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Yapay Zekâ Uygulamasıyla Seramik Nesnelerin Şekilsel Deformasyonun İncelenmesi: ANFIS

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Anahtar Kelimeler:
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Uzman sistemler,
ANFIS

Özet: Seramik endüstrisinde yeni ürünlerin geliştirilmesi ve tasarlanmasında uygun bir formu elde etmek için birçok ilk örnek hazırlamak gereklidir. Çok sayıda deneme üretim sürecinde deformasyona bağlı olarak artan maliyet ve işgücü kaybına yol açmaktadır. Bu çalışmada, seramik endüstrisindeki bu kayıpları azaltmak için yazılım kullanarak bir yapay zekâ modeli geliştirilmesi amaçlanmıştır.
Seramik silindirik nesnelerin deformasyonunu araştırmak için, farklı kimyasal kompozisyonlarda, sinterleme sıcaklıklarında ve sinterleme sürelerinde seramik nesneler üretilmiştir. İlk olarak, silindirik seramik objeler içi boş bir forma dökülmüştür. Bu numunelerin suyunun buharlaştırılmasından sonra, numuneler klasik yöntem kullanılarak geometrik ölçümler (taban, yan ve ağız bölgelerinde) yapıldı. Daha sonra, bu numuneler farklı sinterleme sürelerinde ve seramik fırındaki sıcaklıklarda pişirildi. Silindirik seramik örneklerin taban, yan ve ağız bölgelerindeki deformasyonlar daha sonra klasik yöntem kullanılarak yeniden ölçüldü. Bu deneysel sonuçlardan elde edilen verilerden, MatLab Toolbox kullanılarak ANFIS (Adaptive Neuro Fuzzy Inference System) modeli geliştirildi. Geliştirilen ANFIS modelinde sıcaklık, sinterleme süresi ve seramik örneklerin kimyasal bileşimi giriş parametreleri olarak belirlenirken, deformasyon miktarı çıktı parametreleri olarak belirlendi. Elli sekiz deneyin sonuçları gelişmekte olan modelin eğitimi için kullanılırken, yirmi iki deneyin sonuçları geliştirilen modelin testi için kullanıldı. ANFIS model sonuçları ile deneysel sonuçlar arasındaki ilişkiyi X^2 testi ile karşılaştırdık ve anlamlı bir ilişki bulunmuştur ($p < 0.001$ ve sırasıyla, taban ve yan için $\kappa = 0.3, 0.3$). Fakat ANFIS model sonuçları ile ağız deformasyonu için deneysel sonuçlar arasında anlamlı ilişki bulunamamıştır ($\kappa = 0.06$).

Examining the Formal Deformation of Ceramic Objects by Artificial Intelligence Application: ANFIS

Keywords:
Ceramic,
Deformation,
Expert systems,
ANFIS

Abstract: It is necessary to prepare many prototypes in order to obtain a suitable form in the development and design of new products in the ceramic industry. Numerous trials have led to increased cost and labor loss due to deformation in the production process. In this study is aimed to develop an artificial intelligence model by using software to reduce these losses in the ceramic industry.
In order to investigate deformation of ceramic cylindrical objects, ceramic objects were produced in different chemical compositions, sintering temperature and sintering time. Initially, the cylindrical ceramic objects were poured into a hollow form. After evaporation of the water of these samples, this samples were scanned by using the geometric measurements (in the base, side and mouth regions) were made using classical method. Later, these samples were fired at different sintering times and temperatures in ceramic kiln. The deformations in the base, side and mouth regions of the cylindrical ceramic samples are then re-measured by using classical method. By using the data obtained from these experimental results, ANFIS (Adaptive Neuro Fuzzy Inference System) model was developed by using MatLab Toolbox. While the temperature, sintering time and composition of ceramic specimens are determined as input parameters in the developed ANFIS model, the amount of deformation is determined as output

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parameters. While the results of the Fifty-eight experiments were used for the training of the developing model, while the results of twenty-two experiments were used for the test of the developed model. We compared relation between ANFIS model results and experimental results with X2 test and founded a significant correlation ($p<0.001$ and for base and side $\kappa=0.3$, 0.3, respectively). But it is not found significant relationship between ANFIS model results and experimental results for mouth deformation ($\kappa=0.06$).

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 [1, 2].

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 [2]. Also as a result of recent advances in computer technology, the determination of these deformation can be done with the help of computer software.

Jančíková, Koštial [3] investigated the dependence of the generated mode frequency as a function of a sample thickness and a sample shape of glass laminate specimens by electronic speckle interferometry. The obtained experimental results for differently shaped (thickness, canting and rounding) glass laminate specimens are compared with those of Artificial Neural Networks (ANN). The coincidence of both experimental and simulated results is very good. Fukuda and Hasegawa [4] 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, Yougang [5] show that developed software by using finite elements and fuzzy logic determined the fatigue strength, shell thickness and shell structure of ceramic objects. Jančíková, Zimný [6] 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. invested a model to precision plastic deformation by using fuzzy inference. This model has been used successfully to predict. Pataro and Helman [8] presented a fuzzy logic rules model to the direct determination of sequences of passes for the strip rolling process. Tsutsumi, Hayashi [9] 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, Gommans [10] investigated that aluminum wire bonds, as used in a ceramic air cavity package for special semiconductor, are intrinsically be disposed 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 [11] 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 [12] 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 Adaptive Neuro Fuzzy Inference System (ANFIS). 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 SiO_2 50%, Al_2O_3 19.5%, CaO 9.6 %. We are bought the quartz from Eczacibasi ESAN (98–99% SiO_2 including). Ceramic objects are fired by using an electrical experimental kiln between 1000–1200 ºC in the Kutahya Vocational School, Kütahya Dumlupinar University.

2.1. Firing and Preparation of the Ceramic Specimens

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 SiO_2 55% and 60%). Plaster clay poured into prepared cylindrical form molds and it poured in 27 specimens for one species (total for three species form is 27x3=81). Cylindrical specimens are prepared at dimensions in blank inside with an 8 cm of diameter, 8 cm in high and 0.5 cm in thickness. All specimens are left to resting state at room temperature. Drying specimens are removed from the molds and numbered. Before firing, all specimens are measured dimensions conventional methods.

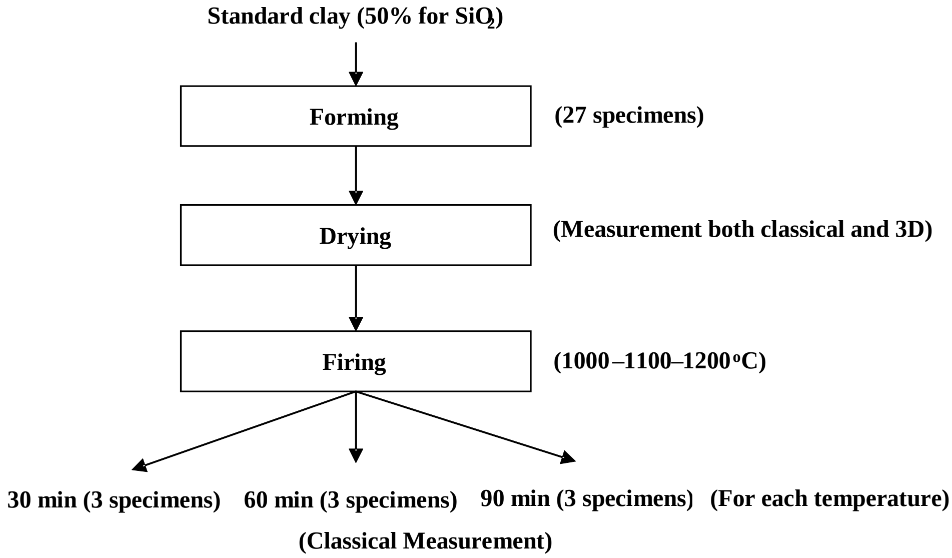

Figure 1. Flow chart for standard clay

Three different form species specimens 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. Flowchart of standard clay (SiO_2 50%) is shown in Figure 1. It was repeated by varying the ratio of contribution to other specimens.

2.2. Computer Software System

Adaptive Neural Fuzzy Inference Systems (ANFIS): While fuzzy logic concept in hybrid this system, it gets into account for the fuzziness and uncertainty, whereas the neuronal network uses adaptability. The hybrid systems which is named as the Sugeno fuzzy model, recommends constructing fuzzy rules between input and output data set. This recommendation is created by using typical fuzzy rule and has the format;

If x is A and y is B then z = f(x,y) (1)

where A and B are demonstrated fuzzy sets in the input variables; *z=f (x,y)* is a crisp function defined by relation between input and output variables. If *f(x,y)* is a first-order polynomial, it defines the first-order Sugeno fuzzy model. If *f* is a constant, it is zero-order Sugeno fuzzy model. An example of a first-order Sugeno type fuzzy inference, involving "*If-then*" rules is as follows:

Rule 1: If x is A_1 and y is B_1 , then $f_1= p_1\ x+ q_1\ y +r_{1u}$ (2)

Rule 2: If x is A_2 and y is B_2 , then $f_2= p_2\ x+ q_2\ y+ r_2$ (3)

In this ANFIS system, the final output is defined the weighted average ($\overline{w}_i$) of each fuzzy inference rule's output [13, 14].

The detailed description of the mathematical relations of each layer seen in the basic ANFIS structure in Figure 2 are presented below.

In the model O_i^j denotes the output of the *i*-th node in *j*-th layer.

Layer 1 (Fuzzification layer): i-th node in this fuzzification layer is an adaptive node with node function;

$$Q_i^1 = A_i\,(x), \quad for\ i = 1,2, or \tag{4}$$

$$Q_i^1 = B_{i-2}\,(y), \quad for\ i = 3,4 \tag{5}$$

where *x* or *y* is the crisp input value to the *i* th node, and A_i or B_{i-2} are linguistic fuzzy membership functions. O_i^j is the output of first layer, and it is the membership degree of a membership functions A or B.

$$O_i^j = \mu A_i(x) = \frac{1}{1+[(x-c_i)/a_i]^{2b_i}} \tag{6}$$

where {a_i, b_i, c_i} is the set parameters to the fuzzy membership functions. The values of these parameters vary according to membership functions type and Equation 3 are used for bell-shaped function, accordingly. Parameters in this layer are referred to premise parameters. The outputs of this layer are the membership values of the premise part.

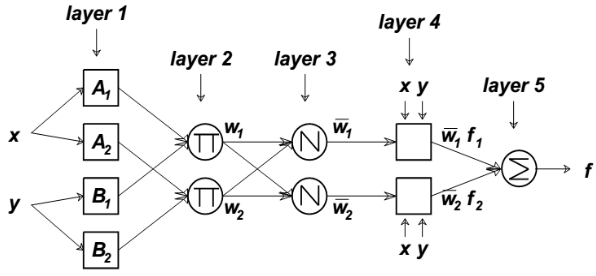

Figure 2. Basic ANFIS block schema.

Layer 2 (Rule inference layer): Each node in this layer computes by using the logic multiplication which is a logic "*AND*" conjunction:

$$O_i^2 = \mu A_i(x).\mu B_i(y) \qquad i = 1,2, \dots \tag{7}$$

Layer 3 (Normalization layer): The *i*-th node in this layer is calculated by the ratio of *i*-th node's fuzzy inference to the sum of the fuzzy inferences of all the nodes:

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2} \qquad i = 1,2,\dots \tag{8}$$

The Layer 3's outputs are generally called as normalized.

Layer 4 (Consequent layer): The *i*-th node in this layer is calculated by multiplying the normal function with the function of node:

$$O_i^4 = \overline{w}_i.f_i = \overline{w}_i.(p_i.x + q_i y + r_i) \tag{9}$$

where w_i is the output of layer 3, and $\{p_i, q_i, r_i\}$ is the parameter set. Parameters in this layer are referred as the consequent parameters.

Layer 5 (Output layer): This layer's single node labeled Σ which is the final output, exhibited as the summation of all incoming signals from Layer 4.

$$O_i^5 = overall\,output = \sum_i \overline{w}_i.f_i = \frac{\sum_i w_i.f_i}{\sum_i w_i} \tag{10}$$

The learning rule is usually the backpropagation gradient descent. This method is applied to the error signals repeatedly from the output layer backward to the input nodes which the derivative of the squared error with respect to each node's output. Another name for this backpropagation learning rule is forward feed neural networks [14, 15].

The designing ANFIS model in this study has the temperature, sintering time and composition of ceramic specimens as the input variables and amount of deformation of ceramic specimens as the one output variables (Figure 3). After designing the model with different learning algorithms and different epochs, best correlations and performances are found through hybrid learning algorithm and 300 epochs. We select three "*gaussmf*" type membership functions in each input variable. Membership functions of three inputs variables are shown in Figure 3.

Parameter values obtained from the ANFIS model are given in Table 1. The trained model is tested only with the input values (22 specimens which separated for testing) and the predicted results were compared to the experimental results.

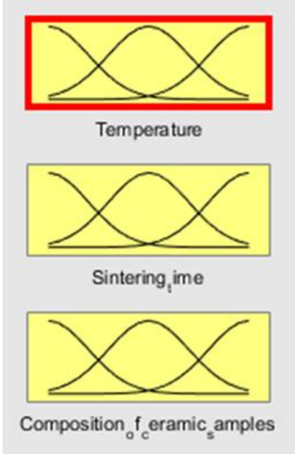

Figure 3. Membership functions of input variables.

Table 1. The values of parameters used in models

PARAMETERS	ANFIS
Number of nodes	78
Number of linear	27
Number of non-linear	27
Total number of parameters	54
Number of training data pairs	58
Number of checking	0
Number of fuzzy rules	27
Error of start training ANFIS model	0.326×10^{-6}

3. RESULTS

We were used 58 and 22 of the experimental specimens for the training and the testing of ANFIS model, respectively (one sample was broken). For 58 specimens, the deformation estimates obtained from the training results of ANFIS are seen in Table1.

Table 2. The comparison of results of the base deformation for cylindrical form of ANFIS testing

		ANFIS		
Classical method		0 mm	1 mm	Total
	0 mm			
	1 mm			
	Total			
Statistically compression		X^2=2.62	P=0.002	κ =0.33

From 22 the testing data, the base deformation for cylinder form of ANFIS training is seen in the Table 2. For the base deformation, ANFIS is defined also non-deformation 14 specimens of non-deformation 10 specimens (71.43%). But four non-deformation specimens are defined also 1 mm base deformation by ANFIS. Hence, 8 specimen's deformation is defined also deformation as 5 specimens by ANFIS (62.5%). We are founding statistically significant correlation of compared between experimental specimens and ANFIS decision for base deformation (P<0.002 and K =0.33).

Table 3. The comparison of results of the side deformation for cylindrical form of ANFIS testing

		ANFIS			
Classical method		0 mm	1 mm	2 mm	Total
	0 mm	0	1	0	1
	1 mm	1	10	7	18
	2 mm	0	3	0	3
	Total	1	14	7	22
Statistically compression		X^2=0.42	P=0.002		κ =0.48

From 22 the testing data, the side deformation for cylinder form of ANFIS training is seen in the Table 3. We are founding statistically significant correlation of compared between experimental specimens and ANFIS decision for side deformation (P<0.05 and κ =0.48).

Table 4. The comparison of results of the mouth deformation for cylindrical form of ANFIS testing

		ANFIS		
Classical method		1 mm	2 mm	Total
	0 mm	4	0	4
	1 mm	6	6	12
	2 mm	2	4	6
	Total	12	10	22
Statistically compression		X^2=6.043	P=0.049	κ =0.06

The mouth deformation for cylinder form of ANFIS training is seen in the Table 4. We are founding statistically significant correlation of compared between experimental specimens and ANFIS decision for side deformation (p<0.049 and κ =0.06).

4. CONCLUSIONS AND RECOMMENDATION

According to findings which have been obtained, our developed 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 developed 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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