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# An Investigation into the Effect of Alloying Elements on the Recrystallization Behavior of 70/30 Brass

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**An Artificial Neural Network (ANN) model has been designed for predicting the effects of alloying elements (Fe, Si, Al, Mn) on the recrystallization behavior and microstructural changes of 70/30 brass. The model introduced here considers the content of alloying elements, temperature, and time of recrystallization as inputs while percent of recrystallization is presented as output. It is shown that the designed model is able to predict the effect of alloying elements well. It is also shown that all alloying elements strongly affect the recrytallization kinetics, and all slow down the recrystallization process. The effect of alloying elements on the activation energy for recrystallization has also been investigated. The results show that Si is the element which increases the activation energy.**

**Keywords** 70/30 brass, activation energy, alloying elements, ANN modeling, recrystallization

## 1. Introduction

Alloying elements and impurities may profoundly affect microstructures of Cu and its alloys during annealing by changing the recovery and recrystallization processes. For example, it is well known that the additions of Fe and other elements like Si to Cu-Zn alloys lead to grain refinement. Moreover, it has been reported that Mn increases ductility, while Si has an opposite effect and results in hardening (Ref 1). So, it seems that understanding the effects of alloying elements may help to control and produce the products with desired properties at lower costs. For example, Oishi et al. developed a new Cu alloy with fine recrystallized grains by investigating the effect of Si and Co on the recrystallization behavior of Cu-10%Zn alloy (Ref 2). They showed that while the addition of silicon to Cu-10%Zn alloys increases the number of nucleation sites, the addition of minute amounts of cobalt to Cu-10%Zn-Si alloys inhibits grain growth (Ref 2).

More recently, Aghaie and Mohebati investigated the effect of Si on recrystallization behavior of brass (Ref 1). They utilized a thermo-mechanical treatment to improve the ductility of 70/30 brass containing 0.35% iron as impurity. They showed contrary to other reports, Si additions increase the grain size of 70/30 brass, and as a result, a superior ductility can be achieved after thermo-mechanical treatment. They attributed the grain coarsening effect to the shape and the nonuniform distribution of Si precipitates (Ref 1).

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From the above discussion, one could conclude that, from an industrial point of view, investigations on the effect of alloying elements on the final structure of alloys can be very important. In this study, the effects of Si, Mn, and Al on the recrystallization behavior of 70/30 brass in the presence of Fe have been investigated. The 70/30 brass is predominantly used for cartridge case production and has an outstanding record of excellent formability coupled with high strength (Ref 1). However, in the recycling process iron as an impurity may inter the alloy and degrade the ductility and formability of the semi-finished products (Ref 1). The aim of the study was to either eliminate or reduce the detrimental effect of unavoidable Fe impurity which enters the composition of brass from recycled raw materials. However, the complexity of the effect of alloying elements led to research on developing a new model to predict the effect of alloying elements. There have been some works regarding the modeling of recrystallization process. Artificial Neural Network (ANN) modeling has proven to be a powerful tool for modeling the final properties and microstructures of processed materials. For example, ANN has been successfully used to predict the properties of dual phase steels (Ref 3) as well as the bake hardenability and the microstructure of processed materials (Ref 4-6). Moreover, it has been successfully used to predict the effect of thermo-mechanical processing on the forming limit diagram (FLD) of low carbon steels (Ref 7). Therefore, the objective of this work is to develop an ANN model to predict the effect of alloying elements on the recrystallization behavior of 70/30 brass.

## 2. Artificial Neural Networks

The foundations of all ANN are the processing elements, also called nodes or neurons that are interconnected and operate in parallel (Ref 8). Although, there are different types of ANN, feed-forward multilayer perceptron is probably the most widely used due to its powerful modeling capability. It consists of three layers: the input, the hidden, and the output layers. The input layer contains the properly scaled input observables upon

**Table 1 Chemical composition of brasses in this study**

| Sample number | Chemical composition, wt.% | | | | | |
|---|---|---|---|---|---|---|
| | Zn | Fe | Si | Al | Mn | Cu |
| 1 (Brass) | 29.89 | 0.02 | 0.001 | 0.002 | 0.001 | Bal |
| 2 (Fe) | 30.25 | 0.30 | 0.0087 | 0.0056 | 0.00002 | Bal |
| 3 (Si) | 29.74 | 0.30 | 0.75 | 0.0012 | 0.0003 | Bal |
| 4 (Al) | 29.18 | 0.30 | 0.0042 | 1 | 0.0023 | Bal |
| 5 (Mn) | 29.74 | 0.30 | 0.03 | 0.0005 | 0.75 | Bal |

which the network is trained. The summation of the input times weights is performed in each of the processing elements in the hidden layer, and the output is sent to either another hidden layer or directly to the output layer.

A neural network is not programed, but trained (Ref 8). The algorithm used for supervised learning of the neural network in this paper is based on the mostly used back-propagation method. The back-propagation training algorithm is an iterative gradient algorithm designed to minimize the main square between the predicted output and desired output (Ref 9).

## 3. Experimental Work

### 3.1 Materials and Experimental Procedure

The elements Fe, Al, Mn, and Si were added to 70/30 brass as the base in the electric furnace equipped with an inert-gas atmosphere controlled system. The chemical compositions of the prepared alloys obtained by spectrophotometery are presented in Table 1.

The melted alloys were cast in a copper mold as slabs of 10 cm × 5 cm × 0.56 cm in dimensions. Then, the cast slabs were cold rolled with 65% reduction in thickness. The prepared samples from cold-rolled slabs were isothermally annealed in a salt bath at temperature of 400, 500, 600, and 700 °C for different holding times including 5-259,200 s. At the end of annealing time, specimens were immediately quenched in water within 5 s. Annealed samples were subsequently mounted, polished, electropolished, and electroetched. Microstructural observations were performed by optical microscope and quantitative measurements of recrystallization progress during annealing were done by point counting method.

The results of experimental tests were divided into two parts: the first part of data was used for neural network training while the second part was used for network testing; about 210 data were used to train the network, while 30 data were used to test the network. It should be mentioned that usually about 15% of data are used to test the network (Ref 6). Therefore, we have selected 30 data to test the network.

### 3.2 ANN Model

In this work, an ANN model has been developed to predict the effect of alloying elements on the recrystallization of 70/30 brass. The input parameters of ANN model were considered as the amount of alloying elements Fe (0.02-0.3), Si (0.001-0.75), Al (0.0005-1) and Mn (0.00002-1), temperature ($T$) (400-700 °C), and time of recrystallization ($t$) (5-259,200 s), while the percent of recrystallization was considered as output. However, before training the network Log ($t$) and $T$/800 were considered as inputs instead of $t$ and $T$, respectively, and then all data were normalized between −1 and 1. To train the network, back-propagation training algorithm was used. Different architectures of neural network (NN) were tested, and among them the best one was selected. The fundamental characteristics of the ANN model used in this study are listed in Table 2. This table shows that only one hidden layer with as few as seven neurons has been used. Such simple architecture may avoid the designed neural network to be over-fitted. Moreover, to prevent the over-fitting, the technique of early stopping was also used.

**Table 2 Features of the designed neural network in this study**

| ANN characteristic | Feature |
|---|---|
| Number of neurons in input layer | 6 |
| Number of neurons in hidden layer | 7 |
| Transfer function | Sigmoid |
| Minimization algorithm | Gradient |

## 4. Results and Discussion

### 4.1 Microstructure

Figure 1 illustrates some representative microstructures at different temperatures. The alloying elements have led to finer microstructure and less sharpness in grain boundaries in all cases. All alloying elements have retarded recrystallization process and in majority of them after relatively long annealing times, recrystallization has not reached completion especially at lower temperatures.

Another point regarding the microstructures of annealed samples is the presence of annealing twins. Annealing twins normally develop in low stacking fault energy materials. However, the mechanism which leads to the formation of twins is not very well understood. One model proposed by Gleiter in 1969 assumes that twins are the results of growth accidents leading to stacking faults, and growth accidents are presumed to increase in frequently as boundary velocity during recrystallization increases (Ref 10, 11).

Another recent theory suggests that since at low temperatures the driving force for growth is low, twining may have been necessary for the growth of grains to continue to complete recrystallization at low temperatures (Ref 11). In other words, when a grain appeared to stagnate in growth, it would often twin and rapid growth would resume. Nevertheless, as the temperatures used in this work are relatively high, it can be concluded that the observed annealing twins are the results of grain boundary accidents. Comparing recrystallized microstructures of different samples at high annealing temperatures shows that grain growth is also slowed down by alloying elements resulting in much finer microstructures than that of sample 1 (brass).

### 4.2 Recrystallization Fraction

By way of example, Fig. 2 shows the recrystallized fraction for samples 1-5 at temperatures of 500 °C.

As it can be seen from this figure, all alloying elements have decreased the recrystallized fraction. Moreover, it seems that Si is the element which mostly has decreased the recrystallized

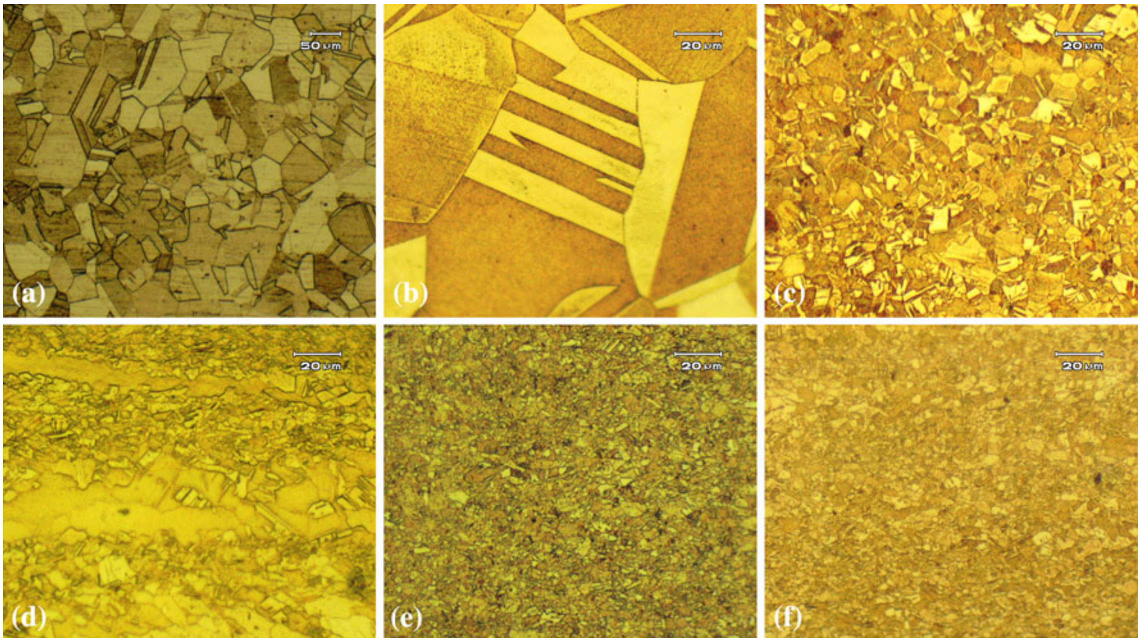


**Fig. 1** Some representative microstructures after recrystallization. (a) Sample 1 (Brass)—$T = 600$ °C, $t = 1800$ s, (b) sample 1 (Brass)—$T = 600$ °C, $t = 3600$ s, (c) sample 2 (Fe)—$T = 500$ °C, $t = 3600$ s, (d) sample 3 (Si)—$T = 500$ °C, $t = 3600$ s, (e) sample 4 (Al)—$T = 500$ °C, $t = 3600$ s, (f) sample 5 (Mn)—$T = 500$ °C, $t = 3600$ s

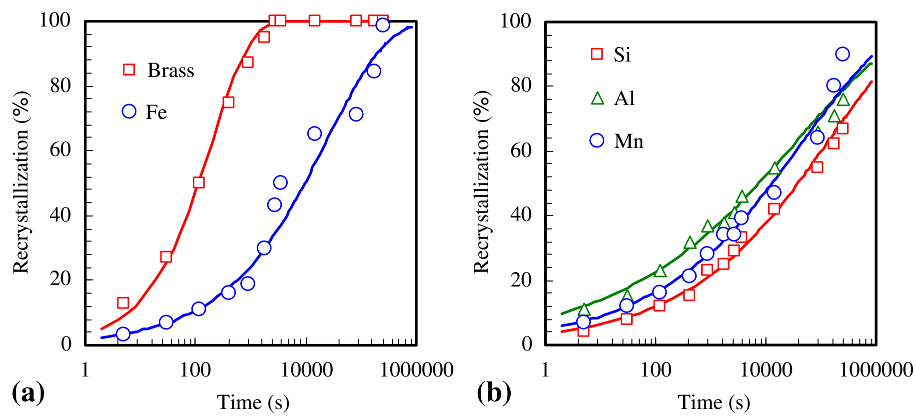


**Fig. 2** Recrystallization fraction (Xa) plotted against time for samples. (a) Samples 1-2 at 500 °C and (b) samples 3-5 at 500 °C

fraction. The variation in recrystallized fraction depending on the chemical composition shows that solute atoms interact with the grain boundaries. If the size of a foreign atom and that parent crystal are different, then there will be an elastic stress field introduced into the lattice by each foreign atom. Therefore, the different influence of each alloying element on the activation energy, and recrystallized fraction, is probably due to the different strain which each element produces on the lattice.

### 4.3 The Activation Energies

To quantitatively investigate the effect of alloying elements, the amount of activation energy for different alloys could be compared as the activation energy is the parameter most sensitive to the chemical composition. To calculate the amount of activation energy, the following relation could be used:

$$t_{0.5} = A \exp\left(\frac{Q}{RT}\right) \qquad \text{(Eq 1)}$$

where $t_{0.5}$ is the time required for 50% recrystallization, $A$ is the constant, $Q$ the activation energy, $T$ the absolute temperature, and $R = 8.314$ J mol$^{-1}$ K$^{-1}$. According to Eq 1, $A$ and $Q$ could be calculated taking Ln ($t_{0.5}$) as a function of $1/T$. Using the experimental data, the magnitude of $t_{0.5}$ was calculated at different temperatures for alloys listed in Table 1. It should be noted that when the exact times of $t_{0.5}$ were not clear, the ranges in which $t_{0.5}$ occurs were selected. By way of example, Fig. 3 shows the used curves for Br, Fe, and Si. The amounts of calculated activation energies are listed in Table 3. As seen from this table, Si is the element which has increased the activation energy. Such difference in the effect

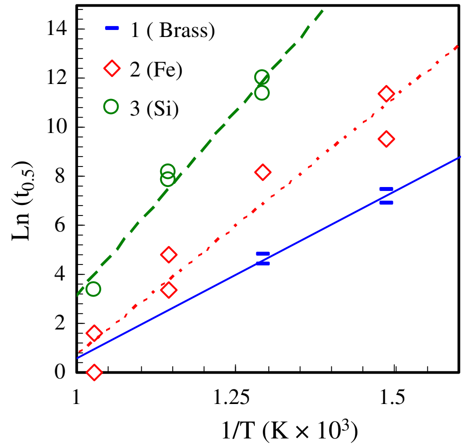


**Fig. 3** The curves of Ln($t_{0.5}$) vs. $1/T$ for calculation the activation energies

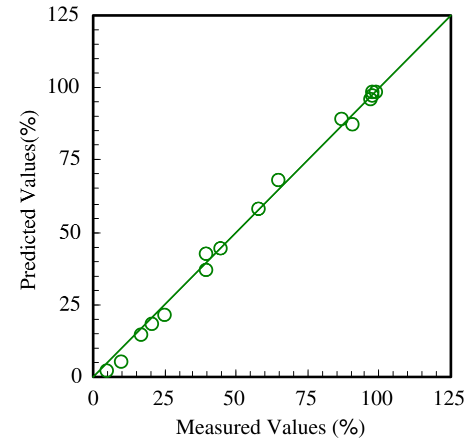


**Fig. 4** Comparison between the results of the model and experimental results, 15 tests data selected randomly from all of the data

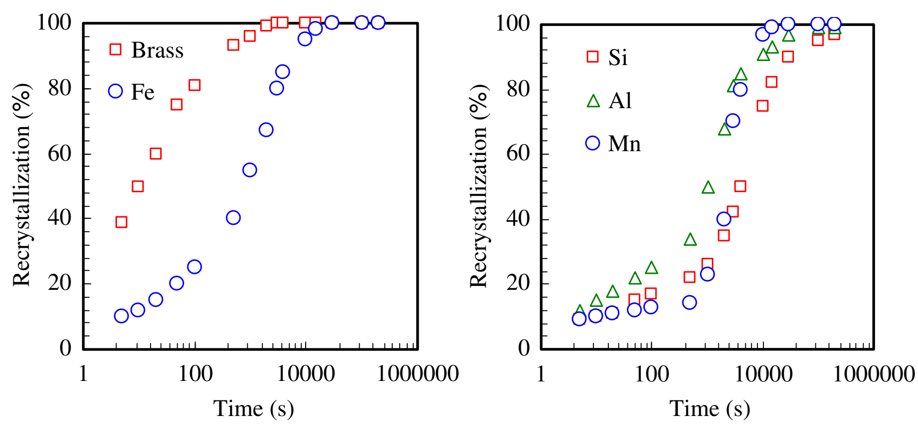


**Fig. 5** Recrystallization fraction curves obtained by designed ANN model for alloys listed in Table 1 at 550 °C

**Table 3 Activation energies for alloys listed in Table 1**

| | $Q$, J/mol | −Ln ($A$) |
|---|---|---|
| 1 (Brass) | 113241.3 | 13.027 |
| 2 (Fe) | 174628.1 | 20.267 |
| 3 (Si) | 248866.2 | 26.757 |
| 4 (Al) | 161319.3-173322 | 17.577 |
| 5 (Mn) | 186431.3-198434 | 20.796 |

of alloying elements on activation energy may be attributed to the difference of the elastic stress field introduced into the lattice by each foreign atom.

### 4.4 Results of the ANN Model

The trained network was then used to compare the predicted and measured values of recrystallized fraction. These comparisons are shown in Fig. 4. As it can be seen, there is a good agreement between the experimental results and the prediction of the model. This agreement indicates that the developed model could be used to predict the recrystallization fraction of 70/30 brass. Figure 5 shows the recrystallized fraction obtained by model for alloys listed in Table 1. As seen in Fig. 5, the results of the model for different alloys show a trend similar to the classical Avrami equation. This agreement again indicates that the designed ANN model was able to learn the training data set well.

## 5. Conclusion

In this study, an ANN has been designed for predicting the effect of alloying elements on the recrystallization behavior of 70/30 brass. The comparison between the experimental results and the results obtained by designed ANN model shows that the model is able to predict the effect of alloying elements. All alloying elements (Fe, Si, Mn, Al) have slowed down the recrystallization kinetics and all have increased the activation energy needed for recrystallization. Si is the element which mostly increases the activation energy.

## References

1. M. Aghaie Kh and A. Mohebati J, Thermomechanical Treatment of 70/30 Brass Containing Iron Impurity, *J. Mater. Sci.*, 2006, **41**, p 7585–7589

2. K. Oishi, I. Sasaki, and J. Otani, Effect of Silicon Addition on Grain Refinement of Copper Alloys, *Matter. Lett.*, 2003, **57**, p 2280–2286
3. A. Bahrami, S.H. Mousavi, and A. Ekrami, Prediction of Mechanical Properties of DP Steels Using Neural Network Model, *J. Alloy Compd.*, 2005, **392**, p 177–182
4. K. Dehghani and A. Shafiei, Predicting the Bake Hardenability of Steels Using Neural Network Modeling, *Matter Lett.*, 2008, **62**, p 173–178
5. C. Capdevila, C. Garcia-Mateo, F.G. Caballero, and C. Garcl′a de Andre's, Neural Network Analysis of the Influence of Processing on Strength and Ductility of Automotive Low Carbon Sheet Steels, *Comp. Mater. Sci.*, 2006, **38**, p 192–201
6. H.C. Qian, B. Xia, S.Z. Li, and W. Fagen, Fuzzy Neural Network Modeling of Material Properties, *J. Mater. Process. Tech.*, 2002, **122**, p 196–200
7. K. Dehghani, A. Shafiei M, and H. Naeimi, Effect of Thermomechanical Processing on Forming Limit Diagrams Predicted by Neural Networks, *Mater. Manufact. Proc.*, 2008, **23**, p 829–833
8. M.G. Smets and W.F.l. Bogaerts, SCC Analysis of Austenitic Stainless Steels in Chloride-Bearing Water by Neural Network Techniques, *Corrosion*, 1992, **48**, p 618–623
9. M.S. Chun, J. Biglou, J.G. Lenard, and J.G. Kim, Using Neural Networks to Predict Parameters in the Hot Working of Aluminum Alloys, *J. Mater. Process. Tech.*, 1998, **86**, p 245–251
10. H. Gleiter, The Formation of Annealing Twins, *Acta Metallurgica*, 1969, **17**, p 1421
11. D.P. Field, L.T. Bradford, M.M. Nowell, and T.M. Lillo, The Role of Annealing Twins During Recrystallization of Cu, *Acta. Matter.*, 2007, **55**, p 4233