Article

Compressive Capacity Prediction of Stirrup-Confined Concrete Columns Using Neuro-Fuzzy System

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Abstract: The compressive capacity of the column is one of the key parameters in the design. The importance of such structural members and their performance under load conditions are very effective in the overall behavior of the structure, and its failure can lead to the collapse of the entire structure. Therefore, determining the capacity of columns is considered an important issue in structural problems. Thus, this article presents an applicable computational framework to predict the compression capacity of stirrups-confined concrete. A machine learning model based on neuro-fuzzy systems was considered to formulate the proposed model. For this purpose, some experimental datasets were gathered from the literature to tune the unknown parameters of the model and evaluate its accuracy. The target, the ratio of the ultimate axial capacity to bearing area, was predicted with consideration of the column properties, including the compressive strength of concrete, stirrups section area, dimension of the stirrups, and the column section. The results showed that the proposed framework could be used as an applicable technique to determine the compressive capacity of the stirrups-confined concrete columns.

Keywords: axial load; concrete column; compressive capacity; stirrup; neuro-fuzzy

1. Introduction

In building structures, the role of columns in the overall performance of the structure is very important. The failure of this element can lead to a great reduction in the strength and even collapse of the whole structure. Therefore, determining the capacity of the columns is one of the most important parameters considered in the design process. Reinforced Concrete (RC) columns, as an axial member, should be able to perform optimally against axial pressures and meet the designer's expectations. Researchers have conducted various laboratory and analytical investigations to understand the behavior of columns better and improve their performance. Dujmović et al. [1] studied the composite columns subjected to axial compressive and bending loads. They found that the design of such columns should be based on the combination of loads. The behavior of RC columns under axial compression loads was investigated by Jain et al. [2]. The proposed effective strengthening methods for the damaged columns concluded that the most efficient technique combines near-surface mounting and external bonding. Miao and Zheng [3] experimentally studied the effects of bond stress on the compressive behavior of RC columns and developed a formulation to estimate the bearing capacity [4–6].

Concrete core has a significant role in the compressive behavior of RC columns. Therefore, some researchers studied this part of columns and its improvements to increase the compressive capacity. Sunayana and Barai [7] studied the performance of RC columns under compression incorporated by recycled coarse aggregates and fly ash. Their results indicated that the load capacity of the columns with recycled aggregates was higher than

those made by natural aggregates. Tian et al. [8] tested some RC columns made of ultra-high performance concrete and investigated their axial behavior. The results showed that these columns provided more axial capacity. Moreover, a model was proposed to predict the axial capacity of composite columns. The compressive capacity of columns containing precast ultra-high performance concrete jackets has been evaluated by Zhang et al. [9]. They showed that sufficient confinement could improve the load bearing of the column. A prediction model was also provided to estimate the ultimate capacity. Zhang et al. [10] investigated the behavior of RC column transfer structures subjected to different axial loads. The results indicated that the load capacity of the columns is increased by the high value of the axial force ratio. Da et al. [11] studied the effect of corrosion on the axial compression behavior of RC columns made by coral aggregates under eccentric loads. Their results showed that the capacity of columns decreases as the eccentricity increases. They also developed a model to estimate the behavior of the considered types of columns. Vijaya et al. [12] experimentally evaluated the compressive behavior of RC columns having manufactured sands and found that the axial capacity of these types of columns was better than elements with only normal sands. Dong et al. [13] experimentally studied the effect of impact loads on the residual axial compression capacity of RC columns and proposed models to determine the capacity.

Due to the complex and non-linear behavior of concrete structural members, the use of more efficient methods than classical statistical techniques is expected. One such method is models based on machine learning (e.g., neural networks and neuro-fuzzy systems). The use of such techniques in determining the behavior of structural elements has been investigated in various studies. Mirrashid and Naderpour [14] have reviewed the applications of machine learning models to estimate the capacity of structural RC members like columns. Using the datasets, Chang and Zheng [15] developed a neural network model to determine the compressive strength of RC circular columns confined with stirrups. They found that their model could estimate the considered goal with an acceptable error. Naderpour and Mirrashid [16] proposed new formulations based on machine learning techniques to assess the moment capacity of RC columns. They used some experimental databases to prepare and evaluate the models. It was found that the machine learning approach is an efficient framework that can be successfully considered for estimating the structural columns. New models based on machine learning methods have been previously provided to predict the ultimate capacity of structural RC members [17]. For this purpose, the moment capacity has been used as a target for RC columns. Five techniques were considered using neural networks and fuzzy systems, and finally, the mathematical frameworks have been extracted from the proposed models. The provided computational formulations also were validated using an experimental database. Failure modes of RC columns are an important issue that can be predicted based on the machine learning approach [18] using the properties of the columns. The prediction of the moment capacity of spirally RC columns was another goal that machine learning techniques were used for in literature [19]. Li et al. [20] proposed a neural network model to predict RC columns' compression behavior with stirrups. They have validated their model and extracted a mathematical formulation from the model to make it more user-friendly.

2. Research Significance

Due to the importance of determining the compressive behavior in RC columns, several analytical and laboratory studies have been conducted on these elements. Most of the mentioned studies are based on providing calculation methods in the framework of statistical and regression techniques. When the system has complex behavior, using classical approaches cannot be a suitable solution. The reason for this is the presence of many influential parameters and non-linear behavior, which practically challenges the effectiveness of such methods. The use of machine learning methods is an alternative and suitable technique with acceptable accuracy, which has also been used to determine the performance of structural elements. Nevertheless, due to the structural complexities of the

machine learning models proposed in the references, presenting the computational relations derived from such models has been omitted in many cases. This reduces the capabilities of predictive models and their uses. Considering the ability of machine learning-based systems, this article used a neuro-fuzzy technique to estimate the compressive behavior of RC stirrups-confined columns. Moreover, to resolve the computational challenge of the model, a mathematical framework from the model was extracted, and relationships were provided. This increases the efficiency of the proposed model and makes it user-friendly.

3. Methodology

One of the most widely used models based on machine learning is Artificial Neural Networks (ANN). The performance of these methods has been evaluated in different sciences. Meanwhile, due to the complexity of the computational structure of such models, especially in cases where the number of nodes is large, extracting relationships from the network structure is not easily possible. However, its various branches and algorithms are still being improved due to the suitable performance of these methods. Today, ANN has a very special place in machine learning-based sciences. Fuzzy Systems (FS) are another approach to Soft Computing (SC), which are widely used in literature because of their ability to consider the uncertainties of the problem and the possibility of applying empirical rules to the problem. In a fuzzy system, each input variable is placed in some categories representing a linguistic expression. Each above type is called a fuzzy Membership Function (MF). For example, if three membership functions are considered for variable number one, each can represent a low, medium, and high value. In addition to the membership function, such systems have a set of fuzzy rules based on model reasoning and output determination. Both characteristics (membership functions and fuzzy rules) must be accurately specified when modeling a fuzzy system. Considering that determining these items is not easily possible and in cases where the model has a lot of complexity, including a large number of input variables, practically determining things such as the number of MF, the type and values of the parameters of each function, and system rules, is a challenge. To solve this problem, the learning ability of neural networks is used, and the determination of the above cases is left to the neural network.

The combination of ANN and FS as Neuro-Fuzzy systems may create a model with the advantages of the above two methods. In fact, in a neuro-fuzzy model, a fuzzy system is the implementation in the layered structure of the neural network. Here, using a set of data, the unknown parameters of the fuzzy model are estimated and verified by the neural network. One of the most famous techniques is Adaptive Neuro-Fuzzy Inference System (ANFIS), introduced by Jang [21]. The use of the ANFIS technique has been previously evaluated in order to determine the behavior of structures, and they have provided acceptable results [22,23]. Due to the advantages of neuro-fuzzy systems, in this article, the ANFIS is used to estimate the compressive behavior of stirrups in confined concrete columns. The details of the proposed ANFIS model and its relationships are presented in the following sections. An example of ANFIS can be seen in Figure 1 for a model with four inputs and three MF for each input.
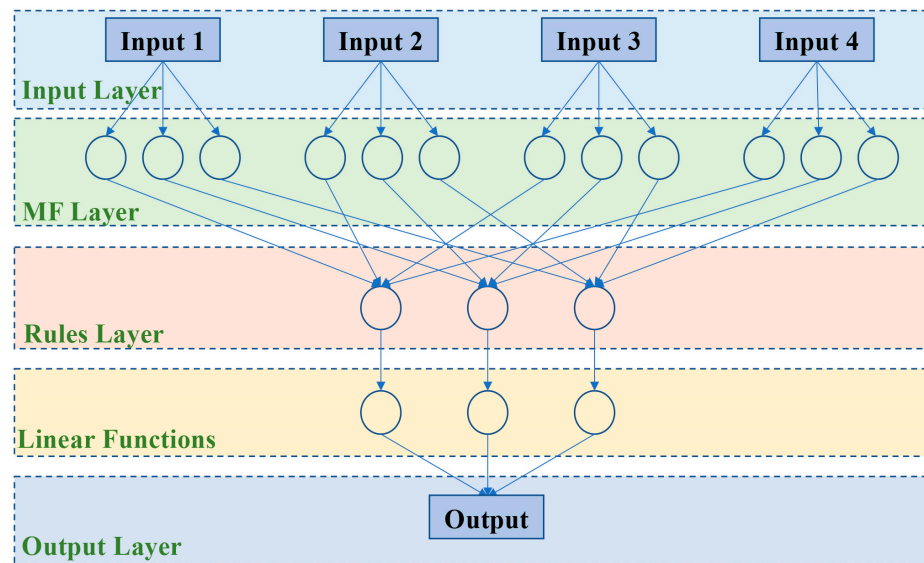
Figure 1. An example of the ANFIS model with four inputs and three membership functions for each input.

4. Database

In machine learning techniques, a set of data is needed. Based on this information, the model's unknown parameters are optimized and determined by learning algorithms. Considering that the approach used in this article is also a machine learning model, a set of laboratory results related to 180 column tests with different details (Figure 2) has been collected from literature [20,24–29]. Then, it is necessary to specify the input variables based on which the value of the target parameter is predicted. This work has been done with a trial and error approach. In total, six input parameters (Table 1), including the compressive strength of concrete, the ratio of the gross supporting area to the bearing plate area, the ratio of the area confined by stirrups to the bearing plate area, the ratio of the duct diameter to the section width, the yield strength of stirrups, and the volumetric ratio of stirrups, are used to determine the output parameter, which is the ratio of axial compressive capacity to the net area of bearing plate minus the duct area, in this article.
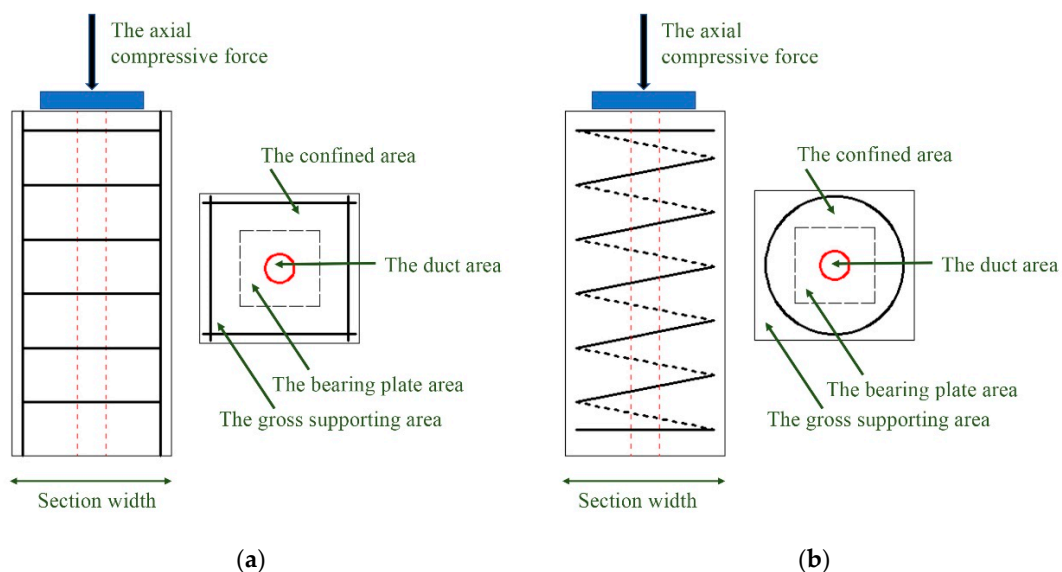
Figure 2. The RC columns considered in this research (adapted from [20]): (**a**) Confined columns with ties; (**b**) Confined columns with spirals.

Table 1. Definition of the variables in this research.

Variable	Role	Description	Unit
X_1	Input 1	The compressive strength of concrete	MPa
X_2	Input 2	The ratio of the gross supporting area to the bearing plate area	-
X_3	Input 3	The ratio of the area confined by stirrups to the bearing plate area	-
X_4	Input 4	The ratio of the duct diameter to the section width	-
X_5	Input 5	The yield strength of stirrups	MPa
X_6	Input 6	The volumetric ratio of stirrups	%
Y	Output	The ratio of axial compressive capacity to the net area of the bearing plate minus the duct area	MPa

From the set of 180 collected data, 85% of the datasets (153 data) were randomly selected and used for the model training process. The remaining 15 percent (including 27 data) has been used to evaluate the accuracy of the model. Table 2 and Figures 3–5 show the details of training and testing data. Another one of the most important pre-processing tasks performed on the data is normalization. By doing this, the range of data is kept in a fixed and small range, which increases the accuracy of the model in prediction. In this article, the range of 0.1 to 0.9 is used to normalize the data using Equation (1).

$$X_{i,n} = 0.8 \frac{X_i - X_{i,min}}{X_{i,max} - X_{i,min}} + 0.1 \tag{1}$$
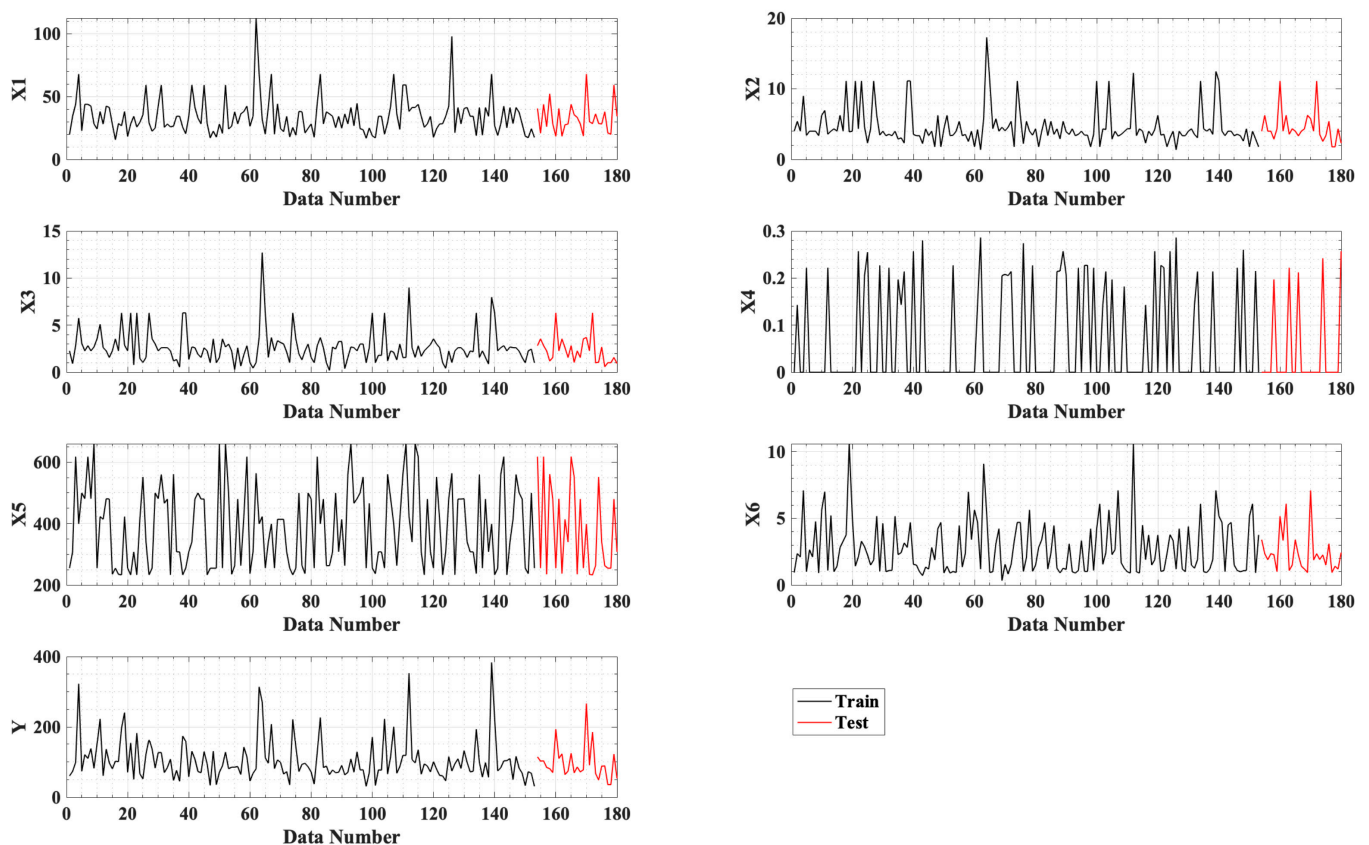
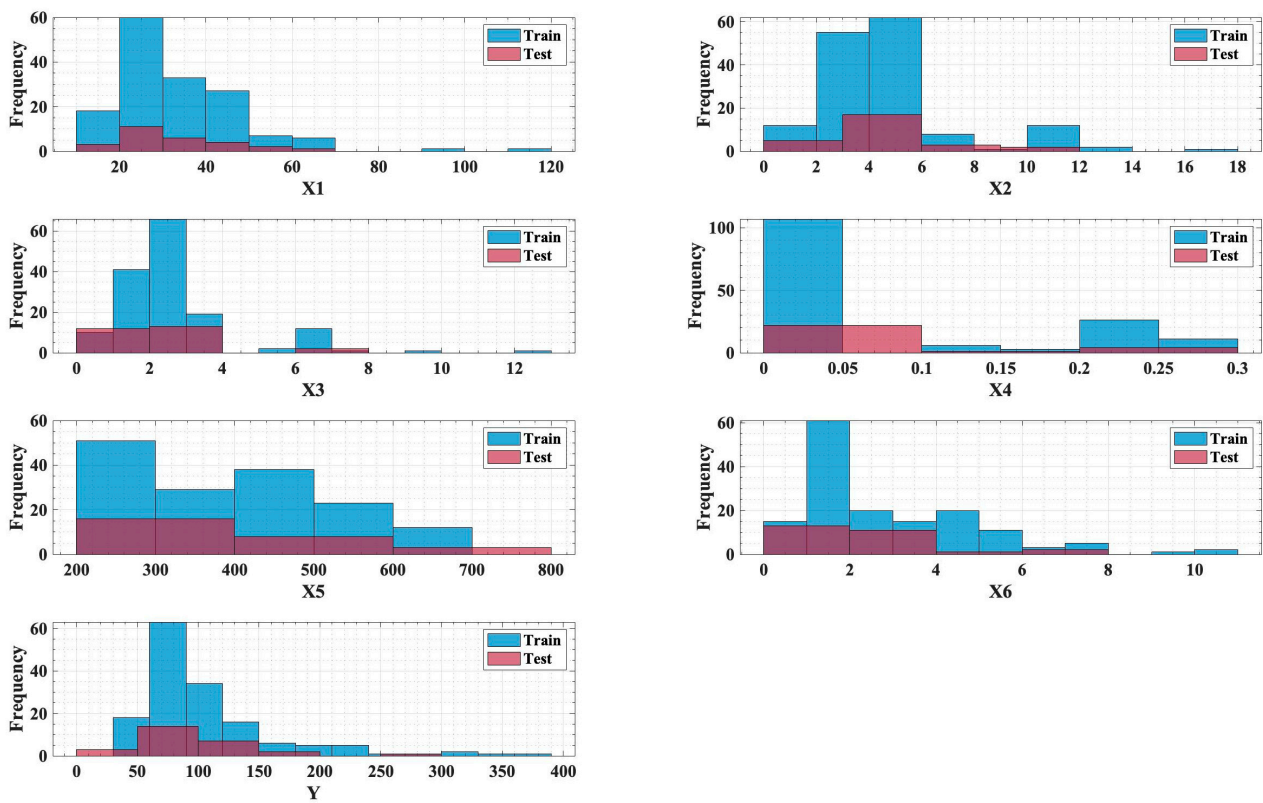**Figure 3.** The values of the variables for each dataset.
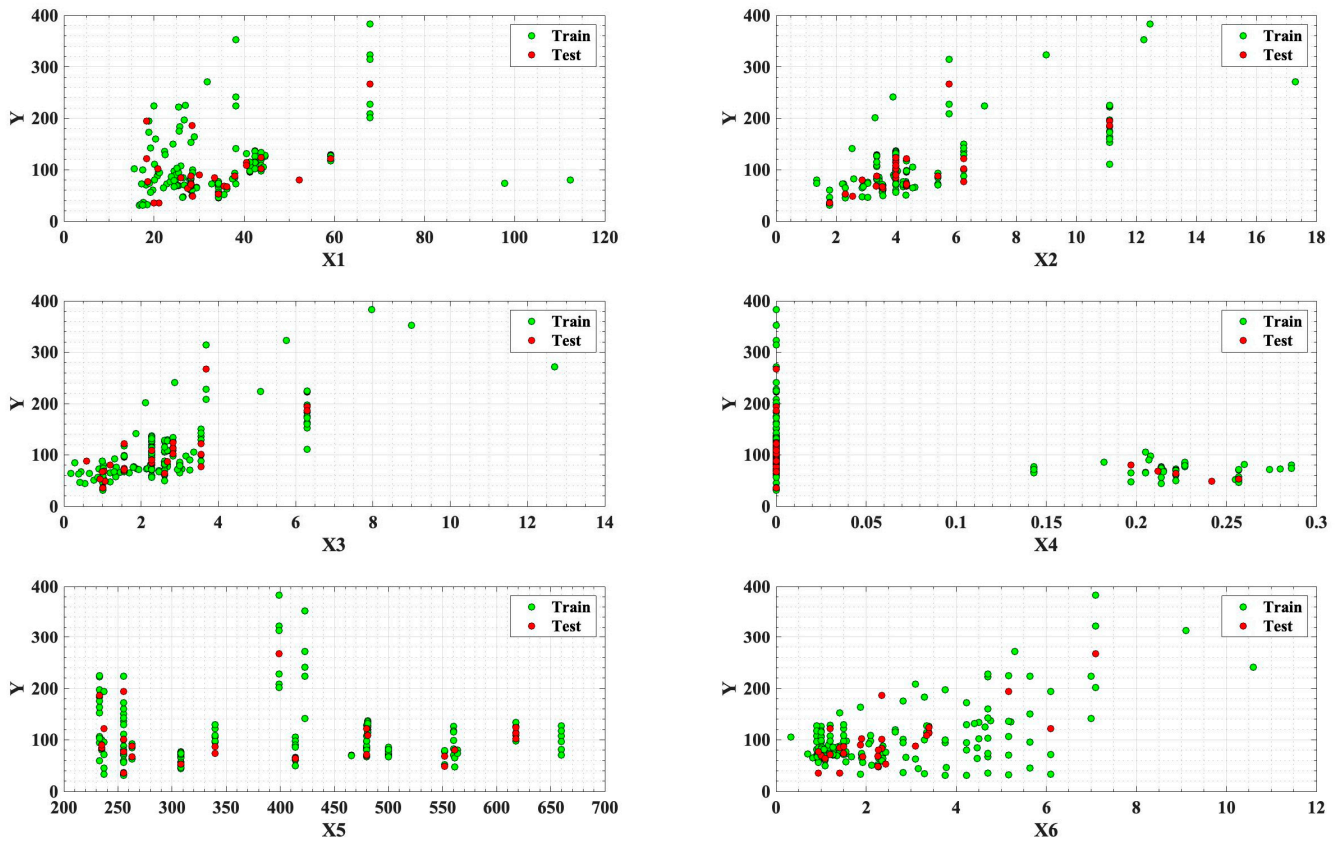
Figure 4. The histogram of the database.

**Figure 5.** The distribution of the training and testing datasets.

Table 2. Statistical information of the considered database.

				Train Data			
Variable	X_1	X_2	X_3	X_4	X_5	X_6	**Y**
Unit	**MPa**	**-**	**-**	**-**	**MPa**	**%**	**MPa**
Minimum	15.60	1.36	0.18	0.00	233.00	0.33	30.67
Maximum	112.30	17.29	12.70	0.29	660.00	10.60	383.39
Median	29.45	4.00	2.27	0.00	399.00	1.99	86.98
St. Dev	14.68	2.64	1.77	0.10	131.07	2.05	60.53
				Test Data			
Variable	X_1	X_2	X_3	X_4	X_5	X_6	**Y**
Unit	**MPa**	**-**	**-**	**-**	**MPa**	**%**	**MPa**
Minimum	17.50	1.78	0.59	0.00	233.00	0.94	31.11
Maximum	67.90	11.11	6.30	0.26	618.00	7.10	266.88
Median	28.55	4.00	2.27	0.00	324.00	2.26	84.50
St. Dev	12.49	2.27	1.46	0.09	141.06	1.54	51.17
				Whole Data			
Variable	X_1	X_2	X_3	X_4	X_5	X_6	**Y**
Unit	**MPa**	**-**	**-**	**-**	**MPa**	**%**	**MPa**
Minimum	15.60	1.36	0.18	0.00	233.00	0.33	30.67
Maximum	112.30	17.29	12.70	0.29	660.00	10.60	383.39
Median	29.20	4.00	2.27	0.00	399.00	2.08	86.32
St. Dev	14.34	2.58	1.73	0.10	132.39	1.97	59.17

St. Dev is the standard deviation.

5. The Proposed ANFIS Model

Using the considered experimental database, the training process of the ANFIS model was done. In order to create the proposed system, a fuzzy c-means algorithm has been used. Based on this, it was determined that the model with eight rules had shown the best performance (Figure 6). The details of the rules are shown in Table 3. In this table, for example, $MF_{3,4}$ means the third membership function of the X_4.
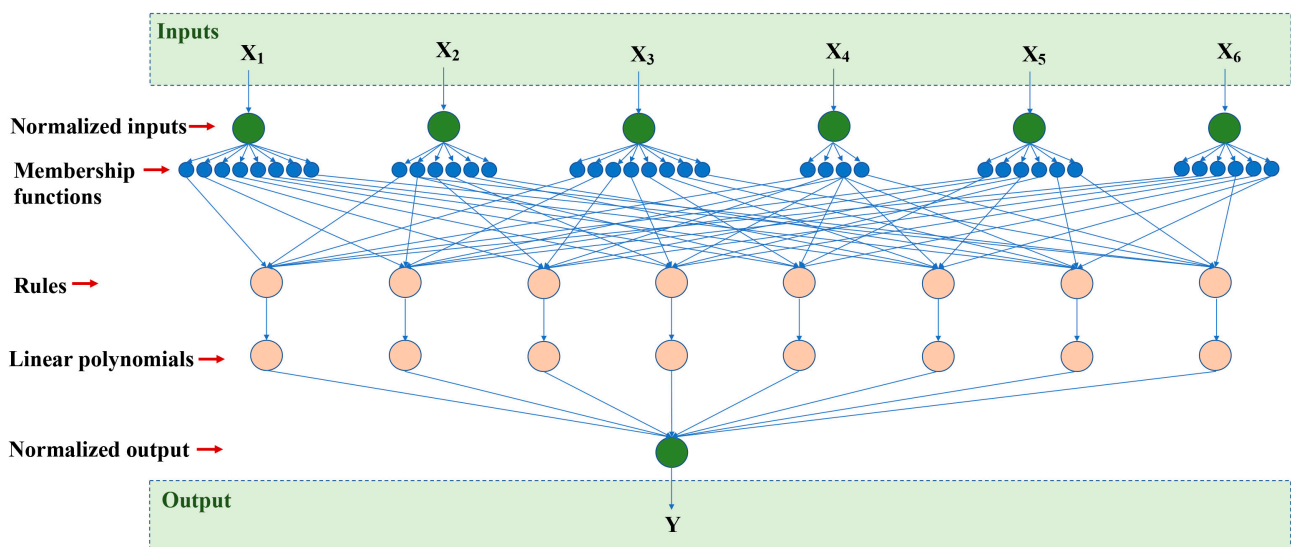

Figure 6. The architecture of the proposed ANFIS.

Table 3. The details of the rules.

Number	The Rule
Rule 1	If X_1 is $MF_{1,1}$ and X_2 is $MF_{1,2}$ and X_3 is $MF_{1,3}$ and X_4 is $MF_{1,4}$ and X_5 is $MF_{1,5}$ and X_6 is $MF_{1,6}$, then Y is Y_1
Rule 2	If X_1 is $MF_{2,1}$ and X_2 is $MF_{2,2}$ and X_3 is $MF_{2,3}$ and X_4 is $MF_{3,4}$ and X_5 is $MF_{2,5}$ and X_6 is $MF_{2,6}$, then Y is Y_2
Rule 3	If X_1 is $MF_{3,1}$ and X_2 is $MF_{3,2}$ and X_3 is $MF_{3,3}$ and X_4 is $MF_{2,4}$ and X_5 is $MF_{3,5}$ and X_6 is $MF_{3,6}$, then Y is Y_3
Rule 4	If X_1 is $MF_{4,1}$ and X_2 is $MF_{4,2}$ and X_3 is $MF_{4,3}$ and X_4 is $MF_{3,4}$ and X_5 is $MF_{4,5}$ and X_6 is $MF_{4,6}$, then Y is Y_4
Rule 5	If X_1 is $MF_{5,1}$ and X_2 is $MF_{2,2}$ and X_3 is $MF_{5,3}$ and X_4 is $MF_{3,4}$ and X_5 is $MF_{1,5}$ and X_6 is $MF_{5,6}$, then Y is Y_5
Rule 6	If X_1 is $MF_{6,1}$ and X_2 is $MF_{5,2}$ and X_3 is $MF_{6,3}$ and X_4 is $MF_{3,4}$ and X_5 is $MF_{3,5}$ and X_6 is $MF_{6,6}$, then Y is Y_6
Rule 7	If X_1 is $MF_{7,1}$ and X_2 is $MF_{6,2}$ and X_3 is $MF_{7,3}$ and X_4 is $MF_{3,4}$ and X_5 is $MF_{5,5}$ and X_6 is $MF_{6,6}$, then Y is Y_7
Rule 8	If X_1 is $MF_{8,1}$ and X_2 is $MF_{2,2}$ and X_3 is $MF_{8,3}$ and X_4 is $MF_{4,4}$ and X_5 is $MF_{6,5}$ and X_6 is $MF_{4,6}$, then Y is Y_8

The proposed model uses the sigmoid membership function for each input variable. Additionally, for each of the inputs X_1 to X_6, a number of 8, 6, 8, 4, 6, and 6 Gaussian membership functions have been used, respectively. These functions can be found in Figure 7. The details of the parameters (mean and variance) of these functions determined from the learning process of the ANFIS model based on 153 datasets are also shown in Table 4.
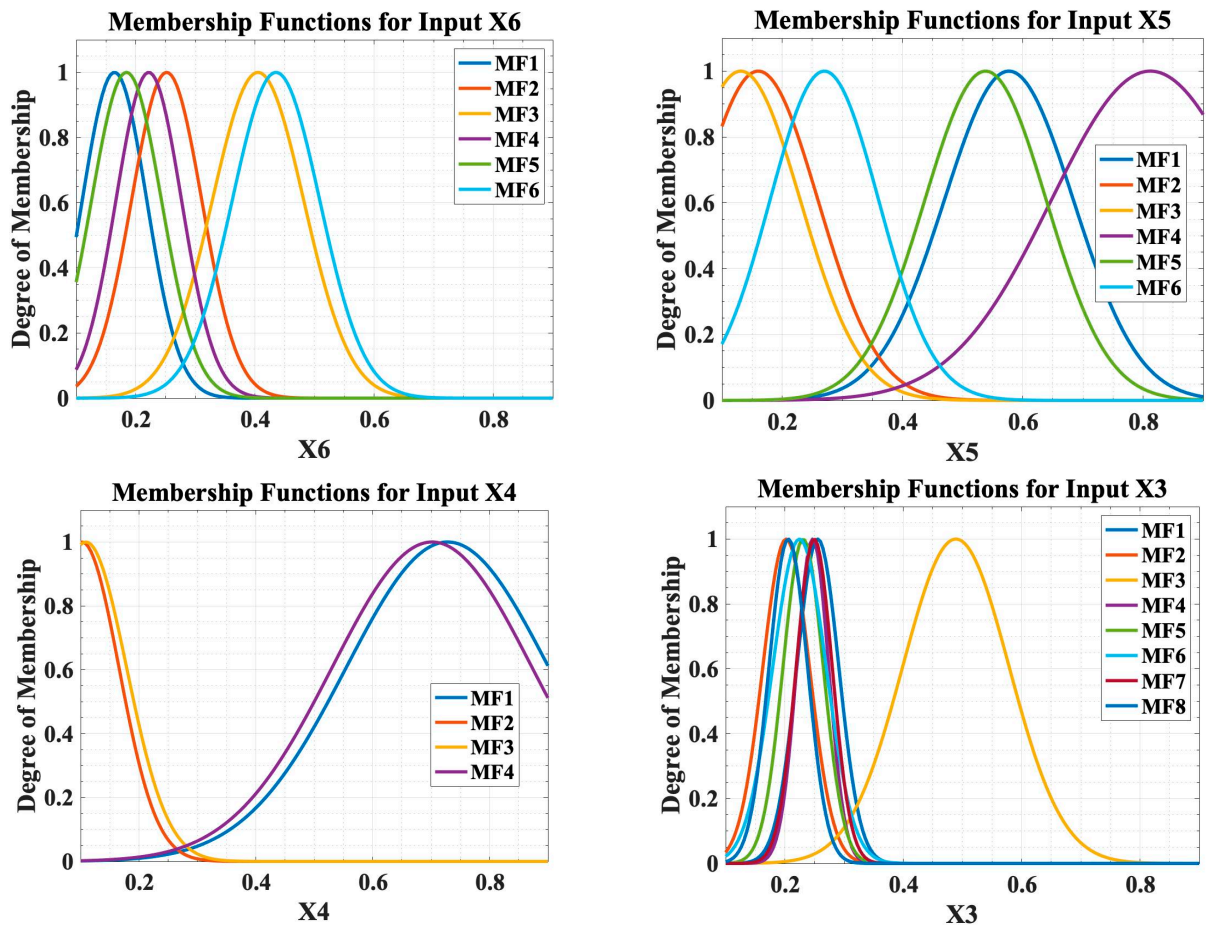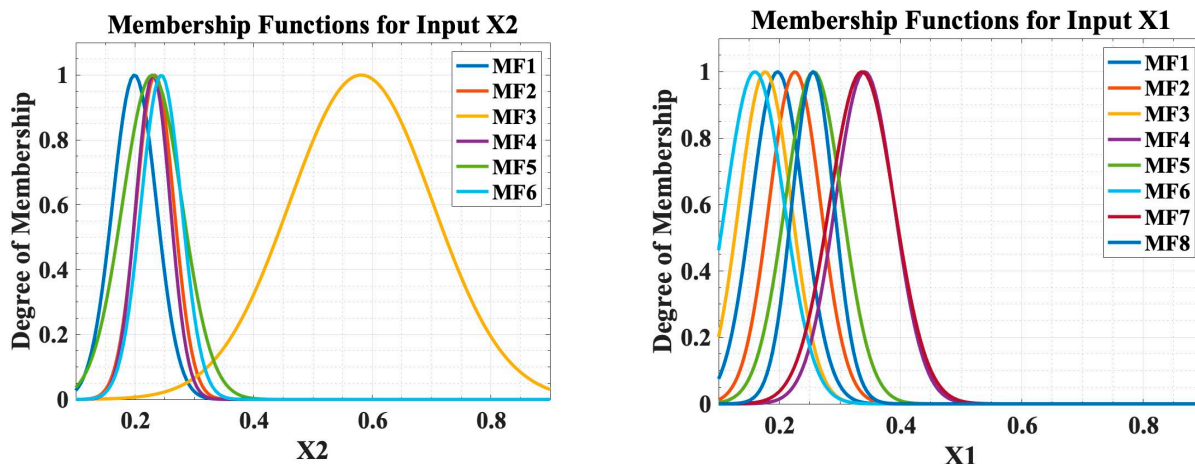

Figure 7. *Cont.*

Figure 7. Membership functions of the input variables.

Table 4. The parameters of the membership functions.

Variable	Parameter	MF 1	MF 2	MF 3	MF 4	MF 5	MF 6	MF 7	MF 8
X_1	Variance	0.043	0.042	0.043	0.048	0.047	0.048	0.053	0.035
	Mean	0.197	0.223	0.177	0.341	0.257	0.160	0.336	0.256
X_2	Variance	0.037	0.032	0.121	0.029	0.050	0.034	-	-
	Mean	0.199	0.234	0.581	0.230	0.229	0.244	-	-
X_3	Variance	0.035	0.039	0.090	0.027	0.034	0.045	0.030	0.033
	Mean	0.256	0.202	0.489	0.247	0.231	0.225	0.250	0.206
X_4	Variance	0.174	0.064	0.070	0.171	-	-	-	-
	Mean	0.728	0.102	0.109	0.702	-	-	-	-
X_5	Variance	0.108	0.100	0.099	0.165	0.101	0.091	-	-
	Mean	0.577	0.160	0.131	0.812	0.538	0.270	-	-
X_6	Variance	0.054	0.059	0.077	0.055	0.059	0.074	-	-
	Mean	0.164	0.252	0.405	0.222	0.184	0.435	-	-

The first step in determining the target variable by the proposed model is to calculate the weight of each rule using Equation (2). The parameters $n_{MF,i}$, m, v, W_r in this equation represents the number of membership functions for the *i*th input, mean, and variance of the membership function, and the weight of the *r*th rule.

$$W_r = \prod_{j=1}^{6} exp\left(\frac{-\left(X_j - m_{j,i}\right)}{2\left(v_{j,i}\right)^2}\right) \quad i = 1, \ldots, n_{MF,i} \tag{2}$$

Based on the mentioned equation, the weights of each rule can be found by Equations (3)–(10) for rules 1 to 8, respectively.

$$W_1 = MF_{1,1}\ MF_{1,2}\ MF_{1,3}\ MF_{1,4}\ MF_{1,5}\ MF_{1,6} \tag{3}$$

$$W_2 = MF_{2,1}\ MF_{2,2}\ MF_{2,3}\ MF_{3,4}\ MF_{2,5}\ MF_{2,6} \tag{4}$$

$$W_3 = MF_{3,1}\ MF_{3,2}\ MF_{3,3}\ MF_{2,4}\ MF_{3,5}\ MF_{3,6} \tag{5}$$

$$W_4 = MF_{4,1}\ MF_{4,2}\ MF_{4,3}\ MF_{3,4}\ MF_{4,5}\ MF_{4,6} \tag{6}$$

$$W_5 = MF_{5,1}\ MF_{2,2}\ MF_{5,3}\ MF_{3,4}\ MF_{1,5}\ MF_{5,6} \tag{7}$$

$$W_6 = MF_{6,1}\ MF_{5,2}\ MF_{6,3}\ MF_{3,4}\ MF_{3,5}\ MF_{6,6} \tag{8}$$

$$W_7 = MF_{7,1}\ MF_{6,2}\ MF_{7,3}\ MF_{3,4}\ MF_{5,5}\ MF_{6,6} \tag{9}$$

$$W_8 = MF_{8,1}\ MF_{2,2}\ MF_{8,3}\ MF_{4,4}\ MF_{6,5}\ MF_{4,6} \tag{10}$$

After calculating the weight of each of the eight fuzzy rules of the ANFIS model, it is necessary to determine the amount of linear functions in the ANFIS structure. In the model presented in this article, for the output part of each rule, there is a linear polynomial (Y_r) in the form of Equation (11). In addition to the mean and variance of the membership functions, the coefficients of linear polynomials are also determined in the training process of the ANFIS. These coefficients are presented in Table 5.

$$Y_r = c_{1,r}X_1 + \cdots + c_{6,r}X_6 + c_{0,r} \qquad r = 1, \ldots, 8 \qquad (11)$$

Table 5. The parameters of linear functions.

Linear Polynomial	C_1	C_2	C_3	C_4	C_5	C_6	C_0
Y_1	0.091	−0.686	1.183	0.007	−0.009	0.537	−0.075
Y_2	0.606	0.344	0.757	−0.035	−0.130	0.112	−0.166
Y_3	0.910	0.152	0.372	−0.015	−0.327	0.570	−0.152
Y_4	0.340	−1.496	−0.754	0.056	0.025	0.480	0.560
Y_5	0.623	−0.383	0.199	0.004	0.027	0.374	0.039
Y_6	0.516	0.422	0.615	−0.070	−0.704	−0.092	0.040
Y_7	0.346	0.980	0.413	0.004	−0.191	0.490	−0.208
Y_8	12.348	0.147	0.331	−0.109	2.446	0.049	−3.589

Using the values obtained for the weights and polynomials, the final output value of ANFIS, Y_n, is determined by Equation (12).

$$0.1 \leq (Y_n = \frac{\sum_{r=1}^{8} W_r Y_r}{\sum_{r=1}^{8} W_r}) \leq 0.9 \qquad (12)$$

Since the data values are normalized before modeling, the obtained output value is also normalized (between 0.1 and 0.9). Therefore, it is necessary to calculate the final value of the ANFIS model by inverting Equation (1). This is done by Equation (13).

$$Y\ (MPa) = 440.9\ Y_n - 13.42 \qquad (13)$$

6. Performance of the Model

In this section, the performance of the obtained model is evaluated. As mentioned earlier, the first data series is used in the training phase of the model. In the training phase, these data, which are the results related to 153 column laboratory tests, have been used to estimate the error in each iteration and improve the performance in the subsequent iterations. The results of the training phase can be seen in Figure 8 for the whole training dataset. As seen in Figure 8, the training phase was done well, and the final model had a very high accuracy in estimating the output values, so there is a very small difference between the values predicted by ANFIS and the laboratory. The Root Mean Squared Error (RMSE) value for the results of this part of modeling for the normalized training dataset is reported to equal 0.0143.
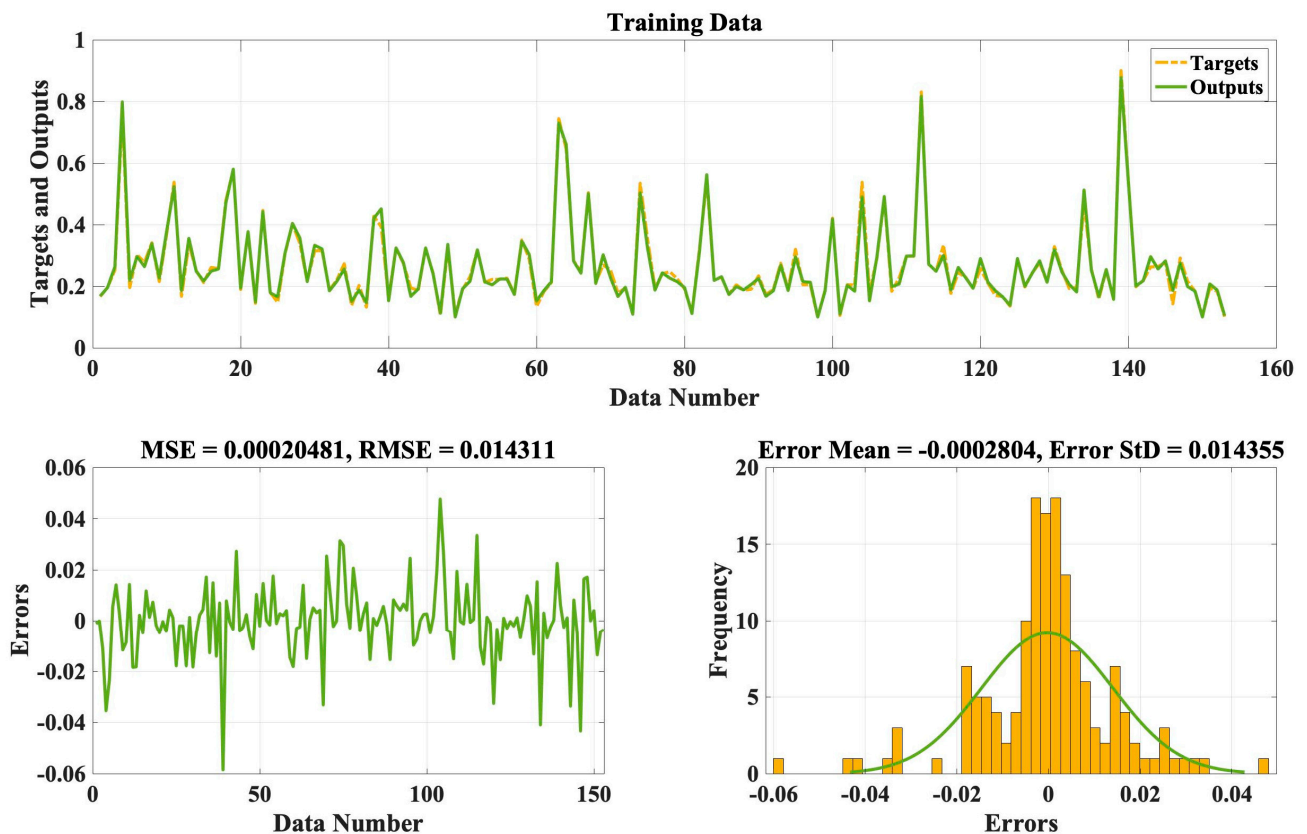
Figure 8. Results of the training data based on normalized values.

Despite the success of the training process, it is necessary to evaluate the model's performance for new data that have not been used in training and to validate the model's accuracy. This task has been done using the test data sets (27 data). By applying this data series to the trained model, the model's calculated error values and ability to estimate the target output value have been checked. The results are depicted in Figure 9.

The RMSE value for the normalized test data sets at this stage was 0.021, which is acceptable. Additionally, compared to the results obtained from the laboratory, the values determined by ANFIS have very little difference. Therefore, it can be concluded that the proposed model and the formulation extracted from it have sufficient reliability and accuracy. The regression plots for the two mentioned phases (train and test) can be seen in Figure 10 for the normalized database. It is clear from the figure that the ANFIS has good agreement with the experimental tests.

As stated in the previous section, the values obtained from ANFIS are normalized (between 0.1 and 0.9), and converting them into real values is necessary. To this end, Equation (13) was presented. Using this equation, the values obtained from the extracted formulation of the ANFIS model were converted into real values, the results of which are depicted in Figure 11. Based on this figure, the average error of the model is equal to 0.283. To determine this value, the difference between the amounts of the laboratory and the ANFIS has been determined and used as an error. The RMSE value of the model for the entire database is 6.834. The histogram of errors also indicates that in most of the data, the errors are close to zero. According to the findings of this section, it can be concluded that the proposed model has a high ability to estimate the target parameter (the ratio of axial compressive capacity to the net area of the bearing plate minus the duct area).
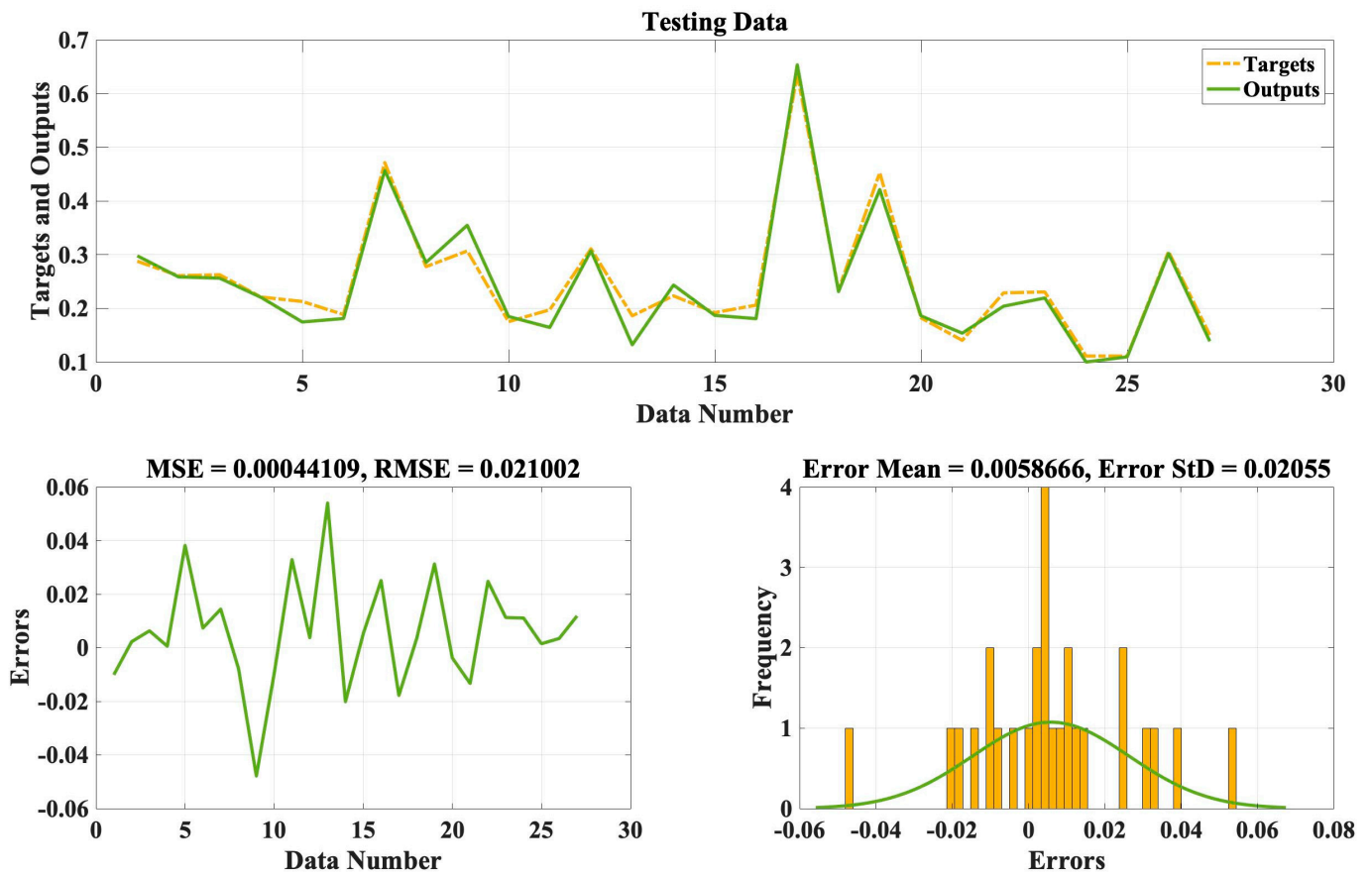
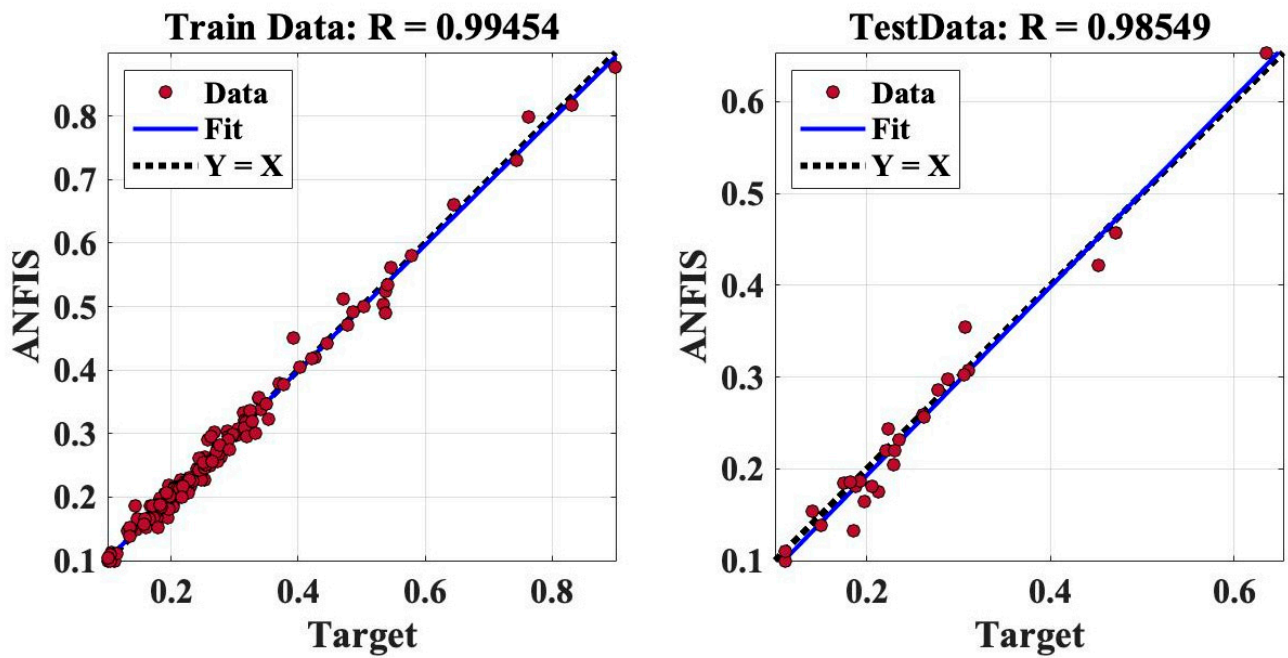**Figure 9.** Results of the testing data based on normalized values.

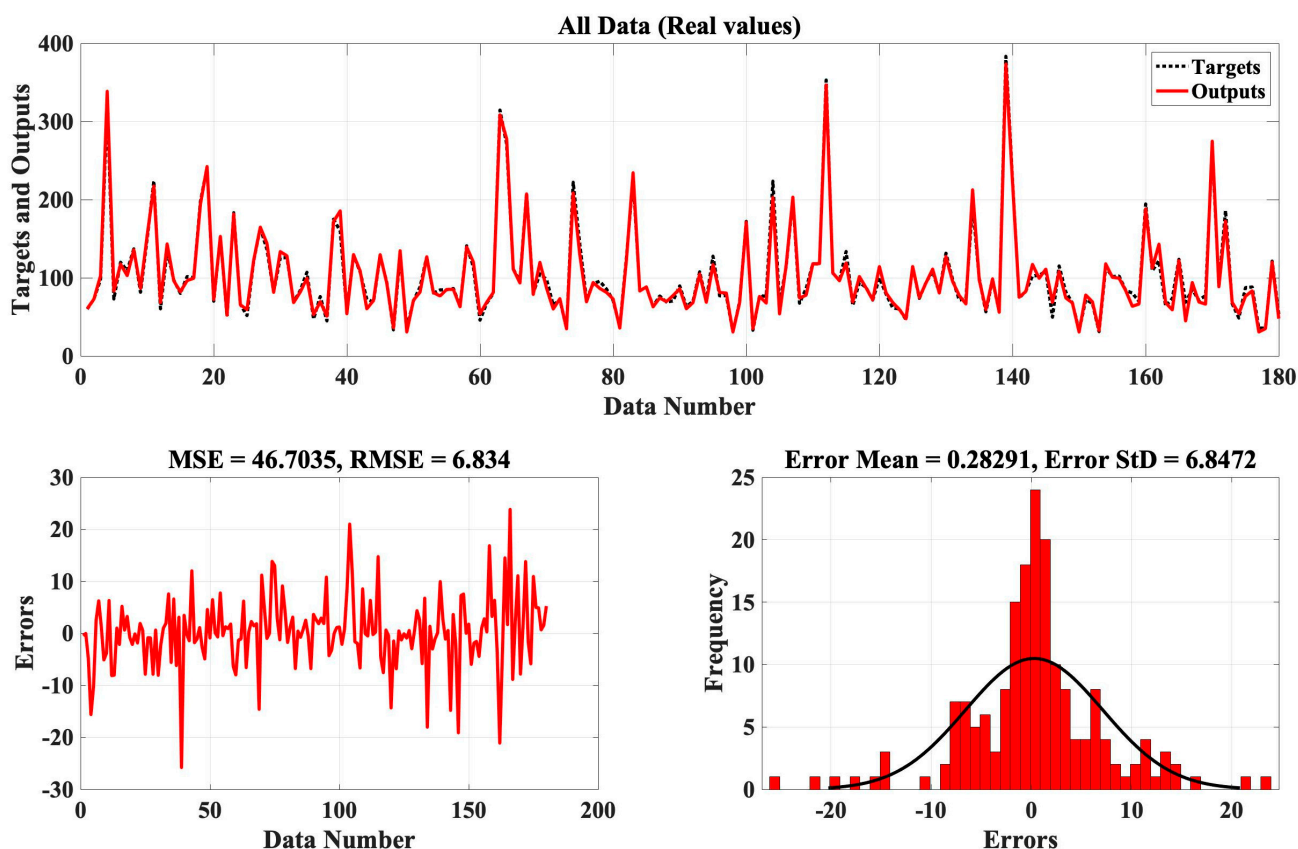**Figure 10.** Regression plots for the training and testing datasets.

Figure 11. Results of the whole database.

7. Sensitivity Analysis

In this section, the sensitivity of the proposed model to the changes in each of the six input variables is examined and evaluated. To do this, six databases containing 20 data were created. In each of the six databases, five input variables have a fixed value (the median value presented in Table 2), and only one of the variables is changed between its minimum and maximum (see Table 2). The output value has been calculated by applying these data to the ANFIS model. The results can be seen in Figure 12.

In Figure 12, the output of the model is shown vs. the variable whose value has been changed. According to the results obtained from the above analysis, it is clear that by increasing the X_1 (the compressive strength of concrete), X_3 (the ratio of the area confined by stirrups to the bearing plate area), and X_6 (the volumetric ratio of stirrups), the output parameter of the model also increases so that there is an almost linear and direct relationship between the input and output variables. In the case of the variable X_4 (the ratio of the duct diameter to the section width), the situation is different, so its increase leads to a decrease in the ANFIS results. Regarding the two variables, X_5 (the yield strength of stirrups) and X_2 (the ratio of the gross supporting area to the bearing plate area), the results show that their changes can decrease or increase the output (the ratio of axial compressive capacity to the net area of bearing plate minus the duct area) of the model, depends on the amount of the input. For example, when the compressive strength of the column increases, the ratio of axial compressive capacity to the net area of the bearing plate minus the duct area also increases. The same results can be seen for the ratio of the area confined by stirrups to the bearing plate area and the volumetric ratio of stirrups, in most cases. The results of the sensitivity analysis also indicated that when the ratio of the duct diameter to the section width increases, the output of the model decreases.
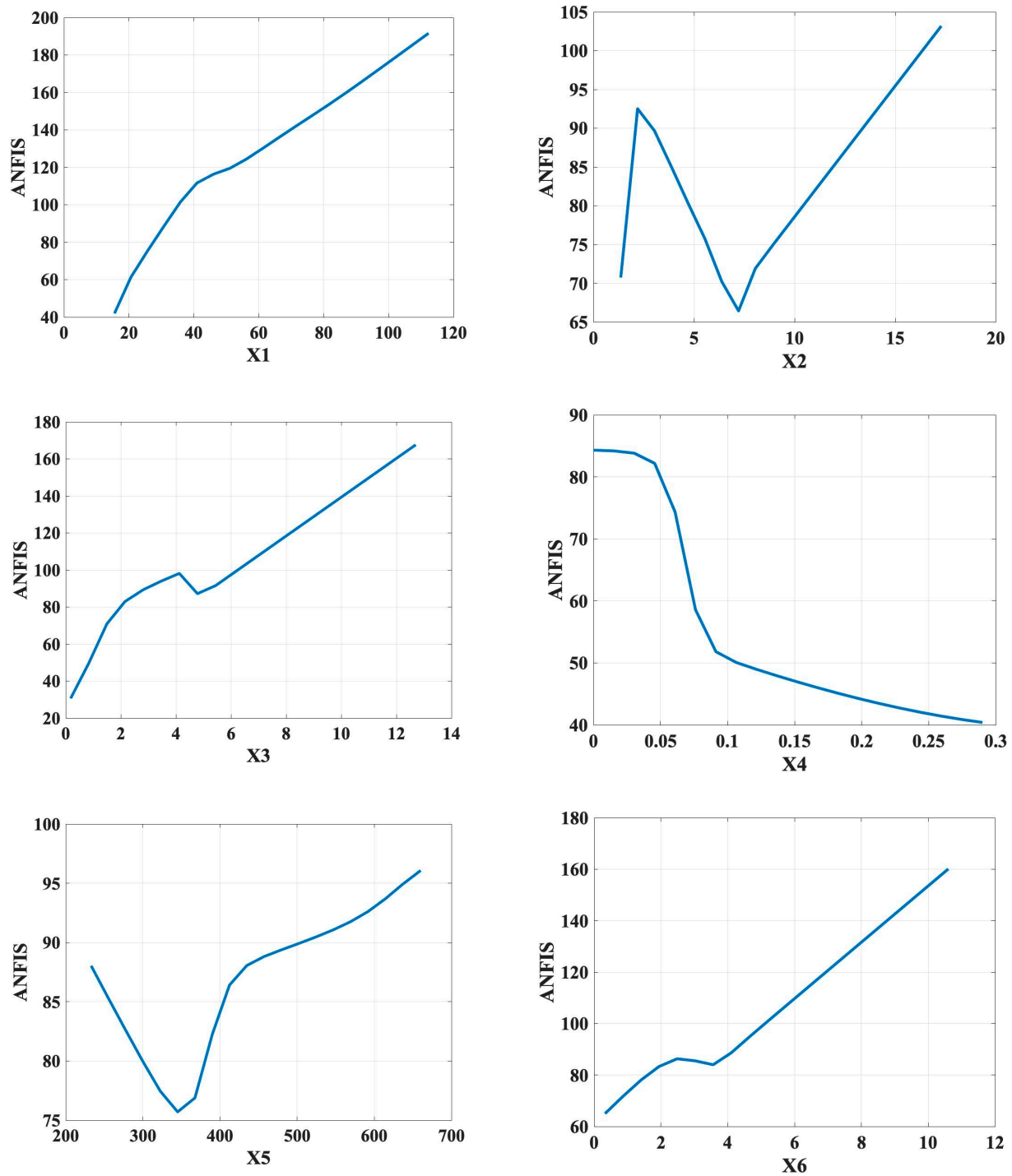
Figure 12. Results of the sensitivity analysis.

8. Comparison Study

In this section, the performance of the relationships proposed in this research, which is also shown for the entire data in Figure 13, is compared with the existing models GB/T 50010-2010 [30], Breen et al. [25], Bonetti [27], and Li et al. [20]. For this purpose, three statistics parameters, including Error mean (Er), determination coefficient (R^2), and RMSE, have been used. The results are presented in Table 6.

(**a**)

(**b**)
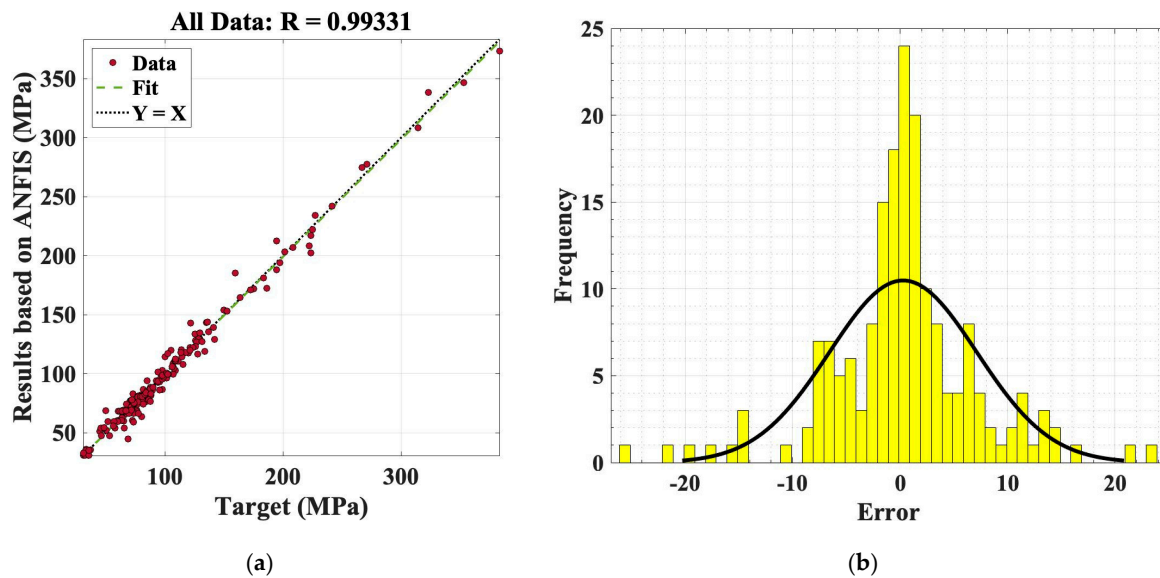
Figure 13. Final results of the proposed formulation based on ANFIS: (**a**) Regression plot for the experimental results vs. ANFIS; (**b**) Error-values obtained from the model.

Table 6. The comparison results.

Parameter	Li et al. [20]	Bonetti [27]	GB/T 50010-2010 [30]	Breen et al. [25]	ANFIS
Er	1.077	0.866	0.979	0.891	0.283
R^2	0.864	0.749	0.816	0.802	0.987
RMSE	21.91	29.72	25.40	26.38	6.83

The minimum of the average error value Er for the other models is equal to 0.866. However, the ANFIS average error was obtained as 0.283, much lower than the error of the other models. For the ANFIS value of 0.99331 for the correlation coefficient (R), the determination coefficient (R^2) is 0.987, which shows the closeness of the laboratory values to the predicted results; the highest value was related to the formulation of this article, which is very close to 1. Regarding the RMSE error, the best value is observed in the ANFIS model. According to the results obtained in this section, it can be seen that the best performance among all models is for ANFIS. Therefore, it can be used as a suitable tool to estimate the target variable, which is the axial compressive capacity ratio to the bearing plate's net area minus the duct area.

9. Conclusions

Most of the analytical and laboratory studies have been conducted based on calculation methods in the literature framework of statistical and regression techniques. However, when the system has non-linear behavior and many influential parameters, using classical approaches cannot be a suitable solution. Although the use of machine learning methods has been previously used to determine the performance of structural elements as an alternative method, presenting the computational relations derived from such models has been neglected in many cases. The main reason for this is the structural complexities of the machine learning models. This article presented a neuro-fuzzy model, namely ANFIS, to predict the target variable. The proposed model has been adjusted and evaluated based on laboratory data. The results showed that the model has a high accuracy for estimating the target parameter. To increase the efficiency of the ANFIS, its formulation was also extracted from the computational structure of the model. The results obtained from the sensitivity analysis show that as the compressive strength of the column increases, the output value also increases. Increasing the ratio of the area confined by stirrups to the bearing plate area

and the volumetric ratio of stirrups can also increase the output parameter. In contrast, with the increase in the value of the ratio of the duct diameter to the section width, a decreasing trend is observed in the target variable. Based on the sensitivity analysis results, the yield strength of stirrups and the ratio of the gross supporting area to the bearing plate area do not constantly affect the changes in the output, and it can increase or decrease depending on the input variable value. In the end, the accuracy of the extracted equations of the ANFIS and the existing techniques was compared, and the errors were examined. The results indicated that the proposed model has the least error among all equations and has the most accuracy. Therefore, it can be used as a predictive model to determine the target variable, which is the axial compressive capacity ratio to the bearing plate's net area minus the duct area.

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