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Research Article

Presenting an Appropriate Neural Network for Optimal Mix Design of Roller Compacted Concrete Dams

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Abstract: In general, one of the main targets to achieve the optimal mix design of concrete dams is to reduce the amount of cement, heat of hydration, increasing the size of aggregate (coarse) and reduced the permeability. Thus, one of the methods which is used in construction of concrete and soil dams as a suitable replacement is construction of dams in roller compacted concrete method. Spending fewer budgets, using road building machinery, short time of construction and continuation of construction all are the specifications of this construction method, which have caused priority of these two methods and finally this method has been known as a suitable replacement for constructing dams in different parts of the world. On the other hand, expansion of the materials used in this type of concrete, complexity of its mix design, effect of different parameters on its mix design and also finding relations between different parameters of its mix design have necessitated the presentation of a model for roller compacted concretemix design. Artificial neural networks are one of the modeling methods which have shown very high power for adjustment to engineering problems. A kind of these networks, called Multi-Layer Perceptron (MLP) neural networks, was used as the main core of modeling in this study along with error-back propagation training algorithm, which is mostly applied in modeling mapping behaviors.

Keywords: Concrete, dam, MATLAB, MLP, RCC

INTRODUCTION

By discovering this fact that human brain performs calculations using a method completely different from common digital computers, studies have started on artificial neural networks which are usually called neural networks. Brain is in fact a very complex and nonlinear computer with a parallel structure. Due to its ability in organizing fundamental elements, i.e., neurons, brain is able to perform many calculations (such as pattern recognition, perception, etc.) with a speed much higher than the fastest modern digital computers (Demuth and Beale, 1998). Genetic algorithm which is based on Darwin's Evolution Theory was first introduced by Holland in 1975 and later (Goldberg, 1989) presented a complete and accurate introduction for this method (Yeh, 1998).

Artificial neural networks are one of the applications of artificial intelligence which is widely used in modeling a large number of engineering and scientific problems. Numerous studies have been conducted on predicting compressive strength of concrete using neural networks (Sarıdemir *et al*., 2009).

Roller compacted concrete is one of the relatively new methods for constructing dams in Iran. Prediction and modeling of mix design and strength of this concrete have the same or even more complexity than other types of concrete. On the other hand, inclusion of all kinds of pozzolans, new additives in concrete mix design and effect of different concrete methods on this concrete have doubled mix and compaction and also complexity of its mix design (Yeh, 1998). Modeling roller compacted concrete by traditional and regression methods is not able to make appropriate prediction considering the existing complexities of this issue because resistance behavior of concrete is affected by nonlinear conditions and also by the smallest components available in the mix and the interaction between these components (Sarıdemir *et al*., 2009). Characteristics of neural networks with error-back propagation training algorithm have made use of this nonlinear modeling method very attractive and suitable for predicting strengths of all kinds of concretes (Gao *et al*., 2006). Therefore, this technique was applied as the main basis of modeling in this research.

RESEARCH METHODOLOGY

Neural networks applied for modeling: Multi-Layer Perceptron (MLP) neural networks with error-back propagation algorithm are one of the most commonly applied tools which have shown an extraordinary

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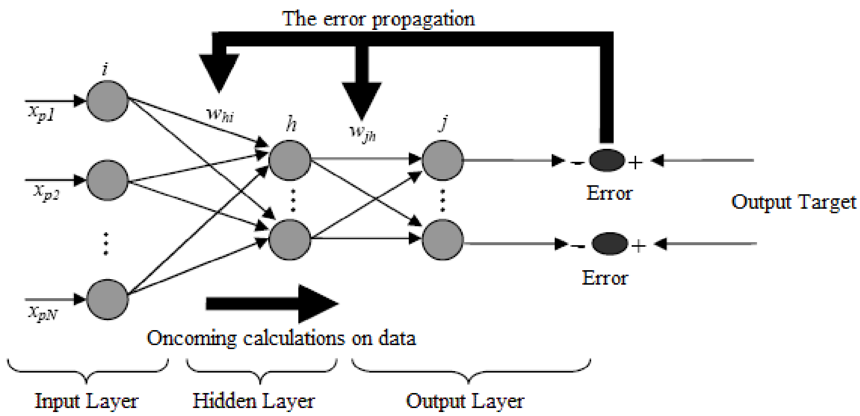

Fig. 1: Structure of neural networks with error-back propagation algorithm

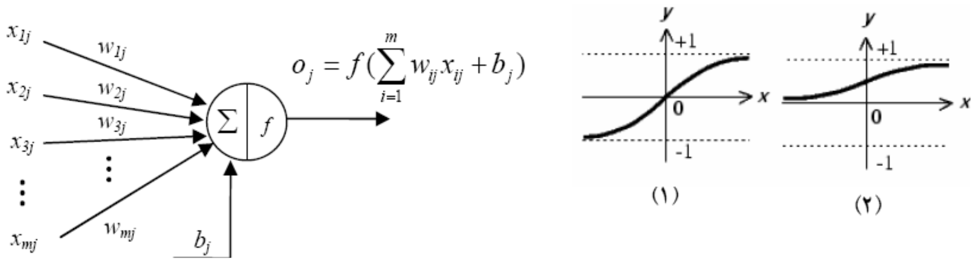

Fig. 2: (Left) neural cell and its mathematical operations, (right 1) hyperbolic tangent function (right 2) sigmoid function

ability in all kinds of nonlinear and linear modeling (Papadakis and Tsimas, 2002). In this research, MLP neural networks with a hidden layer, which acted according to Fig. 1, were used because this structure was able to simulate all kinds of different functions and mappings with a suitable number of processor (neural cells) in the hidden layer (Gao *et al*., 2006). Figure 1 demonstrates structure of the applied network for modeling, which consisted of three input, hidden and output layers forming xp1, xp2, …, xpN as N element inputs and Whi and Wjh as adjustable weights of the network.

These networks act based on processing elements called neural cells Fig. 1. Input layer cells of input vector elements transfer each one of the patterns to the hidden layer without any processing and cells of the hidden layer and output layer process information on their input values based on Fig. 2. Function f is recognized as the stimulation function in this figure and can be linear, hyperbolic tangent or sigmoid function (Sarıdemir *et al*., 2009).

In these neural networks, two procedures are performed. Functional procedure includes application of patterns and input examples to the network and determination of cellular outputs of each layer and transferring the output of each layer to the next one. Error-back propagation procedure starts with comparing result of output layer with target value of each pattern and determining error of this comparison (Relation 1); then, this error is transferred from end layers to the previous ones based on different training algorithms while adjusting weights and biases such that error of the network reaches its lowest level (Sarıdemir *et al*., 2009).

Relation (1): Error functions and network performance:

$$mse = \frac{1}{N.S_0} \sum_{j=1}^{S_0} \sum_{i=1}^{N} (t_{ij} - 0_{ij})^2$$

In Relation (1):

t = Target
O = Model output
i = Output cell
j = Pattern
N = The number of cells in output
S_0 = The number of pattern

Different parameters of neural network in resistance modeling: BP networks with a hidden layer and linear stimulation function in the output layer were used as the basis of modeling. Hyperbolic tangent stimulation function (Tanh) was used in the hidden layer. In addition, MATLAB software was used for the programming required for modeling.

Table 1: Limits of data for mix design

Cementitious materials	limits of data	25~50 (kg/m^3)	5~25 (kg/m^3)	0~5 (kg/m^3)	0~3 (kg/m^3)
110	Maximum	403	806	353	444
	Minimum	451	902	488	608
120	Maximum	399	843	335	440
	Minimum	468	914	483	576
130	Maximum	393	830	332	432
	Minimum	465	907	460	567
140	Maximum	392	751	327	413
	Minimum	486	906	480	560
150	Maximum	441	728	332	496
	Minimum	561	907	383	573

Table 2: Result of W (1, 1), compressive strength for 7 days

Compressive strength 7 days W (1, 1)	25-50 (kg/m^3)	5-25 (kg/m^3)	0-5 (kg/m^3)	0-3 (kg/m^3)	Cement (kg/m^3)	Pozzolan khash
110	857.6825	862.7650	744.7871	1018.7599	-271.3188	-30.1465
120	-4014.6545	1575.4713	-1242.9058	-1259.5986	221.3177	24.5908
130	687.2884	-20.6556	344.5169	354.4187	-95.5121	-10.6125
140	61232.0142	59919.6422	63439.0382	59492.9423	-22969.2980	-3931.0348
150	-48.2507	-48.2741	-192.0378	54.2189	15.6507	1.7390
Compressive strength 7 days W (1, 1)	**Water top water**	**Additive chrysoplast CER**	**Additive chrysotard CHR**	**Additive conplast RP264M**	**Don't wash = 1 Wash = 0**	
110	2331.8400	2586.4581	960.5746	-1312.8770	26128.3625	
120	-1994.0385	3614.0623	494.7499	-3078.1852	1315.5817	
130	701.6738	-2178.5697	-326.5085	-1446.9252	-279.3159	
140	220886.0558	238130.8079	1028.3934	-238014.0819	-38.9949	
150	-106.7477	-644.9751	-209.5466	-439.9155	-151.0030	

Table 3: Result of w (2, 1), b_1 and b_2 and maximum data for compressive strength for 7 days

Compressive strength 7 days	w (2, 1)	b_1	b_2	Max. data
110	67.8715	-2455.6000	68.61720	59.3
120	0.18378	1856.3360	0.83419	64.9
130	-0.23585	-732.4070	0.84413	75.9
140	-0.08802	-173501	0.87284	88.4
150	-70.8489	128.3482	71.35460	119.5

Set of modeling data: The information applied in this modeling was collected from among laboratory mix designs of Zirdan Dam. The collected records included 190 mix designs and data with remarkable error. The defective data in the parameters effective on mix designs and resistance were excluded after revision and, finally, 111 mix designs were applied as the main basis of different models.

Compressive strength modeling data at 7, 28, 90, 180 days, respectively: Considering that mix designs containing 70 to 190 kg/m^{3}of cementitious materials were made with 10 kg stairs, compressive strength relations of mix design were calculated at different ages in order to create resistance prediction model among the collected information.

Model input parameters: Different parameters are effective on resistance of roller compacted consecrate such as the amount and type of cement and pozzolan, sand and gravel, fineness of cement particles, amount of water, sand module, maximum dimension of aggregate, aggregates' granulation and amount and type of additive. In addition to these cases, there are combined parameters which have been called indices effective on resistance (Delatte *et al*., 2003). Among the independent parameters effective on resistance of roller compacted concrete, the parameters and characteristics which were present in the collected information were selected so that they can be used under different conditions. These parameters included: Aggregate 25˷50, Aggregate 5˷25, Sand 0˷5, Sand 0˷3, Cement, Khash pozzolan, Water, additive such as Chrysoplast CER, Chryso Tard CHR, Conplast RP264M and Washing and don't washing materials.

Preparing and standardizing the data: In order to perform calculations, first, it is necessary to standardize raw data between 0 and 1 (Demuth and Beale, 1998). Therefore, input data were standardized considering rate of the maximum and minimum data. This action, which is called data normalization, is more applicable than other standardization methods. After taking the output from network, standardized outputs should be converted to real data to be compared with the observed values. Maximum and minimum limits of data are described in Table 1.

RESULTS

After analyzing the data with MATLAB software neural network, the outputs are presented as weight of

Table 4: Result of W (1, 1), compressive strength for 28 days

Compressive strength 28 days W (1, 1)	25-50 (kg/m^3)	5-25 (kg/m^3)	0-5 (kg/m^3)	0-3 (kg/m^3)	Cement (kg/m^3)	Pozzolan khash
110	304.2699	271.5006	284.6204	304.3659	-87.5631	-9.7292
120	9545.2621	-4926.4887	2384.6857	2322.3635	-292.6772	-32.5199
130	-30.6109	33.9636	15.0429	-7.2057	-5.7240	-0.6360
140	152788.9625	151744.3845	157656.2341	156777.2375	-59248.1740	-6270.6733
150	-783.1546	-798.1840	-2744.5241	537.8686	309.3358	34.3390
Compressive strength 28 days W (1, 1)	Water top water	Additive chrysoplast CER	Additive chrysotard CHR	Additive conplast RP264M	Don't wash = 1 Wash = 0	
110	728.9701	2772.5523	-688.7660	826.0650	1948.0145	
120	3257.0184	-6904.3204	-2073.7938	12054.4859	-10468.0368	
130	1.5363	347.6326	47.9842	-186.3095	-1939.9944	
140	440296.6899	129567.3362	-181491.7105	16241.0049	36068.8599	
150	-1737.1075	-320.4495	3740.8166	-35.5678	-504.9597	

Table 5: Result of w (2, 1), b_1 and b_2 and maximum data for compressive strength for 28 days

Compressive strength 28 days	w (2, 1)	b_1	b_2	Max. data
110	82.25710	-802.5130	82.99000	94.30
120	-0.12829	-2490.3700	0.87240	88.90
130	33.42060	-21.8034	33.72570	106.60
140	-0.09141	-423751	0.87800	123.80
150	-0.14299	2083.6010	0.73674	165.50

Table 6: Result of W (1, 1), compressive strength for 90 days

Compressive strength 90 days W (1, 1)	25-50 (kg/m^3)	5-25 (kg/m^3)	0-5 (kg/m^3)	0-3 (kg/m^3)	Cement (kg/m^3)	Pozzolan khash
110	90.5575	84.8313	90.6119	88.9994	-29.0929	-3.2325
120	2863.2778	-5862.5253	-1647.4708	-1422.8069	794.9786	88.3450
130	-4148.6880	4311.5341	-191.8954	-97.4022	-348.7599	-38.6200
140	194.7366	197.6006	191.8984	235.6504	-29.0349	-82.8525
150	60.6244	64.6324	332.6311	-122.8437	-22.1758	-2.4661
Compressive strength 90 days W (1, 1)	Water top water	Additive chrysoplast CER	Additive chrysotard CHR	Additive conplast RP264M	Don't wash = 1 Wash = 0	
110	219.7201	1561.3317	1383.3550	1201.9453	-155.6943	
120	-7883.7779	-15222.0467	-12040.6101	415.2020	20662.3660	
130	5052.3912	28096.9814	22572.0953	-1522.8943	9276.0029	
140	152.4836	-4896.7036	1983.6598	873.0410	665.3672	
150	60.7262	-441.2291	-10421.1236	-631.5906	18.8333	

Table 7: Result of w (2, 1), b_1 and b_2 and maximum data for compressive strength for 90 days

Compressive strength 90 days	W (2, 1)	b_1	b_2	Max. data
110	16.31780	-245.634	16.60110	104.4
120	0.12899	6719.227	0.83464	109.1
130	-164.47400	-2719.670	-163.51700	123.6
140	0.11192	-507.018	0.90005	141.6
150	0.13146	-154.494	0.86241	188.3

Table 8: Result of W (1, 1), compressive strength for 180 days

Compressive strength 180 days W (1, 1)	25-50 (kg/m^3)	5-25 (kg/m^3)	0-5 (kg/m^3)	0-3 (kg/m^3)	Cement (kg/m^3)	Pozzolan khash
110	-220.5406	-212.9597	-220.6838	-222.7109	68.5733	7.6193
120	2047.2502	-1010.1246	479.4590	548.0719	-72.9755	-8.1094
130	-3199.9818	3743.3125	52.0612	111.5684	-365.7089	-40.6449
140	-71943.8467	-70414.2492	-74495.9859	-69988.6009	26582.4219	843.4920
150	295.3008	297.0688	262.3528	343.8102	-121.5758	-13.5086
Compressive strength 180 days W (1, 1)	Water top water	Additive chrysoplast CER	Additive chryso tard CHR	Additive conplast RP264M	Don't wash = 1 wash = 0	
110	-535.4856	34.5650	474.1010	2996.6691	144.7062	
120	1070.6510	-63.7307	85.6210	-262.3356	5485.6287	
130	4879.5062	25025.2947	20247.5529	-1898.3390	6023.9677	
140	-257860.4159	155.6007	698.6200	-279.1942	-397.4239	
150	891.4534	1363.1841	13469.3763	2011.4399	-7224.7236	

each one of the data in Table 2 and 3 for 7-day resistance, in Table 4 and 5 for 28-day compressive strength, Table 6 and 7 for 90-day compressive strength and in Table 8 and 9 for 180-day compressive strength, which include W (1, 1) weights in Table 1, w (2, 1), b_1 and b_2 in Table 2 and maximum compressive strength of the intended design.

Table 9: Result of w (2, 1), b_1 and b_2 and maximum data for compressive strength for 180 days

Compressive strength 180 days	W (2, 1)	b_1	b_2	Max. data
110	-25.294600	603.6801	26.10030	106.2
120	-0.177350	-644.5090	0.82266	112.7
130	-185.065000	-2814.3700	-184.07700	122.4
140	0.058119	203536.5000	0.87403	151.5
150	-0.129290	-828.7360	0.85081	211.8

Table 10: Data for example

Compressive strength 90 days	25-50 (kg/m^3)	5-25 (kg/m^3)	0-5 (kg/m^3)	0-3 (kg/m^3)	Cement (kg/m^3)	Pozzolan khash
120	401	846	483	482	108	12
Compressive strength 90 days	Water top water	Additive chrysoplast CER	Additive chryso tard CHR	Additive conplast RP264M	Don't wash = 1 Wash = 0	
120	120	0.6	0	0	1	

Table 11: W (1, 1) s with compressive strength 90 days with 120 Kg cementitious materials

Compressive strength 90 days W (1, 1)	25-50 (kg/m^3)	5-25 (kg/m^3)	0-5 (kg/m^3)	0-3 (kg/m^3)	Cement (kg/m^3)	Pozzolan khash
120	2863.2778	-5862.5253	-1647.4708	-1422.8069	794.9786	88.345
Compressive strength 90 days W (1, 1)	Water top water	Additive chrysoplast CER	Additive chryso tard CHR	Additive conplast RP264M	Don't wash = 1 Wash = 0	
120	-7883.7779	-15222.0467	-12040.6101	415.202	20662.366	

The relation according to whom MATLAB program was performed was as Relation (2):

$$\text{Purlin } (W_{2,1} * \text{Tansig } (W_{1,1} * A + b_1) + b_2$$

where, $W_{1,1}$, $W_{2,1}$ and b_1 and b_2 are calculation coefficients by the software and A is initial values of the mix design.

For example, if 90 day compressive strength of a design with total cementitious materials is 120 kg/m^3 and is considered with mix ratios according to Table 10, the following is performed:

First, values of each one of the materials are multiplied by the weights related to the second row of Table 11 for 90 day compressive strength (Table 6), which are W (1,1) s; then, the product is added to value of $b_1$in second row of Table 7.

Afterwards, the answer is considered equal to x and placed in Relation (3):

$$z = \frac{1-e^{-2x}}{1+e^{-2x}}$$

Now, Z is multiplied by value of w (2, 1) in the second row of Table 7 and added to number b_2. At the end, because the relations are normalized based on numbers, one should multiply the product by the maximum data, which equals 109.1 $\frac{kg}{cm^2}$ and the final answer equals: 100.3 $\frac{kg}{cm^2}$.

CONCLUSION

Use of neural networks has changed modeling roller compacted resistance modeling and has included very suitable and accurate results. In the research which was conducted by Sorkon *et al*., very accurate results were presented on the prediction of compressive strength of concrete due to neural networks (Delatte *et al*., 2003). This model was made only once, predicted resistance instantaneously and accurately and could reduce costs of sampling the roller compacted mix design. Compressive strength of the cement mortars including different types of Pozzolan based on neural network without need for performing any laboratory studies has saved costs to a great extent in projects (Yeh, 1998).

By applying these models of resistance prediction and using minimization methods, one can achieve optimal mix designs from the structural and financial aspects considering many specifications of the mix design and without making laboratory samples. Application of these models is very useful for more study of parameters effective on roller compacted concrete. Use of more characteristics of aggregates (type of mineral, conditions of aggregates to prevent separation, etc.), type of the consumed cement and conditions of making samples (mixing time, mixing manner, time interval between completion of mix and concrete work, etc.) besides other input parameters make prediction of resistance more accurate.

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