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"Gheorghe Asachi" Technical University of Iasi, Romania

FLY ASH CONCRETE WITH FIBERS: COMPARISON OF TENSILE STRENGTH USING NEURAL NETWORK AND DESIGN OF EXPERIMENTS METHODS

Daniel Lepadatu[1], Marinela Barbuta[1*], Mircea Rujanu[1], Loredana Judele[1], Raluca Mitroi[2]

[1] "Gheorghe Asachi" Technical University of Iaşi, Faculty of Civil Engineering and Building Services, 43 Mangeron Blvd., 700050 Iaşi, Romania,
[2] "Gheorghe Asachi" Technical University of Iaşi, Faculty of Hydrotechnical Engineering, Geodesy and Environmental Engineering 65, Mangeron Blvd., 700500 Iasi, Romania

Abstract

Neural networks are a series of simple mathematical models, created on the architecture of human brain which gives a superior capacity of learning based on numerous connections established among neurons. The artificial neural networks have strong units of processing which are characterized by an extreme simplicity, but because of their whole interaction, the results are complex. The paper presents the comparison of two methods: mathematical regression and artificial neural network, used for predicting the tensile properties for fly ash cement concrete with fibers. The experimental tests were conducted on 13 mixes obtained on the basis of the central composite design of experiment. The artificial neural network presented a better approximation. The Design of Experiments is a systematic, rigorous approach to engineering problem-solving that applies principles and techniques in the data collection, in order to determine simultaneously the individual and interactive effects of many factors that could affect the output results in any design.

Key words: artificial neural networks, cement concrete, design of experiments, fly ash

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1. Introduction

In the last decades new building materials have been developed because of the new trends in obtaining eco-materials and protecting natural resources. For quite a long time the cement industry has incorporated significant quantities of waste (silica fume, fly ash, blast furnace slag, meta-kaolin, ceramic waste etc.) because of energetic, economic and environmental protection reasons (Harja and Barbuta, 2013; Hossainet al., 2017; Janotka et al., 2010; Sanchez de Rojas et al., 2006; SR EN 197-1, 2011; Tkaczewska, 2014; Wei and Hansen, 2013). In recent years, alternative additions - bagasse ash (Frias et al., 2011; Singh et al., 2000), bamboo leaf ash (Dwivedi et al., 2006; Singh et al., 2007; Villar et al., 2011), paper sludge (Banfol and Frias, 2007) have been studied as components of eco-cements.

The waste or by-products, which in concrete are considered as mineral filler, have become very attractive also for the concrete industry, because of many reasons: the costs of raw materials have increased, the natural resources are limited, and also landfill wastes must be consumed for environment protection. Industrial by-products such as fly ash (Badanoiu and Voicu, 2011; Magureanu and Negrutiu, 2009; Serbanoiu et al., 2017), silica fume, (Barbuta, 2005; Rossignolo, 2007; Tanyldizi, 2013) ground granulated blast furnace, (Bilim et al., 2009), steel slag (Barbuta, 2006), besides the natural additions such as:

* Author to whom all correspondence should be addressed: barbuta31bmc@yahoo.com

marble waste (Belagraa et al., 2017; Hebhoub et al., 2011), volcanic tuff (Harja and Barbuta, 2013), zeolitic rock (Martinez et al., 2006; Uysal and Tanyildizi, 2012) improve the concrete properties due their pozzolanic activity and by their small size which allow to fill the voids of the concrete mass.

More recently the organic waste such as: husk powder (Chidaprasirt and Rukzon, 2008; Habeeb and Mahmud, 2010; Safiuddin et al., 2011), banana leaf ash (Kanning et al., 2014), bagasse ash (Akram et al., 2009) have been used for obtaining concretes with improved properties (by their pozzolanic activity) and reduced costs. For the characterization of these new materials and the prediction of their properties, a high number of experiments are necessary and, because of that, statistical models are often used in designing processes.

In the last few years many researchers have focused on investigating various properties of materials using different methods. Yuan et al. (2014) proposed hybrid models: one was the genetic based algorithm, the other was the adaptive network-based fuzzy inference system, to do research into the structured and unstructured factors which affect the concrete quality. Artificial neural network and the adaptive neuro-fuzzy inference system are used by Amani and Moeini (2012) to predict the shear strength of reinforced concrete. Another hybrid method is proposed by Jiapeng et al. (2010). The authors combine a hybrid genetic algorithm with artificial neural network to optimize hollow concrete bricks with four rectangle enclosures. Cheng et al. (2014) have developed a new method to predict high performance concrete compressive strength using genetic algorithm. Accelerated test methods are proposed by Ramezanianpour et al. (2014) to study microscopic and mechanical properties of ordinary concrete exposed to CO_2 gas and saline water.

Numerous studies and methods are presented in the specialty literature. Our piece of research focuses on the statistical models of the artificial neuronal network type (Almeida, 1997) and mathematical regression (Montgomery and Runger, 2010) (are presented). Mathematical regression uses the method of smallest squares and minimizes the distance square toward the regression line which is the minimizing of errors square. It is the most used statistical method and it explains the mathematical relation between a dependent variable and one or more independent variables. The use of neural network in combination with mathematical regression obtained for tests on materials designed on the base of centered composite design of experiments brings an improvement to the mathematical model. The quality of these numerical models depends on the quality of the learning algorithm, which must be adequate to the studied problem. The association between the biologic neuronal model and the artificial one was possible because in many situations the artificial neurons behave like the human neuron, because the latter incorporates the fundamental characteristics of the biologic neuron, among which learning from examples and strong interconnections among neurons. The training in neural network can be sometimes a very complicated process because the skill is necessary in choosing the parameters which meet the operator's requirements. The neural models can give a desired combination of parameters, eliminating the costs of their obtaining by experimental tests.

The present paper proposes a comparison of predictions concerning the properties of fly ash cement concrete with fiber, by using two methods: mathematical regression and neural network.

By using an experimental design adequate to this type of research we have tried, as this work shows, to obtain a maximum of information with a minimum of experimental tests. I this way we have defined, for the two factors under investigation, an experimental design apt to provide a mathematical model that could be used in estimating the responses that would be envisaged in any desired configuration of the input parameters. The main objectives of this paper are:

- developing and testing a new material – fly ash cement concrete with fiber;
- estimating the mechanical characteristics of this new material by means of two methods:
    1. designing of experiments and response surface methodology for the study of complex and highly nonlinear phenomena;
    2. using artificial neural networks that would complete this complex analysis due to their significant power of adjustment and of learning from examples.
- comparing the results obtained experimentally with those obtained using the two above mentioned predictive methods;
- creating the premise that, by trying to use new additives in the concrete composition, to make use of a methods that would help us in planning, analyzing, and interpreting the results of our research.

It is worth mentioning that, due to the predictive character of the methods used, these estimations may be made for any combination of parameters with values ranging within the frame of the research under investigation.

This paper is developed in several chapters, beginning with an introduction of the two methods used, i.e., the Design of Experiments and the neural networks, after which the experimental part follows, to finally analyze and discuss the results. The conclusions highlight the authors' contribution to this research.

2. Material and methods

2.1. Design of experimental method

The design of experimental methodology has its origin in the '20s when it was initiated by the statistician Sir R.A. Fisher (British statistician - 1925). The first users of this method were the agronomists, who realized very quickly the utility of this technique in the attempt to optimize in an intelligent manner experimental cultures. Towards the '60s, due to the works of Taguchi and Konishi (1987), the experimental planning method was used in Japan to improve the variability of the manufacturing processes in industry. After Japan, this technique was introduced in the U.S.A. in the '80s and then, 10 years later, in Europe.

The Design of Experiments (DOE) is a systematic, rigorous approach to engineering problem-solving that applies principles and techniques for the data collection to determine simultaneously the individual and interactive effects of many factors that could affect the output results in any design.

For researchers, whose findings of new directions in their fields are impossible without experimental design, the technique was and remains an important element in the design and implementation of experimental tests, as it is modern and extremely efficient.

Using DOE method for obtaining materials with high performance properties brings substantial gains, primarily due to a strategy which allows a drastic reduction in the number of experimental tests. Furthermore, this method is highly efficient not only in determining the influence of variable parameters on these new materials, but also in predicting the optimal composition after obtaining the mathematical model.

It is known that the DOE method can be applied to all complex phenomena or processes which can be associated with a black box (Fig. 1). These processes are influenced by: independent variables called factors and denoted by X_i (i is the number of factors) and unknown or uncontrollable variables, denoted by ε. The aim is obtaining an output, a system response Y, which can be called a dependent variable (Montgomery, 2001).

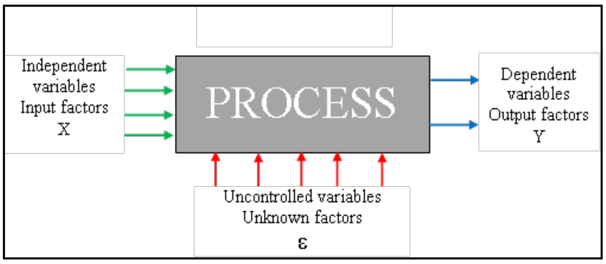


Fig. 1. Black box of the process or system

Among the most used experimental design in this method are the factorial plans, frequently used in the screening technique which aims at reducing the factors with minimal influence on the process or system. Box and Wilson (1951) plans the so called Central Composites Design (CCD – Fig. 2), are mainly used for studying nonlinear phenomena, for which the mathematical model that approximates the behavior of the system is given by equation (1). This equation (Eq. 1) is frequently used to optimize the system response.

$$Y = \beta_0 + \sum_{i=1}^{p} \beta_i \cdot x_i + \sum_{i=1}^{p} \beta_{ii} \cdot x_i^2 + \sum_{i=1}^{p} \sum_{i<j}^{p} \beta_{ij} \cdot x_i \cdot x_j + \varepsilon \quad (1)$$

where: *Y* is the response, x_i are the variables (factors) to be optimized (*i* is the number of these variables), β_o is the independent term, and β_i are the coefficients of the linear term, βii are the pure quadratic coefficients and β_{ij} are the mixed quadratic coefficients (*j* is the number of variables considered to be influences and taken into account when defining the mathematical model), ε represents the noise or error observed in the response *Y* (Montgomery, 2001).

In Fig. 2 there is a composite centered plan for 3 factors, that has in the corners of the cube the maximum and minimum values (±1 in coded factors) for each considered parameter, and the star-shaped or axial points are at a distance δ = radical (i), for the spherical design, where i is the number of factors. The spherical designs are rotatable in the sense that the points are all equidistant from the center.

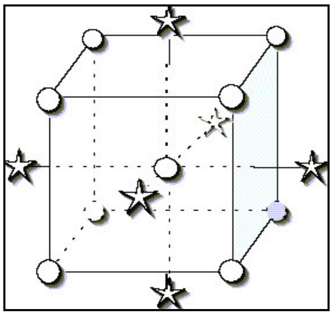


Fig. 2. Central composite design for three factors

Basically, applying the DOE method involves the following steps:

1. Identifying the response function, Y, the variable factors, X and their variation range.
2. Setting the type of experimental design according to the targeted objective
   a. A screening design for ranking and eliminating the non-influential factors
   b. A design for optimizing and determining the results for the studied field
3. Setting the mathematical model that determines the desired result
4. Optimizing the result if needed

2.2. Artificial Neural Network (ANN) model

Neural networks are a series of simple mathematical models, created on the architecture of human brain which gives a superior capacity of learning based on numerous connections established among neurons. The Artificial Neurons Networks – ANN have strong units of processing which are characterized by an extreme simplicity, but because of their whole interaction, the results are complex. In the specialty literature (Almeida, 1997) the ANN represent groups of elements that carry out simple processing, are strongly interconnected and pursue to interact with the surrounding environment in the same manner as biologic brains, having the capacity to learn from their mistakes and errors (Alexandridis et al., 2012; Khan, 2012). The Multi-Layer Perceptrons (MLP) have the neurons arranged in layers, with computation nodes called hidden neurons, whose function is to interfere between the external input and the network output. The hidden layers are enabled to extract higher-order statistics. The MLP (Fig. 3) have more than one hidden layer; however, theoretical works have shown that a single hidden layer is sufficient for an ANN to approximate any complex nonlinear function. The most frequent structure for neural networks in investigations specific to engineering is the MLP type (Almeida, 1997; Kordos, 2005).

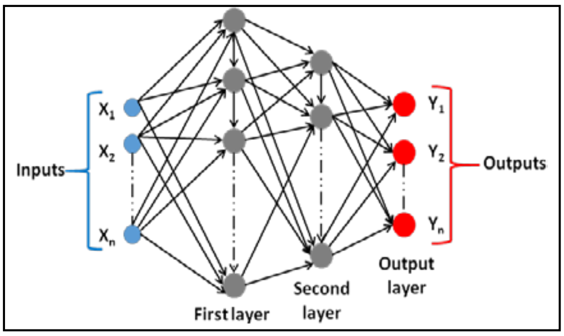


Fig. 3. Multi Layers Perceptron modelling

A back propagation algorithm can be used to train these multilayer feed-forward networks with differentiable transfer functions to perform function approximation, pattern association, and pattern classification. The training of ANNs by back propagation involves three stages: (i) the feed-forward of the input training pattern, (ii) the calculation and back propagation of the associated error and (iii) the adjustment of the weights. This process can be used with a number of different optimization strategies (Barbuta et al., 2012; Diaconescu et al., 2013; Lepadatu et al., 2013). Once the network is trained, it can be tested on a different set of data than that used for training. It is a good approach to divide the given input/output data into two parts: one part (about 70%) is used for training, whereas the other part, usually smaller, is used for testing the neural network model. The testing data set is reserved to validate the trained network.

The training and testing of the networks were performed by means of the Matlab software using the Conjugate Gradient or Levenberg Marquardt algorithm. Similarly to the quasi Newton methods, the algorithm Levenberg-Marquardt was designed for attaining a training speed of second order, without being necessary the computation of Hessian matrix.

In this study, the performances of the ANN were compared with respect to: Mean Squared Error (MSE), Mean Absolute Error (MAE), linear correlation coefficient (r). These performance measures are defined in Eqs. (2-4): where: N is the total of training or testing exemplars, y_i is the network output for exemplar i, d_i is the desired output for exemplar i, $\bar{y}$ is the average network output and $\bar{d}$ is the average desired output.

2.3. Experimental tests

The experimental tests were conducted on 13 mixes of fly ash cement concrete with fibers, which were established by DOE method. For comparison, a witness mix having in composition only fly ash was poured. The experimental results on samples, i.e., flexural strength noted Y_1 and splitting strength noted Y_2 in Table 2, were analyzed using central composite design.

$$MSE = \sum_{i=0}^{N} \frac{(d_i - y_i)^2}{N} \tag{2}$$

$$MAE = \frac{\sum_{i=0}^{N} |d_i - y_i|}{N} \tag{3}$$

$$r = \frac{\frac{\sum_i (y_i - \bar{y})(d_i - \bar{d})}{N}}{\sqrt{\frac{\left(\sum_i (d_i - \bar{d})^2\right)}{N}} \sqrt{\frac{\sum_i (y_i - \bar{y})^2}{N}}} \tag{4}$$

Comparing the experimental results of witness concrete with those of fly ash cement concrete with glass fibers, the tensile strengths for the last concrete were higher than those of the witness (the increase was around 20-25%). The input variables, the length of fibers (X_1) and glass fiber percentages (X_2) with their coded value are given in Table 1. Table 2 presents the design matrix using the central composite design and the parameters selected for the study.

3. Results and discussion

The predicted values from Table 3 were obtained by regression with an error of 0.05%. The coefficient of determination called R-square, is given by r =0.94**,** for Y_1 and r **=** 0.86 for Y_2 which indicates a good approximation for the two responses (Table 3 – DOE columns). The mathematical models achieved through regression are given by the expressions (Eq. 5, 6). In these equations, we can observe that the percentage of fibers definitely influences the two types of concrete resistance through the two coefficients (linear and quadratic), while the fiber length has a slight influence on Y_2 through its linear component.

Table 3 shows the results of the two analyzed responses achieved through experiments using the previously shown methods (DOE and ANN). It also presents the residual errors after comparing the results predicted by DOE and ANN with the experimental ones. According to EN 12390 (2001) the mechanical characteristics of concrete with glass fiber experimentally determined: flexural strength (N/mm^2) – Y_1 and split tensile strength (N/mm^2) -Y_2 which are given in Table 3. The length of fibers (X_1) and glass fiber percentages (X_2) were considered as input variables, while Y_1 and Y_2 were considered as the output values.

Table 1. Range of variables and their coded form

Sample	Variable	Stars points		Lower limit		Central point		Upper limit		Stars points	
		Coded value	Real value	Coded value	Real value	Coded value	Real value	Coded value	Real value	Coded value	Real value
1	X_1	-δ	5	-1	10	0	20	1	30	δ	35
2	X_2	-δ	0.25	-1	0.5	0	1	1	1.5	δ	1.75

Table 2. The design matrix in coded and real values of the CCD

Runs	Coded value		Real value		Y_1	Y_2
	X_1	X_2	X_1	X_2		
1	+1	+1	30	1.5	4.12	3.42
2	+1	-1	30	0.5	2.54	2.05
3	-1	+1	10	1.5	3.92	3.02
4	-1	-1	10	0.5	2.71	2.09
5	-δ	0	5	1	3.36	2.48
6	+δ	0	35	1	4.18	4.43
7	0	-δ	20	0.25	2.34	1.77
8	0	+δ	20	1.75	4.32	4.21
9	0	0	20	1	3.91	4.41
10	0	0	20	1	3.98	4.52
11	0	0	20	1	3.89	4.39
12	0	0	20	1	3.95	4.45
13	0	0	20	1	3.93	4.43

Thus, each ANN presents two input variables and two output variables. In this study, the MLP was used for the modeling of the properties of fly ash concrete with fibers. A few types of MLP neural networks have been used and the optimal topology was determined by the successive trial method. The MLP performances have been evaluated through the comparison of standard deviation – 0.01, correlation between the experimental data and data obtained by predictions and mean absolute percentage error – 0.01. In this respect, the obtained MLP patterns represent a good choice for achieving predictions under various operating conditions, avoiding the need for time - and material-consuming experiments. Some aspects related to the analysis of the optimal values stability are established.

In the present study ANN was trained using 12 data sets, they were then tested using 1 test data sets for the checking-up of results. The following parameters have been used in the neural modeling: the ANN is trained using the back-propagation algorithm and the Conjugate Gradient method, maximum epochs of 10000 and 0.001 learning rate. For the studied functions, the obtained ANN model configuration (Fig. 3) is as follows: **MLP 2:2-9-9-2:2** – 2 neurons in the input layer represent the input variables (such as X_1, X_2), 2 output layer contains a single neuron for each output (for example, Y_1, Y_2) and 9 neurons in the first hidden layer and 9 neurons in the second hidden layer. In the training phase, the statistical parameters: linear correlation coefficient (r), mean squared error (MSE) and mean absolute error (MAE - Table 4) indicate that the neural models describe the studied system well. For the two results which were studied, the neural network allows to predict them with a very high precision - r = 0.98 for Y_1 and r = 0.91 for Y_2 (Table 4) in the stage of training. In Fig. 4 the responses experimentally obtained are given as well as those predicted by ANN and DOE. Fig. 5 shows the residual error. For the two analyzed results, there is to be noticed that their prediction using the two methods was better for Y_1, while the residual errors are bigger for Y_2. We can also state that, although the max error for Y_1 is the one got by ANN (0.41 run 6), for the majority of the other results, the residual errors are much smaller than in the case of DOE. For Y_2 the max value is still the one resulted through ANN (1.37 – run 3). One can see that the resulted errors from prediction with neural networks are much smaller in comparison with those obtained by mathematical regression. This is due to a better approximation of results from prediction with ANN. The response surfaces obtained by ANN prediction from Fig. 6 show the non-linear character of studied responses because of the complex structure of fly ash cement concrete mix that was analyzed. As it can be seen in Fig. 6, the two surfaces show a non-linear relation between the two analyzed results (Y_1 - flexural strength and Y_2 – splitting strength) and the two factors (X_1 – length of fiber, X_2 – fiber percentage) considered in this study. Moreover, for the second analyzed result Y_2 – we get a stronger non-linear character regarding the surface shape which is also confirmed by the smaller value of r=0.91 (Table 3), having a less accurate prediction.

Table 3. Experimental, predicted, and residual values obtained by DOE and ANN of the two responses Y_1 and Y_2

Run	Y_1					Y_2				
	EXP.	***Predicted***		***Residual***		***EXP.***	***Predicted***		***Residual***	
		DOE	***ANN***	***DOE***	***ANN***		***DOE***	***ANN***	***DOE***	***ANN***
1	4.12	4.39	4.11	-0.27	-0.01	3.42	4.24	4.41	-0.82	0.99
2	2.54	2.85	2.53	-0.31	-0.01	2.05	2.62	2.06	-0.57	0.01
3	3.92	3.91	4.12	0.01	0.20	3.02	3.25	4.39	-0.23	1.37
4	2.71	2.74	2.64	-0.03	-0.07	2.09	2.06	1.81	0.03	-0.28
5	3.36	3.41	3.36	-0.05	0.00	2.48	2.52	2.48	-0.04	0.00
6	4.18	3.86	3.77	0.32	-0.41	4.43	3.68	4.39	0.75	-0.04
7	2.34	2.18	2.34	0.16	0.00	1.77	1.59	1.78	0.18	0.01
8	4.32	4.21	4.16	0.11	-0.16	4.21	3.69	4.41	0.52	0.20
9	3.91	3.92	3.92	-0.01	0.01	4.41	4.4	4.35	0.01	-0.06
10	3.98	3.92	3.92	0.06	-0.06	4.52	4.4	4.35	0.12	-0.17
11	3.89	3.92	3.92	-0.03	0.03	4.39	4.4	4.35	-0.01	-0.04
12	3.95	3.92	3.92	0.03	-0.03	4.45	4.4	4.35	0.05	-0.10
13	3.93	3.92	3.92	0.01	-0.01	4.43	4.4	4.35	0.03	-0.08

$$Y_1 = 0.85 + 0.0465X_1 - 0.0013X_1^2 + 3.552X_2 - 1.284X_2^2 + 0.0185X_1X_2 \quad (5)$$

$$Y_2 = -2.786 + 0.248X_1 - 0.0058X_1^2 + 7.24X_2 - 3.141X_2^2 + 0.022X_1X_2 \quad (6)$$

Table 4. Training performances

	Y_1	Y_2
MSE	0.040	0.140
MAE	0.077	0.258
r	0.98	0.91

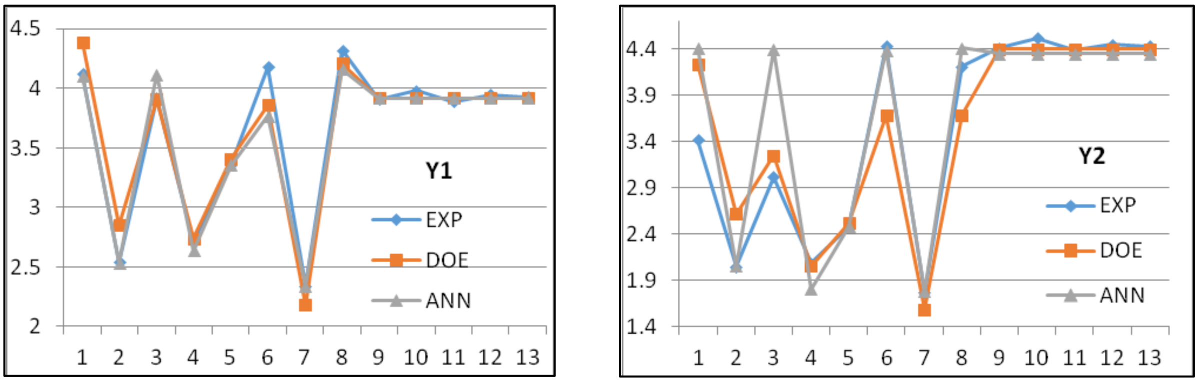


Fig. 4. Experimental responses Y_1 and Y_2 versus predicted by ANN and DOE

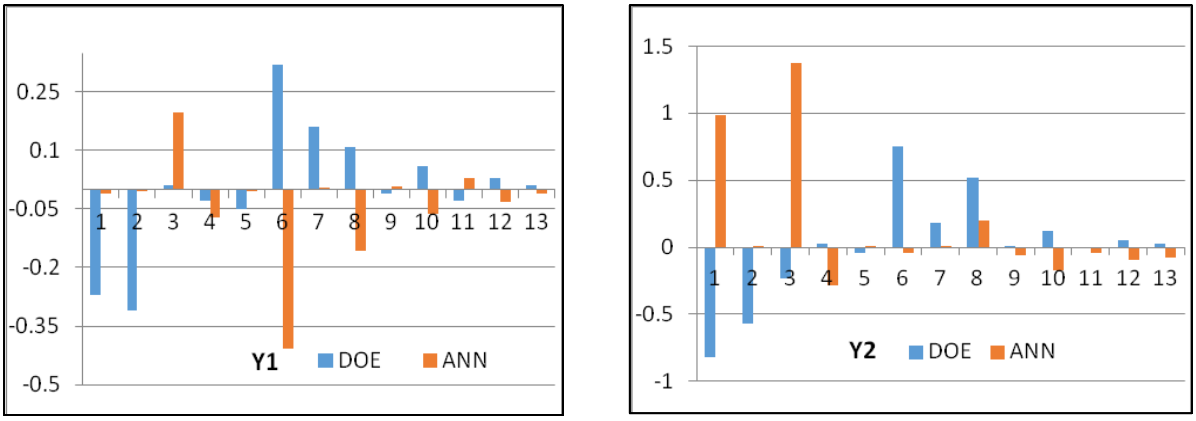
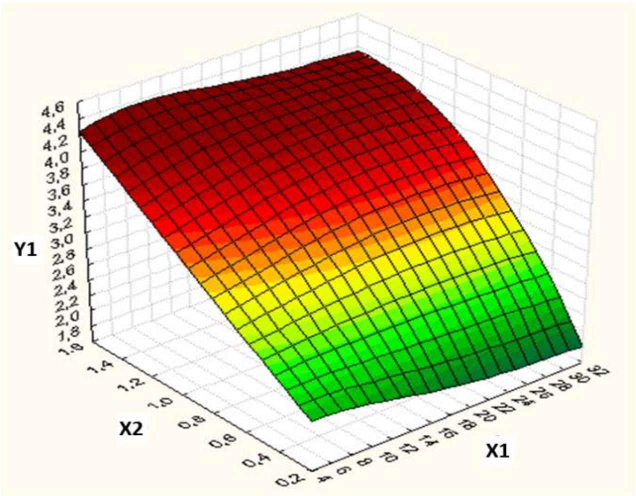


Fig. 5. Comparison of residual error for predicted ANN and DOE



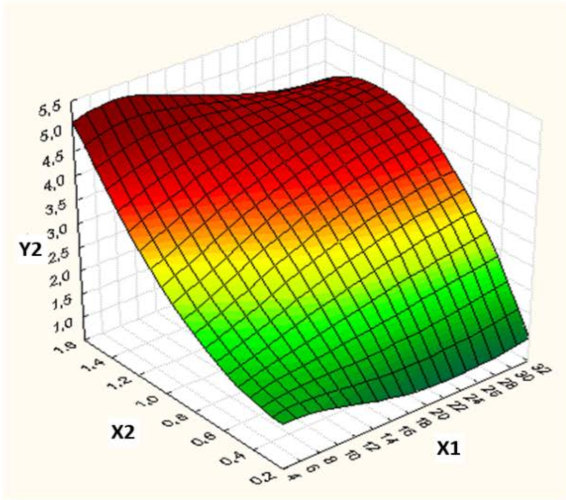


Fig. 6. Response surfaces of ANN predicted outputs – Y_1, Y_2

4. Conclusions

This research study has presented a comparison of predictions concerning tensile properties of fly ash cement concrete with fiber by using two methods: mathematical regression and neural network. A better approximation was obtained with ANN than in the case of mathematical regression, due to the capacity of neural network to adapt to complex models. For prediction, the same neural network was used, which diminished the final adjustment on each model.

The neural network helped us to obtain MLP patterns that represent a good choice in achieving predictions of the variations in operating conditions, making it possible to avoid time and material-consuming experiments.

References

Akram T., Memon S., Obaid H., (2009), Production of low cost self-compacting concrete using bagasse ash, *Construction and Building Materials*, **23**, 703-712.

Alexandridis A., Triantis D., Stavrakas I., Stergiopoulos C., (2012), A neural network approach for compressive strength prediction in cement-based materials through the study of pressure-stimulated electrical signals, *Construction and Building Materials*, **30**, 294-300.

Almeida L.B., (1997), *Handbook of Neural Computation*, IOP Publishing Ltd and Oxford University Press, Oxford.

Amani J., Moeini R., (2012), Prediction of shear strength of reinforced concrete beams using adaptive neuro-fuzzy inference system and artificial neural network, *Scientia Iranica A*, **19**, 242-248.

Badanoiu A., Voicu G., (2011), Influence of raw materials characteristics and processing parameters on the strength of geopolymer cements based on fly ash, *Environmental Engineering and Management Journal*, **10**, 673-681.

Banfol P., Frias M. (2007), Rheology and conduction calorimetry of cement modified with calcinated paper sludge. *Cement and Concrete Research*, **37**, 184-190.

Barbuta M., (2005), Effect of different types of superplasticizer on the properties of high strength concrete incorporating large amounts of silica fume, *Bulletin of the Polytechnic Institute of Iasi, Construction and Architecture Section*, **51,** 69-74.

Barbuta M., (2006), *Utilization of By-Products for Preparing Road Cement Concrete*, Proc. of the International Symposium - *Actual Trends in Highway and Bridge Engineering*, Iasi, Romania, 21-24.

Barbuta M., Diaconescu R.M, Harja M., (2012), Using neural network for prediction of proprieties of polymer concrete with fly ash, *Journal of Materials in Civil Engineering*, **24**, 523-528.

Belagraa L., Beddar M., Bouzid A., (2017), Marble fillers effect on the mechanical performance of a recycled aggregate concrete, *Environmental Engineering and Management Journal*, **16**, 197-204.

Bilim C., Atiş C.D., Tanyildizi H., Karahan O., (2009), Predicting the compressive strength of ground granulated blast furnace slag concrete using artificial neural network, *Advances in Engineering Software*, **40**, 334-340.

Box G.E.P., Wilson K.B., (1951), On the experimental attainment of optimum conditions, *Journal of the Royal Statistical Society,* Series B, **13**, 1-45.

Cheng M.-Y., Firdausi P.M., Prayogo D., (2014), High-performance concrete compressive strength prediction using Genetic Weighted Pyramid Operation Tree (GWPOT), *Engineering Applications of Artificial Intelligence*, **29**, 104-113.

Chidaprasirt P., Rukzon Z., (2008), Strength, porosity and corrosion resistance of ternary blended blend Portland cement rice husk ash fly mortar, *Construction and Building Materials*, **22,** 1601-1606.

Diaconescu R.M., Barbuta M., Harja M., **(**2013)**,** Prediction of mechanical properties of polymer concrete with tyre rubber using neural networks, *Materials Science and Engineering: B*, **178,** 1259-1267.

Dwivedi V.N., Singh N.P., Das S.S., Singh N.B., (2006), A new pozzolanic material for cement industry: bamboo leaf ash, *International Journal of Physical Sciences,* **1**, 106-111.

EN 12390, (2001), Testing hardened concrete. European Committee for Standardization. Brussels, Belgium.

Frias M., Villar E., Savastano H., (2011), Brazilian sugar cane bagasse ashes from the cogeneration industry as active pozzolans for cement manufacture, *Cement and Concrete Composites*, **33**, 490-496.

Habeeb G.A., Mahmud H.B., (2010), Study on properties of rice husk ash and its use as cement replacement material, *Material Research*, **13**, 185-190.

Harja M., Barbuta M., (2013), Influence of different additions on frost-thaw and chemical resistance of polymer concrete, *Advance Science Letters*, **19**, 455-459.

Hebhoub H., Aoun H., Belachia M., Houari H., Ghorbel E., (2011), Use of waste marble as aggregates in concrete, *Construction and Building Materials*, **25**, 1167-1171.

Hossain M.U., Poon C.S., Lo I.M.C., Cheng J.C.P., (2017), Comparative LCA on using waste materials in the cement industry: A Hong Kong case study, *Resources, Conservation and Recycling*, **120**, 199-208.

Janotka I., Palacios M., Varga C., Krajci, (2010), Metakaolin sand a promising addition for Portland cement, *Materiales de Construccion*, **60**, 73-88.

Kanning R.C., Portella K.F., Costa M.R.M., Braganca M.O.G.P., Bonatto M.M., Dos Santos J.C.M., (2014), Banana leaf ashes as pozzolan for concrete and mortar of Portland cement, *Construction and Building Materials*, **54**, 460-465.

Khan M.I., (2012), Predicting properties of High Performance Concrete containing composite cementitious materials using Artificial Neural Networks, *Automation in Construction*, **22**, 516–524.

Kordos M., (2005), *Search-based Algorithms for Multilayer Perceptrons*, PhD Thesis, Silesian University of Technology, Gliwice, Silesia, Poland.

Lepadatu D., Barbuta M., Harja M., Rosu A.-R., (2013), *Mechanical Characteristic Investigation of Fibers Reinforced Polymer Concrete using Artificial Neural Networks*, Proceedings of The 13th International Scientific Conference VSU'2013, **Vol III**, 102-108.

Magureanu C., Negrutiu C., (2009), Performance of concrete containing high volume coal fly ash - green concrete, *WIT Transactions on Engineering Sciences*, **64**, 373-379.

Martinez S., Blanco MT., Gener M., (2006), Pozzolanic reactivity of zeolitic rocks from different Cuban deposits: characterization of reaction products, *Applied Clay Science*, **32**, 40-52.

Montgomery D.C., (2001), *Design and Analysis of Experiments*, 5th edition, Wiley & Sons, Inc., New York.

Montgomery D.C., Runger G.C., (2010), *Applied Statistics and Probability for Engineers*, Third Edition, John Wiley & Sons, Inc., New York.

Ramezanianpour A.A., Ghahari S.A., Esmaeili M., (2014), Effect of combined carbonation and chloride ion ingress by an accelerated test method on microscopic and mechanical properties of concrete, *Construction and Building Materials*, **58**, 138-146.

Rossignolo J.A., (2007), Effect of silica fume and SBR latex on the paste-aggregate interfacial transition zone, *Materials Research*, **10**, 83-86.

Safiuddin M.D., West J.S., Soudky K.A., (2011), Flowing ability of mortars formulated from self-compacting concretes incorporating rice husk ash, *Construction and Building Materials*, **25**, 973-978.

Sanchez de Rojas M.I., Rivera J., Frias M., (2006) Morphology and properties in blended cements with ceramic wastes as pozzolanic material, *Journal of the American Ceramic Society*, **89**, 3701-3705.

Serbanoiu A.A., Barbuta M., Burlacu A., Gradinaru C.M., (2017), Fly ash cement concrete with steel fibers - comparative study, *Environmental Engineering and Management Journal*, **16**, 1123-1128.

Singh N.B, Das S.S., Singh V.D, Dwivedi V.N., (2007), Hydrationof bamboo leaf ash blended Portland cement, *Indian Journal of Engineering & Materials Sciences*, **14**, 69-76.

Singh N.B., Singh V.D., Rai S., (2000), Hydration of bagasse ash-blended Portland cement. *Cement and Concrete Research*, **30**, 1485-1488.

Sun J., Fang L., Han J., (2010), Optimization of concrete hollow brick using hybrid genetic algorithm combining with artificial neural networks, *International Journal of Heat and Mass Transfer*, **53**, 5509-5518.

SR EN 197-1 (2011), Cement. Part 1: Composition, specifications and conformity criteria for common cements. Ministry Order No.1817/2013 published in *Romanian Official Monitor* No.269/14.05.2013.

Taguchi G., Konishi S., (1987), *Orthogonal Arrays and Linear Graphs*, Dearborn, MI, ASI Press.

Tanyldizi H.V., (2013), Variance analysis of crack characteristics of structural lightweight concrete containing silica fume exposed to high temperature. *Construction and Building Materials*, **47**, 1154-1163.

Tkaczewska E., (2014), Effect of size fraction and glass structure of siliceous fly ashes on fly ash cement hydration, *Journal of Industrial and Engineering Chemistry*, **20**, 315-321.

Uysal M., Tanyildizi H., (2012), Estimation of compressive strength of self-compacting concrete containing polypropylene fiber and mineral additives exposed to high temperature using artificial neural network, *Construction and Building Materials*, **27**, 404-414.

Villar E., Valensia E., Santo SF., Savastano H., Frias M., (2011), Pozzolanic behavior of bamboo leaf ash: characterization and determination of kinetic parameters. *Cement and Concrete Composites*, **33**, 68-73.

Wei Y., Hansen W., (2013), Early age strain-stress relashionship and cracking behavior of slag cement mixtures subjected to constant uniaxial restraint, *Construction and Building Materials*, **49**, 635-642.

Yuan Z., Wang L.-N., Ji X., (2014), Prediction of concrete compressive strength: Research on hybrid models genetic based algorithms and ANFIS, *Advances in Engineering Software*, **67**, 156-163.