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Examination and simulation of composite materials Al-Al_2O_3 tribological properties

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ABSTRACT

Purpose: The purpose of this paper is examination and simulation of tribological properties of composite materials based on porous ceramic preforms infiltrated by eutectic aluminium alloy.

Design/methodology/approach: The material for investigations was fabricated by pressure infiltration method of ceramic porous preforms. The eutectic aluminium alloy EN AC – AlSi12 was use as a matrix while as reinforcement were used ceramic preforms fabricated by sintering of Al_2O_3 Alcoa CL 2500 powder with addition of pore forming agents as carbon fibres Sigrafil C10 M250 UNS manufactured by SGL Carbon Group company. The wear resistance was measured by the use of device designed in the Institute of Engineering Materials and Biomaterials. The device realize dry friction wear mechanism of reciprocating movement condition. The simulation of influence of load and number of cycles on tribological properties was by the use of neural networks made.

Findings: The developed technology of manufacturing of composite materials with the pore ceramic Al_2O_3 infiltration ensures expected tribological properties moreover those properties can by simulated by the use of neural network.

Practical implications: The composite materials made by the developed method can find application as the alternative material for elements fabricated from light metal matrix composite material reinforced with ceramic fibrous preforms.

Originality/value: The obtained results show the possibility of manufacturing the composite materials with expected tribological properties by the pressure infiltration method of porous preforms based on the ceramic particles with liquid aluminium alloy.

Keywords: Composites; Infiltration; Simulation; Neural networks

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ENGINEERING MATERIALS PROPERTIES

1. Introduction

Light metal alloy based metal matrix composite materials have the highest priority in application where a combination of wear resistance, low density and high mechanical performance are required, such as in the automotive and aircraft industry [1].

In last years, much interest was focused on the use of Al_2O_3 fibres or particles reinforced aluminium matrix composite materials. The process of manufacturing these composites include solid-state processes such as powder metallurgy (PM) [2,3,4,5], where metal and ceramic powders are blended than hot-pressed, and liquid-state processes such as melt infiltration, blending ceramic powder with molten aluminium than casting, melt stirring, pressurized infiltration and squeeze casting [6,7,8,9,10,11].

The infiltration of ceramic porous preform by a liquid alloy is a cost-effective method for the manufacture of metal matrix composites. In particular, pressure infiltration provides good penetration of pores and channels of preforms by liquid metal. This procedure consist of pushing the molten metal into a preheated preform using a piston (punch of form) and pressures in the range of 50-100 MPa. Despite the good results obtained with this technique, some difficulties remain related with air entrapment into the preform which can be at the origin of voids at metal-ceramic interphases, with detrimental consequences to the mechanical properties. An additional problem is related to the high pressure involved in the process, which implies the development of heavy equipment even for laboratory research. Moreover, high pressure could produce ceramic preform deformation or an inhomogeneous reinforcement distribution along the infiltration direction [9,12].

The relatively poor wear resistance of aluminium alloys has limited their uses in certain tribological environments. Seizure and wear resistance in aluminium alloys could be substantially improved by incorporating of hard ceramic particulates or fibres (e.g., Al_2O_3, SiC, BN, Ti(C,N) and ZrO_2) [13,14,15].

Designing of composite materials with advantageous tribological properties is not easy and is connected with analysis of many factors [16,17]:

- chemical composition of reinforcement,
- portion of reinforcement,
- changes of the shape and size of reinforcement.

The artificial neural networks are a universal tool for a numerical modeling capable of mapping of complex functions. The adaptation of neural networks to fulfilling a definite assignment does not require the determination of an algorithm or recording it in the form of a computer program. This process replaces learning using a series of typical stimulations and corresponding to them desirable reactions. The basic feature of neural networks is their capability to generalization of knowledge for the new data not presented in the learning process. The neural networks do not require collecting and direct access to the knowledge about the issue; they present a tolerance towards discontinuity, accidental disturbances or lacks in the learning set. This fact allows applying them whenever there are problems with data processing and analysis, their classification, prediction or control [18]. For several years, neural networks are more and more often used in the material engineering [19,20,21]. This growing popularity of neural networks results from the possibilities of creating relations between the examined quantities without any knowledge concerning a physical pattern of described phenomena. The results delivered by the neural network very often present bigger compatibility with the empirical data than with the results obtained thanks to the empirical interrelations or mathematic models of the analysed processes.

The goal of this work is examination and simulation of tribological properties of the EN AC - AlSi12 alloy matrix composite material reinforced with the Al_2O_3 preforms fabricated by sintering of Alcoa CL 2500 powder with addition of pore forming agent, fabricated by the pressure infiltration process.

2. Experimental procedure

The material for investigation was produced by he method of pressure infiltration of porous ceramic frameworks with liquid aluminium alloy. The composites matrix consisted of euthetic alloy EN AC – AlSi12 and as the reinforcement the porous ceramic frameworks consisted of sintered Al_2O_3 particles were used.

Ceramic preforms from Al_2O_3 particles were manufactured by Aloca CL 2500 powder sintering method with addition of pore forming agent in form of carbon fibres Sigrafil C 10 M250 UNS from SGL Carbon Group company. The properties and chemical composition of the used carbon fibres and ceramic powder are shown in Tables 1 and 2 respectively.

Manufacturing process of the ceramic preforms comprised:

- preparation of powder and carbon fibres mixture,
- pressing of prepared powder mixture,
- compact sintering.

Table 1.
Properties of Sigrafil C10 M250 UNS carbon fibers [4]

PROPERTY	VALUE
Fiber diameter [μm]	8
Mean fiber length [μm]	135
Fiber density [g/cm^3]	1.75
Tensile strength [GPa]	2.5
Young’s modulus [GPa]	26
Carbon content [%]	>95

The addition of the carbon fibres was 30, 40 and 50 % of weight. Into Al_2O_3 suspension were added the addition of anti-forming agent of the set of carbon fibres Dolapix CE 64 of Company Zschimmer und Schwarz GmbH Company, eliminating their electrostatic interactions. In order to make pressing easier, 1% polyvinyl alcohol Moviol 18-8 solvable in water was added.

The ceramic powder and carbon fibres mixtures were uniaxially pressed in the hydraulic press “Nelke” in steel mold with the inside diameter of 30 mm. The maximum pressure was 100MPa and pressing time was 15 s. Compacts were sintered in “Gero” pipe furnace in air atmosphere (20 l/min). The temperature during the sintering process was ensuring the carbon fibres degradation (heating by 10h in temperature 800 ºC) and Al_2O_3 powder sintering in temperature of 1500 ºC by 2 h. The porosity of the ceramic performs depends on the carbon fibres content 69% at 30% of carbon fibres addition, 75% at 40% of carbon fibres addition and 80% at 50% of carbon fibres addition, respectively.

Table 2.
Properties and chemical composition of Alcoa CL 2500 powder

Diameter D50[μm]	Density [g/cm^3]	Mean mass concentration of elements, wt.%						
		Al_2O_3	Na_2O	Fe_2O_3	SiO_2	CaO	B_2O_3	Others
1.80	3.98	99.80	0.05	0.02	0.01	0.01	0.01	0.10

The internal surfaces of ceramic preforms were coated with nickel in order to improve the Al_2O_3 wettability by the liquid aluminium alloy. Solutions containing metallic Pd were used for activation of the ceramics surface. Reagents were pumped through preforms to cover their internal surfaces on especially designed device.

Uncoated and coated by Ni ceramic preforms were heated in furnace to temperature of 800 ºC. Covered by graphite form was warmed up to 450 ºC (maximal temperature of the press plates) and then fulfilled with preform and liquid alloy EN AC – AlSi12 with temperature of 800 ºC. The whole was covered by the stamp and placed in hydraulic plate press Fontune TP 400. The maximum infiltration pressure was 100 MPa and its influence was 120 s. After solidification obtained materials ware removed from the form and cool down under pressured air stream.

The wear resistance was measured by the use of device designed in the Institute of Engineering Materials and Biomaterials. The device realize dry friction wear mechanism of reciprocating movement condition. The samples preparation for examinations consisted of grinding by the use of abrasive paper with grit # 1200 to obtain flat and smooth surface. On samples prepared in this way there were made investigations with the steel ball 8.7 mm diameter as counter-sample. Investigations were made with different number of cycles 1000, 2000, 3000, 4000, 5000, respectively: 24, 48, 72, 96 and 120 m, friction distance and under different load 2.5, 5, 7.5, 10 N. Samples after examinations were rinsed in ultrasonic washer to clean its surface, and then the degree of wear was established on the base of geometrical measurements of wear track and calculation of its volume. The volume loss as the indicator of absolute wear is used when the mass loss is too small and difficult to estimate.

To evaluate the correlation between the amount of reinforcement phase, load, number of cycles (friction distance) and the abrasive wear expressed by the volume of wear track artificial neural network were used. Models of neural network and their numerical simulation was made in Statistica Neural Networks version 4.0F. The task of neural network development require to determine the following quantities: type of neural network, structure of neural network, function of error, the type and form of the activation function, function of post synaptic potential (PSP), neural network training technique and parameters, variable scaling procedure.

The kind of neural network is determinated mostly by mathematical neuron model, characteristic arrangement of neurons in the network and by the kind of connection between neurons. Generalized regression neural network (GRNN) are construct from four layers: input, radial, regression and output ones. Radial neurons which number is equal to the number of standard, represent the centres of concentration in the training set. Regression layer, construct from linear neurons, has one more neuron than output one. Neurons of that layer have two main tasks: first – realized by neurons which number is equal the number of neural outputs – they calculate the conditional regression for each output variable, and the second one made by singular neuron – calculation of probability density. Each of output layer neuron determines the ratio of conditional regression, calculated for a neuron of previous layer and probability density.

Neural networks with radial base functions (RBF) are build from three layers: input, hidden with radial neurons and output one built-up neurons with linear characteristics. Linear neural networks have only two layers – input and output one. Information are transformed only in output layer. Output layer has a linear function PSP and linear activation function. The most popular kind of artificial neural networks is undoubtedly multilayer perceptron (MLP). In this kind of neural network there is used linear function of post synaptic potential and usually nonlinear activation function. The base significance in the designing of multilayer perceptron structure has the determining of the hidden layer number and the number of neurons in these layers.

In the Table 3 are shown the analysed types of neural networks and corresponding to them characteristic values of parameters. The proper choice of that parameters conditions obtaining of adequate calculation model.

Table 3.
Parameters optimized during designing of neural network

Network type	Training method	Activation funtion	Function PSP	Error function
linear	pseudoinversion	linear	linear	square sum
RBF	k-means, k-closest neighbours, pseudoinversion	linear, linear with saturation, exponential	linear, radial	
GRNN	sampling	exponential, Linear with saturation	ratio, radial, linear	
MLP	error back propagation, conjugation gradients, quasi-Newton, Levenberg-Marquardt, quick propagation, delta-bar-delta	logist linear with saturation, hiperbolic	linear	

Artificial neural networks allow creating the relation between examined quantities without define the mathematical model of analyzed problem. However the main significance has the preparation of representative set of experimental data.

Worked out, on the base of own experimental results, set of data was randomly split in three sub-sets: training set, validation set, test set.

Data from training set were used to determine the weight of each member while network during learning, data from validation set - to evaluate quality of network during training process. Residual part of data (test set) was used for evaluation of the established model after the training phase. The splitting into particular data sets was made randomly.

In order to evaluate the quality of the model, the following methodology was applied: the error-mean square, the standard error deviation, the standard deviation ratio for errors and data, Pearson's correlation coefficient.

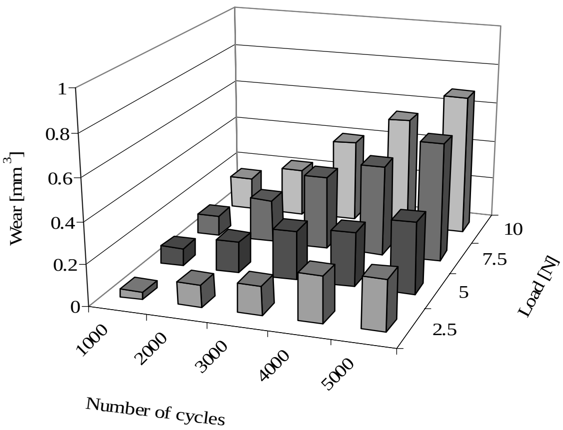
Important coefficient of neural network quality is the standard deviation ratio for errors and data. The model assumed by the network can be consider as correct only in the case when the results presented by the network have error lower than simple evaluation of unknown output value. The simplest method of evaluation output value is assuming mean from output value for training set and show it as a prognosis for data no presented during learning process. In this case mean error is equal to the standard deviation of output value in training set, while the standard deviation ratio is equal to one. The lower error of network prediction the lower standard deviation ratio, for “ideal” prognosis is equal zero. The quality coefficients of the artificial neural network were calculated for training, validation and test sets. The ability of the network to generalization, obtained during learning process, confirms similar values of mean error, the standard deviation ratio, Pearson's correlation coefficient calculated for training, validation and test sets, respectively.

3. Experimental results and their discussion

As a result of tribological measurements there were estimated the wear resistance in the condition of dry friction of composite materials and its matrix (aluminium casting alloy EN AC – AlSi12). There were made investigation of the ceramic content, presence of Ni layer on Al_2O_3, load and number of cycles (friction distance) influence on the wear of investigated materials. The results show that the abrasive wear resistance of composite materials is inversely proportional to the content of ceramic phase apart from the load and number of cycles. The higher content of reinforcement the lower local stresses in the friction zone is caused by bigger number of particles for the surface unit what increases the area of real contact. Wear of all manufactured materials is proportional to the number of cycles under the constant load and to the load by constant number of cycles (Figs 1 and 2).

Coating deposited onto the reinforcement to the improvement it wetability by liquid aluminium alloy, decreases tribological properties of manufactured composite materials. Taking into consideration fact that composite materials with reinforcement covered by nickel are characterized by a little bit smaller content of ceramic phase than materials without Ni coating and its influence on the level of few percent can be neglected.

a)



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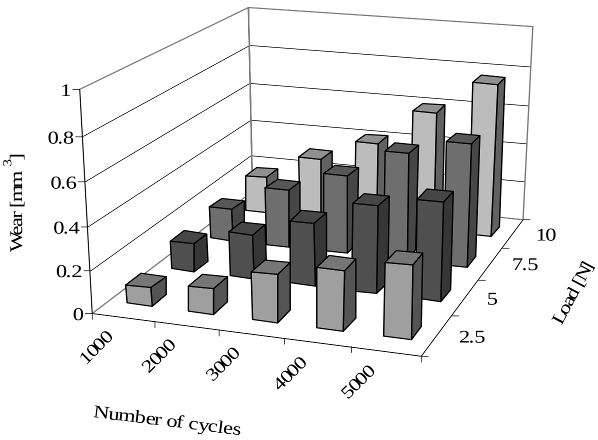

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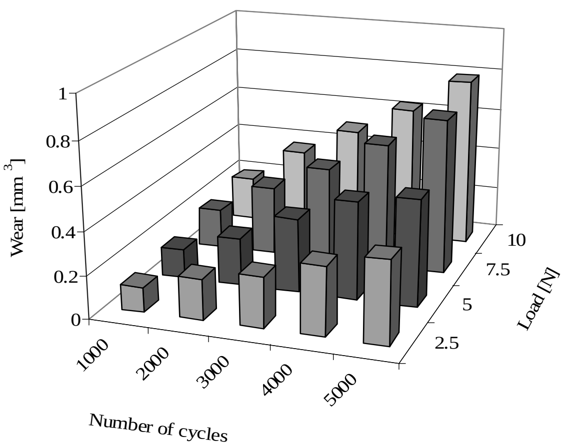
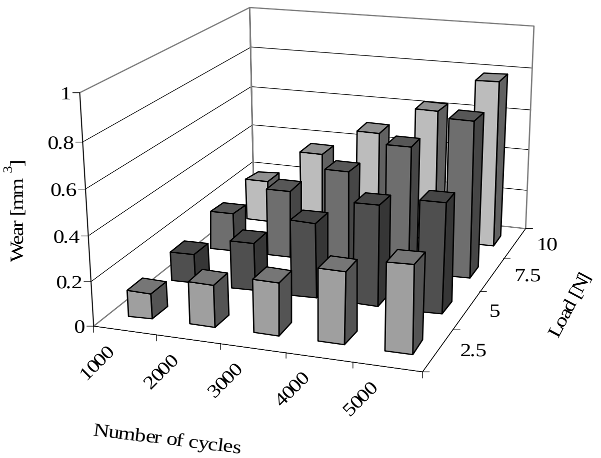


Fig. 1. The influence of load and friction distance on the wear of obtained composite materials with different ceramic content (uncoated reinforcement): a) 31%, b) 25% and c) 20%

a)



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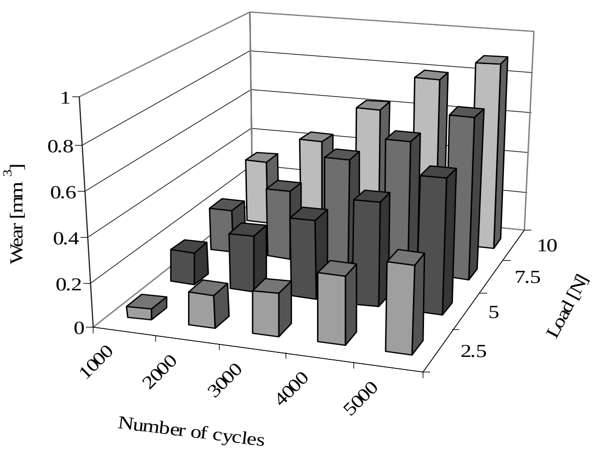

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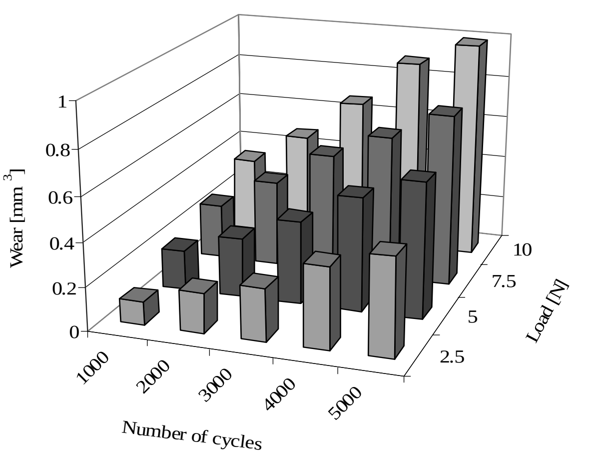

Fig. 2. The influence of load and friction distance on the wear of obtained composite materials with different ceramic content (reinforcement coated by Ni): a) 31%, b) 25% and c) 20%.

For modelling abrasive wear of composite materials reinforced by ceramic preforms artificial neural networks were used calculating the volume of wear loss . As input there was used four variable: content of reinforcement, load, number of cycles and bi-stated nominal variable determining occurring of nickel coating on the surface of ceramic performs. The number of cases in training validation, test set is equal 900, 150, 150, respectively. Values of quality assessment coefficients are presented in Table 4.

Pre-analysis of obtained results allows to choice for further calculations the MLP-type neural network. In the next step of neuron model modeling it was concentrated onto the optimization of neuron number in hidden layer, method and parameters of network training, error function and activation function. The influence of neural number in hidden layer on the error is presented in Fig. 3.

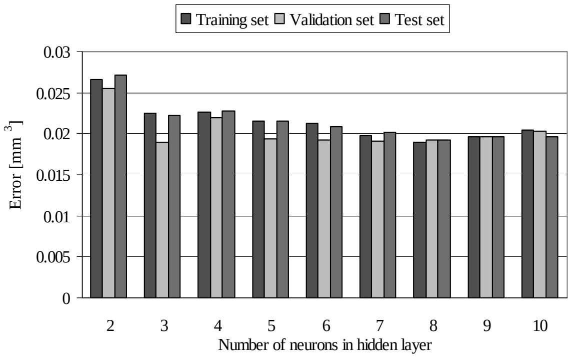

Fig. 3. The influence of neuron number in hidden layer on the network error

The best coefficients assumed for the neural network were obtained for network with a structure 4-8-1 with logistic activation function in hidden layer trained by Levenberg-Marqardt method by 1500 epochs. The scheme of network is show in Fig. 4. Simulation of the load and cycles number influence onto the wear of composite materials is presented in Fig 5.

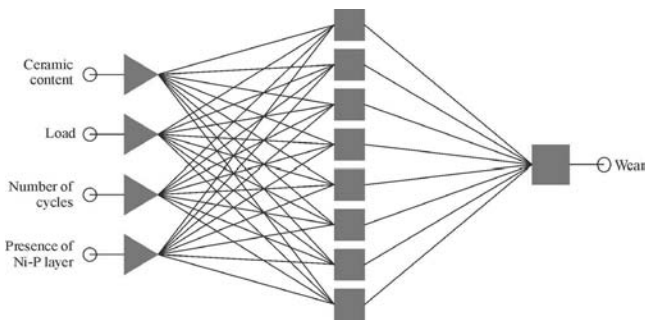

Fig 4. The scheme of neural network MLP 4-8-1 used modeling of tribological properties of composite materials

Table 4.
Characteristic of selected neural network worked out to evaluate abrasive wear of composite materials reinforced by porous ceramic preforms

Network type	Structure of network	Training parameters	Data set			Quality assessment coefficients for neural networks
			Training	Validation	Test	
linear	4-1	PI	0.046	0.048	0.045	Mean error, mm^3
			0.274	0.286	0.264	Ratio of standard deviations
			0.96	0.96	0.96	Pearson's correlation coefficient
GRNN	4-900-2-1	SS	0.105	0.105	0.112	Mean error, mm^3
			0.611	0.589	0.610	Ratio of standard deviations
			0.97	0.97	0.97	Pearson's correlation coefficient
RBF	4-8-1	KM, KN, PI	0.058	0.054	0.057	Mean error, mm^3
			0.348	0.318	0.336	Ratio of standard deviations
			0.94	0.95	0.94	Pearson's correlation coefficient
RBF	4-9-1	KM, KN, PI	0.054	0.050	0.050	Mean error, mm^3
			0.319	0.296	0,301	Ratio of standard deviations
			0.95	0.96	0.95	Pearson's correlation coefficient
RBF	4-10-1	KM, KN, PI	0.040	0.048	0.049	Mean error, mm^3
			0,296	0.282	0.289	Ratio of standard deviations
			0.96	0.96	0.96	Pearson's correlation coefficient
MLP	4-2-1	LM230	0.027	0.025	0.027	Mean error, mm^3
			0.160	0.153	0.161	Ratio of standard deviations
			0.99	0.99	0.99	Pearson's correlation coefficient
MLP	4-3-1	QN753	0.023	0.019	0.022	Mean error, mm^3
			0.140	0.126	0.134	Ratio of standard deviations
			0.99	0.99	0.99	Pearson's correlation coefficient
MLP	4-4-1	QN2077	0.023	0.022	0.023	Mean error, mm^3
			0.137	0.136	0.132	Ratio of standard deviations
			0.99	0.99	0.99	Pearson's correlation coefficient
MLP	4-5-1	QN858	0.022	0.019	0.022	Mean error, mm^3
			0.133	0.124	0.129	Ratio of standard deviations
			0.99	0.99	0.99	Pearson's correlation coefficient
MLP	4-6-1	QN961	0.021	0.019	0.021	Mean error, mm^3
			0.130	0.123	0.125	Ratio of standard deviations
			0.99	0.99	0.99	Pearson's correlation coefficient
MLP	4-7-1	QN1600	0.020	0.019	0.020	Mean error, mm^3
			0.122	0.120	0.124	Ratio of standard deviations
			0.99	0.99	0.99	Pearson's correlation coefficient
MLP	4-8-1	LM1500	0.019	0.019	0.019	Mean error, mm^3
			0.117	0.120	0.119	Ratio of standard deviations
			0.99	0.99	0.99	Pearson's correlation coefficient
MLP	4-9-1	QN1000	0.020	0.020	0.020	Mean error, mm^3
			0.119	0.123	0.126	Ratio of standard deviations
			0.99	0.99	0.99	Pearson's correlation coefficient
MLP	4-10-1	CG1000	0.020	0.020	0.020	Mean error, mm^3
			0.125	0.125	0.119	Ratio of standard deviations
			0.99	0.99	0.99	Pearson's correlation coefficient

Training methods of neural network: SS – Sampling, PI – Pseudoinversion, KN - K-closests neighbours, KM - K-means, BP – Error back propagation, CG – Conjugate gradients, LM - Levenberg-Marquardt, QN - quasi-Newton

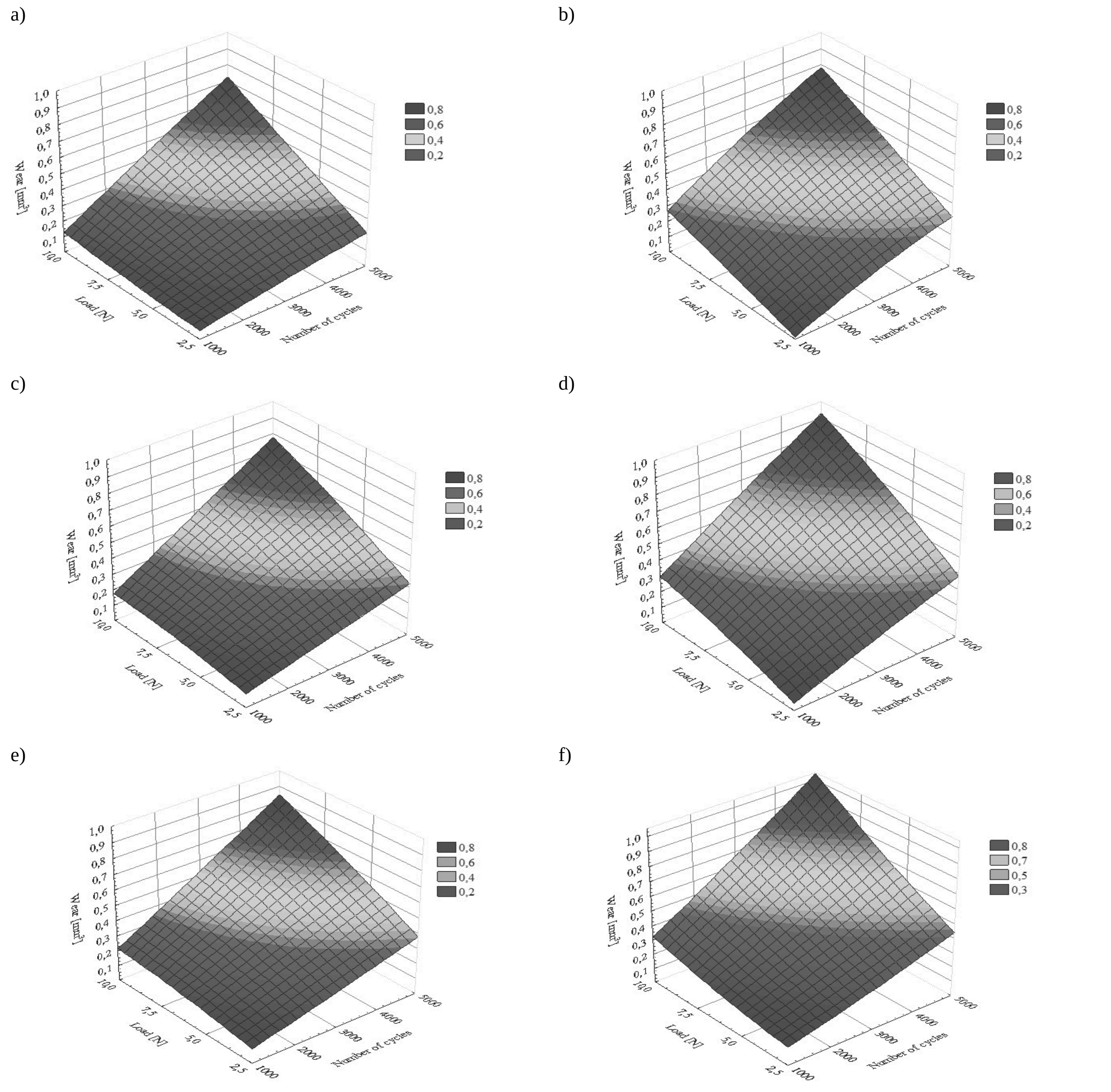

Fig. 5. Simulation of the load and number of cycles influence onto the abrasive wear of composite materials with volumetric portion of ceramic phase: a,b) 31%, c,d) 25% and e,f) 20%, (a, c, e - uncoated reinforcement, b, d, f - reinforcement coated by Ni)

4. Conclusions

It was found that the wear level of composite material manufactured by infiltration method of porous ceramic performs with liquid aluminium EN AC – AlSi12 is directly proportional to the ceramic content, load of counter sample and friction distance (number o cycles).

Worked out model of neural networks allow to determine the abrasive wear of examined materials depending onto the content of ceramic phase, friction distance, load and are fully adequate to obtained results of experimental data. Application of worked out calculation model allow the simulation of the influence of reinforcement, load, friction distance on abrasive wear of manufactured composite materials.

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