Proceedings of the Sixth International Conference on
Soft Computing, Machine Learning and Optimisation in
Civil, Structural and Environmental Engineering
Edited by: P. Iványi, J. Lógó and B.H.V. Topping
Civil-Comp Conferences, Volume 5, Paper 3.2
Civil-Comp Press, Edinburgh, United Kingdom, 2023
doi: 10.4203/ccc.5.3.2

A Comparison of Neural Networks and Random Forest for predicting the subsurface tensile strength of cementitious composites containing waste materials

S. Czarnecki and M. Moj

**Cathedral of Materials Engineering and Construction Processes,
Wroclaw University of Science and Technology, Poland**

Abstract

In this article the accurate model of predicting the eco-friendly mortar's subsurface tensile strength is presented. These eco-friendly mortars were made by substituting in the mortars the mass cement by waste materials: fly ash, granite flour and ground granulated blast furnace slag. These mortars were tested using ultrasonic pulse velocity method and based on the results of these tests the dataset were built. Estimation of the subsurface tensile method were done using hybrid combination of ultrasonic pulse velocity method and soft computing techniques. The accuracy of this method were proved by the very high values of the coefficient of determination around 0.9 and very low values of the mean average percentage error around 5%. These method might be suitable for use in existing structures where experimental destructive test are problematic.

Keywords: neural networks, random forest, cementitious composites, waste materials, floors, subsurface tensile strength

1 Introduction

The production of cement as the basic component of concretes and mortars has an undesirable impact on the environment. During the production of 1 ton of this material, approx. 900 kg of carbon dioxide is emitted, therefore partial replacement of cement with another component may contribute to reducing CO2 emissions to the atmosphere [1]. The main process in which carbon dioxide is formed is the clinkering process [2]. Milling and transport processes produce much smaller amounts of this

chemical. High emissivity and mass production of concrete is responsible for over 7% of global CO_2 emissions [3].
One of the ways to reduce the harmful impact of cement composites on the environment is to replace cement with materials from recycling or production waste as supplementary cementitious material [4] (SCM - supplementary cementitious material) for the sustainable production of ecological cement composites as the most common building materials. It is estimated that the use of cement mixed with additives from industrial waste will reduce CO_2 by 5-20%, depending on the type, amount and properties of the additive used [5].

The practical purpose of the work is to create a machine learning model for predicting the peel strength of the surface layer of ecological cement composites. For this purpose, it is necessary to prepare a database obtained from experimental research, on which machine learning models can be taught.

2 Materials and Methods

2.1. Materials

The research focused on cement composites with a cement to sand ratio of 1:3 modified with fillers in the form of waste granite flour (GP), fly ash (FA) and ground granulated blast furnace slag (GGFBS). It was assumed that the tested cement composites would be used as mortars for floor screeds, the requirements of which were specified in the standards [6, 7]. As one of the most important parameters of such mortars is their peel strength, which should be at least 1 MPa in non-industrial facilities and at least 1.5 MPa in industrial facilities, according to the recommendations of manufacturers of flooring systems. An equally important parameter is also the compressive strength of the presented cement materials, the minimum of which is defined in the range of 20-25 MPa. It was also decided to take into account the impact of the floor maturing time on its physical parameters in the design process.

Twenty three different cement mixtures with different compositions in terms of the amount and type of cement substitutes used were prepared. The first reference mix, marked REF, contained only Portland cement as a binder. In the remaining mixtures, Portland cement was partially replaced with: waste granite meal, fly ash and ground granulated blast furnace slag in the proportions of 10%, 20% and 30%. The amount of water was assumed constant for all mixtures and was determined for the reference composition for the water-cement ratio equal to 0.5.

The mortars were made of CEM I 42.5 cement, which consisted of 95-100% of Portland clinker and 0-5% of secondary components. Its standard compressive strength was at least 42.5 MPa. The sand used in the tests had a specific density of approx. 1600 kg/m^3. Ground granulated blast furnace slag and fly ash came from Górażdże. Waste granite meal came from the processing of granite stones from stonemason's plants in Lower Silesia. Figure 1 shows photos of the cement substitutes used.

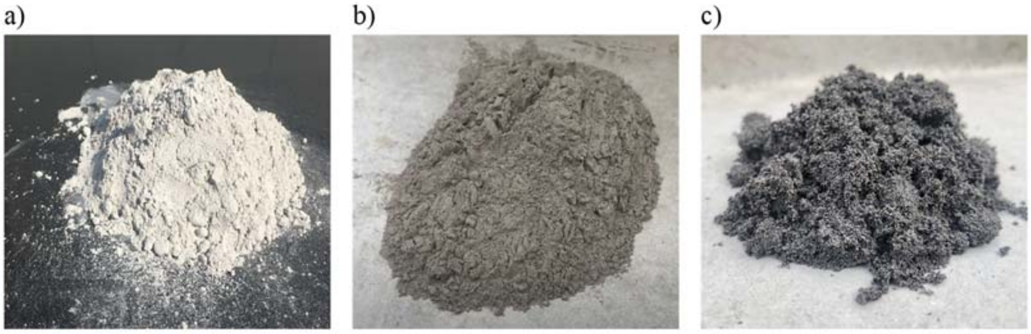


Figure 1. Additives to mixtures of ecological cement composites: a) granite flour, b) fly ash, c) ground granulated blast furnace slag.

Cement, granite flour, fly ash, ground granulated blast furnace slag and fine aggregate were screened in accordance with the procedure specified in PN-EN 933-1 in order to determine the grain size distribution of the given components. The weighed portion of the ingredient was passed through a set of sieves, and then the remaining grains were weighed on each sieve. Figure 2 shows the grain size distributions of the materials used.

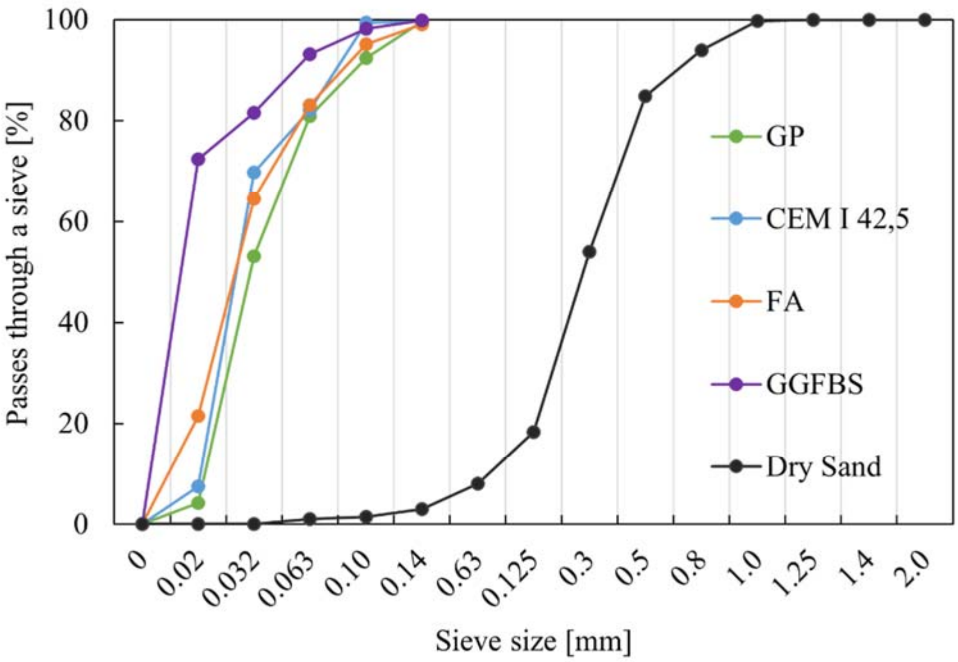


Figure 2. Parameters of materials used for mortars: granulation of cement, granite flour, fly ash and ground granulated blast furnace slag, grain size of dry quartz sand.

2.2. Methods

2.2.1. Ultrasonic Pulse Velocity

Testing with a ultrasonic pulse velocity method is one of the methods of assessing the quality and strength of this material. This method uses the fact that ultrasound travels at different speeds in different materials. During the test, ultrasound is sent through the transducers into the cement composite. They are then picked up by a second transducer which converts them back into an electrical signal. The speed of ultrasonic wave propagation is measured and analyzed to determine the quality and strength of the cement composite, using the formula (1), presented in figure 3:

$$\mathrm{UPV} = \sqrt{\frac{\mathrm{E} * (1 - \mathrm{v})}{\rho * (1 + \mathrm{v}) * (1 - 2 * \mathrm{v})}} \qquad (1)$$

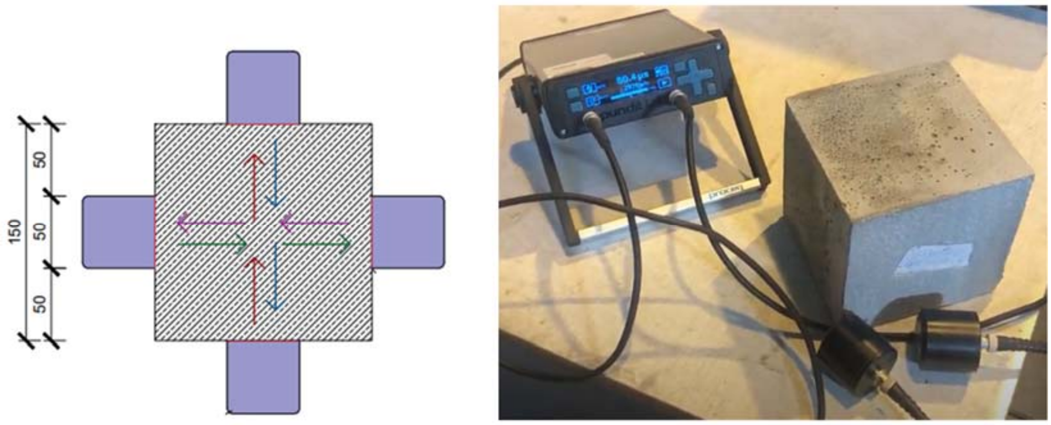


Figure 3. Testing the speed of ultrasonic wave propagation: a) diagram of the application of the heads in the top view, b) testing device.

2.2.2. Neural Networks

An artificial neural network in the form of a multilayer perceptron (MLP) was used for numerical analysis. In this mathematical model, artificial neurons try to imitate the behavior of the biological neuron. Each artificial neural network consists of three types of layers. The input layer collects raw data and uses it in the computational process. Hidden layers collect inputs and generate outputs. The output layers predict the result.

The Orange Data Mining program, in which the analyzes were performed, has three algorithms used to train such networks. It also allows the use of 4 types of activation functions. During ANN modeling, calculations were made for all possible combinations presented in Table 7. In addition, the number of hidden layer neurons was changed in the range from 1 to 35, which allowed to obtain 420 combinations for the machine learning model used.

Inputs	Hidden Neurons	Activation Functions	Learning algorithm
11	1-35	linear Logistics Hyperbolic tangent ReLu	Adam SGN L-BFGS-B

Table. 1. Elements of artificial neural networks in the Orange Data Mining program

2.2.3. Random Forest

Random Forests were also used for numerical analysis. The given machine learning algorithm is popular in the category of supervised learning. This algorithm consists of multiple decision trees that are trained on different subsets of training data and then combined into one. For each decision tree, the algorithm uses a random subset of criteria (database columns) and random samples (database rows) to train the model. This reduces the variance of the model and the risk of overtraining. After training the RF model, they can be used to predict values for new data. In the case of classification, the model selects the class that was selected most often by each decision tree, and in the case of regression, the model selects the average or median of all predictions.

Inputs	Trees depth	Trees number	Minimal subset	Minimal category
11	1-20	20-200	5	2

Table. 2. Elements of random forests in the Orange Data Mining program

The Orange Data Mining program, in which the analyzes were performed, has the ability to change the depth of decision trees and the number of trees in a random forest. It also allows you to set the limit values of the division of subsets smaller than the selected value and to set the number of attributes considered at each division (Table 2). During RF modelling, the number of trees in a random forest was changed in the range from 20 to 200 in increments of 20. Moreover, the depth of trees was changed in the range from 1 to 20, which allowed to obtain 200 combinations for the machine learning model used.

3 Results

In figure 4 the results of the non-destructive experimental tests performed were presented. Moreover in the figure 5 the values of the output parameter which was the subsurface tensile strength are presented.

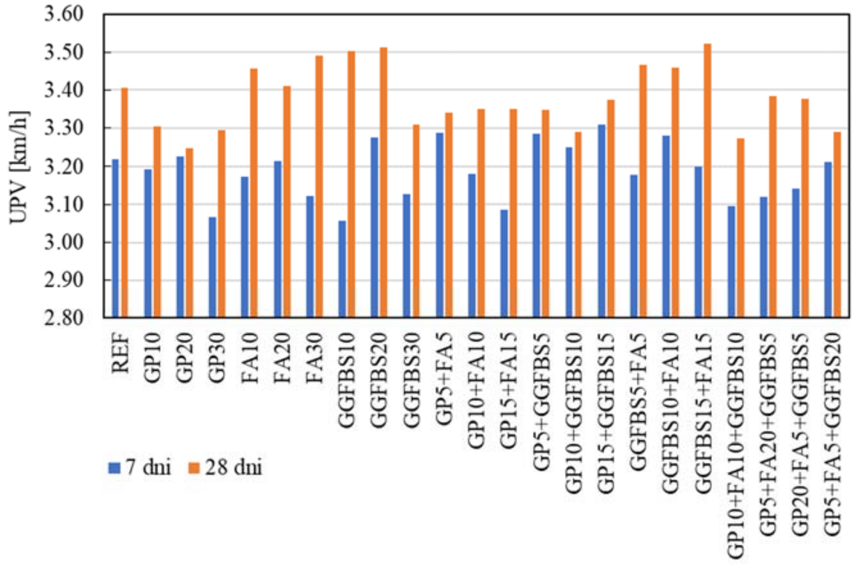


Figure 4. Diagram of average ultrasonic wave propagation speeds.

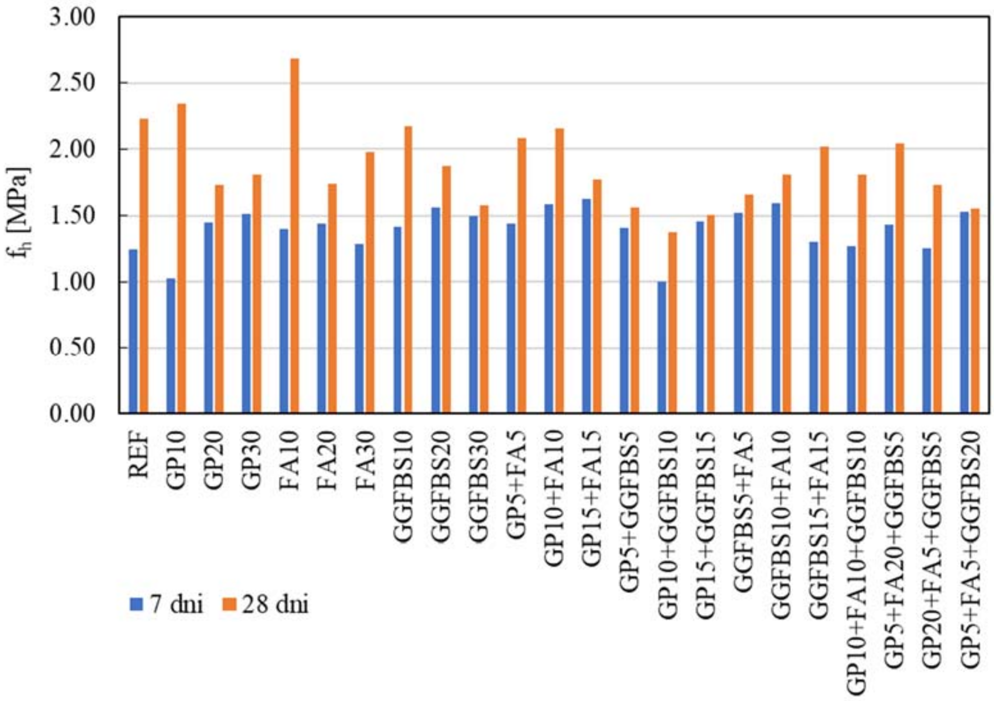
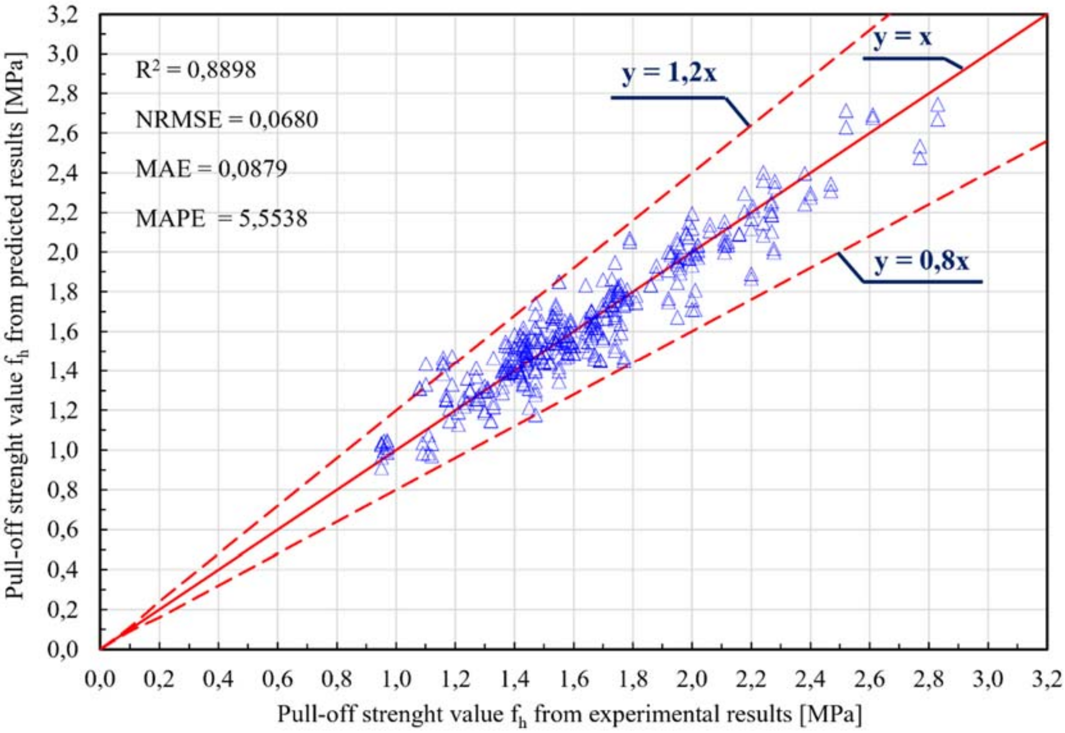


Figure 5. Diagram of the average pull-off strength f_h of the subsurface layer.

It should be emphasized that all samples tested after 28 days, except for the GP10+GGFBS10 test, exceeded the condition of the minimum pull-off strength of industrial floors of 1.5 MPa. In addition, when comparing the early peel strengths (tested after 7 days), it can be seen that all formulations except GP10 and GP10+GGFBS10 had a higher strength than the reference sample. Similar to the work [7], the GP10 and FA10 tests, tested after 28 days, showed a strength higher than the REF test, which indicates the legitimacy of using fly ash or granite flour in floor mortars. Small differences in compressive strength between the tests after 7 and after 28 days for GP15+GGFBS15 and GP5+FA5+GGFBS20 formulas suggest that the given sets of cement substitutes allow for obtaining maximum compressive strength relatively early (7-10 days).

In Figure 6 the results of the prediction of the subsurface tensile strength using two titled methods are presented.



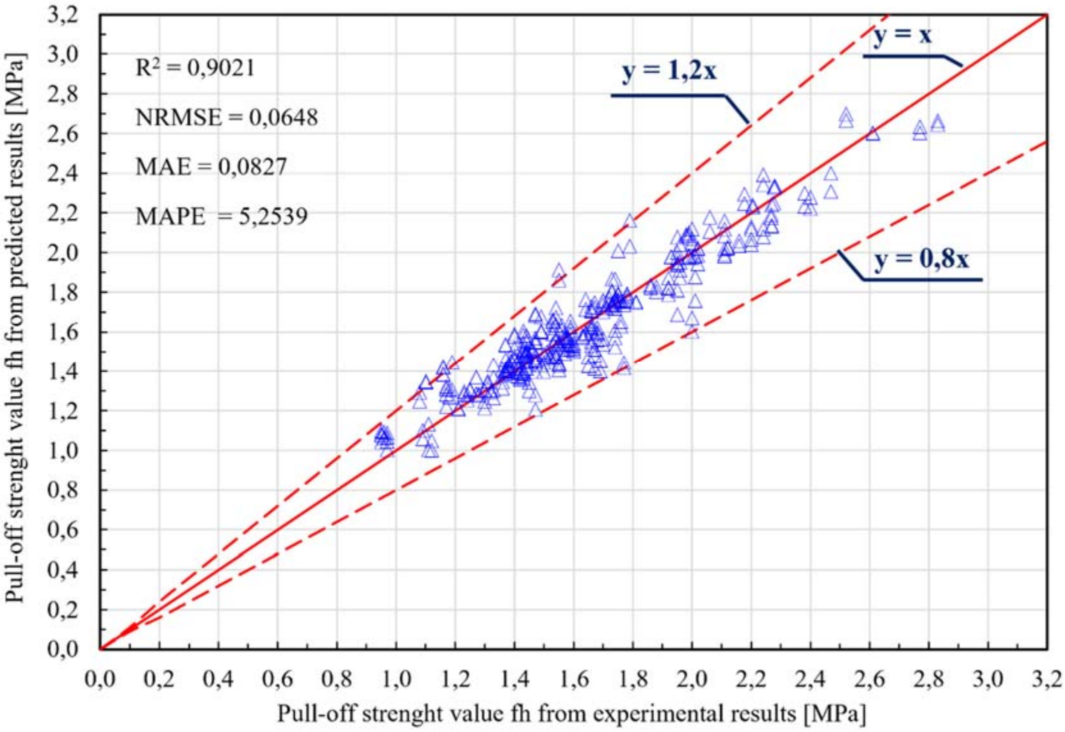


Figure 6. Analyzes performed using: a) neural network and b) random forest.

Analyzing the results obtained by using aforementioned numerical methods it can be seen that both are very accurate in terms of parameters describing their performance. It can be seen by analysing the values of the coefficient of determination R^2 which in both cases are very high and equal to 0.89 for neural networks and 0.90 for random forest.

Moreover it is worth to emphasize that the mean average performance error is around 5% which is on the border of the accuracy of the testing device used during the experimental tests.

4 Conclusions and Contributions

In this paper the Authors presented the comparison of two commonly used techniques for prediction mechanical properties of cementitious composites. In this case the estimated values was the subsurface tensile strength of cementitious composites containing various waste materials such as granite flour, blast furnace slag and fly ash. Even though the methods used are well known and they are commonly used, these research fill the gap in the literature which is evaluation of the subsurface tensile strength of mortars containing waste materials additives and are dedicated to floors production.

While comparing presented in the article models with other in the literature it can be seen that the accuracy of them is very high and they can be successfully used in construction practice.

However this research has limitations which are, firstly the material used in experimental tests. Mortars are commonly used as substrates and added layers in floors however in case of concrete it is known that values of ultrasonic pulse velocity is also affected by the coarse aggregate. Therefore there is a need to continue the tests and try to evaluate these properties with other materials, for example concrete.

Acknowledgements

The authors received funding for preparing the samples from the project, supported by the National Centre for Research and Development, Poland [grant no. LIDER/35/0130/L-11/19/NCBR/2020 “The use of granite powder waste for the production of selected construction products.”].

References

[1] J. Siemieniuk, E. Szatyłowicz, „Reduction of CO_2 emission in cement production proces”, Civil and Environmental Engineering, 9, 81-87, 2018.

[2] B. Lothenbach, K. Scrivener, R.D. Hooton, “Supplementary cementitious materials. Cement and concrete research”, 41(12), 1244-1256, 2011.

[3] M. Ali, R. Saidur, M. Hossain, “A review on emission analysis in cement industries.”, Renew. Sustain. Energy Rev. 15, 2252–2261, 2011.

[4] E. Benhelal, G. Zahedi, E. Shamsaei, et al., “Global strategies and potentials to curb CO2 emissions in cement industry.” Journal of Cleaner Production, 51, 142–161, 2013.

[5] A. Bosoaga, O. Masek, J. Oakey, “CO_2 capture technologies for cement industry.” Energ. Procedia, 1(1), 133–140, 2009.

[6] EN 1504 Products and systems for the protection and repair of concrete structures - Definitions, requirements, quality control and evaluation of conformity - Part 2: Surface protection systems for concrete.

[7] EN 1766 Products and systems for the protection and repair of concrete structures - Test methods - Reference concretes for testing.