Prediction of Thermal Conductivity of Nanofluid Refrigerant based on BP Neural Network and RBF Neural Network

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Abstract

At present, BP or optimized BP Shenten network algorithm is widely used in the prediction of thermal conductivity of nano-fluid refrigerant, which has the problems of single optimization algorithm, large prediction error and lack of comparison between two or more optimization algorithms.Based on the previous experiments, considering influence coefficient of thermal conductivity of nano fluid temperature, volume fraction, refrigerant liquid density, nanoparticles grain of the related factors, and historical data, using a mentor learning of BP and RBF neural network is constructed for different input parameters under the condition of nano fluid refrigerant thermal conductivity model.The test results show that the prediction model of neural network algorithm achieves certain prediction accuracy under different input parameters.

Keywords

Neural Network; Nanometer Refrigerant; Prediction Model.

1. Introduction

In the field of industry, heat conduction is a very important heat transfer mode.Many physical properties of the fluid, such as the type of fluid, Reynolds number, density, and the addition of nanoparticles, will affect the thermal conductivity of the material. In recent years, a number of nanofluid refrigerants have been developed by researchers. Because of the uncertainty of the influencing factors of the fluid thermal conductivity, if you want to get the thermal conductivity of a material under various conditions, it generally needs to rely on a large number of experiments.The experimental data is accurate, but it will consume a lot of human and material resources. Therefore, the thermal conductivity of nanofluids under different conditions can be predicted by combining the physical property information of fluids to quickly obtain the thermal conductivity of nanofluids, which can provide a powerful data basis for other experiments or simulation tests at a low cost, and achieve greater economic and social benefits.

At present, many domestic or using the algorithm of BP neural network combined with numerical optimization algorithm and RBF neural network for nano fluid thermal physical property prediction, and achieved some results, but mostly adopt single method combined with the optimization of the network itself to its prediction model established, the lack of using these two algorithms to the predicted results of the comparative study, the forecast error is relatively large.In response to the above problems, In this paper, considering temperature, volume fraction, refrigerant base liquid density, related factors of nanoparticles and historical experimental data, the BP neural network algorithm learned by the tutor, genetic algorithm, RBF and K-means clustering algorithm -- GA-BP, RBF and K-means BP were used to construct the nanoflow under different input parameters.Model of thermal conductivity of bulk refrigerant.

2. Method

According to the connection mode, neural network can be roughly divided into four categories: forward neural network, feedback neural network, random neural network, self-organizing neural network. According to the learning mode, it can be divided into learning neural network with tutor and learning neural network without tutor.According to the function to be realized, it can be divided into fitting neural network and regression neural network.Among the forward-type neural networks, BP neural network is the most classic and mature one, which has the following advantages:

1. In essence, network realizes a mapping function from input to output, and mathematical theory has proved that it has the function of realizing any complex nonlinear mapping.

This makes it particularly suitable for solving problems with complex internal mechanisms;

2. The network can automatically extract "reasonable" solving rules by learning the instance sets with correct answers, that is, it has self-learning ability;

3. The network has certain ability of promotion and generalization.

So this paper chose this neural network, BP neural network.

The work of neural network is mainly divided into two stages:

1. Learning stage: the connection weights between neurons are modified and adjusted according to certain learning rules, with the purpose of making the training of network achieve the desired effect.

The learning stage can also be divided into two steps: propagation and weight correction;

2. Working stage: after learning in the previous step, the network neurons store and remember the network structure and network parameters determined after learning, and they can keep the same.

Substituting the network input into the trained network will get the corresponding network output.

2.1 BP neural network

Artificial neuron model:

First, enter X1, X2...XN to simulate each synaptic part of the neuron, and these input data will become the data used by the whole neural network for learning. W_{ix} is the weight of the connection when data is entered.In the middle is the mapping function, which realizes the process of transforming the input into the output. In this part of operation, two parts are involved. The $\sum$ part acts as a weighted sum and is used to compute the product of the input and the weight and sum:

$$\mathrm{net_i} = \sum_{j=1}^{n} w_{ij}x_j - \theta \tag{1}$$

Where, net_i represents the expression value of the ith neuron in the internal neuron, which is the product of the input weight w_{ij} of the Jth neuron and the input value x_j, and $-\theta$ is obtained by multiplying the input weight X_0 with its weight.

The other part, as a function, maps the weighted sum and neti to get the output Y_i, whose equation is as follows:

$$\mathrm{y_i} = \mathrm{f(net_i)} \tag{2}$$

Its working mode diagram is shown in Figure 1:

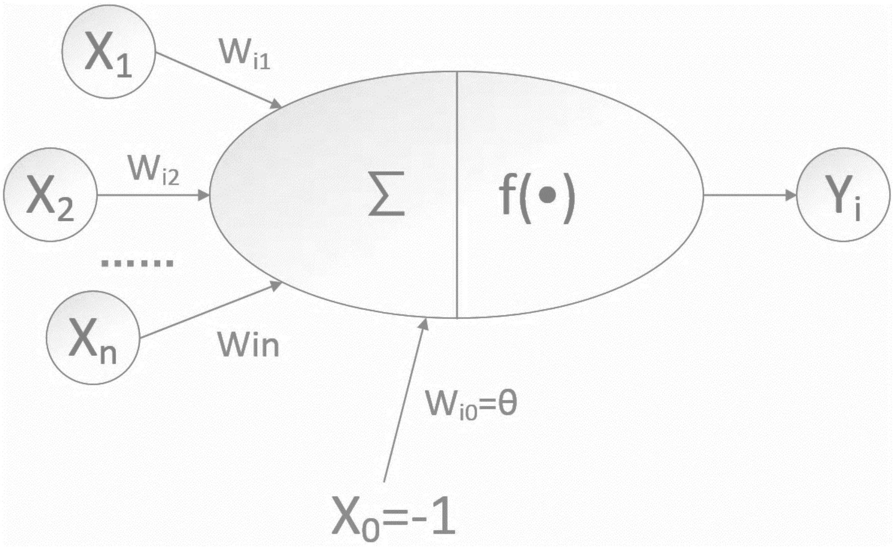

Figure 1. The working mode of BP neural network neurons

The negative feedback learning structure is shown below.

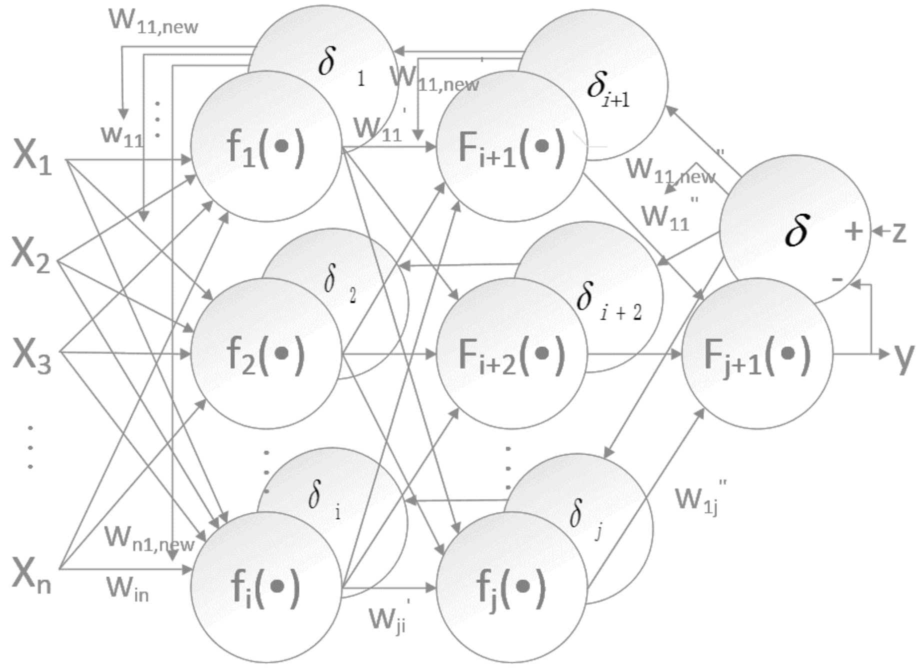

Figure 2. Negative feedback learning structure diagram

2.2 Radial basis function neural network

Compared with BP neural network, radial basis function neural network is still a forward neural network. The difference between it and BP neural network lies in the process of RBF training.The weight of the connection between the hidden layer and the input layer is not determined randomly, but by a fixed way.RBF neural network is a neural network with single hidden layer. We create a following RBF neural network to train it.

Radial basis neuron node activation function adopts radial basis function, which usually defines the monotone function of Euclidean distance between any point in space and a certain center as the activation function.In a neuron model to the distance between the input vector and threshold vector | | X - Cj | | as the independent variables.

Firstly, a certain number of points in the samples used for training were selected as h center C_h of the radial basis function by clustering method.In one of its neurons, a distance is first calculated from the selected center point, and the weight of the calculated distance is calculated by the activation function.N activation functions are selected, and each activation function corresponds to a training data. Gaussian function is taken as its activation function:

$$\mathrm{f(x)} = \mathrm{a}e^{-(x-b)^2/2c^2} \tag{3}$$

Where a,b,c are real constants,Enter the magnitude of the difference vector in the activation function:

$$x=\|X-X^n\| \tag{4}$$

Adjustment of center point of radial basis function,

$$\triangle \mathrm{c}_j = \eta \frac{w_j}{\delta_j^2} \sum_{i=1}^{p} E_i e^{-\frac{1}{2\sigma^2}\cdot||X_i - C_j||} \cdot (X_i - c_j)) \tag{5}$$

Variance adjustment:

$$\triangle \delta_j = \eta \frac{w_j}{\delta_j^3} \sum_{i=1}^{p} E_i e^{-\frac{1}{2\sigma^2}\cdot||X_i - C_j||} \cdot ||X_i - c_j||^2 \tag{6}$$

Adjustment of connection weight between hidden layer and output layer:

$$\triangle w_j = \eta \sum_{i=1}^{p} E_i e^{-\frac{1}{2\sigma^2}\cdot||X_i - C_j||} \tag{7}$$

3. Experimental databank

Neural network needs a lot of relevant experimental data to learn, so as to get the best connection weight to connect two adjacent neurons.In this paper, a total of 337 data from 10 literatures are selected, and the data sources are as follows:

Table 1. Ranges of the variables of collected experimental databank.

Dp[a]	ω[b]	T[c]	ρ[d]	λ[f]	n[g]	Reference
30	0-2	284.52-304.05	553	0.069-0.135	22	Ref1[1]
15-80	0-1	273.15	553	0.06382-0.15004	59	Ref2[2]
20	0.02-0.34	300	424-511.8	0-3.5	108	Ref3[3]
15-80	0.1976-0.9991	300	322	1.06-2.04	20	Ref4[4]
10-100	0.01-7.5	300	560	7-150	17	Ref4[4]
50-100	0.5-2	293.15-313.15	322	1.16-1.45	20	Ref5[5]
20	44201	300-320	511.9	0.1-0.129	30	Ref6[6]
13	0.5-2	293.15	458.5	0.1-0.15	16	Ref7[7]
20	44201	300	511.9	1.1-1.42	20	Rref8[8]
5-25	44201	300	511.9	1.03-1.46	25	Ref9[9]

a Nano particle diameter (nm).

b Weight percent of nanoparticle in nanofluid(%).

c Temperature(K).

d The critical density of the base fluid (m^2/s).

e Thermal conductivity of refrigerant($W/(m^2 \cdot K)$).

f Thermal conductivity of nanorefrigerant($W/(m^2 \cdot K)$).

g Number of experimental data.

4. Results

In the figure below, we used the RBF neural network to predict the convective heat transfer coefficient. In this prediction, we learned all the data including the predicted data, and then predicted the six data points, and the predicted results were as follows:

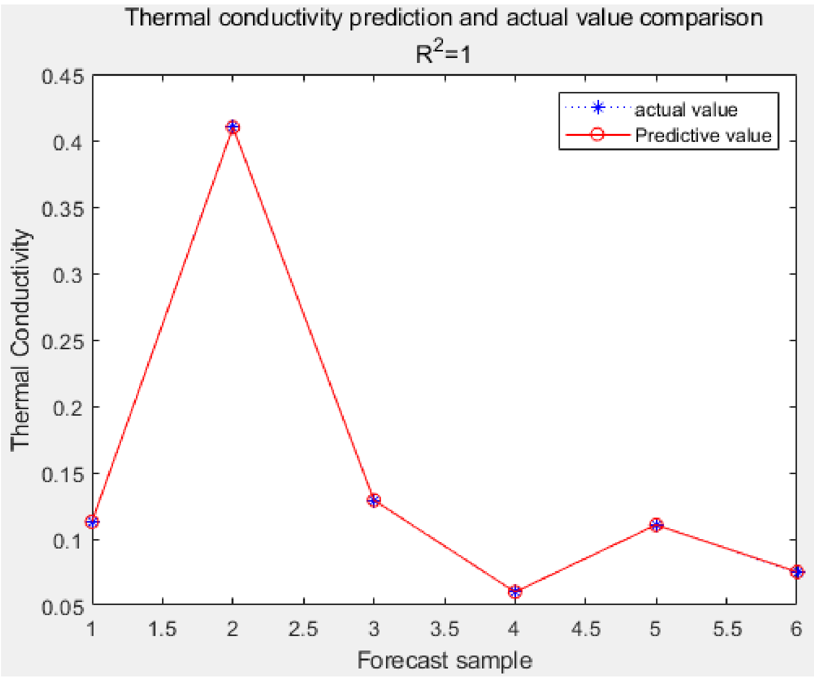

Figure 3. Prediction results of RBF neural network

At the same time, BP neural network was used to predict the same data. Due to the instability of BP network, multiple groups were predicted, and the predicted results were as follows. It can be seen that the results obtained by BP neural network are highly unstable, and the results are as follows:

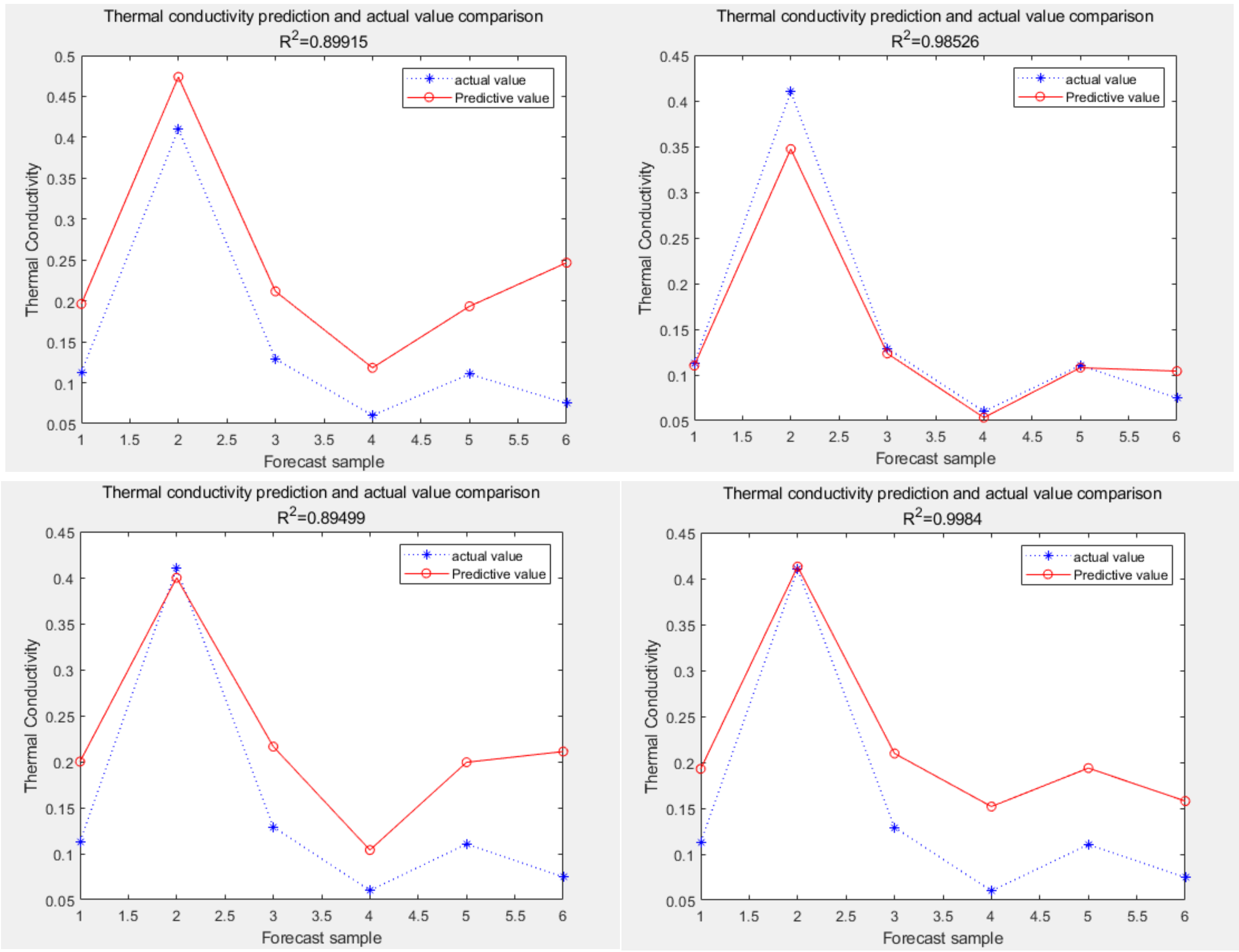

Figure 4. Prediction results of BP neural network

Then, the RBF neural network is used to predict the data points outside the data learning range, and the poor prediction results are obtained.

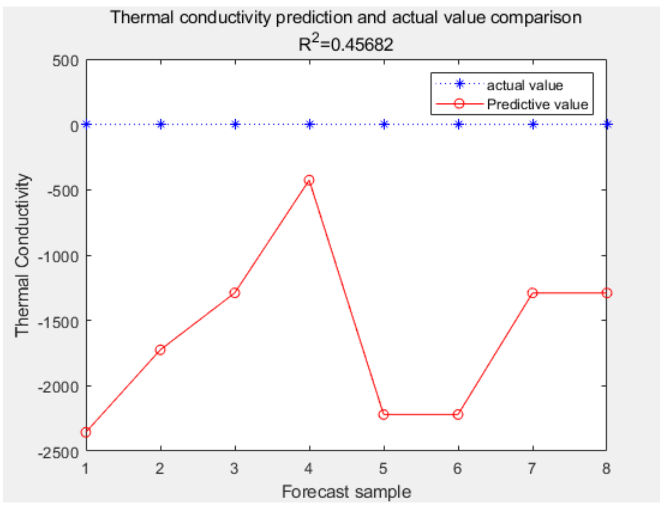

Figure 5. Out-prediction results of RBF neural network

Then, BP neural network is used to predict the data points outside the data learning range, and the results are quite impressive

BP neural network is used to predict points outside the range of data points for five consecutive times:

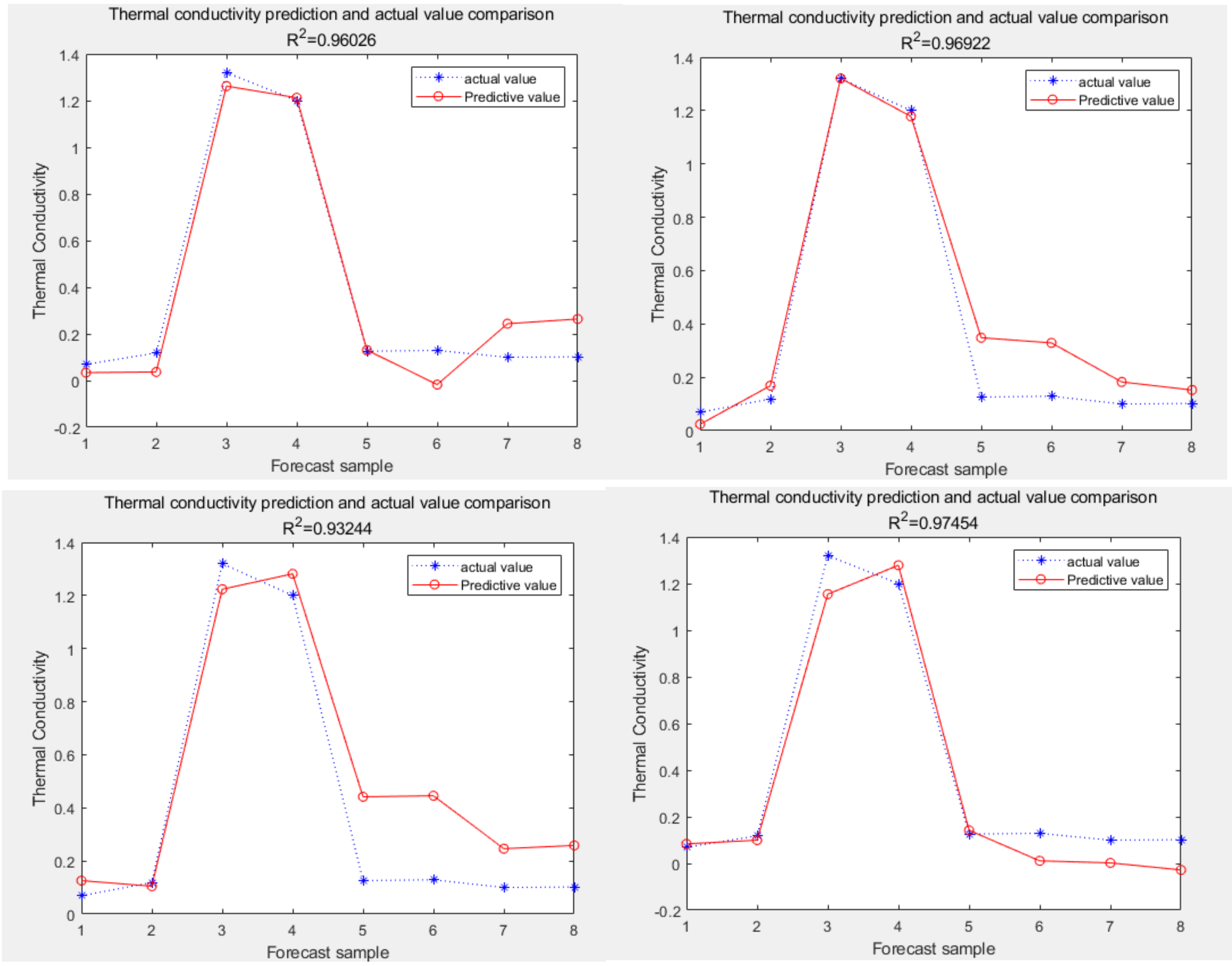

Figure 6. Out-prediction results of BP neural network

By comparison, it can be found that BP neural network has better prediction performance outside the learning data points.

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