Journal of Achievements in Materials and Manufacturing Engineering
VOLUME 21 ISSUE 2 April 2007

Analysis of influence of chemical composition of Al-Si-Cu casting alloy on formation of casting defects

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Received 09.11.2006; accepted in revised form 15.11.2006

Methodology of research

ABSTRACT

Purpose: A methodology of the computer-aided determining relationship between chemical composition of aluminum alloy and castings quality was presented in the paper.
Design/methodology/approach: To resolve the problem artificial neural networks were used. Classification problems were evaluated by the consideration mainly the values of mistakes and correct answers of networks for test data. On the basis of data analyzed by the neural network, which has the best quality classification of chemical composition of tested material, the concentration of alloying elements range, which have an effect on formation casting defects, were developed to eliminate them in the future.
Findings: Combining of all methods making use of chemical composition of aluminium alloy and neural networks will make it possible to achieve a better casting quality.
Research limitations/implications: The presented issues may be use, among others, for manufacturers of car subassemblies from light alloys, where meeting the stringent quality requirements ensures the demanded service life of the manufactured products.
Originality/value: The correctly specified number of chemical composition of aluminum alloy enables such technological process control where the number of castings defects can be reduced by means of the proper correction of the process.
Keywords: Al-Si-Cu alloy; Neural networks; Casting defects; Casting quality

1. Introduction

Quality of castings from aluminium alloys assumes more and more importance in contemporary applications; therefore, one of the main goals in the aluminium industry is the continuous effort on improvement of the quality of molten metal from which castings are made in the technological processes. Properties of materials made from the engineering materials are dependant on their types, chemical composition, and on the type and quality of the technological process of their manufacturing and processing. Manufacturing of castings is connected with a big variety of technological operations and unpredictable phenomena occurring during their manufacturing, which leads to obtaining castings demonstrating defects, and as "defective" are considered castings which are made not in accordance with the pertinent standards and specifications. Casting to the permanent moulds features, first of all, the actual and future technologies of the aluminium alloys processing; however, the tendency has appeared in batch production lastly to come back to casting these alloys into the sand moulds too, made on the highly efficient automatic production lines [1,4,7,9-11].

A very important stage of the technological process quality assessment is acquiring information about the phenomena and transformations occurring in the material during these processes. More and more often the contemporary computer bases tools are used to this end, including the artificial intelligence methods. The rowing interest in these methods is justified by their wide application potential [8,12,13].

2. Investigation methodology

The project goal was to determine the relationships between the concentrations of the particular chemical elements of the W319 aluminium alloy with the chemical composition close to the composition of the EN AC-AlSi7Cu3Mg alloy according to the PN-EN 1706:2001 standard, and quality of the castings made from it.

Quality examinations were carried out on castings of the car engine elements, i.e. blocks and heads from the aluminium alloy. Examinations of the alloy structure and morphology of the casting defects developed in castings from the aluminium alloy in the technological process were carried out on the metallographic microsections, and observations of structures of defects developed in the material were made using the Leica MEF4A light microscope (Fig. 1) and of the fractures on the Opton DSM-940 electron scanning microscope (Fig. 2). Observations of the topography of the casting defects were also made on the Olympus LEXT OLS3000 confocal laser scanning microscope with the micro-electro-mechanical (MEMS) system built in (Fig. 3).

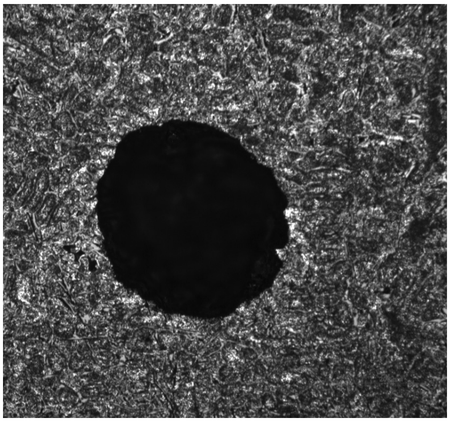

Fig. 1. Morphology of the gaseous casting defect in the EN AC-AlSi7Cu3Mg alloy

Data set for the neural network training was worked out within the framework of the project. The set of 4831 vectors was obtained after rejecting the incomplete cases, containing 25 variables, which referred to the concentrations of the alloying elements in the castings. The chemical compositions of the investigated alloys included the following elements: Si, Fe, Cu, Mn, Mg, Zn, Ti, Cr, Ni. The concentration ranges of the main alloying elements are presented in Table 1.

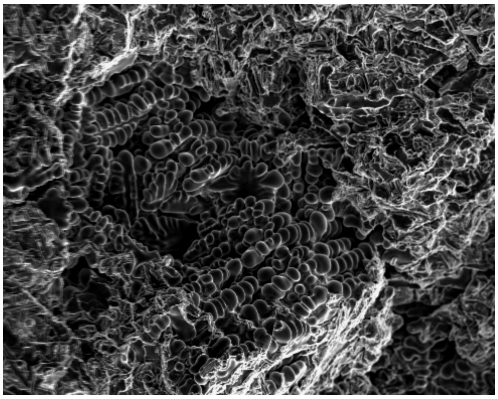

Fig. 2. Dendrites of the contraction cavity developed in the EN AC-AlSi7Cu3Mg alloy

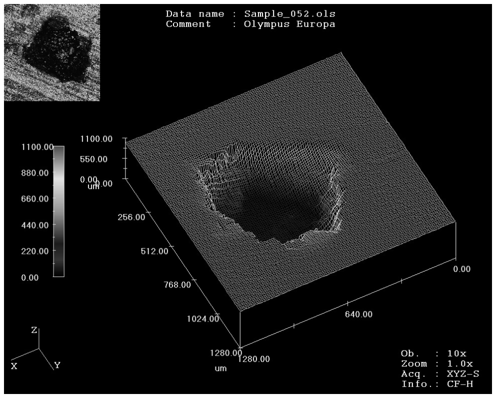

Fig. 3. Topography of the casting defect

Concentration values of the alloying elements in the castings were treated as input signals of the neural network (independent variables); whereas, the quality of castings was assumed as the network output (dependent variable), determined with the X-ray methods. This approach makes product quality forecasting possible affected by variations of the chemical composition of the alloy.

The dependent variable was created based on the ASTM E155 standard naming 8 defect classes for each defect type (Table 2).

It was assumed that castings with defects from classes 1÷3 are made according to quality standards, and they were treated as defective from class 4. In case when castings from the particular day had defects within the 4÷8 class range, the dependent variable was attributed value 1; whereas, for the castings in which defects were found in the 1 ÷ 3 class range, the dependent value was attributed value zero. As the dependent value had a small number of the integers, they were changed to nominal values, which were designated the symbolic names v1 (in case when there were no defects) and v2 (in case of defects).

The number of vectors used to develop the model was limited randomly. Genetic algorithms were used to limit the input

Table 1.
Concentration ranges of the alloying elements in the investigated castings

	Mass fraction of the element, wt %				
	Si	Fe	Cu	Mn	Mg
maximum	7,82590	0,39870	3,78190	0,28420	0,34790
minimum	7,20650	0,28360	3,22070	0,21000	0,24180

	Mass fraction of the element, wt %			
	Zn	Ti	Cr	Ni
maximum	0,24620	0,14920	0,05670	0,09120
minimum	0,03110	0,09650	0,01020	0,00960

variables, searching for the most useful subset of the independent variables. Limiting the variables (chemical elements of the aluminium alloy) was used, networks without the main alloying elements were not analysed. Statistica Neural Networks package was used for calculations.
The data set employed in the model development process using the neural network was split into three subsets: training, validation, and the test one. In each of the analysed topics 50% of the cases were used for modification of the network weights in the training process (training set), 25% for evaluation of the prediction errors in the training process (validation set), and the remaining part of the data was used for the independent assessment of the network model efficiency - after completing the training procedure (testing set). Splitting into the particular subsets was carried out randomly [2,5,6].

Table 2.
Types of the defects taken into consideration in classification

Symbol	Defect type	Number of classes
GH	Gas hole	1÷8
PR	Porosity	1÷8
SC	Shrinkage cavity	1÷8
SP	Shrinkage porosity	1÷8

It was assumed that castings with defects from classes 1÷3 are made according to quality standards, and they were treated as defective from class 4. In case when castings from the particular day had defects within the 4÷8 class range, the dependent variable was attributed value 1; whereas, for the castings in which defects were found in the 1 ÷ 3 class range, the dependent value was attributed value zero. As the dependent value had a small number of the integers, they were changed to nominal values, which were designated the symbolic names v1 (in case when there were no defects) and v2 (in case of defects).

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3. Investigation results

Based on the discussed results one may state the \RBF 25:25-209-1:1 type network obtained the best results for classification of the mass concentrations of the alloying elements due the effect on development of effects in castings from the EN AC-AlSi7Cu3Mg alloy, made with the Cosworth method. Therefore, the scope of analyses below was limited to this single network type.

Having carried out the neural network inputs analysis one can determine which chemical elements are significant in the neural network training process, and which can be discarded, as they do contribute only a little bit to the correct image classification training process. However, one should take into account the possibility of occurring some relationships among the alloying elements. Although the sensitivity analysis shows the loss which can be suffered discarding the particular element, in front of such relationships this coefficient calculated independently for each variable may not reflect the real situation. It is also important that the network does not discard the main alloying elements or modifiers which make changes in the crystallisation process introduced in small quantity into the metal bath, improving the structure and properties of the alloy.

4. Conclusions

The maximum and minimum concentrations of the alloying elements affecting occurrences of defects in castings from the EN AC-AlSi7Cu3Mg aluminium alloy were estimated based on data analysed by the RBF 25:25-209-1:1 network. The determined concentration ranges of the alloying elements affecting occurrences of defects in castings overlap in many cases because of the possibility of occurring of some relationships among the particular elements, and also because of the effect of other casting process parameters not accounted for in the project (e.g., rate of forcing the molten alloy to the mould). Supplementing the developed models with the remaining technological parameters will make optimisation of the casting processes possible.

Table 3.
Concentration ranges of the alloying elements affecting development of defects in castings worked out based on the RBF 25-209-1 network

Range	Mass concentration of the elements, %				
	Si	Fe	Cu	Mn	Mg
$V1_{MAX}$ 1)	7,79720	0,39870	3,71510	0,28240	0,34320
$V2_{MAX}$ 2)	7,78180	0,38760	3,68330	0,27120	0,34790
$V1_{MIN}$ 1)	7,21340	0,29560	3,22070	0,21000	0,25000
$V2_{MIN}$ 2)	7,22530	0,30920	3,30280	0,21550	0,25120
Część wspólna	7,22530 - 7,78180	0,30920 - 0,38760	3,30280 - 3,68330	0,21550 - 0,27120	0,25120 - 0,34320

1) Maximum and minimum values of the element concentration in case when there are no defects in castings
2) Maximum and minimum values of the element concentration in case when there are defects in castings

Range	Mass concentration of the elements, %			
	Zn	Ti	Cr	Ni
$V1_{MAX}$ 1)	0,23390	0,14340	0,05670	0,07990
$V2_{MAX}$ 2)	0,22650	0,14400	0,04550	0,07710
$V1_{MIN}$ 1)	0,04290	0,10010	0,01150	0,00960
$V2_{MIN}$ 2)	0,04250	0,10680	0,01780	0,01250
Część wspólna	0,04290 - 0,22650	0,10680 - 0,14340	0,01780 - 0,04550	0,01250 - 0,07710

1) Maximum and minimum values of the element concentration in case when there are no defects in castings
2) Maximum and minimum values of the element concentration in case when there are defects in castings

Acknowledgements

Authors express their thanks to Prof. Jerry Sokolowski, Head of the Industrial Research Chair in Light Metals Casting Technology of the University in Windsor, Canada, for his help in carrying out the project. Authors also thanks to dr Janusz Madejski.

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