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Intergration of neural networks with NDE for concrete strength prediction

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ABSTRACT: The application of neuro-fuzzy inference system to predict the compressive strengths of concrete is presented in this study. To investigate the influence of various parameters which affect the compressive strength, 2000 data samples were used for the analysis. Adaptive neuro-fuzzy inference system (ANFIS) was introduced for training and testing the data obtained from technical literatures. To reflect the effects of other uncertain parameters and in situ conditions, the results of non-destructive tests (NDT) such as ultrasonic pulse velocity (UPV) test and rebound hammer test were included as input parameters, in addition to mix proportion and curing histories. For the comparative study of the applicability of ANFIS models combined with NDT results, four ANFIS models were developed. These were classified depending on whether the input parameters of ANFIS models include NDT results or not. Among four models, ANFIS-UR model including both UPV test and rebound hammer test results shows best accuracy in the prediction of compressive strength.

1 INTRODUCTION

The text should fit exactly into the type area Concrete is the most widely used construction material in the world. Traditionally, concrete has been made by mixing a few well-defined components: cement, water, fine and coarse aggregates, etc. So concrete has a highly heterogeneous and complex micro structure. Therefore, it is very difficult to predict its constitutive properties and behaviors. The response of concrete to applied stress depends not only on the stress type but also on how a combination of various factors affects porosity of the different components of concrete. The factors include properties and proportions of materials that make up the concrete mixture, degree of compaction and conditions of curing.

In practice, standard uniaxial compression test is commonly used to determine compressive strength. Currently, coring for samples to do load testing is widely adopted in the construction field. However, it is costly and time-consuming to carry out coring. In addition, there is a practical limit to decide how many samples should be taken to represent a structure and how many samples can be taken from a structural element without compromising its integrity. Also, because of the small sample size, it is generally quite difficult to draw reliable or statistically meaningful conclusions. Furthermore, it needs to repair the damage due to coring, which involves additional costs and experimental errors are also inevitable.

Because of these reasons, over a period of many years, a lot of researchers have studied various new techniques to evaluate concrete compressive strength physically or analytically. First, nondestructive techniques have been developed with the intension of easy and reliable assessment of concrete strength. Many researchers have put their efforts to develop a reliable NDT method to complement or replace the existing destructive methods of verifying the strength of in place concrete. In the construction field, rebound hammer test and ultra sonic pulse velocity (UPV) test are most popular and widely used. These tests have many advantages and potential because it is entirely nondestructive in nature, simple to operate, and relatively inexpensive.

In this research, a methodology using an adaptive neuro-fuzzy inference system (ANFIS) was developed to estimate the concrete compressive strength. To consider in situ factors, the NDT results such as UPV and rebound number were included to the input parameters. For the purpose of comparative study, four ANFIS models, ANFIS-B with only basic inputs such as mix proportion, curing condition, and age, ANFIS-U additionally including UPV, ANFIS-R additionally including rebound number, and ANFIS-UR additionally including both UPV and rebound number, were trained and tested. For the validation of the developed ANFIS models, experiments including NDTs and uniaxial compressive test were conducted using 210 cylindrical and 20 cubical specimens which were made with different mix proportions and curing conditions. These specimens were tested at 3, 7, 14, 28, 90, 180, and 365 days after placing the concrete

2 CONCRETE STRENGTH AND NON-DESTRUCTIVE TESTS

2.1 *Compressive strength*

It is well recognized that the prediction of concrete strength is very important in the concrete construction works such as bridges and dams. It is also valuable indicator for engineering judgement. This is because it plays important roles in project scheduling and quality control and provides the time for concrete form removal, re-shoring to slab, and application of pre or post-tensioning. But, the compressive strength of concrete is influenced by many factors including mix proportions, curing conditions such as temperature and humidity and methods of mixing, transporting, placing and testing the concrete such as specimen geometry and loading condition.

Even though water/cement ratio is well known factor that have most effect on concrete strength, concrete strengths corresponding to each water/cement ratio show large variations. Another feature of concrete is that the mechanical strength of concrete increases continuously as a function of time due to the evolution of the hydration reaction of cement. The evaluation of compressive strength with time is of great concern for structural engineers. However, because previous researches generally used limited their own experimental data sets, they are effective only for interpreting specific data set used in their analysis. Even though they demonstrated the effectiveness and applicability of AI systems showing very high accuracy, those can not show how much accurately they can predict compressive strengths in general cases of practical field. Therefore, in this study, to demonstrate and test AI systems as generalized practical prediction tool, various parameters affecting on compressive strength were introduced as input variables and a lot of experimental results were collected and used for the analysis.

2.2 *Non-destructive tests*

Because defects such as crack, wear, and aging of concrete can deteriorate civil structures, continuous inspection and quality control are necessary. In addition to conventional destructive uniaxial compressive test, non-destructive techniques have been developed and commonly used in the concrete construction field. During the past decades, several NDT methods for the prediction of concrete strength have been developed. Among various NDTs, UPV test and rebound hammer test are widely used in the field. But, each of these methods has certain limitations and drawbacks so that it is difficult to get reliable results. The evaluation by non-destructive methods of the actual compressive strength of concrete in existing structures is based on empirical relations between strength and non-destructive parameters. But, such relationships are not suitable for every kind of concrete. Therefore, they need to be calibrated for different mixtures. To improve the accuracy of strength prediction, combined NDT tests were introduced. But it does not show clear relationship in estimating concrete strength with reliable accuracy. As what was mentioned, even though the results of NDTs are widely used for the indicator of the quality of concrete, it is not easy to get reliable results because the relationships between the compressive strength of concrete and rebound number or UPV are not simple. It is widely recognized that the relationship is not unique, but is affected by numerous factors such as the properties and proportion of the constituent materials, age of concrete, presence of microcracks, moisture content, and stresses in the concrete specimens. In general regression analysis, such factors will result in decreasing the accuracy of any proposed regression.

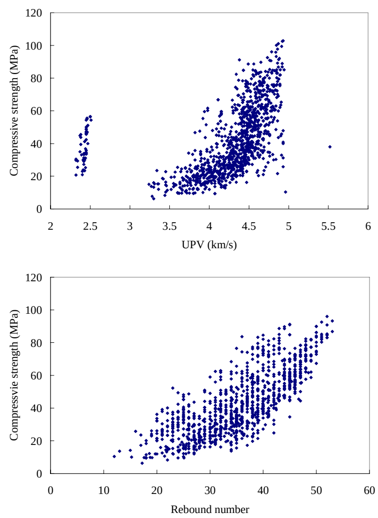


Figure 1. Variation of compressive strength with UPV and rebound number.

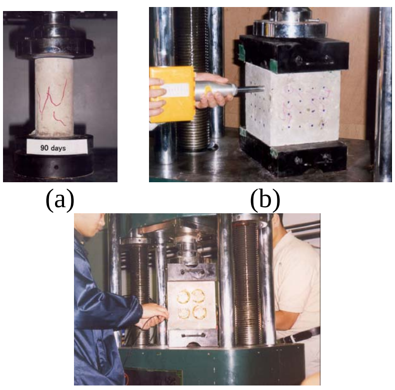
The main purpose of this study is to obtain easy-to-use methodology, based on ANFIS, considering several major parameters which have an effect on concrete strength and reflecting the in situ condition of concrete through the NDT results. Because UPV and rebound number are also affected by several in situ factors, they can not clearly represent the concrete strength using simple Equation forms. Figure 1 shows the variation of compressive strength corresponding to UPV and rebound number. One can notice from this figure, even though experimental test samples showed the same rebound number or the same UPV, those have different compressive strengths with very large variation.

In this study, to consider this characteristic, various material parameters and ages, which are noted to have an effect on UPV and rebound number, were included in the ANFIS models. Even though, the other factors such as the presence of steel reinforcement, surface carbonation of concrete and aggregate type also have an effect on the UPV and rebound number, those were not considered in this study to simplify the ANFIS models in the practical purpose.

2.3 *Experimental work*

For the experimental study, NDTs such as rebound hammer test and UPV test and destructive uniaxial cylinder compressive test were conducted. These experimental results were used as test data sets for validation of ANFIS models developed in this study. For this purpose, specimens with two different shapes such as cylinder and cubic were prepared. Cubical specimens of size 200×200×200mm were used in this experimental work for measuring the UPV and rebound number. And cylindrical specimens of size 100×200mm (ø x H) were tested to obtain compressive strength. Half of all specimens were cured in water with about 20℃. The rest of specimens were exposed to natural outdoor atmosphere for curing period.

The mix proportions of the concrete used in this experiment are given in table 1. Concrete specimens with water/cement ratio of 30, 40, 50, 60, and 70% were prepared and tested at the ages of 3, 7, 14, 28, 90, 180, and 365 days. For each mix proportion, four cubical specimens were prepared and tested using UPV test and rebound hammer test. In measuring the rebound number of the concrete cubes, the cubes were fixed between the platens of the UTM, with the application of a compressive stress of 2.5MPa. For the uniaxial compressive test, 210 cylindrical specimens were prepared (5 mix proportions * 7 ages * 2 curing conditions * 3 specimens). The average test results from the three specimens were used for the test data set of ANFIS models. Table 1 shows the test results obtained from mix proportion No. 2 and 3. It was composed of rebound number, UPV, and compressive strength test results for 3, 7, 14, 28, 90, 180, and 365 days.



(a) (b)

(c)

Figure 2. Experimental study (a) compressive test, (b) rebound hammer test, (c) UPV test.

Table 1. Mix proportions used in experimental study.

No.	W/C (%)	Water (kg/m^3)	S/A (%)	S.P/C (%)	Cement (kg/m^3)	Sand (kg/m^3)	Gravel (kg/m^3)
1	30	175	38	1.1	583	547	994
2	40	185	42	0.5	462	618	990
3	50	185	45	0.5	370	693	983
4	60	185	47	0.5	308	746	976
5	70	185	47	0.4	264	809	940

3 ANFIS MODELS FOR PREDICTION OF CONCRETE STRENGTH

Recently, fuzzy logic, classed as artificial intelligence, has been widely used in civil and environmental engineering problems from the evaluation of concrete structures to transportation control. Fuzzy logic provides a language with syntax and semantics to translate qualitative knowledge into numerical reasoning.

In this study, to propose a proper computational methodology for prediction of concrete compressive strength, neuro-fuzzy system were used. Among various algorithm, ANFIS developed by Jang was chosen to construct the prediction models.

3.1 *Model architectures*

In this study, four ANFIS models were constructed for the purpose of comparison. All four models commonly have basic input parameters from (a) to (l). The ANFIS model without any NDT results as input variables is referred to just as ANFIS-B, the model with UPV test result is referred to as ANFIS-U, the model with rebound number is referred to as ANFIS-R, and the model with both NDT results is referred to as ANFIS-UR.

The architectures of four ANFIS models are shown in Figure 3. Input variables are ategorized as material properties (MP, 10 input variables), curing history (HIS, 2 input variables), and NDT results (NDT, 2 input variables). For simplified schematic drawing, membership function and fuzzy inference engine layers are not depicted. The input variables

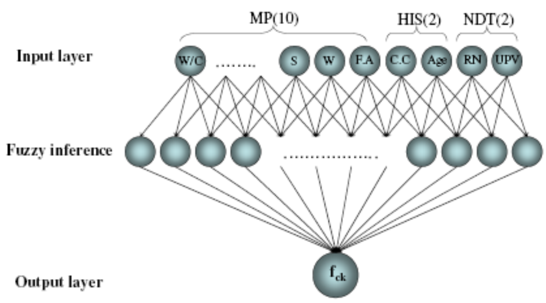


Figure 3. Model architectures.

which were not used in each model are shown as shaded type and dotted line. So these four ANFIS models were trained with 12, 13, 13, and14 input variables.

3.2 *Training and testing of ANFIS models*

Four ANFIS models were trained using data set collected from literatures and tested using the results obtained from the experiments of section 2.3.

Table 2. The range of the input and output values covered in this study.

Input/output variables	Data range used in training	
	Minimum	Maximum
Cement(kg/m^3)	0	900.9
Water (kg/m^3)	118	238
Sand (kg/m^3)	208	879
Gravel (kg/m^3)	386	1285
S.P (%)	0	3.5
Fly ash (kg/m^3)	0	275
Silicafume(kg/m^3)	0	90
Slag (kg/m^3)	0	500
Compressive strength (MPa)	6.3	107.7

a. Collected experimental data

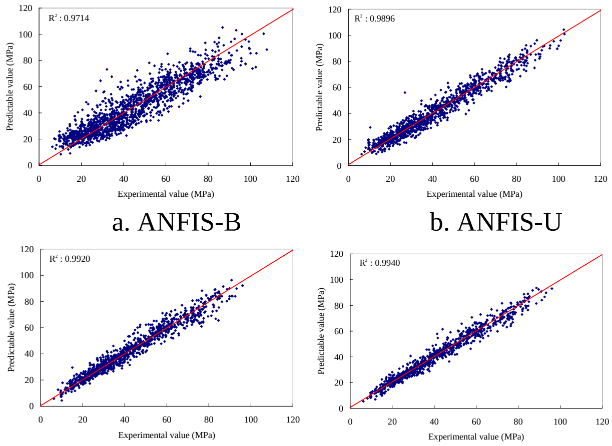
For the training of ANFIS, 1551 test results were collected from previous literatures. The each of collected experimental data set included either UPV or rebound number or both of them. The range of the data set is listed in Table 2. The numbers of input data sets are 1551, 1103, 1040, and 871 for ANFIS-B, ANFIS-U, ANFIS-R, and ANFIS-UR, respectively.

b. Trained ANFIS models

Training for each model was successfully completed. Training data as test data were recalled for checking the trained ANFIS models. The individual trained ANFISs gave reasonable results within 0.97 of absolute fraction of variance (R^2). Figure 4 is an expression of the training results, each point stands for a training vector. The nearer the points show up around the diagonal, the better are the training results. The training errors of the points on the diagonal are zero. In terms of the ratios of the predicted strength to experimental compressive strength, the mean values of these ratios are 1.054, 1.022, 1.013, and 1.007 and COVs are 23.4%, 15.2%, 11.7%, and 10.2%, for the ANFIS-B, ANFIS-U, ANFIS-R, and ANFIS-UR, respectively. One can clearly indicate that ANFIS-UR which has input variables of both UPV and rebound number shows best prediction accuracy.

c. Testing of ANFIS models

Trained ANFIS models were validated with test patterns which were obtained from the experimental



a. ANFIS-B b. ANFIS-U

c. ANFIS-R d. ANFIS-UR

Figure 4. Comparison of experimental strengrhs with predicted results.

study explained in section 2.3. The R^2 values in prediction of test data patterns are 0.9571, 0.9757, 0.9814, and 0.9833 for ANFIS-B, ANFIS-U, ANFIS-R, and ANFIS-UR, respectively. The average values of the experimental to predicted compressive strength ratios are 1.094, 1.061, 1.054, and 1.047, respectively. And COVs are 39.4%, 24.9%, 22.7%, and 7.3%, respectively. The prediction results of ANFIS-B, ANFIS-U, and ANFIS-R showed relatively large errors in the view of practical purpose. However, ANFIS-UR predicted compressive strength with good accuracy.

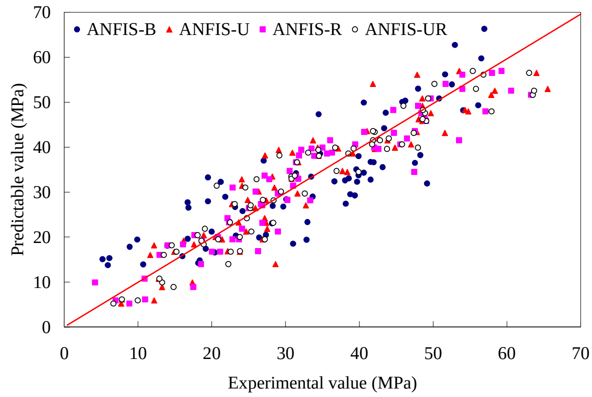


Figure 5. Validation of four ANFIS models using testing data sets.

4 CONCLUSION

A neuro-fuzzy-based technique was presented for predicting the concrete strength using mix proportion and NDT results. For the comparative study, four ANFIS models (ANFIS-B, ANFIS-U, ANFIS-R, and ANFIS-UR) were developed. The models were trained with input and output data sets obtained from literatures. Like previous researches, trained ANFIS-B model can be used to predict the compressive strength at any ages using a mix proportion data. However, because of the various in situ factors, the predicted compressive strength did not show high accuracy. So, in this study, neuro-fuzzy-based models combined with NDT results were proposed. ANFIS-UR model which includes a mix proportion, UPV test, and rebound hammer test results as input parameters showed best prediction accuracy.

For the validation of the ANFIS models, the experiments were conducted using several mix proportions. From each specimen, the results of uniaxial compressive test, UPV test, and rebound hammer test were obtained. The test phase of ANFIS models showed that the trained models can reasonably predict the compressive strength of different input data sets which were not used in the training procedures. In addition, error analysis using *RMSE*, R^2, *MAPE*, and *MPR* and statistical analysis to get statistical parameters of the predicted results were also conducted. Simulation for the performance of the ANFIS model was also presented using varying rebound number and UPV.

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