

AN ADAPTIVE NETWORK BASED FUZZY INFERENCE (ANFIS) MODEL TO PREDICT THE GLAZE COMPOSITIONS AND GLASSING VALUES IN CERAMIC GLAZE APPLICATIONS

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Abstract

In this study, it is aimed to predict the glazing and appropriate glaze composition with computer software to reduce of the product costs during prototype production in the ceramic industry. Hence, formulas were prepared to use washed Uşak Kaolin, Minium and Quartz. Samples were prepared using these formulas and fired at deformation temperatures 950 and 1150 °C. An adaptive network based fuzzy inference (ANFIS) model to predict the glaze compositions and glassing values were chosen as output values while temperature, surface tension and expansion coefficient were chosen as input values. To this end, MatLab 2010 Toolbox package program was used in this study.

A comparative evaluation of the predicted and experimental results has shown that ANFIS model has a high accuracy and absolute relative error is less than 17.39%. As a result of training, high performance was obtained between regression for glaze components $R^2=0.5301$ and $R^2=0.9984$. Likewise, according to test results, high performance was obtained between regression for glassing $R^2=0.8167$ and regressions for glaze components $R^2=0.9996$ and 0.9986 . Moreover, the ANFIS model was an easy and practical method to predict the glaze compositions and glassing values.

Key words: artificial neuronal network, an adaptive network based fuzzy inference, ceramic, chemical properties, glazing, glaze component

1. INTRODUCTION

The principal crystalline phases of the starting powders used for manufacturing traditional ceramics, also known as triaxial, are clays, quartz and feldspars. Traditional ceramics, white ware, sanitary ceramics, bricks, roof and floor tiles and technical ceramics, such as porcelain and mullite bodies, are usually highly heterogeneous due to the wide compositional range of starting powders and the natural clays used as raw materials (Serra et al., 2014). The amount and distribution of the different components of this structure significantly affects the properties of ceramic materials. The use of protective coatings simultaneously characterized by high hardness, abrasive wear resistance, heat and corrosion resistance, high thermal stability, and a relatively low friction coefficient will significantly improve the performance of various products and increase their service life (Pogozhev et al., 2014).

The glaze which is part of the ceramic production is a glassy layer that covers the ceramic surface and decoration as well. It is made up of siliceous sands and borax, potash, soda and lead oxides are added to decrease the melting point of the mixture in such a way as not to modify the ceramic body during the double fired techniques (Ricci et al., 2007). Although there are no strict rules about this, the most widely accepted system is to give recipes with the ingredients' weights as percentages. It makes this much easier to compare one recipe with another. It is also common practice to list the materials as a base glaze in the order: feldspar, clays, frits, fluxes and finally silica (quartz or flint), to a total of 100% (Bailey, 2001) .

The majority of defects in the glaze designs will be concerned with the appearance of the glaze coating on the ceramic. Undoubtedly some of these faults may arise from defects in the glaze, such as crawling

because of the surface tension. And the fundamental cause of crazing is a difference between the degree of contraction of the body and that of the glaze covering it. In this way stress is created between the glaze and body surfaces and if the reaction layer between the two is insufficiently developed then crazing may result (Fraser, 2005). For this reason, the production of the prototype of a large number of ceramic production industries is required. In the research and development processes, during the preparation of these prototype products are labor and a waste of time therefore; is increase of the costs of the product.

Many researchers argued that using expert system such fuzzy logic, artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS) have a lot of benefits. Fuzzy logic based model to simulate the material removal rate in ultrasonic drilling of sillimanite ceramic was studied include design and demonstration (Gill and Singh, 2010). ANFIS model and three optimized nonlinear regression models was established to predict the flow stress of Ti 600 alloy during hot deformation process (Han et al., 2011), and predict the elastic modulus of normal and high strength concrete (Ahmadi-Nedushan, 2012). Application of ANFIS for prediction of the grain size of nanocrystalline nickel coatings as a function of current density, saccharin concentration and bath temperature were presented and compared ANFIS model with ANN approach (Hayati et al., 2011). A model based on ANFIS was presented for predicting impact resistance of aluminum-epoxy laminated composites in both crack divider and crack arrester configurations (Nazari and Didehvar, 2011). Dielectric properties of polyesters which have abundant use in communication cables and power systems was to be determined by means of ANFIS (İnal, 2008). To predictive models by using ANN and ANFIS to predict yield strength and ultimate tensile strength of warm compacted 0.85 wt.% molybdenum prealloy samples was developed (Zare and Vahdati Khaki, 2012). The applicability of ANFIS as an accurate model for the prediction of the mass gain during high temperature oxidation using experimental data obtained for aluminized nanostructured (NS) nickel was presented (Hayati et al., 2012). They reported that ANFIS model can be used to the engineering applications.

In this study, cost and time reducing in the preparation of ceramic's glaze by mean of computer software is aimed to predict the glazing and appropriate glaze composition.

2. MATERIAL, METHOD AND STUDY DESIGN

In this study, ESC1 (Eczacıbaşı granule casting mud) was used in the production of ceramic samples to be glazed. Formulas were prepared in triad diagram using washed Usak kaolin (in west location in Turkey), minium and quartz compound as initial raw material (Table 1).

Table 1. Chemical composition of initial raw materials (% by weight).

	PbO	Na ₂ O	K ₂ O	CaO	MgO	Fe ₂ O ₃	TiO ₂	Al ₂ O ₃	SiO ₂	*LIO
Washed Usak kaolin	-	0.12	4.34	1.75	1.14	0.94	0.1	14.81	71.6	4.73
Milium	97.66	-	-	-	-	-	-	-	-	2.33
Quartz	-	-	-	-	-	-	-	-	100.00	-

*LIO; loss on ignition.

The raw materials to be used in the glaze trials were obtained as ground material and were filtered dry from the steel sieve whose aperture opening was 355 µm (ASTM-45 mesh). The filtered samples were weighed as 100 g samples on Shimadzu scales. The sample blends whose weighing and branding were completed then mixed with water in a porcelain mortar to homogenize the suspension. After this operation, glaze application was done on the samples using pouring method. During every glaze application trial, the glaze layer was assured to be 1 mm. The second series was prepared after completing the series comprising of 171 trials. The firing temperature for the first series was 950 °C

while it was 1150 °C for the second series. Firing was carried out designing the spaces between the trial samples and the heat circulation inside the kiln after completing the drying process. The firing program was conducted as seen in Figure 1 and the cooling process occurred on its own accord without any additional operation within its own cooling capacity.

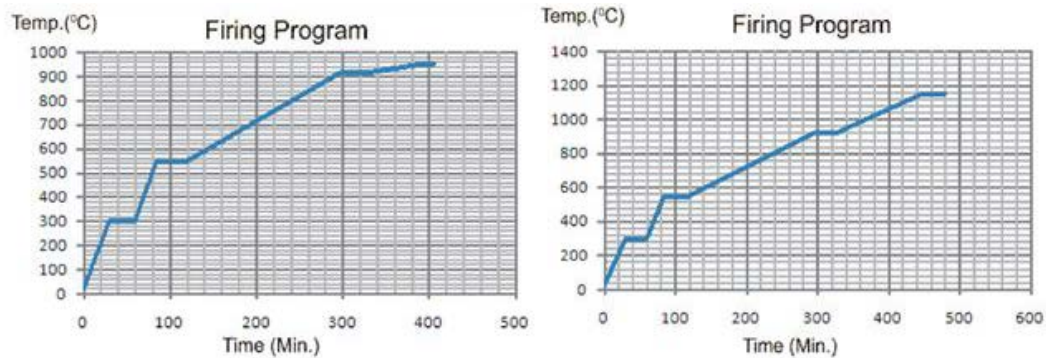


Figure 1. (a) Glazed firing program at 950 °C, (b) glazed firing program at 1150 °C.

Adaptive Neuro-Fuzzy Inference System (ANFIS) Temperature, surface tension, and expansion coefficient were used as ANFIS input variables. ANFIS output variables were composition values of the glaze and glazing. The ANFIS model was formed using MATLAB 2010 Toolbox, Sugeno type, with three inputs and two outputs. Each input variable has three triangular membership functions (Figure 2). The designed ANFIS has been composed of two hidden layers. The input membership functions and rules layer have got 9 and 27 neurons, respectively. In those neurons of the first hidden layer, the rule bases are connected with ‘and’ conjunction.

The rule bases are as follows:

if SF = SF1 and T = T1 and E=E1 then O = O1
 if SF = SF1 and T = T1 and E=E2 then O = O2
 if SF = SF1 and T = T1 and E=E3 then O = O3
 if SF = SF1 and T = T2 and E=E1 then O = O4
 if SF = SF1 and T = T2 and E=E2 then O = O5
 if SF = SF1 and T = T2 and E=E3 then O = O6
 if SF = SF1 and T = T3 and E=E1 then O = O7
 if SF = SF1 and T = T3 and E=E2 then O = O8
 if SF = SF1 and T = T3 and E=E3 then O = O9
 if SF = SF2 and T = T1 and E=E1 then O = O10
 if SF = SF2 and T = T1 and E=E2 then O = O11
 if SF = SF2 and T = T1 and E=E3 then O = O12
 if SF = SF2 and T = T2 and E=E1 then O = O13
 if SF = SF2 and T = T2 and E=E2 then O = O14
 if SF = SF2 and T = T2 and E=E3 then O = O15
 if SF = SF2 and T = T3 and E=E1 then O = O16
 if SF = SF2 and T = T3 and E=E2 then O = O17
 if SF = SF2 and T = T3 and E=E3 then O = O18

if $SF = SF3$ and $T = T1$ and $E=E1$ then $O = O19$

if $SF = SF3$ and $T = T1$ and $E=E2$ then $O = O20$

if $SF = SF3$ and $T = T1$ and $E=E3$ then $O = O21$

if $SF = SF3$ and $T = T2$ and $E=E1$ then $O = O22$

if $SF = SF3$ and $T = T2$ and $E=E2$ then $O = O23$

if $SF = SF3$ and $T = T2$ and $E=E3$ then $O = O24$

if $SF = SF3$ and $T = T3$ and $E=E1$ then $O = O25$

if $SF = SF3$ and $T = T3$ and $E=E2$ then $O = O26$

if $SF = SF3$ and $T = T3$ and $E=E3$ then $O = O27$

SF: Surface Tension

T: Temperature

E: Expansion

O: Output

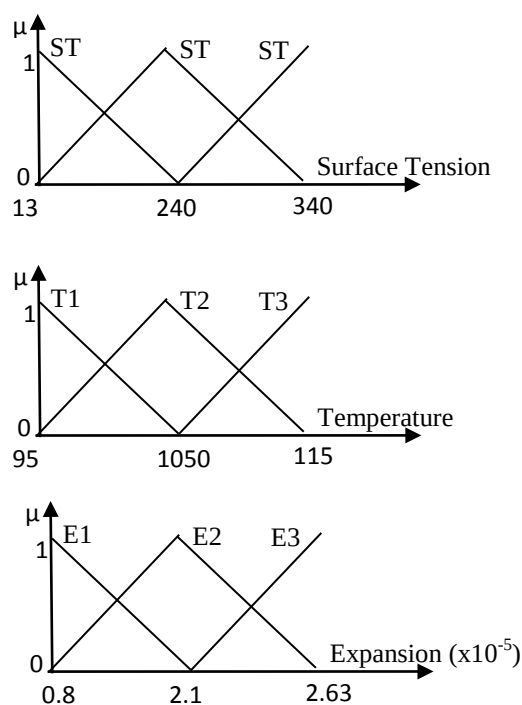


Figure 2. Membership functions of input variables.

The data consisted of 342 samples were used to form the ANFIS training set. The ANFIS model in the above-seen figure 2 is similarly applied for all the chemical compositions and glazing. Performance of the ANFIS training set is presented in Table 2, epoch are used 300 for all the samples. After training the data, the ability of the ANFIS to categorize testing set not in the training set was investigated.

Table 2. The performance of ANFIS training.

Output	PbO	Na ₂ O	K ₂ O	CaO	MgO	Fe ₂ O ₃	TiO ₂	Al ₂ O ₃	SiO ₂	Glazing
Performance	0.549	0.003	0.069	0.030	0.019	0.016	0.002	0.254	0.364	0.408

3. RESULT AND DISCUSSION

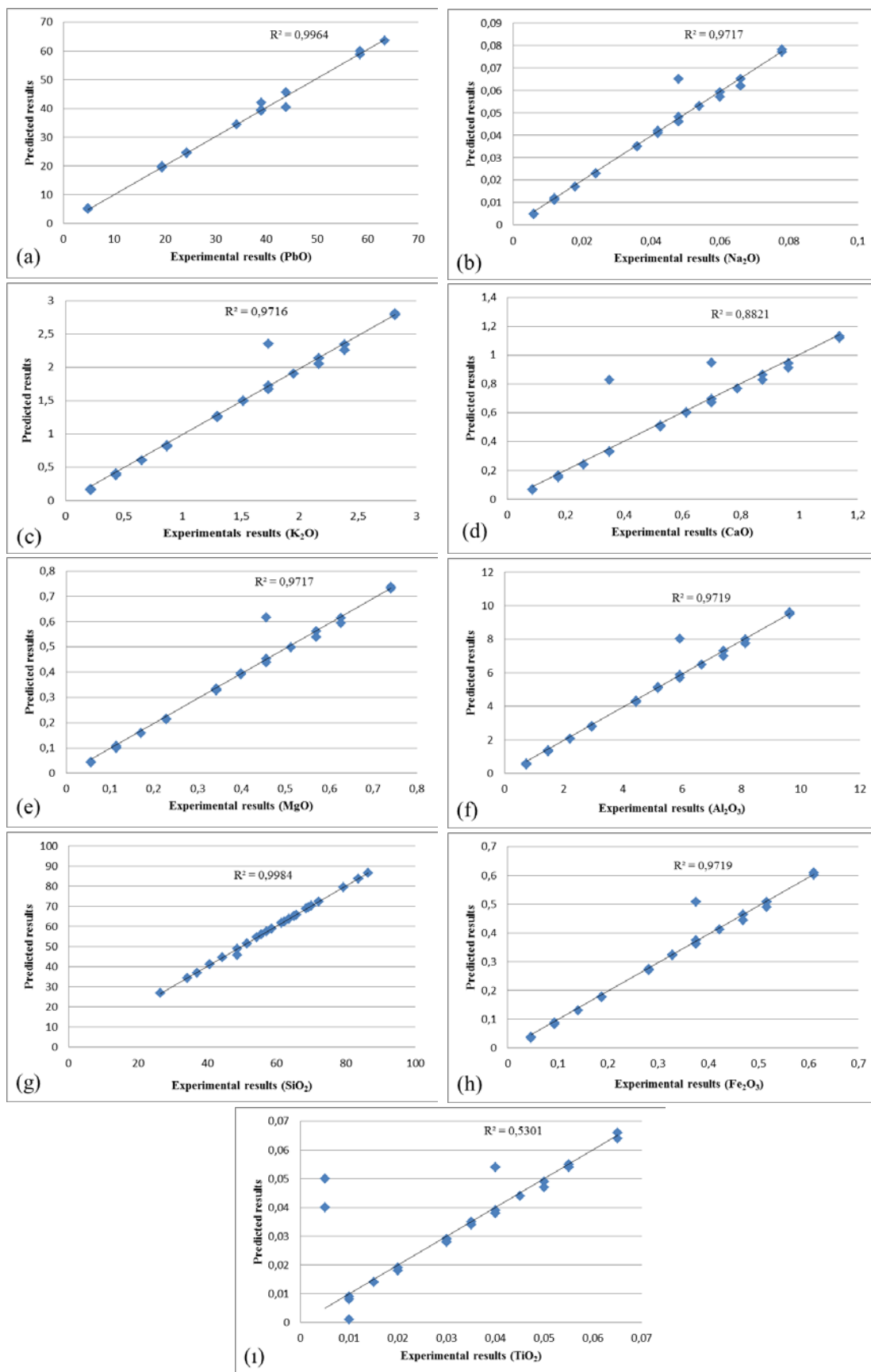


Figure 3. Comparison between the experimental and predicted results glaze composition using ANFIS method.

It is shown the comparison between experimental and predicted glaze composition by ANFIS modeling in Figure 3. Regression coefficient (R) value calculates the correlation between experimental and predicted value. If R^2 value is 1, there is a very close relationship exists between them, zero means a random relationship and greater than 0.9 means the quality is better (Vettivel et al., 2013).

Obviously, the developed model is predicted with high accuracy that we are used eight glaze component (R^2 values between 0.9984 and 0.8821). Hence, it is a bit low that R^2 value of TiO_2 was found to 0.5301. The number of membership functions assigned to each input variable is chosen empirically by examining the desired input-output data or by trial and error. Thus, the accuracy of predicted results could be increased.

The glazing values predicted using the ANFIS have been compared with the real glazing values in the Table 3. It is obviously to see that the predicted glazing for samples is in good agreement with the experimental results. According to experimental results, devitrification 15 of glazing values were the devitrification, 4 were the matt. According to experimental results, matt 8 of glazing values were the matt 4. The experimental results and system for both glassy and glaring samples were in agreement. There is no statistically significant difference between the experimental results and predicted results with the ANFIS in terms of the glazing (Pearson Chi-Square=62.263, significantly $p < 0.001$ and $R^2 = 0.896$).

Table 3. Relationship between ANFIS and experimental results.

		ANFIS				Total
		Devitrifications	Matt	Glossy	Glaring	
Real	Devitrifications	15	0	0	0	15
	Matt	4	4	0	0	8
	Glossy	0	0	2	0	2
	Glaring	0	0	0	1	1
Total		19	4	2	1	26

Both qualitative and quantitative data can be easily included in the ANFIS model. Neural networks perform well in analysis of nonlinear multivariate data. The disadvantages related to the use of neural networks include difficulties of expressing their function in a simple way (Sari et al., 2012).

As a result of these finding, the prediction of the glazing and glaze composition indicates that ANFIS is better and chipper than traditional the trial and error method or the method of calculation formula Seger.

4. CONCLUSIONS

This paper shows that the constructed ANFIS model exhibits a high performance for predicting of the glazing and glaze composition. The initial parameter settings of ANFIS are intuitively reasonable and leading to fast learning, without a prior knowledge. That's why it increases the accuracy of predicted results. Comparing the prediction results of glazing composition by using the ANFIS with regression model, it can be seen that glazing composition matched the experimental data better with the regression values of ANFIS is between $R^2 = 0.5301$ and $R^2 = 0.9984$. It can be concluded that the ANFIS model has the potential of being successfully trained to predict the glaze composition and glazing.

In the research and development processes, during the preparation of these prototype products are labor and a waste time, therefore, is increase of the costs of the product. Application of the ANFIS model over comes all these handicaps as an alternative approach. This means that the proposed model can be used predicted the glaze component percentage in order to in very short time with good accuracy.

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