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Prediction of compressive strength of concrete by neural networks

Ni Hong-Guang, Wang Ji-Zong*

Hebei Institute of Architectural Science and Technology, 199 Guang Ming Street, Handan, Hebei, 056038, People's Republic of China

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Abstract

In this paper, a method to predict 28-day compressive strength of concrete by using multi-layer feed-forward neural networks (MFNNs) was proposed based on the inadequacy of present methods dealing with multiple variable and nonlinear problems. A MFNN model was built to implement the complex nonlinear relationship between the inputs (many factors that influence concrete strength) and the output (concrete strength). The neural network (NN) models give high prediction accuracy, and the research results conform to some rules of mix proportion of concrete. These demonstrate that using NNs to predict concrete strength is practical and beneficial. © 2000 Elsevier Science Ltd. All rights reserved.

Keywords: Fresh concrete; Compressive strength; Concrete; Modeling; Neural networks

1. Introduction

A compressive strength of concrete is a major and important mechanical property, which is generally obtained by measuring concrete specimen after a standard curing of 28 days. Conventional methods of predicting 28-day compressive strength of concrete are basically based upon statistical analysis by which many linear and nonlinear regression equations have been constructed to model such a prediction problem [1]. Usually, the early compressive strength such as 6-hour, 1-day or 3-day strength is embodied in a prediction equation. Obviously, obtaining the tested values of the early strength takes time thus results in time delay in forecasting 28-day strength. Furthermore, choosing a suitable regression equation involves technique and experience and is not a simple thing.

Concrete strength is influenced by lots of factors [2]. If we consider strength prediction as a mapping from the influencing factors to the 28-day compressive strength, then a mapping model can be created by using multi-layer feed-forward neural networks (MFNNs) instead of regression equation. The study of neural networks (NNs) was inspired by biological NNs, and was founded on a semi-empirical base to model the behavior of the biological nerve cell structure. The processing elements (neurons) in a NN simulate the function of the nerve cells in human brain that contains billions of interconnected neurons. These neurons are the fundamental elements of the central nervous system and determine any action that is taken. The MFNN model is one of the most commonly used ANN models, whose application stretches to almost every field. This paper is intended to establish a methodology that would provide an economic and rapid means for future experimental researches, rather than to build a full-scale knowledge-based system model by incorporating most of the fundamental aspects of a NN to solve the complex non-linear mapping for predicting concrete strength.

2. Problem presentation

Concrete is a man-made material created by the proper mixing of cement, coarse aggregate, such as gravel, fine aggregate, such as sand, with adequate and controlled amount of water. Experience has shown that by controlling some parameters of the fresh concrete, such as the grade of cement, the water/cement ratios, dosage of cement, dosage of water and slumps, within specified limits, the long-term properties of the concrete can be improved. Since the fresh concrete data are routinely collected and have been used for the direction of quality control, it appears reasonable to determine that the fresh concrete data can also be used to

* Corresponding author. Tel.: +86-310-6034365; fax: +86-310-6025698.

E-mail address: wangjizong@263.net (J.-Z. Wang).

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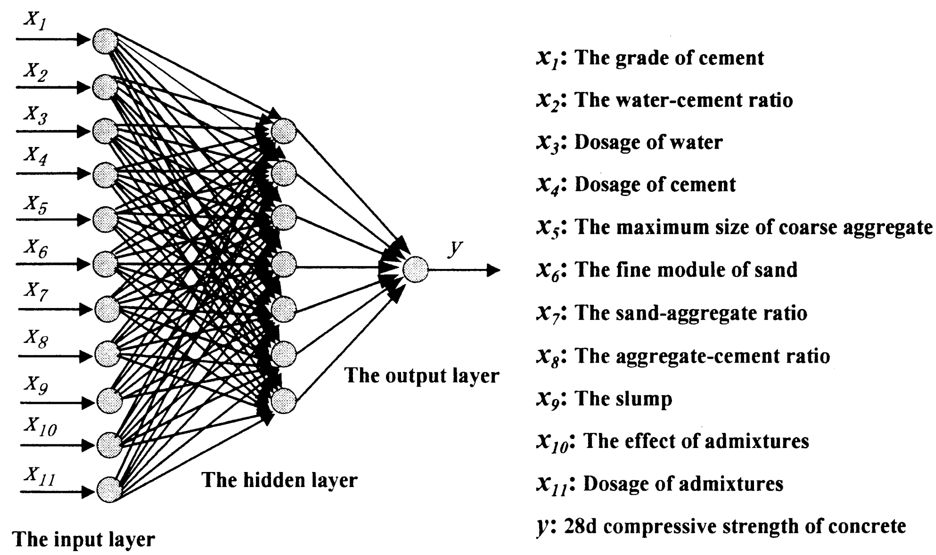

Fig. 1. The architecture of BP network model.

forecast the long-term strength of concrete. Take for example our laboratory work. As many as 14 test parameters were chosen to be the factors (variables) that influence concrete strength. These factors are the following: grade of cement, water/cement ratio, dosage of water, dosage of cement, maximum size of coarse aggregate, fine module of sand, sand/aggregate ratio, aggregate/cement ratio, slump, effect of admixtures, dosage of admixtures, forming conditions, curing conditions and test conditions. Of all the above factors that are obtained during a certain period of time, the following three can be seen as constant factors: forming conditions, curing conditions and test conditions. The remaining 11 factors can readily develop concrete strength. There exists complex nonlinear relationship between these factors and the concrete strength.

A typical MFNN has three layers: the input layer, the hidden layer and the output layer. Hecht-Nielsen [3] proved that a three-layer feed-forward NN could implement any function defined over a compact subset of Euclidean Space.

Like any intelligent models, NN has the capability of learning. The most popular and successful learning algorithm used to train MFNNs in areas [4,5] such as speech and natural language processing, pattern recognition and system modeling is currently the Back-Propagation (BP) algorithm. Thus, we also call MFNNs as BP networks. Through the learning of samples, BP networks attain the induction by adjusting the connecting weights and the thresholds. While learning, the BP networks store the nonlinear information between the influencing factors and the strength in the weight matrix in a dynamic and parallel way, and the network can give the corresponding output (concrete strength) upon the input factors while recalling. These are the two aspects of implementing a BP network. Therefore, it is feasible in theory to predict concrete strength using BP networks.

3. Construction of NN model

As the problem was defined as a nonlinear input–output relation between the influencing factors and 28-day compressive strength, this led us to choose, for our NN, the 11–7–1 architecture (see Fig. 1). That means there are 11 nodes in the input layer corresponding to the 11 factors (11 components of an input vector), seven in the hidden layer, and one in the output layer corresponding to 28-day compressive strength. The nodes (neurons) of neighboring layers are fully connected.

Table 1
Classification of admixtures

Group no. 1 (C = 0.9)	Group no. 2 (C = 0.8)	Group no. 3 (C = 0.7)	Group no. 4 (C = 0.5)
FE-HS	SL-II	MG	782-III
NF	SL-A	JK-6	UEA-M
FDN	CJ-1	861-II	YGU-I
UNF	TZ1-1	MRT	HE-6
RH	TZ1-2		
	RT-B		
	EH		
	AN-4		

There are two batches of data, one from the laboratory work conducted by the authors and the other from a concrete plant in Peking. Each batch has been divided into two sets, one for the network learning called learning set, and the other for testing the network called testing set. Each set is composed of dozens of pairs of input vectors and output vectors (vectors in the input layer called input vectors, and in the output layer called output vectors). An input vector consists of 11 components (x_1, x_2, ..., x_{11}) and an output vector has only one component y. The BP algorithm and construction of NN model have been programmed in C++ by the authors. C++ program is executable on any IBM-compatible PC. A thorough description of BP algorithm may be found in Ref. [3].

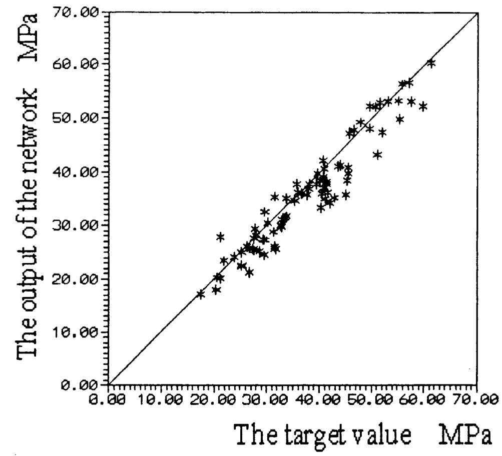

Fig. 3. Learning results of the second batch of data.

4. Experimentation and collection of data

4.1. Experimental work

The authors collected the first batch of data from extensive and detailed laboratory work to construct the learning (training) set and the testing set. Each set consists of dozens of vectors of the influencing factors and the corresponding compressive strength of concrete.

The cement used is Portland cement, grades 425 and 525 (Chinese standard). There are two kinds of coarse aggregates in our experiment, namely, the rounded and the crushed, with maximum size of 31.5 and 40.0 mm. The module of fine aggregate varies from 1.9 to 3.4 mm, the water/cement ratio from 0.35 to 0.70 and the dosage of cement from 257 to 543 kg/m^3. Two kinds of superplasticizers, FE and FDN, were chosen as admixtures. Two kinds of concrete specimens were cast. The first kind, for coarse aggregates with a maximum size of 40 mm, had cubic dimensions of 150×150×150 mm. The other was in cubic dimensions of 100×100×100 mm for coarse aggregates with a maximum size of 31.5 mm. They were cured for 28 days in a curing cabinet (relative humidity in excess of 95%, temperature 23 ± 2°C).

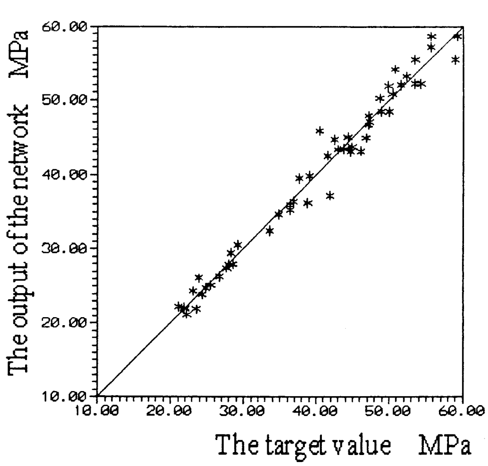

Fig. 2. Learning results of the first batch of data.

As many as 65 mixes and corresponding 28-day compressive strength were obtained. For each mix, there were 11 figures (values of influencing factors) that constitute an input vector to be determined. The 28-day strength makes up an output vector. Therefore, we got 65 pairs of vectors, of which 50 pairs were used to construct the first learning set and the other 15 to construct the first testing set. On a supervised learning algorithm [6], an error term depends on the difference between the target value from testing results and the computational output value from network implementation. The grand total error is the sum of the errors over all neurodes and all patterns. For the learning of a NN, a learning set with more data vectors is needed in order to adjust its weights better. While recalling, and for practical engineering use, the network can yield better results at lower error level. In other words, constructing an accurate NN model is more important, which needs more pairs of experiment data for learning or training. On the other hand, recalling is mainly for an evaluation of network performance, thus sharing fewer pairs of data.

4.2. Collection of data from a concrete mixing plant

The authors collected 100 mixes as the second batch of data from the concrete mixing plant of the Peking Urban Construction Corporation. There were 85 pairs of vectors in the second learning set and 15 in the second testing set. The cement used is Portland cement, grades 325, 425 and 525 (Chinese standard). There are two kinds of coarse aggregates, namely, the rounded and the crushed, with maximum size of 31.5 and 40.0 mm. The module of fine aggregate varies from 1.9 to 3.4 mm, the water/cement ratio from 0.37 to 0.70 and the dosage of cement from 263 to 570 kg/m^3. As many as 21 kinds of super-plasticizers were chosen as admixtures. They were grouped according to their effect on

Table 2
Testing results of the first batch of data

No.	Target output (MPa)	Output by the NN model (MPa)	Absolute error (MPa)	Relative error (%)
1	23.90	23.30	0.60	2.51
2	26.70	26.04	0.66	2.47
3	36.00	37.78	− 1.78	− 4.95
4	34.90	33.16	1.74	4.97
5	44.70	42.90	1.80	4.02
6	48.90	48.19	0.71	1.45
7	28.30	27.02	1.28	4.53
8	46.80	44.55	2.25	4.81
9	48.10	48.84	− 0.74	− 1.55
10	41.30	41.53	− 0.23	− 0.57
11	42.50	44.62	− 2.12	− 4.99
12	50.40	50.74	− 0.34	− 0.67
13	58.90	55.45	3.45	5.86
14	46.60	44.80	1.80	3.86
15	29.20	30.51	− 1.31	− 4.49

reducing water (see Table 1). We assigned to each admixture a coefficient (C) that stands for its effect.

5. Implementing process and results

5.1. Learning phase

After the learning set of the first batch of data was presented to the NN model, we stopped the learning process when the iterations reached 5000, and the grand total learning error decreased from 2.566 to 0.016. Fig. 2 is an expression of the learning results, each point standing for a learning vector. The nearer the points gather around the diagonal, the better are the learning results. The learning errors of the points on the diagonal are zero.

The learning set of the second batch of data was used for another NN model. The ending iterations were also 5000, and the grand total learning error decreased from 6.15 to 0.005. Fig. 3 is an expression of the learning results.

5.2. Testing phase

We use the testing set to evaluate the confidence in the performance of the trained network. Fifteen testing vectors of the first batch of data was used to test the first NN model and the other 15 of the second batch to the second NN model. Tables 2 and 3 are the testing results. The target outputs the output neurode is supposed to have are the actual compressive strength taken from experimental investigation on the concrete specimen [7]. The other outputs in the third column of Tables 2 and 3 denote the computing values by the NN as a result of the feed-forward calculations. From an analysis of the relative errors, it can be noted that the modeling results are reasonably good, especially the ones in Table 2, whereas, the errors in Table 3 are a little higher. This

Table 3
Testing results of the second batch of data

No.	Target output (MPa)	Output by the NN model (MPa)	Absolute error (MPa)	Relative error (%)
1	22.80	22.00	0.80	3.53
2	57.60	53.11	4.49	7.79
3	45.10	45.74	− 0.64	− 1.43
4	28.50	24.86	3.64	12.79
5	51.60	52.91	− 1.31	− 2.53
6	30.30	30.93	− 0.63	− 2.07
7	28.60	25.19	3.41	11.93
8	34.50	35.71	− 1.21	− 3.50
9	28.50	31.59	3.09	− 10.85
10	30.40	31.59	− 1.19	− 3.92
11	44.90	42.65	2.25	5.01
12	42.50	42.71	− 0.21	− 0.50
13	36.10	36.80	− 0.70	− 1.93
14	38.30	38.35	− 0.05	− 0.13
15	29.90	26.07	3.83	12.81

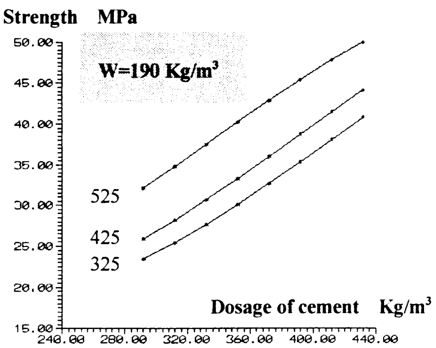

Fig. 4. Effect of the dosage of cement on strength at constant dosage of water. W = dosage of water; C = dosage of cement; S_p = sand/aggregate ratio; M_x = the fine model of sand.

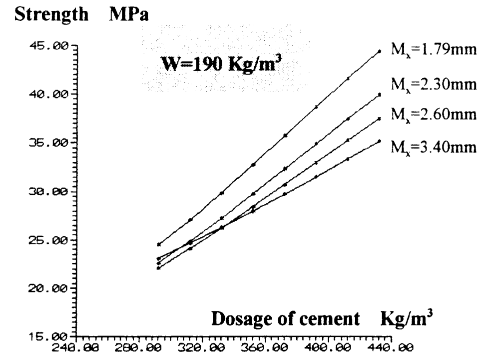

Fig. 6. Effect of the dosage of cement on strength at constant dosage of water. W = dosage of water; C = dosage of cement; S_p = sand/aggregate ratio; M_x = the fine model of sand.

is because their target outputs themselves, taken from the concrete mixing plant, are at a higher error level for complex experimental conditions and interfere with uncertain and stochastic factors.

6. Consistency between NN modeling and experiments

The trained NN models can be used to simulate the effects of some factors on the strength, and the authors obtained functional relations between strength and its corresponding factors, as shown in the following tables. Conclusions drawn from these curves conform to some rules on concrete mix proportioning, which researchers have discovered and accepted. To some extent, the NN models prove reasonable and feasible. The authors got the following simulation results as shown in Figs. 4–7.

Figs. 4–6 show that the compressive strength of concrete is nearly in direct proportion to the dosage of cement, at a constant water dosage of 190 kg/m^3. In Fig. 4, three quasi-linear lines indicate concrete strength with different kind grades of cement (the Chinese standard) as a function of cement dosage. Note the effects of the grade of cement on the strength, too. As can be seen, the strength is roughly directly proportional to the cement dosage, and the higher the grade, the greater the concrete strength. Furthermore, the strength is more sensitive to the grade of cement if the dosage of water is fixed.

Fig. 5 shows five compressive strength lines of concrete of different sand/aggregate ratio with cement dosage at a constant water dosage. The vertical axis is the compressive strength of concrete, and the horizontal one is the dosage of cement in concrete mixtures. As cement dosage increases, concrete strength rises quasi-linearly. In addition, the strength is approximately directly proportional to the cement dosage. Though the sand/aggregate ratio influences the strength, its effect is very slight indeed.

As shown in Fig. 6, the effects of the fine module of sand on concrete strength are greater than the sand/aggregate ratio. When the cement dosage increases, the concrete strength gets higher. These curves with different slope are not parallel to each other. It reveals that the increased strength with an equal growth rate of cement dosage is different from each other for different fine module of sand. At a constant cement dosage, concrete with smaller module of sand possesses greater strength within a certain scope.

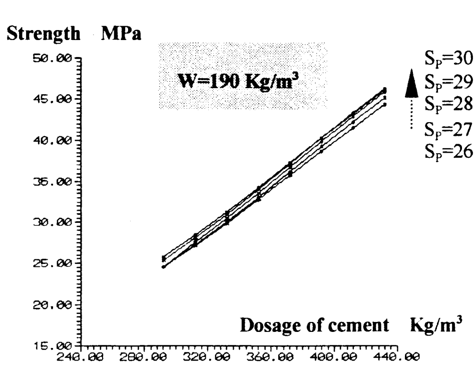

Fig. 5. Effect of the dosage of cement on strength at constant dosage of water. W = dosage of water; C = dosage of cement; S_p = sand/aggregate ratio; M_x = the fine model of sand.

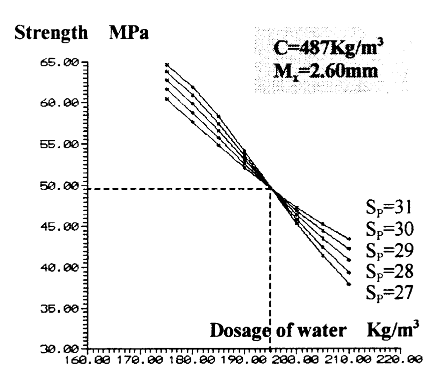

Fig. 7. Effect of the dosage of cement on strength at constant dosage of water. W = dosage of water; C = dosage of cement; S_p = sand/aggregate ratio; M_x = the fine model of sand.

A group of curves are plotted in Fig. 7. The vertical axis is still the compressive strength, while the horizontal is dosage of water. At a constant dosage of cement and a fixed fine module of sand, the effects of the dosage of water on the strength were diagrammed, from which two rules can be drawn. The first is that the dosage of water has a negative effect on the compressive strength. The second is that there is a point at which the curves intersect; and the points indicate that, for different sand/aggregate ratios, there exists a fixed dosage of water, such that it correlates to a constant strength. The rules obtained by the NN models are consistent with those by laboratory work. In addition, these reasonable results indicate that the trained NN models exhibit good performance.

7. Conclusions

(1) MFNN models can be constructed that provide a quick mean of predicting 28-day compressive strength of concrete based on some of its influence factors. This computational intelligent method will be helpful to civil engineers, technologists, ready-mix operators and concrete mixture designers in civil engineering and concrete mixing and batching plants.

(2) NN models attain good prediction accuracy. Some effects of concrete compositions on strength are in accordance with the rules of mix proportioning. Consequently, the application of NN models to concrete strength prediction is practical and has a good future.

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