Journal of Alloys and Compounds 466 (2008) 273–280
Journal of ALLOYS AND COMPOUNDS
www.elsevier.com/locate/jallcom

# Optimization of composition of heat-treated chromium white cast iron casting by phosphate graphite mold

An-hui Cai [a,*], Yong Zhou [a], Jing-ying Tan [a], Yun Luo [a], Tie-lin Li [a], Min Chen [b], Wei-ke An [a]

[a] *Department of Mechanical and Electrical Engineering, Hunan Institute of Science and Technology, Yueyang 414000, PR China*
[b] *Department of Physical and Electronic Engineering, Hunan Institute of Science and Technology, Yueyang 414000, PR China*

Received 16 July 2007; received in revised form 5 November 2007; accepted 11 November 2007
Available online 21 November 2007

**Abstract**

In present work, the difference among orthogonal design, Fuzzy optimum design and artificial neural network ANN was performed on the basis of the optimization of chemical composition of chromium white cast iron. It is found that Fuzzy optimum design is suitable for multi-objective comprehensive evaluation, and the optimum composition of white cast iron is Cr 4%, Si 3.5%, Mn 3% and Cu 1% in the orthogonal array. On the other hand, the orthogonal analysis is suitable for analyzing the effect of each factor on the performances and obtaining the theoretical optimum combination of each factor for the performances and the optimum theoretical performances, respectively. Moreover, the prediction and simulation results show that the RBFANN not only can be used to establish the model with high accuracy for the orthogonal test but also outperforms the traditional orthogonal analysis method. Therefore, the combination of three methods can more effectively deal with the optimization of chemical composition of materials.


*Keywords:* White cast iron; Orthogonal design; Fuzzy optimum design; Artificial neural network

## 1. Introduction

In many grinding abrasion conditions, the chromium white cast iron has replaced wear-resistance materials, such as medium-manganese ductile iron, high-manganese steel and low alloy steel, etc. [1–4]. And it has been applied in grinding ball of ball grinder, lining board, jaw plate and hammerhead, etc. [1–4], resulting in better benefit.

There are many optimization methods for the chemical composition and technology of materials. Orthogonal design is an optimization method for multifactor and multilevel cases based on orthogonal theory. Since the factors and levels present equilibrium distribution and regular comparability, the optimum scheme can be rapidly obtained by variance and range analysis, largely reduce testing numbers, shorten test time and minimize cost. And it has been applied to optimize material's composition, production technology, management and distribution, etc. [5–10]. Wang et al. [5] optimized the catalyst layer composition in PEMFC electrodes by orthogonal test method, with the use of cell voltage–current curve and cyclic voltammogram curve. Xu et al. [6] synthesized silica-supported iron catalysts by orthogonal test method, and found that catalytic activities of these catalysts were high and comparable to industrially relevant precipitated iron catalysts. Chen et al. [7] introduced the orthogonal experiment design method and carried out two rounds of orthogonal experiments for the optimization of the workspace mapping with deficient-DOF space for the PUMA 560 robot and its exoskeleton arm. Anawa and Olabi [8] used Taguchi approach as statistical design of experiment technique for optimizing the selected welding parameters in terms of minimizing the fusion zone and developed mathematical models with better prediction capacity for describing the influence of the selected parameters on the fusion zone area and shape. In addition, Fuzzy optimum design is another method for multi-objective optimization and evaluation based on Fuzzy theory, it has been used for many fields such as management, fault diagnosis and materials design, etc. [11–14]. Liu [13] optimized the convective longitudinal fin array with constant heat transfer coefficient by Fuzzy design. Selim and Ozkarahan [14] developed a supply chain SC distribution network design model

* Corresponding author. Tel.: +86 730 8648516; fax: +86 730 8847048.
*E-mail address:* cah1970@sohu.com (A.-h. Cai).

0925-8388/$ – see front matter © 2007 Elsevier B.V. All rights reserved.
doi:10.1016/j.jallcom.2007.11.042

by using Fuzzy optimum approach, the computational experiments showed that SC distribution network design problem can be handled in a more flexible, robust and realistic manner by this method than by other conventional approaches. Moreover, artificial neural network technique has received extensive attention because of the capacities of self-adaptive, self-organization and self-learning, resulting in solving many problems such as pattern recognition, function approximation, fault diagnosis, system identification, time-series forecasting, etc. [15–24]. Sheikh-Ahmad and Twomey [15] developed an artificial neural network (ANN) constitutive model, which was successfully applied to the sparse high strain-rate regime, for Al 7075-T6 based on the data of orthogonal machining test. Shie [16] optimized dry machining parameters for high-purity graphite in end-milling process by an artificial neural network and the sequential quadratic programming method. The results showed that this algorithm yielded better performance than the traditional methods such as the Taguchi method and the design of experiments approach.

The aims of this paper are to obtain optimum chemical composition for heat-treated chromium white cast iron and compare the differences between and among three optimization methods.

## 2. Experiments

### 2.1. Experimental procedures

The pig iron, steel, ferrochrome, ferromanganese, ferrosilicon (shown in Table 1) and Cu (wt 99.9%) were melted in 12 kg GGW-0.01 medium-frequency induction furnace up to 1500–1550 °C (holding 30 min). A mixed rare earth master alloy was added to the melt at 1450–1500 °C with slight stirring. After holding 20 min and skimming, the melt was poured at 1350–1400 °C into the phosphate graphite mold to form 10 mm × 10 mm × 55 mm standard impact samples. And then, the heat treatment (holding 40 min at 940 ± 10 °C, quenching in blowing air, and then, holding 120 min at 250 ± 10 °C, cooling in the natural air) was performed in SRJX-4-43 heat treatment furnace. The hardness and impact toughness tests were performed on HR150A hard-meter and JB-30A impact toughness tester, respectively.

### 2.2. Experimental plan

For the elaboration of experiments plan, the orthogonal method for four factors at three levels was used. In Table 2, the factors to be studied and the assignment of the corresponding levels are indicated. The chosen array was the $L_9$ ($3^4$) which has 9 rows corresponding to the number of tests (8 degrees of freedom) with 4 columns at three levels, as shown in Table 3. The factors are assigned to the columns. The plan of experiments is made of 9 tests (array rows) in which the first column is assigned to Cr, the second column to Si, the third column to Mn and the forth column to Cu, respectively. The hardness and impact toughness are shown in Table 3.

Table 1
Compositions of charge materials

| Materials | C (wt%) | Cr (wt%) | Si (wt%) | Mn (wt%) |
|---|---|---|---|---|
| Pig iron | 3.76 | – | 1.14 | 0.363 |
| Steel | 0.2 | – | – | – |
| Ferrochrome | 7.8 | 62.03 | 0.98 | – |
| Ferromanganese | 7.0 | – | 4 | 65 |
| Ferrosilicon | – | 0.48 | 75 | 0.48 |

Table 2
Assignment of the levels to the factors

| Level | Cr (wt%) | Si (wt%) | Mn (wt%) | Cu (wt%) |
|---|---|---|---|---|
| 1 | 4 | 0.8 | 0.6 | 0.5 |
| 2 | 5.5 | 2 | 2 | 1 |
| 3 | 7 | 3.5 | 3 | 2 |

Table 3
Orthogonal array $L_9$ ($3^4$) and experimental results

| Experiment no. | Cr | Si | Mn | Cu | Hardness (HRC) | Impact toughness (kJ/m$^2$) |
|---|---|---|---|---|---|---|
| 1 | 1 | 1 | 1 | 1 | 49.4 | 35 |
| 2 | 2 | 1 | 2 | 2 | 54.1 | 36 |
| 3 | 3 | 1 | 3 | 3 | 55.5 | 37 |
| 4 | 1 | 2 | 2 | 3 | 46.1 | 41 |
| 5 | 2 | 2 | 3 | 1 | 53.4 | 42 |
| 6 | 3 | 2 | 1 | 2 | 56.0 | 34 |
| 7 | 1 | 3 | 3 | 2 | 52.9 | 44 |
| 8 | 2 | 3 | 1 | 3 | 53.8 | 32 |
| 9 | 3 | 3 | 2 | 1 | 52.7 | 35 |

## 3. Results and discussion

### 3.1. Orthogonal design

Tables 4 and 5 show the results of the analysis of variance with the hardness and the impact toughness, respectively. The last column of Tables 4 and 5 shows the percentage of contribution ($P$) of each factor on the total variance, indicating the influence degree of each factor on the result. As shown in Table 4, one can observe that the influence of the Cr ($P = 61.5\%$) on the hardness is greatest and that of the Si is minor. At the same time, from the analysis of Table 5, one can observe that the influence of the Mn ($P = 61.1\%$) on the impact toughness is greatest and that of the Cu is minor. The averaged values of the hardness and the impact toughness for each factor (Cr, Si, Mn and Cu) at different levels

Table 4
Variance analysis for hardness test

| Source of variance | Deviations | Degrees of freedom | Variances | $P$ (%) |
|---|---|---|---|---|
| Cr | 47.16 | 2 | 23.58 | 61.5 |
| Si | 3.07 | 2 | 1.53 | 4.0 |
| Mn | 13.96 | 2 | 6.98 | 18.2 |
| Cu | 12.46 | 2 | 6.23 | 16.3 |
| Total | 76.65 | 8 | – | 100 |

Table 5
Variance analysis for impact toughness test

| Source of variance | Deviations | Degrees of freedom | Variances | $P$ (%) |
|---|---|---|---|---|
| Cr | 34.67 | 2 | 17.34 | 26.3 |
| Si | 14 | 2 | 7 | 10.6 |
| Mn | 80.67 | 2 | 40.34 | 61.1 |
| Cu | 2.67 | 2 | 1.34 | 2.0 |
| Total | 132.01 | 8 | – | 100 |