

## Article

# Durability Assessment of PVA Fiber-Reinforced Cementitious Composite Containing Nano-SiO<sub>2</sub> Using Adaptive Neuro-Fuzzy Inference System

Ting-Yu Liu <sup>1</sup>, Peng Zhang <sup>1,\*</sup>, Qing-Fu Li <sup>1</sup>, Shao-Wei Hu <sup>1,2</sup> and Yi-Feng Ling <sup>3</sup> 

<sup>1</sup> School of Water Conservancy Engineering, Zhengzhou University, Zhengzhou 450001, China; tingyliu@163.com (T.-Y.L.); qingfuli66@163.com (Q.-F.L.); hushaowei@cqu.edu.cn (S.-W.H.)

<sup>2</sup> College of Civil Engineering, Chongqing University, Chongqing 400045, China

<sup>3</sup> Department of Civil, Construction and Environmental Engineering, Iowa State University, Ames, IA 50011, USA; yling@iastate.edu

\* Correspondence: zhangpeng@zzu.edu.cn

Received: 15 April 2020; Accepted: 27 April 2020; Published: 28 April 2020



**Abstract:** In this study, the durability of polyvinyl alcohol fiber-reinforced cementitious composite containing nano-SiO<sub>2</sub> was evaluated using the adaptive neuro-fuzzy inference system (ANFIS). According to the structural characteristics of the cementitious composite material and some related standards, the classification criteria for the evaluation indices of cementitious composite materials were clarified, and a corresponding structural framework of durability assessment was constructed. Based on the hypothesis testing principle, the required test data capacity was determined under a certain degree of accuracy, and durability experimental data and expert evaluation results were simulated according to statistical principles to ensure that there were sufficient datasets for ANFIS training. Using an environmental factor submodule as an example, 14 sets of actual test data were used to verify that the ANFIS can quickly and effectively mimic the expert evaluation reasoning process to evaluate the durability of cementitious composites. Compared with other studies related to the durability of cementitious composites, a systematic evaluation system for the durability of concrete was established. We used a polyvinyl alcohol fiber-reinforced cementitious composite containing nano-SiO<sub>2</sub> to conduct a comprehensive evaluation of cementitious composites. Compared with the traditional expert evaluation method, the durability evaluation system based on the ANFIS learned expert experience, stored the expert experience in fuzzy rules, and eliminated the subjectivity of expert evaluation, thereby making the evaluation more objective and scientific.

**Keywords:** cementitious composite; nano-SiO<sub>2</sub>; PVA fiber; durability evaluation; adaptive neuro-fuzzy inference system

## 1. Introduction

Reinforced concrete has served in the construction industry for 140 years [1] since the French engineer Abeck first manufactured reinforced concrete floors in 1879. However, many instances of prematurely failed reinforced concrete have occurred for various reasons [2], resulting in structures failing and failing to reach their specified service life and causing many casualties and property losses. Concrete cannot be used normally and requires much manpower and material resources for maintenance when it loses durability [3]. In addition, structures cannot operate normally and result in great economic losses [4]. Therefore, it is extremely important and necessary to improve the durability of reinforced concrete structures. The most common factor affecting the durability of concrete structures is the crack propagation [5]. The reason for concrete cracking is mainly the structure and components of a cementitious composite material being subjected to compressive stress. However, in most cases,

components develop internal cracks resulting from tensile stress owing to temperature deformation, shrinkage deformation, composite creep, chemical erosion, and mechanical load [6]. Environmental factors also directly affect the durability of cementitious composite materials, such as freeze–thaw cycles [7], chloride penetration [8], and changes in temperature and humidity [9]. Furthermore, cementitious composites have heavy weight, high brittleness, and low tensile strength, which can lead to the brittle fracture and sudden failure of structures and components. These disadvantages have largely limited the wide application of gelled composites and affected the durability of gelled materials [10]. To solve the shortcomings of cementitious composites in the tensile state and to improve the durability of structures and components, researchers have incorporated various fibers into cementitious composites to enhance the toughness of their matrices and to improve their properties. The effects of fibers such as polyvinyl alcohol (PVA) fiber [11], discontinuous microfibers [12], polypropylene fiber [13], steel fiber [14], carbon fiber [15], polyester fiber [16], and nano silica [17] have been investigated. Among the various fibers, PVA fiber is a commonly used gelled composite fiber [18]. Scholars have conducted research on nanometer-doped PVA fiber-reinforced cementitious composites, including work performance, crack resistance, basic mechanical properties, bending resistance [19], durability [20], and microscopic mechanism [21]. A large number of research results show that the incorporation of nanoparticles improves the frost resistance and impermeability of cementitious composites materials [22].

However, at present, there have been relatively few studies on the durability evaluation of PVA fiber-reinforced cementitious composites containing nano-SiO<sub>2</sub>, and the durability evaluation of cementitious composites is not perfect [23]. The traditional expert evaluation method relies too much on the experience of experts. Inevitably, the durability assessment results of a cementitious composite material will be deviated from the actual situation according to the subjective opinions of experts. It is necessary to establish a more objective, scientific, and effective evaluation method for gelled composite materials [24]. Although expert evaluation has been the longest and most widely used durability assessment method [25], two other methods of durability assessment of cementitious composites exist. One is the comprehensive evaluation by means of neural networks [26], and the other is reliability theory based on reliability mathematics [27]. Zhou et al. (2017) utilized gray system theory to evaluate the durability of concrete. Their calculation process was simple and suitable for practical engineering applications, but the value of its resolution coefficient needs to be further optimized and verified [28]. Yu et al. (2017) proposed a probabilistic framework for the durability assessment of concrete structures using reliability and sensitivity analysis based on the uncertainties of the environment and materials in a marine environment [29]. The adaptive neuro-fuzzy inference system (ANFIS) proposed by Jang in the 1990s is a fuzzy inference system that combines the organic combination of fuzzy logic and neural networks [30]. A fuzzy inference system is suitable for expressing fuzzy experience and knowledge but lacks an effective learning mechanism [31]. Neural networks have a self-learning function but cannot express the reasoning of human brain [32]. The ANFIS uses the back-propagation algorithm and least squares method to learn to adjust the premise parameters and conclusion parameters, which can automatically generate If-Then rules. The expert experience contained in the fuzzy rules provides a certain physical meaning to the neural network and allows it to eliminate the black box disadvantages while avoiding the poor learning ability of the fuzzy inference system [33]. At present, many scholars are applying the ANFIS for condition assessment and performance prediction [34–38]. Xu et al. (2016) developed an underwater structural condition assessment system for a bridge based on the ANFIS to provide a good application effect [39]. Wang et al. (2015) used the ANFIS inference system to establish a prediction model for the compressive strength of hollow concrete block masonry. The accuracy of the prediction was significantly better than that of the current standard calculation model [40].

This study applied the ANFIS inference system to assess the durability of PVA fiber-reinforced cementitious composites containing nano-SiO<sub>2</sub>. According to the structural characteristics of cementitious composites and some related standards [41–44], the classification criteria for the evaluation indices of cementitious composite materials were clarified and a structural framework for durability

evaluation was constructed. According to the hypothesis testing principle, the required test data capacity was determined under a certain degree of accuracy. The durability experimental data and expert evaluation results were simulated according to statistical principles to ensure that there were sufficient datasets for the ANFIS training. Using the environmental factor submodule as an example, 14 sets of actual test data were used to verify that the ANFIS can quickly and effectively mimic the expert evaluation reasoning process to evaluate the durability of cementitious composites. Japanese scholars improved the traditional expert evaluation method and proposed a comprehensive evaluation method for buildings. The comprehensive evaluation through three surveys reduced the subjective influence of experts, but the overall evaluation cost was high, and the workload was large [45]. Xu et al. (2019) used the durability evaluation of concrete aqueducts in Gansu Province and the fuzzy analytic hierarchy process (FAHP) to establish a multi-level and multi-indicator evaluation model for the durability of concrete buildings. Their model provided an improved characterization of the durability grade of hydraulic concrete structures and had practical application value [23]. Compared with the traditional expert evaluation method, the durability evaluation system based on the ANFIS was more objective and scientific and lowered the evaluation cost and workload. Most studies have been based on the prediction and evaluation of a certain durability index [46]. In this study, a systematic durability evaluation system of PVA fiber-reinforced cementitious composite containing nano-SiO<sub>2</sub> was established. The ANFIS compensates for the shortcomings of the black box of neural networks and the lack of learning ability of fuzzy systems. It describes the fuzzy relationship between durability and the many uncertain factors that affect the durability of cementitious composites, has better applicability, and provides a new method for durability evaluation of cementitious composites.

## 2. Principle and Structure of ANFIS

### 2.1. ANFIS Principle

#### 2.1.1. ANFIS Structure

The typical structure of the ANFIS can be illustrated by two input vectors and one output vector. The structure diagram is shown in Figure 1, where  $x_1, x_2$  is the input vector of the two input nodes;  $R_1, R_2, Z_1$ , and  $Z_2$  are membership functions, which fuzzify the input vector and then obtain membership degrees corresponding to different levels;  $\Pi$  is the fixed node mark, and the membership degrees  $\mu$  in the second layer are multiplied to obtain the trigger strength weight  $\omega_1, \omega_2$  of each rule;  $N$  denotes the calculation of the normalized credibility, the normalization of the strength of each rule, and then the obtainment of the trigger weight  $\bar{\omega}_1, \bar{\omega}_2$  of each rule in the overall rule.

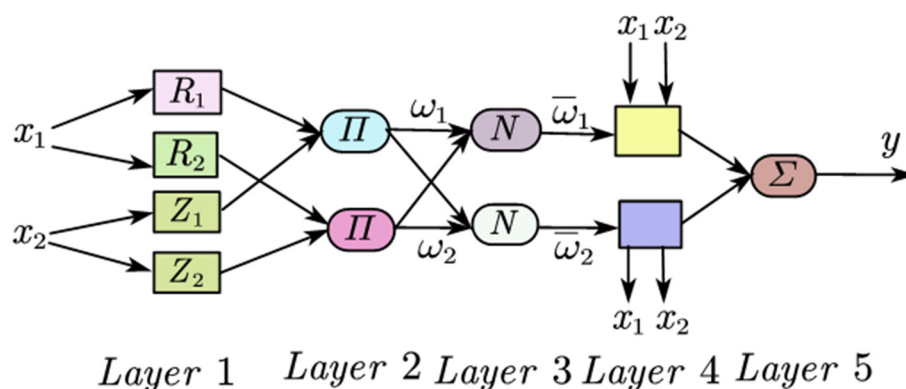


Figure 1. Model structure of adaptive neuro-fuzzy inference system (ANFIS).

The ANFIS algorithm is described as follows [47]:

Layer 1: Fuzzy processing

The membership node function is used to obfuscate the vector  $x_1, x_2$  of the input nodes to obtain different membership degrees  $\mu$ . The shape of the membership function depends on the ranking and value of the previous parameter. Layer 1 is an adaptive unit with the function

$$O_{1,j} = \begin{cases} \mu_{A_j}(x), j = 1, 2 \\ \mu_{B(j-2)}(x_2), j = 3, 4 \end{cases} \quad (1)$$

Layer 2: Rule-based reasoning

The memberships  $\mu$  of the first layer are multiplied to get the trigger strength of each rule as

$$\omega_j = \mu_{A_j}(x_1) \times \mu_{B_j}(x_2), j = 1, 2. \quad (2)$$

Layer 3: Normalization

The trigger strength of each rule obtained in the second layer is normalized to obtain the trigger proportion of the rule in the entire rule base, that is, the probability of applying the rule in the entire reasoning process, which is calculated

$$\bar{\omega}_j = \frac{\omega_j}{\omega_1 + \omega_2}, j = 1, 2. \quad (3)$$

Layer 4: Defuzzification

The output of the fuzzy rules is calculated and the output characteristic parameters of the antecedent are linearly combined to obtain the output as

$$O_{4j} = \bar{\omega}_j f_j = \bar{\omega}_j (f_{1j}x_1 + f_{2j}x_2 + f_{3j}), \quad (4)$$

where,  $\bar{\omega}_j$  is the proportion of the rule relative to the overall rule, and  $\{f_{1j}, f_{2j}, f_{3j}\}$  is the set of linear parameters at the nodes.

Level 5: Output

The calculation result of each rule in the fourth step is deblurred to obtain the exact output. The normalized triggering degrees of each rule are presented as a weighted average as

$$O_{5j} = \sum_j \bar{\omega}_j f_j = \frac{\sum_j \omega_j f_j}{\sum_j \omega_j}. \quad (5)$$

### 2.1.2. ANFIS Learning Algorithm

The ANFIS uses a hybrid learning algorithm in which parameter learning and adjustment is performed simultaneously in the forward transfer and reverse transfers. In forward propagation, the forward parameters are fixed, and when passed to the fourth layer, the backward parameters are updated by least squares estimation. In back propagation, the backward parameters (parameters in the rules) are fixed, the partial derivatives of the forward parameters are calculated according to the loss function (using the chain rule), and the parameters are updated from the reverse direction of the gradient direction.

In the ANFIS learning algorithm [48], the measurement error is the sum of the mean square errors determined as

$$Error = \sum_{i=1}^N E_{rrori} = \sum_{i=1}^N (T_i - O_{rji})^2, \quad (6)$$

where  $E_{rri}$  is the mean square error of the  $i$ -th data output,  $T_i$  is the expected output of the  $i$ -th data group, and  $O_{rji}$  is the  $r$ -th component of the  $i$ -th actual output group.

According to the chain rule, we obtained the partial derivative of  $E_{rri}$  for each parameter as

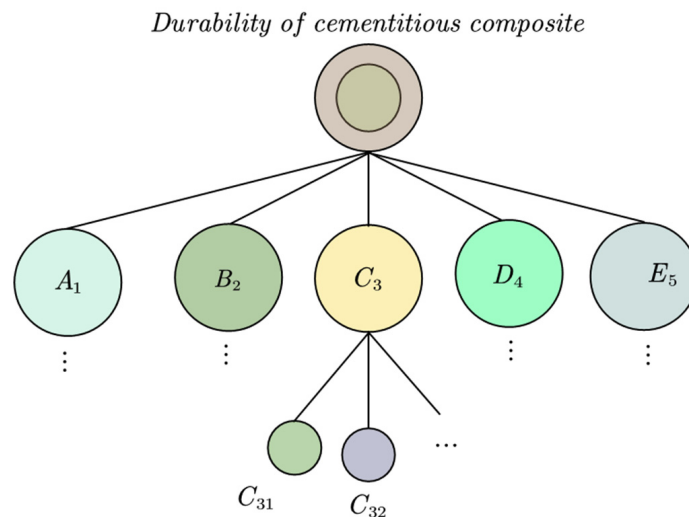
$$\frac{\partial E_{rri}}{\partial O_{rji}} = -2(T_i - O_{rji}), \quad (7)$$

$$\frac{\partial E_{rri}}{\partial \gamma} = \sum_{O' \in S} \frac{\partial E_{rri}}{\partial O'} \frac{\partial O'}{\partial \gamma}, \quad (8)$$

where  $\{S\}$  is the forward element set,  $O'$  is any of the elements, and  $\gamma$  is the forward parameter.

## 2.2. System Topology

Based on the idea of rounding to zero, the system consisted of five subsystems to greatly reduce the complexity of the ANFIS algorithm [49]. The entire system had a tree structure [50]. The parent node of each subsystem and its child nodes formed a subnet. The parent node was the master node, and child nodes were slave nodes. Figure 2 is a tree-like network topology diagram of the durability evaluation of cementitious composites. The concentric circles represent the soundness of the output durability evaluation indices of the cementitious composites, the large circles represent the evaluation result of the single index, and the small circles represent the evaluation indicators of the test items.



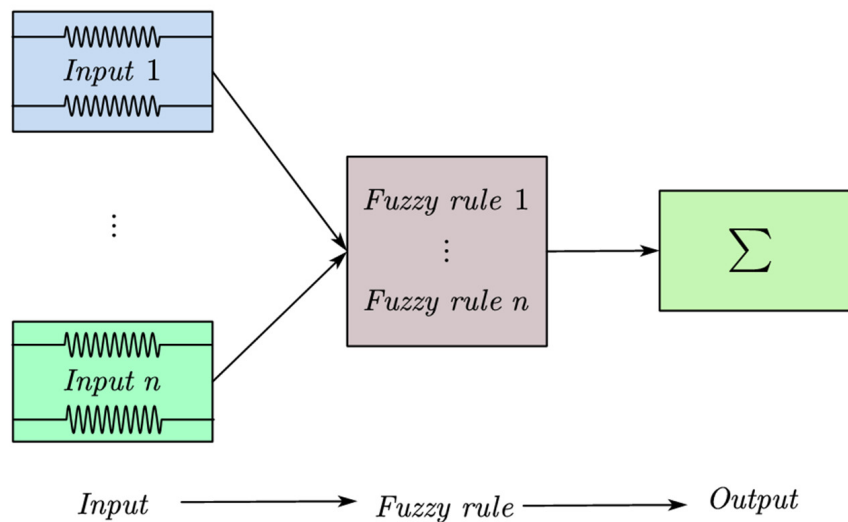
**Figure 2.** Tree network topology of composite durability evaluation.

## 3. Durability Evaluation System Based on ANFIS

The durability evaluation system of cementitious composites based on the ANFIS took full advantage of the complementary advantages of fuzzy systems and neural networks [51]. The ANFIS used a hybrid algorithm of a back-propagation algorithm and the least squares method to learn to adjust the premise and conclusion parameters and automatically generate If-Then rules that contain expert experience in the fuzzy rules. According to the durability evaluation indices and evaluation system, the ANFIS sequentially evaluated from the bottom test indices to the high-level index. This allowed the neural network to eliminate the black box disadvantages, gain certain physical significance, and avoid the poor learning ability of the fuzzy inference system.

Figure 3 presents a framework diagram of the ANFIS for the evaluation of a single indicator. The inference system is a tree-like network topology structure in which the ANFIS submodules of a single evaluation indicator are interconnected. In the figure, the wavy line in the input represents the membership function, and  $\sum$  represents fuzzy synthesis. In the calculation process, the input data were processed by the membership function to obtain memberships of different grades. Memberships

were calculated by fuzzy rules with a certain trigger strength and trigger weight, the results of each rule were obtained, and then the evaluation result of the single index was obtained.



**Figure 3.** ANFIS framework of a single evaluation index.

### 3.1. Evaluation Index System and Index Grading Standards

#### 3.1.1. Evaluation Index System

The selection of the durability indices of a cementitious composite material followed the principles of hierarchy, a combination of qualitative and quantitative indicators, and compatibility combined with actual engineering problems and references [24,52,53]. Each box in Figure 4 represents an indicator, and indicators are determined by one or more input data. The analytic hierarchy process was used to establish a durable evaluation system. Five intermediate indicators—raw materials  $A_1$ , construction and maintenance  $B_2$ , environmental factors  $C_3$ , mix ratio  $D_4$ , and work performance and strength  $E_5$ —were selected and decomposed one by one to obtain 26 leaf indicators. The durability evaluation index system of cementitious composite materials is presented in Figure 4. The evaluation was performed from the leaf indices to the intermediate index, and finally the durability evaluation of the cementitious composite material was obtained.

#### 3.1.2. Classification Standards

A complete evaluation standard for the durability of gelled composites was established using a percentage system. Considering that some uncertain factors cannot be accurately measured, the smaller the number of classifications, the higher the reliability of the results of the durability evaluation. Therefore, the evaluation standard was divided into four or five classification levels. The five levels were excellent (80–100), good (60–80), qualified (40–60), poor (20–40), and dangerous (0–20). The four levels were excellent (75–100), good (50–75), qualified (25–50), and dangerous (0–25). The index classification was performed in accordance with some related standards [41–43] for detailed quantitative evaluation. The results are presented in Table 1.



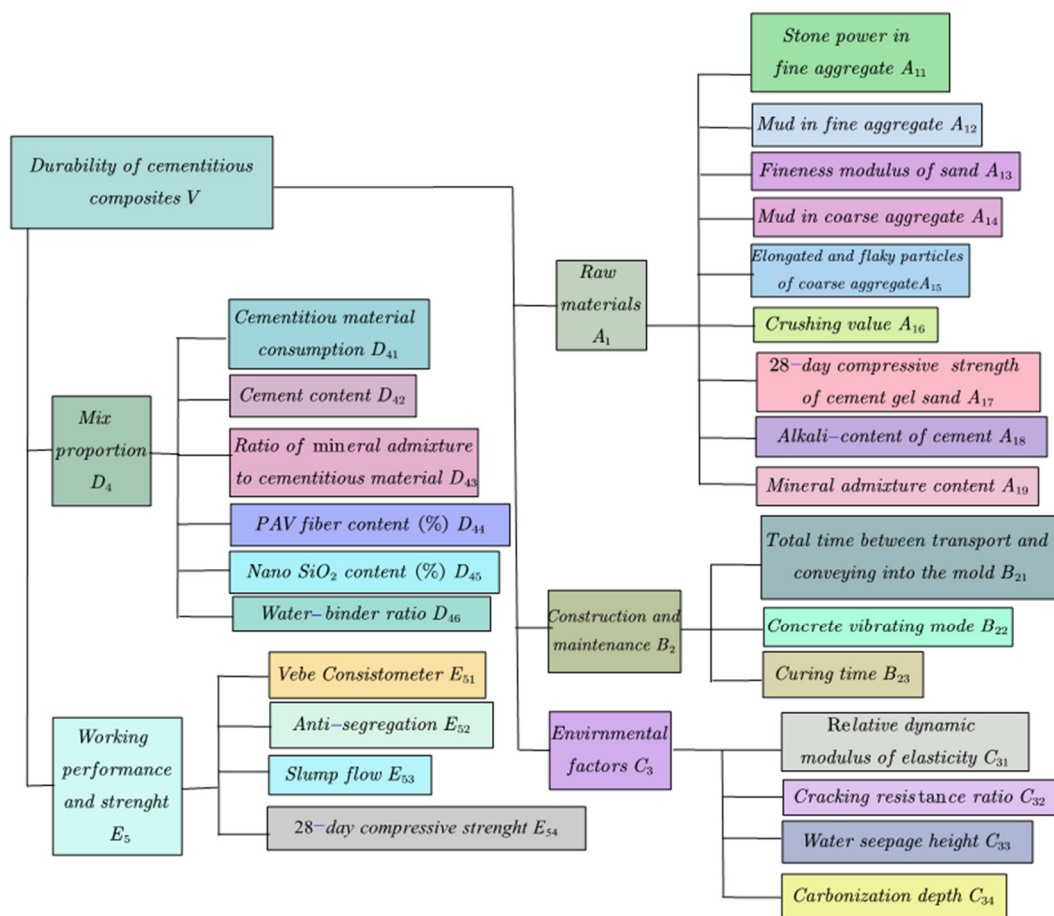


Figure 4. Evaluation index system for the durability of cementitious composite.

Table 1. Evaluation indices and grading standards.

No	Index	Classification				
		First Grade	Second Grade	Third Grade	Fourth Grade	Fifth Grade
1	A <sub>11</sub>	(7.0, 10.0]	(5.0, 7.0]	(3.0, 5.0]	(2.0, 3.0]	(0, 2.0]
2	A <sub>12</sub>	(7.0, 10.0]	(5.0, 7.0]	(3.0, 5.0]	(2.0, 3.0]	(0, 2.0]
3	A <sub>13</sub>	[3.1, 3.7]	[2.3, 3.0]	[1.6, 2.2]	[0.7, 1.5]	(0, 0.6]
4	A <sub>14</sub>	(2.0, ∞)	(1.0, 2.0]	(0.5, 1.0]	(0, 0.5]	
5	A <sub>15</sub>	(25, ∞)	(15, 25]	(8, 15]	(0, 8]	
6	A <sub>16</sub>	(16, ∞)	(12, 16]	(10, 12]	(0, 10]	
7	A <sub>17</sub>	(∞, 32.5]	(32.5, 42.5]	(42.5, 52.5]	(52.5, 62.5]	(62.5, ∞)
8	A <sub>18</sub>	[1.2, ∞)	(0.8, 1.2]	(0.4, 0.8]	(0, 0.4]	
9	A <sub>19</sub>	(0.55, 0.65]	(0.45, 0.55]	(0.35, 0.45]	(0.30, 0.35]	(0, 0.30]
10	B <sub>21</sub>	(240, ∞)	(210, 240]	(180, 210]	(90, 180]	(0, 90]
11	B <sub>23</sub>	(0, 3]	(3, 7]	(7, 14]	(14, 28]	(28, ∞)
12	C <sub>31</sub>	(50, 60]	(60, 70]	(70, 80]	(80, 90]	(90, 100]
13	C <sub>32</sub>	(75, 80]	(80, 85]	(85, 90]	(90, 95]	(95, 100]
14	C <sub>33</sub>	(35, 45]	(30, 35]	(25, 30]	(20, 25]	(5, 20]
15	C <sub>34</sub>	(30, 100]	(20, 30]	(10, 20]	(0.1, 10]	(0, 0.1]
16	D <sub>44</sub>	[0, 0.3]	(0.3, 0.6]	(0.6, 0.9]	(0.9, 1.2]	
17	D <sub>45</sub>	(0, 0.5]	(0.5, 1.0]	(1.0, 1.5]	(1.5, 1.0]	(2.0, 2.5]
18	D <sub>46</sub>	(0.55, 0.6]	(0.50, 0.55]	(0.45, 0.50]	(0.40, 0.45]	(0, 0.40]
19	E <sub>51</sub>	[31, ∞)	[21, 30]	[11, 20]	[6, 10]	[3, 5]
20	E <sub>53</sub>	(0, 200] U (700, ∞)	(200, 350] U (500, 700)	[350, 450]	[450, 500]	
21	E <sub>54</sub>	(0, 40)	(40, 50]	(50, 60]	(60, 70]	(70, 80]

### 3.1.3. Input Items for Durability Evaluation

The indicators used for evaluating the durability of cementitious composites included raw materials, construction and maintenance conditions, environmental factors, mix ratios, and other data that can be obtained through experimentation or observations. Two types of input data were used for the evaluation of the underlying indicators. The first type provided a description of the state of the cementitious composite material and simply divided it into grades. Such indicators were qualitative indicators, and the values in 0.1 increments within the range of 0.1–1.0 given by the gelatinous composite testers or observers were used as input data. The larger the dataset, the better the durability of the cementitious composite. The second type of data were a single numerical index whose test index was an interval value, such as, to name two, carbonization depth and water seepage height. This type of data was imported directly into the system. Depending on the structural characteristics and durability influencing factors of the cementitious composite material, the system selected the 26 input items shown in Table 2 to evaluate five underlying indicators.

**Table 2.** Input items for bottom indicators.

Assessment Indicators	Input Item
Concrete working behavior	Collapsibility, Vebe consistometer, segregation resistance, 28-day compressive strength
Environment function	Relative dynamic modulus of elasticity, cracking resistance ratio, water seepage height, carbonization depth
Mix proportion	Cementitious material consumption, cement content, ratio of mineral admixture to cementitious material, PVA fiber content, nano SiO <sub>2</sub> content, water–binder ratio
Construction and maintenance	Total time between transportation and feeding, concrete vibrating mode, maintenance time
Raw material	Stone power in fine aggregate, mud in fine aggregate, fineness modulus of sand, mud in coarse aggregate, elongated and flaky particles of coarse aggregate, crushing value, 28-day compressive strength of cement mortar, alkali content of cement, type of mineral admixtures

### 3.2. Fuzzy Rules

The fuzzy rule represented the mapping relationship between the input data and the evaluation indices explained here with the construction and maintenance B<sub>2</sub> module [54]. The indicator value (construction and maintenance sound value) was obtained from three input data (total time interval of transport and conveyance into the mold, concrete vibrating mode, and maintenance time). The form of the fuzzy rule is:

$$\text{if } x \text{ is } a, y \text{ is } b \text{ and } z \text{ is } c, \text{ then } r = px + qy + mz + n \quad (9)$$

where  $x$ ,  $y$ , and  $z$  are the input sets, which are the total time interval of transport and conveyance into the mold, concrete vibrating mode, and maintenance time, respectively; and  $r$  is an output variable (construction and maintenance status) automatically generated by the training process in actual use. Taking environmental factor C<sub>3</sub> as an example, this submodule had 625 fuzzy rules, all of which belonged to one fuzzy rule group representing the evaluation index of environmental factors. Other fuzzy indicators were similar to environmental factor C<sub>3</sub>. The entire system had five fuzzy rule groups of ANFIS submodules and one fuzzy rule group for the overall durability evaluation.

### 3.3. Membership Function

Membership function is the basis of fuzzy control. Common types are Z-type, trapezoidal, Gaussian, bell-shaped, triangular, and S-type. In practical applications, the appropriate type of membership function is generally selected based on expert experience and actual conditions. We



performed a normality test on the existing data. Due to the small number of samples, the normality test was based on the Kolmogorov–Smirnov (K-S) results. The test results show that the significances were between 0.7 and 2 greater than 0.05, so the durability of cementitious composites basically followed the normal distribution. The Gaussian function has the characteristics of smooth symmetry and non-linear continuous differentiability. After a series of experiments, the system used a Gaussian membership function to describe the input index as

$$f(x, \theta, a) = e^{-\frac{(x-a)^2}{2\theta^2}} \quad (10)$$

where  $x$  is the input index learned during training. Figure 5 provides a schematic diagram of a Gaussian membership function.

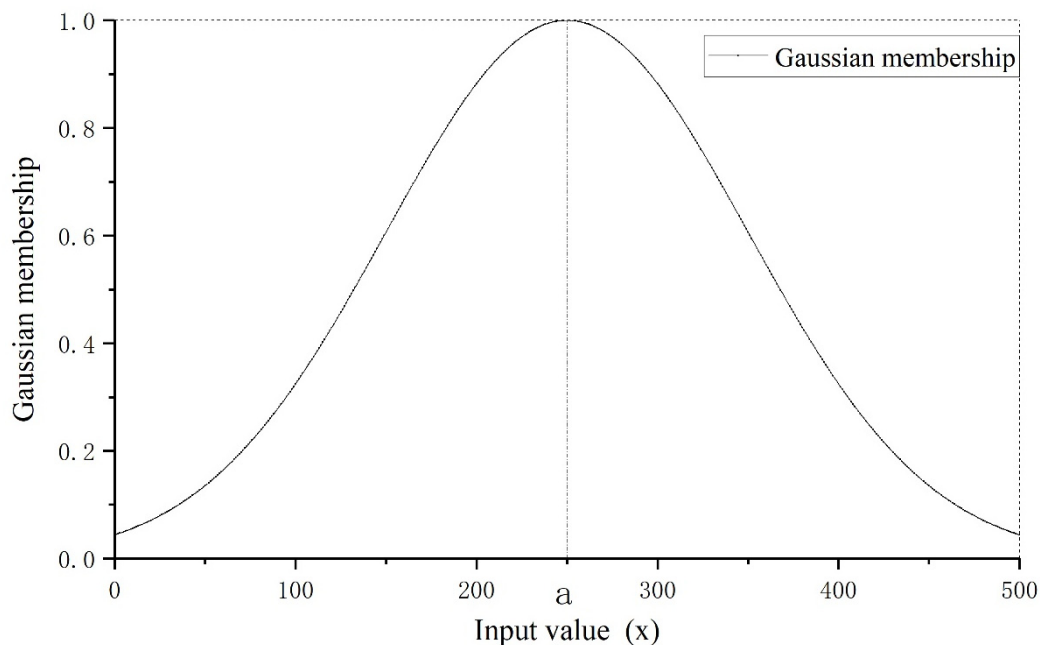


Figure 5. Curve of the Gaussian membership function.

#### 4. Description of ANFIS Submodule

##### 4.1. Simulation of Test Data

###### Generation of Simulation Test Data

The more data obtained from the test, the more accurately the trained ANFIS system can reflect the results of expert evaluation. However, the experimental dataset cannot be too large because obtaining high-quality large-scale experimental datasets requires much manpower and many material resources. Using environmental factor  $C_3$  as an example, according to the determination method of the sample size in the hypothesis test, at a 95% confidence level, when the environmental factor score was 4.99 and the acceptable error range was 1, the required sample capacity was  $n = (1.96 \times 4.99/1)^2 = 95.65$  [55], of which 1.96 was the critical value at a 95% confidence level. Therefore, 100 sets of simulation data were capable of meeting the ANFIS training requirements.

The simulation data were the original 14 experimental data, the initial data were all derived from reference [56] as shown in Table 3, and compositions of mixtures were shown in Table 4. The mixtures 1–5 and 10–13 were prepared to study the influence of PAV fiber on the durability of cementitious composites. The mixtures 6–9 were prepared to study the influence of nano-SiO<sub>2</sub> on the durability of cementitious composites. Mixture 14 was taken as the control mixture. The data generated by the simulation included endurance test results and expert evaluation results. Using

the environmental factor  $C_3$  subsystem as an example, the test dataset included five data elements, each group having four test data, and an expert evaluated the results. The method of generating random numbers by normal distribution and generating expert evaluation results by certain derivation rules to generate simulation test datasets can solve the problem of a lack of high-quality test data [34]. Therefore, to obtain sufficient training samples and ignore the interaction between the cementitious composites, the normal distribution method was used to randomly simulate the experimental data of the cementitious composites. The mean and standard deviation refer to the normal distribution pattern of the original data as shown in Table 5.

Table 3. Initial data.

No.	Relative Dynamic Modulus of Elasticity/%	Cracking Resistance Ratio/%	Water Seepage Height/mm	Carbonization Depth/mm	Score
S1	78.2	85.0	40.2	13.9	13.17767
S2	86.1	87.2	23.1	13.0	21.28441
S3	90.1	92.9	21.2	12.3	24.03373
S4	91.1	97.4	17.5	11.3	25.97210
S5	88.9	99.8	15.4	11.8	26.05322
S6	91.6	97.5	13.7	10.8	26.68299
S7	92.0	97.8	12.1	10.5	27.08332
S8	93.0	98.4	9.9	10.0	27.78438
S9	94.2	99.2	9.0	9.0	28.47065
S10	87.2	94.9	12.3	12.3	25.17145
S11	90.3	97.0	10.4	11.5	26.62340
S12	91.3	99.7	9.9	10.1	27.58360
S13	83.0	52.6	8.5	8.9	22.46571
S14	78.2	85.0	40.2	13.9	13.17767

Table 4. Mix proportions of polyvinyl alcohol (PVA) fiber cementitious composites.

Mix No.	Water	Cement	Fly Ash	Quartz Sand	Water Reducing Agent	PVA Fiber	Nano-SiO <sub>2</sub>
	kg/m <sup>3</sup>	kg/m <sup>3</sup>	kg/m <sup>3</sup>	kg/m <sup>3</sup>	kg/m <sup>3</sup>	%	%
S1	380	650	350	500	3	0	0
S2	380	650	350	500	3	0.3	0
S3	380	650	350	500	3	0.6	0
S4	380	650	350	500	3	0.9	0
S5	380	650	350	500	3	1.2	0
S6	380	644	350	500	3	0.9	1
S7	380	640	350	500	3	0.9	1.5
S8	380	637	350	500	3	0.9	2
S9	380	634	350	500	3	0.9	2.5
S10	380	637	350	500	3	0.3	2
S11	380	637	350	500	3	0.6	2
S12	380	637	350	500	3	1.2	2
S13	380	637	350	500	3	0	2
S14	380	637	350	500	3	0	0

Table 5. Mean and standard deviation of initial data.

Relative Dynamic Modulus of Elasticity/%	Cracking Resistance Ratio/%	Water Seepage Height/mm	Carbonization Depth/mm	Environmental Factor Score
88.23	91.74	17.39	11.38	23.97
5.14	12.44	10.63	1.61	4.99

Using the relative dynamic modulus of elasticity as an example, we selected 100 random numbers with an average value of 88.23 and a standard deviation of 5.14. The distribution of random numbers is shown in Figure 6, where  $C_{31}$  is the random number set of the relative dynamic modulus of elasticity and  $f$  is the number of random occurrences. The simulation process was implemented by SPSS (Statistical Product and Service Solutions, Version 24.0, IBM Corp., Armonk, NY, USA).

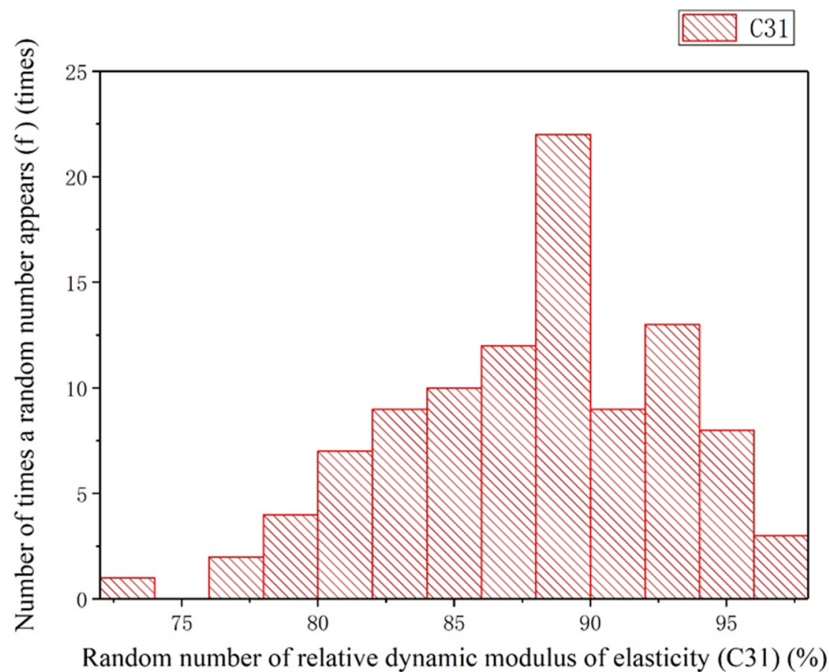


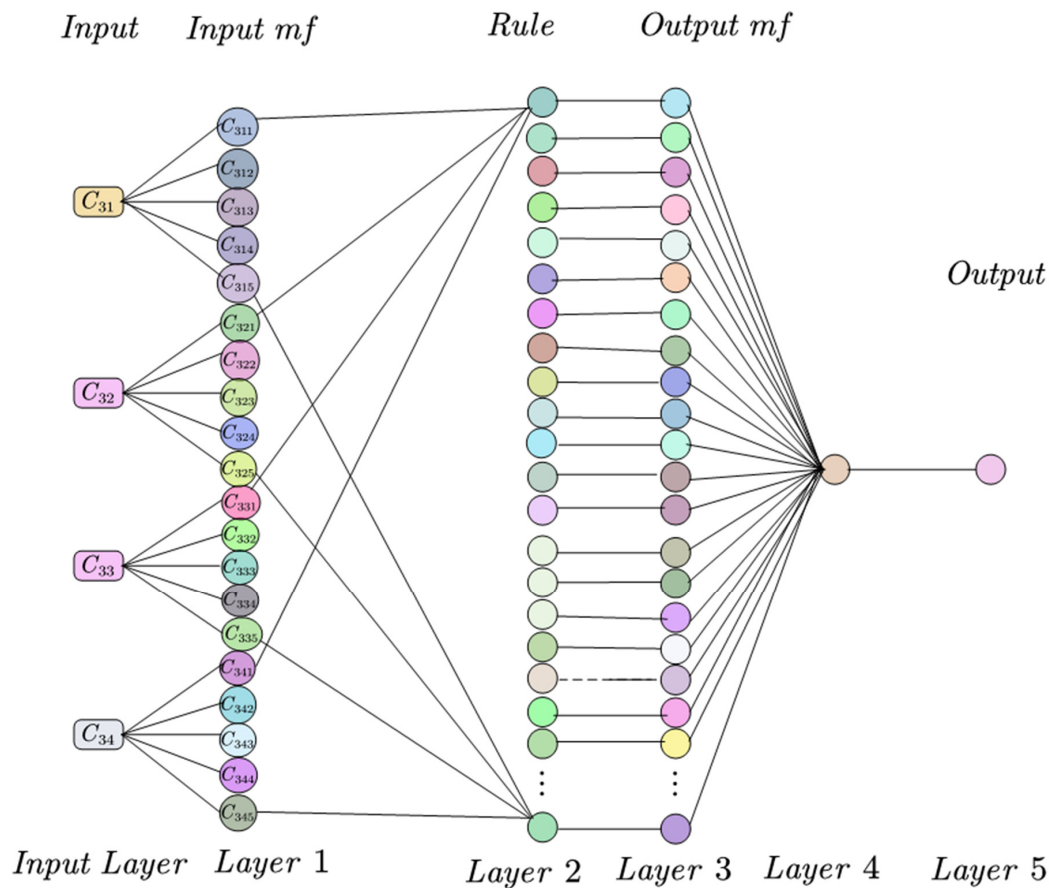
Figure 6. Probability distribution histogram of a random number.

The expert evaluation results to verify system performance were derived from the system's original output in accordance with certain rules. There are two generation rules for simulating expert evaluation results. The first rule is that the normal distribution of expert evaluation data applies directly to the original data, which is the system output before training. The second rule is that the expert evaluation data of the original data are independently shifted by different small increments, which conform to a normal distribution. We first used the second rule to generate twice the number of expert evaluation results required for the dataset and then divided it into two groups. The small offset increments were consistent with a mean of zero and a standard deviation of 0.5. The actual data were used to train the two sets of expert evaluation results to obtain the two trained groups of expert evaluation results. Then, the two groups of data trained each other to obtain the final simulated expert evaluation data.

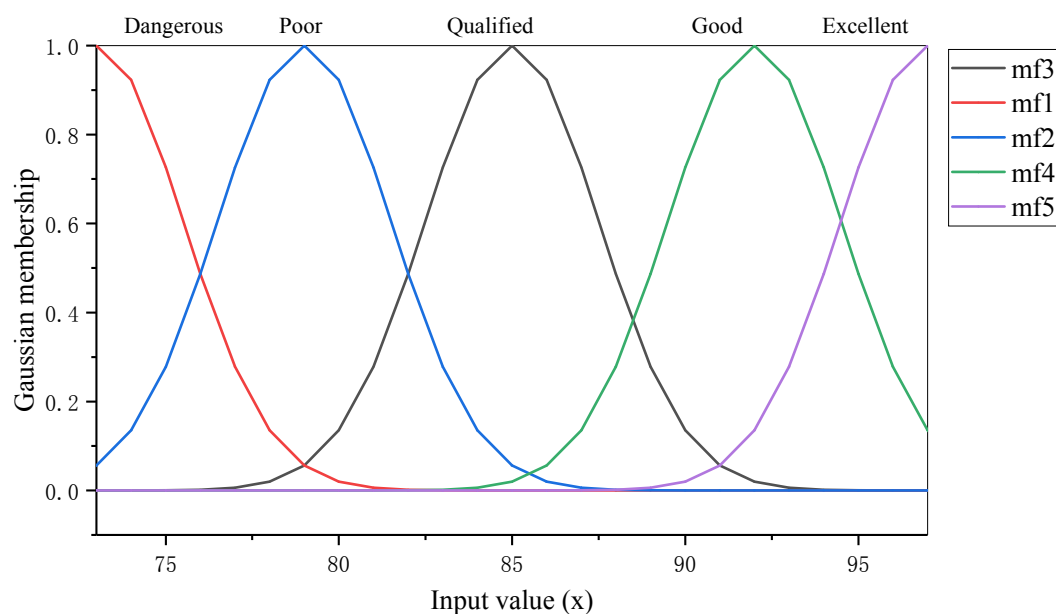
#### 4.2. Implementation of ANFIS Submodule

Using the environmental factor  $C_3$  as an example to illustrate the structure of the ANFIS submodule, Figure 7 shows the ANFIS structural model of  $C_3$ . There were five layers of network structure, including four inputs and one output [57]. According to the classification of the durability evaluation index of cementitious composite material, the membership function structure of the four input units was 5, 5, 5, 5, corresponding to the 20 neural nodes of the second layer; that is, the hierarchical status of each input unit was 5, 5, 5, 5. The membership function curve is shown in Figure 8. The third and fourth layers each had 625 neuron nodes corresponding to the structure's 625 fuzzy rules and the output of each fuzzy rule. The partial membership function rules are shown in Figure 9. The fifth layer had a sound value corresponding to  $C_3$  of the neuron node. After the ANFIS system was set up, the simulation experimental data were input into the system for training, and the training process was implemented

by MATLAB software. After sufficient training, the training error converged to 0.03. The algorithm training completed at epoch 2. The results of experiments show that the algorithm converges quickly and has satisfactory training accuracy.



**Figure 7.** Proposed ANFIS model structure ( $C_{31}$ : relative dynamic modulus of elasticity,  $C_{32}$ : cracking resistance ratio,  $C_{33}$ : water seepage height, and  $C_{34}$ : carbonization depth).



**Figure 8.** Degree function curve.

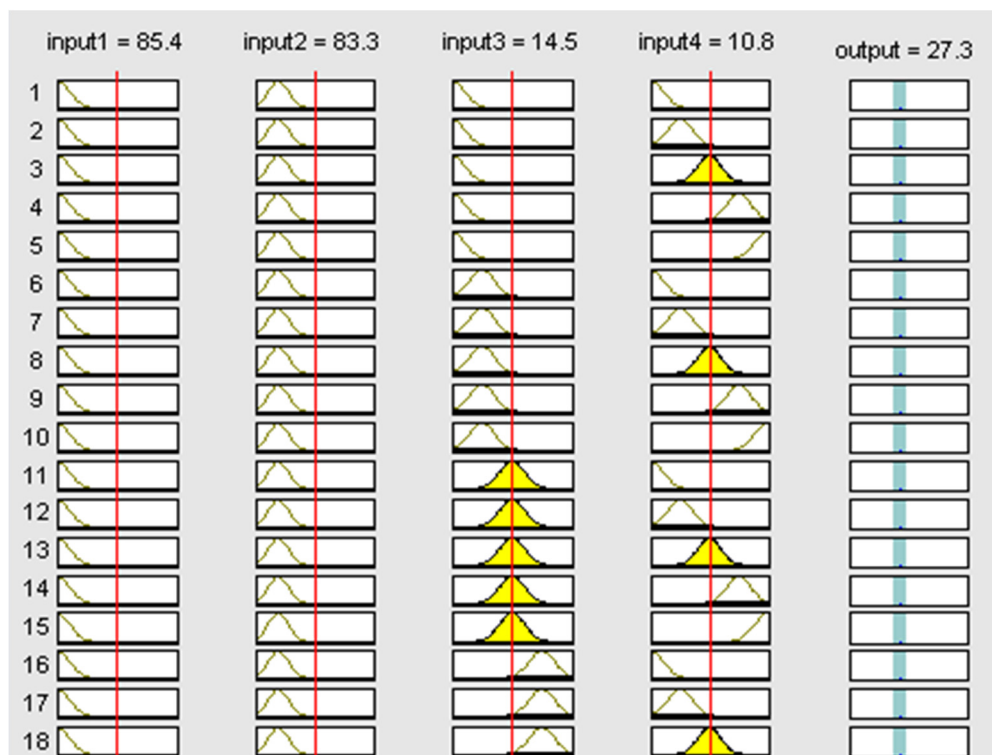


Figure 9. Partial fuzzy rules.

#### 4.3. Verification of System Learning Ability

The reasoning ability of the ANFIS was measured by the similarity between the initial expert evaluation result of the test dataset and the evaluation result of the reasoning system. This measurement reflects the ability of the ANFIS to learn and adjust the parameter value of the membership function and other parameters according to the given dataset. To verify the reasoning ability of the proposed system for practical problems, using environmental factors as an example, the above-mentioned ANFIS system was verified with 14 groups of data obtained from the experiment.

Table 6 shows the comparison of original evaluation results, system output before training and system output after training. Taking five scores as one grade difference, the number of output status grades of the system after training that were consistent with the expert evaluation opinions increased from 5 before training to 12, the number of levels with a difference of 2 or more decreased from 8 before training to 0. In the end, only two data differed by one level. The coincidence rate of the state grade of the indices evaluated by the system before training was 35.7%, and the grade after training is increased to 85.7%. The average test deviation of the direct application of the original expert evaluation data was 10.39, and the average test deviation using the trained expert evaluation data was reduced to 2.93. This indicates that the learning and reasoning ability of the ANFIS after training was improved to some extent. Pearson correlation analysis [58] was used to analyze the expert evaluation and the system output after training to judge the degree of interdependence between the two vectors. The Pearson correlation analysis results are presented in Table 7. It can be perceived from Table 7 that the conspicuousness was 0.947. Therefore, according to Pearson correlation analysis, the correlation was significant [59,60]. The deviation between the reasoning results after ANFIS training and the expert evaluation results in the test data is shown in Figure 10, where the x-axis is the composite material test number. After the system was trained, the output results were closer to the expert evaluation results.

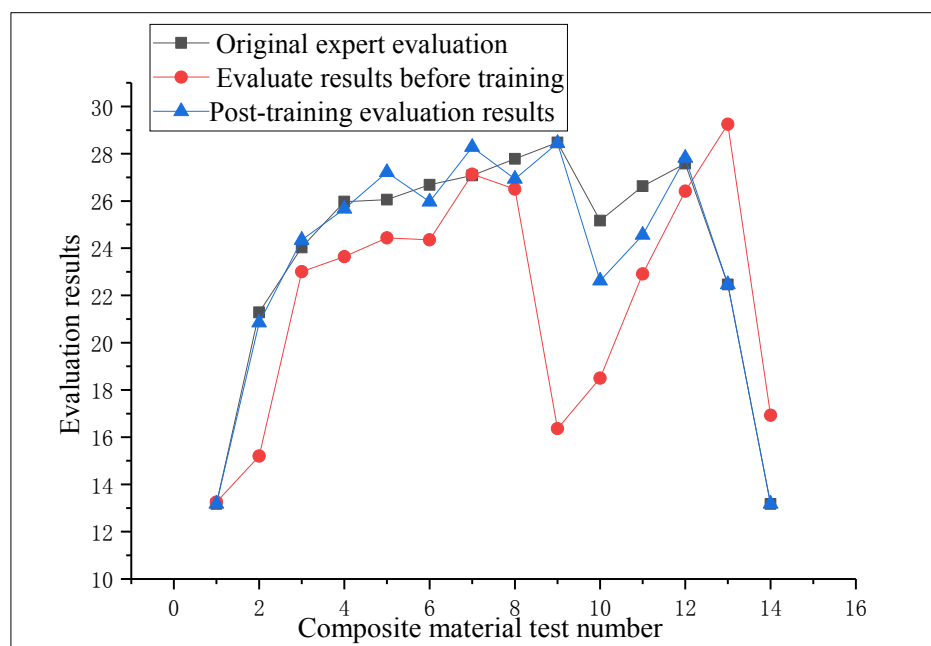
**Table 6.** Comparison of original evaluation results: system output before training and system output after training.

Evaluation Indicators	Expert Evaluation Data	System Output after Training	System Output before Training
S1	13.18	12.8	8.25
S2	21.28	19.34	24.31
S3	24.03	22.87	10
S4	25.97	23.64	21.1
S5	26.05	24.75	17.02
S6	26.68	24.11	19.2
S7	27.08	24.83	16.07
S8	27.78	25.05	16.51
S9	28.47	24.81	50.89
S10	25.17	20.17	19.99
S11	26.62	20.43	24.84
S12	27.58	26.25	16.09
S13	22.47	19.36	8.97
S14	13.18	12.8	8.25

**Table 7.** Results of the correlation analysis.

Project	Correlation Coefficient	Saliency	Number of Cases
Expert evaluation data	1.0	0.947	14
System output after training	1.0	0.947	14

At 0.01 level (double tail), the correlation was significant.

**Figure 10.** Comparison between system output before and after training and expert opinion.

The results show that the evaluation results of the system after training agreed well with the expert evaluation results, and the system after training can quickly and accurately imitate the nonlinear expert reasoning process. The durability evaluation results of cementitious composite materials obtained by the ANFIS reflected the durability of concrete to a certain extent. It served as a guide to identify the weak links, determined the reliability of the existing concrete in time, and acted against the weak links to strengthen the construction quality and optimize the working performance of the cementitious



composite materials. For instance, the score of the S1 evaluation index was 12.8, which belongs to the third level and is relatively low. If the score is lower than the level required by the corresponding specifications, measures need to be taken to improve it. For example, a secondary mixing method, sand enveloped with cement paste or a sand and stone binding method, could be adopted to improve the workability, water retention, and concrete strength.

## 5. Conclusions

(1) The durability of PVA fiber-reinforced cementitious composites containing nano-SiO<sub>2</sub> was evaluated by using a method based on the ANFIS. Moreover, the classification criteria for the evaluation indices of cementitious composite materials were clarified, and a corresponding structural framework of durability assessment was constructed.

(2) The results show that 85.7% of the ANFIS evaluation results were consistent with the expert evaluation results, and only two data differed by one level, which demonstrates that the system simulated the nonlinear expert reasoning process quickly and accurately and had good parameter mathematics. The evaluation results of the ANFIS can serve as a reliable guide for actual concrete construction and maintenance applications.

(3) Using the ANFIS to evaluate the durability of cementitious composite materials is feasible in engineering applications. By comparing the results of ANFIS evaluation with a corresponding evaluation system, the evaluation results can be obtained intuitively. Through the establishment of a corresponding evaluation index system, the system cannot only be used to evaluate the durability of a PVA fiber-reinforced cementitious composite with SiO<sub>2</sub>, but also can be used to evaluate the durability of ordinary concrete and other cementitious composite materials.

**Author Contributions:** Conceptualization, T.-Y.L. and P.Z.; methodology, T.-Y.L., Q.-F.L. and S.-W.H.; formal analysis, T.-Y.L., P.Z., Q.-F.L. and S.-W.H.; investigation, T.-Y.L., P.Z. and Q.-F.L.; resources, P.Z. and S.-W.H.; writing—original draft preparation, T.-Y.L. and P.Z.; writing—review and editing, Q.-F.L., S.-W.H. and Y.-F.L.; visualization, Y.-F.L.; supervision, P.Z.; project administration, Q.-F.L.; funding acquisition, P.Z. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research was funded by the CRSRI Open Research Program (Grant No. CKWV2018477/KY), National Natural Science Foundation of China (Grant No. 51678534), Open Projects Funds of Dike Safety and Disaster Prevention Engineering Technology Research Center of Chinese Ministry of Water Resources (Grant no. 2018006) and Program for Innovative Research Team (in Science and Technology) in University of Henan Province of China (Grant No. 20IRTSTHN009).

**Conflicts of Interest:** The authors declare no conflict of interest.

## References

1. Kong, X.L. Application of Distributed Optical Fiber Sensing Technology in Monitoring of Steel Corrosion. Master's Thesis, Dalian University of Technology, Dalian, China, 2011. (In Chinese).
2. Hooton, R.D. Future directions for design, specification, testing, and construction of durable concrete structures. *Cem. Concr. Res.* **2019**, *124*, 105827. [[CrossRef](#)]
3. Zhao, J. Time Variation and Similarity of Chloride Diffusion Properties of Concrete under Dry Wet Cyclic Environment. Master's Thesis, Zhejiang University of Technology, Hangzhou, China, 2019. (In Chinese).
4. Zhang, L.L. Study on durability of reinforced concrete structure. *Sichuan Build. Mater.* **2012**, *38*, 40–42.
5. Liu, H.Z.; Zhang, Q.; Li, V.; Su, H.Z.; Gu, C.S. Durability study on engineered cementitious composites (ECC) under sulfate and chloride environment. *Constr. Build. Mater.* **2017**, *133*, 171–181. [[CrossRef](#)]
6. Ling, Y.F.; Zhang, P.; Wang, J.; Chen, Y.Z. Effect of PVA fiber on mechanical properties of cementitious composite with and without nano-SiO<sub>2</sub>. *Constr. Build. Mater.* **2019**, *229*, 117068. [[CrossRef](#)]
7. Zhang, P.; Wittmann, F.H.; Vogel, M.; Müller, H.S.; Zhao, T. Influence of freeze-thaw cycles on capillary absorption and chloride penetration into concrete. *Cem. Concr. Res.* **2017**, *100*, 60–67. [[CrossRef](#)]
8. Fu, C.Q.; Ye, H.L.; Jin, X.Y.; Yan, D.M.; Jin, N.G.; Peng, Z.X. Chloride penetration into concrete damaged by uniaxial tensile fatigue loading. *Constr. Build. Mater.* **2016**, *125*, 714–723. [[CrossRef](#)]

9. Zhao, H.T.; Jiang, K.D.; Yang, R.; Tang, Y.M.; Liu, J.P. Experimental and theoretical analysis on coupled effect of hydration, temperature and humidity in early-age cement-based materials. *Int. J. Heat. Mass. Tran.* **2020**, *146*, 118784. [[CrossRef](#)]
10. Dong, W.K.; Li, W.G.; Shen, L.M.; Sun, Z.H.; Sheng, D.C. Piezoresistivity of smart carbon nanotubes (CNTs) reinforced cementitious composite under integrated cyclic compression and impact. *Compos. Struct.* **2020**, *241*, 112106. [[CrossRef](#)]
11. Li, L.; Cao, M.L. Influence of calcium carbonate whisker and polyvinyl alcohol-steel hybrid fiber on ultrasonic velocity and resonant frequency of cementitious composites. *Constr. Build. Mater.* **2018**, *188*, 737–746. [[CrossRef](#)]
12. Zhang, D.; Yu, J.; Wu, H.L.; Jaworska, B.; Li, V.C. Discontinuous micro-fibers as intrinsic reinforcement for ductile Engineered Cementitious Composites (ECC). *Compos. Part B* **2020**, *184*, 107741. [[CrossRef](#)]
13. Deb, S.; Mitra, N.; Majumder, S.B.; Maitra, S. Improvement in tensile and flexural ductility with the addition of different types of polypropylene fibers in cementitious composites. *Constr. Build. Mater.* **2018**, *180*, 405–411. [[CrossRef](#)]
14. Li, H.; Mu, R.; Qing, L.B.; Chen, H.S.; Ma, Y.F. The influence of fiber orientation on bleeding of steel fiber reinforced cementitious composites. *Cem. Concr. Compos.* **2018**, *92*, 125–134. [[CrossRef](#)]
15. Badanoiu, A.; Holmgren, J. Cementitious composites reinforced with continuous carbon fibres for strengthening of concrete structures. *Cem. Concr. Compos.* **2003**, *25*, 387–394. [[CrossRef](#)]
16. Rostami, R.; Zarrebini, M.; Mandegari, M.; Mostofinejad, D.; Abtahi, S.M. A review on performance of polyester fibers in alkaline and cementitious composites environments. *Constr. Build. Mater.* **2020**, *241*, 117998. [[CrossRef](#)]
17. Murthy, A.R.; Ganesh, P. Effect of steel fibres and nano silica on fracture properties of medium strength concrete. *Adv. Concr. Constr.* **2019**, *7*, 143–150.
18. Pakravan, H.R.; Ozbakkaloglu, T. Synthetic fibers for cementitious composites: A critical and in-depth review of recent advances. *Constr. Build. Mater.* **2019**, *207*, 491–518. [[CrossRef](#)]
19. Zhang, P.; Ling, Y.F.; Wang, J.; Shi, Y. Bending resistance of PVA fiber reinforced cementitious composites containing nano-SiO<sub>2</sub>. *Nanotechnol. Rev.* **2019**, *8*, 690–698. [[CrossRef](#)]
20. Zhang, P.; Li, Q.F.; Wang, J.; Shi, Y.; Ling, Y.F. Effect of PVA fiber on durability of cementitious composite containing nano-SiO<sub>2</sub>. *Nanotechnol. Rev.* **2019**, *8*, 116–127. [[CrossRef](#)]
21. Wang, J.Q.; Dai, Q.L.; Si, R.Z.; Guo, S.C. Investigation of properties and performances of Polyvinyl Alcohol (PVA) fiber-reinforced rubber concrete. *Constr. Build. Mater.* **2018**, *193*, 631–642. [[CrossRef](#)]
22. Khan, M.I.; Abbas, Y.M.; Fares, G. Review of high and ultrahigh performance cementitious composites incorporating various combinations of fibers and ultrafines. *J. King Saud Univ. Eng. Sci.* **2017**, *29*, 339–347. [[CrossRef](#)]
23. Xu, C.D.; Yao, Z.P.; Li, Z.; Zhu, X.L.; Wang, M.Y.; Wang, Y. Durability evaluation model and application of concrete structure based on fuzzy analytic hierarchy process. *Hydropower Energ. Sci.* **2019**, *37*, 95–99.
24. Lai, Y.C.; Liu, D.W.; Huang, L.J. Durability evaluation of machine-made sand concrete structure based on cloud model. *Silicate Bull.* **2019**, *38*, 3305–3308.
25. Jin, W.L.; Zhao, Y.X. *Durability of Concrete Structure*; Science Press: Beijing, China, 2014; pp. 299–320.
26. Parichatprecha, R.; Nimityongskul, P. Analysis of durability of high performance concrete using artificial neural networks. *Constr. Build. Mater.* **2009**, *23*, 910–917. [[CrossRef](#)]
27. Zhang, H. Durability reliability analysis for corroding concrete structures under uncertainty. *Mech. Syst. Signal. Process.* **2018**, *101*, 26–37. [[CrossRef](#)]
28. Zhou, X.L.; Yuan, Y.C.; Chen, L. Durability evaluation of in-service concrete structure based on grey correlation degree. *J. Wuhan Univ. Eng.* **2017**, *39*, 169–174.
29. Yu, B.; Ning, C.L.; Li, B. Probabilistic durability assessment of concrete structures in marine environments: Reliability and sensitivity analysis. *China Ocean Eng.* **2017**, *31*, 63–73. [[CrossRef](#)]
30. Jang, J.S.R.; Sun, C.T.; Mizutani, E. Neuro-fuzzy and soft computing, a computational approach to learning and machine intelligence. *Automat. Contr.* **1997**, *42*, 1482–1484. [[CrossRef](#)]
31. Yazdanbakhsh, O.; Dick, S. A systematic review of complex fuzzy sets and logic. *Fuzzy. Set. Syst.* **2018**, *338*, 1–22. [[CrossRef](#)]
32. Xu, X.Z.; Cao, D.; Zhou, Y.; Gao, J. Application of neural network algorithm in fault diagnosis of mechanical intelligence. *Mech. Syst. Signal. Pr.* **2020**, *141*, 106625. [[CrossRef](#)]

33. Boulkaibet, I.; Belarbi, K.; Bououden, S.; Chadli, M.; Marwala, T. An adaptive fuzzy predictive control of nonlinear processes based on Multi-Kernel least squares support vector regression. *Appl. Soft. Comput.* **2018**, *73*, 572–590. [[CrossRef](#)]
34. Di, W.; Xu, X.; Zhang, Z.C. Application of adaptive neural fuzzy inference system in bridge state assessment. *J. Zhejiang Univ. (Eng. Edit.)* **2008**, *42*, 2016–2022.
35. Jie, M.; Niu, H.Y.; Qi, D.Y. Application of adaptive neuro fuzzy inference system in traffic pollutant concentration prediction. *Fuzzy Syst. Math.* **2019**, *33*, 144–152.
36. Wang, Y.L.; Ma, G.; You, H.H. Carbon content modeling of pulverized coal boiler fly ash based on adaptive neural fuzzy inference system. *Therm. Power Gener.* **2018**, *47*, 27–31.
37. Guo, H.W.; Dong, H.Y. Wind speed prediction based on fuzzy neural network. *Electr. Drive Autom.* **2012**, *34*, 1–13.
38. Hou, T. Application of T-S fuzzy neural network in surface water quality assessment of Sanchuan River. *Energ. Energ. Sav.* **2011**, *6*, 54–56.
39. Xu, J.Y.; Pan, X.Y.; Li, S.; Chen, Y. Research and development of bridge underwater structure state assessment system based on ANFIS. *Technol. Highw. Transp.* **2016**, *5*, 73–78. (In Chinese) [[CrossRef](#)]
40. Wang, F.L.; Zhou, Q.; Zhu, F. Prediction of compressive strength of concrete hollow block masonry based on ANFIS. *J. Wuhan Univ. Eng. Edit.* **2015**, *3*, 324–326.
41. *Concrete Durability Inspection and Evaluation Standard*; JG/J 193-2009; National Standard of the People's Republic of China: Shenzhen, China, 2009.
42. GB/T 50746-2008. Code for durability design of concrete. National Standard of the People's Republic of China. In Proceedings of the International Conference on Durability of Concrete Structures, Hangzhou, China, 26 November 2008.
43. *Test Method for Chloride Diffusion Coefficient of Cement*; JC/T 1086-2008; National Standard of the People's Republic of China: Shenzhen, China, 2008.
44. Poston, R.W.; Rabbat, B.G. *ACI 318-14. Building Code Requirements for Structural Concrete and Commentary*; ACI Committee 318; National Standard of the United States of America: Farmington Hills, MI, USA, 2014.
45. Jin, W.L.; Zhao, Y.X. Review and Prospect of research on durability of concrete structures. *J. Zhejiang Univ. Eng. Edit.* **2002**, *36*, 371–379.
46. Zuo, J.B. Prediction of Chloride Diffusion Coefficient of Fly Ash Concrete Based on Artificial Neural Network. Master's Thesis, Nanhua University, Chiayi County, Taiwan, 2012. (In Chinese).
47. Çakıt, E.; Olak, A.J.; Karwowski, W.; Marek, T.; Hejduk, I.; Taiar, R. Assessing safety at work using an adaptive neuro-fuzzy inference system (ANFIS) approach aided by partial least squares structural equation modeling (PLS-SEM). *Int. J. Ind. Ergon.* **2020**, *76*, 102925. [[CrossRef](#)]
48. Wang, J.S. Parameter optimization of ANFIS model based on particle swarm optimization. *J. Pet. Univ.* **2007**, *20*, 41–44.
49. Wei, Y.L. Topology optimization of wireless sensor network based on adaptive artificial immune network algorithm. *Elect. Meas. Techno.* **2020**, *43*, 85–88.
50. Bao, Z.S.; Wang, K.X.; Zhang, W.B. Practical Byzantine fault tolerant consensus algorithm based on tree topology network. *J. Appl. Sci.* **2020**, *38*, 35–49.
51. Zhang, Z.H.; Han, Z.; Xiao, S.X.; Chang, G.Z.; Gan, S.W. Real time prediction of traffic flow based on ANFIS and its realization in MATLAB. *J. Chongqing Jiaotong Univ.* **2007**, *26*, 112–115.
52. Seco, A.; Urmeneta, P.; Prieto, E.; Marcelino, S.; Miqueleiz, L. Estimated and real durability of unfired clay bricks: Determining factors and representativeness of the laboratory tests. *Constr. Build. Mater.* **2017**, *131*, 600–605. [[CrossRef](#)]
53. Pan, H.K.; Yang, Z.S.; Xu, F.W. Study on concrete structure's durability considering the interaction of multi-factors. *Constr. Build. Mater.* **2016**, *118*, 256–261. [[CrossRef](#)]
54. Srokosz, P.E.; Bagińska, M. Application of adaptive neuro-fuzzy inference system for numerical interpretation of soil torsional shear test results. *Adv. Eng. Softw.* **2020**, *143*, 102793. [[CrossRef](#)]
55. Rice, J.A. *Mathematical Statistics and Data Analysis*; Academic Press: Cambridge, MA, USA; Mechanical Industry Press: Beijing, China, 2014; pp. 228–248.
56. Dai, X.B. Study on Durability of Nano Particle and PVA Fiber Reinforced Cement-Based Composite. Master's Thesis, Zhengzhou University, Zhengzhou, China, 2017. (In Chinese).

57. Wu, X. Improvement of Fuzzy System and ANFIS and Its Application in Intelligent Selection of Machining Parameters. Master's Thesis, Jilin University, Changchun, China, 2007. (In Chinese).
58. Erdeljić, V.; Francetić, I.; Bošnjak, Z.; Budimir, A.; Likić, R. Distributed lags time series analysis versus linear correlation analysis (Pearson's  $r$ ) in identifying the relationship between antipseudomonal antibiotic consumption and the susceptibility of *Pseudomonas aeruginosa* isolates in a single Intensive Care Unit of a tertiary hospital. *Int. J. Antimicrob. Agents*. **2011**, *37*, 467–471.
59. Williams, L.L.; Quave, K. *Quantitative Anthropology*; Academic Press: Pittsburgh, PA, USA, 2019; pp. 105–114.
60. Ross, S.M. *Introductory Statistics*; Academic Press: Pittsburgh, PA, USA, 2017; pp. 489–518.



© 2020 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<http://creativecommons.org/licenses/by/4.0/>).