The Neural Network Application on Ceramics Materials Density

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***Abstract* — In this research back propagation neural network (BP) was applied on ceramics material samples, consolidated by sintering data obtained in analyzed experiment in a specific way. The main characteristic of BP is that it is capable to perform arbitrarily input-output data mapping due to large set of adjustable coefficients called weights. Desired mapping is possible to achieve if coefficients are set to proper value and this procedure is called training. At the beginning of training process weights are set to random values. Error is defined as a difference between desired and actual network output and weight coefficients have a contribution in generating error.**

Within experimental from material density values sintering results, measured on a surface, we investigate a possibility to calculate density within sintered structure. In this case BP training procedure is used as a tool to spread values measured on a sample surface – density. In this investigation network errors are replaced with density values obtained in ceramics sintering process. We sucesfully performed this neural network application novelty in ceramics material sciences within sintering process for the case $\rho=5.4x10^3[kg/m^3]$.

***Index Terms* — ceramics, sintering, neural network, error, density.**

I. Introduction

In this research ceramics material samples, consolidated by sintering data obtained in analyzed experiment are explored using back propagation neural network. Back propagation neural network is performing arbitrarily input-output data mapping due to large set of adjustable coefficients, Those coefficients are called weights. If coefficients are set to proper value, then desired mapping can be achieved and this procedure is called training of neural network. At the beginning of this process weights are set to random values, and during training process input-output training data is set to a network. It means that desired input-output mapping is known.

Due to inappropriate weight values mapping is performed with significant error, where error is a difference between desired and actual network output. All weight coefficients have a significant contribution in generating this error. Since this measured error is occurred due to incorrect weight values of a whole network it is necessary to change weights through the whole network in the sense to minimize it. This process starts from the output layer where error is measured and finishes in input layer. This procedure of changing weight values is called training. Training is applied on a whole training set data nummerous times. With the change of the values of the coefficients, through the training, process error decreases and after trainining process is finished further on network mapping is satisfactory even for a new input data on network has not been trained. Training process implies changing all network coefficients starting from network output through the whole network to the input. Since this process performs from network output to network input it is called error back propagataion [1,2,3,4]. So, contribution of all network elements generating output error is calculated. Training process is finished when all input-output data are mapped within predefined error.

The main idea in this paper is to extend the neural network application on processes in sintering and calcualtion of various parameters, within different sintering temperatures intervals. The process of consolidation the ceramics materials at different thermal conditions has a very important relation to density.

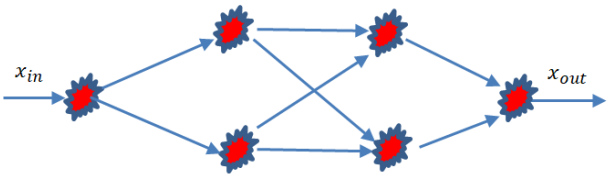

Figure1. The principle scheme neural networks.

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We introduce neural networks (Fig.1) as an efficient tool for application on calculation of different physical parameters. They are very useful, from experimental point of view, because their applciation on results of measurements fit much more extended experimental intervals with exeptible neglected error.

Material structure is assumed as a multi thin layers coating around the both sides grains interconnections. Any signal measured on the material surface could be propagated instead neural network error through the whole structrure. This idea was analyzed in [5,6,7] where relative capacitance measured on a sample surface was propagated through the ceramics structure assuming that ceramic structure can be presented by a neural network, Fig. 1.

Sintering material density value (in last column of Table I) is one of experimentally obtained parameters. These values are measured on a surface. Our goal is to investigate a possibility to calculate density of a sintered material within a sintered structure. In order to solve this problem a possible solution would be a usage of neural networks. Back propagation neural network (BP) seems as an appropriate tool taking into account a training procedure that changes weight coefficient values [8,9,10,11]. Weight values are changed all through whole network proportionately to an error value measured on an output network layer.

In this case BP training procedure is used as a tool to spread values measured on a sample surface – density. Various BP structures are trained to map arbitrary input-output data. During training process an absolute error value measured on an output is used to change weight values through the network. In this investigation network errors are replaced with density values obtained in sintering process, Table 1. first row $\rho=5.4x10^3[kg/m^3]$.

II. Experimental results and methods

The ceramic powder preparation for sintering consolidation for $BaTiO_3$ - ceramics samples is consisted of different steps: (a) measuring and forming a mixture of starting powders with impurities, (b) wet mixing and spraying, (c) molding and process control and (d) preparation, samples sintering and process control. We applied high purity commercial $BaTiO_3$ Murata powder [12] (mean grain size <2μm, 99.9 % purity). We analyzed the influence of sintering parameters on the final $BaTiO_3$-ceramics characteristics, onto the density. Powder mixture was processed into a mill with balls and water and organic binders were added and homogenization was about 48 hours, and the mass was transferred by a membrane pump and dried, so we got desired powder granulation. We tested the material density every hour by a special vessel and after that vibrating sieve was applied. Roughly shaped powder particles were of diameters 10-130μm.

We analized the sintering temperatures (1190-1370ºC) and time (2-3h) with impact of additive CeO_2, $MnCO_3$. For this research paper we stress the relation for pressure 86MPa and density.

TABLE I
Experimental results

sample type	***P [MPa]***	***ρ [kg/m³]***
$BaTiO_3$ – ceramics with basic mixture	86	*5.4x10³*
$BaTiO_3$ -ceramics: composition 0.1%CeO_2+0.14%$MnCO_3$	86	*3.2x10*
$BaTiO_3$ -ceramics: composition 0.1%CeO_2+0.14%$MnCO_3$	86	*3.4x10*

In further theoretical experiment we used concrete data $\rho=5.4x10^3[kg/m^3]$, from the first raw of the Table I.

A. Theoretical experiment and neural network method application

For a network with one neuron in each of two hidden layers errors calculated (Table II) in training process are

TABLE II

neuron	first hidden layer	second hidden layer	output neuron
1	*0.076786*	*0.141702*	*0.185405*

Calculated density ρ in hidden layers (Table III) is

TABLE III

neuron	first hidden layer	second hidden layer	output neuron
1	*2200*	*4300*	*5400*

Error for a network with two neurons in a first hidden layer and one neuron in a second hidden layer (Table IV) is

TABLE IV

neuron	first hidden layer	second hidden layer	output neuron
1	*0.023776*	*0.314802*	*0.887293*
2	*0.045009*		

Calculated density ρ in hidden layers (Table V) is

TABLE V

neuron	first hidden layer	second hidden layer	output neuron
1	*273,9*	*1900*	*5400*
2	*144,6*		

Error for a network with two neurons in a first hidden layer and two neurons in a second hidden layer (Table VI) is

TABLE VI

neuron	first hidden layer	second hidden layer	output neuron
1	*-0.0654*	*-0.2297*	*0.903708*
2	*-0.05848*	*-0.05259*	

Calculated density ρ in hidden layers (Table VII) is

TABLE VII

neuron	first hidden layer	second hidden layer	output neuron
1	*349*	*314*	*5400*
2	*391*	*1372*	

Error for a network with three neurons in a first hidden layer and one neurons in a second hidden layer (Table VIII) is

TABLE VIII

neuron	first hidden layer	second hidden layer	output neuron
1	*-0.04998*	*-0.10846*	*0.668582*
2	*-0.06411*	*-0.16845*	
3	*-0.03064*		

Calculated density ρ in hidden layers (Table IX) is

TABLE IX

neuron	first hidden layer	second hidden layer	output neuron
1	247	*1360*	*5400*
2	518	*876*	
3	*404*		

There is a possibility to calcularte error and ednsity using other neural networks (for example: 3 neurons in first level, 2 neurons in second level; 3 neurons in first level, 3 neurons is second level; 4 neurons in first level, 1 neuron is second level) but this will be part of some future researche.

B. Results and discussion

Obtained and trained neural networks are given on next figures.

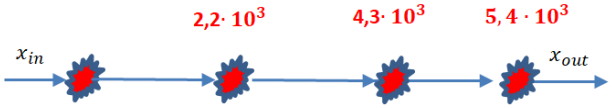

Figure 2. Neural network with one neuron per each hidden layer.

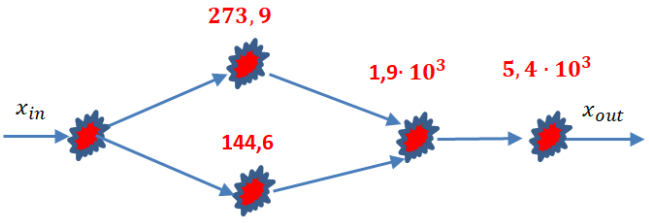

Figure 3. Neural network with two neurons in first hidden layer and one neuron in second hidden layer

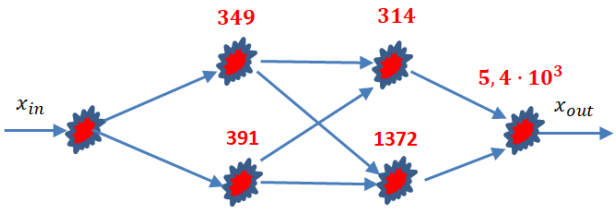

Figure 4. Neural network with two neurons per each hidden layer.

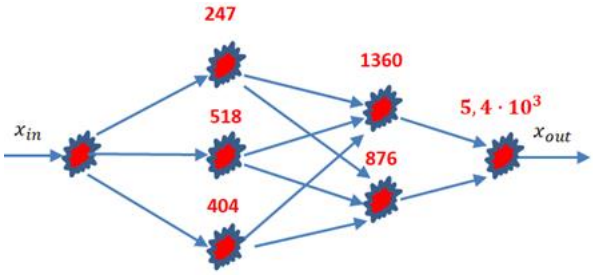

Figure 5. Neural network with three neurons in first hidden layer and two neurons in second hidden layer.

Based on experimentaly consolidated samples and applied the neural networks in three diferente cases shown on Fig.2, Fig.3 and Fig.4, we sucessfully performed this original novelty in getting the samples surface density, based on a theoretical experiment and neural networks calculations.

The advantage in this methodology is within the collecting the ceramics materials densities, from the sample surfaces, based on neural networks. This is efficient and productive way for data densities which is avoiding much more experimental activities and materials and energy and time losses.

III. CONCLUSION

In this research report we explained the neural network method and its application on some results, which are surface density on the experiment. We collected in our experiment a plenty of different results, but we consistently demonstrated this novelty with surface density ρ=*5.4x10^3[kg/m^3]*..

We presented the densities values within the different ceramics sample microstructure levels. Without this method, we could have problem to calculate the desired material density information only by stochastic mathematical approach. On this way, we have very new frontiers in science of sintering ceramics processing and technology howe can get the densities within the whole morphology.

All of this also opens new directions for predicting - designing and prognosis within the ceramics structure, where we would like to form the projective structures on a quit precise way [13,14,15,16,19].

In further experiments and researche we will show how those results, based on surface density, can be calculated on some different neural networks [16,17,18,20], with different shapes and various combination of neurons in hidden layers. We will also show how this approach can be applied for calculation of various other parameters in similar manner, based on obtained experimental results.

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