PREDICTION OF RELIABILITY FOR CORROSIVE RC MEMBER USING INTELLIGENT HYBRID SYSTEM

Hong-Ci Wu

College of Civil & Architectural Eng., Guizhou Univ.of Tech., Guiyang

550003 China

ABSTRACT

In this paper, fuzzy logic, genetic algorithms (GAs) and neural network based on fuzzy rule (NNFR) are co-operatively employed to produce intelligent hybrid system (IHS) and to predict reliability grade for corrosive reinforced concrete (RC) members. The research results are in close agreement with the site data.

1 INTRODUCTION

Predicting reliability for corrosive RC member is a key link to help producing RC structure for high quality and low cost, which may have significant implications in overall lifetime of building structures. Despite such, current decisions on reliability grades are too often made autonomously and without fully investigating the influence of diverse affected reliability aspects and hence the determination of the reliability grade on the safety of the structure. Because many random, fuzzy and uncertain factors (and here linguistic variables) are involved in the procedure of predicting the most suitable reliability grades for the corrosive RC member, in this paper we present an initial attempt to incorporate more aspects of affected reliability, such as bearing capacity, deformation, flaw, strength of reinforcing bar, corrosive level of reinforcing bar, strength of concrete, cohesion between reinforcing bar and concrete, and environmental condition etc. into the reliability prediction and to predict the suitable reliability grades for the corrosive RC member by means of intelligent hybrid system (IHS), consisting of fuzzy logic, genetic algorithms (GAs) and neural network based on fuzzy rule (NNFR)[1-6]. The domain of application for the IHS here is the preliminary reliability prediction of 6 RC beams in a typical China urban environment, and the research results are pretty well.

2 FUZZY REASONING FOR PROBLEM OF RELIABILITY PREDICTION

The problem of reliability prediction for the corrosive RC member can be represented as a procedure of fuzzy reasoning[2-4]. Suppose that n number of m-input and one-output fuzzy rules or fuzzy conditional statements are given. The i-th rule in the if-then form, which describes input-output relation may be written in the following form:

$$R_i\text{: if}\{(x_{1i}=A_{1i}) \wedge (x_{2i}=A_{2i}) \wedge \ldots \wedge (x_{mi}=A_{mi})\} \text{ then}\{y=B_i\}\} \tag{1}$$

where $x_{1i,}\, x_{2i}\, _{\ldots,}\, x_{mi}$ and y are respectively linguistic variables of the input and the output patterns, A_{ji} (j=1, 2, …, m; i=1, 2, …, n) and B_i are fuzzy subsets of x_{ji} and y, respectively.

When an observation (x_{1i}, x_{2i}…, x_{mi}) is given , a fuzzy inference output y can be obtained by using product-sum-gravity fuzzy reasoning method as follows:

$$h_i=A_{1i}(x_1)\, A_{2i}(x_2) \ldots A_{mi}(x_m)=\prod_{j=1}^{m} A_{ji}(x_j) \tag{2}$$

$$y=(\sum_{i=1}^{n} h_i s_i y_i)\,/\,(\sum_{i=1}^{n} h_i s_i)$$

(3)

where h_i (i=1, 2, …, n) is an agreement of the antecedent of the i-th fuzzy rule, s_i is the area of Bi, and y_i is the center of gravity of Bi.

The input patterns here are denoted by means of eight linguistic variables: x_{1i}=bearing capacity, x_{2i}=deformation,

x_{3i}=flaw, x_{4i}=strength of reinforcing bar, x_{5i}= corrosive level of reinforcing bar, x_{6i}=strength of concrete, x_{7i}=cohesion between reinforcing bar and concrete, and x_{8i}=environmental condition. The output patterns is represented by one linguistic variable, y=reliability grade[2-4], these linguistic variables are normalized, thus taking values in the interval [0, 1]. Consequently, The IHS enables us to model the relations (1).

3 A PROCEDURE OF PREDICTING RELIABILITY USING NNFL

The learning capability of the NNFL can be used for automatic fuzzy if-then rules generation. The NNFL can utilize linguistic information from the human expert and measurement data. In other words, linguistic prior knowledge from expert and site can be incorporated into the NNFL to identify and to predict the above problem. The NNFL possess three layers: one input, two hidden and an output layers. In the input layer, eight linguistic variables, i.e. (x_{1i}, x_{2i}, …, x_{8i}) are to be presented to the network. The output layer, with one neuron, is used to predict the reliability grades. When the training input-output variables (x_1, x_2, …, x_m, y^*) are given, the following inference error function is adopted to evaluate an error between y^* and y:

$$E=\sum_{i=1}^{n} (y^* - y)^2 /n \tag{4}$$

Where E is inference error function, y^* the desired output, and y the corresponding fuzzy inference output, and Gaussian-type membership functions A_{ji} and B_i (j=1, 2, …, m; i=1, 2, …, n) of (1) are defined as:

$$A_{ji}(x_j)=\exp(-(x_j - a_{ji})^2 / 2\sigma_{ji}^2) \tag{5}$$

$$B_i(y)=\exp(-(y - y_i)^2 / 2\sigma_i^2) \tag{6}$$

Where a_{ji} and σ_{ji} (j= 1, 2, …, m; i= 1, 2, …, n) are the center and width of A_{ji}, and y_i and σ_i (i=1, 2, …, n) are the center and width of Bi, respectively. Two hidden layers are adopted to realize basis functions h_i and A_{ji} defined by equations (2) and (5), i.e. the membership functions and fuzzy rules are tuned by using a self-tuning learning algorithm. The learning procedure of the self-tuning algorithms is accomplished by minimizing the inference error function E of the network in (4).

4 GENETIC TRAINING ALGORITHMS IN THE PREDICTION

The NNFL is 'trained' by presentation of 20 training-case sets associated with the above input and output patterns. The GAs here are applied to modify / learn the definition of the membership function shapes and / or the composition of the fuzzy rules. In order to do so, the linguistic variables here are further partitioned by fuzzy characteristics: x_{1i}={very strong, strong, moderate, weak, very weak}; x_{2i}= {very small, small, average, large, very large}; x_{3i}={very closed, closed, medium, open, very open}; x_{4i}={very high, high, fair, low, very low}; x_{5i}={very gentle, gentle, common, grave, very grave}; x_{6i}={very high, high, fair, low, very low}; x_{7i}={very tight, tight, moderate, loose, very loose}; x_{8i}={very ideal, ideal, regular, adverse, very adverse}; y_i={a, b, c, d, e}={very reliable, reliable, average, unreliable (to be restored), very unreliable (to be rebuilded or removed)}, each one is composed of five linguistic labels (and here L_{MR}, M=1, 2, …, 8, R=1, 2, …, 5, for example, L_{34} denotes that the flaw in RC member is "open"), thereupon these fuzzy partitions can be obtained from a normalization process in which the universe of discourse of each variable is equally divided into 5 parts.

To overcome the permutation problem (the offspring will duplicate some elements of the permutation and will omit others), we here use a structure of parallelism in genetic learning procedure by dividing the global population into several sub-populations. Each sub-population is evolved on each neuron in the hidden layer and the input layer. Population size=30; number of generation=100; probability of crossover = 0.6; and probability of mutation=0.01. The GAs basically consist of three different genetic operators: selection, crossover and mutation[2,3,5,7,8], we here do not enter into detail.

In the training process, the algorithm stops the corresponding learning process when the inference error function E for identifying training data is less than the threshold δ (and here δ=0.0006), and the final learning iteration t=350.

5 A COMPARISON BETWEEN THE PREDICTED AND THE SITE RELIABILITY GRADES

The trained NNFL is 'tested' by presentation of 6 RC beams from the site. Table 1 shows a comparison between the predicted and the site reliability grades, it seems that the IHS for the reliability grade prediction of RC beams in building structural engineering is altogether efficient, based on Table 1.

Table 1. A Comparison between the Predicted and the Site Reliability Grades

RC Beams	L_{MR}	The predicted	The site
1	L_{13} L_{23} L_{33} L_{44} L_{53} L_{64} L_{73} L_{84}	c	c
2	L_{13} L_{24} L_{33} L_{44} L_{53} L_{63} L_{74} L_{83}	c	c
3	L_{14} L_{23} L_{34} L_{43} L_{54} L_{63} L_{74} L_{83}	c	c
4	L_{12} L_{23} L_{33} L_{42} L_{53} L_{63} L_{72} L_{83}	b	b
5	L_{13} L_{22} L_{33} L_{42} L_{53} L_{63} L_{73} L_{82}	b	b
6	L_{13} L_{24} L_{34} L_{43} L_{54} L_{63} L_{73} L_{84}	c	c

6 CONCLUSIONS

In this study, an initial progress is successfully made in integrating more aspects of affected reliability into the prediction of most suitable reliability grades for the corrosive RC members in building structural engineering by means of the IHS. In this IHS, fuzzy logic, the GAs and the NNFL are combined.

The developed IHS increases the efficiency for solving the random, fuzzy and uncertain problems, and provides the possibility for integrating diverse aspects of affected reliability into the prediction of most suitable reliability grades for the corrosive RC members in building structural engineering.

The application to the prediction of most suitable reliability grades for the corrosive RC beams in building structural engineering yields satisfactory results in close agreement with the site data.

REFERENCES

[1] China Construction Department (2002), Unified Standard for Reliability Design of Building Structures. China Building and Construction Press, Beijing.

[2] Wu, Hong-Ci (2001). Incorporated building design intelligent hybrid systems. J. of Guizhou University of Technology, 30 (1), 76-82

[3] Wu, Hong-Ci (2002). Integrating GA with fuzzy rule system for site layout in building construction. J. of Guizhou University of Technology, 31 (1), 88-93.

[4] Wu, Hong-Ci (1997a). Classifying composite strata using fuzzy mathematics-hierarchy analysis methods. J. of Guizhou Univ. of Tech., 26 (1): 18-24.

[5] Wu, Hong-Ci (1998). Scheduling excavated plan for slope using genetic algorithms. Chinese J. of Rock Mechanics and Engineering, 17 (5), 565-570.

[6] Wu, Hong-Ci (1997b). Modelling constitutive relationship for soil using finite element-neural network hybrid algorithms. Proc. 9th Int. Conf. on Computer Methods and Advances in Geomechanics, 662--668

[7] Davis, L. (1990). A handbook of genetic algorithms, New York.

[8] Pham, D. T. and d. Karaboga. (2000). Intelligent optimisation techniques. Springer-Verlag London Limited, Great Britain.