Neuro-fuzzy application for concrete strength prediction using combined non-destructive tests

U. J. Na*, T. W. Park†, M. Q. Feng* and L. Chung†

University of California Irvine; Dankook University

The application of the neuro-fuzzy inference system to predict the compressive strength of concrete is presented in this study. The adaptive neuro-fuzzy inference system (ANFIS) is introduced for training and testing the data sets consisting of various parameters. To investigate the influence of various parameters which affect the compressive strength, 1551 data pairs are collected from the technical literature. These data sets cover early and late compressive strengths from 3 to 365 days and low and high strength in the range 6·3–107·7 MPa. To reflect the effects of other uncertain parameters and in situ conditions, the results of non-destructive tests (NDTs) such as ultrasonic pulse velocity (UPV) and rebound hammer test are also included as input parameters, in addition to mix proportion and curing histories. For the testing of trained ANFIS models, 20 cube specimens and 210 cylinders are prepared, and compressive test and NDTs are conducted. For the comparative study of the applicability of ANFIS models combined with NDT results, four ANFIS models are developed. Depending on whether the input parameters of ANFIS models include NDT results or not, these are distinguished from each other. Among the four models, the 'ANFIS-UR' model having the parameters for both UPV and rebound hammer test results shows the best accuracy in the prediction of compressive strength.

Introduction

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, and so on. Concrete therefore has a highly heterogeneous and complex microstructure. It is therefore very difficult to predict its constitutive properties and behaviours. 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.[1] The factors include properties and proportions of materials that make up the concrete mixture, degree of compaction and conditions of curing.

To obtain good-quality concrete structures, the concrete placed in a structure must have uniform quality satisfying design criteria without voids and discontinuities. Lack of sufficient attention to placing and curing of concrete such as poor workmanship can result in poor-quality concrete in the structure, even though ready-mixed concrete is used with good quality control. For the quality control of concrete handling work, various tests should be carried out to affirm the strength of the concrete.

In this regard, the strength of concrete is a very valuable property to structural designers and construction engineers. Many properties of concrete such as elastic modulus and impermeability are directly related to the strength. The strengths of concrete include compressive, tensile, flexural, shear and bond. As the uniaxial strength in compression is commonly accepted as a general index of concrete strength, destructive or non-destructive compressive tests are generally conducted to evaluate the concrete quality.

In practice, standard uniaxial compressive test is commonly used to determine compressive strength. Currently, coring for samples to make an experiment on load testing is widely adopted in the construction field. It is, however, 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 whole structure and how many samples can be taken from a structural member without harmful effects

* Department of Civil & Environmental Engineering, University of California Irvine, Irvine, CA, 92697, USA
† Department of Architectural Engineering, Dankook University, 8, Hannamdong, Seoul, 140-714, Korea

on its integrity. Also, because of the small number of samples, it is generally quite difficult to find reliable or statistically meaningful conclusions. Furthermore, experimental errors are inevitable and additional cost is also needed.

For these above 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, non-destructive techniques have been developed with the intension of easy and reliable assessment of concrete strength. Many researchers have put their efforts into developing reliable non-destructive test (NDT) methods to replace the existing destructive methods. In the construction field, both the rebound hammer test and the ultrasonic pulse velocity (UPV) test are most popular and they are widely used. These tests have many advantages and potential benefits because these are entirely non-destructive in nature, easy to operate and relatively inexpensive.

Second, in recent years, the analytical methods using artificial intelligence (AI) such as neural network and fuzzy logic have increasingly been applied to predict concrete strength. The basic strategy for developing AI systems to predict material behaviour is the training process of AI systems based on the results of a series of experiments. If the experimental results for the training process contain relevant information representing the material behaviour, the trained AI systems will be able to predict material behaviours. Even though several researchers have recently proposed new methods for mixing design and predicting the strength using neural network and fuzzy logic, they have not fully investigated the AI systems for predicting the concrete strength; for example, effectively considering various factors affecting the strength of in situ concrete. In particular, a comparative study for AI systems based on NDT results combining mix proportion, curing condition and age has not been presented yet.

In this research, a methodology using an adaptive neuro-fuzzy inference system (ANFIS) is developed to estimate the concrete compressive strength. To consider in situ factors, the NDT results such as UPV and rebound number are included in 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—are trained and tested. For the validation and test of the developed ANFIS models, experiments including NDTs and uniaxial compressive test are conducted using 210 cylindrical and 20 cube specimens, which are prepared with different mix proportions and curing conditions. These specimens are tested at 3, 7, 14, 28, 90, 180 and 365 days after placing the concrete.

From a practical point of view, these proposed ANFIS models including NDT results show a reliable increased accuracy in predicting concrete strength. In particular, the ANFIS model with the results of two different types of NDT, namely ANFIS-UR, provides superior correlation compared with other ANFIS models having a single type of testing, such as ANFIS-U and ANFIS-R. These results will be helpful for construction engineers and structural designers to schedule and manage the concrete works such as form removal and pre- or post-tensioning.

Concrete strength and non-destructive tests

Compressive strength

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

As Fig. 1 shows, even though the water/cement (w/c) ratio is a well-known factor that has the most effect on concrete strength, concrete strengths corresponding to each w/c ratio show large variations. This figure is obtained from collected experiment databases. (For more details, see the section 'Training and testing of ANFIS models'.) In this figure, the values of compressive strength represent the cylinder compressive strength at 28 days. This figure indicates that it is very difficult to predict compressive strength with reliable accuracy and consistency.
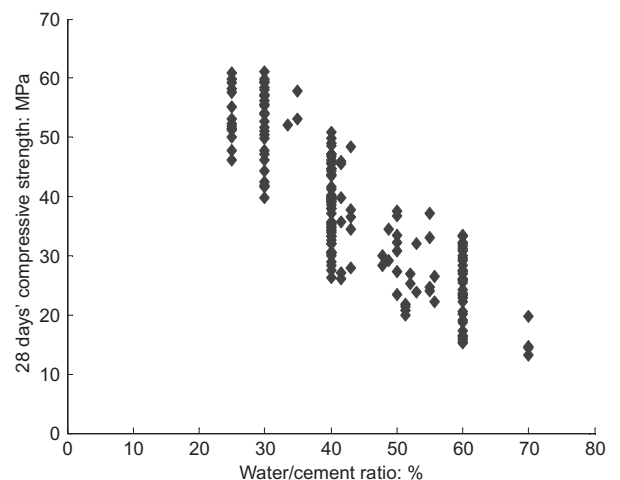

Fig. 1. Variation of compressive strength with w/c ratio (28 days)

Another feature of concrete is that its mechanical strength increases continuously as a function of time owing to the evolution of the hydration reaction of cement. The evaluation of compressive strength with time is of great concern for structural engineers. This feature therefore also needs to be considered in the process of the prediction of compressive strength.

For many years, various methods for predicting concrete strength have been proposed.[2-4] Conventional methods for predicting compressive strength of concrete are basically based upon statistical analyses. Recently, AI systems have also been used to predict the compressive strength of concrete.[5-15] AI systems do not need such a specific equation form: it is enough to prepare sufficient input–output data sets. Also, it can continuously retrain the new data, so that it can conveniently adapt to new data.

As previous researches generally used their own limited experimental data sets, however, they are effective only for interpreting the specific data set used in their analysis. Even though they demonstrated the effectiveness and applicability of AI systems showing very high accuracy, they cannot show how accurately they can predict compressive strengths in general cases of practical field studies. In this study, therefore, to demonstrate and validate the availability of AI systems as a generalised practical prediction tool, various parameters affecting compressive strength are introduced as input variables and a lot of experimental results are collected to develop training data sets.

Non-destructive tests

As defects such as crack, wear and ageing of concrete can deteriorate civil structures, continuous inspection and quality control are necessary. In addition to conventional destructive uniaxial compressive tests, 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, the UPV test and rebound hammer test are widely used in the field. Each of these methods has certain limitations and drawbacks, however, and it is therefore difficult to obtain reliable results.[16,17] Non-destructive methods are based on the empirical relations between strength and non-destructive parameters.[18-20] Such relationships are not, however, suitable for all kinds of concrete: they need to be calibrated for different mixtures. To improve the accuracy of strength prediction, combined NDT tests were introduced.[19,20] It does not, however, show a clear relationship in estimating concrete strength with reliable accuracy. As mentioned, even though the results of NDTs are widely used for the indicator of the quality of concrete, it is not easy to obtain reliable results because the relationships between the compressive strength of concrete and rebound number or UPV are not simple.[21-23] It is widely recognised 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 a decrease in the accuracy of any proposed regression

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. As UPV and rebound number are also affected by several in situ factors, they cannot clearly represent the concrete strength with simple equation forms. Fig. 2 shows the variation of cylinder compressive strength corresponding to UPV and rebound number. In this figure, each dot indicates different experimental results obtained from the section 'Training and testing of ANFIS models'. This figure illustrates that, even though experimental test samples show the same rebound number or the same UPV, they 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 a large effect on UPV and rebound number, are included in the input variables of 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
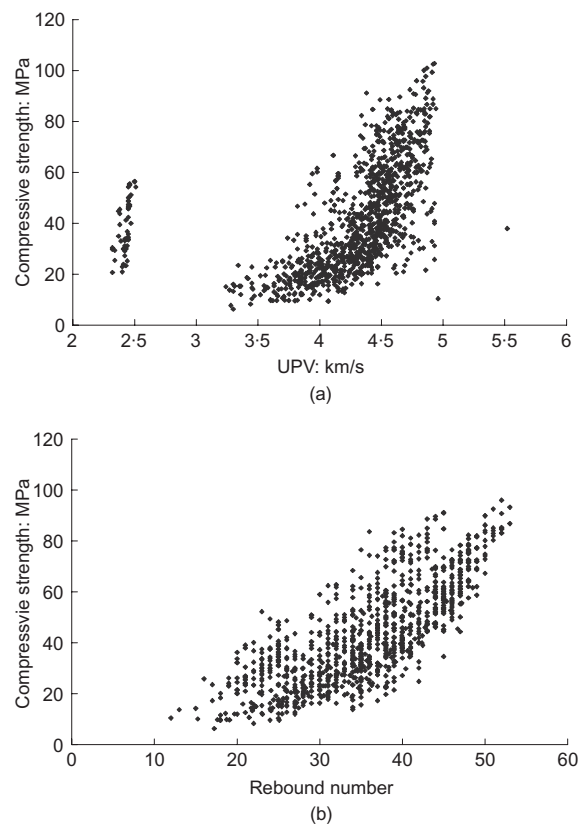

Fig. 2. Variation of compressive strength with (a) UPV and (b) rebound number

rebound number, in order to simplify the ANFIS models in the practical purpose, they are not considered in this study.

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 are used as test data sets for the validation of ANFIS models developed in this study. For this purpose, specimens with two different shapes, namely cylinder and cube, are prepared. Cube specimens of size $200 \times 200 \times 200$ mm are used in this experimental work for measuring the UPV and rebound number. Cylindrical specimens of size 100×200 mm ($\phi \times H$) are tested to obtain compressive strength. Half of all specimens are cured in water of approximate temperature 20°C. The remaining specimens are exposed to natural outdoor atmosphere throughout the curing period.

The mix proportions of the concrete used in this experiment are given in Table 1. Concrete specimens with a w/c 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 cube specimens were prepared and tested using the UPV test and rebound hammer test (see Fig. 3). In measuring the rebound number of the concrete cubes, the cubes were fixed between the platens of the universal testing machine, with the application of a compressive stress of 2·5 MPa. For the uniaxial compressive test, 210 cylindrical specimens were prepared (5 mix proportions × 7

ages × 2 curing conditions × 3 specimens). The average compressive strength of three specimens is used for the test data sets of ANFIS models. Table 2 shows the test results. It is composed of rebound number, UPV, and compressive test results for 3, 7, 14, 28, 90, 180 and 365 days.

ANFIS models for prediction of concrete strength

Recently, fuzzy logic, classed as AI, has been widely used in civil and environmental engineering problems from the evaluation of concrete structures to transportation control.[6,7,24,25] Fuzzy logic provides a language with syntax and semantics to translate qualitative knowledge into numerical reasoning.

In the current study, to propose a proper computational methodology for prediction of concrete compressive strength, a neuro-fuzzy system is used. Among various algorithms, ANFIS developed by Jang[26] is chosen to construct the prediction models.

Overview of neuro-fuzzy models

Fuzzy logic is the process of formulating the mapping from a given input to an output. The mapping then provides a basis from which decisions can be made, or patterns discerned. Fuzzy systems have been successfully applied in fields such as automatic control, data classification, decision analysis and expert systems. Basically a fuzzy system is composed of five parts: fuzzification of the input variables; application of the fuzzy

Table 1. Mix proportions used in experimental study

No.	w/c*:%	Water: kg/m³	s/a†:%	s.p/c‡:%	Cement: kg/m³	Sand: kg/m³	Gravel: kg/m³
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

*Water/cement ratio, †Sand/aggregate ratio, ‡Super plasticiser/cement ratio
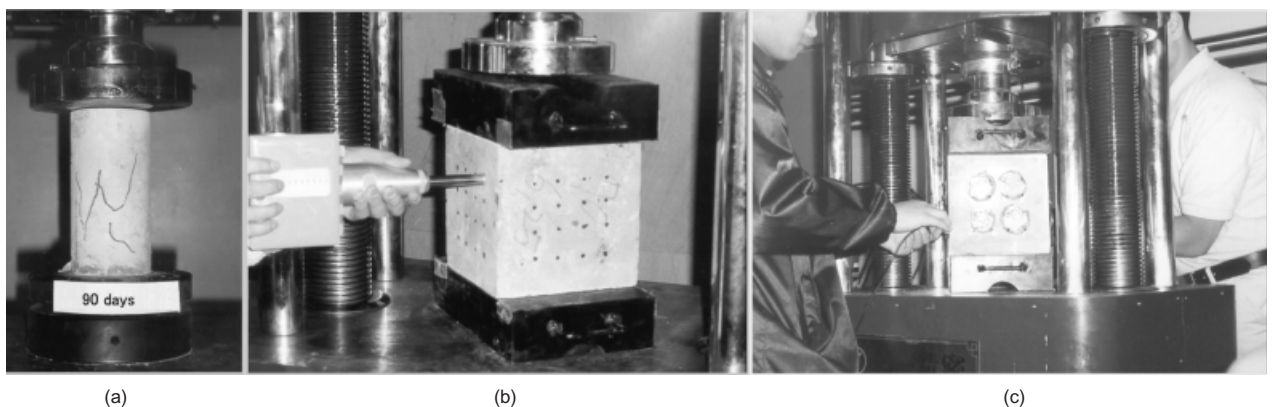

Fig. 3. Experimental study: (a) compressive test; (b) rebound hammer test; (c) UPV test

Table 2. Experimental test results

No.	Mix proportion No. 1			Mix proportion No. 2		
Ages	Rebound number	UPV: km/s	Compressive strength: MPa	Rebound number	UPV: km/s	Compressive strength: MPa
3 days	36·9	4·31	39·6	27·2	3·89	19·5
7 days	38·3	4·40	43·6	33·8	4·14	33·5
14 days	47·8	4·45	52·6	36·4	4·35	39·9
28 days	49·3	4·66	54·1	39·5	4·50	40·6
90 days	55·2	4·71	56·1	45·7	4·72	47·6
180 days	55·5	4·71	56·5	45·9	4·65	48·3
365 days	55·5	4·80	56·9	46·9	4·70	49·2

No.	Mix proportion No. 3			Mix proportion No. 4		
Ages	Rebound number	UPV: km/s	Compressive strength: MPa	Rebound number	UPV: km/s	Compressive strength: MPa
3 days	32·6	3·96	16·7	20·4	3·74	8·9
7 days	34·2	4·25	19·5	21·0	4·17	14·0
14 days	35·5	4·20	30·1	25·3	4·40	31·0
28 days	37·9	4·35	39·4	29·6	4·41	32·9
90 days	43·5	4·49	41·5	30·0	4·50	33·0
180 days	42·1	4·75	41·9	32·4	4·50	33·7
365 days	46·4	4·60	43·2	36·6	4·60	34·7

No.	Mix proportion No. 5					
Ages	Rebound number	UPV: km/s	Compressive strength: MPa			
3 days	14·0	3·48	5·2			
7 days	15·7	3·51	6·1			
14 days	17·1	3·84	16·0			
28 days	20·7	4·13	20·4			
90 days	23·1	4·25	23·3			
180 days	22·6	4·30	24·2			
365 days	26·3	4·30	27·0			

operator (AND or OR) in the antecedent; implication from the antecedent to the consequent; aggregation of the consequents across the rules; and defuzzification. Three middle processes among five parts are included in the fuzzy inference engine of Fig. 4.

The primary mechanism of fuzzy logic is a list of if–then statements called rules. All rules are evaluated in parallel. The most important step to establish the fuzzy model is to generate the rules. Clustering of the input–output data is an intuitive approach to objective rule generation. The idea of clustering is to divide the

output data into a certain number of fuzzy partitions. The appropriate number of clusters is determined so that the sum of the Euclidian distance of the output data from the centre of the clusters is minimised.[27]

The neuro-fuzzy inference system is the advanced fuzzy inference system with learning capability of neural network. The main feature of the neuro-fuzzy inference system is that it can change the fuzzy inference system structure and parameters using the training algorithm. In this study, ANFIS, based on if–then rules of the Takagi and Sugeno's type,[28] is used for predicting the concrete strength. All computations can be presented in diagrammatic form as illustrated in Fig. 5.

If the fuzzy inference system is assumed to have two inputs x and y and one output z

$$\text{Rule 1: If } x \text{ is } A_1 \text{ and } y \text{ is } B_1, \text{ then } f_1 = p_1 x + q_1 y + r_1 \tag{1a}$$

$$\text{Rule 2: If } x \text{ is } A_2 \text{ and } y \text{ is } B_2, \text{ then } f_2 = p_2 x + q_2 y + r_2 \tag{1b}$$

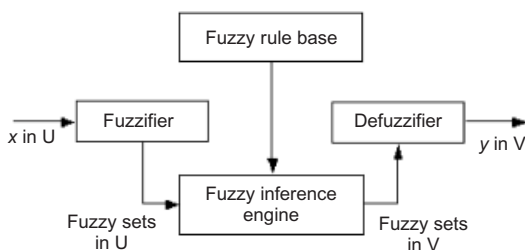In layer 1, the membership functions of fuzzy sets A_i,

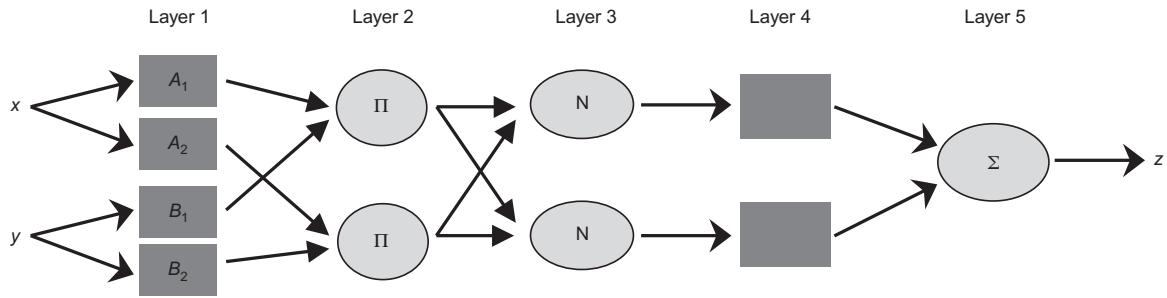*Fig. 4. The structure of the fuzzy system[26]*

Fig. 5. The structure of the ANFIS[28]

B_i, $i = 1$, 2, would exist as $\mu_{A_i}(x)$, $\mu_{B_i}(y)$. Then, for evaluating the rules, circle nodes labelled Π multiply incoming signals and send the product out. This evaluating results in

$$w_i = \mu_{A_i}(x) \times \mu_{B_i}(y), \quad i = 1,\ 2 \tag{2}$$

In layer 3, through the nodes labelled N, the ratios of ith rule's strength are calculated

$$\overline{w_i} = \frac{w_i}{w_1 + w_2}, \quad i = 1,\ 2 \tag{3}$$

Then, the output z can be calculated as

$$z = \sum_i \overline{w_i} f_i \tag{4}$$

As far as the membership functions and rules are concerned, there is no general rule for selecting the shape type and the number of membership functions for each input variable. Membership functions are mainly chosen specifically depending on the problem and to some extent these are selected depending on the quality of training patterns.

Model architectures

In this study, four ANFIS models are constructed for the purpose of comparison. The difference of each ANFIS model is whether or not the each model includes NDT results as input variables. The number of the input nodes is determined from the considered variables that have an effect on concrete strength. The following variables are used as input parameters

(*a*) w/c ratio
(*b*) sand/aggregate ratio
(*c*) unit weight of cement
(*d*) unit weight of sand
(*e*) unit weight of gravel
(*f*) unit weight of water
(*g*) superplasticiser (%)
(*h*) unit weight of fly ash
(*i*) unit weight of silica fume
(*j*) unit weight of slag
(*k*) age
(*l*) curing condition (in water or air)
(*m*) UPV
(*n*) rebound number.

The output node corresponds to compressive strength.

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 Fig. 6. Input variables are categorised as material properties (MP, 10 input variables), curing histories (HIS, 2 input variables) and NDT results (NDT, 2 input variables). For simplified schematic drawing, membership functions and fuzzy inference engine layers in Fig. 5 are not depicted. The input variables which are not used in each model are shown as shaded circles and dotted lines in this figure. These four ANFIS models are therefore trained with 12, 13, 13 and 14 input variables, respectively.

Training and testing of ANFIS models

Four ANFIS models introduced in the section 'Model architectures' were trained using data sets collected from the literature and tested using the experimental results conducted by the authors following the section 'Experimental work'.

Data sets. For the training of ANFIS, 1551 test results are collected from previous research.[29–56] Some collected experimental data pairs have either UPV or rebound number and others have both. The range of the values for each parameter is listed in Table 3. This collected data set is used to construct the training data sets. Even though many researchers focused on these kinds of NDT tests, it is difficult to gather much useful data from their technical literature because they did not show the mix proportion or the exact values of experimental results. Table 4 presents the part of details of the data used for the training of ANFIS models in this study. The compressive strengths of the last column of Table 4 are used for the target values of ANFIS models. The total number of input data pairs are 1551, 1103, 1040 and 871 for ANFIS-B, ANFIS-U, ANFIS-R and ANFIS-UR, respectively.

For the testing of trained ANFIS models, test data sets are prepared from the experimental study explained in
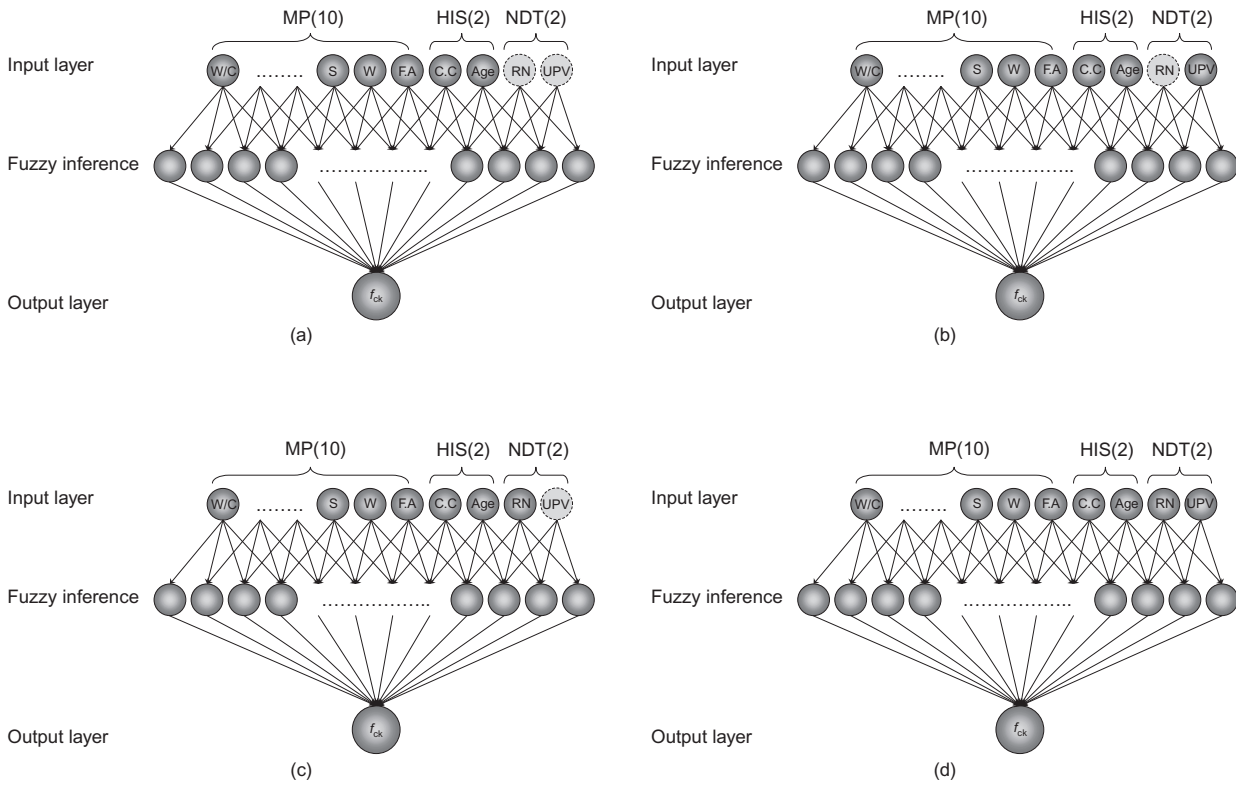
Fig. 6. Model architectures: (a) ANFIS-B: (b) ANFIS-U; (c) ANFIS-R; (d) ANFIS-UR

Table 3. 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
Superplasticiser: %	0	3·5
Fly ash: kg/m^3	0	275
Silica fume: kg/m^3	0	90
Slag: kg/m^3	0	500
Compressive strength: MPa	6·3	107·7

the section 'Experimental work'. To collect the test data, five mix proportions are prepared. Using these specimens, compressive tests and NDTs are conducted under at seven different ages under different curing conditions.

Trained ANFIS models. Training for each model is successfully completed. To evaluate the prediction accuracy of trained systems, the training data are recalled for checking the trained ANFIS models. The predicted compressive strength values of four ANFIS models for the training data are shown in Fig. 7 compared with the actual values observed in the experiments. In this figure, each point represents a training vector. If the points appear closer to the diagonal, it means the accuracy of training results is high. The training errors of the points on the diagonal are zero. In terms of the ratio 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 the coefficients of variation (COVs) are 23·4%, 15·2%, 11·7% and 10·2%, for the ANFIS-B, ANFIS-U, ANFIS-R and ANFIS-UR respectively. More statistical analyses based on the training results will be presented in 'Error analysis of ANFIS models'. Fig. 7 clearly illustrates that ANFIS-UR which has input variables of both UPV and rebound number shows the best prediction accuracy.

Testing of ANFIS models. The predicted compressive strength values of four ANFIS models for the testing data are shown in Fig. 8 compared with the actual values observed in the experiments conducted by the authors. The average values of the experimental to predicted compressive strength ratios are 1·094, 1·061, 1·054 and 1·047 respectively, and the COVs are 39·4%, 24·9%, 22·7% and 7·3% respectively. In practice, the predicted results of ANFIS-B, ANFIS-U and ANFIS-R show relatively large errors. ANFIS-UR predicts, however, compressive strength with good accuracy. More statistical analyses based on the testing results will be presented in 'Error analysis of ANFIS models'.

The results of the testing phase suggest that, although the models were not trained for these data, the ANFIS models, especially ANFIS-UR, were capable of generalising the relationship between the input variables and the output and yielded reasonably good predictions.

Table 4. The examples of collected data sets (in part)

Data set ID No.	W/C	S/A	C	S	G	W	SP: %	FA	SF	Slag	Age: days	Curing	UPV: km/s	RN	Strength: MPa
	%		kg/m³				%	kg/m³			days		km/s		MPa
1	35	47	450	793	943	161·5	2·7	100	50	0	7	Air	4·4	—	47·0
2	35	47	300	807	960	148	2·3	100	50	150	7	Air	4·3	—	39·1
31	40	34·5	377	635	1206	151	0·4	—	—	—	90	Water	4·5	24	37·6
32	43	39	377	707	1106	162	0·6	—	—	—	90	Water	4·55	25	40·6
55	40	40	394	697	1051	175	0·8	44	—	—	7	Water	4·41	23	27·5
56	40	40	350	698	1040	175	0·8	88	—	—	7	Water	4·35	19	23·3
71	25	33·1	648	480	1035	180	—	—	72	—	7	Water	4·706	44	60
89	30	45·1	420	798	1035	140	—	—	47	—	7	Water	4·747	39	51·3
121	35	47	200	791	941	167·5	1·5	—	—	300	28	Water	4·61	—	62·9
122	35	47	0	785	933	163·5	2·3	—	—	500	28	Water	4·79	—	60·3
211	58·8	41	332	746	1093	185	—	—	—	—	3	Water	4·02	—	17·0
212	53·3	39	351	711	1134	187	—	—	—	—	3	Water	4·02	—	17·0
357	40	34	522	540	1049	211	—	—	—	—	90	Air	4·19	37	39·4
358	40	34	478	572	1106	191	—	—	—	—	90	Air	4·18	35	32·1
359	40	34	453	588	1137	181	1·5	—	—	—	180	Air	—	41	35·5
471	60	38·9	318	707	1105	190	—	—	—	—	180	Air	—	37	27·4
509	52	46	355	790	931	188	0·5	—	—	—	365	Air	3·78	36	23·3

W/C = water/cement ratio; S/A = sand/aggregate; C = cement; S = sand; G = gravel; W = water; SP = superplasticeser; FA = fuel ash; SF = silica fume; RN = rebound number
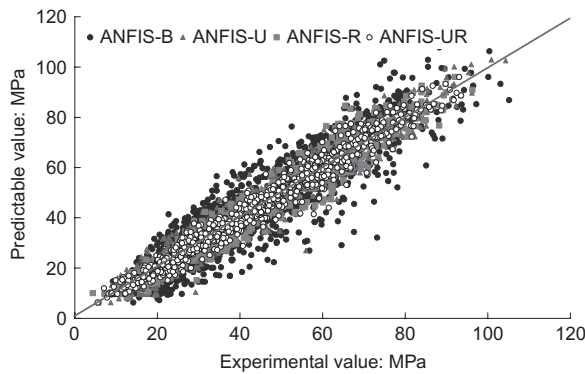

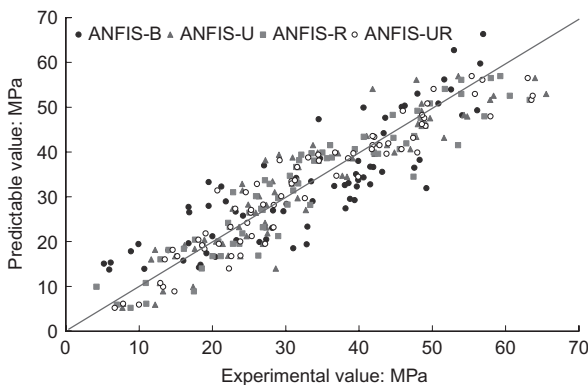*Fig. 7. Comparison of four ANFIS models using training data sets*

Fig. 8. Validation of four ANFIS models using testing data sets

Analysis results and discussion

Error analysis of ANFIS models

To evaluate the prediction accuracy of each ANFIS model, root-mean-square error (RMSE), absolute fraction of variation (R^2), mean absolute percentage error

(MAPE) and mean prediction ratio (MPR) were calculated using the following equations

$$RMSE = \sqrt{\frac{1}{N}\sum_i |a_i - p_i|^2} \qquad (5)$$

$$R^2 = 1 - \left(\frac{\sum_i (a_i - p_i)^2}{\sum_i (p_i)^2}\right) \qquad (6)$$

$$MAPE = \frac{1}{N}\sum_i \left|\frac{(a_i - p_i)}{p_i}\right| \times 100 \qquad (7)$$

$$MPR = \frac{1}{N}\sum_i \left(\frac{p_i}{a_i}\right) \qquad (8)$$

where a_i is the actual compressive strength, p_i is the predicted value and N is total sample number.

Table 5 shows RMSE, R^2, MAPE and MPR values of training and testing data sets for the comparison of the performance of the ANFIS models.

While the statistical parameters of RMSE, R^2, MAPE and MPR of the prediction results of ANFIS-B using the training data set are 8·24, 0·9714, 18·81 and 1·054 respectively, these values of ANFIS-UR are 3·64, 0·9940, 7·5 and 1·007 respectively. All of the statistical parameters demonstrated that ANFIS-UR has the best accuracy and can predict compressive strength very close to experiment results.

To find the statistical characteristics of models, histograms of each ANFIS model are presented and statistical analyses are conducted to find the probability density function. All models are fitted to a log-normal distribution function as in Fig. 9. The mean of log-normal values of compressive strength are 0·025, 0·010, 0·006 and

Table 5. Statistical parameters for four ANFIS models

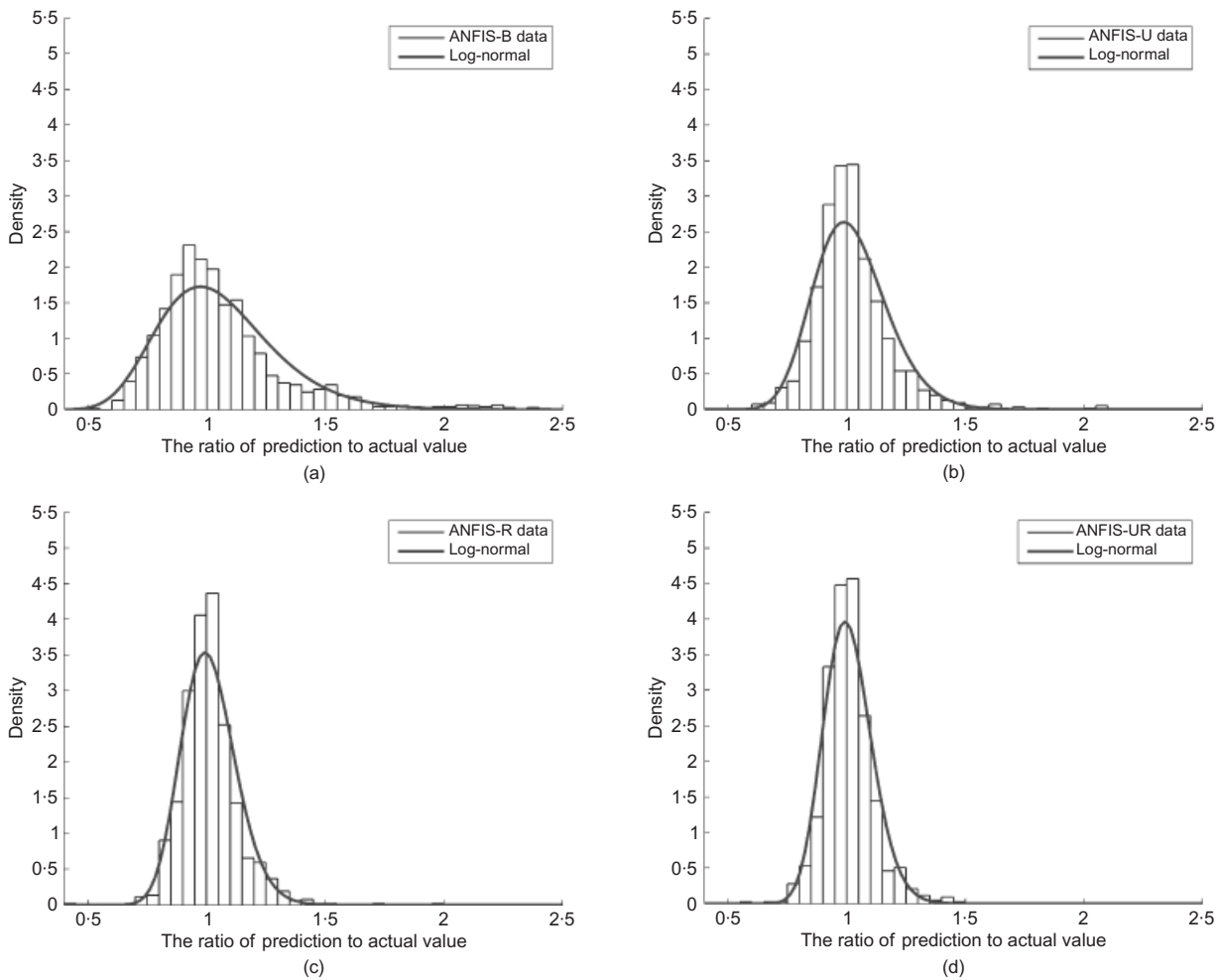| Data	Statistical parameters	ANFIS-B	ANFIS-U	ANFIS-R	ANFIS-UR
Training data set	RMSE	8·24	4·76	4·25	3·64
	R^2	0·9714	0·9896	0·9920	0·9940
	MAPE (%)	18·81	11·32	8·41	7·52
	MPR	1·054	1·022	1·013	1·007
Testing Data set	RMSE	7·31	5·51	4·82	1·07
	R^2	0·9571	0·9757	0·9814	0·9833
	MAPE (%)	27·42	18·24	16·01	10·99
	MPR	1·094	1·061	1·054	1·047

Fig. 9. Statistical analysis for the ratios of prediction to actual values: (a) ANFIS-B; (b) ANFIS-U; (c) ANFIS-R; (d) ANFIS-UR

0·002 for ANFIS-B, ANFIS-U, ANFIS-R and ANFIS-UR respectively, and the standard deviations of log-normal values are 0·231, 0·151, 0·113 and 0·101 respectively. This shows the tendency for the variance of the compressive strength to decrease as the ANFIS models are changed from ANFIS-B to ANFIS-UR. It can also be observed that as the standard deviation increases, the positive skewness of the probability density function also increases.

Simulation for the performance of ANFIS model

As the training data are scarce and limited so that they cannot cover whole parameter space, it is expected

that the trained model may not be able to capture completely the complex interrelationships among physical parameters. Hence, there is a need to validate the performance of the ANFIS models through simulating the behaviour of physical processes. This can be done by testing the models with hypothetical data by varying the values of some input parameters.

The one ANFIS model developed in this research, ANFIS-UR, is used to predict the compressive strengths corresponding to the varying rebound number and UPV. In Fig. 10, based on the results of prediction, the effects of rebound number and UPV are shown as a surface plot of the compression strength. Fig. 10(a) is
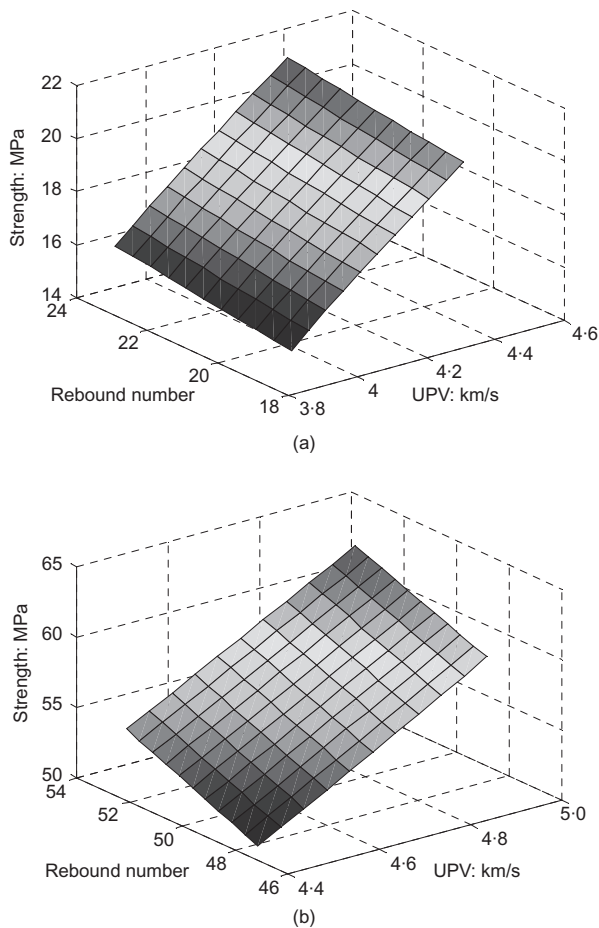
Fig. 10. Surface plots of the compressive strength (28 days): (a) case of w/c 70%; (b) case of w/c 30%

for the concrete sample with 70% of w/c and Fig. 10(b) is for the sample with 30% of w/c. Compressive strengths are predicted for the age of 28 days. For both cases, the effects of rebound number and UPV on compressive strength can be clearly shown in this figure. The effect of increasing rebound number is found to produce higher strength at the same levels of UPV. These surface graphs based on the developed model can be a useful tool for structural engineers and construction managers in the field.

Conclusion

A neuro-fuzzy-based technique is presented for predicting the concrete compressive strength using mix proportions and NDT results. For the comparative study, four ANFIS models (ANFIS-B, ANFIS-U, ANFIS-R and ANFIS-UR) are developed. The models are trained with input and output data sets obtained from the literature. As shown in previous research, trained ANFIS-B model can be used to predict the compressive strength at any ages. Because of the various in situ factors, however, the prediction of compressive strength did not show high accuracy. In the current

study, therefore, a neuro-fuzzy-based model combined with NDT results is proposed. The ANFIS-UR model, which includes a mix proportion, UPV test and rebound hammer test results as input parameters, shows the best prediction accuracy.

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

The conclusions of this study are based on the particular training and testing data sets and the input parameters and architectures of ANFIS models considered herein. Perhaps the accuracy of these results can be improved if more detailed input parameters, for example cement grade, maximum aggregate size, curing temperature, and air entrainment, are introduced. In addition, because mineral admixtures such as fly ash have a feature to retard the rate of strength gain, this kind of age-dependent characteristic needs to be included in the input parameters of the architectures. Even though other architectures of ANFIS models, such as modular AI architectures or separated ANFIS models for each prediction age, can be introduced, all four ANFIS models are constructed using single architecture in the current study. This is because this research focused on the development and demonstration of a generalised easy-to-use model rather than a high-accuracy model for specific data sets. The authors intend to develop a one-set prediction tool that can cover various concrete type such as low to high strength and early to late ages.

Based on the results, it has been found that a numerical technique, neuro-fuzzy model, can be used reliably to predict compressive strengths of concrete, rather than referring to costly experimental investigation. In addition, it can be said that if cost-effective NDT results are combined with AI systems, the accuracy and effectiveness of the strength prediction will increase dramatically. It is also clear that a concrete strength prediction model using combined NDT results, both of UPV and rebound number, provides more accurate prediction results than other models with a single type of testing result. The results of this study will give some helpful information to construction engineers and structural designers and this methodology can be used as a new tool to support the decision process in the concrete construction field as a function of measured NDTs and mix proportions. Further research is required to obtain a better understanding of ANFIS models and to provide

more accurate prediction results. Sensitivity studies and field applicability combining various in situ conditions and NDT results will be the focus of future research.

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