THE PREDICTION OF TUBE'S INPUT LENGTH FOR LOW REYNOLDS NUMBER FLOWS USING TYPE-2 ADAPTIVE NEURO-FUZZY INFERENCE

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Abstract- *This paper presents a type-2 adaptive neuro-fuzzy inference system to predict the length of input into a tube for low Reynolds number flows. First, we established a database of various operating conditions using computational fluid dynamics (CFD) techniques. Thereafter, we created a rule base of optimized membership functions using a type-2 ANFIS training algorithm. Afterwards, a set of input/output data was fed into this system in order to train and validate whole system. Following the validation, we employed the devised system to predict the tube's input length. Finally, the results obtained from the proposed system were compared with a counterpart prediction model to study the system betterment. Consequently, the proposed model can be used to predict the tube's input length as an online estimator. However, the accuracy of this model depends on proper training and adequate selection of data points.*

Keywords: *ANFIS, Extended length, Low Reynolds number, Tube flow.*

1. INTRODUCTION

In our research, the significant input data parameters consist Reynolds number, tube diameter, and input rate. Also, the length of input into a tube is of the most noticeable output parameters.

1.1 Flows with Reynolds number

The viscosity property in flows with Reynolds number is more important than inertia. Therefore, these kind of flows are mostly affected by tangential force due to the viscosity property. In such condition, the shear velocity dispersion increases along the flow direction. In the case of the flows with low Reynolds number, the motion of shear velocity increases along the flow direction. By considering the propagation velocity (dispersion) of these flows in both horizontal and vertical direction, we will have the following equations:

$$U_z = C\frac{v}{d} \tag{1}$$

$$t_{diff} = C_1\frac{D^2}{v} \tag{2}$$

Similarly, t_{diff} increases along with the diameter growth. This change pattern indicates that disperse propagation is an effective factor in low Reynolds number flows and there is a non-linear relation between t_{diff} and R_e. In this relation, t_{diff} varies by each change in R_e or D. For each value of D, t_{diff} decreases by increase in R_e. Also, for all values of R_e, t_{diff} increases by each increment in D.

1.2 Numerical Analysis

In order to generate data for the prediction of input length in a tube with an extended flow, a numerical study is applied in the form of a simulation. We consider the mentioned flow as laminar, incompressible, and without any rotation. In this simulation, the required raw materials are air and water. Also, we assume that the properties of the fluid will remain constant during the simulation process. Furthermore, the governing rules of the simulation with axisymmetric coordinates are as follows:

Continuity equation:

$$\frac{1}{r}\frac{\partial}{\partial r}(\rho r U_r) + \frac{\partial}{\partial z}(\rho U_z) = 0 \tag{3}$$

Axial motion velocity equation:

$$\rho(U_r\frac{\partial U_z}{\partial r} + U_z\frac{\partial U_z}{\partial z}) = -\frac{\partial \rho}{\partial z} + \mu[\frac{1}{r}(r\frac{\partial U_z}{\partial r}) + \frac{\partial^2 U_z}{\partial z^2}] \tag{4}$$

Radial motion velocity equation:

$$\rho(U_r\frac{\partial U_r}{\partial r} + U_z\frac{\partial U_r}{\partial z}) = -\frac{\partial \rho}{\partial z} + \mu[\frac{\partial}{\partial r}(\frac{1}{r}\frac{\partial (rU_r)}{\partial r}) + \frac{\partial^2 U_r}{\partial z^2}] \tag{5}$$

Where, U_r is radial velocity, U_z is axial velocity, μ is the viscosity of the flow, r is radial distance of each point to the central line, and also U_0 is input rate into the tube.

The above equations can be discretized using finite element method and by softwares such as Fluent 6.2 [1]. We normalized the governing equations to generalize this model for further applications.

2. LITERATURE BACKGROUND

Over the last years, many researchers focused on the prediction of tube's input length under laminar flow conditions. In fact, reaching proper tube's input length is not only essential for hydraulic engineers for designing tubular fluid systems but even substantial for scientists who deal with other applications. In this sense, most of the applied methods expected a parabolic form for velocity parameter to make the capability to predict the tube length [2, 3]. Past experimental and analytical methods were predicting the input length with relative accuracy levels [4-7].

In the literature, the input length is defined as the distance from tube's input to the closest place where the tube flow is fully extended. In [8], the required extension of the tube length, the rate of flow, and the frequency oscillation in medium and high Reynolds values were evaluated. This system employs the parameters with the most impact on corrosion such as total and partial pressure of carbon dioxide, and temperature which are input variables into the fuzzy system for computing the corrosion rate of a tube. In some works along with fuzzy logic, an adaptive neural learning technique was employed in order to model the data parameters.

To study the extension of tube length, the statistical quantities of tube flow such as turbulence intensity, asymmetry, and flatness were evaluated in [9]. In this regard, the needed power to dominate the pressure loss along the tube is a significant issue to consider. Also, in [10], a Newtonian fluid with rectangular vent was used to evaluate the pressure loss due to the vent form at low Reynolds number flows. The results showed that the pressure loss is proportional to the average velocity through the vent.

Hydrodynamic and heat transfer characteristics of G-Al_2O_3 nanoparticles inside a circular tube with constant heat flux flow were studied in [11]. To this aim, the 15 diameter G-Al_2O_3 nanoparticles and distilled water as the basic fluid were employed. This study investigated the effects of various concentrations on heat transfer. In addition, the impact of density on friction coefficient was researched. On this subject, [12] presented a new hydrodynamic model using minimum energy dissipation to classify liquid gas flow in horizontal tubes. The model determines the pressure loss of a liquid gas flow without requiring the surface friction coefficient. Moreover, [13] is concentrated on the extension of hydrodynamic length inside the tube flow. [13] tried to devise a new equation for extending the hydrodynamic length based on the analyzed scale by studying a laminar flow.

Currently, sending a probe into liquid-gas junctions with two-phase flows for measuring the properties of waves has been prevalent. In this method, velocity, amplitude, and frequency of wave are determined by the capacitance capability. In this sense, [14] presented a new equation for velocity of waves in low viscous liquids that have two-phase flows. In the equation, the two-dimensional impact of wall and axial conduction on smooth flows within thick tubes is analyzed at boundary conditions. Similarly, [15] proposed two energy equations for heat transfer using the separation of variables technique, one for liquids and the other one for tubes.

The exact estimation of friction factor is important to overcome hydraulic problems. In this regard, [16] used ANFIS for setting Reynolds number and input velocity to estimate the friction coefficient of the channel flow. ANFIS model can be used to evaluate non-linear relations between friction coefficient and its effective factors. Also, this model is known as a significant method to resolve most hydraulic problems in portions other than friction factor. Accordingly, [17] studied an adaptive neuro-fuzzy inference system which models the impact of important parameters on heat transfer and flow properties in heat exchangers using numerical methods.

Table 1

Regression coefficients obtained by various methods.

Row	Author	Year	XD/D	Regression Coefficient
1	Boussinesq	1891	0.065Re	0.404
2	Schiller	1922	0.0288Re	0.865
3	Langhaar	1932	0.0575Re	0.898
4	Nikuradse	1950	0.0625Re	0.87
5	Siegel	1953	0.03Re	0.88
6	Bogue	1959	0.0288Re	0.898
7	Campbell and Slattery	1963	0.0675Re	0.868
8	Collins and Schowalter	1963	0.061Re	0.87
9	Sparrow et al.	1964	0.056Re	0.898
10	McComas	1967	0.026Re	0.868
11	Atkinson et al.	1969	0.59 + 0.056Re	0.898
12	Gupta	1977	0.0675Re	0.898
13	Mohanty and Asthana	1979	0.075Re	0.868
14	Chhebi	2002	0.09Re	0.776
15	Durst et al.	2005	$[0.619^{1.6}+(0.0567Re)^{1.6}]^{1/1.6}$	0.897

Table 2 : ***Input/Output data for analysis.***

Serial No.	Reynolds Number	Diameter	Input Length	Serial No.	Reynolds Number	Diameter	Input Length
100	0.2	0.0005	1.16	200	0.45	0.000044	1.84
150	0.2	0.00075	1.16	250	0.45	0.000556	2.12
200	0.2	0.001	1.36	300	0.45	0.000667	2.28
250	0.2	0.00125	1.32	350	0.45	0.000778	2.6
300	0.2	0.0015	1.4	100	0.5	0.0002	1.92
350	0.2	0.0015	1.36	150	0.5	0.0003	1.6
100	0.3	0.000333	1.16	200	0.5	0.0004	2.12
150	0.3	0.0005	1.32	250	0.5	0.0005	2.52
200	0.3	0.000667	1.24	300	0.5	0.0006	2.64
250	0.3	0.000833	1.64	350	0.5	0.0007	2.88
300	0.3	0.001	1.6	15	0.15	0.001	1.14
350	0.3	0.001167	1.88	20	0.2	0.0001	0.72
100	0.4	0.00025	1.44	25	0.25	0.0001	2.22

150	0.4	0.000375	1.56
200	0.4	0.0005	1.72
250	0.4	0.000625	2.08
300	0.4	0.00075	2.32
350	0.4	0.000875	2.48
100	0.05	0.002	1.44
150	0.05	0.003	1.28
200	0.05	0.004	1.36
250	0.05	0.005	1.28
300	0.05	0.006	1.28
350	0.05	0.007	0.92
100	0.1	0.001	1.04
150	0.1	0.0015	1.2
200	0.1	0.002	1.2
250	0.1	0.0025	1.2
300	0.1	0.003	1.24
350	0.1	0.0035	1.28
100	0.15	0.00667	0.88
150	0.15	0.001	0.96
200	0.15	0.001333	1.08
250	0.15	0.001667	1.12
300	0.15	0.002	1.16
350	0.15	0.002333	1.2
100	0.25	0.0004	1.4
150	0.25	0.0006	1.12
200	0.25	0.0008	1.28
250	0.25	0.001	1.48
300	0.25	0.0012	1.68
350	0.25	0.00014	1.64
100	0.35	0.000286	1.28
150	0.35	0.000429	1.2
200	0.35	0.000571	1.36
250	0.35	0.000714	1.64
300	0.35	0.000857	1.84
350	0.35	0.001	2.04
100	0.45	0.0.000222	1.36
150	0.45	0.000333	1.48
30	0.3	0.0001	0.66
35	0.35	0.0001	0.96
40	0.4	0.0001	1.08
45	0.45	0.0001	1.26
50	0.05	0.001	1.05
450	0.3	0.0015	1.74
60	0.4	0.00015	0.51
75	0.5	0.00015	1.14
90	0.6	0.00015	0.78
105	0.7	0.00015	0.96
120	0.8	0.00015	1.32
135	0.9	0.00015	1.44
150	0.1	0.00015	1.23
60	0.3	0.002	1.08
80	0.4	0.0002	1.5
100	0.5	0.0002	0.96
120	0.6	0.0002	0.87
140	0.7	0.0002	1.44
160	0.8	0.0002	1.56
180	0.9	0.0002	1.68
200	0.1	0.002	1.05
75	0.3	0.0025	2.04
100	0.4	0.00025	0.75
125	0.5	0.00025	1.56
150	0.6	0.00025	0.9
175	0.7	0.00025	1.8
200	0.8	0.00025	2.04
225	0.9	0.00025	2.04
250	0.1	0.0025	1.32
90	0.3	0.0003	1.08
120	0.4	0.0003	0.78
150	0.5	0.0003	1.08
180	0.6	0.0003	0.96
210	0.7	0.0003	1.68
240	0.8	0.0003	2.28
270	0.9	0.0003	2.28
30	0.1	0.001	2.16

Although developing using ANFIS results more efficient and more extendable models, it can be seen that almost all proposed methods estimate too high values for tube's input length. This inaccuracy can be due to inappropriate parameter selection, omit environmental conditions, neglect thermodynamic parameters, and miss physical parameters such as moving and dispersion. ANFIS will be an effcient solution when evaluating the relation between inputs and outputs of a system takes a long time by conventional mathematical methods.

3. ADAPTIVE TYPE-2 NEURO-FUZZY INFERENCE SYSTEM

In 1975, Prof. Zadeh introduced type-2 fuzzy set as an extension to fuzzy theory. Since then, to distinct between traditional fuzzy set and type-2 fuzzy set, the traditional one is called type-1 fuzzy set. It is noteworthy that type-2 fuzzy set has the capability of relegating to membership degrees. So, there is the ability to model and reduce the effects in dealing with uncertainty in type-2 fuzzy. Type-2 fuzzy systems has been used in most of current applications such as time series prediction, pattern recognition, robots control, and the integration of time-varying channels.

Type-2 neuro-fuzzy networks are made by combining the learning ability of neural networks and the inference power of fuzzy systems. An important issue in the design of type-2 neuro-fuzzy networks is choosing the training method. In last years, several training methods for type-2 neuro-fuzzy networks were proposed such as fuzzy clustering, genetic algorithm, particle swarm optimization, and the gradient descent algorithm. In this sense, backward propagation of errors is the most used method for training neuro-fuzzy networks which is called backpropagation in abbreviated form. Despite widespread use in papers, backpropagation has two main weakness; long training time due to inability to convergence and uncertainty in calculating the minimum cost globally. Resolving any of these defects could help to improve the performance of backpropagation. To this aim, some methods are proposed based on adaptive learning of parameters.

3.1. Type-2 Fuzzy Set

Type-2 fuzzy set A is shown as the following:

$$A = \{(x, \mu_A(x)) \mid \forall x \in X\}$$

$$A = \int_{x\in X} \frac{\mu_A(x)}{x} = \int_{x\in X} \left[\int_{u\in J_x} \frac{f_x(u)}{(u)}\right] \Big/ x \qquad (6)$$

Where, X is a family of sets, x is the basic or the main variable which can be pressure or temperature in some applications. Also, $\mu_A(x)$ is the secondary membership function and u is the secondary variable.

Once all secondary membership degrees in a type-2 fuzzy set are 1, that fuzzy set is called interval type-2 fuzzy set.

Type-2 fuzzy systems are usually designed in the form of If-Then rules using Mamdani or Tagaki-Sugeno-Kang models.

3.2. The structure of Type-2 Neuro-fuzzy Networks

The structure of a type-2 neuro-fuzzy network is shown in Fig. 3.1. This network consists of six layers.

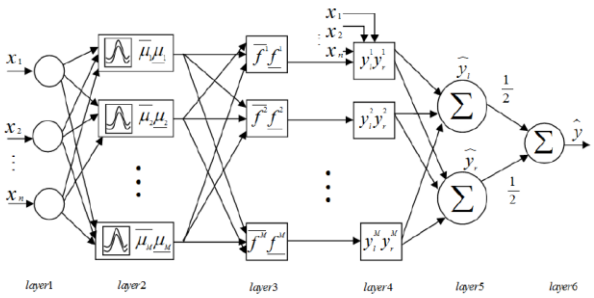

Figure 3.1. The structure of an interval type-2 neuro-fuzzy network.

4. THE PROPOSED METHOD

Our method propose to use type-2 ANFIS for predicting the tube's input length for low Reynolds number flows by neuro-fuzzy inference. We compared the results of our work with [18]. The entire set of experimental data is divided into training, validation, and test sets which is presented in Tab. 3 including 100 data items. Among this data, 83 items are considered as learning set and the other 17 items as test set. Fig. 4.1 shows the flowchart of proposed method which employs type-2 ANFIS.

5. SIMULATION

In order to implement the proposed method, we used MATLAB simulation tools. In Fig. 5.1 and 5.2, the correlation coefficients between predicted and actual values are depicted using type-1 and type-2 ANFIS toolboxes. Also, the comparison between predicted and actual values of tube's input is demonstrated in Fig. 5.3 and 5.4 using type-1 and type-2 ANFIS. Moreover, Fig. 5.5 shows the comparison of error values among type-1 and type-2 ANFIS in predicted tube's input length. As can be seen in the figure, type-2 ANFIS model improved all results compared to type-1 ANFIS.

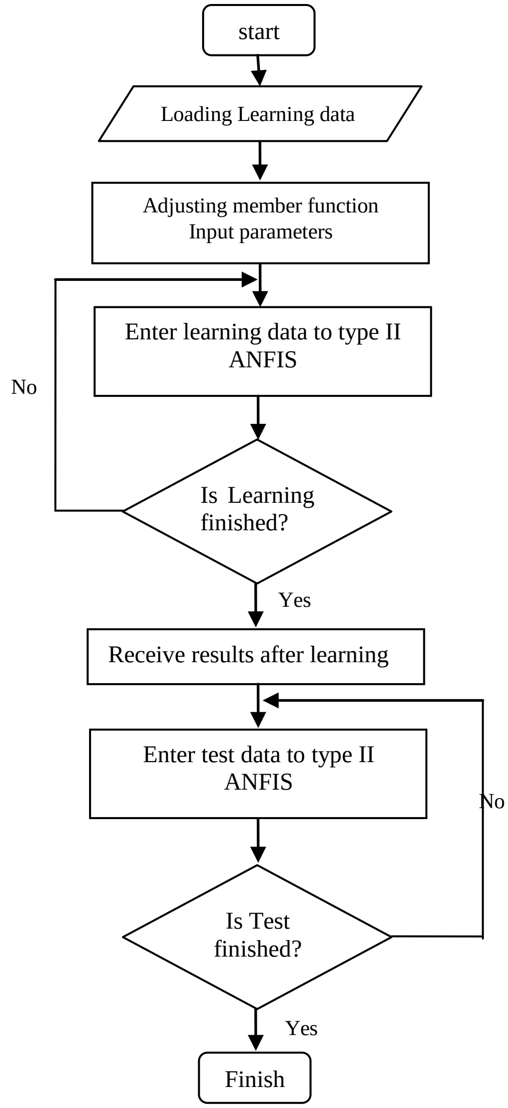

Figure 4.1. The flowchart of the proposed method.

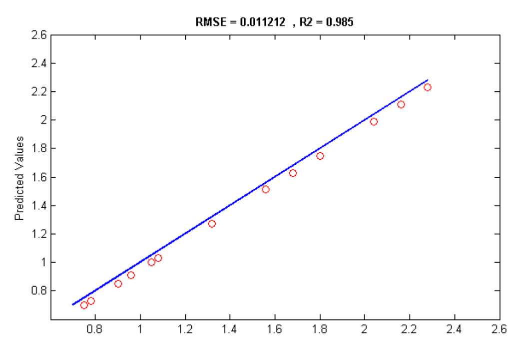

Figure 5.1. The correlation coefficients between predicted and actual values using type-1 ANFIS.

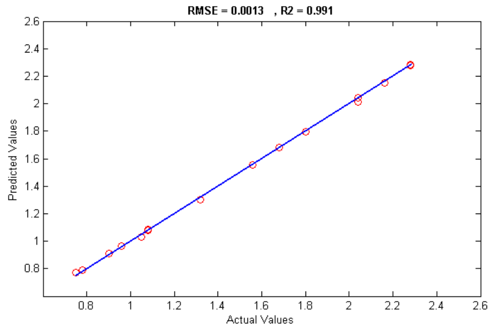

Figure 5.2. The correlation coefficients between predicted and actual values using type-2 ANFIS.

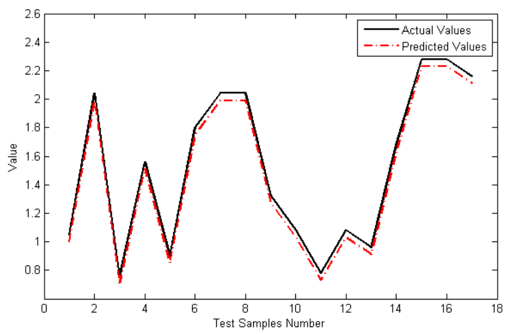

Figure 5.3. The comparison between predicted and actual tube's input length values using ANFIS.

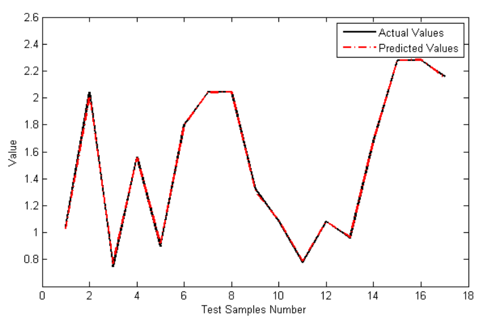

Figure 5.4. The comparison between predicted and actual values of tube's input length using type-2 ANFIS.

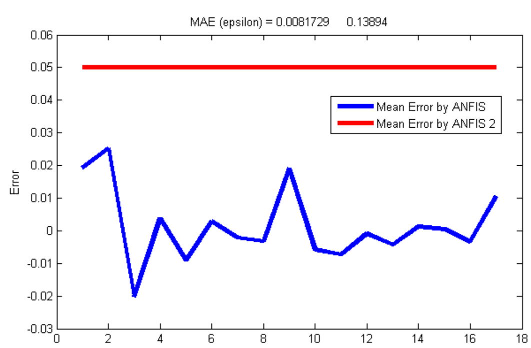

Figure 5.5. The comparison of error values among type-1 and type-2 ANFIS results in tube's input length prediction.

6. CONCLUSION

In this paper, a type-2 neuro-fuzzy controller is proposed to predict the tube's input length for flows with low Reynolds number. In this method which is based on linearization feedback and type-2 neuro-fuzzy, the feedback is estimated using a type-2 neuro-fuzzy network. In this work, simplification of type-2 neuro-fuzzy model was performed in order to reduce the fuzzy rules. Finally, simulation results showed significant improvements by the proposed system in comparison with a type-1 neuro-fuzzy system.

7. FUTURE WORKS

In future, we plan to devise a method with lower complexity using a combinatorial model composed of principal component analysis method to cluster data with the most similarity. Also, we will try to optimize neural network by applying evolutionary computations.

8. TABLE OF NOTATIONS

Symbol	*Meaning*
A	Type-2 fuzzy set
$\overline{f}^{k}$	High ignition capability
$\underline{f}^{k}$	Low ignition capability
r	Radial distance
Re	Reynolds number
t_{diff}	Vertical propagation velocity
U_0	Input rate
U_r	Radial velocity
U_z	Axial velocity
ρ	Fuid density

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