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Prediction of mechanical properties of cast Mg-Al-Zn alloys

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ABSTRACT

Purpose: The aim of this work was to predict the mechanical properties of the cast magnesium alloys of the MCMgAl12Zn1, MCMgAl9Zn, MCMgAl6Zn and MCMgAl3Zn type, by appliance of artificial neural networks.

Design/methodology/approach: In this work there were performed investigations concerning the influence of chemical composition of the Mg-Al-Zn alloys onto the structure and mechanical properties, as well there was carried out the prediction of these properties compared to the mass elements concentration.

Findings: It was also determined the type of phases, which crystallise during the alloy crystallisation process - including the well-known Mg17Al12 phase. It was also investigated which elements have the highest influence on the prediction of properties as a result of changed concentration of particular elements.

Practical implications: The investigations have been performed for the reason to found application possibilities in the foundry industry, as well to make possible an optimisation of the chemical composition by prediction of mechanical properties based on changeable chemical composition of the alloy for the reason to achieve material with desirable structure and mechanical properties.

Originality/value: Chemical composition influences the phases and eutectics crystallised during the solidification process of the alloys, and that fore determine also material structure and properties, as well as allow it to predict these parameters applying artificial neural networks.

Keywords: Magnesium alloys; Structure; Mechanical properties; Computer-aided examinations

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PROPERTIES

1. Introduction

Magnesium alloys gets a huge importance with present demands for light and reliable construction. Magnesium alloys have low density and other benefits such as: a good vibration damping and the best from among all construction materials: high dimension stability, small casting shrinkage, connection of low density and huge strength with reference to small mass, possibility to have application in machines and with ease to put recycling process, which makes possibility to logging derivative alloys a very similar quality to original material [1-7].

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 [4,5].

The optimum use of magnesium and aluminum alloys is possible when their properties, resulting from the structure that may be consciously steered, are exactly known. This shall become possible when the technological factors affecting the creation of structure during crystallization and in solid state and their control are known. Chemical modification properly made and application of appropriate cooling of the casts leads to improved usable properties of the elements produced. Therefore the knowledge how the cast structure changes, along with the change of cooling rate or chemical composition, is very important [8].

Mg-Al alloys show the structure of α solid solution, the eutectic mixture $\alpha+\beta$ and the intermetallic phase γ of $Mg_{17}Al_{12}$ formula. The magnesium alloys possess a wide range of the solid solution, what positively influences their properties. Zinc causes the formation, out of magnesium, the phase system with eutectics in the temperature of 340°C, which consists of the α solid solution with the maximum magnesium solubility of zinc amounting to 6,2%, and the β secondary solid solution on the matrix of the Mg_7Zn_3 intermetallic phase. The Mg-Mn alloys, as opposed to Mg-Al alloys, are characterized by the insignificant range of the α solid solution [9-13].

The development of modern information tools, including artificial intelligence methods, brings about their more common usage in different science and technology disciplines. Also, in the material engineering domain, these trends are recognizable in the world thanks to wide application possibilities, which allow for solving new and classic problems [14-18].

The development of modern IT tools, including artificial intelligence methods, numerical methods, mathematical modelling, computational intelligence, cause that they are more and more often used in various fields of science and technology, allowing the solution of both new issues as well classical ones. At present the advantages resulting from the application of computer aided methods to design and production are undeniable. The time factor decides on success of numerous undertakings. Both modelling and computer simulation enable full integration of material science, education and IT tools, providing the compliance of the developed model after simulation with experimental results, eliminating the necessity for cost- and time-consuming experimental tests with computer simulation, which also has been confirmed in the scope of numerous tests. It seems to be possible that intelligent prediction using the artificial intelligence tools is a next step of a present engineering research and investigation. The processes taking place in materials engineering are related often to incomplete information on temporary changes going on in such process. Logical, neural networks can be used to describe and model such phenomena. The advantages resulting from the application of neural networks more and more decide on their wide use in technology under the conditions of incomplete information on the analyzed system. The growing popularity of neural networks is, without limitation, the result of the opportunity to create correlations between the tested systems, without the knowledge of the physical model of the analyzed phenomena. The results provided by a neural network very often present higher compliance with experimental data, than the results obtained by mathematical models of the analyzed processes. Therefore, artificial neural networks may be applied to numerous engineering applications, including chemical composition of engineering materials, due to the set of selected properties characteristic for the investigated technological process and prediction of their properties based on the assumed chemical composition of the material [19-22].

2. Materials and investigations

The investigations have been carried out on test pieces of MCMgAl12Zn1, MCMgAl9Zn, MCMgAl6Zn, MCMgAl3Zn magnesium alloys in as-cast and after heat treatment states (Table 1) made in cooperation with the Faculty of Metallurgy and Materials Engineering of the Technical University of Ostrava and the CKD Motory plant, Hradec Kralove in the Czech Republic. The chemical composition of the investigated materials is given in Table 2.

Table 1.
Parameters of heat treatment of investigation alloy

Sing the state of heat treatment	Conditions of solution heat treatment		
	Temperature, °C	Time of warming, h	Way coolings
0	As-cast		
	Solution treatment		
1	430	10	Water
2	430	10	Air
3	430	10	In furnace
	Aging treatment		
4	190	15	Air

Table 2.
Chemical composition of investigation alloy

The mass concentration of main elements, %						
Al	Zn	Mn	Si	Fe	Mg	Rest
12.1	0.62	0.17	0.047	0.013	86.96	0.0985
9.09	0.77	0.21	0.037	0.011	89.79	0.0915
5.92	0.49	0.15	0.037	0.007	93.33	0.0613
2.96	0.23	0.09	0.029	0.006	96.65	0.0361

Metallographic examinations have been made on magnesium cast alloy specimens mounted in thermohardening resins. In order to disclose grain boundaries and the structure and to distinguish precisely the particular precipitaions in magnesium alloys as an etching reagent a 5% molybdenic acid has been used. The observations of the investigated cast materials have been made on the light microscope LEICA.

Phase composition and crystallographic structure were determined by the X-ray diffraction method using the XPert device with a copper lamp, with 40 kV voltage.

Observations of thin foil structure were carried out in the JEM 3010UHR JEOL transmission electron microscope using an accelerating voltage of 300 kV.

Hardness tests were made using Zwick ZHR 4150 TK hardness tester in the HRF scale. Tensile strength tests were made using Zwick Z100 testing machine. The results in the work, were statistical worked out, for each measurement of the average value, standard deviation.

3. Methodology of neural networks application

The neural networks have been applied for working out the interrelations between the concentration of alloy elements and the mechanical properties of the magnesium alloys. The data set has been made of the magnesium alloys according to the ASTM B 80 and PN-EN 1735:2001 standards. The range of the concentration of alloy elements, and their mechanical properties, applied to the computer analyses, has been presented in Table 3.

Table 3.
The mass range of elements and mechanical properties

	The mass range of elements, %				Hardness,	Tensile Strength,
	Al	Zn	Mn	Zr	HB	MPa
min	0	0	0	0	45	90
max	10.7	6.5	0.75	1.0	100	310
	Ag	Y	Si	Cu		
min	0	0	0	0		
max	3.0	5.5	1.5	3.0		

For vectors, in which the variables in forms of concentrations of alloy elements and mechanical properties have accepted the values in the specific range, one has accepted that the lower range corresponds to the 0 value and the upper to 1. The data set has been randomly divided into subsets, namely, learning and validating ones, whereas the testing set has been prepared in the analogic way, with the assumption that the vectors have been randomly isolated out of the data set before the application of the variables combination. A nominal variable, defining the state of the material, has been applied: v1 – as cast state and v2 – after the heat treatment respectively. For the network calculating the hardenability and resistance on the basis of the chemical compositions, the number of cases was 183, 96 of which in the learning set, 43 in the validating set, the rest constituting the testing set. The data used in the learning process as well as testing the network have been put to normalization. The kind of the network, the number of neurons in the hidden layer, the method and learning parameters, have been determined, observing the influence of these quantities onto the accepted indicators of the network quality assessment. As the basic indicators of the model quality assessment, the following quantities have been used:

- the mean error of the network forecast,
- the quotient of standard deviation,
- the Pearson correlation coefficient.

With the use of neural networks, the analysis of the influence of the alloy elements onto the mechanical properties of the examined materials, has also been made.

4. Results of materials investigation

As a result of metallographic investigations made on the light microscopes it has been confirmed that the magnesium cast alloys MCMgAl12Zn1, MCMgAl9Zn1, MCMgAl6Zn1, MCMgAl3Zn1 in the cast state and after heat treatment are characterized by a microstructure of the solid solution α (#1) constituting the alloy matrix as well as the γ - $Mg_{17}Al_{12}$(#2) discontinuous intermetallic phase in the forms of plates located mostly at grain boundaries (Figs. 1-4). Moreover, in the vicinity of the β intermetallic phase precipitations the presence of the needle eutectics (α + γ) (#3) has been revealed (Figs. 1, 2).

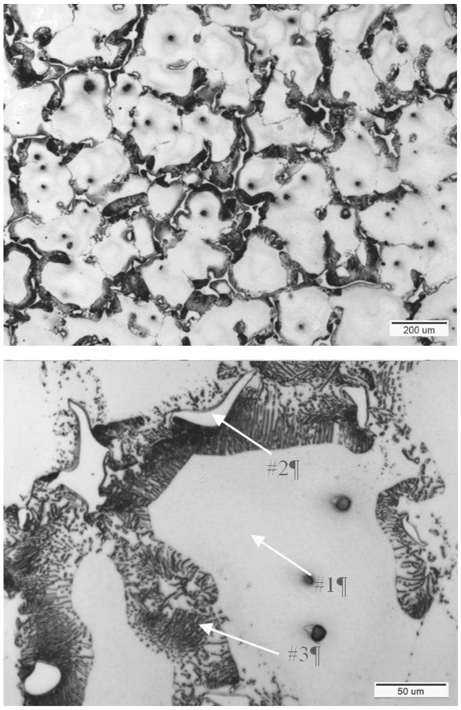


Fig. 1. Microstructure alloy without heat treatment MCMgAl9Zn1

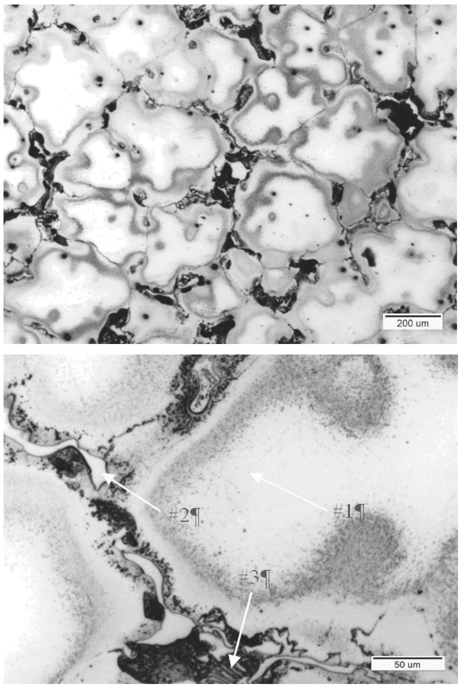


Fig. 2. Microstructure alloy without heat treatment MCMgAl6Zn1

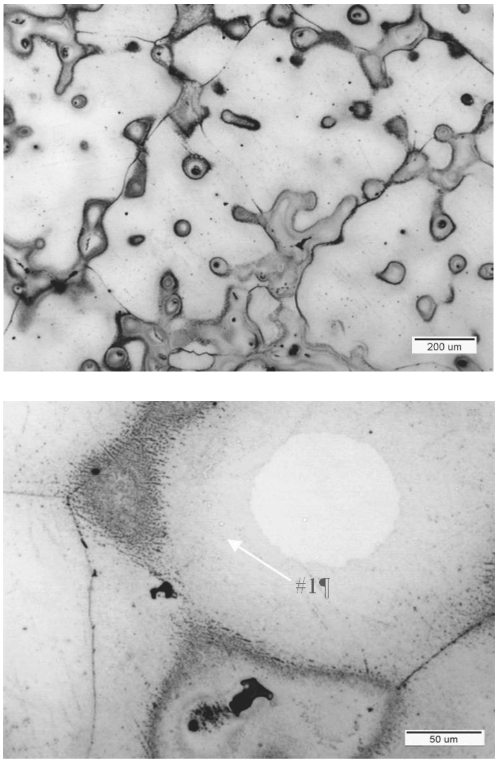


Fig. 3. Microstructure alloy without heat treatment MCMgAl3Zn1

It was state as a result of thin foil investigation performed on the transmission electron microscope, that the structure of the investigated alloys is mainly composed of $Mg_{17}Al_{12}$ (Fig. 5) phase precipitations embedded in the magnesium matrix.

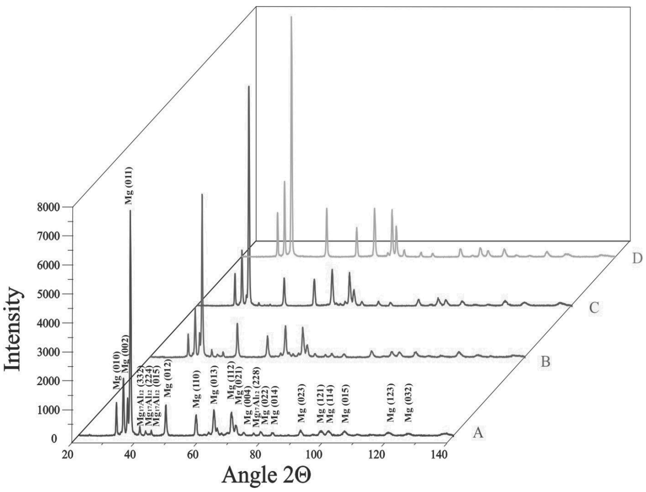


Fig. 4. XRD patterns of the magnesium casting alloys in as-cast state: A – MCMgAl12Zn1, B – MCMgAl9Zn1, C – MCMgAl6Zn1, D – MCMgAl3Zn1

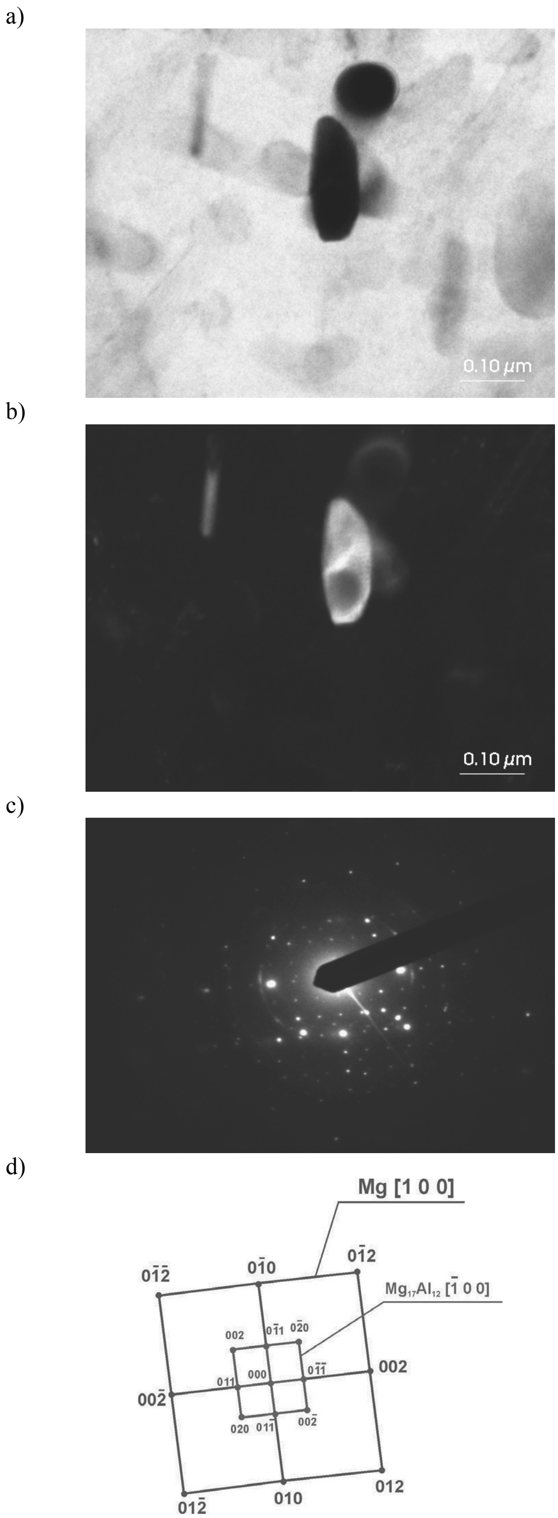


Fig. 5. TEM microstructures of the investigated thin foils, a) bright field image of the $Mg_{17}Al_{12}$ phase, b) dark field image of the $Mg_{17}Al_{12}$ phase particle, c) diffraction pattern of the phase, d) solution of the diffraction pattern

The results of the static tension test make it possible to determine and compare the mechanical and plastic properties of the examined magnesium cast alloys in as cast and after heat-treatment. On the basis of the tests done, one has stated that the biggest resistance to tension in as cast state show the MCMgAl6Zn1 and MCMgAl3Zn1 alloys. It has also been proved that the increase of the Al concentration from 6 to 12% reduces the resistance to tension in as cast state to 170.9±1.64 MPa. The heat-treatment i.e. the solution heat treatment with the furnace cooling and ageing, causes the increase of the resistance to tension. The maximum resistance to tension 294.8±3.31 MPa has been obtained after the ageing of the MCMgAl12Zn1 alloy; one has also observed a significant (by 50%) increase of the resistance to tension for the MCMgAl9Zn1 specimens after ageing. The smallest growth of the resistance to tension after the heat-treatment has been gained for the MCMgAl6Zn1 and MCMgAl3Zn1 materials, 30.3 and 12.4 MPa respectively. The differences in values of the resistance to tension for the alloys subjected to solutioning with water and air cooling amount to 6 MPA maximum (Fig. 6a).

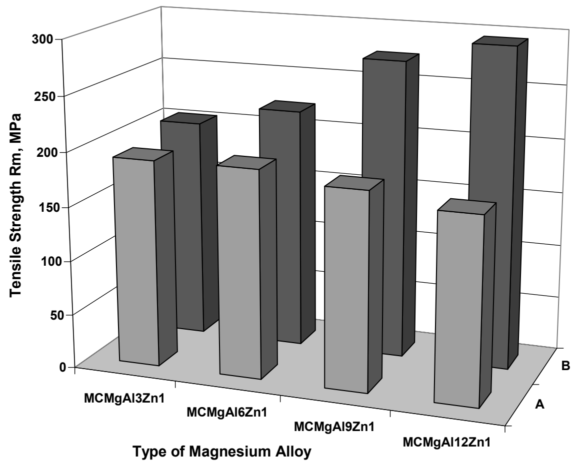
Together with the growth of the concentration of aluminum from 3 to 12% in the analysed alloys, grows their hardness. The biggest hardness 75,4±1,15 HRF in as cast state show the casts from the MCMgAl12Zn1 alloy. It is over two times higher than for the MCMgAl3Zn alloy. Subjecting the material to the heat treatment has caused the increase of its hardness. The MCMgAl12Zn1, MCMgAl9Zn1 and MCMgAl6Zn1 alloys have reached their highest hardness after the ageing. For the cases after the solution heat treatment, the hardness insignificantly decreases in comparison to the initial state (Fig. 6b).

5. Results of neural network application

The quotient of the standard deviations for errors and data has been assumed as the vital indicator of the quality of the model, built with the use of the neural network. The correctness of the assumed by the network model can only be considered if the presented by the network forecast is burdened with the smaller error than the simple calculation of the unknown output value. The easiest way to calculate the output value is to accept the mean value out of the output values for the learning set , and present it as the data forecast not presented during the learning process. In this case the mean error equals the standard deviation for the output value in the learning set, whereas the quotient of the standard deviations accepts value 1. The smaller the error of the prediction of the network, the smaller values are accepted by the quotient of the standard deviations.

To visualize the response of neural networks of the influence of the main alloy additions, namely, Al, Mn and Zn onto the hardness and tensile strength of the examined magnesium alloys, the surface diagrams have been made (Figs. 7-10). The obtained results are estimated values, calculated solely for variants, when the influence of only two alloy elements onto the mechanical properties of the alloys have been examined. It has been accepted that there will be two input variables, whereas the values of the other data remain as stable.

a)



b)

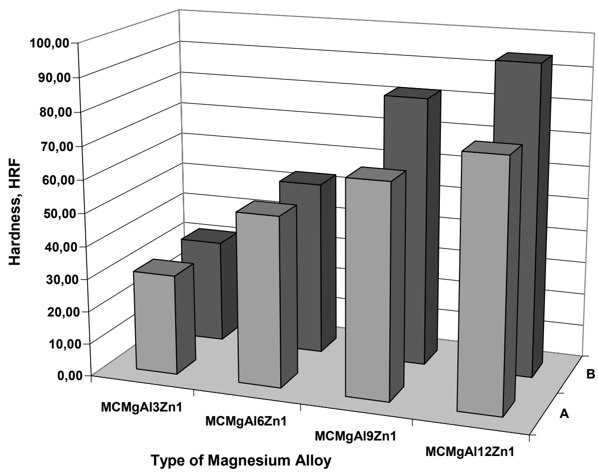


Fig. 6. Diagram of the: a) tensile strength, b) hardness Mg-Al alloys; a) cast state, b) after heat treatment

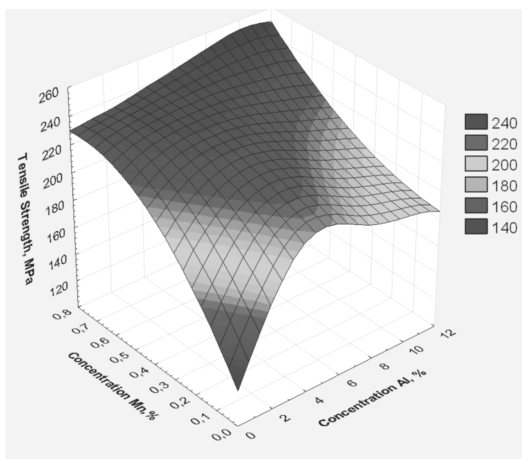


Fig. 7. The mapping diagram of Al and Mn influence on tensile strength

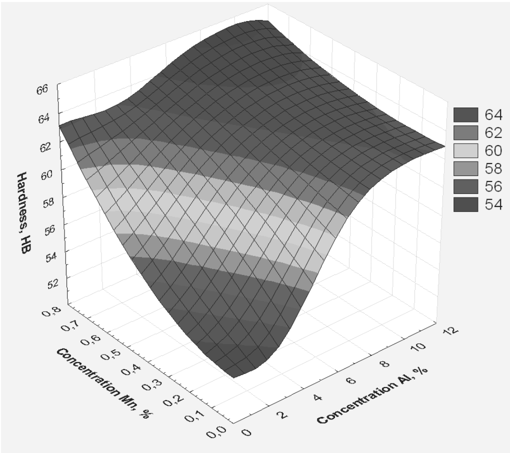


Fig. 8. The mapping diagram of Al and Mn influence on hardness

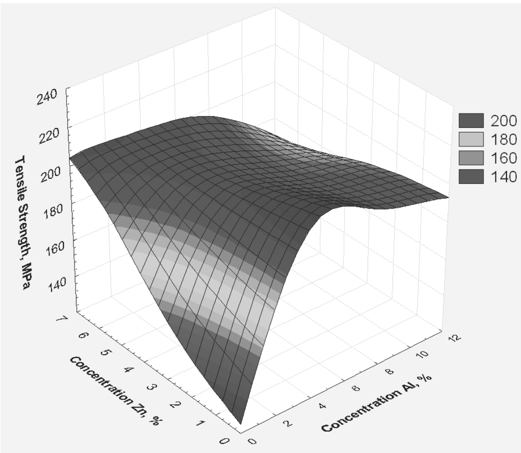


Fig. 9. The mapping diagram of Al and Zn influence on tensile strength

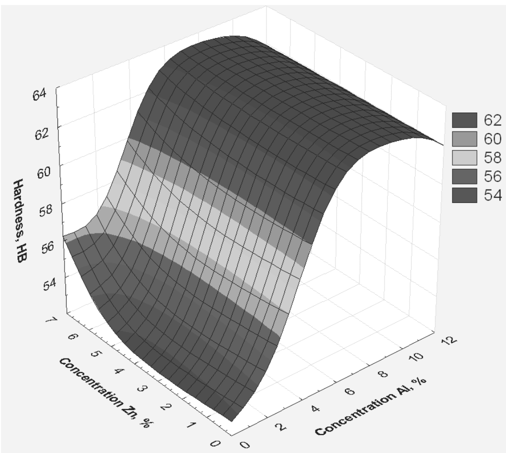


Fig. 10. The mapping diagram of Al and Zn influence on hardness

Among all the analyzed elements, aluminum is the most important addition of Mg-Al alloys, increasing their hardness and tensile strength, with the highest tensile strength at the Al concentration of approximately 6% (Figs. 7-10). Zinc is second, after aluminum component, which has a significant influence on the properties of the magnesium alloys (Figs. 9, 10). As aluminum, it causes the increase of the tensile strength, but only when Al and Mn are present. Whereas manganese causes the increase of the tensile strength as the component of the hard intermetallic phases, the alloy content of which grows together with the participation of Al (Fig. 7).

6. Summary

The worked out, on the basis of the chemical composition of magnesium alloys, model of neural networks, allows to assess the influence of their content onto the resistance properties and hardness of the examined alloys. The use of the neural networks, allows to determine, both, those elements, which have a significant influence on the properties and at what alloy elements concentration that influence accepts the largest values. This allows the prediction of the mechanical properties of the magnesium alloys with the assumption that the boundary values of the alloy elements' concentrations are in the diagrams used for making the model, based on the neural networks.

The presented, on the MCMgAl12Zn1, MCMgAl9Zn, MCMgAl6Zn, MCMgAl3Zn alloy example results, confirm the correlation between the results of the laboratory research of Mg alloys with the results obtained out of the neural networks.

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