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Application of Artificial Neural Network to Predict the Properties of Permeable Concrete

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Abstract The structure of permeable concrete has been the primary reason for its use in construction. Permeable concrete is composed of water, cement, aggregate, and little- to no-fines resulting in the presence of a significant number of voids. This makes permeable concrete an ideal solution to water accumulation issues as it acts as a drainage system. This study employs a feedforward backpropagation artificial neural network model that combines experimental laboratory data from previous studies with appropriate network architectures and training techniques. The purpose of the analysis is to develop a reliable functional relationship, based on water-cement ratio, aggregate-cement ratio, and density parameters, with which to estimate the compressive strength, porosity, and water permeability of permeable concrete. Multiple linear regression correlations are also established to predict and correlate these inputs and outputs. The two derived methods are then compared and discussed. The results reveal that ANN is better to anticipate the permeable concrete properties than regression analysis.

Keywords Artificial Neural Network, Multiple Regression, Permeable Concrete, Compressive Strength, Porosity, Water Permeability

1. Introduction

Permeable concrete has been used as far back as the 1800s, when it was first used as pavement surfacing and load-bearing walls in Europe [1]. Porous concrete, pervious concrete, and no-fines concrete are all terms used to describe permeable concrete. This form of concrete is made up of a single-sized coarse aggregate that fills most of its volume [2]. Unlike conventional concrete, permeable concrete contains little to no fine aggregates and a lesser cement-water mixture that coats the coarse aggregates. As a result, significant voids are formed within its structure, resulting in a highly porous concrete (15 to 35%) that facilitates better air exchange and water infiltration [3, 4]. The void content of permeable concrete ranges from 15 to 25% with a permeability of 2 to 30 mm/s, and density of 1600 to 2000 Kg/m^3 [5].

Due to its high water filtration rate, permeable concrete has been widely used in a range of applications, such as road surfaces, walkways, parking lots, and hydraulic structures [6, 7]. Permeable concrete also benefits environmental issues by reducing soil erosion and recharging groundwater [8]. However, although the increasing porosity of permeable concrete enhances its permeability, it negatively affects its mechanical characteristics [6, 7, 9].

Mixing proportions, such as water-cement ratio and aggregate-cement ratio, significantly affect the compressive strength of permeable concrete. As its cement paste layer is very thin, failure occurs at the binder interface which joins the aggregate together, resulting in a low compressive strength that typically ranges between 5 and 30 MPa [5, 10, 11]. The compressive strength of permeable concrete was found to increase as the water-cement ratio decreased. However, this decreased its void ratio and permeability. Conversely, the permeability and void ratio were found to decrease as the cement content increased [12]. Chen et al. [9] investigated the strength, fracture, and fatigue characteristics of permeable concrete and found that porosity had a more significant impact on flexural strength than compressive strength. Furthermore, when permeable concrete and conventional concrete were compared, permeable concrete had a larger effect size. At all stress levels, polymer-modified pervious concrete exhibited significantly higher fracture toughness and fatigue life than supplemental cementitious material-modified pervious concrete. Doe and Neithalath [13] investigated the effect of porosity on the compressive behavior of permeable concrete and found that the compressive strength reduced by approximately 50% with every 10% increment in porosity.

Kevern et al. [14] investigated the effect of aggregate particle size on pervious concrete and found that the use of single-size particle aggregates significantly improved porosity but lowered strength. Furthermore, the addition of fine sand to the aggregate as well as latex to the mixing process was found to significantly increase the workability and strength of concrete. Aggregate particle size and gradation were also found to affect the porosity, permeability, and compressive strength of permeable concrete. Reducing the aggregate grain size while maintaining the same mix proportion was found to reduce the permeability parameters of permeable concrete. Moreover, the use of additives, such as a water-reducing agents, silica fume, and polymer emulsion, significantly improved the compressive strength and workability of permeable concrete while minimally affecting water permeability [10, 15, 16].

Multivariable linear regression analysis (MLRA), analysis of variance (ANOVA) is the most successful parametric method of analyzing experimental data as it is elegant, practical, and adaptable [17]. However, it is a considerably complex and subtle method to use as there are numerous ANOVA variations, each of which corresponds to a specific experimental situation. As such, it is possible to use the wrong type of ANOVA for a given experimental situation and draw incorrect conclusions from the data [18].

The majority of research on permeable concrete focuses on experimental laboratory work and performing linear regression analysis [7,19], with little emphasis on heuristics methods, particularly artificial neural network (ANN), to construct a functional correlation model that can provide better estimates when the model has several parameters that are correlated and affected by multiple variables.

Machine learning (ML) models study links between inputs and outputs using statistical methods that enable computer systems to learn from a dataset without being explicitly programmed, which could be an effective solution to regression issues [20]. Several unique ML prediction methods have been used in recent decades. Artificial neural networks (ANNs) are one of them.

ANNs are a type of artificial intelligence that has been widely employed in recent times to model human activities in a variety of science and engineering fields [21]. As traditional prediction models are built based on a predefined equation and a small set of data and parameters, if new data is slightly different from the original data, the model's coefficients as well as the form of its equations needs to be updated. ANNs, however, do not require an equation to follow a specific form. All it needs is adequate input and output data. This is because ANNs are capable of continually retraining new data, thereby allowing it to adapt to new data in a convenient manner [22]. Furthermore, ANNs can also characterize and recognize hidden non-linear patterns among large numbers of variables in extremely complex datasets by using a non-linear activation function. They can also relate and correlate distinct factors by storing data according to connection weights, thereby overcoming issues that normally emerge due to a lack of theoretical concepts [23-25].

In recent years, ANNs have been successfully implemented in a variety of civil engineering domains, such as predicting the compressive strength of blended cement-based concrete [26-29] and assessing the compressive strength of concrete subjected to high-temperature levels using destructive and non-destructive testing [30]. ANN models have also been proved to be a viable design tool for predicting the shear strength of steel fiber reinforced concrete (SFRC) beams [31] and anticipating the total bond-slip behavior of circular and square concrete-filled steel tubes (CFSTs) under push-out loading [32].

Saridemir et al. [21] developed ANN models to predict the compressive strength of metakaolin and silica fume-based concretes that had been cured for up to 180 days. The study found that ANNs could accurately estimate the compressive strength of these concretes. Udhayakumar et al. [33] stated that a neural network-based strength model could be used to successfully predict the strength development of fly ash-based concrete over the curing period. Shirgir et al. [34] used ANN to predict the permeability and compressive strength of permeable concrete. The proposed network aimed to depict a valid functional correlation between input independent variables (fine aggregate content, porosity, coefficient of uniformity, water-cement ratio, and specific gravity) and porous concrete permeability and compressive strength as output variables. Overall, data fit and replication of the proposed model were good. As such, the model can estimate permeability and compressive strength without costly lab work. Meanwhile, Chithra et al. [35] compared the performance of ANN and MLRA models in estimating the compressive strength of nano-silica and copper slag-based concretes. They concluded that ANN models had provided better predictions than MLRA models in terms of regression coefficient (R^2) and mean square error (MSE).

Al-Swaidani and Khwies [36] examined the effect of volcanic scoria (VS) on concrete characteristics. Twenty-one concrete mixes were prepared with three water-cement ratios (0.5, 0.6, and 0.7) and seven VS replacement levels (0, 10%, 15%, 20%, 25%, 30%, and 35%). ANN and MLRA were used to predict the compressive strength, porosity, and water permeability of the concrete mixes. It was found that ANN models captured the effects of cement content, VS content, water content, superplasticizer content, and curing duration more accurately than MLRA analysis. Curing time, cement content, VS content, water content, and superplasticizer content significantly impact concrete properties when VS is used as a cement replacement, with curing time being the most influential.

ANN prediction models were also observed to outperform regression methods in several engineering applications, including water level predictions [37], steel surface roughness and tool wear predictions [38,39], and dams deformation predictions under environmental loads [40].

Recent literature for the permeable concrete indicated that ML techniques were used to predict the permeability of permeable concrete [41], with authors emphasizing that permeability is the most crucial functional performance for the permeable concrete. ANN methods were also used to evaluate the compressive strength, porosity, and permeability of permeable concrete [42]. In addition, several correlations were constructed to investigate the density, porosity, and permeability of permeable concrete [43].

This study employed ANN and MLRA to develop predictive equations for the compressive strength, porosity, and water permeability of permeable concrete. The two prediction algorithms were then compared to determine which algorithm could predict these parameters more accurately. Water-cement ratio and aggregate-cement ratio were also used as inputs in the developed models due to their significant impact on the properties of permeable concrete [44-46]. In addition, the density of the concrete was inputted into the models instead of aggregate characteristics, such as size and gradation, because density is easier to measure and more accurately reflects the effect aggregate characteristics have on concrete properties [47, 48]. The analysis was conducted on 409 specimens collected from five different studies.

2. Methodology and Data Collection

In this study, Multiple linear regression analysis (MLRA) and artificial neural network (ANN) were used to predict the unconfined compressive strength (CS), porosity (Por), and water permeability (Per) of permeable concrete. The models were developed to predict these properties with concrete mixing proportions, specifically, water-cement ratio (W/C) and aggregate-cement ratio (A/C). Concrete density (D) was used as an input in the prediction as density is easier and more inexpensive to measure.

2.1. Multiple Linear Regression Analysis (MLRA)

MLRA is a statistical method used to generate the correlation between a dependent or response variable (i.e., a desired outcome) and multiple independent regression variables. This technique is widely used in material modelling, especially of concrete properties [49, 50]. A statistical and mathematical methodology as well as experimental data is all part of this modelling strategy. In research-based studies, MLRA can be utilized for a variety of purposes and has been used for a while as it offers the benefit of creating simple regression constants and assessing the relevance of diverse input variables [51]. The general MLRA equation is shown below (Equation 1), with the dependent variable being a linear function of multiple independent variables.

$$Y = \alpha + \beta_1 X_a + \beta_2 X_b + \ldots + \beta_k X_k \pm e \quad (1)$$

Where Y is the dependent variable; α is the Y-intercept; β_1, β_2, and β_k are the slopes associated with X_a, X_b, and X_k, respectively; X_a, X_b, and X_k are the independent variable values; and e is the error.

2.2. Artificial Neural Networks (ANNs)

ANNs are nonlinear mapping systems that consist of basic processors called neurons connected by weighted connections. A first wave of interest in neural networks arose after the introduction of simpler neurons by McCulloch and Pitts [52]. In neural networks, each neuron receives inputs and produces an output that can be seen as a representation of the local information stored in the connections. Interconnections allow the output signal of a neuron to be sent to other neurons as input. Complex functions can be performed by linking several neurons as the capability of a single neuron is limited. The effectiveness and performance of trained neural networks have been conclusively proven to be influenced by the organization of the neural network, data representation, input-output normalization, and suitable activation function selection [53]. These simple processing units (neurons), with dense parallel interconnections, can produce meaningful answers even when the input to be processed contains errors or is incomplete. It can also analyze data exceptionally quickly when used in real-world issues [54].

This present study used feedforward backpropagation (FB) to create the ANN models. The structure of the FB network is layered with at least three layers: an input layer, an output layer, and one or more hidden layers that allow data to flow from input to output and vice versa. The input layer has the same number of neurons as the input variables of the problem while the output layer has the same number of neurons as the desired number of values derived from the inputs [55]. The hidden layers, however, may have a significant number of hidden processing units depending on the complexity of the phenomenon being modelled. Nonetheless, all issues that can be solved by perception, can be solved with just one hidden layer [56]. Furthermore, the majority of FB-based ANNs have network designs with only one hidden layer [57].

Increasing the number of training samples provides the network with more knowledge on the geometry of the solution surface, thereby increasing the potential accuracy of the network. Conversely, insufficient data samples cause the network to be disorganized. The best data set for training is one that fully covers the modelling domain and has the fewest number of repeating samples (i.e., identical inputs with different outputs). Therefore, 80% of the dataset were chosen at random for calibration (training) while the remaining 20% was used to test the model. The training dataset was used to compute the gradient and update the weights and biases while the testing dataset was used to test the model and optimize its structure. It is noteworthy that ANN is a feasible tool and is widely used to estimate the mechanical properties of concrete [58].

2.3. Experimental Database

The database analyzed in this current study was collected from previous experimental studies [44, 59-62]. Table 1 lists the number of specimens selected from each literature as well as the minimum and maximum ranges of the studied parameters and the mean and standard deviation values of all specimens analyzed. This included specimens chosen for both training and validation.

Table 1. Test results of specimens obtained from multiple existing studies

Reference	No. of Specimens	Range	Water-Cement Ratio (W/C)	Aggregate-Cement Ratio (A/C)	Density (D) (kg/m3)	Compressive Strength (CS) (MPa)	Porosity (Por) (%)	Permeability (Per) (cm/sec)
Ng et al. (2019) [59]	15	Min.	0.36	4.46	1455.98	1.71	12.16	0.34
		Max.	1.24	17.56	1767.75	8.81	14.85	0.99
Thorpe & Zhuge (2010) [60]	5	Min.	0.28	4.00	1926.00	19.00	7.50	0.40
		Max.	0.36	4.00	2248.00	33.20	16.60	1.26
Liu et al. (2021) [61]	9	Min.	0.26	3.17	1957.87	14.30	15.00	1.03
		Max.	0.34	5.40	2178.85	25.60	25.00	1.61
Joshi & Dave (2016) [44]	9	Min.	0.30	4.00	2010.47	9.33	19.56	1.21
		Max.	0.40	4.00	2240.99	14.07	25.99	2.09
Mehrabi et al. (2021) [62]	371	Min.	0.34	2.25	1577.90	8.00	20.70	2.11
		Max.	0.72	8.58	1883.80	28.60	35.70	3.44
Min.			0.26	2.25	1455.98	1.71	7.50	0.34
Max.			1.24	17.56	2248.00	33.20	35.70	3.44
Mean			0.49	5.30	1750.84	17.16	27.22	2.57
Standard Deviation			0.15	2.04	120.73	4.98	4.77	0.58

3. Analysis and Discussion

3.1. Multiple Linear Regression Analysis (MLRA) Modeling

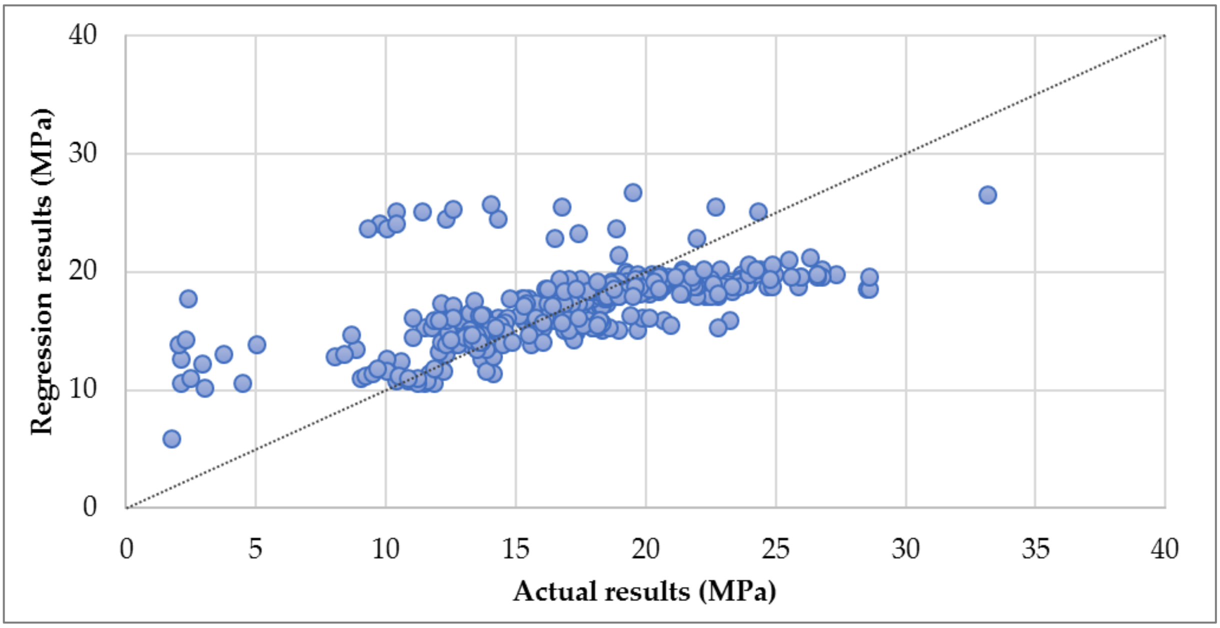
In the present study, 369 sets of data were used to develop the MLRA models to indicate the effects of W/C, A/C, and D on the CS, Por, and Per of permeable concrete (Equations 2, 3, and 4). The ANOVA as well as the parameter estimates of each model was found to be significant, with a 95% confidence level. The developed equations were:

$$CS = -15.915 * \frac{W}{C} + 0.397 * \frac{A}{C} + 0.016 * D - 4.804 \quad (2)$$

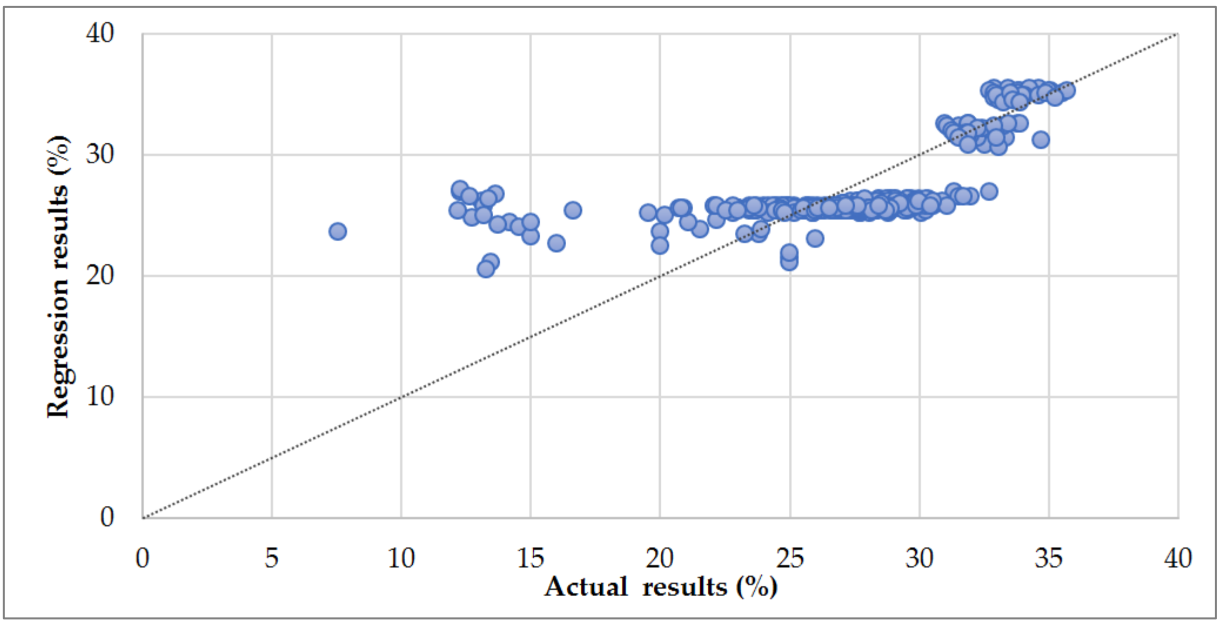
$$Por = 24.113 * \frac{W}{C} - 2.074 * \frac{A}{C} - 0.006 * D + 36.572 \quad (3)$$

$$Per = 2.635 * \frac{W}{C} - 0.236 * \frac{A}{C} - 0.0005 * D + 3.364 \quad (4)$$

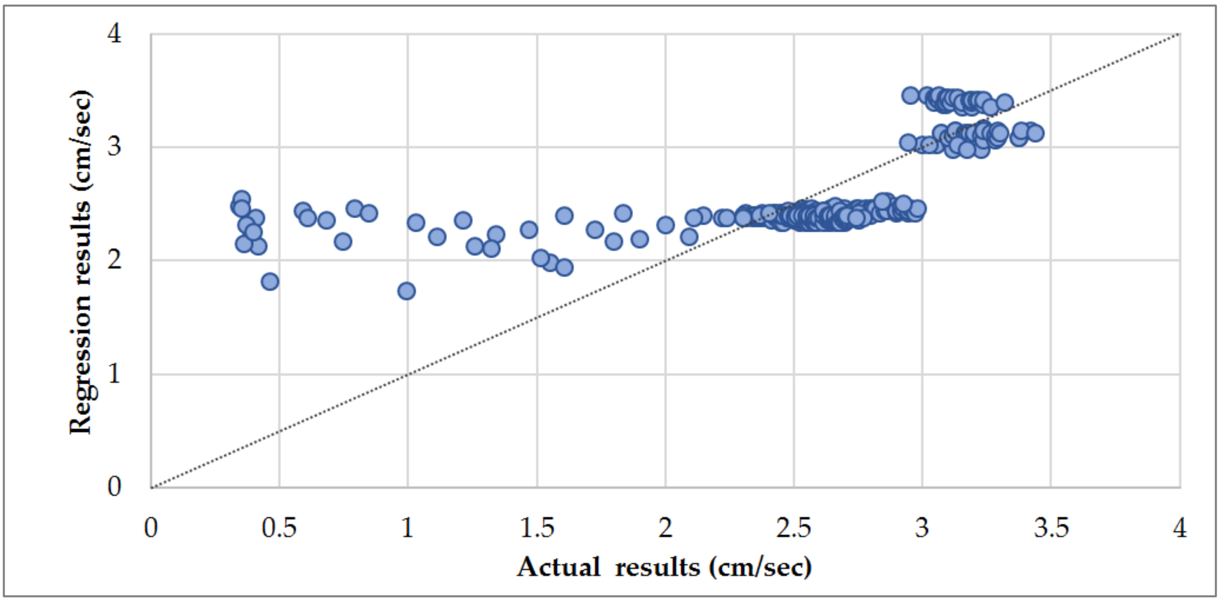
Based on the analysis, the coefficient of determination (R^2) of Equations 2, 3, and 4 were 0.37, 0.42, and 0.32, respectively. Figure 1 shows the actual dataset plotted against the MLRA prediction values for CS, Por, and Per. Clearly, the developed models were not strong enough to predict the CS, Por, and Per to a high degree of accuracy. This was reflected by the low R^2 levels obtained.



(a) Compressive strength



(b) Porosity



(c) Permeability

Figure 1. Training results of the regression model vs. actual data

3.2. Artificial Neural Network (ANN) Modeling

In order to develop an ANN model to predict the CS, Por, and Per of permeable concrete, the 369 sets of data were divided into 294 training and 75 testing datasets. Training dataset was used to optimize the connection link weights of the network for different networks with a varying number of hidden nodes from 1 to 15. The average squared errors (ASE), mean absolute relative error (MARE), and coefficient of determination (R^2) of each trained network were measured and listed to determine statistical accuracy. The testing dataset was utilized to test the trained networks. The trained network with the lowest ASE for testing dataset was defined as the network with the optimum number of hidden nodes. After the optimization, both training and testing datasets were used to train the optimum network to determine the connection link weights of the train-all model. As seen in Figure 2, the optimum number of hidden nodes to be used in the ANN model was five. This was because the network had the lowest $ASE_{testing}$ value at this number of hidden nodes. It is worth mentioning that sigmoidal activation function was used in the network.

Figure 3 shows a 3-5-3 (3 inputs, 5 hidden nodes, and 3 outputs) ANN model schematic. The mathematical equations of the 3-5-3 ANN could be written as seen in Equations 5 and 6.

$$Output_m = \frac{1}{1+e^{-\sum_{i=1}^{5} HN_i*(HN_i - Output_m\ Connection)+Bias_{2m}}} \quad (5)$$

$$HN_i = \frac{1}{1+e^{-\sum_{j=1}^{3} Input_j*(Input_j - HN_i\ Connection)+Bias_{1i}}} \quad (6)$$

After defining the optimum number of hidden nodes, both training and testing datasets were used to train the network to develop the final model and obtain the connection link weights. Table 2 lists the connection link weights of the final model. The statistical accuracy measurements of the final model were ASE = 0.002863, MARE = 8.826, and R^2 = 0.8286. The R^2 of the CS, Por, and Per were 0.75, 0.82, and 0.91, respectively. Figure 4 shows the actual dataset vs. the ANN predicted results for training and testing specimens used to train the final model. Both the statistical accuracy measurements as well as Figure 4 show that the developed model was strong enough to predict the CS, Por, and Per with an acceptable degree of accuracy.

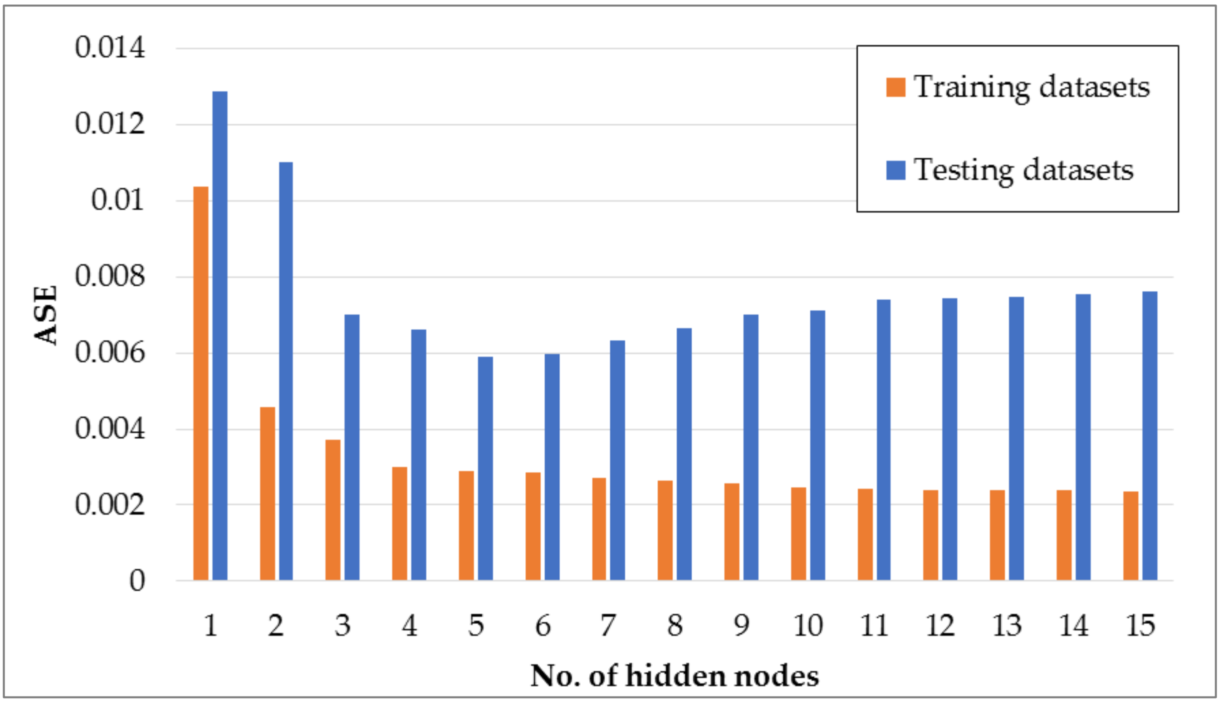


Figure 2. The ASE values of networks with different numbers of hidden nodes

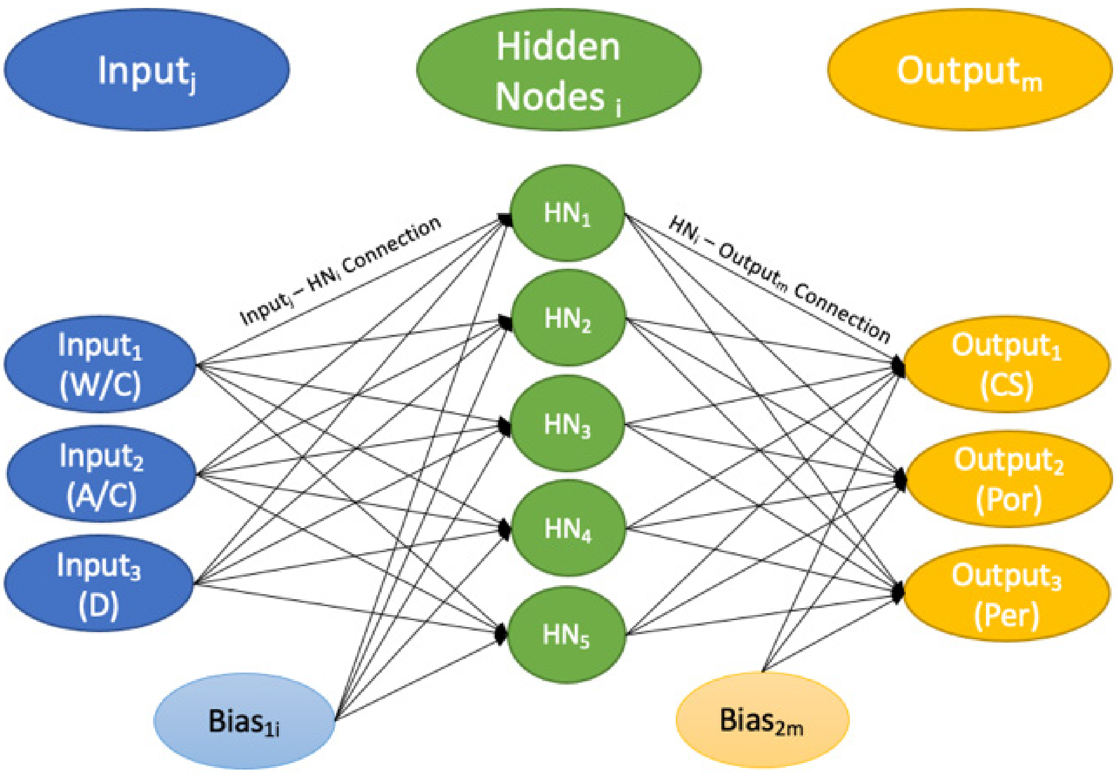
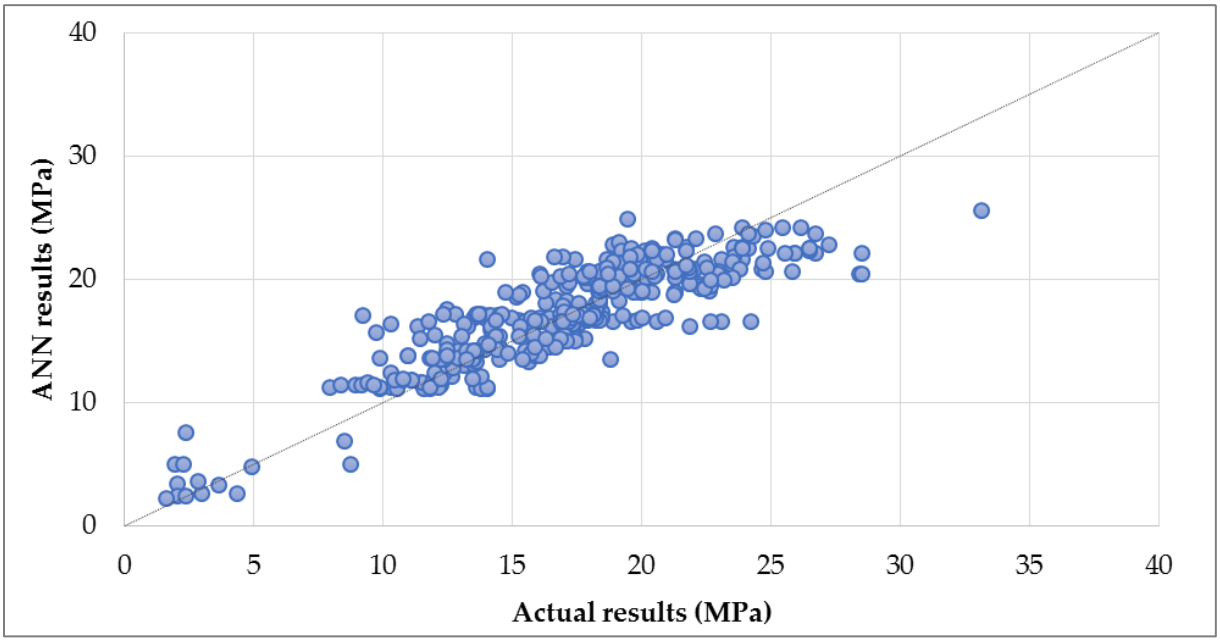
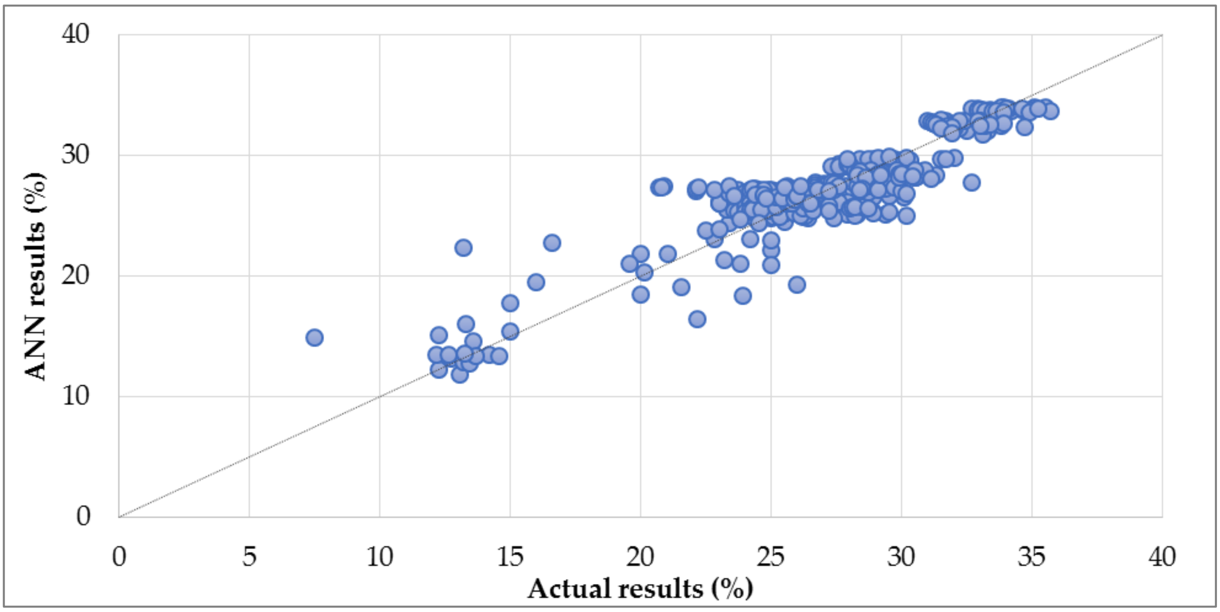


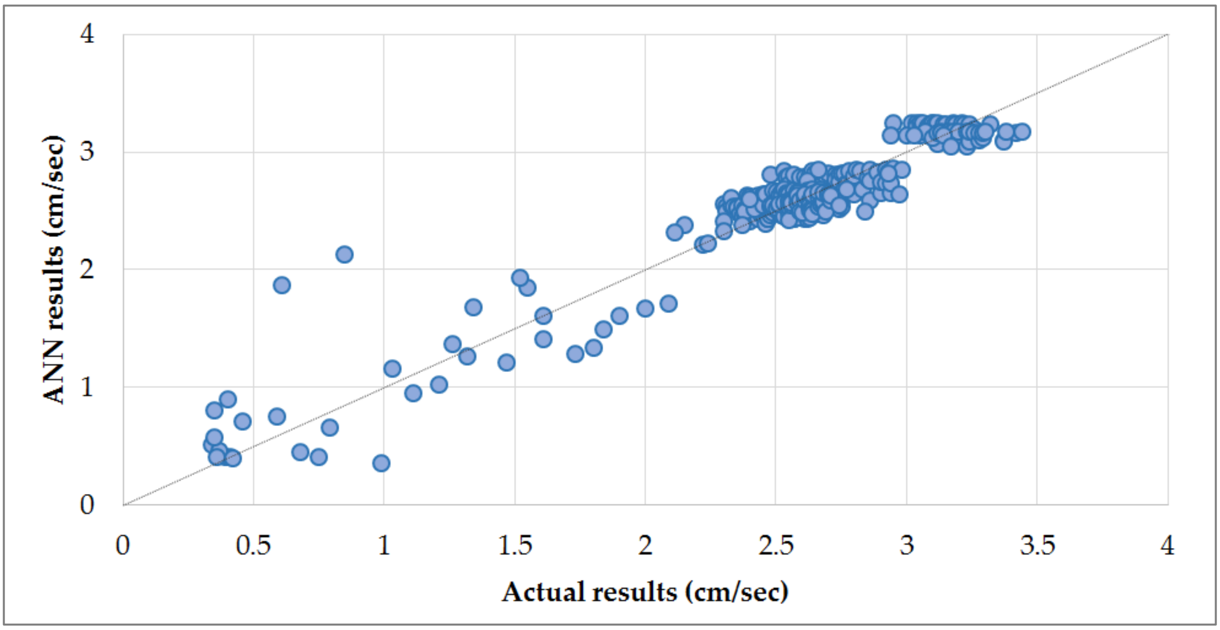
Figure 3. Schematic of the developed 3 inputs, 5 hidden nodes, and 3 outputs ANN model



(a) Compressive strength



(b) Porosity



(c) Permeability

Figure 4. Training results of the ANN model vs. actual data

Table 2. Connection link weights used in the 3-5-3 ANN model

Connection link weights between inputs and hidden nodes ($Input_j$ - HN_i connection)						
$Input_j$	HN_1	HN_2	HN_3		HN_4	HN_5
Water-Cement Ratio (W/C)	-28.6010	7.5392	8.4079		-6.7092	-2.8375
Aggregate-Cement Ratio (A/C)	38.7610	-11.0090	-12.3300		2.1700	-0.3321
Density (D)	-22.9090	-16.0010	-19.4870		7.4561	-7.4188
$Bias_1$	3.0208	6.7226	12.9170		-4.6617	1.0864
Connection link weights between hidden nodes and outputs (HN_i – $Output_m$ connection)						
$Output_m$	HN_1	HN_2	HN_3	HN_4	HN_5	$Bias_2$
Compressive Strength (CS)	-2.1851	-1.1844	4.3207	7.7503	4.2481	-4.5073
Porosity (Por)	-2.1059	1.4339	-0.8967	-3.1137	-3.2726	1.4997
Permeability (Per)	-3.4866	1.0364	-0.2567	-3.2185	-1.4674	0.8455

3.3. Discussion

In order to compare the performances of the ANN and MLRA models, 40 sets of data were used to validate the models. The validation dataset was not used to create the obtained models. Table 3 provides a comparison of the mean values (μ), standard deviations (σ), and R^2 of the developed models based on the prediction results for the validation dataset. These results indicated that the ANN model was more appropriate to model the aforementioned parameters than the MLRA model. Unlike the MLRA model, the σ of the ANN model was closer to zero (0.097 - 0.104) and it had a higher R^2 (0.736 - 0.934).

Figure 5 illustrates the CS, Por, and Per values predicted using the MLRA and ANN models versus the actual values obtained from the cited literature for the validation dataset. The CS, Por, and Per that the ANN model predicted were closer to the 45^o line than that the MLRA model predicted. This indicated that the ANN model had a better performance in the validation of specimens.

After model validation, the developed 3-5-3 ANN model is applied to the investigation of the relationships between mixing proportions (W/C and A/C) and PC properties (CS, Por, and Per). Based on the ANN model prediction results of permeable concrete with an average density of 1750 kN/m^3, Figures 6(a), 6(b), and 6(c) are generated to illustrate the relationships between the mixing proportions and the compressive strength, porosity, and permeability of permeable concrete, respectively.

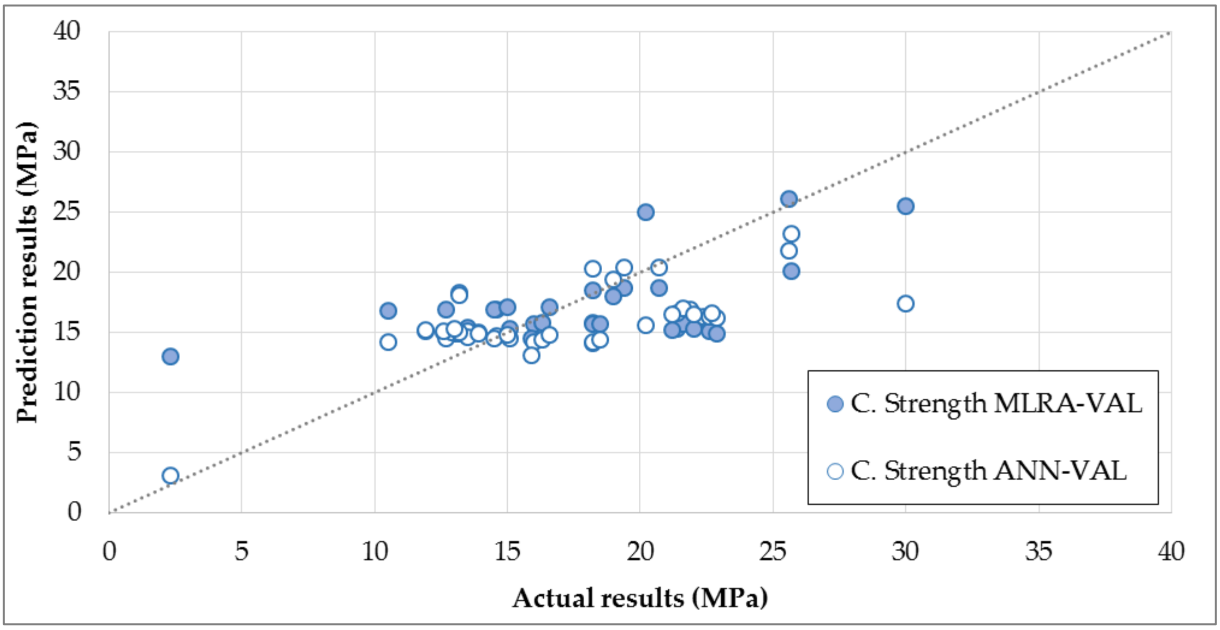
The results illustrated in Figure 6(a) show that for low

A/C ratios (2.5 and 5), increasing the W/C in the permeable concrete mix from 0.3 to 1.2 reduces the compressive strength by 50%. However, the optimal W/C ratios for mixtures with A/C ratios of 7.5 and 10 are 0.6 and 0.9, respectively. On the other hand, increasing the W/C while keeping the A/C constant will result in an increase in both porosity and permeability. The effect of increasing W/C on porosity and permeability is greater for mixtures with low A/C than those with high A/C.

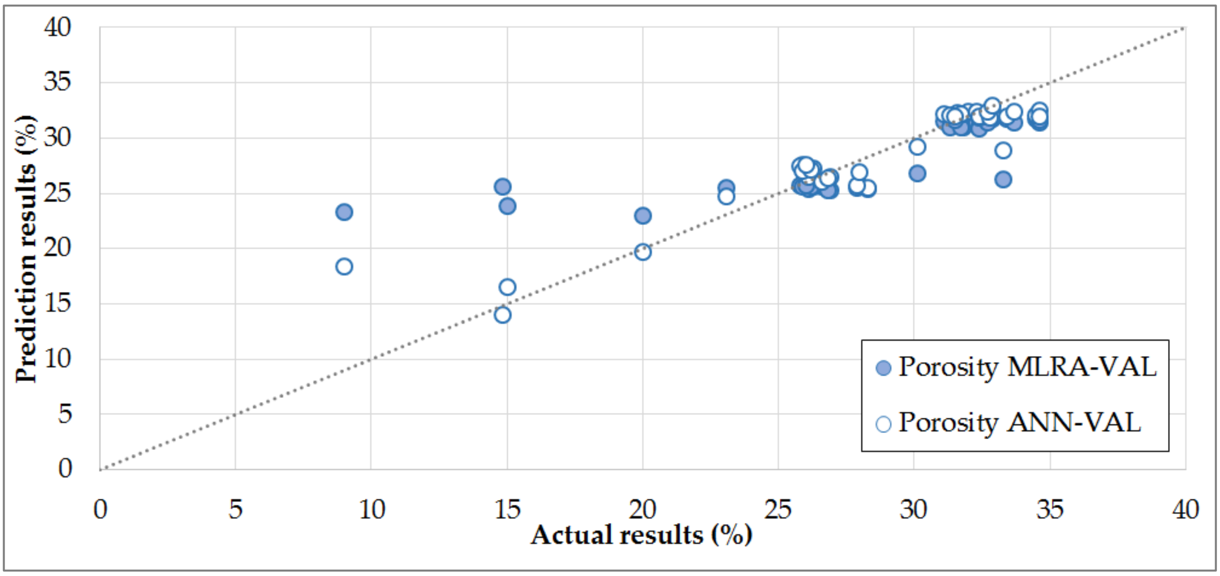
For mixes with low W/C, increasing the A/C while keeping the W/C constant will increase both porosity and permeability. As shown in Figures 6(b) and 6(c), changing the A/C has no effect on these properties of mixtures with a high W/C. (c). These results are in good agreement with the experimental findings of Lian and Zhuge [7].

Table 3. Comparison of the mean values, standard deviations, and coefficient of determination of the proposed MLRA and ANN models for validation specimens

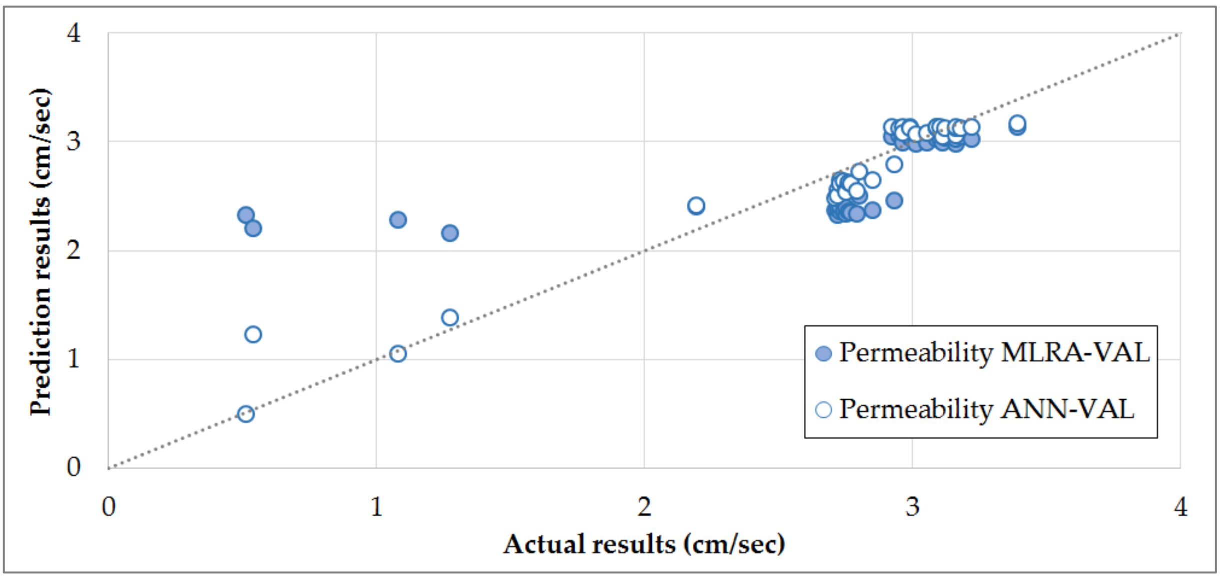
Output	MLRA results			ANN results		
	Mean (μ)	Standard Deviation (σ)	Coefficient of determination (R^2)	Mean (μ)	Standard Deviation (σ)	Coefficient of determination (R^2)
Compressive Strength (CS)	1.041	0.275	0.301	1.093	0.129	0.736
Porosity (Por)	1.002	0.151	0.638	0.997	0.097	0.886
Permeability (Per)	1.005	0.230	0.398	0.999	0.104	0.934



(a) Compressive strength

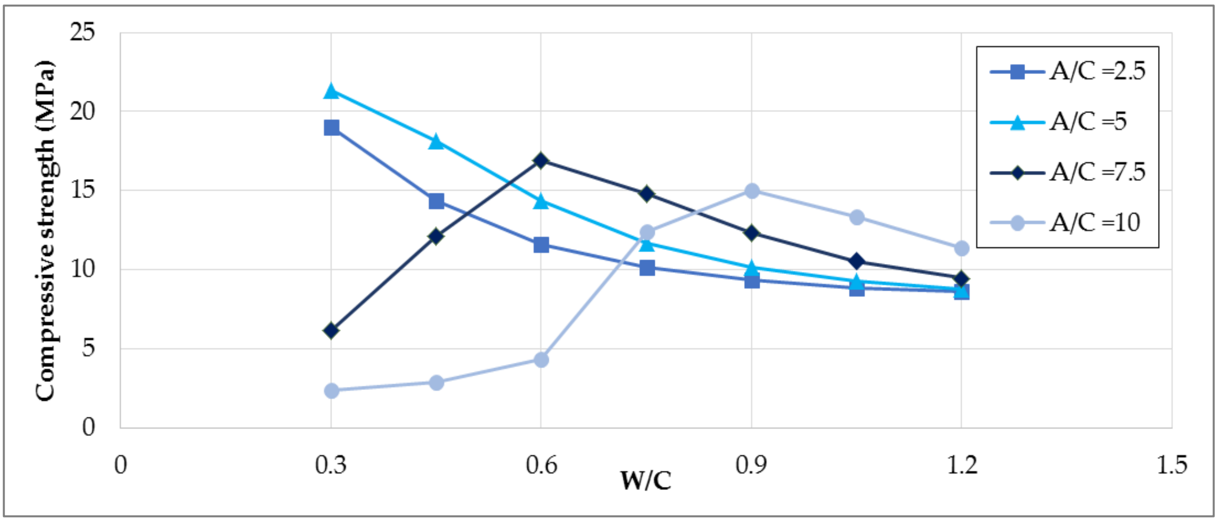


(b) Porosity

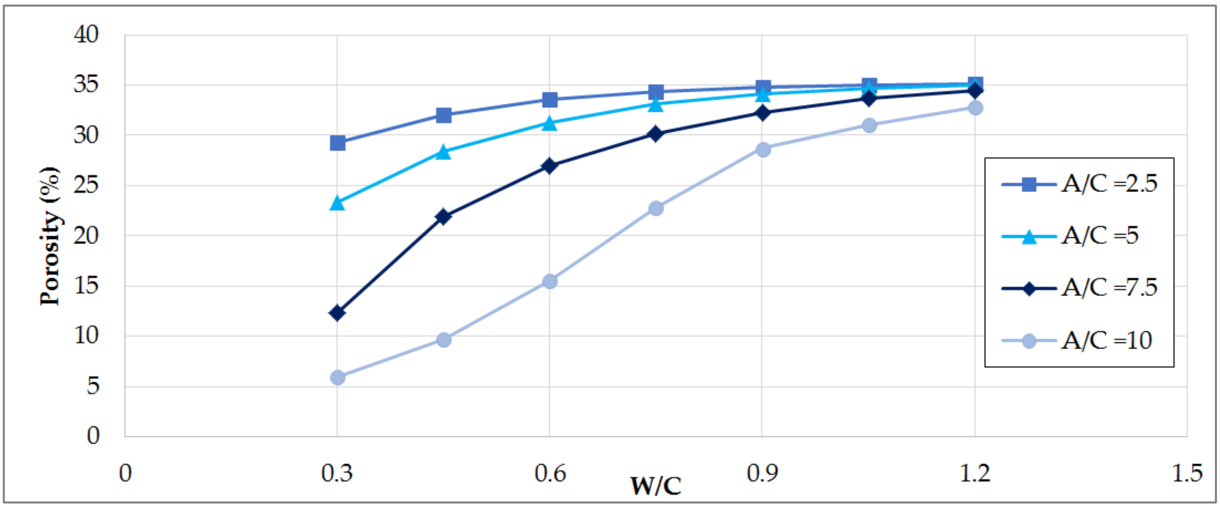


(c) Permeability

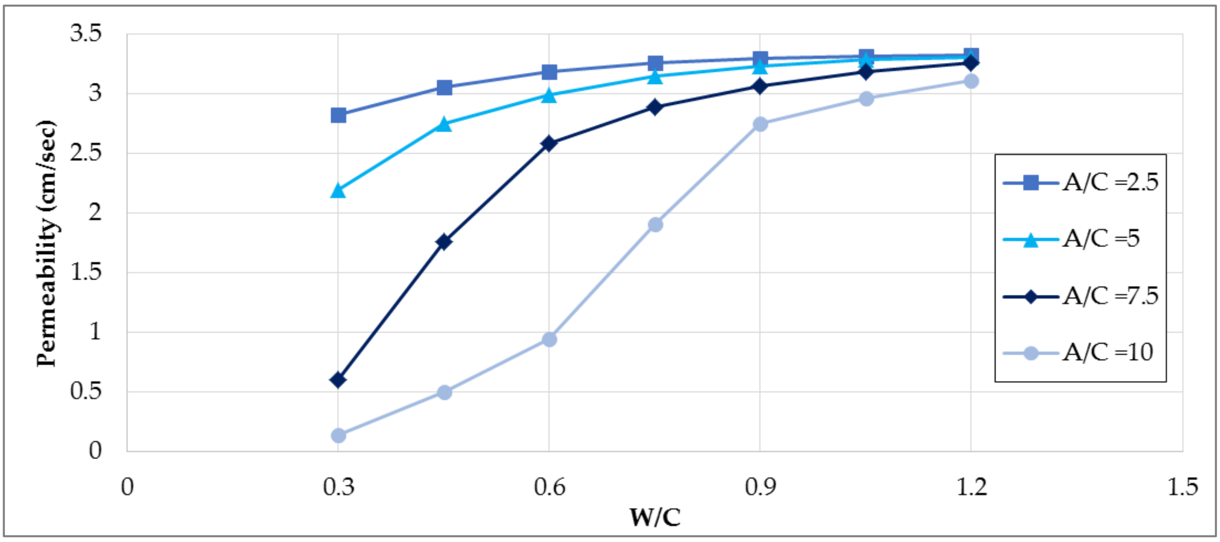
Figure 5. Predicted (a) compressive strength, (b) porosity, and (c) permeability parameters of the ANN and MLRA vs. the actual results of the validation specimens



(a) Compressive strength (CS)



(b) Porosity (Por)



(c) Permeability (Per)

Figure 6. Relations between PC mixing proportions (W/C and A/C) and PC properties (CS, Por, and Per)

4. Conclusions

In this study, artificial neural network and Multiple linear regression analysis are used to predict compressive strength, porosity, and water permeability of permeable concrete. Both models are based on experimental data collected from different cited literature. Inputs, specifically water-to-cement ratio, aggregate-to-cement ratio, and density, are used in the models to obtain a reliable functional relationship. The results reveal that the ANN model is better at predicting the compressive strength, porosity, and water permeability of permeable concrete. Based on mean values, standard deviation, and coefficient of determination of the ANN and MLRA models, the ANN model is the more appropriate model to predict the properties of permeable concrete. The ANN model also provides the lowest σ and the highest R^2 of all the permeable concrete properties investigated. Based on the relations drawn between the different parameters in this study, the theoretical outcomes of the ANN model comes in a good agreement with the previously published experimental studies. Therefore, the developed ANN model can be used by practitioners in the field to anticipate the properties of permeable concrete without expensive and time-consuming experimental laboratory works. On the other hand, the results of this study showed that using the mixing proportions and density are not enough to give high predictability of permeable concrete compressive strength. So that, it is recommended to include aggregate properties such as maximum aggregate size, uniformity coefficient, and coefficient of gradation into the model in further studies.

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