ANFIS and Neural Network for Modeling and Prediction of Ship Squat in Shallow Waters

K. Salmalian, M. Soleimani

Abstract— Squat is defined as the increase of draught of vessel due to its forward movement in shallow water. In this paper the squat parameter is established for Series-60 hull forms vessels in different depths via experimental methods and afterward diverse numerical methods are utilized to model squat. So, some facilities for the ship movement testing in shallow waters are organized. A series of models of the vessel is manufactured and numerous tests are performed attentively. In the present work, capability of the Adaptive-network-based fuzzy inference system (ANFIS) in modeling and predicting squat parameter for ships in shallow waters is demonstrated well. In addition, It is also extracted the mathematical relations between dimensionless squat (S^*) and significant variables namely, block coefficient (CB), dimensionless distance between the seabed and ship floor (δ) and hydraulic Froude Number (Fn_h). Finally, the obtained results of ANFIS modeling are compared with those of a multiple linear regression and GMDH-type neural network. The consequences confirm that the ANFIS-based squat has higher predictability function than other employed methods.

Keywords— ANFIS, GMDH, Squat, Shallow Water, Physical Model.

I. Introduction

To keep a safe passage of a ship in shallow water, it is important to study the relation between ship behaviors and the water depth in shallow waters. Grounding of ships in shallow waters may result in severe damage to the ship and, in extreme cases, may lead to the complete loss of port or channel capabilities. The reduction of the distance between ship floor and seabed, while the ship is moving forward, is called squat [1-3]. One can calculate the squat in shallow water by a number of methods such as analytical method [4], numerical and experimental methods [5] and [6]. Due to the existence of complicated three-dimensional fluid flow around the ship in shallow water, experimental methods are the most viable option and the most accurate method.

Kreitner [7] was the first one who calculated the squat of a given vessel by fundamental equations of fluid mechanics. Havelock [8] obtained the squat of a boat with elliptic hull form through analytical equations. Constantine [9] obtained some equations for the squat by one-dimensional hydraulics theory. Rubin and Naghdi [10] calculated the value of the squat for a certain ship by two-dimensional hydraulics method and verified their results by experimental means. Barras [11] introduced experimental relations for real vessels that now have applications for determining the squat in shallow and narrow canals. Tuck, Taylor and Millward [12] obtained other experimental relations for calculating the squat that has limited application and are not suitable for all ships and velocities. Due to the effects of the squat in shallow waters, the resistance of ships increases. This can be used for testing the physical model and estimating the extra force needed for ships movement in shallow waters.

Commonly, there are many parameters influencing the squat such as block coefficient, the dimensionless distance between the seabed and the floor of ships, and hydraulic Froude Number. Due to the complexity of squat assessment and interrelationships among the influencing parameters, it is difficult to develop a parametric model solution especially for three-dimensional problem. So, a series of experiments must be carried out and then modeling should be done. Soft computing, such as ANFIS or ANN, could be a good approach for modeling and prediction of the squat as an important phenomenon in shallow water for ships. Artificial neural networks (ANNs) have become popular because of their high computational rates, robustness and ability to learn, and they have been used in diverse applications in power systems, manufacturing, optimization, medicine, signal processing, control, robotics, and social/psychological sciences [13, 14]. Group Method of Data Handling (GMDH) algorithm is a self-organizing approach through which gradually complicated models are generated, based on the evaluation of their performances on a set of multi-input-single-output data pairs (X_i, y_i) ($i=1, 2, ..., M$). The GMDH was firstly developed by Ivakhnenko [15] as a multivariate analysis method for complex systems' modeling and identification. This way, GMDH was used to circumvent the difficulty of considering the a priori knowledge of the mathematical model of the process. In other words, GMDH can be used to model complex systems without having specific knowledge of them. The main idea of GMDH is to build an analytical function in a feed forward network based on a quadratic node transfer function [16] whose coefficients are obtained using regression techniques. In fact, real GMDH algorithm in which model coefficients are estimated by means of the least squares method has been classified into complete induction and

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incomplete induction, which represent the combinatorial (COMBI) and multilayered iterative algorithms (MIA), respectively [17]. In recent years, however, the use of such self-organizing network leads to successful application of the GMDH-type algorithm in a broad range area in engineering, science, and economics [15-21]. Fuzzy logic is a problem-solving technique that derives its power from its ability to draw conclusions and generate responses based on vague, ambiguous, incomplete and imprecise information. To simulate this process of human reasoning, it applies the mathematical theory of fuzzy sets, first defined by Lotfi zadeh, in 1965 [22]. ANFIS, developed in the early 90s by Jang [23], incorporates the concept of fuzzy logic into the neural networks to facilitate learning and adaptation.

In this paper, first, the results of experimental method for the squat of commercial vessels in shallow waters are applied. Then, the use of ANFIS with different type of membership functions for modeling and prediction of squat parameters in shallow waters for ships has been demonstrated. After that, a comparison is made between two GMDH-type neural networks and multiple-linear regression models with the best ANFIS model, with respect to Mean Square Error (MSE) of modeling and prediction, on two predefined datasets namely, Training set and Testing set.

II. Experimental Procedure

A. The Principles of the Model Testing of the Squat

For assessing the ship behavior by a model test, one should establish geometrical and kinematical similarities between the ship and its model. Consequently, a dynamic similarity will take place which is the result of the model testing. In most of the cases, the geometrical similarity is defined as scaling down the ship dimensions and water depth by a certain value.

$$\lambda = \frac{L_s}{L_m} = \frac{h_s}{h_m} \tag{1}$$

where λ is called scale, L_s denotes ship length, L_m is model length, h_s is water depth for ship and h_m is water depth for model.

In a case of squat model testing, the kinematical similarity is defined as the Froude Number of a model and the corresponding ship are to be the same and the model is to be large enough, the Reynolds Number of which falls in the turbulent region.

$$Fn_{hm} = Fn_{hs} \Rightarrow \frac{V_m}{\sqrt{gh_m}} = \frac{V_s}{\sqrt{gh_s}}$$
$$\Rightarrow V_m = V_s\sqrt{\frac{h_m}{h_s}} = \frac{1}{\sqrt{\lambda}}V_s \tag{2}$$
$$\mathrm{Re}_m = \frac{V_m L_m}{v_m} > \mathrm{Re}_{Critical}$$

where subscript *m* refers to model and *s* refers to ship, Fn_h is Froude Number based on water depth, V is speed, g is gravitational acceleration and υ denotes kinematic viscosity. The dynamic similarity is achieved if one builds a model and shallow water, which are geometrically similar to the ship and its water depth, equation (1), and model moves forward with the speed of $V_m = \frac{1}{\sqrt{\lambda}}V_s$, then the dynamic similarity will be achieved as follows:

$$S_s = \lambda S_m \tag{3}$$

Practically, there may exist some errors which are called the scale effect. Having enough experience in model testing with particular apparatuses, the scale effect can be minimized or deducted from the test results.

B. Model properties and laboratory preparation

Several tests are planned for the experimental analysis of the ship squat in shallow water. These tests are carried out at the marine laboratory of Sharif University of Technology. To perform the tests, two models are built, a shallow water tank is prepared, and measurement and data recording tools are provided.

Two models with series 60 hull form and block coefficient of CB=0.7 and CB=0.75 and with the scale of 1:40 and 1:70 are precisely manufactured. The main particulars of the models are presented in Table 1.

TABLE 1
MODELS PROPERTIES

No.	Length(m)	Beam(m)	C_B	Model Type
1	2.50	0.31	0.70	commercial
2	2.38	0.323	0.75	commercial

The models are shown in Figures 1 and 2.

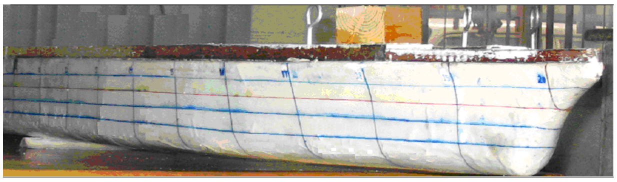

Fig. 1 model with Block coefficient of 0.7

Fig. 2 Model with Block coefficient of 0.75

In order to facilitate a shallow water condition with an exact gap between the model floor and tank bottom, an adjustable false bottom is installed in the tank. The adjustable false bottom enables us to adjust the gap by the accuracy of 0.5 millimeters.

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C. THE SQUAT TEST PARAMETERS

The tests are carried out at 4 different dimensionless depths, $\frac{h}{T}=1.05$, $\frac{h}{T}=1.1$, $\frac{h}{T}=1.15$, $\frac{h}{T}=1.2$

where h is the depth of the water and T is the draft of the model. The tests are begun at the speed of 0.2 m/s and continued by the speed interval of 0.2 m/s for low speeds and 0.1 m/s for high speeds. Following the advice of the ITTC standard, each test is carried out three times and is repeated if the error is high. The test parameters of the models are shown in Tables 2 and 3.

TABLE 2
TEST PARAMETERS OF MODEL WITH CB=0.75

h(cm)	T(cm)	$\frac{h}{T}$	$\delta=\frac{h-T}{h}$
16.8	16	1.05	0.0476
17.6	16	1.1	0.091
18.4	16	1.15	0.13
19.2	16	1.2	0.1667

TABLE 3
TEST PARAMETERS OF MODEL WITH CB=0.7

h(cm)	*T(cm)*	$\frac{h}{T}$	$\delta=\frac{h-T}{h}$
9.45	9	1.05	0.0476
9.9	9	1.1	0.091
10.35	9	1.15	0.13
10.8	9	1.2	0.1667

D. THE TEST RESULTS

In order to introduce a comprehensive equation for the squat, the authors introduce some new dimensionless parameters. These parameters are S^*, dimensionless squat, and δ, dimensionless gap between the seabed and the model floor. The above-mentioned dimensionless parameters in conjunction with hydraulics Froude Number, Fn_h, are used for further analysis. They are as follow:

$$S^*=\frac{S}{h}, \delta=\frac{h-T}{h} \text{ and } Fn_h=\frac{V}{\sqrt{gh}} \quad (4)$$

Tests are carried out for two models at four different depths at several different speeds. The dimensionless squat versus the Froude's Number for CB=0.7 and CB=0.75 are shown in Figures 3 and 4.

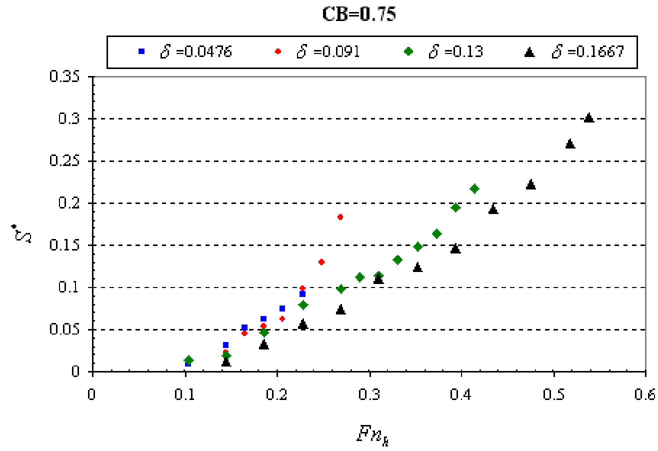

Fig. 3 the test results for C_B=0.75 at four different depths

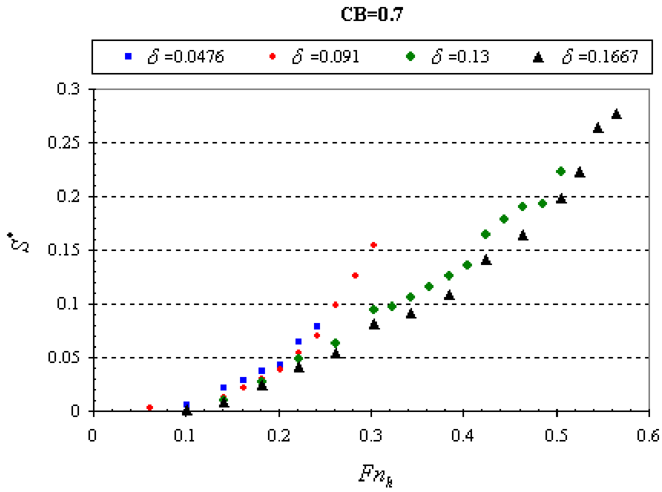

Fig. 4 the test results for C_B=0.7 at four different depths

Tests are continued until the model floor hits the seabed. That is why the test for small δ is cut at low Froude Number where for large δ is continued up to Froude Number of about 0.6.

According to Figures 3 and 4, due to interactions between the tank bottom and the ship floor, the increase in the speed of the model leads to an increase in the squat. It is also shown that as, δ, the dimensionless gap between the seabed and model floor increases, consequently the squat decreases.

III. MODELING USING GMDH-TYPE NEURAL NETWORKS

By means of GMDH algorithm, a model can be represented as a set of neurons in which different pairs of each layer are connected through a quadratic polynomial, and thus produce new neurons in the next layer. Such representation can be used in modeling to map inputs to outputs. The formal definition of the identification problem is to find a function $\hat{f}$ so that it can be approximately used instead of the actual one, f in order to predict output, $\hat{y}$, for a given input vector, $X = (x_1, x_2, x_3, ..., x_n)$, as close as possible to its actual output, y. Therefore, given *M*, to be the observation of multi-input-single-output data pairs so that

$$y_i = f(x_{i1}, x_{i2}, x_{i3}, ..., x_{in}) \quad (i=1,2,...,M), \tag{5}$$

it is now possible to train a GMDH-type neural network to predict the output values, $\hat{y}_i$, for any given input vector , $X = (x_{i1}, x_{i2}, x_{i3}, ..., x_{in})$, that is

$$\hat{y}_i = \hat{f}(x_{i1}, x_{i2}, x_{i3}, ..., x_{in}) \qquad (i = 1, 2, ..., M). \tag{6}$$

The problem is now to determine a GMDH-type neural network so that the square of the difference between the actual output and the predicted one is minimised, that is,

$$\sum_{i=1}^{M} [\hat{f}(x_{i1}, x_{i2}, x_{i3}, ..., x_{in}) - y_i]^2 \rightarrow \min . \tag{7}$$

The full form of the mathematical description can be presented by a system of partial quadratic polynomials consisting of only two variables (neurons) in the form of:

$$\hat{y} = G(x_i, x_j) = a_0 + a_1 x_i + a_2 x_j + a_3 x_i x_j + a_4 x_i^2 + a_5 x_j^2 \tag{8}$$

Consequently, the coefficients of each quadratic function G_i are obtained to optimally fit the output in the whole set of input-output data pair, that is,

The general connection between input and output variables can be expressed by a complicated discrete form of the Volterra functional series in the form of:

$$E = \frac{\sum_{i=1}^{M} (y_i - G_i(x_p, x_q))^2}{M} \rightarrow \min \cdot \tag{9}$$

In the basic form of the GMDH algorithm, all the possibilities of two independent variables out of total *n* input variables are taken in order to construct the regression polynomial in the form of equation (8) that best fits the dependent observations (y_i, *i=1, 2, ..., M*) in a least-squares sense. Consequently, $\binom{n}{2} = \frac{n(n-1)}{2}$ neurons will be built up in the first hidden layer of the feed forward network from the observations $\{(y_i, x_{ip}, x_{iq});\ (i=1,2,...,M)\}$ for different $p, q \in \{1,2,...,n\}$ [19]. In other words, it is now possible to construct *M* data triples $\{(y_i, x_{ip}, x_{iq});\ (i=1,2,...,M)\}$ from the observation, using such $p, q \in \{1,2,...,n\}$ in the form of:

$$\begin{bmatrix} x_{1p} & x_{1q} & y_1 \\ x_{2p} & x_{2q} & y_2 \\ \hline x_{Mp} & x_{Mq} & y_M \end{bmatrix}$$

Using the quadratic sub-expression in the form of equation (8) for each row of *M* data triples, the following matrix equation can be readily obtained as:

$$A\mathbf{a} = Y \tag{10}$$

where $\mathbf{a}$ is the vector of unknown coefficients of the quadratic polynomial as in equation (8)

$$\mathbf{a} = \{a_0, a_1, ..., a_5\}^T \tag{11}$$

and

$$Y = \{y_1, y_2, y_3, ..., y_M\}^T \tag{12}$$

is the vector of output's value from the observation. It can be readily seen that

$$A = \begin{bmatrix} 1 & x_{1p} & x_{1q} & x_{1p}x_{1q} & x_{1p}^2 & x_{1q}^2 \\ 1 & x_{2p} & x_{2q} & x_{2p}x_{2q} & x_{2p}^2 & x_{2q}^2 \\ \hline 1 & x_{Mp} & x_{Mq} & x_{Mp}x_{Mq} & x_{Mp}^2 & x_{Mq}^2 \end{bmatrix}. \tag{13}$$

The least-squares technique from multiple-regression analysis leads to the solution of the normal equations in the form of:

$$\mathbf{a} = (A^T A)^{-1} A^T Y \tag{14}$$

which determines the vector of the best coefficients of the quadratic equation (9) for the whole set of M data triples. It should be noted that this procedure is repeated for each neuron of the next hidden layer, according to the connectivity topology of the network. However, such solution directly taken from solving normal equations (SNE) is rather susceptible to round off errors and, more importantly, to the singularity of these equations.

The evolutionary methods such as genetic algorithms have been widely used in different aspects of design in neural networks because of their unique capabilities of finding a global optimum in highly multi-modal and/or non-differentiable search space [24, 25]. In this work, the design of architecture is performed using Genetic Algorithm (GA). The incorporation of genetic algorithm into the design of such GMDH-type neural networks starts by representing each network as a string of concatenated sub-strings of alphabetical digits. The fitness, (Φ), of each string of the symbolic digits which represents a GMDH-type neural network to the model squat is evaluated in the form of:

$$\Phi = 1/E \tag{15}$$

where *E* is the mean square of the error given by equation (9) is minimized through the evolutionary process by maximizing the fitness, Φ. The evolutionary process starts by randomly generating an initial population of symbolic strings, each as a candidate solution. Using the aforementioned genetic operations of roulette wheel selection, crossover and mutation, the entire populations of symbolic strings is to improve gradually. In this way, GMDH-type neural network models of ship squat with progressively increasing fitness,Φ, are produced until no further significant improvement is achievable. It should be noted that such an evolutionary process was used in conjunction with the normal equation approach for the coefficients of the quadratic polynomials involved in the design of the GMDH-type networks. The details of several types of GMDH neural networks are available in [26].

IV. Adaptive-Network-Based Fuzzy Inference System

In this section, an adaptive-network-based fuzzy inference system–ANFIS is proposed. ANFIS is used for the modeling of nonlinear or fuzzy input and output data, and for the prediction of output according to the input. It uses a combination of the least squares method and back-propagation gradient descent method for training fuzzy inference system membership function parameters to emulate a given training dataset. Functionally, it is equivalent to the combination of neural network and fuzzy inference systems.

In this study, the use of ANFIS is adopted in modeling ship squat in shallow water. ANFIS was first introduced by Jang [27]. The model is based on Takagi–Sugeno inference model [28, 29]. ANFIS uses a hybrid learning algorithm to identify the consequent parameters of Sugeno-type fuzzy inference systems. Furthermore, the Sugeno fuzzy model is assumed to have two inputs, *m* and *n,* and one output, *f*. For a first-order Sugeno fuzzy model, a typical rule set with two fuzzy if–then rules can be expressed as:

Rule 1: If $(m\ is\ A_1)$ and $(n\ is\ B_1)$ then

$$f_1 = p_1 m + q_1 n + r_1 \tag{16}$$

Rule 2: If $(m\ is\ A_2)$ and $(n\ is\ B_2)$ then

$$f_2 = p_2 m + q_2 n + r_2 \tag{17}$$

where p_1, p_2, q_1, q_2, r_1 and r_2 are linear parameters and A_1, A_2, B_1 and B_2 are nonlinear parameters.

The entire system consists of five layers, fuzzy layer, product layer, normalized layer, de-fuzzy layer and total output layer. The relationship between input and output of each layer is discussed in the following sections.

Layer 1 is the fuzzy layer, in which *m* and *n* are the input of nodes A_1, B_1 and A_2, B_2 respectively. A_1, A_2, B_1 and B_2 are the linguistic labels used in the fuzzy theory for dividing the membership functions. The membership relationship between the output and input functions of this layer can be expressed as below:

$$\begin{cases} O_{1,i} = \mu_{A_i}(m), & i = 1,2 \\ O_{1,j} = \mu_{B_j}(n), & j = 1,2 \end{cases} \tag{18}$$

where $O_{1,i}$ and $O_{1,j}$ denote the output functions, and μ_{A_i} and μ_{B_j} denote the membership functions.

Layer 2 is the product layer that consists of two nodes labeled Π. The output W_1 and W_2 are the weight functions of the next layer. The output of this layer is the product of the input signal, which is defined as follows:

$$O_{2,i} = w_i = \mu_{A_i}(m)\mu_{B_i}(n), \quad i = 1,2 \tag{19}$$

where $O_{2,i}$ is the output of Layer 2.

The third layer is the normalized layer, whose nodes are labeled *N*. The function of this layer is to normalize the weight function in the following process:

$$O_{3,i} = \bar{w} = \frac{w_i}{w_1 + w_2}, \quad i = 1,2 \tag{20}$$

where $O_{3,i}$ is the output of Layer 3.

The fourth layer is the defuzzification layer. The nodes in this layer are adaptive nodes. The relationship between the inputs and outputs of this layer can be defined as the following:

$$O_{4,i} = \bar{w}_i(p_i m + q_i n + r_i) \quad i = 1,2 \tag{21}$$

where $O_{4,i}$ is the output of Layer 4, and p_i, q_i and r_i are the linear parameters of the node.

The fifth layer is the output layer, whose node is labeled $\sum$. The output of this layer is composed of all the ingredients of the inputs, which represents the results of the cleaning rates. The output can be expressed as below:

$$O_{5,i} = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}, \quad i = 1,2 \tag{22}$$

where $O_{5,i}$ is the output of Layer 5.

V. ANN and ANFIS Squat Modeling

A. Data Preparation

The parameters of the interest in these multi-input single-output systems, both GMDH-type neural network and ANFIS, that affect the ship squat are block coefficient (CB), the dimensionless distance between the seabed and the ship's floor (δ) and Hydraulics Froude Number (Fn_h), that is described in Section 2 in detail. There has been a total number of 82 input-output experimental data considering 3 input parameters, namely CB, δ, Fn_h and one output namely, dimensionless squat (S^*). In order to demonstrate the prediction ability of both GMDH-type neural networks and ANFIS, the data have been divided into two different sets, namely training and testing sets. For dimensionless squat, training set which consists of 60 out of 82 inputs-output data is used for training both the neural network and ANFIS models. The testing set, which consists of 22 unforeseen inputs-output data samples, is merely used for testing to show the prediction ability of such GMDH-type neural network and ANFIS models during the training process.

B. GMDH-type Neural Network modeling of ship squat in shallow waters

The GMDH-type neural network is now used for such input-output data to find the polynomial model of dimensionless squat in respect to their effective input parameters. In order to genetically design such GMDH-type neural network described in previous section, a population of 50 individuals with a crossover probability of 0.7 and mutation probability of 0.07 has been used in 160 generation which no further improvement has been achieved for such population size. The structure of the evolved GMDH models with 2 and 3 hidden layers is shown in Figure 5.

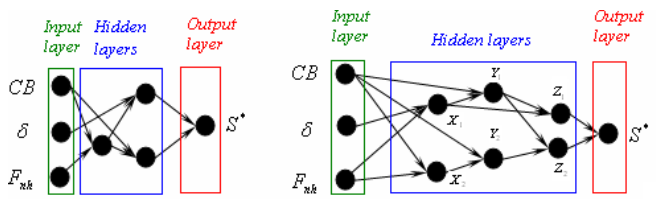

Fig. 5 Structures of GMDH neural network models for dimensionless squat
(a) Two hidden layer with 3 neurons;
(b) Three hidden layer with 6 neurons

Corresponding MSE are calculated as 0.000193 and 0.000114 for training and testing set, respectively. The MSE for GMDH model with 3 hidden layers is 0.000168 and 0.000096 for training and testing sets, respectively. One can define the maximum hidden layers of such GMDH neural networks higher than three until both training and testing errors decrease with increasing the hidden layers. When the number of hidden layers increase, the corresponding testing error increases (in spite of decreasing the training error), too. This is related to a model that has been made with less a hidden layer. When the over-fitting phenomenon happens, consequently, a model with less hidden layer must be chosen as the best model for modeling each process. For the squat modeling with GMDH neural networks, when four hidden layers are predefined for training, the testing error of this trained model is greater than the model with three hidden layers. For these reason, three hidden layers' model has been chosen as the best GMDH model for ship squat in shallow water. The good behavior of GMDH-type neural network model with 3 hidden layers is also depicted in Figure 6.

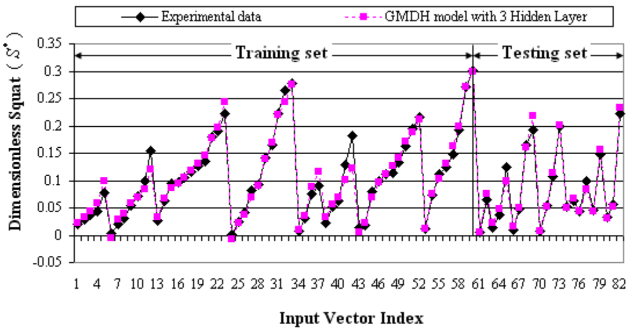

Fig. 6 The variation of Dimensionless Squat with input data samples (GMDH with 3 Hidden Layers)

The corresponding polynomial of such model for dimensionless squat is:

$$X_1 = -0.04741 + 0.40711(\delta) + 0.40148\,(Fn_h) - 1.90223(\delta)^2 + 0.56707(Fn_h)^2 - 1.06244(\delta)(Fn_h)$$

$$X_2 = 0.01047 - 0.02127(CB) - 1.24918(Fn_h) - 0.03633(CB)^2 + 0.47388(Fn_h)^2 + 2.11542(CB)(Fn_h)$$

$$Y_1 = -0.04076 + 0.02084(CB) - 2.57000(X_1) + 0.05161(CB)^2 + 0.46792(X_1)^2 + 4.83719(CB)(X_1)$$

$$Y_2 = -0.00892 + 1.12175(X_2) + 0.00519(CB) + 0.10599(X_2)^2 + 0.01221(CB)^2 - 0.20689(CB)(X_2)$$

$$Z_1 = -0.00076 + 0.54077(Y_1) + 0.52181(X_1) - 34.252389(Y_1)^2 - 39.33575(X_1)^2 + 73.80489(Y_1)(X_1)$$

$$Z_2 = 0.00116 - 1.28813(Y_2) + 2.17806(Y_1) + 59.16837(Y_2)^2 + 53.71903(Y_1)^2 - 12.53774(Y_2)(Y_1)$$

$$S^* = -0.00228 + 0.12841(Z_1) + 0.84450(Z_2) + 37.20074(Z_1)^2 + 35.56609(Z_2)^2 - 72.70769(Z_1)(Z_2)$$

C. ANFIS modeling of ship squat in shallow water

The computation of data for ANFIS is conducted using MATLAB. The ANFIS training includes hybrid method. The parameters of the membership functions are optimized in the identification dataset through back propagation while the consequent parameters are calculated using a linear least squares method. The training epoch number for this optimization is set to be 200. The initial value of step size for the training is set to be 0.01. The ANFIS is a set for training and the tuning algorithm modified the ANFIS parameters to match the training data. Having been verified by the test data set, the dimensionless squat is established using the above neuro-fuzzy algorithm procedure. In the case of choosing triangular membership function for three input parameters, the training process is performed after about 88 epochs of training. The MSE becomes steady, as shown in Figure 7.

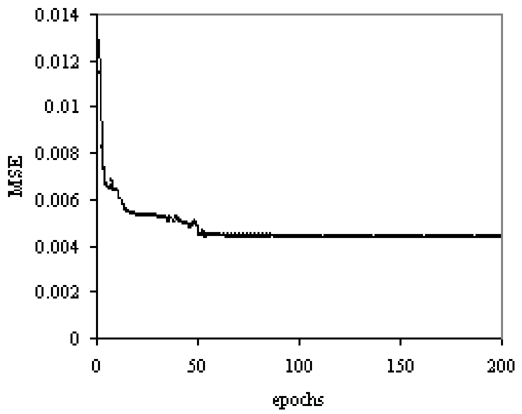

Fig. 7 Convergence of ANFIS training (with triangular membership function)

Under this circumstance, training is regarded as converged. In order to model such three-input single-output set of data, an ANFIS with two linguistic terms in each antecedent which is equivalent to two membership functions for each input variable, is considered. Different models are built, using triangular, bell-shape, Gaussian and trapezoidal membership functions. It should be noted that the number of parameters in each vector of coefficients in the concluding part of each TSK-type fuzzy rule is four, according to the assumed linear relationship of input variables in the consequents. Consequently, $2^3 = 8$ TSK-type fuzzy rules are identified using ANFIS, given in the MATLAB fuzzy logic toolbox. Compared results of such models with different types of membership functions aspect to MSE of training and testing set have been shown in Table 4.

TABLE 4
COMPARISON RESULTS OF VARIOUS ANFIS MODEL WITH DIFFERENT MEMBERSHIP FUNCTION

Mem.Function	Mean Square Error	
	Training Error	Prediction Error
gbellmf	2.20381E-05	5.15621E-05
gaussmf	2.14398E-05	4.78557E-05
trapmf	2.60888E-05	6.29373E-05
trimf	1.93886E-05	3.89049E-05

It can be seen that the triangular membership functions result in the best values for both training and prediction errors. The triangular curve is a function of a vector x, and depends on three scalar parameters a, b and c as given below:

$$f(x,a,b,c) = \begin{cases} 0 & x \le a \\ \dfrac{x-a}{b-a} & a \le x \le b \\ \dfrac{c-x}{c-b} & b \le x \le c \end{cases} \quad \text{or}$$

$$f(x,a,b,c) = \max\left(\min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right), 0\right)$$

Parameters a and b locate the feet of triangle and the parameter c locates the peak. Figure 8 demonstrates the training and prediction behaviors of the ANFIS model obtained using triangular membership functions (trimf).

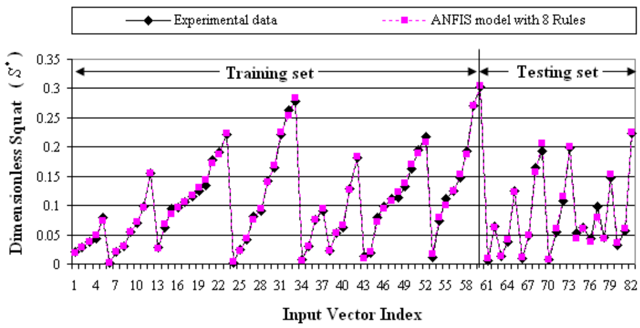

Fig. 8 The variation of Dimensionless Squat with input data samples (Triangular membership function for inputs)

The ANFIS parameter values for inputs premise parameters of this model have been shown in Table 5.

TABLE 5
ANFIS PARAMETER VALUES FOR INPUTS PREMISE PARAMETERS

Input	Mem.Function(trimf)	a	b	c
CB	A1	0.65	0.7	0.7499
	A2	0.7001	0.75	0.8
δ	A3	0.04951	0.09036	0.1268
	A4	-0.05038	0.2294	0.2858
F_{nh}	A5	-0.4134	0.2265	0.5151
	A6	0.08751	0.6278	1.071

Figure 9 shows the architecture of this ANFIS model that includes two membership functions for each input and made 8 rules for this ANFIS model.

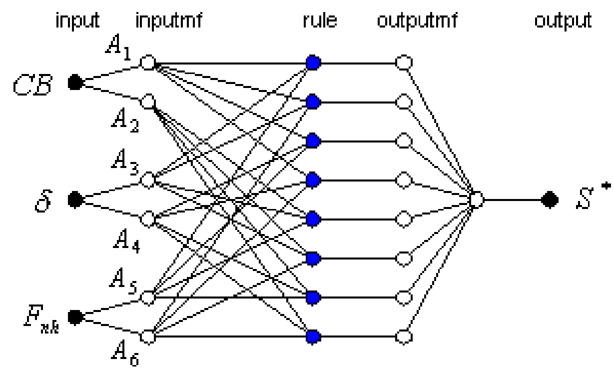

Fig.9 Architecture of designed ANFIS with eight rules (with trimf for input parameters)

Figure 10 and Figure 11 depict the experimental and predicted dimensionless squat (S^*) of proposed ANFIS model, against Froude Hydraulic Number (Fn_h) in two arbitrary dimensionless distance (δ) of each CB.

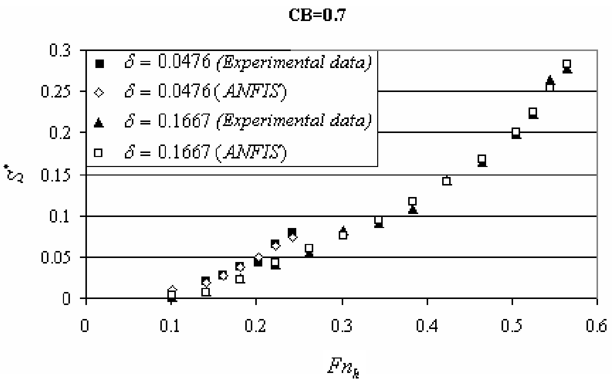

Fig.10 Experimental and predicted dimensionless squat obtained with the ANFIS against Froude Hydraulic Number for Block Coefficient equal to 0.7

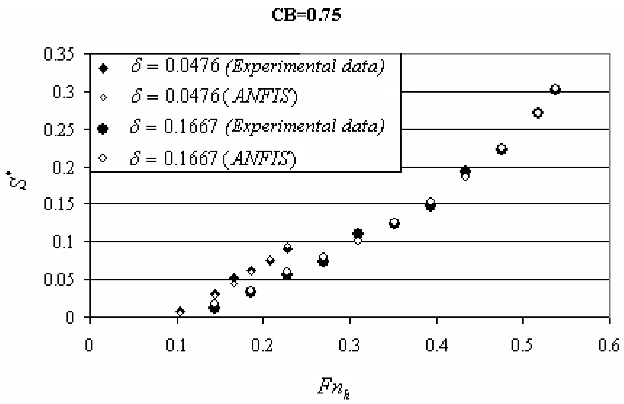

Fig.11 Experimental and predicted dimensionless squat obtained with the ANFIS against Froude Hydraulic Number for Block Coefficient equal to 0.75

Figure 12 shows the triangular membership functions of input variables for which the obtained set of TSK-type fuzzy rules for modeling of a dimensionless ship squat in shallow water are as follow:

*Rule*1 : *If CB is* A_1 *and* δ *is* A_3 *and* Fn_h *is* A_5, *then*
$S^* = 0.02153\ CB + 0.002798\ \delta - 0.5927\, Fn_h + 0.03075.$

*Rule*2 : *If CB is* A_1 *and* δ *is* A_3 *and* Fn_h *is* A_6, *then*
$S^* = 0.06426\ CB + 0.008354\ \delta + 2.103\ Fn_h + 0.09181.$

Rule 3 : *If CB is* A_1 *and* δ *is* A_4 *and* Fn_h *is* A_5, *then*
$S^* = -0.0265\ CB - 0.03465\ \delta + 0.772\ Fn_h - 0.03786.$

Rule 4 : *If CB is* A_1 *and* δ *is* A_4 *and* Fn_h *is* A_6, *then*
$S^* = -0.2024\ CB - 0.6669\ \delta + 1.459\ Fn_h - 0.2892.$

Rule 5 : *If CB is* A_2 *and* δ *is* A_3 *and* Fn_h *is* A_5, *then*
$S^* = 0.1065\ CB + 0.01292\ \delta - 3.077\ Fn_h + 0.142.$

Rule 6 : *If CB is* A_2 *and* δ *is* A_3 *and* Fn_h *is* A_6, *then*
$S^* = 0.8043\ CB + 0.09759\ \delta + 2.329\ Fn_h + 1.072.$

Rule 7 : *If CB is* A_2 *and* δ *is* A_4 *and* Fn_h *is* A_5, *then*
$S^* = -0.03658\ CB + 0.09796\ \delta + 0.8211\ Fn_h - 0.04877.$

Rule 8 : *If CB is* A_2 *and* δ *is* A_4 *and* Fn_h *is* A_6, *then*
$S^* = -0.1287\ CB - 1.7400\ \delta + 1.603\ Fn_h - 0.1717.$

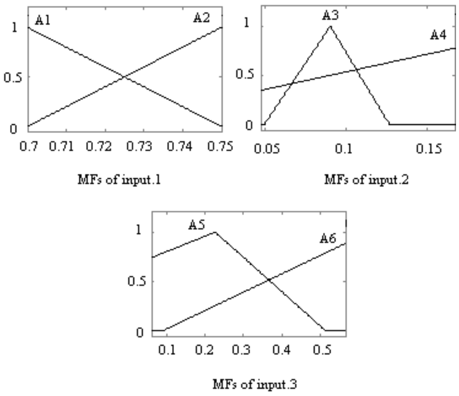

Fig.12 Triangular membership functions of input variables (ANFIS model with eight rules)

VI. Comparison of the ANFIS results with other techniques

In two former sections the GMDH-type neural network and ANFIS, methods are used for modeling and prediction of ship squat in shallow water. In this section, initially, a simple method called multiple linear regressions is used and, eventually, the results of these three methods have been compared. In this part of study, the comparison of these three approaches is made on the basis of the accuracy, R-square fitting parameter (that is, the square of the correlation between the experimental dimensionless squat values and the predicted dimensionless squat values) and train and test performance.

Multiple linear regression analysis is usually used to summarize data as well as to study the relations between variables [30].

Stepwise regression is basically a combination of backward and forward procedures and is probably the most commonly used method [31, 32]. In this method, the first variable is selected in the same manner as in the forward selection. If the variables fail to meet the entry requirements, the procedure terminates with no independent variables entering into the equation. If it passes the criterion, the second variable based on the highest partial correlation is selected. If it passes the entry criterion, it also enters the equation. After the first variable is entered, stepwise selection differs from forward selection: the first variable is examined to see whether it should be removed according to the removal criterion as in backward elimination. In the next step, variables which are not present in the equation are examined for removal. Variables are removed until none of the remaining variables meet the removal criterion. Variable selection terminates when no more variables meet entry and removal criteria [33]. The simple equation obtained for dimensionless squat with multiple regression analysis is:

$$S^* = -0.433 + 0.538\,CB - 0.260\,\delta + 0.620\,Fn_h \qquad (23)$$

The comparison of the GMDH-type neural networks (with 2 and 3 hidden layers), ANFIS (with 8 rules and triangular membership function) and multiple linear regression models is presented in Table 7. The comparison shows that:

(i) the minimum R-square is obtained with the multiple regression model,

(ii) the R-square of ANFIS is higher than that of GMDH-type neural network models,

(iii) The training and test errors of ANFIS are smaller than those of GMDH and regression models.

In brief, it may be stated that ANFIS yields most accurate results.

VII. Conclusions

This paper is conducted to demonstrate the usefulness of the artificial intelligence techniques for the prediction of ship squat in shallow water. GMDH-type neural networks and ANFIS are applied for modeling the ship squat that varies with three effective parameters, namely block coefficient (CB), dimensionless distance between the seabed and ship floor (δ) and Froude Number (Fn_h) that were investigated experimentally. The GMDH-type neural network model with 3 hidden layer and 6 neurons within those layers is selected as the optimum and best network for modeling and prediction of ship squat among other GMDH-type models because of minimum MSE on two predefined sets, the training set and testing set. Eventually, the accuracy of predictions and the adaptability of the ANFIS have been examined. The ANFIS indicated that it is capable to learn the training dataset and accurately predict the output of test data. Triangular membership functions are chosen as the best membership function for ANFIS training of the experimental data. The results obtained with ANFIS and GMDH-type neural networks are compared with each other. These results were also compared with the multiple linear regression method. The comparison showed that the ANFIS performed better than GMDH-type neural networks and multiple linear regressions.

Acknowledgment

The authors wish to express their appreciations to the helpful suggestions and comments of Professor Nader Nariman-Zadeh from Mechanical Department of Guilan University.

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