Light Metals 2012 *Edited by: Carlos E. Suarez*
TMS (The Minerals, Metals & Materials Society), 2012

OPTIMIZATION OF PROCESS PARAMETERS OF PREPARING FOAMED A1-Si ALLOY BASED ON GA-BASED BP NEURAL NETWORK

Jingbo Xu[1], Huimin Lu[1], Qiang Li[1]
[1]School of Materials Science and Engineering, Beihang University, 37 Xueyuan Road, Beijing, 100191, China

Keywords: Foam, Aluminum-silicon alloy, GA-BP, Porosity

Abstract

This paper analyses the dependence of the structures of foamed Al-Si alloy on the process parameters. It takes the aid of back propagation (BP) neural network theory to build the nonlinear mapping relations between the crucial process variables and the quality of pores. Then by the integrating BP neural network and genetic algorithm (GA), the optimized process parameters for high porosity of foamed Al-Si alloy can be searched. The comparisons between experiment results and neural network simulation results show that GA-based on BP method can predict the porosity with higher prediction accuracy. The effects of viscosity on the foam ability are also important. The mechanism of thickening agent has been analyzed theoretically.

Introduction

Foamed metal is a porous material in which gas bubbles are separated by thin metal films. It is always regarded as a new functional material which is widespread in automotive, railway, aerospace and the other applications. Foamed aluminum can be produced by two methods, powder metallurgy and melt foaming [1-3]. Especially, the melting foaming method, which is relatively useful for commercial production because of its low cost compared with other methods, has been developed for the preparation of aluminum foam. This material generally has a closed cell structure which has considerable effect on properties, such as sound absorption, heat transfer and impact absorption [4]. In general, the melt foam is an unstable system and the process of melt foaming is difficult to control due to its multi-variability and invisibility [5].

Successful implementation of computer aided production systems is very important to modern manufacturing field to produce higher quality products at less cost [6]. Recently, neural network (NN) expected to be able to provide an effective tool because of its advantages, which describe nonlinear mapping relations. With the characteristics of strong self-learning, self-organization, robust error toleration and accurate nonlinear relation approximation, artificial neural network can be applied to nonlinear process modeling based on sufficient training. Back-propagation (BP) training algorithm is probably the frequently used one in practical application. Genetic algorithm has parallel search strategy and global optimization characteristics, which makes the trained neural network being higher classification accuracy and faster convergence speed. So it is necessary to combine neural network and genetic algorithm. The nonlinear relationship between input and output presented by NN and the global optimal function of GA are abroad applied in the engineering and scientific research [7, 8]. So these methods supply an efficient path to solve the above problems. At present, it is common to study the optimization of process parameters for aluminum alloy foams by orthogonal experimental design, but the method combining neural network and genetic algorithm has never been researched. This study organized the above advantages to optimize the process parameters for Al-Si alloy foams.

Experimental procedure

Our foaming process consisted of the following steps: 2kg of a A1-7wt%Si alloy melted by mixing Si with high-purity and electrolytic aluminums was melted at 650°C in an graphite crucible in a resistance furnace under atmospheric pressure. For modifying the melt to increase the viscosity, aluminum powder(~37 μm diameter) at 3~6.5 wt.% of the melt was added to the melt and stirred at a constant speed of 800rpm for 7min to make the melt viscous. When the temperature of the melt decreased to 610~635°C, 1 to 2.5 wt.% titanium hydride powder (TiH_2) as a foaming agent (heated in 300°C for two hours) was introduced into the melt at a stirring speed of 1500 rpm. After stirring, the melt remained in the furnace for 5 min to allow the titanium hydride to decompose to form hydrogen gas. The crucible was then taken out of the furnace and directionally solidified in water quenching. In order to gain uniform pore structure, water cooling in all directions were employed during the solidification. Differential thermal analysis (DTA) has been used to study the temperature of the hydrogen release of titanium hydride powders before and after heated. The hydrogen release was monitored in the temperature range of 298~1273K in argon atmosphere at a heating rate of 10K/min. The morphology of the pore structure was characterized by both microscopes and SEM-EDS.

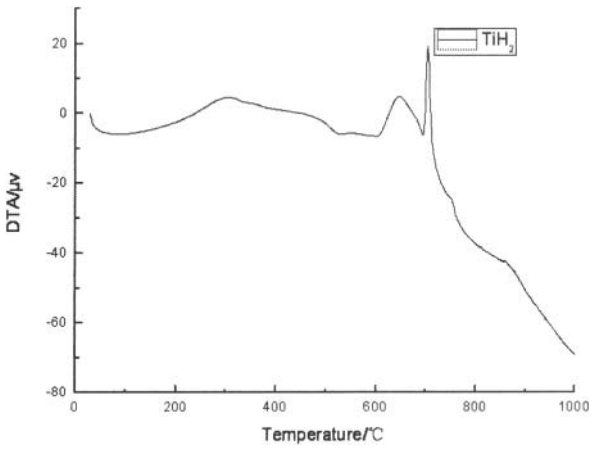

Figure 1. TGA curve of TiH_2

Results and Discussion

Figure 1 shows the comparison of the DTA curve. There are two exothermic peaks between 600°C and 700°Cdue to the thermal decomposition reaction of the titanium hydride. It indicates that the titanium hydride starts to decompose hydrogen at 600°C and decomposes rapidly in heating at 646°C. After TiH_2 decomposed completely, the new titanium which have strong chemical activity at higher temperature will have a chemical reaction with oxygen and nitrogen. Then there will be another peak at 700°C. This result indicates that the holding temperatures have to be maintained in the temperature range from 610°C to 650°C in order to match the melting point of the Al-Si alloy.

Uniform Design

Uniform design method through one set of selective chart to design the experiment scheme. The chart is a short of normalized form, at the same time is the base tool for uniform design. It can be expressed by $U_n(m^k)$. U is the code name of chart, n is row number that means experiment times, m is the number of different codes in every column that means factor levels, k is column number that means the number of specified factors [9]. All the parameters in present work are defined as following. In order to optimize the process parameters, addition of thickening agent, foaming temperature, and addition of foaming agent are considered as the essentially influencing factors. A mapping relationship between variables is set up by NN method. To satisfy the validity and high precision in the relationship, there must be enough multiple typical testing points to join NN study. Six levels are specified for every factor in the appropriate range referenced experiences. The purpose of optimizing process parameters is to get higher porosity. By the above analysis results, $U_6(6^4)$ chart as Table I is made for uniform experiments.

Experiment Results

As carried out in the experiment, the porosity and size of the foamed alloy are also shown in Table I. It shows that the porosity and size of the foamed alloy change with addition of aluminum powder, addition of hydride powder, foaming temperature. At the same time, Figure 2 shows that the control of pore size and porosity influences each other. With the increases of porosity, the size is increasing.

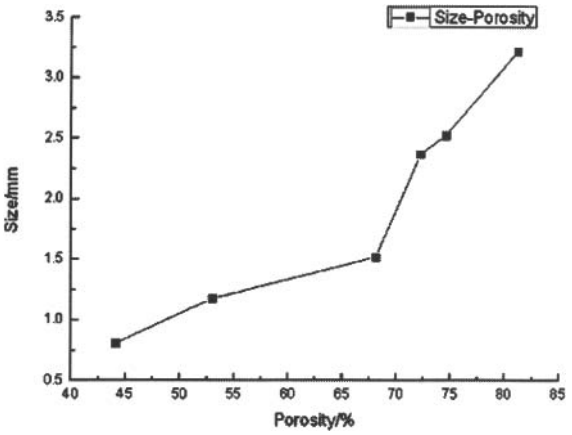

Figure 2. The curve of the pore size with the increasing of porosity.

Table I. Processing Parameters and Result for Foamed Aluminum Alloy of Different Pore

Number	Addition of thickening agent (%)	Addition of foaming agent (%)	Foaming temperature (℃)	Porosity (%)	Size of the pores (mm)
1	3	1.2	615	74.5	2.53
2	3.2	2	625	81.2	3.22
3	3.6	1.6	630	72.2	2.37
4	4.8	1	610	53.0	1.18
5	5	1.5	635	68.1	1.52
6	6.5	2.5	620	44.1	0.81

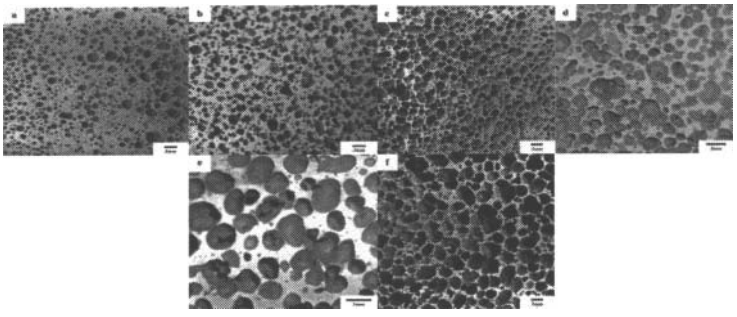

Figure 3. Macrograph of foam structure for different porosity and pore of foamed aluminum alloy (a) P=44.1%, S=0.81mm; (b) P=53.0%, S=1.18mm; (c) P=68.1%, S=1.52mm; (d) P=72.2%, S=2.37mm; (e) P=74.5%, S=2.52mm; (f) P=81.2%, S=3.22mm

Figure 3 shows the macrostructure of the foamed alloy. According to the morphology of the pores, the foamed aluminum alloy with low porosity shows spherical or sphere-like holes, while high porosity (P≥80%) shows polygonal holes.

Simulation results and GA-BP model

BPNN model forming. Factors (addition of thickening agent, addition of foaming agent and foaming temperature) that greater impact on the porosity is selected as input, and the porosity is selected as output.

In all sorts of NN, the most used one is called BP neural network with error depropagation, which can be close to any nonlinear mapping relations and has stable and good generalization capability. The three-layer BP network topology involving one single target output is shown in Figure 4. The hidden layer is a tangent type. It has been proved theoretically that this sort of network can approach to any rational function.

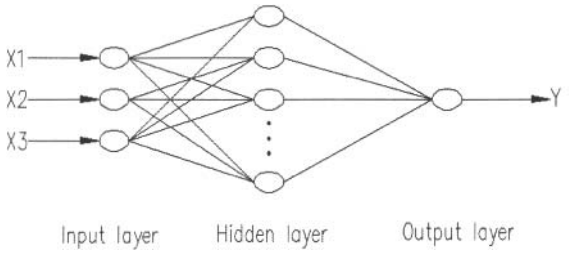

Figure 4. BP net structure

The BP NN model is set up by editing M files with the help of Matlab. All experiments in Table I are taken as input samples and test samples. The NN is trained by changing nerve cell quantity of hidden layer and other factors. According to numerous trainings and the experience of several experiments, the factors are confirmed. When the number of nerve cell is 7, learning rate 0.3, momentum factor 0.95, target error 1E-28, the error of test samples is minimal.

Genetic Algorithm. GA is an optimum searching technique by means of crossover, mutation, and selection that mimicking natural evolution mechanism. Its essence is an efficient, parallel, global search method. It can automatically obtain and accumulate knowledge about the search space, and adaptive control process in order to achieve the optimal solution.

Introducing Genetic Algorithm to Improve BP Neural Network. Although BP has the ability of accurately optimization, it is often plagued by the local minimum point, low convergence or oscillation effects. Thus the prediction accuracy may be affected. There are two problems still exist in the application of BP. One is the determination of the network topology, especially the neuron number in the hidden layer without the guidance of theoretical formula. The other is the problem of convergence accuracy, i.e. how to determine a reasonable number of hidden layer and hidden layer neurons to achieve both the required accuracy and short-training time.

The trouble of falling into local optimum can be resolved by adjusting the initial values, while the slow convergence and oscillation effects is caused by network training falling into local minimum. So the method of GA is usually used for the optimization of BP, which has a strong searching capability and high probability in finding the global optimum solution. Although these two techniques seem quite different in the number of involved individuals and the process scheme, they can do a synergistic combination to provide more power of problem solving than either alone [10-12]. Therefore, many researchers have attempted to combine the two algorithms together in order to achieve the complementary advantages [13, 14].

The principle of the GA-BP algorithm is as following: before the optimization, GA is used to optimize the number of connection weights, the best connection weight and threshold for BPNN from its searching space which contains all the available individuals. After that, a global optimum solution can be achieved. Then, the last generation of individuals is decoded and the corresponding BP network topology, initial connection weights, and thresholds can be achieved. With these values worked as the BP network topology and the initial value, samples can then be trained to obtain the final optimal results [15].

Simulation and experiment results. According to the principle of GA-BP algorithm, the corresponding computing process is programmed and run with MATLAB. The corresponding parameters are set as following: the initial population number N=30, the cross probability P_c=0.8, the mutation probability P_m=0.1, and the error e=0.001. When the error reaches the intended target, the training process of BP will stop. Figure 5 shows the simulation results with GA-BP algorithm.

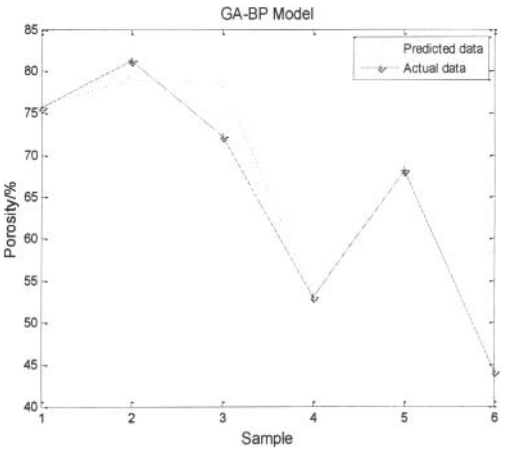

Figure 5. The simulation results with GA-BP algorithm

In the process of GA optimization, with the increase of the evolution of generation, the fitness and sum-square error is becoming convergent and finally achieves the best value, respectively. After about 100 generations of searching, the fitness and the sum-square error has been stabilized, respectively, as shown in Figure 6. The predicted results of GA-BP algorithm are shown in Table II.

Table II. Testing data of GA-BP Model

Data (%)	1	2	3	4	5	6
Predicted data	75.95	78.94	78.54	52.07	68.1	44.1
Actual data	74.5	81.2	72.2	53.0	68.1	44.1

According to the above simulation results of GA-BP algorithm, the optimum process parameters and higher porosity are searched as follows: the addition of thickening agent is 3%; the addition of foaming agent is 1.9%; foaming temperature is 630 ℃ ; the predicted porosity is 86.46%. Based on the optimized process parameters, the actual predicted porosity is 83.87%. As shown in Figure 7, its size is 3.37mm and the biggest among the samples. The error of porosity between the prediction and actual result is 3.1%. It proves the validity and availability of the algorithm.

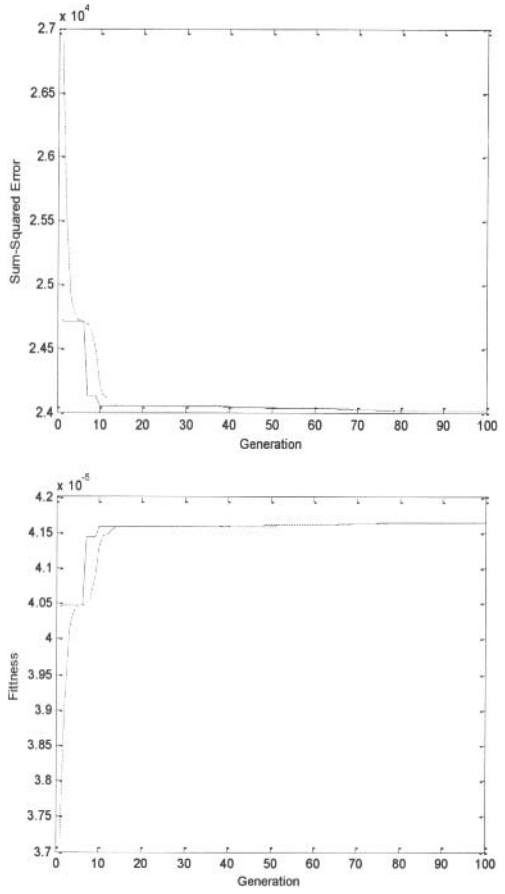

Figure 6. The curve of sum-square error and fitness of GA-BP

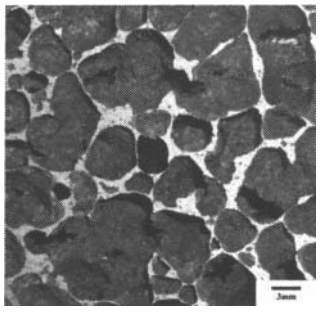

Figure 7. The morphology of the foamed alloy prepared in accordance with the optimum process parameters: P=83.87%, S=3.37mm

Thickening mechanism of aluminum powders

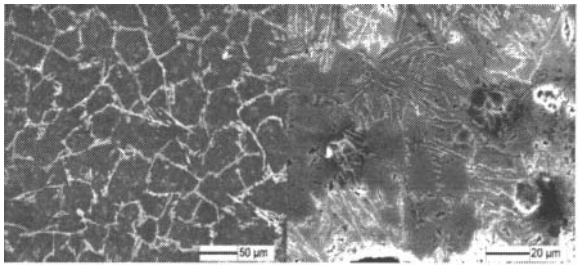

Figure 8. The metallograph of the Al-Si melt before and after adding aluminum powder

The uniformity of the pore structure is an important indicator of aluminum foam structure. To obtain uniform pore structure, it is necessary to make thickening treatment during foaming process.

With the addition of aluminum powder, the viscosity of the melt increases because of particles formation in the melt. Then the increase in viscosity increases the efficacy of the titanium hydride powder addition. Figure 8 shows the morphology of the oxides in the melt. This is because the addition of aluminum powder and subsequent agitation in the atmosphere facilitate oxidation of the aluminum melt and generate fine oxide particles. Due to the lower surface tension between oxides and liquid aluminum, the oxides are easily suspended in the melt, which strengthens internal friction among metal particles. Thus the viscosity of the melt is improved.

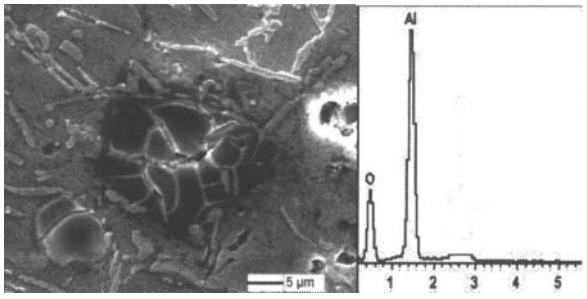

Figure 9. SEM image and EDS pattern of oxide of Al-Si melt after the addition of aluminum powder

To analyze visually the influence of aluminum powder on the viscosity of the melt, it is necessary to carry on a structural analysis to the Al-Si melt with stirring for 7min after adding aluminum powder. Fig.8 shows that there are many black particles precipitated in the grain boundaries. Select an area with black particles to investigate by SEM and EDS.

As shown in Figure 9, there are a lot of O elements except Al in the particles. The weight percentage of O and Al is 33.83% and 66.17%, and the atom percentage is 46.30% and 53.70%. According to this, the black substance is alumina. For further confirmation, Figure 10 indicates that the alumina can also be found in foamed aluminum alloy.

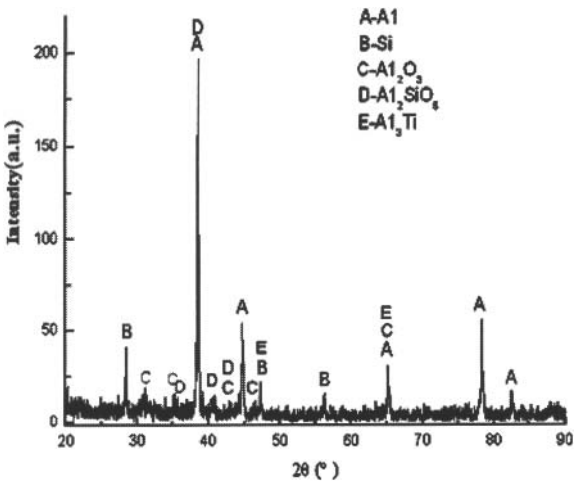

Figure 10. X-ray diffraction spectra of the foamed aluminum alloy

Aluminum powders can also be used to stabilize bubbles that foaming agent decomposes. The stability of bubbles depends on the speed of drainage, the strength of liquid film and the size of gas permeability. After the aluminum powders are added, the small solid particles suspended in the melt adhere to the surface of air bubbles, which blocks drainage, the diffusion of gas and accumulation and growth of bubbles. Then the stability of the bubble is improved.

Conclusion

A three layers BP neural network is set up and trained with the experiment results. The test results show that the nonlinear relations between the foaming parameters and the porosity can be described by the BP neural network.

Using the GA-BP algorithm, the foaming process parameters were optimized with higher porosity. With the optimal parameters, the porosity of foamed aluminum alloy is 86.46% in GA-BP model and 83.87% in experiment result. The two results are well meet with each other. So the GA-BP algorithm is stable and available.

The use of aluminum powder as thickening agent can not only significantly increase the viscosity of liquid aluminum, but also stabilize the foamed bubbles generated from the decomposition of titanium hydride.

Reference

1. J .C.ELLIOTT, U.S. Patent no. 2751289 (1956).

2. H.UNNO, S.AKIYAMA, *Light Metal* (in Japanese) 42 (1987) 37.

3. J .BANHART, *Material Sci. & Eng.* A205 (1996) 221.

4. Zhenlun Song, (Ph.D. Thesis, Southeast University, Nanjing, China, 1998).

5. S.M.Oak, B.J.Kim, W.T.Kim, M.S.Chun, Y.H.Moon, "Physical modeling of bubble of generation in foamed-aluminum," *Journal of Materials Processing Technology,* 130-131 (2002) 304-309.

6. Nursel.Ozturk, Ferruh.Ozturk, "Hybid neural network and genetic algorithm based machining feature recognition," *Journal of Intelligent Manufacturing,* 15 (2004) 287-298.

7. Zou Fengshan, Wang Chengzhi, Huang Yong, "Optimizing Gating System Parameters of Die Casting in Virtue of Artificial Neural Network," *Research Studies on Foundry Equipment,* 6 (2002) 12-14.

8. Shi Feng, Lou Zhenliang, Zhang Yongqing, "Fuzzy Optimization of Cold Extrusion Mold Based on Genetic Algorithm and Neural Network," *CJME,* 38 (2002) 45-49.

9. Pei Zhang, Zhiqiang Xu, Fengshan Du, "Optimizing casting parameters of ingot based on Neural Network and Genetic Algorithm," *Fourth International Conference on Natural Computation*, 707 (2008) 545-548.

10. Y. Gary and H.M. Lu, "Hierarchical Genetic Algorithm for Near-Optimal Feed forward Neural Network Design," *Int. J. Neural Syst.*, 12 (2002) 31-43.

11. X.Yao, "Evolving Artificial Neural Network," *Proc. IEEE*, 87 (1999) 1423–1447.

12. M.Gen and R. Cheng, "Genetic Algorithm and Engineering Optimization" (Wiley, New York, 2000).

13. R.S. Sexton, R.E. Dorsey, and J.D. Johnson, "Toward Global Optimization of Neural Networks: A Comparison of the Genetic Algorithm and Backpropagation," *Decis. Support Syst.*, 22 (1998) 171-185.

14. J.N.D.Gupta, R.S.Sexton, "Comparing Back propagation with a Genetic Algorithm for Neural Network Training," *Omega*, 27 (1999) 679-684.

15. Jingjie Zhang, Chonghai Xu, Mingdong Yi, Bin Fang, "Design of Nano-Micro-Composite Ceramic Tool and Die Material with Back Propagation Neural Network and Genetic Algorithm," *Journal of Materials Engineering and Performance*, 2011