

EXAMINATION OF DEFORMATION OF THE CERAMIC OBJECT USING MULTI-LAYER PERCEPTRON NEURAL NETWORK

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Abstract

In the development and design of new products in ceramic industry unlimited number of trials has to be carried out to obtain the appropriate format due to the deformation. These trials lead to increased costs and loss of labor in the production stage. In this study, it is aimed to develop computer software to reduce these losses in the ceramic industry.

In this study, in different compositions, firing temperatures and sintering times cylindrical form samples are created. These samples, after the drying process have been scanned with the 3D scanner at the same time measured using classical methods. Later on these samples are fired at different sintering times and temperatures in ceramic firing and measured using the same methods. Thus the deformations in the base, side and mouth regions of the cylindrical samples are identified. In the light of this experimental data, we are developed the Multi-Layer Perceptron Neural Network (MLPNN) model by used MatLab Toolbox. In the MLPNN model, the firing temperature, sintering time and composition of ceramic samples have been used as the input data while the amount of deformation is used as the output data. We were used 58 and 22 of the experimental specimens for the training and the testing of MLPNN model, respectively. We founded a significant relationship between MLPNN and experimental data with X^2 test ($p < 0.001$ and for base, mouth and side $\kappa = 0.41, 0.21, 0.48$, respectively).

Key words: ceramic, deformation, expert systems, neural network, three dimensional

1. INTRODUCTION

In material science, deformation refers to any changes in the shape or size of an object due to- an applied force (the deformation energy in this case is transferred through work) or a change in temperature (the deformation energy in this case is transferred through heat). The first case can be a result of tensile (pulling) forces, compressive (pushing) forces, shear, bending or torsion (twisting). In the second case, the most significant factor, which is determined by the temperature, is the mobility of the structural defects such as grain boundaries, point vacancies, line and screw dislocations, stacking faults and twins in both crystalline and non-crystalline solids. The movement or displacement of such mobile defects is thermally activated, and thus limited by the rate of atomic diffusion (<https://en.wikipedia.org/wiki/Deformation>, www.hkmo.org.tr/resimler/ekler/G14C_940ab4746839656_ek.pdf).

The firing temperature and chemical composition of the ceramic clays affects the deformation. When designing new products in ceramic industry, a number of prototype are made to try to find the appropriate format. In this situation, loss of labor, leeway and research costs of employers increased significantly.

Deformation determined by measuring changes in the horizontal and vertical position of object (www.hkmo.org.tr/resimler/ekler/G14C_940ab4746839656_ek.pdf). Also as a result of recent advances in computer technology, the determination of these deformation can be done with the help of computer software.

Jancikova and et al. investigated the dependence of the generated mode frequency as a function of a sample thickness and a sample shape of glass laminate samples by electronic speckle interferometry. The obtained experimental results for differently shaped (thickness, canting and rounding) glass laminate samples are compared with those of artificial neural networks (ANN). The coincidence of both experimental and simulated results is very good. Fukuda and Hasegawa (1989) developed software to

determine the cracking, shrinkage and breaks of ceramics objects which produced in production lines. They take an images of objects in the production line. Images in the data base compared with images of object by using developed fuzzy software. They are determined deformation to ceramic objects. Xianming and et al. (2006), show that developed software by using finite elements and fuzzy logic determined the fatigue strength, shell thickness and shell structure of ceramic objects. Jancikova et al. (2013) designed the neural prediction model for predicting the occurrence of internal defects in rolled products from Cr-Mo steels. They showed that this model estimated to be very fast, inexpensive and useful tool in solving a wide scale of similar metallurgical problems. Ishimaru et al., (1999) invested a model to precision plastic deformation by using fuzzy inference. This model has been used successfully to predict. Pataro and Helman (1999) presented a fuzzy logic rules model to the direct determination of sequences of passes for the strip rolling process. Tsutsumi and et al. (2001) based on the reflection of Hanshin Awaji big earthquake disaster, the target of this study is the development of performance based design method from the point of view of clients. The developed model given higher performance of satisfaction against the earthquake by using soft-computing method. Bielen et al. (2006) investigated that aluminum wire bonds, as used in a ceramic air cavity package for special semiconductor, are intrinsically be disposed to to mechanical fatigue due to temperature and power cycling causing the wires to expand and shrink in a cyclical way. This study demonstrated a finite element model for semiconductor manufacturing. Dinh and Afzulpurkar (2007) studied a developed model using ANNs and co-active neuro-fuzzy inference system in modeling a real, a complicated multi-input–multi-output nonlinear temperature process of roller kiln used in ceramic tile manufacturing line. Nanayakkara and Samarabandu (2003) obtained high-resolution images from low-resolution images using fuzzy inference systems.

In this study, we are aimed a software developing to minimize cost and time loss in the manufacturing process of ceramic objects by using Multi-Layer Perceptron Neural Network (MLPNN). This software determining to deformation of ceramic objects. Therefore, it may be decreasing at the labor, time and cost loss.

2. MATERIAL AND METHOD

We are used the clay the Eczacibasi ECS–1 (Refsan Company) which including to chemical composition have to SiO₂ 50%, Al₂O₃ 19.5%, CaO 9.6 %. We are bought the quartz from Eczacibasi ESAN (98–99% SiO₂ including). Ceramic objects are fired by using an electrical experimental kiln between 1000–1200 °C in the Kutahya Vocational School, Dumlupinar University.

2.1. Firing and preparation of the ceramic samples

Plaster model patterns are obtained at cylindrical form using a molding plaster and replicated. In the study are preferred to form cylinders, because generally in the form of cylindrical and circular structure in the ceramic tableware industry. Plaster clay are prepared in three different species and the first of them is granular clay (ECS-1), the others are obtained by adding mixing different percent of quartz (such as SiO₂ 55% and 60%). Plaster clay poured into prepared cylindrical form molds and it poured in 27 samples for one species (total for three species form is 27x3=81). Cylindrical samples are prepared at dimensions in blank inside with an 8 cm of diameter, 8 cm in high and 0.5 cm in thickness. All samples are left to resting state at room temperature. Drying samples are removed from the molds and numbered. Before firing, all samples are measured dimensions both scanned with a 3D scanner and conventional methods (Figure 1). Three different form species samples are fired at three different temperatures (1000, 1100 and 1200 °C) and three different sintering duration (30, 60 and 90 minutes). After firing, all the measurements are repeated. All 3D scanning measurements were registered in the database in the form of matrix. Flowchart of standard clay (SiO₂ 50%) is shown in Figure 2. It was repeated by varying the ratio of contribution to other samples.

2.2. Computer software system

Artificial neural network (ANN) consisted of an arbitrary number of simple elements called neurons. Neurons in ANN are, as similar in human brains, interconnected (Adhikary and Mutsuyoshi 2006). ANN represents simplified methods of a human brain and uses new methods to solve problems rather than conventional methods with traditional computations which have difficult solution procedures (Trtnik et al. 2009). The simple ANN model layers are contained an input layer, one or more hidden layers and output layer. The two layers are fully interconnected by weight. The input layer neurons collect information from the outside environment and this information transfers to the neurons of first hidden layer without carrying out any calculation. Layers between the input and output layers are named hidden layers and may consist of a large number of hidden layer units. For some problems, which can be solved by a perceptron, it can be used with only one hidden layer. But it is sometimes more efficient to use two hidden layers. The output layer is generated the network predictions to the outside world (Demir, 2008). The typical neural network is consisted of blocks scheme such as inputs, weights (w), bias (b), sum function, activation function and outputs (Figure 3) (Topcu et al. 2008, Parichatprecha and Nimityongskul 2009, Kocak et al., 2015).

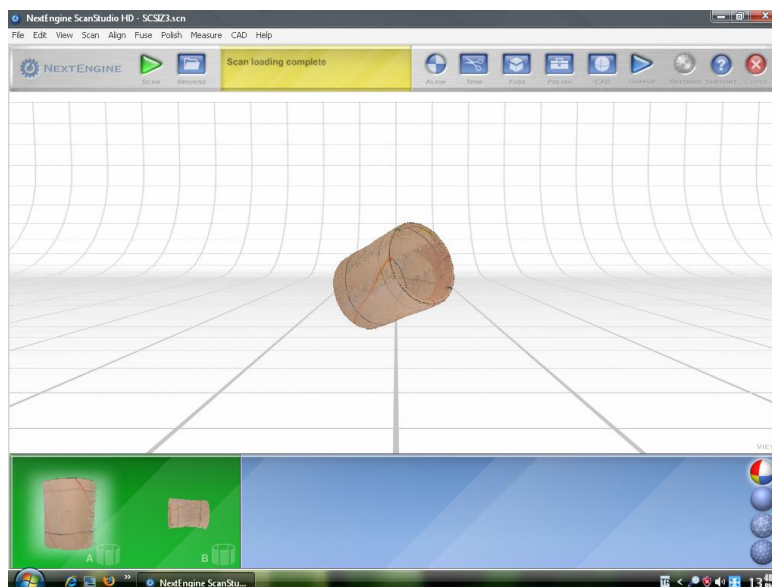


Figure 1. The scanned image of a cylindrical sample using 3D scanner

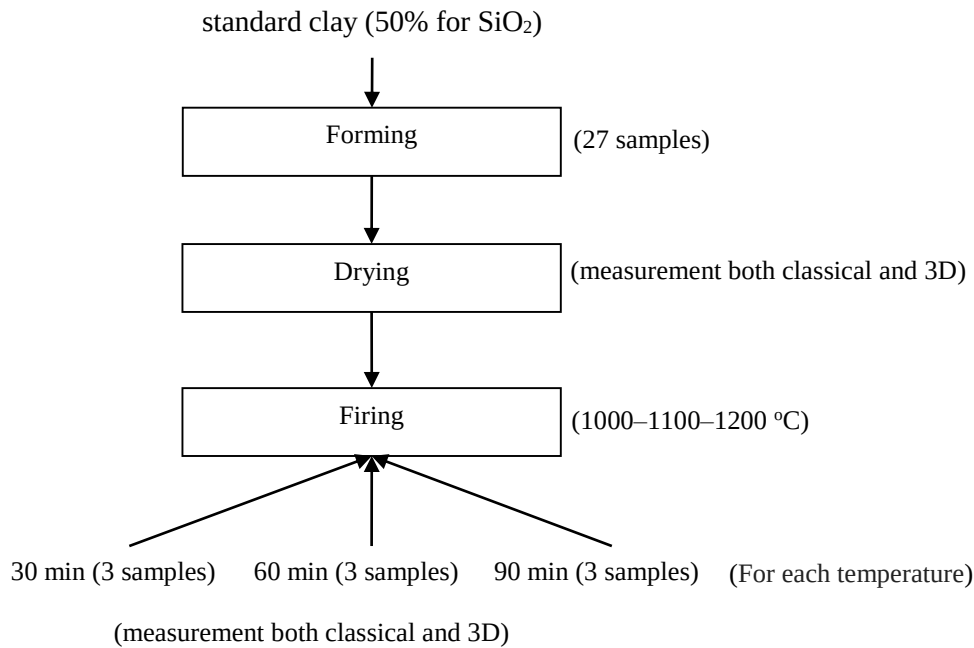


Figure 2. Flow chart for standard clay

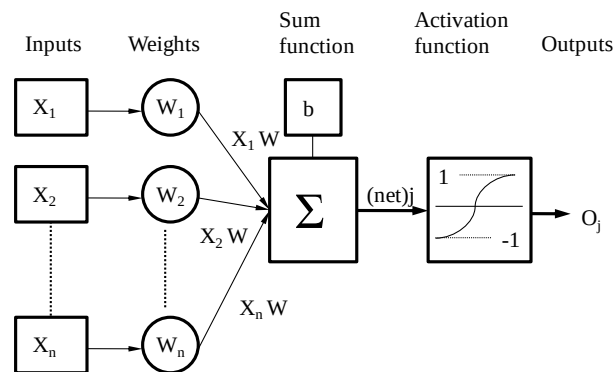


Figure 3. The artificial neuron model

Then, every input is multiplied by the corresponding weight of the neuron connection. The bias (b) is defined as a type of connection weight with a constant nonzero value. It is added to the summation of inputs. The weighted sums of the input components $(net)_j$ are calculated by using Equation.1.

$$(net)_j = \sum_{i=1}^n w_{ij} o_i + b \quad (\text{Equation.1})$$

where $(net)_j$ is the weighted sum of the j_{th} neuron for the input received from the proceeding layer with n neurons, w_{ij} is the weight between the j_{th} neuron in the proceeding layer, o_i is the output of the i_{th} neuron in the proceeding layer. Activation function is a function that processes the net input obtained from sum function and determines the neuron output. In general, the activation function for multilayer feed forward models is determined as the $(f(net)_j)$ sigmoid activation function. The output of the j_{th} neuron $(out)_j$ is computed by using Equation.2 with a sigmoid activation function (Topcu et al. 2008)

$$o_j = f(net)_j = \frac{1}{1 + e^{-\alpha(net)_j}} \quad (\text{Equation.2})$$

where α is constant used to control the slope of the semi-linear region. The sigmoid nonlinearity activates in every layer except in the input layer. The sigmoid function represented by Equation.2 gives outputs in (0, 1). If it desired, the outputs of this function can be adjusted to (-1, 1) interval. As the sigmoid processor represents a continuous function it is particularly used in non-linear descriptions. Because its derivatives can be determined easily with regard to the parameters within (net)_j variable (Topcu et al. 2008).

Our ANN model is called as a multi-layer perceptron neural network (MLPNN). The neurons are 10 and 1 at the first and the second layers in the system, respectively. For training and testing of the neural network model, the firing temperature, sintering time and composition of ceramic samples have been used as the input data while the amount of deformation is used as the output data (deformations of base, side and mouth). Momentum and learning rate values are determined and the MLPNN model are trained according to the MSE through iterations. Parameter values obtained from the MLPNN model are given in Table 1. The trained model is tested only with the input values (22 samples which separated for testing) and the predicted results were compared to the experimental results.

Table 1. The values of parameters used in models

Parameters	MLPNN
Number of input layer neurons	3
Number of hidden layer	2
Number of first hidden layer neurons	10
Number of second hidden layer neurons	10
Number of output layer neuron	3
Error after learning	3.54×10^{-2}
Learning cycle	58

Here in, 58 of the experimental data were used for the training of the model and other 22 experimental data were used for testing the trained model. The designed MLPNN by using MatLab Toolbox consisted of feed-forward back propagation, two hidden layers, training function (Levenberg-Marquardt), adaptation learning function (learngdm), transfer function (tansig) and performance function (MSE-mean squared error) as demonstrated in Figure. 4.

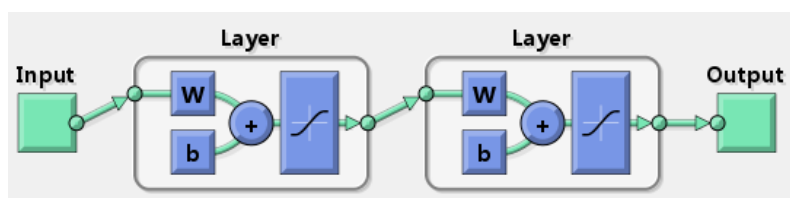


Figure 4. The architecture used in the neural network model for deformation

3. RESULTS

MLPNN models which contain one and two hidden layers are used in order to find more reliable solutions. Determination of optimum number of the hidden layers neurons are very important to accurately predict the parameters used by MLPNN. To find an optimum number of hidden layers, one of the best approaches starts a few numbers of neurons and then slightly increases the number of neurons. This process continues until the selected performance a criterion is observed for each hidden layer neurons.

We were used 58 and 22 of the experimental specimens for the training and the testing of MLPNN model, respectively (one sample was broken). For 58 samples, the deformation estimates obtained from the training results of MLPNN are seen in Table 2, 3 and 4.

From 58 the training data, the base deformation for cylinder form of MLPNN training is seen in the Table 2. For the base deformation, MLPNN is defined also non-deformation 32 samples of non-deformation 37 samples (86.48%). But five non-deformation samples are defined also 1 mm base deformation by MLPNN. Hence, 21 samples deformation is defined also deformation as 11 samples by MLPNN (52.38%). We are founding statistically significant correlation of compared between experimental samples and MLPNN decision for base deformation ($p < 0.001$ and $\kappa = 0.49$).

Table 2. The comparison of results of the base deformation for cylindrical form of MLPNN training

Classical method	MLPNN			
		0 mm	1 mm	Total
	0 mm	32	5	37
	1 mm	10	11	21
	Total	42	16	58
Statistically compression		$X^2=24.62$	$P=0.000$	$\kappa =0.49$

From 58 the training data, the side deformation for cylinder form of MLPNN training is seen in the Table 3. We are founding statistically significant correlation of compared between experimental samples and MLPNN decision for side deformation ($p < 0.05$ and $\kappa = 0.42$).

Table 3. The comparison of results of the side deformation for cylindrical form of MLPNN training

Classical method	MLPNN					
		0 mm	1mm	2 mm	3 mm	Total
	0 mm	2	0	0	0	2
	1 mm	4	40	5	1	50
	2 mm	0	1	5	0	6
	Total	6	41	10	1	58
Statistically compression		$X^2=8.28$		$P=0.002$		$\kappa =0.42$

The mouth deformation for cylinder form of MLPNN training is seen in the Table 4. We are founding statistically significant correlation of compared between experimental samples and MLPNN decision for side deformation ($p < 0.001$ and $\kappa = 0.21$).

Table 4. The comparison of results of the mouth deformation for cylindrical form of MLPNN training

		MLPNN					
		0 mm	1mm	2 mm	3 mm	4 mm	Total
Classical method	1 mm	9	14	8	1	0	32
	2 mm	1	7	14	1	0	23
	3 mm	1	0	0	0	2	3
	Total	11	21	22	2	2	58
	Statistically compression	$X^2=26.83$		P=0.001		$\kappa =0.21$	

For 22 samples, the deformation estimates obtained from the testing results of MLPNN are seen in Table 5, 6 and 7.

Table 5. The comparison of results of the base deformation for cylindrical form of MLPNN testing

		MLPNN		
		0 mm	1 mm	Total
Classical method	0 mm	10	4	14
	1 mm	3	5	8
	Total	13	9	22
	Statistically compression	$X^2=2.62$		P=0.002 $\kappa =0.33$

From 22 the testing data, the base deformation for cylinder form of MLPNN training is seen in the Table 5. For the base deformation, MLPNN is defined also non-deformation 10 samples of non-deformation 14 samples (71.43%). But four non-deformation samples are defined also 1 mm base deformation by MLPNN. Hence, 8 samples deformation is defined also deformation as 5 samples by MLPNN (62.5%). We are founding statistically significant correlation of compared between experimental samples and MLPNN decision for base deformation ($p<0.05$ and $\kappa =0.33$).

Table 6. The comparison of results of the side deformation for cylindrical form of MLPNN testing

		MLPNN			
		0 mm	1mm	2 mm	Total
Classical method	0 mm	0	1	0	1
	1 mm	1	17	3	21
	Total	1	18	3	22
	Statistically compression	$X^2=0.42$		P=0.002	$\kappa =0.48$

From 22 the testing data, the side deformation for cylinder form of MLPNN training is seen in the Table 6. We are founding statistically significant correlation of compared between experimental samples and MLPNN decision for side deformation ($p<0.05$ and $\kappa =0.48$).

The mouth deformation for cylinder form of MLPNN testing is seen in the Table 7. We are founding statistically significant correlation of compared between experimental samples and MLPNN decision for side deformation ($p < 0.05$ and $\kappa = 0.22$).

Table 7. The comparison of results of the mouth deformation for cylindrical form of MLPNN testing

Classical method	MLPNN						
		0 mm	1mm	2 mm	3 mm	4 mm	Total
	1 mm	3	7	1	2	0	13
	2 mm	1	5	1	1	1	9
	Total	4	12	2	3	1	22
Statistically compression		$\chi^2=2.38$		$P=0.003$		$\kappa = 0.22$	

4. CONCLUSION

According to the findings, our system could be used successfully for the determination of base and edge deformation of cylinder objects. However, it did not show the expected performance in the determination of mouth deformation.

The accuracy of the findings in our system should be further developed. Moreover, it should be explored for use in the ceramic industry by applying this method to other geometric forms.

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