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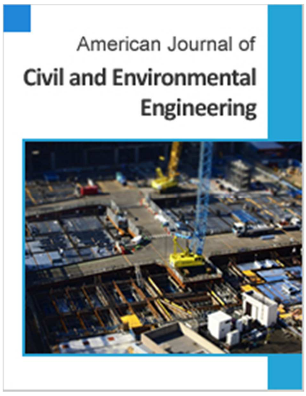

Application of ANN and RBF to Optimize the Properties of the RCC Pavement Containing RHA

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Abstract

An ANN is a system based on the operation of biological neural networks. ANNs have been used in many different applications such as control, electronics, and communications. In this paper, the accurate models based on ANN and RBF in order to predict the permeability and compressive strength in the roller compacted concrete (RCC) pavement specimens with the different contents of the added rice husk ash (RHA) as a supplementary material are presented. The obtained results from the proposed RBF and ANN models are compared with each other and with the experimental data, which show a good agreement between the predicted values and the experimental data. The proposed ANN model is more accurate and reliable than the proposed RBF model. According to the results of this study, the optimal content for increasing of the compressive strength and reducing of permeability was obtained by substituting 9% and 11% of the cement by RHAin gyration number 70, respectively. However, adding a little more than 11% RHA reduced the compressive strength.

1. Introduction

Roller compacted concrete (RCC) is a zero-slump concrete consisting of dense-graded aggregate and sand, cementations materials, and water. Because it contains a relatively small amount of water, it cannot be placed by the same methods used for the conventional concrete. RCC is drier, and looks and feels like damp gravel. It does not require any forms, dowels, reinforcing steel & finishing. Also, the method of compaction is different than the conventional compacted concrete and it is compacted by vibratory or pneumatic-tired rollers [1]. If well designed, the RCC will develop high compressive strength and good durability, i.e. ±60 MPa at 7 days. Moreover, this type of concrete is less sensitive to cracking in relation to the drying shrinkage. Because of its rapid setting, RCC is especially used in road and dam construction. The RCC is quite economic (low cost production and rapid installation) and on the contrary to bituminous binder, it develops high compressive strengths, suitable for the covering roadways [2]. According to the literatures, RCC was firstly used in a timber manufacture plant site in Vancouver during the initials of 1970. The performance of RCC in this site which was under heavy loading traffic and severe abrasive effects was reported to be successful. Since then, RCC pavements have been extensively used in the industrial pavement areas in Canada. In Europe, RCC was initially used in low traffic roads of Spain. Also since 1984 many parking lots and heavy duty military camps were paved by RCC in Texas State of America. After the oil crisis during the 1970 decade, due to the higher construction costs, many conventional asphalt pavements were widely replaced by RCC pavements. In comparison to the flexible pavement, a reduced construction cost of 30% has been reported in the literatures [3]. When compared to conventional pavement and other types of concretes, RCC typically has a higher volume of aggregate and lower binder and water contents, and hence, reduced paste volume. For a given binder content, RCC will typically offer higher strength than the corresponding conventionally compacted pavement concrete [4]. In the last decade, the use of supplementary cementing materials has become an integral part of high strength and high performance concrete mix design. These can be natural materials, by-products or industrial wastes, or the ones requiring less energy and time to produce [5]. One of the most promising materials is rice husk ash (RHA) [6]. Rice husk is produced in millions of tons per year as a waste material in agricultural and industrial processes. It can contribute about 20% of its weight to RHA after incineration. RHA is a highly pozzolanic material [7]. Good pozzolanic activity in RHA results from high specific surface area (100-200 m^2/g), small particle size (<10 μm), low carbon content (<6-8% by weight), and most importantly, high amorphous SiO_2 content (80-90% by weight), among other factors [8]. There are some studies concerning the effect of the RHA on the mechanical properties of the roller compacted concrete pavements (RCCP). During a laboratory study, natural RHA has been utilized in order to partially substitute the mineral aggregate in diverse proportions within the RCC dosage. It was concluded that the addition of 5% RHA to the RCC improves the compressive strength, flexural strength, and modulus of elasticity values. The addition of 5% RHA in the RCC also decreases the cement consumption necessary to reach the desired flexural strength and the quantity of necessary mineral aggregates in RCC dosage [9]. In a similar study, the effects of RHA on the mechanical properties of RCC designed with the original and reclaimed asphalt pavement (RAP) materials have been investigated. The RCC mixes have been produced by the partial substitution of cement with RHA at varying amounts of 3% and 5%. It has been concluded that the addition of 3% RHA reduces the porosity especially after 120 days curing and improves the fatigue resistance. However, the addition of RHA to 5% resulted in the higher porosities and the lower fatigue lives [3]. During an another laboratory research, the effects of addition of RHA in the partial substitution of the mineral aggregate and its influence on the compressive strength, flexural strength and the modulus of elasticity have been investigated. The results revealed that the optimal value for these properties is obtained by substituting 5% of the aggregate by RHA [10]. In this study, the use of artificial neural network (ANN) and radial basis function (RBF) in predicting the permeability and compressive strength in the roller compacted concrete pavement specimens with the different contents of added rice husk ash (RHA) as a supplementary Material is investigated. Mixtures of RCC are dosed, containing 0, 5%, 15%, 30%, 45% and 50% RHA, replacing the cement.

2. Experimental Program

2.1. Materials

An ASTM type I cement of Esfahan cement factory is used. The RHA (used in this work is made in 2 stages: first by burning the husk in free air condition in a special furnace for about 2 hours and then by burning the husk in the electric arc furnace with the capability of discharging the CO_2 content of RHA (Figure 1). The burning temperature is within the range of 530°C to 650°C.

(a) (b)

Figure 1. *Furnace used in this research:(a) Carbonation stage (free air condition), (b) Dicarbonation stage (electric arc furnace).*

The ash was then ground using a ball mill (Figure 2) for 30 minutes and in a disk mill (Figure 3) for 15 minutes. XRD and XRF analysis was performed to determine the level of the silicon dioxide and the silica phases of the produced RHA powder. According to the chemical characteristics by XRF analysis, the RHA has a high level of silicon dioxide, approximately 86%. Also, XRD analysis results showed that the silica is in the amourph phases. This silica is suitable for the pozzolanic reaction with cement.

Figure 2. *Ball mill.*

Figure 3. *Disk mill.*

The fine aggregates include of combination of the natural and crushed sand and the coarse aggregates are the crushed stones with the maximum nominal size of ¾in (19mm). The fine aggregates include of 13% lime filler, 78% crushed sand and 9% natural sand. The comparison of combined gradation of aggregates with ACI 325.10R gradation specifications are given in Figure 4. The water is drinkable water.

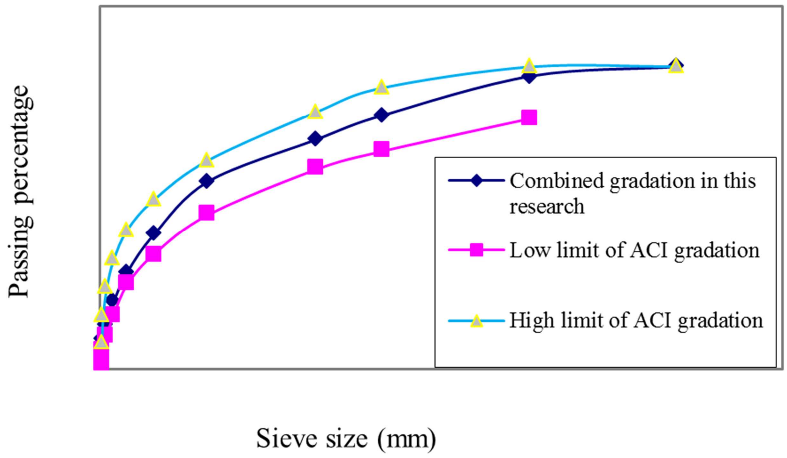

Figure 4. *Comparison of combined gradation with ACI gradation specifications.*

2.2. Mix Combinations and Samples Preparation

The mix proportion of the materials is done based on the soil compaction procedure (standard ASTM D1557). Table 1 presents the composition of the produced and tested concretes. The samples are compacted and prepared with Servopac Gyratory compactor machine in the cylinder molds with 150 mm diameter and 200 mm height. The samples are kept in the water basin for 24 hours and then, they are tested for the compressive strength and the permeability in 7 and 28 days.

Table 1. *Concrete mixture proportions in this research.*

Mix number	OptimalW/(C+RHA) ratio	Water Lit/m^3	Cementitious materials		
			RHA Kg/m^3	Cement Kg/m^3	RHA /Cement (%)
Rcc-P0	0.48	131.52	0	274	0
Rcc-P5	0.5	137	13.7	260	5
Rcc-P15	0.53	145.22	41.1	233	15
Rcc-P30	0.6	164.4	82.2	192	30
Rcc-P45	0.646	177	123.3	151	45
Rcc-P50	0.648	177.55	137	137	50

***Table 1.** Continued.*

Mix number	Total of cementitious material (Kg/m^3)	Cement weight by the total dry materials (%)	Aggregates SandKg/m^3	Gravel Kg/m^3	(Gravel/Sand) ratio
Rcc-P0 Rcc-P5 Rcc-P15 Rcc-P30 Rcc-P45 Rcc-P50	274	13	1155.42	935.55	45.55

3. Computational Intelligence

3.1. Artificial Neural Network

An ANN [11, 12] is a system based on the operation of biological neural networks. ANNs have been used in many different applications such as control, electronics, and communications. Multi-layer perceptron (MLP) networks [13] are the most widely used neural networks that consist of a great number of processing elements called neurons. Neurons are the basic processing elements of neural networks. The synapses of the biological neurons are modeled as weights in the networks. These weights are adjusted based on an error-minimization technique called back-propagation rule. Thus, ANN is a typical non-mechanistic model for modeling complex information and is known to have two intrinsic advantages. The first is its flexible capacity in apprehending the data used for training. Being intrinsically nonlinear, a trained ANN can grasp certain subtle patterns that tend to be overlooked by common statistical methods. The second advantage is its high predictive accuracy, i.e., the predictive capability for ‘‘new’’ data (untrained data). ANNs are the mathematical models, consisting of simple processing elements named neuron running in parallel which are interconnected by weighted and can be generated as one or multiple layers. Figure 5 shows the structure of a neuron where $U_1, U_2, ..., U_t$ are the inputs, $W_{1,1}, W_{1,2}, ..., W_{1,t}$ are the connection weights, b is the bias term and f is the transfer function. The output of the neuron is given by:

$$O = f\left(\sum_{i=1}^{t}\left(U_i W_{1,i}\right) + b\right) \quad (1)$$

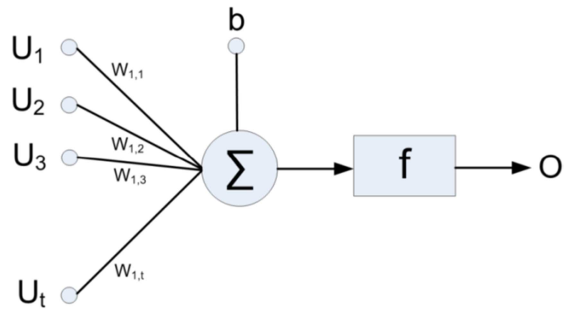

***Figure 5.** The structure of a neuron.*

The ANN structure used in this study is shown in Figure 6. This is called MLP. The MLP networks have minimum three layers one input layer, one or more hidden layer and one output layer. Each layer has a number of processing units (neurons) and each unit is fully connected to all of the units in the preceding layer. In Figure 6, $X_1, X_2, ..., X_n$ are the inputs, $Y_1, Y_2, ..., Y_m$ are the outputs, n is the number of inputs, m is the number of outputs, i is the number of neurons in the first hidden layer and j is the number of neurons in the second hidden layer.

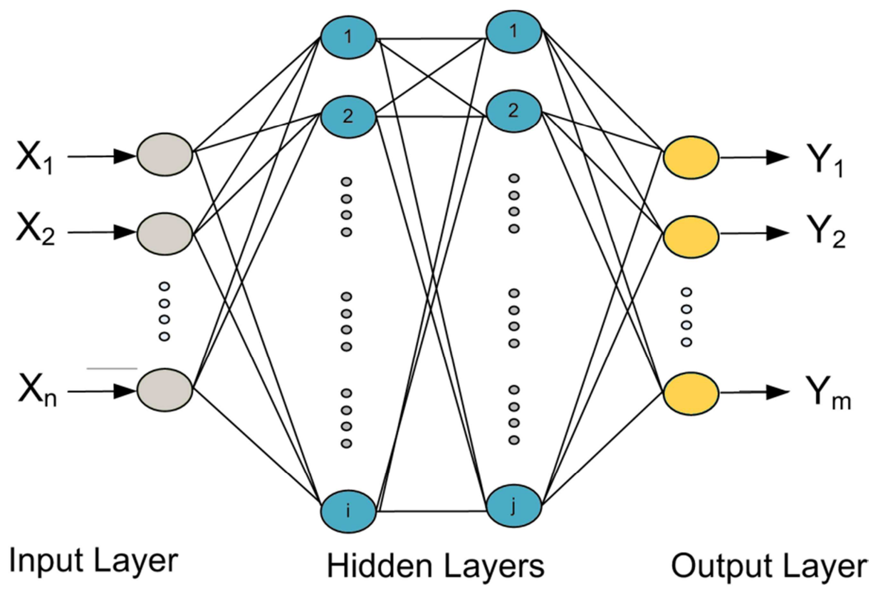

***Figure 6.** MLP neural network.*

3.2. Redial Basis Function

A RBF [14, 15] network is an ANN that uses RBFs as the activation functions. RBFs can fit erratic data. They are used in function approximation, time series prediction, and control due to their good approximation capabilities, faster learning algorithms and simpler network structures. The RBF has a feed forward structure and typically has three layers: an input layer, a hidden layer with a non-linear RBF activation function and a linear output layer as shown in Figure 7. The input layer is made up of the source nodes that connect the network to its environment. The hidden layer consists of a set basis function unit that carry out a nonlinear transformation from the input space to the hidden space. The transformation from the input to the hidden layer is nonlinear and from the hidden layer to the output layer is linear. The output from j^{th} neuron of the hidden layer is given by:

$$Z_j = K\left(\frac{\|x-\mu_j\|}{\sigma_j^2}\right) \qquad j = 1,2,..,k \qquad (2)$$

where K is a strictly positive radially symmetric function (kernel) with a unique maximum at its center (μ_j), which drops off rapidly to zero away from the center. The number of neurons in the hidden layer is k, and σ_j is the width of the receptive field in the input space from unit j. This indirectly indicates that Z_j has a desired value only when the distance $\|x-\mu_j\|$ is smaller than σ_j. The output of the m^{th} neuron in the output layer is given by:

$$y_m(x) = \sum_{j=1}^{k} w_{jm}\, z_j(x) \qquad m = 1,2,..,M \qquad (3)$$

where w_{jm} is the weighting factor.

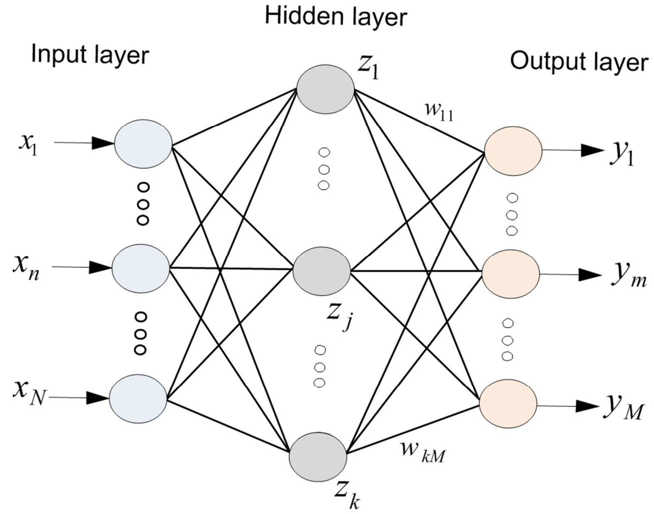

Figure 7. RBF structure.

4. Modeling Approach

In this paper, the accurate models based on the MLP neural network and RBF in order to predict the permeability and compressive strength are presented. The proposed models are shown in Figure 8. In this figure, the input parameters are the mix number and the gyration number and the output parameters are the permeability and the compressive strength. The data set required for training the ANN and RBF models is obtained using the experimental data. The experimental data are divided into two sets: training (about 70%) and testing (about 30%). MATLAB 7.0.4 software was used for training the proposed models.

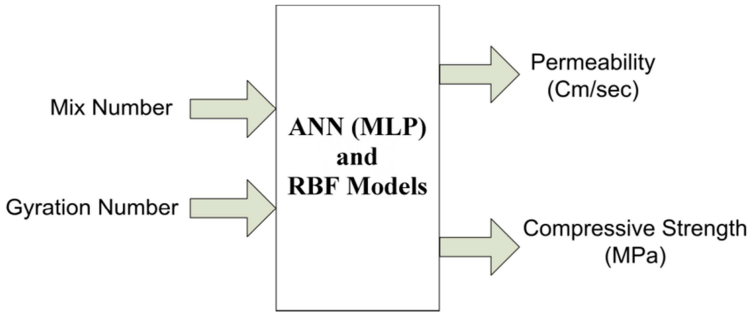

***Figure 8.** The proposed computational intelligence models.*

The training process algorithm to obtain the ANN models is shown in Figure 9. The parameters are set i.e., a (the maximum acceptable MRE%), ε (error) and d (the number of repetition in each process) to determine the number of epochs, acceptable error, and the end of the process conditions. Where the mean relative error percentage (MRE %) is calculated by:

$$MRE\% = 100\times\frac{1}{N}\sum_{i=1}^{N}\left|\frac{X_i(Exp)-X_i(Pred)}{X_i(Exp)}\right| \qquad (4)$$

Where N is the number of data and '*X (Exp)*' and '*X (Pred)*' stand for the experimental and predicted (ANN or RBF) values, respectively. Next *u* is set as a counter for the number of neurons in the first hidden layer, *v* and *j* are also set as the counters for the number of neurons for other hidden layers, and *l* is a frequency counter in each state. Many parameters can be calculated by the network, but the MRE%, which is the ending condition of the process, is calculated. As shown in Figure 9 if MRE%≤ *a*, then the value of *a* is set to MRE%, and the network results are saved. Then the number of neurons is increased by one. When the minimum value of MRE% is obtained, the condition for the optimized ANN structure of the network is achieved.

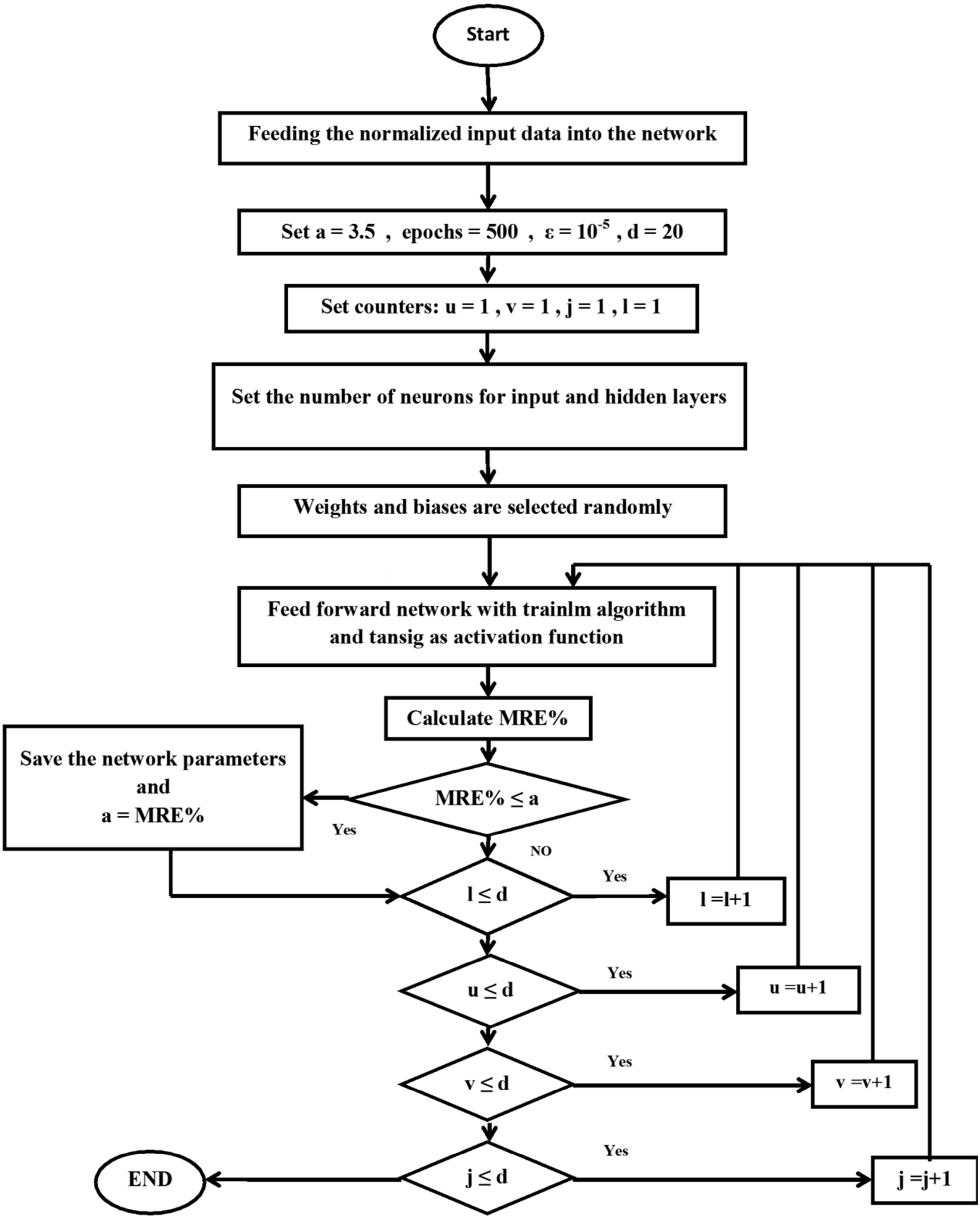

Figure 9. *The ANN training process algorithm.*

5. Results and Discussion

To obtain the best ANN and RBF models, various configurations have been constructed and tested as shown in Table 2.

Table 2. *Comparison between the different computational intelligence structures.*

Network	Structure	Epoch	Outputs	MRE% Train	MRE% Test
ANN (MLP)	2002/3/2	250	Permeability	2	2.85
			Compressive strength	0.742	0.778
	2002/4/2	100	Permeability	1.42	4.23
			Compressive strength	0.56	3.413
	2002/5/2	150	Permeability	0.583	0.741
			Compressive strength	0.26	0.342
	2-3-3-2	300	Permeability	0.657	0.85
			Compressive strength	0.345	0.71
	2-4-2-2	450	Permeability	0.35	2.501
			Compressive strength	1.85	2.278
	2-3-2-3-2	200	Permeability	0.884	1.64
			Compressive strength	0.379	0.47
RBF	2-50-2		Permeability	0.62	2.57
			Compressive strength	0.101	4.657

It is seen that the proposed ANN (MLP) model with 2-5-2 structure (i.e., two neurons in the input layer, 5 neurons in the hidden layer and two neurons in the output layer) has the least MRE%. Therefore, the ANN model with this structure has been selected for our purpose. Table 3 shows the specification of this ANN architecture. Also, in order to examine the performance of the RBF and ANN models, the obtained results are compared with the known results. Figures 10 and 11 show the obtained results for the proposed ANN and RBF models.

Table 3. *Specification of the best proposed ANN model.*

Neural network	MLP
Number of hidden layer	1
Number of neurons in the input layer	2
Number of neurons in the hidden layer	5
Number of neurons in the output layer	2
Learning rate	0.5
Number of epochs	150
Adaption learning function	Trainlm
Activation function	Tansig

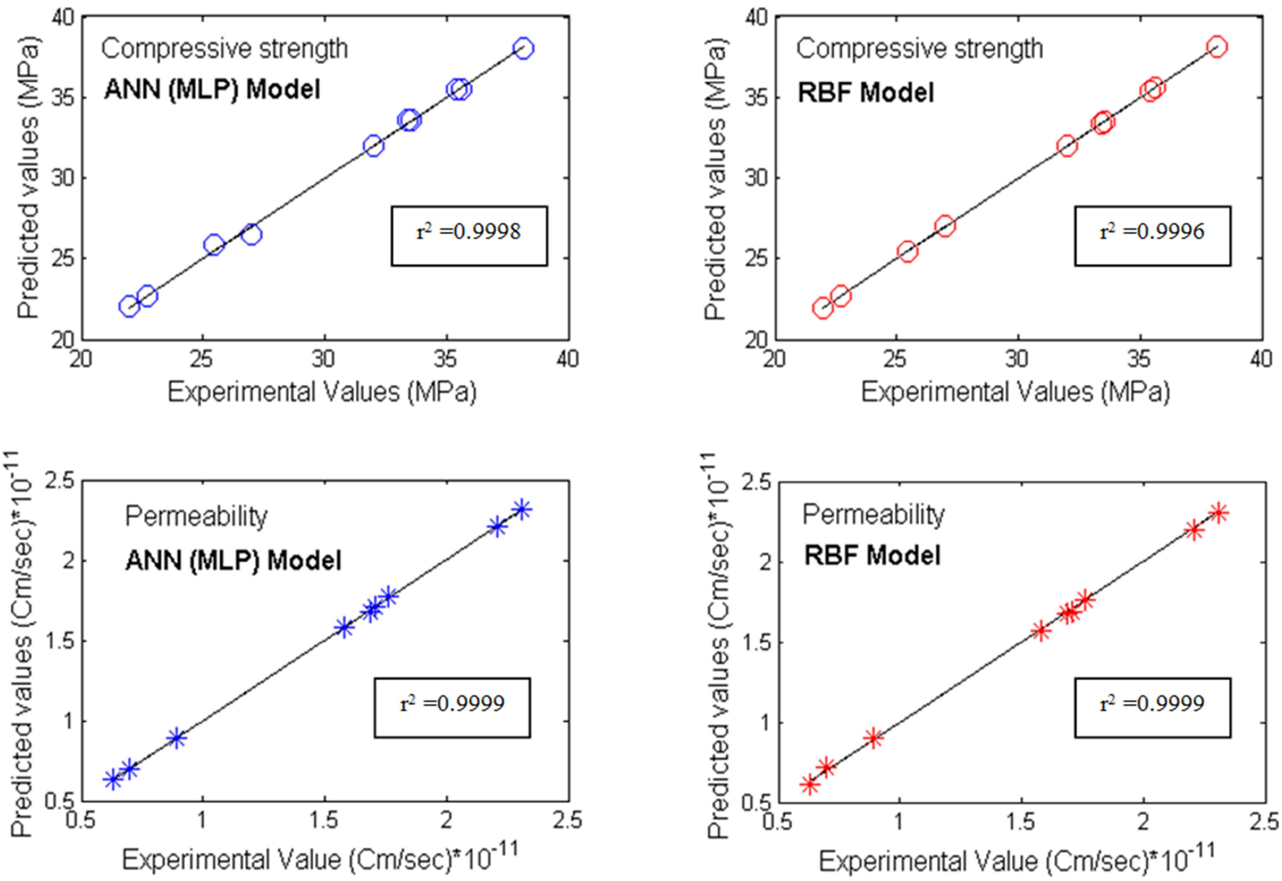

Figure 10. *Comparison of the experimental and predicted results for the training data using the proposed ANN and RBF models.*

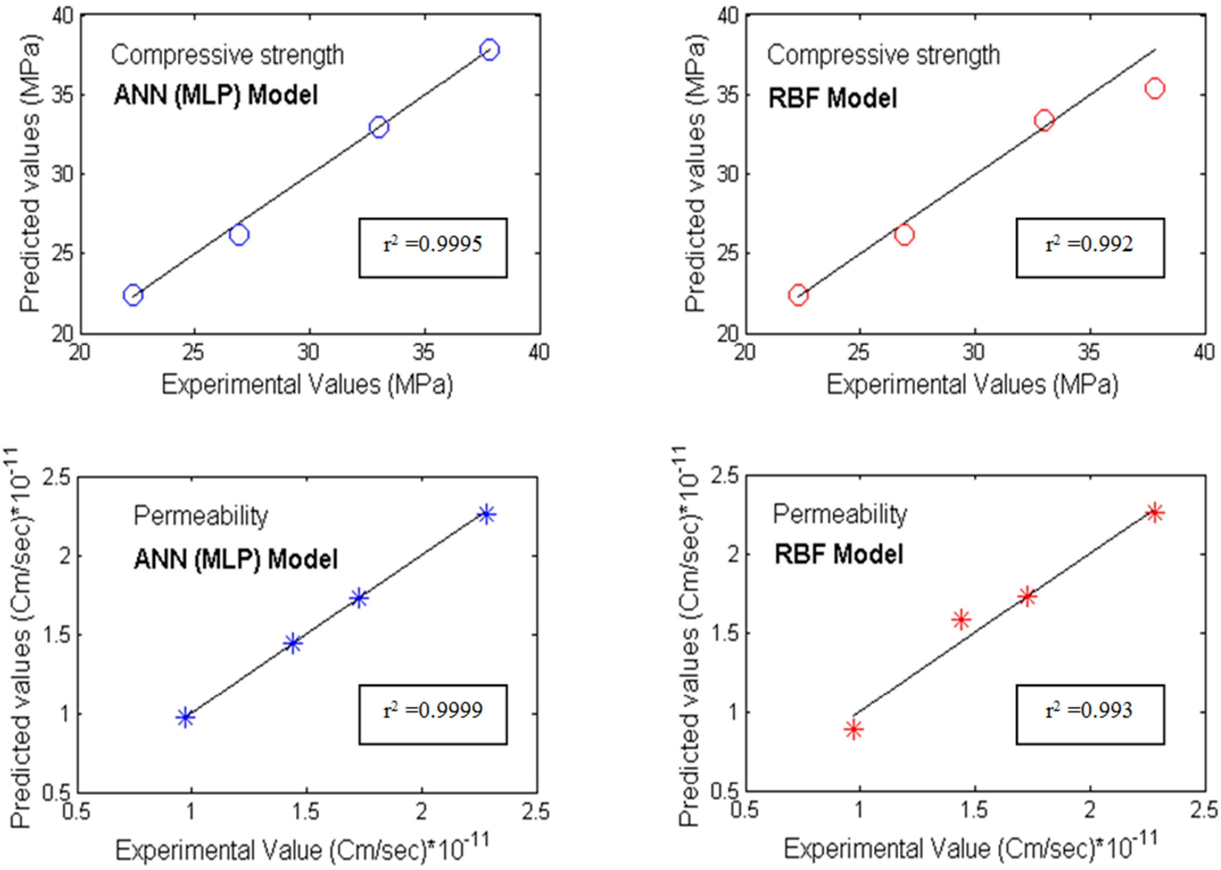

Figure 11. *Comparison of the experimental and predicted results for the testing data using the proposed ANN and RBF models.*

From Table 2 and Figures 10 and 11, it is clear that the predicted permeability and compressive strength by the proposed models is close to the experimental results, which shows the applicability of ANN and RBF networks as the accurate and reliable tools for the prediction of the permeability and the compressive strength. Figures 12 and 13 show the obtained permeability and compressive strength using the best proposed ANN model, respectively. From these figures the maximum compressive strength is obtained 39.32 MPa, in (Mix number, Gyration number) = (9, 70). Also, the minimum permeability is obtained $0.61*10^{-11}$ Cm/Sec, in (Mix number, Gyration number) = (11, 70).

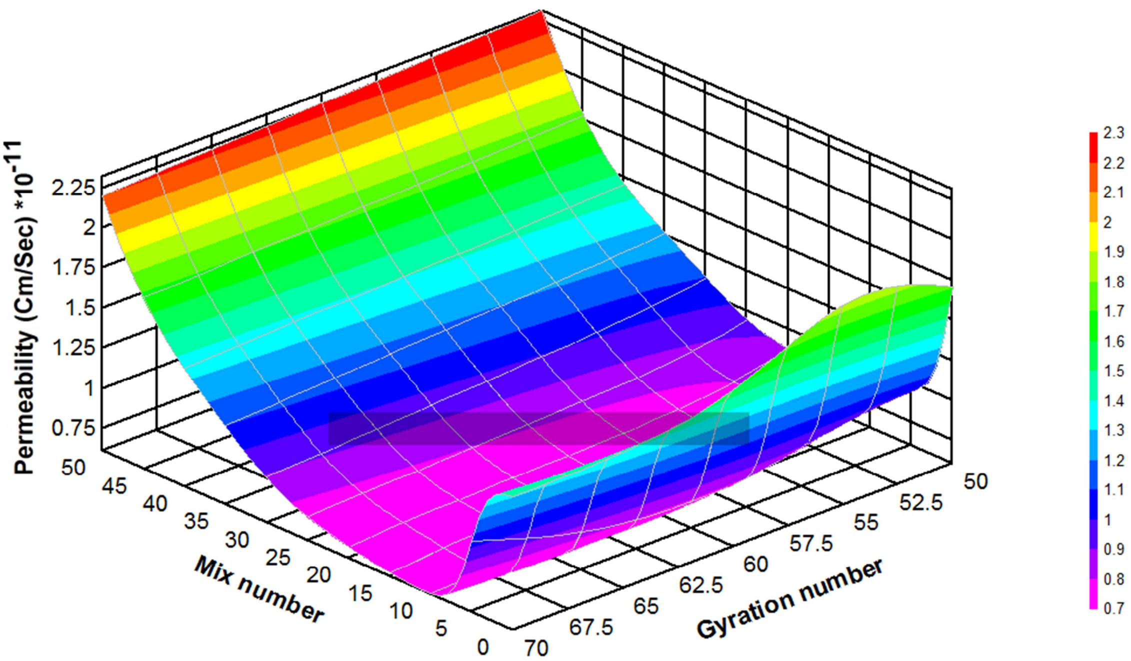

Figure 12. *The obtained permeability using the best proposed ANN model.*

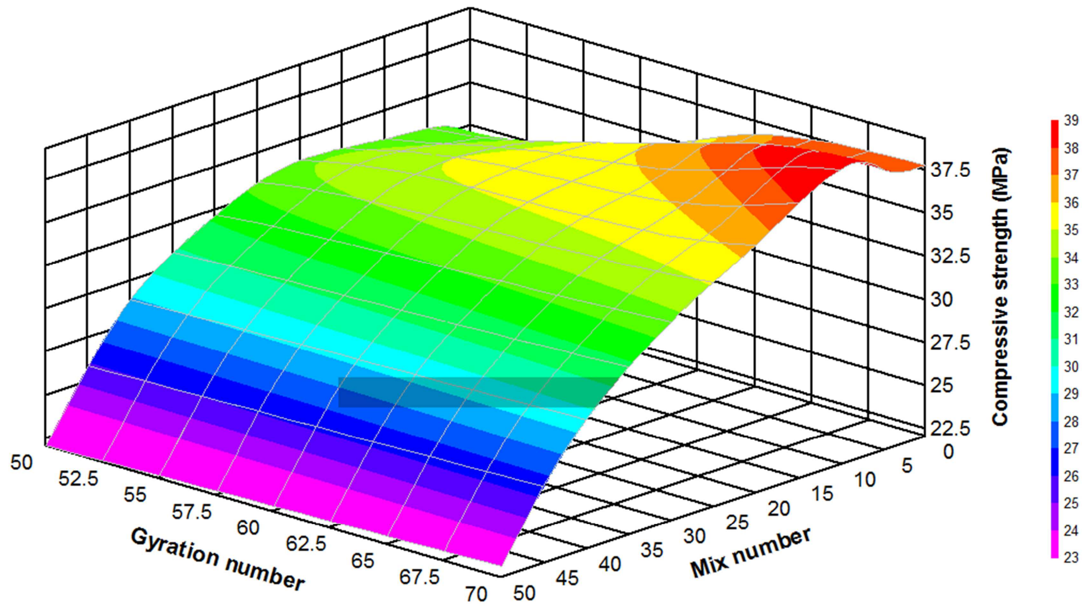

Figure 13. *The obtained compressive strength using the best proposed ANN model.*

Finally, the proposed ANN model can present a mathematical relationship for the permeability and compressive strength as shown in Table 4, where PER, STR, MIX and GYR are stand for the permeability, compressive strength, mix number and gyration number, respectively. Also, Tansig function for variable x is given by:

$$Tansig\,(x) = \frac{2}{1+e^{-2x}} - 1 \tag{5}$$

Table 4. *The obtained equations for the permeability and compressive strength using the best proposed ANN model.*

W13=-0.13	W27=0.128	W68=-0.027
W14=-0.09	B3=-12.22	W78=0.039
W15=0.11	B4=4.51	W39=-0.076
W16=-0.46	B5=-1.83	W49=-0.6
W17=0.085	B6=-5.55	W59=0.31
W23=0.003	B7=-12.97	W69=0.451
W24=-0.026	W38=0.058	W79=-0.180
W25=0.116	W48=0.356	B8=3.15
W26=0.228	W58=-0.057	B9=1.07
Y1=Tansig (MIX *W13+GYR *W23+B3)		
Y2=Tansig (MIX*W14+ GYR *W24+B4)		
Y3=Tansig (MIX*W15+ GYR *W25+B5)		
Y4=Tansig (MIX*W16+ GYR *W26+B6)		
Y5=Tansig (MIX*W17+ GYR *W27+B7)		
PER= Y1*W38+Y2*W48+Y3*W58+Y4*W68+Y5*W78+B8		
STR= Y1*W39+Y2*W49+Y3*W59+Y4*W69+Y5*W79+B9		

6. Conclusions

In this paper, the ANN and RBF are used to present a new model with the minimum error to predict the compressive strength and permeability of RCCP mixes containing RHA as cement replacement. The effect of adding RHA to the roller compacted concrete pavement specimens is modeled and predicted by ANN and RBF. The comparison shows that not only the results of both ANN and RBF models are in good agreement with the experimental data, but also the ANN model is more accurate than the RBF models. This means that the proposed models are reliable and flexible mathematical structures due to their high accuracy and therefore, they can be used to simulate the experiments precisely. According to the results of the laboratory tests and modeling using ANN and RBF, the optimal content for increasing of the compressive strength and reducing of the permeability, was obtained by substituting 9% and 11% of the cement by RHAin gyration number 70, respectively (maximum compressive strength was 39.32 MPa). However, adding a little more than 11% RHA reduced the compressive strength.

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