

# Prediction of the Water Quality Index Using ANFIS Modelling

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## Abstract

Water covered maximum area of earth surface; supply of water mainly depends on surface water. Ponds are act as reservoirs to save water in rainy season. The research study is designed to evaluate the superiority of pond water at the ancient Kamakshi Amman temple in Kanchipuram. Civilization contaminating the pond water, which slowly spreads into the metropolitan area by seeping through the medium of soil. This makes the present water was unhealthy for individual usage. Therefore, it is crucial to assess the water quality of ponds in built-up areas nearer to temples. The current study suggests an effective method for forecasting water quality called the ANFIS (adaptive network fuzzy inference system). The water feature parameters pH, dissolved oxygen (DO), total Dissolved solids (TDS), chloride (Cl), sulphate (SO<sub>4</sub>), iron (Fe), and total coliform count (TCC) at Kamakshi Amman temple pond water from the years 2017-2020 were collected for the analysis work. The elements used to measure the water class are frequently linked, and this creates an evaluation challenge. The uncorrelated measured element values are under a fuzzy process to obtain an improbability through data gathering and testing. The ANFIS modelling produces competent rules and regulations as well as the best allocation of membership action. The conclusions gathered through the ANFIS method were related with investigational standards. It is originate that the predicted standard values of the results are in high-quality concurrence with the investigational value.

**Keywords:** Temple, WQI, Membership Function, ANFIS, Water, Quality.

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## INTRODUCTION

The ecosystem and human health are directly impacted by the value of water. Water is utilised for a variety of things, including drinking, farming, and industrial uses. The worth of water in the ponds has moreover deteriorated radically above the years because of farming overflow transport poisonous molecules, discarding of rubbish and deceased animals, and human being waste next to the channel banks, etc. (Solanki et al. 2007, Shankar & Balasubramanya 2008, Rincy & Tessy 2010, Guru Prasad 2003). Water quality in reservoirs has both theoretical and practical implications (Silva et al 2018). When determining the level of water purity, the water quality parameters physical, element, and organic aspects of the water used to determine its superiority. To address data management concerns and evaluate the success and failure of management techniques for improving water class, the WQI is used globally (Muhammad et al 2015). Calculating a wide range of characteristics is typically used to evaluate the quality of water. As a result, a sizable data set is produced, which must be presented to policy decider, restricted planners, and the public in a comprehensible manner. In light of this, Water

Quality Indexes have been urbanized to transform the massive numbers set into a distinct index (Gazzaz et al 2012). Water Quality Index is considered to be a scaled way of concluding the variety of water quality measured parameters into a straightforward index. As a single statistical value, the index used to interpret water quality (Lohani B.N, Todino G. 1984). Water class parameter values are characterised into five different verities depending on their allowable limits and usage – such as Class A, B, C, D, and Class E based on BIS 1982 standards. The parameters in water class have imbalance which reduces the quality and also causes the class level variations. This critically affects human being life. Therefore, continuous supervision of water worth is important for consumption of water. (Prati 1971, Schaeffer & Konnanur 1977). When continuous monitoring and readings are taken at sample points, the size of the figures grows. Therefore, some forecast work need to be processed in this monitoring so that the time for physical calculation has been saved (Prati 1971, Schaeffer & Konnanur 1977). To compute and forecast the quality of water different types of methods have been used with the aim of decrease the time usage by finding the details from a greater data set and categorize the

excellence using machine learning process (Prati 1971, Schaeffer & Konnanur 1977), ANN - Artificial Neural Network is an AI-based method that has been shown to be not only efficient in managing great quantity of dataset, multifaceted nonlinear initial value and output connection, but also elastic and dominant calculation tool (Singh, KP. et al 2009, Nourani, V. et al 2011, Abba, SI and Elkiran, G. 2017). An artificial neural network model was applied for the forecast of groundwater at Arang of Raipur district, India. The result concluded that deep learning algorithm was found to be superior with higher categorization accuracy (Singha et al. 2021). (Bisht et al. (2019) applied artificial intelligence to guess the water quality in the Ganga River in India using SVM tool, with a prediction precision of 96.66%. Other researchers including (Ahmed et al. 2019, Aldhyani et al. 2020) used Adaptive Neuro-Fuzzy Inference System (ANFIS), RBF (Radial Basis Function), and MLPNN (Multilayer Perception) to predict the water class of different types of River Basins in India. The results of detailed previous studies show that more studies are not available to categorize the Kanchipuram temple pond water quality index by creating an immediate and economical procedure as a substitute to the time-consuming examination approach (Ross 1977). Thus, these information have enthused the investigators to carry out the current work to grade the temple pond water by using a supervised ML technical method.

## LITERATURE REVIEW

The status of the water quality index has been analysed with AI techniques, and this technique has been used by several researchers (Horton RK 1965). Mosleh Hmoud Al-Adhaileh and Fawaz Waselallah Alsaade presented an adaptive neuro-fuzzy inference system algorithm be created to forecast quality index of water. The classification of water's worth is calculated using of Feed-forward neural network (FFNN) and K-nearest neighbours. In the analysis eight significant parameters was used as a data set, seven of which were only considered to show momentous values. The planned method was formed based on these statistical measured parameters. The Predicted results established that the ANFIS model was better-quality for the forecast of WQI values. The highest accuracy of 95% on water quality categorization was achieved by FFNN algorithm. The result exits ANFIS model highly accurate in predicting WQI, and the FFNN model higher strength in classifying the WQI. The ANFIS model has precision through the testing phase, with a regression coefficient of 96.2% for predict the WQI, and the FFNN models obtain the maximum accuracy 100% for WQC. This advanced artificial intelligence method, can support in water purification and management. (Ozturk, B.Y., et al 2014) said that Fuzzy logic method become widely applied in water quality determination of aquatic ecosystems in recent years. It was provided the homogeneity between measured parameters and it was seen that 66% is quality and 34% is very good quality when we calculated annual quality index,

which we obtain according to output value in Apa Dam Lake. This index value states simply and comprehensibly that the water quality of Apa Dam Lake is good quality (Ozturk et al., 2014). (Icaga Y. 2007) concluded that the result about physical and chemical some water quality parameters were evaluated with fuzzy logic in Eber Lake and it can be quite convenient in the evaluation of water pollution by means of fuzzy inference systems related to quality classification and in classification. Paul B. Bokingkito, Lomesindo T. Caparida 2022 explained the data collection procedure, definite water quality elements, and water quality evaluation. In common, the water parameters supervising in the real ecosystem on the pond were capable to handling the data collected. The application of triangular and trapezoidal membership functions in fuzzy logic for water class assessment of the input and output variables shows better accuracy. The Fuzzy logic method was capable to modelling human proficiency successfully. Fuzzy logic produces class membership degrees to water quality parameters, the degree of agreement between the fuzzy logic system and human specialist is not always hundred percent. For example, a person expert might rate a sample water class in 'Excellent' assessment manner, while fuzzy logic takes it as 85% in the 'Excellent' and the remaining 15% in 'Very Good' judgment. It shows 85% agreement among the fuzzy logic assessment and human specialist. Through fuzzy logic the results of water quality assessment have 72.033% of agreement with human experts with have good flexibility of expert expectation and standards of water quality. Muhammad Sani Gaya et al concluded that ANFIS as an amalgam algorithm was engaged with an appropriate inference system, said Takgi-Sugeno-Kang, which works depended on numerous regulations and partisanship function. In this lesson, the ANFIS analysis contains a five key variables and single productivity variable in order to assess the WQI at Palla station. The ANFIS was educated with five dissimilar systems in each sample point, the results shows triangular and gaussian membership system were the most excellent model. The predictions of the clever models are tremendously nearer to the experimental WQI. The intelligent models were extremely precise in calculating the WQI by obtain the DC nearer to unity. The option of method was depends on the capacity and class of the available value. A fuzzy algorithm is heuristic structure explanation that applies if-then regulations to ascertain numerical interaction between the measured input and analysed output parameters (Sharma, D., and Kansal, A. 2011). But, the major difficulty by means of fuzzy logic method is that there is no methodical formula to classify the membership task parameters, which must be encoded by practised awareness about the modelled system. An artificial neural network (ANN) has the capability to study starting an entrance and exit pair and adjust to it in an interaction approach. In the analysis, an amalgam method adaptive neuro-fuzzy inference system (ANFIS) is achieving reputation in commerce with indefinable and tentative areas such as water class categorizations. It is a system that forms

the fuzzy logic assumption structure into the skeleton of neuro adaptive networks. Hence, we have the profit of both ANN and fuzzy algorithm in a solitary structure. The most important reward of the ANFIS model above fuzzy logic systems is that it separates fundamental trouble of explaining the partisanship task elements and getting a amount of fuzzy if-then regulations. The educational ability of ANN is utilized for habitual fuzzy logic if then rule invention and factor creation in ANFIS (W.C. et al 2015). Jang explained the theory of ANFIS and how it has been effectively applied in a variety of water class situations. Yan et al. modified the ANFIS analysis model for differentiating the water superiority position of river and connected its behaviour with ANN. In this learning, WQI of legendary temple pond water was placed in an urban area and analysed by using ANFIS, the parameters are pH, Dissolved Oxygen, Total Dissolved Solids, Chloride, Sulphate, Iron, Total Coliform Count are considered in the prediction of water capability. Therefore, this current study focuses on calculating the WQI by artificial intelligent approaches, conventional method and comparing the results of Kanchipuram temple pond water.

## MATERIALS AND METHODS

### Study Area

The temple pond, which is our current study location, is located in Kanchipuram, Tamil nadu, India. It was the principal of Pallava establishment and is healthy known for its temples, It is a conservative and popular visitor place, with a population larger than 1,70,000. The location point is Fig.1.Kamakshi Amman temple is a nearly 1000 years old temple. Kamakshi Amman has the centre point of amman shrine for all the Shiva lingam temples, so none of the Shiva temples inside Kanchipuram will contain amman shrines. The city is most famous for Kamakshi amman temple, the holy tank in the temple is called pancha ganga. In the past, the temple pond was built for drinking, bathing, pooja purpose as well as to store water during rainy season and improve ground water table in nearby areas. The sample location (Temple pond) has an elevated area of 83.2 m (273 ft) above than the sea level. The measured latitude and longitude values from the GPS device are 12° 50' 27.21"N and 79° 42' 11.00"E. However, the pond water is polluted and the WQI has decreased in current years. For the benefit of future generations, temple pond renovation and historical temple preservation are crucial.



Fig.1. Study area showing Kamakshi amman temple pond

## METHODOLOGY

**Data Collection:** The training phase data was collected from the years 2017 to 2020. The data's was collected year wise. The water quality parameters were pH, dissolved oxygen DO (mg/l), Total Dissolved solids TDS (mg/l), Chloride Cl (mg/l), Sulphate SO<sub>4</sub> (mg/l), Iron Fe (mg/l), and Total coliform count (MPN). Table 1 shows the description of water quality parameter values. A sample of average, and range data for the years 2017 – 2020 is shown in Table 2. BIS 1982 Tolerance limit as shown in Table.2. Due to the limited dataset for the training phase, we have created a synthetic dataset as per the allowable limits for Class C (Jayalakhmidevi & Belagadi 2005, Meenakumari & Hosmati 2003).

**Data Pre-processing:** The collected raw data is constantly noisy and incoherent. Data pre-processing process uses data to enhance the superiority of the model. On occasions when this data has a variety of missing values, the mean imputation procedure is applied to complete these absent values.

Table 1: Feature description of dataset

Attributes Name	Description
pH	Presence of acidity and basic nature of water
DO	Amount of oxygen present in water
TDS	Amount of minerals, salts, metals, cations or anions dissolved in water
Cl	Chloride is the salts resulting from the combination of the gas chlorine with a metal.
SO <sub>4</sub>	Sulphate is one of the major dissolved components of rain.
Fe	Iron is not hazardous to health, it is a secondary contaminant. Essential for good health, iron helps transport oxygen in the blood.
TCC	TCC represents microbial growth in drinking water distribution

Table 2: BIS Class C Tolerance and measured parameter values range and average value in year wise.

Sl. No	Water Quality Parameter	Range (2017-2020)	Average value	BIS surface water standards – Class - C
1.	pH	7.3 – 8.9	8.2	6.5 - 8.5
2.	DO	6.2-6.7	6.5 mg/l	4 and above
3.	TDS	382 – 744	505 mg/l	1500 or less
4.	Cl	84- 136	110 mg/l	600 or less
5.	SO <sub>4</sub>	53 – 74	61 mg/l	400 or less
6.	Fe	0.09 - 0.84	0.585mg/l	50 or less
7.	TCC	400 – 1600	738 MPN	5000 or less

### Calculation of WQI

Water quality is measured in the form of a digit by the Water Quality Index (WQI). This number will give the superiority of water (Puri et al 2015). It also represents the relative weight of every element. For the current study, seven important measured parameters were preferred for analysis, The WQI has been determined based on the permissible limits of surface water Class – C suggested by the Bureau of Indian Standards (BIS). The weighted arithmetic indicator method has been applied for the computation of the water quality index. The quality rating or sub index ( $q_n$ ) was determined using the following equation.

The superiority ranking  $q_n$  for the  $n$  th measured water quality parameters is got from the equation:

$$q_n = 100 (V_n/S_n) \quad (1)$$

$q_n$  – Quality ranking for  $n^{\text{th}}$  water class parameter.

$V_n$  – Estimated rate of the  $n^{\text{th}}$  measured parameter at a certain location point.

$S_n$  – The standard acceptable charge of the  $n^{\text{th}}$  parameter.

$V_i$  – Ideal value of  $n^{\text{th}}$  parameter in clear water. (0 for all other measured parameters expect the parameter pH and dissolved oxygen (7 and 14.6 mg/l).

This formula finalized that  $q_n = 0$  when a contaminant is nil in water while  $q_n = 100$  if the rate of this measured parameter is equivalent to its allowable worth for surface water. Therefore, the greater the worth of  $q_n$ , the most contaminated is the water. However, value ratings for pH and DO have special attention. The standard range of pH for the surface water is 6.5 to 8.5. The calculation value of DO is somewhat complex because the quality of water is improved if it contains more DO value. Thus, the quality rating for pH and DO determined by the subsequent equation

$$q_n = 100[V_n - V_i] / [S_n - V_i] \quad (2)$$

The unit weight calculation was done by a value in reverse relative to the suggested permissible limit value  $S_n$  of the

consequent parameter.

$$W_n = K / S_n$$

$W_n$  = unit weight for the  $n^{\text{th}}$  parameters

$K$  = Constant for proportionality

The unit weight of  $n^{\text{th}}$  parameters  $W_n$  values shown in Table 3.

Which is calculated from the circumstance and  $K = 1$  for identification of ease

The cumulative water quality index was determined by aggregate the quality ranking with the unit power linearly. (Brown et al., 1972)

$$WQI = \sum q_n W_n / \sum W_n \quad (3)$$

The descriptive flow diagram of water quality index calculation is shown in Fig.2.

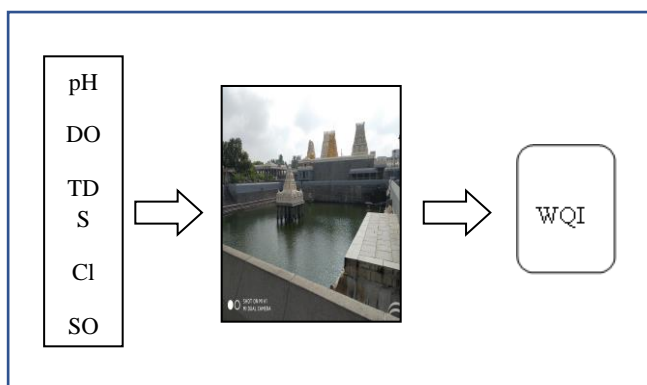


Fig. 2: Descriptive flow diagram for the water quality index

The Water Quality Index and importance of water quality (Chatterji and Raziuddin 2002) is five different types based on WQI values. That can be measured as excellent quality, good quality, poor nature, very poor nature, and unfit for drinking if WQI lie in the series of 0 to 25, 26 to 50, 51 to 75, 76 to 100, 100 and above, respectively.

Table 3: Unit weight of nth parameters  $W_n$  values

CLASS C STANDARDS			
	$S_n$	$(1/S_n)$	$W_n$
<b>pH</b>	8.5	0.117647	0.2996
DO	4	0.25	0.636651
TDS	1500	0.000667	0.001698
CL	600	0.001667	0.004244
So <sub>4</sub>	400	0.0025	0.006367
Fe	50	0.02	0.050932
TCC	5000	0.0002	0.000509
		0.39268	1

### ANFIS Prediction Model

The artificial neural network (ANN) and the fuzzy inference system are connected by the adaptive neuro-fuzzy inference system (Tabari et al. 2012) (ANFIS) (FIS). Fuzzy logic and neural networks are harmonizing technologies. Although a neural network may learn from data and feedback, it has proven challenging to comprehend the knowledge or patterns it has amassed. However, fuzzy logic models are simple to understand since they make utilize of IF-THEN rules, which are linguistic concepts. The fuzzy decision rules can be learned using a neural network, which can be used to create a hybrid intelligent system. The benefit of this method, called ANFIS, is that it may be applied to rationally predict desired results by modelling nonlinear processes. Takagi and Sugeno (1985) initially explored this model scientifically, and they found many realistic applications in control, forecast and inference. The purpose of the current work is to forecast WQI, which can be determined by adopting a novel structural design of ANFIS (Sanikhani H et al 2012). ANFIS is one of the models that explains the adaptive neural network and fuzzy logic qualitative approaching and rectify their respective demerits.

ANFIS a high-quality forecaster and estimator and has an ability of rough calculation equivalent to neural networks; thus, the outcomes can be effortlessly formed with ANFIS (Maher et al 2014). The ANFIS model algorithm has five different layers, and every layer is combined with many numbers of nodes. Each input node is obtained by the preceding layer. The constructed ANFIS model is represented in Fig. 3, which demonstrate that the network contains m inputs ( $A_1, \dots, A_m$ ), everyone contains of n membership process. Furthermore, a level with R fuzzy set of laws as an exist layer is additional for the structure of the current model. The entire amount of layers (N) can be determined for the first level as the result of m, the amount of entries, and n, the amount of membership functions, i.e., ( $N=m \cdot n$ ). The quantity of nodes in the next layer is depends on the amount of fuzzy rules (R). An explanation of the all layer is given (Babajanzade Roshan et al. 2013).

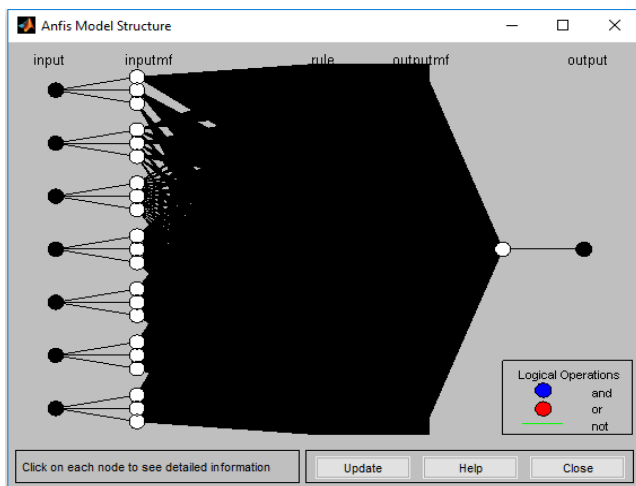


Fig. 3 Developed ANFIS model for Water Quality Index

Layer 1: In first level, crisp entry are changed into the linguistic form using membership process. The following equation is the output layer and expressed as

$$O_{ij}^1 = (X_i), i = 1, \dots, m; j = 1, \dots, n \quad (4)$$

where  $\mu_{ij}$  represents the  $j^{\text{th}}$  membership function for the entry value  $X_i$ . The triangular, trapezoidal and bell member functions are available in fuzzy system.

Layer 2: In this second level, every rigid node can be determined by multiply the linguistic inputs, which were determined in the preceding layer:

$$O_k^2 = W_k = \mu_{1e_1}(X_1) \mu_{2e_2}(X_2) \dots \mu_{me_m}(X_m), \quad (5)$$

$$k = 1, \dots, R; e_1, e_2, \dots, e_m = 1, \dots, n$$

Layer 3: In this corresponding layer, the outcome are centralized by the weighting factor for every node:

$$O_k^3 = \bar{W}_k = \frac{W_k}{W_1 + W_2 + \dots + W_R} \quad (6)$$

Layer 4: In this fourth layer, Takagi-Sugeno fuzzy model – then rules are used to the weighted output of every node:

$$O_k^4 = \bar{W}_k f_k \quad (7)$$

Hence  $f_k$  indicates the output of the  $k^{\text{th}}$  TSK-model fuzzy rules given below:

If ( $X_1$  is  $A_{1n_1}$ ) and ( $X_2$  is  $A_{2n_2}$ ) and  $\dots$  and ( $X_m$  is  $A_{mn_m}$ ), then

$$f_k = \sum_{i=1}^m p_{ie_i} X_i + r_k \quad (8)$$

where  $p_{ie_i}$  and  $r_k$  are called the consequent parameters and  $e_i$ ,

Layer 5: This layer indicates the output structure by the ANFIS architecture:

$$O^5 = Y = \sum_{k=1}^n \bar{W}_k f_k \quad (9)$$

The root mean square error RMSE, E value calculated by the following equations,

$$E = \sqrt{\frac{1}{M} \sum_{z=1}^M (S_z - y_z)^2} \quad (10)$$

$$E' = \sqrt{\frac{1}{M} \sum_{z=1}^M (S_z - y_z)} \quad (11)$$

$$R^2 = 1 - \frac{\sum_{i=1}^N (S_z - y_z)^2}{\sum_{i=1}^N (S_z - \bar{y}_z)^2} \quad (12)$$

$M$  indicates total number of training samples;

$S_z$  indicates experimental output of work;

$y_z$  indicates predicted output of work;

$y_z$  of ANFIS; and  $\bar{y}$  is the averaged output of the network of the current work.

### ANFIS Modelling in Water Quality Index Prediction

The ANFIS system takes inputs from the data gathered on water quality metrics. In the current work, the key parameters of the ANFIS model under deliberation are pH, Dissolved oxygen, TDS, chlorides, Sulphates, Iron, and Total Coliform Count, and the calculated output is the WQI. The connection among WQI and measured given parameters using ANFIS to create the association was in the structure of

$WQI = f(\text{pH}, \text{DO}, \text{TDS}, \text{chlorides}, \text{sulphates}, \text{Fe}, \text{TCC})$  (Sharad Tiwari et al. 2018). The WQI is calculated based on the steps explained in section Calculation of WQI. It is the output for each of the data. Training set and testing set data sets are created from the complete experimental data set. We use a total of 30 data sets. Twenty of the thirty data points are regarded as training data, and ten as testing data. An ANFIS model with five-layers is built during training in the manner described. During training, the second layer's node count is gradually increased, starting with two. The observation was made that as the nodes were increased to seven, the error was converging (decreasing). As a result, the second layer's node count is set at seven, and more analysis is done. One input, three ways of hiding, and one output layer are the names of the five layers.

The network was performed on a Pentium IV desktop computer with MATLAB platform. During the generation of the fuzzy inference system, a triangle membership function is employed for given inputs and a study type membership function is utilized for output (FIS) (Baran et al. 2015). The experimental data sets summarized is adopted to practice the ANFIS structure and the output functions were predicted. The triangular membership function was used in each output with five different levels called very low level (VL), low (L), medium (M), high (H), and very high (VH) is shaped and the consequential linguistic explanations are selected for every variable and denoted by selected fuzzy sets. The starting membership function for the input factor "pH" is shown in Fig. 4. The capability of the ANFIS model is related to that of neural network. An ANN model was created via the identical input parameters. Through trial and error approach, the most favourable neural network structural design (3-3-3-3-3-3) was determined and trained with generalized patterns.

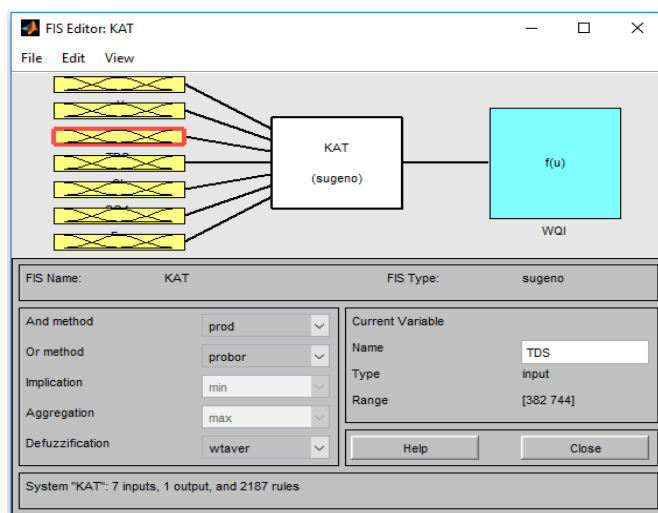


Fig.4. Initial membership function design for the input parameter water quality index

The process goes on progressively after ten iterations due to quicker hybrid learning regulation; it was concluded that the model value are coordinated. Then, 30 data points are utilized for testing to validate the correctness of the planned model.

### RESULTS AND DISCUSSION

In the current work ANFIS structure was applied, in this Sugeno fuzzy rules are utilized, the output represents the linear grouping of inputs. Results of various studies show that the triangle member function has slightest training and testing RMSE values. So, the triangle member function and 2187 rules were created to get the best architecture for the ANFIS model algorithm. Rules for WQI calculation in ANFIS modelling is shown in Fig.5. The training was done by using training data and verifying was done by checking data in ANFIS. The testing records were used to create the replica performance in ANFIS. The initial 70% of the data records were utilized as the training data; the following second data set, 15% was utilized as the examination data, the third, 15% of the data records were used as the testing data. The goal values showed the water quality index calculation. The output for trained, tested, and checked network WQI is shown in Figs. 6,7, and 8, respectively.

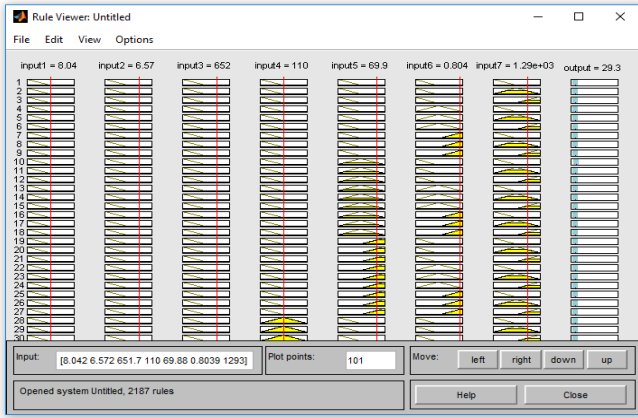


Fig.5. Rules for WQI calculation in ANFIS modelling

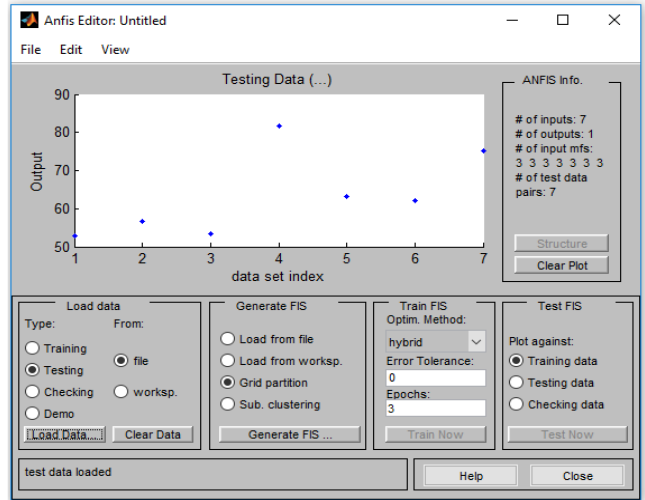


Fig.8. Checking action of ANFIS depends on triangular membership process for WQI

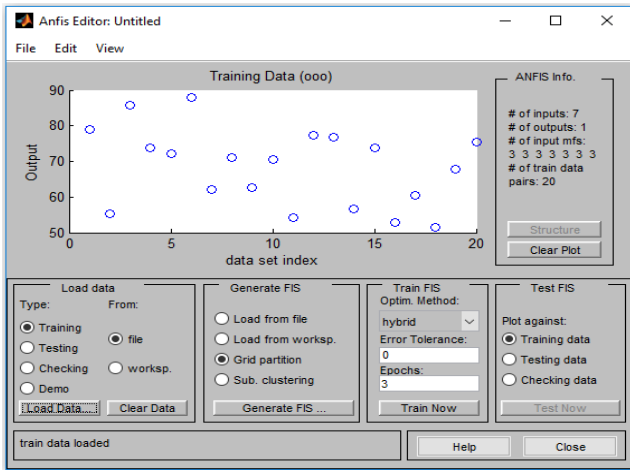


Fig.6. Training action of ANFIS depends on triangular membership process for WQI

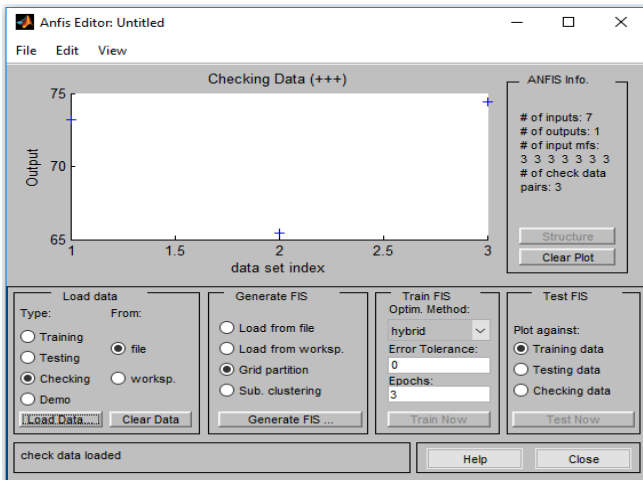


Fig.7. Testing action of ANFIS depends on triangular membership process for WQI

Fig. 9,10 represents the average training error versus iteration number. This system is trained until the error reached to zero. The testing output numerals are given in Table 4. It represents the testing output of trained ANFIS network model. The percentage of error in between the predicted data and investigational values is determined by the following formula.

$$\% \text{ of error} = \left( \frac{\text{Predicted value} - \text{calculated experimental value}}{\text{Experimental value}} \right) \times 100$$

The calculated average error of the forecast of WQI is 3.46, 0.96, and 3.20%, respectively. Investigational output has revealed that the planned MVS can be implementing for automatic forecast of WQI accuracy of 96.8%. The residual examination is carry out by the calculation of residuals from the real and predicted water quality index for teaching numbers set and testing data set. It is watched that residuals are spread equally along the centre line. The data are healthy trained and tested and they account for model variation and non-linearity exists among water quality index with water quality parameters.

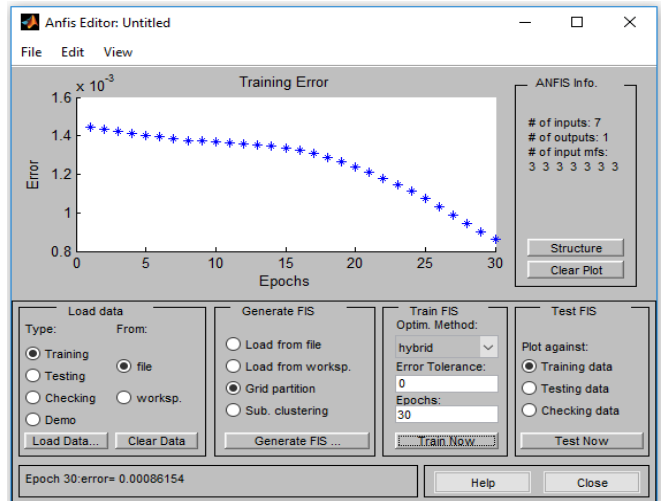


Fig.9. Mean training error versus iteration digit

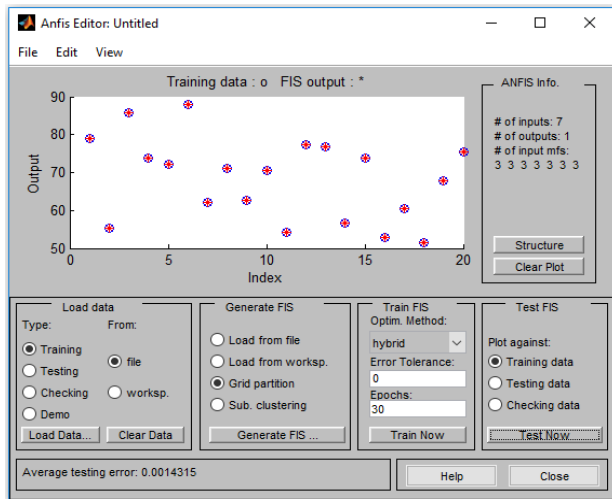


Fig.10. Mean training error against iteration number

The red dots indicate predicted data and the blue dots

indicate actual output. The graphical plots represent the coherence nature of the data circulation. The surface plot of the current work is shown in Fig. 11.

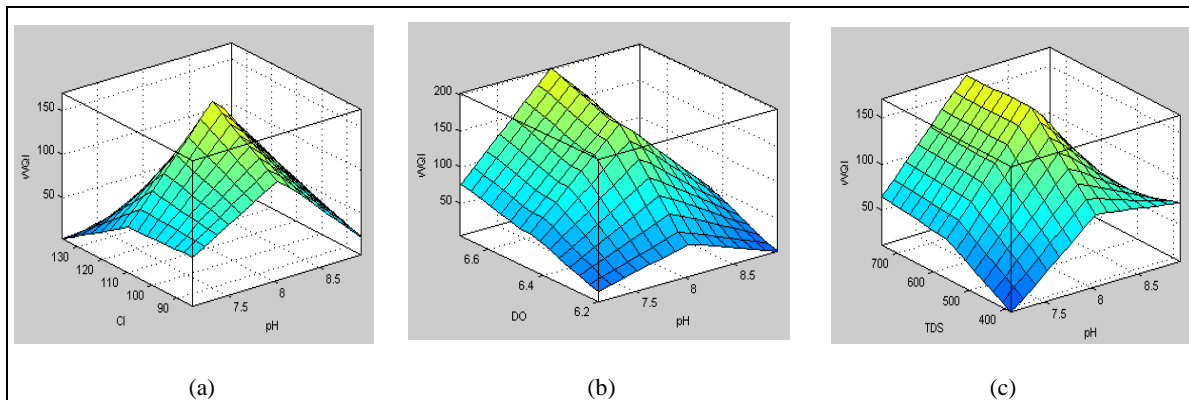


Fig.11. 3D surface plots and variation of WQI with pH and DO, pH and TDS, pH and Cl

An increasing and fluctuating trend of WQI is shown in Fig.11. According to Fig. 11a, b, c, pH, DO, Cl, and TDS had considerable effect on WQI, and an increasing and fluctuating trend of WQI, while an increase in pH with Cl, DO, and TDS combination, the water quality index value gradually increased after reaching certain point 100, the value gradually decreased. The result indicates that dissolved oxygen majorly affects the quality of water because in DO combination the WQI values reaches up to maximum value.

The minimum value of pH is less than 7.5 and DO is less than 6.4 mg/l. The WQI value is less than 50, which shows good quality of water. The WQI value gradually increases and reaches a steep (200) then decreases gradually further increase of pH and DO. The minimum value of pH and Cl, the WQI value, reaches 50. In the combination of pH and Cl, the calculated WQI values gradually increase, reaching a maximum value of 110 and then decreasing gradually. The combination of pH as middle value and TDS as maximum value means the WQI reaches up to 150 as the maximum value.

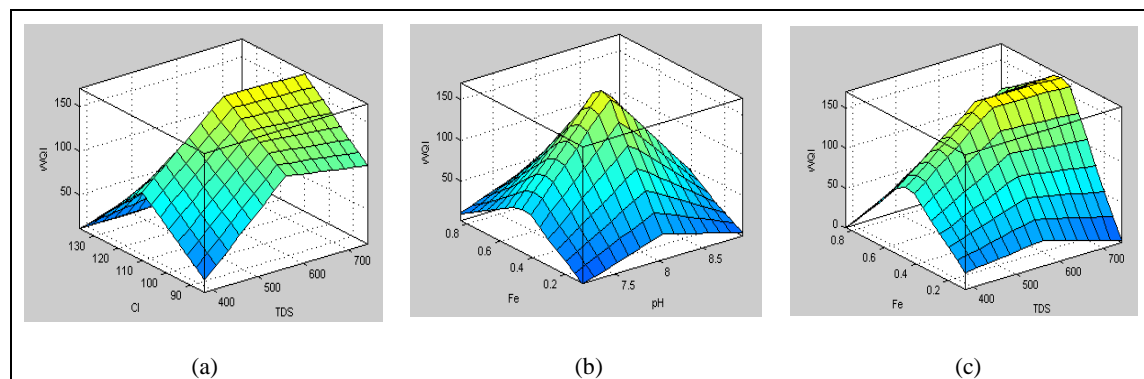


Fig.12. 3D surface plots and variation of WQI with TDS with Cl, pH and Fe, TDS and Fe

Fig.12. illustrates the 3D surface plots and variation of WQI with TDS with Cl, pH and Fe, TDS and Fe. The gradual increase of TDS and Cl causes the gradual increase of WQI and reaches the maximum value. The input pH, Fe and the output WQI of 3D surface plot show a triangular variation. The increase of pH and Fe value increases the WQI value. When it reaches the middle value of pH and Fe axis, the WQI reaches the maximum value then further increase of pH and Fe WQI value decrease gradually and reaches to zero. In TDS and Fe combination, the input values shows gradual variation of TDS, steep variation of Fe produces the maximum value of WQI of 150 at the middle of the two inputs. After the increase of TDS and Fe, the WQI value continues as constant value.

The output predicted by the simulation model represents an excellent concurrence with investigational results for an extensive range of operational conditions. It can be tolerable, taking into account the restricted quantity of training data presented and high error prone to dimensions of water quality index. Thus, the analyzed ANFIS can be utilized to attain a function that maps entry variables to the required procedure exit in a large variety of micro-turning procedure.

## CONCLUSION

Modelling and predicting water quality using AI algorithms is very important for the protection of the environment. The artificial intelligence models were created to forecast and classify water quality for surface water by employing data collected from Kamakshi amman temple pond. The present study explored an artificial intelligence to predict water quality by employing minimal and available water quality parameters. The datasets employed to conduct the research were acquired from different locations sustainability between the years, 2017-2020. WQI was applied to calculate seven important parameters: pH, DO, TDS, Cl, SO<sub>4</sub>, Fe, and TCC. These were considered significant parameters for water quality. The created model was checked with test data, and the mean percentage correctness obtained was 97.25%. These results represents that the ANFIS system

model with triangular membership function is accurate and can be used to predict the water quality index of temple ponds. The calculated result shows the water quality in poor nature. Conventional treatment followed by disinfection process helps the water to convert into good quality. The major investigate challenge is the development of prediction precision of water contamination levels in greater or smaller inputs in dissimilar water origins.

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