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The application of automatic acquisition of knowledge to mix design of concrete

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Abstract

In this paper, an automatic knowledge-acquisition system based on neural networks is created to design concrete mix. This system consists of three models: the mix-design model, the slump-prediction model, and the strength-prediction model; the first model is the core of the system with the other two models supporting the core. Each model is made up of a mix-design database, a knowledge base, a neural network-learning block, and a problem solution block. The automatic acquisition of knowledge is realized through the learning process of a neural network from sample mix designs. The knowledge base is the network itself. This system not only makes full use of the workable mix designs that are already in existence but also provides a quick means to predict the slump and 28-day compressive strength of ready-made concrete. Examples and experimental work show that the application of the system to concrete mix design is practicable.

Keywords: Mix design; Compressive strength; Workability; Neural networks; Knowledge-acquisition system

1. Introduction

With the continuous increase in concrete ingredients concrete gets more and more complicated, and its performance varies greatly. Most traditional mix-design methods [1] dealt with concrete containing only Portland cement (as a binder) without admixtures, and can no longer suit such an "abrupt change" situation [2]. Furthermore, for high performance concrete (HPC), apart from the 28-day compressive strength, workability and endurance are properties generally dealt with. While in the traditional mix-design methods, little is considered for workability and endurance. For a long time, with few references available, concrete engineers have been designing mixes of pumpcrete by "trials" or their personal experience. Some of the mix designs proved to be successful while others were unsuitable and discarded. How can researchers obtain some useful information from the successful mix designs, and where can researchers find a quick and safe way of designing a mix to give the desired properties?

Although trial mixes are necessary and will remain so for a long time, they are not always the answer. The authors of this paper inspected the ready-made concrete plants of Peking Urban Construction Groups and Handan Building & Installation Company and found that the concrete engineers depended heavily on their personal experience to design mixes, despite not always being reliable. Moreover, their demands for a reliable decision-making tool and quick way of designing a mix are imperative. Despite the existence of many good mix designs that these engineers have made in the past, they still have to design them from scratch when confronting a new project. The difficulty is how to tap the useful information from many workable mix designs that have already been in existence.

In author's opinion, the knowledge-acquisition system based on neural network is one of the answers. The first step is to construct database systems by collecting the data of successful mix designs. Second, several neural network models are established to tap and store the rules of mix proportioning by learning from the samples in the database. The last step is to design mixes by implementing the knowledge-acquisition system. With the help of a computer, it is possible not only to make mixes design on screen, but also to simulate the effects of changes in the mixes on the properties such as compressive strength, workability, and endurance.

2. Description of neural network model

A multilayer feed-forward neural network with nonlinear processing elements (the neurons) has the strong capabilities of learning and nonlinear processing, and possesses the toler-

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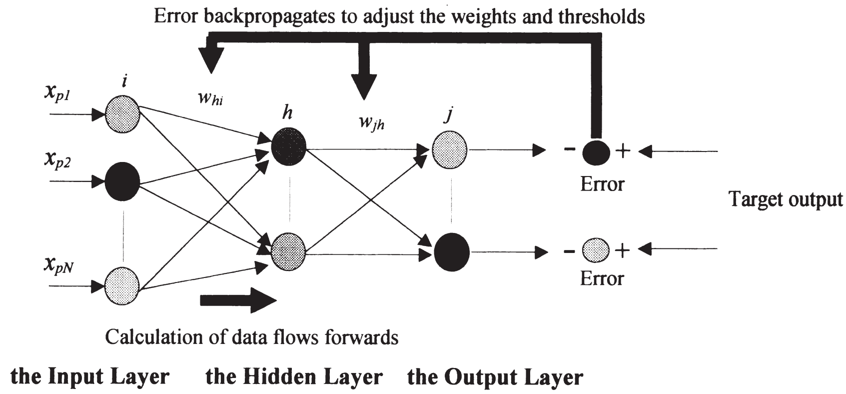

Fig. 1. The architecture of a BP network.

ance characteristics of inaccuracy and uncertainty and robustness, among others. This is one of the most widely used neural network models. A typical multilayer feed-forward neural network (see Fig. 1) has three layers: the input layer, the hidden layer, and the output layer. $x_{p1}, x_{p2}, \ldots, x_{pN}$ are the N components of input vector X_p, and W_{hi} and W_{jh} are the connection weights between nodes of different layers. The nodes (neurons) of neighboring layers are fully connected. The activation function we use is a sigmoid function.

A BP network functions on the basis of a large number of neurons. A neuron is an information-processing element. Neurons in the input layer just transfer the input data to the hidden layer, with no calculations happening. While in the hidden layer and the output layer, a neuron acts as seen in Fig. 2a. A sigmoid function is shown in Fig. 2b, where θ_j is the threshold of neuron j. A thorough background information may be found elsewhere [3].

From the work of Hecht-Nielsen [4,5], it is obtained that a three-layer feed-forward neural network could implement any function defined over a compact subset of Euclidean space. The most popular and successful learning algorithm used to implement multilayer feed-forward neural networks in areas such as speech and natural language processing, pattern recognition, and system modeling is currently the back-propagation (BP) algorithm. So we also call multilayer feed-forward neural networks the BP networks.

The implementation of a BP algorithm involves two processes. The first process is the calculation of data flowing forward from the input layer to the output layer. The second process involves propagating error signals backward from the output layer to the input layer and adjusting the connection weights. The steepest descent strategy is employed to adjust the connecting weights to minimize the error function (cost function). A thorough discussion of BP algorithm can be found in other works [3,6].

Through the learning from samples, BP networks attain the induction by adjusting the connecting weights and the thresholds. Therefore it is feasible to construct BP network models to acquire knowledge in the mix-design samples.

3. System plan and the principle of knowledge acquisition

The great hopes originally placed on expert systems are still far from being fulfilled. Research has brought only limited applicable results. Basically, there are two main approaches to creating a knowledge base in an expert system.

Knowledge representation in a conventional expert system is based on rules. That means a human expert is needed to extract regularities from his experience and to express them in the comprehensible, explicit form of rules. Due to the explicitness of the knowledge, the system has perfect explanation abilities. However, due to some problems in mix design of concrete, the information available is always inaccurate and incomplete in mass data; building such a consistent knowledge base by rules is a difficult matter.

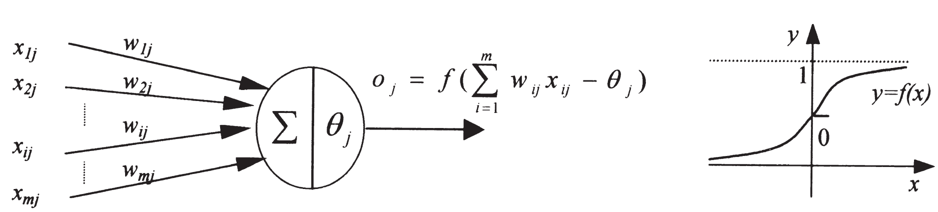

Fig. 2. (left) A neuron and its action; (right) a sigmoid function.

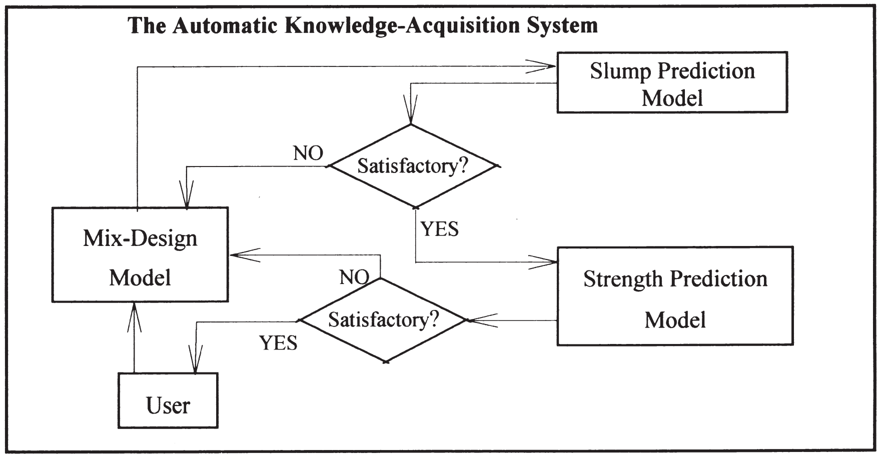

Fig. 3. The architecture of system plan.

The second main approach is connected with the rapid development of neural network theory. In a so-called neural expert system, the knowledge base is a neural network that is created automatically by a learning algorithm from a set of example inferences. We assume that there exists useful information in a set of samples; then acquisition of knowledge in the samples can be performed automatically by implementing a BP network. Building such a system takes just a few weeks, and additional self-learning is possible. The representation of knowledge is based on numerical weights corresponding to the connections among neurons.

Our knowledge-acquisition system is composed of three parts (see Fig. 3): mix-design model, slump-prediction model, and compressive strength-prediction model. The three parts have the same structure as shown in Fig. 4. Every model consists of four blocks: the database, the neural network-learning block, the knowledge base, and the problem solution block.

In such a system, the workable mix designs are stored in the database, through which three sets of learning samples can be constructed to implement three BP networks, respectively. The functions of the three networks are to create three different knowledge bases by which problem solution can be performed in a neural network when a user provides an input to the system. The slump-prediction model and the compressive strength-prediction model are used to ensure the mix designed by the neural network to produce desired properties. If some of the properties are not satisfactory, a user can adjust some parameters in order to get another mix design, then test the properties by simulation on a computer until he gets the desired mix design. If none of the mixes given by the system is good and the user has to design a mix by himself, and if the mix proves to be good, then it can be added to the mix-design database, which makes additional learning possible. Consequently, the knowledge base will become more and more perfect. The whole system was programmed in Visual C++.

4. System design

4.1. Mix-design model

The authors collected data from experimental work and ready-made concrete plants to create the database. For each mix, there were seven pieces of data to make up an input vector of a BP network. They were: the grade of cement, the maximum size and nature of coarse aggregate, the module of fine aggregate, the slump, the 28-day actual compressive strength, and the action of admixtures. An output vector of the network is formed by the corresponding consumption of materials of each mix such as cement, free water, fine and coarse aggregate, admixture, and fly ash. The input vector and the output vector constitute a pair of learning vectors. Dozens of pairs of learning vectors make up a learning sample set. The mix-design information in mass data can be extracted by the learning of a BP network from the sample set. When a learning level is reached, the BP network can be seen as a knowledge base for design mix and ready for use.

If a user set out to design a mix, what he merely needs to do is provide some design information as input to the problem-solution BP network. The information includes the grade of cement, the maximum size and nature of the aggregate, the module of fine aggregate, designed slump, designed

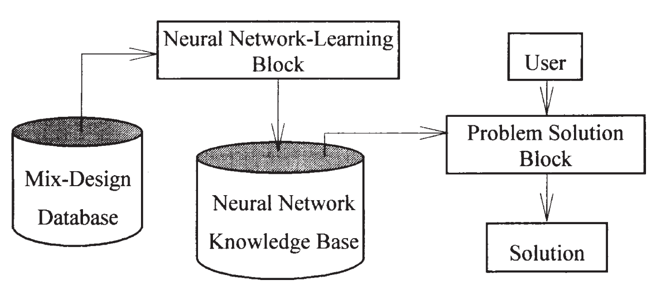

Fig. 4. Knowledge-acquisition and problem solution.

compressive strength of concrete, and the action of admixture that is going to be used. He may expect to get the proportion of the materials consumed to constitute the concrete. Then the system will predict the properties of any mix given by the BP network, which is the function of two other supporting models, namely the slump-prediction model and the compressive strength-prediction model.

4.2. Slump-prediction model

In this model, input vectors of a network consist of factors that have influence over slump. They are cement dosage, free water dosage, the fine/coarse aggregate ratio, the maximum size and nature of coarse aggregate, the module of fine aggregate, admixture dosage, the action of admixture, and fly ash dosage. Output vector of the network is the actual slump. The automatic knowledge acquisition can be performed by a network learning from dozens of pairs of vectors. Upon learning, the nonlinear information between the influencing factors and the slump is stored in a distributed way in the weight matrix of the network. Then the slump-prediction model is ready for forecasting the workability of a mix when an input vector is presented. If the workability is not up to standard, another mix can be provided by a minor adjustment of the input vector in the mix-design model.

4.3. Compressive strength-prediction model

Like the creation of the knowledge base for slump prediction, a number of factors that relate to 28-day compressive strength of concrete need to be chosen as input vector. It is supposed that there exists strong nonlinear relationships between the 28-day compressive strength and the many factors such as the grade of cement, cement dosage, free water dosage, water/cement ratio, cement/aggregate ratio, the maximum size and nature of coarse aggregate, the module of fine aggregate, fine/coarse aggregate ratio, slump, admixture dosage, the action of admixture, and the fly ash dosage. A BP network is constructed to map the nonlinear information from the factors to the compressive strength. The process of learning from samples is also the process of automatic acquisition of knowledge. A user can apply a learned network (knowledge base) to predict the 28-day compressive strength of concrete defined by a mix design. Because no early-aged compressive strength is needed and as a result no time delay is involved, this method of predicting 28-day compressive strength has great advantages over traditional prediction methods that must give the predicted results days after the casting of fresh concrete.

5. Experimental

5.1. Materials

The cement used is Portland cement, grades 425 and 525 (Chinese Standard). There are two kinds of coarse aggregates, namely the rounded and the crushed, with maximum sizes of 31.5 mm and 40.0 mm. The module of fine aggregate varies from 1.9 to 3.4. We chose two kinds of admixtures, the superplasticizer and the air-entrainment. A certain amount of fly ash is added to the mix to save cement and to reduce the content of calcium hydroxide and improve the endurance. Concrete specimens with cubic dimensions of $150 \times 150 \times 150$ mm for coarse aggregates with a maximum size of 40 mm and $100 \times 100 \times 100$ mm for coarse aggregates with a maximum size of 31.5 mm were cast. They were cured for 28 days in a curing cabinet (relative humidity in excess of 95%, temperature 23 ± 2°C).

5.2. Test data and test procedure

At first, we designed 50 mixes in the laboratory by varying the water/cement ratio from 0.30 to 0.70 and varying the slumps from 10 to 200 mm. The 28-day compressive strength ranges from 20 to 60 MPa. These mixes and 35 other mixes collected from the ready-made concrete plants were chosen to create the mix-design database. Later, to test the effectiveness of the automatic knowledge-acquisition

Table 1
Mix designs given by the system

Original data for mix design								Mix designs by the system (kg/m^3)					
Mix no.	Grade of cement	Maximum size (mm)	Nature	Module of sand	Designed slump (mm)	Designed strength (MPa)	Action of admixture	Cement	Free water	Fine aggregate	Coarse aggregate	Admixture	Fly ash
1	425	31.5	0.7	2.6	160	45	0.9	401	192	664	1,052	11.6	62.6
2	425	40.0	0.4	2.3	140	25	0.9	287	183	768	1,094	5.4	79.1
3	525	31.5	0.4	2.3	180	55	0.9	389	188	678	1,047	10.5	68.9
4	425	31.5	0.7	2.3	160	25	0.9	288	195	738	1,070	5.9	93.4
5	525	31.5	0.7	2.6	180	45	0.9	328	187	689	1,093	9.4	80.3
6	525	40.0	0.4	2.6	150	40	0.7	301	174	723	1,138	8.9	70.5
7	525	40.0	0.4	1.9	160	40	0.5	304	179	723	1,098	9.6	78.9
8	525	31.5	0.4	2.3	170	40	0.9	302	187	728	1,082	6.6	87.7
9	425	31.5	0.4	2.3	150	30	0.9	313	194	739	1,060	5.7	84.1
10	425	31.5	0.4	1.9	170	45	0.7	399	198	687	1,004	9.9	72.3
11	425	40.0	0.4	1.9	160	25	0.9	287	189	777	1,057	5.0	87.3
12	425	40.0	0.4	2.6	160	40	0.7	356	184	715	1,081	9.3	62.5

system, 12 mixes (see Table 1) given by the system were chosen to be carried out in experimental work. The actual 28-day compressive strength and slumps were obtained so that a comparison between the designed properties, the predicted properties, and the actual properties was possible. The comparison results are shown in Table 2.

6. Preprocessing and postprocessing of data

The components that form an input vector have different quantitative limits, so a normalization of data is needed. There are kinds of linear translations that can be used to normalize the input vector components to the values between 0 and 1. One of the translations we used in this paper appears in Eq. (1):

$$X_i = \frac{X_{i0} - X_{\min}}{X_{\max} - X_{\min}} = \frac{1}{X_{\max} - X_{\min}} X_{i0} - \frac{X_{\min}}{X_{\max} - X_{\min}}$$
$$= aX_{i0} + b \qquad (1)$$

where X_{i0} and X_i are the ith components of the input vector before and after normalization, respectively, and X_{max} and X_{min} are the maximum and minimum values of all the components of the input vectors before the normalization. The components of the output vector need to be translated from values between 0 and 1 to the actual values of the world by Eq. (2).

$$Y_i = Y_{i0}(Y_{\max} - Y_{\min}) + Y_{\min} \qquad (2)$$

where Y_{i0} and Y_i are the ith components of the output vector before and after translation, respectively, and Y_{max} and Y_{min} are the maximum and minimum values of the world of all the components of the output vectors.

In addition, the nature of coarse aggregate and the action of admixture are qualitative data, and as such need to be changed to quantitative values. For the latter, the authors applied the fuzzy logic to classify this index to three grades: extremely important, with a membership of 0.9; important, with a membership of 0.7; and less important, with a membership of 0.5, according to its effect on compressive strength and workability. If there are no admixtures added to a mix, this index is 0. The nature of coarse aggregate has different effects on compressive strength and workability. For mix design and slump prediction, the authors appointed 0.7 to the index if the coarse aggregate is round and 0.4 to the index if the coarse aggregate is crushed. For compressive strength prediction, the index is 0.4 and 0.7 for the round and the crushed coarse aggregates, respectively.

7. Examples and results

The system was then applied to 12 design mixes, of which the actual slump and the actual 28-day compressive strength were obtained by laboratory work at a later time. The authors intended to consider everything that would happen when making a mix design and made the application of the system as easy as possible. When designing these mixes, the authors had some knowledge about the materials, the designed slump, and the designed 28-day compressive strength. These original data were organized and formed 12 input vectors of the system; then the proportion of materials consumed would be obtained immediately. The system also provided the predicted workability and 28-day compressive strength of concrete defined by these mixes. The 12 sets of original mix-design data and the 12 mixes given by the system are shown in Table 1. The comparison between the designed properties, the predicted properties, and the actual properties is shown in Table 2.

From Tables 1 and 2 an audience will find that the 12 mixes given by the system basically meet the standards of the design. This shows that it is practical to use the automatic knowledge-acquisition system in our research to design concrete mixtures.

In practice, the reliability of our system depends largely on the extent of the mix-design database. It is the authors' opinion that in order to construct a desirable database a large number of mix designs should be collected. While it is easy to amass mix designs for big ready-mixed concrete

Table 2
A comparison between the designed, the predicted, and the actual properties

Mix no.	Designed strength (MPa)	Predicted strength (MPa)	Actual strength (MPa)	Designed slump (mm)	Predicted slump (mm)	Actual slump (mm)
1	45	47.3	47.8	160	169	163
2	25	25.3	25.2	140	144	135
3	55	52.5	57.6	180	164	175
4	25	34.5	28.5	160	165	150
5	45	48.9	44.9	180	168	176
6	40	44.1	39.6	150	155	155
7	40	43.5	44.0	160	163	163
8	40	48.1	40.9	170	162	167
9	30	32.5	32.8	150	160	146
10	45	46.4	46.5	170	174	160
11	25	29.5	29.6	160	150	160
12	40	45.8	42.2	160	160	165

plants, we cannot guarantee the reliability of our system for a small plant that uses just a limited range of mixes.

8. Conclusions

The authors reached the following conclusions.

1. Much useful information in successful mix designs can be tapped to guide the design of other mixes by an automatic knowledge-acquisition system based on neural networks.
2. By controlling the dosage of materials and the action of admixtures, the workability of ready-made concrete can be approximately predicted through a neural network knowledge base.
3. By controlling the grade of cement, the workability, the dosage of materials, and the action of admixtures, the 28-day compressive strength of ready-made concrete can be approximately predicted through a neural network knowledge base.
4. The system in our research will provide a useful decision-making tool for a concrete engineer.

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References

[1] Portland Cement Association, Design and Control of Concrete Mixtures, 12th ed., Portland Cement Association, Skokie, 1979.
[2] F. de Larrard, Batching concrete on our desk, Concrete 9 (1997) 35–38.
[3] P. Werbos, Beyond regression: new tools for prediction and analysis in the behavioral sciences, Ph.D. Thesis, Harvard University Committee on Applied Mathematics, 1974.
[4] R. Hecht-Nielsen, Theory of the back-propagation neural network, in: H. Wechsler (Ed.), Neural Networks for Perception, Vol. 2, Academic Press, San Diego, CA, 1991.
[5] R. Hecht-Nielsen, Mapping Networks: Multi-layer Data Transformation Structures, Neurocomputing, Addison-Wesley, San Diego, CA, 1990.
[6] D.E. Rumelhart, G.E. Hinton, R.J. Williams, Learning internal representations by error-propagation, ICS Report 8506, Institute for Cognitive Science, UCSD, La Jolla, CA.