Journal of Achievements in Materials and Manufacturing Engineering
VOLUME 26
ISSUE 2
February
2008

Modelling of hardness prediction of magnesium alloys using artificial neural networks applications

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Received 08.01.2008; published in revised form 01.02.2008

Manufacturing and processing

ABSTRACT

Purpose: In the following paper there have been presented the optimisation of heat treatment condition and structure of the MCMgAl12Zn1, MCMgAl9Zn1, MCMgAl6Zn1, MCMgAl3Zn1 magnesium cast alloy as-cast state and after a heat treatment.
Design/methodology/approach: Working out of a neural network model for simulation of influence of temperature, solution heat treatment and ageing time and aluminium content on hardness of the analyzed magnesium cast alloys.
Findings: The different heat treatment kinds employed contributed to the improvement of mechanical properties of the alloy with the slight reduction of its plastic properties.
Research limitations/implications: According to the alloys characteristic, the applied cooling rate and alloy additions seems to be a good compromise for mechanical properties and microstructures, nevertheless further tests should be carried out in order to examine different cooling rates and parameters of solution treatment process and aging process.
Practical implications: For comparison of the achieved results on the basis of the performed investigations a computer neural network model was used for analysis of the aluminium content and heat treatment parameters influence on the properties of the worked out cast magnesium alloys.
Originality/value: The advantage of the neural networks is their capability to learn and adapt to the changing condition, as well as their capability to generalise the acquired knowledge.
Keywords: Heat treatment; Mechanical properties; Artificial neural networks; Magnesium alloys

1. Introduction

The development of modern computer tools including methods of artificial intelligence (neural networks) and computer-aided examinations of materials are the reasons they are more and more widely used in different domains of science and technology, both in terms of their classification and calculations, as well as the prediction of the assumed values. Also, in the materials technology domain these trends are often noticeable thanks to their application possibilities which allow to solve new questions as well as those perceived as classical ones [1-7].

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The artificial neural networks are used more and more widely to carry out many tasks. The advantage of the neural networks is their capability to learn and adapt to the changing condition, as well as their capability to generalise the acquired knowledge. Thanks to these properties they can be used in all cases in which employment of the traditional methods is confronted with big difficulties, analytical solutions are impossible or hard to attain, in problems calling for associating and processing the incomplete or inaccurate information [1-7].

Scope of utilisation of foundry magnesium alloys is continuously being extended, so if we want to operate as competitive producers, it is necessary to investigate very actively properties of individual alloys, optimise their chemical composition, study issues of their metallurgical preparation, including heat treatment. Recently, however, increases also utilisation of formed magnesium [8-15].

Magnesium alloys are subjected to heat treatment mostly for the purpose of improvement of their mechanical properties or as an intermediary operation, to prepare the alloy to other specific treatment processes. A change of the heat treatment basic parameters has an influence on a change of the properties. Annealing significantly decreases the mechanical properties and causes improvement of plastic properties, thus facilitating further treatment. Complex evaluation of magnesium alloys requires very often knowledge of elastic-plastic properties at elevated temperatures [8-11].

The rising tendencies of magnesium alloy production, show increased need of their application in world industry and what follows the magnesium alloys become one of the most often apply construction material our century. Therefore it is extremely important to keep a high investigation development of a light alloy issue, furthermore performing in Institute of Material Processes and Computer Technology, Institute of Engineering Materials and Biomaterials, Silesian University of Technology.

The aim of research is to work out the model of neural networks that enables the simulation of the influence of temperature and time of solution heat treatment and ageing, as well as the aluminum concentration onto the hardness of the analyzed magnesium cast alloys.

2. Experimental procedure

The investigations were performed on experimental magnesium alloys MCMgA112Zn1,MCMgAL9z1, MCMgAl6Zn1, MCMgAl3Zn1 in stable state and after heat treatment (table 2). Chemical composition of this materials was conditioned by changeable concentration range of aluminium in accordance with different types of alloy, which changes in range from 3-12% (table 1).

As the basic indicators for evaluation of the model quality following values were used:

- average network forecast error,
- ratio of standard deviations of errors and data,
- Pearson's correlation coefficient.

For data analysis four neural networks models were used:

- multilayer perceptron MLP,
- linear neural networks,
- radial basis functions neural network RBF,
- generalized regression neural networks GRNN,

also the following learning methods:

- back propagation method,
- conjugate gradient,
- quasi-Newtona method,
- fast propagation.

The applied neural networks allow to work out of a interdependence model for:

- aluminium content, temperature and solution treatment time, cooling medium, and hardness,
- aluminium content, temperature and ageing time, cooling medium, and hardness.

3. Discussion of experimental results

The data set has been obtained from the examinations of the hardness of magnesium cast alloys after solution heat treatment (water, air) and annealing in 400, 415 and 430 ºC temperatures in the time of 10, 20 and 30 hours, and also after ageing with air-cooling in temperatures between 150 and 210 ºC and in the time of 5, 10 and 15 hrs.

The data for the solution heat treatment and ageing has been divided randomly into three subsets: learning, validating and testing ones. In case of the network calculating the hardness after solutioning, the number of cases was adequately 68, 20 and 20, whereas for the network calculating the hardness after ageing was 231, 100 and 101. The data from the learning set has been used for the modification of the network weights, the data from the validating set, to evaluate the network during the learning process, while the remaining part of the values (the testing set) has been used for determining the network efficiency after ending completely the procedure of its creating.

The results used in the learning process and the network testing have been put to standardization. Scaling has been used in relation to the deviation from the minimal value, according to the mini-max function. The mini-max function transforms the variable domain to the range (0,1). The type of the network, the number of neurons in the hidden layer (layers), the method and learning parameters have been determined observing the influence of these quantities onto the assumed network quality coefficients.

The quotient of standard deviations for errors and the data has been accepted, as the vital indicator of the model quality, made with the use of the neural network. The correctness of the network model may only be considered in case when the presented by networks forecasts are burdened with a smaller error than the simple estimation of the unknown output value.

For both, the networks calculating the hardening after the solution heat treatment as well as after ageing, as the optimal has been recognized the MLP unidirectional network (multilayer perceptron) with one hidden layer and 5 neurons in the layer. The error function in the form of the sum square has been accepted together with the logistic activation function. The learning method based on the conjugate gradient algorithm has been applied, representing the examples from the learning set for 101 training patterns for the network calculating the hardness after solution heat treatment, and 195 patterns for the network calculating the hardness after ageing.

On the basis of the worked out models of neural networks, the diagrams of the influence of the temperature and solutioning and ageing times have been done, as well as the aluminum content onto the hardness of the analyzed magnesium cast alloys (Fig.1).

Table 1.
Chemical composition of investigated alloys

The mass concentration of main elements, %						
Al	Zn	Mn	Si	Fe	Mg	Rest
12.1	0.617	0.174	0.0468	0.0130	86.9507	0.0985
9.09	0.77	0.21	0.037	0.011	89.7905	0.0915
5.92	0.49	0.15	0.037	0.007	93.3347	0.0613
2.96	0.23	0.09	0.029	0.006	96.6489	0.0361

Table 2.
Parameters of heat treatment of investigated alloys

Sing the state of heat treatment	Solution treatment			Aging treatment		
	Temperature	Time	Cooling	Temperature	Time	Cooling
0	As-cast					
1	430	10	air	-	-	-
2	430	10	water	-	-	-
3	430	10	furnace	-	-	-
4	430	10	water	190	15	air

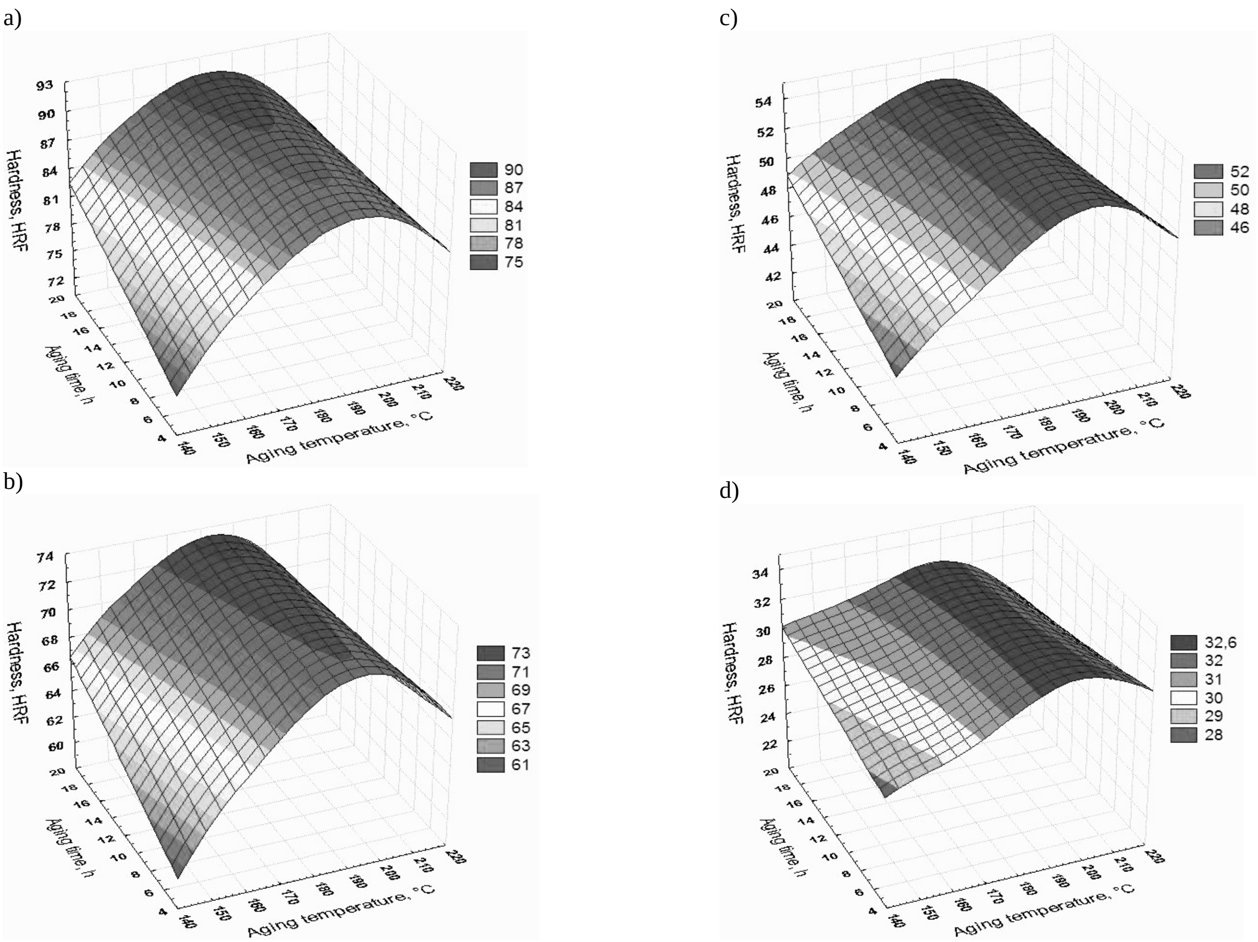

Fig. 1. Simulation of the temperature and ageing time influence on hardness of the cast magnesium alloys a) *MCMgAl12Zn1*, *b) MCMgAl9Zn1*, *c) MCMgAl6Zn1*, *d) MCMgAl3Zn1* by selected solution treatment temperature and time - 430°C and 10 hour

4. Summary

The obtained results explicitly indicate that the most favorable type of the heat treatment in terms of the optimal working conditions and the energy used and the time needed for carrying out the solution heat treatment and ageing, and also in terms of the obtaining the best possible mechanical properties, is the solutioning in the temperature of 430ºC for 10 hours and ageing in the temperature of 190ºC for 15 hours (Fig. 1).

Acknowledgments

This scientific work is fragmentary financed within the framework of scientific financial resources in the period 2007-2008 as a research and development project R15 0702 headed by Prof. L.A. Dobrzański and by Project MSM 6198910015.

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