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THE RESEARCH ON DAMAGE PREDICTION OF CORRODED REINFORCED CONCRETE BASED ON DATA FUSION

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Abstract. *It is hard to predict the corrosion damage existing reinforced concrete in the actual project. To solve the problem, the method of damage prediction of corroded reinforced concrete based on data fusion is first proposed in this paper. The method improves the credibility and accuracy of the raw data by data fusion level. It can be reasonable to select these main effective factors which are temperature, dissolved oxygen, salinity, PH value, oxidation-reduction potential for corrosion damage based on feature level data fusion. Finally, it can give the objective, accurate damage prediction result by using decision level data fusion. Example of engineering simulation shows that the method is feasible, and be able to accurately predict the corrosion damage of reinforced concrete. It is simple, and has the high prediction accuracy.*

1 INTRODUCTION

As the main material, reinforced concrete is widely used in the hydraulic structure. In the harsh marine environment, hydraulic structure at work will be damaged in some degree. This will affect the security of structure itself. Professor P.K Mehta said that the causes for concrete rupture in today's world according to their importance were: the corrosion of reinforcement, the cold damage, physical and chemical effects under erosion environment on the basis of the durability of concrete structure [1]. It can be seen that the corrosion of reinforcement is the primary cause of the damage of concrete structure. About the prediction of the corrosion of reinforcement, many experts and scholars have conducted a lot of research. Morinaga[2], Hui Yun-ling[3] have obtained the models based on experience and large number of locale data.Bazant[4-5], Niu Di-tao[6-7] have deduced the models based on physical and chemical equation. Shen Ru-wei[8] have solved the problem of prediction about the corrosion of reinforcement by using neural network technology, and successfully built the intelligent prediction model . As can be seen from lots of studies, the corrosion of reinforcement in concrete is a very complex process of electrochemistry. The corrosion amount and the corrosion rate is affected by many factors. The interaction between these factors is interrelated. They affect the corrosion occurrence, development all the time, and show a strong nonlinear relationship affecting the process of the corrosion of reinforcement. So, this will cause hardship in the corrosion prediction of reinforcement. The method of damage prediction of corroded reinforced concrete based on data fusion is proposed in this paper. Example of engineering simulation demonstrates that the proposed method is feasibility and superiority.

2 THE RESEARCH ON DAMAGE PREDICTION OF CORRODED REINFORCED CONCRETE BASED ON DATA FUSION

In the actual hydraulic structure, the corrosion of reinforcement will occur to some extent in the complex marine environment. Many factors that affect the steel corrosion influence each other. Combined with the natural environment interference, they make the corrosion process of steel become more complex. The extent of corrosion is also difficult to get an accurate prediction. In this paper, we will make full use of artificial neural network technology to solve the problem of nonlinear mapping of many factors which will influence the process of steel corrosion, thus completing the preliminary prediction of the degree of reinforcement corrosion. The preliminary prediction results will be melded into the final result in the decision fusion center. Prediction precision can be further improved. The model is shown in Figure1.

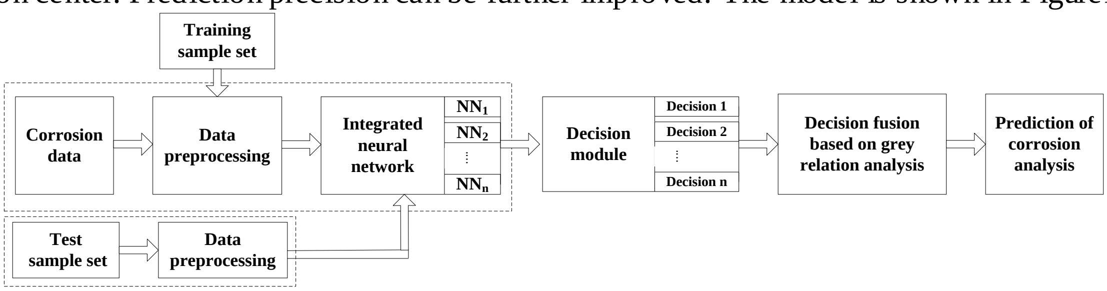

Figure 1: The Corrosion prediction model of reinforcement based on data fusion

2.1 Artificial Neural Network

The artificial neural network is a mathematical model which can complete the parallel process of the information distribution by simplifying, abstracting and simulating certain basic characteristics of the human brain systems. It achieves complex information processing and storing based on massively parallel, interconnected network structure and nonlinear processing means. It has the non-linear, parallel processing, adaptive characteristics, and has been widely used in many fields. Depending on the connections between these neurons, the neural network can be divided into: forward neural network with no feedback, forward neural network with feedback, full connected neural network, and so on. In this paper, we will adopt three-layer forward neural network with feedback based on BP algorithm. The network consists of one input layer, one hidden layer and one output layer. There is no connection in the same layer. The previous layer node's outputs just have an influence on one in back. BP network learning process consists of two steps: the forward propagation of the signal and back propagation of the error. Its model is shown in Figure 2.

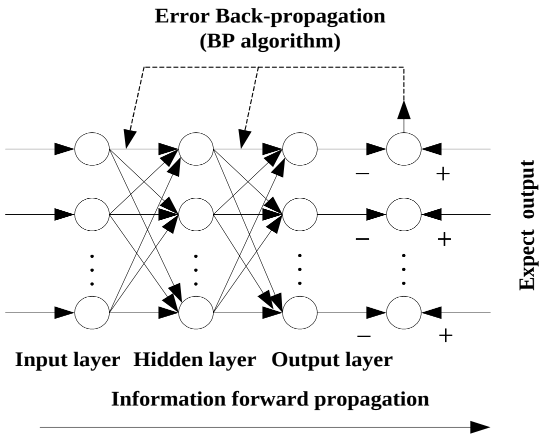

Figure 2: Three-layer Feed-forward Neural Network Model Based on BP Algorithm

2.2 Grey Relation Analysis Theory

The grey relational analysis made the grey relationship of the system that operation mechanism is not clear or can not be accurately described serialize and model, and thus established the grey relational analysis model. And then it can make the grey relationship explicit, quantify, serialize. It takes advantage of quantitative analysis of the dynamic process to study the degree of correlation between the factors of the system. It is very effective for studying ways to control and guide the main behavior of the system through grey correlation degree to quantify the grade of interaction between the various factors or the factors affecting the main behavior. The grey relational analysis has been widely used in practice. Under the ocean environment condition, the mechanism of corrosion of reinforcing steel in concrete is very complex, and the corrosion process is affected by many factors. The relationship between various factors and the extent of corrosion also show the strong nonlinear feature. Therefore, in this paper, we can use the grey relational analysis to quantify the influence of every factor on the extent of corrosion. This will lay a foundation for the prediction of the next step about the degree of reinforcement corrosion. Set the factor sequence affecting the grey system as X_1, X_2, …, X_n, i=1, 2, …n. Namely:

$$X_1=\{X_1(1),X_1(2),\ldots, X_1(m)\}$$
$$X_2=\{X_2(1),X_2(2),\ldots, X_2(m)\}$$
$$\vdots$$
$$X_n=\{X_n(1),X_n(2),\ldots, X_n(m)\}$$

The length of the impact factor is m, while X_i is also called the comparative sequence. Y={Y(1)，Y(2)，…Y(m)} is the sequence of data to reflect the behavioral traits of the grey system. It is also called the reference sequence. The following is the computing process of grey relational analysis:

(1) Generally, the data should be converted into dimensionless index before grey relational analysis. The formula is shown as follows:

$$X_i^{(1)}(k) = \frac{X_i^{(0)}(k)}{X_i^{(0)}(l)} \quad (k=1,2\ldots,m) \tag{1}$$

(2) Take the reference sequence Y as the generatrix, and calculate the difference between the sequence of each comparative sequence and the generatrix in the corresponding time.

$$\Delta_i(k) = \left| Y^{(1)}(k) - X_i^{(1)}(k) \right| \quad (i=1,2, \ldots n; k=1,2\ldots,m) \tag{2}$$

(3) Calculate the grey correlation coefficient between the comparative sequence $X_i(k)$ and the reference sequence Y(k) in the corresponding moment.

$$\xi_i(k) = \frac{\min_i \min_k \Delta_i(k) + \rho \max_i \max_k \Delta_i(k)}{\Delta_i(k) + \rho \max_i \max_k \Delta_i(k)} \quad (i=1,2, \ldots n; k=1,2\ldots,m) \tag{3}$$

Where, ρ is the distinguishing coefficient, and ρ∈(0, ∞). The smaller the value of ρ, the greater its ability to distinguish. Generally, the value of ρ is in the interval (0, 1). Under normal circumstances, take ρ = 0.5 for the best.

(4) Calculate the degree of grey correlation between each sub-sequence X_i and the reference sequence Y. The formula of comprehensive correlative r_i as follows:

$$r_i = \frac{\sum_{k=1}^{m} \xi_i(k)}{m} \quad (i=1,2,\ldots,n) \tag{4}$$

By using the theory of grey correlation analysis, we can conduct the quantitative research about how the internal and external factors affect the degree of reinforcement corrosion in complex environment conditions. This will provide the theory basis for predicting the degree of reinforcement corrosion based on data fusion technology in the next step.

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3 THE APPLICATION OF STEEL CORROSIVE DEGREE PREDICTION BASED ON DATA FUSION

The first page must contain the Title, Author(s), Affiliation(s), Keywords and the Abstract. In this paper, we can validate the method based on the experimental data in the reference [12]. The reference [9] gives the experimental data about the relationship between 3C steel corrosion and seawater environmental parameters. The part of the data will be shown in the following table 1:

NO	Temperature (℃)	DO (mg/L)	Salinity (ppt)	PH	ORP (mv)	corrosion rate (μA/cm^2)
1	25.9	6.71	30.1	5.1	378	16.4
2	29.35	6.09	29	6.3	400	16.9
3	27.9	6.18	31.5	7	363	15.57
4	24	7.95	30.2	8.1	324	13.65
5	28	5.05	31.4	9.2	240	13.24
6	27.32	3.21	29.31	8.2	281	12.91
7	27.87	6.55	31.68	7.2	356	14.06
8	28.27	6.98	28.2	6.6	384	15.47
9	30.7	7.15	31.74	6.5	401	16.28
10	29.37	6.82	30.12	6.2	414	17.11
11	24.27	0.8	32.56	8.1	171	3.61
12	27.45	2.6	35.37	7.96	287	7.94

13	27.23	4.2	31.94	7.89	289	9.63
14	27.48	5.9	32.39	7.83	331	10.578
15	28.75	6.8	32.22	8	340	11.43
16	28.52	8.4	32.1	8.01	345	12.52
17	28.45	9.9	31.95	7.93	309	22.64
18	23.95	7.61	9.17	8.04	231	10.94
19	24.73	6.06	17.33	7.88	321	11.446
20	24.6	7.52	24.42	7.57	210	11.83
21	24.51	7.02	32	8.16	308	12.553
22	23.65	6.51	41.34	7.67	245	8.402
23	16.74	7.11	33.55	8.25	178	10.85
24	21.11	6.03	33.44	8.03	295	11.448
25	25.57	6.7	32.19	8.09	325	11.872

Table 1: The part of the experimental data about the relationship between 3C steel corrosion and seawater environmental parameters

A、Take the first 41 sets of experimental data that have been preprocessed as training samples, and divide them into two groups: (temperature, dissolved oxygen, salinity, PH value, corrosion rate) (temperature, salinity, PH value, oxidation-reduction potential, corrosion rate). And then construct two BP neural network model: take the first set of data as a neural network learning sample, the structure of 4 input nodes, 9 hidden nodes, an output node, namely BPNN (4-9-1), the learning error of network is 0.0001. Take the second set of data as the learning sample a second neural network, the structure of the 4 input nodes, 11 hidden nodes, an output node, namely BPNN (4-11-1), the learning error of network is 0.0001 . After training, the training errors are shown in Figures 3, 4:

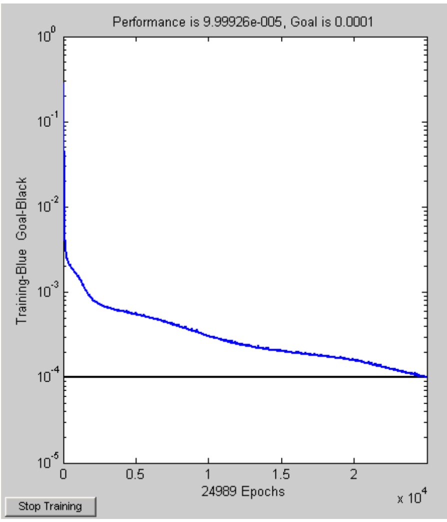

Fig 3: The training result of NN_1

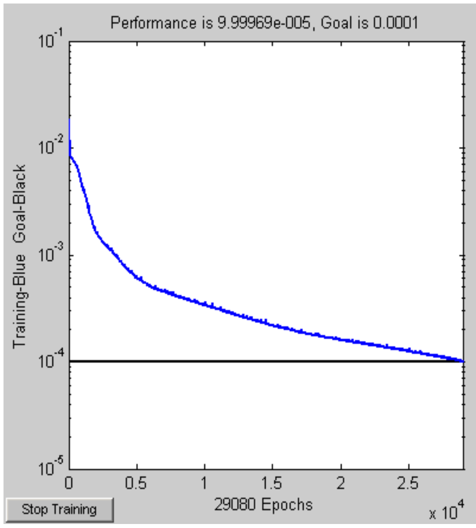

Fig 4: The training result of NN_2

Use the trained network to predict the last five sets data that have been normalized, the results as follows: NN_1=[0.4255 0.4304 0.4440 0.5112 0.5757]; NN_2=[0.3178 0.6366 0.5442 0.8085 0.4018].

B、Based on the grey relational analysis process ,we can obtain the degree of grey correlation about temperature, dissolved oxygen, salinity, pH value, redox potential and the corrosion rate. The degree of grey correlation: R = [0.9176 0.7604 0.8808 0.7829 0.9598]. The greater the degree of grey correlation between influencing factor and the corrosion rate is, the larger the weight of the decision level data fusion is. So we can obtain the weight of every influencing factor in the fusion process: W = [0.2133 0.1768 0.2048 0.1820 0.2231].

C, Finally, the predicting result based on the two networks decision fusion is table 2, table 3 , table 4:

NO	Prediction of NN_1	Measured value	Error
1	0.4255	0.3657	16.35%
2	0.4304	0.5523	22.07%
3	0.4440	0.5818	23.69%
4	0.5112	0.7104	28.04%
5	0.5757	0.4455	29.23%

Table 2: The prediction result of NN_1

NO	Prediction of NN_2	Measured value	Error
1	0.3178	0.3657	13.1%
2	0.6366	0.5523	15.28%
3	0.5442	0.5818	6.46%
4	0.8085	0.7104	13.81%
5	0.4018	0.4455	9.81%

Table 3: The prediction result of NN_2

NO	Prediction based on data fusion	Measured value	Error
1	0.3701	0.3657	1.2%
2	0.5365	0.5523	2.86%
3	0.4956	0.5818	14.82%
4	0.6642	0.7104	6.5%
5	0.4862	0.4455	9.14%

Table 4: The final prediction result based on data fusion

The prediction result that has been reversed normalization will be shown in the following table 5:

NO	Prediction	Measured value
1	10.035	9.93
2	14.1406	14.37
3	13.0203	15.07
4	17.0309	18.13
5	12.7967	11.828

Table 5: The comparison between prediction and measured value

It can be drawn from the above predicting result that the prediction accuracy has been greatly improved after data fusion. This is mainly due to consider a variety of influencing factors in the corrosion prediction process and introduce the theory of grey relational analysis in the fusion process to make the fusion more objective.

4 CONCLUSIONS

The Through the above discussion and analysis, the method of damage prediction of corroded reinforced concrete which can solve the problem that is hard to predict the corrosion damage existing reinforced concrete based on data fusion is effective and high accuracy in this paper. The method improves the credibility and accuracy of the raw data by data fusion level. It introduce the grey relational analysis to obtain the fusion weight. Finally, we can get the predicting result based on decision level data fusion. Example of engineering simulation shows that the method is feasible, and be able to more accurately and objectively predict the corrosion damage of reinforced concrete.

REFERENCES

[1] Mehta P. K. Concrete durability-fifty year's proceeding of the 2nd international conference on concrete durability[Z].ACI SP 126.-1,1991:1-31.

[2] Morinaga S. Prediction of service life of reinforced concrete building based on rate of corrosion of reinforced steel[C].Durability of building materials and components, Proceddings of the 5th international conference held in brighton,UK,1990.

[3] Hui Yun-ling. Assessment and predicted experimental study on corrosive degree of reinforcements in concrete structures[J]. Industrial Construction, 1997,27(6):6-9.

[4] Bazant Z P, et al. Physical model for steel corrosion in concrete sea structures theory[J]. ASCE Joumal of structural division,1977,105(ST6):1137-1153.

[5] Bazant Z P, et al. Physical model for steel corrosion in concrete sea structures application[J]. ASCE Joumal of structural division,1977,105(ST6):1155-1166.

[6] Niu Di-tao, Wang Qing-lin, Wang Lin-ke. Predeterminate model of steel corrosion extent in reinforcement concrete structures before producing corrosion crack[J].Industrial Construction,1996,26(4):8-10.

[7] Niu Di-tao, Wang Qing-lin, Wang Lin-ke. Predeterminate of steel corrosion extent in reinforcement concrete structures after corrosion crack[J].Industrial Construction,1996,26(4):11-13.

[8] Shen Ru-wei. Intelligence model for predict corrosive degree of concrete embedded rebar[J].Concrete,2011(1):37-39.

[9] Liu Xue-qing, Tang Xiao, Wang Jia. Correlation between seawater environmental factors and marine corrosion rate using artificial neural network analysis[J].Journal of Chinese Society for Corrosion and Protection, 2005,25(1):11-14.