STUDY OF CONCRETE EXPANSION DUE TO ASR BASED ON BP NEURAL NETWORKS

Jie Ke*, Min Deng

College of Materials Science and Engineering, Nanjing University of Technology,
No.5 Xin Mofan Road, Nanjing, Jiangsu 210009, China

Abstract

The paper aims to show the applicability of back-propagation (BP) neural networks to alkali-silica reaction (ASR) expansion of concrete. A model based on BP artificial neural networks was constructed, which gave the nonlinear mapping between ASR expansion and its influence factors which include: curing time, curing temperature and particle size of aggregate. According to the prediction results of BP networks, the effects of the three factors on ASR expansion are discussed. As the curing time increases, the total expansion of the concrete increases and then plateaus. High curing temperatures accelerate ASR expansion and also increase the total expansion. The effect of aggregate particle size indicated that there exists a pessimum in particle size of aggregate. This aggregate size causes the maximum obtained ASR expansion. The results showed that BP neural networks exhibited strong potential for predicting ASR expansion in concrete structures.

Keywords: BP neural networks, alkali-silica reaction, expansion

1 INTRODUCTION

Alkali-silica reaction (ASR) has become the worldwide concrete disease due to severe deterioration, causing great economic loss over the past sixty years. Structural distress of concrete due to ASR expansion causes interior deterioration, and Feng Naiqian et al. [1] illustrated examples of cracks and damage due to ASR which covered USA, Canada, Japan and China. The phenomenon exhibited were quite complex.

Several researchers have looked into the characteristic parameters that effect ASR expansion of concrete. Some of the parameters include total alkali content of concrete, aggregate reactivity, curing temperature, humidity and curing time. In order to bridge the gap between expansion in the laboratory and the field, it is normal to elevate the curing temperature and study the effect of temperature on ASR expansion. At the same time, aggregate particle size considered in the lab is much smaller than that in the field. The largest aggregate particle size is 150mm for dam concrete, while fine aggregate is typically used in the lab. It is significant to study the effect of aggregate particle size on ASR expansion. The expansion due to ASR also differs at different curing times. However, there is no exact regression model to express ASR expansion influenced by various factors, even a quantitative mathematic model can not be proposed for single factor exactly. Since ASR expansion is nonlinear and effected by multiple factors, this paper presents a BP neural network algorithm to study the effect of each factor on ASR. A BP neural network is constructed based on experimental data that are arranged in a format of three input parameters which cover the curing temperature, aggregate particle size and curing time and an output parameter that is ASR expansion. Sensitivity analysis of each factor on ASR is conducted, which demonstrates how each factor affects ASR expansion and will be helpful for service life prediction of concrete structures due to ASR.

2 BP NEURAL NETWORKS

2.1 BP neural network model and algorithm

Artificial neural networks developed in recent years are artificial intelligence technologies capable of simulating the biological process of a human brain. It is nonlinear system, in which a great number of simple neurons interconnected by their synapses. An artificial neuron is defined as the basic unit of the neural network. A typical structure of an artificial neuron is given in Figure

* Correspondence to: kejie1982@hotmail.com

1. Multilayer feed-forward network based on back-propagation is one of the most popular and successful algorithms at present. Accordingly, for a given input pattern, a flow of activation is forwarded from the input layer to the output layer via the hidden layer(s) and it produces a unique output. The errors in the output are initiated and they are propagated backward from the output layer to the input layer to adjust the weights and thresholds, as illustrated in Figure 2.

The neural network method could conclude rules only from data themselves and learn the relationship of input/output without any prior knowledge. In particular, it is quite fit for complex and nonlinear system, such as diagnosis, classification, decision-making, planning and scheduling [3], which exhibit strong functionality in the face of systems that are difficult to solve with traditional theories and approaches.

2.2 Application of neural networks in cement and concrete

Over the last two decades, a different modeling method based on neural networks has become popular and has been used by many researchers for a variety of engineering applications. The first application of neural networks in the field of cement and concrete is in 1993, when Wu Shouxin [4] developed a BP neural network model of softening behavior for cracked concrete. Compared with theoretical model, the BP model is more reliable. Since then, there is a wide application of neural networks in cement and concrete covering strength prediction, mixture design, hydration degree, sulfate attack, service life prediction and damage assessment. [5-14]. Most of them used multilayer feed-forward network to construct models, including BP, RBF (Radial Basis Function), and so on. Besides, some researchers combined fuzzy theory and genetic algorithm with neural networks to study complex and nonlinear systems in the field of cement and concrete [15-19]. However, the application of neural network in ASR of concrete is still in its infancy [20].

As the use of neural networks has increased and their success is well documented, many problems have appeared in theory and applications, which restricts its further use. These problems involve generalization ability of multilayer feed-forward networks, architectural design of networks, convergence rate of the algorithm and local minimum. Generalization ability of networks is the most concerning problem. Generalization ability is the ability of trained networks to respond correctly to training and test samples. Generalization ability is the uppermost performance of multilayer feed-forward networks and neural networks without this ability are unvalued.

Commonly used BP neural networks may experience "overfitting" during the training process. The error is very small for training samples, but large for new data outside of the training samples. The network memorizes the trained samples but it lacks the generalization ability for new samples. A method of enhancing generalization ability of network is adjusting the network architecture to make its "fitting" exact. Unfortunately, it is very difficult to foresee what network architecture is suitable for a given system. There are two other strategies of enhancing generalization ability of networks in MATLAB kit tools, namely normalized method and advance-termination training [21]. Min Xilin et al. [22] also proposed that advance-termination training could prevent "overfitting" of the system.

3 BP NEURAL NETWORK MODEL OF ASR

3.1 Experimental data

A Portland cement from Jiangnan-Onada Cement Corp. in Jiangsu Province was used. Its alkali content was 0.55%. The chemical composition of the cement is given in Table 1. The crushed gravel had a complex composition including quartz, feldspar, mica, flint, microcrystalline quartz, cryptocrystalline quartz and undulatory extinction quartz. The aggregates were separately crushed and sieved as 0.16-0.63 mm, 0.63-2.50 mm and 5.00-10.00 mm. Specimens,40mm x 40mm x 160mm, were prepared with each of the three different aggregate particle sizes. Each set of specimens consisted of nine prisms. The water to cement ratio (W/C) was 0.30. The alkali content of the cement was adjusted to 1.2% by adding sodium hydroxide (NaOH) to the mixing water. The specimens were demolded after one day curing in moist chamber (20 °C, RH>95%) and the initial length measurement is taken. The nine prisms were separated into three groups, which were then submersed in 1mol/L NaOH solutions at 40 °C, 60 °C and 80 °C, respectively. At given intervals, the prisms were cooled to 20 °C and their length measured. Expansion of each group of prisms was calculated and 124 sets experimental data were collected for predicting ASR expansion by BP neural networks.

3.2 BP model of ASR

This paper focuses on the effect of aggregate particle size, curing temperature and curing time on ASR expansion. There are a total of 124 data cases, which are divided into three subsets by the advance-termination algorithm. 62 cases are used for training, 31 cases for verification and 31 cases for test. The cases in the training set are used to calculate grads and modify weights and thresholds within the algorithm. The second set is used for verification. These cases are used to check the progress of the algorithm and supervise the error of training set. Training of the neural network is stopped when the error for the verification set begins to increase. The test set is an independent data set, which is used to test the neural network and check its performance with data which have not been used in the training and verification. When verification and test errors are reasonably close together, the network is likely to generalize well.

Hornik et al. [23] proved that a feed-forward neural network containing only a nonlinear hidden layer could approximate any function with precision. The most popular and successful learning algorithm used to implement multilayer feed-forward neural networks is the back-propagation (BP) algorithm. This paper uses a three-layer BP neural network for learning and training. The number of input layer units is three, namely particle size of aggregate, curing temperature and curing time. The number of hidden layer units is six, which ensures the least training error. The number of output layer units is one, which is concrete expansion due to ASR. The BP neural network model developed in this research is illustrated in Figure 3. Levenberg-Marquardt algorithm, the fastest algorithm proposed for training mid-scale feed-forward neural networks, is employed. The training of network is over and converges when 168 training epochs have been completed (Figure 4). The result of the model for ASR expansion prediction is in Figure 5. The parity graph for predicted versus measured expansion, indicates the BP neural network model can learn the nonlinear relationship between the three parameters and ASR expansion.

As shown in Figure 5, the trained BP neural network could not only predict data cases in the training verification sets accurately, but also predict that of the test set exactly, which indicates good generalization ability. The statistical values for ASR expansion in the three sets are given in Table 2. The R^2 values are 0.9988 in training set, 0.9996 in verification set and 0.9983 in test set for ASR expansion. The RMS (root mean square) errors are 0.0182, 0.0108 and 0.0201 for the training, verification, and test sets respectively. All of the statistical values in Table 2 demonstrate that the proposed BP neural network is suitable and the predicted expansion values are similar to the experimental values. A small perceptible deviation was observed for the calculated values. The deviation may be due to a lack of available data needed to train the network on the effects of these parameters, the existence of a non-uniform distribution of variables in the data and experimental error. Increasing and improving data samples can enhance the application ability of BP neural network in predicting the long-term concrete expansion due to ASR. A graphical comparison of experimental data of the test set and BP neural network results is given in Figure 6.

4 RESULTS ANALYSIS AND DISCUSSION

Based on the results of BP model prediction, two dimensional expansion-time curves are shown in Figure 7 through Figure 9. The figures show the measured expansion and BP predicted expansion curves are similar and expansion increased with time as curing time increased. The expansion of specimens with particle size of 0.16-0.63mm leveled off at the later time in figure 9.

The elevated temperature accelerated ASR expansion. Expansion at 80°C was larger than that of 60°C, while expansion at 40°C was the smallest. Carrazedo et al. [25] proved that expansion is influenced by temperature, and the higher temperature, the more concrete expansion with all other conditions remaining constant.

At the same temperature, the particle size of aggregate has an effect on expansion rate of concrete due to ASR, which can be seen in Figure 7 through Figure 9. In this study, the largest expansion occurs when particle size is 0.63-2.5mm. Though the pessimum particle sizes are different among different researchers due to different aggregate, cement, mixes and other factors, research indicates [26-28] that aggregate particle size affects the concrete expansion due to ASR.

5 CONCLUSIONS

The following conclusions are drawn from the research:

- BP neural network model constructed in this paper can predict ASR expansion accurately based on its influence factors: curing temperature, curing time and aggregate particle size.

- The generalization ability of BP networks can be effectively improved by advance-terminating learning method.
- Increasing and improving data samples can enhance the application ability of BP neural network in predicting the long-term expansion of concrete due to ASR.
- When exposed to high curing temperatures, expansion due to ASR is larger than that at low temperatures. The temperature accelerates ASR expansion and maximum expansion is reached in a relatively short time.
- The aggregate particle size has a remarkable effect on ASR expansion. The pessimum particle size for different specimens with the same aggregate is to be investigated.

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Table 1: Chemical composition of cement

SiO_2	Al_2O_3	Fe_2O_3	CaO	MgO	SO_3	LOI	K_2O	Na_2O	Total
21.03	5.06	3.98	63.82	1.08	2.31	1.15	0.58	0.17	99.18

Table 2: Statistical values of proposed model

Statistical parameters	Training set	Verification set	Test set
R^2	0.9988	0.9996	0.9983
RMS	0.0182	0.0108	0.0201

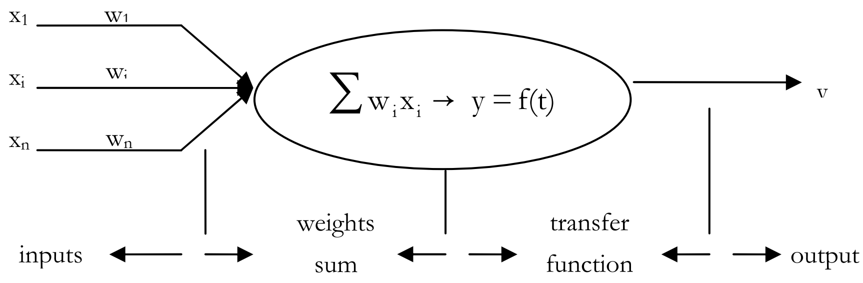

Figure 1: A typical structure of artificial neuron [2]

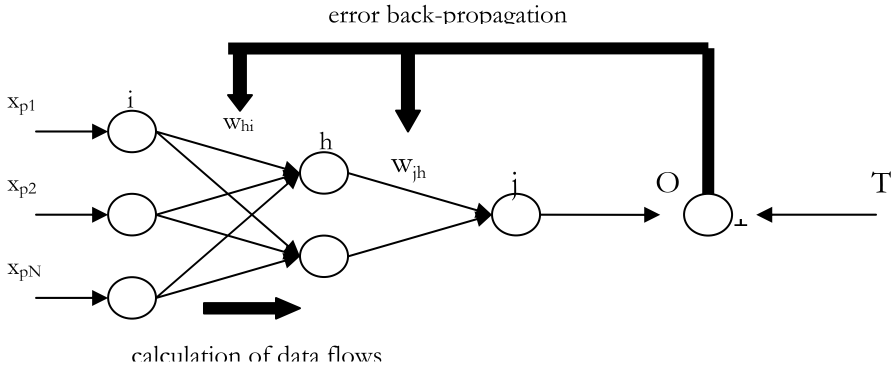

Figure 2: Architecture of BP neural network

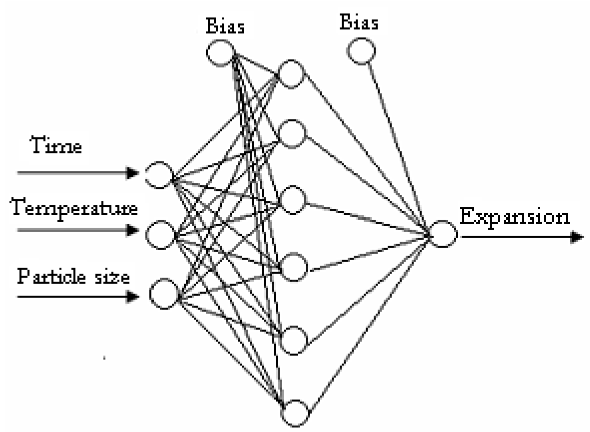

Figure 3: Proposed BP neural networks model

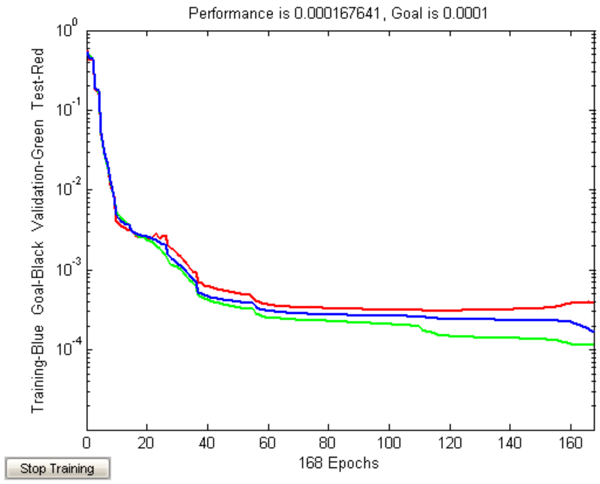

Figure 4: Learning graph for BP neural networks model

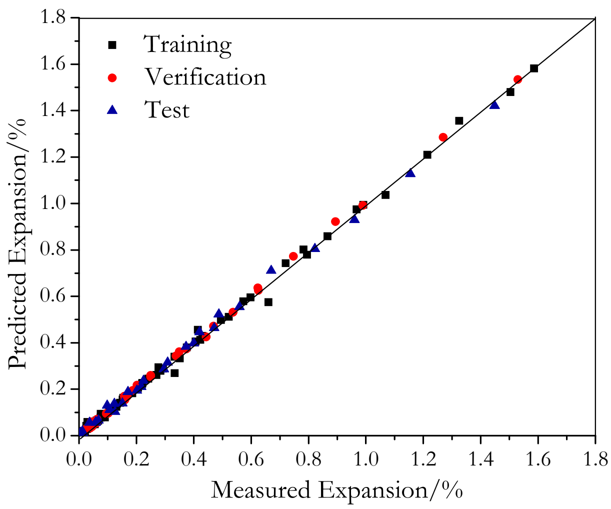

Figure 5: Parity plot for predicted expansion versus measured expansion

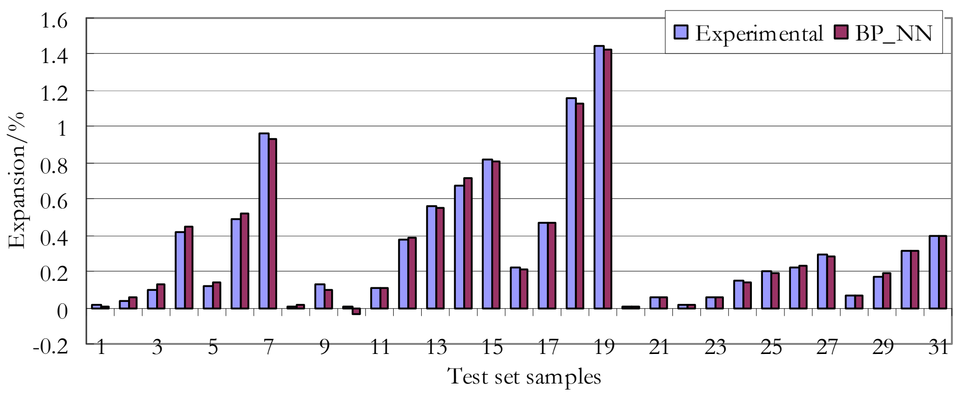

Figure 6: Comparison of experimental ASR expansion with BP neural networks predicted expansion

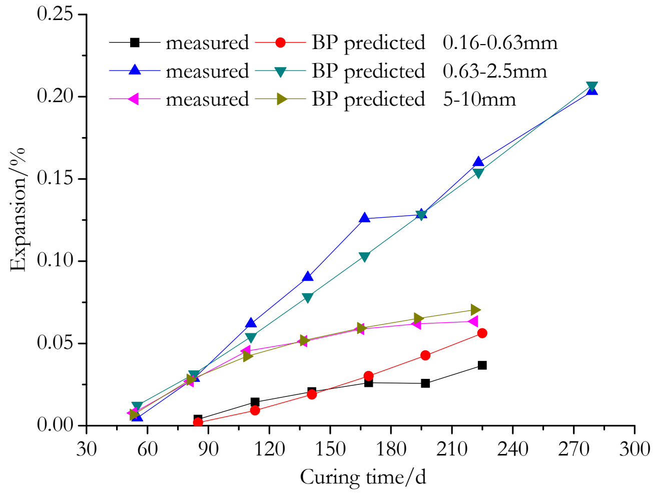

Figure 7 Comparison of measured expansion and predicted expansion at 40°C

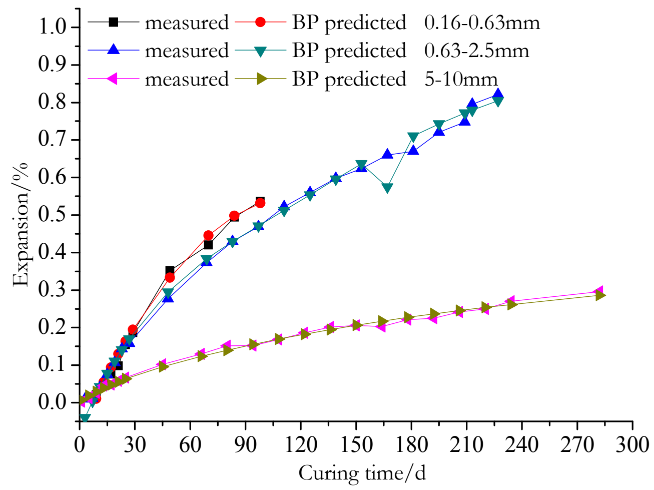

Figure 8 Comparison of measured expansion and predicted expansion at 60°C

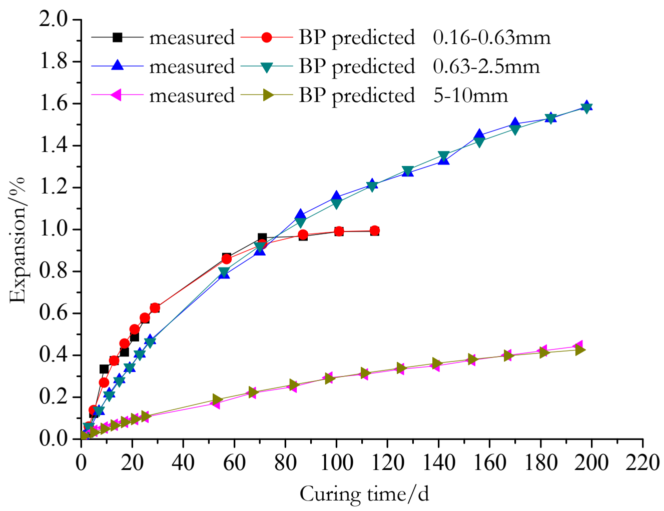

Figure 9 Comparison of measured expansion and predicted expansion at 80°C