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Simulation of aging process of lead frame copper alloy by an artificial neural network①

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Abstract: The aging hardening process makes it possible to get higher hardness and electrical conductivity of lead frame copper alloy. The process has only been studied empirically by trial-and-error method so far. The use of a supervised artificial neural network(ANN) was proposed to model the non-linear relationship between parameters of aging process with respect to hardness and conductivity properties of Cu-Cr-Zr alloy. The improved model was developed by the Levenberg-Marquardt training algorithm. A basic repository on the domain knowledge of aging process was established via sufficient data mining by the network. The results show that the ANN system is effective and successful for predicting and analyzing the properties of Cu-Cr-Zr alloy.

Key words: copper alloy; aging process; Levenberg-Marquard algorithm; artificial neural network
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1 INTRODUCTION

The functions of lead frame in electronic packing are providing channels for electronic signals between devices and circuits, and fixing devices on circuit boards. Lead frame alloys are required to have high strength and good formability as well as high electrical and thermal conductivity . Cu-base alloys are the most popular lead frame alloys and are used in plastic packaging application due to their high thermal and electrical conductivity as well as high strength[1-3]. The aging hardening process in fabrication of lead frame copper alloy makes it possible to get higher mechanical and electrical properties[4-5]. The process has only been studied empirically by trial-and-error method so far[6-8]. For this reason, it is important and indispensable to simulate the aging processes by numerical methods in order to optimize process design.

Being a kind of data mining and artificial intelligence techniques, neural networks(NN) are developed to model the way in which the human brain processes information. A neural network is a massively parallel-distributed processor that has a neural propensity for storing experiential knowledge and making it available for future use. Unlike conventional, explicitly programmed computer programs, neural networks are trained through the use of previous example data and then iteratively adjusted the weights of the neurons until the output for a specific network is close to the desired one. Furthermore neural networks possess many excellent properties such as outstanding nonlinear approximation, auto-adaptation and association capability. As a complex non-linear system, NN models have been widely employed to map the indeterminate relationship between cause and effect variables in many fields[9-11]. In the present work a universal ANN program is designed on the basis of improvement upon BP training algorithms. Using this program, a two-hidden-layer network is constructed to simulate aging processes in fabrication of high properties Cu-0.3%Cr-0.15%Zr alloy.

2 COLLECTION OF INPUT/OUTPUT PARAMETERS

The selection of input/output variables is a very important aspect of neural network modeling. Usually this choice is based on the background of a process. In the present work the followings are used as input parameters: the aging temperature(T) and the aging time(t). Output variables are determined by the properties acquirement: hardness and electrical conductivity.

The knowledge of a specific field is implicated in

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the existing training samples, so an appropriate dataset with good distribution is significant for reliable training and performance of neural networks. To ensure reasonable distribution and enough information containing of the dataset, aging processes are covered with different parameters. The aging temperatures are 400, 450, 500, 550, 600 and 650 ℃; the aging time 0 min, 15 min, 30 min, 45 min, 1 h, 1.5 h, 2 h, 3 h, 4 h, 5 h, 6 h, 7 h, 8 h, 9 h, 10 h, 11 h. So the total samples reach 96.

3 DESIGN OF HIDDEN LAYERS AND NEURONS

Hidden layers perform abstract functions, namely, they can extract characteristic knowledge implicated in input data. So it is the hidden layers that give neural networks the ability to deal robustly with nonlinear and complex problems. However different algorithms of BP networks have different limitations in practice. For instance, it is difficult for a single-hidden-layer network to improve its closeness-of-fit if it has too few hidden nodes; while too many hidden nodes enable it to memorize (over-fit) the training dataset, which produces poor generalization performance. At present there isn't a valid analysis formula for designing hidden layers and "it is an art to decide the quantity of nodes per hidden layer", so a trade-off exists between generalization performance and the complexity of training procedure when designing the topology of a neural network.

A lot of computational instances show that two-hidden-layer neural networks are suitable. If the dimension of input layers N are not too large, N_1 and N_2 are the quantity of nodes in the first and the second hidden layer respectively, $N_1 = N$. Adjusting N_2 ensures both the generalization performance and the rate of the convergence satisfactory. After many times of trial-and-error computation by the ANN program, perfect topology ({2, 2, 4, 2}) of the hardness and conductivity outputs are found.

4 IMPROVEMENT ON BP TRAINING ALGORITHMS

An error back-propagation (BP) network is selected because of its greater capability of association and generalization. The weights of the neurons are iteratively adjusted in accordance with the error correction rule until the output for a specific network is close to the desired output. The classical error correction rule is the steepest descent algorithm, but the method suffers from the drawback that the rate of convergence is reduced rapidly near the extreme points of the objective function; while to the second order algorithms such as Gauss-Newton algorithm, the rate of convergence is reduced rapidly far from the extreme points of the objective function[12].

The method used in this paper is the Levenberg-Marquardt (LM) algorithm (as shown in Fig. 1) which is a kind of quasi-Newton methods. The weights of the neurons are iteratively adjusted by:

$$\boldsymbol{w}(n_0+1) = \boldsymbol{w}(n_0) - (\boldsymbol{J}^{\mathrm{T}}\boldsymbol{J} + \lambda\boldsymbol{I})^{-1}\boldsymbol{g}_h \qquad (1)$$

where $\boldsymbol{g}_h \equiv \boldsymbol{g}/2$, $\boldsymbol{g}$ is the gradient of the error function $\boldsymbol{E}$ with respect to the weight and bias variables $\boldsymbol{w}$; $\boldsymbol{J}^{\mathrm{T}}$ is the transposed matrix of $\boldsymbol{J}$; $\boldsymbol{I}$ is the identity matrix which has the same dimensions with $\boldsymbol{J}^{\mathrm{T}}\boldsymbol{J}$; λ is an adjustable constant multiplier and when it is down to zero, Eqn. (1) is just approximate Newton's method; when λ is large, it becomes the steepest descent algorithm with a small step size (as shown in Fig. 2). Newton's method is faster and more accurate near an error minimum, so the aim is to shift towards Newton's method as quickly as possible. Thus, λ is decreased after each successful step (reduction in performance function) and is increased only when a tentative step would increase the performance function[13].

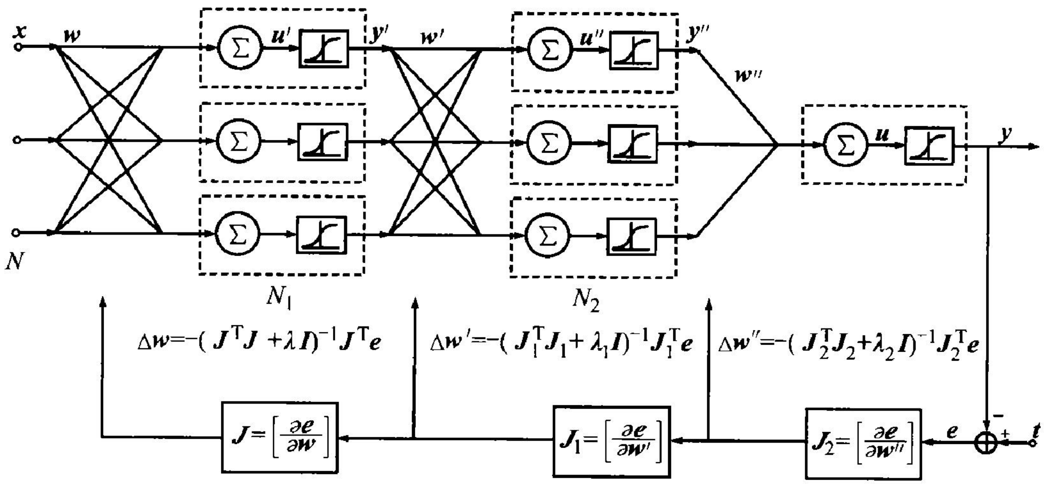

Fig. 1 Model of Levenberg-Marquardt (LM) algorithm

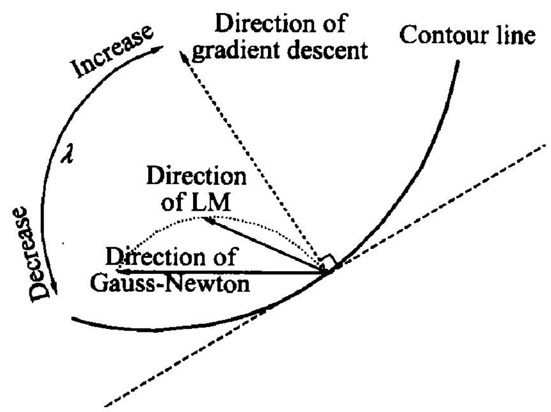

Fig. 2 Descent directions of three algorithms

5 RESULTS AND DISCUSSION OF PREDICTION

To test the generalization performance of the trained networks, the relation between the predicted values from the trained neural network and the tested data are shown in Table 1. Very good agreements between them are achieved (see Table 1), which indicates that the trained networks take on optimal generalization performance. This also demonstrates, as a typical data mining technique, neural networks can find the basic pattern information implied in a great number of experimental data, extract useful rules and then use these rules for obtaining reasonable predicted results.

After neural networks are trained successfully, all domain knowledge extracted out from the existing samples is stored as digital forms in weights associated with each connection between neurons. Making full use of the domain knowledge stored in the trained networks, three-dimensional graph is drawn in Fig. 3. Obviously, the graph exhibits much more professional knowledge.

5.1 Effects of process parameters on hardness

The variation of hardness with increasing temperature and time reveals that the time to peak hardness decreases with increasing temperature as shown in Fig. 3. With enhance of the temperature, the initial kinetic of the precipitation is higher, which leads to shorter time to reach peak hardness. The peak hardness values for 3 h and 4 h are HV 108.6 and HV 108.3 at 503 ℃ and 486 ℃ respectively as shown in Fig. 4 and Fig. 5. At the peak hardness the fuller precipitation is available and the hardening effect is optimum. This indicates that the precipitates are coherent with the matrix.

Fig. 6 is a plot of hardness as a function of time at 500 ℃.

5.2 Effects of process parameters on electrical conductivity

Fig. 7 reveals that the electrical conductivity increases with increasing the time and temperature. The highest conductivity reaches 79.3% IACS at 600 ℃ for 11 h. The higher temperature and the longer time bring about more precipitates. The growth of precipitates reduces the contents of solute atom in matrix and results in a continuous increase in electrical conductivity during the aging. So the conductivity in Cu-0.3Cr-

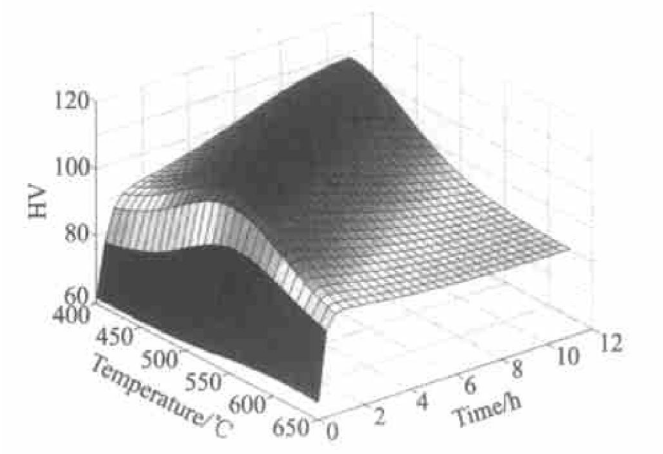

Fig. 3 Hardness with regard to temperature and time

Table 1 Tested data and predicted values

Inputs		Predicted values		Tested data	
Temperature/ ℃	Time/ h	Hardness(HV)	Conductivity(IACS) / %	Hardness(HV)	Conductivity(IACS) / %
450	1	98	45	99	49
450	2	100	55	101	58
450	3	106	68	106	70
470	1	101	54	101	55
470	2	104	65	103	65
470	3	107	75	104	73
500	1	106	67	104	68
500	2	108	75	103	73
500	3	107	76	104	75

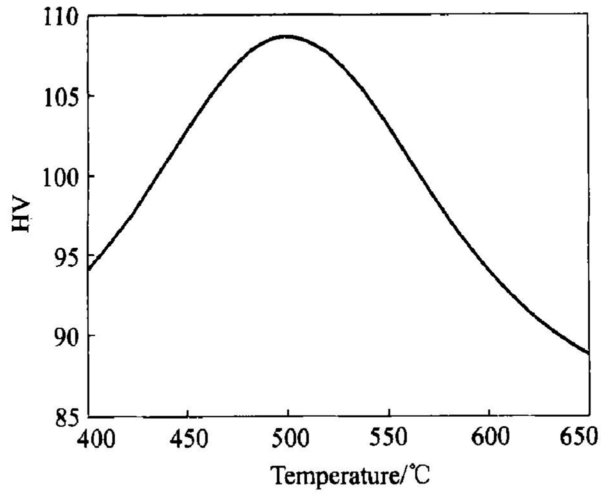

Fig. 4 Hardness with regard to temperature(t= 3 h)

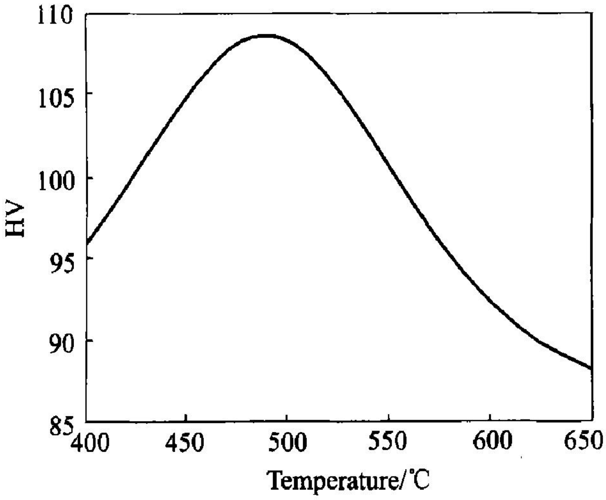

Fig. 5 Hardness with regard to temperature(t= 4 h)

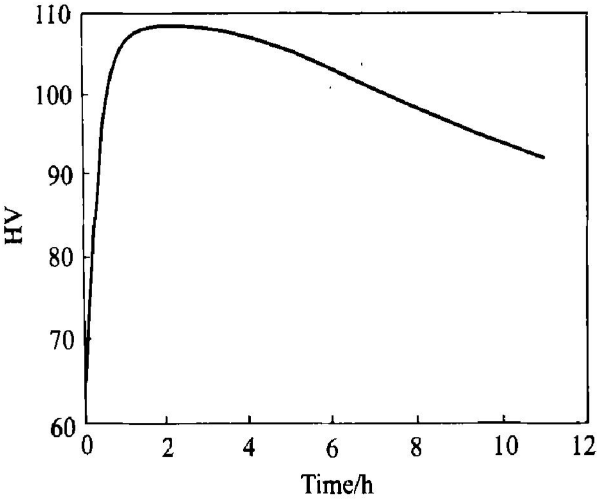

Fig. 6 Hardness with regard to time at 500 ℃

0. 15Zr lead frame alloy remains at a higher level. After 600 ℃ the electrical conductivity decreases slightly, which is attributed mainly to the solution of the precipitates in the matrix again. The solute atoms in matrix can act as obstacles for the movement of conduction electron and increase the density of electron scanning centers — lattice imperfections.

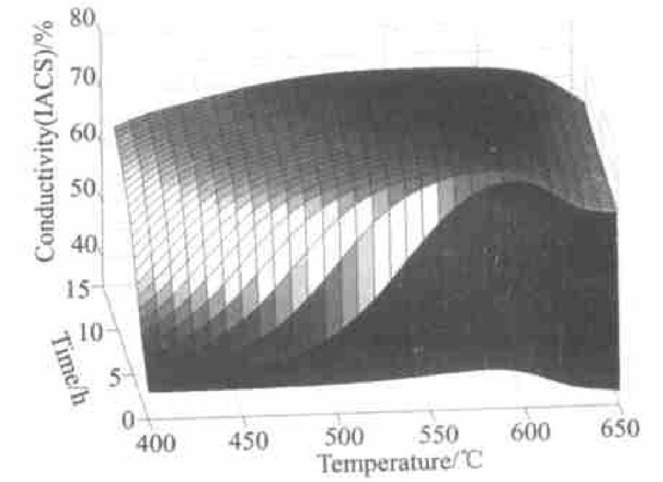

Fig. 7 Conductivity with regard to temperature and time

Fig. 8 shows the conductivity first increases with increasing temperature then decreases.

Fig. 9 shows the conductivity increases with increasing time.

From the preceding analyses, it is suggested that both the hardness and electrical conductivity can be increased through the control of precipitati-

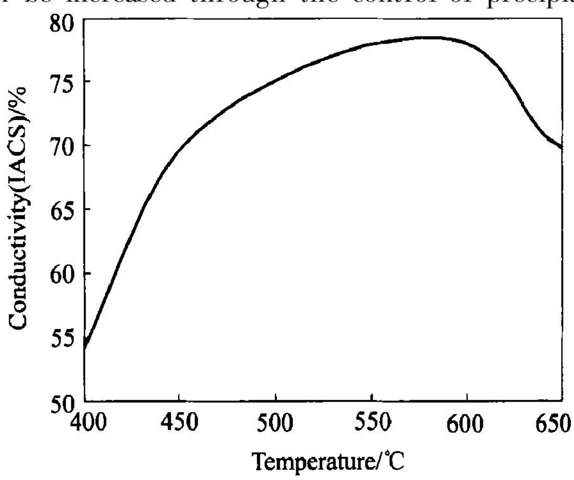

Fig. 8 Conductivity with regard to temperature(t= 4 h)

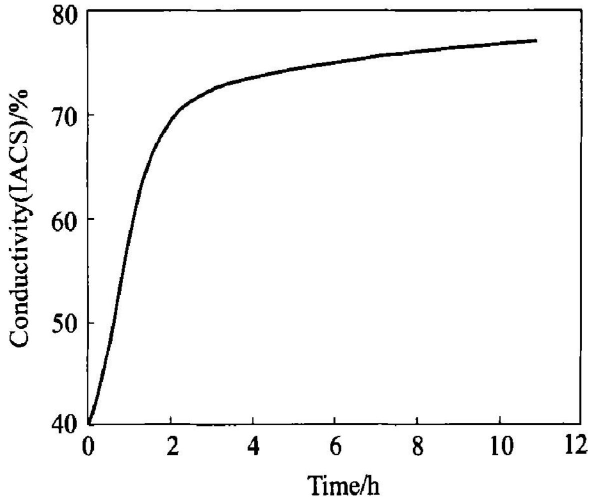

Fig. 9 Conductivity with regard to time at 500 ℃

on during the aging treatment of Cu-0.3Cr-0.15Zr lead frame alloy. The best combination of hardness (between 106 HV and 108 HV) and conductivity (from 71% to 76% IACS) is achieved at 470 − 510 ℃ from 3 h to 4 h for Cu-0.3Cr-0.15Zr lead frame alloy.

6 CONCLUSIONS

1) A neural network model of aging processes has been built. The improved model is developed by the Levenberg-Marquardt training algorithm. High precision of the model and a good generalization performance are demonstrated.

2) The ANN system is effective and successful for predicting and analyzing the properties of Cu-0.3Cr-0.15Zr lead frame alloy. The optimized processing parameters are 470 − 510 ℃ and 3 − 4 h.

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