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Prediction and Analysis of the Aging Properties of Rapidly Solidified Cu-Cr-Sn-Zn Alloy Through Neural Network

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It is known that the strength of a metal can be successfully improved by rapid solidification. The hardness of the rapidly solidified Cu-Cr-Sn-Zn alloy is much higher than that of the solution heat-treated and aged alloy. In this study, multiple-layer, feed-forward, artificial neural network (ANN) modeling has been used to study the hardness and electrical conductivity behavior of a rapidly solidified Cu-Cr-Sn-Zn alloy. The ANN model shows how the aging parameters influence the hardness and electrical conductivity of a rapidly solidified Cu-Cr-Sn-Zn alloy. The ANN modeling also provides encouraging predictions for information not included in the trained set samples, indicating that a backpropagation network is a very useful and accurate tool for property analysis and prediction.

Keywords aging, artificial neural network, Cu-Cr-Sn-Zn alloy, rapid solidification

1. Introduction

The lead frame in electronic packaging is one of the main parts of the integrated circuit. The functions of the lead frame are to provide channels for electronic signals between devices and circuits, and for fixing devices on circuit boards. Lead frame alloys are required to have high strength and high electrical conductivity (Ref 1-4). The Cu-Cr-Sn-Zn alloy is one such material, possessing high electrical conductivity, high strength, press formability, and electroplating potential, as well as attractive bonding and soldering characteristics. However, the research to date on the Cu-Cr-Sn-Zn alloy has only focused on solution heat treatment (SHT) and aging behavior (Ref 5, 6). The strengthening effect from conventional SHT and aging is limited due to the low solubility of Cr in Cu at the SHT temperature as a result of the coarse grain structure. Rapid solidification processing (RSP; i.e., melt spinning) can, for example, lead to an extension of the solute solid solubility of Cr in Cu with a remarkable refinement of the grain size (Ref 7-9). Upon aging, a very fine dispersion of second-phase particles is precipitated in the matrix. As such, dispersion hardening greatly improves strength without degrading the electrical conductivity. The properties that result from SHT and aging as well as RSP and aging are compared in Table 1.

The aging of Cu-Cr-Sn-Zn alloy by trial and error is both costly and time-consuming. For this reason, developing a reliable modeling approach to control and predict the properties of the Cu-Cr-Sn-Zn alloy seems to be both useful and efficient. To this end, an artificial neural network (ANN) approach has been used due to its remarkable information-processing characteristics, including nonlinearity, high parallelism, robustness, fault and failure tolerance, learning capability, the ability to handle imprecise and fuzzy information, and the capability of generalizing information (Ref 10-14). However, applying an ANN to the investigation of the properties of the Cu-Cr-Sn-Zn alloy is a new and unique application of the technique, so the goal of this article was to apply the ANN to the analysis and prediction of the properties for RSP of the Cu-Cr-Sn-Zn alloy.

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2. Experimental Procedure

Ingots of the Cu-Cr-Sn-Zn alloy were induction-melted in a quartz tube and then were "jetted" under pressure using an Ar gas stream onto a rotating Cu roll rotating at a speed of about 2300 rpm. The diameter of the roll was 250 mm. The resulting ribbons were 2 mm wide by 40 to 70 μm thick. Aging treatments were performed on the ribbons in an electric resistance tube furnace in an Ar atmosphere. The temperature accuracy was maintained at ±5 °C. The electrical resistivity of the Cu-Cr-Sn-Zn alloy samples was determined by

Table 1 Properties of solution aged and rapid-solidification processed and aged

Temperature, °C	Time, h	Hardness, HV		Conductivity, % IACS	
		SA	RS	SA	RSA
400	3	108	156	57.8	56.9
450	2	112	141	66.6	63.1
500	0.25	102	178	51.4	60.6
550	0.5	118	165	55.4	63.5

Note: SA, solution-aged; RSA, rapid solidification—processed and aged

Table 2 Measured data and predicted values

Variables	Temperature, °C (time, h) 400 (2.5)	430 (0.5)	450 (3)	480 (0.25)	500 (0.25)	530 (1.5)	550 (2)	580 (1)
Hardness								
Predicted values, HV	142.3	134.1	147.6	157.5	170.0	124.5	111.7	109.0
Tested data, HV	146.1	131.2	144.1	165.0	178.0	128.9	112.0	110.0
Error, %	2.6	2.2	2.4	4.5	4.5	2.5	0.2	0.9
Conductivity								
Predicted values, % IACS	51.5	52.5	61.2	62.8	63.9	65.7	65.2	64.5
Tested data, % IACS	53.2	51.3	64.2	60.4	61.7	65.6	65.6	63.3
Error, %	3.2	2.5	4.7	4	3.6	0.2	0.6	2.9

measuring the resistance of a 60 mm length of ribbon using a ZY9987-type ohmmeter. Microhardness was measured on an HVS-1000 hardness tester (Shandong Laizhou Testing Apparatus, Ltd., Laizhou City, China) using a 25*g* load with a dwell time of 5 s. Every sample was tested five times with an accuracy of ±5%.

To ensure a reasonable data distribution with enough information for the ANN model, an RSP test matrix was established to include the following parameters: aging temperatures of 400, 430, 450, 470, 500, 530, 550, 580, and 600 °C for aging times of 0, 5, 15, 30, 60, 90, 120, 150, and 180 min, respectively. In the ANN model, the input parameters were defined as aging temperature (T) and aging time (t). The output variables, thus, became hardness (H) and electrical conductivity (C).

3. Artificial Neural Network Modeling of the Rapid Solidification Aging Process

Backpropagation, which is one of the most famous training algorithms for multilayer models, is a gradient descent technique that is used to minimize the error in a particular training pattern. The weights of the neurons are iteratively adjusted in accordance with the specified error correction rule until the output for a specific network is close to the desired output.

To ensure stabilization of the algorithm, the values of the input matrix (X) are regularized in the range of 0.1 to 0.9 as follows:

$$X = 0.1 + \frac{0.8(X - \min(X))}{\max(X) - \min(X)} \qquad \text{(Eq 1)}$$

The hidden layers can extract characteristic knowledge implied in input data. So, it is the hidden layers that give the AAN the ability to deal robustly with nonlinear and complex problems. A tradeoff exists between generalized performance and the complex training procedure when designing the topology of an ANN.

In this example, there are many instances in which the two hidden-layer ANN are suitable. If the dimension of input layers are N (and not too great), N_1 and N_2 are the quantities of the nodes in the first and second hidden layer, respectively. At this point, $N_1 = N$, and N_2 can be adjusted to ensure that both the generalized performance and the rate of the convergence are suitable. If the sum of the squared error is established as 0.09, a perfect topology ({2,2,8,2}) of the H and C outputs can be obtained after many trial-and-error computations in the ANN program. The transfer function in the ANN model is log-sigmoid:

$$f = \frac{1}{1 + e^{-x}}$$

4. Results and Discussion

The relations between the predicted values from the trained ANN and the measured data from the experiment are shown in Table 2. The degree of error of the prediction was 4.5 and 4.7%, respectively, for H and C. Good agreement between the predicted values from the trained ANN and the validation data is achieved, indicating that the trained ANN achieves optimal generalized performance.

After the ANN is trained successfully, all domain knowledge extracted from the existing samples is stored in digital form with appropriate weights for each connection between the neurons. Making full use of the domain knowledge stored in the trained ANN, three-dimensional graphs can be drawn (Fig. 1, 3).

Figure 1 shows the way in which C increases with increasing heat treatment time and temperature. After reaching 500 °C, the value of C decreases slightly. At approximately 450 °C (i.e., the initial stage of aging), the conductivity sharply increases and then tends to stabilize. Upon initial aging, the RSP Cu-Cr-Sn-Zn alloy undergoes precipitation due to its extended supersaturation limit and numerous crystal defects. It is the precipitation of particles from the supersaturated solid solution that results in the initial sharp increase of conductivity. For the RSP Cu-Cr-Sn-Zn alloy, precipitation proceeds through the diffusion of solute atoms with the aid of vacancies. The vacancies exist in the RSP Cu-Cr-Sn-Zn alloy at higher concentrations and diffuse rapidly during the initial stage of aging. Their consumption can be expressed by the following equation (Ref 15):

$$N = N_0 e^{-nat}$$

where N is the total number of vacancies, n is the number of vacancy sites, which is constant during heat treatment, a is a constant related to T, and N_0 is the number of vacancies in the supersaturated solid solution. It should be noted that the decay of vacancies is directly related to the change in electrical resistivity of the alloy at each aging temperature. Thus, as the aging time increases, the fewer the number of vacancies that are present in the alloy. Thus, over time, the precipitation process will slow down. This is consistent with the change in C in the Cu-Cr-Sn-Zn alloy that has gone through RSP and aging, as

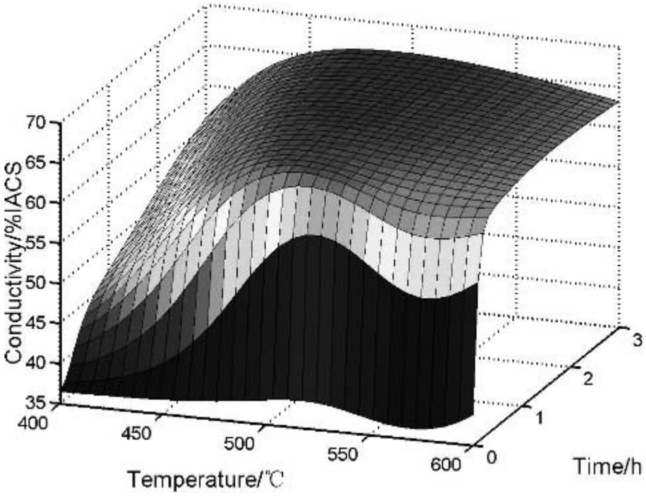

Fig. 1 The surface of C as a function of T and time t

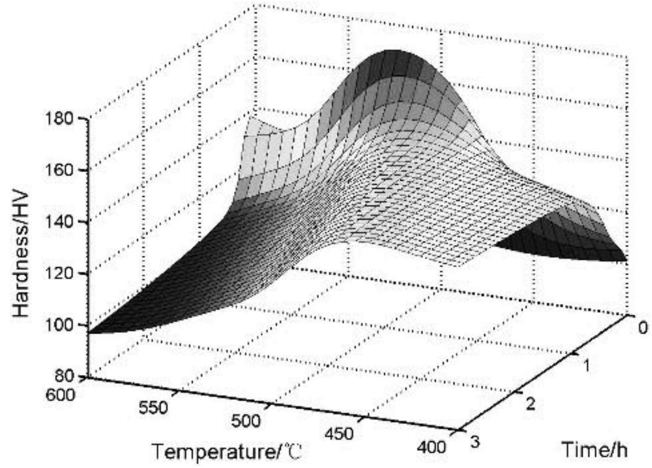

Fig. 3 The surface of H as a function of T and t

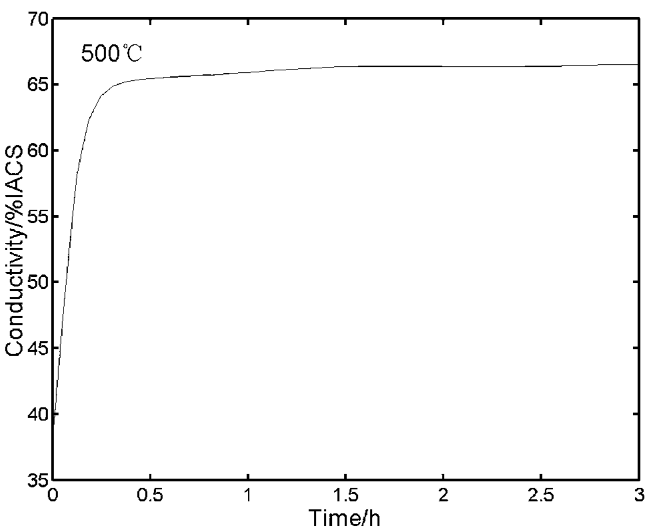

Fig. 2 The C as a function of time at $T = 500$ °C

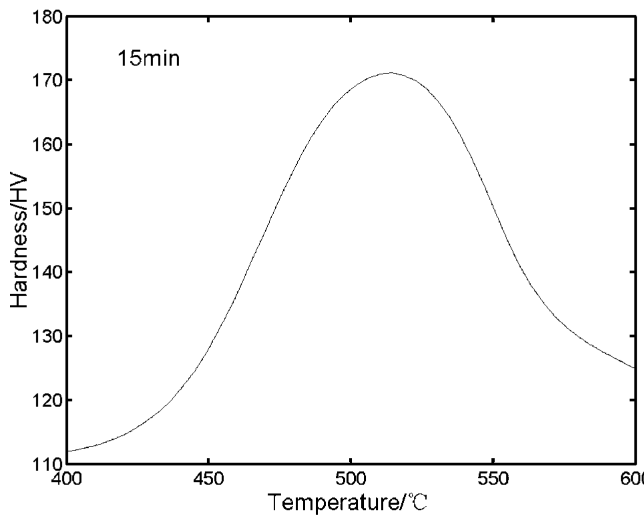

Fig. 4 The H as a function of T at $t = 15$ min

shown in Fig. 2. The conductivity can reach 64% international annealed copper standard (IACS) at 500 °C after 15 min. The maximum conductivity for the RSP and aged Cu-Cr-Sn-Zn alloy is 67% IACS at 500 °C after 3 h.

Figure 1 is the C surface as a function of aging temperature (T) and aging time (t). Figure 2 is the section through this surface showing how C changes with time at 500 °C.

Figure 3 shows the H surface as a function of T and t. During the initial stages of aging, the vacancies speed up the precipitation process and increase the number of nucleation sites for the precipitates. As a result, the dispersion-hardening effect is greatly intensified. At 500 °C, the peak H of 170 HV is achieved after 15 min.

By means of RSP, a significant increase in the solid solubility range of Cr in Cu is achieved. The RSP also refines the microstructure. Upon aging, the supersaturated solid solution precipitates as a very fine dispersion of second-phase particles in the matrix or at the grain boundaries. These fine precipitates, together with the Cu matrix, give rise to the alloy peak H. The H increases with decreasing grain size, following the Hall-Petch relationship.

High H (i.e., 126 HV) still exists at 600 °C after 15 min (as shown in Fig. 4). The thermal stability of the alloy is due to the presence of stable Cr dispersoids distributed throughout the Cu matrix. They have a high melting point and little solubility in the Cu. These dispersoids provide resistance to the motion of the dislocation at elevated temperatures, making a significant contribution to the overall strength of the alloy. This result is consistent with the good elevated temperature properties of the alloy, as shown in Fig. 4.

5. Conclusions

Based on this work, the H and C of the RSP and aged Cu-Cr-Sn-Zn alloy was determined using ANN modeling. From this work, the following conclusions can be drawn:

- RSP and aging can greatly enhance the H and C of a Cu-0.36Cr-0.23Sn-0.15Zn alloy, especially in the early stages of the aging treatment.

- The ANN is a useful approach in the property analysis and prediction of *H* and *C* of a Cu-0.36Cr-0.23Sn-0.15Zn alloy, even when using a limited number of measurements.

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