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Optimal Reheating Condition of Semi-solid Material in Semi-solid Forging by Neural Network

Jae-Chan Choi[1], Young-Ho Kim[1] and Joon-Hong Park[2]

[1] School of mechanical engineering, Pusan National University, Pusan, South Korea
[2] Research Institute of Mechanical Technology, Pusan National University, Pusan, South Korea

ABSTRACT

As semi-solid forging (SSF) is compared with conventional casting such as gravity die-casting and squeeze casting, the product without inner defects can be obtained from semi-solid forming and globular microstructure as well. Generally, SSF consists of reheating, forging, and ejecting processes. In the reheating process, the materials are heated up to the temperature between the solidus and liquidus line at which the materials exists in the form of liquid-solid mixture. The process variables such as reheating time, reheating temperature, reheating holding time, and induction heating power has large effect on the quality of the reheated billets. It is difficult to consider all the variables at the same time for predicting the quality.

In this paper, Taguchi method, regression analysis and neural network were applied to analyze the relationship between processing conditions and solid fraction. A356 alloy was used for the present study, and the learning data were extracted from the reheating experiments. Results by neural network were in good agreement with those by experiment. Polynominal regression analysis was formulated using the test data from neural network. Optimum processing condition was calculated to minimize the grain size and solid fraction standard deviation, or to maximize the specimen temperature average. Discussion is given about reheating process of row material, and results are presented with regard to accurate process variables for proper solid fraction, specimen temperature and grain size.

Keywords : Semi-solid forging, Reheating process, Solid fraction, Neural network, Taguchi method, Regression analysis

1. Introduction

The semi-solid forging (SSF) is a new forging technology in which the billet is heated to the semi-solid state coexisting with liquid and solid phase. Many studies have been done since Fleming and Suery's proposal in 1970s [1,2].

It took about 20 years for the thixoforging process to mature from the status of an academic curiosity to that of a nascent production process. A great number of researchers have studied semi-solid processing rather than conventional process methods such as die casting and squeeze casting which involve various problems; blowhole, segregation and the thermal defect of the die.

The SSF process comprises two steps: reheating of feedstock slugs to the semi-solid state and forging of the semi-solid material into the die. Reheating to the semi-solid state is particularly important in the thixoforging process. In the cases of hypoeutectic Al-Si7Mg (A356, A357) type of alloys, the eutectic must be remelted completely in order to obtain good mechanical properties If this is not the case, unmelted, coalesced, and polyhedral Si crystals remain, then these have an effect on the rheological properties during die filling and on elongation of the finished part. Temperature slightly higher than the eutectic plateau does not adversely affect the mechanical properties, but increase metal loss and decrease slug consistency.

There are many variables in the reheating process. However, it is impossible to actually consider all kinds of variables. Consequently, eight variables were selected;

Table 1 Dimension of the three kinds of the specimen

Specimen size(mm)	ø76× 70	ø60× 70	ø76× 100
L_i, l_i	70, 35	70, 35	100, 50
D_i, d_i	76, 30	60, 24	76, 30
b_i	5	5	5
(A)(B) (C)(D)	Thermocouple positions		

reheating time (RT_1, RT_2, RT_3), reheating temperature ($RTemp_1$, $RTemp_2$), reheating holding time (RHT), induction heating power (Q) and specimen size (SS). Some researches for the reheating process have been reported. Kenney [2] carried out experiments about solid fraction of billets, 60-70%.

G. Hirt [3] assumed that the die temperature could be treated between 150 and 300℃ as an optimum semi-solid forging condition. Young [4] studied the multistage reheating experiment of AlSi7Mg alloys with solid fraction = 60%. R. Cremer [5] controlled the induction heating using sensor. Jung [6] showed the optimal coil dimensions of the commercial induction heating system. However, there are no reports about optimum reheating process using statistical method and artificial intelligence on the semi-solid forging.

Therefore, the optimum reheating conditions of A356 alloy with globular microstructure made by PECHINEY are proposed in this study. In addition, on the assumption that the coil is suitable for the reheating process, the optimum reheating process is demonstrated by using reheating experiments, Taguchi method, Neural networks and regressing analysis.

Besides, this paper describes the development of a neural network model for optimum reheating process. The model uses the data analysis of reheating process variables based on Taguchi method. The developed model is, then, compared with the traditional polynomial regression model to assess the applicability in practice. The microstructures of semi-solid and the heated materials are investigated with optical microscopes; solid fraction, size and distribution of grains are measured with image analysis program.

2. Experimental Conditions for the Optimal Reheating Process

Size of the specimen is shown in Table 1 and photograph of the specimen is shown in Fig. 1. In this experiment, three kinds of the specimen are used and measuring points of the cylindrical specimen are shown in Fig. 2. The reheating processes were experimented by using an induction heating system with the capacity of 50KW and the frequency of 60Hz.

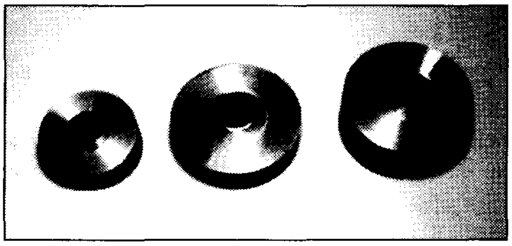


Fig. 1 Photograph of the three kinds of the cylindrical billets

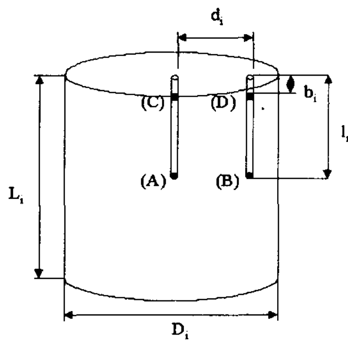


Fig. 2 Schematic drawing and measuring points of the cylindrical specimen

The following parameters were used to determine the optimal reheating conditions as shown in Table 2.

Generally, the relationship between solid fraction and temperature calculated by the following formula [7] or Scheil's equation [8] could predict solid fraction of Al alloys. In the semi-solid forming, fine globular microstructure can be obtained in case of 60-70% in solid fraction [2]. Therefore, in this experiment, rapid quenching of the reheating specimens was carried out at 566℃ with 65% in solid fraction.

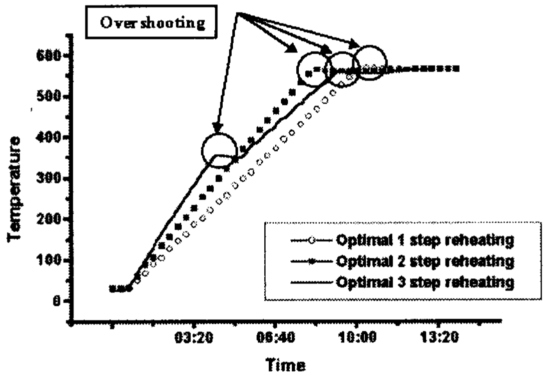
Fig. 3(a) shows general multi-step reheating method.

However, this profile contains a sudden rise in temperature that causes such problems as irregular and non-uniform heating. Fig. 3(b) shows the proposed temperature profile and the application of the variables in this study that make satisfactory temperature control possible.

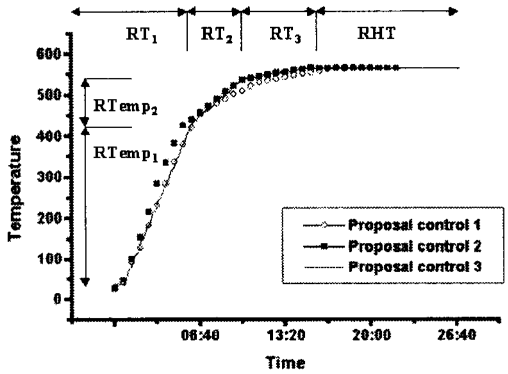
In the present work, Taguchi method for reheating process in A356 alloys has been adopted for preventing too many numbers of experiments and for investigating contribution of the reheating process variables. $L_{27}(3^{13})$ Orthogonal array is adopted to verify effect of the parameters. The selected parameters consist of reheating time (RT_1, RT_2, RT_3), reheating temperature ($RTemp_1$, $RTemp_2$), reheating holding time (RHT), induction heating power (Q), and specimen size (SS). Additionally, solid fraction, temperature of the specimen, and grain size are selected for the quality feature. Variance analysis is performed in order to check effect of the parameters on the reheating process. The properties of Taguchi method for each reheating process variables are investigated in comparison with those of the actual experiments, especially neural network and regression analysis.

Table 2 Range of the variables for the reheating process

Input variables	Processing		
	Min.	Med.	Max.
Reheating time(RT_1 ,A, min)	5	6	7
Reheating time(RT_2 ,B, min)	4	5	6
Reheating time(RT_3 ,C, min)	4	5	6
Reheating temperature ($RTemp_1$, D, ℃)	410	420	430
Reheating temperature ($RTemp_2$, F, ℃)	530	540	550
Reheating holding time (RHT, G, min)	2	7	12
Induction heating power (Q, H, KW)	3	4	5
Specimen size(SS, I, mm)	ø76 × 70	ø60 × 70	ø76 × 100



(a) General reheating method with 1, 2, 3 steps



(b) The proposed temperature profile and application of the variables

Fig. 3 Comparison between general reheating method and the temperature profile proposed in this study

3. Results and Discussions

3.1 Taguchi experimental design method

Reheating process variables of solid fraction, specimen temperature and grain diameter were analyzed from experiment conditions using Taguchi's $L_{27}(3^8)$ orthogonal array. At this time, if induction-heating power is small (3KW), solid fraction does not reach the target value equivalent to 65% as shown in Fig. 4.

As the reheating holding time (G) of specimen temperature becomes longer, more uniform distribution of temperature can be obtained. There are cases in which experimental value has narrow range of the temperature section with regard to comparatively low reheating temperature (F) as shown in Fig. 5.

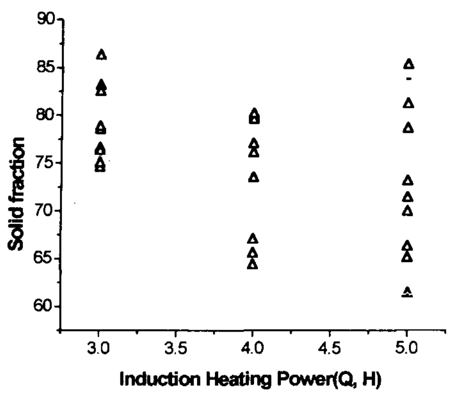


Fig. 4 Effect of induction heating power on solid fraction

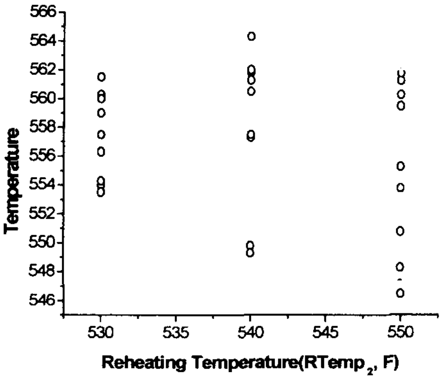


Fig. 5 Effect of reheating temperature on the specimen temperature

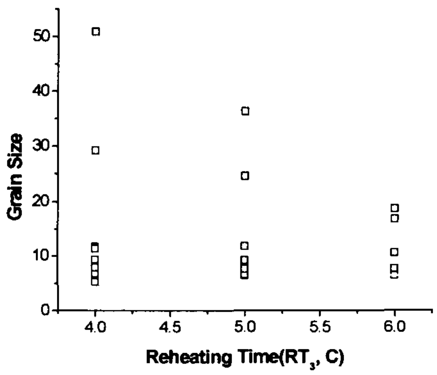
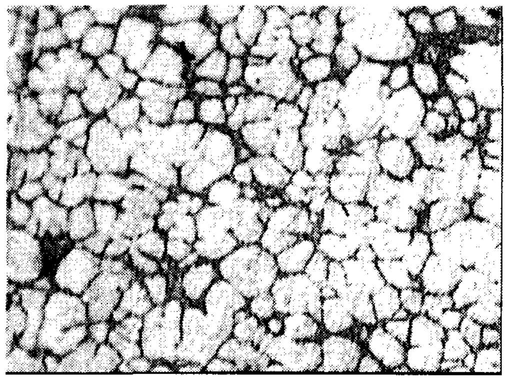
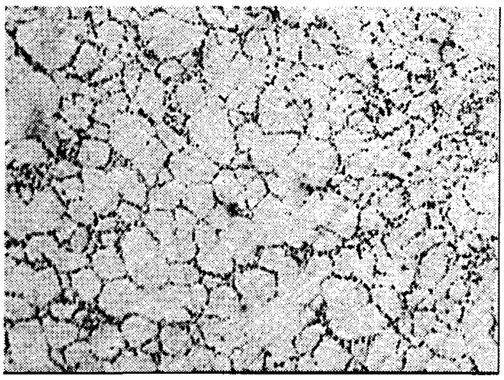


Fig. 6 Effect of reheating time on the grain size

Microstructure of experiment No. 13(65.1%) and No. 17(86.3%) in reheating process of semi-solid aluminum alloy were shown in Fig. 7. Both of the specimens as shown in Fig. 7 were heated up to 566°C in the different manner. However, both microstructures show the clear difference in solid fraction average as 65.1% and 86.3% respectively. It indicates that microstructure is affected not only by temperature but also by other process variables.



(a) Microstructure of the specimen with 65.1% in solid fraction



(b) Microstructure of the specimen with 86.3% in solid fraction

Fig. 7 Microstructure of semi-solid aluminum alloy reheated with the same temperature

Consequently, Fig. 8 shows graph of solid fraction and grain diameter average. As a result, it is found that as solid fraction becomes lower, accuracy of globularization becomes better and the boundary between solid and liquid becomes clearer. Moreover, the lower the reheating temperature (RTemp$_1$, RTemp$_2$), the lower is solid fraction and the smaller is the gradient of specimen temperature. Grain size is apt to exponentially increase, as solid fraction increases.

Table 3 Reheating process experiments and data of solid fraction based on design of experiments

Array	A	B	C	D	F	G	H	I	Solid fraction (%)			Av. (y_i)	S/N
No.	1	2	3	4	5	6	7	8	1	2	3		
1	0	0	0	0	0	0	0	0	74.0	76.0	79.7	76.57	8.3634
2	0	0	0	0	1	1	1	1	76.0	77.0	75.1	76.03	0.9034
3	0	0	0	0	2	2	2	2	76.3	70.0	72.1	73.13	9.9234
4	0	1	1	1	0	0	0	1	81.2	81.0	87.2	83.13	12.4134
5	0	1	1	1	1	1	1	2	74.5	72.4	73.4	73.43	1.1034
6	0	1	1	1	2	2	2	0	66.3	67.3	65.2	66.27	1.1034
7	0	2	2	2	0	0	0	2	74.9	72.8	75.9	74.53	2.5034
8	0	2	2	2	1	1	1	0	80.6	79.8	79.2	79.87	0.4934
9	0	2	2	2	2	2	2	1	69.5	70.2	70.1	69.93	0.1434
10	1	0	1	2	0	1	2	0	85.6	85.0	85.5	85.37	0.1034
11	1	0	1	2	1	2	0	1	75.0	75.2	74.8	75.00	0.0400
12	1	0	1	2	2	0	1	2	78.6	80.0	80.1	79.57	0.7034
13	1	1	2	0	0	1	2	1	69.3	62.7	63.6	65.10	12.8250
14	1	1	2	0	1	2	0	2	79.0	78.3	78.2	78.50	0.1900
15	1	1	2	0	2	0	1	0	66.7	65.7	64.2	65.53	1.5834
16	1	2	0	1	0	1	2	2	61.4	63.1	59.6	61.37	3.0634
17	1	2	0	1	1	2	0	0	85.8	85.5	87.6	86.30	1.2900
18	1	2	0	1	2	0	1	1	78.4	74.6	77.9	77.00	4.2650
19	2	0	2	1	0	2	1	0	66.6	67.3	67.0	67.00	0.1250
20	2	0	2	1	1	0	2	1	78.4	84.2	81.0	81.20	8.4400
21	2	0	2	1	2	1	0	2	79.2	78.8	78.4	78.80	0.1600
22	2	1	0	2	0	2	1	1	79.4	79.1	81.9	80.13	2.3634
23	2	1	0	2	1	0	2	2	80.0	79.7	76.1	78.60	4.7100
24	2	1	0	2	2	1	0	0	74.5	78.2	76.2	76.30	3.4300
25	2	2	1	0	0	2	1	2	63.3	65.4	64.2	64.30	1.1100
26	2	2	1	0	1	0	2	0	70.0	72.3	71.8	71.37	1.4634
27	2	2	1	0	2	1	0	1	79.5	83.6	84.4	82.50	6.9100

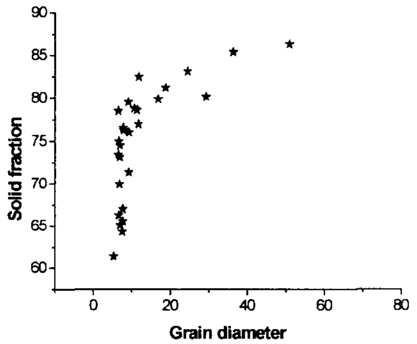


Fig. 8 Relationship between solid fraction and grain diameter average

3.2 Neural network

Using the Taguchi and the artificial neural network, an optimal reheating condition satisfying the right solid fraction control over the reheating specimen is proposed. A three-layer neural network is used and the back propagation algorithm is employed to train the network.

Training of neural networks was performed with back propagation method by using experimental data sets sampled in Taguchi method. This approach saves computing time and storage space. In addition, it provides easy extendibility as new data become available The performance of the trained neural network for the reheating process is evaluated to examine the predictability of the reheating process variables. Furthermore, an optimal solid fraction that satisfied both small temperature gradient and fine grain size is determined by applying the ability of data approximation of neural network. The neural networks reduce the number of experiments for determining the optimal solid fraction of the reheating process.

The back propagation neural networks with 5-4-3 networks in this study, with full interconnection, consist of an output layer, input layer and hidden layer. Each layer has a set number of nodes chosen to fit the problem at hand as shown in Fig. 9.

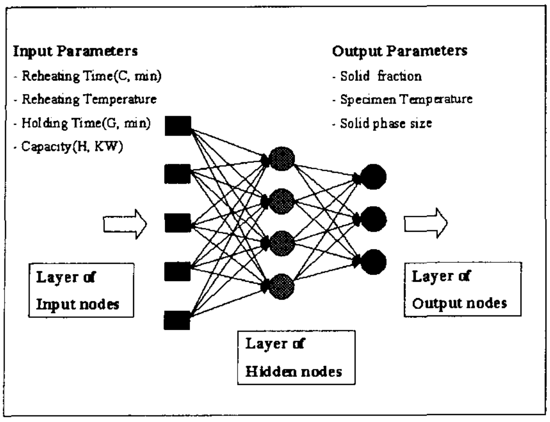
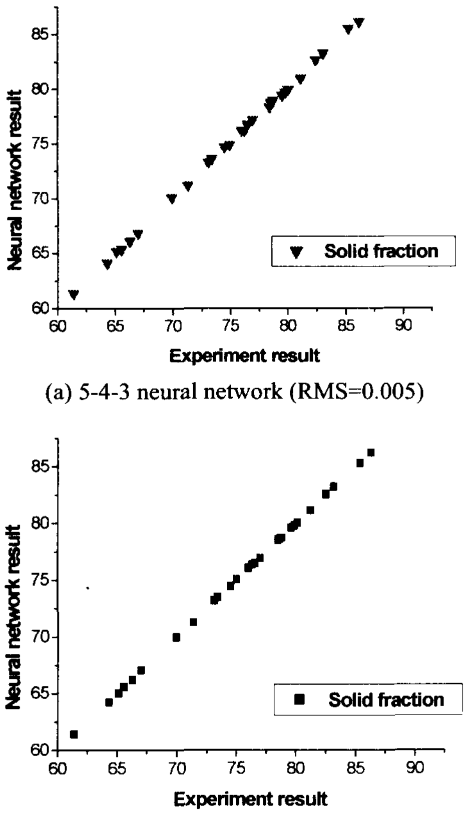


Fig. 9 Back propagation neural network with 5-4-3-network structure

The network learning is performed with the training data to find out the weight matrix and node biases. In order to cope with the long training time of back propagation neural networks, some measures for improving efficiency are taken. The input patterns and target outputs are normalized and scaled within the range -0.5 and 0.5. The learning rate and the momentum are adjusted during the training process for speeding up the convergence. Typical values of learning are 1.0 to 3.0 for the small training data set size, and 0.1 to 0.3 for the large training data set size. In case of the optimum reheating process, a learning rate of 0.2 was used. The values of momentum were kept less than 1.0. Results of the 5-4-3 neural networks and 8-5-3 neural networks learning are shown Table 4.

Table 4 Optimum reheating conditions by neural network

	Experiment	5-4-3 Network	8-5-3 Network
EMS	-	0.00484	0.001916
Iteration	-	2.02×10^7	1.98×10^7
Array	$A_1B_1C_2D_0F_2G_0H_1I_0$	$C_2D_0F_2G_0H_1$	$A_1B_1C_2D_0F_2G_0H_1I_0$
Solid fraction	65.53	65.36	65.59
Temp	560.25	559.40	560.07
Grain diameter	7.70	7.45	7.63



(a) 5-4-3 neural network (RMS=0.005)

(b) 8-5-3 neural network (RMS=0.002)

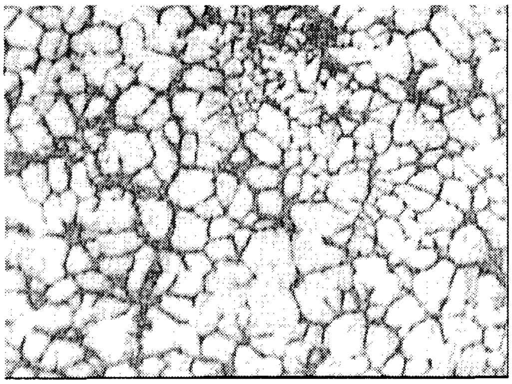
Fig. 10 Comparison of solid fraction average between experiments and neural networks

Fig. 10 shows comparison of solid fraction between experiments and neural networks (5-4-3, 8-5-3). Even though RMS (Root Mean Square) of the 8-5-3-neural network is smaller than that of the 5-4-3-neural network, the test results show that the neural network for the reheating process is able to predict the reheating process parameter values within an acceptable error rate.

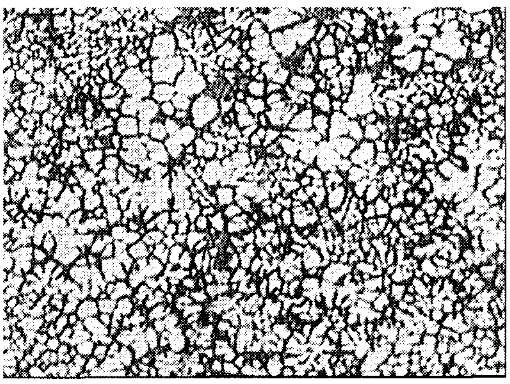
Fig. 11 shows microstructure of the specimen enlarged by 100 times after the reheating process. This microstructure was obtained by using the result of the analysis in Table 4, which shows very fine and globular grains.

3.3 Regression analysis

Statistical analysis of the reheating variables can assess the alterations in the reheating conditions. It will become possible to correctly set up parameters of the equipment and to predict future trends in their changes.



(a) ×100



(b) ×50

Fig. 11 Microstructure obtained by optimum reheating condition in Table 4

It is also a matter of statistics to find out whether or not the "as constant" factors have a significant impact on predictions for a particular model. Regression analysis is to illustrate what kind of information can be obtained when a model used for process variables is analyzed by linear regression. Quantitative characteristics of the model predictive ability is introduced in addition to standard statistical F-tests for model adequacy.

Table 5 shows selection of the best regression model and regression factors. The optimum regression model was established in the 2nd regression model. The results of linear regression analysis enhance the predictive ability of the solid fraction, specimen temperature and grain size.

3.4 Comparison of analysis method

In this study, Taguchi method, neural network, regression analysis, and experiment were performed.

Table 5 Selection of best regression model and regression factors

Reference: X11=X1*X1

Regression model	Object variables	Selected variables	R-square
Selection best regression model	Solid fraction	X4, X6, X7(D, G, H)	0.2982
	Temperature	X4, X6, X8(D, G, I)	0.2312
	Grain diameter	X3, X6, X7(C, G, H)	0.1501
1st regression model	Solid fraction	X3, X4, X5. X6, X7 (C, D, F, G, H)	0.2783
	Temperature		0.2218
	Grain diameter		0.5259
2nd regression model	Solid fraction	X1, X2, X3, X4, X5, X6, X7, X8, X11, X22, X33, X44, X55, X66, X77, X88, X18, X25, X26, X27, X28, X35, X36, X38, X48	0.9998
	Temperature		0.9440
	Grain diameter		0.9967

Table 6 Results of the process variables according to various analysis methods

Analysis method		Solid fraction	Specimen Temp.	Grain diameter
Array	Experiment	65.1000	554.2500	7.0000
$A_1B_1C_2D_0F_0G_1H_2I_1$	Taguchi method	65.3300	556.5000	9.2200
	Neural network	65.1841	554.3728	7.0274
	Regression analysis	66.3809	555.6469	7.3070

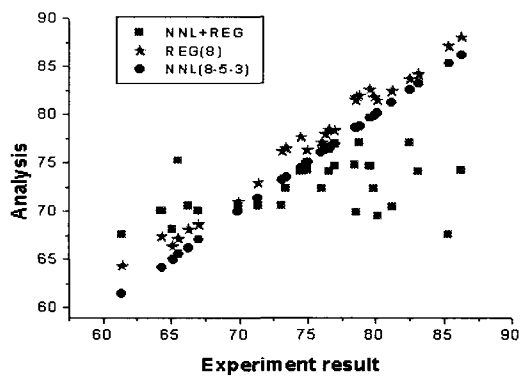


Fig. 12 Comparison of NNL+REG, regression analysis and 8-5-3-neural network for solid fraction average

Table 6 shows the results of the reheating process variables according to various analysis methods. In addition, Fig. 12 shows comparison of results by NNL (Neural Network Learning)+REG, regression analysis, and 8-5-3-neural network for solid fraction average. As shown in Table 6 and Fig. 12, it was found that the result of 8-5-3-neural network was on good agreement with that of experiment.

4. Conclusions

This study has demonstrated that the new method of artificial neural networks and regression analysis is a useful technique to predict the optimum process variables in a reheating process. The conclusion of the present study is as follows.

1. In a reheating process, other process variables as well as temperature should be considered to obtain the desired solid fraction of the semi-solid material.

2. The Taguchi method, artificial neural networks, and regression analysis have been implemented for predicting the optimum solid fraction, specimen temperature and grain size and for investigating effects of the reheating variables on the reheating process.

3. Neural networks have been found effective in selection of the optimal combination of reheating variables in the reheating process. The proposed method can give more economically and effectively feasible means to a reheating process

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