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Adaptive Neuro Fuzzy Inference System (ANFIS) for Prediction of Groundwater Quality Index in Matar Taluka and Nadiad Taluka

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Abstract: ***Adaptive Neuro Fuzzy Inference System (ANFIS) approach is employed in the present study to observe its applicability on Prediction and Forecasting of Groundwater Quality Index Prediction in Matar Taluka and Nadiad Taluka. As per classification based on Groundwater Quality Index, Groundwater Quality of Matar Taluka lies between good water to very poor water, while Groundwater Quality of Nadiad Taluka lies between Good Water to Poor Water. ANFIS system is one of the developing powerful tools to predict such heavy constrained problem with time series analysis by hybrid technique. First Part of the study is to find the GWQI of the Matar Taluka and Nadiad Taluka. Second part of the study is to study is to identify the Best ANFIS model which satisfying two Statistical measures (RMSE, and R^2) during training and validation processes for the duration of 1997 to 2006 of Matar Taluka and Nadiad Taluka.***

Keywords: Groundwater Quality Index, Matar Taluka, Nadiad Taluka, ANFIS.

1. Introduction

Water resources have been the most exploited natural system, since man strode the earth. As a result of increasing, civilization, urbanization, industrialization and other developmental activities, our natural water system is being polluted by different sources. The pollutants coming as a waste to the water bodies are likely to create nuisance by way of physical appearance, odour, taste, quality and render the water harmful for utility. This has resulted in the decrease in the quality of drinking water available. The ground water quality is normally characterized by different physic chemical characteristics. These parameters change widely due to the type of pollution, seasonal fluctuation, ground water extraction, etc. Monitoring of water quality levels is thus important to assess the levels of pollution and also to assess the potential risk to the environment.

Groundwater quality index is one of the most effective tools to communicate information on the quality of water to the concerned citizens and policy makers. It, thus, becomes an important parameter for the assessment and management of groundwater [2].

The ANFIS is a neuro-fuzzy system, which uses a feed-forward network to search for fuzzy decision rules that perform well on a given task. Using a given input/output data set, ANFIS creates a fuzzy inference system whose membership function parameters are adjusted using a back-propagation algorithm alone or combination of a back propagation algorithm with a least mean squares (LMS) method (hybrid learning). This allows the fuzzy systems to learn from the data being modeled. ANFIS provides a method for the fuzzy modeling procedure to learn information from the data set, followed by creation of the membership function parameters that best performs the given task. The ANFIS can simulate and analyze the mapping relation between the input and output data through a learning algorithm to optimize the parameters of a given Fuzzy Inference System (FIS) [1].

2. Study Area

Gujarat state is located in the western part of India. In this study, Matar Taluka and Nadiad Taluka of Kheda district area is selected. The Kheda district is located (between 72° 32’ to 73° 37’ East longitude and between 22°30’ to 23° 18’ North latitude) in Gujarat. The Study was conducted in a pre-monsoon and post-monsoon season of 10 years from 1997 to 2006. Total 768 samples from different localities of Matar Taluka and 1002 samples from different localities of Nadiad Taluka were collected.

3. Methodology

3.1 Groundwater Quality Index

Groundwater quality index is one of the most effective tools to monitor the surface as well as ground water pollution and can be used efficiently in the implementation of water quality upgrading programs. It is one of the aggregate indices that have been accepted as a rating that reflects the composite influence on the overall quality of numbers of precise water quality characteristics [2].

For computing GWQI three steps are followed. In the first step, each of the all parameters has been assigned a weight (wi) according to its relative importance in the overall quality of water for drinking purposes (Table-1). The maximum weight of 4 has been assigned to the parameter TDS, pH and Sulphate due to its major importance in water quality assessment. SAR and Magnesium which is given the minimum weight of 2 as magnesium by itself may not be harmful. In the second step, the relative weight (Wi) is computed from the following equation:

$$W_i = \frac{w_i}{\sum_{i=1}^{n} w_i} \quad (1)$$

Where,
Wi is the relative weight, wi is the weight of each parameter and n is the number of parameters. Calculated relative weight (Wi) values of each parameter are also given in Table-1.

Table 1: Relative Weight (Wi) values of each parameters

Parameters	*Indian Standards*	*Weight (wi)*	*Relative weight (Wi)*
pH	6.5-8.5	4	0.19048
Chloride	250-1000	3	0.14286
Sulphate	200-400	4	0.19048
Ca+2	75-200	2	0.09524
Mg+2	30-100	2	0.09524
SAR	10-255	2	0.09524
TDS	500-2000	4	0.19048
Total		21	1

In the third step, a quality rating scale (qi) for each parameter is assigned by dividing its concentration in each water sample by its respective standard according to the guidelines laid down in the BIS and the result multiplied by 100.

$$q_i = \left(\frac{C_i}{S_i}\right) * 100 \quad (2)$$

Where,
qi is the quality rating, Ci is the concentration of each chemical parameter in each water sample in mg/L, Si is the Indian drinking water standard for each chemical parameter in mg/L according to the guidelines of the BIS.

For computing the GWQI, the SI is first determined for each chemical parameter, which is then used to determine the GWQI as per the following equation,

$$SI = W_i * q_i \quad (3)$$

$$GWQI = \sum_{i=1}^{n} SI_i \quad (4)$$

Where,

SIi is the sub index of ith parameter, qi is the rating based on concentration of ith parameter, n is the number of parameters. The computed WQI values are classified into five types, "excellent water" to "water, unsuitable for drinking".

Table 2: Groundwater Quality classification based on GWQI Value

GWQI Value	*Water Quality*
<50	Excellent Water
50-100	Good Water
100-200	Poor Water
200-300	Very Poor Water
>300	Unsuitable for Drinking

3.2 Adaptive Neuro Fuzzy Inference System (ANFIS)

ANFIS is integration of neural networks and fuzzy logic and have the potential to capture the benefits of both these fields in a sing le framework. ANFIS utilizes linguistic information from the fuzzy logic as well learning capability of an ANN for automatic fuzzy if-then rule generation and parameter optimization. A conceptual ANFIS consists of five components: inputs and output database, a Fuzzy system generator, a Fuzzy Inference System (FIS), and an Adaptive Neural Network. Adaptive Neuro Fuzzy Inference System (ANFIS) is a fuzzy mapping algorithm that is based on Tagaki-Sugeno-Kang (TSK) fuzzy inference system. The Sugeno- type Fuzzy Inference System, which is the combination of a FIS and an Adaptive Neural Network, was used in this study for GWQI Prediction modelling. The optimization method used is hybrid learning algorithms [3], [4].

For a first-order Sugeno model, a common rule set with two fuzzy if-then rules is as follows:

Rule 1: If x_1 is A_1 and x_2 is B_1, then $f_1 = a_1 x_1 + b_1 x_2 + c_1$
Rule 2: If x_1 is A_2 and x_2 is B_2, then $f_2 = a_2 x_1 + b_2 x_2 + c_2$

Where,
x_1 and x_2 are the crisp inputs to the node and A_1, B_1, A_2, B_2 are fuzzy sets, a_i, bi and ci (i = 1, 2) are the coefficients of the first-order polynomial linear functions. It is possible to assign a different weight to each rule based on the structure of the system, where, weights w1 and w2 are assigned to rules 1 and 2 respectively. And f = weighted average The ANFIS consists of five layers, shown in Figure 1. The five layers of model are as follows:

Layer1: Each node output in this layer is fuzzified by membership grade of a fuzzy set corresponding to each input.

$$O_{1,i} = \mu_{Ai}(x_1) \qquad i = 1.2 \quad (5)$$

or

$$O_{1,i} = \mu_{Bi-2}(x_2) \qquad i = 3,4 \quad (6)$$

Where,
x_1 and x_2 are the inputs to node i (i = 1, 2 for x_1 and i = 3, 4 for x_2) and x_1 (or x_2) is the input to the ith node and A_i (or B_{i-2}) is a fuzzy label.

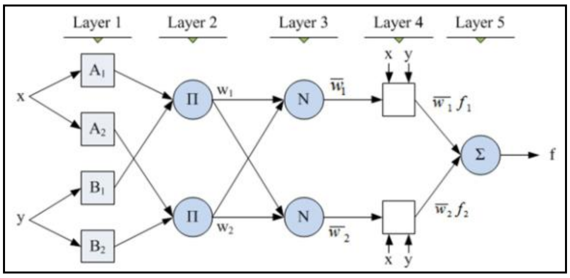

Figure 1: ANFIS Architecture

Layer 2: Each node output in this layer represents the firing strength of a rule, which performs fuzzy, AND operation. Each node in this layer, labeled P, is as Table node which multiplies incoming signals and sends the product out.

$$O_{2,i} = w_i = \mu_{A_i}(x) \cdot \mu_{B_i}(y) \;, \quad i = 1,2 \tag{7}$$

Layer 3: Each node output in this layer is the normalized value of layer 2, i.e., the normalized firing strengths.

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2} \;, \quad i=1,2 \tag{8}$$

Layer 4: Each node output in this layer is the normalized value of each fuzzy rule. The nodes in this layer are adaptive .Here ῷ is the output of layer 3, and {ai, bi, ci} are the parameter set. Parameters of this layer are referred to as consequence or output parameters.

$$O_{4,1} = \overline{w_i} f_i = \overline{w_i}(p_x + q_i y + r_i) \tag{9}$$

Layer 5: The node output in this layer is the overall output of the system, which is the summation of all coming signals.

$$O_{5,1} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{10}$$

In this way the input vector was fed through the network layer by layer. The two major phases for implementing the ANFIS for applications are the structure identification phase and the parameter identification phase. The structure identification phase involves finding a suitable number of fuzzy rules and fuzzy sets and a proper partition feature space. The parameter identification phase involves the adjustment of the premise and consequence parameters of the system.

3.2.1 Development of GWQI Prediction Model in ANFIS

In ANFIS, the datasets divided into training and validation data, and loaded in ANFIS editor as training and testing data keeping 7 groundwater Quality parameters (pH, calcium, magnesium, chloride, sulphate, total dissolved solids, and Sodium Absorption Ratio)as input and Groundwater Quality Index as output of model. The ANFIS editor GUI, MATLAB is shown in figure 2 with loaded data.

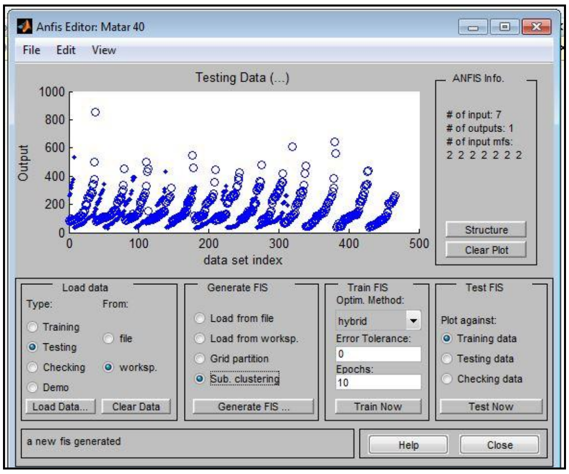

Figure 2: ANFIS Editor GUI

In above figure 2, the " o " represents the training data and " ♦ " represents the testing data.

The FIS generated for Subtractive Clustering function which produces accurate outputs values by using a large number of membership function. The FIS is then train for 10 epoch and 0 error tolerance in order to generate output as Groundwater Quality Index Value.

4. Results and Analysis

4.1 Groundwater Quality Index

After Analysis and Calculation of GWQI the following result is conducted for Matar Taluka and Nadiad Taluka.

Table 3: Water Quality Classification based on GWQI Value – Matar Taluka

GWQI Value	*Water Quality*	*Percentage of Water Samples*		
		Pre Monsoon	Post Monsoon	Overall
<50	Excellent Water	9.794	10	9.9
50-100	Good Water	24.485	27.692	26.09
100-200	Poor Water	31.186	34.615	32.9
200-300	Very Poor Water	23.969	20.513	22.24
>300	Unsuitable for Drinking	10.567	7.179	8.87

As shown in Table 3, the GWQI for 778 Ground water samples ranges from 29.05 to 640.75 almost 64.01 percent of the samples exceeded 100, the upper limit for drinking water. About 32.90 percent of water samples are poor in quality and 22.24 percent of water samples are of very poor quality and should not use directly for drinking purpose. As per the classification based on groundwater quality index 26.09 percent ground water samples shows good quality of water and 9.90 percent sample shows excellent quality of ground water.

Table 4: Water Quality Classification based on GWQI Value – Nadiad Taluka

GWQI Value	*Water Quality*	*Percentage of Water Samples* Pre Monsoon	Post Monsoon	Overall
<50	Excellent Water	12.967	18.458	15.67
50-100	Good Water	52.65	47.67	50.2
100-200	Poor Water	26.7	27.6	27.15
200-300	Very Poor Water	5.305	4.665	4.99
>300	Unsuitable for Drinking	2.358	1.623	2

As shown in Table 4, the GWQI for 1002 Ground water samples ranges from 15.70 to 548.02, almost 34.13 percent of the samples exceeded 100, the upper limit for drinking water. About 27.15 percent of water samples are poor in quality and 4.99 percent of water samples are of very poor quality and should not use directly for drinking purpose. As per the classification based on groundwater quality index 50.20 percent ground water samples shows good quality of water and 15.67 percent sample shows excellent quality of ground water.

4.2 Adaptive Neuro Fuzzy Inference System (ANFIS)

Three models are developed to predict Groundwater Quality of Matar Taluka & Nadiad Taluka using ANFIS.

ANFIS Model-1: 60% - 40%
ANFIS Model-2: 70% - 30%
ANFIS Model-3: 80% - 20%

After developing the best Groundwater quality index prediction Model using ANFIS for each station with the training & validation datasets with 3 combination, comparison is carried out to conclude the best ANFIS model for Matar Taluka & Nadiad Taluka among all models.

Table 5: Best ANFIS Model Developed for Matar Taluka & Nadiad Taluka

Taluka	*Phase*	*ANFIS Model-1* *RMSE*	*r*
Matar	Training	0.253	1
	Validation	21.225	0.973
Nadiad	Training	0.192	1
	Validation	0.151	0.999

Taluka	*Phase*	*ANFIS Model-2* *RMSE*	*r*
Matar	Training	0.248	1
	Validation	0.358	1
Nadiad	Training	0.184	1
	Validation	0.126	0.999

Taluka	*Phase*	*ANFIS Model-3* *RMSE*	*r*
Matar	Training	0.244	1
	Validation	0.412	1
Nadiad	Training	0.180	1
	Validation	0.112	0.999

From the above Table 5 highlighted field shows that the ANFIS Model-2 having RMSE and r value of 0.248 and 1 respectively during training and RMSE and r value of 0.358 and 1 during Validation. Hence ANFIS Model-2 is the best model for Matar Taluka for Groundwater Quality Index Prediction. While ANFIS models having RMSE and r value of 0.180 and 1 respectively during training and RMSE and r value of 0.112 and 0.999 during Validation, Hence ANFIS Model-3 provides best result for Nadiad Taluka for Groundwater Quality Index Prediction.

Charts Given below shows correlation between Predicted GWQI vs. Observed GWQI of ANFIS Model-2 during training and validation for Matar Taluka and ANFIS Model-2 during training and validation for Nadiad Taluka. It's observed that during training and validation, Predicted GWQI and Observed GWQI values are highly correlated in Matar Taluka and Nadiad Taluka.

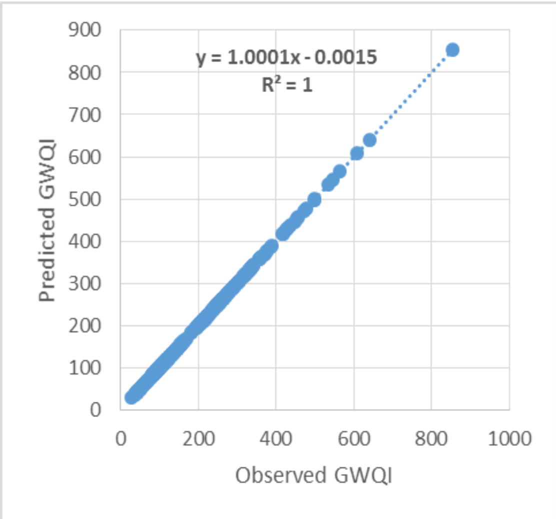

Figure 3: Correlation between Predicted GWQI vs. Observed GWQI of ANFIS Model-2 for Matar Taluka during Training

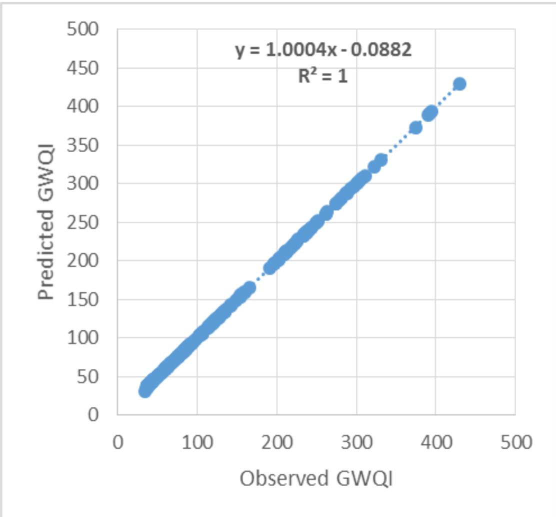

Figure 4: Correlation between Predicted GWQI vs. Observed GWQI of ANFIS Model-2 for Matar Taluka during Validation

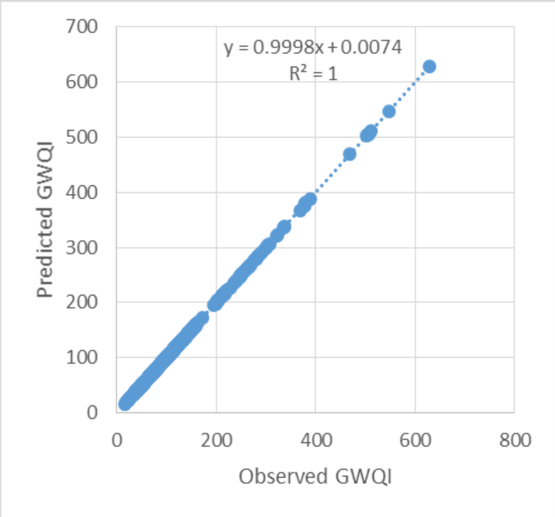

Figure 5: Correlation between Predicted GWQI vs. Observed GWQI of ANFIS Model-3 for Nadiad Taluka during Training

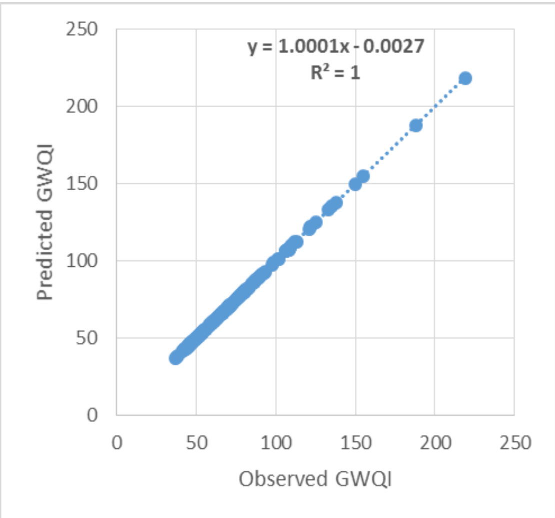

Figure 6: Correlation between Predicted GWQI vs. Observed GWQI of ANFIS Model-3 for Nadiad Taluka during Validation

5. Conclusions and Recommendations

5.1 Conclusions

For Matar Taluka and Nadiad Taluka Groundwater Quality is improved in pre-monsoon season compared to post-monsoon season and The ANFIS Model-2 having RMSE and r value of 0.248 and 1 respectively during training and RMSE and r value of 0.358 and 1 during Validation. Hence ANFIS Model-2 is the best model for Matar Taluka for Groundwater Quality Index Prediction. While ANFIS models having RMSE and r value of 0.180 and 1 respectively during training and RMSE and r value of 0.112 and 0.999 during Validation, Hence ANFIS Model-3 provides best result for Nadiad Taluka for Groundwater Quality Index Prediction.

5.2 Recommendations

The ANFIS Tool can be used for other groundwater quality parameters prediction and results can be compared.

This study is done for the Matar and Nadiad Taluka and can also do this study for the Other Taluka or study areas and the result can be compared.

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Author Profile

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