Applied Computer Science, vol. 18, no. 4, pp. 68–81
doi: 10.35784/acs-2022-29

Submitted: 2022-10-01 | Revised: 2022-11-20 | Accepted: 2022-12-03

Keywords: ANN, the compressive strength, RCA, MLP, RBF

Monika KULISZ [0000-0002-8111-2316]*, *Justyna KUJAWSKA* [0000-0002-4809-2472]**,
Zulfiya AUBAKIROVA [0000-0003-0322-7692]***,
Gulnaz ZHAIRBAEVA [0000-0002-5102-397X]***,
Tomasz WAROWNY [0000-0002-1500-9812]****

PREDICTION OF THE COMPRESSIVE STRENGTH OF ENVIRONMENTALLY FRIENDLY CONCRETE USING ARTIFICIAL NEURAL NETWORK

Abstract

The paper evaluated the possibility of using artificial neural network models for predicting the compressive strength (Fc) of concretes with the addition of recycled concrete aggregate (RCA). The artificial neural network (ANN) approaches were used for three variable processes modeling (cement content in the range of 250 to 400 kg/m^3, percentage of recycled concrete aggregate from 25% to 100% and the ratios of water contents 0.45 to 0.6). The results indicate that the compressive strength of recycled concrete at 3, 7 and 28 days is strongly influenced by the cement content, %RCA and the ratios of water contents. It is found that the compressive strength at 3, 7 and 28 days decreases when increasing RCA from 25% to 100%. The obtained MLP and RBF networks are characterized by satisfactory capacity for prediction of the compressive strength of concretes with recycled concrete aggregate (RCA) addition. The results in statistical terms; correlation coefficient (R) reveals that the both ANN approaches are powerful tools for the prediction of the compressive strength.

1. INTRODUCTION

Machine learning methods have been constantly developing in recent times. One of the methods of machine learning are artificial neural networks (ANN) that are used in various areas of life and science (Machrowska et al., 2020a, 2020b; Karpiński, 2022; Szabelski, Karpiński & Machrowska, 2022; Rymarczyk et al., 2021; Szala et al., 2021; Pytka et al., 2022; Rymarczyk et al., 2019). ANN is one of the important artificial intelligence technique

* Lublin University of Technology, Faculty of Management, Department of Organisation of Enterprise, Poland, m.kulisz@pollub.pl
** Lublin University of Technology, Faculty of Environmental Engineering, Department of Biomass and Waste Conversion into Biofuels, Poland, j.kujawska@pollub.pl
*** D. Serikbayev East Kazakhstan Technical University, School of Architecture and Construction, Kazakhstan, Aubakirova.zulfiya@mail.ru, gulnaz.w@mail.ru
**** Lublin University of Technology, Faculty of Management, Department of Quantitative Methods in Management, Poland, t.warowny@pollub.pl

inspired on the study of biological neural networks that can be applied to studies in the area of construction where there is a database of a problem and the ANN model learns by example (Dantas, Leite & Nagahama, 2013; Parichatprecha & Nimityongskul, 2009). It has been proven to be a powerful modeling technique for complex and nonlinear problems with strong proposed to learning and function approximation (Dahmoune et al., 2015; Hammoudi et al., 2019). At present, the topic of the use of neural networks in various fields of human activity is extremely popular. Many methods and methodologies based on the application of ANN are used in the construction industry for optimization, control, problems of identification and forecasting (Das, Swetapadma & Panigrahi, 2019; Orosa et al., 2019; Pezeshki & Mazinani, 2019; Fei, Youfu & Xuejun, 2019).

In recent years, researchers have begun using artificial neural networks to determine the properties of building materials, including: predicting performance of lightweight concrete with granulated expanded glass and ash aggregate (Kurpinska & Kułak, 2019), designing the composition of cement stabilized rammed earth (Anysz & Narloch, 2019), studying adiabatic temperature rise reflecting hydration degree of concrete (Han et al., 2018), and predicting the compressive strength of cement-based materials exposed to sulfate attack (Chen et al., 2018).

The work presented here evaluates the feasibility of using a neural network model to predict the performance of recycled aggregates (RCAs). ANN techniques are rarely used to predict the performance of RCA and concretes in general due to their complex composition. Topçu and Seridemir (2008) predicted the compressive and splitting tensile strength of recycled aggregate concentrate containing silica fume have been developed at the age of 3, 7, 14, 28, 56 and 96 days. The values are closer to the experimental results obtained from training and testing for in artificial neural networks (Topçu & Saridemir, 2008). Chopra et al. employed an ANN model to predict the compressive strength of concentrate. It was deduced that the best training algorithm is 'Levenberg-Marquardt' algorithm that attains more than 95% on average prediction accuracy (Chopra, Kumar & Kumar, 2015). Atici (2011) applied multiple regression analysis and an artificial neural network in estimating the compressive strength of concrete that contains various amounts of blast furnace slag and fly ash. He showed that the application of an artificial neural network to the prediction of the compressive strength in admixture concrete of various curing times shows great potential in terms of inverse problems, and it is suitable for calculating nonlinear functional relationships, for which classical methods cannot be applied (Atici, 2011).

This study aimed at predicting and modeling the compressive strength of a concrete containing recycled concrete aggregates following 3, 7 and 28 days for different ranges of cement content, percentage of recycled concrete aggregate and the ratios of water contents.

2. MATERIALS AND METHODS

Type I ordinary portland cement was used as a binder content for the experiment. The chemical compositions were illustrated in Table 1. Sand (NS), i.e. crushed limestone with nominal size of 4 mm was used as well; the sand was dried at 105°C. Crushed granite (NSA) was used as concrete aggregate with specific gravity 2.7 and nominal size 19 mm in normal concrete and the recycled concentrate aggregate (RCA) with attached mortar, nominal size 19 mm was used as a replacement of the concrete aggregate. The RCA was obtained from the demolition of an old building and had undergone a crushing process to obtain the required nominal size. The grading of both types of concrete aggregate complied with the grading limits for the crushed-rock aggregate in BS 882:1992 (Gjorv & Sakai, 2014).

2.1. Experimental

The mix design of the concrete was done according to the DoE method, which was targeted at compressive strength of 25 MPa at the 28th day (British Standards Institution, 1988).

Tab. 1. Composition of CEM II B-V 32,5R (CEM II/B-V 32,5 R, n.d.)

Properties	Unit	CEM II B-V 32,5R
Specific surface	($cm^2 \cdot g^{-1}$)	4237
Initial setting time	(min)	243
Compressive strength		
after 2 days	(MPa)	20.3
after 28 days	(MPa)	45.7
Density	($g \cdot cm^{-3}$)	2.83
SO_3 content	(%)	2.28
Chloride ion content	(%)	0.06
Na_2O content	(%)	1.09

The mixture compositions of all mixes are presented in Table 2. Notably, there are five types of mixtures prepared by replacing the concrete aggregate with the RCA at 25%, 50%, 75% and 100% of the total concrete aggregate content. The percentage of replacement was calculated based on the total weight of the concrete aggregate content.

Tab. 2. Mixture proportion for 1 m^3 of concentrate [kg/m^3]

Mixture	% Repl. of recycled aggregates	Cement [kg/m^3]	Water [kg/m^3]	NSA	RCA	Sand
Mix 1	25	250	150	858	286	762
Mix 2	50	250	150	564	564	762
Mix 3	75	250	150	279	836	743
Mix 4	100	250	150	0	110	734
Mix 5	25	400	180	770	257	685
Mix 6	50	400	180	507	507	676
Mix 7	75	400	180	250	751	667
Mix 8	100	400	180	0	988	659
Mix 9	25	350	230	105	105	661
Mix 10	50	350	230	177	177	661
Mix 11	75	350	230	370	70	661
Mix 12	100	350	230	360	320	625
Mix 13	25	350	150	105	105	661
Mix 14	50	350	150	177	177	661
Mix 15	75	350	150	370	70	661
Mix 16	100	350	150	360	320	625

All specimens were cast under laboratory condition and demolded at 24 ± 2 hours after mixing; afterwards, they were fully submerged in water at a temperature of 25 ± 2°C until the age of testing. The testing program introduced the determination of the compressive strength and ultra-sonic pulse velocity test, while the durability was tested through the shrinkage and expansion test, the ratios of water contents and gas permeability test. Testing was carried out in accordance to the British Standard testing procedures.

2.2. Compressive strength test

The compressive strength test was performed according to BS EN 12390-3:2009 using three cubes with the dimensions of 100 mm × 100 mm × 100 mm to obtain an average value (British Standards Institution, 2009). This test was carried out on the specimens at the age of 3, 7 and 28 days.

2.3. Neural network simulation

Modeling was performed using artificial neural networks, via Statistica Neural Networks software. The input neurons were cement content, %RCA and the ratios of water contents, and the output neuron was Fc after 3, 7 and 28 days. In connection with modeling Fc at three time points, three types of models were analyzed, the diagram of which is shown in Figure 1.

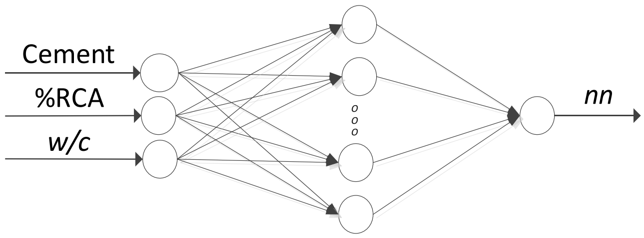

Fig. 1 Schematics of the artificial neural network, where *nn* – Fc after 3, 7 and 28 days

Two types of neural networks were used for modeling: MLP and RBF. The multi-layer perceptron (MLP) is one of the most popular. Characterized by a layered arrangement of neurons and a unidirectional flow of data (from input to output) without feedback. The training of MLP-type networks is possible by using the backward error propagation method. Radial basis function (RBF) networks are a special type of artificial neural networks. They are unidirectional three-layer networks consisting of an input layer, a hidden layer and an output layer. In the hidden layer, there are radial basis functions that correspond to hidden neurons (Karpiński et al., 2022a, 2022b).

In the case of MLP networks, the learning algorithm – BFGS gradient was used, and different activation functions were tested, including: linear, exponential, logistic, tanh and sinus. For RBF networks, the learning algorithm is RBFT, and the activation functions are: Gaussian distribution (hidden neurons) and linear function (output neuron). Networks with one hidden layer were modeled, with a change in the number of neurons in the hidden layer (2–10). The input data set was divided into 75%–25% (learning data – validation data). Due to the small data set, test data was omitted.

The selection of networks was based on indicators such as learning and validation quality as well as learning and validation errors. For each Fc model, 200 networks were learned after 3, 7 and 28 days, from which one of each type was selected.

Learning and validation quality is defined as the correlation coefficient for these sets, calculated according to equation (1):

$$R(y', y^*) = \frac{cov(y', y^*)}{\sigma_{y'}\sigma_{y^*}} \qquad R \, \epsilon < 0{,}1 > \tag{1}$$

where: $\sigma_{y'}$ – standard deviation of reference values,
σ_{y^*} – standard deviation of predicted values,
$cov(y', y^*)$ – covariance.

The errors are defined as the sum of the squared differences between the set values and the values obtained at the outputs of each output neuron, according to the formula (2):

$$Err = \sum_{i=1}^{n}(y_i' - y_i^*)^2 \tag{2}$$

where: n – number of cases in a given set,
y_i' – actual value of Fc for the given set for the *i*-th observation;
y_i^* – predicted value of Fc for the given set for the *i*-th observation.

3. RESULTS AND DISCUSION

3.1. Compressive strength

Table 3 shows the obtained results of the tested mixtures. The results show that the compressive strength of recycled concrete after 3, 7 and 28 days significantly changes under the influence of the cement content and the addition of the recycled concentrate aggregate. Among all the samples, the concrete with 25% RCA addition achieves the highest strength, followed by 50%, 75%, 100% RCA addition.

Tab. 3. Experimental values for compressive strengths of 3, 7 and 28 days for the tested mixtures

Mixtures	Cement [kg/m^3]	%RCA	w/c	Fc [MPa]		
				3	7	28
Mix 1	250	25	0.65	21.1	25.9	27.1
Mix 2	250	50	0.65	18.9	22.1	22.7
Mix 3	250	75	0.65	20.2	22.2	22.9
Mix 4	250	100	0.65	16.8	25.1	26.2
Mix 5	400	25	0.45	32.1	37.7	42.4
Mix 6	400	50	0.45	30.2	36.3	36.3
Mix 7	400	75	0.45	27.4	35.2	36.0
Mix 8	400	100	0.45	21.5	34.6	34.7
Mix 9	350	25	0.65	34.1	36.5	37.0
Mix 10	350	50	0.65	23.8	27.2	29.1
Mix 11	350	75	0.65	19.8	24.1	26.0
Mix 12	350	100	0.65	18.2	22.3	29.2
Mix 13	350	25	0.45	28.8	34.2	37.8
Mix 14	350	50	0.45	27.0	32.4	33.3
Mix 15	350	75	0.45	24.3	31.5	32.4
Mix 16	350	100	0.45	19.4	31.2	31.3

4.2. Modeling results

The results of the obtained modeling with the parameters of the obtained networks are shown in Table 4. The best parameters for MLP networks for Fc modeling after 3 days were obtained for a network with six neurons in the hidden layer, after 7 days and after 28 days for 4 neurons in the hidden layer. In the case of the RBF networks for Fc modeling, after 3 days the best results were obtained for a network with seven neurons in the hidden layer, after 7 days for six neurons, and after 28 days for 7 neurons in the hidden layer. The quality of both learning and validation for all networks exceeds 0.97. In addition, Table 4 shows the R-correlation coefficients (for the entire dataset) between the test data and the modeling data. By analyzing the R-correlation, it can be concluded that the cross-correlation between the experimental data and the data predicted for the networks of both networks is at a very high level (above 0.97).

Tab. 4. Network parameters obtained as a result Fc after 3, 7 and 28 days of modeling.

Modeled Fc	3 days		7 days		28 days	
Network Name	MLP 3-6-1	RBF 3-7-1	MLP 3-4-1	RBF 3-6-1	MLP 3-4-1	RBF 3-7-1
Quality (Training)	0.9907	0.9714	0.9932	0.9951	0.9725	0.9881
Quality (Validation)	0.9941	0.9961	0.9988	0.9989	0.9952	0.9943
Err (Training)	0.2496	0.7526	0.1106	0.1363	0.7565	0.2946
Err (Validation)	0.7861	0.1276	0.0244	0.0422	0.3292	0.3004
Learning algorithm	BFGS 168	RBFT	BFGS 3339	RBFT	BFGS 97	RBFT
Activation (hidden)	Sinus	Gaussian	Logistic	Gaussian	Gaussian	Gaussian
Activation (output)	Exponential	Linear	Exponential	Linear	Sinus	Linear
R(i) correlation	0.9876	0.9773	0.9962	0.9908	0.9903	0.9813

For a more detailed comparison of the results of modeling RBF and MLP networks and real Fc data after 3, 7 and 28 days, the following figures show correlation plots of these relationships – for Fc after 3 days (Figure 2a), Fc after 7 days (Figure 2b), Fc after 28 days (Figure 2c).

Analysis of the following graphs confirms that for both types of RBF and MLP networks, the quality of these models is at an acceptable level. Therefore, it can be concluded that artificial neural networks are a suitable tool for predicting the Fc after 3, 7 and 28 days.

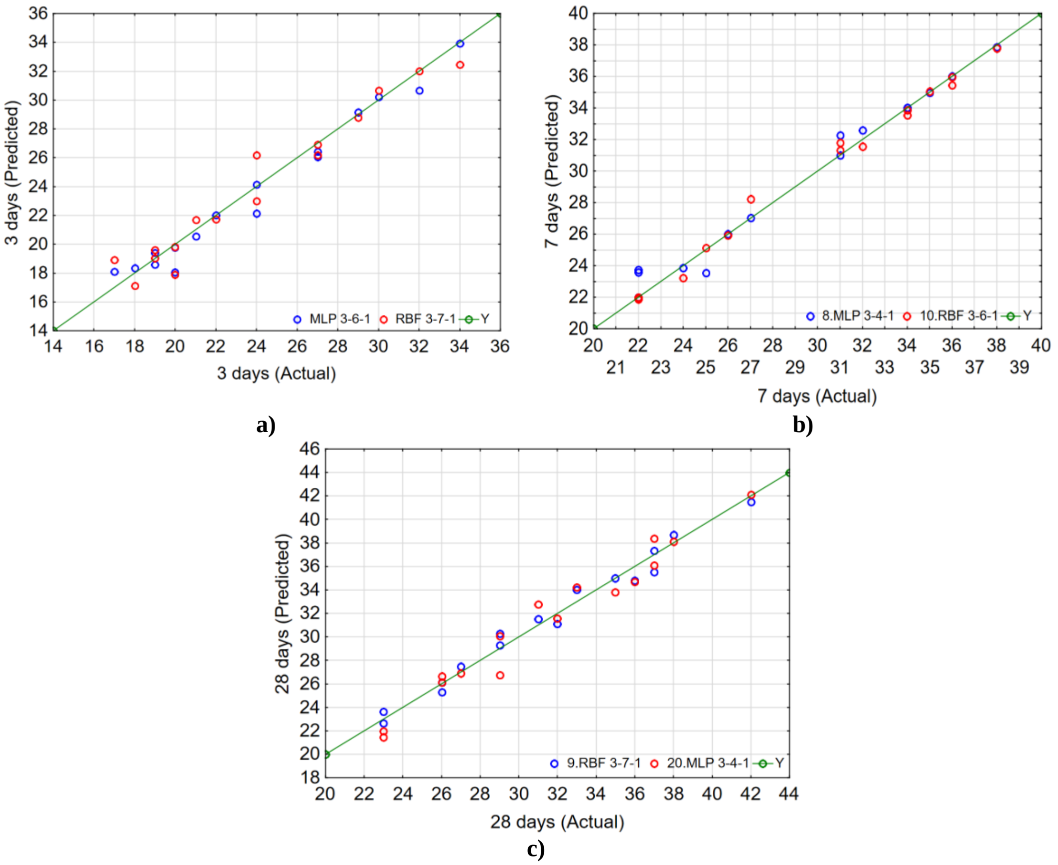

Fig. 2. Correlation graph of comparison between the modeling and actual results of the Fc after 3, 7 and 28 days for MLP and RBF networks

As a result of the modeling, it was possible to predict Fc after 3, 7 and 28 days, using the trained networks by entering the input data into Statistica. The results of the networks are shown for the following figures, for Fc after 3 days depending on %RCA and cement content for MLP network (Fig. 3a) and RBF network (Fig. 3b) and depending on w/c and cement content for MLP network (Fig. 3c) and RBF network (Fig. 3d), for Fc after 7 days depending on %RCA and cement content for MLP network (Fig. 4a) and RBF network (Fig. 4b), and w/c and cement content for MLP network (Fig. 4c) and RBF network (Fig. 4d), as well as for Fc after 28 days depending on %RCA and cement content for MLP network (Fig. 5a) and RBF network (Fig. 5b), and w/c and cement content for MLP network (Fig. 5c) and RBF network (Fig. 5d).

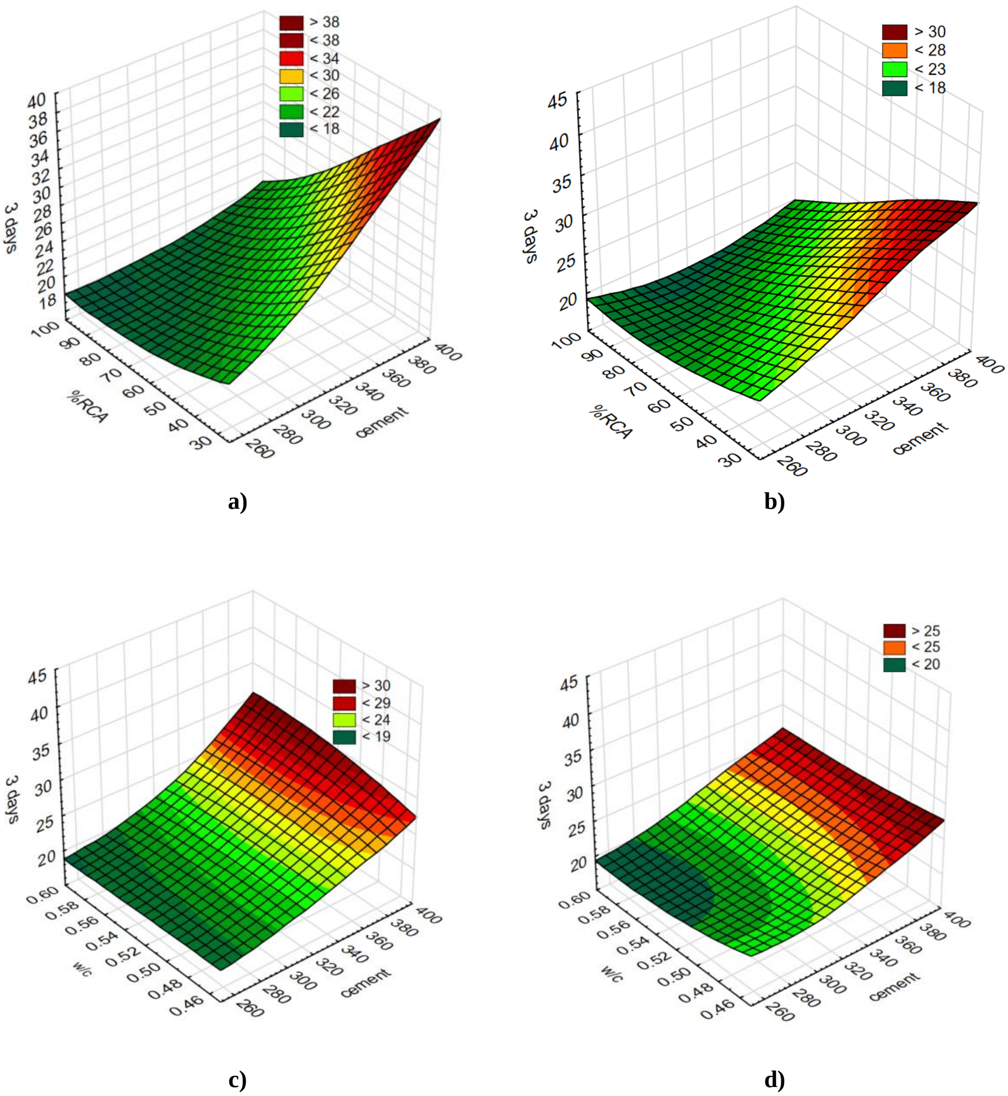

Fig. 3. The network performance results for Fc after 3 days depending on %RCA and cement content for MLP (a) and RBF (b) networks as well as w/c and cement content for MLP (c) and RBF (d) networks

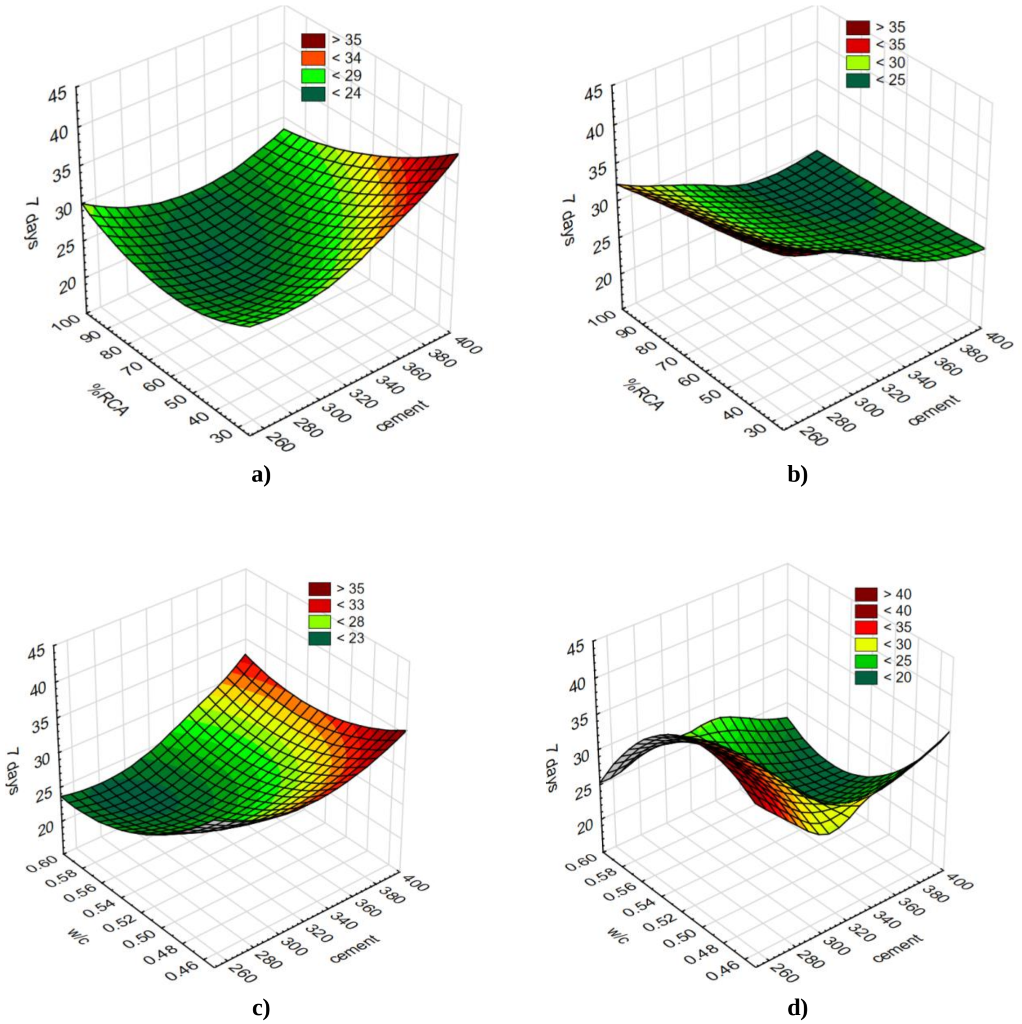

Fig. 4. The network performance results for Fc after 7 days depending on %RCA and cement content for MLP (a) and RBF (b) networks as well as w/c and cement content for MLP (c) and RBF (d) networks

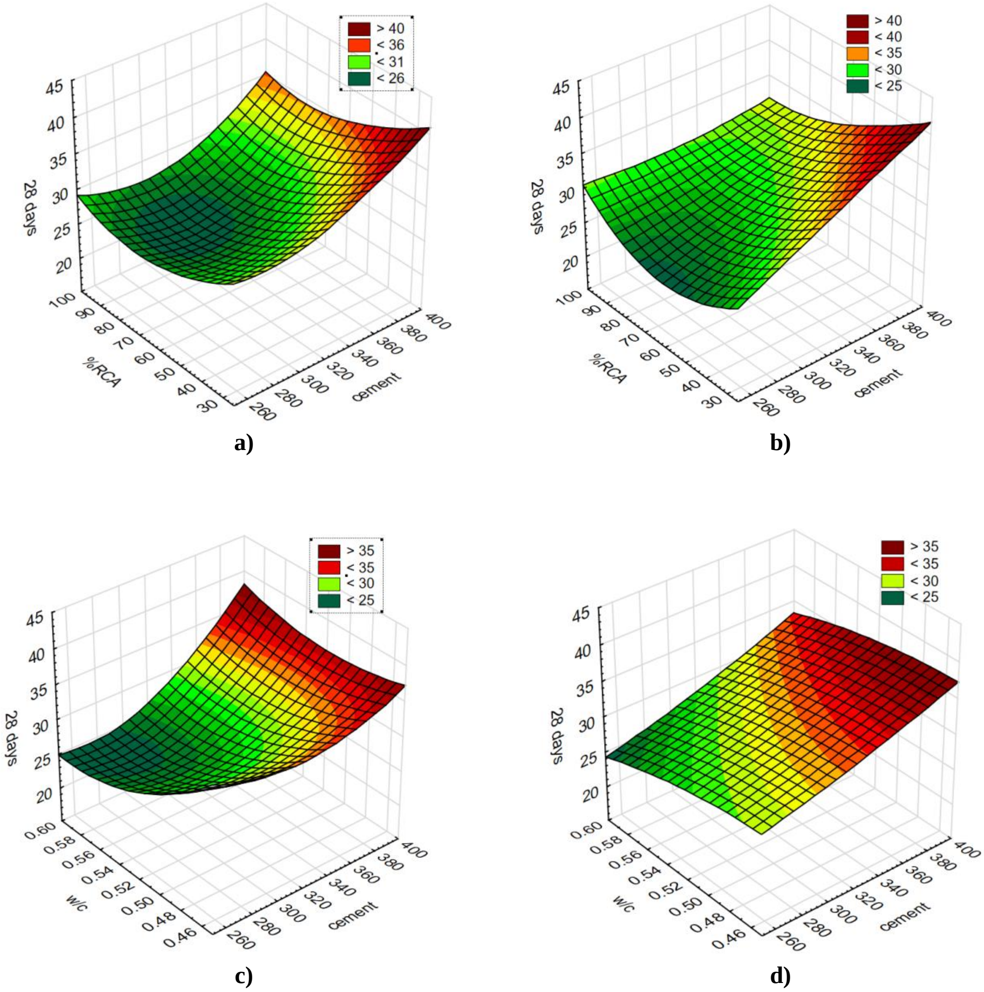

Fig. 5. The network performance results for Fc after 28 days depending on %RCA and cement content for MLP (a) and RBF (b) networks as well as w/c and cement content for MLP (c) and RBF (d) networks

In this study, an artificial neural network was developed to evaluate the compressive strength properties of recycled concrete aggregate based on the input variables, which were: cement content, %RCA, and the w/c ratio. The results of the modeling of compressive strengths after 3, 7 and 28 days and the prediction made enable to conclude that the MLP and RBF networks obtained have a satisfactory ability to predict these values. This is confirmed, among other things, by the R-correlation value of 0.97, the high quality of learning and validation of the network at 0.97, and the learning and validation errors. Comparing the experimental data and simulated values of compressive strengths after 3, 7 and 28 days, it can be concluded that the relative error value does not exceed 15%, which indicates that the network is well trained.

There is little work in the available literature on predicting the compressive strength of RCA concretes, where in most previous studies were particularly centric about high-performance concrete (HPC) containing blast furnace slag (BFS), fly ash (FA) and superplasticizer. The networks created for these types of concrete achieved R^2>90% (Yeh & Lien, 2009; Chou et al., 2011; Deepa, Kumari & Sudha, 2010; Atici, 2011; Erdal, Karakurt & Namli, 2013; Qmran et al., 2016).

The obtained results in statistical terms do not differ much in that respect. Hammoudi et al. (2019) predicted the compressive strength of a concentrate containing RCA after 7, 28 and 56 days. The input data included: content cement, %RCA, slump. For the employed model, he obtained the correlation coefficient of 0.98% (Hammoudi et al., 2019).

Naderpour et al. used an artificial neural network to evaluate the strength properties of recycled aggregate concrete based on input variables: water-cement ratio, water absorption, fine aggregate, recycled concrete aggregate, natural concrete aggregate, water-total material ratio, and 28-day compressive strength. He achieved lower values of correlation coefficient than in the presented study. The correlation values of their neural network for training, validation and testing reached 0.903, 0.89 and 0.829 respectively (Naderpour, Rafiean, & Fakharian, 2018).

The use of ANN model, which based on experimental results showed that it is useful and efficient model to predict the compressive strength. Wider application of ANN methods will facilitate determining the composition of concretes with recycled aggregate addition and manufacturing of new building materials.

4. CONCLUSIONS

The main objective of the study was to present an ANN model for predicting the compressive strength of concrete containing recycled concrete aggregate following 3, 7 and 28 day. The following were used as input date: different ranges of cement content, %RCA and water content ratios.

The following conclusions can be drawn in connection with the research conducted on training artificial neural networks:

– For Fc modeling after 3, 7 and 28 days for both types of RBF and MLP networks, the quality of the models is at an acceptable level. In the case of MLP networks for individual networks the quality of training and validation were respectively – for Fc after 3 days the quality of training it was 0.9907, validation was 0.9941, for Fc after 7 days the quality of training was 0.9932, validation was 0.9988, and for Fc after 28 days the quality of training was 0.9725, validation was 0. 9952. In the case of RBF networks for individual networks, the training and validation quality were as follows: for Fc after 3 days the training quality – 0.9714, validation – 0.9961, for Fc after 7 days the training quality – 0.9951, validation – 0.9989, while for Fc after 28 days the training quality – 0.9881, and validation – 0.9943.
– The networks obtained by modeling Fc after 3, 7 and 28 days show satisfactory predictive ability, as evidenced by the obtained correlation values R. These are $R_{MPL – 3\ days}$ = 0.9876, $R_{MPL – 7\ days}$ = 0.9962, $R_{MPL – 28\ days}$ = 0. 9903, $R_{RBF – 3\ days}$ = 0.9773, $R_{RBF – 7\ days}$ = 0.9908, $R_{RBF – 28\ days}$ = 0.9813. Thus, it can be concluded that artificial

neural networks are an effective tool that can be used to predict compressive strengths after 3, 7 and 28 days.
- The trained networks show the relationships between the input data (cement content, %RCA and the ratios of water contents) and the output data (Fc after 3, 7 and 28 days), allowing the determination of the corresponding values of the analyzed indicators after the input of the set parameters into the network .
- A model to predict the compressive strength of concretes with recycled coarse aggregates can be the basis for creating optimal concrete compositions with RCA. It will save time and effort, as well as eliminate the costs that are incurred when manufacturing new construction materials.

Funding

This research was funded by the Polish Ministry of Science and Higher Education, grant numbers: FD-20/IM-5/061/2022 and FD-NZ-062/2022.

Conflicts of Interest

The authors declare no conflict of interest.

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