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A comparison of different fuzzy inference systems for prediction of catch per unit effort (CPUE) of fish

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Present work was aimed to design Mamdani- Fuzzy Inference System (FIS), Sugeno -FIS and Sugeno-Adaptive Neuro-Fuzzy Inference System (ANFIS) model for the prediction of CPUE of fish. The system was implemented using MATLAB fuzzy toolbox. A prediction of CPUE was made using the models trained. The accuracy of fuzzy inference system models was compared using mean square error (MSE) and average error percentage. Comparative study of all the three systems provided that the results of Sugeno-ANFIS model (MSE =0.05 & Average error percentage=11.02%) are better than the two other Fuzzy Inference Systems. This ANFIS was tested with independent 28 dataset points. The results obtained were closer to training data (MSE=0.08 and Average error percentage=13.45%).

[Keyword - Artificial Neural Networks (ANNs), Fuzzy Inference System (FIS), Adaptive Neuro-Fuzzy Inference System (ANFIS), Catch per Unit Effort (CPUE)].

Introduction

Catch per unit effort (CPUE) is used widely in fisheries management and marine conservation efforts as a direct proxy of abundance[1, 2]. CPUE values were estimated as the total catch of fish per hour (in kg per fishing effort or hour). A fish catch forecast or prediction is based on the number of environmental factors. The environmental factors-Chlorophyll-a and diffuse attenuation coefficients (Kd_490) were taken as input variables for fish catch prediction (in terms of CPUE). Chlorophyll-a (Chl-a) is the primary phytoplankton pigment for photosynthesis of marine algae in the ocean which is the main food for fish that determine the fish assemblage area or potential fish zone. So, Chl-a was incorporated in prediction models, was expressed in mg/m^3. Besides Chl-a, Kd_490 may be used to describe the optical properties of ocean water. It increases with biomass and decreases with non-algal turbidity[3]. Kd_490 gives a clear idea of transparency of the water column and assumes importance, as predator fish species (viz., tuna, sharks, jacks, etc.) depend on sighting the prey for efficient foraging. It is expressed in m^{-1}. The retrieval of these factors for forecasting involves fuzziness in both spatial and temporal resolution as many times we could not get the value at a particular space and time. We would rely on other low or high spatial resolution and also on different temporal resolution-composite value retrieved from weekly or fortnightly or monthly data. Fuzziness is involved during the different stage of image processing of said factors. Therefore, the fuzzy had been incorporated in various aspects and ambiguities in these factors for better prediction of catch[4]. The said environmental data, being inherently fuzzy in nature, had a very high non-linear relationship with fish catch, requires highly complex processing. The Artificial Neural Networks (ANN) method is very robust in dealing with non-linear relationships[5] and has been preferred by many authors over linear statistical models. To integrate the best features of fuzzy systems and neural networks, Adaptive Neuro-Fuzzy Inference System model (ANFIS) was also applied to the obtained data set. The ANFIS is ideal for uncertain, ambiguous and complex estimation and forecasting[6]. The fuzzy inference system had been used in ranking and classification of fishing area[7]. ANFIS had been used in carrying capacity assessment for cage fish farm in Daya Bay, China[8]. The work done in Agrawal et al., (2013)[9], Ghatage et al., (2012)[10] and Esmaeili et al., (2012)[11] is purely based on ANFIS technique. Mamdani Mamdani FIS had been used to classify

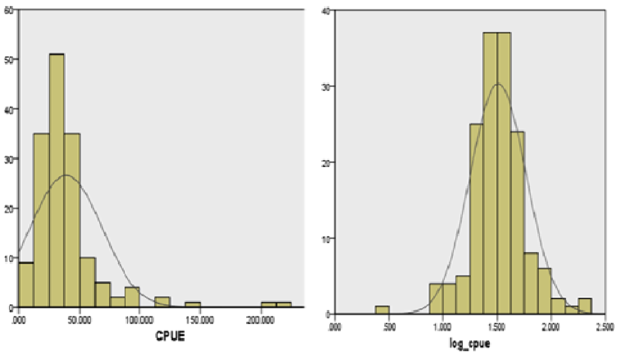

Fig.1 — Distribution of CPUE and log (CPUE)

sites for aquaculture development[12]. In the present study, Mamdani- Fuzzy Inference System (FIS), Sugeno -FIS and Sugeno-Adaptive Neuro-Fuzzy Inference System model (ANFIS) were used for the prediction of Catch per Unit Effort (CPUE) of fish using a set of a continuous predictor (environmental) variables-chlorophyll-a and diffuse attenuation coefficient (Kd_490).

Materials and Methods

The potential fishing zone advisory data from December 2007 to December 2009 of Gujarat coastal region (Enclosed within North latitude 16.37 to 23.20^{0}N and East Longitude 66.45 to 73.15^0 E) was obtained from Indian National Centre for Ocean Information Services (INCOIS), Hyderabad, India. These data include fishing and operational data as well as spatial and temporal variables. Fishing and operational data series incorporated the name of the boat, gear, duration of the trip (fishing effort); whereas spatial and temporal variable data included, the date and exact geographical coordinates of each fishing set. Other Spatio-temporal data included (i) Catch rates in terms of CPUE which is a fishery performance index representing the success of fishing from commercial fishery statistics; CPUE values were estimated as the total catch of fish (in kg per fishing effort); (ii) daily or composite days Chlorophyll-a and diffuse attenuation coefficient (Kd_490) in the study area were obtained from Moderate Resolution Imaging Spectroradiometer (MODIS) sensor with scale measurements (4*4 km). The daily images of said variables were processed in SeaDAS software taking L1A MODIS image. Composite eight days or fortnightly data were obtained from MODIS level 3 standard binned images archived by the Ocean Biology Processing Group (OBPG) as an ASCII file.

In this study, our emphasis was on the influence of environmental variables (chlorophyll-a and Kd_490) on CPUE. The CPUE data had too much variability; hence the logarithmic transformation was applied[2] (Fig.1). Min-Max Normalization method was used in this study. The data was normalized in [0, 1]. The Min-Max normalization scales the numbers in a dataset to improve the accuracy of the subsequent numeric computations. Tseng et al. (2002)[13], Nayak et al. (2004)[14], Niskaa et al. (2004)[15], Karunasinghe and Liong (2006)[16], Oliveira and Meira (2006)[17], Gareta et al. (2006)[18], Aznarte et al. (2007)[19], and Jain and Kumar (2007)[20] used this method to estimate time series functions using heuristic approach.

If x_{old}, x_{max} and x_{min} are the original, maximum and minimum values of the raw data, respectively and x'_{max}, x'_{min} are the maximum and minimum of the normalized data, respectively, then the normalization of x_{old} called x'_{new} can be obtained by the following transformation function:

$$x'_{new} = (x_{old} - x_{min})/(x_{max} - x_{min})\,(x'_{max} - x'_{min}) + x'_{min} \quad \dots (1)$$

where $x'_{max} = 1$ and $x'_{min} = 0$ as data is normalized in [0, 1]

The relationship between variables was highly nonlinear for log(CPUE) prediction, and it is likely that the traditional statistical method of prediction may fail in such cases. Three models were designed for the prediction of log(CPUE) using Mamdani, Sugeno, and Sugeno- ANFIS techniques. In the Mamdani method, output membership function is given by the modeler whereas in Sugeno method the output membership function is linear and is derived from existing data. Mamdani method is widely accepted for capturing expert knowledge[21], also it allows us to describe the expertise in more intuitive, more human-like manner[22]. Sugeno method is computationally efficient and works well with optimization and adaptive techniques, which makes it very attractive for dynamic nonlinear systems. The Sugeno- ANFIS model was used for modeling the log(CPUE) using the concept of Fuzzy and ANNs. Triangular membership function was used in all FIS analysis because of simplicity and computational efficiency[23]. Three linguistic terms (Low, Medium and High) were used for membership functions.

In the present study, we attempted to forecast log(CPUE) with the help of fuzzy logic based approximate reasoning. This process used the concept

Table 1 — The value of a1, a2 and constant for low, medium and high log(CPUE) linguistic labels of the triangular membership function

log(CPUE) linguistic labels	a1	a2	Constant
Low log(CPUE)	-0.379	0.431	0.244
Medium log(CPUE)	0.422	-0.561	0.524
High log(CPUE)	-4.144	4.583	0.683

of a pure fuzzy logic system where the fuzzy rule base consists of a collection of fuzzy IF-THEN rules[24]. The fuzzy inference engine used these fuzzy IF-THEN rules to determine a mapping from fuzzy sets in the input universe of discourse to fuzzy sets in the output universe of discourse based on fuzzy logic principles[24]. In order to build the models, we defined the fuzzy sets consist of two parameters: Chlorophyll-a and Diffuse attenuation coefficient (Kd_490) as the input variables and log(CPUE) as an output variable. Each variable had three linguistic terms.

a) Mamdani's Method: Mamdani's Fuzzy Inference Method is the first rule-based model and most commonly seen fuzzy methodology developed by Mamdani, E.H and Assilian S. (1975)[25]. Mamdani model combines inference results of rules using superimposition and not the addition. Hence it is a non-additive rule model. The Mamdani model use rules whose consequent part is Fuzzy Set:

R_i :*If* x_1 is A_{i1} and x_2 is A_{i2} and … and x_p is A_{ip} is *Then* y is C_i, i=1,2,…,M … (2)

Where 'M' is the number of fuzzy rules, $x_j \in U_j$ (j=1, 2,…p) are the input variables, $y \in Y$ is the output variable, and A_{ij} and C_i are fuzzy sets characterized by membership functions $\mu A_{ij}((x_j)$ and $\mu C_i(y)$ respectively. The steps in the system are Fuzzify inputs, Apply fuzzy operator, Apply implication method, Aggregate all outputs, Defuzzification http://www.mathworks.in/products/fuzzy-logic) [30].

Sugeno, or Takagi-Sugeno-Kang (T-S), a method of fuzzy inference was introduced in 1985; it is similar to the Mamdani method in many respects. The first two parts of the fuzzy inference process, fuzzifying the inputs and applying the fuzzy operator, are the same. The main difference between Mamdani and Sugeno is that the Sugeno output membership functions are either linear or constant.

A typical rule in a Sugeno fuzzy model has the linear form.

If Input 1 = *x* and Input 2 = *y*, then
Output is $z = ax + by + c$ … (3)

For a zero-order Sugeno model, the output level *z* is a constant *(a=b =0).*

The steps of implementing Sugeno fuzzy systems are similar to Mamdani systems except the output is linear. The linear relationship that exists between two independent variables and one depended variable can be termed as

$$Y = a_1X_1 + a_2X_2 + \text{constant} \quad \ldots (4)$$

Y is log(CPUE) value, and X_1 and X_2 are Chlorophyll-a and Diffuse attenuation coefficient (Kd_490). The said two parameters and the output are subjected to multiple regression analysis with the least square fit and hence determined the coefficient for low, medium and high log(CPUE) linguistic labels which were shown in Table 1.

The values of a1, a2 are given as Params of respective membership functions in Matlab in the form of [a1 a2 constant](http://www.mathworks.in/products/fuzzy-logic)[30]. The Sugeno- ANFIS technique was originally presented by Jang in 1993 (Jang et al., 1993)[26]. ANFIS is an adaptive network. An adaptive network is composed of nodes and directional links associated with the network. It is called adaptive because some, or all, of the nodes, have parameters which affect the output of the node. These networks are capable of learning a relationship between inputs and outputs. ANFIS combines the benefits of the two machine learning techniques (Fuzzy Logic and Neural Network) into a single technique[26]. An ANFIS works by applying Neural Network learning methods to tune the parameters of a Fuzzy Inference System (FIS)[9].

The steps required to implement ANFIS to modeling are: define input and output values; define fuzzy sets for input values; define fuzzy rules; and create and train the Neural Network. To implement and test the proposed architecture, MATLAB Fuzzy Logic Toolbox (FLT) from MathWorks was selected as the development tool. The ANFIS editor GUI menu bar can be used to load a FIS training initialization, save the trained FIS, and open a new Sugeno system to interpret the trained FIS model.

Using a given input/output data set, the toolbox function *anfis* constructs a fuzzy inference system (FIS) whose membership function parameters are tuned (adjusted) using either a backpropagation algorithm alone or in combination with a least squares type of method. This adjustment allows fuzzy systems to learn from the data they are modeling.

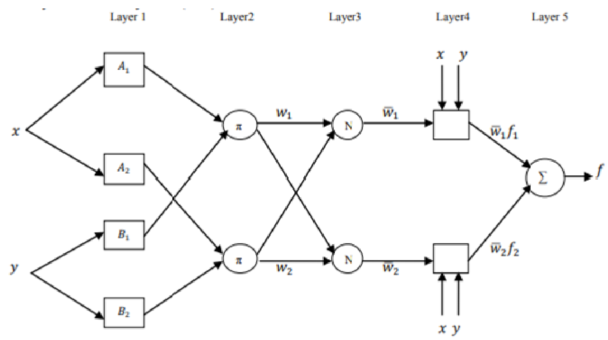

Fig. 2 — ANFIS Architecture (Agrawal et al., 2013)[9]

Steps in developing a model using ANFIS

Step 1: Loading Data

Step 2: Initializing and Generating FIS

Step 3: Viewing FIS Structure

Step 4: ANFIS Training

Step 5: Testing Data against the Trained FIS

Training data set that contains the desired input/output data of the system was loaded to train and modeled the FIS. The FIS was loaded from the Sugeno type fuzzy inference system prepared earlier for log(CPUE) modeling. The partitioning method selected was grid partitioning, and is a data clustering technique wherein each data point belongs to a cluster to some degree that is specified by a membership grade. Then the new FIS is generated, and the structure of new FIS is determined. The structure of the network is shown in figure 2.

The number of membership functions must be equal to the number of rules. To present the ANFIS architecture, two fuzzy IF-THEN rules based on a first-order Sugeno model are considered:

(1): $IF\ x\ is\ A_1$ AND $y\ is\ B_1,\ THEN\ f_1 = p_1x + q_1y + r_1$.

(2): $IF\ x\ is\ A_2$ AND $y\ is\ B_2,\ THEN\ f_2 = p_2x + q_2y + r_2$.

Where: x and y are the inputs, A_i and B_i are the fuzzy sets, f_i are the outputs within the fuzzy region specified by the fuzzy rule, and p_i, q_i, and r_i are the design parameters that are determined during the training process. ANFIS has five-layer architecture. Each layer is explained in detail below. In Layer (1), all the nodes are adaptive nodes. The outputs of Layer (1) are the fuzzy membership grade of the inputs, which are given by the following equations:

$$O_{1,i} = \mu A_i(x),\ i = 1,2,3 \quad \dots (5)$$
$$O_{1,j} = \mu B_j(y),\ j = 1,2,3 \quad \dots (6)$$

Where x and y are the inputs to node i and B_j are the linguistic labels (low, medium, high) associated with this node function. (x) and $\mu B_j(y)$ can adopt any fuzzy membership function (Triangular membership function was considered in this example). In Layer (2), the nodes are fixed nodes. This layer involves fuzzy operators; it uses the AND operator to fuzzify the inputs. They are labeled with π, indicating that they perform as a simple multiplier. The output of this layer can be represented as .

$$O_{2,i} = w_i = \mu A_i(x) * \mu B_j(y), i, j = 1,2,3 \quad \dots (7)$$

These are the so-called firing strengths of the rules. In Layer (3), the nodes are also fixed nodes labeled by N, to indicate that they play a normalization role to the firing strengths from the previous layer. The output of this layer can be represented as

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2}, i = 1,2 \quad \dots (8)$$

(Agrawal et al., 2013)[9]

Outputs of this layer are called normalized firing strengths. In Layer (4), the nodes are adaptive. The output of each node in this layer is simply the product of the normalized firing strength and a first-order polynomial (for a first-order Sugeno model). The output of this layer is given by

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i(p_i x + q_i y + r_i), i = 1,2, \quad \dots (9)$$

(Agrawal et al., 2013)[9]

Where $\bar{\omega}$ is the output of Layer (3), and p_i, q_i, and r_i are the consequent parameters. In Layer (5), there is only one single fixed node labeled with Σ performs the summation of all incoming signals. The overall output of the model is given by

$$O_{5,i} = \sum_i \bar{w} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}. \quad \dots (10)$$

(Agrawal et al., 2013)[9]

The learning algorithm for ANFIS is a hybrid algorithm that is a combination of gradient descent and least squares methods. In the forward pass of the hybrid learning algorithm, node outputs go forward until Layer (4) and the consequent parameters are determined by the least squares. In the backward pass, the error signals propagate backward, and the premise parameters are updated using gradient descent[26].The rules were formed by first-order Sugeno fuzzy model after Sugeno and Kang (1988)[27]; Takagi and Sugeno (1985)[28]. The changing laws of two inputs vs. output were plotted as a surface graph.

Results and Discussion

Input variables of FIS were: Chlorophyll-a and Diffuse attenuation coefficient (Kd_490). The output variable is log(CPUE). All the variables accept values in the normalized range [0, 1]. The normalized interval contains three fuzzy sets such as: "Low", "Medium" and "High". The membership functions of all the fuzzy sets are a triangular function. Eq.(11), Eq.(12) and Eq.(13) show mathematical equations of membership expressions. These fuzzy sets are shown in Table 2. The design of FIS, different membership function and surface view of log (CPUE) under Mamdani method were shown in Figure 3, 4 and 5 respectively.

$$\mu_L(x) = \{\ 1 \text{ if } x=0 \quad = (0.4-x)/0.4, \text{ if } 0\leq x\leq 0.4 \quad = 0 \text{ if } x>0.4\ \} \quad \ldots (11)$$

$$\mu_M(x) = \{\ (x-0.1)/0.4, \text{ if } 0.1\leq x\leq 0.5 \quad = 1 \text{ if } x=0.5 \quad = (0.9-x)/0.4, \text{ if } 0.5\leq x\leq 0.9\ \} \quad \ldots (12)$$

$$\mu_H(x) = \{\ (x-0.6)/0.4, \text{ if } 0.6\leq x\leq 1 \quad = 1 \text{ if } x=1\} \quad \ldots (13)$$

The output membership function of log(CPUE) under Sugeno method is linear. This linear data is derived from existing data through regression analysis. The Params given to the different linguistic labels of log(CPUE) were shown in Table 1. The design of FIS, surface view of log(CPUE) and different membership function were shown in Fig. 6, 7 and 8 respectively. The outputs are analyzed using the rule viewer in the View menu (Fig. 9) Matlab provides ANFIS tool to model the data based on neuro fuzzy systems. The major objective is to create membership functions for inputs and outputs from the existing data. The FIS system was structured by selecting two inputs namely: Chlorophyll-a, and Diffuse attenuation coefficient (Kd_490) and one output as log(CPUE) value. Loaded training and testing dataset in the ANFIS model were shown in Figure 10. After the training, the structure of the FIS was generated.

De- normalization was done to compare the predicted value using the equation (1). Forecasting accuracy of a model is commonly measured in terms of Mean Square Error (MSE) or in terms of Average Error. Lower the MSE or average error, better the forecasting method. Summary of results obtained from different FIS model using triangular membership functions was shown in Table 3. The MSE and average error percentage calculated comes to be 0.25 and 31.25 respectively for log(CPUE) prediction in Mamdani method.The MSE is defined as

$$\text{Mean Square Error} = \frac{\sum_{i=1}^{n} (\text{actual value}_i - \text{forecasted value}_i)^2}{n}$$

And forecasting error as

$$\text{Forecasting error (in percent)} = \frac{|\text{forecasted} - \text{actaul value}|}{\text{actual value}} \times 100$$

$$\text{Average forecasting error (in percent)} = \frac{\text{sum of forecasting error}}{\text{numbers of errors}}$$

Similarly, the Sugeno model was used for the same database. The MSE and average error percentage for log(CPUE) prediction come to be 0.19 and 27.79 respectively in the Sugeno method. The results obtained with ANFIS method had 0.25 MSE and 11.02 average errors as a percentage. The MSE and average error percentage were also calculated on independent 28 data set points, and they were shown in Table 3.

Table 2 — Classification of Input and Output field

Input field	Output field	Range	Fuzzy sets
Chl-a, Kd,	log(CPUE)	0-0.4	Low=L
		0.1 -0.9	Medium=M
		0.6-1	High=H

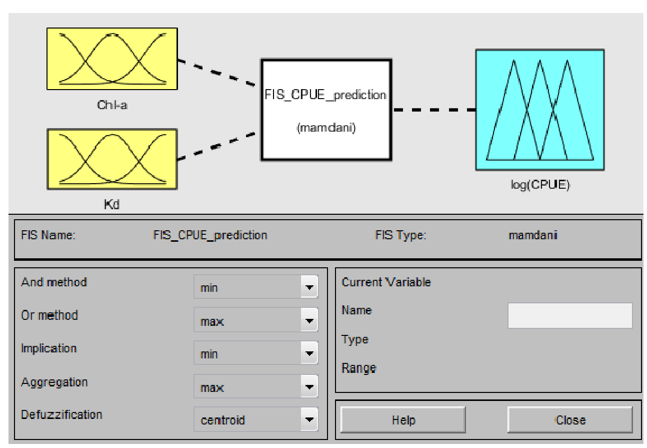

Fig.3 — Design of log(CPUE), FIS (Mamdani Method)

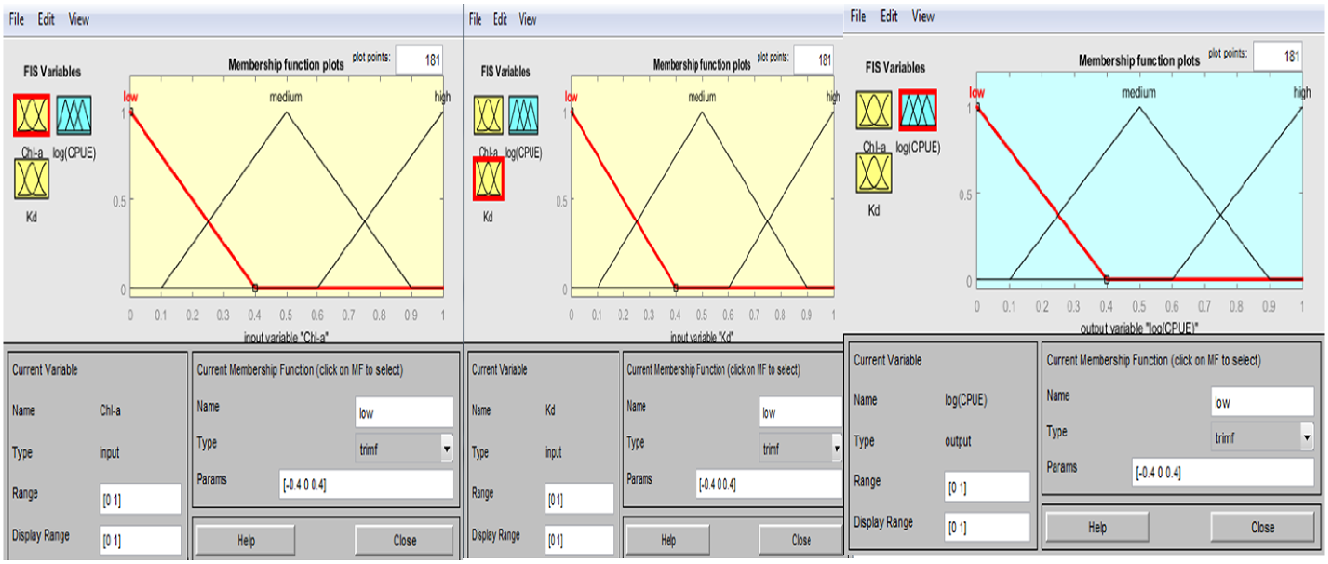

Fig.4 — Membership functions of Chlorophyll-a, Kd, log(CPUE) in Mamdani method

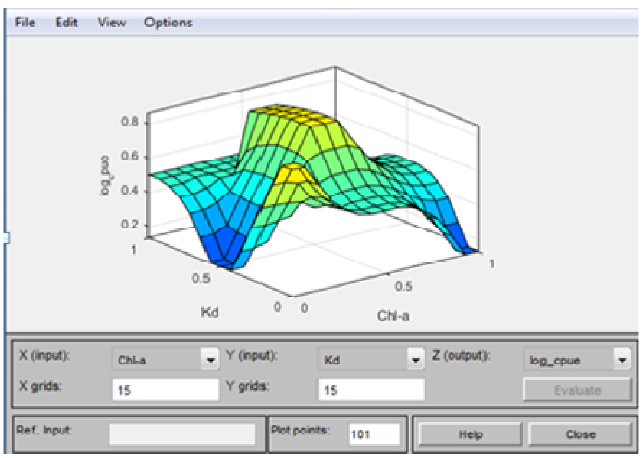

Fig.5 — The Surface view of log (CPUE) with respect to inputs Chl-a and Kd in Mamdani FIS

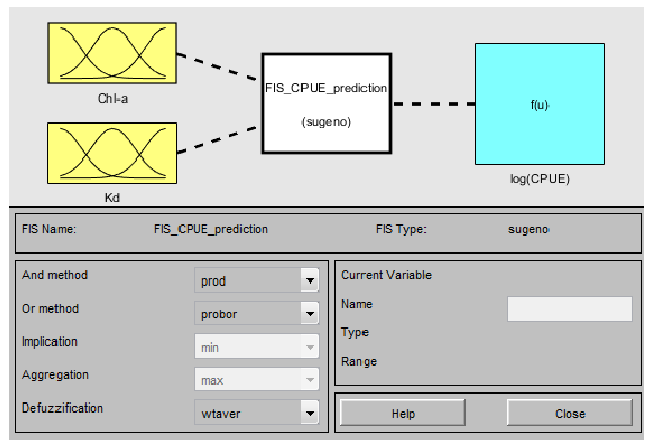

Fig.6 — Design of log(CPUE), FIS (Sugeno Method)

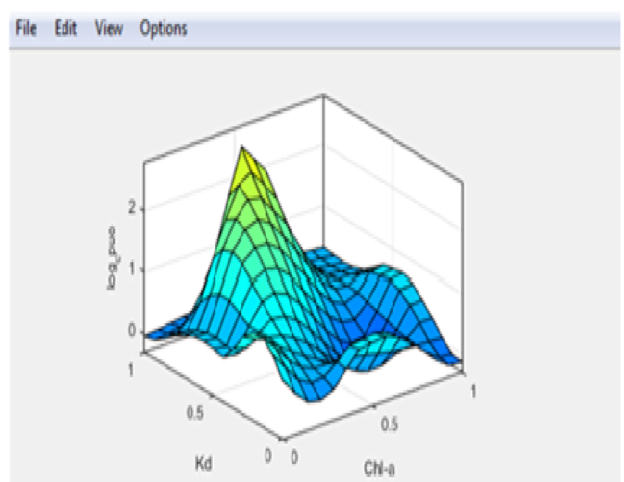

Fig.7 — The Surface view of log(CPUE) with respect to inputs Chl-a and Kd in Sugeno FIS

MSE and average error percentage in case of ANFIS were remarkably less than the other FIS method. The experimental results of this study and the similar researches have shown that combination of artificial neural networks, and Fuzzy logic, neural networks Fuzzy (ANFIS method) has been successful and predictive errors have been remarkably decreased.

Hence it could be concluded that the ANFIS model constructed using triangular membership function performed better among all the FIS methods, concerning above-said accuracy measure on complete 138 data points and also on independent 28 test data set. Also, it was found that Sugeno method using triangular membership function performed better as the comparison to Mamdani method in terms accuracy measure, mean square

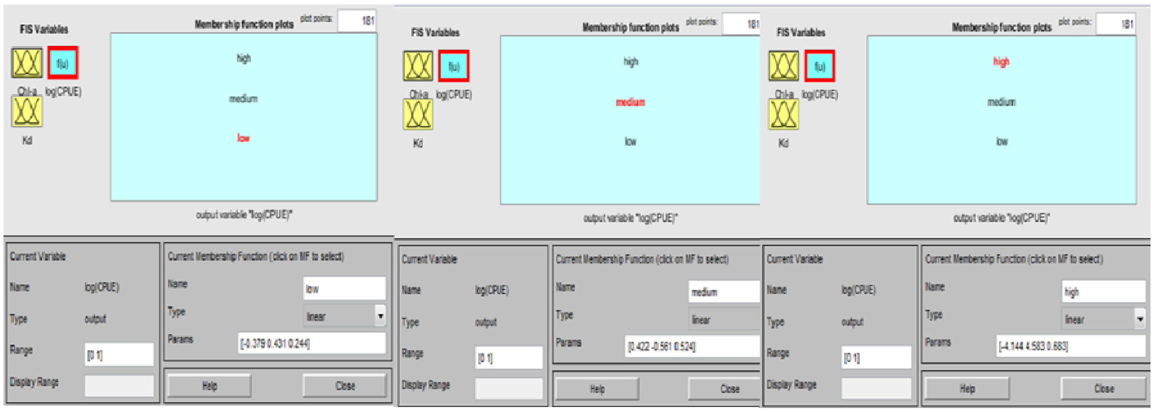

Fig.8 — Output membership function of low, medium and high, log (CPUE) potential in Sugeno FIS

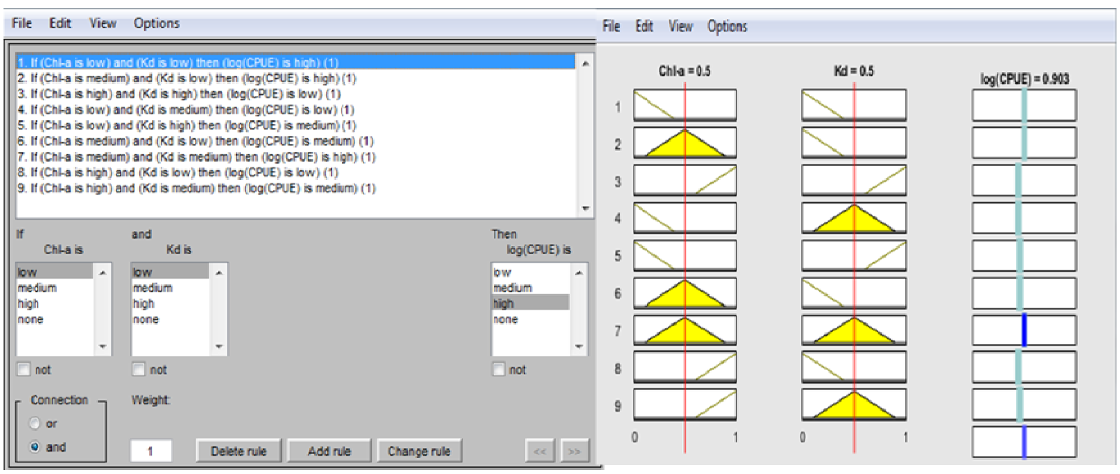

Fig. 9 — FIS rule editor & viewer with inputs-Chl-a & Kd and output-log (CPUE) in Sugeno FIS

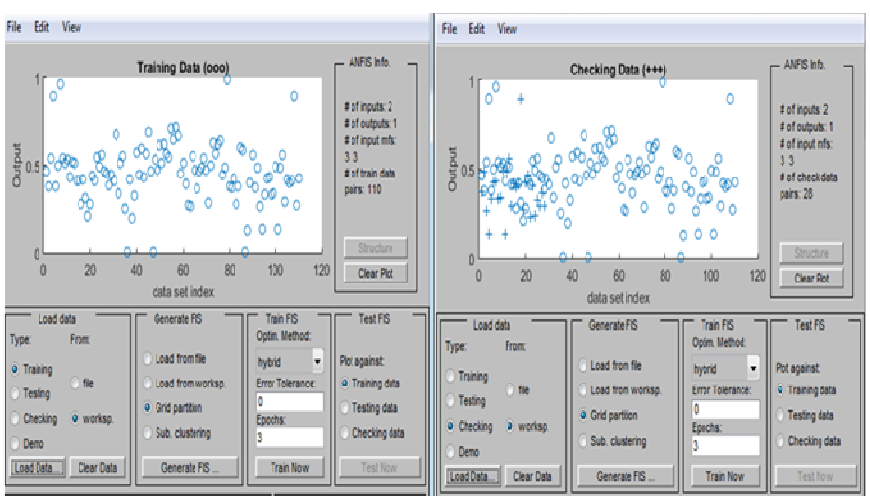

Fig. 10 — loading of training and testing data

error (MSE) and average error percentage on the above said data.

The predicted value of log(CPUE) obtained from different FIS methods after de-normalization on independent 28 test data points after model trained were shown in Table 4 with real values of log(CPUE). The predicted values with ANFIS method were closer with actual values as compared to Mamdani and Sugeno

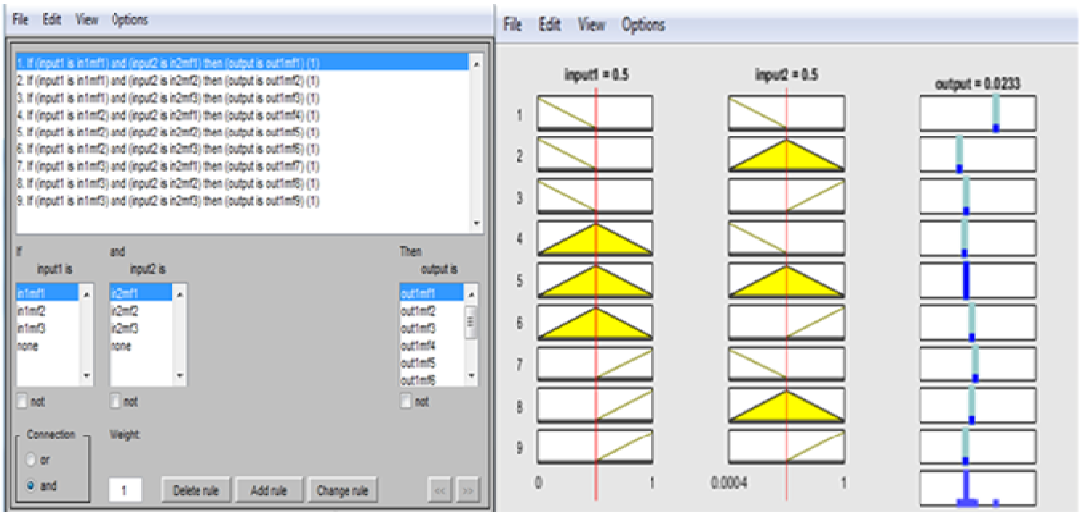

Fig. 11 — FIS rule editor & viewer with two (2) inputs and one (1) output in ANFIS model

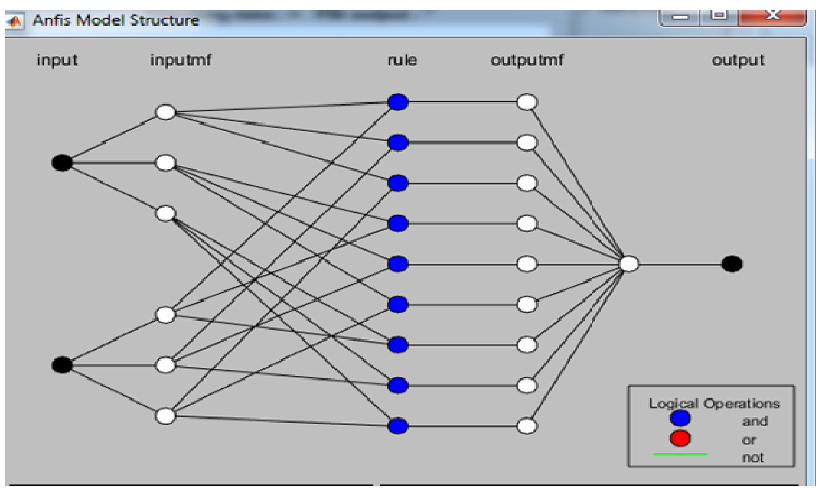

Fig. 12 — Structure of FIS developed by ANFIS for log(CPUE) Predictio modeling

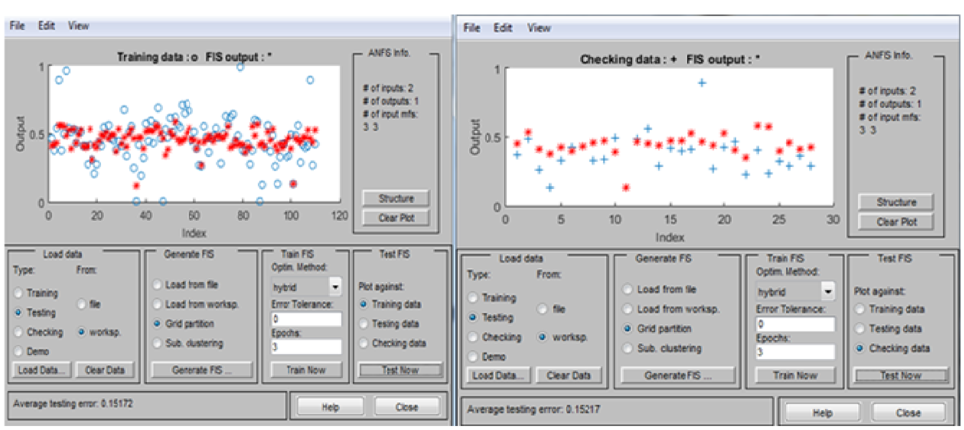

Fig.13 — Average testing error on training and testing data

method. Considering that, ANFIS in compare to Mamdani and Sugeno methods in performance evaluation of different criteria was superior; this method could be recommended for predicting log (CPUE).

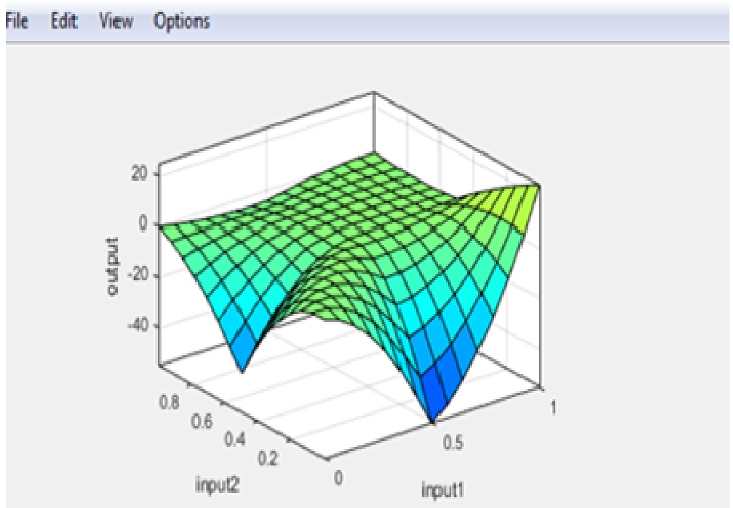

Fig:14 — The Surface view of log (CPUE) with respect to inputs Chl-a and Kd in ANFIS

Table 4 — Predicted value of log (CPUE) in different FIS on 28 independent test data points

Original log(CPUE) Value	ANFIS Output	Mamdani FIS Output	Sugeno FIS Output
1.518	1.469	2.040	1.984
1.217	1.416	1.894	1.876
1.438	1.668	2.048	1.896
1.217	1.663	2.048	1.890
1.334	1.459	1.916	1.978
1.290	1.534	2.047	1.874
1.387	1.485	1.692	1.753
1.294	1.488	2.040	2.028
1.270	1.488	2.040	2.028
1.585	1.542	2.043	2.004
1.504	1.527	2.043	2.013
1.905	1.473	2.013	2.013
1.988	1.515	2.043	1.971
2.217	1.532	2.044	1.958
1.979	1.461	1.928	1.958
1.953	1.483	2.039	2.028
1.968	1.496	2.041	2.013
1.622	1.610	2.046	1.966
1.344	1.619	2.046	1.947
1.690	1.614	2.046	1.946
1.817	1.630	1.722	1.794
1.733	1.545	1.670	1.775
1.602	1.613	1.605	1.745
1.646	1.562	2.046	1.912
1.618	1.463	1.881	1.927
1.431	1.556	2.044	1.984
1.376	1.489	2.041	1.996
1.601	1.568	1.646	1.776

Table 3 — Summary of results obtained from different FIS model using Triangular membership function

Methods	Mean Square Error (MSE)		Average Error Percentage	
	Training Data	Testing Data	Training Data	Testing Data
Mamdani Method	0.25	0.22	31.25	27.78
Sugeno Method	0.19	0.18	27.79	25.63
ANFIS	0.05	0 .08	11.02	13.45

Conclusion

To manage the uncertainty in the processes of CPUE prediction, different Fuzzy Inference System (FIS) were used. Fuzzy sets are suitable for approximate reasoning and allow decision-making with estimated values where information is incomplete or uncertain[29]. This study introduced the initial attempts for catch per unit effort (CPUE) prediction of fish using Mamdani- Fuzzy Inference System (FIS), Sugeno FIS and Sugeno-Adaptive Neuro-Fuzzy Inference System model (ANFIS). The comparative study of all the three systems suggested that the result of Sugeno-ANFIS model was better than the two other Fuzzy Inference Systems. The developed ANFIS model was tested with 28 independent dataset points. The results obtained were very encouraging in terms of MSE and average error percentage.Sugeno-type ANFIS has an advantage that it is integrated with the neural network to tune the FIS parameters by the hybrid approach which is the combination of backpropagation and least square method using the input/output training data. This reveals application potential of ANFIS technique in the prediction of CPUE of fish.

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