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Adaptive Neuro Fuzzy Inference System based Water Quality Index for Godavari River (India)

Jyotiprakash G. Nayak[1], Vinayak K.Patki[2], Rashmi J. Nayak[3], Ramgopal Sahu[4],Mithun B. Patil[5] Yashwant Patil[6]

[1] Associate Professor, Department of Civil Engineering, Sandip Institute of Technology and Research Centre, Nashik, Maharashtra, India.

[2] Professor, Department of Civil Engineering, Nagesh Karajgi Orchid College of Engineering and Technology, Solapur, Maharashtra, India.

[3] Assistant Professor, Engineering Sciences and Humanities Department, Sandip Institute of Engineering and Management, Nashik, Maharashtra, India.

[4] Assistant Professor, Department of Civil Engineering, Sandip Institute of Technology and Research Centre, Nashik, Maharashtra, India

[5] Associate Professor, Department of Computer science and Engineering Nagesh Karajgi Orchid College of Engineering and Technology, Solapur, Maharashtra, India.

[6] Assistant Professor, Department of Civil Engineering, Rajarambapu Institute of Technology, Sakhrale, Islampur,Maharashtra, India.

Corresponding Author-vinayakpatki1976@gmail.com

Abstract: Water Quality Index (WQI) is a comprehensive tool, which is used to assess the water quality status of the streams. In the present study water quality status of the Godavari River at Nashik has been assessed at fourteen water quality monitoring stations (WQMS) located at bathing ghats and bridges along the course of the River. For Assessment of the water quality, prevalent National Sanitation Foundation Water Quality Index (NSFWQI) values have been determined at these WQMS using pH ,DO, BOD,Turbidity and Total solids parameter values. It is observed that NSFWQI has its inherent limitations and fails to give the representative results of water quality in the region of higher water pollution. To overcome this limitation, Artificial Intelligence techniques like Fuzzy logic, Artificial Neural Network (ANN) and ANFIS are employed. ANFIS approach integrates the merits of Fuzzy logic and ANN approach .In view of this, Adaptive Neuro Fuzzy Inference System (ANFIS) has been employed for the present study, using Triangular, Trapezoidal, Gaussian and Bell membership functions(MF). It has been observed that Gaussian and triangular MF gives better results for Eleven and three number of sampling stations, respectively. Therefore, the Gaussian MF model outperforms other MF models of the ANFIS approach for the study.

Keywords: Water Quality Index; Adaptive Neuro Fuzzy Inference System; Coefficient of Correlation; Membership Function; Water Quality.

1. Introduction

Water quality determination is of paramount importance to assess the suitability of water streams for different uses like drinking, bathing, irrigation etc. Rather than comparing the values of various water quality (i.e. WQ) parameters, the WQI value based on these WQ parameters should be determined at a station [1,2].The WQI value so obtained gives the representative picture of the water quality at a station [3].To determine the WQI , the four step approach had been used by the researchers [4].The steps involved are i) Finalising the WQ parameters to be considered in the region ii) Sub-index values determination iii) Deciding the parameter weightages iv) Deciding the final index equation based on aggregation of the parameters. To decide the WQ parameters, previous literature

of regional work study should be referred [5] .Along with that proposed use of stream also becomes a decisive factor. Sub-indices development is done to nullify the effect of the different units of the parameters. Sometimes ‘Sensitivity’ issue is observed , under these cases , utilisation of equal weights is recommended (Nayak et al.,2020). Additive and multiplicative methods employed for aggregation of the parameters, but both suffers from ‘eclipsing’ and ‘ambiguity’ issues respectively [6] . In view of these reasons, need of a WQI based based on artificial intelligence techniques is felt for highly polluted streams [7].
High value of BOD and total suspended solids (TSS) are indicators of highly polluted streams. Some of the most most prevalent WQI like NSFWQI fails to give representative result in the region of high BOD and TSS, hence utilisation of WQI based on artificial intelligence techniques should be practiced [8] . Godavari is one of the largest River in India, and flows from Nashik district in Maharashtra to Narsapuram in Andhra Pradesh. But due to inadequate sewage treatment facilities at Nashik, Godavari has got severely polluted and has been included under Priority I River , due to BOD value more than 30 mg/l [9]. People take holy dip in Godavari, on the occasion of every religious hindu festival Therefore, there is an urgent need to develop a WQI, which is truly representative of the water quality status of the river. Fuzzy logic and artificial neural network approach are the two important artificial intelligence techniques, based on which WQI has been developed for identification of true water quality status of streams [10-13]. In the present study adaptive neuro fuzzy inference system approach has been adopted, since in incorporates the merits of both Fuzzy logic and ANN approach [14-15].

2. Materials and Methods

2.1 Study Area

Evaluation of the Godavari River's water quality along a 24 km stretch in Nashik City was the objective of the study. The river stretch is shown in **fig1**.

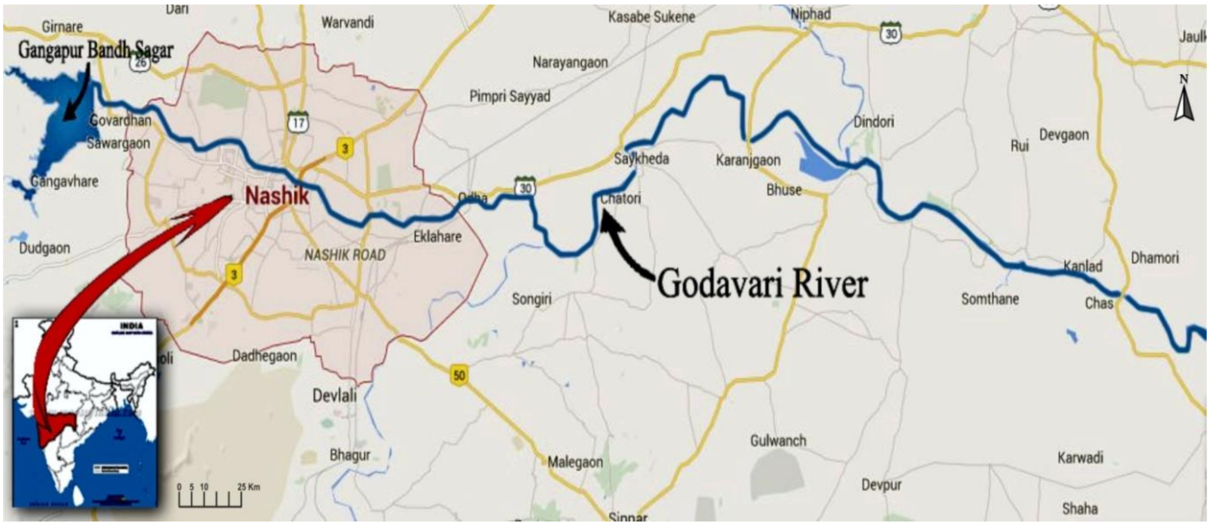

Figure 1. Map of Godavari River of Area of Study

Fourteen river water quality test stations were chosen for the investigation, ranging in location from the Gangapur dam to Dasak village. The sample stations are identified as S1 through S14 in Figure 2. At a depth of 30 cm below the surface of water, water samples were collected for analysis once per month for four years. All of the parameters were looked at utilising recognised methods [16] . Based on survey work along the river to pinpoint point and nonpoint sources of wastewater addition in the specified portion of the Godavari river, Figure 2 was produced. The survey revealed that the chosen portion of the Godavari river is being contaminated by point and nonpoint pollution sources. These are the main pollution sources, and figure 2 designates them as P1 through P12 [8,17].

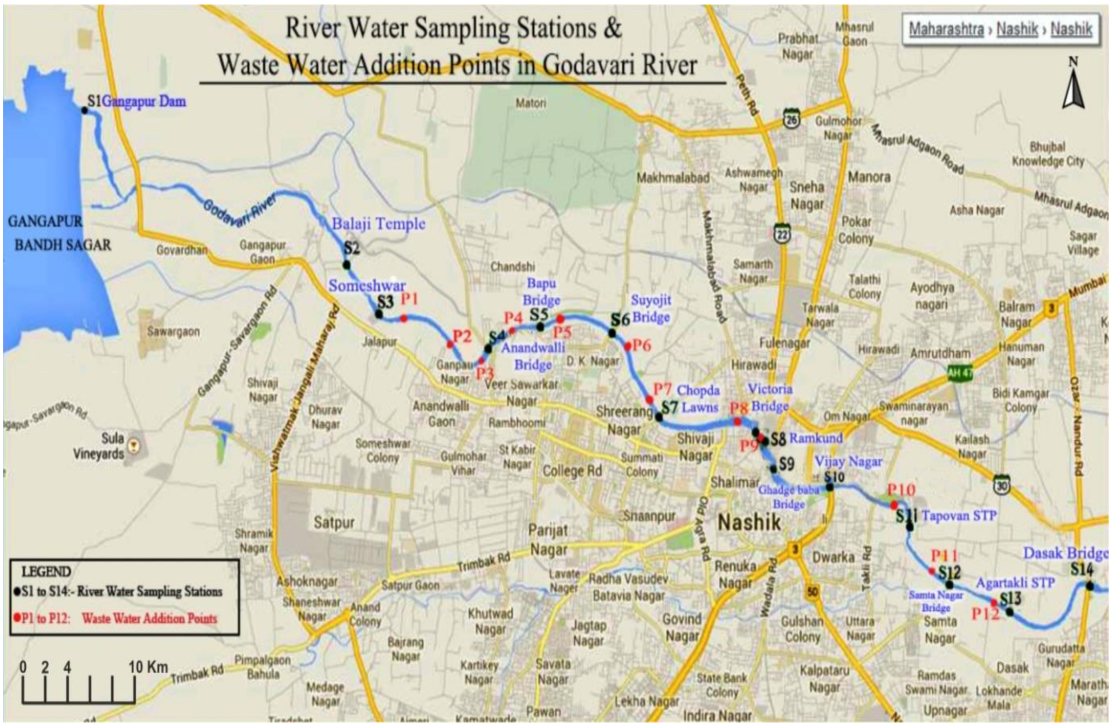

Figure 2. Map of WQ stations and sewage Infiltration Points in Godavari at Nashik

2.2 National Sanitation Foundation Water Quality Index(NSFWQI)

The study employed the National Sanitation Foundation Water Quality Index (NSFWQI), one of the most widely used indices in the entire globe, to ascertain the value of WQI at the chosen WQ stations [5,19,20]

$$\text{NSFWQI} = \sum W_i Q_i \tag{1}$$

In the current investigation, five parameters—pH, DO, BOD, total solids, and turbidity—were taken into account for the computation of the NSFWQI [8]

2.3 Architecture of ANFIS Model

The design of an ANFIS model with two input variables is depicted by Fig. 3. In the study first-order Sugeno FIS with the prevalent two rules was utilised [14]

In order to generate an output f from an input vector [x,y] supplied, fuzzy reasoning is demonstrated in Fig. 4. The corresponding equivalent ANFIS architecture is presented in Fig. 3. The output f is the weighted average of the outputs from each rule, and the firing strengths w_1 and w_2 are typically calculated as the product of the membership grades in the premise section. The ANFIS technique uses five layers to produce the final product: Fuzzification, Rule operation, Normalization, Consequence, and Aggregation layer[21].

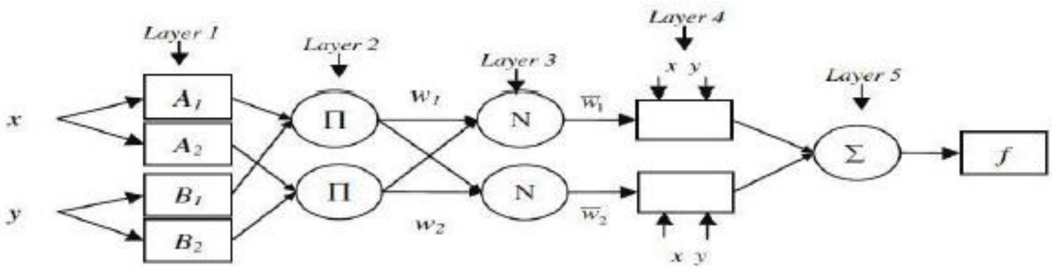

Figure 3. Process Flow Diagram of ANFIS Architecture [25]

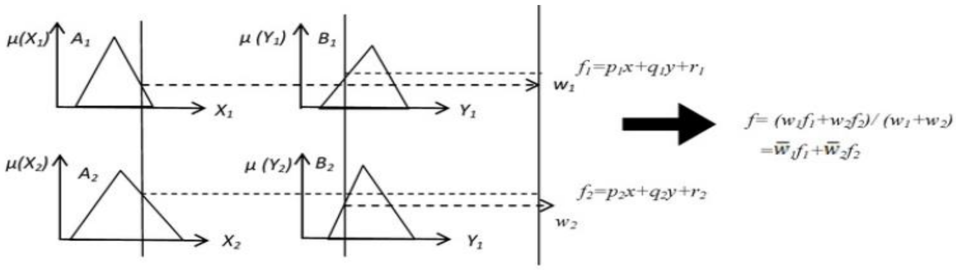

Figure 4. Reasoning Scheme of ANFIS[24]

2.4 Evolution of WQI using ANFIS Method

In the undertaken study WQI for Godavari has been developed using ANFIS approach abbreviated as ANFIS-WQI. As discussed that water quality monitoring was done at selected WQ stations along the Godavari River from 2013 to 2016. Therefore, in order to develop the ANFIS-WQI, training data for selected stations was used from 2013 to 2015, and testing data for 2016 was used to evaluate the ANFIS.. The ANFIS-WQI was developed using bell membership functions, gaussian, triangular, and trapezoidal functions [22]. The training and testing data was separately maintained in MATLAB Workspace in MS-Excel Files. In the beginning, the training data was loaded from the workspace using the 'Load Data' section of the ANFIS GUI as presented in **fig. 5.**

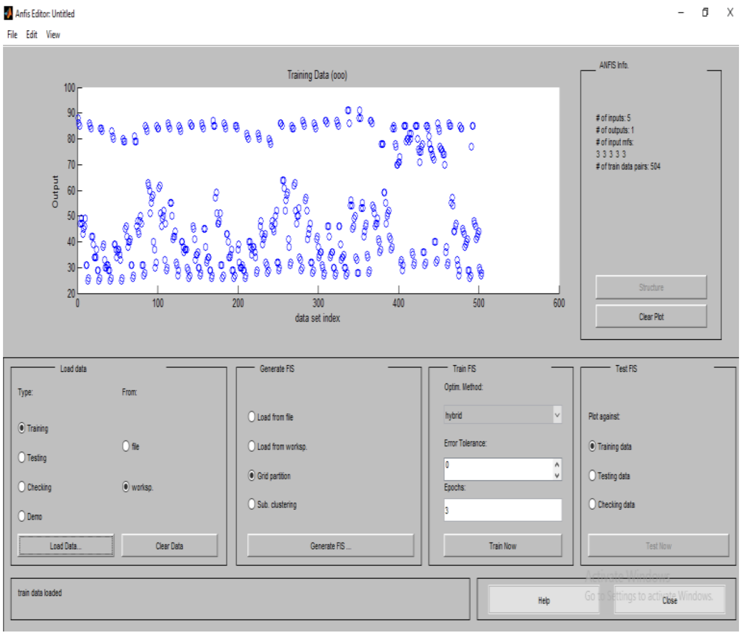

Figure 5. Loading of Training data in ANFIS toolbox

On the X-Axis data set index represents the number of input data rows, therefore on X-axis after loading the training data on the X-axis blue circles are visible upto 504 numbers. While on the Y-axis , the output represents the values of target NSFWQI corresponding to 504 data sets.

For Generation of FIS, Grid Partition system was used . Grid Partition system is also the most widely used system used for generation of FIS [23,24].To generate the FIS, Four number of membership functions(MFs) were selected .

Therefore (No.of M.F.)$^{\text{No,.of Parameters}}$= 4^5 = 1024 No. of rules were generated by the F.I.S.

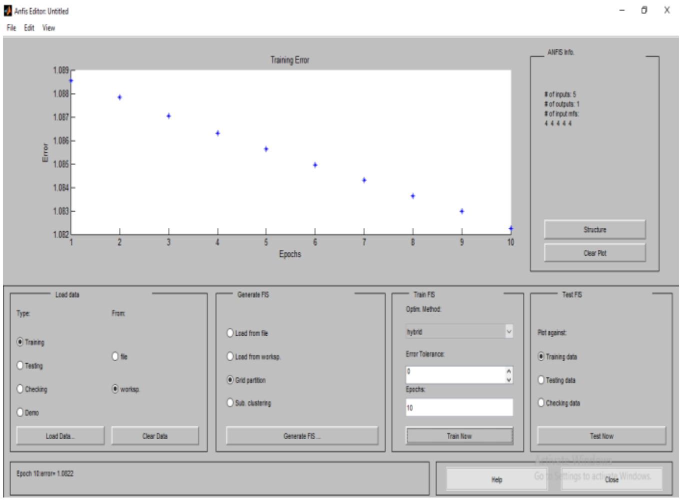

Figure 6. View of Training Error during Generation of FIS

To train the FIS ‘Hybrid’ optimization method was selected [25]. The Error tolerance was kept as ‘0’ and number of ‘Epochs’ were kept as ‘40’.On training the FIS with training data, training was done using checking data to identify the optimum number of ‘Epochs’. Training error during generation of FIS is shown in **fig.6**

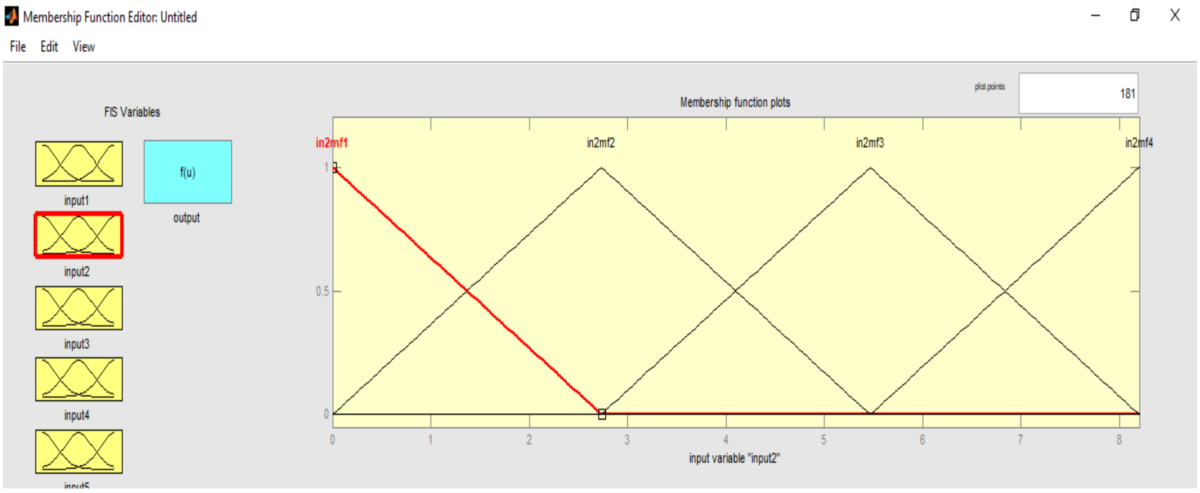

Figure 7. Triangular MF for DO for ANFIS-WQI development

On comparing the checking Error with training error ,optimum number of ‘Epochs’ were identified as ‘10’ for the present study. Therefore, then FIS was trained for ten number of ‘Epochs’. Triangular MF for DO parameter for development of ANFIS-WQI has been presented in fig. 7. Testing of FIS was done against the Checking data and satisfactory results were obtained, then results of ANFIS-WQI were obtained for the entire data.

Two criteria mean square error (MSE) and coefficient of correlation (C_C) have been used to determine the prediction accuracy of the ANFIS models produced in the current study [26,27]).where,

MSE $=\frac{1}{n}\sum_{i=1}^{n} [observed\ value - predicted\ value]^{2}$ and Coefficient of Correlation is

$$C_c = \frac{\sum_{i=1}^{n} (x_i - x')(y_i - y')}{\sqrt{\sum_{i=1}^{n} (x_i - x')^2 (y_i - y')^2}}$$

Station No.	Membership Function	Training		Testing	
		MSE	Cc	MSE	Cc
1	Bell	2.18	0.85	143.38	0.71
	Triangular	1.92	0.87	640.74	0.43
	Trapezoidal	3.15	0.77	10019.1	0.26
	Gaussian	**0.63**	**0.96**	**69.30**	**0.89**
2	Bell	1.04	0.93	125.55	0.59
	Triangular	0.97	0.93	295.80	0.47
	Trapezoidal	1.15	0.92	115.15	0.60
	Gaussian	**0.80**	**0.94**	**81.84**	**0.90**
3	Bell	1.39	0.87	1063.85	0.32
	Triangular	1.40	0.86	1839.70	0.12
	Trapezoidal	1.32	0.87	739.70	0.75
	Gaussian	**1.14**	**0.96**	**384.76**	**0.94**
4	Bell	0.23	0.99	4715.92	0.05
	Triangular	0.25	0.99	3004.13	0.19
	Trapezoidal	0.48	0.99	1682.87	0.22
	Gaussian	**0.10**	**0.99**	**1085.18**	**0.90**
5	Bell	0.66	0.99	350.49	0.73
	Triangular	0.58	0.99	41.97	0.91
	Trapezoidal	1.69	0.99	305.27	0.62
	Gaussian	0.30	0.99	**40.87**	**0.97**
6	Bell	0.56	0.99	238.79	0.76
	Triangular	**0.49**	**0.99**	**36.75**	**0.95**
	Trapezoidal	1.12	0.99	350.51	0.86
	Gaussian	0.98	0.99	63.15	0.90
7	Bell	0.91	0.99	727.07	0.48
	Triangular	**0.32**	**0.99**	**123.66**	**0.97**
	Trapezoidal	0.96	0.99	277.01	0.67
	Gaussian	0.62	0.99	156.03	0.64
8	Bell	0.65	0.99	36.74	0.89

	Triangular	**0.58**	**0.99**	**6.32**	**0.98**
	Trapezoidal	1.57	0.99	194.82	0.96
	Gaussian	1.24	0.99	32.68	0.90
9	Bell	0.48	0.99	2562.19	0.44
	Triangular	0.30	0.99	1240.81	0.56
	Trapezoidal	1.05	0.99	5785.08	0.03
	Gaussian	**0.22**	**0.99**	**199.35**	**0.97**
10	Bell	0.37	0.99	2099.22	0.67
	Triangular	0.25	0.99	2540.34	0.39
	Trapezoidal	1.18	0.99	3759.82	0.57
	Gaussian	**0.24**	**0.99**	**1211.46**	**0.96**
11	Bell	1.55	0.94	4313.25	0.05
	Triangular	1.21	0.95	2208.12	0.06
	Trapezoidal	2.62	0.91	1230.60	0.60
	Gaussian	**0.63**	**0.98**	**434.746**	**0.69**
12	Bell	3.54	0.89	1083.93	0.60
	Triangular	4.77	0.85	1820.53	0.57
	Trapezoidal	4.42	0.86	8232.40	0.04
	Gaussian	**1.17**	**0.97**	**994.57**	**0.71**
13	Bell	0.10	0.99	4567.24	0.23
	Triangular	0.09	0.99	2093.03	0.42
	Trapezoidal	0.13	0.99	3980.66	0.37
	Gaussian	0.03	0.99	**1348.90**	**0.51**
14	Bell	0.10	0.99	4476.13	0.31
	Triangular	0.19	0.98	3852.2	0.31
	Trapezoidal	0.46	0.96	5464.01	0.16
	Gaussian	**0.04**	**0.99**	**882.43**	**0.37**

Table 1. Stationwise Error Analysis of ANFIS Models

3. Results and Discussions

In the study, the ANFIS model for WQI has been developed using the parameters of study such as pH, DO, BOD, total Solids and turbidity. Trapezoidal, triangular, bell, and Gaussian membership functions have all been used in the development of ANFIS models. The ANFIS system creates its own if-then rules and provides the parameters for the membership function. It has the benefit of making it possible to extract fuzzy rules from numerical data. During the study, four membership functions were selected and five parameters were considered, so a total 1024 number of Rules were generated by the ANFIS model for the prediction of WQI. The NSFWQI and ANFIS WQI values have been taken as the observed and predicted values, respectively. The projected ANFIS WQIs have been validated using modelling performance criteria in the form of Mean square error (MSE) and coefficient of correlation (Cc). Error analysis for chosen stations' training and testing of ANFIS models is shown in table 1.

Table 2. Sampling Station wise Best Fitting Model for ANFIS Approach

Station No	Membership Function	Coefficient of Correlation (Cc)	Station No	Membership Function	Coefficient of Correlation (Cc)
1.	Gaussian	0.89	8	Triangular	0.98
2.	Gaussian	0.90	9	Gaussian	0.97
3	Gaussian	0.94	10	Gaussian	0.96
4	Gaussian	0.90	11	Gaussian	0.69
5	Gaussian	0.97	12	Gaussian	0.71
6	Triangular	0.95	13	Gaussian	0.51
7	Triangular	0.97	14	Gaussian	0.37

Table 3. Sampling Station wise Best Fitting Model for Fuzzy logic Approach [8]

Station No.	Membership Function	Defuzzification Method	C_c	Station No.	Membership Function	Defuzzification Method	C_c
1	Trapezoidal	MOM	0.87	8	Triangular	Bisector	0.97
2	Triangular	Bisector	0.86	9	Triangular	Bisector	0.97
3	Triangular	Centroid	0.93	10	Triangular	Bisector	0.97
4	Triangular	Centroid	0.87	11	Triangular	Bisector	0.68
5	Triangular	Centroid	0.97	12	Triangular	Bisector	0.69
6	Triangular	Bisector	0.94	13	Triangular	MOM	0.47
7	Triangular	Bisector	0.96	14	Triangular	Bisector	0.33

In table 2 sampling station wise best-Fitting model for ANFIS approach has been presented. It is evident from table 1 that the coefficient of correlation for most of the stations, during training is close to one, for all four membership functions. From table 2, it is evident that Gaussian and triangular MF gives better results for eleven and three number of sampling stations, respectively. Therefore the Gaussian MF models outperform other MF models of the ANFIS approach. The Authors have also developed WQI using fuzzy logic approach in their previous study [8] and the best fuzzy models have been shown in table 3. On comparing the values of Cc from table 2 and 3, it is ascertained that accuracy of ANFIS models is more than Fuzzy models.

4. Conclusions

It has been observed that widely used indice for water quality identification named as 'NSFWQI' cannot give realistic result of WQ status in the region of highly polluted rivers of Indian subcontinent. To overcome the limitations of conventional water quality indices, WQIs based on artificial intelligence approaches like Fuzzy logic and ANFIS have been explored by the authors for ascertaining the real status of water quality in the selected study area. In the present study ANFIS approach has demonstrated its ability to provide better results as compared to Fuzzy logic approach. It has been recognized that ANFIS approach involving Gaussian and triangular membership function gives better results for eleven and three number of water quality sampling stations respectively. Therefore, in this study, the Gaussian membership function model outperforms other membership function models of the ANFIS approach. The utilization of ANFIS approach involving Gaussian MF is therefore recommended for ascertaining the real status of the water quality of highly polluted Rivers of Indian subcontinent.

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