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Research Article

Prediction of capillary absorption and compressive strength, applying multiple linear regression and artificial neural networks in concrete with natural pozzolana addition

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Highlights:

- Prediction models for capillary absorption and compressive strength in pozzolan-added concrete were evaluated.
- Artificial neural networks outperformed multiple regression models in predictive accuracy.
- The addition of 15% pozzolan significantly improved the mechanical properties of concrete.

Abstract: Cement is the fundamental binder of concrete, and its manufacture has a significant impact on the environment; therefore, it is necessary to look for eco-sustainable alternatives, including additions such as natural pozzolana, which affect the internal matrix of concrete and therefore the compressive strength and capillary absorption of concrete. In this context, prediction models for capillary absorption and compressive strength of concrete with pozzolana additions have been determined by applying linear multiple regression tools and artificial neural networks which will help reduce laboratory testing costs and times. For this purpose, 16 types of mixtures were designed with w/c ratios of 0.40, 0.45, 0.50 and 0. 55 and addition of 10, 15 and 20% of pozzolana; 160 cylindrical samples were manufactured and tested in laboratory, the values of capillary absorption and compressive strength at 28 and 56 days of curing were determined; the effect of each variable on the results obtained indicated that 15% pozzolana significantly improved the properties studied; using the data of the manufacturing variables of each design and the results of capillary absorption and compressive strength, prediction models were obtained for both properties; the best back propagation neural networks (BPNN) structure is [10,20,10,1], with $R^2_{compression}$=0. 9486 and $R^2_{capillary\ absorption}$=0.9756; while the models obtained with multiple linear regression obtained $R^2_{compression}$ = 0.9391 and $R^2_{capillary\ absorption}$ = 0.8693; both techniques showed a high reliability for the prediction of compressive strength and capillary absorption.

Keywords: Pozzolans, capillary absorption, compression, linear multiple regression, artificial neural network.

List of abbreviation:

ANN - artificial neural networks

MLR - multiple linear regression

NP - natural pozzolana

BPNN back - propagation neural networks

w/c - water-to-cement ratio

1. Introduction

The development of prediction models in the field of civil engineering materials, especially for concrete, is especially important in the use of materials due to their reliability and accuracy. Mathematical prediction of concrete quality and variables can be complemented with techniques such as regression analysis and artificial neural networks (Tam et al., 2022). Currently, there is an environmental concern regarding the scarcity of natural resources, and an emerging trend to mitigate this impact. Several studies have used construction and demolition wastes (Dantas, 2013). Lothenbach, Scrivener and Hooton, (2011) reused industrial manufacturing by-products as cementitious materials, among them natural pozzolanas. Similarly, Tam et al. (2022), used a substitute of CO_2 in the aggregate of the mix design to decrease the extraction of natural materials and thus preserve the environment which allow us to reduce CO_2 emissions.

Likewise, several investigations have been developed with the objective of studying the influence of supplementary cementitious materials (SCM), mainly natural pozzolana, on the mechanical, rheological, and durability properties of fresh and hardened concrete (Hammat et al, 2021; López and Castro, 2010). The presence of SCM influences the amount and type of hydrated calcium silicates (HCS) formed in cementitious systems and thus the volume, porosity, and ultimately the durability of such systems (Lothenbach et al., 2011; Taşdemir, 2003). Several studies demonstrate the increase of compressive strength by the addition of natural pozzolanas and various SCMs (Deboucha et al., 2015; Hammat et al., 2021). Capillary absorption can not only reflect the microstructure of concrete surface, but also reflect the durability, concrete performance, and compressive strength in pozzolanic materials (Taşdemir, 2003; Zhuang, 2022). However, the compressive strength and capillary absorption are highly dependent on the degree of fineness and pozzolanic activity of SCM admixtures (Hammat et al., 2021; Taşdemir, 2003).

The diverse behavior of pozzolana requires extensive testing to learn more about its behavior pattern. However, extensive testing requires quantities of materials, time, and cost. In addition, human errors and various laboratory conditions introduce another element of uncertainty in laboratory results (al-Swaidani et al., 2022). Therefore, to improve studies and reduce the cost and time required for testing, models based on experimental data that predict compressive strength and capillary absorption with an acceptable range of error can be recommended (Deshpande, 2014). Techniques such as linear and nonlinear regression analysis and, more recently, various artificial neural networks are available to evaluate the effects of various manufacturing variables on concrete performance. Multiple linear regression (MLR) is the simplest method that has been used to predict concrete properties (al-Swaidani et al., 2022).

Several studies and multiple linear regression (MLR) models with the addition of pozzolanic materials to concrete have shown excellent results in predicting compressive strength values obtained in the laboratory (Waghmare et al., 2021). According to Deshpande et al. (2014), the application of nonlinear regression models and tree model to analyze the behavior of concrete is feasible, however, Dantas et al. (2013) recommends that the choice of a suitable regression equation involves technique and experience. As MLR does not produce reliable predictions (due to its low flexibility), different machine learning methods have been widely used to estimate concrete properties more accurately (al-Swaidani et al., 2022). The compressive and tensile strengths of concrete are the properties that are mainly predicted by artificial neural network (ANN). Some studies have been published showing that ANNs can model complex and nonlinear relationships between parameters affecting the compressive strength of concrete with zeolite addition (Waghmare et al., 2021).

In recent years, various studies have demonstrated the high effectiveness and reliability of artificial neural networks (ANN) to predict various properties of hardened concrete using multiple variables. Such is the case of Divyah Nagarajan et al. (2020), who developed artificial neural networks (ANN) with which they were able to accurately predict flexural, tensile, and compressive strengths based on only five manufacturing variables, where they obtained high correlation coefficients, greater than 0.90, for those properties. Meanwhile, İbrahim Özgür Deneme (2020) used gene expression programming (GEP) and neural networks based on seven variables to predict the compressive strength of fly ash self-compacting concrete and found that neural network (ANN) models outperformed to genetic models (GEP) in prediction accuracy. Moreover, there are even records of investigations where natural pozzolana (NP) additions were employed as a replacement for cement at the nanoscale, they came to employ the techniques of MLR and ANN. The importance of the nano pozzolana study is evidenced by its correlation and performance analysis results could be effectively predicted using ANN and MLRN techniques, with ANN being the most accurate (al-Swaidani et al., 2022).

Therefore, there is evidence that ANN methods are very accurate in predicting factors that are the basis of concrete properties, i.e., it can be expected that it will have the same result when analyzing the mechanical, physical and chemical properties of concrete. From the literature review, the importance of applying techniques such as MLR and ANN for the prediction of the compressive strength and capillary absorption of concrete with natural pozzolana (NP) was noted, since there is scarce information, and the techniques mentioned have a good approximation to the values obtained in laboratory conditions. The novelty lies in the development of accurate predictive models to determine the compressive strength and capillary absorption of concrete with natural pozzolana additions that will allow to save manufacturing costs and waiting time in the tests, therefore, the objective of this work is to determine predictive models using multiple linear regression analysis (MLR) and neural networks (ANN) for the compressive strength and capillary absorption of concrete with pozzolana.

2. Materials and methods

The experimental program of this study was designed to investigate the compressive strength and capillary absorption of concrete mixtures containing various percentages of pozzolana for mix ratios.

2.1. *Materials*

In the present investigation, 16 concrete batches were designed, using the same materials: Portland cement type I, natural pozzolana, super plasticizing admixture, aggregates from the Jicamarca quarry and potable water.

2.1.1. Cement

The cement used was Portland type I, brand SOL. Table 1 shows its mineralogical phases based on the requirements of ASTM C150.

Table 1. Mineralogical phases of Portland cement according to ASTM C150 standard.

Mineral phase	Proportion by weight (%)
C_2S	13.15
C_3S	53.60
C_3A	9.66
C_4AF	9.34

2.1.2. Aggregates

The aggregates used in this research come from the Jicamarca quarry and meet the requirements of the ASTM C33 standard. The characteristics are presented in Table 2.

Table 2. Physical properties of aggregates according to ASTM standards.

Property	Test standard	Units	Fine aggregate	Coarse aggregate
Loose unit weight	ASTM C127-128	kg/m^3	1692	1456
Compacted unit weight	ASTM C127-128	kg/m^3	1815	1663
Specific mass weight	ASTM C127-128	g/cm^3	2.68	2.69
Surface dry mass specific gravity	ASTM C127-128	g/cm^3	2.70	2.72
Apparent specific weight	ASTM C127-128	g/cm^3	2.74	2.77
Absorption percentage	ASTM C127-128	%	0.83	1.18
Modulus of fineness	ASTM D422		2.82	6.74

2.1.3. Chemical composition of UNACEM's natural pozzolana

The chemical analysis shows that the sum of the percentages of silicon dioxide (SiO2), aluminum oxide (Al2O3) and ferric oxide (Fe2O3) is 81.12%, which is higher than the minimum requirement established in ASTM C618 (2005): 70%.

Table 3. Chemical composition of UNACEM natural pozzolana.

Chemical analysis	Values (%)
Silicon dioxide (SiO_2)	51.15
Aluminum oxide (Al_2O_3)	8.03
Iron oxide (Fe_2O_3)	21.94
Calcium oxide (CaO)	1.18
Magnesium oxide (MgO)	0.32
Sulfur trioxide (SO_3)	5.43
Potassium oxide (K_2O)	1.09
Sodium oxide (Na_2O)	1.15

2.1.3.1. Pozzolana strength activity index (ASTM C311)

The compressive strength was compared between mortars with 20% pozzolana and mortars without addition. The dosage and strength activity indexes are presented in Table 4.

Table 4. Dosage and pozzolanic activity index according to ASTM C311 standard.

Materials	Control mortar	Mortar with 20% pozzolana	Resistant activity index
Portland cement type I (g)	500	400	------
Pozzolana	0	100	------------
Sand	1375	1375	-------
# of samples prepared	6 buckets of mortar	6 buckets of mortar	---------
Average strength at 7 days (kg/cm^2)	206	158	77
Average resistance at 28 days (kg/cm^2)	317	281	89

According to ASTM C618, the resistant activity index must be greater than 75% for its use as a supplementary material; in the case study, a value of 89 was obtained.

2.1.4. Additive

The super plasticizing admixture used was Sika viscocrete-20HE, chemically based on an aqueous solution of modified polycarboxylates. It has a density equal to 1.08 kg/l, light brown color and complies with the requirements of ASTM C 494 type F.

2.2. Mix design

For the mix designs, w/c ratios = 0.40, 0.45, 0.50 and 0.55 were used; the percentages in weights of pozzolana addition were 10%, 15% and 20%; the curing ages of the samples were 28 and 56 days; the sand/stone weight ratio was 60/40. Table 5 shows the 16 dosages used, varying the pozzolana content. The ID is shown: w/c-P-% pozzolana.

Table 5. Mix designs with various w/c ratios and pozzolana content.

ID.	Cement (kg)	Pozzolana (kg)	Water (kg)	Sand (kg)	Stone (kg)	Plasticizing additive (l)
0.40-P-0	380	0	152	982.8	910.6	6.46
0.45-P-0	360	0	162	978.7	906.8	5.76
0.50-P-0	320	0	160	1019.4	907.4	5.12
0.55-P-0	300	0	165	1021.8	909.5	4.80
0.40-P-10	342	38	152	980.2	908.1	6.46
0.45-P-10	324	36	162	976.2	904.5	5.76
0.50-P-10	288	32	160	1017.1	905.4	5.12
0.55-P-10	270	30	165	1019.7	907.6	4.80
0.40-P-15	323	57	152	978.8	906.9	6.46
0.45-P-15	306	54	162	974.9	903.3	5.76
0.50-P-15	272	48	160	1016.0	904.4	5.12
0.55-P-15	255	45	165	1018.7	906.7	4.80
0.40-P-20	304	76	152	977.5	905.7	6.46
0.45-P-20	288	72	162	973.7	902.2	5.76
0.50-P-20	256	64	160	1014.9	903.3	5.12
0.55-P-20	240	60	165	1017.6	905.8	4.80

2.3. Methodology

2.3.1. Methods of testing of concrete

The present research is an experimental investigation. Table 6 summarizes the main tests performed on the different samples of concrete with pozzolana.

Table 6. Laboratory tests on pozzolana concrete.

Method	Norm	Dimensions of samples	Indicator	n
Compressive strength	ASTM C39	10x20 cm	kg/cm^2	64 cylinders
Capillary absorption	ASTM 1585	10x3 cm	$kg/m^2*s^{0.5}$	128 discs
Mix design	ACI-211.1	10x20 cm	Weights	16 designs
Wet curing	ASTM C-31	10x20 cm 10x3 cm	Age (days)	192 samples

Figure 1. Concrete samples with pozzolana addition.

2.4. Methods for data analysis and modeling

2.4.1. Linear multiple regression analysis

Minitab software was used to estimate the multiple linear regression analysis (MLR) equation and predict the compressive strength and capillary absorption of concrete with pozzolana addition. The multiple regression equation was obtained by defining the relationship between the independent variables of the mix dosage and the single dependence variance or condition.

2.4.2. Artificial neural networks

The independent variables of the concrete include cement, addition, water, sand, stone, plasticizing additive, the water/cement ratio, pozzolana and age in days. To model the neural network to estimate compressive strength, a matrix P with 9 rows and 64 columns was formed. The resistance values of the samples, measured in the laboratory, form the matrix T with one row and 64 columns. While for capillary absorption a P matrix is formed with 9 rows and 128 columns. The capillary absorption values of the test tubes, measured in the laboratory, form the T matrix with one row and 128 columns. For practical reasons in the use of programs, the databases for both the compression resistance study and the capillary absorption study are denoted with the same symbols: P and T.

2.4.2.1. Database preparation for neural networks

First, the rows of P and T must be transformed into rows with zero mean and standard deviation 1. This is achieved with the following MATLAB2018a function:

$$[\mathrm{pn}, \mathrm{Est1}] = \mathit{mapstd}(P) \text{ and } [\mathrm{tn}, \mathrm{Est2}] = \mathit{mapstd}(T) \tag{1}$$

Where pn and tn are the normalized matrices of P and T respectively, Est1and Est2 are automatically created structures containing, among other things, the values of the means and standard deviations. Secondly, highly correlated variables must be reduced, this is obtained with the MATLAB function, which follows:

$$[\mathrm{ptrans}, \mathrm{Est3}] = \mathit{processpca}(\mathrm{pn}, 0.001) \tag{2}$$

Where pn is the normalized P matrix and p trans is the matrix where the rows of pn have been transformed and reduced to a smaller number, using principal component analysis, which by making use of the eigenvalues and eigenvectors of the co-variance matrix of pn, constructs a matrix M that when multiplied to pn converts it into p trans. Est3 is a structure containing, among other things, the M matrix, and its inverse.

2.4.2.2. Structuring of back propagation neural networks (BPNN)

The problem is to obtain a mathematical model that, knowing the values of the manufacturing variables, provides an approximate value of the compressive strength and capillary absorption. Consequently, supervised neural networks will be used. For this kind of networks, the basic unit is the artificial neuron, which comprises a variable b that is the bias, a matrix $w = [w_1, w_2, \dots \dots, w_n]$that are the weights of the neuron and an activation or transfer function $f: \Re \rightarrow \Re$.

The number of weights in w depends on the number of components of the data (input) which is a numerical matrix $d = [d_1, d_2, \dots, d_n]^T$, which in this case are the values of the manufacturing variables of a test tube, which enters the artificial neuron. The response (output) of the neuron, for this data is:

$$q = f(wd + b), \text{ where: } wp = w_1 d_1 + w_2 d_2 + \cdots \dots + w_n d_n \quad (3)$$

In this measure a neuron is a real function of (n+1) variables. A layer of neurons is a vector transformation with vector variable. Neural networks are concatenations of layers of neurons, that is a composition of vector functions. The last layer, in this case, is a function with real values and vector variable. The following MATLABR2018a function was used to structure the neural networks:

$$net = newff(rango, [c1, c2, c3, c4, ..], \{'f(s)', 'f(s)', 'f(s)', \dots, 'g(s)'\}, 'trainlm') \quad (4)$$

Where the rank matrix contains the minima and maxima of the rows of the “p trans” matrix. In the matrix $[c1, c2, c3, c4, ..]$. c1 is an integer indicating the number of neurons in the first layer, c2 the number of neurons in the second layer and so on. Correspondingly, the transfer functions are chosen, which in this case are:

$$f(s) = \tanh(s) = \frac{\exp(s) - \exp(-s)}{\exp(s) + \exp(-s)} \quad (5)$$

$$g(s) = s \quad (6)$$

With the function f(s)=tanh(s) biunivocal transforms the values of s to values within the open interval < -1 , 1> .This improves the numerical approximations of the functions and their partial derivatives, during their training.

The following expression: “trainlm” corresponds to the algorithm for minimizing the root mean square error function between the values of capillary absorption T measured in the laboratory and the values provided by the re network. The algorithm is based on the papers by Levenberg (1944) and Marquardt (1963).

2.4.2.3. Preparation of the database for BPNN training

The training of the network is carried out in three phases: Training, Validation and Testing. MATLAB (R2018a; 64-bit-(win64)), has the following function to divide columns: [trainInd, valInd, testInd] = divideint(N, a, b, c) where the ratios: a, b, c are positive numbers and with sum equal to 1. The choice of these is up to the user. This function divides the numbers ranging from 1 to N into three disjoint sets interleaved. In the case 0.50, 0.25, 0.25; for validation it takes the numbers in class [2], for testing, those in class [3] and for training, those in classes [1] and [4].

In the case of compressive strength, three groups of the columns of the matrices P and T are taken using the equivalence classes modulo 4, restricted to the set of integers {1, 2, ..., 64}. These classes are: [2] ={2, 6,...,62}; [4]={4,8,...,64},[1,3]={1, 5,...,61, 3, 4,...,61}. As the columns of P and T are numbered from 1 to 64, the columns used in the three phases are extracted with these classes; for training they are extracted with classes [1, 3], for validation with class [4] and for test with class [2], with 32, 16 and 16 columns respectively.

Whereas, in capillary absorption, three groups of the columns of the matrices P and T are taken using the equivalence classes module 4, restricted to the set of integers {1, 2, ..., 128}. These classes are: [2] ={2, 6,...,32}; [4]={4,8,...,32},[1,3]={1, 5,...,125, 3, 7,...,127}. As the columns of P and T are numbered from 1 to 128, the columns used in the three phases are extracted with these classes; for training they are extracted with classes [1, 3], for validation with class [4] and for test with class [2], with 64, 32 and 32 columns respectively. So, the choice of the classes is arbitrary, what must be considered is that approximately 50% of the columns must be used in the training, 25% in the validation and 25% in the Test as suggested by MATLAB. These choices can also be made randomly but avoiding the duplicity of the columns for each of the three phases and repeating the process hundreds or thousands of times, to achieve a good training of the neural network.

2.4.2.4. Training of BPNN

The function for training each of BPNN is as follows:

$$[net, Est4] = train(net, Enp, Vet, [\,], [\,], val, test) \tag{7}$$

Where net is the network created with equation (4). For compressive strength: Enp, VEt are 32-column matrices of ptrans and tn respectively, chosen with the class [1,3]. In addition, "val" are 16-column matrices of "ptrans" and "tn", chosen with equivalence classes [2]. tests are 16-column matrices of ptrans and tn, chosen with equivalence classes [4].

For capillary absorption. Enp, VEt are 64-column matrices of ptrans and tn respectively, chosen with class [1,3]. val are 32-column matrices of ptrans and tn, chosen with equivalence classes [2], test are 32-column matrices of ptrans and tn, chosen with equivalence classes [4].

3. Experimental results and analysis

3.1. Compressive strength

Table 7 shows the compressive strength corresponding to the average of 4 values obtained in the test cylinders for each water/cement ratio and percentage of pozzolana at 28 days. According to Table 7, the higher the water/cement ratio the lower the compressive strength. These results are like those obtained by Medeiros-Junior et al. (2019).

Table 7. Compressive strength at 28 days of curing kg/cm^2.

ID	0.40	0.45	0.50	0.55
Control resistances	633	562	502	451
Resistances 10% pozzolana	714	629	561	501
Resistance 15% pozzolana	745	651	573	508
Resistance 20% pozzolana	697	627	555	502
% Resistance Variation	18%	16%	14%	13%

It is observed that for the same w/c ratio and pozzolana contents up to 15%, compressive strengths increased up to 18%; this could be attributed to the higher pozzolanic reaction due to the reaction of the amorphous silica (SiO_2) present in the NP with the $Ca(OH)_2$ produced by the hydration of Portland cement to give additional C-S-H formation, thus giving higher strength of the blended cement mortars (McCarthy and Dyer, 2019).

However, for mixes with 20% pozzolana, lower strengths were obtained with respect to mixes with 10 and 15% Pozzolana, for all w/c evaluated. The highest and lowest increase in strength was found for w/c = 0.40 and 0.55, respectively. In general, it was observed that the addition of up to 15% pozzolana produced increases in compressive strength in all the cases studied.

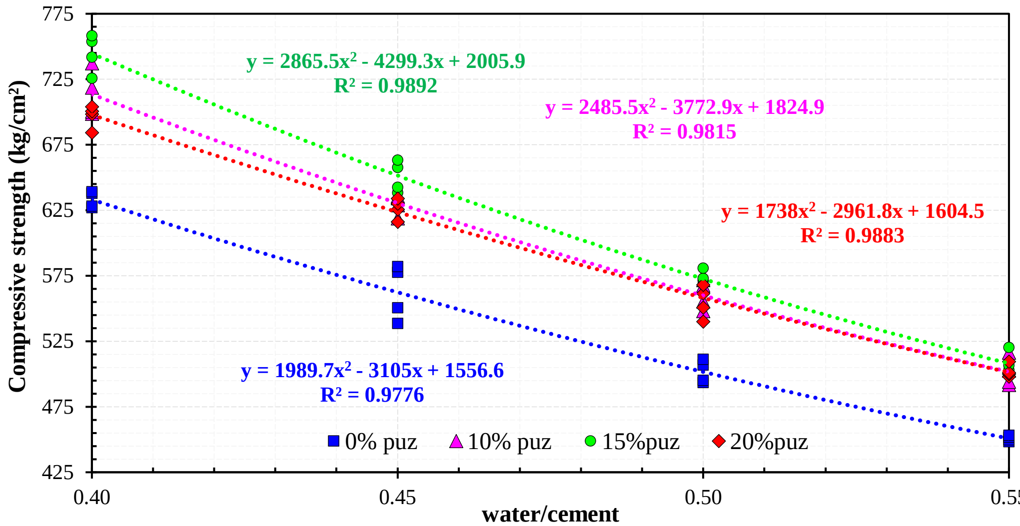

Figure 2. Compressive strength at 28 days of curing.

Pozzolanic mineral additions have high fineness, which generates increases in the compressive strength of concrete (Taşdemir, 2003). However, Deboucha et al. (2015) found that the compressive strength decreases by increasing the amount of natural pozzolanas (NP) and blast furnace slag (BFS) in replacement of cement at ages of 7, 28 and 90 days.

Also, Hammat et al. (2021) asserts that increasing the pozzolana content delays the compressive strength at ages up to 28 days, because the pozzolanic reaction is slow, but a beneficial effect on the compressive strength could be observed at later ages. In this investigation, at 28 days, increases in strength were observed with 10 and 15% pozzolana content, while for 20% pozzolana content, strength decreased.

3.2. Capillary absorption rate results

Table 8 shows that at higher w/c values, ages 28 and 56 days, the capillary absorption rate increases, and that for the same w/c ratio, age 28 days, with 0, 10% and 15% pozzolana, the absorption rate decreases. However, for pozzolana contents of 20%, an increase in the absorption rate is observed with respect to mixtures with 10 and 15% pozzolana; according to the study of López and Castro (2010), the higher the pozzolana content, the higher the capillary absorption rate.

Table 8. Capillary absorption rates kg/m^2*s $^{0.5}$ of concrete at ages of 28 and 56 days.

ID	Age (days)	0.40	0.45	0.5	0.55
Control samples	28	0.0100950	0.0132750	0.0145500	0.0153250
10% pozzolana		0.0071800	0.0096050	0.0115250	0.0119750
15% pozzolana		0.0044325	0.0065600	0.0075150	0.0085475
20% pozzolana		0.0053267	0.0080567	0.0100175	0.0114500
Control samples	56	0.006255	0.007695	0.010203	0.011350
10% pozzolana		0.004340	0.005250	0.006048	0.006723
15% pozzolana		0.003838	0.004698	0.005305	0.005713
20% pozzolana		0.002925	0.003913	0.004838	0.005553

The results obtained at 56 days denoted a decrease in capillary absorption in mixtures with up to 20% pozzolana: according to H. Yanguatin et.al (2017). This behavior can be associated with a more vigorous pozzolanic activity at late curing ages.

Finally, according to Taşdemir (2003) micro filler materials with fine particles fill both interfaces and bulk paste, and the absorptivity coefficient of concrete decreases.

Medeiros et al (2019) showed that concretes with higher pozzolana content presented higher capillary sorption for water/cement ratios lower than 0.60. This behavior is attributed to the reduction of pore diameters and densification of the microstructure that caused much higher surface tension forces.

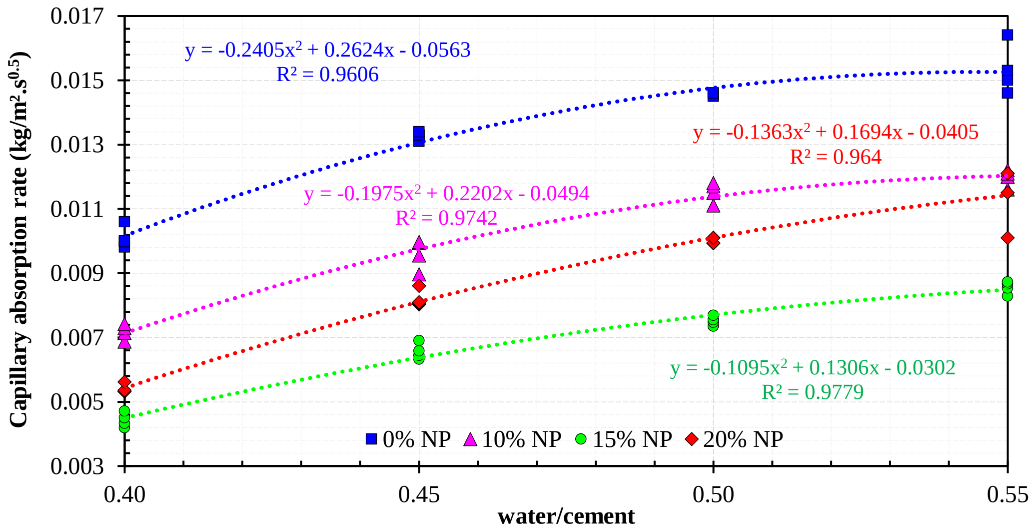

Figure 2. Capillary absorption at 28 days of curing vs water/cement ratio.

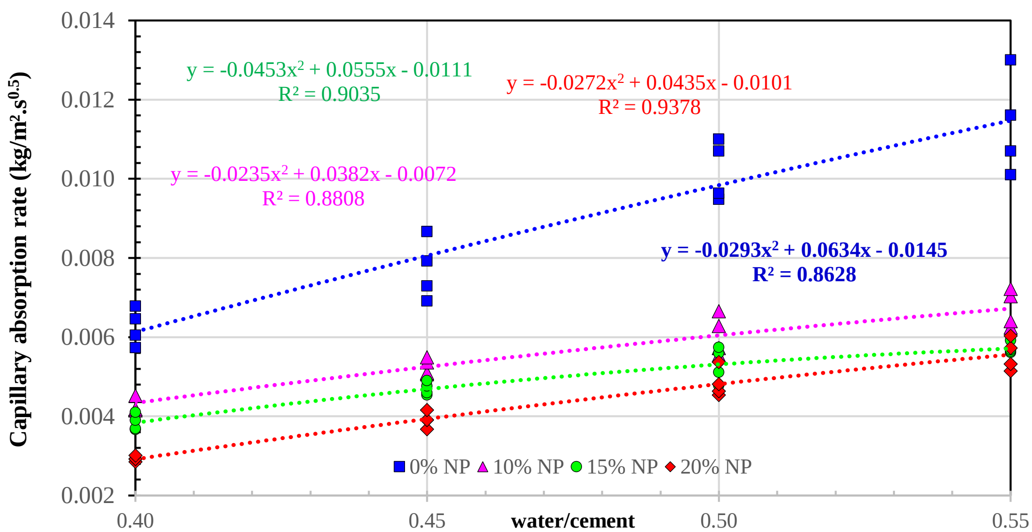

Figure 3. Capillary absorption at 56 days of curing vs water/cement ratio.

3.3. Multiple linear regression analysis

3.3.1. Linear multiple regression analysis applied to the compressive strength

Equation (1) was obtained from 64 experimental data of compressive strength, six key independent variables were considered: cement, pozzolana, water, sand, stone and additive, and the MLR method was applied; as can be seen in the equation, the dependent variable (f'c) is a function of the independent variables with their respective equivalent coefficients.

$$f'c = 469370 - 146.8 \text{ cement (kg)} - 168.3 \text{ pozzolana (kg)} - 554 \text{ water (kg)} - 198 \text{ sand (kg)} - 134.7 \text{ stone (kg)} - 1723 \text{ plasticizer (l)} \quad (1)$$

Table 9. Summary of the model.

S	R-sq.	R^2 (adjusted)	R-sq. (pred)
21.9905	93.91%	93.27%	92.41%

3.3.2. Linear multiple regression analysis applied to capillary absorption rate.

The capillary absorption rate values shown in Table 11 were used; seven key independent variables were considered: cement, pozzolana, Water, sand, stone, additive and age; and the MLR method was applied; as shown in equation (9), the dependent variable (S) is a function of the independent variables with their respective equivalent coefficients.

$$S = -1.19 - 0.00012 \text{ cement (kg)} - 0.00031 \text{ pozzolana (kg)} + 0.0115 \text{ water (kg)} + 0.00332 \text{ sand (kg)} - 0.00538 \text{ stone (kg)} + 0.176 \text{ plasticizer (l)} - 0.000135 \text{ age (days)} \quad (8)$$

Table 10. Summary of the model.

S	R^2	R^2 (adjusted)	R^2 (pred)
0.0012301	87.09%	86.32%	85.23%

3.4. Analysis of BPNN

3.4.1. Neural networks applied to the compressive strength

The variables statistics shown in Table 11 contains the minimum, maximum, mean, mode, standard deviation (Std) and Pearson CCR correlation of the manufacturing variables (occupying the first 9 rows) with resistance. The highest correlations, in absolute value, correspond to variables V6, V7 (92%) and to variables V3 and V4. The lowest correlations occur with variables V5 and V8. The last CCR column of Table 11, are the values of the correlation of the variables with resistance. The NaN value is indeterminate because the variable V9 or age is constant (28 days).

Table 11. Statistics and correlation of manufacturing variables with compressive strength.

Variables	Number	Min	Max	Mean	Mode	Std dev.	CCR
Cement (kg)	V1	240.00	380.00	301.75	288.00	38.99	0.48
Addition (kg)	V2	0.00	76.00	38.25	0.00	26.34	0.43
Water (kg)	V3	152.00	165.00	159.75	152.00	4.97	-0.81
Sand (kg)	V4	973.70	1021.80	998.00	973.70	20.96	-0.83
Stone (kg)	V5	902.20	910.60	906.14	903.30	2.28	-0.16
Plasticizer (kg)	V6	4.80	6.46	5.53	4.80	0.66	0.92
w/c	V7	0.40	0.55	0.48	0.40	0.06	-0.92
Pozzolan content (%)	V8	0.00	20.00	11.25	0.00	7.64	0.30
Age (days)	V9	28	28	28	28	0	NaN
Compressive strength (kg/cm^2)	V10	450.77	744.93	86.30	588.17	450.77	1

Six BPNNs were trained, the structures of which are shown in Table 12, the first three networks respecting the recommendations of various authors, who suggest that the number of neurons in the first layer should coincide with the number of variables entered, which in this case was 3, because p trans in a 3 x 64 matrix. Each of the 6 BPNNs delivered in a Re matrix the approximate values of the compressive strengths of the 64 specimens. The correlation between Re and T for each structure is R; the BPNN that has the highest correlation R=0.9739, is the sixth one in Table 12 and we will denote it BPNN6. It is observed that this network does not comply with the recommended rule, since it has 15 neurons in its input layer. There is no proven mathematical justification for this recommendation, since these are statements based on statistics.

Table 12. R, m, b, MSE and RMSE coefficients of BPNN with inputs P and T.

Structure	R	m	b	MSE	RMSE
[3, 30, 30, 1]	0.959803	0.963407	23.086817	564.586304	23.761025
[3,15, 5, 1]	0.934997	0.900894	62.447416	898.788867	29.979808
[3, 20, 10,1]	0.932110	0.912549	39.985462	1058.077407	32.528102
[10, 20, 1]	0.972080	0.927397	45.015686	391.053334	19.775068
[10, 20, 10,1]	0.932240	0.806496	113.550275	943.413954	30.715044
[15, 20, 10, 1]	0.973964	0.938322	40.142486	373.470266	19.325379

In Table 13, the column of the class intervals of the error E=|T-Re| are presented, as well as the absolute frequencies and the relative frequencies of E.

Table 13. Error between grid response and laboratory measured compressive strengths.

Structure	Class intervals	Absolute freq.	Relative freq.
[15, 20, 10, 1]	[0.1289500 - 9.5425361>	23	0.3593750
	[9.5425361 - 18.9561223>	21	0.3281250
	[18.9561223 - 28.3697084>	13	0.2031250
	[28.3697084 - 37.7832946>	3	0.0468750
	[37.7832946 - 47.1968807]	4	0.0625000

Table 14 shows the R values and the coefficients m, b of the linear regression lines for each phase and the total for BPNN6. The high accuracy and reliability of the predictive model with BPNN6 are consistent with the results of Divyah Nagarajan et al. (2020), who also obtained correlation coefficients of 0.94 for neural network models that predict compressive strength with 5 manufacturing variables: cement, coarse aggregate, fine aggregate, superplasticizer and the water ratio cement (w/c). While our BPNN6 structure with 10 manufacturing variables presents a higher R^2 value of 0.97 compared to the network formulated by Divyah Nagarajan et al. (2020) and Deneme (2020). This corroborates the effectiveness of neural networks in capturing the complex relationships between manufacturing variables and concrete properties. The results of BPNN, with its high correlation and low error rates, align with our results obtained, further validating the superiority of neural networks in this domain over other methods such as GEP (Deneme, 2020) and the MLR that presents good approximation but still less reliable than ANNs.

Table 14. Correlation R^2 and the coefficients of the equation of the straight line.

Structure	Coefficients	Training	Validation	Test	Total
[15, 20, 10, 1]	R	0.9700034	0.9802277	0.9716686	0.9739636
	m	0.9751695	0.9114266	0.8747787	0.9383216
	b	18.9736498	53.6294435	83.3737255	40.1424862

Table 15 shows the variables and designs for which the minimum and maximum strength of the concrete samples are given. It is observed that the minimization and maximization of the resistance are influenced by the variables: Addition, the w/c ratio and the pozzolana; with values: [0.00, 0.55, 0.00] and [57.00, 0.40, 15.00] respectively. The values of the other variables are similar.

Table 15. Minimum and maximum compressive strength variables and design.

Variables	Minim	Max.
Design	0.55/Puz0	0.40/Puz15
Cement (kg)	300.00	323.00
Addition (kg)	0.00	57.00
Water (kg)	165.00	152.00
Sand (kg)	1021.80	978.80
Stone (kg)	909.50	906.90
Plasticizer (kg)	4.80	6.46
Water/cement	0.55	0.40
Pozzolan content (%)	0.00	15.00
Age(days)	28.00	28.00
Compressive strength	448.38	758.14

3.4.2. Neural networks applied to the capillary absorption of concrete

This section presents the statistics of the variables. Table 1 contains the minimum, maximum, mean, mode, standard deviation (std) and Pearson CCR correlation of the manufacturing variables (occupying the first 9 rows) with capillary absorption. The highest correlations, in absolute value, correspond to the variables V2 (-62%) and are followed by the variables V9 and V8 with (-0.58) and (-0.57) correlation respectively. The lowest correlations occur with variable V1 (0.04).

Table 15. Statistics and correlation of manufacturing variables with capillary absorption.

Variables	Number	Min	Max	Media	Mode	Std	CCR
Cement (kg)	V1	240.00	380.00	301.75	288.00	37.90	0.04
Addition (kg)	V2	0.00	76.00	38.25	0.00	25.60	-0.62
Water (kg)	V3	152.00	165.00	159.75	152.00	4.83	0.41
Sand (kg)	V4	973.70	1021.80	998.00	973.70	20.38	0.44
Stone (kg)	V5	902.20	910.60	906.14	903.30	2.22	0.35
Plasticizer Additive (L)	V6	4.80	6.46	5.53	4.80	0.64	-0.46
w/c	V7	0.40	0.55	0.48	0.40	0.06	0.46
Puzolana (%)	V8	0.00	20.00	11.25	0.00	7.42	-0.57
Age(days)	V9	28.00	56.00	42.00	28.00	14.06	-0.58
Capillary Absorption ($kg/m^2*s^{0.5}$)	V10	2.850E-03	1.640E-02	3.306E-03	7.821E-03	1.000E-02	1.00

The last CCR column of Table 1 contains the values of the correlation of the variables with the capillary absorption, measured in $kg/m^2*s^{0.5}$. Results of the training of the 6 BPNN structures.

Table 16. Coefficients R, m, b, MSE and RMSE

Response: ANN with entrance P and T					
Structure	R^2	m	b	MSE	RMSE
[5, 30, 30, 1]	0.8747544	0.7816817	0.0018490	0.0000026	0.0015970
[5,15, 5, 1]	0.9776479	0.9679636	0.0004086	0.0000005	0.0007086
[5, 20, 10,1]	0.9873944	1.0031284	0.0000649	0.0000003	0.0005350
[10, 20, 1]	0.9877384	0.9949809	0.0001632	0.0000003	0.0005307
[10, 20, 10,1]	0.9818114	0.9742225	0.0002918	0.0000004	0.0006302
[15, 20, 10, 1]	0.9854844	0.9991123	0.0001307	0.0000003	0.0005779

Table 16 shows the 6 BPNN structures, with different structures, the first 3 respecting the recommendations of various authors, who suggest that the number of neurons in the first layer should coincide with the number of variables entered, which in this case is 5. After training the 6 networks, each of them delivered a Re matrix with the approximate values of the capillary absorption T, measured in the laboratory. The neural network with the highest correlation R^2=0.9877, between Re and T, is the fourth in the list and is denoted BPNN4, which does not comply with the rule. This rule is not always fulfilled because there is no proven mathematical justification.

Table 17. Error between laboratory measured capillary absorption and BPNN4 response.

Structure	Class intervals	Absolute freq.	Relative freq.
[10, 20, 1]	[0.00000679 - 0.00038704 >	91	0.71093750
	[0.00038704 - 0.00076729 >	22	0.17187500
	[0.00076729 - 0.00114754 >	7	0.05468750
	[0.00114754 - 0.0015278 >	4	0.03125000
	[0.00152780 - 0.00190805]	4	0.03125000

Table 18 shows the error class intervals E=||T−Re| and the absolute and relative frequencies. The capillary absorption measured in laboratory differs from the approximate value given by BPNN4, this difference E for 88.28% of the specimens is in the range [0.0000067892, 0.00076729] measured in ($kg/m^2*s^{0.5}$).

Table 18. The correlation R and the coefficients of the equation of the line for the neural network ANN4

[10, 20, 1]	Coefficients	Training	Validation	Test	Total
	R	0.9700034	0.9802277	0.9716686	0.9739636
	m	0.9751695	0.9114266	0.8747787	0.9383216
	b	18.9736498	53.6294435	83.3737255	40.1424862

Table 19 shows the values of R and the coefficients m, b of the linear regression lines of each phase and of the total, for BPNN4. The value of R in each of the six BPNNs, of the total stage, coincides in 3 decimal places with the average of the R's for the three phases: training, validation and test.

Table 19. Minimum and maximum capillary absorption variables and design.

Variables	Minimum capillary absorption	Maximum capillary absorption
Design	0.04/Puz20	0.55/Puz0
Cement (kg)	304.00	300.00
Addition (kg)	76	0.00
Water (kg)	152.00	165.00
Sand (kg)	977.5	1022.00
Stone (kg)	905.7	906.50
Plasticizer (kg)	6.46	4.80
w/c	0.40	0.55
Pozzolan content (%)	20.00	0.00
Age(days)	56.00	28.00
Capillary absorption	0.002850	0.016400

Table 20 shows the variables and designs for which the minimum and maximum Capillary Absorption of the concrete samples are given. It is observed that the minimization and maximization of the Capillary Absorption are influenced by the variables: addition, water/cement ratio, pozzolana and age; with values: [76, 0.40, 20, 56] and [0.00, 0.55, 0.00,28] respectively. The values of the other variables do not differ much.

4. Application of BPNN and MLR models

4.1. Compressive strength

Applying the models derived from the multiple regression analysis (MLR) and the selected BPNN, the compressive strength values were calculated, as well as the average error between the experimental values and the values calculated with the mathematical models; where it is observed that for MLR the errors are between [7.83-34.48] kg/cm^2 while for BPNN they are between [4.59-34.63] kg/cm^2. The details are presented in Table 19.

Table 20. Results obtained from modeling using MLR and BPNN.

Water/cement	Pozzolana (%)	f'c (kg/ cm²)	MLR (kg/cm²)	Error MLR	BPNN (kg/cm²)	Error BPNN
0.40	0	633	650	17.21	646	12.54
0.40	10	714	688	26.14	690	23.38
0.40	15	745	719	25.54	744	11.02
0.40	20	697	731	34.48	695	6.96
0.45	0	562	575	17.70	559	17.70
0.45	10	629	609	20.60	650	20.88
0.45	15	651	642	10.26	639	11.93
0.45	20	627	642	15.80	632	6.74
0.50	0	502	508	7.83	490	11.42
0.50	10	561	547	13.86	595	34.63
0.50	15	573	557	16.85	555	18.95
0.50	20	555	580	24.64	584	28.61
0.55	0	451	465	14.70	455	4.59
0.55	10	501	494	8.27	492	9.62
0.55	15	508	492	15.51	530	22.00
0.55	20	502	510	7.72	515	13.06

The graphical representation of the compressive strength results and the coefficients of determination (R^2) of the BPNN and MLR models can be detailed in Figure 5. In addition, it is evident that both the RML and BPNN models can satisfactorily predict values like those obtained in the laboratory.

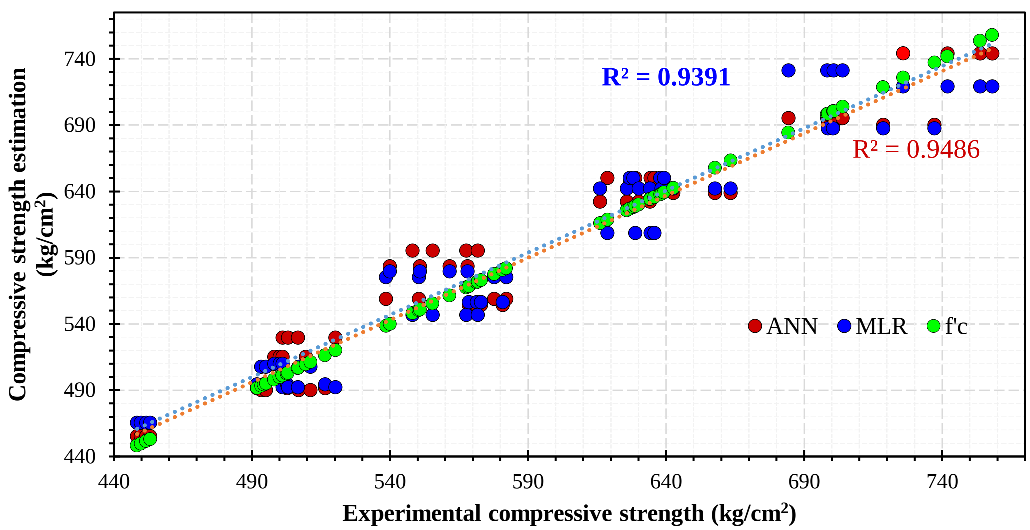

Figure 4. Comparison of compressive strength prediction using BPNN and MLR models with experimental results.

4.2. Capillary absorption rate

Applying the formulas derived from the multiple regression analysis (MLR) and the selected BPNN; the capillary absorption values were calculated, as well as the average error between the experimental values and the values calculated with the mathematical models. It is observed that for MLR the errors are between [0.000133-0.00231] $kg/m^2*s^{0.5}$ while for ANN between [0.000087-0.001047] $kg/m^2*s^{0.5}$. The details are presented in Table 21.

Table 21. Capillary absorption errors at 28 days of curing, calculated with MLR and BPNN.

Water/cement	Pozzolana (%)	Curing age (days)	Experimental ($kg/m^2*s^{0.5}$)	MLR ($kg/m^2*s^{0.5}$)	BPNN ($kg/m^2*s^{0.5}$)	Error MLR ($kg/m^2*s^{0.5}$)	Error BPNN ($kg/m^2*s^{0.5}$)
0.40	0	28	0.010095	0.010277	0.010271	0.000341	0.000340
0.40	10	28	0.007180	0.008071	0.007344	0.000949	0.000202
0.40	15	28	0.004433	0.006367	0.004580	0.001963	0.000213
0.40	20	28	0.005327	0.004994	0.005384	0.000338	0.000100
0.45	0	28	0.013275	0.012113	0.013118	0.001131	0.000166
0.45	10	28	0.009605	0.009532	0.009960	0.000350	0.000360
0.45	15	28	0.006560	0.008345	0.007082	0.001842	0.000522
0.45	20	28	0.008057	0.006952	0.008401	0.001125	0.000308
0.50	0	28	0.014550	0.013520	0.014892	0.001024	0.000477
0.50	10	28	0.011525	0.010728	0.011380	0.000800	0.000521
0.50	15	28	0.007515	0.009499	0.007573	0.002008	0.000117
0.50	20	28	0.010018	0.008807	0.010524	0.001166	0.000506
0.55	0	28	0.015325	0.014211	0.015789	0.001137	0.000624
0.55	10	28	0.011975	0.011915	0.012073	0.000216	0.000175
0.55	15	28	0.008548	0.010664	0.008710	0.002170	0.000389
0.55	20	28	0.011450	0.009082	0.010541	0.002331	0.001047
0.40	0	56	0.006255	0.006459	0.000365	0.006617	0.000443
0.40	10	56	0.004340	0.004317	0.000175	0.004470	0.000175
0.40	15	56	0.003838	0.002583	0.001254	0.003670	0.000172
0.40	20	56	0.002925	0.001247	0.001678	0.003029	0.000104
0.45	0	56	0.007695	0.008331	0.000801	0.008374	0.000679
0.45	10	56	0.005250	0.005793	0.000543	0.005321	0.000175
0.45	15	56	0.004698	0.004590	0.000133	0.004727	0.000113
0.45	20	56	0.003913	0.003255	0.000658	0.003930	0.000132
0.50	0	56	0.010203	0.009713	0.000648	0.010915	0.000918
0.50	10	56	0.006048	0.006912	0.000865	0.006007	0.000368
0.50	15	56	0.005305	0.005711	0.000420	0.005429	0.000360
0.50	20	56	0.004838	0.005039	0.000367	0.004687	0.000272
0.55	0	56	0.011350	0.010375	0.001112	0.011095	0.000401
0.55	10	56	0.006723	0.008106	0.001383	0.006777	0.000403
0.55	15	56	0.005713	0.006905	0.001193	0.005673	0.000087
0.55	20	56	0.005553	0.005307	0.000329	0.005908	0.000441

In addition, the graphical distribution of the capillary absorption results and the coefficients of determination (R^2) of the BPNN and MLR models can be seen in Figure 6, which shows a greater similarity between the values obtained in the laboratory using the BPNN model and the MLR model.

Furthermore, Figure 6 represents the comparison between the values obtained from laboratory (S) and the capillary absorption results and the values obtained through the BPNN and MLR models. In addition, the determination coefficients (R^2) of each regression method are presented. Where the BPNN models show a lower standard deviation and a greater similarity between the values obtained in the laboratory with an R^2 value of 0.9756, while using MLR, values were obtained with a greater deviation than the BPNN due to the limitations that the model presents. However, the MLR obtained an acceptable R^2 value of 0.8693, indicating the possible tendency of capillarity to this regression method.

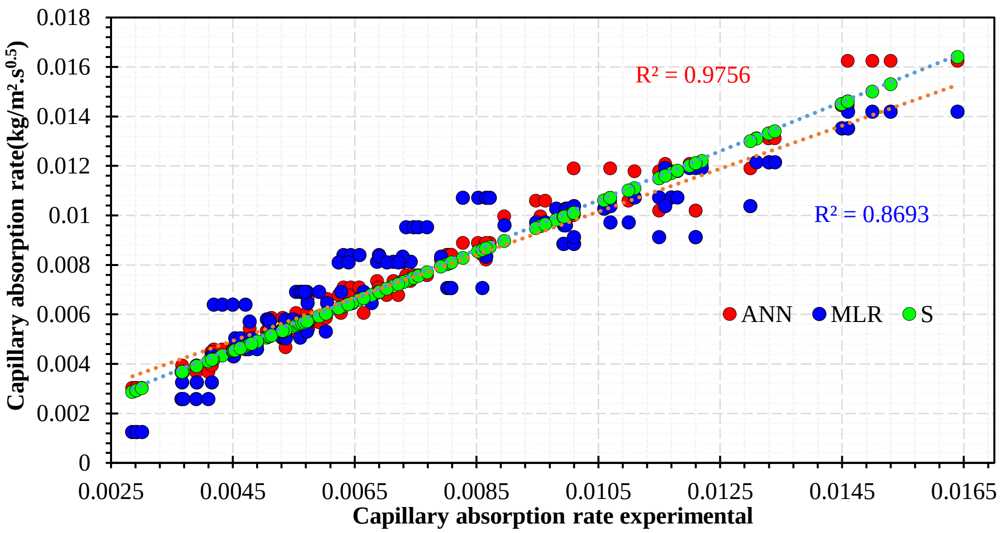

Figure 5. Comparison of capillary absorption prediction using BPNN and MLR models with experimental results.

5. Conclusions and comments

1. It is feasible to predict the capillary absorption and compressive strength of concrete with pozzolana addition, applying the techniques of multiple linear regression (MLR) and back propagation artificial neural networks (BPNN) obtaining high determination coefficients in both models.
2. The determination of these prediction models facilitates obtaining results prior to carrying out tests with great reliability, reducing times, since they normally require laboratory tests, which implies test trials and waiting times. Furthermore, in contribution to the sustainability of concrete by designing more durable and resistant concrete with an optimal dosage in the use of resources.
3. The BPNN demonstrates better model prediction and approximation with a better coefficient of determination (R^2) with respect to MLR in both compressive strength and capillary absorption modeling.
4. The optimal addition of pozzolana was 15% to replace cement due to its excellent performance in terms of compression resistance and low capillary absorption.

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