

Application of Gamma Test and Neuro-Fuzzy Models in Uncertainty Analysis for Prediction of Pipeline Scouring Depth

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Abstract

The process involved in the local scour below pipelines is so complex as to make it difficult to establish a general empirical model to provide accurate estimation for scour. This paper describes the use of an adaptive neuro-fuzzy inference system (ANFIS) and a Gamma Test (GT) to estimate the submerged pipeline scour depth. The data sets of laboratory measurements were collected from published literature and used to train the network or evolve the program. The developed networks were validated by using the observations that were not involved in training. The performance of ANFIS was found to be more effective when compared with the results of regression equations and GT Network modelling in predicting the scour depth of pipelines.

Keywords

Pipelines, Local Scour, Gamma Test, ANFIS

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1. Introduction

Scour is a major cause for the failure of underwater pipeline. Interactions between the pipeline and its erodible bed under strong current and/or wave conditions may cause scouring around the pipelines. This process involves the complexities of both the three-dimensional flow pattern and the sediment movement. Scouring underneath the pipeline may expose a section of the pipe, causing it to become unsupported in the stream. If the free span of the pipe is long enough, the pipe may experience resonant flow-induced oscillations, leading to settlement and subsequently structural failure. Accurate estimate of the scour depth is important in the design of submarine pipelines [1]. The estimation of the scour characteristics of underwater pipelines continues to be a concern for hydraulic engineers.

A number of empirical formulas have been developed in the past to estimate equilibrium scour depth below pipeline, including [1]-[6]. A summary of these equations is shown in Table 1.

Predictive approaches such as artificial neural networks (ANNs) and adaptive neuro-fuzzy inference systems (ANFIS) have been recently shown to yield effective estimates of scour around hydraulic structures. ANNs have been reported to provide reasonably good solutions for hydraulic engineering problems, in cases of highly non-linear and complex relationship among the input-output pairs in corresponding data.

The objective of this study is to develop a predictive model for scour depth, and in particular 1) to develop an ANFIS model with the aid of Gamma Test, 2) to evaluate the uncertainty inherent by using ANFIS and Gamma Test models for scour depth estimation in clear-water condition and (3) to compare the results obtained the ANFIS model with the empirical methods.

2. Local Scour below Underwater Pipelines

The variables influencing the equilibrium scour depth d_s below a pipeline in a steady flow over a bed of uniform, spherical and cohesion less sediment as shown in Figure 1 are: flow condition, sediment characteristics, and pipe geometry. The scour depth can be represented by the following general functional relationship:

$$d_s = f(\rho, \rho_s, \nu, V, Y, g, d_{50}, S_0, D) \tag{1}$$

where ρ = fluid density, ρ_s = sediment density, ν = fluid kinematic viscosity, V = Average velocity, Y =

Table 1. Empirical formulae for estimate pipeline scour depth.

Author	Equation
Chao and Hennessy (1972)	$q_{bot} = V_0 \left(H - \frac{R^2}{2H - R} \right),$ $V_{bot} = \frac{q_{bot}}{(H - R)} = V_0 \left[\frac{2 \left(\frac{H}{R} \right)^2 - \left(\frac{H}{R} \right) - 1}{2 \left(\frac{H}{R} \right)^2 - 3 \left(\frac{H}{R} \right) + 1} \right] \text{ for } H \geq R,$ <p style="text-align: center;">$H - R = \text{maximum scour depth}$</p>
Kjeldsen et al. (1973)	$d_s = 0.972 \left(\frac{V_0^2}{2g} \right)^{0.2} D^{0.8}$
Ibrahim and Nalluri (1986)	$\frac{d_s}{D} = 4.706 \left(\frac{V_0}{V_c} \right)^{0.89} \left(\frac{V_0}{\sqrt{gY}} \right)^{1.43} + 0.06 \text{ clear water}$ $\frac{d_s}{D} = 0.084 \left(\frac{V_0}{V_c} \right)^{-0.3} \left(\frac{V_0}{\sqrt{gY}} \right)^{-0.16} + 1.33 \text{ live bed}$
Dutch research group	$d_s = 0.929 \left(\frac{V_0^2}{2g} \right)^{0.26} D^{0.78} d_{50}^{-0.04}$
Moncada-M. and Aguirre-Pe(1999)	$\frac{d_s}{D} = 0.9 \tanh(1.4F) + 0.55, \frac{d_s}{D} = 2F \operatorname{sech} \left(1.7 \frac{e}{D} \right)$

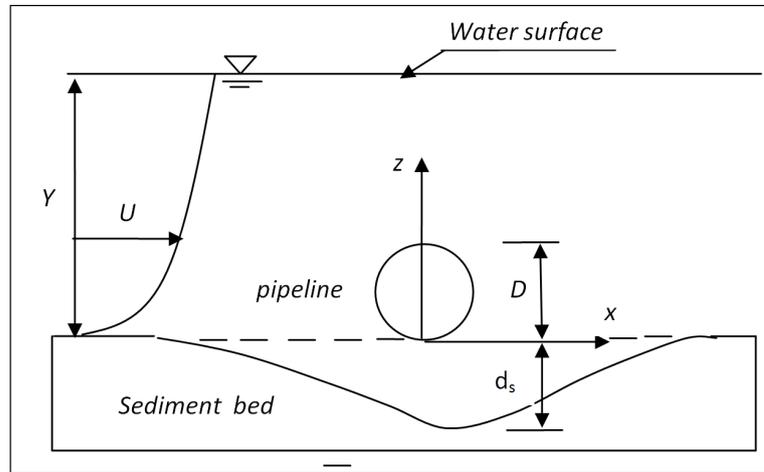


Figure 1. Local scour below pipeline in river crossing.

flow depth, g = gravitational acceleration, d_{50} = particle mean diameter, S_0 = slope of the energy line, D = diameter of the pipe, and d_s = equilibrium scour depth.

The nine independent variables in Equation (1) can be reduced to a set of six non-dimensional parameters. The Buckingham theorem applied to Equation (1), selecting ρ , V and D as repeating variables, leads to:

$$\frac{d_s}{D} = \phi \left(\tau_*, \frac{Y}{D}, \frac{D}{d_{50}}, R_p, S_0, F \right) \quad (2)$$

where τ_* = dimensionless Shields parameter related to sediment transport; $\frac{D}{d_{50}}$ = dimensionless soil characteristics,

$R_p = \frac{VD}{\nu}$ = Reynolds number, $F = \frac{V}{\sqrt{gY}}$, Froude number, and V = Average velocity, the influence of

Reynolds number is considered negligible under a fully turbulent flow over a rough bed ([7] [8]). The data were collected from a number of references namely [6] [9]. The whole collected data consists of 215 data set. **Table 2** shows the range of variation of collected data and its parameters.

3. Development of ANFIS

During the last two decades, researchers have noticed that the use of soft computing techniques as an alternative to conventional statistical methods based on controlled laboratory or field data has provided significantly better results. Neural network (NN) and ANFIS are the most widely used branches of soft computing in hydraulic engineering. Within the larger field of hydraulics, a few researchers have dealt with the scour around and downstream of hydraulic structures using NN [10] [11]. This study presents ANFIS and Gamma Test (GT) as an alternative tool in the prediction of scour below pipeline scour.

Therefore, the present study is based on a new soft computing technique, combined neural and fuzzy networks.

3.1. Neuro-Fuzzy System

The most important characteristics of these methods are the ability to implement human knowledge by tongue labels and fuzzy rules, nonlinearity of these systems and their adaptability [12]. It utilizes human expertise. In fuzzy systems, relationships are represented explicitly in the form of the if-then rules. In neural networks, the relations are not explicitly given, but are encoded in the designated networks and parameters. Neuro-fuzzy systems combine semantic transparency of rule-based fuzzy systems with the learning capability of neural networks. Depending on the structure of the if-then rules, two main types of fuzzy models are distinguished as mamdani (or linguistic) and Takagi-Sugeno models. The mamdani model is typically used in knowledge-based (expert) systems while the Takagi-Sugeno model is used in data-driven systems.

Table 2. Data variation.

Parameters	Unit	Data Rang	Mean	Std Dev
a) Range of different input-output parameters used for the estimation of scour depth				
Velocity (u)	cm/s	21.8 - 73.6	44.67	12.46
Flow depth (Y)	cm	3.8 - 28	13.43	6.21
Particle mean diameter (d_{50})	mm	0.48 - 7.6	1.92	1.61
Diameter of the pier (D)	cm	2.34 - 7	4.37	1.44
Equilibrium scour depth (d_s)	cm	0.02 - 11.3	4.75	2.39
b) Range of different non-dimensional input-output parameters used for the estimation of scour depth				
dimensionless Shields parameter (τ_*)		0.038 - 0.70	0.23	0.17
normalized flow depth (Y/D)		1.06 - 7	3.14	1.2
pipeline diameter cross section of sediment size (D/d_{50})		3.28 - 145.8	38.17	31.41
Froude number (Fr)		0.2 - 0.83	0.46	0.15
Non-dimensional equilibrium scour depth (d_s/D)		0.008 - 1.66	1.04	0.32

Based on the above statements, combining of fuzzy systems, which work on logical rules, with artificial neural networks, which extract knowledge from numerical information, we can develop models that simultaneously use numerical formation and tongue statements to model any phenomenon. This combined method of artificial neural network and fuzzy systems is named the adaptive neuro-fuzzy inference system ([13]-[16]). A fuzzy system is one based on logical rules of if-then statements. The most common type of fuzzy systems is the Sugeno fuzzy system in which fuzzy rules are stored in a rule base station. The rules in this system are

$$\text{if } x_1 \text{ is } A_1 \text{ and } x_2 \text{ is } A_2 \cdots x_n \text{ is } A_n \text{ then } y = f(x_1, x_2, \dots, x_n) \quad (3)$$

where A_1 , A_2 and \cdots A_n are the fuzzy sets. In this system, if the section of the rule is a fuzzy value and the result section of the rule is a real function of the input values and usually is a linear statement such as: [17]. ANFIS network architecture is shown in Figure 2.

$$a_1x_1 + a_2x_2 + \cdots + a_nx_n \quad (4)$$

3.2. Training of the ANFIS Model Using Genfis2 and Genfis3

In order to begin the training an FIS structure is needed first. The FIS structure specifies the parameters of FIS system for learning. Genfis2 function meets these requirements because it generates a Sugeno-type FIS structure using subtractive clustering and requires separate sets of input and output data as input arguments. When there is only one output, Genfis2 may be used to generate an initial FIS for ANFIS training. Genfis2 accomplishes this by extracting a set of rules that models the data behavior. In order to find optimum cluster centers, several cluster radii were examined and the radius of 0.5 for clusters, proved to yield the best results [18]. Since clustering is sensitive to the range of elements in the input vector, the data set was normalized within the unit hypercube. The rule extraction method first uses the subclust function to determine the number of rules and antecedent membership functions and then uses linear least squares estimation to determine each rule's consequent equations. This function returns a FIS structure that contains a set of fuzzy rules to cover the feature space. The numbers of rules were 9 and 18 for dimensional and non-dimensional combinations, respectively (Figure 3(a) and Figure 3(b)).

Another Fuzzy interface system using for training of the ANFIS model is Genfis3. It generates an FIS using fuzzy c-means (FCM) clustering by extracting a set of rules that models the data behavior. The function requires separate sets of input and output data as input arguments. When there is only one output, you can use genfis3 to generate an initial FIS for ANFIS training. The rule extraction method first uses the FCM function to determine the number of rules and membership functions for the antecedents and consequents. The functional set and op-

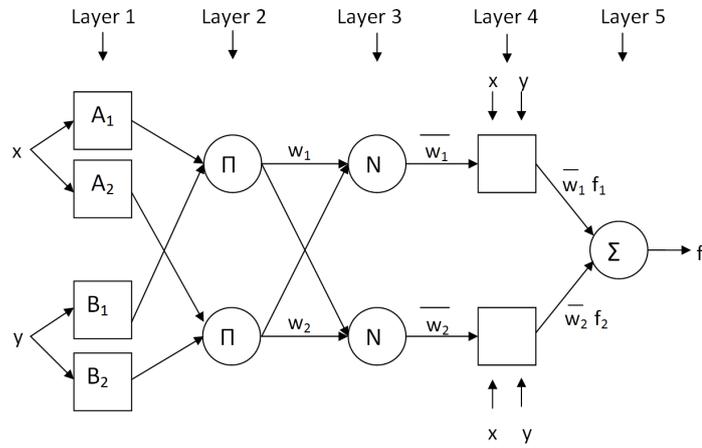
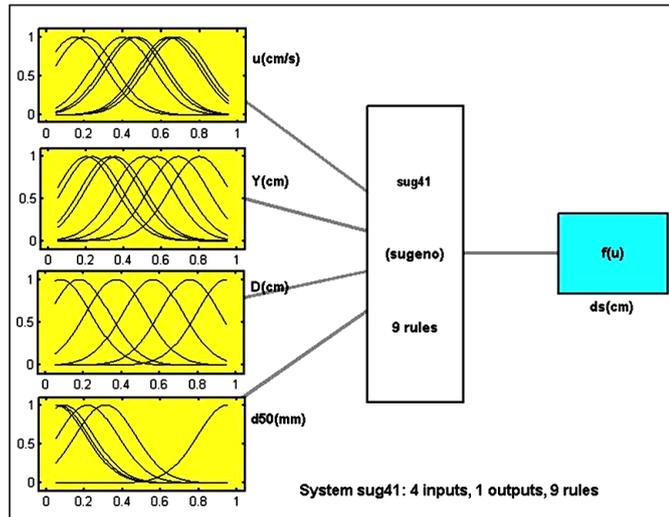
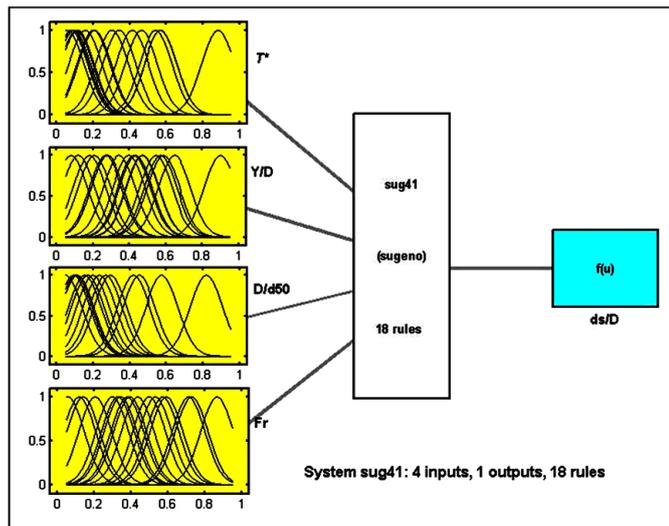


Figure 2. ANFIS network architecture.



(a)



(b)

Figure 3. ANFIS models: (a) Genfis2 model; (b) Genfis3 model.

erational parameters for dimensional analysis in best combination used in the ANFIS modeling in this study are listed in **Table 3**.

In this study, attempts were made to improve the GT to illustrate the best combination of nonlinear model inputs prior to model construction and evaluation for selection of the best input parameter for ANFIS network and to yield a better prediction of scour depth below an underwater pipeline.

3.3. Development of ANFIS Model

How the data are presented for training is one of the most important aspects of ANN and ANFIS models. Often this can be done in more than one way [19]. The authors collected such data from several references such as [6], [9]. The whole data set consists 215 data points. The ANFIS model was developed using the same input variables.

A code was developed in MATLAB to perform the analysis. Before applying the ANFIS algorithm, all data must be normalized. In order to normalize the data, they are transformed into the range of [0.05, 0.95]. The following formula is used for the normalization of data:

$$X_n = 0.05 + 0.9 \frac{X_r - X_{\min}}{X_{\max} - X_{\min}} \tag{5}$$

where X_n and X_r are the normalized and the original inputs; and X_{\min} and X_{\max} are the minimum and maximum of input ranges, respectively.

Out of the total of 215 input-output pairs, about 75% (161 sets), are randomly selected, were used for training, whereas the remaining 25% (54 sets) were employed for testing. Five of nine parameters in (1) namely fluid density, the buoyant sediment density, fluid dynamic viscosity, gravitational acceleration and the slope of energy line are constant in all experiments. Therefore, the first combination involves just four of the nine parameters in Equation (1) as the input pattern and the equilibrium scour depth (d_s) as the output pattern. The second combination includes four non-dimensional parameters of Equation (2), the normalized equilibrium scour depth ($\frac{d_s}{D}$) as the input and output patterns respectively. Both of the combinations mentioned above of inputs have been used for the ANFIS model.

4. New Input Selection Model: Gamma Test

The selection of model input variables is a complex issue, even for linear multivariable regression analysis and nonlinear models such as ANN. Choosing the optimum inputs to arrive at good predictions is important in non-linear modeling. This paper demonstrates a new model ‘‘Gamma Test’’ to identify the best combination and number of input data to make a prediction with the best possible accuracy. The Gamma Test is a non-linear analysis tool which allows quantification of the extent to which a smooth relationship exists within a numerical input/output

Table 3. Parameters of ANFIS models for dimensional analysis in best combination.

Rule Parameters	ANFIS	
	Training of the ANFIS model using Genfis2 (subtractive clustering)	Training of the ANFIS model using Genfis3 (fuzzy c-means clustering)
Rule 1	[0.1255 -0.6761 0.5241 -0.7729 0.4106]	[0.07086 0.3199 0 0]
Rule 2	[0.2284 -0.3918 0.9777 0.173 0.1064]	[0.06754 0.4445 0 0]
Rule 3	[1.13 0.1192 0.4859 -1.985 0.1239]	[0.06815 0.353 0 0]
Rule 4	[-0.3304 0.6991 -0.1687 1.279 0.09621]	[0.08313 0.5967 0 0]
Rule 5	[0.6013 0.9184 0.3647 -0.2692 -0.4788]	[0.09327 0.2105 0 0]
Rule 6	[1.124 0.2302 0.256 -0.2427 -0.01926]	[0.06589 0.4481 0 0]
Rule 7	[-0.8196 0.3539 0.8058 0.332 0.4059]	[0.1432 0.7998 0 0]
Rule 8	[2.059 0.257 -0.05244 -3.504 0.3668]	[0.08337 0.5635 0 0]
Rule 9	[-0.1408 -1.259 0.7326 -121.7 116.1]	[0.07432 0.2955 0 0]

data set. The Gamma Test was first reported by [20]-[21], and later enhanced and discussed in detail by many researchers [22]-[27]. There is very limited work published using the Gamma Test in hydrology (examples include water level and flow modeling in the River Thames by [26], daily solar radiation prediction by [28], Daily pan evaporation modeling in a hot and dry climate by [29] and comparison of LLR, MLP, Elman, NNARX and ANFIS Models in solar radiation estimation by [30].

The Gamma Test estimates the minimum mean square error (MSE) that can be achieved when modeling the unseen data with any continuous nonlinear models. The basic idea is quite distinct from the earlier attempts with nonlinear analysis. Suppose we have a set of data observations of the form

$$\{(x_i, y_i), 1 \leq i \leq M\} \quad \text{where} \quad \begin{cases} \text{input } x_i \in R^m \\ \text{output } y_i \in R^m \end{cases} \quad (6)$$

in which input vectors are confined to some closed bounded set $c \in R^m$, and the corresponding outputs are scalars. The vectors x contain predicatively useful factors influencing the output y . The relationship between an input x and its corresponding output y can be expressed as:

$$y = f(x) + r \quad (7)$$

f is some smooth unknown function representing the system and r is a random variable having expectation zero representing noise. Without loss of generality it can be assumed that the mean of the r distribution is zero (since any constant bias can be subsumed into the unknown function f) and that the variance of the noise $\text{Var.}(r)$ is bounded.

The domain of a possible model is now restricted to the class of smooth functions which have bounded first partial derivatives. The Gamma statistic is an estimate of the model's output variance that cannot be accounted for by a smooth data model.

The Gamma Test can estimate $\text{Var.}(r)$ directly from the data, even though function f is unknown. This estimate is calculated by computing the following equations called a delta function:

$$\delta_M(k) = \frac{1}{M} \sum_{i=1}^M |x_{N[i,k]} - x_i|^2 \quad 1 \leq k \leq p \quad (8)$$

$$\gamma_M(k) = \frac{1}{2M} \sum_{i=1}^M |y_{N[i,k]} - y_i|^2 \quad 1 \leq k \leq p \quad (9)$$

where $|\dots|$ denotes Euclidean distance, $N(i, k)$ denotes the index of the k^{th} nearest neighbor to x_i and y_i , p is the number of near neighbors. Thus $\delta_M(k)$ is the mean square distance to the k^{th} nearest neighbor and $y_{N[i,k]}$ is the corresponding output of $x_{N[i,k]}$. Γ is the intercept of the linear regression line of $\gamma_M(k)$ versus $\delta_M(k)$ for $1 \leq k \leq p$, estimates $\text{Var}(r)$ and is known as the Gamma statistic. In order to compute Γ a least squares regression line is constructed for the p points $(\delta_M(k), \gamma_M(k))$

$$\gamma = A\delta + \Gamma \quad (10)$$

It can be shown that

$$\gamma_M(k) \xrightarrow{\text{yields}} \text{Var}(r) \text{ in probability as } \delta_M(k) \rightarrow 0 \quad (11)$$

Calculating the regression line gradient can also provide helpful information on the complexity of the system under investigation. First, it is remarkable that the vertical intercept Γ of the y - (or Gamma) axis offers an estimate of the best MSE achievable, utilizing a modeling technique for unknown smooth functions of continuous variables [31]. Second, the gradient offers an indication of model's complexity (a steeper gradient indicates a model of greater complexity).

The Gamma Test is a non-parametric method and the results apply regardless of the particular techniques used to subsequently build a model of f . We can standardize the result by considering another term V_{ratio} , which returns a scale invariant noise estimate between zero and one. V_{ratio} is defined as:

$$V_{ratio} = \frac{\Gamma}{\sigma^2(y)} \quad (12)$$

where, $\sigma^2(y)$ is the variance of y . V_{ratio} close to zero indicates that there is a high degree of predictability of

the given output y . The reliability of Γ statistic can be determined by running a series of Gamma Tests for a definite number of unique data points (M), to establish the size of data set required to produce a stable asymptote. This is known as an M-test. The M-test also helps us to decide how much data we are likely to need to obtain a model of a given quality, in the sense of predicting with mean square error around the noise level. The M-test result would avoid the over fitting of a model beyond the stage where the MSE on the training data is smaller than $\text{Var}(r)$ and help us to decide the required data length to build a meaningful model. For model identification is used from full embedding section to determine which combination yields the smallest absolute Gamma value. The Gamma Test analysis can be performed using winGammaTM software implementation [26].

5. Uncertainty Analysis

In order to measure and compare the uncertainty related to the results of ANFIS models, there needs to compare some objective criteria. In this study we used coefficient of determination (R^2), root mean squared error (RMSE) and mean absolute error (MAE):

$$R^2 = 1 - \frac{\sum_{i=1}^N (o_i - t_i)^2}{\sum_{i=1}^N (o_i - \bar{o}_i)^2} \tag{13}$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^N (o_i - t_i)^2}{N}} \tag{14}$$

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^N |o_i - t_i| \tag{15}$$

where t_i denotes the target values of equilibrium scour depth (cm), while o_i and \bar{o}_i denotes the observed and average observed values of equilibrium scour depth (cm), respectively, and N is the data point number. The sensitivity analysis of independent Parameters for the Validation set of ANFIS model type Genfis2 are given in **Table 4**.

Gamma Test is used to measure uncertainty by Gamma value, gradient and V_{ratio} . This paper demonstrates all combinations of input data that affect the pipeline scour depth by using full embedding. A full embedding tries every combination of inputs to determine which combination yields the smallest absolute Gamma value. It returns the number of results requested. If there are m scalar inputs then there are $2^m - 1$ meaningful combinations of inputs (15 in this study). The best one of these different combinations can be determined by observing that with the minimum Gamma value, which indicates a measure of the best MSE. Thus, we performed the Gamma Tests in different dimensions varying the number of inputs to the model and minimum value of Γ was observed when we used every fourth input for two data sets. The gradient (A) is considered as an indicator of

Table 4. The sensitivity analysis for Independent Parameters for the Validation set (Genfis2).

Parameter type	Model	RMSE	MAE	R^2	ANFIS Rule
dimensional	$d_s = f(u, Y, D, d_{50})$	0.0742	0.39	0.96	9
	$d_s = f(u, Y, D)$	0.1013	0.473	0.91	6
	$d_s = f(Y, D, d_{50})$	0.0803	0.394	0.95	7
	$d_s = f(u, D, d_{50})$	0.116	0.5124	0.89	4
Non-dimensional	$d_s/D = f(\tau^*, Y/D, D/d_{50}, Fr)$	0.0137	0.0711	0.83	18
	$d_s/D = f(\tau^*, D/d_{50}, Fr)$	0.0212	0.1128	0.72	8
	$d_s/D = f(\tau^*, Y/D, D/d_{50})$	0.0159	0.790	0.82	14
	$d_s/D = f(\tau^*, Y/D, Fr)$	0.0179	0.0903	0.77	19

model complexity. V_{ratio} is the measure of predictability of given outputs using available inputs. An input data set with low values of MSE, gradient and V_{ratio} is considered as the best scenario for the modeling. Four representative combinations for each data set (include the best one) are tabulated in **Table 3**. From **Table 3** we can deduce that the combination of four parameters in two data sets can make a good model compared with other options. The relative importance of inputs are $D > Y > u > d_{50}$ and $\tau_* > D/d_{50} > Fr > Y/D$ for first and second combinations, respectively.

The quantity of sufficient input data to predict the desirable output was analyzed using the Gamma Test.

6. Result and Discussion

In this study, different combinations of input data (non-dimensional data sets) were explored to assess their influence on the scour depth modeling (**Table 3**). The ANFIS model was developed and tested for predicting the pipeline scour depth. The dimensional parameter combinations included the flow velocity; flow depth; particle mean diameter; diameter of the pipe; and the equilibrium scour depth. A dimensional analysis was used to determine the parameter for underwater pipeline scour. The Combination of non-dimensional parameters include the dimensionless Shields parameter related to sediment transport; pipeline diameter cross section of grain size (d_{50}); and the Froude number. Each parameter (except energy slope) in Equations (1) and (2) was considered in turn in the ANFIS for the sensitivity analysis. The results show that, of the parameters in Equation (1), the mean particle size (d_{50}) has the most significant effect on the scour depth and the flow discharge has the least effect on it.

Similarly, for non-dimensional parameters in Equation (2), sensitivity analysis shows that dimensionless Shields parameter (τ_*) and Y/D have respectively the most and the least effect on normalized scour depth. The quantity of input data required to predict the desirable output was analyzed using the M-Test with various data lengths for two combinations. This shows that a training data length of 173 and 158 is sufficient for the Gamma statistics to become stable and low respectively for dimensional (original data) and non-dimensional combinations. Statistical results of different combination are in **Table 5**. For simulation with the ANFIS model, we generate an FIS structure from data using subtractive clustering with 9 rules. To assess the performance of the ANFIS model, observed equilibrium scour depth values are plotted against the predicted ones. **Figure 4** and **Figure 5** illustrate the results with the performance indices between predicted and observed data for the validating (testing) data sets, for dimensional and non-dimensional respectively. As can be seen from **Table 6**, the first

Table 5. Comparison of performance of the ANFIS model used based on statistical criteria.

Parameter combination	Training Model	R2		RMSE		MAE	
		Training	Validation	Training	Validation	Training	Validation
Dimensional	subtractive Clustering	0.95	0.96	0.0365	0.0742	0.38	0.39
	Fuzzy C means	0.63	0.81	0.1139	0.1567	0.89	0.72
Non-dimensional	subtractive Clustering	0.87	0.83	0.008	0.013	0.083	0.071
	Fuzzy C means	0.70	0.53	0.0136	0.0318	0.123	0.176

Table 6. The Gamma Test results on the pipeline depth scour data set.

Parameter	Dimensional					Non-dimensional			
	u, Y, D, d_{50}	U, Y, D	Y, D, d_{50}	u, D, d_{50}	τ_* , Y/D, D/ d_{50} , Fr	τ_* , D/ d_{50} , Fr	τ_* , Y/D, D/ d_{50}	τ_* , Y/D, Fr	
Gamma (Γ)	0.013	0.011	0.014	0.039	0.047	0.057	0.063	0.076	
Gradient (A)	0.124	0.215	0.227	0.147	0.54	1.105	0.56	0.78	
Standard error	0.0027	0.0027	0.0035	0.0133	0.0089	0.0099	0.014	0.016	
V-ratio	0.053	0.043	0.057	0.158	0.191	0.231	0.254	0.304	
Near neighbors	10	10	10	10	10	10	10	10	
M	215	215	215	215	215	215	215	215	
Mask	1111	1110	0111	1011	1111	1011	1110	1101	

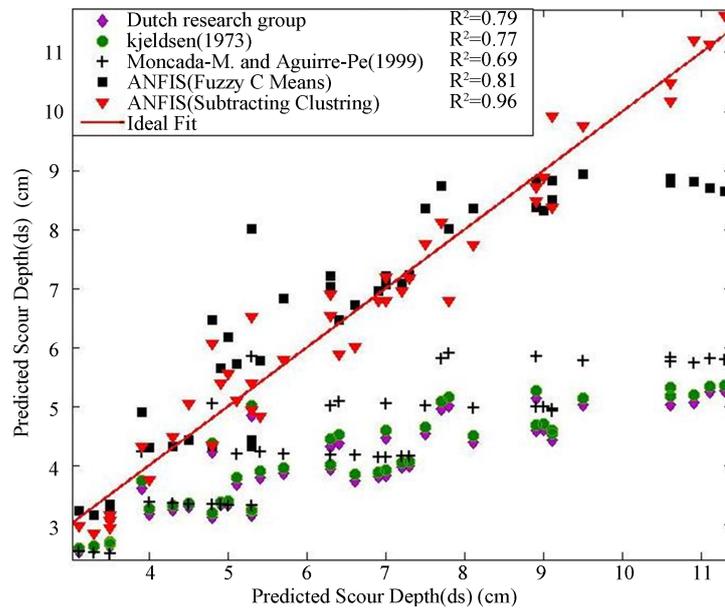


Figure 4. Observed versus predicted scour depth for dimensional parameter-validation (testing).

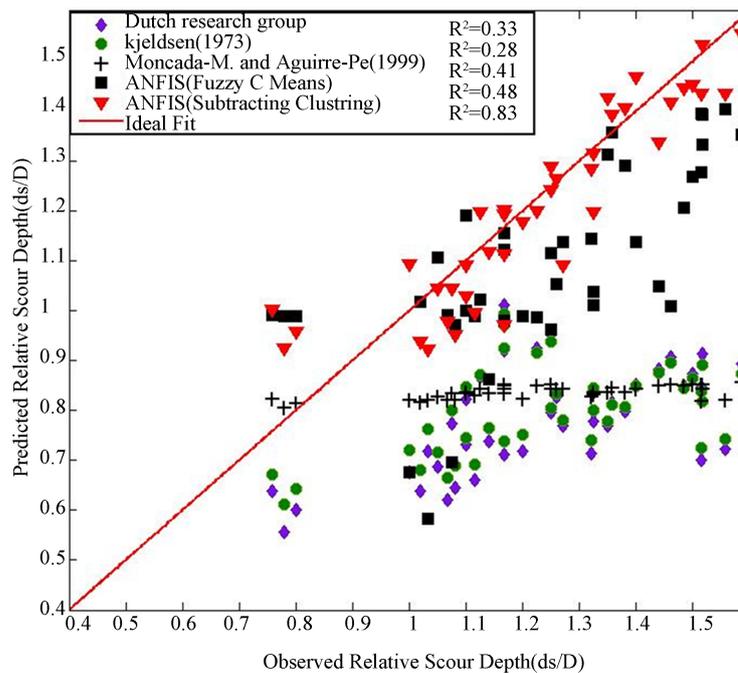


Figure 5. Observed versus predicted scour depth for non dimensional parameter-validation (testing).

combination (original data) has better ability to predict scour depth. The result for the original data show a high coefficient of determination (R^2), also the RMSE in the second combination is better than the first combination in both training and validation periods but this variation is low compare with R^2 variation. This study is useful for applications of pipeline scour for field conditions because the ANFIS model was developed with wide range of data, which could be deemed as the closest to field conditions, particularly helping to identify parameters that most likely define scour processes and explain scour variability, and ANFIS model is shown to agree well with actual measurements.

7. Conclusion

The application of a relatively new soft computing approach of ANFIS to predict the local pipeline scour depth was described. An ANFIS and GT model was developed to predict the values of the relative scour depth from laboratory measurements. A new approach was presented to estimate the equilibrium depth scour below underwater pipelines from optimum data sets with the ANFIS and GT modeling techniques. The application of the ANFIS in this study is another important contribution to scour depth estimation methodologies for pipes. The present study indicates that employing the original data set yielded a network that can predict measured pipeline scour depth more accurately than standard regression analysis based formulas [1] [3]-[6] that under- and over predict scour depths. Further work is required to collect field data of scour at pipeline to train the GP approach and validate its usefulness.

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