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Application of ANFIS to Estimate Shear Strength of Concrete Beams

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Abstract: Fuzzy theory was used to accurately evaluate the shear strength of concrete beams used in various infra-structures. Extensive experimental datasets of experimental tests covering a wide range of test parameters of concrete beams were used for training and validation of the proposed fuzzy-based model. The strength-prediction obtained by the proposed model was compared to the validation group of test data. The results showed that the fuzzy-based model reasonably predicts concrete shear strength.

Key words: AI・Fuzzy theory・ANFIS・Concrete infra-structures・Strength prediction

INTRODUCTION

THE complexity of the concrete shear problem in various infra-structures is attributed to the ambiguity of modeling parameters (e.g. concrete cracking strength) and the difficulty in precise measurement of parameters (e.g. cracking angle) [1]; this precise measurement of parameters cannot be captured by the classical empirical approaches used in the existing design codes for concrete infra-structures. Therefore, a more robust modeling technique is needed which can account for the dependence of concrete shear strength on a number of interacting variables and the inherent uncertainty (randomness, vagueness and ambiguity) in concrete shear modeling and definitions. In the present study, an alternative design method using fuzzy set theory was developed to predict the shear strength of concrete beams. Fuzzy set theory is based on the principles of intelligent learning from examples of previous test data [2].

Fuzzy Set: The fuzzy sets defined by the degree of membership could represent non-random uncertainty due to fuzziness, vagueness and/or ambiguity [3]. Various methods for establishing membership functions have been developed and used according to the complexity level and information characteristics; in addition, automated methods such as inductive reasoning and clustering techniques can practically provide additional procedures to develop membership function [4-5]. Mathematical representations and operations of the fuzzy theory can be found elsewhere [1, 6].

The membership function of a fuzzy set *A* over a domain X is denoted $\mu_{\underset{\sim}{A}}$ and is defined as

$$\mu_{\underset{\sim}{A}} : X \to [0, 1] \tag{1}$$

For each $x \in X$, the value $\mu_{\underset{\sim}{A}}(x)$, which ranges between zero and one, is the degree of membership of *x* to the fuzzy set $\underset{\sim}{A}$. Among various types of membership functions (Gaussian, triangular, bell-shape, etc.) used in fuzzy set theory, the bell-shape membership function was adopted in the present study.

$$\mu_{\underset{\sim}{A}}^{k}(x_j) = \frac{1}{1 + \left| \dfrac{x_j - {x_c}_j^{\,k}}{w_j^{\,k}} \right|^{2q_j^k}} \tag{2}$$

where, $x_{c\,j}^{k}$, w_j^k and q_j^k are the parameters representing the center, top width and shape of the membership function, respectively, defining the k[th] fuzzy set defined over the j[th] input parameter of *x*.

Fuzzy-Based Model Estimating Shear Strength Of Concrete Beams: In addition, the adaptive network-based fuzzy inference system (ANFIS) suggested by Jang [2] was used to optimize design parameters for Sugeno systems [7,8]. Fig. 1 shows the structure of ANFIS [2] used in this study. In the ANFIS algorithm, input parameters first n eed to be determined (see layer 1 of Fig. 1).

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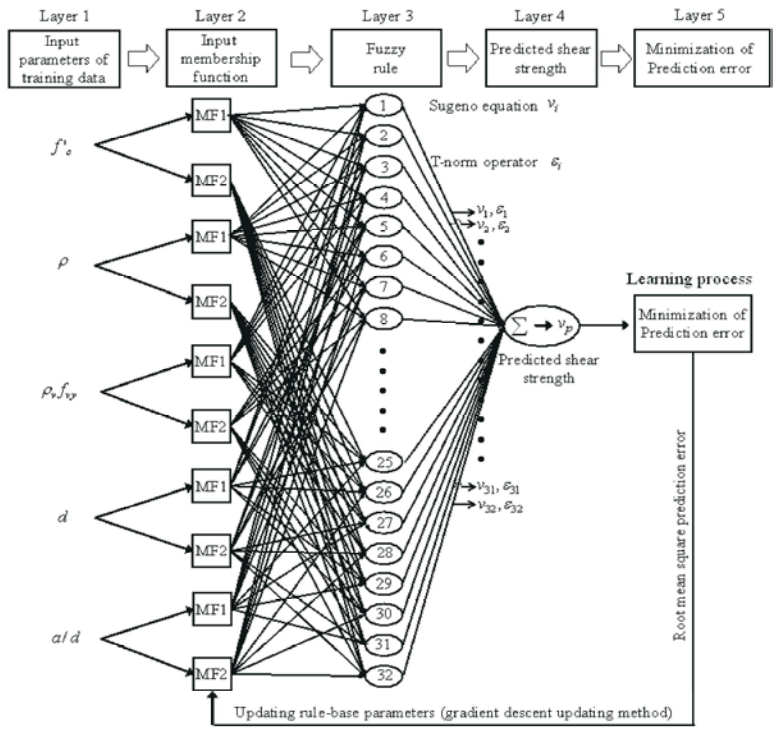

Fig. 1: Architecture of Adaptive Network Based Fuzzy Inference System (ANFIS) for fuzzy model and learning process to establish optimal rule base [2]

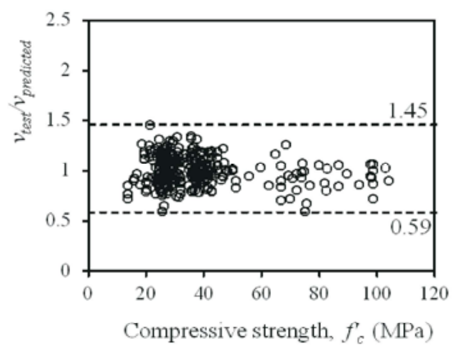

Fig. 2: Strength prediction obtained by fuzzy-based model rule base

The second layer in ANFIS is the fuzzification process in which the type and number of the membership function for each input parameter are determined. The third step in ANFIS is to establish the fuzzy rule-base which describes the output (shear strength) defined for each fuzzy set. The exemplar in the fuzzy rule-base is defined using the 'if-then' rule [7, 8].

$$\text{If } f'_c \in \underset{\sim}{A}^k_f,\ \rho \in \underset{\sim}{A}^k_\rho,\ \rho_v f_{vy} \in \underset{\sim}{A}^k_{\rho_v f_{vy}} \text{ and } d \in \underset{\sim}{A}^k_d \text{ then } v_i = a_i f'_c + b_i \rho + c_i \rho_v f_{vy} + d_i d + e_i \quad (3)$$

where $\underset{\sim}{A}^k_f$, $\underset{\sim}{A}^k_\rho$, $\underset{\sim}{A}^k_{\rho_v f_{vy}}$ and $\underset{\sim}{A}^k_d$ are the k[th] fuzzy set (k = 1, 2, … N_j) defined on the fuzzy domains of concrete compressive strength f'_c, tension reinforcement ratio ρ, the amount of shear reinforcement $\rho v f v y$ and effective depth d, respectively. N_j is the total number of fuzzy sets defined over the j[th] input parameter. Equation [3] represents the i[th] rule in the fuzzy rule-base. a_i, b_i, c_i, d_i and e_i are known as consequent coefficients that define the output side of the i[th] rule in the fuzzy rule-base.

By considering the T-norm (minimum-multiplication) operator (Đ) to capture the influence of interaction between input parameters on the output, the weight (ε_i) of the i[th] rule in the fuzzy rule-base can be computed as

$$\varepsilon_i = \frac{\prod_{j=1}^{T(=4)} \frac{1}{1+\left|\frac{x_j - x_{cj}^{k}}{w_j^{k}}\right|^{2q_j^{k}}}}{\sum_{i=1}^{R(=16)} \prod_{j=1}^{T(=4)} \frac{1}{1+\left|\frac{x_j - x_{cj}^{k}}{w_j^{k}}\right|^{2q_j^{k}}}} \quad \text{for } i = 1,2,...R(=16) \qquad (4)$$

T represents the total number of input parameters (here T = 4). R is the number of fuzzy rules and a function of the number of input variables (T). N_j is the number of fuzzy sets and defined on each input domain (see layer 3 of Fig. 1). Then, the shear strength, v_p, of slender concrete beams can be computed as

$$v_p = \left(\sum_{i=1}^{R(=16)} \varepsilon_i v_i\right) / \left(\sum_{i=1}^{R(=16)} \varepsilon_i\right) \qquad (5)$$

where v_i is the output of the i[th] rule in the fuzzy rule-base and ϵ_i represents the weight of the i[th] rule in the fuzzy rule-base (Equations [3] and [4]) (see layer 4 of Fig. 1).

Model Validation: For training and testing the fuzzy-based model, 636 test datasets that were reported to have failed in shear (no flexural failure) were used. The dimensions and properties of the specimens used for training and testing the fuzzy-based model are summarized elsewhere.

Table 1 shows the premise parameters of membership functions for compressive strength f'_c, reinforcement ratio ρ, the amount of shear reinforcement ($\rho v f v y$) and effective depth d, obtained from the training process.

The shear strength of the specimens predicted by the fuzzy-based model is presented in Figure 2. As shown, the strength ratios ($V_{test}/V_{predicted}$) of test results to prediction by the fuzzy-based model have a mean value of 0.99 and a standard deviation of 14.4 percent.

CONCLUSION

The proposed on fuzzy learning method is applicable to simply supported slender concrete beams used in infra-structures and yields acceptable accuracy in the prediction of concrete shear strength. A total of 636 test specimens from a shear databank were used in training and testing the proposed model (330 for training and 306 for testing). It is important to note that the training datasets were not used in the testing process. The fuzzy-based model shows a good accuracy in strength prediction of concrete beams.

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