Optimization of heat treatment conditions of magnesium cast alloys

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Abstract. In this paper there are presented results of the optimization of heat treatment conditions, which are temperature and heating time during solution heat treatment or ageing as well the cooling rate after solution treatment for MCMgAl12Zn1, MCMgAl9Zn1, MCMgAl6Zn1, MCMgAl3Zn1 cast magnesium alloys. A casting cycle of alloys has been carried out in an induction crucible furnace using a protective salt bath *Flux 12* equipped with two ceramic filters at the melting temperature of 750±10ºC, suitable for the manufactured material. The heat treatment involve the solution heat treatment and cooling in different cooling mediums as well water, air and furnace. The improvement of the manufacturing technique and chemical composition as well as of heat treatment and cooling methods leads to the development of a material designing process for the optimal physical and mechanical properties of a new developed alloy.

1. Introduction

A contemporary technological development makes it necessary to look for new constructional solutions that aim at the improvement of the effectiveness and quality of a product, at the minimization of dimension and mass as well as the increasing of reliability and dimension stability in the operation conditions. For a dozen or so years one can observe a rising interest in the non-ferrous metals alloys including magnesium alloys. The dynamic industrial development puts some higher and higher demands to the present elements and constructions. These demands belong production and research newer and newer materials for materials engineering materials with relation to predictable work conditions and arise needs. Magnesium alloys gets a huge importance with present demands for light and reliable construction. 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 [[5], [6], [7], [8], [9].

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], [2], [3], [4]].

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

2. Experimental procedure

The investigations were performed on experimental magnesium alloys MCMgA112Zn1, MCMgAl9z1, MCMgAl6Zn1, MCMgAl3Zn1. 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).

Table 1. Chemical composition of investigated alloys

The mass concentration of main alloying 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

The material has been cast in dies with betonite binder because of its excellent sorption properties and shaped into plates of 250x150x25 mm. The cast alloys have been heated in an electrical vacuum furnace *Classic 0816 Vak* in a protective argon atmosphere.

The optimization of the heat treatment ie. the temperature and time of heating during the solution heat treatment and ageing and the cooling rate after the solutioning, has been carried out based on the hardness test including, in all, a few dozen of possible combinations. The optimization has been used to work out the methodology of material designing of the most favorable physical and mechanical properties of the MCMgAl12Zn1, MCMgAl9Zn1, MCMgAl6Zn1 and MCMgAl3Zn1 alloys. The solution heat treatment (water, air, furnace) for the examined materials has been carried out in the temperatures of 400, 415 and 430 C in the time of 10, 20 and 30 hours. Whereas after solutioning in the water, the ageing has been made together with air cooling in the ranges of temperatures from 150 to 210 every 20 C and in times of 5, 10 and 15 hours. For each specimen, five tests have been done respectively and the arithmetic mean calculated, receiving 27 cases of the mean hardness for each of the alloys after the solution heat treatment and 108 cases after the ageing. The obtained matrix included altogether 540 cases of the mean values, gained from the hardness tests for the after solution heat treatment and ageing states (Fig. 1-4).

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.

As the basic coefficients 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

3.1. Optimization of heat treatment conditions

On the basis of the hardness tests one has stated that the changes of the temperature in ranges between 400 and 430 C, as well as the changes of the solution heat treatment time of between 10

and 30 hours, do not significantly influence the diversification of hardness of the particular alloys, as the revealed differences of measurements change in the range of the permissible error.
The increase of the aluminum concentration in the alloys from 3 to 12 % has caused the increase of the mean hardness of the specimen after the solution heat treatment with the furnace cooling up to 49,5 HRF, water cooling – to 32,6 HRF and air cooling – to 41,9 HRF. The highest hardness values, measured for the MCMgAl12Zn1, MCMgAl9Zn1, MCMgAl6Zn1 alloys, have been obtained for the specimen after the solution heat treatment with furnace cooling, as well as the water-cooled specimen for the MCMgAl3Zn1 material.
The carried out ageing after the water solution heat treatment of the specimen of the MCMgAl12Zn1, MCMgAl9Zn1, MCMgAl6Zn1, MCMgAl3Zn1 magnesium cast alloys has influenced the increase of hardness, depending both on the temperature and time of the solutioning as well as the temperature and the ageing time.
The highest hardness values have been obtained for the specimen exposed to solutioning in the temperature of 430 C for 10hrs and ageing in 190 C for 15 hours. It has also been stated that the application of the precipitation hardening for the magnesium cast alloys with the aluminium concentration of 6% - MCMgAl6Zn1, MCMgAl3Zn1, causes a small increase of the mechanical properties. The highest difference of the mean hardness – 19,8 HRF in relation to the state after the water solution heat treatment has been obtained for the MCMgAl12Zn1 alloys.

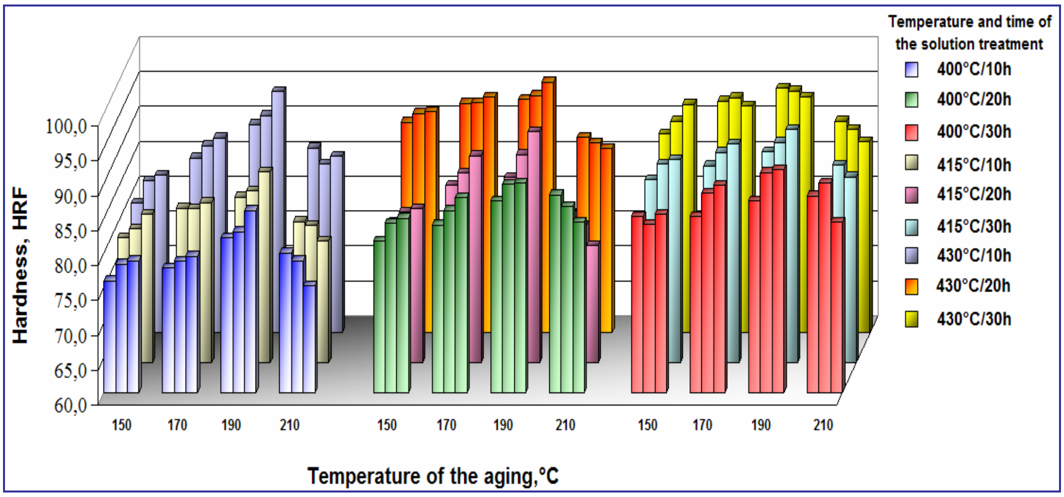

Fig. 1. Average hardness values for the cast magnesium alloys MCMgAl12Zn1 after ageing for 5, 10 and 15 hours at a temperature from 150 to 210°C, in steps of 20°C

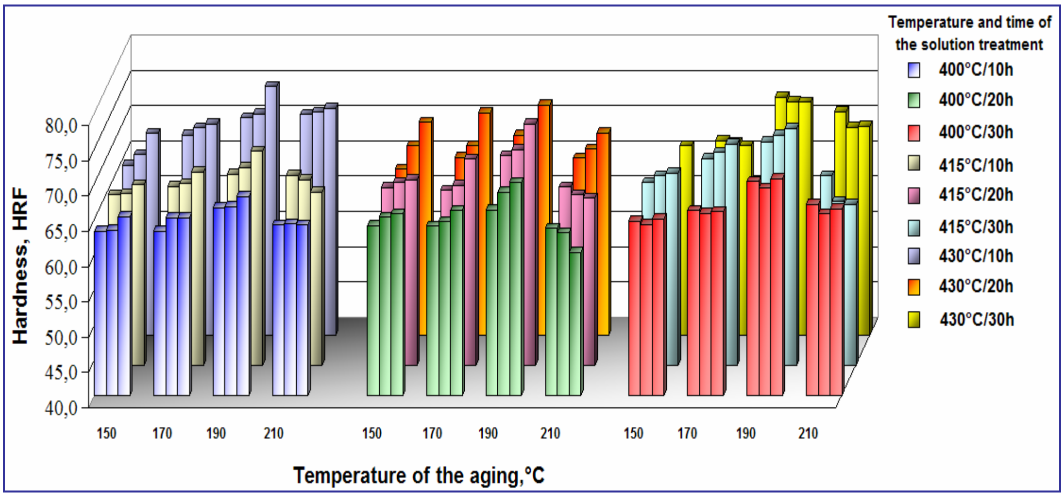

Fig. 2. Average hardness values for the cast magnesium alloys MCMgAl9Zn1 after ageing for 5, 10 and 15 hours at a temperature from 150 to 210°C, in steps of 20°C

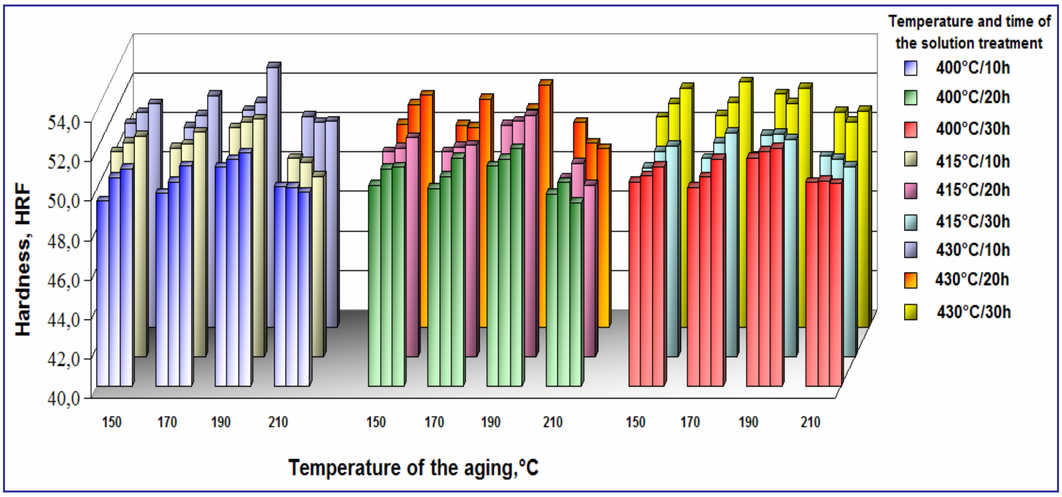

Fig. 3. Average hardness values for the cast magnesium alloys MCMgAl6Zn1 after ageing for 5, 10 and 15 hours at a temperature from 150 to 210°C, in steps of 20°C

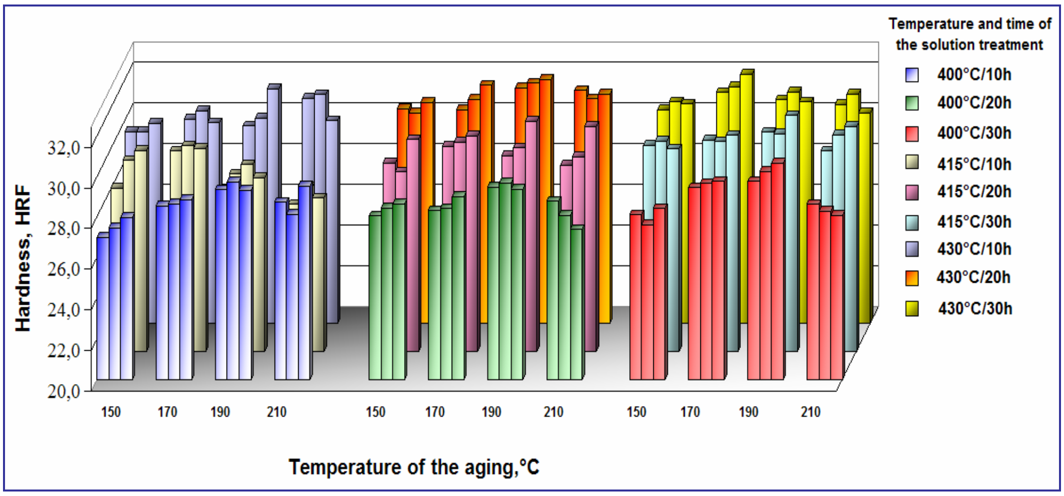

Fig. 4. Average hardness values for the cast magnesium alloys MCMgAl3Zn1 after ageing for 5, 10 and 15 hours at a temperature from 150 to 210°C, in steps of 20°C

3.2. Neural network model

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. 5).

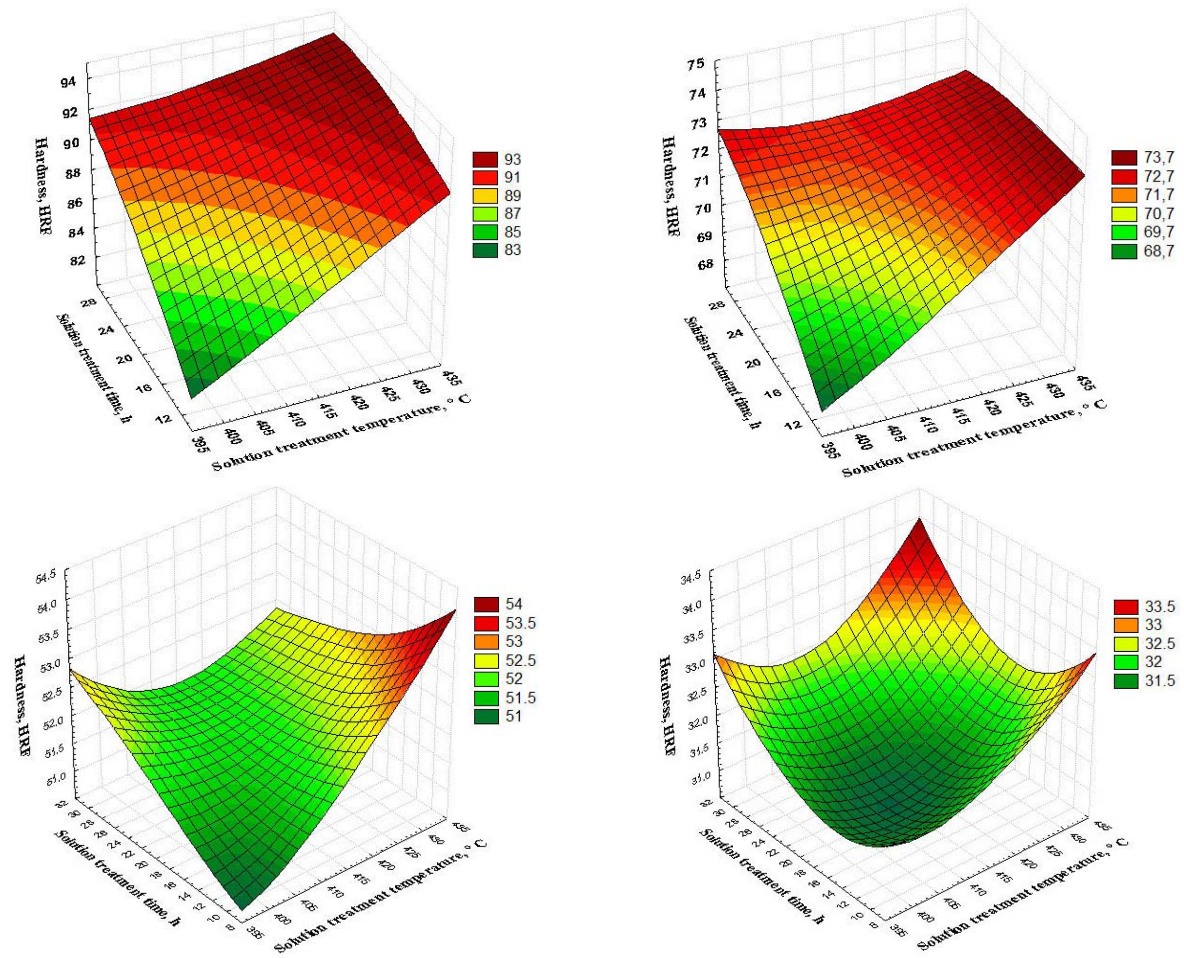

Fig. 5. Simulation of the temperature and solution heat treatment time influence on hardness of the MCMgAl12Zn1 cast magnesium alloys by selected ageing temperature and time - 190°C and 15 hours, the results are achieved using a computer neural network simulation

The above obtained results, explicitly show that the most beneficial kind of the heat treatment both in terms of the optimum working conditions and the time and energy used for carrying out the solutiong and ageing, as well as getting the most advantageous mechanical properties, is the solution heat treatment in the temperature of 430 C for 10 hours and ageing in the temperature of 190 C for 15 hours (Table 2).

Table 2. Optimal heat treatment parameters of the investigated alloys

Heat treatment process	Parameters of heat treatment		
	Temperature , °C	Heating time, h	Cooling method
0	As-cast		
1 – solution heat treatment	430	10	water
2 – solution heat treatment	430	10	air
3 – solution heat treatment	430	10	furnace
4 – aging	190	15	air

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. 1-5, Table 2).

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