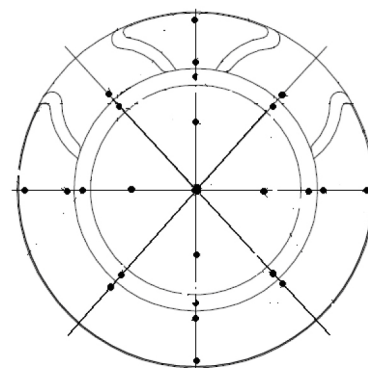


Figure 2(a). Hardness plug measure points distribution-top view.

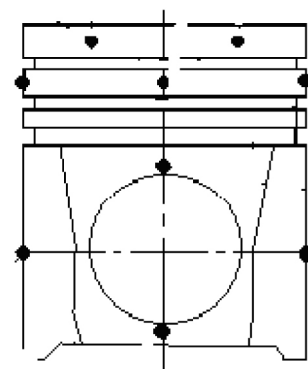


Figure 2(b). Hardness plug measure points distribution-front view.