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Compressive Strength Prediction of Green Ultra-high Performance Concrete (GUHPC) Based on Fuzzy Artificial Neural Network

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Abstract: *As a megalopolis, Beijing has witnessed frequent extreme rainfall events in recent years (such as the "July 20" rainstorm in 2021), and the subway system is prone to leakage due to the threat of rainwater infiltration due to its deep burial underground. Leakage in subway structures can lead to steel corrosion and concrete deterioration, affecting driving and operational safety. Traditional sealing materials (such as ordinary concrete) have problems such as slow strength growth and insufficient toughness, making it difficult to adapt to dynamic loads and complex environments. Green ultra-high performance concrete (GUHPC) is considered a new generation of building materials that is in line with sustainable development. It has high strength, high toughness, and can resist crack propagation. Traditional standards require GUHPC strength to be based on a 28d age, but in emergency repair or rapid construction scenarios, long testing cycles limit material application efficiency, and there is an urgent need to establish a rapid prediction model. The compressive strength of GUHPC is closely related to the composition of cement, fly ash, silica fume and sand, etc. In this study, 175 sets of GUHPC-related data were collected and an artificial neural network, combined with IF-THEN fuzzy rules, was used to develop a model that can better predict the 28d compressive strength of GUHPC. The evaluation indexes of RMSE, R^2 and MAPE reflect the good prediction performance of this model, indicating that it is completely reliable for predicting the compressive strength of GUHPC.*

Keywords: *Building materials; Compressive strength prediction; Fuzzy artificial neural network; GUHPC*

1. Introduction

In recent years, global climate change has intensified and extreme rainfall events have occurred frequently, posing unprecedented challenges to urban flood prevention and safety. Under the attack of rainstorm, the safety problem of urban drainage system and underground space is particularly prominent. In the "July 20" extremely heavy rainstorm event in 2021, some subway lines in Beijing will be shut down and the structure will seep water due to rain back, which will not only cause serious economic losses, but also threaten the safety of the public. The massive underground building system has been exposed to high humidity environments for a long time, and leakage has become a "hidden killer" of subway structural safety. Continuous leakage not only accelerates steel corrosion and causes concrete degradation, but may also lead to catastrophic consequences such as structural collapse. Therefore, efficient and reliable leakage sealing technology has become a key link in urban flood prevention.

Traditional concrete sealing materials have exposed defects such as slow strength growth and insufficient toughness when dealing with subway leakage problems, making it difficult to meet the engineering needs in complex environments. In the past decades, the increasing attention on global warming and other major ecological changes has spurred debates in various fields of science and engineering [1]. The concrete industry is being blamed for these ecological changes. Considerations for sustainable development, such as environmental regulations and natural resources protection, play a significant role in new requirements of the construction industry[2]. In recent years, the global concrete production has reached 12 billion tons per year, consuming about 1.2 billion tons of silicate cement with one ton of silicate cement producing over one ton of CO_2[1], which contributes hugely to the greenhouse effect. Therefore, the emergence of environment-friendly concrete as a new material has been widely addressed by scholars in recent years.

This is especially true for concrete structures, because the production of raw material cement is highly energy consuming[3] and produces a lot of carbon dioxide. It is unrealistic to try to reduce the impact on the environment in the process of concrete production and to ignore factors such as the material performance and the durability[4]. Aghdasi et al. named the green ultra-high performance fiber concrete as G-UHP-FRC[5]. G is an abbreviation for green, which means that the cement is partially replaced by industrial by-products such as fly ash (FA) class F and ground granulated blast-furnace slag (GGBFS). This study names the green ultra-high performance concrete as GUHPC, which is used in a large number of applications such as bridge reinforcement, road rehabilitation, house facade reinforcement, tunnels, etc. and has considerable demand. The ultra-high performance concrete is a cement-based composite material with cement as the base material, fly ash, silica fume, microbeads and other components as cementitious supplementary materials, mixed with coarse aggregates. The compressive strength of ultra-high performance concrete is generally above 150 MPa, with high compatibility, durability, ductility, and toughness[6]. Compressive strength is one of the most important mechanical properties of concrete, which depend on elements such as mix proportions, material quality, water-cement ratio, cement dosage, and the age of concrete [7, 8]. Therefore, predicting the compressive strength of ultra-high performance is an important and complex task. At present, most of the compressive strength values of concrete are obtained through tests, but the standard compressive strength requires 28 days of concrete curing, which is a waiting process that consumes a lot of time. Predicting the compressive strength of concrete can reduce the number of attempts to fit the ratio, thus reducing test time and saving materials.

At present, the prediction of compressive strength has been carried out for different types of concrete or mortars. Sun et al. considered the fly ash fineness and the replacement ratio upgraded finer fly ash. They found that the upgraded finer fly ash can replace more cement, thus realizing energy saving and CO_2 emission reduction[9]. Sarıdemir predicted the compressive strength of mortars containing metakaolin. The study reported that pozzolanic admixtures can be used for reducing the cement content in mortar and concrete production[10]. Ly et al. made predictions for the strength of manufactured sand concrete[11] and Ding et al. [12] proposed a forecast model of long-term compressive strength.

There have been research results using artificial intelligence methods and machine learning algorithm modeling to predict the compressive strength of concrete. Many researchers have used deep learning, artificial neural networks (ANN), evolutionary neural networks, and neural expert systems to predict the compressive strength of recycled aggregate concrete, concrete containing construction waste, and self-compacting concrete containing low ash[13-19]. Dao et al. used an adaptive network-based fuzzy inference system (ANFIS) and an artificial neural network to predict the compressive strength of geopolymer concrete and then a sensitivity analysis was carried out[20]. Cheng et al.[21] presents an AI approach named as the self-Adaptive fuzzy least squares support vector machines inference model (SFLSIM) for predicting compressive strength of rubberized concrete. The model can alleviate human efforts in model establishment which is developed as a hybrid intelligent model to achieve higher prediction accuracy. Yan et al., Behnood et al., Chou et al. reported a support vector machine (SVM) method and a regression tree method for predicting elastic modulus of high strength concrete[22-24]. They consider that SVM has better generalization capability than ANN model. Sobhani et al. compared the prediction of five slump concrete among the regression model, neural network model, and ANN model, and obtained that the neural network and ANFIS are more feasible[25]. Nguyen et al.[26] predicted the late compressive strength of concrete based on feedforward neural networks (FNN) and comprehensively evaluated the performance of the statistical results of 1000 simulations, obtaining Pearson's correlation coefficient (R), root mean square error (RMSE), and mean square error (MAE) for training and testing. The results were superior to the classical machine learning algorithms. Chopra et al. used three machine learning techniques, decision tree model, random forest model, and neural network model for predicting the 28d, 56d, and 91d compressive strength of concrete[27]. The test index coefficient determination (R^2) and root mean square error (RMSE) of the neural network showed the best test performance among the three models. Behnood et al. used the M5P model tree algorithm to predict the compressive strength of normal and high-performance concrete based on 1912 collected data and then developed an effective mathematical equation[28]. Deng et al. used a deep learning technique based on the convolutional neural network (CNN) that made excellent predictions of the compressive strength of recycled concrete[13]. Naderpour et al., Duan et al. and Dantas et al. made predictions for environment-friendly concrete with recycled aggregates and construction waste by using an artificial neural network based on their design[14,15,19]. According to the results, the artificial neural network may be a better method to predict the compressive strength of GUHPC.

Considering the types of input quantities and output quantities, Bui et al. collected 1133 compressive samples of high-performance concrete from published datasets. They used eight parameters as input quantities and the compressive strength as the output quantity to simulate in the firefly modified ANN model[7]. They obtained experimental indices R, RMSE, MAE, MAPE respectively, with excellent model performance. Öztaş et al. ran a neural network model in Matlab to predict the compressive strength of high-strength concrete (HSC)[29]. They found that the mean absolute percentage error of compressive strength was less than 1.956208% and the R^2 value of compressive strength for the test group was 99.93%. Abuodeh et al. selected four materials of ultra-high performance concrete: cement, fly ash, silica fume, and water as input parameters and combined the neural network with the sequential feature selection (SFS) and the neural interpretation diagram (NID) to calculate R^2 and NMSE[30]. Zhang et al. used a neural network to predict the compressive strength of ultra-high performance concrete containing cementitious supplementary materials (SCMs) such as fly ash and silica fume[31]. The results showed the high accuracy of the artificial neural network with MAPE, RMSE and R^2 respectively.

Existing studies have shown that quite reliable results can be obtained for predicting the compressive strength of concrete using artificial intelligence methods and machine learning methods. However, the above methods are more often used to predict general performance concrete and high-performance concrete. For newer materials, GUHPC, for example, there are fewer results so far and there is a relatively blank state. According to current regulations, the strength performance of UHPC needs to be based on the results of a 28 day age test, which greatly limits its rapid application in emergency flood control projects. This study is based on the flood prevention and subway safety requirements in Beijing, focusing on the application of GUHPC in the sealing of subway building leaks. This paper aims to predict the 28d compressive strength of GUHPC, using the fuzzy artificial neural network method to obtain the law between predicted and actual experimental values, and finally achieve the purpose of predicting the compressive strength of GUHPC.

In Section 2, the paper outlines the background of artificial neural network and the structure of ANFIS. The proposed ANFIS modeling is described in Section 3, followed by a demonstration of data collection in the experimental case in Section 4. Then the results and the model evaluation results are showed in Section 5. Finally, the paper is concluded in Section 6.

2. Methodology

2.1. Background of Artificial Neural Network

Artificial neural networks (ANNs) are models based on semi-empirical knowledge of biological nervous systems and are used to simulate the structural behavior of biological nerve cells. A neural network consists of many processing elements connected by a chain of variable weights and generally consists of neurons in an input layer (also called nodes or processing units), neurons in one or several hidden layers, and neurons in the output layer. The adjacent layers are fully linked to each other by weights, and the input layer neurons receive information from the outside world and pass it to the neurons in the hidden layer without any computation [10, 32]. The input layer receives information from the external world, the input layer contains a large number of hidden processing units with the output layer [33], and finally, the neurons in the output layer generate network predictions for the external world. Except for the input layer, each layer of neurons first computes a linear combination of the outputs of the neurons in the previous layer and then adds the deviation, which is the weight. Then, the neurons in the hidden layer apply a nonlinear function to their inputs as an activation function [25].

2.2. Structure of ANFIS

Adaptive neuro-fuzzy inference systems (ANFIS) are hybrid neuro-fuzzy networks used to model complex systems [25]. ANFIS accomplishes prediction by using fuzzy sets and a code model consisting of IF-THEN fuzzy rules combined with a human-like reasoning process for fuzzy systems [34]. A typical neural network consists of an input, a summation function, a log-sigmoid activation function, and an output. The structure of the fuzzy artificial neural network constructed in this paper takes cement (C), fly ash (FA), silica fume (SF), sand (SD), and water (WT) as input parameters into the system. After the interaction between the input parameters, the weights are adjusted by the neural network system and are combined with the fuzzy rules, and after two hidden layers of transmission, the final output is the compressive strength (CS).

3. Modeling Process of ANFIS

Using the information acquired from published papers, the work in this paper is organized as follows:

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First, this paper describes the concept of fuzzy artificial neural network and the process of the model buildings, and then the model is trained using the collected data. The performance of the model prediction was evaluated by the root mean square (RMS), R^2, and MAPE, and finally we obtained a model applicable to the prediction of compressive strength of GUHPC.

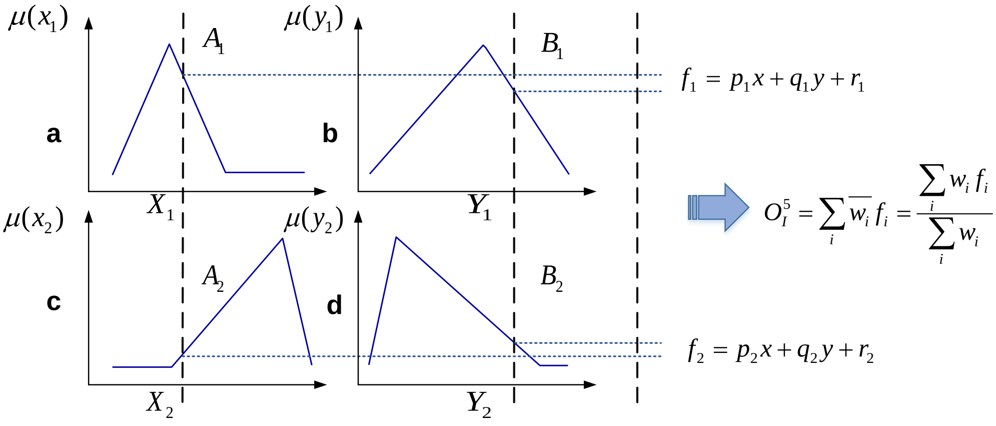

Figure 1: a. b. c. d. show the fuzzy rules of $X_1.Y_1.X_2.Y_2$

The input is the information that enters the cell from other cells in the outside world. The weight is an indication of the degree of influence of the input set or another processing element in the upper layer on that processing element. The summation function is a function that calculates the influence of inputs and weights on the elements in the process [17, 35]. The weighted sum of the components is calculated by the following equation:

$$(network)_j = \sum_{i=1}^{n} (w_{ij}x + b) \tag{1}$$

Where $(network)_j$ is the output of neurons, w_{ij} is the weight connecting the previous layer to the next layer, b is the bias weight, n is the number of neurons per layer, f is the activation function, and the log-sigmoid activation function in this paper is as follows:

$$(out)_j = f(network)_j = \frac{1}{1+e^{-\beta(network)_j}} \tag{2}$$

Where β is the constant used to control the slope of the semi-linear region, the sigmoid nonlinear function is activated at every layer except the input layer [17]. Using the ANFIS model structure with two input variables as an example, it is assumed that the rules of ANFIS contain Takagi and Sugeno's two IF-THEN rules [36]:

If x is A and y is B, then

$$z = f(x, y) \tag{3}$$

Figure 1 shows the fuzzy rules, where A and B are the fuzzy sets of prior terms and $z = f(x, y)$ is the output term. In consideration, there are two IF-THEN rules in the first-order of Takagi and Sugeno's model.

Rule1: If x is A_1 and y is B_1, then

$$f_1 = p_1x + q_1y + r_1 \tag{4}$$

Rule2: If x is A_2 and y is B_2, then

$$f_2 = p_2x + q_2y + r_2 \tag{5}$$

Layer 1- The output of each node in this layer is expressed as an affiliation function of A_i.

$$O_i^1 = \mu_{A_i}(x) \tag{6}$$

Layer 2- In this layer, each node multiplies the input signals and sends out the multiplication. The output of each node represents the weight of a rule.

$$w_i = \mu_{A_i}(y) \times \mu_{B_i}(y) \tag{7}$$

Layer 3- The i th node triggers the ratio of the weight of the i th rule to the sum of the weights of all rules.

$$\overline{w_i} = w_i / (w_1 + w_2 + \cdots w_n) \tag{8}$$

Layer 4- This layer is the output of Layer 3

$$O_i^4 = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i) \tag{9}$$

Layer 5- This layer calculates the total output as a weighted average sum of all signals [32]

$$O_i^5 = \sum_i \overline{w_i} f_i = \sum_i w_i f_i \Big/ \sum_i w_i \tag{10}$$

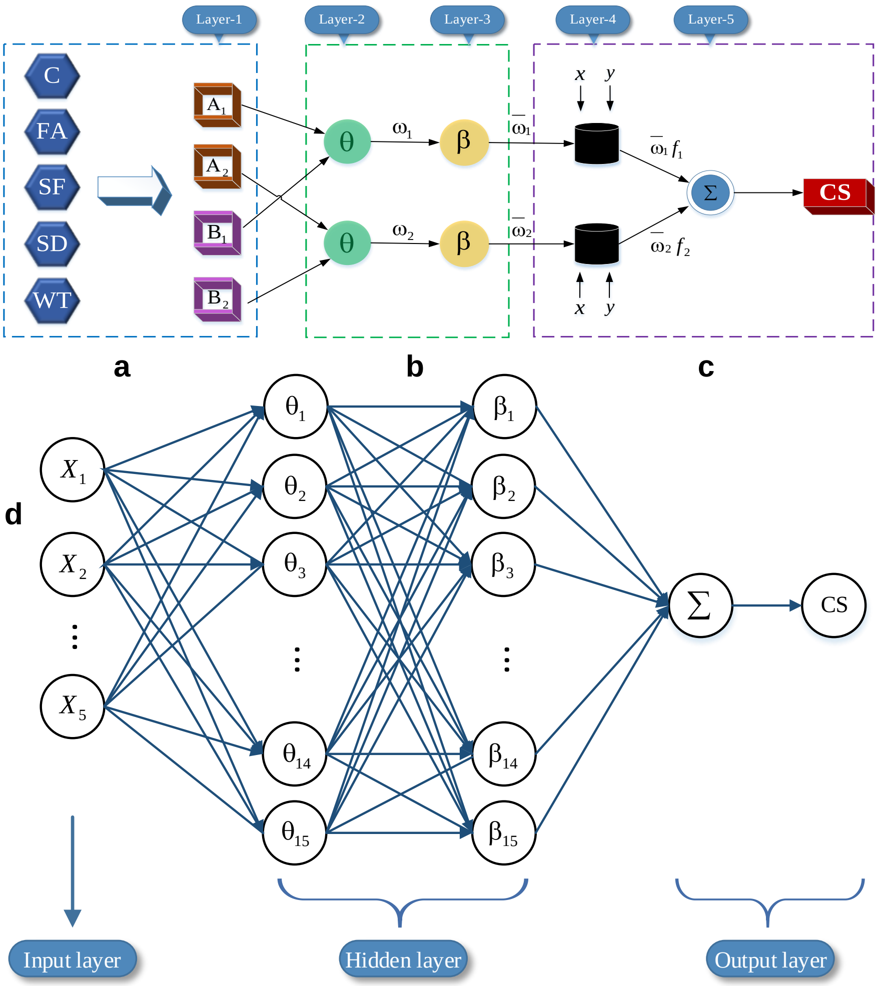

Figure 2 (a) Five input parameters. (b) Two hidden layers of the fuzzy artificial neural network structure. (c) The output layer of the fuzzy artificial neural network with output parameters of compressive strength. (d) The complete structure of the fuzzy artificial neural network containing 5 input variables, 2 hidden layers, 15 hidden layer nodes and one output trained in this study.

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Table 1 shows the properties of the fuzzy artificial neural network constructed in this paper

Table 1: Properties of fuzzy neural network structures

Parameters	**ANFIS**
Number of input layer nodes	5
Hidden layers	2
Number of hidden layer nodes	15
Number of output layer nodes	1
Training epochs	1000
Error tolerance	0

4. Data Collection

The success of the fuzzy artificial neural network model proposed in this paper in predicting the compressive strength of GUHPC depends on the quality of the experimental data for training. The research in this paper is based on the specificity and the substitution of construction materials used in GUHPC, and the collection of experimental data from published papers that meet the definition of GUHPC to create a database for use in this study. The experimental data of GUHPC were collected from published papers[16,37,38] and organized into the database of this paper. Figure 2 shows the structure of the artificial neural network constructed in this paper, with cement (C), fly ash (FA), silica fume (SF), sand (SD), and water (WT) as input parameters, containing two hidden layers, and compressive strength (CS) as output parameters. Table 2 offers the range of data for each parameter.

Table 2: Each parameter's variation range in the database

Variables		**Unit**	**Database**		
			Minimum	Maximum	Average
C	Input	kg/m^3	160	1600	553.14
FA		kg/m^3	0	448	100.54
SF		kg/m^3	0	367.95	87.09
SD		kg/m^3	0	1898	884.26
WT		kg/m^3	16.56	334.5	132.29
CS(Experiment)	Output	MPa	10.2	217	88.15
CS(Prediction)		MPa	10.2	217	88.08

5. Results and Discussion

5.1. Model Training

The Matlab platform is used to build a fuzzy neural network, and the collected GUHPC database is divided into two parts: the training set and the prediction set. The model is trained and tested for its predictive performance, and the results are imported into the origin for plotting and analyzing. Table 3 shows the specific data of 145 GUHPCs in the training set and Table 4 shows the specific data of 30 GUHPCs in the prediction set.

5.2. Predicted Effectiveness

Figure 3 shows the linear fitting results of the training set and the prediction set. Figure 3a shows the fitted slope of 0.9939 and the fitted correlation coefficient of 0.996 for the simulated results and the experimental values of the training set. Figure 3b shows the fitted slope of 0.9439 and the correlation coefficient of 0.98 for the simulated results and the experimental values of the prediction set. Both the fitted slope and the correlation coefficient are very close to 1, indicating that the simulated results have low dispersion and high linear correlation with the experimental values, which confirms that the model is possibly reliable for prediction.

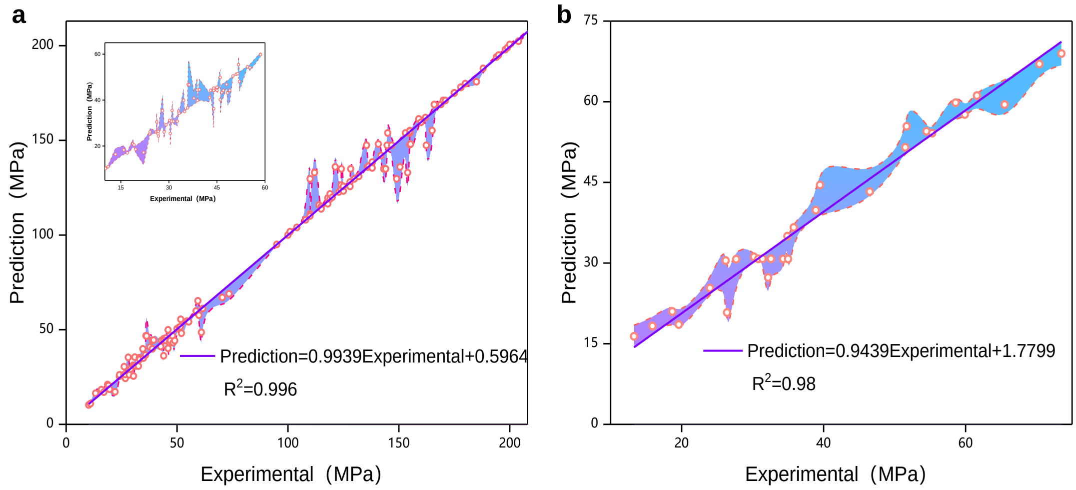

Figure 3: Linear fitting of the training and prediction sets

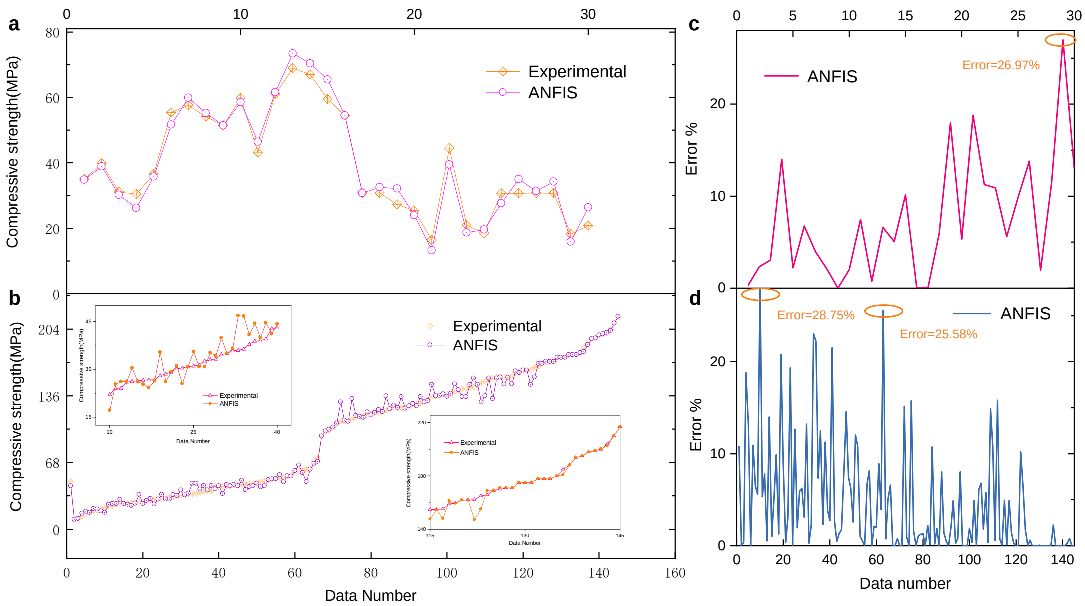

Figure 4: Experimental results and prediction errors for training and prediction sets

Figure 4 shows the simulation results of the training and the prediction sets compared with the experimental values. From the data comparison in Figure 4b, it can be seen that a greater GUHPC compressive strength in the training set, corresponds to a higher prediction accuracy. There are two data points with errors reaching 28.75% and 25.59% in Figure 4d, and most of the remaining points have errors below a 15% prediction accuracy. 51 sets of data (about 1/3 of the training set data volume) basically reach an accurate prediction, and the overall prediction performance of the training set is satisfying. Similarly, Figure 4a shows the comparison between the simulation results and the experimental values of the prediction set. Figure 4c has one data point with an error of 26.97%, and most of the remaining points have an error of prediction accuracy less than 15%, with 9 sets of data (about 1/3 of the prediction set) basically achieving an accurate prediction, and the prediction set as a whole demonstrated a strong prediction performance.

Figure 5 shows the proposed triangular affiliation function for the input variables using 175 sets of data. The affiliation function consists of 5 input parameters and one output, and the premise parameter subspace is determined by clustering the 175 sets of data. For f_c, five rules were obtained: If (C is C mf_i) and (FA is FA mf_i) and (SD is SD mf_i) and (SF is SF mf_i) and (WT is WT mf_i), then (f_c is f_c mf_i)

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$i = 1,2,3,4,5$

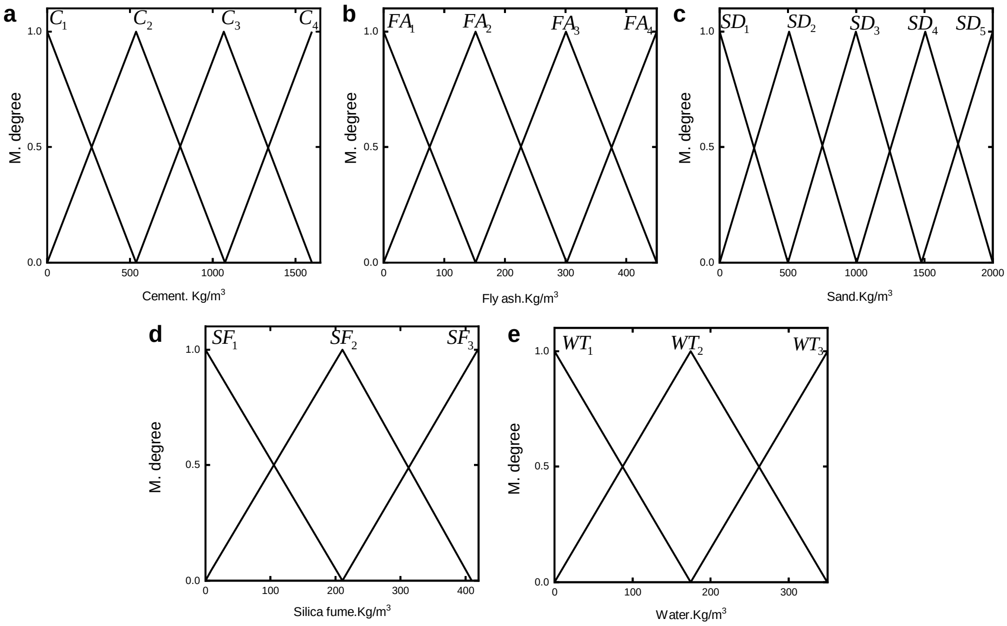

Figure 5: Plot of affiliation function for 5 parameters

5.3. Modeling Performance

Three experimental metrics, the root mean square error (RMSE), the absolute fraction of variance (R^2), and mean absolute percentage error (MAPE) , are used to evaluate the prediction effectiveness of fuzzy artificial neural networks. RMSE is calculated using the equation:

$$RMSE = \sqrt{\frac{1}{p}\sum_i |t_i - o_i|^2} \tag{11}$$

Where p is the total number of data in the data set, t_i is the true value of the experimental data, and o_i is the output value of the model. The absolute fraction of the variance(R^2) was calculated by the equation:

$$R^2 = 1 - \left[\sum_i (t_i - o_i)^2 \Big/ \sum_i (o_i)^2 \right] \tag{12}$$

MAPE was calculated by using equation [34]:

$$MAPE = \left\| \left[\frac{1}{p} \sum_{i=1}^{p} \frac{(t_i - o_i)}{o_i} \right] \right\| \times 100 \tag{13}$$

The absolute difference between a single predicted value and the experimental value is calculated using Error:

$$Error = \left| \left(\frac{t_i - o_i}{o_i} \right) \right| \times 100 \tag{14}$$

Table 5 shows the evaluation metrics for the reliability of the trained model, where the training set has a RMSE of 5.3510, R^2 of 0.9978, and MAPE of 4.6103%; the testing set has a RMSE of 2.9952, R^2 of 0.9950, and MAPE of 7.3265%.

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Table 3: Comparison of experimental results(exp.) and ANFIS model prediction results for 145 groups of data in the training set

f_c (GUHPC1-37)		f_c (GUHPC38-73)		f_c (GUHPC74-109)		f_c (GUHPC110-145)	
Exp.	**ANFIS**	**Exp.**	**ANFIS**	**Exp.**	**ANFIS**	**Exp.**	**ANFIS**
49	44.22	39.5	44.52	110	110.00	150.56	135.92
10.2	10.20	42.7	41.12	112	132.97	153	153.91
11	10.96	43	44.22	114	115.86	154	132.97
13.3	16.38	44	36.21	115	115.01	155	153.84
15.9	18.29	44	45.20	115	113.82	155	155.14
17	17.00	44	44.22	118	119.48	155	147.70
18.7	20.98	45	45.60	118	116.48	155	154.83
19.1	20.43	45	44.22	119	119.00	155.3	148.05
19.6	18.56	46	49.89	119	121.69	159	161.33
22.1	17.16	46	40.15	120	119.88	160	159.53
24	25.35	46.5	43.27	121.32	135.92	162	162.00
24.1	26.14	47	44.22	123	122.74	162	162.02
26	26.14	48	46.79	124	126.35	162.4	147.34
26.2	30.47	48.3	43.11	124	124.01	165	155.11
26.4	26.14	49	44.22	124.1	134.93	166	168.93
26.6	25.29	50	50.52	125	123.26	169	168.97
26.7	24.30	51	51.28	125	125.63	170	171.04
26.7	26.36	51.5	51.50	128	128.00	171	171.00
28	35.35	51.7	55.44	128	125.63	171	171.00
28.5	26.14	52	48.08	128.3	134.93	175	175.00
29.1	29.21	54.5	54.50	130	129.66	175	175.10
30.2	31.15	55.3	54.15	132	130.97	175	175.00
30.4	25.47	58.6	59.80	135.5	147.34	178	178.00
30.8	30.77	59.4	65.23	135.9	135.90	178	178.03
31	35.50	59.9	57.62	136.4	136.38	178	178.00
31.4	30.79	61	48.57	137.9	137.91	180	179.97
32.6	30.77	61.6	61.14	138	135.42	185	180.94
33	35.20	70.4	67.01	138	138.51	188	188.00
33.2	34.26	73.5	68.95	140.8	148.05	194	193.99
34.6	39.88	95	95.04	142	142.00	195	194.98
34.9	35.00	100	100.00	143.2	134.93	198	197.94
35.8	36.61	101	101.78	144.1	134.93	199	198.98
36	46.80	104	103.98	144.7	147.34	200	200.60
36.3	46.66	108	107.97	145	153.91	204	202.37
37.8	40.79	110	129.67	146.8	147.34	210	210.00

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38.8	44.36	110	111.06	149	129.67	217	217.00
49	44.22	110	110.00	150.56	135.92	150.56	135.92
10.2	10.20	39.5	44.52	110	110.00	153	153.91
11	10.96	42.7	41.12	112	132.97	154	132.97
13.3	16.38	43	44.22	114	115.86	155	153.84
15.9	18.29	44	36.21	115	115.01	155	155.14
17	17.00	44	45.20	115	113.82	155	147.70
18.7	20.98	44	44.22	118	119.48	155	154.83
19.1	20.43	45	45.60	118	116.48	155.3	148.05
19.6	18.56	45	44.22	119	119.00	159	161.33
22.1	17.16	46	49.89	119	121.69	160	159.53
24	25.35	46	40.15	120	119.88	162	162.00
24.1	26.14	46.5	43.27	121.32	135.92	162	162.02
26	26.14	47	44.22	123	122.74	162.4	147.34
26.2	30.47	48	46.79	124	126.35	165	155.11
26.4	26.14	48.3	43.11	124	124.01	166	168.93
26.6	25.29	49	44.22	124.1	134.93	169	168.97
26.7	24.30	50	50.52	125	123.26	170	171.04
26.7	26.36	51	51.28	125	125.63	171	171.00
28	35.35	51.5	51.50	128	128.00	171	171.00
28.5	26.14	51.7	55.44	128	125.63	175	175.00
29.1	29.21	52	48.08	128.3	134.93	175	175.10
30.2	31.15	54.5	54.50	130	129.66	175	175.00
30.4	25.47	55.3	54.15	132	130.97	178	178.00
30.8	30.77	58.6	59.80	135.5	147.34	178	178.03
31	35.50	59.4	65.23	135.9	135.90	178	178.00
31.4	30.79	59.9	57.62	136.4	136.38	180	179.97
32.6	30.77	61	48.57	137.9	137.91	185	180.94
33	35.20	61.6	61.14	138	135.42	188	188.00
33.2	34.26	70.4	67.01	138	138.51	194	193.99
34.6	39.88	73.5	68.95	140.8	148.05	195	194.98
34.9	35.00	95	95.04	142	142.00	198	197.94
35.8	36.61	100	100.00	143.2	134.93	199	198.98
36	46.80	101	101.78	144.1	134.93	200	200.60
36.3	46.66	104	103.98	144.7	147.34	204	202.37
37.8	40.79	108	107.97	145	153.91	210	210.00
38.8	44.36	110	129.67	146.8	147.34	217	217.00
38.9	39.83	110	111.06	149	129.67		

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Table 4: Comparison of experimental results and ANFIS model predictions for 30 data sets in the prediction set

f_c **(GUHPC1-15)**		f_c **(GUHPC16-30)**	
Experimental	**ANFIS**	**Experimental**	**ANFIS**
34.9	35.0026	54.5	54.4968
38.9	39.8297	30.8	30.7737
30.2	31.1498	32.6	30.7737
26.2	30.4666	32.2	27.2984
35.8	36.611	24	25.3513
51.7	55.4353	13.3	16.3799
59.9	57.6229	39.5	44.517
55.3	54.1528	18.7	20.9846
51.5	51.5018	19.6	18.5623
58.6	59.8028	27.7	30.7167
46.5	43.2734	35	30.7547
61.6	61.1403	31.4	30.7927
73.5	68.9452	34.3	30.7547
70.4	67.0099	15.9	18.2948
65.5	59.4713	26.4	20.7912

Table 5: Experimental indicators for neural network models

Indicators	Training	Testing
RMSE	5.3510	2.9952
R^2	0.9978	0.9950
MAPE(%)	4.6103	7.3261

6. Conclusion

In this study, 175 sets of data collected from open sources that meet the definition of GUHPC are used to form a database, and 83% of the data (145 sets) are used as the training set and 17% of the data (30 sets) are used as the prediction set. Developing an artificial neural network combined with Takagi and Sugeno's first-order hypothetical IF-THEN fuzzy rule for ANIFS model, the following results are obtained:

With C. FA. SF. SD. WT as the five input variables and the ANFIS model as the only output variable, the ANFIS model has generated accurate predictions for both the training and the prediction sets, indicating that the ANFIS model proposed in this study is feasible for predicting the compressive strength of GUHPC 28d.

The results of the three indexes used to evaluate the reliability and predictive accuracy of the training model are ideal, with an RMSE of 2.9952, an $R^2$of 0.9950, and a MAPE of 7.3265%.The three evaluation indexes prove that the ANFIS model of this study achieves a very accurate prediction of the compressive strength of GUHPC with excellent performance.

The overall GUHPC without silica fume in the database exhibits a compressive strength below 100 MPa, and for these GUHPC, the prediction error is high compared to other GUHPC with compressive strengths above 100 MPa in the database. The presents an error of about 15%. This indicates that the model is more applicable to GUHPC with higher compressive strengths.

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In general, artificial neural networks are more dependent on the size and the quality of experimental data. In this study, they are improved by a combination with fuzzy rules, and reliable prediction results are obtained, which shows the feasibility of the improved method.

References

[1] Mosaberpanah M A, Eren O. CO2-full factorial optimization of an ultra-high performance concrete mix design. European journal of environmental and civil engineering, 2018. 22(4): p. 450-463.

[2] Naderpour H, Rafiean A H, Fakharian P. Compressive strength prediction of environmentally friendly concrete using artificial neural networks. Journal of Building Engineering, 2018. 16: p. 213-219.

[3] Malhotra VM. Making concrete "greener" with fly ash. Concr Int 1999; 21(5):61–6.

[4] Lim C H, Yoon Y S, Kim J H. Genetic algorithm in mix proportioning of high-performance concrete. Cement and Concrete Research, 2004. 34(3): p. 409-420.

[5] Aghdasi P, Ostertag C P. Green ultra-high performance fiber-reinforced concrete (G-UHP-FRC). Construction and Building Materials, 2018. 190: p. 246-254.

[6] Ahmad S, Hakeem I, Maslehuddin M. Development of an optimum mixture of ultra-high performance concrete. European journal of environmental and civil engineering, 2016. 20(9): p. 1106-1126.

[7] Bui D K, Nguyen T, Chou J S, et al. A modified firefly algorithm-artificial neural network expert system for predicting compressive and tensile strength of high-performance concrete. Construction and Building Materials, 2018. 180: p. 320-333.

[8] Hong-Guang, Ni, Ji-Zong, et al. Prediction of compressive strength of concrete by neural networks, Cem. Concr. Res. 30 (8) (2000) 1245–1250

[9] Sun Y, Wang K Q, Lee H S. Prediction of compressive strength development for blended cement mortar considering fly ash fineness and replacement ratio. Construction and Building Materials, 2021. 271: p. 121532.

[10] Sandemir M. Predicting the compressive strength of mortars containing metakaolin by artificial neural networks and fuzzy logic. Advances in Engineering Software, 2009. 40(9): p. 920-927.

[11] Ly, Pham, Dao, et al. Improvement of ANFIS Model for Prediction of Compressive Strength of Manufactured Sand Concrete. Applied sciences, 2019. 9(18): p. 3841.

[12] Ding X, Li C, Xu Y, et al. Experimental study on long-term compressive strength of concrete with manufactured sand. Construction and Building Materials, 2016. 108: p. 67-73.

[13] Deng F, He Y, Zhou S, et al. Compressive strength prediction of recycled concrete based on deep learning. Construction and Building Materials, 2018. 175: p. 562-569.

[14] Duan Z H, Kou S C, Poon C S. Prediction of compressive strength of recycled aggregate concrete using artificial neural networks. Construction and Building Materials, 2013. 40: p. 1200-1206.

[15] Dantas A, Leite M B, Nagahama K. Prediction of compressive strength of concrete containing construction and demolition waste using artificial neural networks. Construction & building materials, 2013. 38: p. 717-722.

[16] Siddique R, Aggarwal P, Aggarwal Y. Prediction of compressive strength of self-compacting concrete containing bottom ash using artificial neural networks. Advances in Engineering Software, 2011. 42(10): p. 780-786.

[17] Topu L B, Sardemir M. Prediction of mechanical properties of recycled aggregate concretes containing silica fume using artificial neural networks and fuzzy logic. Computational Materials Science, 2008. 42(1): p. 74-82.

[18] F Khademi, Akbari M, Jamal S M, et al. Multiple linear regression, artificial neural network, and fuzzy logic prediction of 28 days compressive strength of concrete. Frontiers of Structural and Civil Engineering, 2017. 11(1): p. 90-99.

[19] YU Jie, ZHANG Guodong, LIU Xin, YU Kequan, YU Jiangtao. Machine Learning-Based Prediction of Compressive Strength of Concrete with Recycled Glass Aggregates. STRUCTURAL ENGINEERS. 2025, 41(6): 62-74

[20] Dong V, Dao, Hai-Bang, et al. Artificial Intelligence Approaches for Prediction of Compressive Strength of Geopolymer Concrete. Materials, 2019. 12(6): p. 983.

[21] Cheng M Y, Hoang N D. A Self-Adaptive Fuzzy Inference Model Based on Least Squares SVM for Estimating Compressive Strength of Rubberized Concrete. International Journal of Information Technology & Decision Making, 2016. 15(03): p. 603-619.

[22] Yan K, Shi C. Prediction of elastic modulus of normal and high strength concrete by support vector machine. Construction and Building Materials, 2010. 24(8): p. 1479-1485.

[23] Behnood, Olek, Glinicki, et al. Predicting modulus elasticity of recycled aggregate concrete using M5' model tree algorithm. Construction and Building Materials, 2015. 94: p. 137-147.

ISSN 2616-5767 Vol.9, Issue 1: 59-71, DOI: 10.25236/AJETS.2026.090108

[24] Chou J S, Chiu C K, Farfoura M, et al. Optimizing the Prediction Accuracy of Concrete Compressive Strength Based on a Comparison of Data-Mining Techniques. Journal of computing in civil engineering, 2011. 25(3): p. 242-253.
[25] Sobhani J, Najimi M, Pourkhorshidi A R, et al. Prediction of the compressive strength of no-slump concrete: A comparative study of regression, neural network and ANFIS models. Construction and Building Materials, 2010. 24(5): p. 709-718.
[26] Nguyen, T, Ly H, Mai H T, et al. Prediction of Later-Age Concrete Compressive Strength Using Feedforward Neural Network. Advances in Materials Science and Engineering, 2020. 2020: p. 1-8.
[27] Palika C, Kumar S R, Man Ee K K, et al. Comparison of Machine Learning Techniques for the Prediction of Compressive Strength of Concrete. Advances in Civil Engineering, 2018. 2018: p. 1-9.
[28] Ab A, Vb B, Mmg A, et al. Prediction of the compressive strength of normal and high-performance concretes using M5P model tree algorithm. Construction and Building Materials, 2017. 142: p. 199-207.
[29] Öztaş A, Pala M, Özbay E, et al. Predicting the compressive strength and slump of high strength concrete using neural network. Construction and Building Materials, 2006. 20(9): p. 769-775.
[30] Abuodeh O R, Abdalla J A, Hawileh R A. Assessment of compressive strength of Ultra-high Performance Concrete using deep machine learning techniques. Applied Soft Computing, 2020. 95: p. 106552.
[31] Zhang J, Zhao Y, Li H. Experimental Investigation and Prediction of Compressive Strength of Ultra-High Performance Concrete Containing Supplementary Cementitious Materials. Advances in Materials Science and Engineering, 2017. 2017: p. 1-8.
[32] Mansour M Y, Dicleli M, Lee J Y, et al. Predicting the shear strength of reinforced concrete beams using artificial neural networks. Engineering Structures, 2004. 26(6): p. 781-799.
[33] Adhikary B B, Mutsuyoshi H. Prediction of shear strength of steel fiber RC beams using neural networks. Construction and Building Materials, 2006. 20(9): p. 801-811.
[34] Mishra, Amit, Zaheeruddin. PAPR Reduction in OFDM Signals: An Adaptive-Network-Based Fuzzy Inference Approach. Wireless personal communications, 2017. 92(2): p. 587-601.
[35] lker, Bekir, Topu, et al. Prediction of compressive strength of concrete containing fly ash using artificial neural networks and fuzzy logic. Computational Materials Science, 2008. 41(3): p. 305-311.
[36] Takagi T, Sugeno M. Derivation of fuzzy control rules from human operator's control actions. in knowledge representation and decision analysis. 1983.
[37] Sonebi M. Medium strength self-compacting concrete containing fly ash: Modelling using factorial experimental plans. Cement and concrete research, 2004. 34(7): p. 1199-1208.
[38] Ghezal A, Khayat K H. Optimizing self-consolidating concrete with limestone filler by using statistical factorial design methods. ACI Mater J, 2002.