WATER QUALITY ASSESSMENT IN DISTRIBUTION SYSTEM USING ARTIFICIAL INTELLIGENCE

Thesis

Submitted in partial fulfillment of the requirements for the degree

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DOCTOR OF PHILOSOPHY

by

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D E C L A R A T I O N

by the Ph.D. Research Scholar

I hereby declare that the Research Thesis entitled **"Water Quality Assessment in Distribution System Using Artificial Intelligence"** which is being submitted to the **National Institute of Technology Karnataka, Surathkal** in partial fulfillment of the requirements for the award of the Degree of **Doctor of Philosophy** in **Civil Engineering** is *a bonafide report of the research work carried out by me*. The material contained in this Research Thesis has not been submitted to any University or Institution for the award of any degree.

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C E R T I F I C A T E

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ABSTRACT

In this study various artificial intelligence techniques have been compared for assessment and prediction of water quality in various zones of municipal distribution system using six physico-chemical characteristics viz. pH, alkalinity, hardness, dissolved oxygen (DO), total solids (TS) and most probable number (MPN). Fuzzy expert system, artificial neural network (ANN) and adaptive neuro fuzzy inference system (ANFIS) were used for the comparative study. The proposed expert system includes a fuzzy model consisting of IF-THEN rules to determine WQI based on water quality characteristics. The fuzzy models are developed using triangular and trapezoidal membership functions with centroid, bisector and mean of maxima (MOM) methods for defuzzification. In ANN method the cascade feed forward back propagation (CFBP) and feed forward back propagation (FFBP) algorithms were compared for prediction of water quality in the municipal distribution system. The comparative study was carried out by varying the number of neuron (1-10) in the hidden layer, by changing length of training dataset and by changing transfer function. ANFIS models are developed by using triangular, trapezoidal, bell and Gaussian membership function. Further, these artificial intelligence techniques are compared with multiple linear regression technique, which is the commonly used statistical technique for modelling water quality variables. The study revealed that artificial neural network (ANN) outperforms other modelling techniques and is a robust tool for understanding the poorly defined relations between water quality variables and water quality index (WQI) in municipal distribution system. This tool could be of great help to the distribution system operator and manager to find change in WQI with changes in water quality varibles.

Keywords: **Water distribution system, Water quality index, Fuzzy logic, ANN, ANFIS, Neurons.**

CONTENTS

ABBREVIATIONS AND NOTATIONS

ANN	Artificial Neural Network
ANFIS	Adaptive Neuro Fuzzy Inference System
BOD	Biochemical Oxygen Demand
Cc	Coefficient of Correlation
CFBP	Cascade Forward Back Propagation
COD	Chemical Oxygen Demand
COM	Centre of Maxima
DO	Dissolved Oxygen
DIN	Dissolved Inorganic Nitrogen
FFBP	Feed Forward Back Propagation
FIS	Fuzzy Interference System
GIS	Geographic Information System
GRNN	General Regression Neural Network
ICMR	Indian Council Medical Research
Logsig	Logsigmoidal
MAE	Mean Absolute Error
MLD	Million Liters per Day
MOM	Mean of Maxima
MLR	Multiple Linear Regression
MLP	Multi Layer Perceptron
MVRA	Multivariate Regression Analysis
MPN	Most Probable Number
MRE	Mean Relative Error
ON	Organic Nitrogen
PSO	Particle Swarm Optimization
QP	Quick Propagation
RBNN	Radial Basis Neural Network
RMSE	Root Mean Square Error
SS	Suspended Solids
STEM	Shifted Time Exponential Model

STPM	Shifted Time Power Model
SUTRA	Saturated Unsaturated Transport
Tansig	Tansigmoidal
TA	Total Alkalinity
TDS	Total Dissolved Solids
TH	Total Hardness
TN	Total Nitrogen
TP	Total Phosphorus
TOC	Total Organic Carbon
T-S	Takagi-Sugeno
TS	Total Solids
TSS	Total Suspended Solids
VLSI	Very Large Scale Integrated
WPI	Water Pollution Index
WQI	Water Quality Index
FWQI	Fuzzy Water Quality Index
W_i	Unit Weight of Water Quality Parameter
q_i	Water Quality Rating
μ	Membership Function

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CHAPTER 1

INTRODUCTION

1.0 GENERAL

Safe water is a precondition for health and development and a basic human right, yet it is still denied to hundreds of millions of people throughout the developing world. Water related diseases caused by unsafe water supplies coupled with poor sanitation and hygiene cause around 3.4 million deaths every year, mostly among children. Despite continuing efforts by governments, civil society and the international community, over a billion of people still do not have access to improved water sources. Water distribution system plays a vital role in presenting a desirable life quality to the public. The welfare level of a country is measured with the amount of water consumption for each person and the quality of the provided water (Kumar *et al.*, 2009). Now a days, scarcity of water is a limiting factor for sustainable growth. Therefore preserving its availability and quality is a key issue (Uricchio *et al.*, 2004). The quality of water is the most important environmental, social and political issue at the global level.

1.1 FAILURE OF WATER QUALITY IN THE DISTRIBUTION SYSTEM

A typical modern water supply system comprises the water source (aquifer or surface water source including the catchment basin), treatment plants, transmission mains, and the distribution system which includes pipes and distribution tanks. While water quality can be compromised at any component, failure at the distribution level can be extremely critical because it is closest to the point of delivery and the residual disinfectant may not be sufficient to restrict the regrowth of microorganisms or to give protection against other contamination processes. Kleiner (1998) classified water quality failure, that compromise either the safety or the aesthetics of water in distribution networks into the following major categories:

- Intrusion of contaminants into the distribution system through system components whose integrity was compromised or through misuse or cross-connection or intentional introduction of harmful substances in the water distribution system;

- Regrowth of microorganisms in the distribution network;
- Microbial (and/or chemical) breakthroughs and by-products and residual chemicals from the water treatment plant;
- Leaching of chemicals and corrosion products from system components into the water;
- Permeation of organic compounds from the soil through system components into the water supplies.

Intrusion of contaminants into the water distribution system can occur through storage tanks (animals, dust carrying bacteria, infiltration) and pipes. Intrusion of contaminants through water mains may occur during maintenance and repair events, through broken pipes and gaskets, and cross-connections (Geldreich, 1990). Whenever the water pressure in a pipe is very low or negative, the risk of contamination through back flow or through leaky pipes increases. This can happen when the pipe is de-pressurized for repair or when the pipe is used for fire extinguishing or during transient pressures. Low or negative pressures, coupled with unprotected cross- connections and/or contaminated soils, and/or leaky sewers in the pipe vicinity create a high risk of contaminant intrusion especially if the pipe is deteriorated with cracks and pinholes.

Growth of biofilm in the distribution system leads to deterioration of water quality. Biofilm is a deposit consisting of microorganisms, microbial products and detritus at the surface of pipes or tanks. Bacteria can enter from the treatment plant into the distribution system because it is virtually difficult to design a treatment plant with 100% efficiency. Moreover, its efficiency decreases over the period of time. Under favourable conditions, such as nutrient supply (e.g., organic carbon) in the water and long residence time, these bacteria can attach themselves to surfaces, rejuvenate and grow in storage tanks and on rough inner surfaces of water mains. The regrowth of organisms in the distribution system results in an increased chlorine demand, which has two adverse effects: (a) a reduction in the level of free available chlorine may hinder the system's ability to contend with local occurrences of contamination (US EPA, 1999), and (b) an increased level of disinfection to satisfy the chlorine demand of biofilm results in higher concentrations of disinfection by-products (DBPs). Disinfection is used to inactivate or kill pathogens. Chlorine has been highly successful in reducing the incidences of waterborne infections in human beings, but harmful DBPs are formed in the presence of Natural Organic Matter (NOM) and bromide (from the source water) during chlorination. Other commonly used disinfectants are chloramines (combined chlorine), chlorine di-oxide and ozone. Ozone reacts with NOM and produces aldehydes, ketones and inorganic by-products. Ozone and chlorine di-oxide in the presence of bromide ion produce bromate and chlorate (and chlorite), respectively, which may have adverse effects on human health (US EPA, 1999).

Corrosion giving rise to red water, which is one of the most common causes of water quality failure and leads to loss of aesthetics rather than a hazard to human health. Internal corrosion of metallic pipes and plumbing devices increases the concentration of metal compounds in the water. Different metals go through different corrosion processes, but in general low pH water, high dissolved oxygen, high temperature, and high levels of dissolved solids increase corrosion rates. Heavy metals such as lead and cadmium may leach into the water from pipes, causing significant health effects. Secondary metals such as copper (from home plumbing), iron (distribution pipes) and zinc (galvanized pipes) may leach into water and cause taste, odour and colour problems in addition to minor health related risks (Kleiner, 1998).

Permeation is a phenomenon in which contaminants (notably hydrocarbons) migrate through the pipe (plastic) wall. Three stages are observed in permeation phenomenon: (a) organic chemicals present in the soil partition between the soil and plastic wall, (b) the chemicals defuse through the pipe wall, and (c) the chemicals partition between the pipe wall and the water inside the pipe (Kleiner, 1998). In general, the risk of contamination through permeation is relatively small as compared to other mechanisms.

1.2 WATER QUALITY MONITORING

Water quality is generally defined by a collection of upper and lower limits on selected possible contaminants in water (Maier, 1999). Water quality indicators (parameters or classes) can be classified into three broad categories: physical, chemical and biological contaminants. Within each class, a number of quality variables are considered. The acceptability of water quality for its intended use depends on the magnitude of these indicators (Swamee and Tyagi, 2000) and it is often governed by regulations. A water quality failure (WQF) event is often defined as an excess of one or more water quality indicators from specific regulations, or in the absence of regulations, exceeds the guidelines or self-imposed customer-driven limits.

As stated earlier, the physical, chemical and biological processes occurring in water distribution pipes are numerous and complex. A wealth of literature is available, describing the overall water quality represented by an aggregate index using various statistical and mathematical techniques. Sinha *et al.* (1994) combined pH, chloride concentration, turbidity, residual chlorine, conductivity and most probable number (MPN) into a single water quality index (0-100) through a weightage technique to represent an overall water quality at various nodes in the distribution system. Sadiq *et al.* (2004) suggested a framework for the analysis of aggregative risk associated with water quality failure in the distribution system. To monitor the quality of water in the distribution system, physical, chemical and biological parameters are recorded from routine grab sampling, followed by an analysis in the laboratory or using portable kits in the field. Regular monitoring programs help to identify a Water Quality Failure (WQF) if water quality indicators exceed regulatory regimes.

1.3 NEED OF ARTIFICIAL INTELLIGENCE FOR WATER QUALITY IN MUNICIPAL DISTRIBUTION SYSTEM

Water distribution system plays a vital role in presenting a desirable quality of life to the public. A typical modern water supply system comprises the water source (aquifer or surface water source), transmission mains, treatment plant and distribution network. The water quality varies temporally and spatially at source, treatment plant and in the distribution network. The water quality in the distribution system deteriorates due to pipe age, corrosion of pipe material, intrusion of contaminants through leakage and cross connections, leaching of pipe material, formation of biofilm in the pipes (Kiéné *et al.*, 1998) etc. and hence many uncertainties are involved till the water reaches to users tap. A number of numerical models have been proposed to evaluate the changes of water quality within water distribution systems due to the above causes (Liou and Kroon, 1987; Males *et al.*, 1987; Rossmann, 2000; Pirozzi *et al.*, 2002; Osfeld, 2005; Woolschlager *et al.*, 2005). The predictive capability of such models have also been used, in recent years, both to reduce, to a strict minimum, the quantities of chlorine normally placed on the water distribution systems for preserving human health (Cozzolino *et al.*, 2005; Gao *et al.*, 2010), and to reduce the risk of contamination resulting from accidental phenomena or intentional attacks (Cozzolino *et al.*, 2006; Cozzolino *et al*., 2011; Nyende-Byakika *et al*., 2012). Unfortunately, sometimes it is not possible to reconstruct all the data and information necessary for the numerical simulation of changes that specific water quality indices suffer from the sources up to the various users. As a consequence, other kinds of approaches have to be used to assess the water quality characteristics within municipal water distribution systems.

Water quality index is a risk communication tool used to describe the status of water by translating a large amount of non-commensurate data into a single value (Ott, 1978). Swamee and Tyagi (2000) have discussed in detail the pros and cons of different techniques and approaches available for evaluating the overall index of water quality. A significant amount of literature is available on the evaluation and management of water systems using WQI. For this purpose, physical, chemical, and biological water quality indicators (sub-indices) are aggregated in a 'meaningful' way using various statistical and mathematical techniques (Ott, 1978). These aggregation approaches generally include logical operators (e.g., minimum, maximum), averaging operators (e.g., arithmetic average, weighted average, geometric mean, weighted product), and many others like simple addition, root sum power, root sum-square and multiplicative forms. (Somlikova and Wachowiak, 2001; Silvert, 2000; Sinha *et al.*, 1994; Ott, 1978). Swamee and Tyagi (2000) have discussed advantages and shortcomings of different aggregation techniques available for the evaluation of WQI. In the aggregation process, recognition of two potential pitfalls, namely exaggeration and eclipsing, is important. Exaggeration occurs when all water quality indicators individually possess lower value i.e. lower than the maximum permissible values, yet the WQI comes out very high. Eclipsing is the reverse phenomenon, where one or more of the water quality indicators are of relatively high value, yet the estimated WQI comes out as unacceptably low. These phenomena are typically affected by the method of aggregation; therefore the challenge is to determine the best aggregation method that will simultaneously reduce both exaggeration and eclipsing.

The decision on the assessment of water quality implies that the water quality is desirable, acceptable, not acceptable, good or bad. These decision variables are linguistic in nature. These linguistic variables are invariably imprecise in nature indicating uncertainties involved. Various methods are discussed in the literature on water quality and decision making. But most of the reports on the water quality reveal that deterministic approach in decision making by comparing values of water quality parameters with prescribed limits provided by different regulatory bodies is used without considering uncertainties at various steps (Dahiya *et al*., 2007). One way of avoiding the difficulty in uncertainty handling in water quality assessment is to introduce a margin of safety or degree of precaution before applying a single value to drinking water quality standards. The same technique was also used by other researchers in the field of environmental engineering (Kumar *et al*., 2009). The regulatory limits for various pollutants/contaminants in drinking water proposed by various regulatory bodies have several limitations due to variation in intake of water by individuals during different seasons throughout the year. Prescribed criteria from any regulatory body contain uncertainties, as these are the extrapolated values from the data either from animal experiments or epidemiological studies (Dahiya *et al*., 2007). Conventional water quality regulations contain quality classes which are crisp sets and limits between different classes that have inherent imprecision (Silvert, 2000). Traditional methods of water quality classification use crisp set and the concentration values which are close or far from the limits and are considered in same class. Secondly, the various water quality parameters are, usually in different quality classes and this may confuse a non-expert on this subject. Using fuzzy logic, firstly quality limits of traditional classification were considered into continuous form. Therefore, the evaluation sensitivity of concentration increased. Secondly, the quality classes were combined to get one value, which represents quality classes of all parameters (Icaga, 2007).

Although, parametric statistical and deterministic models have been the traditional approaches for modelling the water quality, these require vast information on various sub-processes in order to arrive at the end results. In recent years several studies have been conducted on water quality forecast models (Chen *et al*., 2003). However, a large number of factors affecting the water quality have a complicated nonlinear relation with the linguistic variables; traditional data processing methods are no longer good enough for solving the problem (Singh *et al*., 2009). This opens a new avenue for the application of artificial intelligence rather than probabilistic or statistical techniques. Various empirical formulae are used by the researchers to calculate WQI for ground and surface water quality assessment. There is no such empirical formula for assessment of water quality in the municipal distribution system.

1.4 THESIS OUTLINE

This thesis is organised as follows:

Chapter 2 describes the various studies conducted to assess and predict the water quality for surface and ground water sources. It also includes the prediction studies on water distribution system and the objectives of research work.

Chapter 3 provides information about the various techniques of artificial intelligence used in this research work. Chapter 4 includes methodology adopted, information regarding study area, data collection and water quality analysis to find out Water Quality Index in various zones of municipal distribution system.

Chapter 5 includes the findings of various techniques of artificial intelligence and comparison of results obtained by Fuzzy Logic (FL), Artificial Neural Network (ANN), Adaptive Neuro Inference System (ANFIS) and Multiple Linear Regression (MLR).

Chapter 6 includes concluding remarks of study conducted for assessment of water quality in municipal distribution system.

CHAPTER 2

LITERATURE REVIEW AND OBJECTIVES

2.0 GENERAL

The quality of water in the municipal distribution system is a subject of ongoing concern. Deterioration of water quality in the distribution system has initiated serious management efforts in many countries. Most ecological and water related decisions are difficult to make without careful modelling, prediction and analysis of water quality. Accurate predictions of future phenomena are the lifeblood of optimal water quality management in the municipal distribution system. Computer science and statistics have improved modelling approaches. Traditional methods hardly address the non-linearity, uncertainty, subjectivity, and complexity of the cause-effect relationship between water quality variables and water quality status. This chapter includes various techniques of artificial intelligence used in the past for prediction and assessment of water quality.

2.1 ARTIFICIAL INTELLIGENCE FOR GROUNDWATER QUALITY

Monitoring of groundwater quality and qualitative decision making on the basis of data is a challenge for environmental engineers and hydrologists as every step from sampling to analysis contains uncertainties. The regulatory limits for various pollutants/contaminants in drinking water proposed by various regulatory bodies have several limitations due to variation in intake of water by individuals during various seasons throughout the year. Prescribed criteria from any regulatory body contain uncertainties as these are the extrapolated values from the data either from animal experiments or epidemiological studies (Dahiya *et al*., 2007). The Artificial Neural Network (ANN) method is regarded as a potentially useful tool for modeling complex non-linear system, whereas Fuzzy Logic (FL) and Adaptive Neuro-Fuzzy Inference System (ANFIS) are useful in the cases wherein uncertainties and imprecision is involved (Yan *et al*., 2010).

2.1.1 Prediction of Ground Water Quality

In most Mediterranean and Asian countries groundwater is the primary resource for drinking and irrigation. Scarcity of water is the limiting factor for sustainable growth. Therefore preserving its availability and quality is a key issue. Furthermore, excessive groundwater withdrawal is a risk factor, because it causes sea water intrusion phenomena resulting in progressive groundwater salinisation (Uricchio *et al*., 2004).

Holger and Dandy (2000) presented a review of modelling issues and applications on neural networks for forecasting and prediction of water resource variables. In their paper, the steps that should be followed in the development of such models are outlined. These include the choice of performance criteria, the division and pre-processing of the available data, the determination of appropriate model inputs and network architecture, optimization of the connection weights (training) and model validation. The vast majority of the networks were trained using the back-propagation algorithm.

Kuo *et al.* (2004) attempted to forecast the groundwater quality in the Blackfoot disease area, Taiwan. The groundwater quality in this area varies due to seawater intrusion and arsenic pollutants. Three types of ANN models were established to evaluate learning performance of the training model. Model 'A' includes five concentration parameters viz. Electrical conductivity (EC), chloride (Cl), sulphate ($SO_{4)}$, phosphate (K) and magnesium (Mg) as input variables to determine seawater intrusion and three variables viz. Alkalinity, total organic carbon (TOC) and arsenic (AS) to determine arsenic pollutants, respectively, where as model B and C used only one concentration parameter from each. Model C used two season data for training, where as models A and B used data from one season for training. The study revealed that model C outperforms model A and B and can describe complex variation of groundwater quality and be used to perform reliable forecasting. Shamim *et al.* (2004) conducted a study on use of ANN model for forecasting ground water contamination due to heavy metals. ANN model was used for predicting the concentration of iron (Fe), copper (cu) and lead (Pb) in ground water. The model was applied to real data from groundwater in Faisalabad, the largest industrial city of Pakistan. The city has more than 8000 big and small industrial units. The data for both the lined and unlined channel was obtained from Pakistan Council of Research in Water Resources. The predicted concentration showed good correlation with observed concentrations. Coppola *et al.* (2005) compared ANN algorithm and linear regression for predicting specific conductance in an unconfined coastal aquifer located near a high capacity municipal supply well. Initial specific conductance, total precipitation, mean daily temperature and total pumping extraction were used as input variables. The specific conductance was considered as output variable. The study revealed that ANN algorithm outperforms linear regression model and showed good correlation with actual measured values. The absolute mean prediction error achieved by ANN algorithm was 1.1%. Khandelwal and Singh (2005) compared multivariate regression analysis (MVRA) and ANN model for prediction of sulphate, chloride, chemical oxygen demand (COD), total dissolved solids (TDS) and total suspended solids (TSS) in mine water. The study was conducted by using pH, temperature and hardness as input variables. The study showed that predictions by ANN models are very satisfactory as compared to MVRA, and seem to be a good alternative for pollutants prediction in mine water.

Tumez *et al.* (2006) used ANFIS model for predicting electrical conductivity by using concentration of positively charged ions (Na, Ca, Mg, K) as input variables. The study revealed that ANFIS model outperforms traditional methods of modeling electrical conductivity based on dissolved solids in water, even though ANFIS uses less information. Spatial and temporal quality distribution is an important factor in groundwater management. Due to sampling sites deficit, high cost and time limit, spatial and temporal distribution modeling of aquifer contaminants is needed. Farahmand *et al.* (2010) compared kriging, ANN and ANFIS models for prediction of electrical conductivity and chloride. The electrical conductivity and chloride are two important indicators for ground water quality assessment. In kriging method, for spatial and temporal quality parameters, spherical model was the dominant type of model that fitted the data. Different artificial neural networks were developed and hidden layer structure with four neurons was observed as the most efficient structure. ANFIS models were developed by using gaussian, bell, and trapezoidal shaped membership functions. The study showed that ANFIS model performed better as compared to kriging and ANN models. ANFIS model with bell shaped membership function was observed as the best fitting model for estimation of electrical conductivity and chloride.

Banerjee *et al.* (2011) compared ANN and saturated unsaturated transport (SUTRA) models for estimating safe pumping rate to maintain groundwater salinity in Kavaratti Island on West cost of India. Feed forward ANN algorithm was used for forecasting the salinity under varying pumping rates (8000-50000 lit/day). The study revealed that ANN predictions are more accurate than SUTRA model and it was also found that the pumping rate should be below 13000 lit /day to stabilize groundwater salinity within 2.5%. Zare *et al.* (2011) conducted the study to find the ability of ANN model to forecast groundwater nitrate of Arak aquifer, Iran. In this study ANN and linear regression (LR) methods were compared to predict concentration of nitrate in groundwater. The study showed that using the measured parameters is convenient to model nitrate concentration with acceptable and appropriate accuracy and ANN and LR methods are able to predict nitrate concentration at the desirable level of accuracy. Comparison of ANN analysis with LR model showed that ANN requires fewer parameters with more accuracy in comparison to LR models.

2.1.2 Assessment of Groundwater Quality

The groundwater quality analysis involves variables such as acceptable, desirable and non-acceptable, which are linguistic in nature. Dahiya *et al*. (2007) used fuzzy synthetic evaluation approach to get the certainty value of linguistic variables such as desirable, acceptable and not acceptable, which are generally used for water quality analysis. They analysed the groundwater quality of Atelli block, Haryana, India. The study revealed that, out of 42 samples collected, 4 samples are in desirable category with certainty value 35-38%, 23 samples are in acceptable category with degree of certainty 37-75% and remaining 15 samples are in not acceptable category with degree of certainty 44-100%. Similar methodology was adopted by Kumar *et al.* (2009) for assessment of ground water quality of a Riyamanglam zone of Tichirapalli, to get certainty values of linguistic variables. The study revealed that out of 30 samples collected, 4 samples comes in desirable class with certainty level of minimum 8% and maximum 78%, 14 samples are classified in acceptance category with certainty level of 50% and rest 13 samples are in not acceptable class with certainty level of 100 %.

Nonpoint source pollutants (fertilizers), irrespective of their origin, are transported overland and through the soil by precipitation and excess irrigation water (Novotny, 2005). Muhammetoglu and Yardimci (2006) used fuzzy logic approach to assess the groundwater pollution below agricultural field. The data collected from Kumluca plain of Turkey was used to develop the model. Water pollution index (WPI) was developed using nitrate, nitrite, orthophosphate and seepage index as input variables. Defuzzification was carried out using centre of maxima (COM) and mean of maxima (MOM) methods. The study revealed that there is good agreement between fuzzy results and monitored field results. Rai (2008) developed Fuzzy Water Quality Index (FWQI) for ground water classification of Kolkata city. The water quality parameters such as temperature, BOD, pH, nitrate and coliform were taken as input variables, where as FWQI was taken as output variable. The study revealed that fuzzy approach relates certainty value to the linguistic terms and the ground water quality in Kolkata city is good with a certainty value of 92% except at Haldia station, which is nearer to Indian Oil Company (IOC) refinery.

2.2 ARTIFICIAL INTELLIGENCE FOR SURFACE WATER QUALITY

Surface water quality impairment is often a trigger for conflict in a watershed, simply because degraded water quality means that desired uses are not possible or are not safe. Unfortunately the developmental activities that have taken place throughout the country gave a bad impact to the environment, especially about water quality. This has become a sensitive issue, which not only affects human health, but also the entire environment. The developmental activities not only affect the water quality, but also the aquatic lives that live in it. The management of surface water quality is a major environmental challenge. One of the major challenges is in determining point and non-point sources of pollutants. The discharge of industrial and municipal wastewater can be considered a constant polluting source. Most acceptable ecological and social decisions are difficult to make without careful modelling, prediction and analysis of surface water quality for typical development scenarios. Water quality prediction enables a manager to choose an option that satisfies large number of identified conditions.

2.2.1 Classification of Surface Water Quality

Traditional classification methods of the water quality parameters use crisp set, and the concentrations values which are close or far from the limits are considered in same classes. Moreover, usually, several parameters are considered in quality determination; therefore, differences of the classes of the parameters may be vague, especially, in public consideration. Fuzzy synthetic evaluation which generally uses a numerical scale to represent water quality and provides an alternative methodology for aggregating the values of the parameters to various quality features have been studied and used in environmental quality evaluation since the 1990s (Ludwig and Tulbure,1996; Liou *et al.*, 2003; Liou and Lo, 2005). Lu and Lo (2002) developed a multivariable tropic state indexing method, for diagnosing water quality and evaluated this method using fuzzy synthetic evaluation. Batisha (2003) conducted an investigation on water quality classification using multi-layer perceptron ANNs. The classification of water quality data is a typical pattern recognition problem that poses many difficulties. Traditional methods for classifying high volumes of such data into large numbers of classes based on statistical parametric methods often do not give sufficient descriptive accuracy for discriminating the number of classes required. The study revealed that multilayer perceptron neural networks offers a good classification method and competes well with the traditional techniques used in statistical parametric methods.

Adriaenssens *et al.* (2004) used fuzzy logic for decision support in ecosystem management. The study revealed that the fuzzy logic seems to be very promising in domains such as sustainability, environmental assessment and predictive models. Zhou *et al.* (2006) conducted study using Particle Swarm Optimization (PSO) based neural network for water quality classification and prediction. The data investigated from Yangtze river (China) was used for the study. The water quality parameters such as pH, DO, salts of permanganic acid (CODMn) and ammonical nitrogen (NH_3-N) were used for water quality classification and prediction. In this study, results obtained by PSO based neural network model were compared with observed field results and results obtained by time series forecasting model. The study revealed that PSO based neural network is a robust algorithm and could be extended to other real world pattern classification and prediction applications.

Icaga (2007) used fuzzy evaluation for water quality classification. The traditional classification methods of water quality parameters use crisp set, and the concentration values which are close or far from the limits are considered in same class. In this fuzzy model, traditional quality classes are transformed into continuous form and then the concentration values of different water quality parameters are summed into fuzzy rules, finally, defuzzification of these summed values develops water quality index. This developed water quality index was used for surface water quality classification. Yan *et al.* (2010) compared ANFIS and ANN models for classifying water quality status of river. Several physical and inorganic chemical indicators including DO, COD and ammonia-nitrogen were used for classification. A data set (nine weeks, total 845 observations) was collected from 100 monitoring stations in all major river basins in China and used for training and validating the model. The study revealed that 89.59% of the data was correctly classified by using ANFIS model. This performance was more competitive as compared to artificial neural networks. It was also observed that the ANFIS model with Gaussian membership function performed better as compared with other membership functions for water quality classification.

2.2.2 Prediction of Surface Water Quality

In recent years, ANNs have been used intensively for prediction and forecasting in a number of water-related areas, including water resource study (Liong *et al.* 1999, Muttil and Chau 2006, El-Shafie *et al.* 2008), oceanography (Makarynskyy 2004), and environmental science and river water quality (Grubert 2003). Rounds (2002) compared ANN and linear regression model for estimation of the daily mean and hourly concentrations of DO in the Tualatin River at the Oswego Dam, Portland, USA. The ANN and LR models were constructed using the data collected during May-October of 1991-2000. In this study physical and meteorological parameters were used as input variables viz. stream-flow, ambient air temperature, solar rays and precipitation. The study revealed that linear regression models fail to understand the long-term patterns in the DO data, providing weak correlation results. However, the developed neural network models were successful in predicting patterns in the DO data sets on daily, weekly, and seasonal period scales.

Juahir *et al.* (2004) used ANN model for estimating water quality index (WQI) in the Langat River Basin, Malaysia. In this study the modeling data was divided into two sets. For the first set, ANNs were trained, tested and validated using six independent water quality variables as input parameters viz. DO, BOD, COD, pH, suspended solids and ammoniacal-nitrate. Consequently, multiple linear regression (MLR) was applied to eliminate independent variables that exhibit the lowest contribution in variance. Independent variables that accounted for approximately 71% of the variance in WQI are DO, BOD, suspended solids and ammoniacal-nitrate. The COD and pH contributed only 8% and 2% to the variance, respectively. Thus, in the second data set, only four independent variables were used to train, test and validate the ANNs. The study showed that the correlation coefficient obtained in estimating WQI given by six independent variables is 0.92, which is slightly better than correlation coefficient given by four independent variables (0.91). This demonstrates that ANN is capable of estimating WQI with acceptable accuracy when it is trained by eliminating few input variables which contributes less in estimating WQI. Altunkaynak *et al*. (2005) used Takagi–Sugeno (T-S) fuzzy model for prediction of DO at two stations located in Golden Horn, China. The T-S fuzzy model was used to predict DO concentration of the next month from DO concentrations of the last two antecedent months.

Schmid and Koskiaho (2006) used multi layer perceptron (MLP) type of ANN model for forecasting DO in the Finnish free water surface wetland at Hovi, Finland. Yeon *et al.* (2008) compared ANN and ANFIS models using time series data for forecasting DO and total organic carbon (TOC) concentration in the Pyeongchang river, South Korea. The ANN and ANFIS models have shown good results for the simulation of TOC, whereas neural network model has shown better results than ANFIS model for forecasting DO. He and He (2008) used ANN model for predicting faecal indicator bacteria (FIB) at several seashores, altered stations and changed periods in base-flow or heavy-rains circumstances. The model was developed using temperature, electrical conductivity, pH, turbidity, water outlets flow, rainfall, and time lapse after heavy rains as input variables. The prediction results after testing the model with different data sets showed that the developed ANN model is a robust tool for predicting count of faecal indicator bacteria. Palani *et al.* (2008) developed ANN models for predicting salinity, water temperature, DO and Chlorophyll-a concentrations in Singapore coastal waters. The study was carried out using fourteen input variables viz. temperature, salinity, pH, secchi depth (SD), DO, ammonium (NH_4), nitrite (NO_2), nitrate (NO_3), total nitrogen (TN), phosphate (PO_4), total phosphorus (TP), nitrate nitrogen ($NO_2 + NO_3$), dissolved inorganic nitrogen (DIN = $NH_4 + NO_2 + NO_3$), organic nitrogen (ON = TN—DIN), and organic phosphorous (OP = TP —PO_4). The study revealed that ANN architecture with back propagation algorithm with three hidden layers with sigmoidal activation functions (Ward Net) is better architecture for the temperature and salinity prediction whereas the general regression neural network (GRNN) is better for DO and Chlorophyll-a Prediction. Huiqun and Ling (2008) compared fuzzy inference system and ANN model for predicting BOD, total nitrogen (TN) and total Phosphorus (TP) in Dongchang Lake, Liaocheng, China. The study revealed that performance of ANN model is better than fuzzy model for prediction of BOD, TN and TP.

Feed forward neural network with back propagation learning algorithm was used by Singh *et al.* (2009) for forecasting DO and BOD concentration in Gomati River, India. This study was carried using pH, total solids, total alkalinity, total hardness, chloride, phosphate, potassium, sodium, ammonium nitrogen, nitrate nitrogen and COD as input variables. Dogan *et al.* (2009) carried out a study to investigate the ability of ANN model to improve the accuracy of BOD estimation. ANN model was optimized for number of hidden layers and number of neurons in the hidden layer. The study revealed that ANN architecture having one hidden layer with three neurons gives the best predictions for BOD estimation. Najah *et al.* (2009) predicted WQI at Johar river surface waters using ANN model. The study was conducted for prediction of total dissolved solids, electrical conductivity and turbidity. The study showed that the ANN predictions show less than 10% mean error. Sundarambal *et al.* (2009) developed ANN model for predicting weekly DO concentration in Singapore seawater. The study was conducted by using water temperature, salinity, pH, secchi depth (SD), Chlorophyll-a as input variables and DO as output variable. The results showed that the neural network models are more accurate at simulating the dissolved oxygen of very complex seawater. Talib et al. (2009) used ANN model for one month ahead forecasting of water quality using BOD as a water quality indicator. Testing for BOD is a time consuming task as it takes five days from data collection to analysing with lengthy incubation of samples (referred to as BOD_5). The hyperbolic tangent transfer function was selected for input and output, with sum of squares as an output error function. Eight water quality parameters were used as input variables viz. temperature, pH, salinity, nitrate, phosphate, turbidity, dissolved solids and E-coli with an output of month lag BOD. The study revealed that ANN could reasonably forecast one month ahead BOD in terms of timing and magnitude. Study also revealed that phosphate is the most important input variable for BOD prediction.

Najah *et al.* (2011) used multi-layer perceptron neural network (MLP-NN) for predicting DO at Johor river basin, Malaysia. Five water quality parameters were used for modelling viz. Temperature, pH, electrical conductivity, nitrate and ammonia nitrogen. In this study, two scenarios were introduced; the first scenario was to establish the prediction model for DO at each station based on five input parameters, while the second scenario was to establish the prediction model for DO based on the five input parameters and DO predicted at previous station (upstream). To evaluate the effect of input parameters on the model, the sensitivity analysis was carried out. It was found that the most effective inputs were oxygen-containing (NO_3) and oxygen demand (NH_3-NL). On the other hand, temperature and pH were found to be the least effective parameters, whereas electrical conductivity contributed the lowest to the proposed model. The study showed that results for second scenario were more adequate than the first scenario, with a significant improvement for all stations. Determining COD requires costly analysis which places a financial burden on the national water quality monitoring network.

Najah *et al*. (2011) compared multi-layer perceptron neural networks (MLP-ANN), ensemble neural networks (E-ANN) and support vector machine (SVM) to predict concentration of DO, BOD and COD in Johor river, Malaysia. The study revealed that support vector machine performed better as compared to multilayer perceptron neural network and ensemble neural network. The error in prediction was less than 5% for support vector machine technique of artificial intelligence. Soliman *et al*. (2011) used ANN model for the prediction of the COD in the Rosetta Branch, in the north-west of the Nile Delta, Egypt. The study was conducted by using BOD, DO and water temperature as the input variables. The study showed that the % error between the actual and predicted values varied from to 0 to 14%. Sarani *et al.* (2011) compared artificial neural network and multivariate linear regression model for prediction of sodium adsorption ratio (SAR). The study was conducted by using chloride, conductivity, alkalinity and total dissolved solids as input parameters. The study showed that ANN performs better for prediction of sodium adsorption ratio.

Gazzaz *et al.* (2012) conducted a study to describe design and application of feed-forward three-layer perceptron neural network model for computing the water quality index for Kinta River, Malaysia. The study was conducted using twenty three input variables viz. temperature; turbidity; conductivity; pH; suspended solids, dissolved solids, total solids, ammonia nitrogen , DO, BOD, COD, sodium, potassium, calcium, magnesium, nitrate nitrogen, chloride, phosphate phosphorous, arsenic, zinc, iron, counts of the Escherichia coli bacteria and counts of the total coliform bacteria. The study showed that the optimal network architecture was 23-34-1 and that the best WQI predictions were associated with the quick propagation (QP) training algorithm; a learning rate of 0.06; and a QP coefficient of 1.75. The approach used in this study offers useful and powerful alternative to WQI computation and prediction, especially in the case of WQI calculation methods which involve lengthy computations and use of various sub-index formulae for each value, or range of values, of the constituent water quality variables.

Kisi *et al.* (2012) compared radial basis neural network (RBNN) and ANFIS models for predicting DO concentration. The study was conducted by using four input variables viz. pH, discharge, temperature, and electrical conductivity. The study showed that the RBNN model with three inputs (viz. temperature, pH, and electrical conductivity) was found to be slightly better than the ANFIS model with only temperature as input variable. The results showed that the temperature is the most effective parameter to estimate DO concentration and ANFIS model can be successfully used for prediction of DO if only temperature data is available. Areerachakal (2012) compared the predictive ability of ANFIS and ANN models to estimate the BOD on data from 11 sampling sites of Saen Saep canal in Bangkok, Thailand. The five parameters of water quality viz. DO, COD, ammonia nitrogen, nitrate nitrogen and total coliform bacteria were used as the input variables for the development models. The study revealed that the ANN model performs better as compared to ANFIS model and provides a higher correlation coefficient (R=0.73) and a lower root mean square error (RMSE=4.53) than the corresponding ANFIS model.

The data arising from monitoring stations and experiments may be polluted by noise signals owing to systematic errors and random errors. This noisy data make the prediction task relatively difficult. To overcome this difficulty Ahmad *et al.* (2012) have used an augmented wavelet de-noising technique with neuro fuzzy inference system (WDT-ANFIS). The study was carried out for prediction of DO, BOD and COD. Two scenarios were introduced in this study viz. first scenario was to construct prediction model for water quality parameters at each station, while the second scenario was to construct prediction model based on value of same parameter at previous station (upstream) and both were based on twelve input parameters. The study revealed that the second scenario performed more adequately than the scenario first with significant improvement ranging from 0.5% -3%.

Heydari *et al.* (2013) used ANN models for predicting the monthly values of DO and specific conductance for a Delaware river at a station located at Pennsylvania site of the U.S. The study was conducted by using combinations of pH and temperature, pH and discharge, temperature and discharge, pH, temperature and discharge as input variables. The monthly data of four water quality parameters for the time period 1995-2006 was selected for this analysis. In developing the ANN model for prediction of DO and specific conductance, configuration 4-5-1 and 4-6-1 yielded optimal with 5 and 6 neurons in hidden layer respectively. The study showed that DO and specific conductance in the Delaware river can be predicted with acceptable accuracy from a small set of physical and meteorological measurements. Emamgholizadeh *et al.* (2013) compared multilayer perceptron (MLP), radial basis neural network (RBNN) and ANFIS for forecasting BOD, DO and COD in Karoon river, Iran. Nine input parameters were used for the analysis viz. Electrical conductivity, turbidity, pH, calcium, Magnesium, sodium, phosphate, nitrate and nitrite. The study showed that the computed values of COD, BOD and DO using both

ANN and ANFIS were in close agreement with their respective measured values. The sensitivity analysis was carried out to determine the relative importance of contribution of the input variables. The results showed that the phosphate is the most effective parameter for prediction of BOD, DO and COD.

2.2.3 Assessment of Surface Water Quality

Chang *et al.* (2001) used fuzzy synthetic evaluation technique to assess water quality condition in comparison with the output generated by conventional procedure such as water quality index. The study was based on a set of data collected at several sampling stations of the Tseng-Wen river system in Taiwan. The fuzzy water quality index (FWQI) was developed by considering pH, DO, BOD, COD, suspended solids, ammonia nitrogen and chloride as input variables. The study revealed that the fuzzy synthetic technique successfully harmonizes inherent discrepancies, complex conditions and uncertainties involved in water quality assessment. Haiyan (2002) used various methods which could be divided into five general categories to assess environmental quality. These categories are: (1) expert assessment; (2) index assessment; (3) economic analytical method; (4) operational assessment and (5) fuzzy comprehensive assessment. In the study, the fuzzy comprehensive assessment was applied to assess the quality of air, water and soil in Zhuzhou City, Hunan Province, China, based on the monitoring data of 1997 and National Environmental Quality Standards of China. The assessment procedure comprises five steps: (1) select assessment parameters and establish assessment criteria; (2) establish membership functions of each assessment parameter to assessment criteria at each level; (3) substitute the monitoring data of each assessment parameter at each monitoring site and national standards into the membership functions; (4) allocate the weights of each assessment parameter at each monitoring site to get a weight matrix; (5) carry out the fuzzy algorithm.

Zaheer and Bai (2003) made a study on an application of ANN for water quality management. The study was conducted for river Hanjiang (China) to evaluate the effects of waste load from various kinds of domestic and industrial sources on water environment. The study revealed that ANN is useful tool for evaluating relative effects of pollutants in river system during decision making process.Panda *et al.*

(2004) reported that monitoring of water quality in lakes using usual water sampling and laboratory analysis is very costly and waste of time. Using artificial neural networks to predict the water quality with measurable data has a potential to make the water quality determination procedure cost-effective, fast and realistic. The radial basis function neural network (RBFNN) model was used to predict the concentrations of chlorophyll-a and suspended matter in the lake water. Shen *et al.* (2005) investigated the status of combined heavy metal and organo-chlorine pesticide pollution and evaluated the soil environmental quality of the Taihu lake watershed using a fuzzy comprehensive assessment. The evaluation was carried out in six steps such as (1) selecting of assessment parameters, (2) establishing the membership functions, (3) calculating the membership function matrix, (4) calculating the weights matrix, (5) determination of the fuzzy algorithm and (6) statistical treatment of data. The study revealed that the fuzzy comprehensive assessment method provides a scientific basis for analyzing and evaluating the environmental quality of soil. Prato (2005) proposed a fuzzy logic approach for evaluating ecosystem sustainability, and stated that the fuzzy logic approach is more appropriate than the conventional crisp sets approach to evaluating the strong sustainability of an ecosystem.

Deshpande and Raje (2006) used fuzzy description to assess the water quality of river, Ganga, for bathing purpose. The study was carried by using coliform, DO, BOD, pH and turbidity as input variables. The study revealed that the quality of water in Ganga River at Varanasi for bathing is acceptable with certainty value of 0.98. Bai *et al.* (2009) developed Fuzzy Water Quality Index (FWQI) by using DO, BOD, COD, pH, suspended solids and ammonia nitrogen as input variables to analyse the quality of semenith river, Malaysia. The results obtained provides better quality index with 90% perfection. Lermontov *et al*. (2009) compared the FWQI with $WQI_{Obj.}$, $WQI_{Sub.}$, WQI_{PAL}, WQI_{min}. and WQI_{CETB}. The study revealed that the proposed FWQI seems to be reliable and consistent with traditional methods.

2.3 ARTIFICIAL INTELLIGENCE FOR PREDICTING MISSING VALUES

Diamantopoulou *et al.* (2005) developed ANN models for predicting the monthly missing values of the six water quality parameters viz. nitrates, specific conductivity, DO, sodium, calcium and magnesium at the Axioupolis station, of

Axios River, Greece. The monthly data of these six water quality parameters and discharge (Q), at the Axioupolis station, for the time period 1980-1994 was selected for this analysis. The training of neural networks was carried out by the cascade correlation algorithm which is a feed-forward and supervised algorithm. Kalman's learning rule was used to modify the artificial neural networks weights. The networks were designed by putting weights between neurons, by using the hyperbolic-tangent function of training. The number of neurons in the hidden layer was determined based on the maximum value of coefficient of correlation. The study revealed that ANN models can be used for the prediction of water quality parameters and for finding the missing values of time series of water quality parameters.

Diamantopoulou *et al*. (2005) have developed ANN models to fill the monthly missing values of three water quality parameters viz. nitrates, specific conductivity and DO, at the Sidirokastro station of Strymon river, Greece. The monthly data of thirteen water quality parameters viz. nitrates, specific conductivity, DO, water temperature, sulphates, sodium, potassium, magnesium, calcium, total phosphorus, pH, chlorides, bicarbonates, ammonia and discharge (Q) , at the Sidirokastro station of Strymon river, for the time period 1980-1990 were selected for this analysis. For neural network construction, monthly data randomly partitioned into training (90% of total data) and testing (10% of all data sets), were used. The study showed that the neural network models can be used for the prediction of water quality parameters and allow the filling of the missing values of time series of water quality parameters.

2.4 ARTIFICIAL INTELLIGENCE FOR DISTRIBUTION SYSTEM

Deterioration rate of cast iron pipes, used in the distribution system was predicted by Najjaran *et al.* (2004) using fuzzy inference system. The fuzzy inference system was developed by considering soil resistivity, redox potential, pH, sulphide and percentage (%) of fine clay as input variables and corrosivity potential as output variable. The study revealed that corrosivity potential reasonably correlates with the deterioration rate. Christodoulou et al. (2006) used an integrated GIS-based decision support system for determining relationships between water main break rates and influential risk factors such as a pipe's age, diameter and material, the corrosivity of the soil, the operating pressure and temperature, possible external loads (including highway traffic) and prior pipe breaks. ANN model was developed to find water main break rates and life cycle for each of the individual pipes in the network by using number of previously observed breaks, material type, length and diameter of each pipe as input variables. Using fuzzy logic prioritization was done. GIS was used to represent the results in a convenient manner so that pipe managers can take a suitable decision.

Achim *et al.* (2007) compared shifted time power model (STPM), shifted time exponential model (STEM) and ANN model for prediction of pipeline failure using a large database which is neither complete nor fully accurate (noisy). The STPM and STEM are the statistical methods. The shifted time power model gives results in total number of failures and the shifted time exponential model gives results in number of failures per year. These models are based on age and failure histories and used a shifted time parameter and a variable rate parameter. The study revealed that ANN outperforms the statistical models, where databases are relatively large and noisy.

Tabesh *et al.* (2009) compared ANN, ANFIS and multivariate regression models for predicting pipe failure rate (number of accidents per year per unit length). The study was conducted by using length, diameter, age, pressure and depth of burial of pipe as an input variables and the output was the failure rate. In this study eighty percent of the data was used for training of the network, 15% for testing and 5% for verification of the result in the ANN model. These three models were applied to a real case study involving a large water distribution network in Iran and the results of model predictions were compared with measured pipe failure data. The results showed that the outcomes of artificial neural network model are more realistic and accurate in the prediction of pipe failure rates and evaluation of mechanical reliability in water distribution networks.

Ho *et al.* (2010) developed a methodology to assess water leakage and to prioritize pipeline replacement based on the integration of a seismic-based ANN model and geographic information system (GIS). The pipeline break-event data was collected from the Taiwan water corporation pipeline leakage repair management system. Pipe diameter, pipe material and the number of magnitude-3+ earthquakes were used as the input factors and the number of monthly breaks was used as the prediction output for ANN model development. This study was the first attempt to consider earthquake data in the break-event ANN prediction model. Spatial distribution of the pipeline break-event data was analyzed and visualized by GIS. Using this, the users can easily figure out the hotspots of the leakage areas. A north eastern township in Taiwan, frequently affected by earthquakes, was chosen as the case study. The study revealed that GIS-based hybrid artificial neural network model is more effective as compared to traditional processes for prioritizing the order of pipe replacement in a water distribution network.

Jafar *et al.* (2010) used ANN to predict the failure rate and estimate the optimal replacement time for the individual pipes in an urban water distribution system. The multilayer feed forward neural network was used for the study. The study was conducted using three indicators viz. physical (materials, length, diameter, thickness, and age), environmental (type of soil, location in the street) and operational (pressure and protection) as input variables. The influence of the input indicators on the failure of the water network was analysed by statistica and sensitivity analysis software. This analysis showed that the number of previous failures has a major influence on the occurrence of new failures (a pipe which has suffered from failure presents a high risk of future failure). The influence of the length, diameter and age of the mains was also significant, while the location, type of material and variation of the pressure have a moderate influence on failure. Finally the thickness and the type of soil have a low impact on failure; consequently they can be neglected. On the basis of these results, six models were constructed. They are classified according to the input indicators: three stratifications of material (plastic ``PLA", cement ``AMC", metallic ``FER" ``ductile or cast iron"), two stratifications of the number of failures (low, high), and a global model ``GLO" (all data). This study showed that the ANN model could be effectively used to assist decision-makers in the elaboration of an optimal strategy for investment in maintenance and rehabilitation of an urban water network.

Bubtiena *et al.* (2011) used ANN model for predicting the pipe breaks. The model was applied to real world water distribution system of Benghazi city, Libya. In this study multilayer feed forward back propagation algorithm with two hidden layers having five and two neurons in the respective hidden layers was used for modelling. The tansigmoidal activation function was used in first hidden layer, logsigmoidal in second hidden layer and purelinear in activation function for the output layer. The results showed that ANN model predictions shows good correlation with observed data having error of 3% during training and less than 10% during testing.

2.5 OBJECTIVES OF RESEARCH WORK

A review of literature indicated that several studies have been conducted on prediction and assessment of groundwater and surface water quality using artificial intelligence but the number of attempts of artificial intelligence for water quality in the distribution system is very limited in literature. It is necessary to conduct a study wherein various techniques of artificial intelligence for water quality prediction and assessment in the distribution system can be compared on a single platform with reference to influencing parameters.

In this study it was proposed to compare various techniques of artificial intelligence and commonly existing statistical technique i.e. Multiple Linear Regression (MLR) technique for predicting and assessing water quality in the distribution system and validating the same with observed water quality. Following works were proposed to be carried out

1) To predict and assess the water quality in the distribution system using fuzzy inference system at various locations in the city.
2) To check the suitability of ANN models for water quality prediction, assessment and to find the best fitting ANN model.
3) To check suitability of hybrid neuro fuzzy inference system for forecasting and assessing water quality at various locations.
4) Use of multiple linear regression technique for water quality prediction and assessment.
5) Validating the above results with field results.

CHAPTER 3

BASICS OF ARTIFICIAL INTELLIGIENCE

3.0 GENERAL

Artificial intelligence techniques such as fuzzy logic (FL), artificial neural network (ANN) and adaptive neuro fuzzy inference system (ANFIS) have been used as efficient alternative tools for modeling of complex water resources systems and widely used for forecasting. Fuzzy logic is a system consisting of three conceptual components, including (1) a rule-base, containing a selection of fuzzy if-then rules; (2) a data-base, defining the membership functions used in the fuzzy rules and (3) an inference system, performing the inference procedure upon the rules to derive an output (Zhang, 2009). Fuzzy logic models focus on the use of heuristics in the system description. The models can be seen as logical models that use if-then rules to establish qualitative and quantitative relationships among variables. Their rule-based nature allows the use of information expressed in the form of natural language statements, making the model transparent for interpretation (Vernieuwe *et al.*, 2005). ANN has the ability to learn from input and output pairs and adapt to it in an interactive manner. ANFIS method, which integrates ANN and FL was proposed by Jang (1993). ANFIS has the potential to capture the benefits of both the methods in a single framework. ANFIS eliminates the basic problem in fuzzy system design (defining the membership function parameters and obtaining a set of fuzzy if-then rules) by effectively using the learning capability of ANN for automatic fuzzy if-then rule generation and parameter optimization (Nayak *et al.*, 2004).

3.1 BASICS OF FUZZY LOGIC

Fuzzy control system is commonly defined as a system which emulates a human expert. A fuzzy controller consists of three operations: fuzzification, inference and defuzzification as shown in Fig. 3.1. In fuzzy logic system, the knowledge of the human is put in the form of a set of fuzzy linguistic rules. These rules would produce approximate decisions, just as a human would. The human expert observes quantities by observing the inputs, and leads to a decision or output using his judgment. The human expert can be replaced by a combination of a fuzzy rule-based system (FRBS) and a block called as defuzzifier. The inputs are fed into the fuzzy rule based system, where physical quantities are represented into linguistic variables with appropriate membership functions. These linguistic variables are then used in a set of fuzzy rules within an inference engine, resulting in a new set of fuzzy linguistic variables. In defuzzification stage, the variables are combined and changed to a crisp output which represents an approximation to actual output.

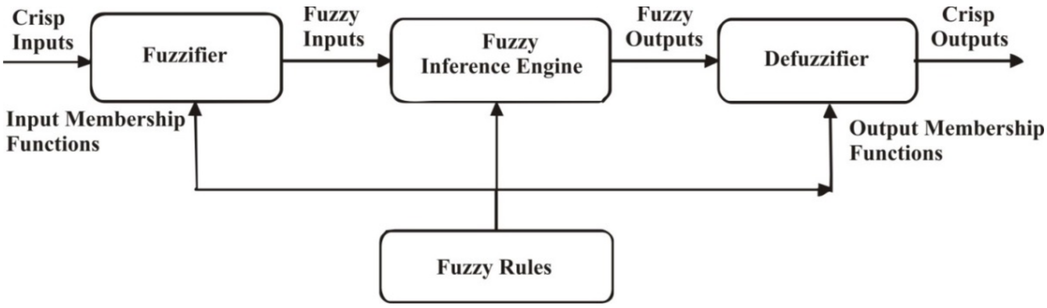


Fig. 3.1 Fuzzy Logic Control System

3.1.1 Fuzzy Sets

A fuzzy set is represented by a membership function defined on the universe of discourse. The universe of discourse is the space where the fuzzy variables are defined. The membership function gives the grade, or degree, of membership (μ) within the set, of any element of the universe of discourse. The membership function maps the elements of the universe onto numerical values in the interval [0, 1]. A membership function value of zero implies that the corresponding element is definitely not an element of the fuzzy set, while a value of unit means that the element fully belongs to the set. A grade of membership in between corresponds to the fuzzy membership to set (Zrilic *et al.*, 2000).

3.1.2 Fuzzification

Fuzzification is the process of decomposing a system input and/or output into one or more fuzzy sets. A fuzzy set is defined in terms of a membership function which maps the domain of interest, e.g. concentrations, onto the interval [0, 1]. The shape of the curves shows the membership function for each set. In this study the trapezoidal and triangular membership functions were assigned to each subset. Many types of curves can be used, but triangular or trapezoidal shaped membership functions are the most common. Fuzzy sets span a region of input (or output) value graphed with the membership. Any particular input is interpreted from this fuzzy set and a degree of membership is interpreted. The membership functions should overlap to allow smooth mapping of the system. The process of fuzzification allows the system inputs and outputs to be expressed in linguistic terms so that rules can be applied in a simple manner to express a complex system.

3.1.3 Defuzzification

After fuzzy reasoning we get output in the form of fuzzy sets which needs to be translated into a crisp value. The objective is to derive a single crisp numeric value that best represents the inferred fuzzy values of the linguistic output variable. Defuzzification is such inverse transformation which maps the output from the fuzzy domain back into the crisp domain. Some defuzzification methods tend to produce an integral output considering all the elements of the resulting fuzzy set with the corresponding weights. Other methods take into account just the elements corresponding to the maximum points of the resulting membership functions (Rondeau *et al*., 1997).

3.2 BASICS OF ARTIFICIAL NEURAL NETWORK (ANN)

Neural networks have been successfully used across an extraordinary range of problem domains, in areas as diverse as finance, medicine, engineering, geology, physics and biology. The excitement stems from the fact that these networks are attempts to model the capabilities of the human brain. From a statistical perspective neural networks are interesting because of their potential use in prediction and classification problems. Artificial neural networks (ANNs) are non-linear data driven self-adaptive approach as opposed to the traditional model based methods. They are powerful tools for modeling, especially when the underlying data relationship is unknown. ANNs can identify and learn correlated patterns between input data sets and corresponding target values. After training, ANNs can be used to predict the outcome of new independent input data. ANNs imitate the learning process of the human brain and can process problems involving non-linear and complex data even if the data is imprecise and noisy. Thus they are ideally suited for the modeling of agricultural data which is known to be complex and often non-linear.

A very important feature of these networks is their adaptive nature, where "learning by example" replaces "programming" in solving problems. This feature makes such computational models very appealing in application domains where one has little or incomplete understanding of the problem to be solved but where training data is readily available. These networks are "neural" in the sense that they may have been inspired by neuroscience but not necessarily because they are faithful models of biological neural or cognitive phenomena. In fact majority of the network are more closely related to traditional mathematical and/or statistical models such as non-parametric pattern classifiers, clustering algorithms, nonlinear filters, and statistical regression models than they are to neurobiology models.

3.2.1 Characteristics of Artificial Neural Network

- The NNs exhibit mapping capabilities, that is, they can map input patterns to their associated output patterns.
- The NNs learn by examples. Thus, NN architectures can be trained with known examples of a problem before they are tested for their “inference” capability on unknown instances of the problem. They can, therefore, identify new objects previously untrained.
- The NNs possess the capability to generalize. Thus, they can predict new outcomes from past trends.
- The NNs are robust systems and are fault tolerant. They can, therefore, recall frill patterns from incomplete, partial or noisy patterns.
- The NNs can process information in parallel, at high speed, and in a distributed manner.

3.2.2 Working of Artificial Neural Networks

The terminology of artificial neural networks has developed from a biological model of the brain. A neural network consists of a set of connected cells. The neurons receive impulses from either input cells or other neurons and perform some kind of transformation of the input and transmit the outcome to other neurons or to output cells. The neural networks are built from layers of neurons connected so that one layer receives input from the preceding layer of neurons and passes the output on to the subsequent layer.

A neuron is a real function of the input vector (y_j.....y_k). The output is obtained as per equation 3.1.

$$f(x) = fa_i + [\sum_n^k W_{ij} \times Y_j] \tag{3.1}$$

Where f is a function, typically the sigmoid (logistic or tangent hyperbolic) function. A graphical presentation of neuron is shown in the Fig.3.2.

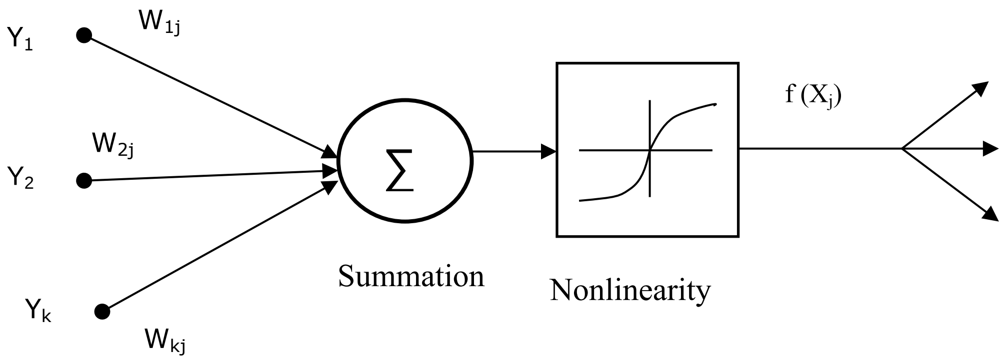


Fig. 3.2 Structure of Neuron

Mathematically a neural network is a function consisting of compositions of weighted sums of the functions corresponding to the neurons. Feed-forward networks are especially useful in function approximation when a set of inputs and outputs is all that is known of the system. Feed-forward networks have their neurons arranged in layers. These layers have connections to the layers either side, as shown in Fig. 3.3. This figure shows a network with p inputs and s outputs.

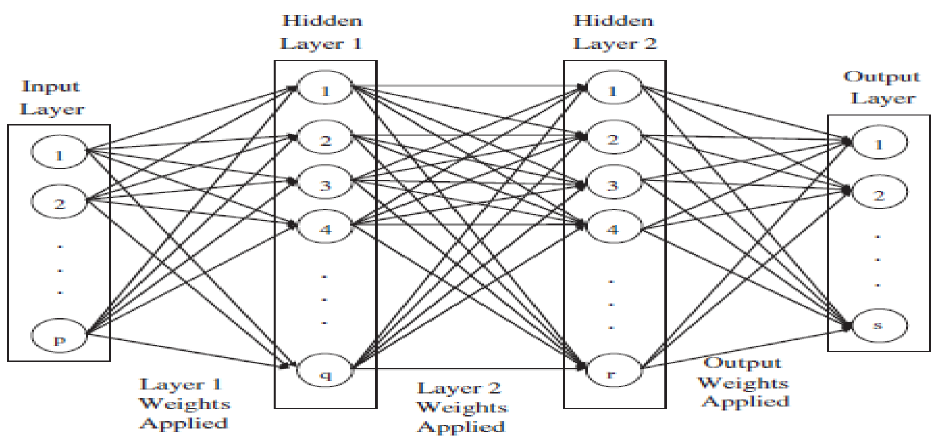


Fig. 3.3 Feed-Forward Back Propagation Neural Network Architecture

There are two layers of hidden neurons, 1 and 2, with q and r neurons in each, respectively. In designing a feed forward neural network, it is necessary to determine heuristically the combinations of the number of hidden layers and the number of neurons in each to obtain the optimum combination. Common notation for the number of layers in a network is described as being the number of hidden layers plus the output layer, since these are the layers that process the information (Sobhani *et al.*, 2010).

3.2.3 Training Algorithms

a) Feed-Forward Back Propagation (FFBP) Algorithm

For feed forward ANN's, the error back propagation algorithm with the gradient descent update rule is most commonly employed. It is the most popular algorithm used for training ANNs. It has got two steps. In the first step each input pattern of the training data set is passed through the network from the input layer to the output layer. The Feed Forward Back Propagation (FFBP) Architecture used for this study is shown in Fig.3.4. The network output is compared with the desired target output and in the second step an error is computed and is propagated back towards the input layer with the weights being modified.

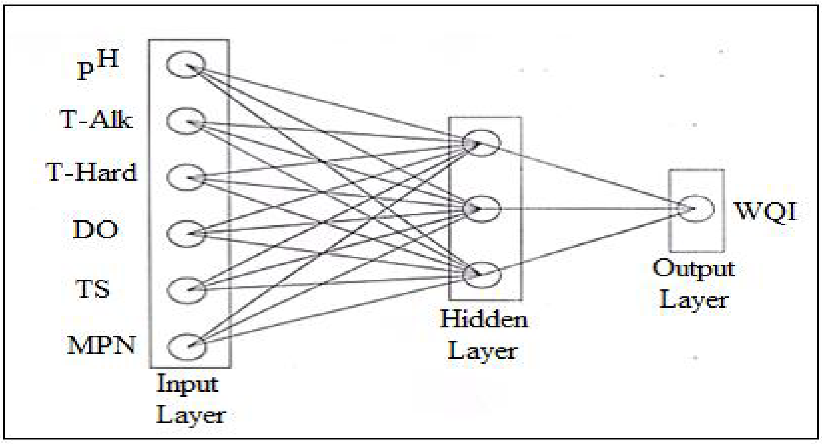


Fig. 3.4 Feed-Forward Back Propagation Architecture

$E=\sum p_{\ p=1}(Y_{\text{observed}} - Y_{\text{predicted}})$

(3.2)

Where, E = Error, which is propagated back towards the input layer to adjust the weight

$Y_{observed}$ = Observed output

$Y_{predicted}$ = Predicted output

p = Number of output nodes

P = Number of training patterns

Back propagation uses the Δ (delta) rule to adjust the connectivity weights. During training, weights need continuous adjustment from iteration t to t+1.The adjustment □W t+1, which is required in iteration (t+1), is assumed linearly related to the negative gradient of Error (E) with weight (w) in iteration t. The constant of proportionality in this linear relation is known as the learning rate (h). Mathematically this relation can be expressed as follows

$$\Delta W(t+1) = h\left(-\frac{\partial E}{\partial W}\right)_{w=w(t)} \qquad (3.3)$$

Using the equation the weight □W t+1can be expressed as

$$W(t+1) = W(t) - h\left(\frac{\partial E}{\partial W}\right)_{w=w(t)} \qquad (3.4)$$

For improving the convergence the following modification is of equation is used.

$$W(t+1) = W(t) - h\left(\frac{\partial E}{\partial W}\right)_{w=w(t)} + \mu\,\Delta W(t) \qquad (3.5)$$

Where, (μ) is the momentum factor as it imparts the momentum to the rate of convergence (Hornik *et al.*, 1989).

b) Cascade Forward Back Propagation (CFBP) Algorithm

The CFBP algorithm is the basis of a conceptual design for accelerating learning in artificial neural networks developed by Fahlman and Lehiere (1990). It is so named because it combines features of the back-propagation and cascade-correlation algorithms. Like other algorithms for learning in artificial neural networks, the CFBP algorithm (Fig.3.5) specifies an iterative process for adjusting the weights of synaptic connections by descent along the gradient of an error measure in the vector space of synaptic-connection weights. The error measure is usually a quadratic function of the differences between the actual and the correct outputs. CFBP models are similar to feed-forward networks, but include a weight connection from the input to each layer and from each layer to the successive layers.

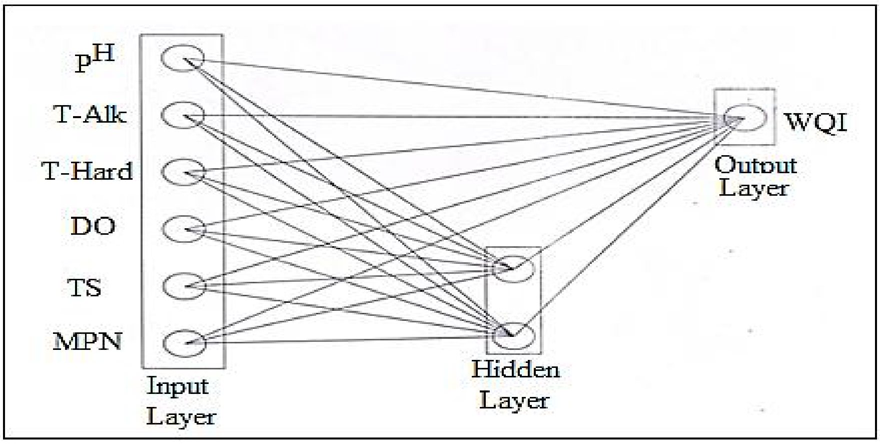


Fig. 3.5 Cascade Forward Back Propagation Architecture

There are two common criteria to stop training a network: (1) training cycles (epochs); and (2) desired errors. Dawson and Wilby (2001) suggested typical application of 20,000 to 100,000 training cycles (epochs) to train the network when steepest descent method is used. The other criterion is to limit the difference between desired output and output calculated by the network. The training process may be brought to halt using either the worst error difference after complete presentation of all input output patterns, or the root mean square error summed over all patterns. In practice, it is sometimes necessary to apply or compare both approaches to ensure the capability of the trained network in generalizing on the tested samples and application. The errors of tested samples is generally higher than the error of training sample as the network is trained to reduce the latter, not the former. However, the over-trained network would occasionally result in over fitting. Over fitting means the network can converge and yield a minimum or desired error in training samples but it cannot generalize well when validated with testing sample. The weights that produce the lowest error on the test sample would be used for the model.

3.3 ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

ANFIS proposed by Jang (1993) can construct an input–output mapping based on a given initial fuzzy system and available input–output data pairs by using a learning procedure. The adaptive network simulates a fuzzy inference system represented by the fuzzy if–then rules. The hybrid network of ANFIS system is functionally equivalent to Sugeno's inference mechanism (Fuller, 1999).

3.3.1 Architecture of ANFIS Model

The architecture of an ANFIS model with two input variables is shown in Fig.3.6. Suppose that the rule base of ANFIS contains two fuzzy IF–THEN rules of Takagi and Sugeno's type as follows:

Rule 1: If x is A_1 and y is B_1, then f1 = $p_1x + q_1y + r_1$,

Rule 2: If x is A_2 and y is B_2, then $f_2 = p_2x + q_2y + r_2$

Fuzzy reasoning is illustrated and also the corresponding equivalent ANFIS architecture is shown in Fig. 3.6. The functions of each layer are described as follows: Layer 1 – Every node i in this layer is a square node with a node function. Then the framework of ANFIS will be able to build as shown in Fig.3.7. The node function in each layer can be described as follows:

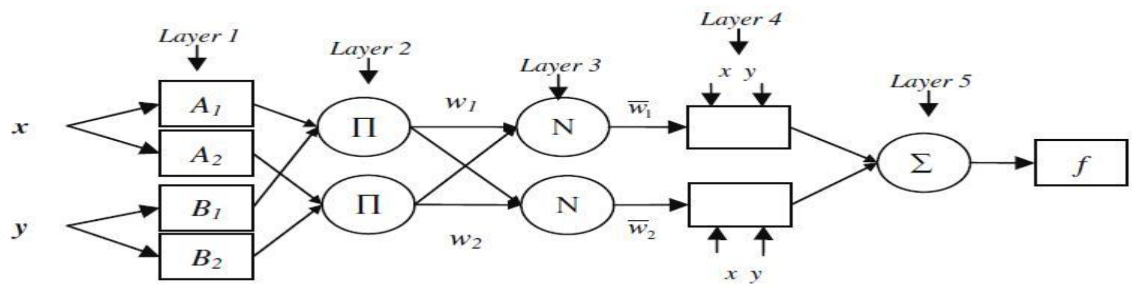


Fig. 3.6 Schematic Diagram of ANFIS Architecture

Layer1. Each node in this layer is an adjustable node, indicated by square node, with node function as

$$O_i^1 = \mu_{Ai}(X), \quad i = 1,2 \tag{3.6}$$

$$O_i^1 = \mu_{Bi-2}(Y), \quad i = 3,4 \tag{3.7}$$

Where, x (or y) is the input of node, Ai (or Bi) is the linguistic variable. The membership function (μ) generally adopts bell-shape with maximum and minimum equal to 1 and 0, respectively.

$$\mu_{Ai}(X) = \frac{1}{1 + \{(\left(X - \frac{c_i}{a_i}\right)^2)\}^{bi}} \tag{3.8}$$

Where, $\{a_i, b_i, c_i\}$ stands for the parameter set. If we change the values of these parameters set, the bell-shape function will be changed in accordance. Meanwhile, the membership functions are also different in linguistic label A. In this layer, the parameters are called as premise parameters.

Layer2. Each node in this layer is a fixed node, indicated by circle node, with node function to be multiplied by input signals to serve as output signal

$$O_i^2 = w_i = \mu_{Ai}(X) * \mu_{Bi}(Y), \quad i = 1,2 \tag{3.9}$$

The output signal w_i means the firing strength of a rule.

Layer3. Each node in this layer is a fixed node, indicated by circle node, in order to normalize firing strength with node function we must calculate the ratio of this node firing strength to the sum of $w_{1+}w_2$

The firing strength is:

$$O_i^3 = \overline{w_i} = \frac{w_i}{w_1 + w_2} \quad l = 1,2, \tag{3.10}$$

Layer4. Each node in this layer is an adjustable node, indicated by square node, with node function as

$$O_i^4 = \overline{w_i} f_i = w_l(p_i x + q_i y + r_i), \quad i = 1,2, \tag{3.11}$$

where, w_l is the output of Layer 3, $\{p_i, q_i, r_i\}$ is parameter set which is referred as the consequent parameters.

Layer5. Each node in this layer is a fixed node, indicated by circle node, with node function to compute the overall output by

$$O_i^5 = \Sigma_{i=1}^2 \overline{w_i} f_i = \frac{\Sigma_{i=1}^2 w_i}{w_1 + w_2}, \quad i = 1,2, \tag{3.12}$$

Explicitly, this layer sums the node's output in the previous layer to be the output of the whole network. From the frame works of ANFIS, it is observed that if the parameters in the premise part are fixed, the output of the whole network system will be the linear combination of the consequent parameters i.e.

$$f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 \tag{3.13}$$

based on this characteristic, the node outputs go forward till layer 4, the resulting parameters can be identified by the least square method in the forward learning.

On the other hand, the error signal goes backward till layer 1, the premise parameters can be updated by the gradient descent method in the backward learning. This learning procedure is referred as hybrid-learning. The merit of hybrid-learning procedure is to obtain the optimal premise parameters and consequent parameters in the learning process (Sobhani *et al*., 2010).

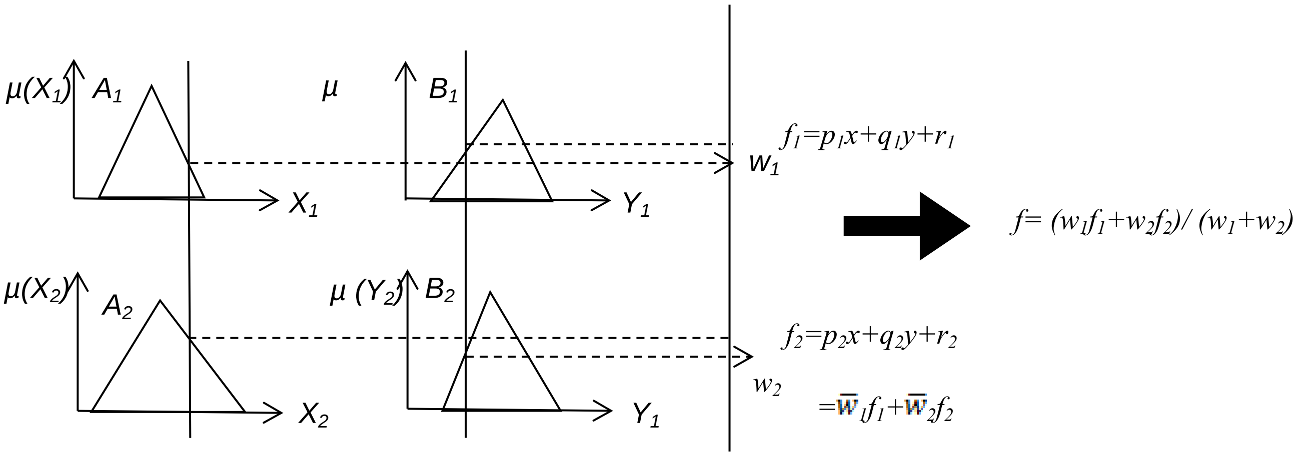


Fig. 3.7 Reasoning Scheme of ANFIS

3.4 BASICS OF MULTIPLE LINEAR REGRESSION (MLR) TECHNIQUE

Multiple linear regression determines the relationship between two or more independent variables and a dependent variable by fitting a linear equation to observed data. Every value of the independent variable is associated with a value of the dependent variable. The general purpose of Multiple Linear Regression (MLR) is to learn more about the relationship between several independent or predictor variables and a dependent or criterion variable. The Multiple Linear Regression (MLR) equation takes the form

$$Y=\beta_0+\beta_1X_1+\beta_2X_2+\beta_3X_3+\beta_4X_4+\beta_5X_5+ \text{-------} + \beta_nX_n \tag{3.14}$$

Where Y represents target result, X_1, X_2, X_3, X_4, X_5, --- X_n represents quality characteristics of input variables. The term linear is used because equation is linear function of the unknown parameter β_1, β_2, β_3, β_4 and β_5 are often called as partial regression coefficients. The term β_0 represents intercept.

CHAPTER 4

MATERIALS AND METHODS

4.0 GENERAL

The assessment of water quality in the municipal distribution system was carried out by finding Water Quality Index (WQI) in various zones of municipal distribution system. The Water Quality Index in various zones of the distribution system was calculated by considering six water quality parameters viz. pH, alkalinity, hardness, total solids, DO and MPN. The weighted index method was used to calculate water quality index. The prediction of water quality index was carried out by using various artificial intelligence techniques and multiple regression technique. The best fitting model was selected based on modelling performance criterions. The details of methodology followed, water quality data collection, calculation of WQI and modelling performance criterions are mentioned in the following sections of this chapter.

4.1 METHODOLOGY

A five step work methodology has been adopted for the study. Fig.4.1 shows the overview of methodology used in this study. MATLAB®7.10, Release14 has been used to develop Fuzzy, ANFIS and ANN models.

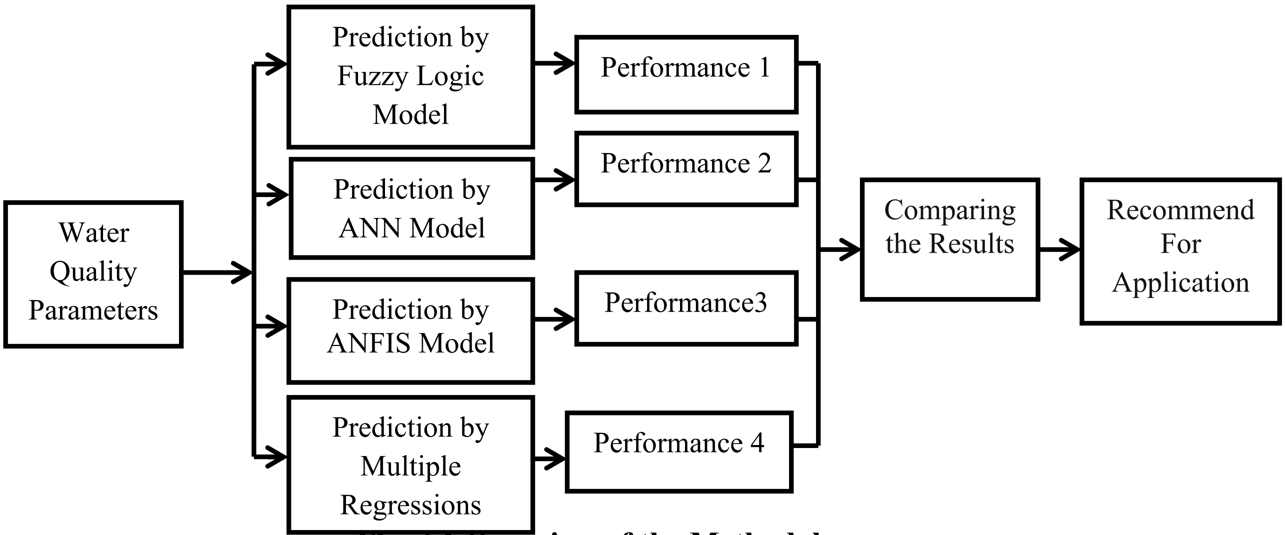


Fig. 4.1 Overview of the Methodology

4.2 DATA COLLECTION AND PREPROCESSING

The municipal water distribution system of Solapur, India, is taken as a case study for prediction and assessment of water quality in the distribution system. Solapur relies mainly on surface water supply for drinking, industrial and other domestic purposes. There are three sources of surface water supply: (1) Ujjani Dam Reservoir about 100 km west of the city, (2) Bhima River at village Takli about 30 km south of the city and (3) Ekrukh Tank near village Hipparga about 3 km north of main city. Arrangements have been made for direct supply of 90 million liters per day (MLD) of water to Solapur from Ujjani Dam, which is basically a hydro-electric-cum-irrigation project. Bhima river scheme at Takli is designed to supply about 120 MLD of water; it collects the released water from Ujjani Dam. Ekrukh Tank, constructed for irrigation purposes in 1871, can supply up to 27 MLD of water. There are three water treatment plants (water works) for these three water sources. To meet the fluctuations in the demand of water, the water from Ujjani Dam and Ekrukh Tank is mixed at Bhavani Peth water works and the water from all three water sources is mixed at Hill Service Reservoir, Jule Solapur. Fig.4.2 shows the location details of these three sources of water. The water quality at these three sources varies spatially and temporally. There is no fixed proportion of mixing of water at Bhavani Peth and Hill Service reservoir due to which, the resulting water quality is difficult to predict.

The water is distributed to Solapur city by dividing it into twenty nine zones, the location details of which are shown in Fig.4.2. The zone details are mentioned in Table 4.1. When water from these two mixing stations is distributed through network of pipes to various zones, the water quality in the distribution system deteriorates due to pipe age, corrosion of pipe material, intrusion of contaminants through leakage and cross connections, leaching of pipe material, formation of biofilm in the pipes etc., and hence many uncertainties are involved till the water reaches the consumers tap. The zone wise water quality data for year 2008, 2009 and 2010 was collected from Solapur Municipal Corporation, Solapur. The samples were collected monthly from all twenty nine zones and then physico-chemical properties of water Such as pH, dissolved oxygen, total alkalinity, total Hardness, total solids and most probable number were analysed as per standard method (APHA, 2005).

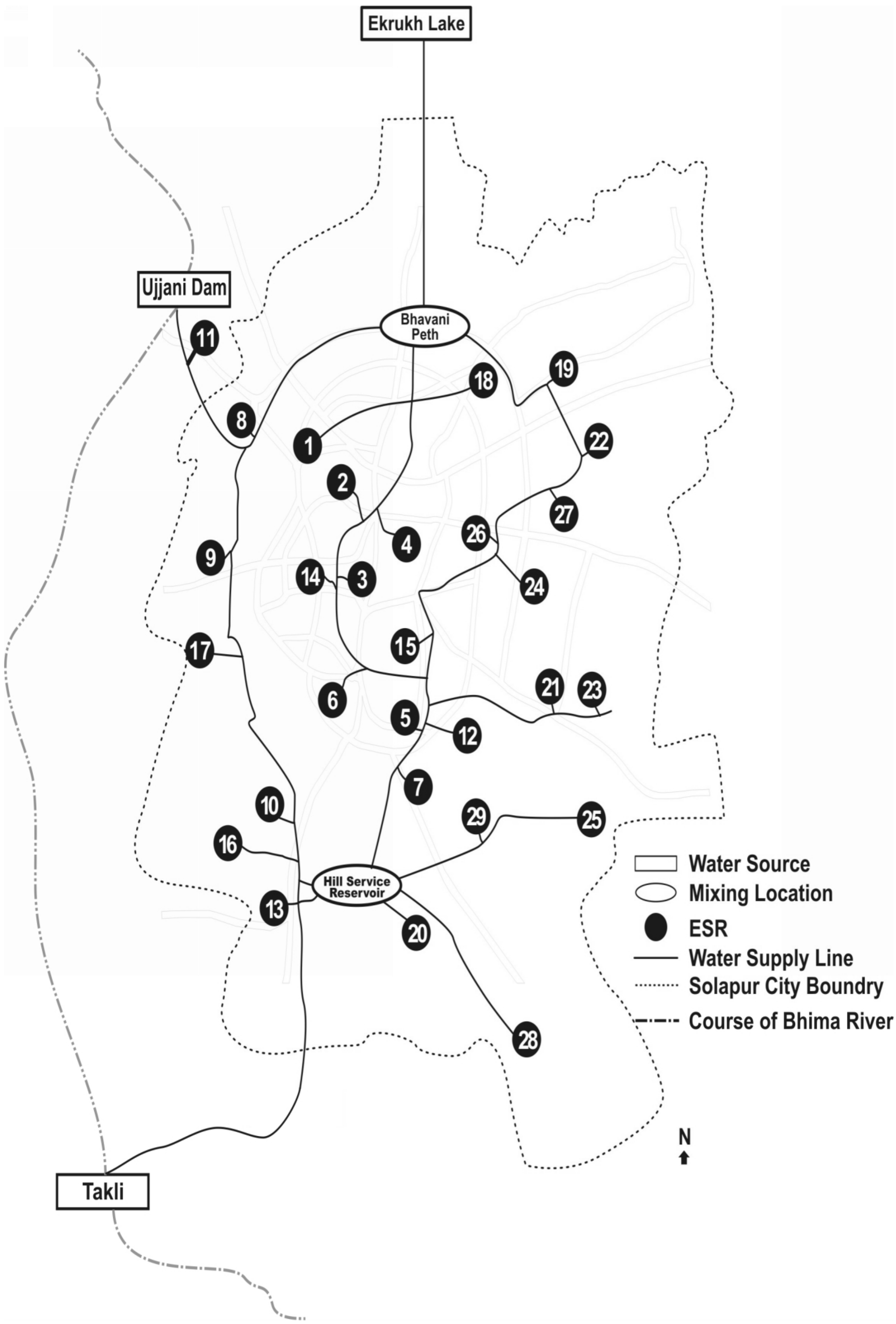


Fig. 4.2 Location Details of Water Sources

Table 4.1 Zone and Water Tank Location Details

Zone No.	Water Tank	Water Supply Area
1	Kasturba Budhwar Peth	Budhwar Peth, Balives Chowk area, Budhle lane, Sarda Plot, Samrat Chowk, Bhavani Peth ,Maratha Vasti, Tuljapur Ves, Kashi Kapde lane, Hanuman Nagar, Namdev Nagar, Homkar Nagar, Mantri Chandak Nagar, Sahir Vasti, Mukund Nagar, Ravji Sakharam Prashala.
2	Percival Area Near Parishad	South Kasba, North Kasba, Murarji Peth, Navi Peth, Datt Chowk, Mullababa Tekdi, Ramlal Chowk, Juni Mill Chawl, Zunje Lane, Tole Lane, Gavandi Area, Bakshi Lane, Mahalaxmi Milk Dairy till Panjrapol Chowk.
3	Siddheshwar Zilla Parishad Compound Area	Vijapur Ves, Foujdar Chawdi, Old Vitthal Mandir Area, Patva lane, Tilak Chowk Area, Mallikarjun Temple Area.
4	High-level Civil hospital	Shanivar Peth, Telangi Pacha Peth, Rahul Gandhi Slum area, Jamkhandi Bridge, Rajendra Chowk, Jodbasavanna Chowk, Kanna Chowk, Sakhar Peth, Ganesh Peth, Budhwar Market, Vijapur Ves till Kontam Chowk and Kumbhar Ves, Manik Chowk, Madhla Maruti Area, Shukurwar Peth, Jodbhavi Peth Area, Tilak Chowk Area, Guruwar Peth Area.
5	D.S.P Raised Area	Gandhinagar Area, Saat rasta Solapur Society, Gurunanak Nagar Chowk Area, Moulali Chowk, Qureshi lane, Darasha Hospital, Chuna Bhatti Area (Limestone Kiln Area) till Huma Hotel, Kumtha Naka Area, Milk Dairy.
6	D.S.P Lowered Area	Modi, Shoba Nagar, Saat Rasta Area, Soni Nagar, Morya Society, Revan Siddheshwar Nagar, Yetiraj Hotel till Modi police Station, Chintalwar Vasti, Pankha Vihir, Municipal Colony, Akanksha Society, Uplap Vasti, Shindhi Khana.
7	Jule Solapur Raised Area	Jule Solapur Area, Mhada Colony, Dhonde Nagar, Waman Nagar, Dnyaneshwar Nagar, Kalyan Nagar, Kinara Hotel, ESI Hospital, Antrolikar Nagar.
8	Avanti Nagar Water Tank	Avanti Nagar, Abhimanshri, Hande Plot, Mote Vasti, Jai Malhar Chowk, Prabhakar Maharaj Road, Mahesh Society, Bhagwati Society, S.T.Stand Area, Satyam Shivam Society.
9	Ujjani Main Line Mariaai Chowk	Mariaai Chowk, Damani Nagar, Thobde Vasti, Gavali Vasti, Bhaiyya Chowk, Degaon Deshmukh Patil Vasti, Amrai Shete Vasti, Pratiksha Colony, Habbu Vasti, Mithila Nagar, Ashirwad Nagar, Lakshmi Vishnu Chawl, Dongaon Road Area.

Table 4.1 Zone and Water Tank Location Details (Continued…….)

Zone No.	Water Tank	Water Supply Area
10	Indira Nagar Statue	Indira Nagar, Garibi Hatao Slums, Koli Samaj Society, Iranna Vasti, Utkarsh Nagar, Bhushan Nagar and other areas.
11	Bale Village Ujjani Crossroad	Bale Kegaon, Ambika Nagar, Barshi Road Area.
12	D.S.P Raised Area	Area behind Taluka police Station, Ambedkar Nagar, Vikas Nagar, Shikshak Society, Bharat Society, Gurunanak Nagar, Shandar Chowk, Shastri Nagar Slum Area, Keshav Nagar, Pandurang Vasti, Panchasheel Takshasheel Nagar.
13	Nehru Nagar Water Tank	Sundaram Nagar, Anand Nagar, Nirapam Society, Ashok Nagar, Nehru Nagar, S.T.Colony, Bennur Nagar, Mahalaxmi Nagar, Chatrapati Society, 22 Society Vijapur Road Area.
14	High Level	Railway line, Duffrin chowk, Employment Chowk Area, Railway Station Area.
15	High Level Round Tank	Bedarpool, Patrakar Nagar, Lodhi Lane Area.
16	Aditya Nagar	Sonamata Nagar, Mashal Vasti, Dwarka Nagar, Sushil Nagar, Kamala Nagar, Brhamachaitanya Nagar, Aditya Nagar, Nirmiti Vihar, Jai-Jui Nagar, Siddheshwar Nagar, Indira Nagar Area
17	Settlement Salgar Vasti Water Tank	Railway line, Duffrin chowk, Employment Chowk Area, Railway Station Area.
18	Dayanand Water Tank	Bhavanipeth, Ghongde Vasti, Indira Resident, Satpute Vasti, Jodbhavi peth, Netaji Nagar, Maddi Vasti.
19	Mehtab Nagar Tank	Shelgi Village, Ramdev Nagar, Amarnath Nagar and Area, Vidi Gharkul Area.
20	Jule Solapur	Lokmanya Nagar, Mantri Chandak Nagar, Industrial Estate, Nai Zindagi Area.
21	Mitragotri Gentyal Tank	M.I.D.C Area, Neelam Nagar, Akashwani Area, Vinayak Nagar, Sunil Nagar, Asha Nagar.
22	Percival Area Near Parishad	Vidi Gharkul A.B.C Group, Sagar Chowk, Rangraj Nagar, Rajeshwar Nagar, Sangameshwar Nagar.
23	Mitragotri Tank	Satyasai Nagar, Ashok Chowk, Sant Tukaram Chowk, Pacha Peth, Bapuji Nagar,Jawahar Nagar, Area Near Pathrut Chowk, Madhav Nagar, Kumtha Naka, Hudko.

Table 4.1 Zone and Water Tank Location Details (Continued…….)

Zone No.	Water Tank	Water Supply Area
24	Sadhu Waswani175 H.P	Karnik Nagar, Ekta Nagar, Padma Nagar, Saibaba Chowk, Satter Foot Road Area, Kamtam Nagar, Paccha Peth.
25	Sadhu Waswani75 H.P Pump	Extended Area Near Kumtha Naka, Huccheshwar Math Area, Swagat Nagar, 1,2 Krushna Society, Balaji society, Hanuman Nagar, Tai Chowk.
26	Bhadravati Tank	Bhadravati Peth, Datta Nagar, Ravivar Peth, Jodbhavi Peth, Jodbassavanna Chowk, Daji Peth, Joshi Area, Kavita Nagar,
27	High Level 150 H.P. Pump	Gawai Peth, Market Yard 256 Area, Shanti Nagar.
28	Jule Solapur	Gandhinagar 1 to 6 , Vidi Gharkul, Rangrj Nagar, Mahesh Nagar, A.B. Group, Venkatesh Nagar, Vajreshwar Nagar, Shewta Nagar, Kalpana Nagar, Konda Nagar, Yatiraj Nagar.
29	Low Level Round Tank	Hotgi Road, Hatture Area, Majrewadi Area. Lodhi Lane Area, Amarnath Nagar and Nai Zindagi Area.

4.2.1 Water Quality Index (WQI)

The Water Quality Index (WQI) was calculated for each month by using weighted index method and by considering six physico–chemical characteristics viz. pH, DO, alkalinity, hardness, total solids and MPN. Tables 4.2-4.30 show the physico-chemical characteristics of water and the calculated water quality indices (WQI) in various zones of city.

$$WQI = \sum \frac{Wiqi}{Wi} \qquad (4.1)$$

Where, q_i = Quality rating for the i water quality parameters (i = 1, 2, 3 ---------)

w_i = Unit weight of water quality.

Table 4.2 Physicochemical Characteristics of Water for Zone One

Month	pH	Alkalinity in mg/l	Hardness in mg/l	DO in mg/l	TS in mg/l	MPN /100ml	WQI
Jan.2008	7.36	176	228	3.84	402.4	0	90.8
Feb. 2008	7.26	132	148	6.6	648.7	0	94
Mar.2008	7.68	144	180	5.96	743	11	30.4
Apr.2008	7.85	152	168	6.28	613.8	0	93
May 2008	7.39	164	172	5.96	702.3	0	90.4
Jun. 2008	7.35	156	208	4.68	730.6	0	88
Jul. 2008	7.38	172	204	4.36	750.7	14	28
Aug. 2008	7.28	168	208	6.92	420.3	0	95.6
Sep.2008	7.79	160	212	6.28	424.2	21	35.6
Oct.2008	7.71	164	192	8.2	741.5	0	92.8
Nov.2008	7.35	156	196	8.52	670.2	0	95.4
Dec.2008	7.28	164	188	7.88	634.4	0	95.4
Jan. 2009	7.79	172	192	6.28	650.4	0	93
Feb. 2009	7.79	172	192	6.28	650.4	0	93
Mar. 2009	7.35	152	212	6.28	692.3	0	93
Apr. 2009	6.25	140	188	6.6	692.3	0	84
May 2009	6.83	192	192	6.28	831.1	0	88.6
Jun. 2009	6.89	160	196	6.92	678.7	0	91.2
Jul. 2009	6.45	152	192	5	748.2	8	43
Aug. 2009	7.5	232	196	7.24	797.2	9	56.8
Sep. 2009	7.32	144	192	8.12	500	11	95.4
Oct. 2009	6.35	156	196	5.32	525.6	0	84
Nov. 2009	7.12	160	192	6.28	521.2	5	69
Dec. 2009	7.1	164	184	6.92	518.1	0	93
Jan. 2010	7.1	156	188	6.92	520.4	20	33
Feb. 2010	6.83	160	188	4.68	518.7	0	88.8
Mar. 2010	6.69	148	192	5	510.5	0	88.8
Apr. 2010	7.44	156	192	6.28	505.6	0	93
May 2010	7.48	158	184	7.56	622.1	0	95.4
Jun. 2010	7.32	180	192	4.68	524.6	0	90.6
Jul. 2010	6.9	156	204	5.4	675.2	0	91.2
Aug. 2010	7.82	134	210	6.2	775.3	0	93
Sep. 2010	7.68	200	188	6.92	426.2	0	95.6
Oct. 2010	7.42	182	194	4.68	854.2	14	28
Nov. 2010	7.28	164	212	7.56	653.2	21	35.4
Dec. 2010	7.56	172	204	7.88	745.2	0	92.8

Table 4.3 Physicochemical Characteristics of Water for Zone Two

Month	pH	Alkalinity in mg/l	Hardness in mg/l	DO in mg/l	TS in mg/l	MPN /100ml	WQI
Jan.2008	6.98	164	200	4.68	684.2	17	30.6
Feb. 2008	7.96	108	200	6.92	689.9	11	32
Mar.2008	8	408	432	5.64	385.4	21	35.6
Apr.2008	7.87	168	212	7.56	536.2	11	35.4
May 2008	7.32	172	208	5.64	725	8	54.4
Jun. 2008	7.48	168	212	6.28	674.8	0	93
Jul. 2008	7.13	164	208	5.64	767.9	21	30.4
Aug. 2008	7.33	160	212	6.28	650.2	21	33
Sep.2008	8.18	156	204	6.28	996	21	27.8
Oct.2008	7.69	168	208	5	585	17	30.6
Nov.2008	7.86	148	192	7.56	604.2	17	35.4
Dec.2008	7.33	172	196	5.64	840.6	14	30.4
Jan. 2009	8.18	160	204	6.6	589.7	14	33
Feb. 2009	8.18	160	204	6.6	589.7	21	33
Mar. 2009	7.35	168	208	6.92	521.5	14	33
Apr. 2009	7.49	164	172	6.28	581.8	2	81
May 2009	7.49	372	180	5.64	551.8	21	33
Jun. 2009	7.55	168	176	6.6	590.2	20	33
Jul. 2009	7.56	160	172	5.64	566.3	17	33
Aug. 2009	7.6	136	176	6.28	572.3	21	33
Sep. 2009	7.96	164	172	5.96	652.8	21	33
Oct. 2009	7.56	164	180	5.32	663.9	11	33
Nov. 2009	7.65	172	196	5.64	652.1	21	33
Dec. 2009	7.55	148	196	5.96	647.2	21	33
Jan. 2010	7.71	164	192	6.28	654.7	21	33
Feb. 2010	7.63	152	192	5.32	670.2	21	33
Mar. 2010	7.7	156	184	5.64	657.8	20	30.6
Apr. 2010	7.79	164	204	5	680.2	20	33
May 2010	7.35	166	172	6.2	666.2	17	33
Jun. 2010	7.62	172	196	6.4	746.2	21	30.4
Jul. 2010	7.84	148	208	5.4	852.3	17	30.4
Aug. 2010	7.62	152	192	6.2	954.3	21	25.4
Sep. 2010	7.15	160	200	4.2	523.3	21	35.4
Oct. 2010	7.95	172	164	7.52	875.4	21	30.4
Nov. 2010	7.23	156	174	5.2	698.5	21	33
Dec. 2010	7.46	160	196	6.6	745.6	11	30.4

Table 4.4 Physicochemical Characteristics of Water for Zone Three

Month	pH	Alkalinity in mg/l	Hardness in mg/l	DO in mg/l	TS in mg/l	MPN /100ml	WQI
Jan.2008	6.58	184	208	3.4	602.6	0	82.8
Feb. 2008	7.85	160	192	8.84	616.1	0	95.4
Mar.2008	8	408	432	5.64	385.4	21	34.6
Apr.2008	7.39	164	212	7.24	716.9	9	56.8
May 2008	7.53	148	216	5.64	648.7	14	33
Jun. 2008	7.13	160	212	5	467.1	7	69.2
Jul. 2008	7.15	164	204	6.6	609.4	0	93
Aug. 2008	7.49	168	212	7.56	688.3	0	95.4
Sep.2008	7.74	152	208	5.64	670.3	0	93
Oct.2008	7.7	156	216	5.64	750.9	20	30.4
Nov.2008	7.73	180	216	9.48	774.4	0	92.8
Dec.2008	7.49	164	212	6.6	854	0	90.4
Jan. 2009	7.74	156	220	7.24	793.2	11	32.8
Feb. 2009	7.74	156	220	7.24	793.2	0	92.8
Mar. 2009	7.35	160	212	7.24	825.1	0	92.8
Apr. 2009	7.79	168	204	7.24	821.9	0	92.8
May 2009	7.38	148	204	6.92	848.6	0	90.4
Jun. 2009	7.46	168	196	5.32	716.4	21	30.4
Jul. 2009	7.78	136	196	5	840.4	0	88
Aug. 2009	7.74	116	208	7.88	823.6	0	92.8
Sep. 2009	7.69	148	212	6.28	810.5	0	90.4
Oct. 2009	7.55	140	204	5.32	830.3	0	90.4
Nov. 2009	7.89	152	212	6.28	813.4	2	78.4
Dec. 2009	7.85	168	216	7.24	862.8	0	92.8
Jan. 2010	7.34	152	208	5.32	807.8	0	90.4
Feb. 2010	7.46	144	204	6.28	804.1	0	90.4
Mar. 2010	7.73	160	196	4.04	871.2	0	88
Apr. 2010	7.39	160	196	5.64	880.7	0	90.4
May 2010	7.56	164	196	6.24	666.2	14	33
Jun. 2010	7.23	172	212	7.24	744.2	0	92.8
Jul. 2010	7.54	168	204	5.32	670.25	0	93
Aug. 2010	7.94	152	192	6.6	856.3	0	90.4
Sep. 2010	7.53	184	216	8.56	784.2	17	32.8
Oct. 2010	7.64	172	196	6.2	847.3	0	90.4
Nov. 2010	7.72	168	204	6.92	985.6	0	87.8
Dec. 2010	7.81	140	212	7.88	652.3	0	95.4

Table 4.5 Physicochemical Characteristics of Water for Zone Four

Month	pH	Alkalinity in mg/l	Hardness in mg/l	DO in mg/l	TS in mg/l	MPN /100ml	WQI
Jan.2008	7.3	180	210	4.5	600	14	30.6
Feb. 2008	7.67	180	188	7.88	680.7	21	35.4
Mar.2008	7.43	168	188	7.24	630.25	14	32.8
Apr.2008	7.45	176	188	7.88	708.3	0	95.4
May 2008	7.51	160	196	5.32	689.9	11	35.6
Jun. 2008	7.58	172	196	5.32	447.1	0	90.4
Jul. 2008	7.63	176	188	6.28	765.6	14	30.4
Aug. 2008	7.58	164	196	5.64	750.1	21	33
Sep.2008	7.84	168	220	6.92	695.9	0	90.4
Oct.2008	7.43	160	232	8.2	728.4	11	32.8
Nov.2008	7.86	180	236	6.6	836.4	8	57
Dec.2008	7.58	176	196	6.28	541.1	11	30.4
Jan. 2009	7.84	172	188	8.2	828.1	0	92.8
Feb. 2009	7.84	172	188	8.2	828.1	2	83.4
Mar. 2009	7.35	176	192	5.96	681.7	0	90.4
Apr. 2009	7.71	116	180	7.88	707.6	4	83.4
May 2009	7.99	176	184	6.28	692.1	8	54.4
Jun. 2009	7.33	156	172	5	718.3	0	88
Jul. 2009	7.56	152	172	6.92	700.3	21	33
Aug. 2009	7.59	192	172	5.96	688.3	11	35.6
Sep. 2009	7.83	160	176	6.6	486.5	14	33
Oct. 2009	7.36	152	176	6.28	478.8	14	33
Nov. 2009	7.26	180	180	5	471.2	14	30.6
Dec. 2009	7.39	156	196	6.28	474.5	21	33
Jan. 2010	7.44	168	204	5.64	478.1	5	69
Feb. 2010	7.33	144	208	4.68	470.6	0	90.6
Mar. 2010	7.45	160	212	8.2	482.4	0	95.4
Apr. 2010	7.48	148	204	6.92	892.2	0	90.4
May 2010	7.4	162	172	4.5	702.36	21	28
Jun. 2010	7.84	172	180	5.4	854.2	17	30.4
Jul. 2010	7.62	182	196	6.28	547.3	0	93
Aug. 2010	7.95	194	236	4.2	852.3	17	28
Sep. 2010	7.82	174	220	8.2	693.2	11	32.8
Oct. 2010	7.99	156	196	5.32	756.1	11	30.4
Nov. 2010	7.62	168	192	6.6	853.6	17	30.4
Dec. 2010	7.48	134	208	6.28	852.3	0	90.4

Table 4.6 Physicochemical Characteristics of Water for Zone Five

Month	pH	Alkalinity in mg/l	Hardness in mg/l	DO in mg/l	TS in mg/l	MPN /100ml	WQI
Jan.2008	7.42	160	212	5.96	689.6	0	93
Feb. 2008	7.89	176	216	6.28	650.4	0	93
Mar.2008	7.68	144	208	7.56	654.5	0	95.4
Apr.2008	7.6	164	236	6.6	722.2	0	90.4
May 2008	7.83	168	212	5.64	616.1	0	93
Jun. 2008	7.58	156	224	5	461.2	0	93.2
Jul. 2008	7.48	148	216	6.28	690.1	0	93
Aug. 2008	6.89	156	220	6.28	730.1	0	90.4
Sep.2008	7.67	164	228	7.56	770.7	0	92.8
Oct.2008	7.56	168	208	6.92	779.5	0	90.4
Nov.2008	7.84	156	240	8.52	806.4	0	92.8
Dec.2008	6.89	148	224	8.2	740.3	0	92.8
Jan. 2009	7.67	160	212	5.96	877.9	0	90.4
Feb. 2009	7.67	160	212	5.96	877.9	0	90.4
Mar. 2009	7.35	168	212	6.6	750.8	0	90.4
Apr. 2009	7.61	156	204	6.28	715.4	0	90.4
May 2009	7.56	160	196	7.88	750.1	0	90.4
Jun. 2009	7.47	180	188	5.32	720.3	0	90.4
Jul. 2009	7.62	160	188	7.88	740.1	0	90.4
Aug. 2009	7.7	144	184	6.28	754.8	21	30.4
Sep. 2009	7.78	144	188	5	923.4	0	87.8
Oct. 2009	7.52	156	192	5.96	936.2	0	87.8
Nov. 2009	7.59	160	188	5.64	721.4	0	90.4
Dec. 2009	7.63	144	184	5.64	926.3	0	90.4
Jan. 2010	7.4	176	188	5	941.4	0	87.8
Feb. 2010	7.47	164	192	4.04	937.8	0	87.8
Mar. 2010	7.48	164	188	4.36	948.6	0	87.8
Apr. 2010	7.55	168	188	6.28	957.8	0	87.8
May 2010	7.56	164	192	5.4	756.2	0	90.4
Jun. 2010	7.84	156	204	6.2	856	0	90.4
Jul. 2010	7.35	174	188	7.84	658.2	0	93
Aug. 2010	7.94	196	164	6.6	542	21	33
Sep. 2010	7.85	188	184	5.96	523.5	0	93
Oct. 2010	7.14	160	192	8.2	658.8	0	93
Nov. 2010	7.26	158	212	8.5	756.8	0	90.4
Dec. 2010	7.85	194	196	5.32	893.4	14	27.8

Table 4.7 Physicochemical Characteristics of Water for Zone Six

Month	pH	Alkalinity in mg/l	Hardness in mg/l	DO in mg/l	TS in mg/l	MPN /100ml	WQI
Jan.2008	7.48	168	212	4.68	671.1	0	90.6
Feb. 2008	7.82	88	200	6.92	589.7	0	93
Mar.2008	7.71	152	200	7.24	640.1	0	95.4
Apr.2008	7.72	180	200	5.64	709.5	0	90.4
May 2008	7.84	156	204	5.96	680.7	0	93
Jun. 2008	7.35	148	224	6.28	755.1	0	90.4
Jul. 2008	7.38	164	212	7.24	686.9	0	95.4
Aug. 2008	7.28	160	228	5.64	750	0	90.4
Sep.2008	7.96	152	208	6.28	700.5	0	90.4
Oct.2008	8	160	208	6.28	687.8	0	93
Nov.2008	7.92	164	232	7.56	789.5	0	92.8
Dec.2008	7.28	160	216	4.04	841.7	0	88
Jan. 2009	7.96	152	208	6.28	825.9	17	30.4
Feb. 2009	7.96	152	208	6.28	825.9	0	90.4
Mar. 2009	7.35	148	212	6.92	785	0	90.4
Apr. 2009	7.72	172	196	5.64	785	0	90.4
May 2009	7.67	164	192	5.64	742.3	0	90.4
Jun. 2009	7.69	156	196	5.64	719.1	0	90.4
Jul. 2009	7.71	144	196	6.28	730.4	11	30.4
Aug. 2009	7.73	188	192	7.24	730.9	0	92.8
Sep. 2009	7.94	168	196	7.24	813	0	92.8
Oct. 2009	7.26	160	192	5.32	788.2	0	90.4
Nov. 2009	7.89	156	184	5	814.6	0	88
Dec. 2009	7.56	152	196	7.24	807.2	0	92.8
Jan. 2010	7.44	148	192	4.68	820.2	0	88
Feb. 2010	7.69	160	196	3.4	824.6	0	85.6
Mar. 2010	7.56	152	184	5.96	830.4	0	90.4
Apr. 2010	7.46	172	204	5.64	880.8	0	90.4
May 2010	7.56	156	192	6.2	765.3	0	90.4
Jun. 2010	7.86	162	208	5.4	695.5	21	33
Jul. 2010	7.64	188	212	7.25	562.31	0	95.4
Aug. 2010	7.15	196	192	7.32	964.8	0	90.2
Sep. 2010	7.95	152	228	7.25	672.3	17	35.4
Oct. 2010	7.63	162	200	4.06	865.2	0	88
Nov. 2010	7.72	148	182	4.64	746.9	0	88
Dec. 2010	7.62	152	212	5.62	856.2	0	90.4

Table 4.8 Physicochemical Characteristics of Water for Zone Seven

Month	pH	Alkalinity in mg/l	Hardness in mg/l	DO in mg/l	TS in mg/l	MPN /100ml	WQI
Jan.2008	7.7	180	236	6.6	814.1	0	90.4
Feb. 2008	7.87	168	200	6.6	793.2	0	90.4
Mar.2008	7.69	160	220	7.24	792	0	92.8
Apr.2008	7.71	164	224	6.28	615.6	0	93
May 2008	7.49	160	212	5	686.9	0	90.6
Jun. 2008	7.49	168	208	5.96	700.1	0	90.4
Jul. 2008	7.65	168	204	6.92	702.3	0	90.4
Aug. 2008	7.63	164	208	6.6	796.1	0	90.4
Sep.2008	7.69	164	216	5.96	650.8	0	93
Oct.2008	7.78	168	208	6.6	499.9	0	95.6
Nov.2008	7.85	156	208	7.24	479.1	0	98
Dec.2008	7.69	168	196	6.28	450.5	0	95.6
Jan. 2009	7.69	160	192	7.24	447.9	0	98
Feb. 2009	7.69	160	192	7.24	479.1	0	98
Mar. 2009	7.35	168	188	5.96	450.5	0	95.6
Apr. 2009	7.89	156	192	6.28	447.9	0	95.6
May 2009	7.85	152	188	6.6	681.7	0	93
Jun. 2009	7.88	168	184	5.96	707.6	0	90.4
Jul. 2009	7.34	140	188	5.64	756.3	0	90.4
Aug. 2009	7.45	164	184	6.92	856.32	0	90.4
Sep. 2009	7.44	164	188	6.28	730.1	0	90.4
Oct. 2009	7.56	164	188	5.32	770.7	0	90.4
Nov. 2009	7.99	164	188	6.92	779.5	0	90.4
Dec. 2009	7.95	160	192	6.28	806.4	0	90.4
Jan. 2010	7.79	168	196	5	740.3	0	88
Feb. 2010	7.88	156	204	5	877.9	0	88
Mar. 2010	7.63	144	184	5.64	689.9	0	90.4
Apr. 2010	7.81	160	212	6.28	447.1	0	95.6
May 2010	7.68	156	224	6.2	765.6	14	30.4
Jun. 2010	7.74	152	192	7.24	750.1	0	92.8
Jul. 2010	7.98	160	196	5.4	695.9	0	93
Aug. 2010	7.85	152	188	6.42	728.4	0	90.4
Sep. 2010	7.83	168	208	5.84	836.4	0	90.4
Oct. 2010	7.74	156	196	6.4	541.1	0	93
Nov. 2010	7.93	196	184	7.26	828.1	0	92.8
Dec. 2010	7.52	180	216	8.45	828.1	0	92.8

Table 4.9 Physicochemical Characteristics of Water for Zone Eight

Month	pH	Alkalinity in mg/l	Hardness in mg/l	DO in mg/l	TS in mg/l	MPN /100ml	WQI
Jan.2008	7.7	200	212	4.36	685.9	0	90.6
Feb. 2008	7.86	192	200	5.96	828.1	0	90.4
Mar.2008	7.7	180	212	5.32	701.3	0	90.4
Apr.2008	7.91	168	200	5.64	410.5	0	95.6
May 2008	7.81	160	220	6.28	381.2	0	95.6
Jun. 2008	7.85	164	164	5.32	630.2	0	93
Jul. 2008	7.88	152	172	6.28	770.6	14	30.4
Aug. 2008	7.89	172	164	7.88	670	0	95.4
Sep.2008	7.83	168	208	6.6	649	0	93
Oct.2008	7.95	160	212	6.92	430.4	0	95.6
Nov.2008	7.38	164	192	8.2	635.6	0	95.4
Dec.2008	7.89	148	204	6.92	643.6	17	33
Jan. 2009	7.83	160	208	6.92	655.7	8	57
Feb. 2009	7.83	160	208	6.92	655.7	0	93
Mar. 2009	7.35	172	212	7.24	450.78	0	98
Apr. 2009	7.82	172	204	6.92	406.8	0	95.6
May 2009	7.39	124	196	6.92	419.8	0	95.6
Jun. 2009	7.6	136	192	6.28	417.3	0	95.6
Jul. 2009	7.44	156	196	6.6	426.5	0	95.6
Aug. 2009	7.48	160	180	5.96	433.1	0	95.6
Sep. 2009	7.98	172	196	5.64	499.9	0	95.6
Oct. 2009	7.26	148	184	3.4	479.1	0	90.8
Nov. 2009	7.32	168	188	6.28	450.5	0	95.6
Dec. 2009	7.36	144	188	6.92	447.9	0	95.6
Jan. 2010	7.39	144	196	6.28	501.4	0	93
Feb. 2010	7.6	168	212	6.92	505.3	0	93
Mar. 2010	7.83	156	208	5	509.1	0	90.6
Apr. 2010	7.3	164	196	5.32	498.1	0	95.6
May 2010	7.56	168	212	6.2	648.2	0	93
Jun. 2010	7.45	160	204	4.6	759.3	21	28
Jul. 2010	7.35	156	172	6.26	563.2	0	93
Aug. 2010	7.85	172	164	7.24	864.2	0	92.8
Sep. 2010	7.45	152	208	6.28	986.3	0	87.8
Oct. 2010	7.96	164	172	6.6	526.2	0	93
Nov. 2010	7.12	156	184	5.84	786.2	0	90.4
Dec. 2010	7.65	168	196	6.92	865.3	0	90.4

Table 4.10 Physicochemical Characteristics of Water for Zone Nine

Month	pH	Alkalinity in mg/l	Hardness in mg/l	DO in mg/l	TS in mg/l	MPN /100ml	WQI
Jan.2008	7.89	200	212	5	702.12	0	88
Feb. 2008	7.95	140	208	1.48	877.9	0	80.8
Mar.2008	7.43	168	208	5.32	727.9	0	90.4
Apr.2008	7.97	172	208	5.96	631.4	0	93
May 2008	7.57	164	208	5.64	387.1	0	95.6
Jun. 2008	7.68	176	204	5.64	751.8	0	90.4
Jul. 2008	7.54	184	216	6.28	734.7	0	90.4
Aug. 2008	7.58	168	208	7.24	694.1	0	95.4
Sep.2008	7.78	172	208	7.24	593.4	0	95.4
Oct.2008	7.68	172	204	4.04	589	0	90.6
Nov.2008	7.82	156	204	7.88	654.5	0	95.4
Dec.2008	7.58	180	208	6.6	674.2	0	93
Jan. 2009	7.78	164	216	6.28	616.2	0	93
Feb. 2009	7.78	164	216	6.28	616.2	8	57
Mar. 2009	7.35	148	216	6.28	501	0	93
Apr. 2009	7.45	180	208	5.96	502.3	0	93
May 2009	7.5	168	204	6.6	638	21	33
Jun. 2009	7.26	172	204	1.48	637.8	0	83.4
Jul. 2009	7.4	160	208	6.92	525.1	0	93
Aug. 2009	7.56	160	192	6.28	640.7	0	93
Sep. 2009	8.01	132	204	6.92	506.4	0	93
Oct. 2009	7.88	132	216	7.88	487.7	8	62
Nov. 2009	7.8	156	196	5.32	501	0	93
Dec. 2009	7.84	152	196	5.96	497.8	0	95.6
Jan. 2010	7.48	140	196	4.68	521.8	0	90.6
Feb. 2010	7.26	152	208	6.28	526.7	0	93
Mar. 2010	7.4	160	196	5.32	527.6	0	90.6
Apr. 2010	7.6	148	212	6.28	558.4	0	93
May 2010	7.3	156	202	6.2	562.3	0	93
Jun. 2010	7.64	172	216	5.6	745.6	21	30.4
Jul. 2010	7.25	140	192	4.2	625.3	0	90.6
Aug. 2010	7.96	164	208	7.25	756.8	0	80.8
Sep. 2010	7.84	180	212	5.46	854.6	0	90.4
Oct. 2010	7	184	192	6.62	986.3	0	87.8
Nov. 2010	7.36	180	204	7.45	568.4	0	95.4
Dec. 2010	7.25	152	216	6.6	743.2	0	90.4

Table 4.11 Physicochemical Characteristics of Water for Zone Ten

Month	pH	Alkalinity in mg/l	Hardness in mg/l	DO in mg/l	TS in mg/l	MPN /100ml	WQI
Jan.2008	7.69	168	224	5.32	695.2	0	93
Feb. 2008	7.85	172	204	6.28	743	0	90.4
Mar.2008	7.56	184	204	8.52	702.3	0	92.8
Apr.2008	7.57	180	192	7.24	784.6	0	92.8
May 2008	7.75	176	200	5.32	380.8	0	95.6
Jun. 2008	7.72	180	212	6.6	432.2	0	95.6
Jul. 2008	7.38	172	208	5.96	695.2	0	93
Aug. 2008	7.63	156	212	6.92	725	0	90.4
Sep.2008	7.35	168	204	6.92	669.3	0	93
Oct.2008	7.63	164	188	5.64	582.4	0	93
Nov.2008	7.36	176	200	6.28	680.2	0	93
Dec.2008	7.35	164	216	7.88	778.4	0	92.8
Jan. 2009	7.94	176	212	5.64	688.9	5	69
Feb. 2009	7.94	176	212	5.64	688.9	0	93
Mar. 2009	7.35	164	208	6.28	495.3	0	95.6
Apr. 2009	7.55	176	192	6.28	627	8	57
May 2009	7.6	172	188	6.28	788.4	0	90.4
Jun. 2009	7.56	160	196	4.04	778.2	0	88
Jul. 2009	7.44	164	188	5	787.4	0	88
Aug. 2009	7.4	155	180	5.96	780.7	0	90.4
Sep. 2009	7.3	168	196	6.6	563.3	0	93
Oct. 2009	7.46	168	192	4.68	533.3	0	90.6
Nov. 2009	7.45	148	200	6.28	559.1	0	93
Dec. 2009	7.5	164	208	5.64	495.3	0	95.6
Jan. 2010	7.55	160	200	4.68	527.5	0	90.6
Feb. 2010	7.56	168	192	3.72	530.2	8	52.2
Mar. 2010	7.5	152	184	6.28	530.7	0	93
Apr. 2010	7.42	156	188	5.64	765.2	0	90.4
May 2010	7.56	164	200	6.6	562.36	0	93
Jun. 2010	7.84	152	212	6.5	826.6	0	90.4
Jul. 2010	7.26	168	196	4.5	946.2	14	25.4
Aug. 2010	7.89	172	204	5.15	523.2	0	93
Sep. 2010	7.64	196	188	4.91	723.2	0	88
Oct. 2010	7.75	176	180	5.5	865.3	7	66.4
Nov. 2010	7	160	192	7.25	562.3	0	95.4
Dec. 2010	7.45	164	208	5.16	963.5	0	87.8

Table 4.12 Physicochemical Characteristics of Water for Zone Eleven

Month	pH	Alkalinity in mg/l	Hardness in mg/l	DO in mg/l	TS in mg/l	MPN /100ml	WQI
Jan.2008	7.5	154	235	7.25	710.52	0	92.8
Feb. 2008	7.86	164	204	5.5	385.4	0	95.6
Mar.2008	8	188	204	5.96	725	0	90.4
Apr.2008	7.85	136	156	5.96	642.2	0	93
May 2008	7.12	164	192	5	687.8	0	90.6
Jun. 2008	7.18	160	192	5.64	778.6	0	90.4
Jul. 2008	7.53	156	196	6.28	687.3	0	93
Aug. 2008	7.25	164	192	6.28	670.2	0	93
Sep.2008	7.44	160	216	7.56	751.2	0	92.8
Oct.2008	7.92	168	212	3.4	684.4	0	88.2
Nov.2008	7.81	168	196	8.84	620.6	0	95.4
Dec.2008	7.86	172	188	6.28	702.9	0	90.4
Jan. 2009	7.44	168	196	6.28	866.4	8	54.4
Feb. 2009	7.44	168	196	6.28	866.4	0	90.4
Mar. 2009	7.35	172	196	8.52	863.5	0	92.8
Apr. 2009	7.89	192	192	7.24	650.6	0	95.4
May 2009	7.79	164	188	5	679.8	0	90.6
Jun. 2009	7.39	164	196	3.72	624.1	11	28.2
Jul. 2009	7.79	152	192	6.28	677.3	0	93
Aug. 2009	7.83	140	196	6.6	680.2	0	93
Sep. 2009	7.15	164	200	5.64	505.9	0	93
Oct. 2009	7.78	160	196	4.68	664.5	14	30.6
Nov. 2009	7.65	136	204	6.28	509.6	0	93
Dec. 2009	7.37	140	208	6.28	513.4	0	93
Jan. 2010	7.46	168	212	6.28	501.7	0	93
Feb. 2010	7.39	176	204	5	507.8	0	90.6
Mar. 2010	7.59	168	212	5.64	503.2	0	93
Apr. 2010	9.85	152	204	6.6	523.4	0	93
May 2010	7.56	168	196	6.2	698.2	0	93
Jun. 2010	7.86	172	192	5.4	756.5	0	90.4
Jul. 2010	7.36	156	184	4.2	563.7	0	90.6
Aug. 2010	7.45	172	172	3.84	854.6	21	25.6
Sep. 2010	7.96	196	204	7.53	742.6	0	92.8
Oct. 2010	7.25	184	212	5.4	982.3	14	27.8
Nov. 2010	7.64	136	204	6.6	568.2	0	93
Dec. 2010	7.45	144	196	6.6	745.1	0	90.4

Table 4.13 Physicochemical Characteristics of Water for Zone Twelve

Month	pH	Alkalinity in mg/l	Hardness in mg/l	DO in mg/l	TS in mg/l	MPN /100ml	WQI
Jan.2008	7.51	132	204	5.64	703.9	0	90.4
Feb. 2008	7.83	152	216	6.92	628.2	20	33
Mar.2008	7.78	144	196	5.64	648.7	21	33
Apr.2008	7.71	176	212	6.92	684.7	7	69
May 2008	7.52	176	200	5.64	706.7	14	30.4
Jun. 2008	7.58	168	212	4.68	749.4	0	90.4
Jul. 2008	7.83	160	208	5.96	876.8	0	90.4
Aug. 2008	7.29	168	212	5.96	725	0	90.4
Sep.2008	7.98	172	220	6.28	750	0	90.4
Oct.2008	8.03	172	216	5	856.3	0	88
Nov.2008	7.89	152	212	7.24	883	0	92.8
Dec.2008	7.73	160	220	5.64	896.3	0	90.4
Jan. 2009	7.98	172	212	7.24	878.4	5	68.8
Feb. 2009	7.98	172	212	7.24	878.4	0	92.8
Mar. 2009	7.35	160	208	6.28	753.4	0	90.4
Apr. 2009	7.23	168	200	6.92	330.7	0	95.6
May 2009	7.34	160	196	6.6	304.3	0	95.6
Jun. 2009	7.12	152	208	6.92	324.6	0	95.6
Jul. 2009	7.39	168	208	6.92	306.8	21	35.6
Aug. 2009	7.4	160	212	5.96	324.3	0	95.6
Sep. 2009	7.85	156	208	5.32	863.5	17	30.4
Oct. 2009	7.49	148	208	5.32	860.4	0	90.4
Nov. 2009	7.5	156	212	6.6	860.2	8	54.4
Dec. 2009	7.48	156	216	6.92	856.3	21	30.4
Jan. 2010	7.79	164	208	7.24	865.5	8	56.8
Feb. 2010	7.12	160	208	4.68	870.4	21	28
Mar. 2010	7.48	148	204	5.32	807.2	0	90.4
Apr. 2010	7.77	160	212	7.24	868.7	0	92.8
May 2010	7.45	164	204	5.4	733.4	0	90.4
Jun. 2010	7.75	188	212	4.6	753.4	21	28
Jul. 2010	7.84	174	192	5.4	840.2	0	90.4
Aug. 2010	7.61	196	188	7.26	741.2	0	92.8
Sep. 2010	7.96	184	212	4.64	738.7	0	88
Oct. 2010	7.63	160	216	5.62	748.5	17	30.4
Nov. 2010	7.35	174	208	6.6	740.6	0	90.4
Dec. 2010	7.71	160	212	8.25	856.32	0	92.8

Table 4.14 Physicochemical Characteristics of Water for Zone Thirteen

Month	pH	Alkalinity in mg/l	Hardness in mg/l	DO in mg/l	TS in mg/l	MPN /100ml	WQI
Jan.2008	7.7	196	200	5.32	645.3	0	93
Feb. 2008	7.47	184	216	6.6	630.25	0	93
Mar.2008	7.95	180	216	7.56	689.9	0	95.4
Apr.2008	7.74	176	188	6.6	582.3	0	93
May 2008	7.69	156	208	6.28	648.7	0	93
Jun. 2008	7.53	144	212	6.92	710.3	17	30.4
Jul. 2008	7.53	156	216	7.24	706.2	17	32.8
Aug. 2008	7.7	156	212	6.92	691.2	0	93
Sep.2008	8.01	160	208	6.28	596.6	0	93
Oct.2008	7.58	152	204	6.28	678.4	0	93
Nov.2008	8.13	176	188	7.88	619.8	0	95.4
Dec.2008	7.86	144	196	7.56	755.6	0	95.4
Jan. 2009	8.01	160	204	6.92	619.5	0	93
Feb. 2009	8.01	160	204	6.92	619.5	21	33
Mar. 2009	7.35	172	212	7.56	889.3	0	92.8
Apr. 2009	7.89	160	192	6.28	553.4	21	33
May 2009	7.78	168	188	6.92	587.6	0	93
Jun. 2009	7.45	164	212	6.28	542.1	0	93
Jul. 2009	7.48	164	216	6.28	592.1	2	93
Aug. 2009	7.5	152	208	6.28	590.5	0	93
Sep. 2009	7.63	160	212	3.72	471.3	0	90.8
Oct. 2009	7.68	156	208	4.68	495.9	0	93.2
Nov. 2009	7.65	164	208	6.92	481.6	0	95.6
Dec. 2009	7.36	160	204	6.92	487.7	0	95.6
Jan. 2010	7.34	156	192	5.32	511.3	0	93
Feb. 2010	7.45	140	196	5	513.4	0	90.6
Mar. 2010	7.89	164	184	6.28	519.3	0	93
Apr. 2010	7.58	164	196	5.96	570.8	0	93
May 2010	7.89	172	216	6.2	750.7	0	90.4
Jun. 2010	7.54	184	208	7.26	726.4	12	32.8
Jul. 2010	7.69	196	204	5.4	730.6	0	90.4
Aug. 2010	7.96	152	204	6.2	714.2	0	90.4
Sep. 2010	8.12	160	208	6.4	656.7	0	93
Oct. 2010	7.53	144	192	5.4	764.3	0	90.4
Nov. 2010	7.95	152	204	5.2	714.5	17	30.4
Dec. 2010	7.12	176	216	5.8	653.2	0	93

Table 4.15 Physicochemical Characteristics of Water for Zone Fourteen

Month	pH	Alkalinity in mg/l	Hardness in mg/l	DO in mg/l	TS in mg/l	MPN /100ml	WQI
Jan.2008	7.3	124	196	5	626.2	0	90.6
Feb. 2008	7.69	168	192	5.96	654.5	0	93
Mar.2008	7.68	176	196	6.6	616.1	0	93
Apr.2008	7.78	160	204	5.96	1011	0	82.6
May 2008	7.61	148	212	6.6	689.9	5	69
Jun. 2008	7.46	160	208	6.28	733.5	8	54.4
Jul. 2008	7.89	164	208	6.6	708.5	21	30.4
Aug. 2008	7.3	160	208	7.24	716.8	21	32.8
Sep.2008	7.64	172	212	5.64	696.8	0	93
Oct.2008	7.63	164	204	5.96	690.8	0	93
Nov.2008	7.56	176	228	9.8	790.2	21	32.8
Dec.2008	7.84	156	216	8.1	786	11	32.8
Jan. 2009	7.3	148	212	8.84	820.7	0	92.8
Feb. 2009	7.3	148	212	8.84	820.7	1	92.8
Mar. 2009	7.35	164	220	6.92	652.3	21	33
Apr. 2009	7.85	148	208	6.28	717.8	0	90.4
May 2009	7.56	156	204	6.28	748.3	0	90.4
Jun. 2009	7.57	168	196	6.6	713.3	14	30.4
Jul. 2009	7.55	168	208	5.96	750.6	0	90.4
Aug. 2009	7.59	180	204	6.92	743.6	0	90.4
Sep. 2009	7.76	152	208	5.64	733.4	21	30.4
Oct. 2009	7.55	168	204	5.32	753.4	11	30.4
Nov. 2009	7.5	148	204	6.6	840.2	21	30.4
Dec. 2009	7.55	164	212	6.28	741.2	0	90.4
Jan. 2010	7.78	148	212	5.96	738.7	0	90.4
Feb. 2010	7.57	156	196	4.36	748.5	21	28
Mar. 2010	7.85	164	188	6.92	740.6	0	90.4
Apr. 2010	7.45	160	188	6.28	750.2	0	90.4
May 2010	7.86	164	208	5.4	420.7	0	95.6
Jun. 2010	7.76	156	196	4.6	447.2	0	93.2
Jul. 2010	7.82	184	192	6.6	425.7	0	95.6
Aug. 2010	7.76	172	188	5.8	438	21	35.6
Sep. 2010	7.76	148	192	4.4	423.8	0	93.2
Oct. 2010	7.35	156	196	5.6	431.9	11	35.6
Nov. 2010	7.77	164	196	6.6	426.7	0	95.6
Dec. 2010	7.78	196	208	5.2	437.8	0	95.6

Table 4.16 Physicochemical Characteristics of Water for Zone Fifteen

Month	pH	Alkalinity in mg/l	Hardness in mg/l	DO in mg/l	TS in mg/l	MPN /100ml	WQI
Jan.2008	7.15	232	196	7.24	696.3	0	95.4
Feb. 2008	7.79	216	204	7.88	640.1	0	95.4
Mar.2008	7.63	168	208	8.2	680.7	0	95.4
Apr.2008	7.97	156	216	6.28	676.2	0	93
May 2008	7.53	152	224	7.88	616.1	0	95.4
Jun. 2008	7.83	156	216	6.6	750.7	0	90.4
Jul. 2008	7.38	168	212	7.24	726.4	0	92.8
Aug. 2008	7.15	164	216	6.92	730.6	0	90.4
Sep.2008	7.34	160	208	7.24	714.2	0	92.8
Oct.2008	7.35	156	200	8.2	656.7	0	95.4
Nov.2008	7.35	156	224	7.9	764.3	0	92.8
Dec.2008	7.92	148	212	7.56	714.5	0	92.8
Jan. 2009	7.15	156	212	5.32	733.4	0	90.4
Feb. 2009	7.15	156	212	5.32	733.4	0	90.4
Mar. 2009	7.35	168	212	6.6	482.9	8	59.6
Apr. 2009	7.88	160	212	5.64	799.2	0	90.4
May 2009	7.64	168	196	7.24	778.1	0	92.8
Jun. 2009	7.58	168	204	7.24	793.2	14	32.8
Jul. 2009	7.46	160	196	6.92	789.4	11	30.4
Aug. 2009	7.48	144	212	6.28	783.4	0	90.4
Sep. 2009	7.89	168	216	6.28	511.2	21	33
Oct. 2009	7.46	144	212	7.24	506.8	0	95.4
Nov. 2009	7.42	152	216	6.28	498.5	21	35.6
Dec. 2009	7.69	152	208	5.96	832.2	0	90.4
Jan. 2010	7.56	132	204	6.28	888.5	11	30.4
Feb. 2010	7.85	164	212	6.28	880.6	0	90.4
Mar. 2010	7.88	152	204	5.96	900.3	0	87.8
Apr. 2010	7.48	144	212	3.72	627.8	0	88.2
May 2010	7.64	168	196	5.4	753.2	0	90.4
Jun. 2010	7.53	142	172	6.2	796.2	0	90.4
Jul. 2010	7.89	196	202	7.24	856.2	21	32.8
Aug. 2010	7.96	188	206	6.4	965.3	0	87.8
Sep. 2010	7.42	164	220	8.24	653.2	21	35.4
Oct. 2010	7.63	144	212	5.88	853.2	0	90.4
Nov. 2010	7.84	172	196	6.6	963.5	0	87.8
Dec. 2010	7.26	176	188	8.2	759.3	14	32.8

Table 4.17 Physicochemical Characteristics of Water for Zone Sixteen

Month	pH	Alkalinity in mg/l	Hardness in mg/l	DO in mg/l	TS in mg/l	MPN /100ml	WQI
Jan.2008	7.85	136	204	4.68	726	0	88
Feb. 2008	8.18	180	228	5.64	792	0	90.4
Mar.2008	7.92	184	212	6.6	686.9	0	93
Apr.2008	7.86	168	204	8.2	641.7	0	95.4
May 2008	7.61	172	220	6.6	680.7	0	93
Jun. 2008	7.93	168	204	6.6	767.9	0	90.4
Jul. 2008	7.35	164	216	6.92	718.9	0	90.4
Aug. 2008	7.85	168	212	7.88	674.8	0	95.4
Sep.2008	8.18	164	212	6.92	650	0	93
Oct.2008	7.86	152	220	5.96	591.5	0	93
Nov.2008	7.85	152	192	8.2	629.2	0	95.4
Dec.2008	7.85	160	196	7.24	712.8	0	92.8
Jan. 2009	7.85	172	192	7.56	650.3	0	95.4
Feb. 2009	7.85	172	192	7.56	650.3	0	95.4
Mar. 2009	7.35	176	188	6.92	437.8	0	95.6
Apr. 2009	7.65	160	188	7.24	657.8	0	95.4
May 2009	7.89	156	188	5.64	688.9	0	93
Jun. 2009	7.85	140	184	6.28	667.8	0	93
Jul. 2009	7.81	152	196	6.6	680.4	0	93
Aug. 2009	7.67	408	196	5.32	692.8	0	93
Sep. 2009	7.3	160	192	7.24	661.4	11	35.4
Oct. 2009	7.66	172	188	3.72	660.6	0	88.2
Nov. 2009	7.64	168	196	5.32	669.8	0	93
Dec. 2009	7.89	160	192	5.64	668.1	0	93
Jan. 2010	7.64	152	164	7.24	658.2	0	95.4
Feb. 2010	7.23	160	172	3.72	652.5	0	88.2
Mar. 2010	7.65	156	184	6.28	647.6	0	93
Apr. 2010	7.56	156	196	5	678.4	0	90.6
May 2010	7.56	164	204	5.8	582.4	0	93
Jun. 2010	7.23	198	212	6.6	680.2	0	93
Jul. 2010	7.98	196	204	4.4	778.4	0	88
Aug. 2010	7.45	136	208	7.62	688.9	17	35.4
Sep. 2010	7.12	146	212	6.8	688.9	0	93
Oct. 2010	7.98	124	216	5.2	495.3	0	95.6
Nov. 2010	7.45	184	196	8.16	627	14	35.4
Dec. 2010	7.63	172	188	5.4	788.4	0	90.4

Table 4.18 Physicochemical Characteristics of Water for Zone Seventeen

Month	pH	Alkalinity in mg/l	Hardness in mg/l	DO in mg/l	TS in mg/l	MPN /100ml	WQI
Jan.2008	7.63	116	152	5	763.2	0	88.4
Feb. 2008	7.74	148	208	1.75	701.3	0	80.8
Mar.2008	8.03	168	208	7.24	381.2	0	98
Apr.2008	7.73	136	152	7.24	650.1	0	95.4
May 2008	7.79	152	216	5	650.4	14	30.6
Jun. 2008	7.15	160	208	5.96	609.4	0	93
Jul. 2008	7.58	168	204	7.24	671.2	0	95.4
Aug. 2008	7.63	172	208	6.92	467.1	0	95.6
Sep.2008	7.74	168	224	7.56	702.1	0	92.8
Oct.2008	7.73	164	220	6.92	457.4	0	95.6
Nov.2008	7.63	156	168	7.88	466.5	0	98
Dec.2008	7.38	152	176	7.56	489.3	0	98
Jan. 2009	7.63	152	180	6.92	486	0	95.6
Feb. 2009	7.63	152	180	6.92	486	0	95.6
Mar. 2009	7.35	156	192	5.96	420.3	0	95.6
Apr. 2009	9.85	136	188	6.92	477.2	0	95.6
May 2009	7.67	160	188	6.92	594.3	0	93
Jun. 2009	7.23	164	180	1.8	595	0	83.4
Jul. 2009	7.3	144	184	3.4	547.2	0	88.2
Aug. 2009	7.45	144	188	6.28	580.5	21	33
Sep. 2009	7.36	140	184	6.28	482.9	0	95.6
Oct. 2009	7.86	160	200	4.68	492.7	14	35.6
Nov. 2009	7.88	156	196	6.28	487.4	0	95.6
Dec. 2009	7.23	136	192	5.32	479.4	0	95.6
Jan. 2010	7.63	144	184	5.64	926.3	0	87.8
Feb. 2010	7.56	144	184	4.68	430.1	4	83.6
Mar. 2010	9.85	148	196	5.64	513.7	0	93
Apr. 2010	7.48	164	192	6.28	486	0	95.6
May 2010	7.5	160	196	5.4	556.3	0	93
Jun. 2010	7.68	168	174	6.6	783.5	0	90.4
Jul. 2010	7.45	172	184	6.92	856.6	0	90.4
Aug. 2010	7.89	172	212	5.4	693.4	17	33
Sep. 2010	7.63	152	220	7.56	986.5	0	90.2
Oct. 2010	7.45	160	184	5.84	894.1	14	30.4
Nov. 2010	7.56	172	164	6.2	589.6	0	93
Dec. 2010	7.29	172	172	6.63	965.2	0	87.8

Table 4.19 Physicochemical Characteristics of Water for Zone Eighteen

Month	pH	Alkalinity in mg/l	Hardness in mg/l	DO in mg/l	TS in mg/l	MPN /100ml	WQI
Jan.2008	7.76	192	144	3.72	428.5	0	91.8
Feb. 2008	7.84	192	168	8.2	727.9	10	32.8
Mar.2008	7.58	180	144	6.28	387.1	0	96.6
Apr.2008	7.86	132	168	5.32	478.2	11	35.6
May 2008	7.35	160	180	5.64	589.7	8	57
Jun. 2008	7.31	156	184	5.64	765.4	0	90.4
Jul. 2008	7.83	164	192	6.28	567.4	0	93
Aug. 2008	7.76	160	184	5.64	447.1	21	35.6
Sep.2008	7.84	172	208	6.92	555.2	21	33
Oct.2008	7.86	168	236	6.92	414	0	95.6
Nov.2008	7.76	156	172	7.24	500.1	20	35.4
Dec.2008	7.82	164	180	6.28	478.3	0	95.6
Jan. 2009	7.76	160	184	7.88	496.3	8	62
Feb. 2009	7.76	160	184	7.88	496.3	21	38
Mar. 2009	7.35	152	188	6.28	892.1	0	90.4
Apr. 2009	7.77	148	172	6.28	420.7	0	95.6
May 2009	7.78	148	168	6.28	447.2	0	95.6
Jun. 2009	7.56	152	184	5	425.7	0	93.2
Jul. 2009	7.6	144	188	7.24	438	11	38
Aug. 2009	7.62	168	188	4.68	423.8	0	93.2
Sep. 2009	7.55	164	188	5.96	431.9	21	35.6
Oct. 2009	7.56	152	188	6.28	426.7	0	95.6
Nov. 2009	7.59	144	192	5.96	437.8	14	35.6
Dec. 2009	7.89	152	196	6.28	440.2	0	95.6
Jan. 2010	7.67	164	196	4.68	427.8	14	33.2
Feb. 2010	7.43	156	192	5	427	0	93.2
Mar. 2010	7.77	172	204	5.32	432.4	0	95.6
Apr. 2010	7.89	160	188	5	450.8	0	93.2
May 2010	7.62	172	162	5.8	695.3	0	93
Jun. 2010	7.84	148	174	6.6	526.3	0	93
Jul. 2010	7.23	156	196	6.2	452.3	21	35.6
Aug. 2010	7.96	172	184	7.28	526.3	0	95.4
Sep. 2010	7.84	196	192	7.44	478.6	0	98
Oct. 2010	7.52	184	196	6.2	658.1	17	33
Nov. 2010	7.45	144	188	6.6	586.5	0	93
Dec. 2010	7.86	182	192	5.8	451	0	95.6

Table 4.20 Physicochemical Characteristics of Water for Zone Nineteen

Month	pH	Alkalinity in mg/l	Hardness in mg/l	DO in mg/l	TS in mg/l	MPN /100ml	WQI
Jan.2008	7.89	144	152	4.68	384.6	0	93.2
Feb. 2008	7.67	124	164	7.24	702.3	0	92.8
Mar.2008	7.63	132	168	6.6	380.8	0	95.6
Apr.2008	7.84	132	176	5.96	381.7	0	95.6
May 2008	7.49	164	172	6.28	793.2	0	90.4
Jun. 2008	7.48	172	176	5.96	690.1	0	93
Jul. 2008	7.83	156	192	6.6	625.4	0	33
Aug. 2008	7.89	164	176	6.6	461.2	0	95.6
Sep.2008	7.67	160	176	7.24	394.4	0	38
Oct.2008	7.84	168	201	8.2	439.9	0	38
Nov.2008	7.89	160	184	6.6	485.2	0	35.6
Dec.2008	7.31	156	184	5.64	765.4	0	90.4
Jan. 2009	7.69	160	192	7.24	494.2	0	98
Feb. 2009	7.35	160	164	7.24	479.7	0	38
Mar. 2009	7.35	164	196	5.64	780.8	0	90.4
Apr. 2009	7.58	156	180	6.28	440.9	0	35.6
May 2009	7.62	156	164	6.6	457.2	0	95.6
Jun. 2009	7.43	160	180	4.68	437.1	0	93.2
Jul. 2009	7.42	164	192	5.96	448.2	0	95.6
Aug. 2009	7.45	144	192	6.28	462.6	0	95.6
Sep. 2009	7.45	136	192	6.28	428.4	0	95.6
Oct. 2009	7.58	144	204	5	420.3	0	93.2
Nov. 2009	7.5	160	208	5.32	425.7	0	95.6
Dec. 2009	7.85	160	212	7.24	421.6	0	98
Jan. 2010	7.78	152	204	5.64	422.3	0	95.6
Feb. 2010	7.56	160	176	5.32	931.4	0	87.8
Mar. 2010	7.58	160	196	6.28	429.6	0	95.6
Apr. 2010	7.85	144	196	6.28	478.7	0	95.6
May 2010	7.56	132	184	5.3	546.9	0	93
Jun. 2010	7.32	144	192	5.8	658.2	8	57
Jul. 2010	7.63	136	192	6.6	458.6	0	95.6
Aug. 2010	7.96	156	204	7.24	586.2	0	95.4
Sep. 2010	7.85	168	212	6.6	456.3	0	95.6
Oct. 2010	7.75	172	210	8.48	485.2	0	98
Nov. 2010	7.89	132	180	4.8	548.2	0	90.6
Dec. 2010	7.42	160	164	6.4	486.2	0	95.6

Table 4.21 Physicochemical Characteristics of Water for Zone Twenty

Month	pH	Alkalinity in mg/l	Hardness in mg/l	DO in mg/l	TS in mg/l	MPN /100ml	WQI
Jan.2008	7.3	188	172	4.04	799.3	0	88
Feb. 2008	7.96	164	248	7.24	743	0	92.8
Mar.2008	7.45	172	180	6.92	687.8	0	93
Apr.2008	7.92	172	196	6.28	682.4	0	93
May 2008	7.74	168	204	5.96	828.1	0	90.4
Jun. 2008	7.34	168	212	5.64	686.9	0	93
Jul. 2008	7.56	164	224	7.56	464.8	0	95.6
Aug. 2008	7.3	172	212	6.92	755.1	0	90.4
Sep.2008	7.96	168	192	6.28	712.8	0	90.4
Oct.2008	7.92	160	184	5.96	835.1	0	90.4
Nov.2008	7.3	164	240	6.92	798.4	0	90.4
Dec.2008	7.35	152	232	5.96	700.3	0	90.4
Jan. 2009	7.3	156	228	7.24	934	0	90.2
Feb. 2009	7.3	156	228	7.24	934	0	90.2
Mar. 2009	7.35	160	208	5.96	678	0	93
Apr. 2009	7.68	164	204	5.64	800.8	0	90.4
May 2009	7.45	164	196	6.92	803.7	0	90.4
Jun. 2009	7.56	172	196	6.92	883.1	0	90.4
Jul. 2009	7.58	160	204	5.96	530.9	0	93
Aug. 2009	7.58	152	204	6.92	823.7	0	90.4
Sep. 2009	7.57	160	212	4.36	920.1	0	85.4
Oct. 2009	7.78	160	204	5.32	927.5	0	87.8
Nov. 2009	7.7	156	208	5.32	911.2	0	87.8
Dec. 2009	7.88	144	212	6.28	892.1	0	90.4
Jan. 2010	7.62	168	216	5.64	922.7	0	87.8
Feb. 2010	7.89	164	208	4.36	770.9	0	90.6
Mar. 2010	7.68	168	212	6.92	918.7	0	87.8
Apr. 2010	7.88	148	208	7.24	928.8	0	90.2
May 2010	7.78	160	240	8.1	837.8	0	92.8
Jun. 2010	7.65	152	228	4.6	816.6	0	88
Jul. 2010	7.42	164	204	6.6	853.8	0	90.4
Aug. 2010	7.96	148	232	6.2	848.1	0	90.4
Sep. 2010	7.82	172	212	5.8	842.4	0	90.4
Oct. 2010	7.45	172	196	7.24	824.5	0	92.8
Nov. 2010	7.95	160	208	6.6	756.5	0	90.4
Dec. 2010	7.65	168	216	5.96	865.3	0	90.4

Table 4.22 Physicochemical Characteristics of Water for Zone Twenty One

Month	pH	Alkalinity in mg/l	Hardness in mg/l	DO in mg/l	TS in mg/l	MPN /100ml	WQI
Jan.2008	7.36	164	196	7.24	648.7	0	95.4
Feb. 2008	7.69	160	236	6.6	800.9	0	90.4
Mar.2008	7.48	156	236	6.6	706.7	0	30.4
Apr.2008	7.85	156	212	7.88	704.21	0	92.8
May 2008	7.63	176	220	5.96	877.9	0	90.4
Jun. 2008	7.73	172	232	6.28	702.3	0	30.4
Jul. 2008	7.3	180	216	5.64	843.8	0	33
Aug. 2008	7.36	172	232	7.24	700.1	0	92.8
Sep.2008	7.69	172	208	6.6	711.4	0	30.4
Oct.2008	7.85	168	196	7.56	754.3	0	92.8
Nov.2008	7.36	168	232	7.24	800.9	0	32.8
Dec.2008	7.48	168	224	8.23	842.9	0	32.8
Jan. 2009	7.36	172	220	8.2	843.3	0	92.8
Feb. 2009	7.36	172	220	8.2	843.3	0	92.8
Mar. 2009	7.35	156	212	6.6	790.6	0	90.4
Apr. 2009	7.71	160	200	6.92	840.1	0	90.4
May 2009	7.67	164	204	6.28	842.5	0	90.4
Jun. 2009	7.89	156	196	6.6	830.6	0	90.4
Jul. 2009	7.95	156	208	6.28	840	0	90.4
Aug. 2009	7.8	160	212	6.6	831.2	0	90.4
Sep. 2009	7.58	156	208	4.68	779.6	0	88
Oct. 2009	7.66	172	208	7.24	827.5	0	92.8
Nov. 2009	7.71	164	212	7.24	770	0	92.8
Dec. 2009	7.45	140	204	6.28	474.5	0	95.6
Jan. 2010	7.48	140	212	6.28	786.5	0	90.4
Feb. 2010	7.9	160	204	7.24	698.1	0	95.4
Mar. 2010	7.71	152	216	7.24	780.8	14	32.8
Apr. 2010	7.65	152	212	6.92	778.1	14	30.4
May 2010	7.45	156	224	5.4	774.6	0	90.4
Jun. 2010	7.96	164	212	6.92	865.2	0	90.4
Jul. 2010	7.82	172	192	7.24	586.2	0	95.4
Aug. 2010	7.65	160	184	4.68	845.6	17	28
Sep. 2010	7.32	156	240	5.64	874.6	0	90.4
Oct. 2010	7.76	152	232	6.64	754.6	0	90.4
Nov. 2010	7.98	160	228	7.24	968.2	0	90.2
Dec. 2010	7.42	164	204	6.28	756.3	0	90.4

Table 4.23 Physicochemical Characteristics of Water for Zone Twenty Two

Month	pH	Alkalinity in mg/l	Hardness in mg/l	DO in mg/l	TS in mg/l	MPN /100ml	WQI
Jan.2008	7.55	160	195	4.68	685	0	90.6
Feb. 2008	7.83	154	188	6.5	690.3	0	93
Mar.2008	7.85	160	188	6.28	725.39	0	93
Apr.2008	7.38	168	188	5.32	589.7	0	93
May 2008	7.72	164	188	5	743	0	88
Jun. 2008	7.21	152	192	5.64	770.6	5	66.4
Jul. 2008	7.13	156	208	7.28	826.3	0	92.8
Aug. 2008	7.55	160	192	6.28	630.2	0	93
Sep.2008	7.83	160	192	7.9	600.1	0	95.4
Oct.2008	7.38	164	204	8.1	596.8	0	95.4
Nov.2008	7.55	164	196	7.88	690.3	0	95.4
Dec.2008	7.13	172	188	7.56	463.5	0	98
Jan. 2009	7.55	160	192	6.28	637.8	0	93
Feb. 2009	7.55	160	192	6.28	637.8	0	93
Mar. 2009	7.35	164	196	6.28	771.7	0	90.4
Apr. 2009	7.79	172	188	5.96	662.3	0	93
May 2009	7.78	168	184	7.88	678.2	0	95.4
Jun. 2009	7.9	168	196	5.64	659.8	0	93
Jul. 2009	7.85	168	204	5.64	682.4	0	93
Aug. 2009	7.85	180	204	5.32	690	0	93
Sep. 2009	7.85	164	204	4.04	644.2	0	90.6
Oct. 2009	7.96	168	192	6.92	624.3	0	93
Nov. 2009	7.91	172	196	6.92	650.3	0	93
Dec. 2009	7.67	156	192	5.32	659.1	0	93
Jan. 2010	7.56	160	188	5.96	648.7	0	93
Feb. 2010	7.55	156	192	6.28	650.3	0	93
Mar. 2010	7.79	160	196	5	650.4	0	90.6
Apr. 2010	7.26	160	192	6.28	658.9	0	93
May 2010	7.67	164	188	5.6	654.2	0	93
Jun. 2010	7.84	160	196	5.2	785.2	0	90.4
Jul. 2010	7.89	172	192	6.26	563.2	11	33
Aug. 2010	7.62	156	208	7.48	496.2	0	98
Sep. 2010	7.45	172	196	6.92	741.8	0	90.4
Oct. 2010	7.35	168	212	5.8	543.9	0	93
Nov. 2010	7.96	168	204	8.42	674.9	0	95.4
Dec. 2010	7.62	172	208	6.92	580.9	0	93

Table 4.24 Physicochemical Characteristics of Water for Zone Twenty Three

Month	pH	Alkalinity in mg/l	Hardness in mg/l	DO in mg/l	TS in mg/l	MPN /100ml	WQI
Jan.2008	7.21	160	192	6.6	703.9	11	31.4
Feb. 2008	7.78	156	200	6.92	827.6	0	90.4
Mar.2008	7.36	152	192	7.56	672.2	0	95.4
Apr.2008	7.82	164	224	6.6	724.4	0	90.4
May 2008	7.73	160	212	5.32	648.7	0	93
Jun. 2008	7.25	164	228	5.96	734.7	0	90.4
Jul. 2008	7.33	160	212	5.64	679.7	0	93
Aug. 2008	7.21	164	228	4.68	751.8	0	88
Sep.2008	7.78	156	208	4.68	696.2	11	30.6
Oct.2008	7.82	152	216	6.28	770.1	21	30.4
Nov.2008	7.21	160	212	6.6	827.6	17	30.4
Dec.2008	7.58	164	208	7.88	850.1	0	92.8
Jan. 2009	7.21	164	204	6.92	937.1	0	87.8
Feb. 2009	7.69	160	192	7.24	494.2	0	98
Mar. 2009	7.35	168	208	7.88	841.2	2	80.8
Apr. 2009	7.82	152	196	7.24	788.8	0	92.8
May 2009	7.99	172	192	6.6	821.3	0	90.4
Jun. 2009	7.55	164	188	3.72	793.7	20	25.6
Jul. 2009	7.61	152	192	6.92	800	7	66.4
Aug. 2009	7.66	168	196	6.28	800.5	0	90.4
Sep. 2009	7.23	148	196	6.28	787.8	17	30.4
Oct. 2009	7.63	140	208	6.28	792.8	0	90.4
Nov. 2009	7.6	148	216	6.6	814.8	0	90.4
Dec. 2009	7.78	160	212	6.6	809.7	17	30.4
Jan. 2010	7.8	148	204	5.32	791.4	0	90.4
Feb. 2010	7.56	140	196	3.4	788.6	0	85.6
Mar. 2010	7.82	148	204	6.28	793.4	21	30.4
Apr. 2010	7.59	164	212	6.28	799.1	21	30.4
May 2010	7.32	152	204	6.48	756.23	0	90.4
Jun. 2010	7.96	148	192	7.24	986.25	21	30.2
Jul. 2010	7.84	164	208	5.46	845.6	21	30.4
Aug. 2010	7.56	172	212	6.64	657.2	17	33
Sep. 2010	7.82	160	188	4.68	748.6	0	88
Oct. 2010	7.96	168	196	7.88	568.3	17	35.4
Nov. 2010	7.24	172	192	8.42	659.3	14	35.4
Dec. 2010	7.62	184	208	6.6	856.2	0	91.4

Table 4.25 Physicochemical Characteristics of Water for Zone Twenty Four

Month	pH	Alkalinity in mg/l	Hardness in mg/l	DO in mg/l	TS in mg/l	MPN /100ml	WQI
Jan.2008	7.7	140	264	6	784.5	0	90.4
Feb. 2008	7.44	176	232	7.24	768.2	0	92.8
Mar.2008	8.01	176	264	6.6	753.2	0	90.4
Apr.2008	7.81	172	248	6.28	768.2	0	90.4
May 2008	7.79	160	224	6.6	743	0	90.4
Jun. 2008	7.58	172	244	5.64	687.3	0	93
Jul. 2008	7.61	164	232	6.6	649.1	0	93
Aug. 2008	7.7	168	244	3.72	778.6	0	85.6
Sep.2008	7.44	164	228	5.64	778.6	0	90.4
Oct.2008	7.81	156	220	5.96	803.5	0	90.4
Nov.2008	7.7	156	232	3.72	510.2	0	88.2
Dec.2008	7.35	152	224	5.96	420.1	0	95.6
Jan. 2009	7.7	160	216	5.64	878.1	0	90.4
Feb. 2009	7.7	160	216	5.64	878.1	11	30.4
Mar. 2009	7.35	156	216	6.28	912.3	0	87.8
Apr. 2009	7.59	172	208	7.24	798.7	13	32.8
May 2009	7.55	164	204	5.64	827.3	2	78.4
Jun. 2009	7.88	148	196	5.32	790.3	0	90.4
Jul. 2009	7.81	176	204	5.96	807.8	0	90.4
Aug. 2009	7.56	188	196	5.96	837.8	0	90.4
Sep. 2009	7.56	156	192	8.05	816.6	0	92.8
Oct. 2009	7.23	140	196	5.96	853.8	21	30.4
Nov. 2009	7.84	156	192	6.28	848.1	0	90.4
Dec. 2009	7.46	152	196	6.92	842.4	0	90.4
Jan. 2010	7.46	156	192	6.28	824.5	0	90.4
Feb. 2010	7.56	152	196	5	830.7	21	30.4
Mar. 2010	7.6	156	192	6.28	827.6	0	90.4
Apr. 2010	7.89	168	196	5.96	771.7	0	90.4
May 2010	7.64	140	208	6.62	756.3	0	90.4
Jun. 2010	7.77	188	216	5.42	896.3	21	30.4
Jul. 2010	7.85	172	196	7.24	845.2	14	32.8
Aug. 2010	7.46	156	216	6.28	854.2	0	90.4
Sep. 2010	7.74	188	192	5.96	741.8	17	30.4
Oct. 2010	7.56	172	232	8.28	836.5	0	92.8
Nov. 2010	7.89	160	220	5.8	792.5	0	90.4
Dec. 2010	7.75	156	224	6.6	832.1	0	90.4

Table 4.26 Physicochemical Characteristics of Water for Zone Twenty Five

Month	pH	Alkalinity in mg/l	Hardness in mg/l	DO in mg/l	TS in mg/l	MPN /100ml	WQI
Jan.2008	7.62	160	200	5	663.7	0	90.6
Feb. 2008	7.98	152	212	7.56	739.2	0	92.8
Mar.2008	7.55	152	200	7.24	680.3	0	95.4
Apr.2008	7.89	152	212	6.92	739.2	0	90.4
May 2008	7.69	156	208	5.96	385.4	0	95.6
Jun. 2008	7.61	144	228	5.32	876.8	0	90.4
Jul. 2008	7.63	152	224	6.28	707.8	0	90.4
Aug. 2008	7.62	160	228	5.32	749.4	0	90.4
Sep.2008	7.98	160	232	6.28	759.6	0	90.4
Oct.2008	7.89	124	228	6.92	735.6	0	90.4
Nov.2008	7.62	168	220	6.92	816.4	0	90.4
Dec.2008	7.49	160	232	6.92	890.3	0	90.4
Jan. 2009	7.62	148	224	7.24	830.2	0	92.8
Feb. 2009	7.62	148	224	7.24	830.2	0	92.8
Mar. 2009	7.35	164	220	6.28	851.4	0	90.4
Apr. 2009	7.67	156	204	6.28	723.1	0	90.4
May 2009	7.6	160	196	5.96	840.4	0	90.4
Jun. 2009	7.65	160	204	5	840.7	0	88
Jul. 2009	7.66	160	204	5	823.8	21	28
Aug. 2009	7.68	144	212	6.28	799.4	0	90.4
Sep. 2009	7.43	160	204	5.64	844.8	0	90.4
Oct. 2009	7.56	172	208	6.28	835.4	0	90.4
Nov. 2009	7.45	160	204	6.28	882.1	11	30.4
Dec. 2009	7.81	168	196	6.28	870.3	0	90.4
Jan. 2010	7.81	144	196	5	841.2	11	28
Feb. 2010	7.69	148	200	4.68	850.3	0	88
Mar. 2010	7.42	160	196	5.64	847.1	0	90.4
Apr. 2010	7.99	152	184	5.32	858.1	0	90.4
May 2010	7.86	124	212	5.4	756.2	21	30.4
Jun. 2010	7.85	160	204	6.92	865.1	0	90.4
Jul. 2010	7.64	168	200	5.32	784.54	0	90.4
Aug. 2010	7.54	144	196	6.28	859.3	17	30.4
Sep. 2010	7.82	160	208	5.96	841.2	17	30.4
Oct. 2010	7.83	152	196	4.68	863.2	0	88
Nov. 2010	7.81	148	184	7.24	784.3	0	92.8
Dec. 2010	7.42	172	196	6.26	842.3	17	30.4

Table 4.27 Physicochemical Characteristics of Water for Zone Twenty Six

Month	pH	Alkalinity in mg/l	Hardness in mg/l	DO in mg/l	TS in mg/l	MPN /100ml	WQI
Jan.2008	7.67	152	192	8.52	750	0	92.8
Feb. 2008	8.01	160	220	7.59	722.8	0	92.8
Mar.2008	7.78	192	220	7.24	664.2	0	95.4
Apr.2008	8.13	168	224	5.96	722.8	0	90.4
May 2008	7.36	164	212	6.6	628.2	5	69
Jun. 2008	7.72	148	220	6.6	706.2	0	90.4
Jul. 2008	7.25	160	216	7.88	670.8	0	95.4
Aug. 2008	7.67	156	220	6.92	710.3	0	90.4
Sep.2008	8.01	156	212	5.96	744.5	0	90.4
Oct.2008	7.74	168	208	8.2	740.4	0	92.8
Nov.2008	7.67	164	232	5.96	875.1	0	90.4
Dec.2008	7.85	172	216	8.2	932.8	0	90.2
Jan. 2009	7.67	164	212	8.2	825.2	0	92.8
Feb. 2009	7.67	164	212	8.2	825.2	0	92.8
Mar. 2009	7.35	160	204	8.2	653.9	0	95.4
Apr. 2009	7.6	160	196	6.92	757.6	0	90.4
May 2009	7.55	160	196	7.24	788.4	0	92.8
Jun. 2009	7.66	172	204	5.64	748.4	0	90.4
Jul. 2009	7.54	140	196	5.64	778.4	0	90.4
Aug. 2009	7.54	180	208	5.96	700.6	0	90.4
Sep. 2009	7.56	168	204	5.64	900.4	0	90.4
Oct. 2009	7.38	160	204	5.32	973.8	0	87.8
Nov. 2009	7.4	168	212	7.24	969.1	0	90.2
Dec. 2009	7.3	164	204	7.24	653.4	0	95.4
Jan. 2010	7.3	140	212	7.24	975.6	0	90.2
Feb. 2010	7.65	156	204	3.4	981.1	0	83
Mar. 2010	7.44	164	188	6.28	622.4	0	93
Apr. 2010	7.32	152	196	6.28	914.7	0	87.8
May 2010	7.26	160	212	7.24	775.6	0	92.8
Jun. 2010	7.64	140	196	5.46	865.2	0	90.4
Jul. 2010	7.98	144	204	6.92	956.3	21	27.8
Aug. 2010	7.35	168	188	8.2	745.6	0	92.8
Sep. 2010	7.84	172	196	7.88	685.3	0	95.4
Oct. 2010	7.77	144	204	5.96	754.2	0	90.4
Nov. 2010	7.775	160	196	6.92	865.3	0	90.4
Dec. 2010	7.62	160	228	5.32	749.4	0	90.4

Table 4.28 Physicochemical Characteristics of Water for Zone Twenty Seven

Month	pH	Alkalinity in mg/l	Hardness in mg/l	DO in mg/l	TS in mg/l	MPN /100ml	WQI
Jan.2008	7.71	180	196	6.6	583.5	0	93
Feb. 2008	7.64	140	192	7.56	704.4	8	56.8
Mar.2008	7.89	148	196	7.88	640.3	9	59.4
Apr.2008	7.56	148	188	5.32	704.4	0	90.4
May 2008	7.3	168	188	6.28	630.25	0	93
Jun. 2008	7.58	164	208	5	708.5	21	28
Jul. 2008	7.29	172	204	7.24	734.1	0	92.8
Aug. 2008	7.71	164	208	7.24	733.5	0	92.8
Sep.2008	7.64	168	220	7.24	733.5	0	92.8
Oct.2008	7.56	160	192	7.56	779.2	0	92.8
Nov.2008	7.71	172	192	7.56	833.1	9	56.8
Dec.2008	7.68	176	196	8.1	863	15	32.8
Jan. 2009	7.71	168	192	8.24	849.2	0	92.8
Feb. 2009	7.71	168	192	8.24	849.2	1	92.8
Mar. 2009	7.35	176	192	6.92	900	14	30.4
Apr. 2009	7.51	148	192	7.24	791.8	0	92.8
May 2009	7.54	156	188	6.92	682.5	0	93
Jun. 2009	7.77	160	196	6.92	724.5	17	30.4
Jul. 2009	7.7	156	192	6.28	688.4	11	33
Aug. 2009	7.44	176	196	5.64	689.7	0	93
Sep. 2009	7.52	160	196	5	849.5	0	90.4
Oct. 2009	7.39	148	192	6.28	862.1	0	90.4
Nov. 2009	7.45	140	196	5.64	832.6	0	90.4
Dec. 2009	7.6	168	196	6.92	820.8	0	90.4
Jan. 2010	7.6	160	188	6.92	851.4	21	30.4
Feb. 2010	7.69	168	192	3.72	853.4	0	85.6
Mar. 2010	7.95	152	188	6.28	857.6	0	90.4
Apr. 2010	7.8	140	188	5.64	848.8	0	90.4
May 2010	7.71	164	192	8.25	791.4	21	32.8
Jun. 2010	7.67	156	164	7.24	788.6	0	92.8
Jul. 2010	7.89	156	196	6.28	793.4	0	90.4
Aug. 2010	7.95	152	180	6.28	799.1	17	30.4
Sep. 2010	7.8	160	164	5.96	756.23	0	90.4
Oct. 2010	7.58	160	180	5	986.25	17	25.4
Nov. 2010	7.45	156	192	5	756.3	0	88
Dec. 2010	7.56	172	192	6.28	853.2	0	90.4

Table 4.29 Physicochemical Characteristics of Water for Zone Twenty Eight

Month	pH	Alkalinity in mg/l	Hardness in mg/l	DO in mg/l	TS in mg/l	MPN /100ml	WQI
Jan.2008	7.75	200	185	7.36	750	0	92.8
Feb. 2008	7.34	152	184	6.6	701.1	0	90.4
Mar.2008	7.36	156	184	7.24	680	0	35.4
Apr.2008	7.35	172	188	6.6	701.1	0	90.4
May 2008	7.75	160	192	6.6	654.5	0	33
Jun. 2008	7.48	172	200	5.96	726.4	0	90.4
Jul. 2008	7.58	168	196	7.24	649.1	0	95.4
Aug. 2008	7.75	160	200	8.2	731.7	0	32.8
Sep.2008	7.34	176	208	6.92	600.1	0	93
Oct.2008	7.35	164	204	8.2	729.3	0	32.8
Nov.2008	7.75	168	196	7.56	690.3	0	95.4
Dec.2008	7.72	164	192	5.32	464.3	0	35.6
Jan. 2009	7.75	156	196	6.28	619.2	0	93
Feb. 2009	7.75	156	196	6.28	619.2	0	93
Mar. 2009	7.35	184	196	7.24	658.2	0	95.4
Apr. 2009	7.48	136	180	6.28	656.3	0	93
May 2009	7.28	164	176	6.28	618.7	0	33
Jun. 2009	7.58	156	184	5.96	647.8	0	93
Jul. 2009	7.51	164	180	5.32	631	0	93
Aug. 2009	7.58	168	188	6.92	628.9	0	93
Sep. 2009	7.7	160	184	5.32	644.2	0	93
Oct. 2009	7.5	140	188	5.96	642.3	0	93
Nov. 2009	7.56	152	196	6.28	650.3	0	93
Dec. 2009	7.42	160	192	6.28	671.3	0	93
Jan. 2010	7.42	156	196	6.28	651.9	0	93
Feb. 2010	7.65	144	188	5	657.8	0	90.6
Mar. 2010	7.85	152	192	6.92	647.8	0	93
Apr. 2010	7.45	148	184	6.28	634.8	0	93
May 2010	7.85	164	196	6.6	779.2	0	90.4
Jun. 2010	7.36	172	196	3.72	833.1	0	85.6
Jul. 2010	7.48	164	204	6.92	863	0	90.4
Aug. 2010	7.36	164	196	6.28	849.2	0	90.4
Sep. 2010	7.36	160	208	6.28	849.2	0	90.4
Oct. 2010	7.35	160	204	7.24	900	0	92.8
Nov. 2010	7.71	160	204	5.8	791.8	0	90.4
Dec. 2010	7.56	172	192	6.26	789.6	0	90.4

Table 4.30 Physicochemical Characteristics of Water for Zone Twenty Nine

Month	pH	Alkalinity in mg/l	Hardness in mg/l	DO in mg/l	TS in mg/l	MPN /100ml	WQI
Jan.2008	7.63	168	188	6.6	756.02	14	30.4
Feb. 2008	7.88	164	188	7.24	768.8	20	32.8
Mar.2008	7.95	268	188	6.6	695.2	21	30.4
Apr.2008	7.85	160	196	7.24	768.8	11	32.8
May 2008	7.69	176	188	5.32	743	0	30.4
Jun. 2008	7.28	180	192	4.36	750.7	14	88
Jul. 2008	7.38	172	200	6.28	770.3	0	90.4
Aug. 2008	7.63	172	192	7.88	777.1	0	32.8
Sep.2008	7.88	176	200	7.56	710.3	11	32.8
Oct.2008	7.85	168	200	5.96	792.1	21	30.4
Nov.2008	7.63	180	204	7.88	906.4	11	30.2
Dec.2008	7.35	172	212	6.28	910	21	87.8
Jan. 2009	7.63	180	204	7.24	733.3	0	92.8
Feb. 2009	7.63	180	204	7.24	733.3	0	92.8
Mar. 2009	7.35	172	212	6.92	920.5	0	87.8
Apr. 2009	7.39	168	196	5.32	863.4	0	90.4
May 2009	7.48	160	192	7.56	700.2	0	95.4
Jun. 2009	7.68	148	188	5.64	760.4	0	90.4
Jul. 2009	7.64	160	184	6.92	717.8	0	90.4
Aug. 2009	7.56	144	184	6.6	721.4	0	90.4
Sep. 2009	7.35	156	184	4.04	924.1	2	71
Oct. 2009	7.51	160	180	7.24	922.8	21	30.2
Nov. 2009	7.59	160	192	6.92	912.4	8	51.8
Dec. 2009	7.58	156	188	5.32	905.4	0	87.8
Jan. 2010	7.6	172	196	5.64	913.1	20	27.8
Feb. 2010	7.8	152	192	4.68	920.2	0	85.4
Mar. 2010	7.61	168	196	5.64	919.2	0	87.8
Apr. 2010	7.65	164	188	7.24	902.4	0	90.2
May 2010	7.36	140	196	5.32	790.3	21	30.4
Jun. 2010	7.48	188	204	5.96	807.8	17	30.4
Jul. 2010	7.36	172	196	5.96	837.8	0	90.4
Aug. 2010	7.36	156	192	8.12	816.6	17	32.8
Sep. 2010	7.35	188	196	5.96	853.8	21	30.4
Oct. 2010	7.71	172	192	6.28	848.1	0	90.4
Nov. 2010	7.67	160	196	6.92	842.4	17	30.4
Dec. 2010	7.89	168	192	6.28	824.5	0	90.4

4.2.2 Rating Scale (q_i) for Water Quality Parameters

The rating scale was prepared for range of values of each parameter the rating varies from 0 to 100 and is divided into five intervals. The rating $q_i = 0$ implies that the parameter present in water exceeds the standard maximum permissible limits and water is severely polluted. On the other hand $q_i = 100$ implies that the parameter present in water has most desirable value. The other ratings fall between these two extremes and are $q_i = 40$, $q_i = 60$ and $q_i = 80$ indicating excessively polluted moderately polluted and less polluted respectively. The rating scale for all six water quality parameters is given in Table 4.31.

Table 4.31 Rating Scale (q_i) to Calculate WQI

Parameters	Ranges of Water Quality Parameter				
pH	7-8.5	8.6-8.7	8.8-8.9	9.0-9.2	>9.2
		6.8-6.9	6.7-6.8	6.5-6.7	<6.5
DO (mg/lit)	>7	5.1-7	4.1-5	3-4	<3
Alkalinity (as mg/lit of Caco$_3$)	21-50	50.1-70	70.1-90	90.1-120	>120
		15.1-20	10.1-15	6-10	<6
Hardness (as mg/lit of Caco$_3$)	0-150	150.1-300	300.1-150	450.1-600	>600
TS (mg/lit)	<500	500-700	701-900	901-1000	>1000
MPN (per/100 ml)	<1	2-4	5-7	8-10	>10
Rating	100	80	60	40	0
Extent of pollution	**Clean**	**Slight pollution**	**Moderate pollution**	**Excessive pollution**	**Severe pollution**

4.2.3 Unit Weight (w_i) for Water Quality Parameters

Unit weight for each quality parameter was calculated by the value proportional to the permissible limits

Therefore,

$$w_i \ \alpha \ 1/v_i \tag{4.2}$$

$$\text{or} \quad w_i = K/v_i \tag{4.3}$$

Where, K = Constant of proportionality, w_i = Unit weight of factor, v_i = Maximum Permissible limit. As recommended by Indian council of Medical Research (ICMR) value of K was calculated as

$$K = \sum_{i=1}^{6} \frac{1}{Vi} \tag{4.4}$$

Where, $\sum_{i=1}^{6} \frac{1}{Vi} = \frac{1}{Vi\,(pH)} + \frac{1}{Vi\,(TS)} + \frac{1}{Vi\,(Hardness)} + \frac{1}{Vi\,(Total\ Alkalinity)} + \frac{1}{Vi\,(DO)} + \frac{1}{Vi\,(MPN)}$

The permissible limit of each water quality parameter given by Indian Council of Medical Research (ICMR) and their corresponding weights calculated by weighted index method are mentioned in the Table 4.32. The quality of water is categorised from very bad to excellent on the basis of average Water Quality Index (Tiwari and Mishra, 1985). Water quality classification based on average water quality index is shown in Table 4.33.

Table 4.32 Water Quality Factors: Their ICMR Standard and Assigned Unit Weights

Water Quality Factors	ICMR Standards	Unit Weight (w_i)
pH	7-8.5	0.09
Total Solids (mg/lit)	<500	0.13
Hardness (as mg/lit of Caco$_3$)	<300	0.05
Alkalinity (as mg/lit of Caco$_3$)	<120	0.01
DO (mg/lit)	>5	0.12
MPN (per/100 ml)	<1	0.6

Table 4.33 Water Quality Classification Based on Avg.WQI

Value of WQI	Quality of Water
91-100	Excellent
71-90	Good
51-70	Medium
26-50	Bad
00-25	Very Bad

The Water quality classification in the distribution system on the basis of average water quality index for Solapur city is shown in Table 4.34. From Table 4.34 it can be observed that out of twenty nine zones in the study area, for zone twenty two and twenty eight water quality is excellent, for zone four, twenty three and twenty nine water quality is medium, for zone two water quality is bad and for remaining twenty three zones water quality is good.

Table 4.34 Zone Wise Water Quality Index

Zone	Avg.WQI Value	Classification
1	75.33	Good
2	35.85	Bad
3	77.95	Good
4	55.37	Medium
5	85.88	Good
6	84.37	Good
7	80.58	Good
8	87.29	Good
9	86.28	Good
10	86.79	Good
11	84.06	Good
12	73.20	Good
13	82.77	Good
14	70.24	Good
15	77.72	Good
16	87.904	Good
17	84.227	Good
18	72.57	Good
19	83.63	Good
20	83.86	Good
21	74.89	Good
22	90.64	Excellent
23	66.69	Medium
24	78.75	Good
25	78.995	Good
26	89	Good
27	73.29	Good
28	92.39	Excellent
29	62.14	Medium

4.3 Normalisation of Raw Dataset

The normalisation of dataset is required before using it for developing ANN models. The collected water quality dataset was normalized by using max-min normalisation formula. The Maximin normalisation Formula is as follow,

$$\text{Normalisation} = \frac{V - Min\ A}{Max\ A - Min\ A}\left(new\_Max\ A - new\_Min\ A\right) + (new\_MinA) \qquad (4.5)$$

Where,

V= raw data set value of parameters,

Min A= the minimum value of Water Quality Parameter

Max A= the maximum value of Water Quality Parameter

new _ Max A = 1

new_ Min A = 0 or -1.

4.4 MODELING PERFORMANCE CRITERIONS

In order to evaluate the prediction accuracy of FL, ANN, ANFIS and MLR models three criterions were used for comparative evaluation of the performance of these models. The criterions employed are Mean Absolute Error (MAE), Mean Relative Error (MRE) and Coefficient of Correlation (Cc) (May *et al.* 2008).

4.4.1 Mean Absolute Error (MAE)

MAE is a quantity used to measure how close forecasts or predictions are to the eventual outcomes. Expressed in words, the MAE is the average over the verification sample of the absolute values of the differences between forecast and the corresponding observation. The mean absolute error is given by

$$MAE = 1/n\sum_{i=1}^{n}|observed - predicted| \tag{4.6}$$

4.4.2 Mean Relative Error (MRE)

The relative error is the absolute error divided by the magnitude of the exact value. It is generally expressed as percentage and helps us to calculate the ratio between true error and the true value.

$$\text{MRE} = 1/n\sum_{i}^{n}\frac{(Observed\ value - Predicted\ Value)}{Observed\ Value}\times 100$$

(4.7)

4.4.3 Coefficient of Correlation (Cc)

It is a measure of the strength of the linear relationship between two variables. It is defined in terms of the (sample) covariance of the variables divided by their (sample) standard deviations.

$$Cc = \frac{\sum_{i=1}^{N}(x - x')(y - y')}{\sqrt{\sum_{i=1}^{N}(x - x')^2(y - y')^2}} \tag{4.8}$$

Where, n = the number of data patterns in the dependent data set, x= the observed values, y= the predicted values, x'= mean of the observed values and y'= mean of the predicted values.

CHAPTER 5

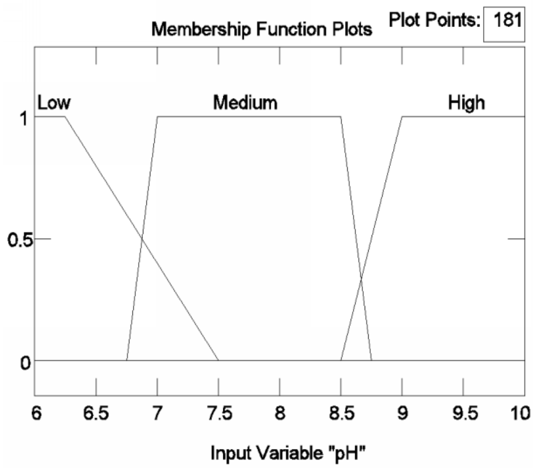
RESULTS AND DISCUSSION

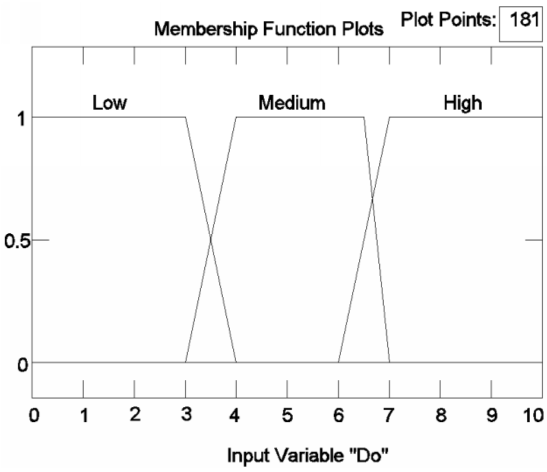
5.0 GENERAL

This chapter provides results of the study conducted for assessment of water quality in various zones of municipal distribution system. The prediction of water quality index in various zones of distribution system was carried out by using artificial intelligence techniques, such as Fuzzy Logic, ANN and ANFIS. Prediction of water quality index was also carried out by using multiple linear regression technique, which is a statistical modelling technique, generally used for linear relationship between input and output variables. The obtained results of artificial intelligence techniques and statistical technique were validated with observed field values of water quality index. The detailed results are presented in the following sections of this chapter.

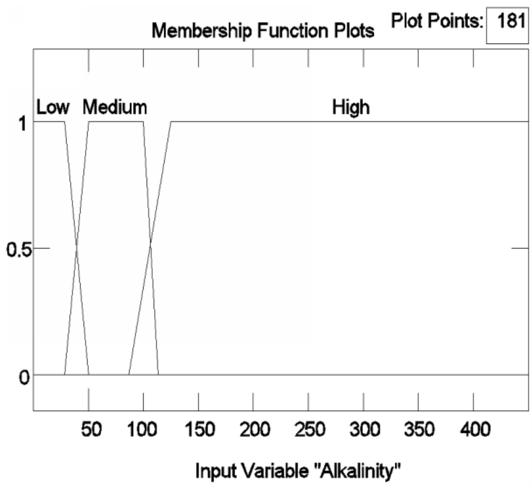
5.1 FUZZY MODEL FOR PREDICTION OF WATER QUALITY

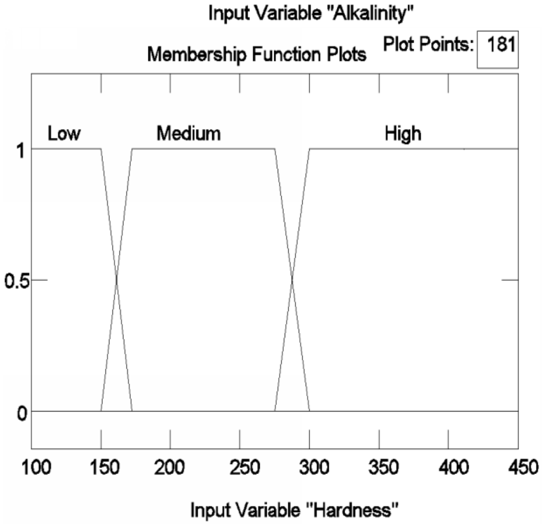
The fuzzy model for water quality in the distribution system has been developed. The fuzzy models were trained using 2/3 rd data of the collected dataset and tested for remaining1/ 3 rd dataset. In this study, each of the six input water quality determinants have been divided into three subsets of water quality viz. low, medium and high. Fuzzification is the process of decomposing a system input and/or output into one or more fuzzy sets. A fuzzy set is defined in terms of a membership function which maps the domain of interest, e.g. concentrations, onto the interval [0, 1]. The shape of the curves shows the membership function for each set. In this study the trapezoidal and triangular membership functions were assigned to each subset as shown in Fig. 5.1 and Fig. 5.2. The ranges for input and output parameters for trapezoidal and triangular membership function are given in Tables 5.1 to 5.4. Ranges for fuzzy sets given in Tables 5.1 to 5.4 have been selected to evaluate water quality by means of an aggregated index called Fuzzy Water Quality Index (FWQI). The output variable fuzzy water quality index has been divided into four subsets viz. poor, medium, good and excellent.



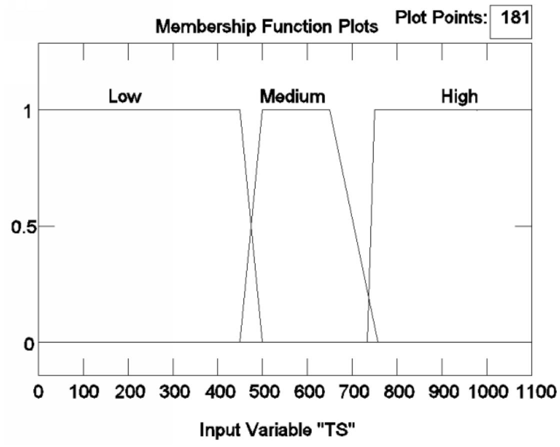


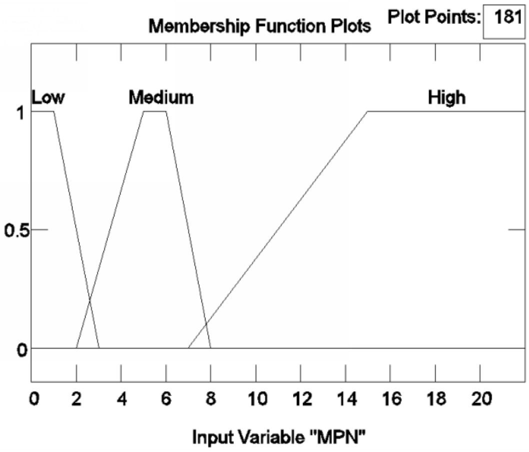
a)Trapezoidal MF for pH **b)Trapezoidal MF for DO**





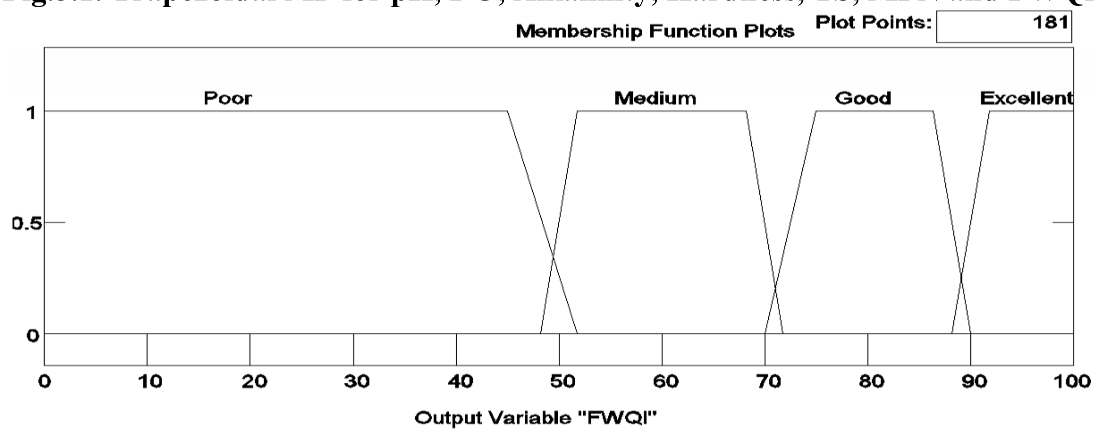
c)Trapezoidal MF for Alkalinity **d)Trapezoidal MF for Hardness**





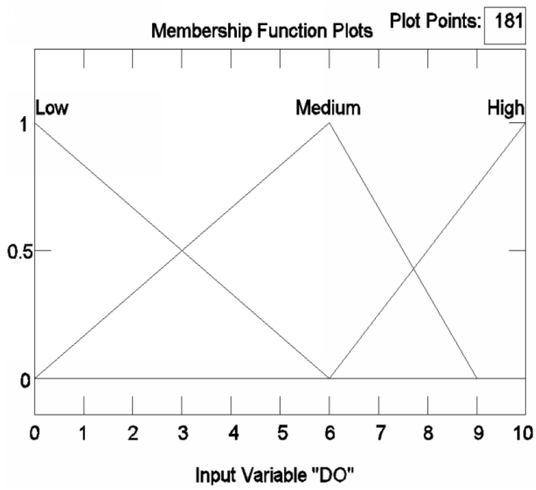
e)Trapezoidal MF for TS **f)Trapezoidal MF for MPN**

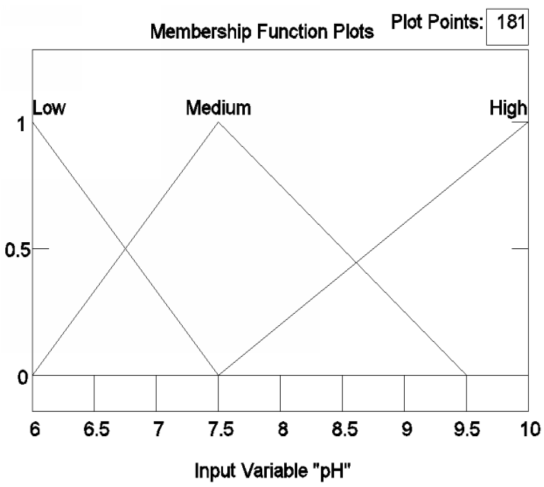
Fig.5.1. Trapezoidal MF for pH, DO, Alkalinity, Hardness, TS, MPN and FWQI



g) Trapezoidal MF for FWQI

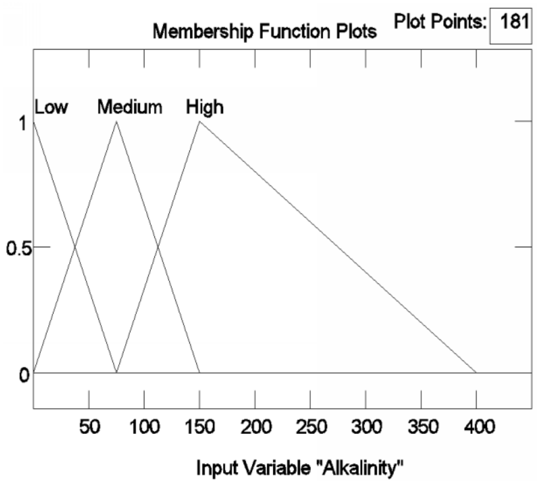
Fig.5.1. Trapezoidal MF for pH, DO, Alkalinity, Hardness, TS, MPN and FWQI

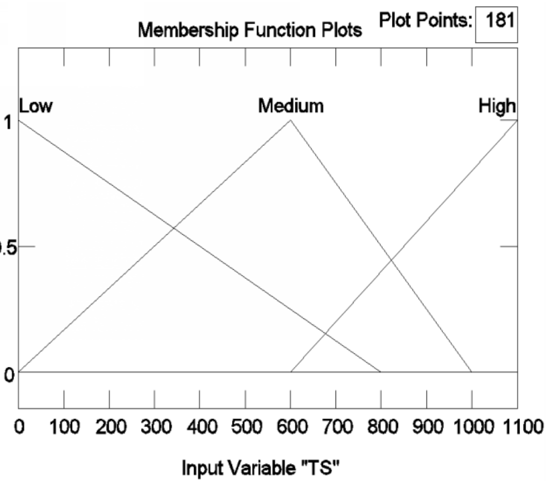




a) Triangular MF for DO

b) Triangular MF for pH

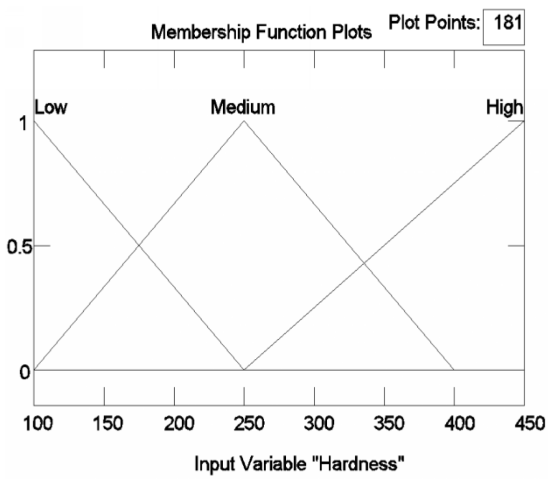


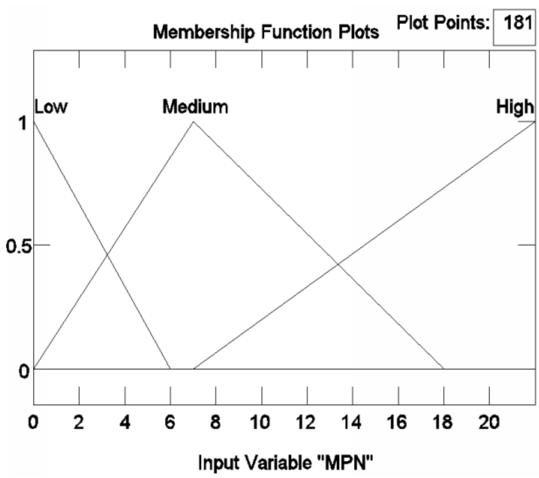


c)Triangular MF for Alkalinity

d)Triangular MF for TS

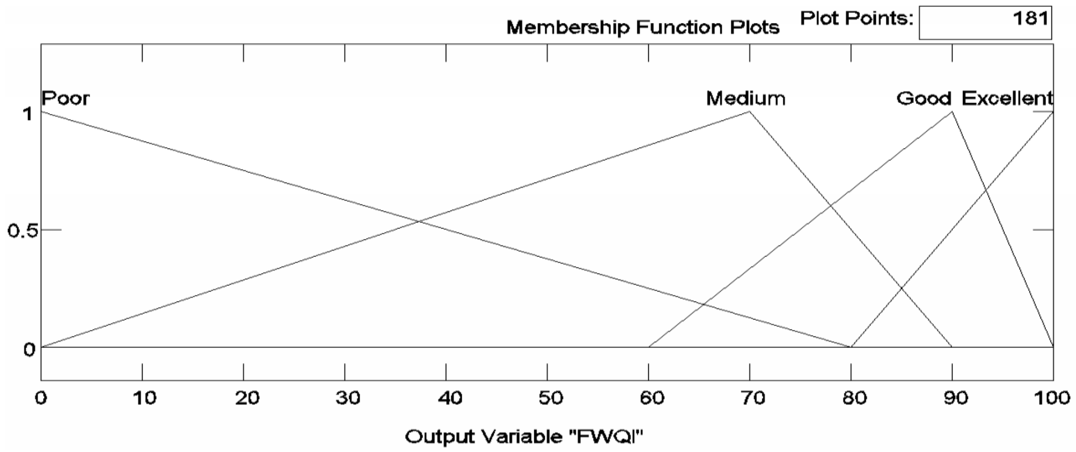
Fig. 5.2. Triangular MF for DO, pH, Alkalinity, TS, Hardness, MPN and FWQI





e)Triangular MF for Hardness

f)Triangular MF for MPN



g) Triangular MF for FWQI

Fig. 5.2. Triangular MF for DO, pH, Alkalinity, TS, Hardness, MPN and FWQI

Table 5.1: Input Parameter Ranges for Trapezoidal Membership Function

Determinants	Low				Medium				High			
	a	b	c	d	a	b	c	d	a	b	c	d
pH	0	0	6.3	7.5	6.8	7	8.5	8.7	8.5	9	10	10
DO	0	0	3	4	3	4.5	6.5	7	6	7	10	10
Alkalinity	0	0	35	50	40	55	90	110	90	110	420	420
Hardness	0	0	150	170	150	180	280	300	270	310	450	450
TS	0	0	450	500	450	500	650	750	730	750	1100	1100
MPN	0	0	1	3	2	5	6	8	7	15	21	21

Table 5.2: Output Parameter Ranges for Trapezoidal Membership Function

Determinant	Poor				Medium				Good				Excellent			
	a	b	c	d	a	b	c	d	a	b	c	d	a	b	c	d
WQI	0	0	45	52	48	50	65	72	0	75	85	90	87	91	100	100

Table 5.3: Input Parameter Ranges for Triangular Membership Function

Determinants	Low			Medium			High			Range
	a	b	c	a	b	c	a	b	c	
pH	6	6	7.5	6	7.5	9.5	7.5	10	10	0 -1

DO	0	0	6	0	6	9	6	10	10	0 -1
Alkalinity	20	20	80	20	80	150	80	160	400	0 -1
Hardness	100	100	250	100	250	450	250	450	450	0 -1
TS	0	0	800	0	600	100	600	1100	1100	0 -1
MPN	0	0	6	0	7	18	7	21	21	0 -1

Table 5.4: Output Parameter Ranges for Triangular Membership Function

Determinant	**Poor**			**Medium**			**Good**			**Excellent**			**Range**
WQI	a	b	c	a	b	c	a	b	c	a	b	c	0 -1
	0	0	80	0	70	90	60	90	100	80	100	100	

Defuzzification is such inverse transformation which maps the output from the fuzzy domain back into the crisp domain. In this study centroid method, mean of maxima (MOM) method and bisector method are used for defuzzification. The variables are combined into rules using the concept of 'AND' operator. The fuzzy operator minimum was used as most of the variables are independent in nature. No weight to any rule was assigned as the entire rule carries equal weight to calculate WQI.

For e.g. 1) If pH is medium, DO is medium, Alkalinity is high, Hardness is medium, TS is low and MPN is low then WQI is excellent.

Similarly, fifteen rules are obtained from available data points and number of fuzzy sets considered. Although the possible rule combination may be more but in real field situation effective rules are less. All fifteen rules are shown explicitly in Table 5.5. The rule viewer to FWQI is shown in Fig.5.3.

Table 5.5: Fuzzy Rules

Sr. No.	**pH**	**DO**	**Alkalinity**	**Hardness**	**Total Solids**	**MPN**	**WQI**
1	Medium	Medium	High	Medium	Low	Low	Excellent
2	Medium	High	High	Medium	Low	Low	Excellent
3	Medium	Medium	High	Medium	Medium	Low	Excellent
4	Medium	High	High	Medium	High	Low	Good
5	Medium	High	High	Medium	High	Low	Good
6	Medium	Medium	High	Medium	High	Low	Good

7	Medium	Medium	High	Medium	Low	High	Medium
8	Medium	Medium	High	Medium	High	High	Poor
9	Medium	High	High	Medium	High	High	Poor
10	Medium	High	High	Medium	Low	High	Medium
11	Medium	Medium	High	Medium	Medium	Medium	Medium
12	Medium	Medium	High	Medium	Low	Medium	Medium
13	Medium	Medium	High	Medium	Medium	Low	Good
14	Medium	High	High	Medium	Medium	Low	Good
15	Medium	Medium	High	Medium	Low	Low	Good

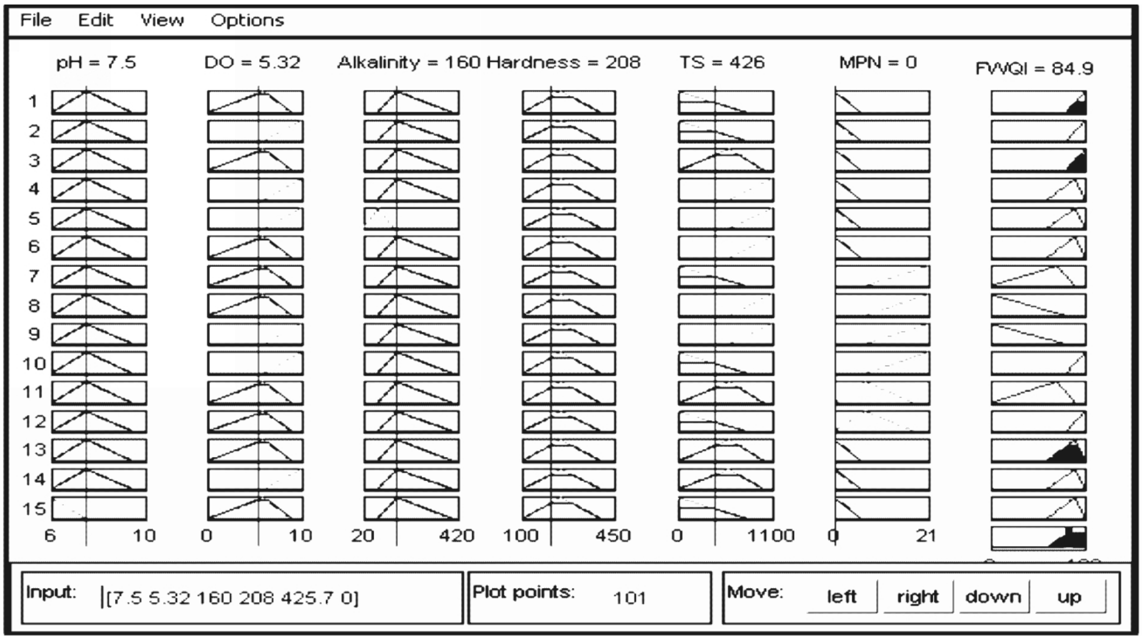


Fig. 5.3 Rule Viewer of Fuzzy Water Quality Index (FWQI)

The water quality in the distribution system for various zones in Solapur city has been assessed with FWQI. The validation of predicted FWQI was carried by comparing the predicted values with observed field results. The error analysis during training and testing of fuzzy models for various zones is mentioned in the Table 5.6. It can be observed from Table 5.6 that model performance changes with change in membership function and defuzzification method. The best fitting model for each zone was selected on the basis of Coefficient of Correlation (Cc) between the observed and predicted values. The shape of membership function was also selected based on same argument. Higher the Coefficient of Correlation (Cc) better is the model performance and if the Coefficient of Correlation for various models are same, then the model which gives less Mean Relative Error (MRE) was selected. The best fitting fuzzy model for each zone is mentioned in the Table 5.7.

From Table 5.7 it is observed that out of twenty nine zones in the study area, for twenty seven zones triangular membership function performs better as compared to trapezoidal membership function. From Table 5.7 it can also be observed that triangular membership function outperforms trapezoidal membership function for all water quality classes viz. excellent good, medium and poor. The better performance of triangular membership function for all water quality classes could be due to single permissible limit value assigned by the regulatory bodies.

From Table 5.6 and 5.7 it is observed that the MOM method of defuzzification performs better as compared to bisector and centroid method for good and excellent water quality classes. The performance of all three methods of defuzzification (i.e. Centroid, MOM and Bisector) was found to be more or less uniform for bad and medium water quality classes. For bad water quality class the performance of centroid method was found to be marginally better as compared to MOM and bisector methods, whereas performance of bisector method was found to be marginally better for medium water quality class. Overall the performance of MOM method of defuzzification was found to be reasonably good for all water quality classes. The better performance of MOM method of defuzzification could be due to unsymmetrical shape of triangular membership function, as appeared in Fig.5.2.

Table 5.6: Zone wise Error Analysis for of Fuzzy Models

Zone	Membership Function	Defuzzification Method	Training			Testing		
			MAE	MRE	Cc	MAE	MRE	Cc
1	Triangular	Centroid	10.58	16.72	0.87	13.91	32.42	0.72
		Bisector	11.68	20.51	0.72	13.73	32.32	0.72
		MOM	**8.55**	**16.60**	**0.85**	**11.49**	**31.46**	**0.73**
	Trapezoidal	Centroid	15.66	21.71	0.62	16.58	36.76	0.41
		Bisector	14.73	20.28	0.74	16.57	36.81	0.41
		MOM	14.72	20.29	0.76	16.35	36.68	0.41
2	Triangular	**Centroid**	**14.70**	**42.50**	**0.78**	**10.30**	**32.23**	**0.75**
		Bisector	16.20	47.87	0.64	10.67	33.89	0.50

		MOM	15.56	46.43	0.78	12.48	39.76	0.59
	Trapezoidal	Centroid	14.04	41.70	0.81	11.99	37.08	0.74
		Bisector	14.06	41.74	0.81	12.00	37.11	0.74
		MOM	14.23	42.36	0.80	12.50	38.84	0.73
3	**Triangular**	Centroid	9.56	15.98	0.96	10.62	15.06	0.83
		Bisector	9.11	15.38	0.96	7.68	11.51	0.97
		MOM	**7.27**	**13.30**	**0.96**	**5.90**	**11.10**	**0.97**
	Trapezoidal	Centroid	11.85	18.87	0.89	11.17	16.41	0.95
		Bisector	11.62	18.52	0.90	11.23	16.48	0.95
		MOM	12.68	20.27	0.85	11.36	16.86	0.94
4	**Triangular**	**Centroid**	**14.60**	**36.90**	**0.85**	**8.88**	**20.37**	**0.97**
		Bisector	14.57	36.65	0.85	9.11	20.63	0.96
		MOM	14.20	37.78	0.80	9.31	25.27	0.91
	Trapezoidal	Centroid	17.00	43.37	0.67	8.71	20.90	0.94
		Bisector	16.35	41.34	0.71	9.18	21.84	0.94
		MOM	16.37	41.31	0.71	10.18	23.73	0.93
5	**Triangular**	Centroid	7.35	8.64	0.99	8.21	14.04	0.98
		Bisector	6.96	8.11	0.99	7.88	13.24	0.98
		MOM	**3.10**	**3.65**	**0.98**	**5.52**	**10.90**	**0.98**
	Trapezoidal	Centroid	8.47	9.85	0.97	9.64	14.14	0.96
		Bisector	8.37	9.74	0.96	9.68	14.23	0.96
		MOM	8.29	9.79	0.95	9.69	14.55	0.96
6	**Triangular**	Centroid	7.76	10.55	0.97	7.18	11.42	0.99
		Bisector	7.33	10.10	0.96	6.78	10.87	0.95
		MOM	**4.55**	**8.55**	**0.96**	**4.63**	**8.16**	**0.96**
	Trapezoidal	Centroid	10.68	12.65	0.90	10.67	16.63	0.99
		Bisector	10.68	12.70	0.90	10.70	16.67	0.99
		MOM	10.63	12.74	0.90	10.70	16.67	0.99

Table 5.6: Zone wise Error Analysis of Fuzzy Models (Continued…)

Zone	**Membership Function**	**Defuzzification Method**	**Training**			**Testing**		
			MAE	**MRE**	**Cc**	**MAE**	**MRE**	**Cc**
7	**Triangular**	Centroid	11.56	25.78	0.91	8.98	16.59	0.99
		Bisector	**10.50**	**24.60**	**0.94**	**7.42**	**12.41**	**0.99**
		MOM	15.80	31.98	0.90	7.32	17.24	0.93
	Trapezoidal	Centroid	14.30	34.32	0.85	8.81	14.68	0.96
		Bisector	14.30	34.37	0.85	8.80	14.71	0.96
		MOM	14.33	34.50	0.85	9.07	15.56	0.96
8	**Triangular**	**Centroid**	10.35	13.90	0.98	7.95	10.07	0.99

		Bisector	9.97	13.48	0.98	7.47	9.32	0.99
		MOM	**6.69**	**11.40**	**0.97**	**3.49**	**3.97**	**0.99**
	Trapezoidal	Centroid	5.93	8.46	0.94	8.13	9.65	0.99
		Bisector	5.75	8.32	0.94	8.30	9.84	0.99
		MOM	5.08	7.71	0.94	7.89	9.71	0.99
9	**Triangular**	Centroid	7.70	9.95	0.95	6.78	8.48	0.98
		Bisector	7.20	9.36	0.95	6.38	7.84	0.98
		MOM	**3.67**	**5.55**	**0.97**	**2.83**	**3.60**	**0.98**
	Trapezoidal	Centroid	11.43	14.95	0.62	6.92	8.64	0.98
		Bisector	11.56	15.08	0.62	7.08	8.90	0.98
		MOM	12.83	16.50	0.54	6.55	8.50	0.97
10	**Triangular**	Centroid	8.06	8.99	0.95	7.81	11.34	0.96
		Bisector	7.58	8.44	0.96	7.28	10.35	0.96
		MOM	**3.13**	**3.54**	**0.98**	**4.35**	**6.99**	**0.98**
	Trapezoidal	Centroid	8.02	9.04	0.94	7.57	9.25	0.97
		Bisector	8.13	9.16	0.94	7.72	9.46	0.98
		MOM	7.86	8.89	0.93	7.29	9.35	0.97
11	**Triangular**	Centroid	9.42	14.91	0.95	9.83	12.78	0.88
		Bisector	9.06	14.55	0.95	9.28	11.54	0.89
		MOM	**5.57**	**11.50**	**0.94**	**7.68**	**11.16**	**0.92**
	Trapezoidal	Centroid	9.89	15.60	0.85	9.72	11.47	0.90
		Bisector	10.02	15.75	0.85	9.93	11.94	0.87
		MOM	9.38	15.04	0.85	9.45	11.72	0.90
12	**Triangular**	Centroid	9.67	17.10	0.94	6.96	11.60	0.99
		Bisector	9.38	16.74	0.94	6.45	10.35	0.99
		MOM	**7.27**	**17.70**	**0.91**	**3.85**	**6.99**	**0.99**
	Trapezoidal	Centroid	12.23	23.97	0.80	10.38	15.88	0.97
		Bisector	12.38	24.20	0.80	10.52	16.10	0.96
		MOM	12.26	25.12	0.76	11.02	17.52	0.97

Table 5.6: Zone wise Error Analysis for of Fuzzy Models (Continued…)

Zone	**Membership Function**	**Defuzzification Method**	**Training**			**Testing**		
			MAE	**MRE**	**Cc**	**MAE**	**MRE**	**Cc**
13	**Triangular**	Centroid	10.97	16.96	0.95	8.30	13.90	0.95
		Bisector	11.25	19.40	0.83	8.00	13.62	0.98
		MOM	**5.15**	**9.24**	**0.96**	**3.70**	**8.31**	**0.99**
	Trapezoidal	Centroid	10.85	17.58	0.98	8.75	15.94	0.99
		Bisector	11.08	17.83	0.97	9.00	16.21	0.99
		MOM	10.87	17.60	0.95	8.18	15.32	0.99
14	**Triangular**	Centroid	8.89	18.46	0.87	10.25	17.80	0.73

		Bisector	**8.29**	**17.60**	**0.82**	**9.73**	**17.17**	**0.74**
		MOM	9.12	24.65	0.85	6.40	13.45	0.72
	Trapezoidal	Centroid	10.39	21.63	0.62	7.11	15.28	0.41
		Bisector	10.48	21.80	0.74	7.11	15.28	0.41
		MOM	10.55	22.26	0.76	7.21	15.44	0.41
15	**Triangular**	Centroid	9.58	15.23	0.78	7.21	14.66	0.72
		Bisector	9.38	15.15	0.64	6.95	14.34	0.50
		MOM	7.17	14.08	0.78	5.14	12.10	0.59
	Trapezoidal	Centroid	12.54	19.03	0.81	8.21	15.05	0.74
		Bisector	12.47	18.93	0.81	8.23	15.09	0.74
		MOM	**13.30**	**20.10**	**0.80**	**8.42**	**15.96**	**0.75**
16	**Triangular**	Centroid	10.53	12.54	0.96	8.84	13.85	0.83
		Bisector	10.16	12.22	0.96	8.62	13.39	0.97
		MOM	**6.75**	**9.00**	**0.94**	**4.14**	**7.27**	**0.97**
	Trapezoidal	Centroid	9.47	11.18	0.89	8.99	13.95	0.95
		Bisector	9.49	11.21	0.90	78.33	99.65	0.95
		MOM	9.23	10.93	0.85	8.92	13.87	0.94
17	**Triangular**	Centroid	12.46	17.93	0.85	15.75	26.70	0.97
		Bisector	12.17	17.65	0.85	15.20	25.49	0.96
		MOM	**9.41**	**15.00**	**0.95**	**13.48**	**25.17**	**0.98**
	Trapezoidal	Centroid	14.21	20.37	0.67	14.75	24.91	0.94
		Bisector	14.03	20.18	0.71	14.75	24.94	0.94
		MOM	13.55	19.64	0.71	14.73	25.21	0.93
18	**Triangular**	**Centroid**	**12.60**	**25.30**	**0.87**	**16.49**	**32.90**	**0.73**
		Bisector	12.53	25.37	0.72	16.56	33.04	0.72
		MOM	12.54	29.02	0.85	13.97	31.17	0.72
	Trapezoidal	Centroid	18.23	38.36	0.62	14.82	32.19	0.41
		Bisector	17.83	37.92	0.74	15.25	32.65	0.41
		MOM	17.46	37.21	0.76	16.07	33.50	0.41

Table 5.6: Zone wise Error Analysis for of Fuzzy Models (Continued…)

Zone	Membership Function	Defuzzification Method	Training			Testing		
			MAE	MRE	Cc	MAE	MRE	Cc
19	**Triangular**	Centroid	12.33	20.83	0.78	9.73	10.45	0.72
		Bisector	12.13	20.70	0.64	9.37	10.04	0.50
		MOM	**11.10**	**22.90**	**0.80**	**5.58**	**6.03**	**0.79**
	Trapezoidal	Centroid	14.58	32.73	0.81	7.15	7.96	0.74
		Bisector	13.88	31.27	0.81	7.03	7.84	0.74
		MOM	13.57	31.26	0.80	6.33	7.08	0.75
20	**Triangular**	Centroid	7.17	9.82	0.96	7.30	11.57	0.83
		Bisector	6.81	9.29	0.96	6.90	10.62	0.97

		MOM	**3.70**	**5.85**	**0.96**	**4.17**	**6.69**	**0.98**
	Trapezoidal	Centroid	10.73	16.71	0.89	9.41	12.51	0.95
		Bisector	10.71	16.62	0.90	9.42	12.54	0.95
		MOM	10.71	16.81	0.85	9.63	13.22	0.94
21	**Triangular**	Centroid	9.65	18.36	0.85	8.16	14.01	0.97
		Bisector	**9.38**	**17.70**	**0.95**	**7.85**	**13.32**	**0.98**
		MOM	7.94	16.96	0.80	7.18	17.25	0.91
	Trapezoidal	Centroid	11.97	20.98	0.67	10.18	14.46	0.94
		Bisector	11.97	20.98	0.71	10.22	14.57	0.94
		MOM	11.99	21.40	0.71	10.59	15.80	0.93
22	**Triangular**	Centroid	9.14	10.01	0.92	12.71	17.25	0.60
		Bisector	8.68	9.50	0.90	11.73	17.03	0.59
		MOM	**5.85**	**6.35**	**0.95**	**8.98**	**14.00**	**0.74**
	Trapezoidal	Centroid	9.35	10.30	0.87	12.88	16.57	0.65
		Bisector	9.39	10.35	0.87	13.15	16.85	0.65
		MOM	8.78	9.71	0.84	12.73	16.41	0.64
23	**Triangular**	Centroid	8.99	16.21	0.96	7.37	17.70	0.95
		Bisector	**10.70**	**22.80**	**0.86**	**7.07**	**16.95**	**0.95**
		MOM	6.38	14.92	0.94	8.69	24.40	0.93
	Trapezoidal	Centroid	9.62	16.49	0.96	9.77	22.38	0.93
		Bisector	9.67	16.60	0.95	9.78	22.40	0.93
		MOM	11.79	23.36	0.95	10.28	24.05	0.93
24	**Triangular**	Centroid	7.41	10.41	0.97	6.28	10.02	0.99
		Bisector	**7.01**	**9.99**	**0.98**	**5.87**	**9.24**	**0.99**
		MOM	5.10	10.54	0.93	6.13	13.42	0.99
	Trapezoidal	Centroid	8.51	11.15	0.99	9.39	15.12	0.99
		Bisector	8.45	11.12	0.98	9.38	15.09	0.99
		MOM	8.46	11.45	0.98	9.88	16.70	0.99
25	**Triangular**	Centroid	7.39	9.67	0.99	10.52	17.56	0.83
		Bisector	7.15	9.38	0.99	10.13	25.14	0.81
		MOM	4.67	7.74	0.95	7.46	20.01	0.95
	Trapezoidal	Centroid	11.28	13.32	0.80	11.86	26.28	0.84
		Bisector	11.31	13.34	0.80	11.85	26.25	0.84
		MOM	**11.50**	**13.80**	**0.80**	**8.83**	**16.35**	**0.99**

Table 5.6: Zone wise Error Analysis for of Fuzzy Models (Continued…)

Zone	Membership Function	Defuzzification Method	Training			Testing		
			MAE	MRE	Cc	MAE	MRE	Cc
26	**Triangular**	Centroid	8.36	9.27	0.89	6.63	7.33	0.99
		Bisector	**7.94**	**8.80**	**0.88**	**6.53**	**7.29**	**0.99**
		MOM	4.39	4.82	0.79	5.24	9.02	0.98
	Trapezoidal	Centroid	11.05	12.14	0.84	9.48	11.13	0.98
		Bisector	10.98	12.07	0.83	9.53	11.23	0.98

		MOM	10.95	12.04	0.79	9.54	11.55	0.98
27	**Triangular**	Centroid	9.27	15.25	0.96	5.13	7.89	0.99
		Bisector	**8.25**	**13.40**	**0.97**	**4.90**	**6.94**	**0.99**
		MOM	5.57	10.83	0.96	5.28	11.96	0.99
	Trapezoidal	Centroid	12.03	21.11	0.90	8.43	13.39	0.99
		Bisector	12.06	21.17	0.90	8.45	13.45	0.99
		MOM	12.10	21.47	0.90	8.95	15.15	0.99
28	**Triangular**	Centroid	14.73	15.81	0.11	7.11	7.78	0.46
		Bisector	14.49	15.56	0.12	6.95	7.62	0.53
		MOM	**11.50**	**12.40**	**0.15**	**3.53**	**3.87**	**0.61**
	Trapezoidal	Centroid	14.60	15.66	0.00	9.15	10.06	0.45
		Bisector	14.74	15.80	0.00	9.28	10.20	0.43
		MOM	14.23	15.26	0.01	9.02	9.91	0.39
29	**Triangular**	Centroid	13.77	28.43	0.70	3.98	6.59	0.99
		Bisector	**15.40**	**33.30**	**0.61**	**3.53**	**5.18**	**0.99**
		MOM	15.69	36.83	0.57	6.71	18.06	0.99
	Trapezoidal	Centroid	18.25	36.50	0.59	7.72	15.42	0.99
		Bisector	18.28	36.52	0.59	7.73	15.48	0.99
		MOM	18.78	37.63	0.59	13.23	23.21	0.84

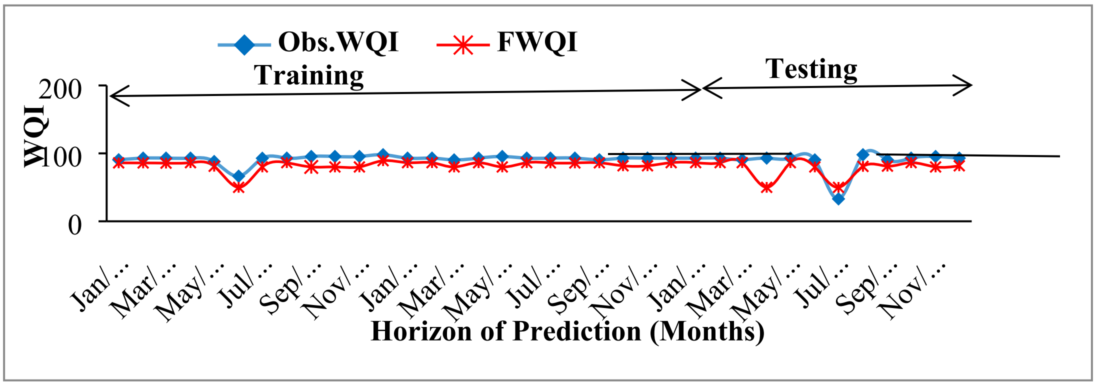
Table 5.7: Zone wise Best Fitting Fuzzy Model

Zone N0.	**Water Quality Class**	**Membership Function**	**Defuzzification Method**	**Correlation Coeff. (Cc)**
2	Bad	Triangular	Centroid	0.75
4	Medium	Triangular	Centroid	0.97

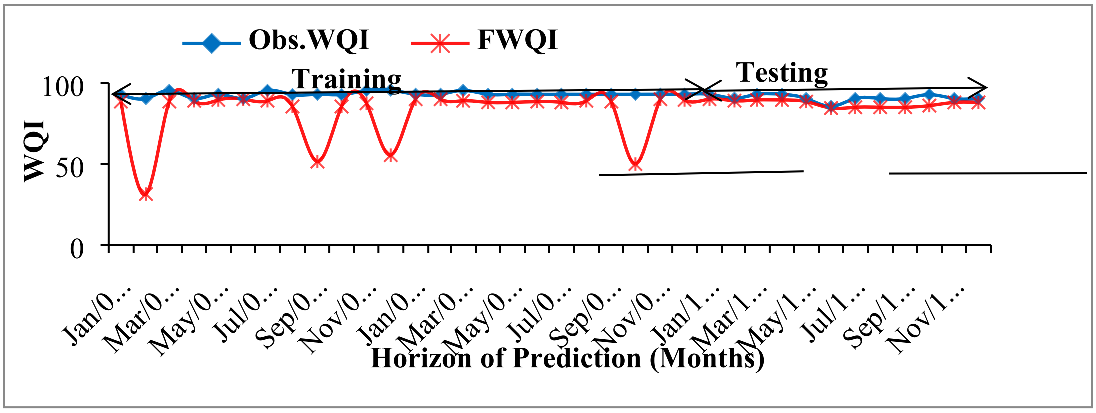
23			Bisector	0.95
29			Bisector	0.99
1	Good	Triangular	Centroid	0.75
3			MOM	0.73
5			MOM	0.98
6			MOM	0.96
7			Bisector	0.99
8			MOM	0.99
9			MOM	0.98
10			MOM	0.98
11			MOM	0.92
12			MOM	0.99
13			MOM	0.99
14			Bisector	0.74
15		Trapezoidal	MOM	0.75
16		Triangular	MOM	0.97
17			MOM	0.98
18			Centroid	0.73
19			MOM	0.79
20			MOM	0.98
21			Bisector	0.98
24			Bisector	0.99
25		Trapezoidal	MOM	0.99
26		Triangular	Bisector	0.99
27			Bisector	0.99
22	Excellent	Triangular	MOM	0.74
28			MOM	0.61

5.1.1 Fuzzy Predictions for Various Water Quality Classes

Prediction performance of fuzzy models was assessed by selecting few typical zones from each water quality class. Fuzzy model behaviour for zone twenty two and twenty eight, where water quality is excellent, is shown in Fig.5.4. Fuzzy model behaviour for zones four, twenty three and twenty nine, where water quality is medium, is shown in Fig.5.5. Fuzzy model behaviour, for zone second, where water quality is bad, is shown in Fig.5.6. The typical fuzzy model behaviour for zone fourteen, where water quality is good, is shown in Fig.5.7. The performance of fuzzy model is overall good with inferior performance during selective months as appeared in Figs.5.4 (b), 5.5 (c) and 5.6 during training. From Fig. 5.4 to 5.7 it is observed that the testing performance of fuzzy models is consistently better for overall period of study and for all water classes.

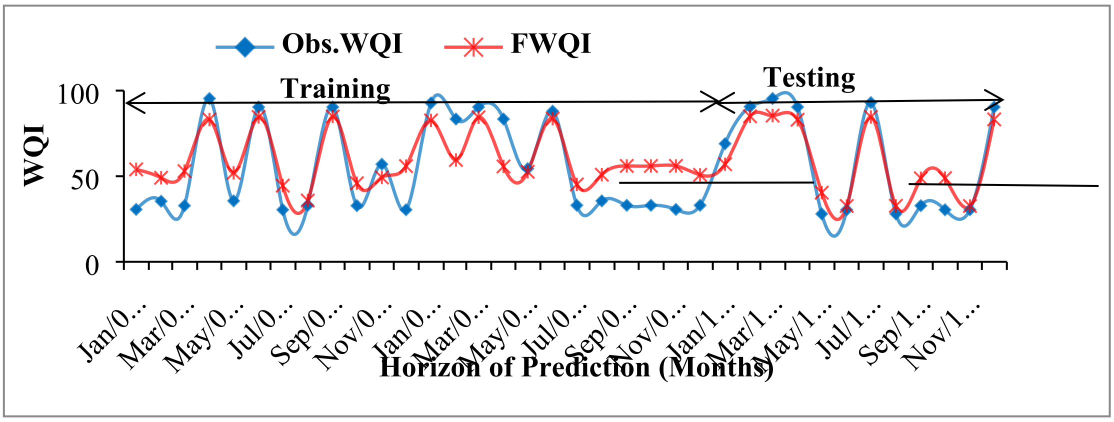


(a)

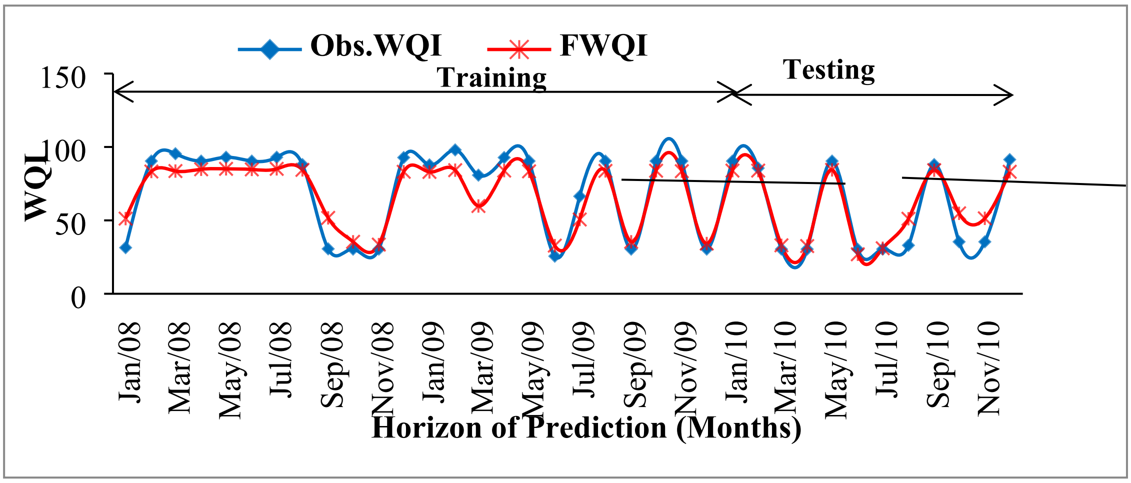


(b)

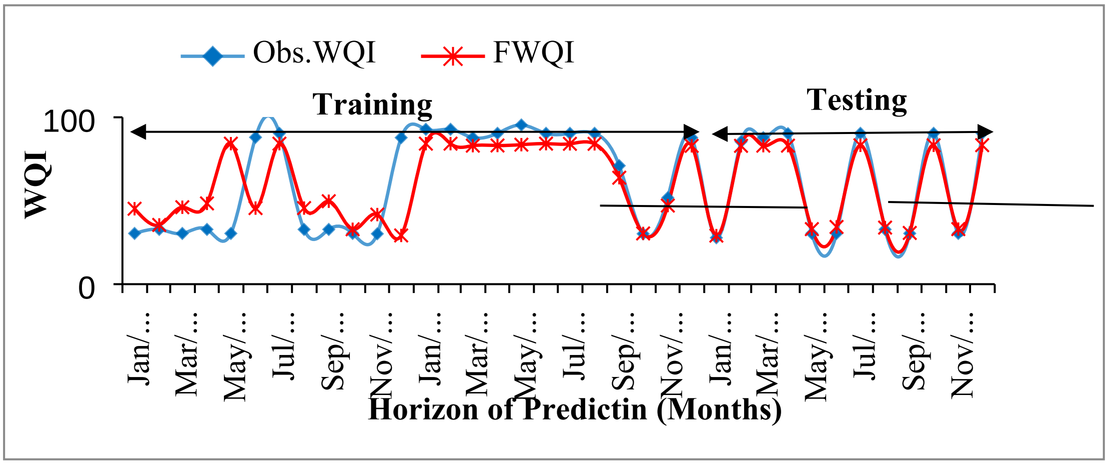
Fig.5.4 Fuzzy Model Predictions of Water Quality for zones of Excellent Water Quality a) Zone Twenty Two (Avg. WQI- 90.64) b) Zone Twenty eight (Avg .WQI- 92.39)



(a)



(b)



(c)

Fig.5.5 Fuzzy Model Predictions of Water Quality for zones of Medium Water Quality a) Zone Four (Avg.WQI-55.37) b) Zone Twenty three (Avg.WQI-66.69) c) Zone Twenty nine (Avg.WQI-62.14)

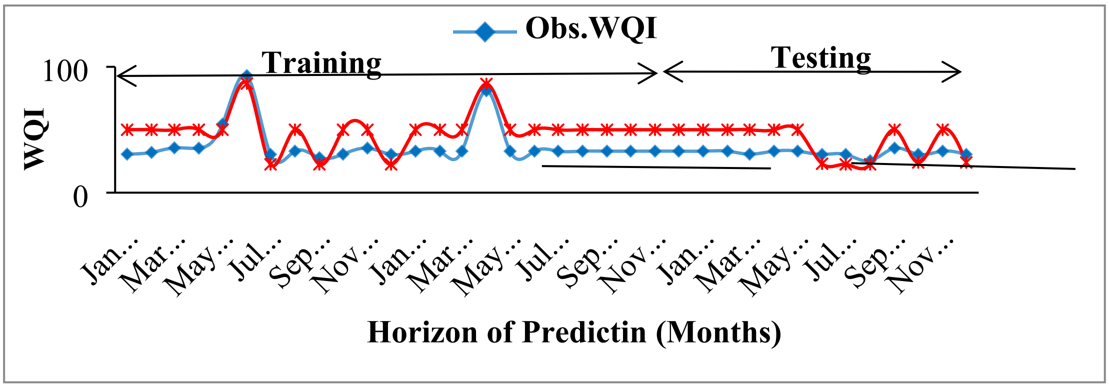


Fig.5.6 Fuzzy Model Predictions of Water Quality for Zone of Bad Water Quality (Zone Two with Avg. WQI- 35.85)

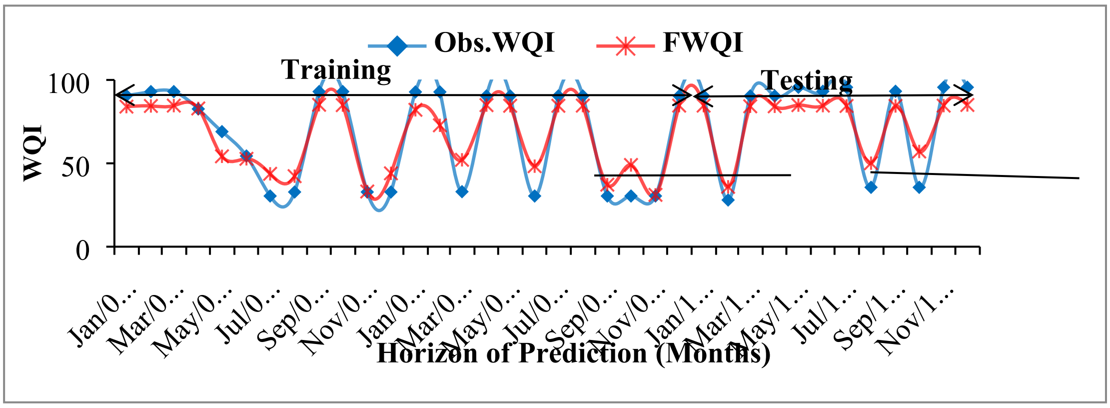


Fig.5.7 Fuzzy Model Predictions of Water Quality for Zone of Good Water Quality (Zone Fourteen with Avg.WQI-70.24)

5.2 ARTIFICIAL NEURAL NETWORK FOR PREDICTION OF WATER QUALITY

Different ANN models were developed using training data set and tested in order to determine optimum number of neurons in the hidden layer, best fitting transfer function, best suited training algorithm and optimum length of training dataset. The best fitting ANN model for each zone was selected by comparing the coefficient of co-relation (Cc) during testing. Higher the Coefficient of Correlation (Cc) better is the model performance and if the Coefficient of Correlation for various models are same, then the model which gives less Mean Relative Error (MRE) was selected. The ANN architecture for WQI prediction is composed of one input layer with six input variables, one hidden layer in which number of neurons are varied from one to ten and one output layer with one output variable. In this study Feed Forward Back Propagation (FFBP) and Cascade Forward Back Propagation (CFBP) algorithm were compared for the prediction of WQI in the various zones of municipal distribution system. The constructed ANN models for prediction of the WQI were trained using the Levenberg-Marquardt algorithm (LMA). The LMA is much faster than other algorithms used in back propagation (Ying *et al.*, 2007). Tansigmoidal, Purelinear and Logsigmoidal transfer functions were used to construct the ANN models for various zones in the study area. The effect of influencing parameters on prediction efficiency was studied by selecting one typical zone from each water quality class. The Zone second from bad water quality class (35.85), fourth zone (55.37) from medium water quality class, zone three (77.95) from good water quality class and zone twenty two (90.64) from excellent water quality class were selected for the study. The value mentioned in the bracket indicates average WQI.

5.2.1 Effect of Transfer Function

The assessment for effect of transfer function on prediction performance was carried out by using Feed Forward Back Propagation (FFBP) and Cascade Forward Back Propagation (CFBP) algorithm for zone two, four, three and zone twenty two having water quality class bad, medium, good and excellent respectively. The error analysis during training and testing for these four zones is mentioned in the Tables 5.8 to 5.39. The performance of ANN models was assessed for four lengths of training data sets, viz. 50%, 60%, 66.66% and 90%. From Tables 5.8 to 5.39 it is observed that model performance varies considerably with change in transfer function. The best fitting ANN model for each zone is mentioned in Table 5.40. From Table 5.40 it is observed that, out of twenty nine zones in the study area, for twenty zones Tansigmoidal, for five zones Purelinear and for remaining four zones Logsigmoidal transfer function performs better. From Table 5.40 it is also observed that tansigmoidal transfer function performs better for bad, medium and good water quality classes whereas for excellent water quality class purelinear transfer function performs marginally better as compared to tansigmoidal transfer function. Overall performance of tansigmoidal transfer function was found satisfactory for water quality prediction. The better performance of tansigmoidal transfer function could be due to strong nonlinearity between input variables and output variable for all quality classes.

Table 5.8 Error Analysis for Zone Two (Avg.WQI-35.85) with Bad Water Quality Using CFBP Algorithm (With 50% Training Length)

Transfer Function	Data	Error Analysis	No. of Neurons									
			1	2	3	4	5	6	7	8	9	10
Tansigmoidal	Training	MAE	7.413	6.036	11.370	9.743	9.775	7.829	6.474	5.275	26.292	17.817
		CC	0.730	0.915	0.738	0.908	0.729	0.617	0.744	0.872	0.255	0.287
		MRE	19.588	14.299	20.940	18.729	28.202	20.703	14.150	12.168	77.541	49.887
	Testing	MAE	3.567	4.462	4.453	4.315	4.403	5.528	3.050	2.215	19.826	3.669
		CC	0.067	0.246	-0.230	-0.174	-0.202	-0.221	-0.008	0.302	-0.265	-0.175
		MRE	11.074	13.741	13.712	13.263	13.629	17.561	9.503	6.996	63.059	11.638
Purelinear	Training	MAE	6.569	24.058	14.902	29.197	8.645	**44.434**	9.045	8.381	16.598	12.651
		CC	0.892	-0.046	0.362	-0.416	0.849	**0.686**	0.795	0.859	-0.327	0.509
		MRE	16.493	65.343	40.526	74.306	24.497	**128.554**	25.091	23.624	33.919	33.378
	Testing	MAE	4.043	18.309	9.840	22.998	10.666	**24.116**	11.862	10.428	12.933	9.669
		CC	0.061	0.119	-0.219	-0.500	0.330	**0.506**	-0.341	0.161	-0.260	0.287
		MRE	12.629	57.628	31.257	74.165	33.766	**73.906**	37.128	33.161	41.282	30.991
Logsigmoidal	Training	MAE	23.824	26.611	23.656	25.725	23.656	26.611	23.900	23.669	26.611	23.817
		CC	0.952	-0.055	0.946	0.731	0.946	-0.096	0.952	0.946	0.057	0.947
		MRE	73.444	76.598	73.237	75.645	73.237	76.598	73.501	73.253	76.598	73.424
	Testing	MAE	28.400	28.400	28.400	28.400	28.400	28.400	31.111	28.400	28.400	31.201
		CC	-0.182	0.000	-0.181	-0.186	3.6E-15	3.6E-15	3.6E-15	3.6E-15	3.6E-15	-0.001
		MRE	89.660	89.660	89.660	89.660	89.660	89.660	98.170	89.660	89.660	98.427

Table 5.9 Error Analysis for Zone Two (Avg.WQI-35.85) with Bad Water Quality Using CFBP Algorithm (With 60% Training Length)

Transfer Function	Data	Error Analysis	No. of Neurons									
			1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Tansigmoidal	**Training**	**MAE**	4.838	6.219	1.690	3.885	3.505	1.050	3.849	1.794	1.301	1.239
		CC	0.905	0.764	0.977	0.937	0.945	0.993	0.940	0.956	0.989	0.986
		MRE	13.513	17.414	3.363	9.651	6.145	3.007	9.505	3.787	3.493	2.787
	Testing	**MAE**	3.556	7.543	2.755	2.551	2.850	4.176	3.990	1.675	3.562	4.525
		CC	0.531	-0.158	0.102	0.090	0.004	-0.041	-0.117	0.369	-0.220	0.011
		MRE	10.759	24.003	8.759	8.103	8.960	13.183	12.607	5.409	11.516	14.363
Purelinear	**Training**	**MAE**	10.005	7.444	**8.793**	8.708	32.608	7.278	7.649	10.714	7.987	8.742
		CC	0.629	0.823	**0.763**	0.776	-0.142	0.825	0.834	0.661	0.815	0.619
		MRE	28.928	19.655	**23.269**	25.384	92.591	18.948	21.391	31.128	22.426	23.682
	Testing	**MAE**	9.231	5.896	**13.467**	9.384	20.924	6.581	6.888	10.776	8.271	9.930
		CC	-0.394	0.101	**0.612**	-0.297	0.445	-0.058	-0.110	-0.676	-0.251	-0.456
		MRE	29.126	18.536	**31.359**	29.059	65.701	20.493	21.435	35.108	25.519	31.115
Logsigmoidal	**Training**	**MAE**	24.336	24.341	24.365	26.755	24.355	26.755	24.361	24.340	24.348	24.336
		CC	0.947	0.948	0.950	-0.039	0.948	-3.3E-16	0.949	0.948	0.948	0.947
		MRE	75.018	75.023	75.055	77.768	75.040	77.767	75.048	75.022	75.032	75.018
	Testing	**MAE**	28.686	28.686	28.686	28.686	28.686	28.686	28.686	28.686	28.686	28.686
		CC	-0.159	-0.159	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
		MRE	91.554	91.554	91.554	91.554	91.554	91.554	91.554	91.554	91.554	91.554

Table 5.10 Error Analysis for Zone Two (Avg.WQI-35.85) with Bad Water Quality Using CFBP Algorithm (With 66% Training Length)

Transfer Function	Data	Error Analysis	No. of Neurons									
			1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Tansigmoidal	**Training**	**MAE**	3.197	19.503	8.089	10.137	6.169	6.304	1.185	1.497	4.089	3.679
		CC	0.797	0.411	0.665	0.665	0.822	0.716	0.982	0.989	0.935	0.865
		MRE	8.966	57.507	22.469	29.672	16.884	14.381	3.583	3.854	10.998	10.023
	Testing	**MAE**	2.122	17.973	5.403	5.351	3.489	4.092	3.181	1.949	2.111	5.763
		CC	0.143	-0.062	0.489	-0.214	0.248	0.481	0.040	0.236	0.304	-0.476
		MRE	6.805	57.361	16.336	17.137	11.041	12.732	10.217	6.404	7.015	18.984
Purelinear	**Training**	**MAE**	9.747	9.052	10.317	9.797	7.969	8.059	8.731	8.135	8.096	**13.403**
		CC	0.700	0.788	0.454	0.723	0.824	0.798	0.762	0.804	0.749	**0.817**
		MRE	26.862	26.260	25.634	28.364	22.835	22.476	25.705	23.397	21.666	**32.850**
	Testing	**MAE**	5.614	6.997	7.487	6.298	6.927	6.903	10.921	5.697	5.926	**8.870**
		CC	0.211	0.354	0.294	-0.124	-0.115	-0.254	0.399	0.457	0.588	**0.706**
		MRE	17.881	22.726	24.020	20.039	21.764	21.517	35.537	18.753	19.316	**28.666**
Logsigmoidal	**Training**	**MAE**	24.592	24.592	24.592	24.592	24.592	25.090	26.803	24.592	24.592	24.658
		CC	0.948	0.948	0.948	0.948	0.948	0.948	0.736	0.948	0.948	0.951
		MRE	75.687	75.687	75.687	75.687	75.687	76.302	78.201	75.687	75.687	75.768
	Testing	**MAE**	28.900	28.900	28.900	28.900	28.900	28.900	28.900	28.900	28.900	28.900
		CC	1.7E-15	1.7E-15	1.7E-15	1.7E-15	1.7E-15	1.7E-15	1.7E-15	1.7E-15	1.7E-15	1.7E-15
		MRE	92.976	92.976	92.976	92.976	92.976	92.976	92.976	92.976	92.976	92.976

Table 5.11 Error Analysis for Zone Two (Avg.WQI-35.85) with Bad Water Quality Using CFBP Algorithm (With 90% Training Length)

Transfer Function	Data	Error Analysis	No. of Neurons									
			1	2	3	4	5	6	7	8	9	10
Tansigmoidal	Training	MAE	19.013	4.898	2.208	0.920	1.656	8.027	1.381	1.518	3.610	10.867
		CC	-0.088	0.850	0.982	0.996	0.982	0.845	0.980	0.989	0.938	-0.009
		MRE	51.475	12.340	6.140	2.868	4.871	22.949	3.946	4.458	8.130	24.926
	Testing	MAE	11.832	6.502	6.658	2.782	11.224	6.325	4.747	3.587	2.375	2.375
		CC	-0.839	-0.453	-0.567	-0.273	-0.782	-0.500	-0.325	-0.716	-0.331	-0.331
		MRE	38.026	21.122	21.884	9.026	36.543	20.150	15.316	11.638	7.631	7.631
Purelinear	Training	MAE	**9.637**	8.730	4.903	7.780	6.944	9.384	6.067	7.683	8.335	7.662
		CC	**0.955**	0.664	0.261	0.654	0.789	0.596	0.780	0.801	0.758	0.754
		MRE	**5.397**	25.361	8.030	22.134	19.459	26.705	15.714	21.777	24.410	22.219
	Testing	MAE	**1.832**	8.174	1.173	9.232	8.031	11.815	7.841	7.755	13.141	7.021
		CC	**0.974**	-0.589	-0.015	-0.305	-0.289	-0.805	0.036	-0.171	-0.098	-0.422
		MRE	**3.082**	26.687	3.680	29.990	26.379	38.117	25.638	25.346	42.383	23.064
Logsigmoidal	Training	MAE	24.664	25.278	24.908	26.042	26.303	26.303	25.411	25.278	26.468	24.618
		CC	0.946	0.734	0.946	0.737	-0.009	-0.003	0.907	0.734	-0.031	0.944
		MRE	76.942	77.708	77.251	78.529	78.810	78.810	78.629	77.707	79.285	76.893
	Testing	MAE	39.200	27.933	27.933	39.200	27.933	27.933	27.933	27.933	27.933	27.933
		CC	-0.500	9.6E-16	9.6E-16	9.6E-16	9.6E-16	9.6E-16	9.6E-16	9.6E-16	9.6E-16	9.6E-16
		MRE	126.684	89.623	89.623	123.764	89.623	89.623	89.623	89.623	89.623	89.623

Table 5.12 Error Analysis for Zone Two (Avg.WQI-35.85) with Bad Water Quality Using FFBP Algorithm (With 50% Training Length)

Transfer Function	Data	Error Analysis	No. of Neurons									
			1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Tansigmoidal	**Training**	**MAE**	14.656	21.276	9.977	6.048	7.030	4.186	4.558	22.072	10.792	7.152
		CC	-0.056	-0.198	0.576	0.880	0.687	0.941	0.917	-0.270	0.456	0.764
		MRE	29.552	51.078	21.767	16.758	19.689	10.488	12.549	54.443	29.234	20.101
	Testing	**MAE**	11.900	11.900	10.283	11.501	13.089	10.872	10.747	16.550	15.368	11.374
		CC	0.116	3.6E-15	0.464	-0.162	-0.354	-0.058	-0.172	0.439	0.566	-0.095
		MRE	21.812	21.812	19.335	21.055	26.172	19.751	19.060	36.650	34.000	20.609
Purelinear	**Training**	**MAE**	9.992	**12.935**	9.304	12.272	21.108	8.063	8.683	12.778	8.047	27.967
		CC	0.859	**0.587**	0.819	0.121	0.620	-0.027	0.790	0.616	0.874	0.382
		MRE	29.307	**36.231**	27.353	24.760	62.079	11.616	24.565	34.916	23.122	84.225
	Testing	**MAE**	23.196	**18.952**	17.149	12.138	24.270	9.000	15.952	23.327	18.695	27.174
		CC	-0.093	**0.624**	-0.586	-0.644	0.587	-0.232	0.061	-0.044	-0.088	0.197
		MRE	52.544	**42.531**	38.509	24.550	65.715	14.678	33.902	52.895	40.174	73.605
Logsigmoidal	**Training**	**MAE**	24.322	26.611	23.656	26.611	26.611	23.902	23.656	24.320	26.611	26.655
		CC	0.946	-0.056	0.946	-0.122	2.9E-16	0.953	0.946	0.946	-0.128	0.767
		MRE	73.954	76.598	73.237	76.598	76.598	73.594	73.237	74.058	76.598	76.785
	Testing	**MAE**	26.611	26.611	26.611	26.611	26.611	26.610	26.611	26.611	26.611	26.678
		CC	0.006	0.398	-0.190	0.076	3.6E-15	-0.242	-0.186	-0.175	-0.080	0.569
		MRE	76.598	76.598	76.598	76.598	76.598	76.598	76.598	76.598	76.598	76.813

Table 5.13 Error Analysis for Zone Two (Avg.WQI-35.85) with Bad Water Quality Using FFBP Algorithm (With 60% Training Length)

Transfer Function	Data	Error Analysis	No. of Neurons									
			1	2	3	4	5	6	7	8	9	10
Tansigmoidal	Training	MAE	2.572	8.581	1.173	0.915	5.855	2.765	1.314	2.770	**0.414**	1.326
		CC	0.963	0.547	0.978	0.993	0.881	0.989	0.995	0.968	**0.999**	0.982
		MRE	5.684	18.672	2.691	2.921	9.781	5.215	3.623	5.353	**1.293**	3.334
	Testing	MAE	1.726	3.960	1.902	2.885	2.166	3.104	1.911	7.442	**11.465**	2.033
		CC	-0.158	0.007	0.358	-0.651	0.020	0.176	0.055	0.089	**0.790**	0.167
		MRE	5.917	12.398	6.162	9.408	7.102	9.923	6.227	23.768	**24.729**	6.798
Purelinear	Training	MAE	7.803	7.794	7.279	9.273	7.641	7.200	9.209	7.267	7.824	20.345
		CC	0.829	0.794	0.723	0.644	0.795	0.817	0.597	0.824	0.674	0.392
		MRE	20.407	20.667	15.095	24.070	19.217	18.204	23.701	19.012	22.088	61.914
	Testing	MAE	7.568	8.215	2.825	5.974	5.162	6.026	7.111	6.676	10.798	26.417
		CC	-0.258	0.356	0.267	0.144	0.048	-0.197	-0.081	-0.315	-0.421	-0.584
		MRE	23.392	26.320	8.944	19.335	16.075	18.583	22.154	20.990	33.394	88.094
Logsigmoidal	Training	MAE	26.755	26.756	26.755	26.755	26.796	24.344	24.353	24.881	26.767	24.336
		CC	0.471	0.611	0.988	-0.088	0.551	0.947	0.948	0.947	0.561	0.947
		MRE	77.767	77.771	77.767	77.767	77.937	75.027	75.037	75.691	77.820	75.018
	Testing	MAE	28.686	28.687	28.686	28.686	28.725	28.686	28.686	28.686	28.699	28.686
		CC	-0.291	0.167	-0.141	-0.229	0.352	-0.201	-0.106	-0.159	0.466	-0.200
		MRE	91.554	91.557	91.554	91.554	91.678	91.554	91.554	91.554	91.595	91.554

Table 5.14 Error Analysis for Zone Two (Avg.WQI-35.85) with Bad Water Quality Using FFBP Algorithm (With 66.66 % Training Length)

Transfer Function	Data	Error Analysis	No. of Neurons									
			1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Tansigmoidal	**Training**	**MAE**	9.202	8.685	1.612	2.230	1.731	3.472	12.276	7.394	10.281	3.867
		CC	0.516	0.536	0.977	0.969	0.956	0.906	-0.032	0.839	-0.068	0.923
		MRE	17.454	17.329	3.330	4.613	4.156	9.638	26.060	20.353	20.515	9.823
	Testing	**MAE**	3.192	3.634	2.210	2.274	2.125	3.373	4.097	4.084	4.097	2.089
		CC	0.356	-0.177	-0.058	-0.542	-0.076	-0.173	-0.188	-0.186	-0.138	0.365
		MRE	9.992	11.317	7.303	7.531	7.042	11.176	12.748	12.705	12.748	6.721
Purelinear	**Training**	**MAE**	**26.809**	24.866	26.809	26.809	24.635	26.809	26.809	24.728	26.828	26.809
		CC	**0.902**	0.955	0.000	0.000	0.954	0.000	0.000	0.952	0.371	0.000
		MRE	**78.207**	75.984	78.207	78.207	75.761	78.207	78.207	75.836	78.280	78.207
	Testing	**MAE**	**6.489**	29.057	4.485	5.102	5.137	8.112	7.297	5.820	6.742	13.843
		CC	**0.809**	0.419	-0.125	-0.778	-0.064	-0.285	-0.349	-0.013	-0.194	-0.516
		MRE	**26.22**	92.987	14.030	17.221	16.066	26.301	23.016	18.140	20.931	45.886
Logsigmoidal	**Training**	**MAE**	41.940	26.906	7.486	8.164	6.811	15.005	10.454	9.112	7.489	14.516
		CC	0.565	-0.204	0.791	0.529	0.818	0.471	0.649	0.742	0.815	0.565
		MRE	127.067	77.090	19.043	17.898	17.181	44.424	29.348	25.856	20.975	42.785
	Testing	**MAE**	28.900	28.900	28.900	28.900	28.900	28.900	28.900	28.900	28.900	28.900
		CC	1.7E-15	1.7E-15	1.7E-15	1.7E-15	1.7E-15	1.7E-15	1.7E-15	1.7E-15	-0.130	1.7E-15
		MRE	92.976	92.976	92.976	92.976	92.976	92.976	92.976	92.976	92.976	92.976

Table 5.15 Error Analysis for Zone Two (Avg.WQI-35.85) with Bad Water Quality Using FFBP Algorithm (With 90% Training Length)

Transfer Function	Data	Error Analysis	No. of Neurons									
			1	2	3	4	5	6	7	8	9	10
Tansigmoidal	Training	MAE	4.690	1.041	2.481	1.927	2.076	1.328	2.799	0.934	**6.771**	3.937
		CC	0.338	0.991	0.892	0.960	0.982	0.985	0.837	0.995	**0.995**	0.827
		MRE	7.449	2.570	6.657	5.438	5.921	3.626	8.197	2.834	**13.464**	8.659
	Testing	MAE	2.128	1.347	3.130	3.038	1.521	4.886	0.723	1.875	**0.563**	2.622
		CC	-0.966	0.017	-0.781	-0.398	0.523	-0.041	0.859	0.336	**0.993**	-0.634
		MRE	6.861	4.339	10.093	9.683	4.967	15.990	2.261	6.121	**1.834**	8.499
Purelinear	Training	MAE	7.268	6.841	27.298	6.605	6.857	7.590	8.198	9.923	7.724	8.430
		CC	0.780	0.815	-0.406	0.687	0.800	0.985	0.735	0.604	0.754	0.758
		MRE	20.555	20.017	78.502	17.050	20.008	20.371	23.584	28.808	22.702	24.666
	Testing	MAE	10.487	10.485	34.222	4.530	11.005	7.369	10.856	16.435	11.502	11.971
		CC	-0.392	-0.424	0.396	-0.413	-0.453	-0.543	-0.645	-0.408	-0.408	-0.471
		MRE	34.023	33.996	109.455	14.812	35.694	24.094	35.709	53.071	37.269	38.780
Logsigmoidal	Training	MAE	26.303	26.303	25.748	26.303	24.712	26.114	24.674	24.621	26.303	26.303
		CC	0.987	-0.009	0.734	-0.222	0.946	0.874	0.946	0.944	0.734	0.044
		MRE	78.810	78.810	78.213	78.810	76.997	78.600	76.953	76.897	78.810	78.810
	Testing	MAE	27.933	27.933	27.867	27.933	27.934	27.933	27.933	27.933	27.867	27.933
		CC	-0.501	0.922	-1.000	-0.113	-0.496	-0.500	-0.499	-0.501	-1.000	-0.500
		MRE	89.623	89.623	89.421	89.623	89.624	89.623	89.623	89.623	89.421	89.623

Table 5.16 Error Analysis for Zone Four (Avg.WQI-55.67) with Medium Water Quality Using CFBP Algorithm (With 50% Training Length)

Transfer Function	Data	Error Analysis	No. of Neurons									
			1	2	3	4	5	6	7	8	9	10
Tansigmoidal	Training	MAE	11.863	18.683	25.306	24.137	**26.243**	26.669	27.903	23.540	22.906	19.743
		CC	0.627	0.444	0.185	0.343	**0.605**	0.034	-0.020	0.229	0.338	0.443
		MRE	29.019	29.991	34.897	35.439	**54.040**	65.924	52.930	40.811	55.389	38.430
	Testing	MAE	30.172	26.804	18.803	39.469	**16.909**	35.857	33.463	31.994	35.966	37.754
		CC	0.112	-0.227	0.513	-0.475	**0.519**	-0.285	-0.229	-0.351	-0.384	-0.078
		MRE	80.488	44.754	28.725	87.284	**40.107**	95.239	83.713	69.224	91.589	102.198
Purelinear	Training	MAE	25.525	27.271	29.922	24.828	25.294	25.699	31.187	25.663	33.793	29.335
		CC	0.232	0.176	-0.079	0.221	0.156	0.177	0.015	0.072	-0.241	0.001
		MRE	45.265	56.288	47.774	55.413	57.969	62.992	71.770	43.030	76.943	48.473
	Testing	MAE	27.595	39.713	34.018	40.087	25.736	31.363	33.119	28.778	34.164	35.576
		CC	0.041	-0.090	-0.117	-0.469	0.392	0.103	0.208	0.009	0.091	-0.493
		MRE	55.651	105.128	74.605	105.974	68.820	84.558	89.174	75.568	88.280	72.856
Logsigmoidal	Training	MAE	23.534	23.529	25.219	28.833	24.580	25.706	24.087	25.878	27.359	28.601
		CC	0.394	0.439	0.317	-0.070	0.235	0.417	0.381	0.078	0.152	-0.091
		MRE	53.720	56.089	55.237	75.282	55.395	55.854	58.088	62.918	70.301	73.988
	Testing	MAE	35.772	32.911	27.212	38.406	31.534	29.189	31.555	32.668	33.475	36.449
		CC	-0.156	0.070	0.494	0.063	0.161	0.286	0.177	0.232	0.177	0.067
		MRE	99.900	93.192	74.058	115.883	87.557	81.422	90.064	94.529	96.790	106.714

Table 5.17 Error Analysis for Zone Four (Avg.WQI-55.67) with Medium Water Quality Using CFBP Algorithm (With 60% Training Length)

Transfer Function	Data	Error Analysis	No. of Neurons									
			1	2	3	4	5	6	7	8	9	10
Tansigmoidal	Training	MAE	27.962	26.389	23.481	26.049	24.698	27.124	22.116	24.005	25.364	26.291
		CC	0.046	0.217	0.498	0.258	0.345	-0.019	0.613	0.509	0.353	0.297
		MRE	73.935	64.292	58.231	61.235	65.835	64.977	56.843	59.731	61.209	62.349
	Testing	MAE	31.414	27.023	31.668	30.179	29.399	26.101	28.207	29.379	31.425	34.166
		CC	0.238	0.384	-0.213	-0.283	0.123	0.494	0.246	-0.022	-0.220	-0.378
		MRE	85.107	73.133	80.233	76.385	77.964	69.593	76.975	73.347	81.347	89.665
Purelinear	Training	MAE	26.304	25.070	23.787	29.623	21.894	25.654	24.139	26.643	22.545	24.704
		CC	0.156	0.228	0.259	0.053	0.291	0.070	0.237	0.072	0.288	0.180
		MRE	60.728	57.353	49.386	70.603	46.562	57.162	54.421	66.296	46.528	42.653
	Testing	MAE	29.690	31.580	32.583	31.636	39.465	29.104	49.535	28.473	30.029	29.758
		CC	-0.005	-0.331	-0.412	-0.050	-0.141	-0.051	-0.620	0.186	-0.177	0.020
		MRE	76.248	73.783	72.730	92.742	90.975	68.424	119.457	75.569	63.551	55.199
Logsigmoidal	Training	MAE	24.567	20.196	6.380	22.103	5.414	**24.960**	7.703	25.376	26.694	18.677
		CC	0.256	0.287	0.847	0.122	0.862	**0.537**	0.761	-0.005	0.300	0.360
		MRE	60.550	39.470	17.403	35.201	8.527	**35.143**	22.680	46.214	68.270	34.125
	Testing	MAE	28.875	25.942	30.749	33.821	27.460	**21.848**	36.056	27.358	32.707	25.811
		CC	0.101	0.196	0.087	-0.279	0.074	**0.354**	-0.142	-0.014	-0.055	0.150
		MRE	67.125	63.600	76.482	75.429	54.902	**33.067**	92.404	53.759	82.346	48.669

Table 5.18 Error Analysis for Zone Four (Avg.WQI-55.67) with Medium Water Quality Using CFBP Algorithm (With 66.66% Training Length)

Transfer Function	Data	Error Analysis	No. of Neurons									
			1	2	3	4	5	6	7	8	9	10
Tansigmoidal	Training	MAE	6.063	6.175	6.176	6.632	4.271	4.105	6.868	8.228	13.907	19.675
		CC	0.891	0.948	0.935	0.881	0.941	0.977	0.929	0.838	0.694	0.614
		MRE	12.705	10.913	10.807	15.034	7.407	9.959	11.186	13.456	35.883	52.029
	Testing	MAE	8.853	5.229	5.184	12.241	5.341	5.471	17.284	10.844	10.077	30.807
		CC	0.872	0.957	0.970	0.744	0.956	0.975	0.722	0.744	0.885	0.311
		MRE	12.245	11.661	7.639	34.988	9.021	11.426	33.000	26.883	25.966	94.747
Purelinear	Training	MAE	10.397	8.309	9.200	9.130	8.609	12.323	9.966	9.320	10.506	14.968
		CC	0.901	0.898	0.897	0.895	0.907	0.879	0.867	0.913	0.881	0.840
		MRE	24.934	22.382	21.916	23.024	22.011	26.280	21.999	21.290	29.269	39.811
	Testing	MAE	7.901	10.665	9.612	10.252	10.800	14.172	17.470	9.921	11.199	14.306
		CC	0.931	0.912	0.915	0.921	0.917	0.927	0.708	0.925	0.900	0.890
		MRE	17.788	30.769	25.388	24.342	25.922	32.375	33.363	20.832	28.036	33.626
Logsigmoidal	Training	MAE	18.385	19.806	21.184	21.950	23.012	24.859	21.707	**20.282**	20.991	18.276
		CC	0.966	0.948	0.890	0.700	0.658	0.496	0.856	**0.936**	0.823	0.965
		MRE	55.191	56.771	59.151	59.292	60.374	62.499	59.002	**57.358**	58.230	55.062
	Testing	MAE	17.363	19.062	20.758	22.601	21.019	28.743	23.984	**18.646**	20.449	18.745
		CC	0.940	0.918	0.836	0.641	0.765	0.386	0.921	**0.997**	0.833	0.919
		MRE	56.298	58.085	60.466	62.041	60.156	68.740	63.957	**57.915**	59.632	57.835

Table 5.19 Error Analysis for Zone Four (Avg.WQI-55.67) with Medium Water Quality Using CFBP Algorithm (With 90% Training Length)

Transfer Function	Data	Error Analysis	No. of Neurons									
			1	2	3	4	5	6	7	8	9	10
Tansigmoidal	Training	MAE	22.767	26.293	29.912	29.617	27.619	24.997	16.721	7.103	23.873	35.111
		CC	0.330	0.114	-0.127	0.001	-0.080	0.175	0.481	0.823	0.302	0.050
		MRE	50.739	56.688	67.898	55.549	45.122	54.716	30.269	16.668	63.544	101.153
	Testing	MAE	18.715	19.526	37.218	20.375	18.939	17.655	55.865	37.969	19.162	43.780
		CC	0.795	0.593	-0.980	0.892	0.959	0.669	-0.999	0.502	0.557	0.782
		MRE	49.227	47.785	81.286	24.602	34.470	57.731	141.579	121.261	52.177	140.787
Purelinear	Training	MAE	26.498	26.396	23.268	23.271	25.156	28.250	25.477	24.593	23.764	23.725
		CC	0.230	0.124	0.266	0.235	0.299	0.175	0.049	0.265	0.306	0.327
		MRE	47.919	60.333	44.248	40.670	59.779	73.657	48.819	58.746	55.345	52.851
	Testing	MAE	31.793	31.571	21.743	22.251	29.787	30.097	26.464	21.932	20.948	20.412
		CC	-0.997	0.082	0.649	0.638	0.999	0.986	-0.039	0.518	0.997	0.988
		MRE	44.536	87.010	45.650	54.927	92.452	83.678	57.193	59.855	60.701	59.166
Logsigmoidal	Training	MAE	27.354	26.965	25.926	28.841	26.260	**26.515**	26.100	29.130	26.784	24.042
		CC	-0.121	0.164	0.291	0.045	0.238	**0.999**	0.204	0.053	0.178	0.490
		MRE	64.160	62.514	63.447	71.227	65.433	**65.556**	63.730	77.940	64.063	63.999
	Testing	MAE	30.434	30.455	21.020	30.792	30.105	**22.255**	31.191	30.056	23.553	33.748
		CC	-0.322	-0.932	0.993	-0.560	0.999	**0.999**	-0.500	0.999	0.997	0.501
		MRE	79.224	79.296	68.825	80.592	78.871	**70.239**	81.716	92.113	73.172	107.376

Table 5.20 Error Analysis for Zone Four (Avg.WQI-55.67) with Medium Water Quality Using FFBP Algorithm (With 50% Training Length)

Transfer Function	Data	Error Analysis	No. of Neurons									
			1	2	3	4	5	6	7	8	9	10
Tansigmoidal	Training	MAE	**6.689**	5.482	2.097	4.429	7.718	12.650	5.812	4.753	3.026	23.212
		CC	**0.960**	0.963	0.995	0.949	0.799	0.780	0.844	0.903	0.975	0.479
		MRE	**14.972**	15.640	4.439	9.570	22.611	18.896	14.939	8.326	5.554	62.709
	Testing	MAE	**6.242**	7.308	3.424	8.797	14.803	10.518	3.485	8.246	3.915	27.335
		CC	**0.993**	0.972	0.984	0.818	0.741	0.785	0.986	0.845	0.966	0.318
		MRE	**18.368**	20.246	8.448	17.021	43.179	17.536	8.218	23.351	7.367	75.120
Purelinear	Training	MAE	12.303	9.855	10.956	9.303	12.130	13.163	9.378	8.751	9.569	13.058
		CC	0.836	0.910	0.861	0.891	0.899	0.857	0.926	0.926	0.908	0.805
		MRE	27.631	20.880	23.230	23.956	21.744	25.543	23.239	21.584	22.555	29.239
	Testing	MAE	17.445	9.745	15.851	10.082	13.006	15.201	9.700	11.683	11.619	24.627
		CC	0.807	0.905	0.756	0.898	0.844	0.769	0.923	0.881	0.869	0.562
		MRE	51.207	23.925	39.577	29.055	25.727	31.057	25.060	29.889	27.685	60.305
Logsigmoidal	Training	MAE	14.876	19.069	14.398	14.476	24.299	15.828	16.164	20.711	15.406	17.228
		CC	0.962	0.887	0.961	0.959	0.429	0.945	0.868	0.700	0.886	0.851
		MRE	43.662	50.301	43.162	43.244	54.314	44.779	45.152	51.016	44.368	46.433
	Testing	MAE	21.872	28.985	24.591	24.113	28.212	21.935	23.238	27.455	22.161	25.645
		CC	0.996	0.532	0.754	0.737	0.607	0.962	0.826	0.442	0.947	0.655
		MRE	68.213	84.030	71.188	70.557	75.214	68.179	69.697	77.548	68.507	72.691

Table 5.21 Error Analysis for Zone Four (Avg.WQI-55.67) with Medium Water Quality Using FFBP Algorithm (With 60% Training Length)

Transfer Function	Data	Error Analysis	No. of Neurons									
			1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Tansigmoidal	**Training**	**MAE**	3.307	1.789	5.330	9.530	16.049	20.803	6.220	17.710	3.832	1.556
		CC	0.958	0.996	0.973	0.901	0.830	0.518	0.913	0.612	0.979	0.994
		MRE	5.448	3.398	9.670	20.448	43.063	42.348	13.561	26.073	7.400	3.642
	Testing	**MAE**	4.634	3.691	7.146	16.744	18.278	23.609	14.409	16.307	9.358	13.602
		CC	0.985	0.982	0.979	0.728	0.678	0.674	0.672	0.842	0.822	0.665
		MRE	10.896	7.559	13.941	39.555	53.730	47.932	28.899	22.804	18.391	29.246
Purelinear	**Training**	**MAE**	9.550	8.614	9.038	8.177	10.720	12.147	9.124	8.427	10.162	11.088
		CC	0.905	0.925	0.922	0.901	0.887	0.780	0.930	0.926	0.882	0.845
		MRE	22.150	23.993	21.726	22.615	24.346	29.921	19.473	19.392	22.618	23.943
	Testing	**MAE**	13.002	7.145	10.747	9.749	13.356	14.393	11.741	12.060	14.034	16.271
		CC	0.899	0.942	0.916	0.910	0.857	0.825	0.907	0.908	0.797	0.799
		MRE	27.787	20.891	24.598	29.710	36.287	31.935	24.262	28.728	34.285	33.215
Logsigmoidal	**Training**	**MAE**	18.847	21.733	**17.534**	17.704	17.267	17.095	23.361	22.443	30.359	18.807
		CC	0.965	0.807	**0.965**	0.966	0.966	0.964	0.664	0.810	0.261	0.955
		MRE	53.057	58.902	**51.625**	51.835	51.321	51.139	58.975	59.661	83.336	53.107
	Testing	**MAE**	21.538	22.719	**19.978**	20.681	19.638	20.240	26.988	24.198	32.556	21.650
		CC	0.941	0.803	**0.997**	0.985	0.945	0.981	0.458	0.937	0.105	0.980
		MRE	64.682	67.828	**13.094**	64.097	62.596	63.387	72.816	69.748	98.638	65.358

Table 5.22 Error Analysis for Zone Four (Avg.WQI-55.67) with Medium Water Quality Using FFBP Algorithm (With 66.66 % Training Length)

Transfer Function	Data	Error Analysis	No. of Neurons									
			1	2	3	4	5	6	7	8	9	10
Tansigmoidal	**Training**	**MAE**	2.202	2.696	**1.728**	10.014	2.190	8.647	12.039	4.617	5.621	4.521
		CC	0.995	0.979	**0.997**	0.869	0.994	0.753	0.750	0.947	0.908	0.929
		MRE	4.790	5.013	**4.064**	18.906	4.353	17.600	25.592	10.663	9.476	7.015
	Testing	**MAE**	13.032	3.996	**4.782**	11.992	6.375	15.519	24.938	11.742	9.318	23.913
		CC	0.663	0.978	**0.991**	0.919	0.975	0.656	0.336	0.772	0.864	0.394
		MRE	26.735	8.148	**12.479**	23.834	17.862	27.443	53.247	24.508	14.859	42.295
Purelinear	**Training**	**MAE**	9.419	19.771	9.933	11.649	8.810	9.604	12.995	9.526	16.195	9.054
		CC	0.913	0.660	0.907	0.877	0.912	0.911	0.821	0.867	0.855	0.912
		MRE	22.146	38.880	25.613	28.411	20.982	24.265	29.698	24.588	42.955	22.935
	Testing	**MAE**	12.829	29.699	11.596	9.063	11.387	11.438	14.146	11.899	12.231	9.952
		CC	0.936	-0.036	0.921	0.930	0.896	0.919	0.842	0.888	0.906	0.913
		MRE	30.133	58.915	25.591	21.911	25.541	25.698	36.098	25.980	33.335	24.585
Logsigmoidal	**Training**	**MAE**	19.298	21.337	27.278	20.374	19.521	22.694	20.890	18.701	23.429	21.248
		CC	0.967	0.926	0.363	0.954	0.901	0.800	0.823	0.965	0.709	0.904
		MRE	56.216	60.345	66.930	58.195	56.525	61.042	57.984	55.580	63.066	58.983
	Testing	**MAE**	18.802	20.328	30.491	18.805	19.374	23.480	24.061	18.414	21.763	27.105
		CC	0.998	0.932	-0.263	0.887	0.915	0.623	0.549	0.924	0.793	0.245
		MRE	58.032	60.537	78.423	60.236	58.463	63.428	63.546	57.486	62.152	73.209

Table 5.23 Error Analysis for Zone Four (Avg.WQI-55.67) with Medium Water Quality Using FFBP Algorithm (With 90 % Training Length)

Transfer Function	Data	Error Analysis	No. of Neurons									
			1	2	3	4	5	6	7	8	9	10
Tansigmoidal	Training	MAE	2.435	3.410	3.922	4.218	31.003	3.158	8.428	2.361	6.314	3.445
		CC	0.986	0.984	0.950	0.965	0.532	0.986	0.809	0.989	0.882	0.971
		MRE	5.099	7.874	7.085	7.761	89.501	7.464	18.789	4.317	13.841	9.083
	Testing	MAE	20.472	19.520	19.067	19.608	20.448	19.119	20.363	20.364	21.430	19.420
		CC	0.258	0.857	0.931	0.993	0.476	0.886	0.013	0.647	-0.398	0.987
		MRE	25.251	22.705	22.713	23.633	25.715	25.786	23.658	25.512	26.456	23.607
Purelinear	Training	MAE	8.550	8.677	10.412	8.745	8.509	9.733	8.762	10.101	8.901	8.233
		CC	0.929	0.932	0.909	0.927	0.933	0.986	0.934	0.901	0.932	0.932
		MRE	22.535	23.128	25.082	22.372	21.620	22.391	21.815	24.160	20.965	20.566
	Testing	MAE	9.958	9.086	10.223	13.089	13.548	8.693	7.577	8.977	9.020	10.053
		CC	0.902	0.935	0.908	0.920	0.932	0.978	0.953	0.984	0.943	0.918
		MRE	29.111	27.897	30.326	38.200	35.178	26.941	24.235	25.422	28.414	29.984
Logsigmoidal	Training	MAE	19.162	**18.773**	17.015	27.017	16.107	18.711	17.251	19.675	17.810	18.826
		CC	0.794	**0.861**	0.963	0.174	0.967	0.953	0.948	0.895	0.877	0.799
		MRE	53.268	**55.513**	50.889	62.715	49.861	52.875	51.222	55.540	52.730	54.958
	Testing	MAE	21.495	**21.175**	22.341	30.155	22.680	21.769	21.349	23.309	21.468	23.782
		CC	0.999	**0.999**	0.999	0.972	0.998	0.998	0.998	0.984	0.999	0.998
		MRE	69.335	**68.981**	70.271	80.160	70.646	69.639	69.174	73.182	69.306	71.865

Table 5.24 Error Analysis for Zone Three (Avg.WQI-77.95) with Good Water Quality Using CFBP Algorithm (50% Training Dataset)

Transfer Function	Data	Error Analysis	No. of Neurons									
			1	2	3	4	5	6	7	8	9	10
Tansigmoidal	Training	MAE	17.272	7.845	3.607	0.702	**4.269**	6.367	3.800	1.069	5.228	0.825
		CC	0.942	0.958	0.952	0.935	**0.964**	0.876	0.960	0.955	9.4E-01	0.886
		MRE	24.554	10.629	5.526	0.822	**7.115**	13.845	6.110	2.302	7.875	1.577
	Testing	MAE	42.791	4.799	3.343	6.843	**4.615**	11.167	2.228	5.231	2.643	27.528
		CC	0.920	0.843	0.990	0.325	**0.996**	0.831	0.769	0.716	0.879	0.642
		MRE	57.220	5.651	3.820	8.003	**6.491**	12.836	2.594	6.381	3.281	43.696
Purelinear	Training	MAE	4.604	11.464	4.205	7.273	6.566	26.254	9.340	10.045	22.215	10.209
		CC	0.954	0.904	0.974	0.927	0.958	0.661	0.779	0.931	0.249	0.840
		MRE	11.763	16.397	8.526	16.302	13.211	45.012	21.452	17.439	57.865	22.837
	Testing	MAE	3.992	11.469	6.285	7.484	7.662	14.616	4.373	7.808	14.244	6.293
		CC	0.975	0.705	0.901	0.866	0.918	0.425	0.965	0.887	-0.113	0.978
		MRE	6.163	15.550	8.885	12.253	12.185	19.127	7.262	11.412	29.936	7.565
Logsigmoidal	Training	MAE	10.306	10.409	10.508	10.267	10.516	10.476	9.299	10.089	10.235	10.627
		CC	0.542	0.944	0.978	0.999	0.955	0.834	0.982	0.997	0.936	0.998
		MRE	28.874	28.950	29.086	28.788	29.109	29.186	27.627	28.588	28.755	31.087
	Testing	MAE	5.483	6.427	6.619	19.744	5.686	7.005	8.599	8.898	6.061	11.969
		CC	-0.286	0.939	0.980	0.901	0.974	0.803	0.989	0.923	0.987	-0.265
		MRE	12.547	13.670	13.869	28.491	12.820	14.256	16.114	16.422	13.200	19.860

Table 5.25 Error Analysis for Zone Three (Avg.WQI-77.95) with Good Water Quality Using CFBP Algorithm (With 60% Training Length)

Transfer Function	Data	Error Analysis	No. of Neurons									
			1	2	3	4	5	6	7	8	9	10
Tansigmoidal	Training	MAE	3.266	4.337	3.122	0.827	4.409	5.078	1.091	1.858	**2.997**	13.724
		CC	0.981	0.944	0.985	0.998	0.963	0.990	0.999	0.994	**0.971**	0.701
		MRE	4.955	6.972	4.832	1.396	6.167	8.499	1.357	3.156	**4.899**	20.215
	Testing	MAE	3.225	4.733	4.035	1.958	4.229	4.731	2.808	2.555	**2.099**	8.278
		CC	0.991	0.905	0.976	0.992	0.976	0.995	0.977	0.987	**0.994**	0.805
		MRE	4.181	6.414	6.272	2.371	5.773	6.400	3.484	3.424	**2.661**	9.975
Purelinear	Training	MAE	5.003	3.984	3.984	9.400	4.568	4.166	9.867	6.495	6.928	6.997
		CC	0.964	0.969	0.893	0.966	0.883	0.971	0.848	0.956	0.937	0.825
		MRE	9.548	9.421	9.421	19.675	9.720	8.770	20.576	12.066	16.057	16.230
	Testing	MAE	6.022	3.689	9.032	4.593	5.069	4.364	8.818	6.233	8.217	6.300
		CC	0.953	0.984	0.964	0.973	0.968	0.972	0.963	0.991	0.965	0.944
		MRE	10.190	6.359	11.784	7.127	8.889	7.736	14.102	10.478	16.656	10.161
Logsigmoidal	Training	MAE	8.681	8.951	9.614	8.820	9.098	7.994	7.892	8.113	18.289	7.714
		CC	0.949	0.970	0.976	0.937	0.941	0.945	0.949	0.954	0.256	0.962
		MRE	23.842	24.254	25.055	24.279	24.389	23.123	22.996	23.228	43.458	22.723
	Testing	MAE	5.851	7.210	7.944	7.559	7.660	5.702	5.641	8.156	7.780	5.991
		CC	0.963	0.889	0.986	0.919	0.897	0.982	0.978	0.812	0.979	0.944
		MRE	14.769	16.339	17.283	16.828	16.912	14.635	14.560	17.483	16.933	14.963

Table 5.26 Error Analysis for Zone Three (Avg.WQI-77.95) with Good Water Quality Using CFBP Algorithm (With 66.66 % Training Length)

Transfer Function	Data	Error Analysis	No. of Neurons									
			1	2	3	4	5	6	7	8	9	10
Tansigmoidal	Training	MAE	7.244	3.725	1.381	4.874	0.788	**1.892**	1.563	10.578	1.804	2.289
		CC	0.889	0.947	0.996	0.950	0.998	**0.992**	0.994	0.759	0.995	0.979
		MRE	15.771	5.563	2.083	8.074	1.060	**2.963**	2.239	22.389	2.686	3.520
	Testing	MAE	8.093	10.202	2.351	5.234	1.208	**0.825**	2.174	9.389	1.667	1.470
		CC	0.976	0.772	0.994	0.960	0.999	**0.999**	0.994	0.821	0.993	0.998
		MRE	16.510	12.224	3.149	7.356	1.932	**1.233**	2.949	21.219	1.999	2.229
Purelinear	Training	MAE	7.367	3.991	7.819	4.740	31.374	4.147	4.886	12.788	3.994	10.426
		CC	0.954	0.968	0.939	0.967	0.411	0.966	0.958	0.838	0.965	0.785
		MRE	12.122	8.356	15.440	9.081	45.527	8.223	10.338	23.632	9.894	20.160
	Testing	MAE	7.968	4.251	8.907	6.633	29.213	4.688	2.707	12.362	2.698	4.694
		CC	0.973	0.981	0.952	0.964	0.953	0.969	0.984	0.943	0.993	0.967
		MRE	12.410	7.516	15.039	9.768	37.352	7.696	5.263	21.467	4.496	7.265
Logsigmoidal	Training	MAE	7.515	7.964	7.851	7.180	7.455	8.697	8.016	8.084	7.849	7.644
		CC	0.936	0.920	0.932	0.959	0.953	0.945	0.947	0.953	0.950	0.950
		MRE	21.413	21.979	21.802	20.948	21.310	22.788	21.942	22.389	21.745	21.522
	Testing	MAE	7.082	6.457	6.640	6.540	6.993	6.589	6.461	8.501	6.348	6.207
		CC	0.970	0.987	0.985	0.984	0.959	0.986	0.982	0.860	0.968	0.984
		MRE	17.500	16.806	17.002	16.894	17.414	16.954	16.814	19.117	16.704	16.533

Table 5.27 Error Analysis for Zone Three (Avg.WQI-77.95) with Good Water Quality Using CFBP Algorithm (With 90% Training Length)

Transfer Function	Data	Error Analysis	No. of Neurons									
			1	2	3	4	5	6	7	8	9	10
Tansigmoidal	**Training**	**MAE**	1.458	2.323	1.119	1.413	1.425	1.902	**1.210**	1.511	4.557	4.528
		CC	0.995	0.989	0.994	0.994	0.995	0.991	**0.995**	0.990	0.978	0.970
		MRE	2.025	3.520	2.065	2.326	2.140	2.641	**1.720**	2.068	6.491	6.660
	Testing	**MAE**	2.071	1.412	2.541	2.678	2.385	1.363	**0.706**	0.701	4.200	2.719
		CC	0.993	0.897	0.370	0.840	0.881	0.937	**0.993**	0.985	0.179	0.912
		MRE	2.334	1.569	2.838	2.988	2.665	1.481	**0.794**	0.778	4.729	3.012
Purelinear	**Training**	**MAE**	4.417	4.362	5.147	3.837	4.373	5.901	8.633	4.911	4.142	3.770
		CC	0.966	0.957	0.966	0.966	0.959	0.863	0.957	0.960	0.968	0.969
		MRE	8.493	10.895	9.120	8.927	10.219	13.723	16.069	9.497	8.194	8.628
	Testing	**MAE**	3.976	1.281	3.417	1.561	2.003	1.135	6.521	7.689	5.152	1.510
		CC	-0.871	0.978	0.017	0.983	0.994	0.971	-0.942	-0.820	-0.592	0.890
		MRE	4.246	1.421	3.655	1.730	2.244	1.207	7.291	8.309	5.554	1.667
Logsigmoidal	**Training**	**MAE**	7.812	7.280	7.955	8.500	8.703	8.026	7.276	8.862	7.282	7.768
		CC	0.960	0.953	0.953	0.865	0.776	0.949	0.968	0.939	0.966	0.954
		MRE	21.652	21.092	21.847	24.095	24.954	21.933	21.044	22.845	21.033	21.646
	Testing	**MAE**	2.630	1.741	1.959	0.798	1.640	1.321	3.431	1.539	2.974	2.061
		CC	0.894	0.948	0.932	0.980	0.932	0.870	0.928	0.870	0.821	0.945
		MRE	2.961	1.914	2.203	0.879	1.814	1.425	3.889	1.711	3.272	2.281

Table 5.28 Error Analysis for Zone Three (Avg.WQI-77.95) with Good Water Quality Using FFBP Algorithm (With 50% Training Length)

Transfer Function	Data	Error Analysis	No. of Neurons									
			1	2	3	4	5	6	7	8	9	10
Tansigmoidal	Training	MAE	12.892	2.156	**3.328**	6.366	4.651	2.154	4.098	1.948	4.300	6.920
		CC	0.723	0.986	**0.968**	0.956	0.969	0.991	0.976	0.979	0.909	0.843
		MRE	15.713	3.643	**4.692**	12.764	7.367	3.588	9.484	3.489	5.628	15.431
	Testing	MAE	6.515	2.341	**1.883**	3.008	4.481	1.851	4.282	6.923	7.413	3.690
		CC	0.940	0.984	**0.991**	0.979	0.931	0.988	0.960	0.871	0.882	0.970
		MRE	7.634	2.887	**2.528**	4.754	5.212	2.574	7.684	8.217	8.390	4.372
Purelinear	Training	MAE	15.086	10.655	5.634	21.663	21.139	18.936	3.868	4.800	9.402	5.416
		CC	0.674	0.836	0.967	0.536	0.916	0.642	0.969	0.969	0.899	0.967
		MRE	37.779	24.440	10.374	33.727	55.630	34.406	8.807	9.715	19.830	9.485
	Testing	MAE	8.211	7.247	6.928	15.427	4.359	14.678	3.976	6.163	6.735	7.481
		CC	0.821	0.969	0.898	0.556	0.950	0.782	0.975	0.922	0.905	0.877
		MRE	18.362	9.535	10.455	20.264	7.104	20.970	7.290	9.210	10.484	10.184
Logsigmoidal	Training	MAE	10.112	9.316	9.482	9.513	10.061	9.490	9.158	9.612	26.967	9.979
		CC	0.936	0.960	0.957	0.954	0.939	0.955	0.960	0.960	-0.351	0.953
		MRE	28.700	27.672	27.860	27.872	28.585	27.875	27.480	27.992	46.914	28.454
	Testing	MAE	9.738	7.991	8.348	12.167	10.597	5.940	9.666	8.055	27.522	5.701
		CC	0.617	0.767	0.769	0.615	0.672	0.903	0.748	0.804	-0.981	0.944
		MRE	17.460	15.364	15.816	20.064	18.302	13.037	17.278	15.454	36.866	12.787

Table 5.29 Error Analysis for Zone Three (Avg.WQI-77.95) with Good Water Quality Using FFBP Algorithm (With 60% Training Length)

Transfer Function	Data	Error Analysis	No. of Neurons									
			1	2	3	4	5	6	7	8	9	10
Tansigmoidal	Training	MAE	4.175	1.107	2.138	**0.601**	0.893	1.431	2.927	2.191	7.178	5.277
		CC	0.976	0.999	0.995	**0.999**	0.999	0.989	0.963	0.990	0.901	0.806
		MRE	6.002	1.958	3.372	**1.011**	1.345	2.245	6.341	3.165	9.430	13.064
	Testing	MAE	7.938	4.225	1.975	**1.686**	1.964	2.602	3.218	2.667	7.078	11.631
		CC	0.806	0.893	0.989	**0.993**	0.992	0.988	0.975	0.984	0.885	-0.439
		MRE	9.733	4.876	2.468	**2.385**	2.454	3.468	4.087	3.500	9.352	30.258
Purelinear	Training	MAE	4.804	10.664	7.147	4.415	19.433	12.114	4.683	8.364	9.598	9.184
		CC	0.967	0.953	0.863	0.960	0.270	0.382	0.959	0.915	0.843	0.924
		MRE	9.138	15.761	16.604	10.922	49.261	29.059	9.185	15.543	17.524	17.276
	Testing	MAE	6.313	9.889	5.406	3.017	16.143	6.504	6.111	7.010	5.715	9.458
		CC	0.950	0.986	0.957	0.986	0.047	0.922	0.962	0.906	0.957	0.977
		MRE	9.456	11.903	8.877	4.870	36.077	10.790	10.479	13.002	8.740	14.825
Logsigmoidal	Training	MAE	9.838	8.302	8.503	7.885	8.196	7.993	7.792	11.522	8.511	8.539
		CC	0.945	0.938	0.961	0.964	0.973	0.944	0.959	0.966	0.965	0.982
		MRE	25.135	23.474	23.681	22.921	23.456	23.125	22.820	27.438	23.760	23.985
	Testing	MAE	8.873	6.441	7.655	6.563	10.368	5.763	5.801	8.781	7.189	5.796
		CC	0.842	0.941	0.865	0.966	0.678	0.980	0.977	0.981	0.901	0.978
		MRE	18.252	15.418	16.837	15.654	19.949	14.708	14.718	18.184	16.275	14.777

Table 5.30 Error Analysis for Zone Three (Avg.WQI-77.95) with Good Water Quality Using FFBP Algorithm (With 66.66 % Training Length)

Transfer Function	Data	Error Analysis	No. of Neurons									
			1	2	3	4	5	6	7	8	9	10
Tansigmoidal	Training	MAE	2.352	1.842	4.504	**1.012**	5.299	2.756	2.031	1.924	2.786	1.559
		CC	0.991	0.996	0.979	**0.997**	0.853	0.944	0.985	0.990	0.991	0.989
		MRE	3.924	2.930	7.855	**1.542**	11.554	6.576	3.162	2.926	4.055	1.814
	Testing	MAE	4.394	2.933	3.507	**0.703**	10.321	7.421	1.643	2.786	4.109	8.058
		CC	0.959	0.984	0.997	**0.999**	0.698	0.795	0.997	0.984	0.979	0.772
		MRE	5.457	3.464	5.660	**0.775**	14.489	12.627	2.392	4.599	5.326	10.384
Purelinear	Training	MAE	4.401	5.581	5.017	5.132	4.377	7.299	5.039	6.991	4.555	7.044
		CC	0.960	0.949	0.955	0.969	0.967	0.828	0.961	0.833	0.948	0.817
		MRE	10.438	9.361	8.634	10.252	8.900	16.366	10.160	15.955	10.226	18.295
	Testing	MAE	2.986	7.734	7.135	4.968	4.617	5.365	3.767	5.337	4.546	4.848
		CC	0.993	0.917	0.936	0.967	0.979	0.966	0.983	0.961	0.983	0.940
		MRE	5.729	11.476	11.105	7.893	8.110	8.510	8.163	8.892	9.044	11.464
Logsigmoidal	Training	MAE	8.060	7.286	8.300	8.664	7.202	7.141	9.895	7.509	9.424	9.161
		CC	0.965	0.957	0.943	0.944	0.957	0.958	0.894	0.962	0.871	0.952
		MRE	22.007	21.078	22.315	22.767	20.979	20.899	24.115	21.374	24.443	23.203
	Testing	MAE	6.040	7.693	7.055	8.487	8.641	6.376	9.128	7.842	9.854	7.089
		CC	0.995	0.856	0.957	0.813	0.873	0.974	0.863	0.900	0.747	0.978
		MRE	16.346	18.226	17.476	19.121	19.265	16.733	19.778	18.371	21.559	17.493

Table 5.31 Error Analysis for Zone Three (Avg.WQI-77.95) with Good Water Quality Using FFBP Algorithm (With 90% Training Length)

Transfer Function	Data	Error Analysis	No. of Neurons									
			1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Tansigmoidal	**Training**	**MAE**	3.966	4.190	1.440	3.754	1.157	0.497	1.828	0.968	0.677	**1.610**
		CC	0.958	0.953	0.992	0.986	0.997	1.000	0.987	0.997	0.999	**0.987**
		MRE	7.295	7.633	2.195	5.276	1.713	0.742	2.889	1.787	0.921	**2.227**
	Testing	**MAE**	2.983	2.559	1.483	2.784	1.649	3.276	2.654	2.056	1.481	**1.315**
		CC	-0.981	-0.016	0.934	0.896	0.955	0.571	0.888	0.543	0.786	**0.999**
		MRE	3.260	2.765	1.647	3.006	1.842	3.659	2.910	2.330	1.677	**1.110**
Purelinear	**Training**	**MAE**	4.035	3.918	7.219	3.671	4.969	5.179	4.273	3.829	4.133	8.181
		CC	0.971	0.970	0.877	0.972	0.944	0.943	0.969	0.973	0.968	0.922
		MRE	8.442	8.855	13.836	8.800	10.906	10.939	9.165	8.256	8.254	17.238
	Testing	**MAE**	4.542	3.866	11.179	0.976	4.877	6.378	2.855	3.673	7.085	6.374
		CC	-0.527	-0.432	-0.956	0.998	-0.751	-0.911	-0.102	-0.689	-0.870	-0.983
		MRE	4.925	4.197	12.154	1.071	5.288	6.902	3.061	4.027	7.702	7.039
Logsigmoidal	**Training**	**MAE**	7.618	8.589	7.738	7.657	7.682	8.280	8.433	7.388	7.761	7.402
		CC	0.967	0.964	0.954	0.946	0.973	0.908	0.958	0.955	0.970	0.971
		MRE	21.441	22.580	21.589	21.511	21.501	22.271	22.419	21.229	21.644	21.176
	Testing	**MAE**	2.811	1.935	3.631	3.847	2.180	2.364	2.476	0.843	1.802	1.346
		CC	0.884	0.999	0.915	0.933	0.954	0.953	0.906	0.980	0.967	0.885
		MRE	3.140	2.061	4.059	4.332	2.404	2.647	2.668	0.920	1.998	1.434

Table 5.32 Error Analysis for Zone Twenty Two (Avg.WQI-90.64) with Excellent Water Quality Using CFBP Algorithm (With 50% Training Length)

Transfer Function	Data	Error Analysis	No. of Neurons									
			1	2	3	4	5	6	7	8	9	10
Tansigmoidal	Training	MAE	0.744	0.907	0.540	1.096	1.102	2.803	1.290	5.834	0.529	2.527
		CC	0.980	0.981	0.994	0.954	0.967	0.857	0.972	-0.009	0.993	0.973
		MRE	0.808	0.994	0.593	1.177	1.182	3.062	1.383	7.063	0.582	2.890
	Testing	MAE	4.140	3.775	3.375	3.927	4.198	4.949	5.239	7.678	3.803	5.182
		CC	0.861	0.914	0.968	0.948	0.905	0.792	0.902	0.710	0.938	0.946
		MRE	8.043	7.746	7.265	7.859	8.449	8.971	9.329	11.926	7.914	10.370
Purelinear	Training	MAE	1.032	1.148	0.731	2.108	2.587	0.877	**0.926**	2.630	0.607	0.693
		CC	0.974	0.972	0.988	0.371	-0.149	0.980	**0.986**	-0.342	0.992	0.980
		MRE	1.250	1.235	0.781	2.898	3.544	0.934	**1.151**	3.583	0.660	0.752
	Testing	MAE	2.430	2.952	2.316	5.009	5.581	2.909	**1.211**	5.065	1.573	1.458
		CC	0.986	0.976	0.985	-0.298	-0.449	0.983	**0.997**	-0.415	0.994	0.994
		MRE	5.508	4.437	4.055	12.450	13.064	4.903	**1.888**	12.510	2.532	2.261
Logsigmoidal	Training	MAE	1.825	2.460	1.976	1.937	1.429	1.967	2.617	1.548	3.857	1.685
		CC	0.820	0.147	0.777	0.743	0.875	0.845	0.854	0.877	0.750	0.930
		MRE	2.480	3.310	2.532	2.496	1.915	2.498	3.221	2.038	4.566	2.199
	Testing	MAE	3.977	4.467	4.560	5.463	5.890	4.832	5.211	4.066	5.907	4.996
		CC	0.544	-0.229	0.632	0.614	0.564	0.657	0.835	0.757	0.908	0.808
		MRE	10.419	11.595	10.688	11.215	11.724	10.556	10.956	9.724	12.075	10.722

Table 5.33 Error Analysis for Zone Twenty Two (Avg.WQI-90.64) with Excellent Water Quality Using CFBP Algorithm (With 60 % Training Length)

Transfer Function	Data	Error Analysis	No. of Neurons									
			1	2	3	4	5	6	7	8	9	10
Tansigmoidal	Training	MAE	7.889	0.416	1.440	0.679	2.803	2.399	1.017	5.192	1.802	0.419
		CC	-0.056	0.994	0.928	0.990	0.948	0.878	0.928	0.466	-0.013	0.991
		MRE	9.146	0.445	1.562	0.851	3.005	2.637	1.110	5.716	2.540	0.453
	Testing	MAE	8.404	3.617	3.923	3.838	8.319	4.163	3.727	8.038	6.361	4.882
		CC	0.707	0.985	0.950	0.951	0.705	0.942	0.973	0.676	-0.271	0.955
		MRE	13.735	8.548	8.892	8.813	13.652	9.288	8.676	13.351	15.889	9.933
Purelinear	Training	MAE	0.686	5.627	0.602	0.759	**1.226**	1.060	2.571	0.685	2.055	0.645
		CC	0.988	0.693	0.990	0.987	**0.963**	0.985	0.947	0.990	-0.164	0.991
		MRE	0.740	6.250	0.659	0.821	**1.337**	1.284	3.064	0.738	2.832	0.695
	Testing	MAE	1.808	8.164	1.991	1.281	**0.888**	1.408	4.972	2.006	5.839	1.958
		CC	0.996	0.119	0.994	0.998	**0.998**	0.997	0.965	0.994	-0.418	0.994
		MRE	3.573	16.463	3.489	2.312	**1.210**	2.060	10.760	3.673	15.358	3.574
Logsigmoidal	Training	MAE	1.322	1.624	1.632	2.817	1.848	1.713	1.818	1.227	1.417	2.087
		CC	0.924	0.833	0.844	-0.116	0.834	0.832	0.835	0.836	0.812	0.753
		MRE	1.730	2.104	2.063	3.593	2.295	2.155	2.279	1.647	1.844	2.594
	Testing	MAE	4.841	5.133	5.405	6.303	5.334	4.556	5.047	6.597	5.013	6.073
		CC	0.855	0.695	0.731	-0.481	0.786	0.839	0.799	-0.385	0.787	0.066
		MRE	12.082	12.843	12.693	15.848	12.612	11.771	12.321	15.922	12.270	14.904

Table 5.34 Error Analysis for Zone Twenty Two (Avg.WQI-90.64) with Excellent Water Quality Using CFBP Algorithm (With 66.66 % Training Length)

Transfer Function	Data	Error Analysis	No. of Neurons									
			1	2	3	4	5	6	7	8	9	10
Tansigmoidal	**Training**	**MAE**	1.462	0.830	0.530	6.592	0.799	0.624	6.115	1.031	0.542	0.801
		CC	0.408	0.985	0.991	0.415	0.967	0.983	0.052	0.940	0.982	0.975
		MRE	2.031	0.915	0.575	7.057	0.863	0.685	6.970	1.111	0.592	0.850
	Testing	**MAE**	8.937	4.168	3.875	11.340	4.424	5.244	8.525	7.169	7.729	4.964
		CC	-0.179	0.982	0.988	-0.107	0.966	0.954	0.066	0.722	0.649	0.961
		MRE	19.867	9.977	9.621	22.832	10.202	11.247	18.524	13.150	13.716	10.771
Purelinear	**Training**	**MAE**	1.114	0.716	2.935	0.816	0.836	2.079	0.683	1.214	0.878	**0.743**
		CC	0.964	0.988	-0.717	0.985	0.986	-0.258	0.988	0.984	0.982	**0.988**
		MRE	1.334	0.778	4.060	0.888	0.904	2.822	0.739	1.485	0.943	**0.802**
	Testing	**MAE**	3.855	1.830	11.687	2.360	2.349	7.288	1.712	3.555	2.667	**1.653**
		CC	0.980	0.997	-0.963	0.994	0.994	-0.917	0.997	0.994	0.989	**0.997**
		MRE	8.599	3.284	32.342	4.280	4.636	20.579	3.189	8.584	4.313	**2.985**
Logsigmoidal	**Training**	**MAE**	1.799	1.370	3.875	1.022	1.481	2.221	1.330	1.117	1.520	0.888
		CC	0.689	0.910	0.034	0.910	0.779	0.192	0.937	0.937	0.896	0.982
		MRE	2.314	1.754	4.667	1.384	1.880	2.859	1.712	1.492	1.999	0.953
	Testing	**MAE**	6.485	5.397	6.910	7.038	6.627	6.428	5.239	6.447	5.437	2.046
		CC	-0.431	0.879	0.441	0.613	0.663	-0.439	0.894	0.903	0.885	0.996
		MRE	17.335	13.824	16.467	15.606	15.293	17.391	13.645	14.958	13.961	3.993

Table 5.35 Error Analysis for Zone Twenty Two (Avg.WQI-90.64) with Excellent Water Quality Using CFBP Algorithm (With 90% Training Length)

Transfer Function	Data	Error Analysis	No. of Neurons									
			1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Tansigmoidal	**Training**	**MAE**	0.488	0.486	1.883	0.942	0.694	1.300	0.615	1.885	3.575	6.031
		CC	0.996	0.996	0.970	0.984	0.993	0.845	0.957	0.863	0.854	0.556
		MRE	0.522	0.519	2.040	1.081	0.761	1.552	0.677	2.366	4.071	6.820
	Testing	**MAE**	1.639	9.981	4.086	0.961	2.684	2.626	2.320	2.941	4.128	4.200
		CC	-0.819	-1.000	0.533	0.938	-0.987	-0.820	-1.000	-0.962	-1.000	0.487
		MRE	1.758	10.516	4.370	1.024	2.857	2.805	2.454	3.150	4.417	4.493
Purelinear	**Training**	**MAE**	0.639	0.610	**0.724**	0.490	0.969	0.609	0.652	0.595	0.686	0.643
		CC	0.994	0.995	**0.995**	0.993	0.995	0.994	0.995	0.992	0.995	0.996
		MRE	0.686	0.704	**0.795**	0.575	1.231	0.656	0.731	0.640	0.758	0.727
	Testing	**MAE**	1.673	1.342	**0.803**	1.035	2.426	0.872	1.167	0.831	0.648	0.875
		CC	-0.926	0.878	**0.989**	0.748	0.662	0.812	0.853	0.773	0.934	0.885
		MRE	1.794	1.435	**0.858**	1.111	2.599	0.929	1.250	0.887	0.687	0.940
Logsigmoidal	**Training**	**MAE**	0.329	4.612	1.489	0.965	0.696	0.924	1.307	0.455	0.416	0.871
		CC	0.926	0.493	-0.178	0.913	0.921	0.904	0.846	0.918	0.930	0.537
		MRE	0.350	5.376	1.928	1.036	0.750	0.995	1.447	0.489	0.452	1.111
	Testing	**MAE**	4.084	4.192	2.411	2.524	1.899	2.627	1.705	2.329	0.435	2.839
		CC	-1.000	-0.883	0.777	-0.999	-0.989	-0.995	-0.922	-0.621	0.888	-0.999
		MRE	4.348	4.484	2.583	2.704	2.030	2.806	1.824	2.501	0.466	3.050

Table 5.36 Error Analysis for Zone Twenty Two (Avg.WQI-90.64) with Excellent Water Quality Using FFBP Algorithm (With 50% Training Length)

Transfer Function	Data	Error Analysis	No. of Neurons									
			1	2	3	4	5	6	7	8	9	10
Tansigmoidal	Training	MAE	3.727	0.987	1.909	0.351	1.766	0.885	1.365	1.662	6.321	1.119
		CC	0.661	0.975	0.887	0.995	0.974	0.961	0.968	0.789	0.045	0.977
		MRE	4.146	1.094	2.016	0.373	2.198	0.942	1.579	2.311	7.589	1.239
	Testing	MAE	9.396	5.701	3.904	6.022	3.266	4.936	5.040	4.755	12.892	4.485
		CC	0.446	-0.180	0.936	-0.204	0.982	0.702	0.650	0.746	-0.123	0.841
		MRE	13.904	12.913	7.899	13.540	7.881	8.980	10.244	9.625	20.939	8.702
Purelinear	Training	MAE	0.923	1.271	0.653	0.739	1.606	1.215	2.316	1.353	0.925	**0.629**
		CC	0.976	0.949	0.992	0.989	0.898	0.973	0.631	0.968	0.986	**0.990**
		MRE	0.984	1.610	0.704	0.791	2.019	1.465	3.003	1.629	1.038	**0.711**
	Testing	MAE	2.806	3.564	1.576	2.056	4.107	3.320	4.497	2.837	2.060	**1.493**
		CC	0.978	0.928	0.995	0.990	0.814	0.962	0.353	0.973	0.988	**0.994**
		MRE	4.462	7.993	2.672	3.525	9.447	6.742	11.105	5.575	2.793	**2.213**
Logsigmoidal	Training	MAE	1.734	2.876	9.421	3.127	1.385	2.218	2.178	2.216	1.533	2.897
		CC	0.950	0.389	0.028	0.636	0.841	-0.212	0.566	0.492	0.913	-0.111
		MRE	2.223	3.690	10.439	3.767	1.864	3.157	2.926	2.934	2.028	3.858
	Testing	MAE	3.903	5.393	10.124	7.569	3.862	5.006	4.172	5.476	4.789	4.501
		CC	0.964	-0.470	0.138	0.402	0.941	-0.701	0.890	0.464	0.731	0.535
		MRE	9.540	12.854	16.247	13.498	9.495	12.426	9.854	11.597	10.496	10.967

Table 5.37 Error Analysis for Zone Twenty Two (Avg.WQI-90.64) with Excellent Water Quality Using FFBP Algorithm (With 60% Training Length)

Transfer Function	Data	Error Analysis	No. of Neurons									
			1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Tansigmoidal	**Training**	**MAE**	0.703	1.906	0.985	0.974	0.749	1.949	4.546	1.113	2.128	1.760
		CC	0.990	0.804	0.973	0.973	0.989	0.908	0.025	0.958	-0.104	0.939
		MRE	0.797	2.097	1.060	1.129	0.851	2.167	5.487	1.233	2.904	1.919
	Testing	**MAE**	3.820	5.194	3.674	8.143	3.933	3.671	6.736	5.234	8.077	5.346
		CC	0.977	0.843	0.985	-0.086	0.981	0.988	0.982	0.863	-0.171	0.856
		MRE	8.970	10.442	8.674	16.968	9.156	8.715	14.004	10.400	17.773	10.629
Purelinear	**Training**	**MAE**	1.807	0.594	1.739	1.871	0.749	0.683	3.073	**0.773**	0.717	0.633
		CC	0.489	0.989	0.701	0.449	0.988	0.985	0.555	**0.988**	0.984	0.988
		MRE	2.428	0.646	2.293	2.503	0.804	0.735	3.676	**0.835**	0.770	0.683
	Testing	**MAE**	5.849	1.874	5.875	5.882	2.182	1.621	6.199	**1.387**	2.482	2.098
		CC	-0.430	0.994	0.098	-0.411	0.992	0.997	0.248	**0.998**	0.988	0.994
		MRE	15.368	3.363	14.591	15.394	3.803	2.964	15.071	**2.597**	4.253	4.037
Logsigmoidal	**Training**	**MAE**	1.311	2.712	3.395	1.593	1.925	2.312	1.671	1.806	1.598	2.065
		CC	0.930	0.900	0.918	0.882	0.112	0.849	0.491	0.752	0.880	0.352
		MRE	1.718	3.392	4.130	2.053	2.627	2.788	2.279	2.264	2.089	2.722
	Testing	**MAE**	4.875	6.521	6.838	5.454	6.193	5.543	4.683	6.258	5.880	6.050
		CC	0.860	-0.550	0.692	0.763	-0.491	0.805	0.884	0.599	-0.307	0.070
		MRE	12.117	16.078	15.655	12.766	15.671	12.845	12.021	13.585	15.013	14.892

Table 5.38 Error Analysis for Zone Twenty Two (Avg.WQI-90.64) with Excellent Water Quality Using FFBP Algorithm (With 66.66 % Training Length)

Transfer Function	Data	Error Analysis	No. of Neurons									
			1	2	3	4	5	6	7	8	9	10
Tansigmoidal	Training	MAE	1.219	0.774	2.489	0.637	11.307	0.698	1.849	2.566	1.542	1.014
		CC	0.968	0.984	0.744	0.981	0.479	0.978	0.133	0.803	0.758	0.955
		MRE	1.316	0.824	2.719	0.727	12.268	0.856	2.533	2.770	1.661	1.100
	Testing	MAE	4.421	4.026	4.987	8.391	13.360	7.297	4.528	5.825	7.855	5.647
		CC	0.942	0.989	0.945	0.458	0.490	0.514	0.966	0.849	0.593	0.912
		MRE	10.298	9.770	11.271	19.481	19.864	18.431	10.989	11.739	14.158	11.575
Purelinear	Training	MAE	0.823	5.778	1.431	1.754	0.905	2.592	2.340	0.801	**0.716**	1.873
		CC	0.985	0.503	0.899	0.580	0.982	0.854	0.457	0.985	**0.987**	0.293
		MRE	0.886	6.464	1.813	2.303	1.041	2.779	3.175	0.860	**0.772**	2.494
	Testing	MAE	2.353	7.340	5.114	6.690	2.857	5.113	9.417	2.684	**2.005**	7.125
		CC	0.994	0.797	0.892	0.118	0.991	0.942	0.904	0.992	**0.996**	0.683
		MRE	4.268	14.969	13.162	17.474	6.252	6.379	24.987	4.615	**3.685**	18.935
Logsigmoidal	Training	MAE	1.353	1.327	2.382	1.291	1.439	1.545	3.437	1.132	2.564	2.345
		CC	0.916	0.936	0.821	0.626	0.954	0.872	0.924	0.884	0.359	0.699
		MRE	1.733	1.716	2.841	1.793	1.834	1.946	4.059	1.511	3.187	2.823
	Testing	MAE	5.369	5.530	6.605	6.968	5.290	6.065	7.621	5.995	7.389	6.871
		CC	0.897	0.886	0.726	0.233	0.909	0.836	0.958	0.913	0.355	0.657
		MRE	13.791	13.951	15.132	18.039	13.709	14.557	16.823	14.464	18.318	15.418

Table 5.39 Error Analysis for Zone Twenty Two (Avg.WQI-90.64) with Excellent Water Quality Using FFBP Algorithm (With 90% Training Length)

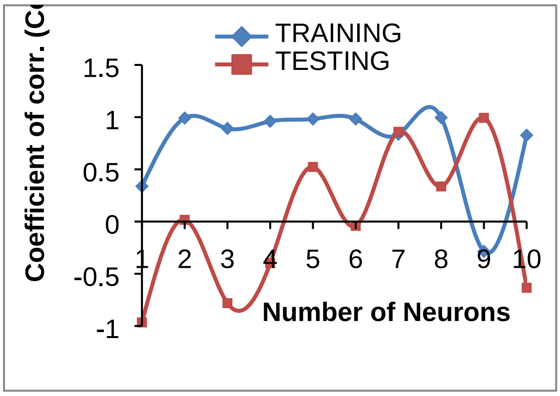
Transfer Function	Data	Error Analysis	No. of Neurons									
			1	2	3	4	5	6	7	8	9	10
Tansigmoidal	Training	MAE	1.912	1.043	0.855	0.802	1.595	1.383	2.065	2.246	5.735	4.303
		CC	0.964	0.986	0.997	0.995	0.987	0.989	0.876	0.955	0.447	-0.157
		MRE	3.835	1.244	1.011	0.997	2.708	2.149	2.621	3.482	9.492	8.888
	Testing	MAE	1.375	1.266	1.414	1.293	1.670	0.666	1.365	1.850	2.813	3.515
		CC	0.672	0.459	0.342	0.043	-0.993	0.811	0.056	0.687	0.845	-0.995
		MRE	1.476	1.360	1.520	1.382	1.760	0.716	1.459	1.971	3.024	3.772
Purelinear	Training	MAE	1.320	1.334	1.041	0.839	0.985	1.582	1.170	0.868	0.973	0.931
		CC	0.987	0.989	0.993	0.995	0.994	0.990	0.991	0.994	0.994	0.994
		MRE	1.606	2.146	1.187	0.953	1.123	3.044	1.883	0.986	1.115	1.044
	Testing	MAE	0.813	0.860	0.869	1.153	0.728	0.840	1.392	0.807	1.564	1.528
		CC	0.933	0.771	0.931	0.582	0.877	0.799	0.258	0.850	-0.668	0.832
		MRE	0.867	0.924	0.931	1.234	0.768	0.900	1.494	0.864	1.676	1.638
Logsigmoidal	Training	MAE	1.850	2.189	**2.301**	3.040	3.868	2.239	3.345	3.147	1.972	3.615
		CC	0.921	0.922	**0.907**	0.939	-0.045	0.950	0.899	0.682	0.921	0.249
		MRE	3.927	4.281	**4.465**	5.483	8.074	4.605	5.893	5.672	4.059	7.639
	Testing	MAE	1.453	1.186	**1.291**	1.472	0.680	1.569	1.848	3.312	2.861	3.845
		CC	0.359	-0.500	**0.989**	-0.991	0.892	-0.931	0.901	0.398	-0.999	0.589
		MRE	1.560	1.264	**1.369**	1.549	0.724	1.667	1.978	3.543	3.071	4.127

Table 5.40 Zone wise Best Fitting ANN Models

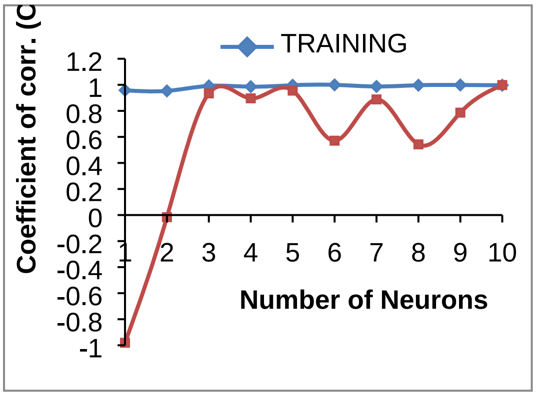
Zone No.	Water Quality Class	Type of Neural Network	Transfer Functions	No. of Neurons	Cc	MRE (%)	MAE
2	Bad	Feed	Tansigmoidal	9	0.993	1.83	0.562
4	Medium	Feed	Tansigmoidal	3	0.99	12.47	4.78
23		Cascade	Purelinear	3	0.996	3.14	5.4
29		Cascade	Tansigmoidal	3	0.979	3.81	1.78
1	Good	Cascade	Purelinear	2	0.852	21.37	214.6
3		Feed	Tansigmoidal	4	0.999	0.703	0.775
5		Cascade	Logsigmoidal	3	0.993	18.46	177.58
6		Cascade	Tansigmoidal	3	0.687	35.24	656.22
7		Feed	Logsigmoidal	3	0.397	41.704	655.966
8		Cascade	Logsigmoidal	5	0.67	16.27	175.71
9		Feed	Tansigmoidal	3	0.671	19.778	320.39
10		Cascade	Tansigmoidal	3	0.99	2.375	9.031
11		Feed	Tansigmoidal	6	0.999	2.19	2.393
12		Cascade	Tansigmoidal	3	0.999	2.88	2.728
13		Feed	Tansigmoidal	3	0.998	1.77	2.88
14		Cascade	Tansigmoidal	2	0.994	4.78	8.78
15		Cascade	Tansigmoidal	3	0.997	3.15	4.49
16		Cascade	Tansigmoidal	3	0.995	1.65	5.66
17		Feed	Tansigmoidal	8	0.837	23.92	266.81
18		Feed	Tansigmoidal	3	0.998	2.294	3.347
19		Cascade	Logsigmoidal	3	0.996	1.83	6.55
20		Cascade	Tansigmoidal	3	0.994	8.76	305.018
21		Feed	Tansigmoidal	3	0.997	2.66	4.22
24		Cascade	Tansigmoidal	8	0.999	0.92	0.46
25		Cascade	Tansigmoidal	3	0.999	3.59	2.77
26		Cascade	Purelinear	3	0.997	2.046	4.188
27		Cascade	Tansigmoidal	3	0.998	4.42	5.18
28	Excellent	Feed	Purelinear	3	0.864	18.37	285.861
22		Cascade	Purelinear	5	0.998	1.21	0.887

5.2.2 Effect of Number of Neurons in Hidden Layer

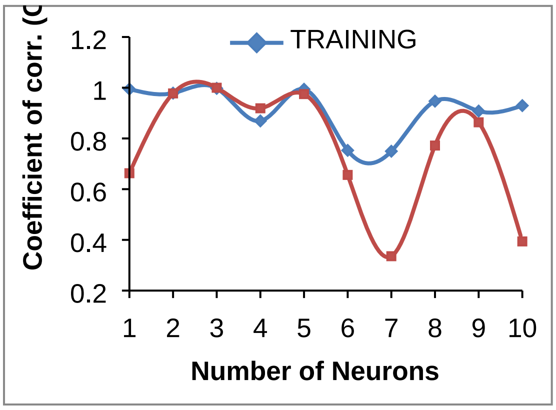
The performance of ANN models was assessed by changing hidden layer structure. In hidden layer number of neurons are varied from 1-10. Fig.5.8 shows the performance of ANN model during training and testing for the typical zone two, four, three and twenty two. From Fig.5.8 and Tables 5.8 to 5.39 it is observed that the model performance changes considerably with change in number of neurons in the hidden layer. From Table 5.40 it is observed that hidden layer structure with three neurons performed better for prediction of water quality in the distribution system. The zone wise best fitting hidden layer structure changes due to zone wise change in statistical values (mean, standard deviation, variance etc.) for various water quality parameter viz. pH, alkalinity, hardness, DO, total solids and MPN.



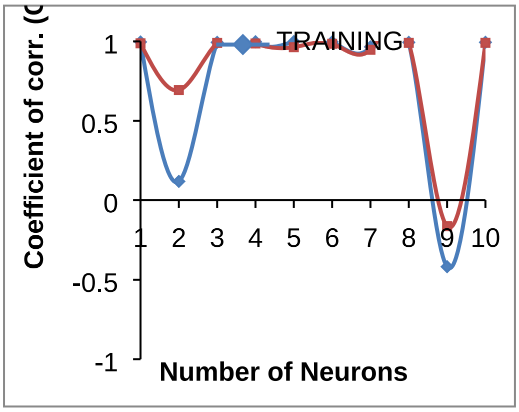
a) Zone Two



b) Zone Twenty Three



c) Zone Four

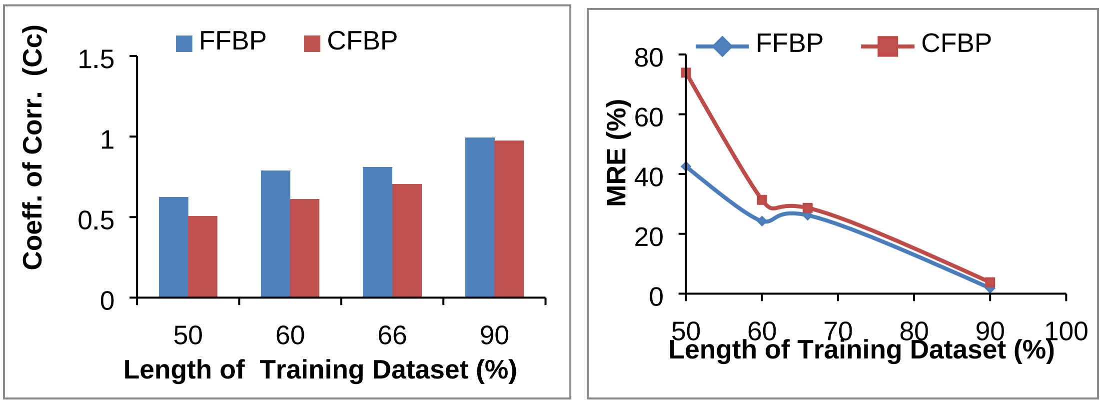


d) Zone Twenty Two

Fig. 5.8 Relationship between Coeff. of Corr. (Cc) and No. of Neurons in the Hidden Layer for Zone a) Two, b) Three, c) Four and d) Twenty two

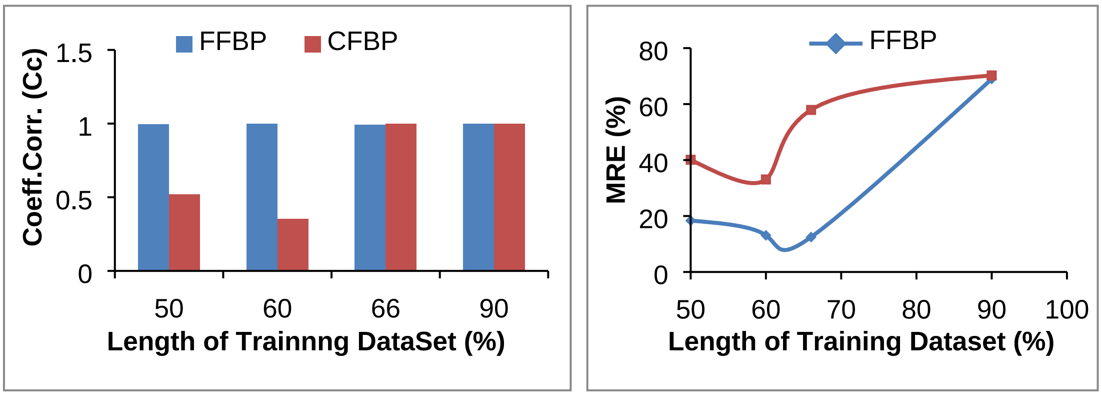
5.2.3 Effect of Length of Dataset

In order to check the effect of length of data set on prediction performance of the ANN model, four different lengths of training data set were used. These four training length of data sets are 50%, 60%, 66.66% and 90% of total dataset. From Figs. 5.9 to 5.12 it is observed that for bad water quality class 90 % of training dataset length, for medium and good water quality class 66% of training dataset length and for excellent water quality class 60 % of training dataset length gives good prediction performance. This eventually indicates that as water quality deteriorates more length of training dataset is required to train the ANN models. This could be due to more length of dataset is required by the ANN model to find change in Water Quality Index (WQI) with change in concentration of water quality variables.



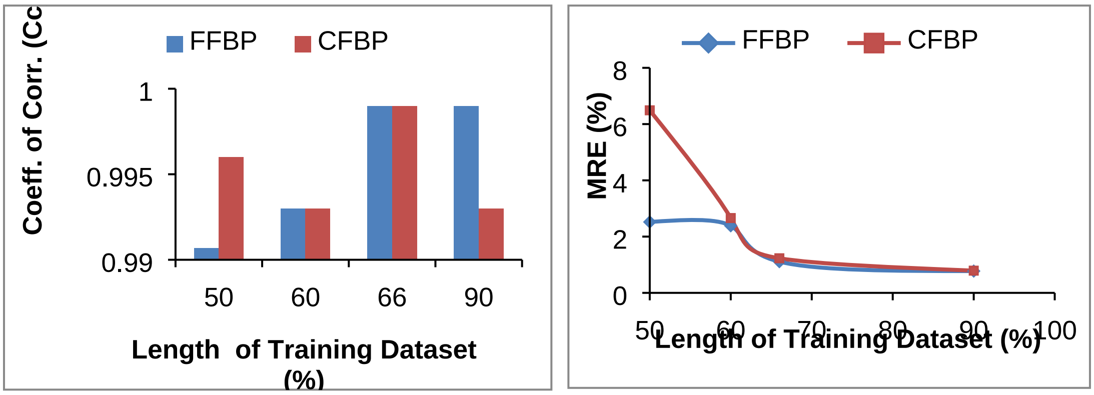
(a) (b)

Fig. 5.9 Relationship between Length of Training Dataset (%) and (a) Coeff. of Correlation (Cc) (b) MRE (%) for Zone Two (Avg.WQI-35.85)



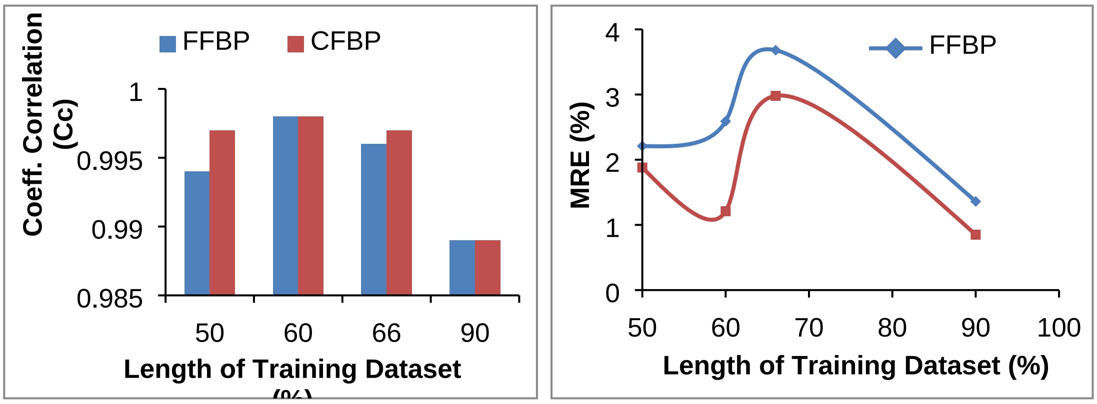
(a) (b)

Fig. 5.10 Relationship between Length of Training Dataset (%) and (a) Coeff. of Correlation (Cc) (b) MRE (%) for Zone Four (Avg.WQI-55.37)



(a) **(b)**

Fig. 5.11 Relationship between Length of Training Dataset (%) and (a) Coeff. of Correlation (Cc) (b) MRE (%) for Zone Three (Avg.WQI-77.95)



(a) **(b)**

Fig. 5.12 Relationship between Length of Training Dataset (%) and (a) Coeff. of Correlation (Cc) (b) MRE (%) for Zone Four (Avg.WQI-90.64)

5.2.4 Comparison of Cascade Forward Back Propagation (CFBP) and Feed Forward Back Propagation (FFBP) Algorithms

From Table 5.41 and Figs. 5.9-5.12 it is observed that FFBP algorithm outperforms CFBP algorithm for bad, medium and good water quality class whereas for excellent water quality class CFBP algorithm performs marginally better as compared to FFBP model. Overall FFBP model outperforms CFBP model for water quality prediction in municipal distribution system. The better performance of FFBP model eventually indicates that less training is required by ANN model to adjust the weight for prediction of water quality. This is because, in FFBP model only output layer is connected to input layer to adjust the weight that give for FFBP network less training to adjust the weight, whereas in the CFBP structure each layer neuron relates to all previous layer neurons that gives ANN more training to adjust the weight.

Table 5.41 Performance Comparison of CFBP with FFBP Algorithms

Zone Details	Water Quality Status	F.F.B.P				C.F.B.P		
		Length of Data set (%)	Cc	MRE	MAE	Cc	MRE	MAE
Zone no. 2 With Avg. WQI 35.85	Bad	50	0.62	42.53	18.95	0.50	73.90	24.11
		60	0.79	24.27	11.46	0.61	31.35	13.46
		66	0.80	26.22	6.48	0.70	28.66	8.86
		90	**0.99**	**1.834**	**0.56**	0.97	3.82	1.83
Zone no. 4 With Avg. WQI 55.37	Medium	50	0.99	18.36	6.24	0.51	40.1	16.90
		60	0.99	13.09	19.97	0.35	33.06	21.84
		66	**0.99**	**12.47**	**4.78**	0.99	57.91	18.64
		90	0.99	68.98	21.17	0.99	70.23	22.25
Zone no. 3 With Avg. WQI 77.95	Good	50	0.99	2.52	1.88	0.99	6.49	4.61
		60	0.99	2.385	1.68	0.99	2.66	2.09
		66	**0.99**	**0.775**	**0.70**	0.99	1.23	0.82
		90	0.99	1.11	1.31	0.99	0.79	0.70
Zone no. 22 With Avg. WQI 90.64	Excellent	50	0.99	2.21	1.49	0.99	1.88	1.21
		60	0.99	2.59	1.38	**0.99**	**1.21**	**0.88**
		66	0.97	3.68	2	0.99	2.98	1.65
		90	0.98	1.36	1.29	0.98	0.85	0.808

5.2.5 Performance of ANN for Various Water Quality Classes

Prediction performance of ANN models was assessed by selecting typical zone from each water quality class. ANN model behaviour for zone two, where water quality is bad, is shown in Fig.5.13 (a). ANN model behaviour for zones four, where water quality is medium, is shown in Fig.5.13 (b). ANN model behaviour, for zone three, where water quality is good, is shown in Fig.5.13(c). The typical fuzzy model behaviour for zone twenty two, where water quality is excellent, is shown in Fig.5.13 (d). From Figs.5.13 (a) to 5.13(d) it is observed that ANN model predictions shows good correlation with observed WQI during training as well as testing for all water quality classes. The better performance of ANN model for all water quality classes could be due to nonlinear relation between input and output variables.

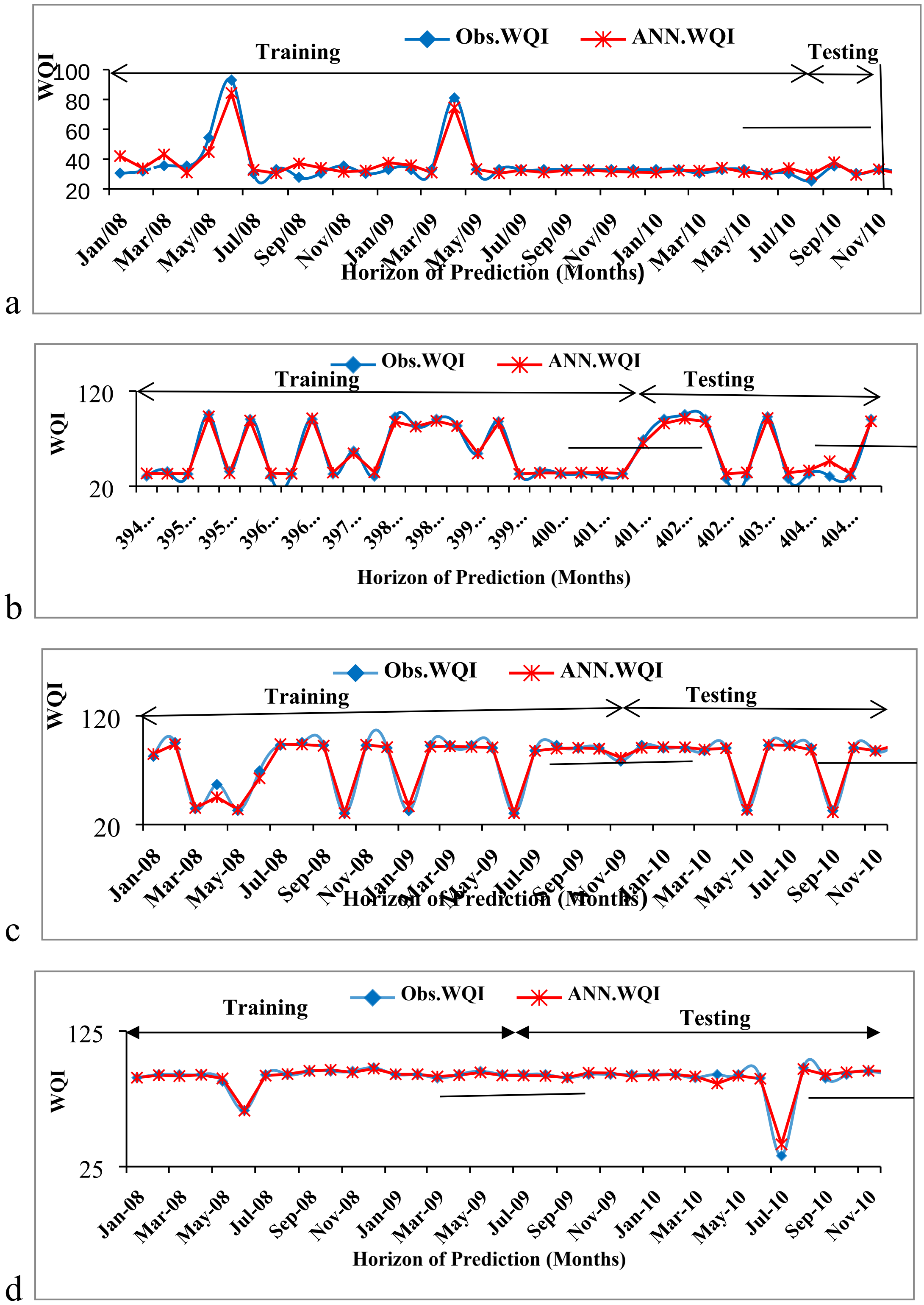


Fig. 5.13 ANN Predictions of Water Quality for different Zones a) Zone Two With Bad Water Quality b) Zone Four with Medium Water Quality c) Zone Three with Good Water Quality d) Zone Twenty Two with Excellent Water quality

5.3 ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM MODEL FOR PREDICTION OF WATER QUALITY

In ANFIS model the water quality index (WQI) is characterized as a function of various variables such as pH, alkalinity, hardness, DO, total solids and MPN. The relationship between water quality index and input variables can be expressed as

$$WQI= f\,(pH, alkalinity, hardness, DO, total\ solids, MPN)$$

ANFIS models were developed by using triangular, trapezoidal, bell and Gaussian membership functions. The ANFIS system defines the membership function parameters and creates if-then rules on its own. It has the advantage of allowing the extraction of fuzzy rule from numerical data. In this study 250 rules were generated by ANFIS editor to predict the WQI. The error analysis during training and testing of ANFIS models is shown in the Table 5.42. It can also be observed from Table 5.42 that ANFIS model with Gaussian membership function shows better predictions followed by triangular membership function. Out of twenty nine zones in study area, for eighteen zones Gaussian membership function, for eight zones triangular membership function and for remaining three zones bell membership function shows better prediction. It can be observed from the Table 5.42 that for all four membership functions during training error is zero and coefficient of correlation (Cc) one. This indicates that all four models capture the trend fully and there is no scatter during training. The predicted WQI shows high degree of correlation with observed WQI during training but during testing ANFIS models performance decreases considerably for all water quality classes. Figs.5.14 to 5.17 shows poor performance of developed ANFIS model during testing for bad, medium, good and excellent water classes respectively. The poor performance of ANFIS could be due to creating more rules, classifying limits for subsets and fixing overlapping pattern on its own by the ANFIS editor.

Table 5.42: Zone wise Error Analysis of ANFIS Models

Zone	Membership Function	Training			Testing		
		MAE	MRE	Cc	MAE	MRE	Cc
1	Bell	0	0	1	22.56	35.99	0.86
	Triangular	0	0	1	**16.22**	**26.84**	**0.89**
	Trapezoidal	0	0	1	39.82	35.94	0.66
	Gaussian	0	0	1	20.49	32.31	0.85
2	Bell	0	0	1	9.77	32.19	0.43
	Triangular	0	0	1	**9.80**	**31.78**	**0.48**
	Trapezoidal	0	0	1	10.58	34.82	0.41
	Gaussian	0	0	1	9.35	30.66	0.46
3	Bell	0	0	1	5.96	8.219	0.96
	Triangular	0	0	1	5.55	10.23	0.95
	Trapezoidal	0	0	1	6.39	12.32	0.95
	Gaussian	0	0	1	**5.14**	**7.900**	**0.97**
4	Bell	0	0	1	39.43	66.87	0.51
	Triangular	0	0	1	**33.02**	**51.56**	**0.54**
	Trapezoidal	0	0	1	52.10	85.47	0.03
	Gaussian	0	0	1	59.07	66.87	0.21
5	Bell	0	0	1	32.71	56.92	0.63
	Triangular	0	0	1	41.60	56.35	0.66
	Trapezoidal	0	0	1	31.95	47.05	0.46
	Gaussian	0	0	1	**31.43**	**46.04**	**0.66**
6	Bell	0	0	1	36.36	53.02	0.65
	Triangular	0	0	1	36.36	49.73	0.61
	Trapezoidal	0	0	1	38.99	49.75	0.61
	Gaussian	0	0	1	**35.34**	**48.87**	**0.66**
7	Bell	0	0	1	43.77	52.41	0.43
	Triangular	0	0	1	53.58	55.26	0.39
	Trapezoidal	0	0	1	40.67	71.89	0.32
	Gaussian	0	0	1	**37.50**	**48.21**	**0.47**
8	Bell	0	0	1	30.52	63.21	0.50
	Triangular	0	0	1	52.69	62.09	0.56
	Trapezoidal	0	0	1	36.17	38.80	0.32
	Gaussian	0	0	1	**31.26**	**45.20**	**0.57**
9	Bell	0	0	1	40.06	49.49	0.47
	Triangular	0	0	1	48.87	50.07	0.56
	Trapezoidal	0	0	1	40.38	59.87	0.41
	Gaussian	0	0	1	**40.00**	**49.15**	**0.58**

Table 5.42: Zone wise Error Analysis of ANFIS Models (Continued…)

Zone	Membership Function	Training			Testing		
		MAE	MRE	Cc	MAE	MRE	Cc
10	Bell	0	0	1	33.93	48.25	0.68
	Triangular	0	0	1	45.64	48.54	0.70
	Trapezoidal	0	0	1	34.18	61.77	0.51
	Gaussian	0	0	1	**32.48**	**46.40**	**0.70**
11	Bell	0	0	1	22.90	35.98	0.88
	Triangular	0	0	1	33.42	35.78	0.86
	Trapezoidal	0	0	1	22.94	48.29	0.76
	Gaussian	0	0	1	**21.81**	**34.39**	**0.89**
12	Bell	0	0	1	33.04	54.32	0.61
	Triangular	0	0	1	53.77	50.08	0.57
	Trapezoidal	0	0	1	36.27	77.46	0.37
	Gaussian	0	0	1	**32.21**	**49.13**	**0.62**
13	Bell	0	0	1	30.06	51.94	0.16
	Triangular	0	0	1	**33.36**	**34.94**	**0.60**
	Trapezoidal	0	0	1	37.95	77.52	0.57
	Gaussian	0	0	1	28.54	51.51	0.56
14	Bell	0	0	1	22.89	51.34	0.70
	Triangular	0	0	1	**57.56**	**34.39**	**0.83**
	Trapezoidal	0	0	1	41.83	77.52	0.45
	Gaussian	0	0	1	37.84	51.51	0.76
15	Bell	0	0	1	29.80	49.37	0.70
	Triangular	0	0	1	44.73	48.39	0.67
	Trapezoidal	0	0	1	30.25	66.24	0.41
	Gaussian	0	0	1	**28.86**	**49.37**	**0.73**
16	Bell	0	0	1	21.99	29.35	0.61
	Triangular	0	0	1	32.81	29.82	0.62
	Trapezoidal	0	0	1	22.15	42.55	0.49
	Gaussian	0	0	1	**22.05**	**28.98**	**0.62**
17	Bell	0	0	1	**35.54**	**38.33**	**0.52**
	Triangular	0	0	1	48.14	48.34	-0.06
	Trapezoidal	0	0	1	30.64	64.05	0.40
	Gaussian	0	0	1	32.76	41.32	0.51
18	Bell	0	0	1	41.82	59.01	0.57
	Triangular	0	0	1	**54.92**	**56.17**	**0.61**
	Trapezoidal	0	0	1	44.60	73.20	0.43
	Gaussian	0	0	1	43.31	57.342	0.57

Table 5.42: Zone wise Error Analysis of ANFIS Models (Continued…)

Zone	Membership Function	Training			Testing		
		MAE	MRE	Cc	MAE	MRE	Cc
19	Bell	0	0	1	36.68	50.114	0.46
	Triangular	**0**	**0**	**1**	**57.03**	**42.042**	**0.54**
	Trapezoidal	0	0	1	44.25	64.133	0.36
	Gaussian	0	0	1	38.63	44.018	0.52
20	Bell	0	0	1	31.54	44.216	0.57
	Triangular	**0**	**0**	**1**	**39.88**	**45.978**	**0.66**
	Trapezoidal	0	0	1	31.52	55.205	0.46
	Gaussian	0	0	1	37.01	50.192	0.50
21	Bell	0	0	1	34.07	41.960	0.54
	Triangular	0	0	1	41.43	41.847	0.49
	Trapezoidal	0	0	1	32.38	56.228	0.45
	Gaussian	**0**	**0**	**1**	**31.86**	**40.336**	**0.54**
22	Bell	0	0	1	39.19	52.153	0.35
	Triangular	**0**	**0**	**1**	**56.61**	**46.452**	**0.38**
	Trapezoidal	0	0	1	43.90	66.009	0.23
	Gaussian	0	0	1	42.43	50.657	0.37
23	Bell	0	0	1	26.67	56.187	0.70
	Triangular	0	0	1	37.16	50.161	0.67
	Trapezoidal	0	0	1	28.82	69.102	0.51
	Gaussian	**0**	**0**	**1**	**26.95**	**52.213**	**0.71**
24	Bell	0	0	1	14.34	32.649	0.97
	Triangular	0	0	1	23.57	32.782	0.97
	Trapezoidal	0	0	1	13.43	46.373	0.86
	Gaussian	**0**	**0**	**1**	**12.68**	**30.989**	**0.98**
25	Bell	0	0	1	27.35	52.012	0.75
	Triangular	0	0	1	37.06	53.243	0.79
	Trapezoidal	0	0	1	27.95	67.291	0.65
	Gaussian	**0**	**0**	**1**	**26.57**	**50.343**	**0.79**
26	Bell	0	0	1	33.59	45.051	0.47
	Triangular	0	0	1	54.38	42.655	0.53
	Trapezoidal	0	0	1	35.88	65.227	0.21
	Gaussian	**0**	**0**	**1**	**28.82**	**37.460**	**0.58**
27	Bell	0	0	1	36.34	53.205	0.60
	Triangular	0	0	1	50.45	58.737	0.65
	Trapezoidal	0	0	1	35.06	74.248	0.34

Table 5.42: Zone wise Error Analysis of ANFIS Models (Continued…)

Zone	Membership Function	Training			Testing		
		MAE	MRE	Cc	MAE	MRE	Cc
28	Bell	**0**	**0**	**1**	**29.04**	**37.416**	**0.66**
	Triangular	0	0	1	47.01	32.333	0.58
	Trapezoidal	0	0	1	33.63	52.106	0.51
	Gaussian	0	0	1	33.28	37.048	0.62
29	Bell	**0**	**0**	**1**	**32.12**	**54.861**	**0.66**
	Triangular	0	0	1	40.24	60.553	0.52
	Trapezoidal	0	0	1	30.21	76.616	0.59
	Gaussian	0	0	1	28.07	48.648	0.65

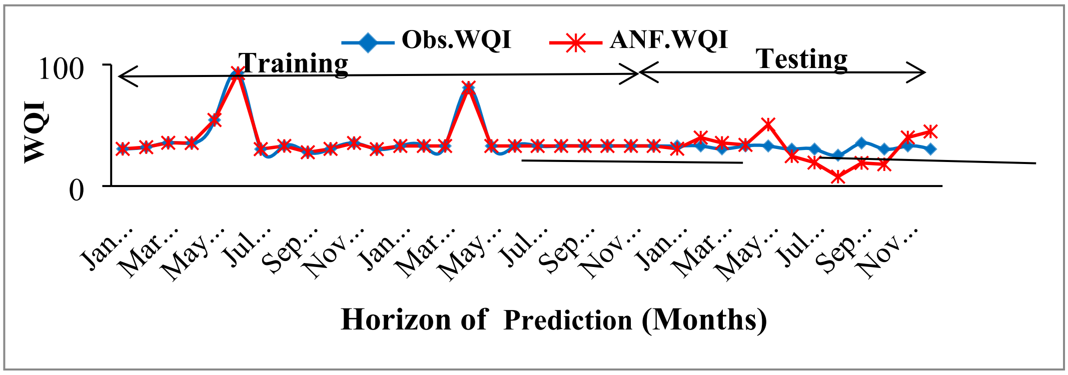


Fig. 5.14 ANFIS Predictions of Water Quality for Zone Two with Bad Water Quality (Avg.WQI-35.85)

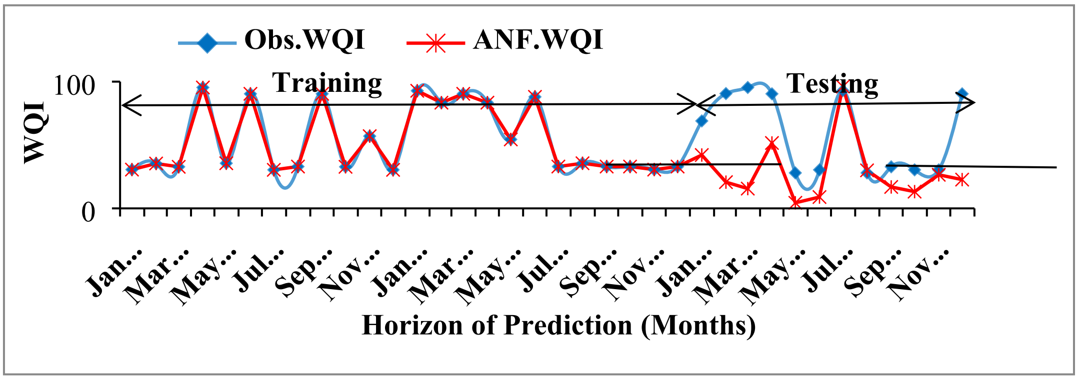


Fig. 5.15 ANFIS Predictions of Water Quality for Zone Four with Medium Water Quality (Avg.WQI-55.37)

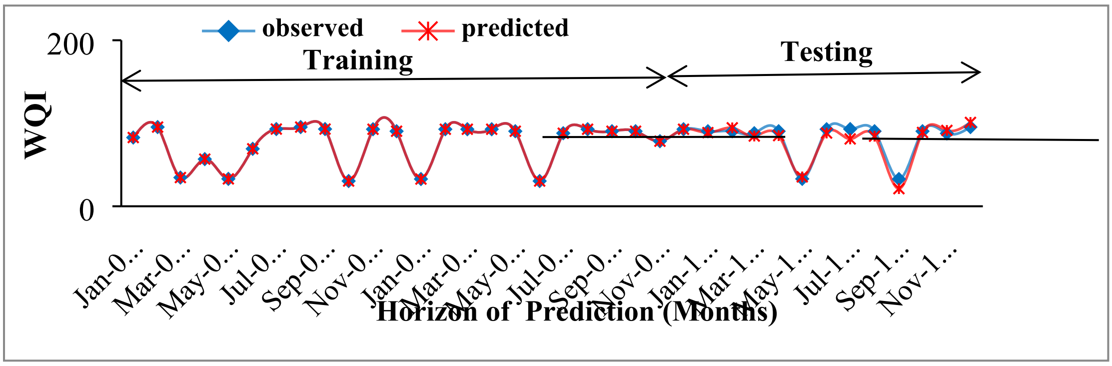


Fig. 5.16 ANFIS Predictions of Water Quality for Zone Three with Good Water Quality (Avg.WQI-77.95)

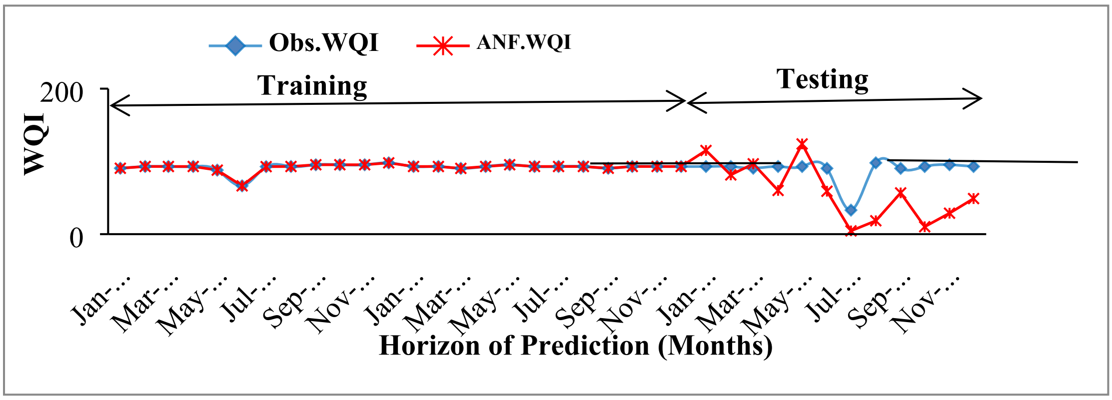
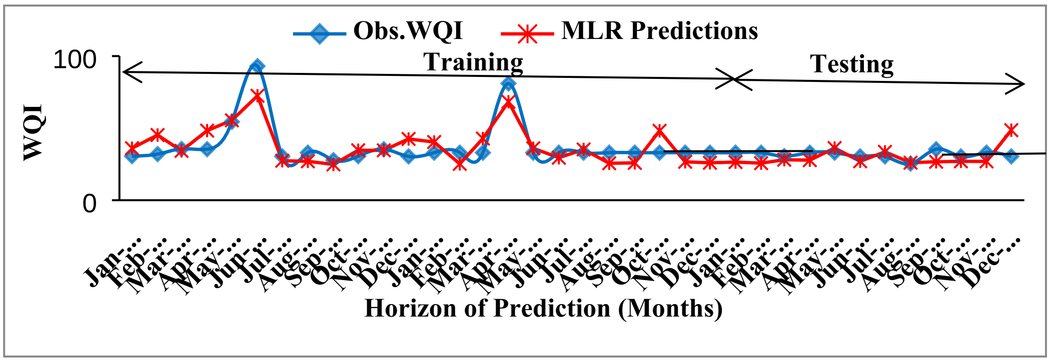


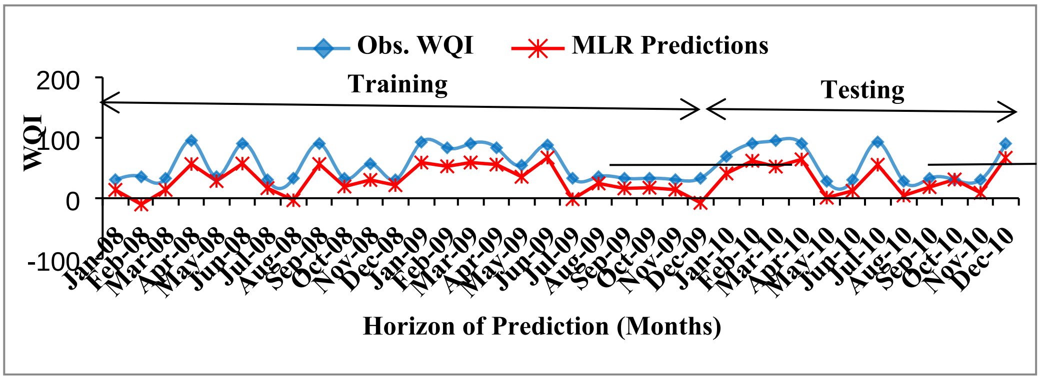
Fig. 5.17 ANFIS Predictions of Water Quality for Zone Twenty Two with Excellent Water quality (Avg.WQI-90.64)

5.4 MULTIPLE LINEAR REGRESSION MODEL (MLR) FOR PREDICTION

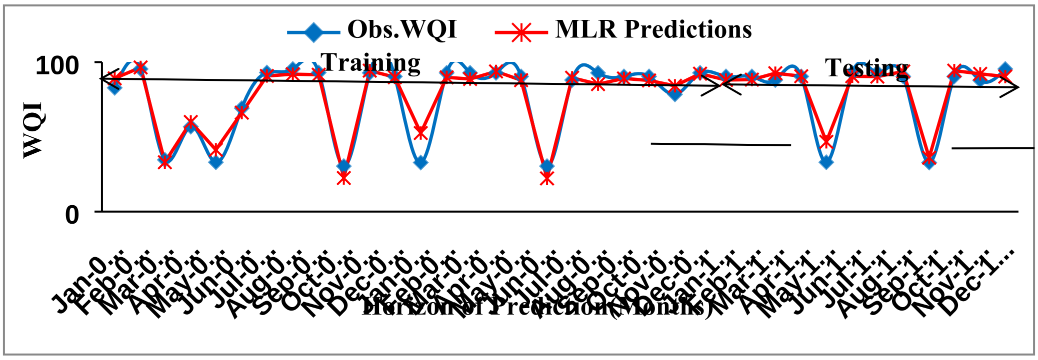
Multiple linear regression model is a statistical technique used for prediction. In this study it was used for prediction of water quality index (WQI) in the various zones of municipal distribution system. In this method 2/3 rd of total data set (two years) was used to obtain the regression intercept (B) and partial regression coefficients (B_1, B_2, B_3-----) of the linear regression equations. The regression intercept and coefficients for each zone are shown in Table 5.43. The zone wise error analysis for regression model is shown in Table 5.44. Figs.5.18 (a) to 5.18 (d) shows performance of multiple regression models for zone two, four, three and twenty two with water quality class bad, medium, good and excellent respectively. From Fig.5.18 (a) to 5.18 (d) it is observed that the linear regression model captures the trend but tends to underestimate or overestimate the high or low WQI values.



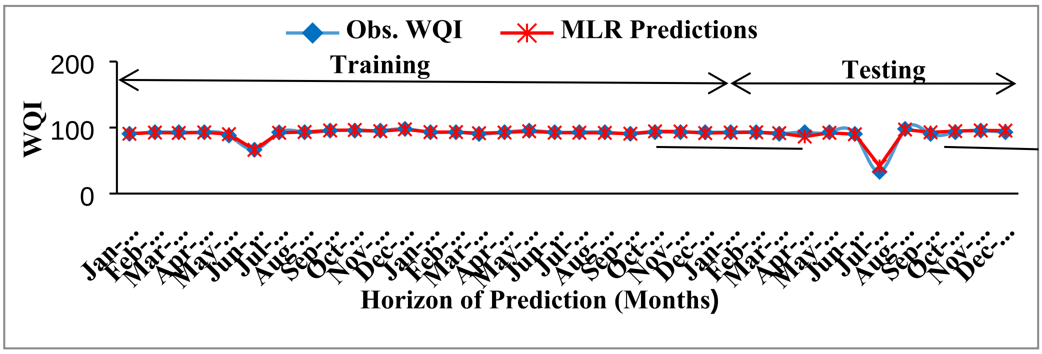
a



b



c



d

Fig.5.18 MLR Model Predictions of Water Quality for Different Zones a) Zone Two With Bad Water Quality b) Zone Four with Medium Water Quality c) Zone Three with Good Water Quality d) Zone Twenty Two with Excellent Water quality

Table 5.43: Regression Intercepts and Coefficients

Zone	B(intercept)	Partial Regression Coefficients					
		B_1	B_2	B_3	B_4	B_5	B_6
1	41.23	4.38	-0.03	0.08	5.73	-0.05	-3.31
2	82.01	-2.36	0.04	-0.01	0.42	0.00	-2.17
3	51.50	6.39	0.15	-0.13	0.14	-0.01	-3.39
4	100.34	1.64	-0.17	-0.11	-1.89	0.02	-3.14
5	87.26	1.44	-0.05	-0.03	-0.47	-0.01	-2.90
6	49.10	2.47	0.03	0.06	10.35	0.00	-4.16
7	175.87	-1.43	0.04	-0.23	0.78	-0.06	-2.25
8	91.31	-0.27	0.04	-0.01	1.31	-0.02	-3.86
9	158.32	-2.79	0.06	-0.29	1.83	-0.01	-3.13
10	89.81	-1.28	0.04	0.05	0.67	-0.01	-4.49
11	76.83	2.00	-0.13	-0.01	1.66	-0.01	-4.66
12	34.02	5.73	-0.22	0.27	1.28	-0.02	-3.13
13	66.85	3.37	0.05	-0.02	0.95	-0.01	-3.17
14	142.60	-8.48	-0.02	0.13	1.25	-0.03	-3.09
15	14.42	3.72	0.08	0.31	-0.29	-0.04	-3.58
16	83.04	1.94	0.01	-0.03	1.42	-0.01	5.27
17	119.80	-2.20	-0.08	-0.02	2.66	-0.02	-3.41
18	118.55	-7.55	0.15	0.14	-1.04	-0.03	-3.07
19	231.46	-15.72	0.02	-0.09	1.44	-0.03	-3.84
20	77.04	1.36	0.02	0.01	1.14	-0.01	-2.94
21	157.89	-4.99	-0.17	-0.11	3.11	0.00	-3.65
22	86.80	-0.05	0.02	0.03	1.22	-0.01	-4.82
23	21.67	6.38	-0.05	0.07	1.53	0.00	-3.45
24	183.71	-9.34	-0.12	0.00	1.18	-0.01	-3.77
25	49.47	5.59	0.02	0.04	-0.31	-0.02	-3.43
26	105.87	-2.75	0.04	0.01	1.09	-0.01	-4.98
27	37.99	1.37	0.06	0.23	-0.45	-0.01	-3.79
28	97.49	1.06	0.00	-0.03	1.36	-0.02	-0.05
29	716.66	-85.52	-0.11	0.72	-4.09	-0.11	-1.09

Table 5.44: Zone wise Error Analysis of Multiple Regression Models

Zone	Training			Testing		
	MAE	MRE	Cc	MAE	MRE	Cc
1	5.53	8.21	0.93	9.48	24.38	0.73
2	7.21	19.41	0.83	5.69	17.81	-0.08
3	4.11	8.55	0.97	3.97	7.10	0.98
4	24.67	52.49	0.91	24.36	47.48	0.95
5	17.26	20.33	0.99	15.64	20.91	0.97
6	2.04	4.33	0.98	3.97	10.67	0.99
7	8.01	13.17	0.87	7.97	16.86	0.96
8	1.22	2.42	0.99	3.29	7.97	0.98
9	1.93	2.74	0.98	3.95	5.91	0.97
10	0.80	0.87	0.99	1.92	2.86	0.99
11	1.50	3.05	0.99	4.73	14.80	0.98
12	3.36	6.83	0.99	6.31	12.58	0.97
13	3.04	5.16	0.99	5.56	11.94	0.98
14	6.26	21.57	0.95	5.66	22.43	0.94
15	3.96	7.36	0.97	8.07	16.48	0.95
16	0.72	0.78	1.00	4.59	11.58	0.99
17	2.14	4.44	0.99	6.94	17.63	0.74
18	7.47	16.17	0.94	5.71	11.19	0.96
19	2.85	5.35	0.99	3.61	4.51	0.93
20	0.78	1.07	1.00	11.62	21.20	0.61
21	3.53	8.65	0.98	3.68	8.06	0.99
22	0.71	0.77	0.99	2.15	3.68	0.99
23	9.30	18.11	0.97	11.21	28.92	0.99
24	3.55	7.45	0.96	5.82	16.25	0.98
25	2.77	5.84	0.96	4.02	12.02	0.97
26	0.75	0.82	0.98	1.88	14.41	0.99
27	3.20	7.16	0.98	6.68	16.66	0.98
28	0.93	0.99	0.75	1.28	1.40	0.77
29	13.34	29.10	0.82	30.72	67.42	-0.06

5.5 OVERALL COMPARISON OF ALL MODELS

The overall comparison of all modelling techniques has been made for all water quality classes (viz. bad, medium, good and excellent) by comparing coefficient of correlation (Cc) and mean relative error (MRE).

5.5.1 Comparison for Bad Water Quality Class

Figs. 5.19 and 5.20 show comparative performance of Fuzzy, ANN, ANFIS and MLR models for prediction of Water Quality Index (WQI) in municipal distribution system for zone two bearing bad water quality class. From Figs. 5.19 and 5.20 it can be observed that prediction performance of ANN model is considerably better and showed high coefficient of correlation (Cc) and low mean relative error, which is around 2 %.

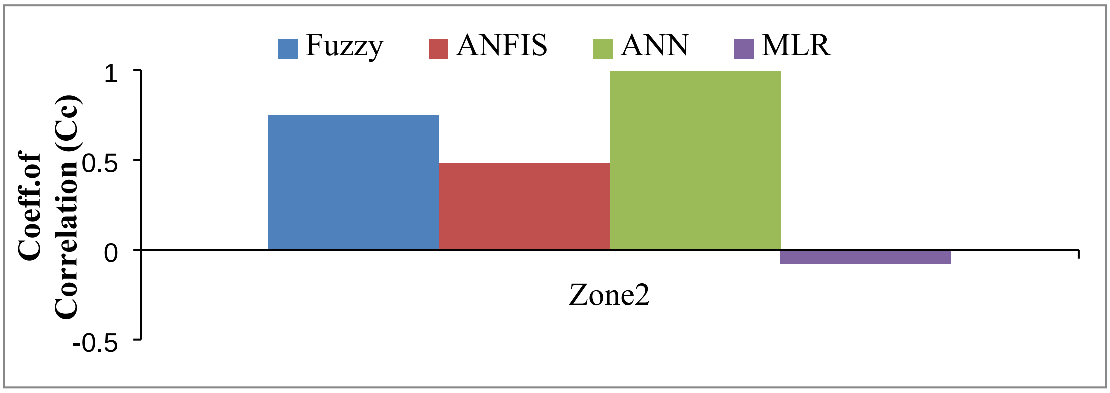


Fig. 5.19 Performance of Various Models in terms of Coeff. of Correlation (Cc) for Bad water Quality

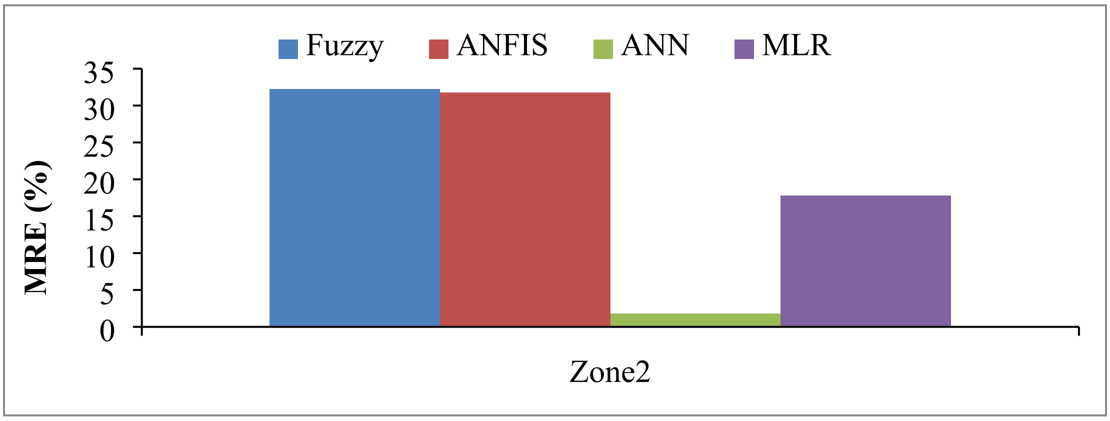


Fig. 5.20 Performance of Various Models in terms of MRE (%) for Bad water Quality

5.5.2 Comparison for Medium Water Quality Class

The performance of Fuzzy, ANN, ANFIS and MLR models for prediction of Water Quality Index (WQI) in municipal distribution system for zone four, Twenty- three and Twenty- nine bearing medium water quality class has been shown in figs. 5.21 and 5.22. From Figs. 5.21 and 5.22 it can be observed that ANN model outperforms other modelling techniques for all three zones and showed high coefficient of correlation (Cc) and low mean relative error, which varied from 3-11%.

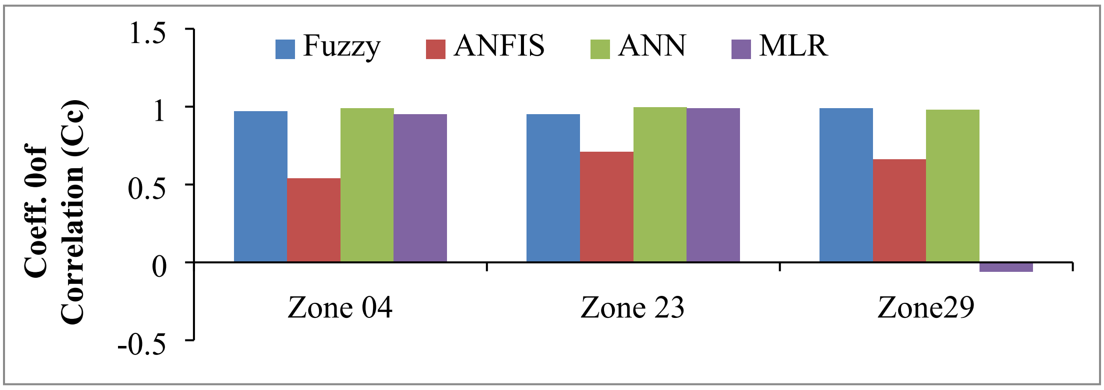


Fig. 5.21 Performance of Various Models in terms of Coeff. of Correlation (Cc) for Medium Water Quality

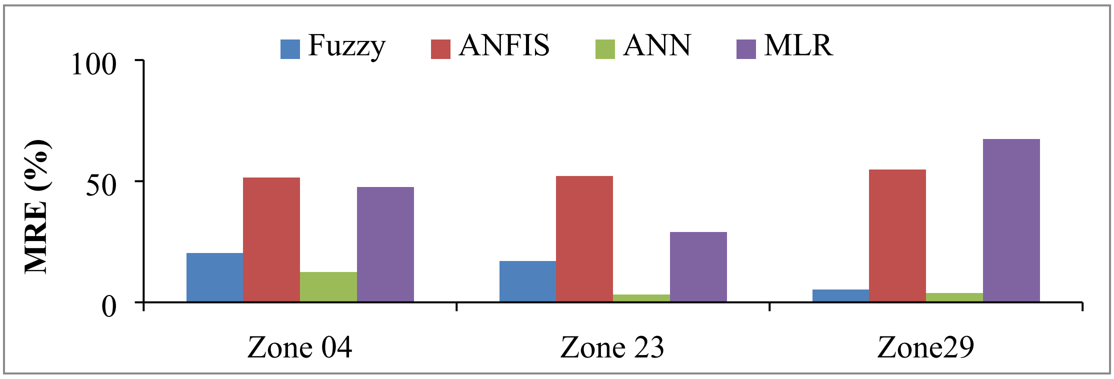


Fig. 5.22 Performance of Various Models in terms of MRE (%) for Medium Water Quality

5.5.3 Comparison for Good Water Quality Class

The performance of Fuzzy, ANN, ANFIS and MLR models for prediction of Water Quality Index (WQI) in municipal distribution system for zones one, three, five to Twenty- one and Twenty-four to Twenty-seven bearing good water quality has been shown in figs. 5.23 and 5.24. From figs. 5.23 and 5.24 it is observed that ANN show high coefficient and low mean relative error almost for all the zones bearing good water quality class. The performance of ANN model has been observed to be more consistant as compared to other modelling techniques.

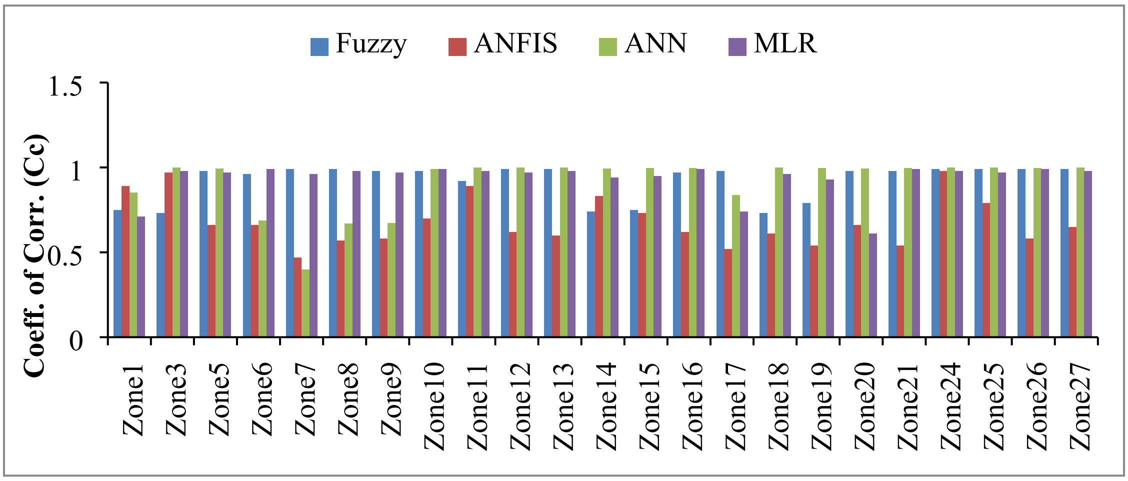


Fig. 5.23 Performance of Various Models in terms of Coeff. of Correlation (Cc) for Good Water Quality

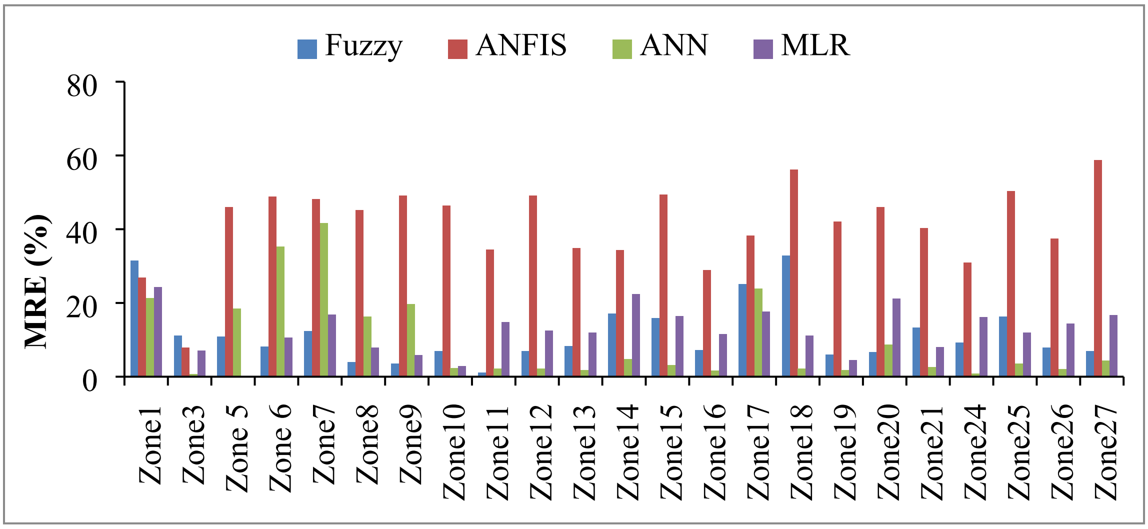


Fig. 5.24 Performance of Various Models in terms of MRE (%) for Good Water Quality

5.5.4 Comparison for Excellent Water Quality Class

The performance of Fuzzy, ANN, ANFIS and MLR models for prediction of Water Quality Index (WQI) in municipal distribution system for zones Twenty- two and

Twenty- eight bearing excellent water quality has been shown in figs. 5.25 and 5.26. From figs. 5.25 and 5.26 it is observed that ANN show high coefficient for both the zones and show mean relative error comparetively very low.

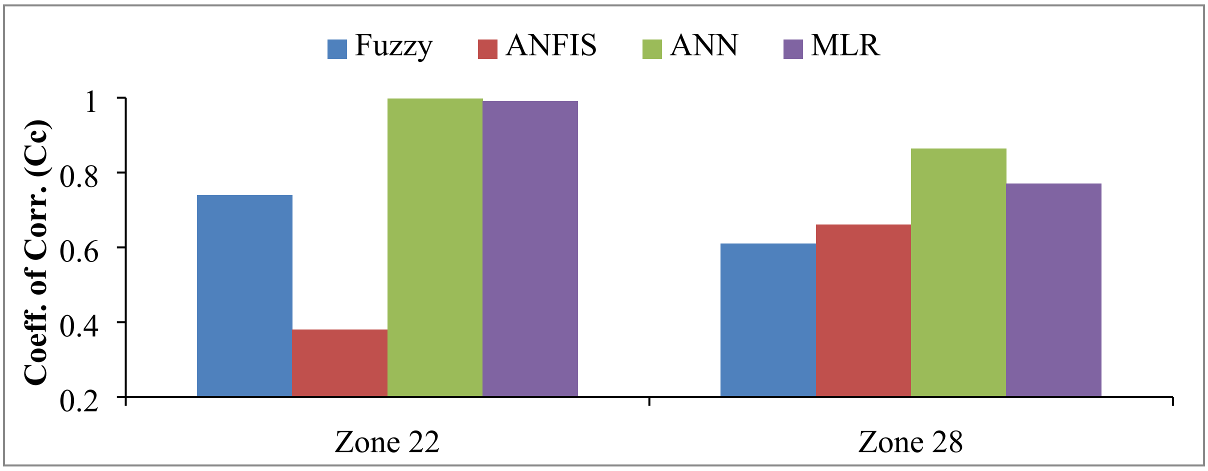


Fig. 5.25 Performance of Various Models in terms of Coeff. of Correlation (Cc) for Excellent Water Quality

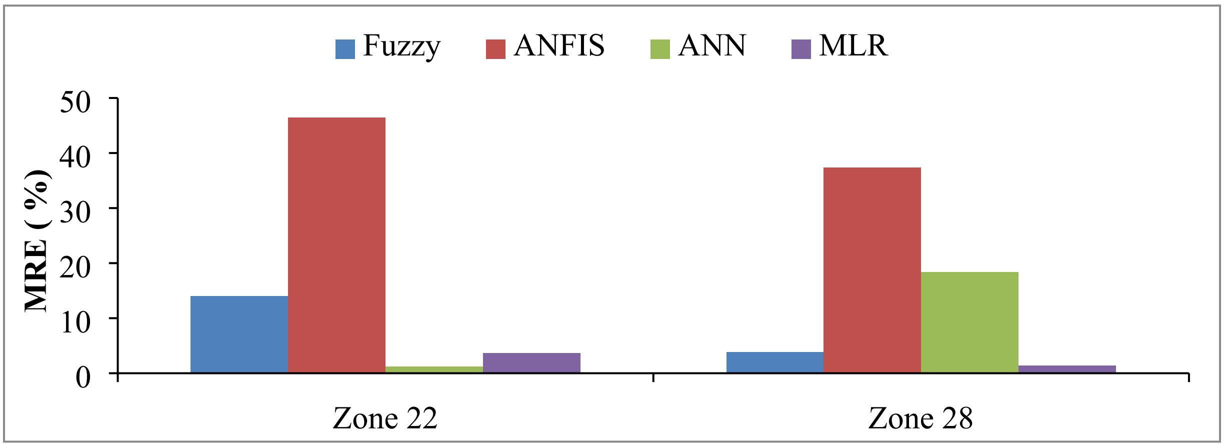


Fig. 5.26 Performance of Various Models in terms of MRE (%) for Excellent Water Quality

Overall from figs.5.19 to 5.26 it can be observed that ANN outperforms other modelling techniques for all water quality classes. Which eventually indicates that ANN is a robust tool for understanding the poorly defined relations between water quality variables and WQI in municipal distribution system. This tool could be of great help to the distribution system operator and manager to find change in WQI with changes in water quality varibles.

CHAPTER 6

CONCLUSIONS

The study on prediction of water quality index (WQI) in the distribution system for Solapur city, India, has been carried out by using fuzzy logic, artificial neural network (ANN), adaptive neuro fuzzy inference system (ANFIS) and multiple linear regression (MLR) models. Initially fuzzy inference system was used for water quality prediction. In this method triangular and trapezoidal membership functions were assigned to fuzzy sets. Defuzzification was carried by using centroid, mean of maxima and bisector method. In ANN method the cascade feed forward back propagation (CFBP) and feed forward back propagation (FFBP) algorithms were compared for prediction of water quality in the municipal distribution system. The comparative study was carried by varying the number of neuron (1-10) in the hidden layer, by changing length of training dataset and by changing transfer function. In ANFIS model the prediction for water quality was carried out by using triangular, trapezoidal, bell and gaussion membership function. Further, these artificial intelligence techniques were compared with MLR technique, which is a commonly used statistical technique for prediction. Performance of these models was validated by comparing the predicted results with the observed field results. The study revealed that

1) ANN outperforms other modelling techniques such as Fuzzy Logic, Adaptive Neuro-Fuzzy Inference System and Multiple Linear Regression Technique for predicting water quality.

2) Performance of tansigmoidal transfer function was found to be more consistent for all water quality classes.

3) The hidden layer structure with three neurons is the best fitting hidden layer structure for predicting water quality.

4) As water quality deteriorates more length of training dataset is required to train the ANN models.

5) FFBP algorithm outperforms CFBP algorithm for all water quality classes.

6) ANN models represent non-linear water quality dynamics more accurately and efficiently than that of their linear counterparts.

7) The data required for monitoring water quality and development of actual WQI during operation could be very large. The distribution system operators may not have the required skill. In such situations, a tool using the ANN can help water quality system managers to find changes in WQI with changes in water quality variables.

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