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# An optimized Adaptive-Neuro Fuzzy Inference System (ANFIS) for reliable prediction of entrance length in pipes

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**Abstract: In this paper, an attempt has been made to predict and evaluate the entrance length in pipe for low Reynolds number flow using evolutionary-optimized Adaptive-Neuro Fuzzy Inference System (ANFIS). For optimization purpose, evolutionary algorithm namely particle swarm optimization (PSO) is adopted. We trained and tested the model using 100 experimental records from computational fluid dynamics (CFD) technique that established the basic dataset under various working conditions such as air and water. This experimental data set is included input parameters namely Reynolds number, pipe diameter, and inlet velocity and entrance length as output parameter. The dataset is divided to two part for training and testing with 87 and 13 data number respectively. The structure of developed PSO-optimized ANFIS model in comparison with another models is very simple such that the model is composed of 3 membership functions for each input and only 27 rules in rule base. Evaluation of predicted entrance length values obtained by the optimized model was performed by using indicators such as coefficient of determination (R2) = 0.9966 and Root Mean Square Error (RMSE) = 0.011 that prove satisfactory efficiency of this model. The model can also be used for prediction of online entrance length without any constraint in selection of data points or training phase.**

**Keywords: ANFIS, Development pipe length, Optimization, Particle swarm optimization, Reliable prediction.**

## Introduction

The knowledge of the entrance length is not only required for fluid engineers for design of pipe systems but also it is required for researchers to resolve critical problems related to it. Since the very early time [1] there have been a lot of efforts resulted in a variety of designs to obtain fully developed flow in a short pipe length. So, prediction of entrance length of pipe with appropriate accuracy for laminar flow condition in pipes had attracted attention of many scientists. Some analytical, experimental, and numerical approaches that are most important can be referred herein as some of the sample references [2-7]. From Table 1 contributions of researchers are presented chronologically (XD and D, are the entrance length and diameter of the pipe respectively and Re denotes Reynolds number).

**Table 1: Prediction of entrance length in laminar pipe flow using Predictive equations**

| No | Author(s) | Year | Method | Ratio of entrance length to pipe diameter ($X_D/D$) |
|---|---|---|---|---|
| 1 | Collins and Schowalter | 1963 | Analytical | 0.061Re |
| 2 | Sparrow et al. | 1964 | Analytical | 0.056Re |
| 3 | McComas | 1967 | Experimental | 0.026Re |
| 4 | Atkinson et al. | 1988 | Numerical | 0.59 + 0.056Re |
| 5 | Chhebi | 2002 | Analytical | 0.09Re |
| 6 | Durst et al. | 2005 | Numerical | $[0.619^{1.6} + (0.0567\,Re)^{1.6}]^{1/1.6}$ |
| 7 | Mrutyunjaya et al | 2012 | Intelligent | No mentioned |

Investigation of proposed methods illustrated that most of the methods proposed earlier usually over estimating the entrance length of pipe in low laminar flow condition even recently developed models also. This phenomena might be due to the fact that some parameters with higher avail like environmental condition, selection of proper inlet parameters, influence of thermodynamic parameters, physical parameters such as convection and diffusion are not taken into account. Presently rapid development in intelligence computing not only reduces the repetitive effort of experimentation but also it eliminates complicated computations. Outstanding past studies by using soft computing techniques is artificial neural network model for estimation of friction factor in smooth open channel flow [8]. In [9] has been proved that the use of adaptive-neuro fuzzy inference system (ANFIS) for modeling of ground-coupled heat pump system is very useful and practical. Generally, when relationship between input and output in a system is difficult to develop using mathematical equations, analytical and numerical methods and it becomes annoying and time consuming, an easily implementable technique like ANFIS can be selected. The rest of this paper is organized as follow. In section 2 the mechanism of developed pipe length and low Reynolds number are briefly described. Then, in section 3 theoretical routines of ANFIS architecture, its training and validation phases, Particle Swarm Optimization (PSO) algorithm, and its utilization on optimizing the proposed model are presented. After developing the optimized ANFIS model to predict the entrance length of pipe in low Reynolds number, dataset will be introduced and simulation results are compared with another traditional models in section 4. Finally in section 5, our focus is on future works, challenges and conclusion.

## The mechanism of developed pipe length and low Reynolds number

As turbulent flow enters the pipe, regarding to the no-slip velocity condition at the wall, the fluid sudden next to the wall obstructs and thus, creates high velocity gradients before uniform flow is reached. Due to this happening, rate of energy decadence and therefore, pressure drop also increases. The obstacle at the pipe wall causes the centerline flow to move faster as mass flow rate is constant. When fully developed condition of flow is achieved, the maximum velocity at the pipe centerline becomes ninety nine percent of theoretical maximum. The closest location, i.e. the distance from the inlet of pipe to the location of fully developed pipe flow is defined as the entrance length [7]. A low Reynolds number flow is described as the flow where inertia plays less important role than viscosity and so, flow is more affected by tangential force due to viscosity rather than inertia. Hence, diffusive momentum transfer is intensified in the direction of the flow. From Figure 1 it can be inferred that ratio of development length to the developed flow velocity ($t_{diff}$) varies with both Reynolds number and diameter. When Reynolds number enlarges, $t_{diff}$ reduces for all of values of diameter and $t_{diff}$ increases as diameter increases for any value of Reynolds number. The pattern of variation illustrates that diffusion is an important factor in lower Reynolds number flows and there exists a nonlinear relationship between $t_{diff}$ and Reynolds number.

## Theoretical routines

### A. ANFIS architecture

ANFIS that is abbreviation of Adaptive Neuro-Fuzzy Inference System is an adaptive system which is based on combination of artificial neural network (ANN) and fuzzy inference system (FIS) capabilities. A novel architecture which can serve as a basis for creating a set of fuzzy if-then rules with appropriate membership functions to generate the specified input–output pairs is called Adaptive-Network-based Fuzzy Inference System or simply ANFIS. This recommended method has been found in many practical applications including decision analysis, forecasting, operation management and control prediction system, etc. In ANFIS approach, neural networks construct patterns which further assist adjustments into the environments. Fuzzy inference systems integrate human knowledge and represent interfacing and decision-making. ANFIS is thus a back propagation algorithm which is based on the accumulation of input-output data. Both neural network and fuzzy logic [10] are model-free estimators and share the common ability to count uncertainties and noise. Both of them code the knowledge in a parallel and distributed architecture ina numerical framework. Hence it is feasible to convert fuzzy logic architecture to a neural network and vice versa. This makes it attainable to mix the benefits of neural network and fuzzy logic together. A network obtained this way could use excellent training algorithms that neural networks have at their disposal to obtain the parameters that would not have been possible in fuzzy logic architecture. Moreover, the network that is obtained in this way would not remain a black box, since this network would have fuzzy logic capabilities to interpret in terms of linguistic variables [11]. If we compose these two intelligent approaches, it will be achieve good reasoning in quality and quantity. In other words, we have fuzzy reasoning and network calculation. ANFIS structure organizes two parts like fuzzy systems. The first part is the antecedent part and the second part is the consequent part, which are connected to each other by rules in network form. If we want to show the ANFIS network architecture in five layers, It can be described as a multi-layered neural network as shown in Figure 2 [12].

Here, for ANFIS structure, two inputs with two labels (A, B) for each input are considered. The first layer performs a fuzzification process, the second layer executes the fuzzy AND (T-norm) of the antecedent part of the fuzzy rules, in the third layer the membership functions (MFs) are normalized, the fourth layer is responsible of consequent part of the fuzzy rules, and finally the last layer computes the output of fuzzy system by summarizing the outputs of layer fourth. The feed forward equations of ANFIS in accordance with layers ordering in figure 1 are as follows:

Layer (1) explanation: Each node in this layer generates a membership grade of a linguistic label. Usually, membership functions are used as Gaussian-shaped with minimum and maximum equal to 0and 1respectively, such as:

$$mA_i(x) = f(x;\sigma,c) = \exp(-(x-c)^2/2\sigma^2) \quad (1)$$

Where x is the input and $A_i$ is the linguistic label in related to this node. Premise parameters namely c and σare the curve mean and the variance which change the shapes of the membership function.

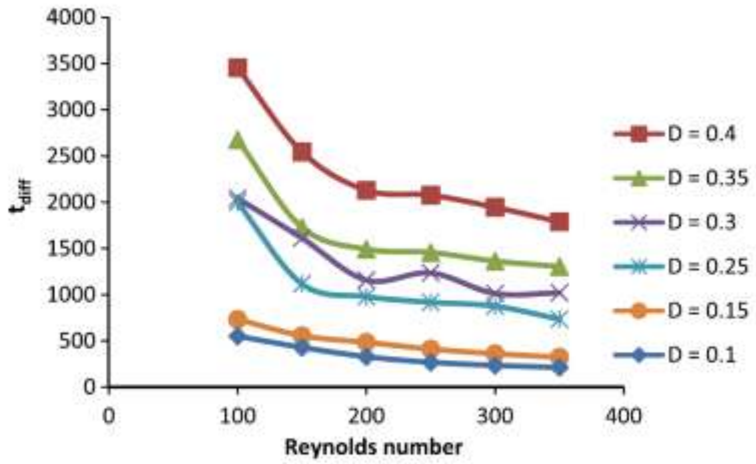



**Figure 1. Variation of $t_{diff}$ with Reynolds number [7]**

Layer (2) explanation: Via T-norm (multiplication), each node calculates the firing strength of each rule:

$$w_i = mA_i(x) * mB_i(y), (i = 1, 2) \quad (2)$$

Layer (3) explanation: Layer 3 includes fixed nodes which determine the ratio of the firing strengths of the rules (normalized firing strengths):

$$\overline{w_i} = w_i / w_1 + w_2, (i = 1, 2) \quad (3)$$

Layer (4) explanation: Likewise, in layer 4 the nodes in this layer are adaptive and equal and consequent within the rules:

$$\overline{w_i} f_i = \overline{w_i}(p_i + q_i y + r_i) \quad (4)$$

The parameters in this layer ($p_i$,$q_i$,$r_i$) are to be evaluated and are referred to as the consequent parameters.
Layer (5) explanation: Ultimately, in the final analysis in layer 5, there is a single node hereto figure the overall output:

$$\text{Overalloutput} = \sum_i^n \overline{w_i} f_i = \sum_i w_i f_i / \sum_i w_i \quad (5)$$

This reveals that the input vector is fed through the network layer by layer and the description of the ANFIS architecture above explicitly indicates that, the basic strength of this approach is dependent on producing fuzzy rules from a given input–output data set. In continuation of discussion, ANFIS method is trained by using evolutionary computation.

### B. Learning algorithm for ANFIS training

Jang [8] introduced four methods to update the parameters of ANFIS structure, as listed below according to their computation complexities:

1. Gradient decent only: all parameters are updated by the gradient descent.
2. Gradient decent only and one pass of LSE: the LSE is applied only once at the very beginning to get the initial values of the consequent parameters and then the gradient decent takes over to update all parameters.
3. Gradient decent only and LSE: this is the hybrid learning.
4. Sequential LSE: using extended Kalman filter to update all parameters.

These methods update antecedent parameters by using GD or Kalman filtering. These methods have high complexity. Hence, a number of approaches have been proposed for learning rules and for obtaining an optimal set of rules. For example, Kumar et al [11] presented an Intelligent Learning method via Neural Network and Genetic Algorithm for Fuzzy Logic Controllers but the convergence in their approach was not appropriate. Hence, in this paper we introduced a method with lower complexity and fast convergence based on particle swarm optimization algorithm [14].

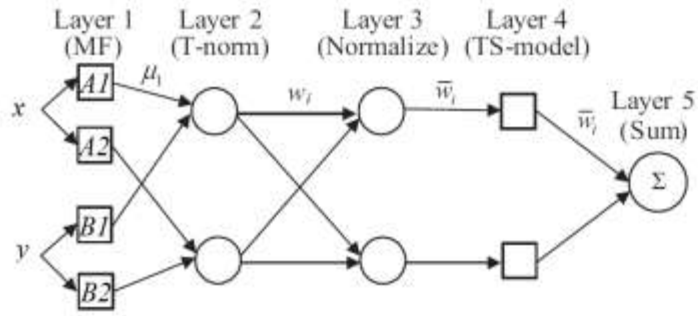



**Figure 2. ANFIS architecture**

### C. Particle swarm optimization algorithm

The particle swarm optimization (PSO) algorithms are a population-based search algorithms based on the simulation of the social behavior of birds within a flock [15]. They all work in the same way, which is, updating the population of individuals by applying some kind of operators according to the fitness information obtained from the environment so that the individuals of the population can be expected to move toward better solution areas. In the PSO each individual flies in the search space with velocity which is dynamically adjusted according to its own flying experience and its companion flying experience, each individual is a point in the D- dimensional search space. Generally, the PSO has three major algorithms. The first is the individual best. This version, each individual compares position to its own best position, $p_{best}$, only. No information from other particles is used in these type algorithms. The second version is the global best. The social knowledge used to drive the movement of particles includes the position of the best particle from the entire swarm. In addition, each particle uses its history of experience in terms of its own best solution thus far. In this type the algorithms is presented as:

1. Initialize the swarm,p(t), of particles such that the position $\vec{x}_i(t)$ of each particle $p_i \in p(t)$is random within the hyperspace, with t = 0.
2. Evaluate the performance F of each particle, using its current position $\vec{x}_i(t)$ .
3. Compare the performance of each individual to its best performance thus far:

   IfF( $\vec{x}_i(t)$ )<$p_{best(i)}$then:

   $$p_{best(i)} = F(\vec{x}_i(t)) \tag{6}$$

   $$\vec{x}_{pbest(i)} = \vec{x}_i(t) \tag{7}$$

4. Compare the performance of each individual to global best particle:

   If F( $\vec{x}_i(t)$ )<$g_{best(i)}$ then:

   $$g_{best(i)} = F(\vec{x}_i(t)) \tag{8}$$

   $$\vec{x}_{gbest(i)} = \vec{x}_i(t) \tag{9}$$

5. Change the velocity vector for each:

   $$\vec{v}_i(t) = \vec{v}_i(t-1) + p_1 + (\vec{x}_{pbest(i)} - \vec{x}_i(t)) + p_2(\vec{x}_{gbest(i)} - \vec{x}_i(t)) \tag{10}$$

   Where $p_1$ and $p_2$ are random variables. Kennedy studied the effects of the random variables on the particle's trajectories and claimed that $p_1+p_2 \leq 4$ guarantees the stability of PSO. The second term above is referred to as the cognitive component, while the last term is the social component.
6. Move each particle to a new position:

   $$\vec{x}_i(t) = \vec{x}_i(t-1) + \vec{v}_i(t) \tag{11}$$

   $$t = t+1$$

7. Go to step 2, and repeat until convergence.

### Training ANFIS parameters using PSO

In this section, the way PSO employed for updating the ANFIS parameters is described. The ANFIS has two types of parameters which need training namely the antecedent and the consequent parameters. The membership functions are assumed Gaussian as in equation (1), and their parameters are c and σ, where first is the curve mean and latest is the variance which with changing them, the shapes of the membership function change. Also, the parameters of consequent part are trained during optimization algorithm and here are represented with $p_i$, $q_i$, and $r_i$. There are 2 trainable parameters in antecedent part. Each of these parameters has N genes, Where N represents the number of MFs. Each chromosome in consequent part has (I+1) × R genes that R is equal to Number of rules and I denotes dimension of data inputs. For example each chromosome in consequent part in figure 1 has 6 genes. Parameters are initialized randomly in first step and then are being updated using PSO algorithms. In each iteration, one of the parameters set are being updated. I.e. in first iteration for example 'c' is updated then in second iteration σ is updated and then after updating all parameters, again the first updated parameter is considered and so on. In the learning procedure the aim is to minimize the objective function of sum of error squares as follows:

$$E(k) = \frac{1}{2}\left(y^d(k) - y(k)\right)^2 \tag{12}$$

Here, $y^d$ and y are the desired and the predicted output values of the network at sample k, respectively. Also, the $n^{th}$ chromosome can be represented as:

$$U^n = [(c_{ij}^n\ \sigma_{ij}^n\ p_{ij}^n\ q_{ij}^n\ p_j^c],\ i = 1: N_{input},\ j = 1: N_{rule} \tag{13}$$

### Dataset & data normalization

One of the most important stages in the ANFIS technique is data collection. For this purpose, the pipe flow is simulated using computational fluid mechanics (CFD) technique to generate data for prediction of entrance length in pipe for developed flow [7]. The flows supposed to be laminar, incompressible, steady, developing and without swirl. The materials contemplated in this simulation are water and air. The fluid characteristics are also assumed to be constant. The governing equations (14 - 16) are given as follows; Continuity Equations:

$$\frac{1}{r}\frac{\partial}{\partial r}(\rho r U_r) + \frac{\partial}{\partial z}(\rho U_z) = 0 \tag{14}$$

Axial momentum equation:

$$\rho\left(U_r\frac{\partial U_z}{\partial r} + U_z\frac{\partial U_z}{\partial z}\right) = -\frac{\partial P}{\partial z} + \mu\left[\frac{1}{r}(\mathrm{r}\frac{\partial U_z}{\partial r}) + \frac{\partial^2 U_z}{\partial z^2}\right] \tag{15}$$

Radial momentum equation:

$$\rho\left(U_r\frac{\partial U_r}{\partial r} + U_z\frac{\partial U_r}{\partial z}\right) = -\frac{\partial P}{\partial z} + \mu\left[\frac{\partial}{\partial r}(\frac{1}{r}\frac{\partial(\mathrm{r}U_r)}{\partial r}) + \frac{\partial^2 U_r}{\partial z^2}\right] \tag{16}$$

In above equations, $U_r$ = radial velocity, $U_z$ = axial velocity, μ = co-efficient ofviscosity of the fluid, r = radial distance at any point from the centerline, ρ = density of fluid, z = axial distance at any point alongthe pipe, and $U_0$ = uniform inlet velocity along the pipe. The governing equations are discretized with finite volume method and simulated using computational fluid mechanics (CFD) technique. Finally, one hundred data points are generated through simulation. Sixty data samples use water as working fluid whereas forty data samples use air. Entire experimental data set is divided into training and testing data sets. In the present study, a total of 100 entrance lengths records as shown in Table 2 (3 data samples rather than all of them) are used. Among 100 data, 83 are considered as training and 17 as testing data. The range of input and output parameters have been defined in table 3. In the process of ANFIS, sometimes raw data may not be suitable to be utilized, when values of input and output parameters are extremely low or high, thus raw data needs to undergo preprocessing. Therefore scaling of data should be performed. One approach for scaling of data is performed with following formula equation (17) which normalizes the data to values between 0 and 1[16]:

$$X'_i = x_i - x_{\min} / x_{\max} - x_{\min} \tag{17}$$

Where $X_i$ is original value of parameter, $X'_i$ is normalized value of $X_i$, $X_{min}$ and $X_{max}$ are minimum and maximum values of parameter that is related to $X_i$.

### Generalization performance of the model

Three indexes, i.e., mean absolute error (MAE), root mean square error (RMSE) and coefficient of determination (R2), were adopted for generalization performance evaluation. They are formulated by equations (18 - 20), respectively:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\hat{y}_i - y_i\right| \tag{18}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\hat{y}_i - y_i\right)^2} \tag{19}$$

$$R^2 = \sum_{i=1}^{n}\left(\hat{y}_i - \bar{y}\right)^2 / \sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2 \tag{20}$$

Where n denotes the number of samples, $y_i$ represents the i[th] target value, $\hat{y}_i$stands for the predicted value for the i[th] sampleand $\bar{y}$is the mean target value for all target samples.

**Table 2: Data set samples (input and output data used for analysis) [7].**

| Serial no. | Reynolds number | Diameter | Inlet velocity | Entrance length |
|---|---|---|---|---|
| 1 | 100 | 0.2 | 0.0005 | 1.16 |
| 2 | 150 | 0.2 | 0.00075 | 1.16 |
| 3 | 200 | 0.2 | 0.001 | 1.36 |

**Table 3: Input and output parameters used for entrance length prediction modeling and their ranges.**

| No. | Parameters | Type | Unit | Range (min-max) |
|---|---|---|---|---|
| 1 | Reynolds number | Input | - | 15-450 |
| 2 | Diameter | Input | millimeter | 0.05 - 0.9 |
| 3 | Inlet velocity | Input | Meter/second | 0.000022 – 0.007 |
| 4 | Entrance length | Output | meter | 0.51 – 2.88 |

## Results and discussion

First of all, from Tables 4, it can be viewed that the regression performance of PSO-optimized ANFIS model surpasses than models under the same training and test conditions. The model generated also predicts the entrance length with accurately compared to earlier proposed analytical and experimental models. It has been seen from Table 4 that the earlier developed traditional models predicts entrance length with coefficient of determination (R2) up to 0.98. But proposed model in this work can predict with coefficient of determination (R2) as high as 0.995. All predicted data points were well within the 1:1 slope line. This clearly indicates the ability of optimized ANFIS for prediction of entrance length and it reveals that the regression effect fitted by generated models is better than another models. After utilizing optimization method, c and σ values for each input obtained that has been illustrated in table 5. Figure 3 shows membership functions according to this values. In table 6, 14 test samples with their actual and predicted entrance length using proposed method has been presented. Figures 4-7 illustrate the relationship between the measured and predicted entrance length in both of training and testing phases by using predictor model with their overlapping and respective coefficient of determination. Furthermore, it can be found in figure 8 that the MAE index estimated by PSO-optimized ANFIS model is 0.0081 and error rate changes between -0.02 to 0.027. Finally, The ANFIS architecture is shown in figure 9.

## Conclusion & Future works

In this paper, we presented the model based on optimized adaptive neuro fuzzy inference system that predicted the entrance length of Pipe for low Reynolds number flows with high accuracy. In the simulation procedure we adopted data set that had obtained from analysis package FLUENT 6.2. Further, ANFIS network is trained by evolutionary algorithm namely particle swarm optimization (PSO) and used to predict the entrance length for low Reynolds number flow where diameter of the pipe, inlet uniform axial velocity, and Reynolds number are considered as input parameters and entrance length as output parameter. For future works, this study can be extended to calculate entrance length for higher Reynolds number with both Newtonian and non-Newtonian flow conditions.

**Table 4: Comparisons of coefficient of regression ($R^2$) for most important predictive models**

| No | Author(s) | Year | ($X_D$/D) | Number of rules & MFs | $R^2$ |
|---|---|---|---|---|---|
| 1 | Collins and Schowalter | 1963 | 0.061Re | - | 0.87 |
| 2 | Sparrow et al. | 1964 | 0.056Re | - | 0.898 |
| 3 | McComas | 1967 | 0.026Re | - | 0.868 |

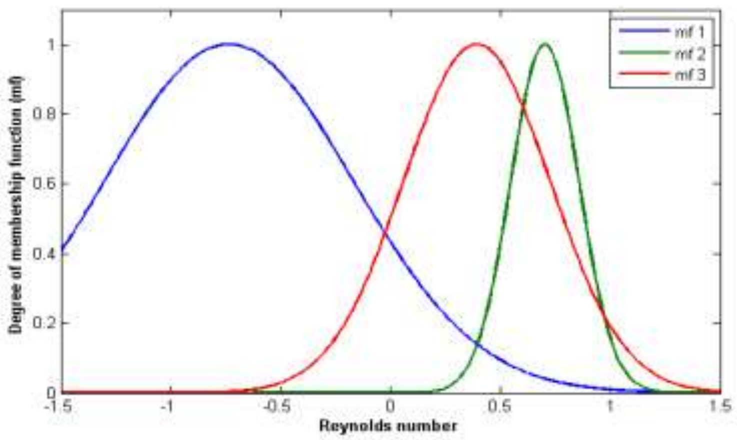
| | | | | | |
|---|---|---|---|---|---|
| 4 | Atkinson et al. | 1988 | 0.59 + 0.056Re | - | 0.898 |
| 5 | Chhebi | 2002 | 0.09Re | - | 0.776 |
| 6 | Durst et al. | 2005 | $[0.619^{1.6} + (0.0567\,Re)^{1.6}]^{1/1.6}$ | - | 0.897 |
| 7 | Mrutyunjaya et al | 2012 | - | 343&21 | 0.98 |
| 8 | Present work | | - | 27&9 | **0.996** |

**Table 5: Obtained values of c and σ (premise parameters) after execution of optimization phase**

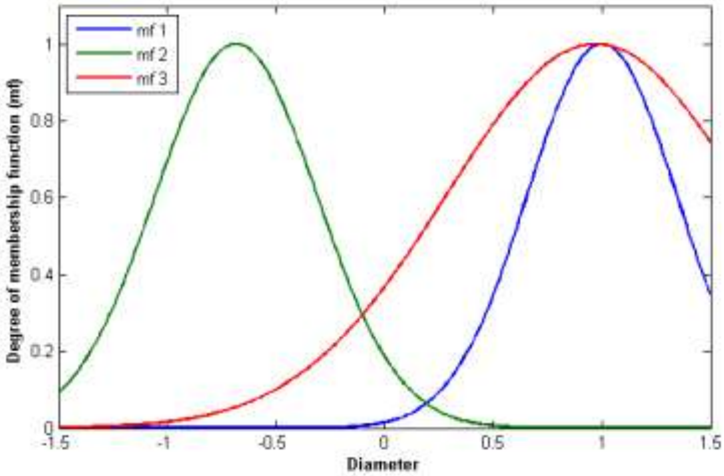
| Input name | Rule 1 | Rule 2 | Rule 3 |
|---|---|---|---|
| Reynolds number | C = -0.73593<br>σ = 0.56812 | C = 0.70207<br>σ = 0.15456 | C = 0.39241<br>σ = 0.33417 |
| Diameter | C = 1<br>σ = 0.34424 | C = -0.68412<br>σ = 0.37272 | C = 0.97067<br>σ = 0.68613 |
| Inlet velocity | C = 1<br>σ = 0.60638 | C = -0.6034<br>σ = 0.38965 | C = -0.64185<br>σ = 0.70198 |

**Table 6: Application of the predictive model on the test data points and obtained results (column 6)**

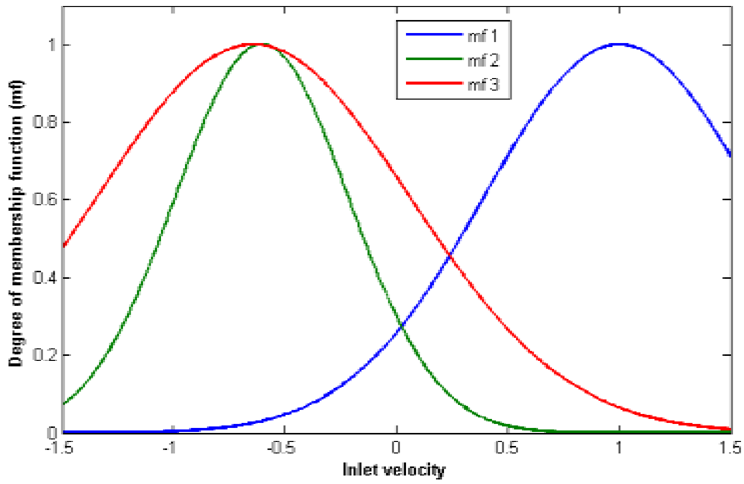
| Serial no. | Reynolds number | Diameter | Inlet velocity | Actual entrance length | Predicted Entrance length |
|---|---|---|---|---|---|
| 1 | 200 | 0.1 | 0.002 | 1.05 | 1.030683 |
| 2 | 75 | 0.3 | 0.0025 | 2.04 | 2.01471 |
| 3 | 100 | 0.4 | 0.00025 | 0.75 | 0.770131 |
| 4 | 125 | 0.5 | 0.00025 | 1.56 | 1.556221 |
| 5 | 150 | 0.6 | 0.00025 | 0.9 | 0.909111 |
| 6 | 175 | 0.7 | 0.00025 | 1.8 | 1.797122 |
| 7 | 200 | 0.8 | 0.00025 | 2.04 | 2.042115 |
| 8 | 225 | 0.9 | 0.00025 | 2.04 | 2.043291 |
| 9 | 250 | 0.1 | 0.0025 | 1.32 | 1.300812 |
| 10 | 90 | 0.3 | 0.0003 | 1.08 | 1.085791 |
| 11 | 120 | 0.4 | 0.0003 | 0.78 | 0.787344 |
| 12 | 150 | 0.5 | 0.0003 | 1.08 | 1.080883 |
| 13 | 180 | 0.6 | 0.0003 | 0.96 | 0.964271 |
| 14 | 210 | 0.7 | 0.0003 | 1.68 | 1.678754 |
| 15 | 240 | 0.8 | 0.0003 | 2.28 | 2.279627 |
| 16 | 270 | 0.9 | 0.0003 | 2.28 | 2.283431 |
| 17 | 30 | 0.1 | 0.001 | 2.16 | 2.149501 |




**(a)**




**(b)**




(c)

**Figure 3. Membership functions for inputs during generating FIS structure, optimized by PSO algorithm (a) Reynolds number (b) Diameter (c) Inlet velocity.**

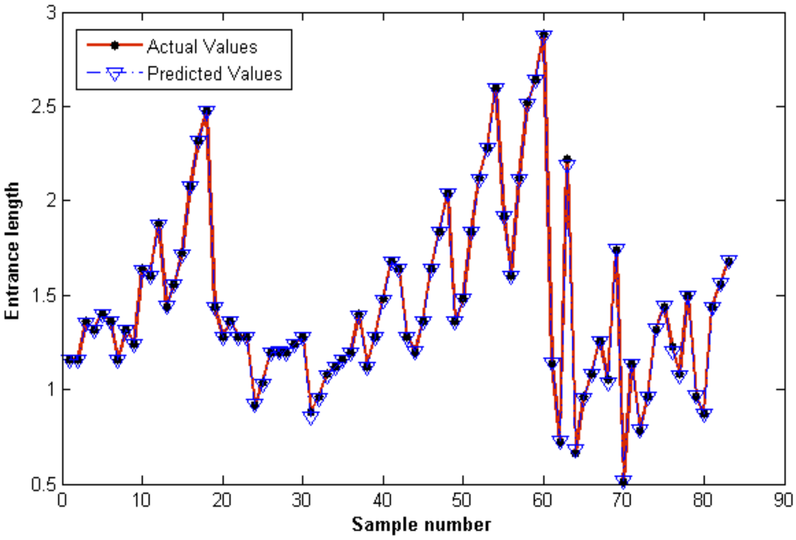



**Figure 4. Comparison of actual and predicted entrance length (training data).**

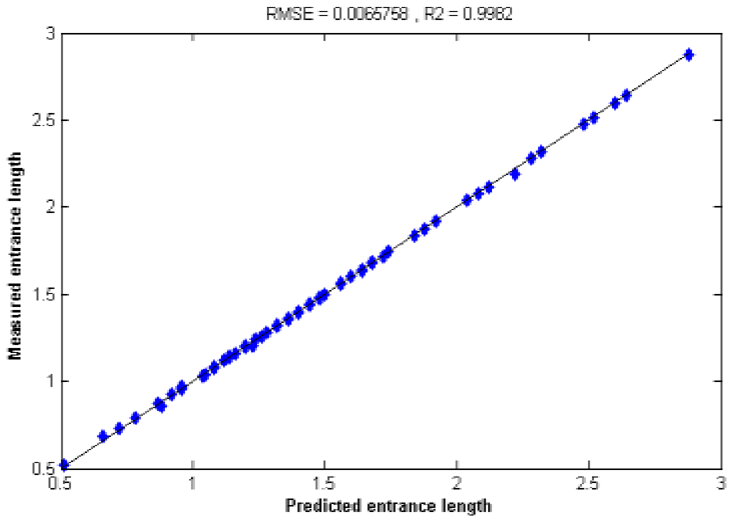



**Figure 5. Correlation of predicted and actual data (training).**

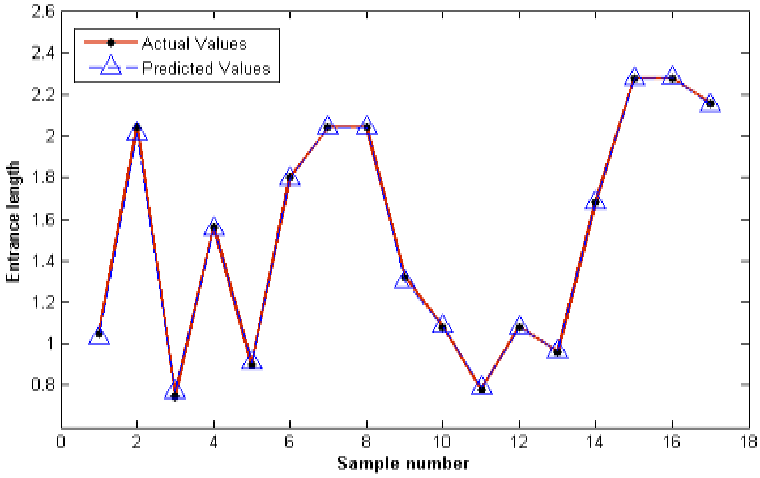



**Figure 6. Comparison of actual and predicted entrance length (testing data).**

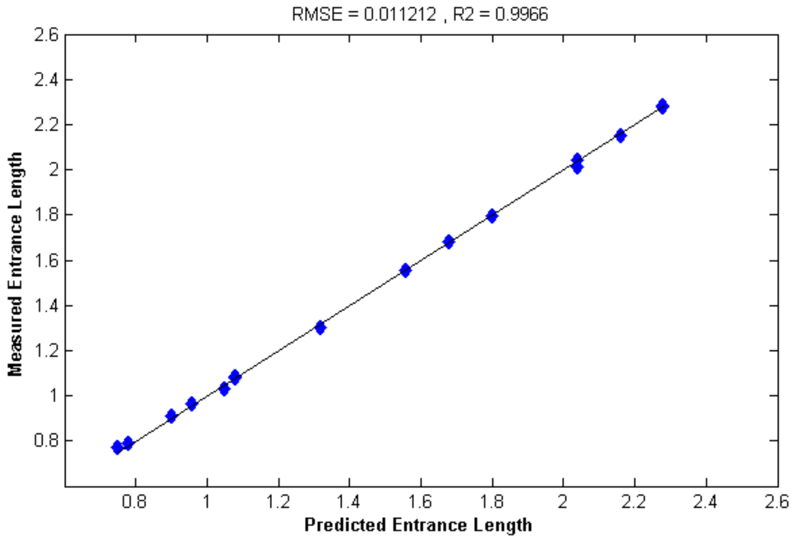



**Figure 7. Correlation of predicted and actual data (testing).**

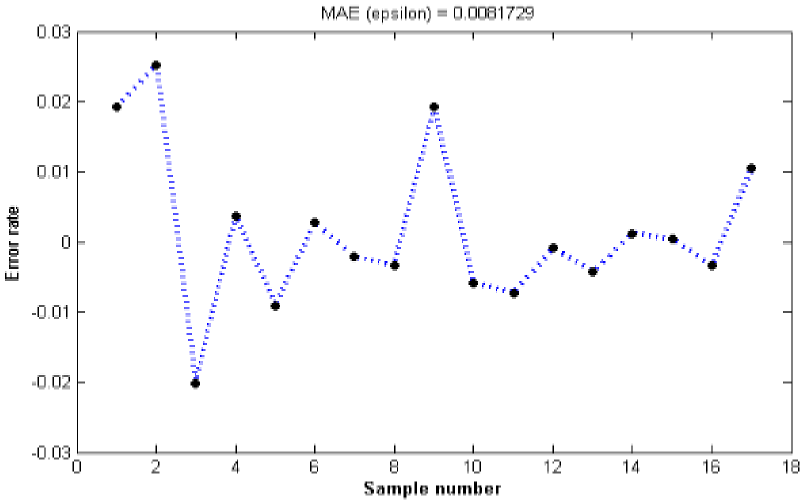



**Figure 8. Mean absolute error (MAE) and residual error in testing phase**

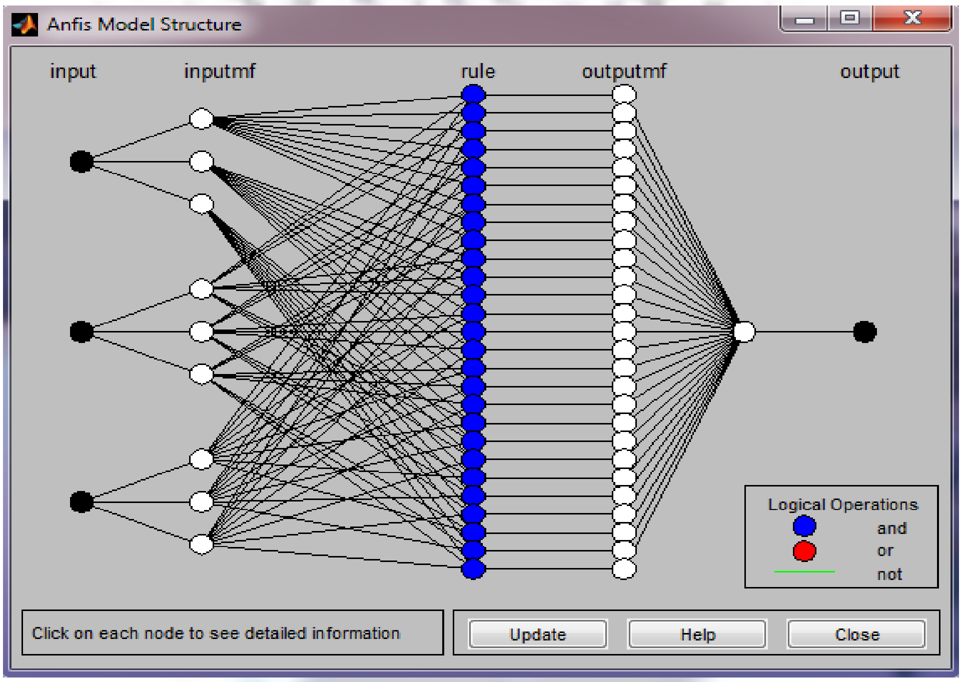



**Figure 9. Architecture of ANFIS for prediction entrance length in pipe (3 membership functions for each input and totally, 21 rules in the rule bae).**

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