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Full Length Research Paper

A model of adaptive neural-based fuzzy inference system (ANFIS) for prediction of friction coefficient in open channel flow

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Friction coefficient factor in free surface smooth channel with rectangular cross-section is generally affected by Reynolds number and wall roughness and can be determined with laboratory or field measurements. In application, according to researchers, correct selection of friction coefficient is substantially critical to estimate hydraulic problems correctly. In this paper an ANFIS is set up in which Reynolds number, velocity and discharge are used as inputs to estimate friction coefficients of an open channel flow (FC). By using experimental data from the laboratory, learning algorithm and training are applied according to ANFIS model. As a result, simulation results are compared with experimental friction coefficient results. A good correlation is obtained between the experimental data and predicted results. It is shown that when provided with correct and sufficient samples, ANFIS model can be used to predict the non-linear relationship between friction coefficient and the factors which affect it. It is concluded that, in practice, ANFIS model can be used as a suitable and effective method and general hydraulic problems which are mostly based on laboratory tests can be analyzed with ANFIS model.

Key words: Open channel, friction coefficient, ANFIS.

INTRODUCTION

In hydraulic engineering, the friction coefficient is a crucial parameter in designing water structures, the calculation of velocity distribution and an accurate determination of energy losses. The distribution of shear stress is uniform in two-dimensional flow and the value of mean shear stress can be calculated using the force-balance equation. However the flow in open channel of finite aspect ratio is three dimensional and wall shear stress is not distributed uniformly on the wetter perimeters due to existence of free surface and secondary current. The calculation of friction coefficient is not a trivial task due to the complexity of the problem in open channel with finite aspect ratio. Furthermore, while the conventional approaches are capable of providing adequate accuracy in prediction of the friction coefficient in pipe flow, it is known that the accuracy of the conventional methods is insufficient in open channel flow. As the friction coefficient is a fundamental parameter in calculation of fluid discharge, new and accurate techniques are still highly demanded (Bilgil and Altun, 2008).

In stable uniform flows velocity, depth, flow cross section and discharge are same for every cross section. Energy line, bottom of the channel and the water surface are parallel to each other. By calculating the friction losses occurring during the flow, the slope of energy line can also be calculated. The velocity formula used in the calculation of uniform flow is $V = C\sqrt{RS}$. Here C is the coefficient which represents the resistance of the flow (Chezy coefficient). This coefficient is dependent on factors such as "V" average velocity, "R" hydraulic radius, channel roughness and viscosity. This formula can be derived by considering two hypotheses (Çeçen, 1982).

First hypothesis: This hypothesis, which was proposed by Chezy, expresses that friction force on the wall is proportional to square of the velocity.

Second hypothesis: This hypothesis, which was proposed by Brahms, is the fundamental principle of uniform flow. It shows that "Gsinα" weight force which provides the flow of the liquid in general sense is equal to total friction force.

The formula that is used most in open channels is

Manning formula. This formula was developed empirically (Bilgil, 1998). Through the studies he performed, (Manning, 1895) Manning searched for a dimensionless velocity equation and proposed following two formulas.

$$V = C' \sqrt{gRJ}\left[1 + \frac{0,22}{\sqrt{PoR}}\left(R - 0,15Po\right)\right] \quad (1)$$

$$V = CR^{2/3} J^{1/2} \quad (2)$$

Here C and C' are coefficients, Po is atmosphere pressure, J is hydraulic slope, g is gravitational acceleration and V is average velocity.

Of these equations that are defined with his name, Equation (2) received more credit from the researchers. However, he did not give credit to this equation of his in an article he published later. As a reason, he said that Equation (2) is not homogenous in terms of dimension whereas Equation (1) is more homogenous dimensioned and therefore, it should be used (Manning, 1895).

It is absolutely accepted by the majority that roughness and geometric shape are effective in determination of parameter n in Manning's equation. It is known that velocity and time are not effective on factor n. Chow (1959) prepared a very comprehensive n values table for different situations in free surface flows. Barnes (1967), on the other hand, prepared an album by describing different n values and natural channel status with colored figures and examples.

Yen (1991), tried to come up with a relationship between f and n by equating the velocity in Manning formula with the velocity in Darcy-Weisbach formula and prepared a table. By analyzing historical development of Manning formula in an excellent fashion, Dooge (1991) decided in clear terms that resistance coefficient n is not homogenous. He accepted that there is an inverse proportion (1/n) between C and n in Manning value. By modifying the Manning formula Yen (1991) derived the velocity equation as given below and formed n_g roughness values table which is suitable for channel flows and pipe flows.

$$V = \frac{1}{n_g} R^{2/3} \sqrt{gJ} \quad (3)$$

Yen (199) has given the below f = n_g relationship for pressurized and free surface flows.

$$\frac{n_g}{k_s^{1/6}} = \frac{-\left(\frac{R}{k_s}\right)^{1/6}}{4\sqrt{2}\log\left(\frac{k_s}{14,83R} + \frac{2,52}{\mathrm{Re}\sqrt{8}}\left(\frac{R}{k_s}\right)^{1/6}\frac{k_s^{1/6}}{n_g}\right)} \quad (4)$$

Ciray (1994) has modified the discharge equation, which yields better results and covers various factors such as secondary flows, irregular boundary shear and W/h ratio, and proposed the use of the equation given below for friction coefficient in free surface smooth flows.

$$n_m^{-1} = \frac{g^{1/2}}{R^{1/6}} \frac{2C_T^{1/2}}{n_T + 2}\left\{A + BLn\left[\left(\frac{C_T}{\exp(n_T + 2)}\right)^{1/2} h^+\right]\right\} \quad (5)$$

In this equation n_m corresponds to n coefficient in Manning equation whereas water depth h and kinematical viscosity ϑ are accepted to be $h^+ = \frac{hU_\tau}{\vartheta}$, and $K(I)_T = C_T X^{+n_T}$, respectively. The expression $K(I)_T$ represents boundary shear at channel bottom. X^+ in the equation is made dimensionless as $X^+ = \frac{X}{W/2}$. C parameter of Chezy equation can also be expressed as $C = \frac{1}{n} R^{1/6} = \sqrt{\frac{8g}{f}}$ and used as friction coefficient of pressure flows which are easily worked out. in which n and *f* Manning and Darcy-Weisbach resistance coefficients, *g* gravitational acceleration. One of the most important studies on smooth pipe flow is carried out by Prandtl (1960), which is given as

$$\frac{1}{\sqrt{f_b}} = 2.0\log\left(Re_b\sqrt{f_b}\right) - 0.8 \quad (6)$$

where $f_b = \left(2gDh_L / LV_b^2\right)$ friction coefficient in smooth pipe flow, *D* pipe diameter, *g* gravitational acceleration, h_L/L head loss due to friction per unit lengths, V_b average pipe velocity, $\mathrm{Re}_b = \left(\rho V_b D/\mu\right)$ Reynolds number, ρ fluid density, μ dynamic viscosity.

Prandtl's equation provides a good agreement between friction coefficient and Reynolds number. Studies on smooth open channel flow are presented in literature by Chow (1959), Dooge (1991), Reinus (1961), Tracy and Lester (1961), Rao (1969), Powell (1970), Pillia (1970, 1997), Kazemipour and Apelt (1982), Myers (1982), Syamala (1988), Rahman et al. (1997), Çıray (1999), Bilgil (1998), Tinkler (1997), Yen (2002). However, the results from these studies show that as good agreement between friction coefficient and Reynolds number as in smooth pipe flow have not been established yet. In this study, an efficient approach to estimate the friction coefficient via an Adaptive neuro-fuzzy inference system "ANFIS" is proposed. A training process is carried out

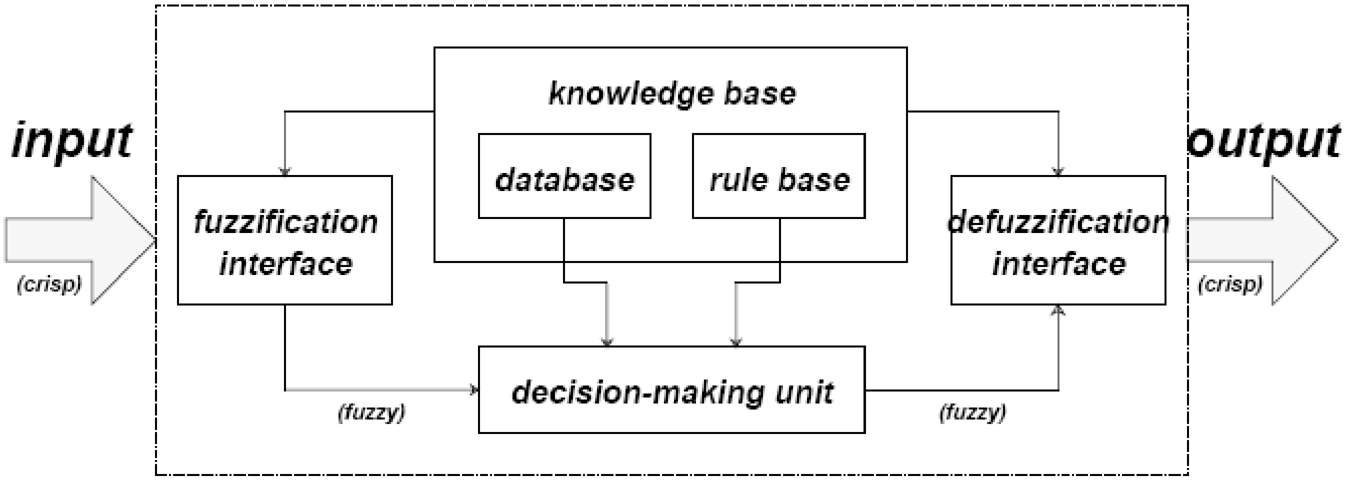

Figure 1. General structure of the ANFIS

using experimental data to train ANFIS. In training, the measured flow parameters are introduced to ANFIS as input parameters, while friction coefficient as target parameter. The estimated value of the friction coefficient is then used in Manning Equation to predict the fluid discharge in the open channel flow. A comparison is carried out between the proposed ANFIS based approach and the conventional ones. Results show that the proposed ANFIS approach is in good agreement with the experimental results when compared to the conventional ones. Recently, there is a growing body of artificial intelligent approaches in civil engineering (Karunanithi et al., 1994; Grubert, 1995; Sanchez et al., 1998; Altun et al., 2006, Subasi, 2009; Kisi, 2004; Topçu, and Sarıdemir, 2008; Başyiğit et al., 2010; Terzi, 2007; Yarar et al., 2009; Kisi et al., 2009).

ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

ANFIS is the implementation of fuzzy inference system (FIS) to adaptive networks for developing fuzzy rules with suitable membership functions to have required inputs and outputs. FIS is a popular and cardinal computing tool to which fuzzy if-then rules and fuzzy reasoning compose bases that performs mapping from a given input knowledge to desired output using fuzzy theory. This popular fuzzy set theory based tool have been successfully applied to many military and civilian areas of including decision analysis, forecasting, pattern recognition, system control, inventory management, logistic systems, operations management and so on. FIS basically consist of five subcomponents (Topçu and Saridemir, 2008), a rule base (covers fuzzy rules), a database (portrays the membership functions of the selected fuzzy rules in the rule base), a decision making unit (performs inference on selected fuzzy rules), fuzzification inference and defuzzification inference. The first two subcomponents generally referred knowledge base and the last three are referred to as reasoning mechanism (which derives the output or conclusion).

An adaptive network is a feed-forward multi-layer Artificial Neural Network (ANN) with; partially or completely, adaptive nodes in which the outputs are predicated on the parameters of the adaptive nodes and the adjustment of parameters due to error term is specified by the learning rules. Generally learning type in adaptive ANFIS is hybrid learning (Jang, 1993). General structure of the ANFIS is illustrated in Figure 1.

DEVELOPED ANFIS MODEL AND FINDINGS

ANFIS model developed in this research using MATLAB toolbox has three inputs (Q-V-Re) and an output (FC) as illustrated in Figure 2. While developing the model 94 experimental data used. After experimenting different learning algorithms with different epochs, best correlations was found through hybrid learning algorithm and 100 epochs. In the model 6 "trimf" membership functions were selected for each input. The numerical range were used for Q (0.5-19), for V(0.0279-1,413), for Re(7920-$1726*10^5$) respectively. Membership functions of inputs are displayed in Figure 3a, b and c. Also the membership functions are detailed in Tables 1, 2 and 3.

Model 216 rule defines the relationship between inputs and outputs. While training the model error change is seen in Figure 4. After training, the model was tested only using input data by defuzzification monitor. The models defuzzification monitor is shown in Figure 5. Figure 6 shows matching figure of the measured results with the results obtained from developed ANFIS model.

The adequacy of the developed ANFIS was evaluated by considering the coefficient of determination (R^2) and the root mean squared error (RMSE).

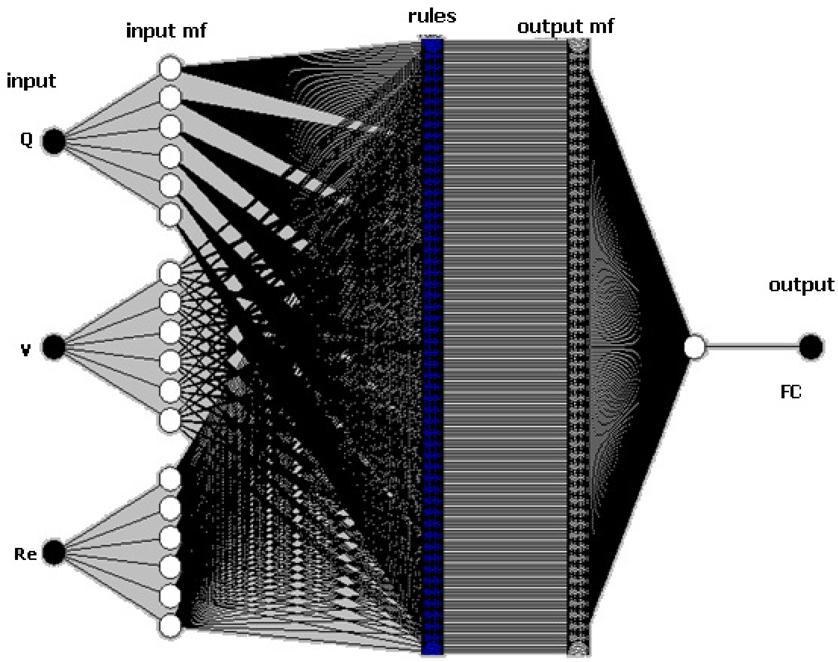

Figure 2. General structure of the model.

a

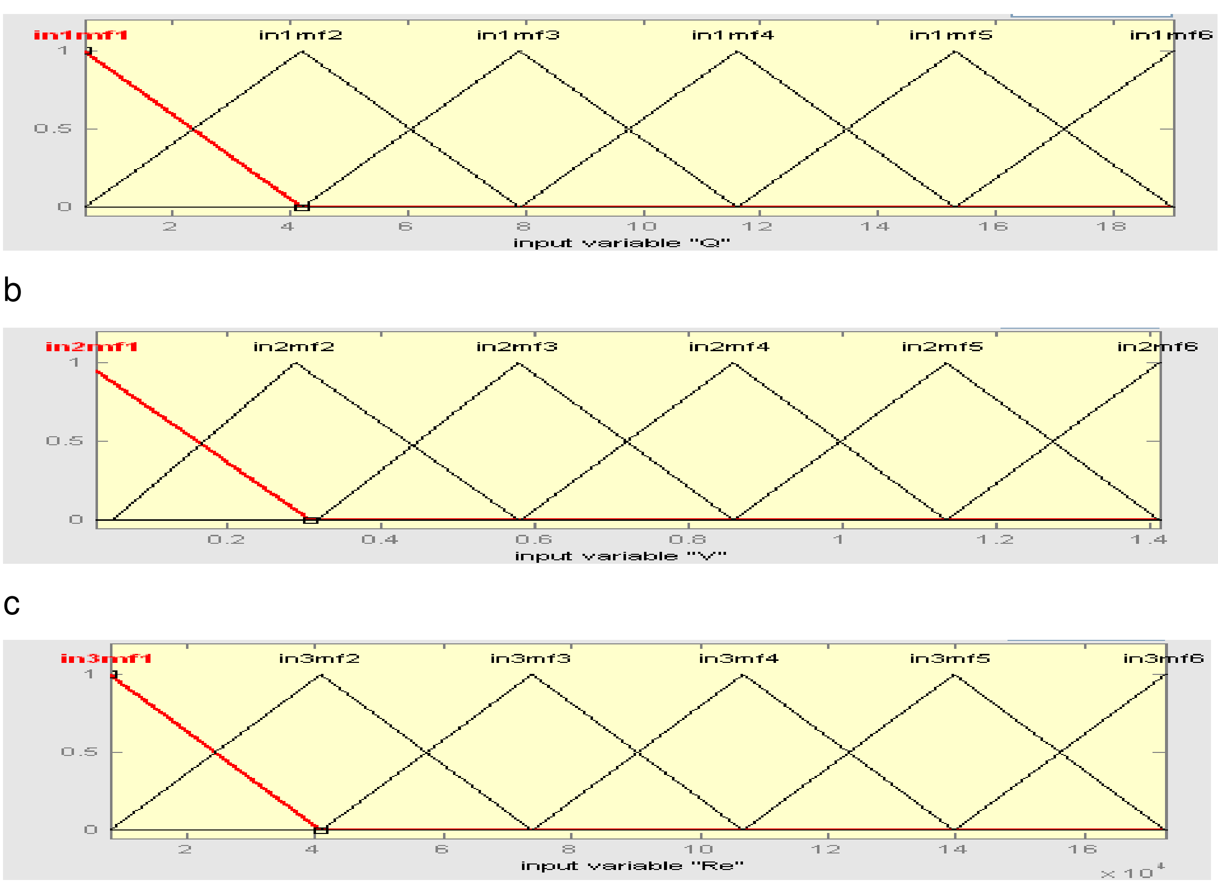

Figure 3 (a,b,c). Membership functions of inputs.

Table 1. Membership functions details for Q.

Input 1 Name='Q'
Range=[0.5 19]
NumMFs=6
MF1='in1mf1':'trimf',[-3.2 0.499511901669204 4.20237739317276]
MF2='in1mf2':'trimf',[0.499660698173184 4.19879489796152 7.90018712015187]
MF3='in1mf3':'trimf',[4.19915582319934 7.8991682263209 11.6000465512245]
MF4='in1mf4':'trimf',[7.89995297697801 11.5998275301719 15.299917129494]
MF5='in1mf5':'trimf',[11.5999521555313 15.2999213376594 18.9999930482892]
MF6='in1mf6':'trimf',[15.2999686850696 18.9999784920591 22.7]

Table 2. Membership functions details for V

Input 2 Name='V'
Range=[0.0279 1.413]
NumMFs=6
MF1='in2mf1':'trimf',[-0.24912 0.0139037287442927 0.308501377124837]
MF2='in2mf2':'trimf',[0.0499501325107948 0.288381133422171 0.57934578871329]
MF3='in2mf3':'trimf',[0.316172370111406 0.579218812197247 0.859135646167306]
MF4='in2mf4':'trimf',[0.58162852067594 0.858508720296616 1.13597559417856]
MF5='in2mf5':'trimf',[0.858893071415528 1.13594425535557 1.41299967810983]
MF6='in2mf6':'trimf',[1.13597446445295 1.4129998538734 1.69002]

Table 3. Membership functions details for Re

Input 3 Name='Re'
Range=[7920 172632]
NumMFs=6
MF1='in3mf1':'trimf',[-25022.4 7919.99999993359 40862.4000011903]
MF2='in3mf2':'trimf',[7920.00000034735 40862.3999998859 73804.7999997588]
MF3='in3mf3':'trimf',[40862.3999997574 73804.7999999449 106747.200000023]
MF4='in3mf4':'trimf',[73804.7999998745 106747.199999988 139689.600000003]
MF5='in3mf5':'trimf',[106747.199999946 139689.599999994 172632]
MF6='in3mf6':'trimf',[139689.599999995 172631.999999998 205574.4]

$$R^2 = 1 - \left\{ \left[\sum_{i=1}^{n} \left(F_{i(\text{observed})} - F_{i(\text{model})} \right)^2 \right] \Big/ \left[\sum_{i=1}^{n} \left(F_{i(\text{observed})} - F_{(\text{mean})} \right)^2 \right] \right\} \quad (7)$$

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left(Fi_{\text{observed}} - Fi_{\text{predicted}} \right)^2} \quad (8)$$

where n is the number of observed data, Fi(observed) and Fi(model) are observed FC values and ANFIS results, respectively. For FC prediction by ANFIS using observed data, R^2 and $RMSE$ values were found as 0,984638 and 0,00012422 respectively.

Conclusıons

As the formation of secondary flow cells in the flows are important for small *W/h* values, in open channels, the analysis of the free surfaces are usually more complex than that of pressured flows. Rao (1969) and Myers (1982) studied the relation between *W/h* and Reynolds number, however, they have not reached a conclusive result. Findings of Rao and Myers showed that uncertainty would begin when *W/h* ratios were smaller than 6, and 4 respectively. The experimental findings indicate that the friction loss coefficient become a highly complex function the measured parameters when channel

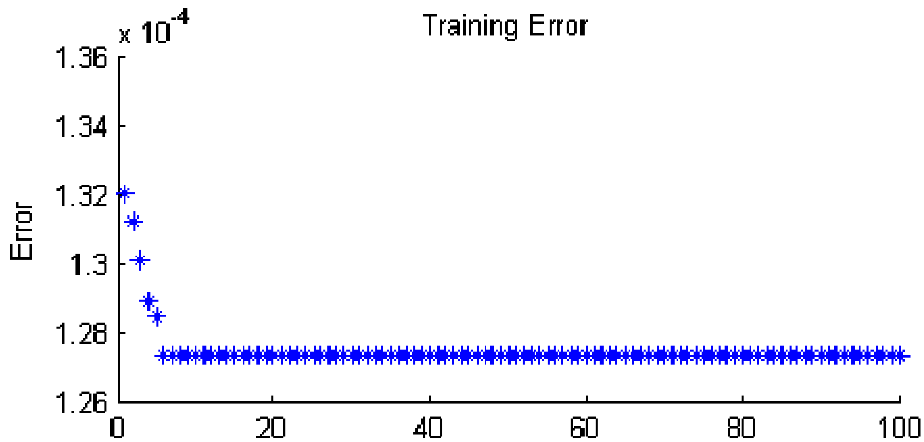

Figure 4. Error change during training.

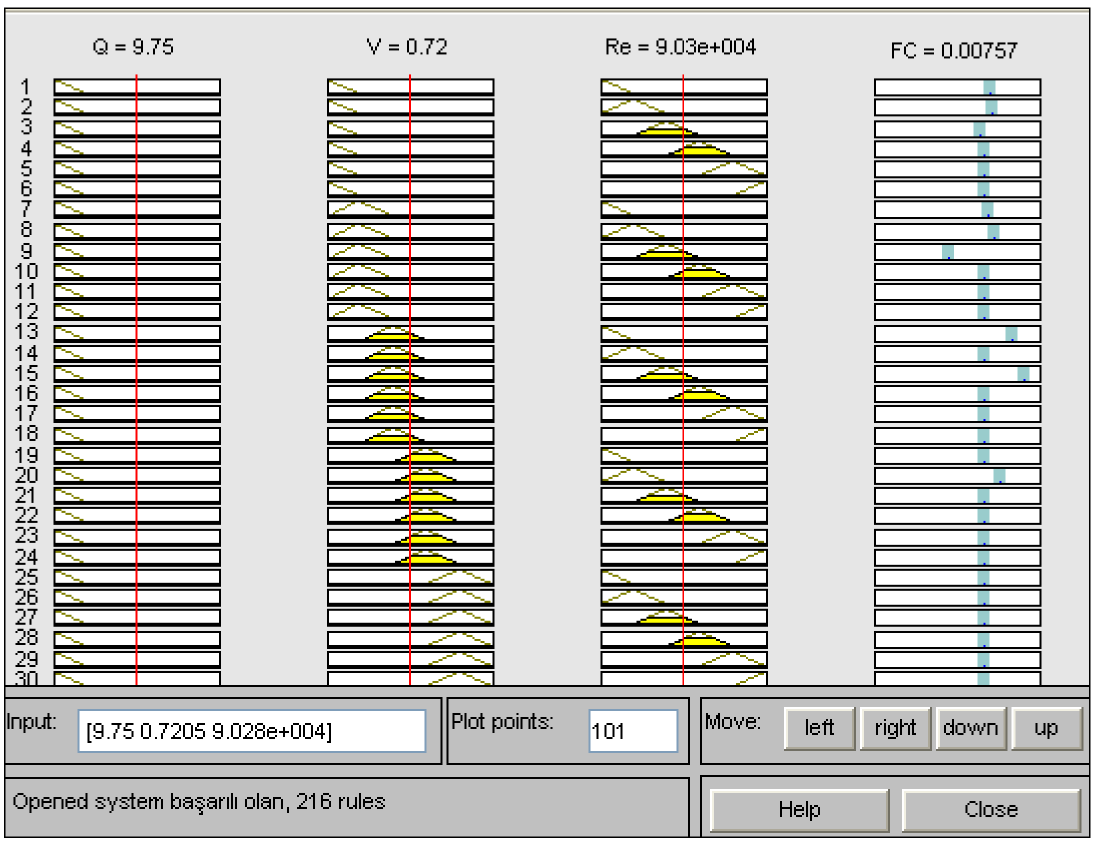

Figure 5. Defuzzification monitor of the model.

geometry is changed to square (Altun et al., 2006).

Many researchers stated that the average friction factor in open channels is nearly 10% higher than that of pipes under same conditions. Therefore, usage of pipe flow equations in calculation of friction factor may lead significant error in channel flows as indicated by Bilgil (1998). However, there is no simple relation between the friction coefficient and Reynolds number and *W/h* ratios in the literature. It is a common practice in literature to calculate the friction coefficient in Manning formulation, using Manning approach. However, this approach has an inherent error due to simplification to establish a formula. The proposed neural network approach, instead, is an attempt to map the measured parameters into friction

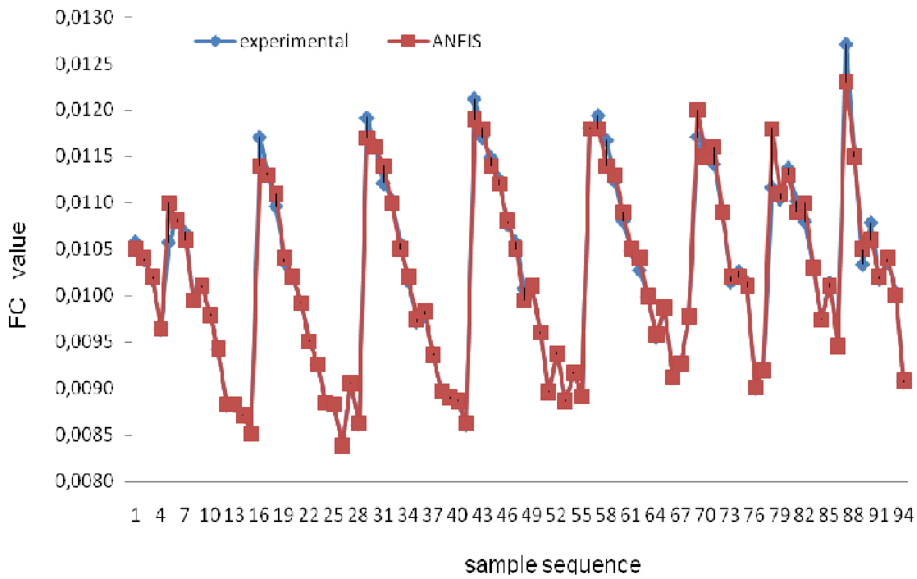

Figure 6. Matching figure of experimental results and developed ANFIS model results.

coefficient without any simplification. So the inherent error would not be expected to exist (Altun et al., 2006).

A neuro-fuzzy model is presented to estimate the fraction coefficient in open channel flows. The model is trained to estimate the friction factor from given experimental parameters of the channel and flow. It was found that the ANFIS model approach show high efficiency in the prediction of water discharge in smooth open channel. (R^2 and *RMSE* values were found as 0.984638 and 0.00012422 respectively). The application of ANFIS approach may be generalized to in smooth channels other than rectangular cross sectional area such as triangular, trapezoid, circular etc. as well as in rough channels with free surface flow.

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