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# WAVE FORECASTING IN ARABIAN SEA USING ADAPTIVE NETWORK FUZZY INFERENCE SYSTEM

J. Vimala[1], G. Latha[2]

***Abstract***: *The National Data buoy program of the National Institute of Ocean Technology, under Ministry of Earth Sciences established moored buoys in Indian seas in 1997 and since then, has been working on the maintenance of buoy network in shallow as well as deep seas. Based on the 12 years of experience in the maintenance of buoys, it has been realized that the average life of a buoy in the sea is 5 to 6 months as they are prone for damages due to vandalism. In particular it is very difficult to maintain shallow water buoys as they are more vulnerable. Hence a continuous measurement of wave parameters has been a challenging task. In view of this and based on the literature survey on wave forecasting, it is clear that soft computing tools are efficient for wave forecasting when it becomes site specific. Unlike numerical models which require huge computational effort, these techniques are cost effective for site specific applications. This paper presents the work carried out on wave forecasting by applying of fuzzy logic using the wave measurements at DS2 location in the Arabian Sea (Lat: 10$^o$ 00' 26"N, Lon: 72$^o$ 30' 21"E) with long period record. The data sets have been trained, tested and used for forecasting upto 24 hours.*

***Keywords***: *fuzzy inference system; forecasting; correlation coefficient.*

## INTRODUCTION

The veracious predictions of significant wave height (Hs) are of immense importance in ocean and coastal engineering applications. Significant wave height is calculated as the average of the highest one-third of all of the wave heights during the sampling period. The phenomenon of generation of ocean waves depends on a number of atmospheric and meteorological factors and hence is a very complex process. Although there exist a number of wave height estimation models, they do not consider all causative factors without any approximation and consequently their results are more or less a general approximation of the overall dynamic behaviour. As the prediction is by and large a random process, modeling with the help of Fuzzy Inference system (FIS) could be beneficial.

One of the most useful tools presented within the context of fuzzy sets theory to deal with nonlinear, but ill-defined, mapping of input variables to output variables is what is known as

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Fuzzy Inference Systems (FISs). A FIS is a framework that simulates the behavior of a given system as IF–THEN rules through knowledge of experts or past available data of the system.

Generally, a fuzzy IF–THEN rule involves two parts. The first is IF part and the second is THEN part which are called premise and consequent parts, respectively. One type of proposed FISs in the literature is the so-called Takagi and Sugeno FIS in which the consequent variable of each rule is defined as a combination of input (premise) variables. Then the final output is the weighted average of each rule's output. In this study, the subtractive clustering method was used to estimate the optimum number of IF–THEN rules and to determine the membership functions. An Adaptive-Network-Based Fuzzy Inference System (ANFIS) is a Sugeno type FIS in which the problem of fine-tuning membership functions of premise variables is carried out by a feed-forward neural network. ANFIS provides a methodology for the fuzzy modelling procedure to learn information about a data set, in order to compute the membership function parameters that best allow the associated FIS to track the given input–output data.

Fuzzy logic has emerged as a mathematical tool to deal with the uncertainties in human perception and reasoning. It also provides a framework for an inference mechanism that allows for approximate human reasoning capabilities to be applied to knowledge-based systems. On the other hand, artificial neural networks have emerged as fast computation tools with learning and adaptivity capabilities. Recently, these two fields have been integrated into a new emerging technology called fuzzy neural networks which combines the benefits of each field.

## SITE DESCRIPTION AND DATA COLLECTION

Data Buoy was first deployed in Off Lakshadweep in February 1998. At regular intervals, the buoy system have been serviced or replaced with a fully tested buoy system to ensure continuous data return. Sensor calibrations are carried out before deployment of buoys to ensure the quality of data.

| | | |
|---|---|---|
| Latitude ($^o$N) | : | 10° 00' 26"N |
| Longitude ($^o$E) | : | $72^0$ 30' 21"E |
| Depth | : | 1800 meters |

**Buoy Location**

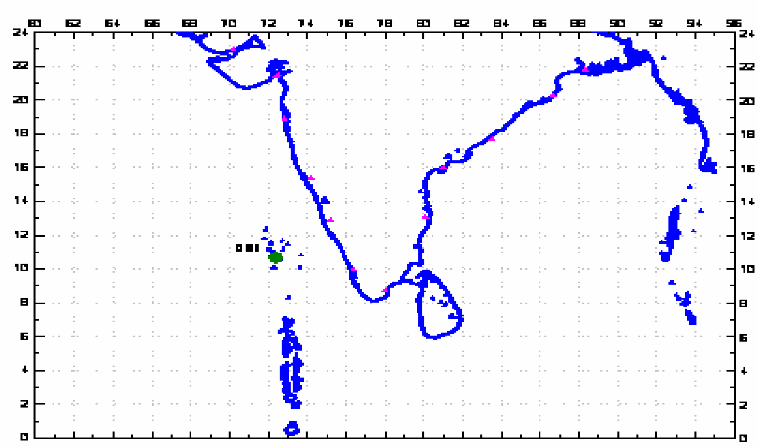


**Table 1: Number of data used**

| Data Set | No. of Data used |
|---|---|
| Training set | 4100 |
| Testing set | 4100 |

The data used were significant wave heights for the time period 2001 - 2003. Out of this, the data of period Jan 2001-Jun 2002 was used for training and the data for the period July 2002 - Dec 2003 is used for testing.

Once the required data was collected, the development of the model was done using Adaptive network based fuzzy interference (ANFIS). MATLAB was used for implementing ANFIS. The ANFIS simulated wave parameter for short lead times (three and six hours) perform generally better than the ones developed for longer lead time.

## WORKING OF ADAPTIVE NETWORK BASED FUZZY INFERENCE SYSTEM

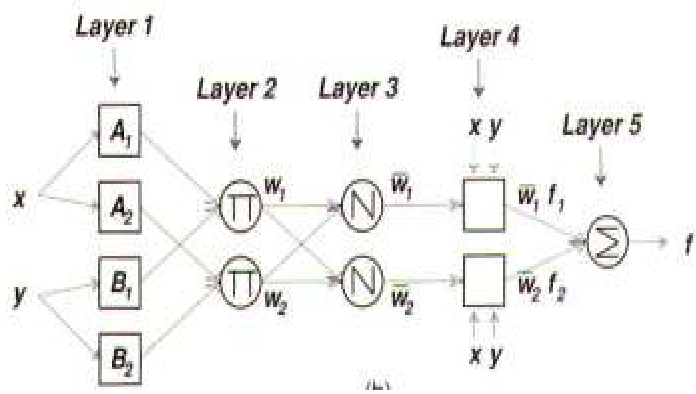



**Fig1. Structure of ANFIS**

Fig. 1 shows the structure of ANFIS including two inputs x, y, and one output f and two rules which were described in the below.

### *Forms of fuzzy rules*

Rule 1 : if (x is A1) and (y is B1) then ($f1 = p1x+ q1y + r1$)
Rule 1 : if (x is A2) and (y is B2) then ($f2 = p2x+ q2y + r2$)

In these rules, x and y are input variables, f is output variable. *Ai* and *Bi* are parameterized fuzzy sets.

The first layer is the fuzzifying layer in which Ai and Bi are the linguistic labels. The output of the layer is the membership functions of these linguistic labels. The second layer calculates the firing strength for each rule quantifying the extent to which any input data belong to IF-THEN rule. The output of the layer is the algebraic product of the input signals. The third layer is the normalization layer. Every node in this layer calculates the ratio of the ith rule's firing strength to the sum of all rules' firing strengths. The fourth layer is output of every node. The fifth layer computes the overall output as the summation of all incoming signals, which represents the results of wave height.

The output of each node is:

$$O_{1,i} = \mu_{A_i}(x) \qquad for\ i = 1,2$$

$$O_{1,i} = \mu_{B_{i-2}}(y) \qquad for\ i = 3,4$$

So, the $O_{1,i}(x)$ is essentially the membership grade for $x$ and $y$.

The membership functions could be anything but for illustration purposes we will use the bell shaped function given by:

$$\mu_A(x) = \frac{1}{1 + \left|\frac{x - c_i}{a_i}\right|^{2b_i}}$$

where $a_i, b_i, c_i$ are parameters to be learnt. These are the premise parameters.

Every node in this layer is fixed. This is where the t-norm is used to 'AND' the membership grades - for example the product:

$$O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y), \quad i = 1,2$$

Layer 3 contains fixed nodes which calculates the ratio of the firing strengths of the rules:

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2}$$

The nodes in this layer are adaptive and perform the consequent of the rules:

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i)$$

The parameters in this layer ($p_i, q_i, r_i$) are to be determined and are referred to as the consequent parameters.

There is a single node here that computes the overall output:

$$O_{5,i} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$$

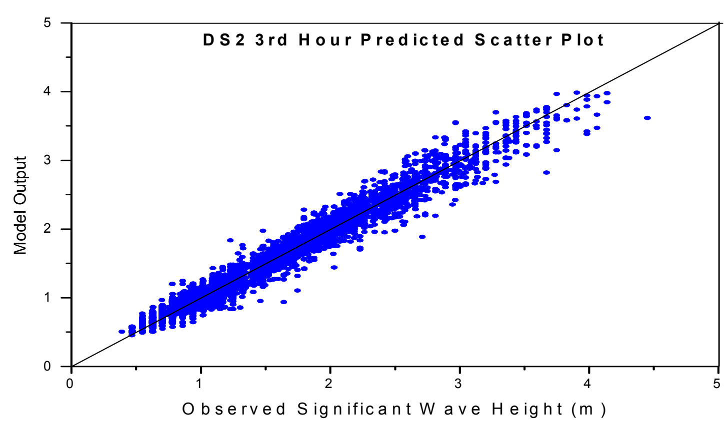
This then is how, typically, the input vector is fed through the network layer by layer. We now consider how the ANFIS learns the premise and consequent parameters for the membership functions and the rules.

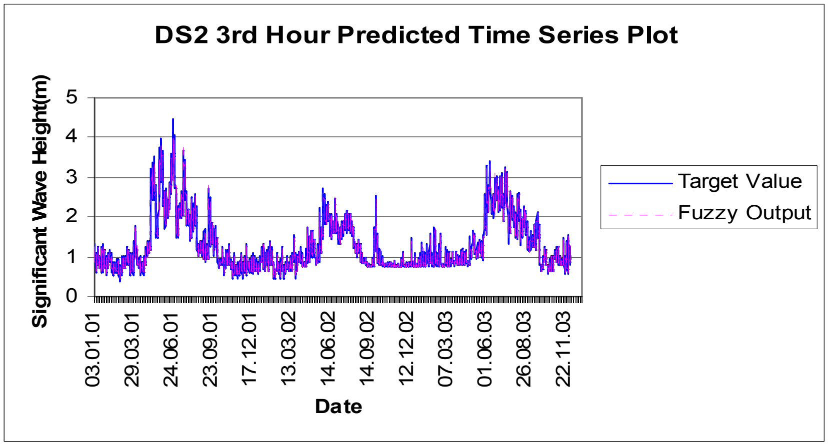
In ANFIS, the premise and consequent parameters are optimized using a hybrid learning algorithm. In this way, a two-step process is used for the learning or adjustment of the network parameters. In the first step, the premise parameters are kept fixed and the information is propagated forward in the network to Layer 4, where the consequent parameters are identified by a least-squares estimator. In the second step, the backward pass, the consequent parameters are held fixed while the error is propagated and the premise parameters are modified using a gradient descent algorithm. The only user specified information is the number of membership functions for each input and the input–output training information.

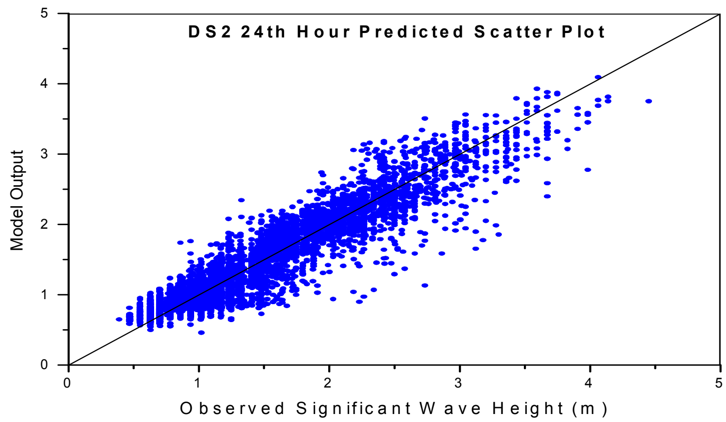
An Adaptive-Network-Based Fuzzy Inference System (ANFIS) (Jang, 1993) is a Sugeno type FIS in which the problem of fine-tuning membership functions of premise variables is carried out by a feed-forward neural network. ANFIS combines the advantages of both neural networks (e.g. learning capabilities, optimization capabilities, and connectionist structures) and fuzzy inference systems (e.g. human like 'IF–THEN' rule thinking and ease of incorporating expert knowledge). The basic idea behind these neuroadaptive learning techniques is very simple. They provide a methodology for the fuzzy modeling procedure to learn information about a data set, in order to compute the membership function parameters that best allow the associated FIS to track the given input–output data. ANFIS is based on the premise of mapping a FIS into a neural network structure so that the membership functions and consequent part parameters are optimized using a hybrid learning algorithm. In this algorithm, parameters of the membership functions are determined by a neural network back-propagation learning algorithm while the consequent parameters by the least square method.

## RESULT AND DISCUSSION

Comparisons between the network output and the observation value have been carried out using both qualitative as well as quantitative measures. The qualitative assessment is made with the help of time history plots, where deviation from the ideal fit line across the entire range of predictions is immediately seen (Fig.2). A variety of error measures serve the quantitative requirement and they include the correlation coefficient (r), Root Mean Square Error (RMSE), Mean Absolute Error (MAE) (Table 2).





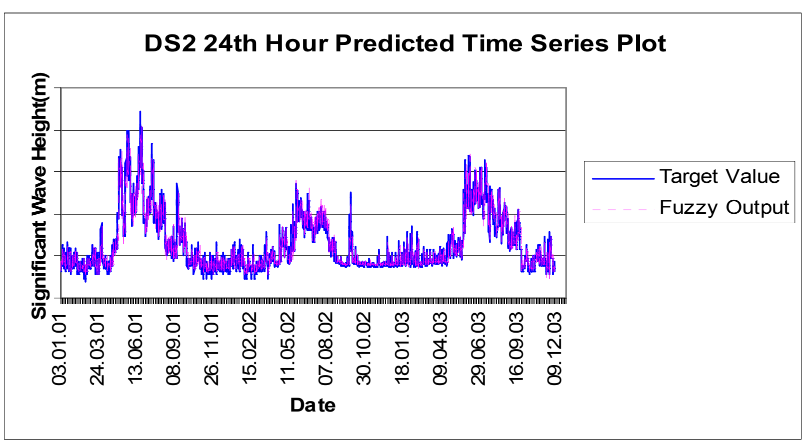




**Fig2. Significant Wave height comparisons between Observed and Forecast value**

| Statistics | $03^{rd}$ hr | $06^{th}$ hr | $12^{th}$ hr | $24^{th}$ hr |
|---|---|---|---|---|
| Correlation Coefficient | 0.99 | 0.98 | 0.97 | 0.95 |
| RMSE | 0.011 | 0.016 | 0.026 | 0.041 |
| MAE | 0.0001 | 0.0005 | 0.00054 | 0.0054 |

**Table 2. Verification statistics of Hs simulations with different lead times**

The results show different levels of performance of each of the ANFIS in terms of the root mean square error and correlation coefficient. The behavior changed according to the parameter being predicted and the period of forecasting.

## CONCLUSION

In this paper, wave parameter is predicted using soft computing tool such as ANFIS. The data set used in this study predicted wave height from deep water location in Off Lakshadweep. The first one was used as training data to develop the models and the second one was used to verify the models. The correlation coefficient between Hs from the ANFIS was significantly high, ranging from 0.95 to 0.99; the highest correlation (0.99) is in the 3rd. The coefficient of correlation(R) was0.85, RMSE, and MAE were 0.011, 0.0001 and 0.234m respectively (Table2). This correlation coefficient for periods of 2001-2003 proves that the fuzzy model is suitable to forecast wave height in the Arabian Sea.

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## APPENDIX I

**Correlation coefficient (r):**

$$r = \frac{\sum xy}{\sqrt{\sum x^2 \sum y^2}}$$

Where $x = (X - \overline{X})$ , $y = (Y - \overline{Y})$ , X = Observed values, $\overline{X}$ =Mean of X, Y = Predicted value, $\overline{Y}$ =Mean of Y. The summation in the above equation as well as in the following two equations is carried out over all 'n' number of testing patterns.

**Mean Absolute Error (MAE)**

The Mean Absolute Error is (MAE) the sum of the absolute values of the differences between corresponding forecasted and observed values, divided by the total number of events. The MAE is individually calculated for each forecast category.

$$MAE = \frac{\sum |X - Y|}{n}$$

**Root Mean Square Error (RMSE)**

The Root Mean Square Error (RMSE) is the square root of the sum of the squares of the differences between corresponding forecasted and observed values, divided by the total number of events. The RMSE is individually calculated for each forecast category.
Mean square error (mse),

$$mse = \frac{\sum (X - Y)^2}{n}$$

Root mean square error (rmse),

$$rmse = \sqrt{\frac{\sum (X - Y)^2}{n}}$$

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