Evaluation of chloride diffusion in concrete using PSO-BP and BP neural network

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Abstract. Chloride diffusion is the major causes of deterioration of concrete structures in engineering. Because chloride diffusion experiments are time consuming, it is desired to develop a model to predict the chloride diffusion in concrete. In this paper, the optimizing of particle swarm algorithm (PSO) on BP neural network is adopted to predict the chloride penetration in concrete. For purpose of building these models, training and testing pattern is gathered from the technical literature. PSO-BP neural network can improve BP disadvantage. PSO-BP neural network is better precision than BP neural network through the results of PSO-BP, BP and experiments. The research results demonstrate that PSO-BP neural network is an effective tool in the prediction of chloride diffusion.

1. Introduction
Concrete is one of the most widely used construction materials. Concrete structures show degradation of durability as well as structural performance in severe environmental condition. Chloride ion diffusion is the main reason for rapid decreases in the durability of concrete structures, so chloride diffusion is a big concern when durability of concrete is considered. A large number of experiments costs time and money, it is urgent that developing a model can be found to evaluation of chloride penetration facilitate engineering application.

In the last decades, neural network technology has been successfully applied to many applications in civil engineering as well as in other fields. Many researchers made good use of various methods for predicting properties of concrete [1-3]. Chloride diffusion in concrete was the analysis by using neural network adopted cascades-correlation algorithm [4]. There are many kinds of forms of artificial neural network such as back-propagation (BP) neural network, Radial Basis Function (RBF) neural network, forward neural network. BP has one of more widely using in ANN because of its simple structure, easy implementation and strong robustness but it also has some inherent weaknesses, such as the algorithm is easy to fall into local minimum point and slow convergence speed and so on.

In this paper, BP neural network which is optimized by particle swarm optimization (PSO) algorithm so that PSO-BP effectively overcomes BP’s defects of slow convergence, unstable solution, liable to fall into local minima, and initial value sensitivity. PSO-BP and BP are used to evaluation of chloride diffusion in concrete. For purpose of verifying the adaptability of this model, chloride diffusion coefficient and chloride profile used in training and testing pattern are gathered from the technical literature [5]. The results of PSO-BP and BP models with the corresponding experimental values are also compared.
2. PSO-BP neural network

BP neural network is one of more widely applied prediction models. However, the BP algorithm has the defects of low efficiency, slow constringency velocity, and local infinitesimal. PSO algorithm is superior in function optimization performance with unconstrained nonlinear condition, which is usually can be found directly find the global optimal solution [6]. To achieve the optimal constringency velocity and to improve BP, PSO is adopted to carry out the global optimization of BP in this paper. First train the network with PSO algorithm and then refine the search on a small scale with BP algorithm to find a mapping law between the input and output that are implicit in the structure and the interconnection weights of the neural network.

2.1. PSO Algorithm

PSO is a global randomly optimization algorithm. The algorithm can be used to solve optimization problems [7]. The idea of PSO algorithm comes from artificial life and evolutionary computation theory. It mainly derived from the characteristics of the migration and gathering of the birds during seeking food. In the algorithm, the solution for each optimization is to be considered as a flying bird in the solution space, and a bird is abstracted as a particle. All particles have a fit determined by the function of optimization. The velocity of each particle will determine its direction and distance. Particles know so far they found the best location and the location now. This can be seen as particles own flight experience. In addition, each particle also knows so far all the particles found that the best position in the entire group, which can be seen as particles companion's experience. Particles will determine the next step in the movement through their own experience and companion the best experience.

PSO initializes a group of random particles first, and then particles are following the current optimum particles in the solution space, in other words, it finds the optimal solution by iteration. A basic PSO algorithm is presented as following.

Suppose m particles in d dimensional space, the position of particle I is expressed as \( X_i = (x_{i1}, x_{i2}, \ldots, x_{id}) \), the speed of particle I can be written as \( V_i = (v_{i1}, v_{i2}, \ldots, v_{id}) \), \( i = 1, 2, \ldots, m \). Put \( x_i \) into the aim function \( f(x_i) \) and their fitness, the optimal position by particle I is \( p_i = (p_{i1}, p_{i2}, \ldots, p_{id}) \), and the optimal position sought by overall particle swarm is \( p_g = (p_{g1}, p_{g2}, \ldots, p_{gd}) \). The update operation of particle state is as follows:

\[
\begin{align*}
    v_{ij}(k + 1) &= w \times v_{ij}(k) + c_1 r_1 [p_{ij} - x_{ij}(k)] + c_2 r_2 [p_{gj} - x_{ij}(k)] \\
    x_{ij}(k + 1) &= x_{ij}(k) + v_{ij}(k + 1)
\end{align*}
\]

where \( j = 1, 2, \ldots, d \), \( r_1, r_2 \) are the random number in \([0,1]\), \( c_1, c_2 \) are accelerated coefficients, generally, \( v_{max} \) is a constant.

2.2. BP neural network

BP is a kind of multi-layer feed forward network. All neurons in each layer have a connection to all the neurons in the next layer. Each input layer neurons is responsible for receiving input information from the outside world and transmitted to the middle layer neurons. The middle layer is the internal information processing layer. According to the change of information ability, the middle layer can be designed for single hidden layer or hidden layer structure, and the last hidden layer to output layer information of each neuron, after being further processing, it completes a learning study which is from the output layer to the outside world output information processing results. When actual output is not desired output, it will be in the error propagation stages. Three layer networks are adopted in this paper.

2.3. PSO–BP neural network design

The PSO–BP is an optimization algorithm combining the PSO with the BP to train the neural network. The fundamental idea for this hybrid algorithm is that at the beginning stage of searching for the optimum, the PSO is employed to accelerate the training speed. The PSO–BP algorithm’s searching
process is started from initialization to group of random particles. First, all the particles are updated velocity and position according to the Equations.(1) and (2), the weights of BP neural network correspond to the position of particles , the result of algorithm is to form a weighting matrix ,corresponding to the PSO an optimal position and then network parameters are got further accurate by BP algorithm, the optimal parameter combination can get accurate at this time until searching the optimum network parameters. Due to the particle swarm algorithm instead of the initial neural network optimization, the network only search parameter optimization on the basis the optimal solution so the PSO-BP algorithm effectively improves the precision and speed of network optimization.

PSO algorithm is used to search for the best position that coordinates the optimal connection weights and thresholds of the BP network, so that the mean square error (MSE) is then expressed:

\[
MSE = \frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{n} (y_{ij}^d - y_{ij})^2
\]

3. Analysis for chloride penetration in concrete using PSO-BP and BP models

In this study, the PSO-BP and BP neural networks performed under MATLAB programming. The various errors in PSO-BP and BP models are expressed as the root mean squared (RMS) error, the absolute fraction of the variance \((R^2)\) and mean absolute percentage error \((MAPE)\), respectively. They calculated in terms of Equation.(4)-Equation.(6).

\[
RMS = \sqrt{\frac{1}{p} \sum_{j=1}^{p} |y_j - o_j|^2}
\]

\[
R^2 = 1 - \frac{\sum_{j=1}^{p} (y_j - o_j)^2}{\sum_{j=1}^{p} (o_j)^2}
\]

\[
MAPE = \frac{1}{p} \sum_{j=1}^{p} \left| \frac{o_j - t_j}{o_j} \right|
\]

Where \(t_j\) is the target value of \(j\) th pattern, \(o_j\) is the output value of \(j\) th pattern, and \(p\) is the number of patterns.

3.1. Estimation of chloride diffusion coefficient with PSO-BP and BP neural network algorithm

A series of concrete in various mix designs and duration time (28days,91days,180days and 270 days) is selected in the experiment. The different mineral admixtures such as granulated blast-furnace slag (GGBS),fly ash (FA) and silica fume (SF) are adopted in the experiment. Chloride diffusion experiment is provided in ASTM C1202 and the calculation of the diffusion coefficient is performed by an electrical method. The detailed procedure of specimen preparation and testing can be found in [14]. In all models, we adopted 8 input layers. They represent W/B ratio, unit weight of OPC, GGBS, FA, SF, sand, coarse aggregate, duration time. One output is chloride diffusion coefficient. The values of parameters used in PSO-BP and BP models are given as Table1. Tansig function is used in input layers as the transfer function.

3.2. PSO-BP and BP neural network chloride diffusion coefficient results and discussion

In the training and testing pattern of PSO-BP and BP models, experimental data from the literature [5]. 80 data of experiment results were used for training whereas remainder 40 data the experiment were employed for testing in PSO-BP and BP network. Decrease in error with training is plotted as Figure 1. Optimized by PSO algorithm weights a threshold value is very close to the final results, the error of the adjustable range is very small, so It can be seen that PSO-BP algorithm's convergence curve is relatively flat.
Table 1. The values of parameters used in models.

| Parameters                        | PSO-BP | BP  |
|-----------------------------------|--------|-----|
| Number of input layer units       | 8      | 8   |
| Number of hidden layer            | 1      | 1   |
| Number of hidden layer units      | 17     | 17  |
| Number of output layer units      | 1      | 1   |
| Learning rate                     | 0.1    | 0.1 |
| Target epochs                     | 1000   | 1000|
| Mean square error                 | 0.001  | 0.001|

Figure 1. Decrease in error with repeated training of learning using (1) PSO-BP and (2) BP models.

The testing results of PSO-BP and BP in this study are shown as Table 2. Chloride diffusion coefficient is the largest when data order is 21, so it is clearly the optimization of mixing as order 21 which corresponding the parameters are W/B ratios 47%, fly ash 30% replacement ratio and OPC 70% replacement ratio. The absolute error distribution of PSO-BP and BP is given in Figure 2. In absolute error distribution of results from PSO-BP and BP, the absolute minimum error is 0.00 which is predicted by PSO-BP. Also, the maximum absolute error is 0.62, which came from the results in the BP model.

Figure 2. The absolute error of results in different models.

It is obviously found that the testing results predicted chloride diffusion coefficient from PSO-BP and BP models are close to experimental results in Figure 3. The statistical values of the test in PSO-BP and BP models as RMS, $R^2$, and MAPE were found as Table 3. While the statistical values of RMS, $R^2$ and MAPE from training in PSO-BP were found as 0.1217, 0.9787 and 12.7278, respectively, these values of testing as 0.1473, 0.9666 and 14.0444, respectively. Similarly, while the statistical values of RMS, $R^2$ and $MAPE$ from training in BP were found as 0.1115, 0.9824 and 12.6625, respectively, these
values of testing as 0.1682, 0.9570 and 16.1546, respectively. The minimum of $R^2$ is 0.9570 for testing set in BP. It can be seen that the results of PSO-BP model is more precise than the results of BP model through these values.

Table2. Testing data for comparison of experimental results with testing results predicted from models.

| Data order | Duration time (days) | W/B (%) | Unit weight (kg/m³) | Diffusion coefficient $\times 10^{-11}$ (m²/s) |
|------------|----------------------|---------|---------------------|-----------------------------------------------|
|            |                      |         | C                  | GGBS FA SF Sand Aggregate                     | Experimental | PSO-BP | BP     |
| 1          | 28 42                | 400 0   | 0 0 0 787 976      | 1.50 1.6 1.44                                 |
| 2          | 91 42                | 400 0   | 0 0 0 787 976      | 1.40 1.27 1.33                                |
| 3          | 180 42               | 400 0   | 0 0 0 787 976      | 1.10 0.9 1.03                                 |
| 4          | 270 42               | 400 0   | 0 0 0 787 976      | 0.94 0.71 0.83                                |
| 5          | 28 47                | 250 107 | 0 0 835 956        | 1.20 1.24 1.31                                |
| 6          | 91 47                | 250 107 | 0 0 835 956        | 0.84 1.06 1.02                                |
| 7          | 180 47               | 250 107 | 0 0 835 956        | 0.80 0.78 0.81                                |
| 8          | 270 47               | 250 107 | 0 0 835 956        | 0.64 0.66 0.70                                |
| 9          | 28 37                | 227 227 | 0 0 760 943        | 0.63 0.59 0.47                                |
| 10         | 91 37                | 227 227 | 0 0 760 943        | 0.37 0.24 0.24                                |
| 11         | 180 37               | 227 227 | 0 0 760 943        | 0.25 0.24 0.22                                |
| 12         | 270 37               | 227 227 | 0 0 760 943        | 0.24 0.22 0.26                                |
| 13         | 28 37                | 409 0   | 45 0 760 943       | 1.40 1.34 1.33                                |
| 14         | 91 37                | 409 0   | 45 0 760 943       | 0.91 1.02 1.01                                |
| 15         | 180 37               | 409 0   | 45 0 760 943       | 0.77 0.72 0.60                                |
| 16         | 270 37               | 409 0   | 45 0 760 943       | 0.63 0.55 0.54                                |
| 17         | 28 42                | 320 0   | 80 0 774 961       | 1.60 1.33 1.44                                |
| 18         | 91 42                | 320 0   | 80 0 774 961       | 1.00 1.03 1.10                                |
| 19         | 180 42               | 320 0   | 80 0 774 961       | 0.69 0.78 0.71                                |
| 20         | 270 42               | 320 0   | 80 0 774 961       | 0.58 0.63 0.68                                |
| 21         | 28 47                | 250 0   | 107 0 820 939      | 2.00 1.39 1.38                                |
| 22         | 91 47                | 250 0   | 107 0 820 939      | 0.95 1.13 1.08                                |
| 23         | 180 47               | 250 0   | 107 0 820 939      | 0.74 0.87 0.91                                |
| 24         | 270 47               | 250 0   | 107 0 820 939      | 0.62 0.72 0.80                                |
| 25         | 28 42                | 340 0   | 40 20 777 965      | 0.78 0.75 0.83                                |
| 26         | 91 42                | 340 0   | 40 20 777 965      | 0.54 0.54 0.62                                |
| 27         | 180 42               | 340 0   | 40 20 777 965      | 0.41 0.43 0.45                                |
| 28         | 270 42               | 340 0   | 40 20 777 965      | 0.33 0.42 0.39                                |
| 29         | 28 37                | 340 0   | 91 23 749 929      | 0.60 0.52 0.56                                |
| 30         | 91 37                | 340 0   | 91 23 749 929      | 0.41 0.39 0.52                                |
| 31         | 180 37               | 340 0   | 91 23 749 929      | 0.35 0.33 0.56                                |
| 32         | 270 37               | 340 0   | 91 23 749 929      | 0.29 0.31 0.52                                |
| 33         | 28 47                | 232 107 | 0 18 832 952       | 0.61 0.66 0.56                                |
| 34         | 91 47                | 232 107 | 0 18 832 952       | 0.48 0.49 0.37                                |
| 35         | 180 47               | 232 107 | 0 18 832 952       | 0.31 0.33 0.30                                |
| 36         | 270 47               | 232 107 | 0 18 832 952       | 0.29 0.33 0.30                                |
| 37         | 28 42                | 200 140 | 60 0 773 959       | 0.65 0.81 0.72                                |
| 38         | 91 42                | 200 140 | 60 0 773 959       | 0.40 0.62 0.50                                |
| 39         | 180 42               | 200 140 | 60 0 773 959       | 0.36 0.5 0.38                                 |
| 40         | 270 42               | 200 140 | 60 0 773 959       | 0.29 0.48 0.30                                |
4. Conclusions
The study demonstrates that the PSO-BP and BP neural network can give good predictions for chloride diffusion in concrete. The optimizing of PSO algorithm on BP neural network can greatly shorten the error of the adjustable range of BP and improve the accuracy of the prediction. The factors affecting chloride diffusion of concrete is various and the corresponding experiments are time-consuming, however these neural network analysis are black-box approaches and the user need not know much about the physical mechanism of the chloride diffusion. These models can be used to predict the chloride diffusion coefficient and the chloride concentration with different time and depth. For these reasons, the PSO-BP is becoming a useful tool in the prediction of chloride diffusion in concrete and it will provide an effective method to assess the life prediction for concrete structures.

![Figure 3. Distribution of the results of different models.](image)

| Statistical parameters | PSO-BP model | BP model |
|------------------------|--------------|----------|
|                        | Training set | Testing set | Training set | Testing set |
| RMS                    | 0.1217       | 0.1473    | 0.1115       | 0.1682       |
| R²                     | 0.9787       | 0.9666    | 0.9824       | 0.9570       |
| MAPE(%)                | 12.7278      | 14.044    | 12.6625      | 16.1546      |

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