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Evaluation of the effect of aggregate on concrete permeability using grey correlation analysis and ANN

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Abstract. In this study, the influence of coarse aggregate size and type on chloride penetration of concrete was investigated, and the grey correlation analysis was applied to find the key influencing factor. Furthermore, the proposed 6-10-1 artificial neural network (ANN) model was constructed, and performed under the MATLAB program. Training, testing and validation of the model stages were performed using 81 experiment data sets. The results show that the aggregate type has less effect on the concrete permeability, compared with the size effect. For concrete with a lower w/b, the coarse aggregate with a larger particle size should be chose, however, for concrete with a higher w/c, the aggregate with a grading of 5-20 mm is preferred, too large or too small aggregates are adverse to concrete chloride diffusivity. A new idea for the optimum selection of aggregate to prepare concrete with a low penetration is provided. Moreover, the ANN model predicted values are compared with actual test results, and the average relative error of prediction is found to be 5.62%. ANN procedure provides guidelines to select appropriate coarse aggregate for required chloride penetration of concrete and will reduce number of trial and error, save cost and time.

Keywords: coarse aggregate; permeability; concrete; grey correlation analysis; artificial neural network

1. Introduction

Concrete is considered as a durable construction material, however, when the structure is in severe environmental condition, concrete still shows degradation of durability. Chloride induced corrosion of the reinforcing steel is known as a major cause of the degradation of durability performance and further the structural safety of concrete structures. In order to protect the reinforcing steel from corrosion, it is necessary to make reasonable selection of concrete materials and optimal design of mixture proportions.

The existent studies about the influence of materials on chloride penetration in concrete are mainly focus on the cementitious matrix materials (Chindaprasirt *et al.* 2007, Wongkeo *et al.* 2014), since it is often assumed that most rock aggregates used in concrete are inert packing

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material. In fact, aggregate occupy about 70% of concrete total volume, it is normal to expect that aggregate quality could determine concrete performance. For instance, the occasional micro-cracks on the coarse aggregate, its porosity, rough texture and the physical and chemical connection between the cement paste and the aggregate, all of these factors can influence the microstructure of the interfacial transition zone (ITZ) (Elsharief *et al*. 2003) and then the concrete durability. For example, in studying the influence of physical and geometrical properties of granite and limestone aggregate on the durability of a C20/25 strength class concrete, Torgal and Gomes (2006) has found that the aggregate size and absorption played the major role in concrete durability. Pereiar *et al*. (2009) also studied the influence of aggregate type, size, as well dry or water saturated condition on the durability of concrete with a w/c of 0.44, and it was found that concrete durability properties were significantly affect by the aggregate size and its water content. This is mainly due to the influence of aggregate physical properties on the ITZ, which is very important to concrete durability. Moreover, the chemical compositions of aggregate may also have certain effect on the ITZ (Tasong *et al*. 1998). A chemical reaction between carbonate aggregate and cement paste has been observed (Monteiro and Metha 1986). Therefore, it is essential to discuss the relevance of choice of natural coarse aggregate to produce more durable concrete.

Grey theory was put forward by Deng (1985), its character is to study the small sample, poor information and uncertainty problem. In this theory, any random process is considered to be a grey value, which varied in the range of a certain magnitude and time zone. Although the objective system is complex and the data is in a mess, it always has some intrinsic rules. The grey correlation analysis can process the limited and irregular data, and the major factors that influencing the target value can be found out. Therefore, the grey correlation analysis (GCA) has been widely applied to the economic, agriculture and engineering (Wei *et al*. 2015).

In addition, to evaluate the chloride penetration of concrete, a reasonable prediction for the diffusion coefficient of chloride ion is basically required. However, it is difficult to obtain chloride diffusion coefficients from experiments due to time and cost limitations. Therefore, it is better to find a method, which can predict the chloride penetration of concrete with different coarse aggregates more convenient and quickly. In recent years, with the development of computer and life science, artificial neural network (ANN) theory and the model has been developed rapidly and successfully used in many fields of engineering (Ji *et al*. 2006; Bal and Buyle-Bodin 2010; Khan 2012). The neural network modeling approach is simpler and more direct than traditional statistical methods, particularly when modeling nonlinear multivariate interrelationships, thus it has attracted more and more attention.

The aim of this study is to analyze the relationship between coarse aggregate factors (e.g., grading, water absorption, density, etc.) and chloride penetration of concrete, thereby finding the key factors of influence, and construct an ANN model for predicting, which can reduce the experimental workload greatly. For this purpose, the coarse aggregates with different particle sizes, water absorptions, densities and strengths were used to prepare concrete with different water-cement ratios, and the chloride diffusion coefficients of concrete at different ages were tested. The data collected from the experiments are used to make the grey correlation analysis, and develop the neural network model. The results obtained are expected to provide some theoretical basis and a predictive tool for the optimum selection of aggregate to prepare concrete with a low chloride penetration.

2. Experimental program

Table 1 Mixture proportions of concrete (kg/m^3)

w/b	Water	Cement	Sand	Crushed stone	Fly ash	Water-reducer
0.31	160	425	650	1061	98	7.32
0.38	160	340	669	1128	78	3.34
0.47	160	278	687	1154	64	1.54

Note: The proportion of crushed stone is that of limestone aggregate.

2.1 Materials

Grade 42.5 Ordinary Portland Cement and Class Ⅰ fly ash were used in all mixtures. Three different types of coarse aggregate were selected for this study, include: limestone, granite and basalt, and for each type, three different particles sizes of coarse aggregate (5-10 mm, 5-20 mm and 5-30 mm) were used. Fine aggregate used was river sand with a fineness modulus of 2.8 and a specific gravity of 2.61. A naphthalene-based superplasticizer was used.

2.2 Mixture proportions

Three groups of concrete were prepared with water-cement ratios (*w/b*) of 0.31, 0.38 and 0.47, the mixture proportions of concrete are shown in Table 1. For each group of concrete, three different types and particle size of coarse aggregate were used on a constant paste-aggregate volume ratio. The slump of fresh concrete was controlled within 70-90 mm by adjusting the amounts of superplasticizer.

2.3 Chloride penetration test

Concrete specimens with dimensions of 100×100×50 mm were used for chloride diffusion study. They were immersed in the sodium chloride solution with a concentration of 4 mol/L, and saturated by vacuum pumping. The diffusion coefficient of chloride ion was obtained using a rapid chloride penetrant method (Li *et al*. 1998), which is based on the Nernst-Einstein equation

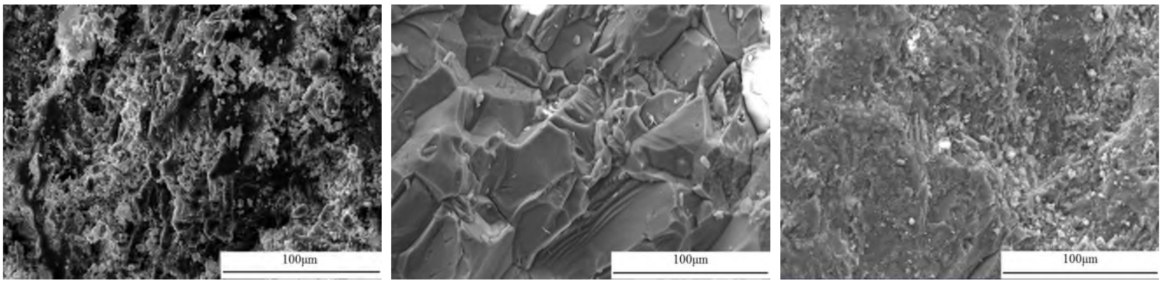
$$D_i = \frac{RT\sigma_i}{Z_i^2 F^2 C_i} \tag{1}$$

where D_i is the diffusion coefficient of chloride ion; R is the gas constant (R=8.314J/(mol·K)); T is the absolute temperature; σ_i is the partial conductance of chloride ion; Z_i is the charge number of chloride ion; F is the Faraday constant (F=96500C/mol); C_i is the particle concentration of chloride ion.

2.4 Experimental results and discussion

2.4.1 Microstructure and physical properties of coarse aggregate

The SEM micrographs for the three types of coarse aggregate (limestone, granite and basalt), are shown in Fig. 1. It can be seen that the limestone aggregate, which formed by deposition, has a rough surface and porous structure. By contrast, the granite and basalt aggregates, which both belong to igneous rock, have denser structure. The granite aggregate have a smooth surface and



(a) Limestone (b) Granite (c) Basalt

Fig. 1 SEM micrographs of coarse aggregate

Table 2 Physical properties of coarse aggregates

Type of aggregates		Limestone	Granite	Basalt
Specific gravity		2.64	2.86	2.73
Compressive strength/MPa		65	148	112
Porosity/%		1.95	0.76	0.83
Water absorption/%	15min	0.87	0.28	0.39
	1h	0.90	0.29	0.41
	3h	0.95	0.32	0.44
	24h	1.13	0.38	0.52

Table 3 Distribution of coarse aggregate size

Aggregate	Normal size/mm	Cumulative sieve residue/%						
		Square mesh sieve size/mm						
		2.36	4.75	9.50	16.0	19.0	26.0	31.5
Limestone	5-10	100	92	12	—	—	—	—
Limestone	5-20	100	95	75	30	10	—	—
Limestone	5-30	100	95	85	55	35	15	5
Granite	5-10	100	95	14	—	—	—	—
Granite	5-20	100	96	78	25	8	—	—
Granite	5-30	100	96	87	59	40	17	3
Basalt	5-10	100	94	13	—	—	—	—
Basalt	5-20	100	94	80	35	7	—	—
Basalt	5-30	100	95	86	57	38	15	3

good crystallization, whereas the surface of basalt aggregate is relative rough. The structure of coarse aggregate would not only affect its physical properties (e.g., strength, water absorption, etc.), but also affect its combination with the cement paste.

The physical properties of coarse aggregates are presented in Table 2. Water absorptions of coarse aggregates were carried out at different times of immersion in water. As shown in the table, the absorptions of limestone, granite and basalt aggregates at 1h were 0.90, 0.29 and 0.41% by weight of aggregate, respectively. It can be seen that all the three types of coarse aggregate have a low permeability. Granite aggregate has the highest strength and the lowest water absorption.

Table 4 Parameters of coarse aggregate and concrete durability

Series	Aggregate	Normal size /mm	$\overline{R}$ /mm	W_a /%	γ	f /MPa	w/b	D_{Cl^-}/(×10^{-8}cm^2/s)		
								7d	28d	56d
1	limestone	5-10	6.27	0.9	2.64	65	0.31	4.15	3.43	1.89
2	limestone	5-20	8.04	0.9	2.64	65	0.31	3.09	2.57	1.56
3	limestone	5-30	8.59	0.9	2.64	65	0.31	3.02	2.51	1.34
4	granite	5-10	7.12	0.3	2.86	148	0.31	2.97	2.18	1.22
5	granite	5-20	8.41	0.3	2.86	148	0.31	2.85	2.12	1.18
6	granite	5-30	9.33	0.3	2.86	148	0.31	2.56	2.05	1.13
7	basalt	5-10	6.86	0.4	2.73	112	0.31	2.39	1.77	1.17
8	basalt	5-20	7.94	0.4	2.73	112	0.31	2.31	1.60	1.15
9	basalt	5-30	8.92	0.4	2.73	112	0.31	2.25	1.58	1.09
10	limestone	5-10	6.27	0.9	2.64	65	0.38	5.58	5.03	3.48
11	limestone	5-20	8.04	0.9	2.64	65	0.38	4.63	4.69	2.65
12	limestone	5-30	8.59	0.9	2.64	65	0.38	5.37	4.76	3.28
13	granite	5-10	7.12	0.3	2.86	148	0.38	5.37	4.88	3.79
14	granite	5-20	8.41	0.3	2.86	148	0.38	4.88	4.24	3.06
15	granite	5-30	9.33	0.3	2.86	148	0.38	5.21	4.67	3.64
16	basalt	5-10	6.86	0.4	2.73	112	0.38	3.95	3.16	2.45
17	basalt	5-20	7.94	0.4	2.73	112	0.38	3.56	2.69	1.94
18	basalt	5-30	8.92	0.4	2.73	112	0.38	4.03	3.01	2.58
19	limestone	5-10	6.27	0.9	2.64	65	0.47	7.32	6.63	5.13
20	limestone	5-20	8.04	0.9	2.64	65	0.47	6.29	5.71	4.29
21	limestone	5-30	8.59	0.9	2.64	65	0.47	7.87	7.25	5.52
22	granite	5-10	7.12	0.3	2.86	148	0.47	6.85	6.22	4.98
23	granite	5-20	8.41	0.3	2.86	148	0.47	6.97	6.36	4.93
24	granite	5-30	9.33	0.3	2.86	148	0.47	7.48	6.83	5.91
25	basalt	5-10	6.86	0.4	2.73	112	0.47	5.75	5.04	3.96
26	basalt	5-20	7.94	0.4	2.73	112	0.47	5.53	4.83	3.77
27	basalt	5-30	8.92	0.4	2.73	112	0.47	6.07	5.42	4.73

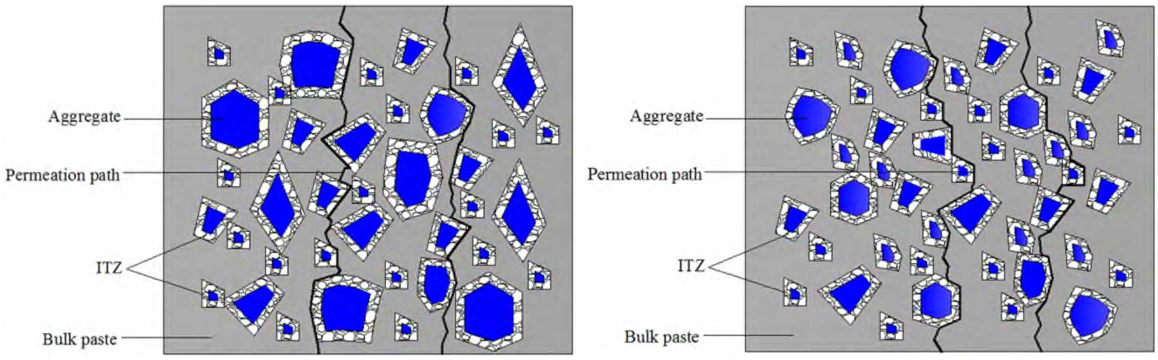
Table 3 shows the size distribution of coarse aggregates.

In order to analyze the relationship between coarse aggregate and concrete permeability quantitatively, the index $\overline{R}$ is proposed to characterize the grading parameter as follows

$$\overline{R} = \sqrt[3]{\frac{3V_a}{4\pi N_V}} \tag{2}$$

where $\overline{R}$ is the average particle size of aggregates; V_a is the volume fraction of aggregates in concrete; N_V is the total number of aggregates per unit volume of concrete.

Sun (2012) has proposed the total number of aggregates per unit volume of concrete as



(a) Larger aggregates (b) Smaller aggregates

Fig. 2 Diagram of the tortuosity effect of aggregate on concrete

$$N_V = \sum_{i=1}^{M} \frac{18 V_a c_i}{\pi \left(d_{i+1}^3 - d_i^3\right)} \ln\left(\frac{d_{i+1}}{d_i}\right) \quad (3)$$

where d_i and d_{i+1} are the diameters of adjacent sieve; c_i is the volume fraction of aggregates retained on some sieve that has a diameter between d_i and d_{i+1}, $d_i < d_{i+1}$; M is the total numbers of sieves used, and the sum of di over the M sieves equals 1.

The calculations of average particle size ($\overline{R}$) and 1h-water absorption (W_a) of aggregates, as well as their strength (f) and specific gravity (γ) were listed in Table 4.

2.4.2 Chloride penetration test

The chloride diffusion coefficients of concrete at 7, 28 and 56 days were evaluated, and the results are also listed in Table 4 correspondingly. It can be seen that, for concrete with a low *w/b*, a larger aggregate decreases the chloride penetration in it. However, for concrete with a high *w/b*, too large or too small aggregate are adverse to concrete impermeability. In this study, the chloride diffusion coefficient of concrete prepared with a particle size of 5-20 mm aggregate is the lowest. This can be explained by the positive and negative effect of aggregate on the transport performance of cement based materials.

Usually, the rock aggregate is considered to be non-penetrative phase, thus the incorporation of the aggregate in cement paste has a dilution effect on the concrete permeability. Furthermore, the existence of aggregate elongates the diffusion path compared with the net cement paste, and all of these can decrease the chloride penetration. In this study, the paste-aggregate volume ratio is constant, hence the dilution effect can be ignored, and the smaller the particle size of aggregate is, the more tortuous the permeation path is, as shown in Fig. 2. However, the decrease of aggregate size also increases the volume fraction of the porous ITZ, which is known to be the weakest region in ordinary concrete (Erdem *et al*. 2012). When the *w/b* is low, the hardened cement paste has a dense structure, so the negative effect of the ITZ is more significant (Delagrave *et al*. 1997). However, with the increase of the *w/b*, the structure of the cement paste becomes less dense, and then the positive tortuosity effect goes into prominent, thus too large aggregate is adverse to concrete impermeability, furthermore, a larger aggregate would accumulate more water film around it, which leads to a more porous structure of the ITZ.

Regarding coarse aggregate types, the concrete mixes produced using granite and basalt aggregate, present lower chloride penetration compared to that using limestone aggregate. This can be explained as follows, on one hand, the granite and basalt aggregates with high density and low water absorption are good for concrete impermeability. On the other hand, they are formed by the volcanic eruption, and have higher chemical activity, which may improve the microstructure of the ITZ to a certain degree.

3. Grey correlation analysis

3.1 Analytical procedure

3.1.1 Determination of analysis series

The data series that reflect the behavior character of the system is called reference series (or parent series), can be given by

$$Y = \{y(k) | k = 1,2,\cdots,n\} \tag{4}$$

The data series that consist of factors influencing the behavior of system is called comparison series (or subsequence), can be given by

$$X_i = \{X_i(k) | k = 1,2,\cdots,n\}, i = 1,2,\cdots,m \tag{5}$$

3.1.2 Non-dimensional processing of variable

In view that the data of the various factors may be of different dimensions, it is hard to compare with each other, therefore in grey correlation analysis, the data should be handled dimensionlessly as follows

$$x_i(k) = \frac{X_i(k)}{X_i(l)}, k = 1,2,\cdots,n; i = 0,1,2,\cdots,m \tag{6}$$

$X_i(l)$ can be the initial value or the mean value or the interval value of the comparison series. In this paper, the data of various factors is comparable in order of magnitude, thus the initialization value processing method is adopted.

3.1.3 Calculation of correlation coefficient

The correlation coefficient of y(k) and xi(k) can be calculated as follows

$$\varepsilon_i(k) = \frac{\min\limits_i \min\limits_k |y(k) - x_i(k)| + \lambda \max\limits_i \max\limits_k |y(k) - x_i(k)|}{|y(k) - x_i(k)| + \lambda \max\limits_i \max\limits_k |y(k) - x_i(k)|} \tag{7}$$

where λ is the resolution ratio, the general range of λ is (0, 1), in this study, λ=0.5; $\varepsilon_i(k)$ is the correlation coefficient, which indicates the relative difference between reference and comparison curves of *i* factor in the *k* moment.

3.1.4 Calculation of correlation degree

The correlation coefficients obtained above are the correlation values of reference and comparison series at various moments, hence there are more than one values. However, the scattered information is not good for the overall comparison. Consequently, it is necessary to average these coefficients as the correlation degree (r_i) between reference and comparison series, which can be expressed as follows

$$r_i = \frac{1}{n}\sum_{k=1}^{n}\zeta_i(k), k = 1,2,\cdots,n \tag{8}$$

3.1.5 Sequence of correlation degree

At last, rank the correlation degree. If $r_1 < r_2$, it indicates that the reference series y is more similar to the comparison series x_2.

3.2 Grey correlation between coarse aggregate and chloride penetration of concrete

In this study, select data series of average particle size ($\overline{R}$), water absorption (W_a), specific gravity (γ) and strength (f) of coarse aggregates and *w/b* as the comparison series, and select the chloride diffusion coefficients of concrete (D_{Cl^-}) as the reference series. Table 4 shows the specific data. Then take the chloride penetration of concrete at 28 days as an example to analyze the influence of coarse aggregate on it, the process is as follows

The processed subsequence matrix is expressed as

$$A = \begin{bmatrix} 1.000 & 1.000 & 1.000 & 1.000 & 1.000 \\ 1.282 & 1.000 & 1.000 & 1.000 & 1.000 \\ 1.370 & 1.000 & 1.000 & 1.000 & 1.000 \\ 1.136 & 0.333 & 1.083 & 2.277 & 1.000 \\ 1.341 & 0.333 & 1.083 & 2.277 & 1.000 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1.423 & 0.444 & 1.034 & 1.723 & 1.531 \end{bmatrix} \tag{9}$$

And the processed parent series matrix is expressed as

$$B = \begin{pmatrix} 1.000 & 0.749 & 0.732 & 0.636 & 0.618 & \cdots & 1.580 \end{pmatrix}^T \tag{10}$$

The matrix of absolute difference between parent series and subsequence is evaluated as

$$\Delta_{ij} = \begin{bmatrix} 0.000 & 0.000 & 0.000 & 0.000 & 0.000 \\ 0.533 & 0.251 & 0.251 & 0.251 & 0.251 \\ 0.638 & 0.268 & 0.268 & 0.268 & 0.268 \\ 0.500 & 0.302 & 0.448 & 1.641 & 0.364 \\ 0.723 & 0.285 & 0.465 & 1.659 & 0.382 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0.158 & 1.136 & 0.546 & 0.143 & 0.049 \end{bmatrix} \tag{11}$$

Table 5 Results of the grey correlation analysis

Factors	7d		28d		56d	
	Correlation degree	Sequence	Correlation degree	Sequence	Correlation degree	Sequence
$\overline{R}$	0.718	2	0.681	2	0.686	2
W_a	0.711	3	0.668	3	0.678	3
γ	0.633	4	0.626	4	0.617	5
f	0.576	5	0.575	5	0.635	4
w/b	0.810	1	0.767	1	0.740	1

And the matrix of correlation coefficient is evaluated as

$$\varepsilon_{ij} = \begin{bmatrix} 1.000 & 1.000 & 1.000 & 1.000 & 1.000 \\ 0.612 & 0.770 & 0.770 & 0.770 & 0.770 \\ 0.568 & 0.758 & 0.758 & 0.758 & 0.758 \\ 0.627 & 0.735 & 0.652 & 0.338 & 0.697 \\ 0.537 & 0.747 & 0.643 & 0.336 & 0.687 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0.842 & 0.425 & 0.606 & 0.855 & 0.945 \end{bmatrix} \tag{12}$$

Finally, the matrix of correlation degree can be calculated as follows

$$\gamma = \begin{pmatrix} 0.681 & 0.668 & 0.626 & 0.575 & 0.767 \end{pmatrix} \tag{13}$$

The grey correlation results are listed in Table 5. It can be seen that for chloride penetration of concrete, the *w/b* has the highest correlation degree, which indicates that it is primary influencing factor. In other words, it demonstrates that coarse aggregate is less sensitive to concrete permeability, compared with *w/b*. Furthermore, for concrete with different coarse aggregates, the average particle size is the major influencing factor, followed by the water absorption regardless of curing ages. Combined with the chloride penetration results of concrete as shown in Table 4, it is conclude that for concrete with a lower *w/b*, the coarse aggregate with a larger $\overline{R}$ should be chose, on the premise of meeting the workability and mechanical properties of concrete. However, for concrete with a higher *w/b*, the aggregate with a particle size of 5-20 mm is preferred, too large or too small aggregates are adverse to chloride penetration of concrete. Compared with the size effect, the aggregate types have less effect on the concrete permeability.

4. Artificial neural network

4.1 Development of ANN

In this study, the ANN was developed and performed under MATLAB programming. The learning algorithm adopted to train the network model in this study is the Levenberg–Marquardt

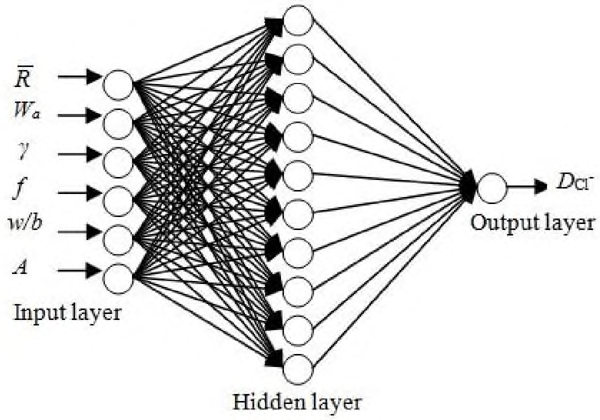


Fig. 3 Architecture of ANN for predicting chloride penetration of concrete

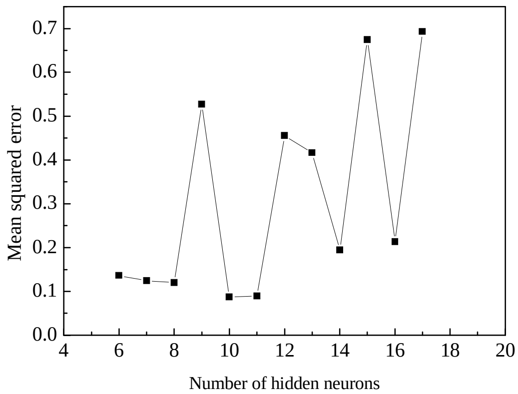


Fig. 4 Error generated by different number of neurons

algorithm (Parka *et al*. 2005). The ANNs model is developed, trained and tested by using a total of 81 data sets. To test the reliability and accuracy of the models, 20% of the total data sets were randomly selected as testing sets, while the remaining 65 samples were used to train the network. In order to eliminate the magnitude difference between the variables, a normalization method is used to deal with the input and output data in this study as follows, which can scale all the data in the 0 to 1range.

$$\overline{x_i} = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{14}$$

where x_i is the input or output data; xmin is the minimum data; $x_{\max}$ is the maximum data; $\overline{x_i}$ is the data after normalization.

To predict the chloride penetration of concrete with different coarse aggregate, take the six factors that influence the chloride penetration in concrete as the input layer neurons: $\overline{R}$, W_a, γ and f of aggregates, *w/b* and curing age (A), take D_{Cl^-} as the output layer neuron. Currently, there is no rule for determining the optimal number of neurons in the hidden layer or the number of hidden

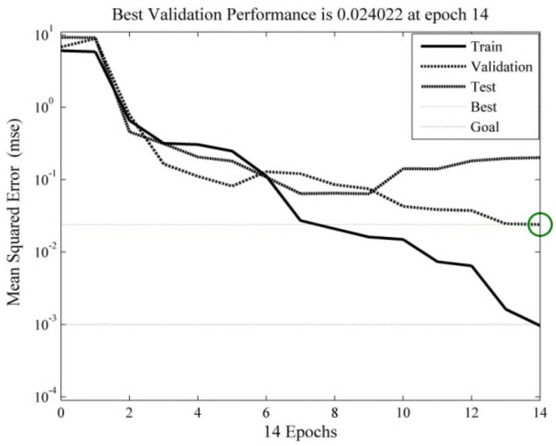


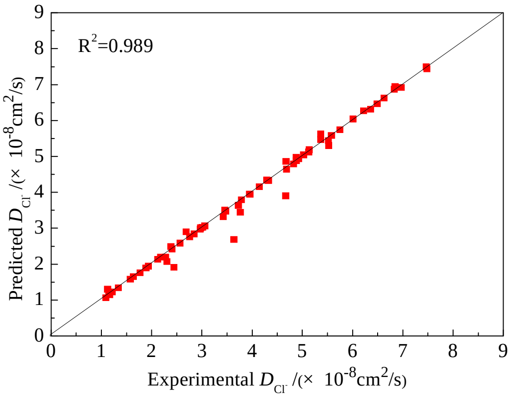
Fig. 5 Reduction in error over training time

Table 6 Parameters of coarse aggregate and concrete durability

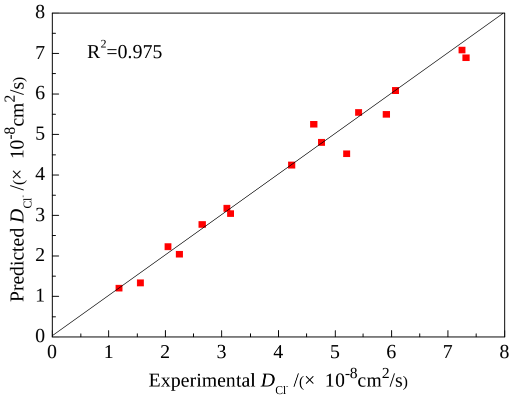
No.	*w/b*	$\overline{R}$ /mm	W_a /%	γ	*f* /MPa	*A* /d	Measured value /($\times10^{-8}$cm^2/s)	Predicted value /($\times10^{-8}$cm^2/s)	*E*/%
1	0.31	8.04	0.9	2.64	65	7	3.09	3.17	2.59
2	0.31	8.92	0.4	2.73	112	7	2.25	2.04	9.33
3	0.31	9.33	0.3	2.86	148	28	2.05	2.22	8.29
4	0.31	8.04	0.9	2.64	65	56	1.56	1.33	14.74
5	0.31	8.41	0.3	2.86	148	56	1.18	1.20	1.69
6	0.38	8.04	0.9	2.64	65	7	4.63	5.25	13.39
7	0.38	9.33	0.3	2.86	148	7	5.21	4.52	13.24
8	0.38	8.59	0.9	2.64	65	28	4.76	4.80	0.84
9	0.38	8.41	0.3	2.86	148	28	4.24	4.24	0
10	0.38	6.86	0.4	2.73	112	28	3.16	3.04	3.80
11	0.38	8.04	0.9	2.64	65	56	2.65	2.77	4.53
12	0.47	6.27	0.9	2.64	65	7	7.32	6.89	5.87
13	0.47	8.92	0.4	2.73	112	7	6.07	6.08	0.16
14	0.47	8.59	0.9	2.64	65	28	7.25	7.08	2.34
15	0.47	8.92	0.4	2.73	112	28	5.42	5.54	2.21
16	0.47	9.33	0.3	2.86	148	56	5.91	5.49	7.11

layers, except through experimentation. A single hidden layer has been found to be satisfactory for many problems. The architecture of prediction model for the chloride diffusivity of concrete consists three layers as shown in Fig. 3.

In the total network development process, the selection of the number of neurons in the hidden layer is the most challenging part. For determine the optimal number of hidden layer nodes, neural networks with different number of hidden layer neurons were trained. The data from the training set was used to determine the number of neurons in the hidden layer, which resulted in the least error between the neural network output and the experimental data. The hidden layer neuron number was varied and the resulting mean-square-error (MSE) between the network outputs and the corresponding experimental outputs were determined and plotted in Fig. 4. It can be seen that the error is minimum when the number of neurons is 10.



(a) Training set



(b) Testing set

Fig. 6 Performance of the ANNs model for predicting the chloride diffusion coefficient of concrete

Table 7 Physical properties and size distribution of coarse aggregates

Aggregate	Normal size /mm	Specific gravity	Compressive strength /MPa	1h-water absorption /%	Cumulative sieve residue/% Square mesh sieve size/mm				
					2.36	4.75	9.50	16.0	19.0
Granite	5-20	2.79	110	0.4	100	98	67	17	4
Limestone	5-20	2.70	90	0.8	100	94	56	12	2

4.2 ANN for predicting chloride penetration in concrete

The training of a neural network is stopped when the error falls below a user-specified level, or when the user-defined number of training iterations has been reached. In this case, 1000 iterations were planned for the final training process, as this was found adequate in a series of test runs. From Fig. 5 it can be seen that after 14 times of the network training, the error had been reduced to the specified level of 0.001, and the training of the neural network was stopped.

The predicted values obtained using ANN for the testing samples were listed in Table 6, and the relative error (E) between predicted value and measured value of concrete chloride diffusion coefficient can be calculated using Eq. (15).

$$E = \left| \frac{P - M}{M} \right| \times 100\% \tag{15}$$

where P is the predicted value, M is the measured value.

From the relative error results as shown in Table 6, it can be seen that the maximum error of the prediction is 14.74%, and the minimum error is 0%, and the predicted value is very close to the measured value. Moreover, the average relative error is 5.62%, which meets the requirement of engineering.

The performance of the ANNs model for predicting the total chloride diffusion coefficients of training and testing sets is illustrated in Fig. 6. It shows the experimental results on the horizontal axis and the predicted results on the vertical axis, and can be seen that there is a good correlation between experimental and predicted values for complete data set. The results illustrate that the

Table 8 Mixture proportions of concrete (kg/m^3)

w/b	Water	Cement	Sand	Crushed stone	Fly ash	Ground slag	Water-reducer
0.33	147	200	758	1 024	111	134	4.45
0.35	147	189	768	1 038	105	126	4.20
0.37	147	179	778	1 050	99	119	3.97

Note: The proportion of crushed stone is that of granite aggregate.

Table 9 Mixture proportions of concrete/(kg/m^3)

No.	*w/b*	$\bar{R}$ /mm	W_a /%	γ	f /MPa	A /d	Measured value /($\times 10^{-8}$cm^2/s)	Predicted value /($\times 10^{-8}$cm^2/s)	E/%
1	0.33	8.60	0.4	2.79	110	28	2.8	2.7	3.57
2	0.35	8.60	0.4	2.79	110	28	3.0	3.3	10.00
3	0.37	8.60	0.4	2.79	110	28	3.6	3.7	2.78
4	0.33	8.60	0.4	2.79	110	56	1.5	1.2	20.00
5	0.35	8.60	0.4	2.79	110	56	2.0	1.6	20.00
6	0.37	8.60	0.4	2.79	110	56	2.3	2.0	13.04
7	0.33	7.47	0.8	2.70	90	28	2.9	2.6	10.34
8	0.35	7.47	0.8	2.70	90	28	3.2	3.0	6.25
9	0.37	7.47	0.8	2.70	90	28	3.8	3.3	13.16
10	0.33	7.47	0.8	2.70	90	56	1.9	2.1	10.53
11	0.35	7.47	0.8	2.70	90	56	2.1	2.4	14.29
12	0.37	7.47	0.8	2.70	90	56	2.5	2.7	8.00

ANN model is successful in learning the relationship between the different input and output parameters, and show the ability of the network to predict the influence of coarse aggregate on the diffusivity of chloride ion in concrete with high precision.

4.3 Application of ANN forecast model in practical engineering

At first, we are trying to apply the ANN model in the experiment data on chloride diffusivity of concrete has published so far, and compare these results with this study. However, the modeling parameters ($\bar{R}$, W_a, γ and f) of coarse aggregate were not entirely given in the literature. We have tried to estimate the missing aggregate parameters, and found that a little change of the aggregate parameter has a great influence on the prediction results. Therefore, some data of concrete chloride diffusivity in practical engineering were collected, and the ANN model was applied for prediction.

4.3.1 Materials

Grade 42.5 Portland Cement type Ⅱ, Class Ⅰ fly ash and S95 ground slag were used in all mixtures. Two types of coarse aggregate (granite and limestone) with a continuous grading of 5-20 mm were used in this project, the physical properties and size distribution of them were presented in Table 7. Fine aggregate used was river sand with a fineness modulus of 2.9 and a specific gravity of 2.63. Poly carboxylic acid (PCA) high performance water reducer was used.

4.3.2 Mixture proportions

Three groups of concrete were prepared with *w/b* of 0.33, 0.35 and 0.37, the mixture

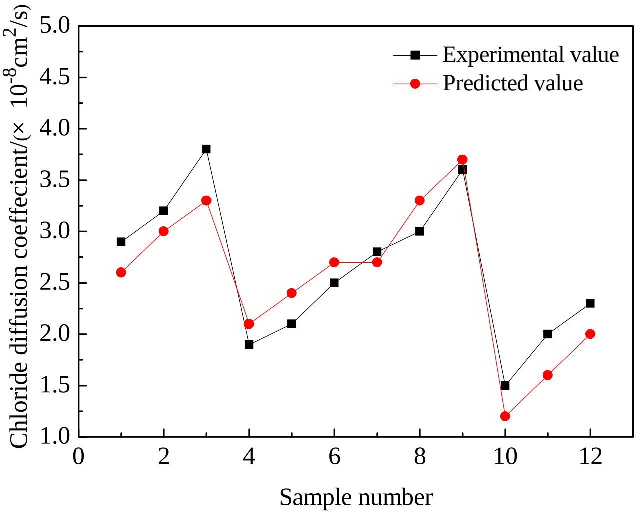


Fig. 7 Comparison of experimental and predicted chloride diffusion coefficient of concrete

proportions of concrete are shown in Table 8. For each group of concrete, two types of coarse aggregate were used on a constant volume fraction.

4.3.3 Experimental results and ANN model predictions

The chloride diffusion coefficient of concrete measured at 28 and 56 days and predicted values obtained using ANN model were listed in Table 9, as well as the relative error between them.

It can be seen that the maximum error of the prediction is 20.0%, and the minimum error is 2.78%, moreover, by calculation the average relative error is 11.0%. Although the prediction error of the project samples is larger than that of the test samples, it is still acceptable in the engineering field. Fig. 7 shows the comparison of experimental and predicted chloride diffusion coefficient of concrete, it can be observed that the predictions made by neural network closely matches with the experimental data.

5. Conclusions

• The grey correlation model can make the sensitivity analysis of the effect of coarse aggregate with various factors on the chloride penetration of concrete well, and the quantitative results show that the average particle size is the major influencing factor, followed by the water absorption regardless of curing ages. Compared with the size effect, the aggregate types have less effect on the concrete permeability.

• For concrete with a lower *w/b*, the coarse aggregate with a larger $\overline{R}$ should be chose, on the premise of meeting the workability and mechanical properties of concrete. However, for concrete with a higher *w/b*, the aggregate with a particle size of 5-20 mm is preferred, too large or too small aggregates are adverse to chloride penetration of concrete. A new idea for the optimum selection of aggregate to prepare concrete with a low penetration is provided.

• A multi-layer back propagation method has been adopted for the development of ANN model.

Based on the 81 data sets from the experiments of the influence of the particle size, water absorption, specific gravity and strength of coarse aggregate, water-binder ratio and curing age on the chloride penetration of concrete, the proposed 6-10-1 model is developed, trained and tested. Moreover, the model predicted values are compared with actual test results.

• The average relative error of prediction of test results is found to be 5.62% and the coefficient of determination (R^2) is 0.98. Such error levels are considered acceptable in the field of engineering. The results indicate that the developed model is successful in learning the relationship between the different input and output parameters, and can predict the chloride diffusivity with adequate accuracy required for practical design purpose. ANN procedure provides guidelines to select appropriate coarse aggregate for required chloride diffusivity of concrete and will reduce the number of trial and error, save cost and time.

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