

Original paper

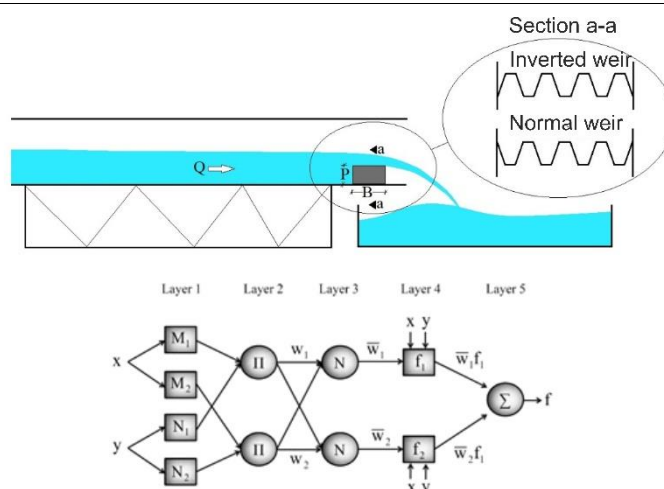
Sensitizing influenced factors on discharge of labyrinth weirs using ANFIS model

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GRAPHICAL ABSTRACT



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ABSTRACT

In the article, through the adaptive neuro-fuzzy inference system (ANFIS), a sensitivity analysis is conducted on the variables affecting the discharge capacity of the weir. To this end, the variables affecting the discharge capacity of labyrinth weirs are initially identified. Then, using these input parameters, seven ANFIS models are developed for conducting the sensitivity analysis. After that, the most optimal membership function number for the ANFIS model is chosen. In other words, by conducting the trial and error process, the best number of the membership functions in terms of time and modeling accuracy are selected. Then, the sensitivity analysis is performed for the ANFIS models and the superior ANFIS model is chosen finally. The accuracy of the superior model in both the validation and testing artificial intelligence (AI) methods is in an acceptable range. For example, the scatter index (SI), correlation coefficient (R) and the Nash-Sutcliffe efficiency coefficient (NSC) for the model in the testing mode are obtained 0.049, 0.964 and 0.924, respectively. It should be noticed that the outcomes of the sensitivity analysis show that the ratio of the weir head to the weir crest and the Froude number are introduced as the most effective input parameters. Eventually, a computer code is proposed to estimate the discharge capacity of labyrinth weirs by this model.

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1. Introduction

A weir is generally applied to adjust and measure flow in open channels in irrigation-drainage systems, water transmission network and water and wastewater treatment plants. The shape of the weir has a direct impact on its discharge capacity and this type of structures is employed in various forms like labyrinth, triangular, rectangular and

circular. It can be claimed that a labyrinth weir has a greater discharge capacity compared to equivalent rectangular ones because of its longer effective length. It can be satated that the discharge capacity is the most important parameter for designing a weir which is interms of hydraulic parameters and geometric features of the channel and weir. Thanks to the significance of weirs, a lot of laboratory, analytical and numerical works have been performed on the hydraulics of labyrinth weirs. As an

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example, several studies were conducted on labyrinth weirs (Bagheri and Heidarpour. 2010; Emiroglu and Naylar. 2005; Hay and Taylor 1970; Kumar et al. 2011; Taylor. 1968; Tullis and Young. 2007; Tullis et al. 1995; Wormleaton and Soufiani. 1998; Wormleaton and Tsang. 2000). Subsequently, Crookston et al. (2012) studied the flow behavior of trapezoidal labyrinth weirs. They simulated the hydraulics of the passing flow over this type of longitudinal weirs using the FLOW-3D numerical model. In addition, it is shown that the numerical model forecasts discharge coefficient values and flow rates with acceptable accuracy. Then, Crookston and Tullis (2012) using experimental measurements and analyzing physical models, presented some formulae for designing broad-crested labyrinth weirs. They introduced the discharge coefficient as the effective parameters of design and compared the outcomes of the relationships with the observational values and approved that the approach is sufficiently accurate. Next, Carollo et al. (2017) evaluated the hydraulics of triangular weirs. They suggested some equations for computing the discharge passing over this type of weirs and stated that the mentioned relationship can also be used for broad-crested weirs.

Different numerical models, artificial neural network and neuro-fuzzy techniques are employed as efficient, powerful tools for simulating and predicting different hydraulic and hydrological phenomena (Akhbari et al. 2017; Azimi et al. 2018; Parsaei and Haghiabi. 2015). Besides, due to the importance of the discharge coefficient of weirs, such methods have been implemented for modeling and estimating the discharge coefficient of the structures. For example, some researchers simulated the discharge coefficient of weirs by different artificial intelligence techniques (Akhbari et al. 2017; Azimi et al. 2017; Azimi et al. 2019; Ebtehaj et al. 2015; Khoshbin et al. 2016). Moreover, Baylar et al. (2008) evaluated aeration of rectangular weirs using the ANFIS network. Haghiabi et al. (2017) modeled the discharge capacity of labyrinth weirs by employing the MPL artificial neural network and the ANFIS model. They analyzed the results and asserted that the ANFIS more has higher accuracy. In addition, Roushangar et al. (2017) simulated the discharge capacity of labyrinth weirs through the ANFIS and GEP models. Through the analysis of the outcomes, it was showed that the GEP model had better performance. Furthermore, Roushangar et al. (2018) estimated the discharge capacity of arced and labyrinth weirs using the Support Vector Machine.

In one hand, the discharge coefficient of weirs is considered as one of the most important and effective parameters for designing an optimal weir. Owing to the importance of the discharge coefficient, many studies have been conducted on it by different researchers. In other hand, different neuro-fuzzy and neural network techniques have been widely utilized for modeling and estimating the discharge capacity of weirs. In this article, for the first time, a sensitivity analysis is conducted on the parameters affecting the discharge capacity of labyrinth weirs by the ANFIS model. Initially, all effective input dimensional variables the target function are detected and then seven distinctive ANFIS models are developed using them. Also, the most optimal number of the ANFIS model membership functions (MF) is also selected. After that, the observed values are classified to two groups including the validation and testing data. After training the ANFIS models, their results are tested. Subsequently, the superior model and the most important parameters are introduced through the conduction of a sensitivity analysis. Finally, a computer code is proposed for simulation of the discharge capacity of the labyrinth weirs.

2. Methodology

2.1. Adaptive neuro-fuzzy inference systems (ANFIS)

A fuzzy logic model is a system based on IF-Then logic rules, which are not analyzable, by classical probability theories. The starting point for building a fuzzy system is to obtain a set of IF-THEN rules. So, having a way to determine the information available to set these rules is considered as an effective tool. In the meantime, due to different training capabilities, neural networks can create a suitable linkage between input and output variables. Therefore, the hybrid use of fuzzy logic model and neural networks (NNS) can be utilized as a powerful tool called "adaptive neural fuzzy inference system (ANFIS)" in various problems. In this method, the fuzzy section creates the linkage between the input and output variables and the variables associated with the fuzzy section MF is optimized using the NNS. The ANFIS model was introduced for the first time by Jang (1993). The structure of this network for a model with two inputs (x and y) is presented in Fig. 1. The values of these two parameters, fed by two input nodes, are transmitted using membership functions (MF) to provide the output value. The Gaussian

function has smooth properties and its shape has sharp points. In addition, the number of parameters that need to be optimized during the training process is also small. Due to the good efficiency of the Gaussian MF in many applied studies and its expressed properties, this function is used in this article.

$$\mu_{M_i}(x) = \exp\left(-\frac{\|x - c_i\|^2}{2\sigma_i^2}\right) \quad (1)$$

In this respect, c and σ are Gaussian membership function variables that can be optimized over the training modes. The process is also calculated for the input y ($\mu_{N_i}(y)$). After calculating the membership functions, their values are multiplied in the next layer as Eq. 2.

$$w_i = \mu_{M_i}(x)\mu_{N_i}(y) \quad (i=1,2) \quad (2)$$

The outcome of this relationship is known as firing strength of the rule. Next, the normalized firing strength is calculated by Eq. 3.

$$\bar{w}_i = \frac{w_i}{\sum w_i} \quad (i=1,2) \quad (3)$$

In the next layer, using the weighted factor (Eq. 3), the contribution of the i th rule is computed with respect to the total output. Assuming the i th rule as Eq. 4, the output of this node is calculated as Eq. 5.

$$\text{If } x \text{ is } M_i \text{ and } y \text{ is } N_i, \text{ Then } f_i = p_i x + q_i y + r_i \quad (4)$$

$$\bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i) \quad (5)$$

where, $\{p_i, q_i \text{ and } r_i\}$ are factors of the ANFIS result section that are optimized over the training mode. In the last step, the sum of all input signals is presented as the network output. The final output of ANFIS is computed as follows.

$$\begin{aligned} f &= \sum_i \bar{w}_i f_i = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 \\ &= \bar{w}_1 (p_1 x + q_1 y + r_1) + \bar{w}_2 (p_2 x + q_2 y + r_2) \\ &= (\bar{w}_1 x) p_1 + (\bar{w}_1 y) q_1 + (\bar{w}_1 r_1) + (\bar{w}_2 x) p_2 + (\bar{w}_2 y) q_2 + (\bar{w}_2 r_2) \end{aligned} \quad (6)$$

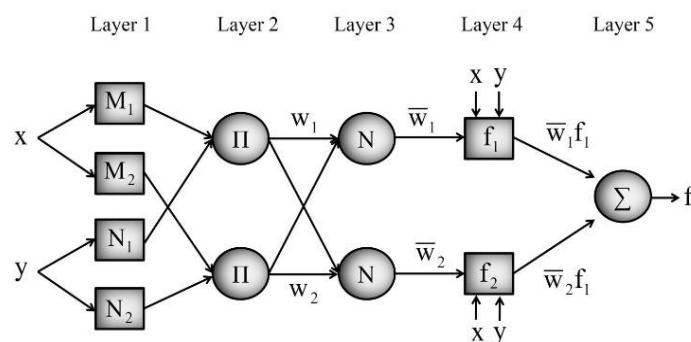


Fig. 1. General ANFIS structure (Jang. 1993).

2.2. Physical model

In the study, Seamons' (2014) laboratory measurements are employed for verifying the results of the ANFIS models. In this experimental model, the measurements have been conducted in a rectangular flume with the length 14.6 m, width 1.2 m and height 0.9 m. The flume slope in all experiments is zero and the channel is horizontal. Seamons (2014) measured the experimental for the weir in two modes: normal orientation labyrinth weirs (NLWs) and inverted orientation labyrinth weirs (ILWs). He also managed to measure the flow rate (Q), the weir head (H_T), the weir crest (P), cycle sidewall angles (α), the length of the weir crest (L_c), the total length of the weir (W), the length of apex geometry (A), and the width of a single cycle (w). In Fig. 1, a layout of Seamons' (2014) model is shown.

2.3. Discharge coefficient of labyrinth weir

The discharge capacity of a side weir can be as a function of the discharge passing over the weir (Q), the effective length (L_e), the head above the weir (H_T) and gravitational acceleration (g) as follows.

$$C_d = \frac{3}{2} \frac{Q}{\sqrt{2g} L_c H_T^{3/2}} \quad (7)$$

In other words, the discharge capacity of the weirs is in terms of the following parameters (Seamons. 2014).

$$C_d = f(Fr, H_T/P, \alpha, L_c/W, A/w, w/P) \quad (8)$$

In this article, the variables of Eq. 8 can be applied for simulating the discharge capacity of the ANFIS models. The combination of the input variables for developing the numerical models is depicted in Fig. 3.

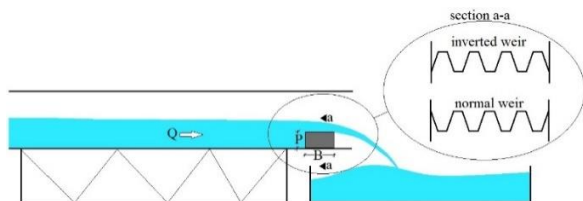


Fig. 2. Layout of experimental model.

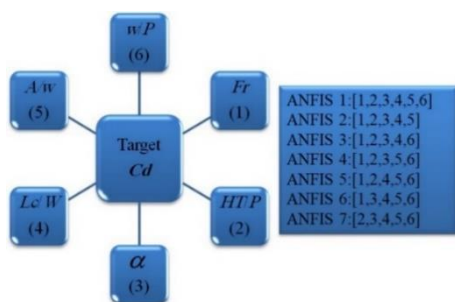
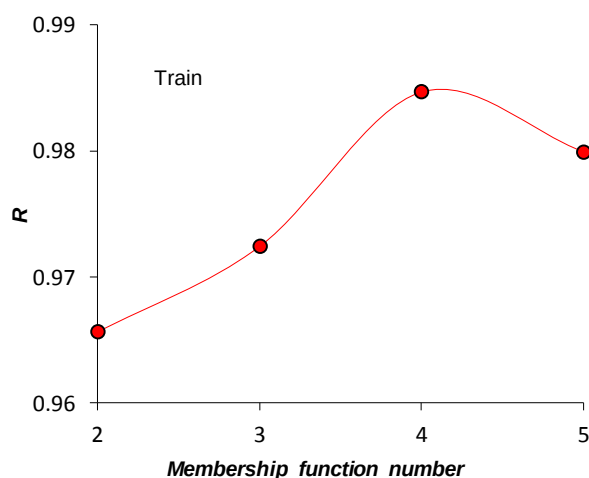


Fig. 3. Combinations of input parameters for developing artificial intelligence models.

2.4. Goodness of fit

In order to examine the performance of the introduced the numerical models, the correlation coefficient (R), variance accounted for (VAF), root mean square error (RMSE), scatter index (SI), mean absolute error (MAE) BIAS, and the nash-sutcliff proficiency coefficient (NSC) are used as follows.

$$R = \frac{\sum_{i=1}^n (F_i - \bar{F})(O_i - \bar{O})}{\sqrt{\sum_{i=1}^n (F_i - \bar{F})^2 \sum_{i=1}^n (O_i - \bar{O})^2}} \quad (9)$$



$$VAF = \left(1 - \frac{\text{var}(F_i - O_i)}{\text{var}(F_i)} \right) \times 100 \quad (10)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (F_i - O_i)^2} \quad (11)$$

$$SI = \frac{RMSE}{\bar{O}} \quad (12)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |F_i - O_i| \quad (13)$$

$$BIAS = \frac{1}{n} \sum_{i=1}^n (F_i - O_i) \quad (14)$$

$$NSC = 1 - \frac{\sum_{i=1}^n (O_i - F_i)^2}{\sum_{i=1}^n (O_i - \bar{O})^2} \quad (15)$$

where, O_i denotes observational values, F_i represents predicted values by numerical models, $\bar{O}$ is the averaged observational data and n is the number of observational values. The applied criteria do not present a simultaneous comparison of the mean and variance of the models. Therefore, the Akaike information criterion is computed for comparing the predicted target function as follows.

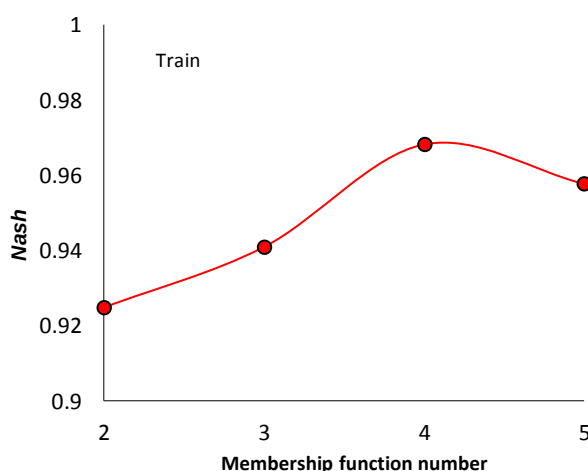
$$AIC = n \times \ln(RMSE) + 2k \quad (16)$$

where, k is the number of simulated variables used in the numerical model. The AIC is a criterion for appropriate adaption of a statistical model. It is applied as a criterion for selecting the model and simultaneously provides the complexity and accuracy of the model. In this article, about 70 % of the experimental data are applied to train the numerical models and 30 % for testing them. It is worth mentioning that the total number of the experimental measurements is 347. In the next sections, the number of the membership functions is initially examined. Next, the best model and important input parameters are detected by a sensitivity analysis. It should be noted that in the article only the test results are provided.

3. Results and discussion

3.1. Number of membership function

Initially, the membership functions (MFs) number of the ANFIS is examined. The MFs has a direct impact on the modeling accuracy. By contrast, by increasing the number of the MFs, the computational time is noticeably increases. In Figs. 4 and 5, the variations of different statistical indices versus the number of the membership functions are shown in both the training and testing modes.



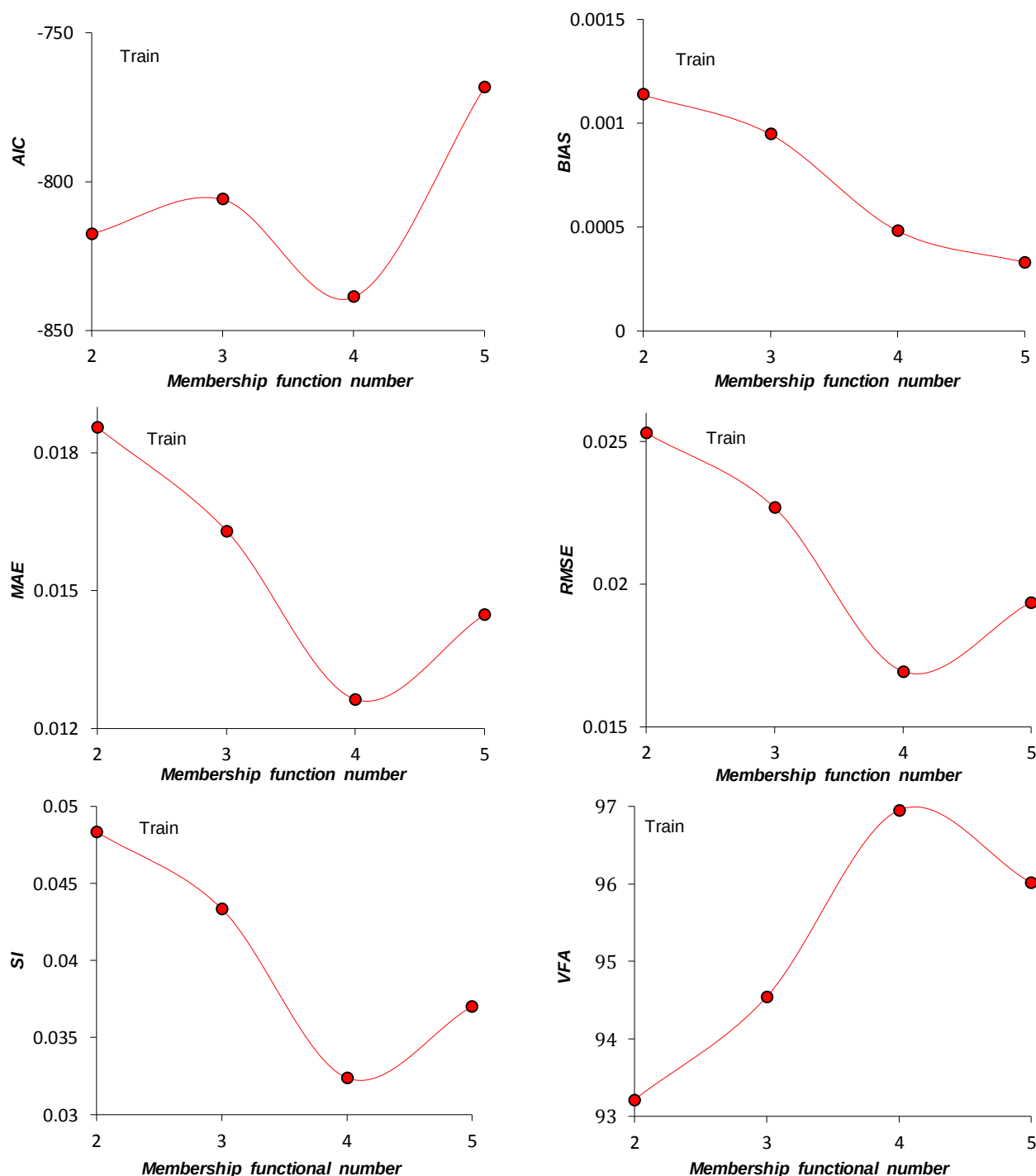


Fig. 4. Variations of the number of membership functions against different statistical indices for training mode.

It should be note that in this study the number of the membership functions is initially taken into account equal to 2. Then, this parameter increases until recanting 3, 4 and 5 in the next steps. As can be seen, as the number of membership functions increases, the modeling accuracy increases as well. It should also be mentioned that increasing the number of membership functions to more than 4 has no significant impact on the modeling results, so that all the indices in both training and testing modes demonstrate that the accuracy of the ANNIS network modeling with 4 membership functions are more than the model with 5 membership functions. But another considerable note is that the accuracy of the ANFIS model with two membership functions is very close to the model with 4 membership functions, but the computational time by this model is much higher and several times the ANFIS model with two membership functions. Due to the closeness of the results of the ANNIS models with 2 and 4 membership functions and the very high computational time of the model with 4 membership functions, so the

number of optimal membership functions in this study for simulating the target function (discharge coefficient) by the ANFIS model is considered equal to 2. In addition, the comparison of the target function (discharge coefficient) simulated through the ANFIS method with different membership functions in the training and testing modes is illustrated in Fig. 6. For instance, for the ANFIS model with two membership functions, the RMSE, MAE and NSC in the training mode are respectively obtained 0.025, 0.019 and 0.925. For this model, SI, BIAS and VAF for the testing mode are respectively calculated 0.049, -0.003 and 93.122. Moreover, for the model with 3 membership functions, the values of BIAS, MAE and SI in the testing mode are estimated -0.002, 0.016 and 0.038, respectively. For the training mode of this model, the VAF and RMSE are equal to 94.543 and 0.023, in turn. By contrast, for the ANFIS model with 4 membership functions in the testing mode, SI, NSC and MAE are estimated 0.031, 0.972 and 0.013, in turn.

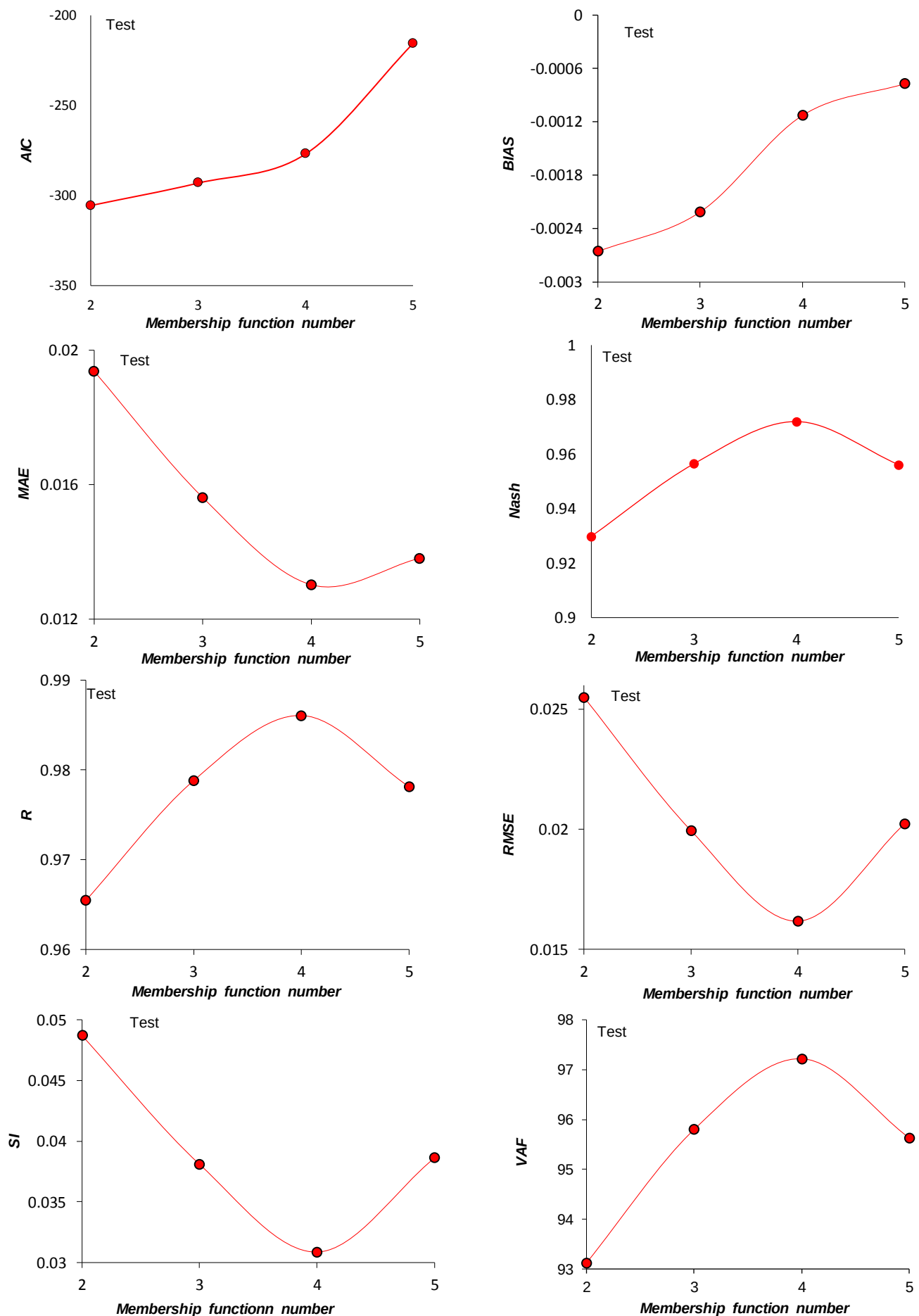


Fig. 5. Variations of the number of membership functions against different statistical indices for testing mode.

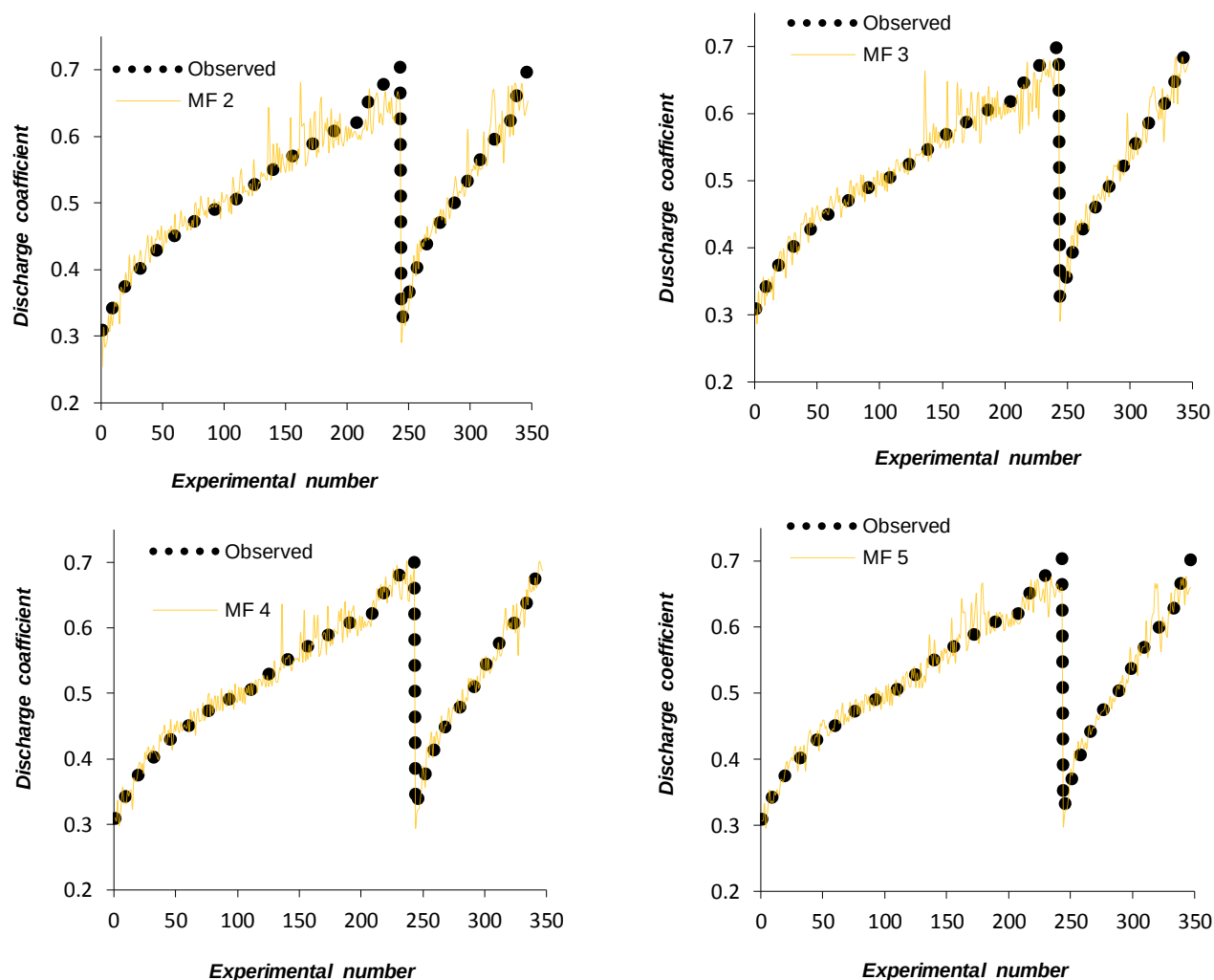
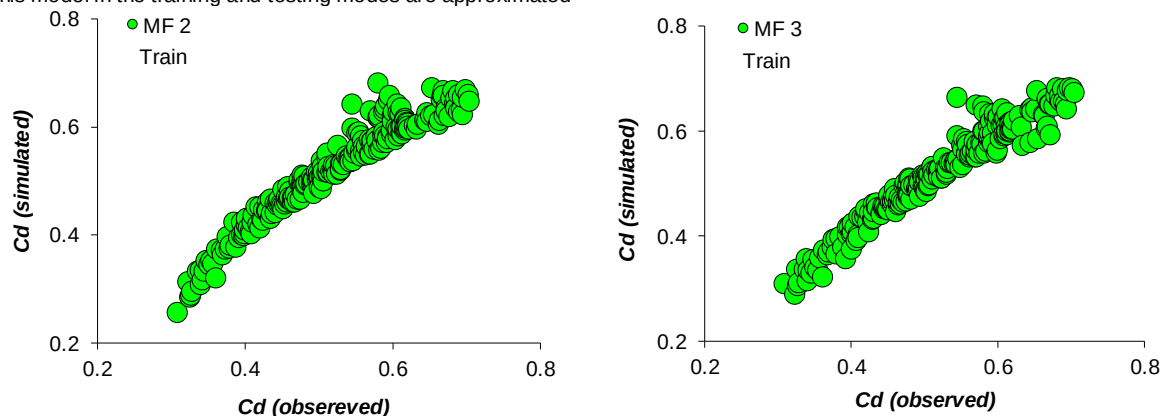


Fig. 6. Comparison of simulated and observed discharge coefficients for different membership functions.

Furthermore, the RMSE, VAF and BIAS for the ANFIS model in the training mode are obtained 0.017, 96.951 and 0.0005, respectively. Also, for the ANFIS model whose membership function number is equal to 5, the values of NSC, RMSE and VAF in the training mode are calculated 0.958, 0.019 and 96.014, respectively. It must be stated that the SI, MAE and BIAS for the testing mode of the ANFIS model are yielded 0.039, 0.014 and -0.0008, respectively. In Figs. 7 and 8, the scatter plots of the ANFIS model for different membership functions in both the training and testing modes are shown. For the ANFIS model with two membership functions, the R value in the testing and training modes are obtained 0.956 and 0.966, respectively. However, the AIC index for this model in the training and testing modes are approximated

-817.528 and -305.562, respectively. Furthermore, R and AIC for the testing mode of the ANFIS model with three membership functions are 0.979 and -293.102, respectively. In contrast, for the model with 4 membership functions, the correlation coefficient values for the testing and training modes are 0.986 and 0.985, respectively. Additionally, the AIC index for the ANFIS model with 5 membership functions in the training and testing modes are estimated -768.352 and -215.656, respectively. Thus, according to the simulation results, the number of the MFs for modeling the target function by the ANFIS model is considered equal to 2 and the next modeling is conducted by this number of membership functions.



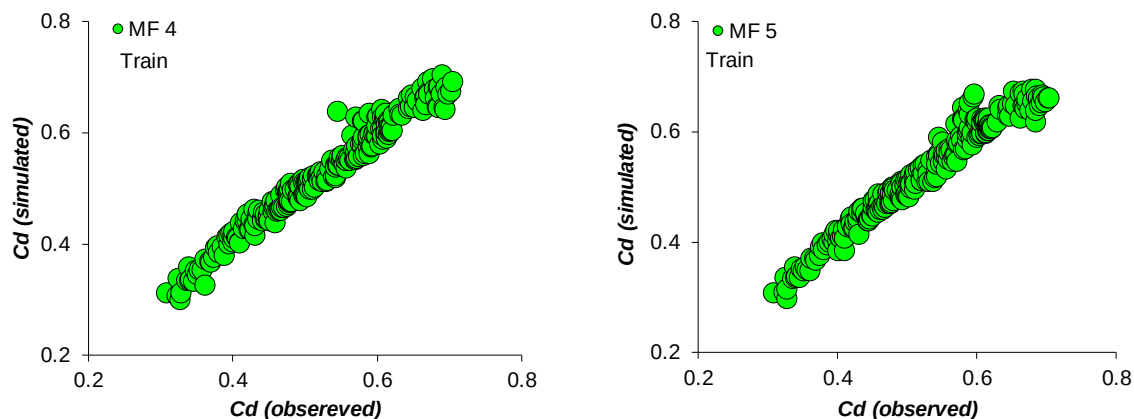


Fig. 7. Scatter plots of different membership functions for training mode.

3.2. Sensitivity analysis

In Figs. 9 and 10, the results of the ANFIS methods in both the training and testing modes are shown. In this section, the sensitivity analysis of the developed ANFIS models is evaluated. It should be noted that for detecting the superior model and also the effective parameters, seven distinctive ANFIS models are defined. In other words, using the dimensionless input parameters, seven ANFIS models are developed and the results of all models are evaluated. ANFIS 1 method estimates the target function by means of all input parameters. In other words, ANFIS 1 models using all the inputs Fr , H_T/P , α , L_c/W , A/w , w/P . Also, so as to detect the most effective input factors, the influence of each of the input parameters is neglected and six ANFIS models including ANFIS2 to ANFIS6 are presented. For example,

ANFIS2 estimates the target value as a function of the dimensionless parameters Fr , H_T/P , α , L_c/W , A/w . For ANFIS 2, the effect of the input factors w/P is removed. Furthermore, the influence of the input parameter A/w for ANFIS 3 is eliminated and the model predicts the C_d by the parameters Fr , H_T/P , α , L_c/W , w/P . It is worth mentioning that the impact of the L_c/W is removed for ANFIS 4 and this model predicts the C_d using the parameters Fr , H_T/P , α , A/w , w/P . In addition, the impact of the dimensionless parameter α is neglected for ANFIS 5 model and this model approximates the objective function values by the dimensionless parameters Fr , H_T/P , L_c/W , A/w , w/P . It should be noted that ANFIS 6 estimates the C_d using the dimensionless parameters Fr , α , L_c/W , A/w , w/P and the impact of the parameter H_T/P is removed for it. However, the effect of the Fr is removed for ANFIS 7 and the model estimates the C_d by H_T/P , α , L_c/W , A/w , w/P .

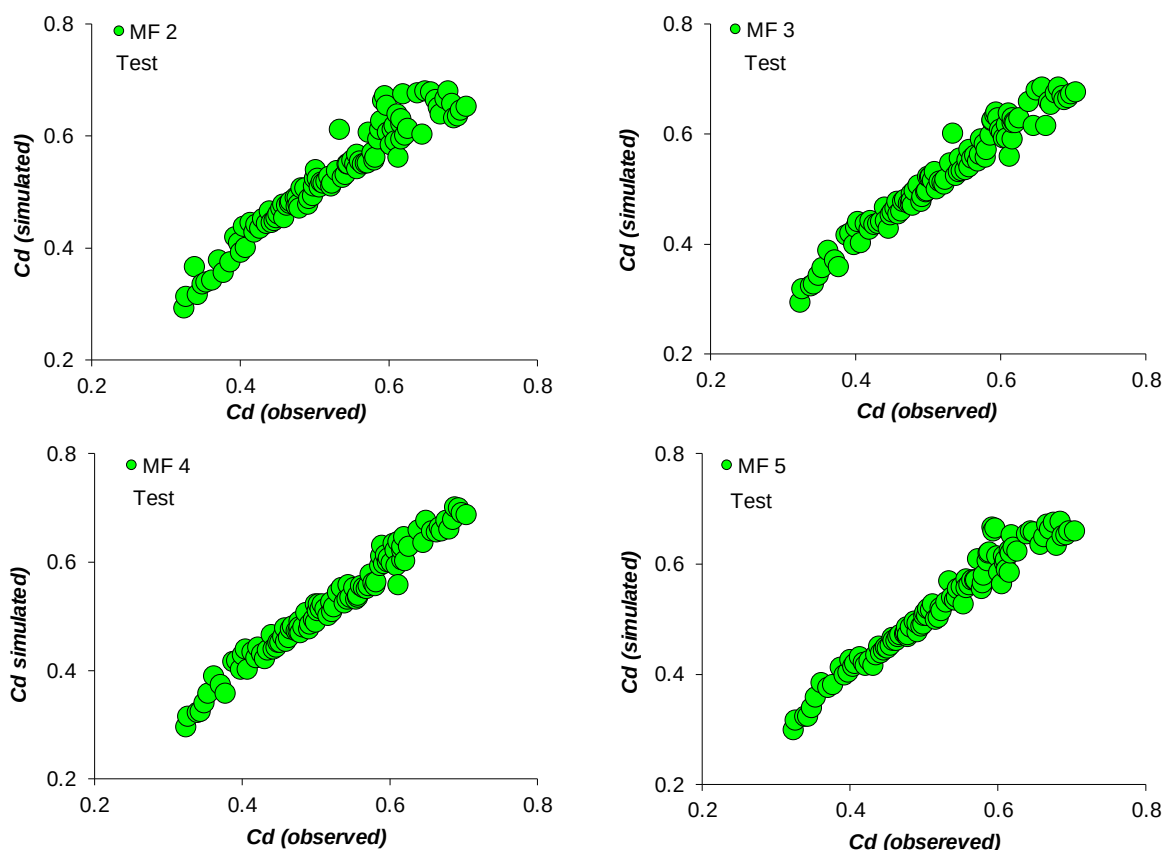


Fig. 8. Scatter plots of different membership functions for testing mode.

Also, the comparison of the simulated and observed discharge coefficients for all ANFIS models is shown in Fig.11. Regarding to the modeling results, ANFIS 1 estimates the discharge coefficient values in both the training and testing modes with acceptable accuracy. For example, VAF, MAE and VAF for the training mode of the ANFIS 1 model are respectively computed 0.025, 0.019 and 93.216. Also, for the

testing mode of the model, the NSC, SI and BIAS are respectively obtained 0.930, 0.049 and -0.003. For ANFIS 2 model the MAE, SI and VAF in the testing mode are calculated equal to 0.023, 0.055 and 91.152, respectively. Moreover, for ANFIS 2 model, the BIAS, RMSE and NSC in the training mode are estimated to be 0.0006, 0.030 and 0.895, in turn. Additionally, for ANFIS 3 model, the SI, MAE and RMSE

in the training mode are equal to 0.048, 0.018 and 0.025, respectively. However, NSC, SI and VAF for the testing mode of this model are obtained 0.924, 0.049 and 92.871, respectively. It is worth mentioning that the efficiency of ANFIS 3 in both the training and testing modes is better than the other ANFIS models and the model owns the lowest error and highest accuracy amongst all of them. In addition, for the ANFIS4 in the testing mode, VAF, MAE and SI are estimated to be 92.628, 0.020 and 0.050, respectively. Additionally, RMSE, NSC and BIAS for the training mode of this model are 93.195, 0.925 and 0.0005, in turn. Also, the VAF, SI and NSC for ANFIS5 in the testing mode are calculated 93.148, 0.049 and 0.929, in turn. Moreover, the RMSE, BIAS and MAE for the training mode of this artificial intelligence model are

0.027, 0.001 and 0.020, respectively. It should be mentioned that among all ANFIS models, ANFIS6 has the lowest accuracy and the highest error. As an example, the SI, VAF and NSC for the training mode of ANFIS6 are 0.062, 88.853 and 0.871, respectively. Also, RMSE, BIAS and MAE for the testing mode of this model are 0.033, -0.004 and 0.024, respectively. After ANFIS6, ANFIS7 has the lowest accuracy in simulating the C_d . For ANFIS 7, the RMSE, MAE and SI in the testing mode are estimated to be 0.029, 0.023 and 0.055, respectively. Furthermore, the values of NSC, VAF and BIAS in the training mode of the model are computed 0.855, 89.789 and 0.001, in turn.

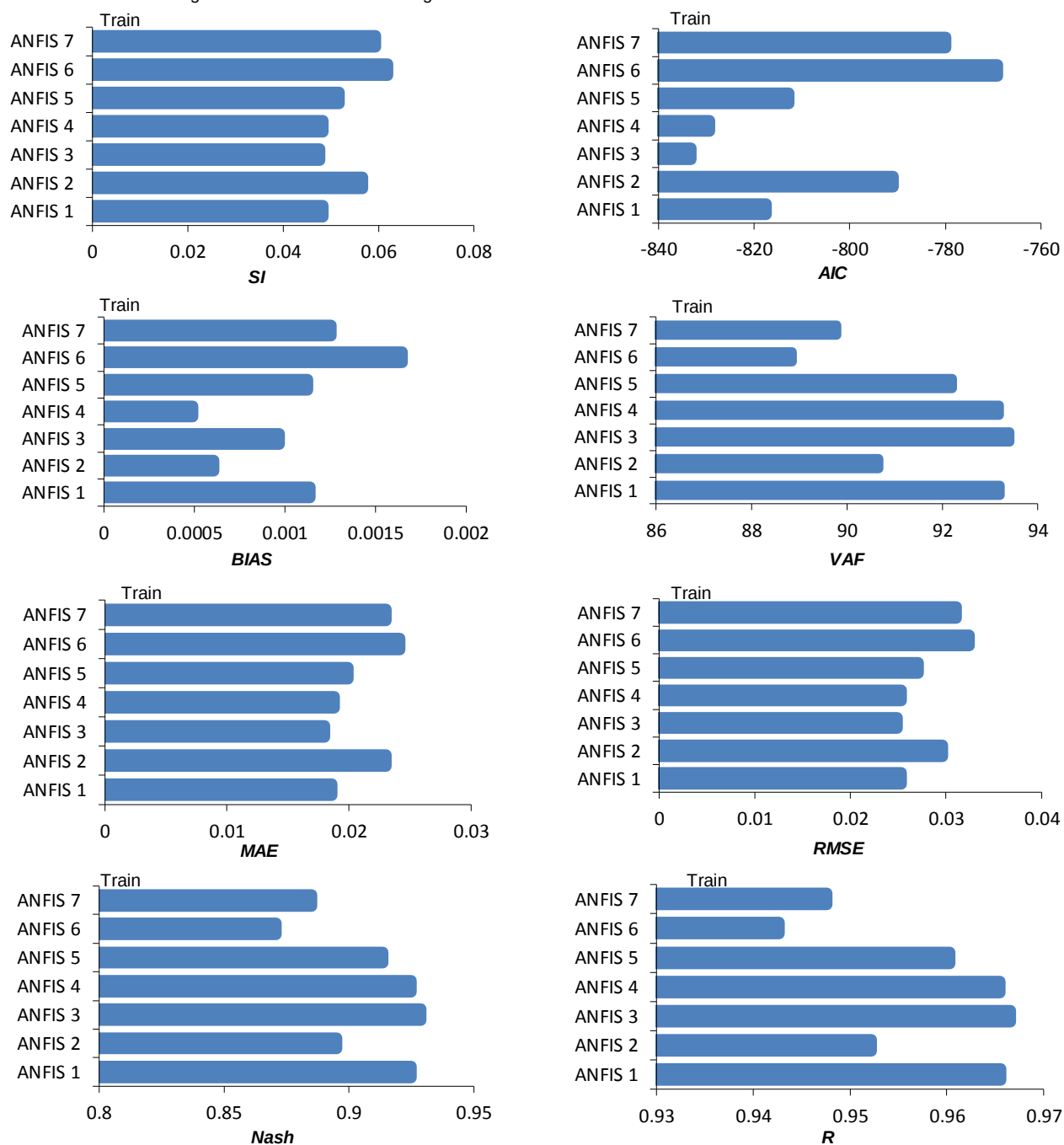


Fig. 9. Results of different statistical indices for ANFIS models in training mode.

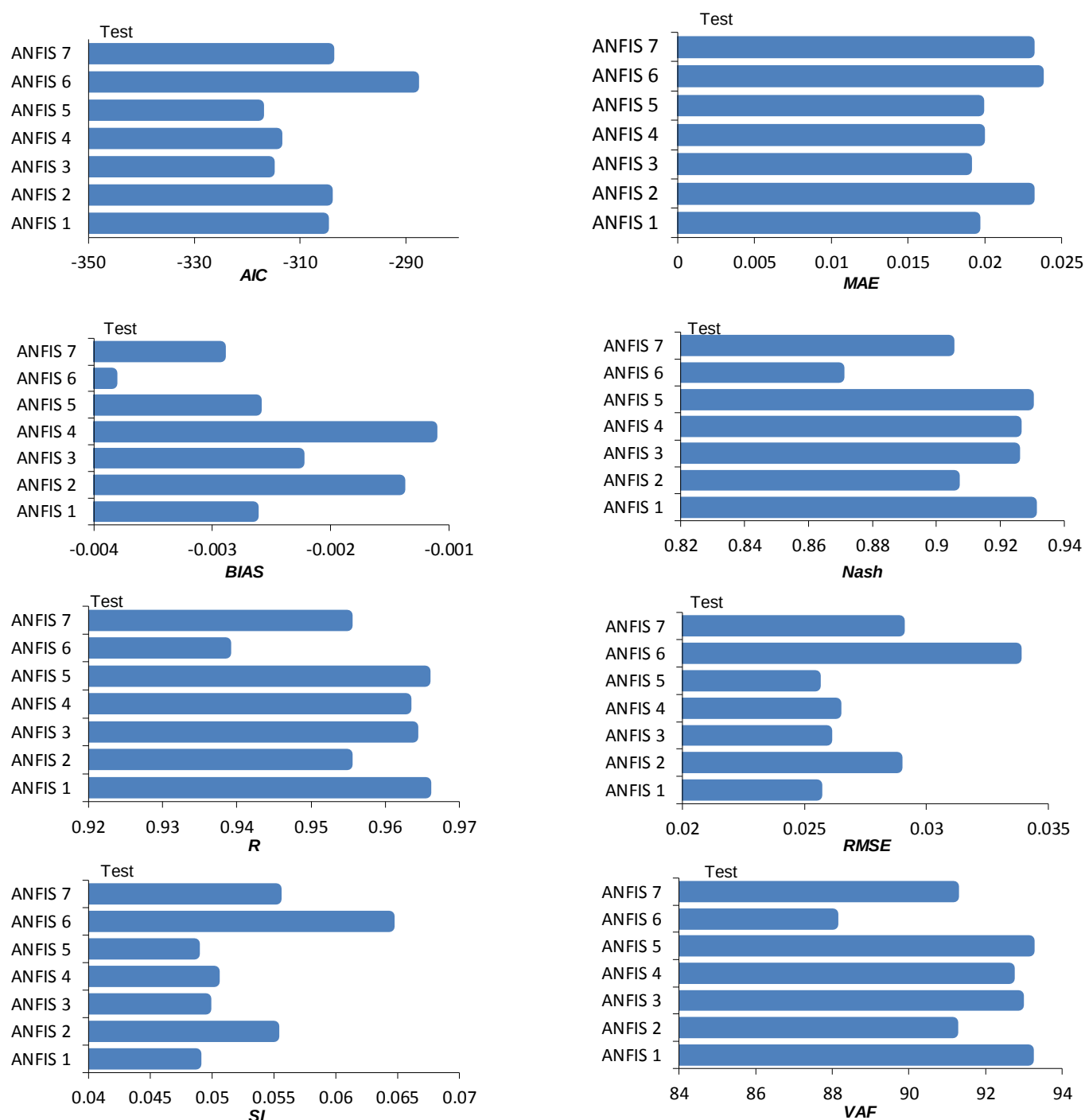


Fig. 10. Statistical indices for ANFIS models in testing mode.

The scatter plots for seven ANFIS methods in both the training and testing modes are shown in Figs. 12 and 13. For ANFIS1, the R value for the training and testing modes are obtained 0.966 and 0.965, respectively. In contrast, the AIC index for this model in testing and training modes is -305.562 and -817.528, respectively. Moreover, the R and AIC for the ANFIS 2 model in the training mode are 0.952 and -790.949, while these values for the testing mode are obtained 0.955 and -304.907, respectively. For ANFIS3, the values of AIC and R in the training mode are approximated to be -833.222 and 0.967, respectively. It is worth noting that the R values of ANFIS 4 in the testing and training modes are obtained 0.963 and 0.965, respectively. For ANFIS5, the

values of AIC and R in the testing mode are calculated -317.768 and 0.965, respectively.

Furthermore, for the training mode of ANFIS5, the correlation coefficient and the AIC index are 0.960 and -812.770, respectively. Also, the correlation coefficient for the testing and training modes of ANFIS6 is 0.939 and 0.943, respectively. In addition, AIC in the testing and training situations of the ANFIS 6 method are estimated to be -769.128 and -288.589, respectively. Also, for ANFIS7 in the testing mode, the values of AIC and R calculated -304.570 and 0.955, respectively, while in the training mode of the model, the R and AIC are equal to 0.948 and -779.900, in turn.

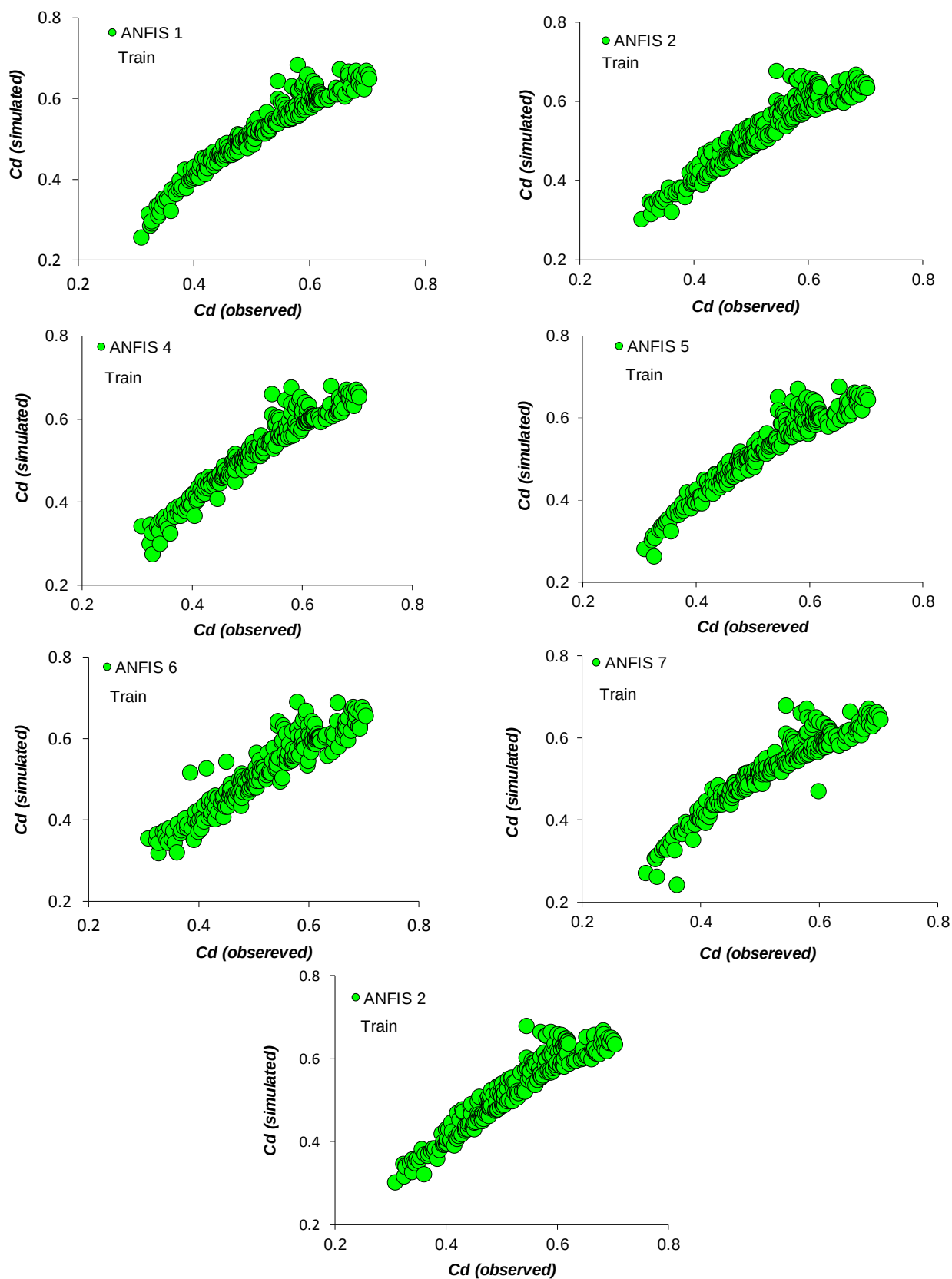


Fig. 12. Scatter plots of different membership functions in training mode.

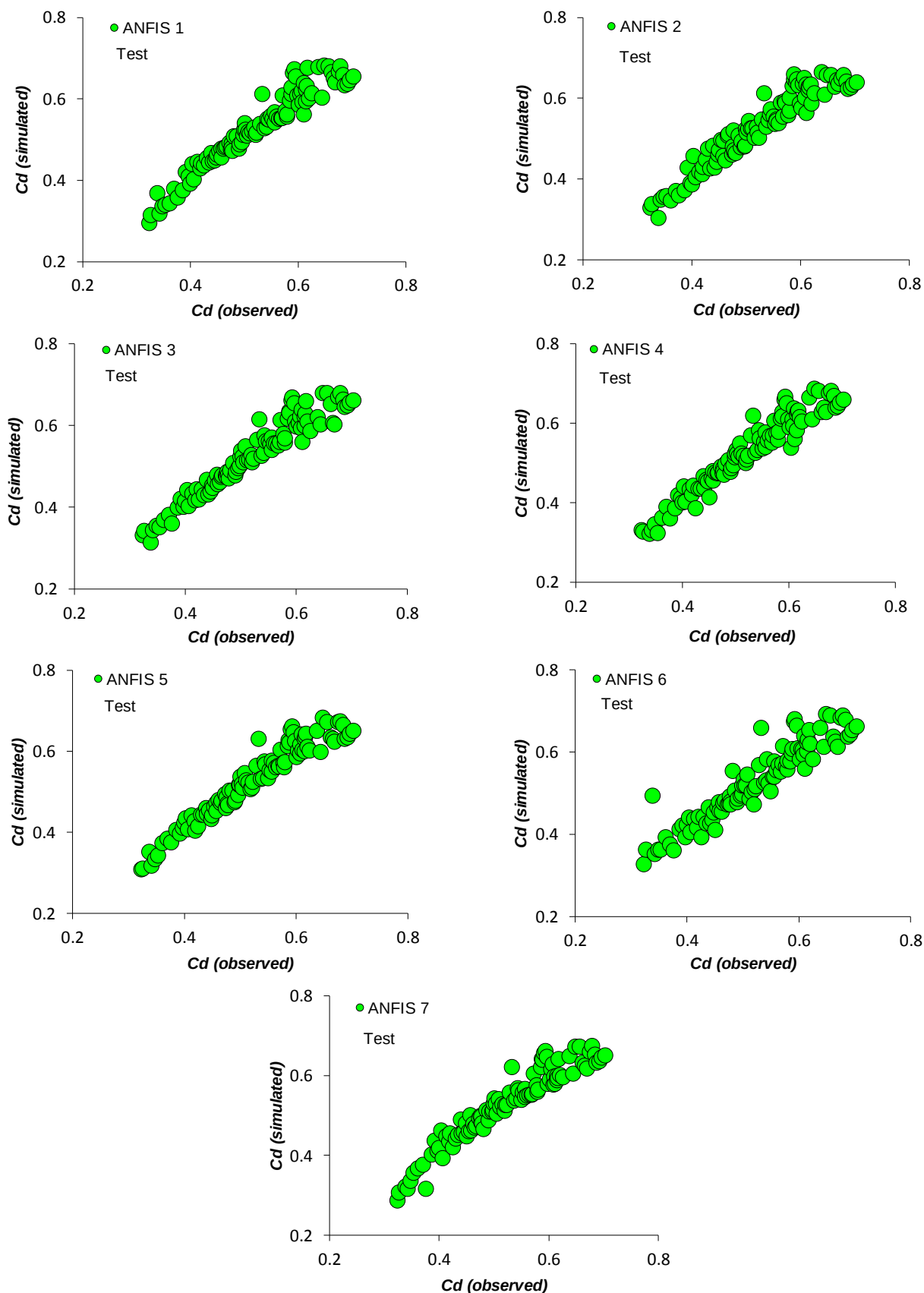


Fig. 13. Scatter plots of different membership functions in testing mode.

4. Conclusions

In the article, the discharge coefficient of labyrinth weirs in a rectangular channel was simulated by the adaptive neuro-fuzzy inference system (ANFIS). In other words, the superior ANFIS model

and the factors affecting the target function were detected through the conduction of a sensitivity analysis. The most important findings of the present study are presented as follows:

-Initially, all effective variables on the discharge coefficient including $Fr, H_T/P, \alpha, L_c/W, A/w, w/P$ were detected.

-Using these input parameters, seven different models (ANFIS1 to ANFIS7) were developed.

-Then, the most optimal number of the membership functions was chosen equal to 2 by conducting a trial and error procedure. The modeling accuracy and simulation time by this number of the membership functions were evaluated in an acceptable range. For example, for the training mode of ANFIS2 which had two membership functions, the R, VAF and MAE were predicted 0.966, 93.216 and 0.025, in turn.

-The superior model was selected through the conduction of a sensitivity analysis. In other words, ANFIS3 which was a function the parameters $Fr, H_T/P, \alpha, L_c/W, w/P$ estimated the target function with acceptable precision in both the training and testing modes. As an example, the correlation coefficient, RMSE and NSC for the testing mode of ANFIS3 were computed 0.964, 0.026 and 0.924, in turn.

-Moreover, the results of the sensitivity analysis indicated that the dimensionless parameters $Fr, H_T/P$ were the most important parameters in simulating the target function by the ANFIS model.

-Lastly, a simple computer code was presented for estimating the discharge coefficient by engineers and researchers.

It is suggested that the performance of ANFIS model compares to other artificial intelligence techniques. Also, efficiency of labyrinth weirs can be compared with rectangular weirs.

Superior model computer code

```
clc
clear all
close all
x=xlswread('book3','sheet1');
a1=x(:,1);
a2=x(:,2);
a3=x(:,3);
```

```
a4=x(:,4);
% a5=x(:,5);
a6=x(:,6);
TestInputs=[a1 a2 a3 a4 a6];
TestTargets=[a6];
data.TestInputs=TestInputs;
data.TestTargets=TestTargets;
x=data.TestInputs;
t=data.TestTargets;
fis=genfis3(x,t,'sugeno',2);
clc
fis.input(1).mf(1).params = [0.1365 0.1044];
fis.input(1).mf(2).params = [0.1482 0.1832];
fis.input(2).mf(1).params = [0.2505 0.3676];
fis.input(2).mf(2).params = [0.2271 0.2754];
fis.input(3).mf(1).params = [0.4223 12.0116];
fis.input(3).mf(2).params = [1.1985 14.9150];
fis.input(4).mf(1).params = [0.2716 1.9940];
fis.input(4).mf(2).params = [0.4976 1.4541];
fis.input(5).mf(1).params = [0.4290 1.6913];
fis.input(5).mf(2).params = [0.5134 1.6424];
fis.output.mf(1).params = [0.8354 -0.8272 0.1366 -0.4420
0.0411 0.0114];
fis.output.mf(2).params = [-0.7172 -0.0120 1.8874 0.0430
0.0708 -27.8289];
Cd=evalfis(data.TestInputs,fis);
```

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