The Prediction of Sn-Ag Solder Properties Based on BP Algorithm of Artificial Neutral Network

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Abstract

In this paper, the prediction of properties of the lead-free solders were focused on by using the BP neural network. Then different algorithm and parameter of BP neural network has been used in the training process, and the results have been analyzed for obtaining the optimum algorithm and parameter. The influence of adding In. Bi, Sb, RE Cu to Sn-Ag alloy to tensile strength, shear strength and the solidification temperature of Sn-Ag alloy was discussed in this paper. So the input variables are the contents of In. Bi, Sb, RE, Sn, Ag, Cu, and the output variable the tensile strength, shear strength and the solidification temperature of Sn-Ag alloy respectively. 15 groups of data were chosen for training of the model and 3 groups of data for prediction. The results show that the predicted data are good agreement with ones for the given experimental conditions. The accuracy and applicability for the present neural network modeling are thus verified.

Introduction

Lead free solders are increasingly used in interconnection systems for electronic packages as a result of pending legislation in the European Union, environmental and health concerns, and market competition[1]. Many studies are focuses on designing a lead-free solder to instead of conditional Sn-Pb solder. The properties of the materials are influence by many factors which are very complicated. The complicated relationship which relate to the new material design among composition, process and properties of the new materials are not known clearly. Neural networks are parameterized non-linear models used for empirical regression and classification modeling. Their flexibility enables them to discover more complex relationships between the data than traditional linear statistical models. It is very fit for material design and the prediction of the properties.

The electronics industry appears to be focusing on Sn-Ag as the alloy of choice for lead- free electronics assembly because Sn-Ag alloy have good mechanical properties and good welding ability[1]. So Sn-Ag alloy are studied in this paper. There are many factors influence the properties of the Sn-Ag alloy, so we use neural networks to obtain the law of the complicated relationships.

1. BP Neural Network

There are many kinds of artificial neural networks, such as perceptron, counter propagation, GMDH networks, RBF network and Hopfield model[2]. BP neural network is error back propagation network. BP neural network consisted of a input layer, a output layer and one or more than one hidden layers. The nodes in the same layer do not influence each other. This specification of the network structure, together with the set of weights, is a complete description of the formula relating the inputs to the output. Once the network is trained, estimation of the outputs for any given inputs is very rapid. BP neural network is an information treating technology that learns the relationship between a group of input data and a group of output results[3]. The influence of adding In. Bi, Sb, RE Cu to Sn-Ag alloy to tensile strength, shear strength and the solidification temperature of Sn-Ag alloy was discussed in this paper So BP neural network is very fit for solute our problem.

2. Variables and Data of the Model

The main factor influence the properties of the Sn-Ag alloy is the amount of the alloy. While adding different amount of element, the properties of the Sn-Ag alloy are changed. In Sn-Ag lead-free solder alloys, under the interaction of multi-composition, the addition of the element In and Bi can decreases the solidification temperature obviously Sb can increase the solder joints tensile and shear strength but RE on the contrary. The joints tensile and shear strength of the solders both decrease when the content of Ag is up to 1.5% or more.

Hence, the amounts of In、Ag、Bi、RE、Cu、Sn、Sb are included as variables. All of the data used in the analysis were obtained from the appendix of the reference 4.

3. The constitution of the model

BP Neural Network has single-layer or multi-layers. The transfer function in the hidden units is sigmoid function. The transfer to the output layer is purelin function. The constitution of the BP neural network was divided into 4 steps:

Searching for the number of the hidden layer
Searching for the number of the units in every layer
Searching for the optimum training function
Searching for the optimum learning speed

3．1 The number of the hidden layer

In theory, one S function in the hidden layer and one linear output layer could approach to any rational function[5]. But using more hidden layer could decrease the number of the hidden units in one hidden layer. It could do good effect. Increasing the number of the layer indeed make the model more complicated, but it improves the precision of the model.

The principle of searching the number of the hidden layer is as the following: firstly one layer was chosen for the model. If it is not fit for the model, increase one more layer. At the same time decrease the number of the units in one layer. In this paper it was found that three is fit for our model. Fig.1 shows the training result in different number of the layer. It easy found that the model contain 3 hidden layer could approach to the goal error in 3000 times.

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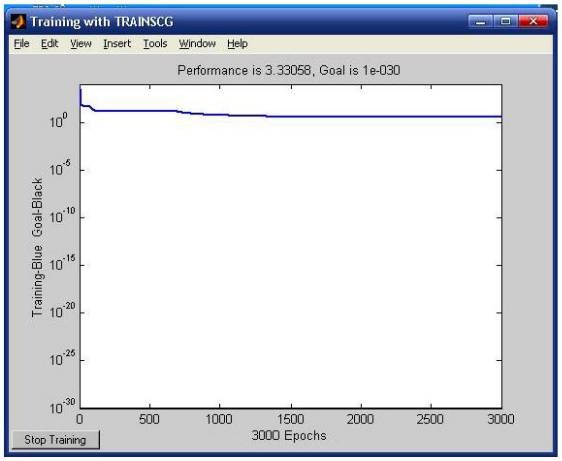
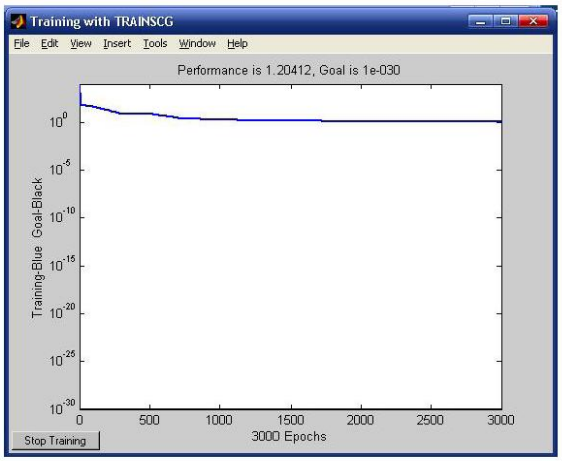
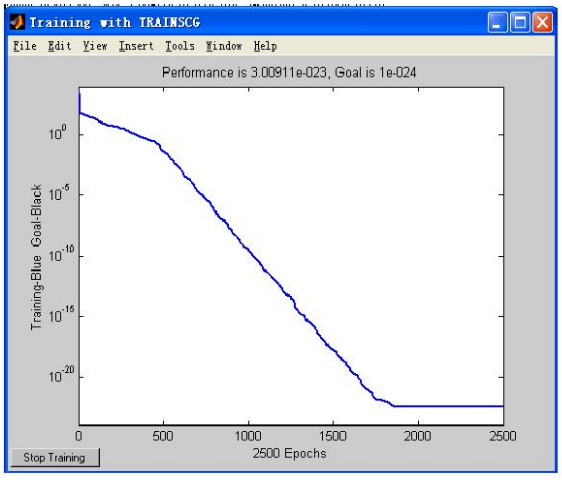


（a） training process of 1 hidden



（b） training process of 2 hidden layers



（c） training process of 3 hidden

Fig1. The training process of different hidden layer

on the input and output. And there is no experimental formula could use. So we must try many times to find the optimum number of the hidden units. Fig 2 shows that larger

3. 2 The number of the units in every layer

The veracity and the availability of the model is determined by some reason. And the most important reason is the number of the units in every layer[5]. The number of the hidden units depended

numbers of hidden units did not give significantly lower values. The test set error has a minimum at 40 hidden units.

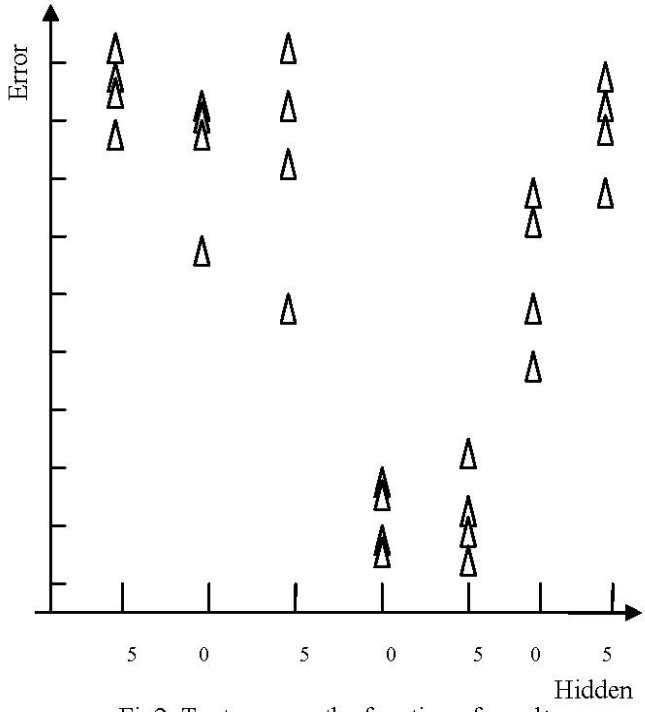


Fig2. Text error as the function of number of hidden units

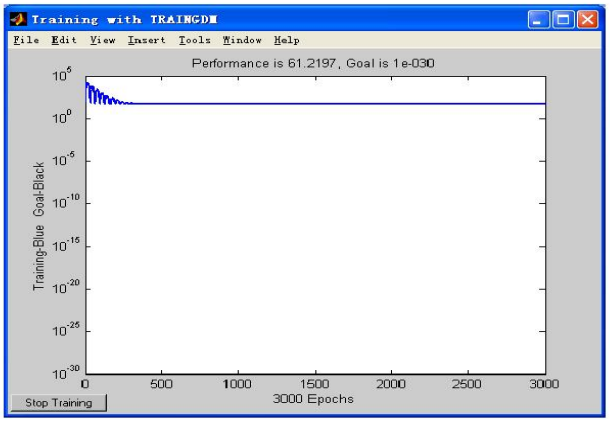
The input variables are the contents of In. Bi, Sb, RE, Sn, Ag, Cu, and the output variable the tensile strength, shear strength and the solidification temperature of Sn-Ag alloy. Then the structure of the network is 7×40×40×40×1. The paper chooses 15 groups of data for training of the model and 3 groups of data for prediction.

3．3 Searching for the optimum training function

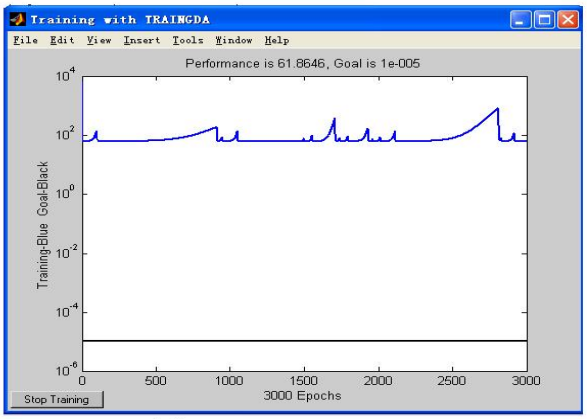
Searching for the optimum training function is very important. The training function not only influence the precision of the prediction but also make the training time more longer. Fig.3 shows that using different training function could obtain different testing error. We can see from the Fig.3 besides Conjugate Gradient Algorithm (trainscg) other algorithm can not approach the goal error.

3．4 Searching for the optimum learning speed

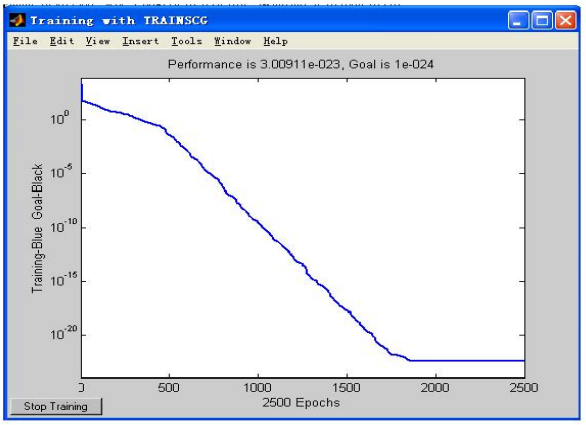
The optimum learning speed could make the error approach to the goal error very fast. If the learning speed is big, it would make the error vibrate. If the learning speed is small, it make the training time longer. 0.01 is very fit for the model in this paper.



(a) TRAINGDM error curve



(b) TRAINGDA error curve



(c) TRAINSCG error curve

Fig.3 Error curve in different training function

Table1. The comparison of the test data and predict data

tensile strength			shear strength			solidification temperature		
test	prediction	error	test	prediction	error	test	prediction	error
77.47	74.89	3.22%	26.9601	29.08	7.29%	184.3974	187.8	1.81%
72.85	72.88	0.04%	31.8372	32.41	4.94%	213.5584	203.8	4.57%
77.94	75.85	2.67%	38.9534	38.91	0.14%	198.8296	204.8	2.92%

4. Prediction of properties of Sn-Ag solder

The structure and the parameter of the model has been confirmed. The model is used to predict the tensile strength, shear strength and the solidification temperature of Sn-Ag alloy. Table 1 shows the result of the prediction. It was found from the table that the error between test data and predict data is almost lower than 5%. Only one error is 7%

The reason that arouse the error maybe from three aspect:

(1)The process of the measure the shear strength is not exact.

(2)The number of the data for training is not big.

(3)The distribution of the data is not well-proportion.

5. Conclusions

(1)Using artificial neural network to predict the property of the lead-free solder is feasible.

(2) It provides a new route for the designing of lead-free solder, thus saving the time and labor.

(3) If the number of data of training is big enough, the prediction results would be more precision.

Acknowledgments

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References

1. Guo, F., Lead-free Soldering Technology and Application, Science Press (Beijing, 2006), pp.4-38.
2. Gavard, L., "Bayesian neural network model for austenite formation in steels", *Materials Science Technology*. Vol. 12, (1996), pp. 453～463
3. Kohonen, T., "An Introduction to Neural Computing", *Neural Networks*, Vol. 1, (1998), pp. 3～16

4. Hwang, J., "Lead-free solder:Sn-Ag-Cu Allay", Downloaded from www.smthome.net/article/19.htm
5. Bhadeshia, H., "Impact toughness of C-Mn steel arc welds- Bayesian neural network analysis", *Material Science Technology*, Vol. 10, (1995), pp. 1046~1051

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