Water quality modeling in an untreated effluent dominated urban river

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By

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CERTIFICATE

It is certified that the work contained in the thesis entitled "**Water Quality Modeling in an Untreated Effluent Dominated Urban River**", by Girija.T.R (Registration No. 0161 0401), is an original piece of work carried out under my supervision and that this work has not been submitted elsewhere for any degree.

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In memory of my parents

ABSTRACT

The procedure presented builds a bridge between computational intelligence and ecologic modeling by applying fuzzy rule-based model, artificial neural network, multiple linear regression for the prediction of dissolved oxygen which is one of the most important water quality indicators in an urban tributary of River Brahmaputra, Assam, India.

The study was aimed at evaluating application of three data-driven models in predicting dissolved oxygen and developing an ANN-based DO management strategy. By analyzing the key physical, chemical and biological parameters for samples drawn from key locations, an assessment of the dissolved load and pollution levels at different segments in the river was made. Pollution limit exceedance was measured by examining spatial and temporal variations, and the primary data were used, both for training and validating the models. Water samples were collected from 15 stations along the river during the winter (December 2003, 2004), pre-monsoon (April 2004), post monsoon (August 2004), during the flood (October 2004), in the dry (February 2005) seasons and during the premonsoon showers (April 2005). Environmental system selected for this study was river Bharalu, an urban tributary of River Brahmaputra, Assam India.

All the sampling stations except the origin point and the location at River Brahmaputra were highly degraded in terms of biochemical oxygen demand, total phosphorus, and dissolved oxygen. Biochemical oxygen demand, total phosphorus, alkalinity, conductivity, total dissolved solids, potassium, hardness and chloride showed comparatively higher correlation coefficient (above 50%). Concentrations of biochemical oxygen demand as well as total phosphorus were observed to be significant while dissolved oxygen was observed to be well below the maximum allowable level of 4 ppm. High levels of biochemical oxygen demand as well as total phosphorus and low DO was a clear indication of excess quantity of organic wastes as well as aquatic weeds**.** Based on the correlation coefficients between different parameters, four sensitive parameters, namely biochemical oxygen demand (BOD), total Phosphorus (TP), conductivity and alkalinity were selected as input variables to predict DO for the environmental system

under study to develop a fuzzy rule based model and an artificial neural net work model. A multiple linear regression model was also developed for comparison.

Out of the generated primary data sets 59 data sets were used for developing fuzzy rule based model. A three- layer feed forward artificial neural network (ANN) model having four input neurons, one output neuron and seven hidden neurons with tansig and logsig as transfer functions gave satisfactory results in terms of root mean square error and Nash efficiency. A multiple linear regression model was also developed using the same input and output variables to have a comparison with the performance of the best-fit ANN model. Of the three models developed ANN was observed to be the best.

Sensitivity analysis was carried out with the best-fit simulated model using partial derivative method to find the contribution of single variable as well as the interaction of the variable. Interaction of variable is proved to have meaning than finding the contribution of single variable for ecological modeling. Contour plots prepared using parameters of the simulated neural network can successfully optimize the parameters for the environmental system studied and can be used as an effective tool for the decision makers to get an idea about combination of parameters, which can maintain the system under study within the acceptable or the desirable level.

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b1	Bias matrix connecting input layer and hidden layer
b2	Bias matrix connecting hidden layer and output layer
Dj	Derivative of output with respect to its input
dji	Partial derivative of i^{th} input of j^{th} observation
K	Regression coefficient
μ	Membership function
nP_i	Normalized value of i^{th} input variable
nt	Normalized value of output variable
Pi	Input value of i^{th} data set
P_{max}	Maximum value of input variable
P_{min}	Minimum value of input variable
r	Correlation coefficient
R^2	Coefficient of determination
RMSE	Root mean square error value
SSDi	Sum of the squared partial derivative for i^{th} input
t_i	Output value of the i^{th} data set
W1	Weight matrix connecting the input layer and the hidden layer
W2	Weight matrix connecting the hidden layer and the output layer

ANN	Artificial neural network
GIS	Geographical Information System
BIS	Bureau of Indian Standards
BOD	Biochemical oxygen demand
COA	Center of area
COG	Center of gravity
COS	Center of sums
DO	Dissolved oxygen
EDTA	Ethylene diamine tetra acetic acid
LOGSIG	Logarithmic sigmoid function
MLR	Multiple linear regression model
MOM	Means of maxima
PaD	Partial derivative
SVM	Support vector machine
TDS	Total dissolved solids
TI	Total iron
TP	Total phosphorus
TS	Total solids
TANSIG	Tangent sigmoid function
USPH	United States public health
WHO	World health organization

CHAPTER ONE

INTRODUCTION

1.1 THE CONTEXT

The growing problem of degradation of our river ecosystems has necessitated the monitoring of water quality of various rivers to evaluate their primary production capacity, utility potential and to plan restorative measures. As opined by Gorchev, (1996), in the third world countries, 80% of all diseases are directly related to poor drinking water and unsanitary conditions. The industrial units located at the outskirts of cities, intensive agricultural practices, and indiscriminate disposal of domestic and municipal wastes are the sources of contamination for the river water and groundwater. Thus, constant monitoring of river water and groundwater quality is needed so as to record any alteration in the quality and outbreak of health disorders as well as for water quality management (Olajire & Imeokaparia, 2001). Because of the complexity of environmental data sets, in particular, with regard to the ecosystem functioning, decision makers need reliable support on the effects of the management options they eventually consider.

1.2 NEED FOR MODELING

Prediction models are considered useful for river basin management and are used to predict behaviour of water quality with respect to changes in pollution loads and hydrological conditions. Models allow us to simulate changes in our ecosystem due to changes in population, land use or pollution management. These simulations allow us to predict changes, negative or positive, within our ecosystem due to management actions such as improved sewage treatment, reduced fertilizer or manure application on agricultural land, or controlling urban growth. In order to maintain water quality with in the standards, various computational tools are being used. Ecosystem management combines the structuring and understanding of ecological information to facilitate the decision making in order to meet the society goals. Water quality predictive models include both mathematical expressions and expert scientific judgement. They include process-based models and data based models. Modeling is the linkage between pollution source and the instream water quality of a given water body.

1.3 DATA DRIVEN MODELS

Models used in ecosystem management have to deal with a large number of uncertainties exist due to the complex physical and biochemical processes involved in these systems. Traditional modeling of physical processes is often named physically based modeling (or knowledge based modeling) because it tries to explain underlying processes. Those models require preparation of extensive input data sets and a time consuming calibration and verification process that is often too expensive for small utilities and municipalities. On the contrary, the so called data driven models borrow heavily from artificial intelligence techniques are based on a limited knowledge of the modeling process and rely on the data describing input and output characteristics. Hence such models are suited for modeling ecosystems to deal with uncertainties arising out of limitation of knowledge of underlying processes. The predictive methods used for forecasting different environmental variables employs connectionist method like neural networks, SVMs, fuzzy rule based systems etc.

1.3.1.RULE BASED MODELS

Rule-based models often deal with the linguistic aspect. The linguistic aspect could be based on two different approaches in ecosystem management: (1) expert knowledge and/or ecological (monitoring) data are available in a linguistic format and because of the imprecision of the natural language, we are dealing with linguistic uncertainty; (2) ecosystem managers want the models developed for decision support to be interpretable and transparent. Rule based models can also work with epistemic uncertainty, integrating imprecision and variability inherent to ecological data. (Adriaenssens et al., 2004). Because of these aspects, approaching ecosystem management by reasoning according to the principles of 'fuzzy logic', in particular by means of fuzzy-rule based models, are found to be appropriate.

1.3.2.ARTIFICIAL NEURAL NETWORK MODEL

The use of ANN is particularly useful when the physical world is not fully defined, when the model has many uncertainties in terms of model coefficients and/or input parameters, and when there is extensive data for training the network. This is essentially a non-linear `black-box' approach, which assumes a set of prescribed intermediate relations that enables the output(s) to be predicted from a number of input parameters. The parameters of these relations (the network) can be obtained by `training' the network using past data; the success of the prediction is then tested against future data or known data sets that were not used in the training set.

1.3.3.MULTIPLE LINEAR REGRESSION MODEL

Linear regression model is a simple example of a data driven model. Coefficients of the regression equation are trained on the basis of the available existing data and then for a new value of independent (input) variable it gives an approximation of an output variable value. When it is required to model the relationship between two or more explanatory variables and a response variable multiple liner regression is used. Every value of the independent variable x is associated with a dependant variable y.

1.4 THE PRESENT STUDY

In the present study, water quality analysis of river Bharalu, a tributary of the river Brahmaputra in Assam, was carried out for modeling and prediction. After careful consideration of the possible attributes, parameters analyzed were pH, dissolved oxygen, biochemical oxygen demand, hardness, alkalinity, total dissolved solids, total solids, chloride, total phosphorus, total iron, sodium, potassium, and calcium. Based on the analysis results, assessment of the dissolved load and pollution levels at different segments of the river was made and pollution limit exceedance was measured by examining spatial and temporal variations. All these parameters were found to influence the water quality to different degree, and the data generated was used for training, and validating the models. Enironmental system selected for the study and of the sampling locations is shown in Figure 1.

1.5 OBJECTIVES OF THE PRESENT STUDY

Dissolved oxygen is only one of the vital characteristics of an open watercourse and it has traditionally been used as a variable of water quality. This selection is based on the relationship observed between its concentration decrease and its non-desirable effects on the water column. If the dissolved oxygen concentration in a particular environmental system could be predicted only from data that are collected in real time, then river managers would be better able to manage the river's water quality. The river's dissolved oxygen is influenced greatly by physical and meteorological factors, but whether the concentration of dissolved oxygen concentration can be predicted from such factors with any accuracy was unknown. The purpose of this study was to determine the extent to which the dissolved oxygen concentration in the Bharalu river can be predicted solely from, the selected sensitive parameters that are having comparatively higher correlation with dissolved oxygen using fuzzy rule base, multiple linear regression and artificial neural network modeling techniques and to have a comparison among different methods. Sensitivity analysis was carried out for evaluating the contribution of single input as well two-way interaction by using partial derivative method and the most influencing input variable and the pair of variables were identified. Contour plots were drawn keeping the values of two parameters fixed and giving increments to the other two parameters. This enables the decision makers to decide on which parameter level should be controlled and to what extend.

1.6 THE APPROACH

Rigorous laboratory analysis of samples was carried out to find the seasonal variation of the water quality of River Bharalu. Three data driven models namely the fuzzy rule based model, artificial neural network, and multiple linear regression were developed and their performance were studied and compared. Parametric studies were carried out with the best-fit simulated model to assess the contribution of each variable as well as by interaction and to investigate optimized region of the variables to be maintained for the environmental system under study with good ecological status.

A thorough literature review was undertaken that covered studies on water quality monitoring, analysis and use of different ecological models for water quality prediction. This review is reported in Chapter 2. Methodology adopted to carry out the analysis of water samples, documenting the results and land use characteristics of the system studied are explained in chapter 3. Results and interpretation of analysis of the water samples are detailed in chapter 4. The approaches selected for the three data driven models viz, fuzzy rule based model, artificial neural network model and the multiple linear regression model and parametric studies are presented in chapter 5. Chapter 6 deals with the performance of the models studied and interpretation of the results. Finally major conclusions of the study are presented in chapter 7.

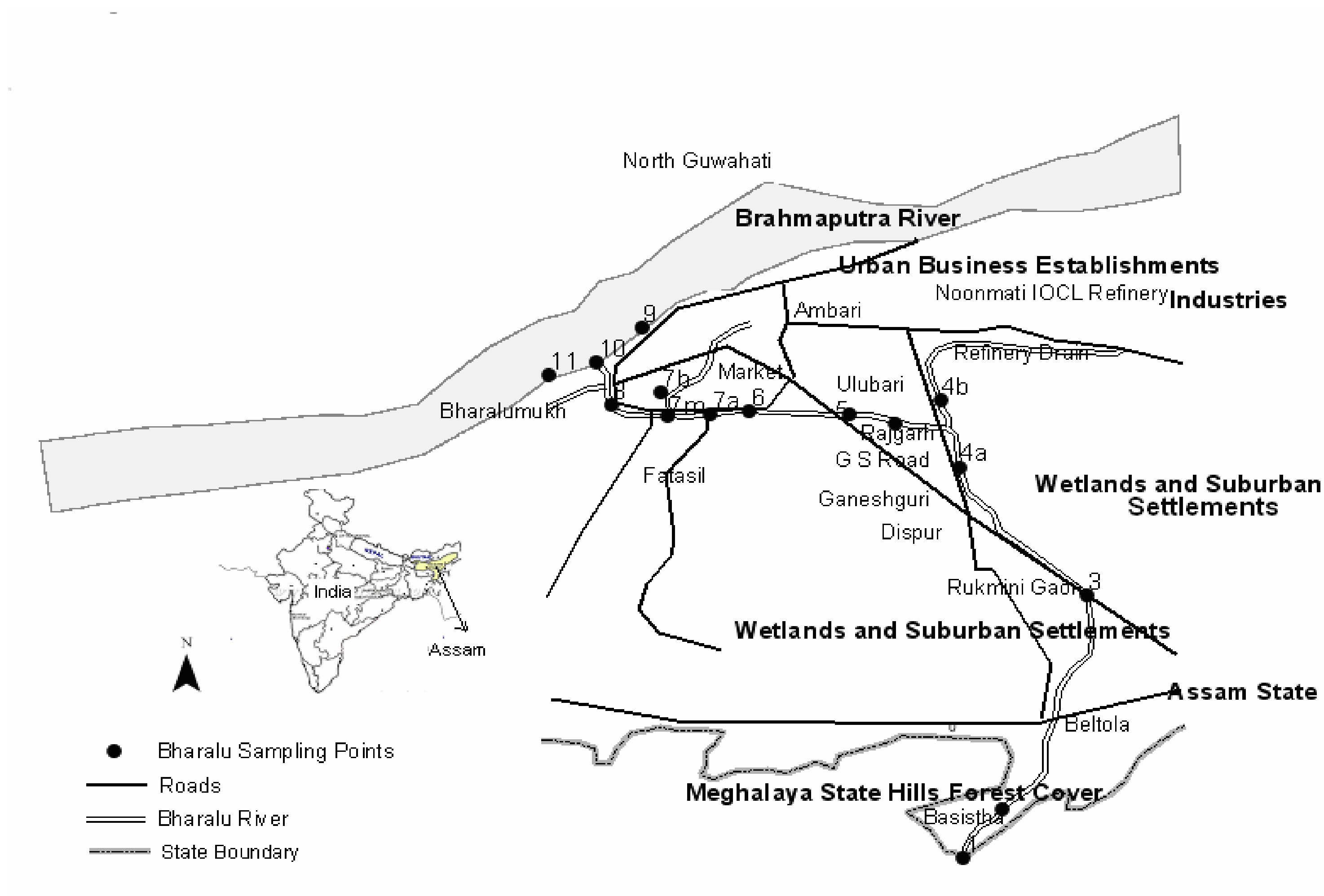


Figure.1 Environmental system selected for the study showing sampling locations

CHAPTER
TWO

LITERATURE REVIEW

2.1 INTRODUCTION

Environmental pollution, mainly of water resources, has become of public interest. Not only the developed countries have been affected by environmental problems, but also the developing nations suffer the impact of pollution, due to disordered economic growth associated with the exploration of virgin natural resources (Gibbs, 1972). Dissolved oxygen is an important indicator describing the general health of water bodies, and it can be used to estimate community metabolism of a stream in terms of gross photosynthesis and respiration rates. Different land use may alter the relative importance of photosynthesis and respiration in streams. Fluctuation of DO near saturation, with diurnal variation due to temperature and metabolism, implies relatively healthy waters. A marked depression of DO below saturation indicates the stream receiving untreated wastewater or an excessive amount of nutrients from non-point source pollution (Wilcock, 1986, Wang et al., 2003).

2.2 STUDIES ON WATER QUALITY ASSESSMENT\

Investigation on New Zealand's surface water quality by Smith and Maasdam, 1994 revealed that vast majority samples were within the acceptable standards and criteria for a variety of river water uses and the waters can be classed as being of relatively low ionic strength. Relatively high conductance in very few locations, which was due to the geo thermal, input of high BOD_5 in one location as a consequence of industrial wastewater discharge was observed.

Water quality and reaeration aspects of Whangamaire stream (North Island, New Zealand) were studied by Wilcock et al., (1995) to explain the observed DO levels. Studies showed that respiration was dominant in the lower reach where photosynthetic activity was inhibited by shade. It was opined in the study that better riparian management and reduced nutrient inputs are likely to improve stream water quality.

Studies conducted on Epic creek which is a distributary of the Nun River the in Niger delta by Izonfuo and Bariweni, (2001) recommended proper management of wastes and controlling and monitoring of other human activities to ensure that the runoff would have a minimum effect on the creek. Concentrations of chloride, sulphate, phosphate, nitrate and ammonia were found to increase during the rainy season, which means that runoff water contributes a significant proportion of these constituents into the Epic creek. Human activities were found to be the cause of higher levels of several parameters in the creek than that in the upstream.

Silva and Sacomani, (2001) carried out a study to determine the water quality in the Pardo River located in Botucatu region in Brazil, with certain chemical physical indicators, coliforms and chemical species of samples taken monthly. Principal component analysis (PCA) was applied to normalize data to assess association between variables and has achieved meaningful classification of hydro chemical variables and of river water samples based on seasonal and spatial criteria. The application of multivariate statistical techniques to the data collected in this study showed that the Pardo River water quality is changed because it received water with high salt content causing damage and degradation. Diffuse pollution was identified as a cause of water quality degradation in the Pardo River. Other parameters, such as geology, land use, topography, storm flow, weather, etc., can control or increase the amount of nutrients released by the drainage basin throughout the length of the Pardo River.

Patterns of historical watershed nutrient inputs were compared by Stow et al., (2001) with in-river nutrient loads for the Neuse River. Studies showed that there was a substantial increase in the nitrogen and phosphorus inputs as a result of intensified animal production, but this increase was not reflected in changes in river loadings. It was concluded that it could be due to the terrestrial storage in ground water or riparian zones preventing or slowing the transport of nutrients from an on-land source to the river channel or denitrification and volatilization in agricultural and riparian soils that remove nitrogen from watershed before it enters the river.

Smith, (2001) presented a case study of storm water and sediment analysis for conventional pollutants in flood control sumps of the city of Dallas, along the Trinity

River, which is channelized and leveed through most of the city. Pollutant analysis at both pumping station and sump outfall suggested that rigorous sampling is needed to obtain reliable results and collection of storm water samples in the vicinity of the sump pumping station and selected outfalls as a function of time would enable estimation of pollutant loads to and discharged from the sump, and estimation of pollutant removal in the sump by settling and other physical- chemical processes.

Study on pollution assessment in the Keiskamma River and in the impoundment downstream was carried out by Fatoki et al., (2003) over a one-year period by using standard physico chemical method. Significant pollution of the river and the impoundment from the Keiskammahoek Sewage Treatment Plant (KSTP) was indicated for electrical conductivity, nutrients and oxygen-demanding substances.

The use of the WQI (water quality index) and the dissolved oxygen deficit (D) as simple indicators of a watershed pollution was investigated and compared in the Municipality of Las Rozas (north-west of Madrid, Spain) by Sanchez et al., (2006). The quality of the water in Guadarrama and Manzanares rivers and Paris Park ponds, the main watersheds of this area was investigated during 2 years (from September 2001 to September 2003). The monitoring of the Las Rozas watersheds demonstrated that water quality of Guadarrama watershed was slightly affected in the section of the river within this town. It was found that the WQI was very useful for the classification of the waters monitored. A high linear relationship between the WQI and the oxygen deficit (D) of the samples was found. The classifications of water based on the two methods coincided in 93% of the samples studied. This allowed the determination of WQI based on the values of the oxygen deficit. It was found that water quality was influenced by the climatic conditions, the highest qualities being observed during the winter.

A study was carried out by Woli et al., (2004) to evaluate the quality of river water by analysis of land use in drainage basins and by estimating the N budgets in the drainage basins of Shibetsu River (Shibetsu area) and Bekkanbeushi River (Akkeshi area) in eastern Hokkaido, Japan. The evaluation of water quality was up-scaled to the regional level in Hokkaido by using the Arcviewy GIS and statistical information. The linear regression results showed that the correlation between NO –N concentration and the proportion of upland in the drainage basins was highly and positively significant for both the areas. Study results indicated that the impact factors were highest for intensive livestock farming areas; medium for mixed agriculture and livestock farming, and the lowest for grassland-based dairy cattle and horse farming areas. The results of a simple regression analysis showed that the impact factors had a significant positive correlation with the cropland surplus N (r=0.93, P<0.01), chemical fertilizer N (r=0.82, P<0.05), and manure fertilizer N (r=0.76, P<0.05), which were estimated by using the N budget approach. Using the best-correlated regression model, impact factors for all cities, towns and villages of the Hokkaido region were estimated. The regression analysis indicated that the predicted NO–N concentrations were significantly correlated (r=0.62, P<0.001, n=203) with the measured NO –N concentrations, reported previously. It was concluded that by estimating the proportions of upland fields in drainage basins, and calculating cropland surplus N it is possible to predict river water quality with respect to NO–N concentration.

The application of a battery of toxicity and genotoxicity tests on pore water in parallel and in combination with physico-chemical analyses and benthic macro invertebrate community investigations is discussed by Isidori et al,(2004) to assess the environmental quality of the Volturno River in South Italy. Toxicity testing was performed on the rotifer *Brachionus calyciflorus* and the *crustacean Daphnia magna*. Genotoxicity was determined by the SOS chromotest and Mutatox system. The physico-chemical characterization of the surface waters showed a declining trend from up-river to down-river for dissolved oxygen and conductivity. Also, chemical variables showed a worsening along the river axis showing an increase in ammonium, phosphates, sulfates, and heavy metals. The assessment of macro invertebrates reflected the general ecological deterioration occurring to chemical as well as toxic and genotoxic pollution. A strong correlation was observed between the benthic community composition and the sediment contamination of toxic and genotoxic substances.

Taebi and Droste, (2004) conducted an analysis to investigate the pollution loads in urban runoff compared to point source loads as a first prerequisite for planning and management of receiving water quality. Unit loads were estimated in storm water runoff, raw sanitary wastewater and secondary treatment effluents in Isfahan, Iran. Results indicated that the annual pollution load in urban runoff is lower than the annual pollution load in sanitary wastewater in areas with low precipitation but it is higher in areas with high precipitation. Two options, namely, advanced treatment (in lieu of secondary treatment) of sanitary wastewater and urban runoff quality control systems (such as detention ponds) were investigated as controlling systems for pollution discharges into receiving waters. The results revealed that for Isfahan, as a low precipitation urban area, advanced treatment is a more suitable option, but for high precipitation urban areas, urban surface runoff quality control installations were more effective for suspended solids and oxygen-demanding matter controls, and that advanced treatment is the more effective option for nutrient control.

Judova and Jansky, (2005) evaluated the water quality in rural areas in the Czech part of Labe River catchment using the example of Slapanka River catchment. This river drains a typical landscape of Ceskomoravska Highland. It was observed that agriculture and production of municipal wastewater resulting in increased eutrophication caused increased amount of organic substances and nutrients. Identifying the type of the pollution source is helped by regression analysis using data from the public monitoring network. Eleven sampling sites were selected for evaluating the water quality. Physical and chemical analyses of the samples collected during the field monitoring in the years 2001–2003 revealed that in long-term development water quality has improved in all monitored parameters during the last 15 years. Least significant improvement was found with the concentration of nitrate nitrogen. The water quality within the whole catchment area still remained low. To reduce the influence of pollution sources, it was recommended that the sanitation of diffuse sources of pollution from small settlements with less than 2000 inhabitants, and a successive change from agricultural management and intensive mass production to extensive ways, especially in mountain and sub-mountain areas.

Castane et al., (2006) presented the results of the evaluation of the surface water quality of Reconquista River through a multivariate analysis of physico chemical parameters determined in a monitoring campaign carried out in 1995.It was observed that nitrites, phenols and $N-NH_4^+$ exceed the allowed limits in all stations and an DO content in an acute depressed level in the downstream. PCA (principal component analysis) was in the ordination of the samples (sites, season and physico chemical parameters) an observed that the first principal component showed positive correlation with $N-NH_4^+$, conductivity, orthophosphate, BOD_5, COD and alkalinity and negative correlation with DO. The results suggested that the anthropogenic contamination was the major source for the predominance of contamination parameters and that did not change significantly with time.

Runoff carries a variety of ions, some introduced from the atmosphere, some from land surface, and some from man-made sources. The ions and other substances carried into the streams or rivers in higher concentrations may result in pollution. (de Vlaming et al., 2004; Izonfuo and Bariweni, 2001; Tsiouris et al., 2002). Martin et al., (1998) reported pollution of water bodies due to pollutant transport through runoff along with uncontrolled discharge of untreated and partially treated sewage, and identified effects of runoff on water bodies including nutrient enrichment, deterioration of water quality, destruction of spawning grounds for aquatic life and general fish kill.

2.3 ECOLOGICAL MODELING

A number of water quality management models have been developed in the past for the allocation of assimilative capacity of a river system. Model results help in setting the amount of waste that can be disposed in to, the river from various point and non point sources with out violating the water quality standards. The intended purpose of these models is to provide economic and technologically feasible solutions acceptable to both the pollution control agency and the dischargers.

2.3.1 MATHEMATICAL MODELS

Water quality of river Sava, Slovenia was investigated by Drolc and Koncan, (1996) and a surface water quality model, QUAL2E was applied to estimate the impact of discharged wastewater on quality of the river. On the basis of model predictions it was estimated that wastewater should be treated to reach BOD value below 30 mg/L during low flow period to maintain the dissolved oxygen level above 5 mg/L.This model was limited to the simulation of time periods with constant stream flow and waste loads. Freitas et al.,(1997) developed a steady- an unsteady state models based on QWASI fugacity approach an describing chemical fate in high arctic lakes and it was applied to Amituk and Char lakes on Cornwallis island, NWT, Canada, focusing on ΣDDT. Model results indicated that the Arctic lake act as conduits not sinks for chemicals. Most loadings were from snowmelt that entered through stream inflow an most is exported from the lake. Low suspended particle due to low productivity in the lake resulted in conveyance of minimal chemical to the sediments. Study also revealed that harsh climatic conditions that freezes the system for most of the year, thereby limiting the hydrological and limnological processes and biological productivity which resulted in the relatively high mobility of contaminants in the study area. The accuracy of the calculations rests on the water column and sediment volumes of the two lakes, the estimates of which are relatively uncertain.

A root zone water quality model (RZWQM) was designed by Hanson et al., (1999) to predict hydrologic and chemical response, including potential for ground water contamination of agricultural management systems. Maximum N uptake rate, plant respiration, specific leaf area and the effect of age at the time of propagule development and senescence were used to calibrate the plant production and yield component. Predictions matched the observed data in most cases but discrepancies occurred in predicting N uptake, particularly for the Missouri no – till management system resulting in larger discrepancies in predicted crop biomass and yield. Hence further work is required to improve the definition of N mineralization pool.

One dimensional water quality model to asses the long –term fate of 2-3-7-8-tetra chlorodibenzo-p-dioxin (TCDD) in three compartments (water sediment, fish) of a river was developed by Giri et al., (2001) using the literature data on various model parameters. The impact of uncertainty in several model parameters was studied by means of Monte Carlo simulations assuming that the uncertain parameters are uncorrelated and can be modeled by three probability distributions. The study indicated that predictions based on a purely deterministic approach may be significantly (10%-70%) off the target in presence of uncertainty in model parameters and it was difficult to model accurately the true nature of randomness in a model parameter. The study also showed that the nature of the uncertainty, in addition to its magnitude could also significantly affect the model results.

It is understood from the review of literature on mathematical models that the common feature of most of the models is the use of rate parameters to describe processes occurring in the water body. The reliability of the model is a function of among other things, how well these parameters reflect the processes they are intended to describe. Water quality management problems are characterized by various types of uncertainties at different stages of the decision making process to arrive at the optimal allocation of the assimilative capacity of the river system. The type of uncertainties that has received much attention is that due to randomness associated with various components of a water quality system. Two major components considered for randomness are river flow and effluent flow. Another type of uncertainty prominent in the management of water quality system is the uncertainty due to randomness associated with describing the goals related to water quality and pollutant abatement. Desirable and permissible water quality criteria and minimal pollutant treatment levels are set up depending on the environmental objectives. In such cases intelligent approaches are more suitable to predict water quality, which has many virtues such as high estimating precision, automatic parameter amendment. In a majority of cases, establishing the limits is not precise but rather contains an element of vagueness. Thus the multiple objectives in a water quality system are not only conflicting but are also vague to some extent. Multiple and conflicting objectives that are vague can be mathematically quantified and incorporated in to the management models using principles of fuzzy decision – making.With fuzzy modeling we can represent imprecise data and produce imprecise output in the form of fuzzy numbers, with minimal input data requirements and without the need of a large number of computations.

2.3.2 FUZZY MODELS

A fuzzy rule based model was developed by Shresta et al., (1996) for developing reservoir operation rules and the methodology was illustrated using a case study of Tenkiller Lake on Oklahoma, USA. The premises were total storage of the reservoir, incoming flow, forecast demand states and time of the year. The consequence is the actual volume released to meet the demands. Studies showed that the construction of the fuzzy rules only necessitated the definition of premises and consequences as fuzzy sets and the selection of DOF threshold ε, a training set was used with a simple algorithm. Model set was transparent and easy to understand due to its rule-based structure, which mimics the human way of thinking, even when preset release rules are not applied.

In a study done by Menzl et al., (1996), a self-adaptive computer based pH measurement and controlling system was developed and tested. This system was found to be very efficient since it was able to control the pH value more effectively and with a very short response time in comparison with a common PID (proportional integral derivative) controller. Using the self adaptive fuzzy controller it was also possible to control the pH value of systems with an extremely small buffer capacity, even using acids and bases of high concentrations. The response time of the fuzzy controller was dependent on the grade of adaptation of the configuration to the conditions. Their applications were the pH control of fermentation processes and the neutralization of wastewater streams. The adaptability of the controller predetermines its use in systems with frequently changing conditions. As the rule-base of the fuzzy controller could easily be increased, it was possible to adapt and optimize the system to specialized use by including further expert know how.

A fuzzy waste- load allocation model, FWLAM was developed by Sasikumar and Mujumdar, (1998) for water quality management of a river system using fuzzy multiple-objective optimization. The model could incorporate the aspirations and conflicting objectives of the pollution control agency and dischargers. The vagueness associated with specifying the water quality criteria and fraction removal levels is modeled in a fuzzy framework. The goals related to pollution control agency and dischargers are expressed as fuzzy sets. The membership functions of these fuzzy sets were considered to represent the variation of satisfaction levels of the pollution control agency and dischargers in attaining their respective goals. The, MAX-MIN and MAX-BIAS formulations were proposed for FWLAM. This model provided the flexibility for the pollution control agency and dischargers to specify their aspirations independently and the waste treatment cost curves could be eliminated. It was concluded that FWLAM could be used for water quality management of a water body by giving appropriate transfer function.

A decision analysis based model (DAPS 1.0, Decision Analysis of Polluted Sites) was developed by Mohamed and Cote, (1999) to evaluate risks that polluted sites might pose to human health. In the developed model, pathways are simulated via transport models (i.e. groundwater transport model, runoff erosion model, air diffusion model, and sediment diffusion, and resuspension model in water bodies). Quantitative estimates of risks are calculated for both carcinogenic and non-carcinogenic pollutants. Being very heterogeneous, soil and sediment systems are characterized by uncertain parameters. An inference model using fuzzy logic has been constructed for reasoning in the decision analysis. The developed programme, was unique in its kind because it contained four transport models namely a groundwater transport model (PC_CTIS), a runoff And erosion model (GLEAMS 2.10), a soil air diffusion and dispersion model, and a sediment diffusion and resuspension model and also it used certain concepts of fuzzy set theory to model uncertainty in the risk analysis. The predicted pollutant concentrations, calculated via the transport models, are then used as inputs to the health risk assessment model. Depending on the exposure scenario, the model calculated pollutant intake through different media. It, then, assesses the toxicity by calculating carcinogenic and/or non-carcinogenic risk factors for each pollutant. For the investigated case study, the results indicated that the site does not pose a serious threat to human health and therefore, does not need to be remediated.

Water quality management of a river system was addressed in a fuzzy and probabilistic framework by Sasikumar and Mujumdar, (2000). In this study two types of uncertainty, namely randomness and vagueness, were treated simultaneously in the management problem. A fuzzy set based definition that is more general case of existing crisp –set – based definition of low water quality was introduced. The event of low water quality at a checkpoint in the river system was considered as a fuzzy event. The risk of low water quality was then defined as the probability of fuzzy event of low water quality. A fuzzy set of low risk that considered a range of risk levels with appropriate membership values was introduced. Different goals associated with the management problem were expressed as fuzzy sets and the resulting management problem was formulated as a fuzzy multi objective optimization problem. The model was applied to hypothetical river system to illustrate the fuzzy probabilistic modeling in the water quality management of a river system. This model was expected to act as an aid to decision making for water quality management of a river system.

Silvert, (2000) illustrated the fuzzy methodology by examples based on research to evaluate of the effects of finfish mariculture on coastal zone water quality. Four fuzzy sets were defined representing nil, moderate, severe and extreme impacts. To make the interpretation easy, the four memberships were combined to produce a simple comprehensive score, which represents an overall measure of the environmental quality. Study concluded that fuzzy logic could be applied to the development of environmental indices in a way that resolves problems like incompatible observations and implicit value judgement. It could deal with differing perceptions of environmental risks as different weights could be assigned to different types of observations.

Abebe et al., (2000) described a fuzzy rule-based approach applied for reconstruction of missing precipitation events. The working rules are formulated from a set of past observations using an adaptive algorithm. A case study was carried out using the data from three precipitation stations in Northern Italy. The performance of this approach was compared with an artificial neural network and a traditional statistical approach. The results indicate that within the parameter sub-space where its rules are trained, the fuzzy rule-based model provided solutions with low mean square error between observations and predictions. The problems that have yet to be addressed are over fitting and applicability outside the range of training data.

A method based on fuzzy set theory was applied by Buzas, (2001) to get more reliable information about water system from scarce databases. Monitored daily flow and water quality data of the medium size Zala River in Hungary were considered as elements of fuzzy sets. Fuzzy rules were generated from data pairs (flow, suspended solids concentration, water temperature, and phosphorus load as inputs and output, respectively) from which combined rule bases were setup. These rule bases can be considered as a tool of mapping from the input space to the output space using defuzzification procedure. This method, which is trainable and can learn from observations, is capable to generate daily phosphorus loads and annual balance with acceptable accuracy when it is trained only by weekly, biweekly or monthly data pairs. This tool was found to be well suited to utilize better the information content of scarce observations. Monitoring costs could be considerably decreased without substantial information loss since sampling of expensive and labour intensive parameters could be reduced.

Foundations of an expert system to map landscape features related to salinity, based in a South American case study was presented by Metternicht, (2001). Three rule-based expert systems using fuzzy sets and fuzzy linguistic rules to formalize the expert knowledge about the actual possibility of changes to occur were designed and implemented within a geographical information system (GIS). The outputs of the fuzzy knowledge-based system were three maps representing ‘likelihood of changes’, ‘nature of changes’ and ‘magnitude of changes’. These maps were then combined with landscape information and analysis of the spatial association among these variables, represented in different GIS layers, is undertaken to derive an exploratory hazard prediction model. Because the classification model differentiated among saline and alkaline areas, it was possible to evaluate the nature of the salinity changes, i.e. whether an area may become more saline, alkaline, or saline–alkaline which were important information for decision-makers and land planners, because different reclamation measures could be adopted according to the salinity type. The approach provided a fast way of assessing the likely extent of salinity at regional level, enabling the integration of a variety of data sources and knowledge. This monitoring model could help to evaluate the effectiveness of salinity control and management action plans. The fuzzy expert system offered great flexibility, as experts could re-define fuzzy rules to adapt the knowledge-based system to different local conditions. In areas where soil reclamation or salinity action plans were implemented, a decrease by one degree in salinity over a certain period of time could be considered as a likely change, such an expert system would enable to detect and account for the effectiveness of soil reclamation measures.

Fuzzy optimization model was developed for seasonal water quality management of a river system by Mujumdar and Sasikumar, (2002), which addressed the uncertainty in a water quality system in a fuzzy probability framework. Randomness associated with the water quality indicator is linked to the occurrence of low water quality (fuzzy event) using the concept of probability of a fuzzy event. Here, two levels of uncertainty, one that is associated with low water quality and the other with low risk are quantified and included in the model. Seasonal variations of the river flow were taken in to account to find out the seasonal fraction removal for the pollutants. The membership functions of fuzzy sets of low water quality represents the degree of low water quality associated with the discrete states of water quality in a season. Using the membership function for low water quality and steady state probability distribution for the water quality states, the fuzzy risk of low water quality is evaluated. Fuzzy risk forms the argument of the membership function of the fuzzy goals of the pollution control agency. Considering the goals of the pollution control agency and dischargers as fuzzy goals with appropriate membership functions, the water quality management model is formulated as a fuzzy optimization model.

Utilizing the rainfall intensity, and slope data, a fuzzy logic algorithm was developed to estimate sediment loads from bare soil surfaces, in a study done by Tayfur et al., (2003). Considering slope and rainfall as input variables, the variables were fuzzified into fuzzy subsets with triangular membership functions. The relations among rainfall intensity, slope, and sediment transport were represented by a set of fuzzy rules. The fuzzy rules relating input variables to the output variable of sediment discharge were laid out in the IF-THEN format. The commonly used weighted average method was employed for the defuzzification procedure. The sediment load predicted by the fuzzy model was in satisfactory agreement with the measured sediment load data. The results revealed that the fuzzy model performed better than ANN and other physically based model under very high rainfall intensities over different slopes and over very steep slopes under different rainfall intensities. This was closely related to the selection of the shape and frequency of the fuzzy membership functions in the fuzzy model.

An indicator model for evaluating trends in river quality using a two stage fuzzy set theory to condense efficiently monitoring data is proposed by Meyliou et al., (2003). This candidate data reduction method used fuzzy set theory in two analysis stages and constructed two different kinds of membership degree functions to produce an aggregate indicator of water quality. First, membership functions of the standard. River pollution index (RPI) indicators, DO, BOD_5, SS, and NH_3-N were constructed as piecewise linear distributions on the interval [0,1]. The extension of the convergence of the fuzzy c-means (FCM) methodology was then used to construct a second membership set from the same normalized variables as used in the RPI estimations. Weighted sums of the similarity degrees derived from the extensions of FCM are used to construct an alternate overall index, the River quality index (RQI). The RQI provides for more logical analysis of disparate surveillance data than the RPI, resulting in a more systematic, less ambiguous approach to data integration and interpretation. In addition, this proposed alternative provided a more sensitive indication of changes in quality than the RPI. A case study of the Keeling River was presented to illustrate the application and advantages of the RQI. Fuzzy theory provided a method that permitted an investigator to determine how much a particular set of monitoring measures represented elements of good quality as well as elements of bad quality. The model proposed in this research was a new creative idea in environmental evaluation index. It provides a less subjective, more sensitive, and more efficient model for evaluating quality and changes in quality.

A fuzzy logic (FL) model was developed by Chen and Mynett, (2003) to predict algal biomass concentration in the eutrophic Taihu Lake, China. In this fuzzy model, a method combining data mining techniques with heuristic knowledge is developed. It used (PCA) principal component analysis to identify the major abiotic driving factors and to reduce dimensionality. Self-organising feature map (SOFM) technique and empirical knowledge were applied jointly to define the membership functions and to induce inference rules. As indicated by the results, the fuzzy model successfully demonstrated the potentials of exploring "embedded information" by combining data mining techniques with heuristic knowledge. The developed method had also been introduced to the European Commission project Harmful Algal Bloom

Expert System (HABES). SOFM was successfully used to search for suitable fuzzy set definitions and inference rules directly from data. Heuristic knowledge was incorporated when there was no data available about other important factors. The method has proved to be promising as indicated by the results of modeling algal biomass (Chl-a) concentration in the eutrophic Taihu Lake.

Applications of fuzzy logic for decision support in ecosystem management are reviewed and assessed by Adriaenssens et al., (2004) with an emphasis on rule-based models. In particular, the identification, optimization, validation, the interpretability and uncertainty aspects of fuzzy rule-based models for decision support in ecosystem management are discussed. The application of fuzzy logic seemed to be very promising in domains such as sustainability, environmental assessment and predictive models. It was opined by the authors that hybrid techniques would be used in future to overcome problems such as input variable selection and optimization of rules and membership functions within the fuzzy rule-based models and more stringent methodologies and reliable results would be required to convince managers and policy makers to apply fuzzy models in practice.

A fuzzy logic model was developed by Soyupak and Chen, (2004) to estimate pseudo steady state chlorophyll-a concentrations in a very large and deep dam reservoir, namely Keban Dam Reservoir (Turkey), which is also highly spatial and temporal variable. The estimation power of the developed fuzzy logic model was tested by comparing its performance with that from the classical multiple regression model. The data included chlorophyll-a concentrations in Keban lake as a response variable, as well as several water quality variables such as PO_4 phosphorus, NO_3 nitrogen, alkalinity, suspended solids concentration, pH, water temperature, electrical conductivity, dissolved oxygen concentration and Secchi depth as independent environmental variables. The model was found to be capable of empirically approximating the underlying non-linear relationship and could provide a crisp and simple functional relationship among the input and output according to the rules. Once developed the model could be beneficially used during monitoring activities.

Svoray et.al., (2004) presented a model to assess herbaceous plant habitats in a basaltic stony environment in a Mediterranean region. The model is based on GIS (geographic information systems), remote sensing and fuzzy logic, while four indirect variables, which represent major characteristics of herbaceous habitats, are modeled: rock cover fraction; wetness index (WI); soil depth; and slope orientation (aspect). A linear unmixing model was used to measure rock cover on a per pixel basis using a Landsat TM summer image. The wetness index and local aspect were determined from digital elevation data with 25m ×25m-pixel resolutions, while soil data were gathered in a field survey. The modeling approach adopted assumed that water availability played a crucial role in determining herbaceous plant production in Mediterranean and semi-arid environments. The model rules were based on fuzzy logic and are written based on the hypothesized water requirements of the herbaceous vegetation. The results showed that on a polygon basis there was positive agreement between the model proposed and previous mapping of the herbaceous habitats carried out in the field using traditional methods. Intrapolygon tests showed that the use of a continuous raster data model and fuzzy logic principles provide an added value to traditional mapping. The model could also be used to study the relationship between water availability and ecosystem productivity on a regional scale.

A model for a Wildfire Destruction Danger Index has been proposed by Kaloudis et al., (2005) as a tool for effective fire management planning which made use of fuzzy set theory for the representation and management of uncertainty. Based on the theories of fuzzy sets and support logic, conceptual system architecture and an implementation of a prototype WFDDI-DSS was described. It provided information about the future level of fire risk and facilitates the determination of the appropriate measures that should be applied, appropriate equipment, the organization of fire fighting forces, the scheduling of related educational activities and of campaigns that aim at increasing the population awareness.

Lee and Chang, (2005) applied an interactive fuzzy approach to develop a water quality management plan in a river basin for solving multi-objective optimization problems involving vague and imprecise information related to data, model formulation, and the decision maker’s preferences. This approach was presented as a sustainable water quality management strategy in which the decision makers and the environmental analysts put forward their views on three major economic and environmental factors: river water quality, assimilative capacity, and treatment cost of wastewater. This methodology is illustrated in a case study of multi-objective water quality management in the Tou-Chen River Basin in northern Taiwan. For an economic an environmental balance in a river system, the study indicated that for the constraint of the same equitable removal levels a higher water quality level may be achieved at the monitoring stations.

A grey fuzzy optimization model is developed by Karmakar and Mujumdar, (2006) for water quality management of river system to address uncertainty involved in fixing the membership functions for different goals of Pollution Control Agency (PCA) and dischargers. The developed model, Grey Fuzzy Waste Load Allocation Model (GFWLAM), had the capability to incorporate the conflicting goals of PCA and dischargers in a deterministic framework. The imprecision associated with specifying the water quality criteria and fractional removal levels are modeled in a fuzzy mathematical framework. To address the imprecision in fixing the lower and upper bounds of membership functions, the membership functions themselves are treated as fuzzy in the model and the membership parameters are expressed as interval grey numbers, a closed and bounded interval with known lower and upper bounds but unknown distribution information. The model provided flexibility for PCA and dischargers to specify their aspirations independently, as the membership parameters for different membership functions, specified for different imprecise goals are interval grey numbers in place of a deterministic real number. In the final solution optimal fractional removal levels of the pollutants were obtained in the form of interval grey numbers thus enhancing the flexibility and applicability in decision-making, as the decision-maker gets a range of optimal solutions for fixing the final decision scheme considering technical and economic feasibility of the pollutant treatment levels. Application of the model was illustrated with case study of the Tunga–Bhadra river system in India.

In a study conducted by Adriaensseas et al., (2006), fuzzy knowledge-based models were constructed for the prediction of abundance levels of the macroinvertebrate taxa Asellus and Gammarus in river basins in Flanders (Belgium) and the results were validated by means of empirical data from the Zwalm river basin.

Although the fuzzy models are based on a small set of input variables and the inference system is relatively simple, their performance was observed to be comparable to that of other modeling techniques, such as classification trees. In comparison to other predictive modeling techniques (ANN, multivariate analysis), fuzzy models have the advantage to be simple (relations between input and output variables can be explained in a linguistic-based rule base) and robust (performance is not depending on training and new input variables and rules can be easily added). The developed fuzzy models for the prediction of Gammarus and Asellus in rivers seemed to perform well and can have practical application in the decision support related to water management. They can be improved, mainly through the implementation of habitat characteristics and by the hybridization of fuzzy logic with data-based modeling techniques, which ease the optimization of the models.

In a work done by Marchini and Marchini, (2006) the conversion of qualitative scheme of lagoon of Venice into a fuzzy logic model, which considered four input variables namely abundance of marine species; abundance of lagoon species; abundance of oligohaline species and total abundance of the sessile macrozoobenthos was presented. Three fuzzy sets describe abundance levels (low, medium, high) for each one of the four variables; the 81 (3^4) resulting combinations were associated to the six ecological sectors, for a total of 486 "if . . . then" rules. Two different interpretations of the inference process, and combined their results with the "crisp weighting" technique to obtain the fuzzy membership grades to the six ecological sectors were used. The results are in agreement with the literature information. Since all the methods suggested in literature depend on the subjective knowledge of the experts, this model claimed to represent the first proposal of an objective procedure to identify ecological sectors using the biocoenosis living on hard bottoms. The fuzzy logic approach had shown to be a useful tool to deal with subjective classifications and to model human experience and knowledge, so its application in this kind of problems is to be recommended.

Time series based neural network and fuzzy logic models were developed for fish recruitment analysis using fish stock–recruitment data incorporating environmental information in a study done by Chen and Harel, (2006). Data from the

Pacific halibut stock with the Pacific Decadal Oscillation (PDO) index as the environmental variable was used for the model development. The neural network model was developed based on the multi-layer feed-forward neural network model with back propagation learning algorithm. The fuzzy logic model was developed based on the fuzzi-fication of the PDO index into two fuzzy sets denoted as “positive” and “negative” regimes. It was demonstrated that the fuzzy logic model outperformed the traditional Ricker stock–recruitment model, the Ricker model with PDO as covariate and the neural network model as measured by several diagnostic criteria. In addition, the simple Ricker stock–recruitment model corrected with the autoregressive time series residuals outperformed the Ricker model with PDO as covariate, neural network model and fuzzy logic model ignoring the time series residuals.

Broekhoven et al., (2006) applied a fuzzy rule based approach to a microinvertbrate habitat suitability-modeling problem. Fuzzy classifiers were applied to a modeling problem concerning the habitat suitability of river sites along spring to small rivers in the central and western plains of Europe for 86 micro invertebrate species. Four models were developed for each species including ‘ammonium concentration’, ‘nitrate concentration’,’ phosphate concentration’ or ‘electrical conductivity’ as third input variable in addition to the primary two input variables ‘stream width’ and ‘stream velocity’ and four value between 0 and 1 as output indicating the degree to which the river site is concerned ‘not suitable’ respectively ‘lowly’, ‘moderately’ and ‘highly’ suitable for the species to establish a population. It was concluded that the fuzzy rule based modeling approach showed to hold valuable properties when developing habitat suitability models meant to support river management.

Takagi Sugeno fuzzy method was presented by Altunkanayk et al., (2005) for predicting future monthly water consumption values of Istanbul city in Turkey from three antecedent water consumption amounts, which are considered as independent variables. Mean square error (MSE) values for different model configurations are obtained, and the most effective model is selected. . The TS fuzzy model did not have restrictive assumptions such as the stationarity and ergodicity, which are primary requirements for the stochastic modeling. . In the prediction procedure only lag one was considered. It is observed that the TS fuzzy model preserved the statistical properties. This model also helped to make predictions with less than 10% relative error.

Three data-driven water level forecasting models were presented and discussed by Alvisi et al., (2006) in which one is based on the artificial neural networks approach, while the other two are based on the Mamdani and the Takagi-Sugeno fuzzy logic approaches, respectively. All of them were parameterized with reference to flood events alone, where water levels were higher than a selected threshold. The analysis of the three models was performed by using the same input and output variables. However, in order to evaluate their capability to deal with different levels of information, two different input sets were considered. The analysis was made with great attention to the reliability and accuracy of each model, with reference to the Reno river at Casalecchio di Reno (Bologna, Italy). It was shown that the two models based on the fuzzy logic approaches performed better when the physical phenomena considered were synthesized by both a limited number of variables and IF-THEN logic statements, while the ANN approach increased its performance when more detailed information was used. As regards the reliability aspect, it was shown that the models based on the fuzzy logic approaches might fail unexpectedly to forecast the water levels, in the sense that in the testing phase, some input combinations were not recognized by the rule system and thus no forecasting was performed. This problem does not occur in the ANN approach.

The development of fuzzy models for use in ecosystem management, however, is still in the explorative stadium. Most of the applications based on fuzzy modeling have been set up by trial and error, and are mainly limited to the domain of environmental assessment.

2.3.3 ARTIFICIAL NEURAL NETWORK MODELS

Artificial neural networks were introduced and applied as a new, promising model type by Recknagel et al., (1997) for modeling and prediction of algal blooms. The neural network applications were developed and validated by limnological time-series from four different freshwater systems. The water-specific time-series comprised cell numbers or biomass of the ten dominating algae species as observed over up to twelve years and the measured environmental driving variables. The resulting predictions on succession, timing and magnitudes of algal species indicated that artificial neural networks could fit the complexity and nonlinearity of ecological phenomena apparently to a high degree. Artificial neural networks (ANNs) are non-linear mapping structures based on the function of the human brain. They had been shown to be universal and highly flexible function approximators for any data. These make powerful tools for models, especially when the underlying data relationships are unknown (Esquerre et al., 2004).

Maier and Dandy, (1997) used ANN to model the incidence of a specific genus of cyanobacteria (Anabaena sp.) in the River Murray at Morgan (Australia), with the dual objectives of forecasting algal concentrations to give prior warning of impending blooms and to identify the factors that affect the blooms of Anabaena. The model inputs included weekly values of turbidity, colour, temperature, flow and the concentrations of total nitrogen, as well as soluble and total phosphorus. The results obtained were very promising as the model was able to forecast most major variations in Anabaena concentrations (timing and magnitude) for an eight-year period two weeks in advance. A sensitivity analysis carried out on the model inputs indicated that all input variables are important, with no one variable being dominant. The artificial neural network model was able to successfully forecast concentrations of Anabaena, two weeks in advance. The relative magnitude and timing of the forecasts were very good. Using lagged inputs significantly improved the performance of the model. A sensitivity analysis of the model inputs revealed a complex relationship between the input variables and concentrations of Anabaena. No one variable was found to be dominant, with all input variables contributing. There appeared to be a strong inverse relationship between Anabaena concentrations and colour and turbidity and a strong positive relationship between Anabaena concentrations and temperature. It was concluded that the reason for not observing a clear cut relationship between Anabaena and nutrient levels was probably the high absolute nutrient levels which do not limit algal growth and advection of algae from lagoons into the main channel of the river could be the reason for the appearance of algal blooms on the falling limbs of the flood hydrograph.

The artificial neural network (ANN) modeling technique was used by Zhang and Stanley, (1997) to establish a model for forecasting the raw-water colouring in a large river. A general ANN modeling scheme was also recommended for the rest of the raw-water parameters. Some optimization issues involved in the modeling phases and the potential applications of ANN in the water treatment industry were also discussed. Results indicate that the ANN modeling scheme showed much promise for water quality modeling and process control in water treatment. The ANN modeling approach seemed promising and it is a fast and flexible way to incorporate multiple input parameters and target parameters into one model.

Lek et al., (1999) described the development and validation of an artificial neural network (ANN) for the purpose of estimating inorganic and total nitrogen concentrations in streams The model had eight independent input variables of watershed parameters consisting of five on land use features (the percentage of sub watershed areas under forest, agriculture, urban, wetland and other categories), mean annual precipitation, animal unit density and mean stream flow) and two dependent output variables (total and inorganic nitrogen concentrations in the stream). The predictive quality of ANN models was judged with "hold-out" validation procedures. After ANN learning with the training set of data, a correlation coefficient R of about 0.85 in the testing set was obtained. Thus, ANNs were found to be capable of learning the relationships between drainage area characteristics and nitrogen levels in streams, and showed a high ability to predict from the new data set. On the basis of the sensitivity analyses the relationship between nitrogen concentration and the eight environmental variables was established.

Development of a neural network model for estimating primary production of phytoplankton was studied by Scardi and Harding Jr, (1999). Data from the enriched estuary in the eastern United States, Chesapeake Bay were used to train, validate and test the model. Error back propagation multiplayer perceptron was used for training an observed to outperform the conventional models. Sensitivity analysis revealed that total chlorophyll in the photic zone is the most influential input parameter and the least influential variable was salinity. Classical multilayer perceptron model (MLP) was used in this study. River discharge and solar radiation variables are used as inputs to the MLP model. The choice of these variables is dictated by what are perceived to be the predominant processes that control pH in the Middle Loire River, which was typically eutrophic during the low-flow summer period. The influence of the previous day's flows and radiation was evaluated in the calibration and verification test. The best network found to simulate pH was one with two input nodes and three hidden nodes. The inputs were: daily discharge and a variable called 'Index of anterior radiation', i.e. calculated as an exponential smoothing of the daily radiation variable. When calibrated over 4 years of data and tested (i.e. verified) for a one-year independent set of data, the model proved satisfactory on pH simulations, with accuracies in the order of 86%. After elaborating the pH model, the Student test and the cumulative Page–Hinkley test were applied for automatic detection of changes in the mean of the residuals from the ANN pH model. This analysis had shown that such tests are capable of detecting a measurement error occurring over a short period of time (1–4 days). The results presented in this paper indicated that ANN clearly gave satisfactory responses in the modeling of pH as a function of hydro meteorological data such as discharge and solar radiation

A three layer Levenberg–Marquardt feed forward learning algorithm was used to model the eutrophication process in three water bodies of Turkey (Keban Dam Reservoir, Mogan and Eymir Lakes) by Karul et al., (2000). Despite the very complex and peculiar nature of Keban Dam, a relatively good correlation was observed between the measured and calculated values. For Mogan and Eymir, which are much smaller and more homogenous lakes compared to Keban Dam Reservoir, correlation values as high as 0.95 were achieved between the measured and calculated values. Neural network models were able to model non-linear behavior in eutrophication process reasonably well and could successfully estimate some extreme values from validation and test data sets which were not used in training the neural network Chlorophyll-a was the most successfully estimated parameter by the neural network model. Both the results of Keban Dam Reservoir and Mogan and Eymir lakes were reasonably well. For cases where phytoplankton species were used as output parameters, the model was not as successful as in chlorophyll-a models, which was primarily due to the amount and nature of the available phytoplankton data. This study showed that non-linear relationships in the eutrophication phenomenon could be modeled reasonably well and the behavior of eutrophication in Mogan and Eymir lakes was more successfully estimated due to their smaller sizes and more homogenous structures. It was also proved from the study that a neural network model could estimate values that lie outside the boundaries of the training set, i.e. never introduced to the system before. It was concluded that along with the chlorophyll-a concentrations, neural network models can also be used to estimate the densities of certain species as functions of environmental parameters and when coupled with temporal models that can estimate environmental conditions these models can be used as algal bloom estimators.

Artificial Neural Network (ANN) approach that can be used to forecast the future pollutant concentrations and hydraulic heads of a groundwater source was described by Gumrah et al., (2000). In order to check the validity of the approach, a hypothetical field data as a case study were produced by using groundwater simulator (MOC). The future chlorine concentrations and hydraulic heads were estimated by applying both the long-term and the short-term ANN predictions. An approach to overcome the effects of using the data of a single well was proposed by favoring the use of data set for a neighbour well. The higher errors for the long-term ANN predictions were obtained at the observation wells, which were away from an injection well. In order to minimize the difference between the results of long-term ANN approach and flow simulation runs; the short-term prediction was applied. The use of short-term prediction for the wells away from an injection well was found to give highly acceptable results when the long-term prediction fails.

A model to quantify the interaction between abiotic factors and algal genera in Lake Kasumigaura, Japan was developed by Wei et al., (2001) using artificial neural network technology. Proliferation of algal blooms of Microsystis, Phormidium and Synedra could be successfully predicted and validated using the ANN model. Sensitivity analysis showed that pH is one of the key factors limiting the growth of Phormodium in Lake Kasumigaura.An approach of quantifying the biotic response to combinations of different changes of four abiotic factors (COD, pH , T-P, and T-N) was developed based on the orthogonal design. The simulated output indicated that the dominant genera Microcystis, Phormidium, Oscillatoria and Synedra were alkalophilic.

In a study done by Lischeid., (2001), artificial neural networks were applied to investigate the SO_4 dynamics in the runoff of a small-forested catchment susceptible to SO_4 deposition.. The model was used to investigate long-term trends in sub-regions of the phase space spanned by the identified input variables. According to the model, decreasing emissions had a significant effect on runoff SO_4 concentration only during the first severe storms at the end of the vegetation period. This suggested to focus on these events as indicators for recovery of the topsoil layers. The results of the study presented here demonstrated the potential of artificial neural networks to analyze hydro chemical time series. They allowed for investigating the driving forces of the SO_4 dynamics in a small catchment's runoff and its response to long-term changes of one of the driving forces. In the catchments studied, a recovery of stream water due to decreasing sulfate emissions was clearly visible only in a certain sub-region of the phase space. The changing soil chemical status was most clearly reflected during the first discharge peaks at the end of the vegetation period. The conceptual model developed based on these results was consistent with additional data from a comprehensive monitoring measurement program. It was recommended to focus on these events in order to assess beginning long-term changes of a catchment's geochemical status. Efficient empirical data analysis techniques like artificial neural networks were recommended for the analysis of long-term time series. It was felt that assessing the catchment's future hydro chemical development focusing on these data might be a strategy superior to conventional trend analysis.

Artificial neural network models were developed to simulate daily mean and hourly DO concentrations in the Tualatin River at the Oswego Dam by Rounds, (2002). The DO at that site was affected by its solubility as well as biological processes such as algal photosynthesis and respiration, sediment oxygen demand, biochemical oxygen demand, and ammonia nitrification. The effects of these biological processes were hypothesized to be constrained by a small set of physical and meteorological factors: stream flow, air temperature, solar radiation, and rainfall. Neural network and regression models were built to test this hypothesis, using data from May-October of 1991-2000. Neural network models, however, were successful in predicting patterns in the DO data on daily, weekly, and seasonal time scales where as multiple linear regression models produced poorly correlated results. ANN model performance was good and the predictions often were better than those from a USGS process-based model of the Tualatin River. The process-based model was found to be most useful for providing insight into how the river works, identifying important processes, and testing the effects of point sources and management strategies. Thus it was concluded that the ANN model has tremendous potential as a forecasting tool, but yields less insight into the specifics of riverine processes.

Haejin Ha and Stenstrom, (2003) proposed a neural network approach to examine the relationship between storm water quality and various types of land use. The neural model used a Bayesian network and has 10 water quality input variables, four neurons in the hidden layer, and five land-use target variables (commercial, industrial, residential, transportation, and vacant). Using this model 92.3 percent of correct classification and 0.157 root-mean-squared error on test files could be obtained. Based on the neural model, simulations were performed to predict the land-use type of a known data set, and the simulation accurately described the behavior of the new data set thus demonstrating that a neural network could be effectively used to produce land-use type classification with water quality data. An approach for identifying opportunities for water quality improvement could be developed using this concept. Such information could provide opportunities for better management to control storm water pollution.

Sharma et al., (2003) developed two artificial neural network (ANN) models, a trainable fast back-propagation (FBP) network and a self-organizing radial basis function (RBF) network, for simulation of subsurface drain outflow and nitrate-nitrogen concentration in tile effluent. The available field data were divided into training and testing scenarios, with the training file consisting of eight inputs and two outputs. A sensitivity analysis was performed by varying the network parameters to minimize the prediction error and determine the optimum network configuration. The best architecture for the FBP model comprised of 20 neurons in the hidden layer and a learning rate of 0.02, while the RBF network with a tolerance of 20 and a receptive field of 15 yielded 547 neurons in the hidden layer. Overall, the performance of the RBF neural network was superior to the FBP model in predicting the concentration of nitrate-nitrogen in drain outflow due to the application of manure and/or fertilizer. This information, in turn, could be used for proper fertilizer management; thereby, reducing not only the loss of valuable nitrogen fertilizer but also the potential for pollution of subsurface water by nitrate.

Artificial neural network models were used to model alum dosing of southern Australian surface waters by Maier et al., (2004). Two process models and a process inverse model were developed. Model 1 used the values of a selection of raw water quality parameters and that of the applied alum dose to predict the turbidity, colour and UVA-254 of the treated water. Model 2 used the values of a selection of raw water quality parameters, the desired values of treated water turbidity, colour and UVA-254 and the applied alum dose as model inputs. Model 3 was a process inverse model which used the values of a selection of raw water quality parameters and the desired values of treated water turbidity, colour and UVA-254 as model inputs, while predicting the optimal applied alum dose. The model outputs were the residual aluminum concentration and pH of the treated water. The performance of the models is found to be very good, with correlation (R^2) values ranging from 0.90 to 0.98 for the process model 1 and that of Model 2, with R^2 values of 0.96 and 0.85. An R^2 value of 0.94 is obtained for the process inverse model used to predict optimum alum doses. Two simulation tools, Sim TTP and Sim WT, were developed to enable operators to obtain optimum alum doses easily and to control the alum dosing rate automatically. Both simulation tools provided a graphical user interface that makes it easy for operators to determine the optimal alum dose or to gain a better understanding of the relationship between raw water qualities, applied alum dose and treated water quality.

Multilayer perceptron (MLP) and functional-link neural networks (FLN) were developed by Esquerre et al., (2004) to predict inlet and outlet biochemical oxygen demand (BOD) of an aerated lagoon operated by International Paper of Brazil. In Part

I, predictive models for both inlet and outlet BOD for the aerated lagoon were developed using linear multivariate regression techniques. Second part provided a novel approach for developing PLS–FLN model structures. Comparing the FLN and MLP approaches with the approaches proposed in this study, PLS–FLN and PLS–MLP, respectively, when a considerable number of samples is available (data set 1), it was observed that, although PLS did not improve the MLP nonlinear mapping, it did improve the second-order FLN for both outlet and inlet BOD prediction. No significant differences were observed between FLN and PLS–FLN results using first-order monomers. One of the biggest challenges of this research was to deal with the high incidence of missing values in the recorded data, a common situation for industrial data records. When only a small number of data are available (data set 2), the combined use of PLS and neural networks had shown to provide prediction results that have statistical parameters significantly higher than those obtained using these techniques separately. For this case study, the PLS–MLP approach was the best of any method evaluated, but there still appeared to be room for improvement. The results reported in this paper showed the improvement in modeling capabilities achieved on using MLP neural networks instead of just the linear multivariate regression techniques. Improvements in outlet BOD prediction using dynamic instead of steady state modeling, as opposed to the inlet BOD prediction, is clearly observed. These results agreed with those obtained by the linear multivariate regression techniques. Caution was required when neural networks models (or any other empirical models) were extrapolated beyond the range of the data analyzed or to other systems, because microbial activities and most wastewater quality parameters of biological treatment systems are site-specific variables.

Application of neural networks to model complex relationship between soil parameters loading conditions and collapse potential was investigated by Basma and Kallas, (2004). Back propagation neural network was used to assess collapse potential and it was trained using experimental data. Input variables were soil coefficient of uniformity, initial water content, compaction unit weight, applied pressure at wetting, percent sand and percent clay. 82 data sets were used to train the network and the model consisting of 8 hidden neurons was observed to be the most successful.

Simulated results with testing data and validation data proved that the neural networks are very efficient in assessing the complex behaviour collapsible soil using minimal processing of data.

An ANN was developed by Riad et al., (2004), and used to model the rainfall-runoff relationship, in a catchment located in a semiarid climate in Morocco. The multilayer perceptron (MLP) neural network was chosen for use in the current study. The results and comparative study indicate that the artificial neural network method is more suitable to predict river runoff than classical regression model. The results obtained showed clearly that the artificial neural networks were capable of model rainfall-runoff relationship in the arid and semiarid regions in which the rainfall and runoff are very irregular, thus, confirming the general enhancement achieved by using neural networks in many other hydrological fields.

In a study done by Daliakopoulosa et al., (2005), the performance of different neural networks in a groundwater level forecasting is examined in order to identify an optimal ANN architecture that can simulate the decreasing trend of the groundwater level and provide acceptable predictions up to 18 months ahead. Messara Valley in Crete (Greece) was chosen as the study area as its groundwater resources have being overexploited during the last fifteen years and the groundwater level has been decreasing steadily. Seven different types of network architectures and training algorithms were investigated and compared in terms of model prediction efficiency and accuracy. The different experiment results showed that accurate predictions could be achieved with a standard feedforward neural network trained with the Levenberg–Marquardt algorithm providing the best results for up to 18 months forecasts. By means of trial and error, an optimum network and parameter configuration for all three networks was derived. During calibration, the values that correlated better with all networks where those of a 5-month moving window through the data series. Neural networks have proven to be an extremely useful method of empirical forecasting of hydrological variables. An attempt was made to identify the most stable and efficient neural network configuration for predicting groundwater level in the Messara Valley. The groundwater in the area has been steadily decreasing since the late 1980s due to overexploitation due to intensive irrigation. A total of seven different ANN configurations were tested in terms of optimum results for a prediction horizon of 18 months. The most suitable configuration for this task proved to be a 20-3-1 feed forward network trained with the Levenberg– Marquardt method as it showed the most accurate predictions of the decreasing groundwater levels. From the results of the study it can also be inferred that the Levenberg–Marquardt algorithm was found to be more appropriate for this problem since the RNN also performs well when trained with this method. Moreover, combining two or more methods of prediction should also be considered as in our case the FNN-LM method tended to underestimate events when the rest of the methods overestimated them. In general, the results of the case study are satisfactory and demonstrate that neural networks can be a useful prediction tool in the area of groundwater hydrology.

Almasril et al., (2005) proposed a methodology using modular neural networks (MNN) to simulate the nitrate concentrations in an agriculture-dominated aquifer. This MNN-based model was applied to the Sumas-Blaine aquifer; a heavily agricultural area in northwest Washington State. The methodology relied on geographic information system (GIS) tools in the preparation and processing of the MNN input output data. The basic premise followed in developing the MNN input/output response patterns was to designate the optimal radius of a specified circular-buffered zone centered by the nitrate receptor so that the input parameters at the upgradient areas correlate with nitrate concentrations in ground water. A three-step approach that integrates the on-ground nitrogen loadings, soil nitrogen dynamics, and fate and transport in ground water was described and the critical parameters to predict nitrate concentration using MNN were selected. The sensitivity of MNN performance to different MNN architecture was assessed. The applicability of MNN was considered for the Sumas-Blaine aquifer of Washington State using two scenarios corresponding to current land use practices and a proposed protection alternative. The results of MNN were further analyzed and compared to those obtained from a physically based fate and transport model to evaluate the overall applicability of MNN. The physical and chemical processes that impact nitrate occurrences in ground water were studied to designate the input output response patterns. In order to achieve the optimal MNN performance, MNN was developed for different combinations of internal parameters. The MNN-based approach was found to be simple, economical and utilizes the available data from local agencies and different studies and reports. The development of MNN did not require the entire input space of the influential parameters. A sub vector of this input space was sufficient for MNN to efficiently predict the distribution of nitrate concentration. The approach followed throughout this paper was in the utilization of non-uniform optimal well zone radii as opposed to a uniform radius produced better MNN performance. MNN performance proved to be superior when considering the upgradient contributing areas of nitrate receptors in formulating the input output response patterns. The use of both upgradient and down gradient areas gave inferior predictions. The performance of MNN deteriorated with noisy data indicating that MNN is sensitive to errors in the input data. ANN was less accurate than MNN in predicting the spatial distribution of nitrate concentration. It should be kept in mind that this conclusion cannot be generalized since the performance of ANN or MNN relies mainly on the physical phenomenon in hand and the input parameters that were considered in the formulation of the training and testing sets. Long-term simulations performed by MNN to assess the effectiveness of future management alternatives rationally predicted the areas of potentially high nitrate concentrations. Although MNN performed less robustly compared to the simulations of a classical fate and transport model, the results showed that MNN is promising for a complex physical system analyzed here and future work should focus on including more subsurface-specific parameters to improve MNN performance.

Relationship between sewage odour and BOD were determined by Engin et al., (2005) using ANN model. An electronic nose was used for the purpose of characterizing sewage odours. Samples collected at different locations of a wastewater treatment plant were classified using an Artificial Neural Network (ANN) trained with a back-propagation algorithm. Additionally, the same method was used to determine the relation between sewage sample odours and their related biochemical oxygen demand (BOD) values. The overall results have indicated that ANNs can be used to classify the sewage samples collected from different locations of a wastewater treatment plant. Moreover, the electronic nose output could be used as an indicator in monitoring the biochemical activities of wastewaters. In this study, an electronic nose was used to characterize sewage odours. The nose produced 12 outputs from its sensor array at each sampling. The nose, exposed to sewage samples collected from different locations (inlet works, settlement tank, activated sludge and final effluent) of a wastewater treatment plant, produced outputs consisting of 12 elements each from its corresponding sensor. These data were then analyzed using neural networks in order to evaluate the ability of the electronic nose in responding to sewage samples. Additionally, the relationship between sewage odours and BOD was investigated. It was seen that ANNs as a pattern recognition technique offers a valuable method for sewage classification and on-line BOD detection. This method is quite rapid to apply and reproducible to monitor the biological content of sewage compared to conventional BOD analysis. One problem here was the inherent variability of the product under examination. Sewage odours are not easily characterized or quantified and therefore represent a particular problem in sewage treatment plant operation. Especially in a treatment plant treating wastewater of domestic and light industrial origin, with frequently changing loads, it was difficult to produce a correlation between sewage odour and BOD. It was believed that with more data points, better results could be achieved. However, even with a limited amount of data, the results with ANNs were quite satisfactory. The correlation of sewage odours and their corresponding BOD values was over 90%, and for the classification of sewage samples, the correlation was as high as 99%. It may be concluded that an electronic nose could be used to classify different sewage samples and, moreover, can be used as a detector for BOD.

An artificial neural network (ANN) technique was used by Velver de Ramirez et al., (2005) to construct a nonlinear mapping between output data from a regional ETA model ran at the Center for Weather Forecasts and Climate Studies/National Institute for Space Research/Brazil, and surface rainfall data for the region of Sa˜o Paulo State, Brazil. The objective was to generate site-specific quantitative forecasts of daily rainfall. The test was performed for six locations in Sa˜o Paulo State during the austral summer and winter of the 1997–2002 period. The analysis was made using a feed forward neural network and resilient propagation-learning algorithm. Meteorological variables from the ETA model (potential temperature, vertical component of the wind, specific humidity, air temperature, precipitable water, relative vorticity and moisture divergence flux) are used as input data to the trained networks, which generate rainfall forecast for the next time step. Additionally, predictions with a multiple linear regression model were compared to those of ANN. In order to evaluate the rainfall forecast skill over the studied region a statistical analysis was performed. The results showed that ANN forecasts were superior to the ones obtained by the linear regression model thus revealing a great potential for an operational suite. An analysis of two statistical models developed for rainfall forecast in the Sa˜o Paulo State, Brazil, showed that an ANN had a better performance than an MLR model and being a nonlinear mapping tool, was more suitable for rain (nonlinear physics) forecasts. The analyzed study cases suggested that ANN provided better results than the ETA model regarding the statistical criteria used, although it should be borne in mind that the comparison has been done between point forecasts (ANN) against areal predictions (ETA model), which is certainly not as much accurate. However, the comparison is reasonable since the aim of this study is to obtain a more specific rainfall forecast using NWP available data. The final results suggested that the ANN model could be an important tool for local rain forecasting, although not replacing the forecasters' experience, but complementing it with extra information (in addition to output model, satellite images, etc.) thus rendering his (her) task less arduous.

A study was done by Wang et al., (2005), that links ArcIMS, a Web-based Geographic Information System (GIS) software to ROUT, a national and regional scale river model which evolved from the US Environmental Protection Agency's Water Use Improvement and Impairment Model, to create a WWW-GIS-based river simulation model called GIS-ROUT. GIS-ROUT to predict chemical concentrations in perennially flowing rivers throughout the continental United States that receive discharges from more than 10,000 publicly owned wastewater treatment plants (WWTPs). The WWTP chemical loadings were calculated from per capita per day disposal of product ingredients and the population served by each plant. Each WWTP, containing data on treatment type and influent and effluent flows, was spatially associated with a specific receiving river segment. Based on user defined treatment-type removal rates for a particular chemical, an effluent concentration for each WWTP was calculated and used as input to the river model. Over 360,000 km of rivers are modeled, incorporating dilution and first order loss of the chemical in each river segment. The addition of WWW and GIS to ROUT represents an integration of the latest developments in digital databases, the Internet, GIS and simulation modeling. One important advantage of the GISROUT is that the system components are integrated and at the same time, independent from each other. While the database was the centerpiece of the system, it was developed independent of the simulation model. Separate modules were used to execute the model and view the results, however, those modules were linked through a graphic user interface (GUI). The separate yet linked functions provide flexibility for maintaining, updating, and using the system. With the use of GIS it was possible to access and provide a wide range of spatial analytical functions to prepare data for river modeling. The identification of upstream to downstream relationships of river segments, finding the discharge location of WWTPs on rivers, and grouping rivers by major drainage basins are some of the examples. This model is the user-friendly Internet-based interface and the interface provides access to all functions via buttons and interactive user input screens, thereby increasing the usability of such a sophisticated model. Sharing data and simulation results was another advantage of the GIS-ROUT. An easy access to modeling results provides a platform for a user to define simulation scenarios, such as the area (national or regional), parameters (chemical and physical characteristics), and loadings (consumer population and per capita consumption). Using the GIS-Rout model does not require high computing power of the client computers. In addition, it brings a complicated model to its users (who are not necessarily modelers) with easily understandable terms, maps and tables. The user-friendly display and query capabilities allow dynamic manipulation of model output and a two-way communication between the system and its user. The relationships between WWTP discharge and receiving river concentrations can be evaluated in addition to the identification of 'hot-spots', where environmental concentrations are expected to be high. The GIS-Rout model introduces the loading factors by market region, which provides an opportunity to model the effect of different per capita usages of an ingredient based on different consumer preferences and life styles. This was a significant step forward from the original Rout model, which assumes a uniform consumer behavior throughout the country. The regionalized loading factors, in conjunction with the population served by WWTPs in the regions, can provide more realistic estimates of consumer ingredients entering rivers in different geographic areas of the country. The capability of incorporating market region into river modeling in GIS-Rout is expected to promote further research on regional consumer.

An artificial neural network model and a multivariate logistic regression model were used by Brion et al., (2005) for predicting PCR-identified human adenovirus (ADV), Norwalk-like virus (NLV), and enterovirus (EV) presence or absence in shellfish harvested from diverse countries in Europe. The results of this analysis showed that ANN models predicted all types of viral presence and absence in shellfish with better precision than MLR models for a multicountry database. For overall presence/absence classification accuracy, ANN modeling had a performance rate of 95.9%, 98.9%, and 95.7% versus 60.5%, 75.0%, and 64.6% for the MLR for ADV, NLV, and EV, respectively. ANN models were able to illuminate site-specific relationships between microbial indicators chosen as model inputs and human virus presence. A validation study on ADV demonstrated that the MLR and ANN models differed in sensitivity and selectivity, with the ANN model correctly identifying ADV presence with greater precision.

Relative performance of artificial neural networks and the conceptual model SALTMOD was studied by Sarangi et al (2006) in simulating subsurface drainage effluent and root zone soil salinity in the coastal rice fields of Andhra Pradesh, India. Three ANN models namely, Back Propagation Neural Network (BPNN), General Regression Neural Network (GRNN), and Radial Basis Function Neural Network (RBFNN) were developed and observed that BPNN performed better than SALTMOD in predicting salinity of drainage effluent from salt affected subsurface drained rice fields.

Various different networks of the multilayer perceptron MLP type of ANN were developed by Schimid and Koskiaho, (2006) in modeling near-bottom concentrations of dissolved oxygen in the Finnish free water surface wetland at Hovi.The study concluded that this class of models showed adequate predictive abilities in a very complex ambient with processes evolving at a wide range of spatio temporal scales and the models were able to learn and generalize the mechanism of convective oxygen transport in the wetland pond studied.

The current state-of-the-art of the integration of artificial intelligence in to water quality modeling was reviewed by Chau, (2006) in which algorithm and methods studied include knowledge based system, genetic algorithm, artificial neural network, and fuzzy inference system. It was opined that most of the studies in ANN employed almost all possible environmental parameters as input variable without considering the optimal choice amongst them.

The literature revealed that data driven models could provide a very useful and accurate tool to solve problems in water resources studies and management.

2.4 PARAMETRIC STUDIES

Generalization ability of the network is related to the sensitivity of the output of the multilayer perceptron to small input changes. Dimopoulos et al., (1995) proposed a new index and presented a way of improving these sensitivity criteria and this methodology was adopted by Gevrey et al., (2003) in the study, which reviewed seven methods that can give the relative contribution and/or the contribution profile of the input factors were compared. The methods studied were the ‘PaD’ (for Partial Derivatives) method, the ‘Weights’ method, the ‘Perturb’ method, the ‘Profile’ method, the ‘classical stepwise’ method, ‘Improved stepwise, ‘Improved stepwise b’. The data tested in this study concerns the prediction of the density of brown trout spawning redds using habitat characteristics. The PaD method was found to be the most useful as it gave the most complete results, followed by the profile method that gave the contribution profile of the input variables. The Perturb method allowed a good classification of the input parameters as well as the Weights method that has been simplified but these two methods lack stability. Next came the two improved stepwise methods (a and b) that both gave exactly the same result but the contributions were not sufficiently expressed. Finally, the classical stepwise methods gave the poorest results.

A modification of partial derivative method PaD2 was implemented by Gevrey et al (2006) to analyse the contribution of all possible pair wise contributions of input variables taking in to account the two way interactions between the variables using simulated ANN model for an ecological data. Model was developed to predict the density of brown trout spawning redds using 10 habitat characteristics namely the wetted width, area with suitable spawning gravel, for trout per linear meter of river, surface velocity, water gradient, flow/width, mean depth, standard deviation of depth, bottom velocity, standard deviation of bottom velocity, mean speed/mean depth. Multilayer feed forward neural network with a back propagation algorithm was used for modeling and PaD2 was applied to study the two-way interactions of the input variables. From the contribution profile patterns, it was seen that the predicted density of the redds closely correspond to ecological reality. Contribution of the variables which were not significantly differentiated with the PaD were revealed with the PaD2.

2.5 CONCLUSIONS

It is clear from the literature that data driven models are more suitable to predict water quality, which has many virtues such as high estimating precision and automatic parameter amendment. Capability of fuzzy rule based model to capture the information under the form of premises and rules is also proved. The model is transparent and easy to understand due to its rule-based structure, which mimics the human way of thinking. Artificial neural networks are also non-linear mapping structures based on the function of the human brain. They are proved to be universal and highly flexible function approximators for any data, which makes powerful tools for models, especially when the underlying data relationships are unknown. Beyond the predictive realm of ANN, sensitivity studies revealed that it is possible to quantify the explanatory contribution of the predictor variables in the network. Adding new methods to ANNs allowing the analysis of the contributions of the different variables will help in understanding the ecological phenomenon and finally in finding solution to act on it, restore it and improve the environmental conditions for life.

CHAPTER
THREE

WATER QUALITY ANALYSIS AND LANDUSE CLASSIFICATION

3.1 THE ENVIRONMENTAL SYSTEM CONSIDERED FOR THE STUDY

Figure 3.1 shows the map of the study area and description of the sampling locations is given in Table 3.1 Originating in the foothills of the Khasi Hills of Meghalaya state in Northeast India, the Bharalu enters the Guwahati city through its southeastern corner. It flows through the densely populated residential and commercial areas of the city and along the way, meets a major drain carrying storm water runoff from the public sector Guwahati refinery and domestic waste water inputs from a large area in the city before its confluence with the river Brahmaputra at Bharalumukh. The northeastern region, especially the floodplains of the Brahmaputra, is dotted with a large number of wetlands or beels, which possess tremendous ecological significance as unique habitats for an exquisite variety of flora and fauna. The beels function as floodwater retention basins and traditional fisheries. Over 3,500 such wetlands have been identified in Assam, of which 177 are more than 100 ha. in size (Goswami and Das, 2003).

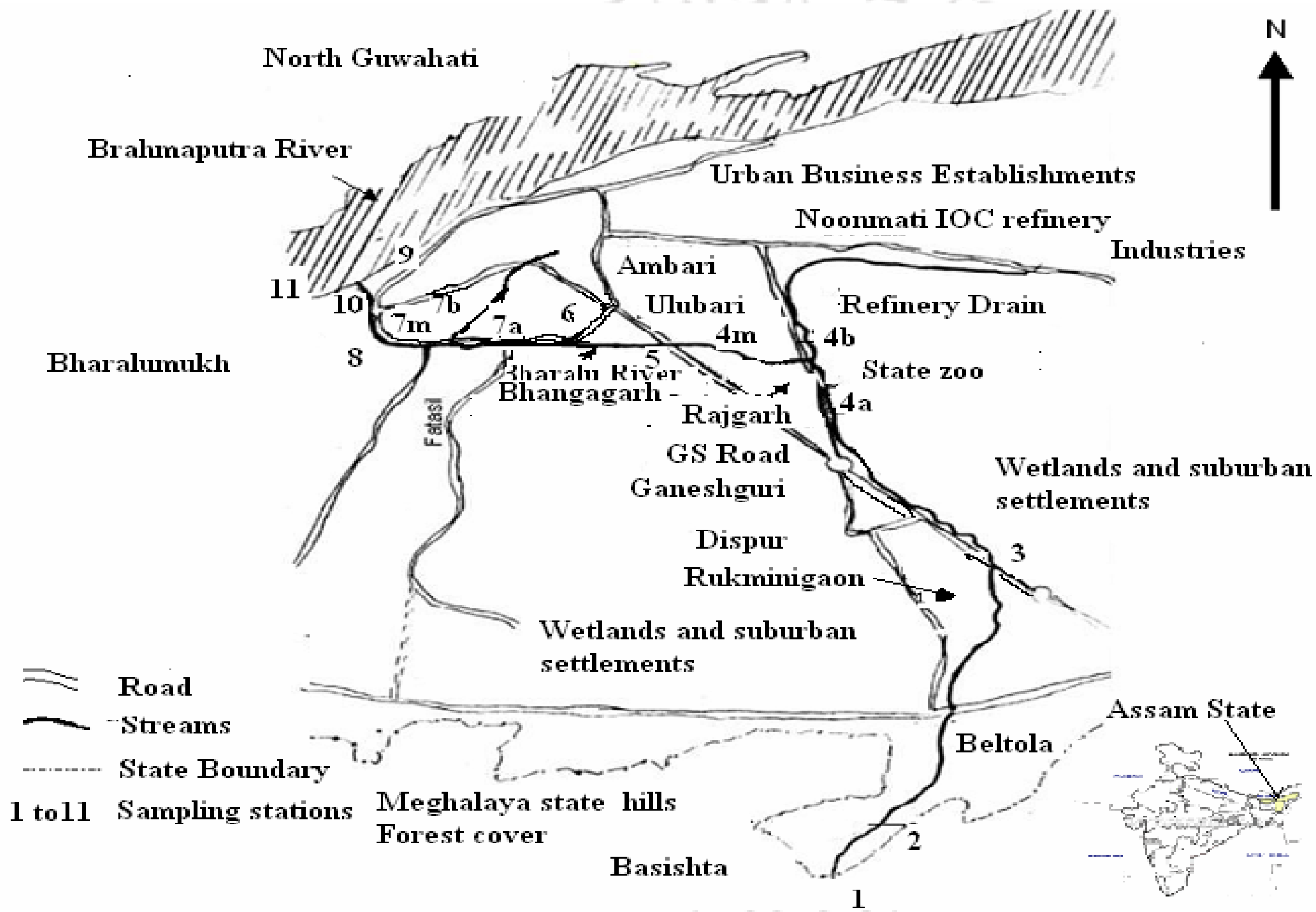


Figure 3.1. Guwahati City Drainage

Table 3.1 Description of the sampling locations

Sample location No	Description
1	Basistha upstream area (hilly watershed).
2	Bifurcation point of Basistha and Bahini (opposite to a military office).
3	Rukmini Gaon (populated residential area).
4a	Opposite to the Neelamani Phukan Park (commercial area).
4b	Near RGB Road East Bye lane 8 (residential area).
4m	Opposite to Jonali Path (adjoining urban traffic zone)
5	Bhangagarh bridge (busy street crossing)
6	Nepali Mandir-Rehabari (commercial area)
7a	Chabipool –Natun Basti (residential commercial area)
7b	Near Guwahati Koborosthan Masjid-Fatasil (busy Market area)
7m	Meeting point of 7A &7B at Fatasil (drainage confluence)
8	Bharalu sluice gate (500m before discharge point to the main river)
9	Brahmaputra river (before the confluence of Bharalu).
10	Bharalu river (just before joining Brahmaputra).
11	Downstream of Brahmaputra (after confluence of Bharalu).

(Also refer to Figure 3.1 for graphical location of sampling points).

3.2 MATERIALS AND METHODS

Bharalu river was sampled for the period from December 2003 to April 2005 (December ’03, April ’04, August ’04, October’04, December’04, February ’05, April ’05) from, the above15 stations. For convenience of discussion, the sampling periods have been classified as:

December: Winter

February : Dry

April : Pre monsoon

August : Receding monsoon

October : Post monsoon.

Sampling points were selected considering the following points:

- The origin of the watershed where no pollutants are expected
- The intermediate points which serve as the major drainage points of wastes as inputs
- Confluence with the main river

Samples of 5 liters each were collected manually in pre-cleaned polyethylene bottles

3.2.1 ANALYTICAL METHODS AND INSTRUMENTS

pH, Conductivity and Total Dissolved Solids were measured soon after the collection of the samples using digital meters. Total alkalinity was determined by titrating the sample with 0.02 N H_2SO_4 using methyl orange as indicator and hardness by EDTA titrimetric method. Concentration of chloride was obtained by Argentometric method. DO was determined by the modified wrinkler method and BOD by BOD method. Determination of other chemical components was carried out by spectrophotometric method as follows: total phosphorus by digestion and measurement with molybdophosphoric reagent; total iron measurement with o-phenanthrolene reagent, aluminum using erichrome cyanine-R and sulphate by turbidimetry with barium chloride reagent. Concentrations of sodium, potassium and calcium were determined by flame photometer and total solids were determined by gravimetric method. All the parameters were determined following recommended analytical methods of APHA 1998. Hardness, Chloride, DO and BOD were analyzed following the titration methods discussed in the Standard methods (APHA, 1998).

3.2.2 RECOMMENDEDWATER QUALITY CRITERIA

Standards of acceptable limits of surface water pollutants are presented in Table 3.2. Desirable level is the requirement for the cleanest water, which can be used for drinking purpose, and maximum permissible level is that needed for irrigation purpose. Above the maximum permissible level is the objectionable level.

After analysis pollutant concentrations were tabulated and presented graphically. Values were standardized between 0 and 1 in such a way that maximum permissible limit corresponds to a value of 1 and desirable limit corresponds to a value of 0. This representation was done to produce the levels of pollutants of each location in one single plot. The level above 1 corresponds to the objectionable level.

Between 0 and 1 is the acceptable level. The blocks in the negative side represents the concentrations below the desirable level, which corresponds to the requirement for Class A type water or the cleanest water quality.

3.2.3 CALCULATION OF CORRELATION COEFFICIENT

Correlation coefficient indicates strength and direction of a linear relationship between two random variables. In other words it is a statistical measure of how well the data lies along the regression line or how well the two variables are correlated. It is a calculated number, which indicates the degree to which two sets of numbers are statically related. Mathematical formula for computing correlation coefficient (r) is,

$$r = \frac{\sum xy - \frac{\sum x \sum y}{N}}{\sqrt{(\sum x^2 - \frac{(\sum x)^2}{N})(\sum y^2 - \frac{(\sum y)^2}{N})}}$$

Where x and y are two variables whose correlation with each other is to be found out and N is the number of data sets. Coefficient ranges from –1 to 1. A value of 1 shows that a linear equation describes the relationship perfectly and positively with all data points lying on the same line and with y increasing with x. A score of –1 shows that all data points lie on a single line but that y increases as x decreases. A value of 0 shows that a linear model is inappropriate, that there is no linear relationship between the variables. In the present study, the generated data obtained after analyzing the water quality was tabulated and the correlation coefficients of each parameter with dissolved oxygen were found out with the help of Microsoft excel work sheet. Those parameters with comparatively higher correlation coefficient as well as which crossed the desirable limit were selected as input variables for further studies including developing fuzzy rule base, multiple linear regression model and artificial neural network model.

Table 3.2. Acceptable levels of surface water pollutants.

Parameter	Desirable limit	Max.Permissible limit	Organization /Body
pH	7 –8.5	6.5 – 9.2	WHO
Conductivity	750 µ S/cm	2500 µ S/cm	WHO
TDS	500 mg/L	1000 mg/L	WHO
Total solids	500 mg/L	1500 mg/L	WHO
Alkalinity	200 mg/L	600 mg/L	BIS
Total Hardness	200 mg/L	500 mg/L	WHO
BOD	4 mg/L	12 mg/L	EPA
Chloride	250 mg/L	600 mg/L	WHO
Sulphate	200 mg/L	400 mg/L	BIS
Calcium	75 mg/L	200 mg/L	ICMR/BIS
Total phosphorus	0.2 mg/L	1 mg/L	EPA
Total Iron	300 µg/L	1500µg/L	WHO
Sodium	200 mg/L	200 mg/L	WHO
Potassium	200 mg/L	200 mg/L	WHO
Dissolved Oxygen	6 mg/L	4 mg/L	USPH standards, IS: 2296-1982

WHO - World Health Organization

BIS - Bureau of Indian Standards

ICMR - Indian Council of Medical Research

EPA -Environmental Protection Agency

USPH -United States Public Health

3.3 LAND USE CLASSIFICATION

Based on two classification schemes viz., American Planning Association "Land-Based Classification Standard" and U.S. Geological Survey

"Land-Use/Land-Cover Classification System for Use with Remotely Sensed Data", the USGS scheme was adopted for the study with slight modifications in level II classification of the various land uses. This scheme is resources based and not just area based which provides scope for effective watershed model development.

Procedure adopted for urban land use classification

3.3.1 GEOMETRIC CORRECTION

The LISS – 3 image purchased from NRSA was geometrically registered to Polyconic/Everest projection system with Toposheets No. N 78/12 and N 78/16 and GPS navigational survey.

3.3 2 IMAGE ENHANCEMENT

Nonlinear contrast enhancement technique, also known as uniform distribution stretch is adopted to make features like vegetation, land, water, and habitation. This type of stretching applies the greatest contrast enhancement to the range of DNs occurring most frequently in the reflectance histogram, resulting in a loss of information in the white and black ranges, the loss being not so severe as in the case of a linear contrast stretch. Non-linear stretch is applied to standard FCC of the image. Conventionally, three primary colours, viz., blue, green, and red, are used in the green, red, and infrared bands, respectively, to generate a standard FCC.

3.3.3 IMAGE CLASSIFICATION

A Multispectral classification is performed in FCC image of Guwahati area by supervised classification method. The spectral reflectance data is extracted to define the different land-use classes. More than 25 training sample were collected for each class to get the proper spectral signature. The data derived from these training samples are utilized as the basis for classification.

ERDAS spectral profile was extensively used to identify the correct spectral signature for different classes. Supervised classification was performed with MAXIMUM LIKELYHOOD algorithm. The spectral separability and contingency of those training areas chosen are analyzed. Overall Accuracy was assessed using error matrix. Classified map data of overall accuracy 95.8% in terms of geographic and spectral similarity with ground truth is accepted as standard for the Guwahati city.

3.3.4 FIELD VERIFICATION

The standard classified map generated from IRS LISS-3 was further verified and compared in the following ways: IRS LISS-III image of 23.5m resolutions was merged with IRS PAN of 5.8m resolutions and land-use/land-cover feature was compared. Classified data of year 2003 as found from LISS 3 imagery were compared with 2000 and 1998 of LISS III imageries. Field survey was carried out with GPS handset to collect critical location to verify those points.

3.3.5 GIS MODEL DEVELOPED

Geo Graphical information system developed for this study using ARC GIS platform has four layers of information. The soil layer, land use pattern map (Figure 3.2) derived from remote sensing imageries, river and road network, contours using topo sheets are embedded in different layers. Using GIS, the catchment is delineated into sub catchments for each node of observations and the details are presented in Table 3.3 (Wang and Hjelmfelt 1998). Different layers are used to study the influence of catchment characteristics over the water quality data.

3.5 SUMMARY

Laboratory analysis was carried for the water samples collected from selected locations of River Bharalu for assessing its pollution status. This was also aimed to identify the sensitive parameters that adversely affect the system studied and also to identify the sensitive locations. Correlation coefficients of the parameters were found out to get an idea about the highly correlated parameters and also to decide the input parameters to be selected for dissolved oxygen prediction modeling.

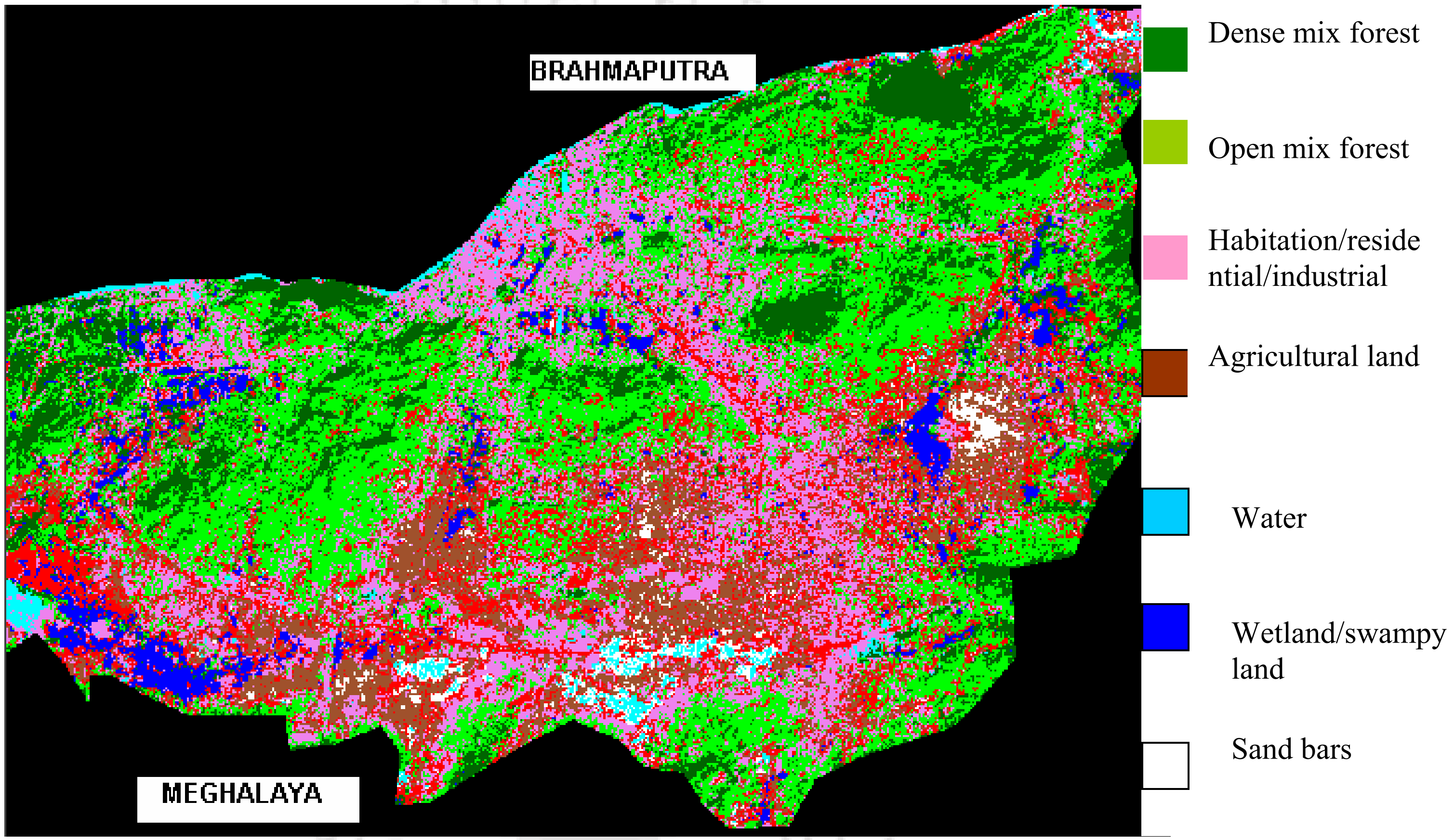


Figure3.2.Land use pattern map.

Table 3.3: Details of catchment area of sampling points from GIS model and remote sensing data.

Sampling points	Channel length (m)	Catchment area (m2)	Land use pattern	Soil type classification
1	27151.311	18876056.933	Open mixed forest	Fine loamy, mixed, hyperthermic, Plinthic Paleudalf
2	49028.065	52915647.684	Closed Mixed Forest	Fine loamy, mixed, hyperthermic, Plinthic Paleudalf
3	16239.776	12373189.482	Medium residential	Rock outcrop/Sandy/Marshy/ Buildup
4a	27773.620	21374206.180	Medium residential	Rock outcrop/Sandy/Marshy /Buildup
4b	14866.452	10008875.919	Medium residential and Heavy Industry	Rock outcrop/Sandy/Marshy/ Buildup
4m	34148.593	31430373.751	Medium residential	Rock outcrop/Sandy/Marshy/ Buildup
5	35704.012	34313150.904	Medium residential	Rock outcrop/Sandy/Marshy/ Buildup
6	38977.597	38880382.204	Medium residential	Rock outcrop/Sandy/Marshy/ Buildup
7a	39815.297	39875789.265	Medium residential	Rock outcrop/Sandy/Marshy/ Buildup
7b	11225.719	15532749.029	Heavy residential	Rock outcrop/Sandy/Marshy/ Buildup
7m	39904.826	45482850.236	Medium residential	Rock outcrop/Sandy/Marshy/ Buildup
8 & 10	50655.411	58736757.689	Medium residential	Rock outcrop/Sandy/Marshy/ Buildup

CHAPTER
FOUR

RESULTS AND DISCUSSION ON WATER QUALITY ANALYSIS

4.1 WATER QUALITY ANALYSIS

Location1 is the origin of River Bharalu ahead of Basistha with a catchment area of 20 km^2 of hilly watershed with open mixed forest and fine loamy soil. Location 1 meets the requirements for class A type quality (Figure 4.1) except for total phosphorus, total iron, and chemical oxygen demand during the summer season after 3 days of heavy rain. The pH of all the samples were within the permissible levels with a range of (6.84 – 7.68), the minimum value being for the samples collected during April'04 after the premonsoon shower with maximum value of 7.68 during December'04. Dissolution of CO_2 from the atmosphere during the premonsoon shower could be the reason for comparatively lower values of pH than the dry season. Values of conductivity ranged from 44 µS/cm to 104 µS/cm which are well within the desirable level of 750 µS/cm. High ionic concentrations (104 mg/L) during premonsoon shower indicates dissolution of ion rich runoff water from the catchment area, followed by dilution during monsoon season, and getting concentrated during the low flow period. Increasing trend during the low flow indicates the presence of subsurface flow, which is rich in ion via rock dissolution also. Concentration of total dissolved solids varied from 22mg/L to 67 mg/L, which showed similar trend as conductivity. TS (Total solids) varied from 52mg/l during the driest season in February'05 to 450 mg/L during the monsoon season in August'05. Elevated levels during the monsoon season show the effect of turbulence caused by the flow. Alkalinities were in the range of 22 mg/L as $CaCO_3$ in August'04 to 83 mg/L as $CaCO_3$ during the premonsoon shower. Values of hardness varied from 8 mg/L during the winter season to 32 mg/L during the premonsoon shower. Comparatively higher levels in conductivity, TDS (total dissolved solids), alkalinity and hardness during the premonsoon shower indicate presence of dissolved salts

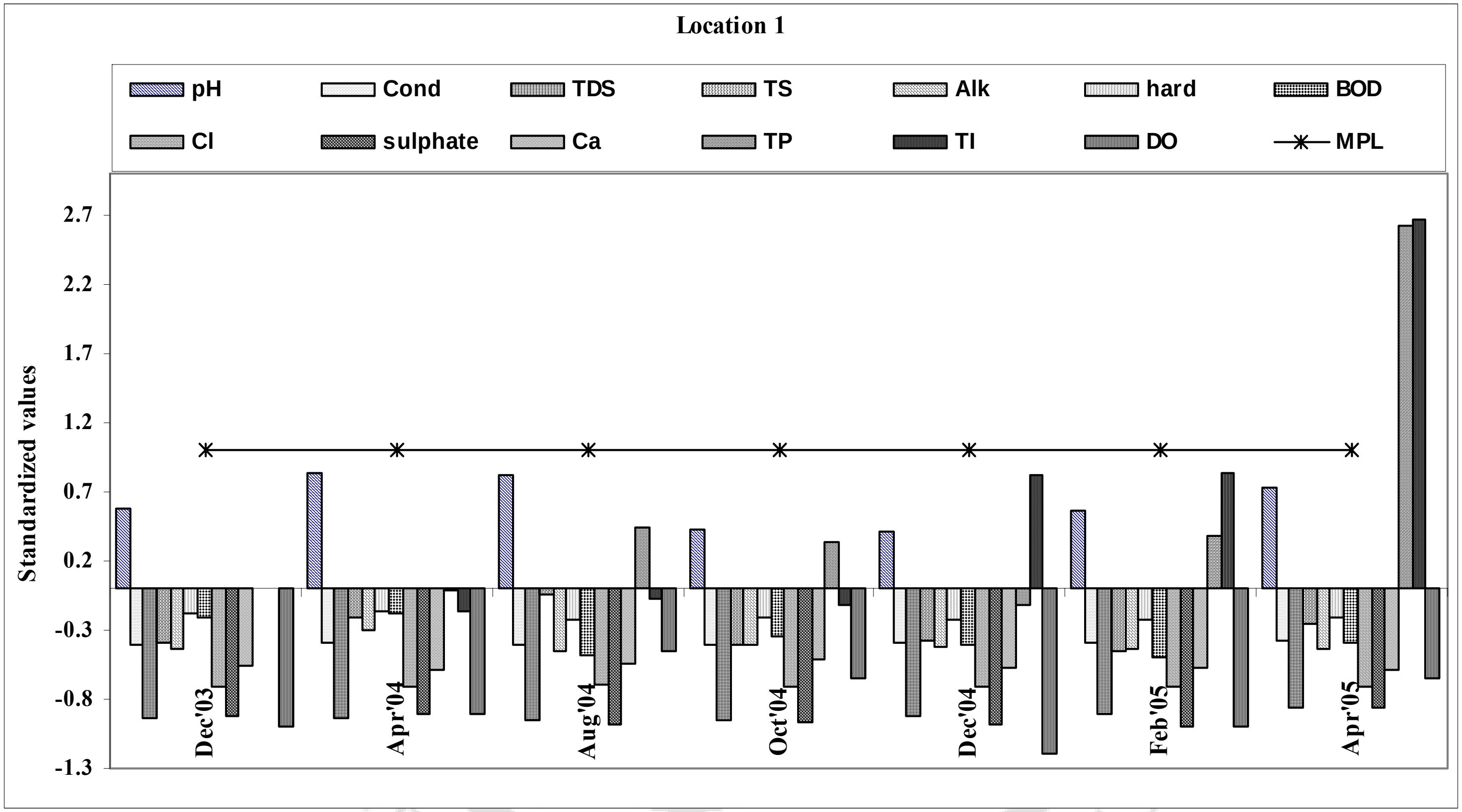


Figure 4.1 Pollution status of location 1based on standardized value of concentration of different parameters Cond - conductivity, TDS – total dissolved solids, TS – total solids, Alk – alkalinity, hard – hardness, BOD – biochemical oxygen demand, Cl – chloride, Ca- calcium, TP – total phosphorus, TI – total iron, DO – dissolved oxygen, MPL – maximum permissible level

drained from the forested catchment area. Low concentrations of BOD (biochemical oxygen demand) with values ranging from 0 mg/L during the driest season in February to 2.6 mg/L in the summer season after a premonsoon shower indicates that the location is free from domestic waste which is true as the location is the origin point with no habitation. Low concentrations of chloride the range 0 mg/L to 9.5 mg/L, maximum observed during the monsoon season in the month of August'04, which is also a clear indication of absence of sewage waste. Sulphate ranged from 1.1 mg/L in dry season to 27 mg/L during the pre monsoon shower, concentration of calcium varied from 0.6 mg/L in the summer season to 11.1 mg/L during the post monsoon season. All these observations indicate less pollution from domestic or industrial waste. TP (total phosphorus), which is an indication of presence of decayed organic matter, and nutrients that promote the growth of aquatic weeds, showed a minimum value of 0.1 mg/L during winter and a maximum value during the summer season in April after 3 days heavy rain. Land use of the upper part of the area is mainly agricultural with significant thick forest. Surface runoff through the catchment area could be the possible sources of elevated levels of total phosphorus in summer during the premonsoon shower. Concentrations of TI (total iron) were observed to below the desirable level during the months of April'04 (99 µg/L), August'04 (206 µg/L) and October'04 (159 µg/L) with a sudden increase in values (1287 µg/L) in the month of December'04, 1300 µg/L during the dry season in February'05 and 3500 µg/L during April'05. Earth cutting for developmental works, increased settlement along the hill slopes and ground water intrusion as a result of lowering of water level in the study area during the dry season could be the causes of elevated level of iron in the water sample. DO (Dissolved oxygen) was in the range of 6.9 mg/L to 8.4 mg/L, which was higher than the minimum desirable level of 6 mg/L These observations showed that station is not much polluted directly by the human interference but from the land use pattern. As the water flows downstream, the pollution level increased as evident from Figure 4.2.

Location 2 that is about 3 kms downstream of location 1 with catchment area of 53 km^2 included residential area too besides forest area and few wetlands. It carries the waste from the nearby temple premises as well as the domestic wastes showing elevated levels of BOD (biochemical oxygen demand), TP (total phosphorus), TI (total iron) and DO (dissolved oxygen) compared to location 1 in all seasons. pH showed similar trend as that of location 1 with a minimum value of 6.4 (slightly below the allowable level of 6.5) in the monsoon season (August' 04) and the maximum of 7.1 during the post monsoon season (October' 04). Conductivity, TDS, TS, alkalinity and hardness showed similar trend as station1. Values of conductivity ranged from 59 μS/cm (December' 04) to 112 μS/cm (April '04), which are below the desirable range of 750 μS/cm. Concentrations of TDS were also below the desirable limit of 500 mg/L, with maximum value of 61 mg/L in the month of February'05. Elevated levels during the low flow period show the presence of subsurface flow rich in ionic concentration. TS (Total solids) were observed to have crossed the desirable limit of 500 mg/L during the monsoon season with a concentration of 738 mg/L and minimum concentration of 62 mg/L during dry season. This indicates the presence of suspended solids brought down by the runoff water. Alkalinity too lied within the desirable limit of 200 mg/L with values ranging from 28 mg/L during the monsoon and a maximum value of 145 mg/L during the premonsoon shower. Values of hardness, which, varied between 14 mg/L during winter and 34 mg/L (premonsoon shower) were within the desirable limit of 100 mg/L. It was observed that the chloride concentrations were well below the desirable level of 250 mg/L for all the seasons sampled, with a maximum concentration of 7 mg/L during the premonsoon shower. Chloride penetrates into natural waters from soil, natural layers of salt, municipal and industrial sewage and wastes of animal origin, which is evident from the observations. Concentrations of sulphate showed higher value (146.7 mg/l) during the premonsoon shower. Maximum concentrations of calcium was14.4 mg/L, during the low flow period in December '03 which is also below the desirable level of 75 mg/L. Concentrations of sodium and potassium were also observed to be within the allowable limit of 100 mg/L with maximum values of 18.5 mg/L and 5 mg/L during the monsoon season in August'04 respectively. Maximum value values of BOD observed was 10.7 mg/L in the month of December '03 and monsoon brought down the BOD level to 0.3 mg/L. Increased level of BOD

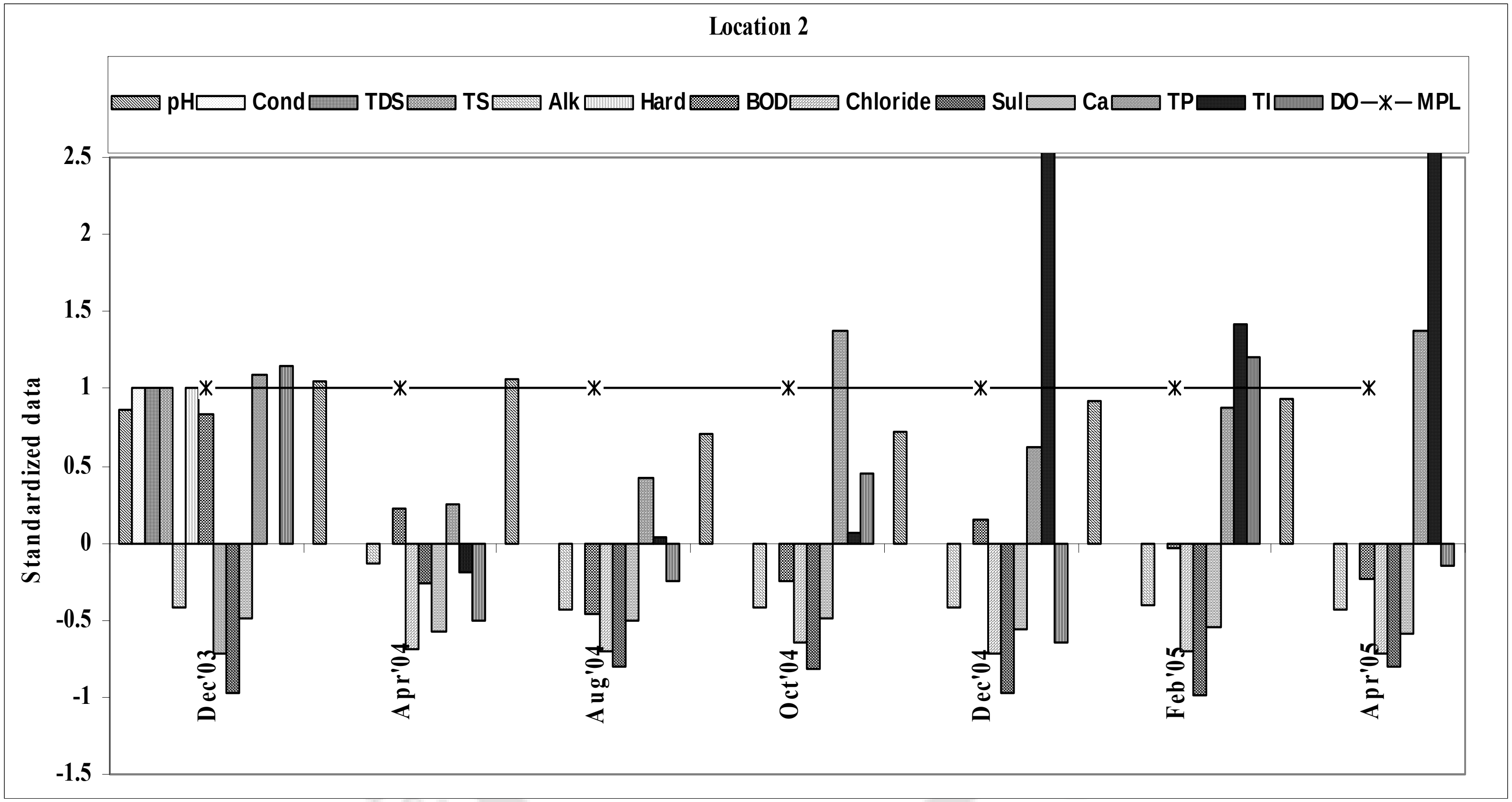


Figure 4.2 Pollution status of location 2 based on standardized value of concentration of different parameters Cond - conductivity, TDS – total dissolved solids, TS – total solids, Alk – alkalinity, hard – hardness, BOD – biochemical oxygen demand, Cl – chloride, Ca- calcium, TP – total phosphorus, TI – total iron, DO – dissolved oxygen, MPL – maximum permissible level

indicates increased level of organic waste with time and lack of dilution during low flow period. Concentrations of TP exceeded the maximum allowable limit during the flood in October ’04 (1.3 mg/L) and during the summer season (1.3 mg/L) after 3 days heavy rain. An elevated level of total phosphorus in December ’03 reflects the presence of aquatic weeds in the location. Water passing through the wetlands and the agricultural area might have increased the total phosphorus level during the flood in October’04 and the premonsoon shower in April ‘05. Total iron seemed to be higher than the maximum permissible level during the month of December’04 (7260 μg/L) February’05 (2000 μg/L), and April’05 (8900 μg/L). Frequent earth cutting and ground water intrusion (base flow) during the dry season could be the possible causes of increased levels of total iron. Dissolved oxygen did not meet the minimum allowable requirement of 4 mg/L during the low periods in December’03 (3.7 mg/L) and in February’05 (3.6 mg/L) At other times of sampling, DO varied from 5.1 mg/L to 7.3 mg/L.

Trend of increasing pollution with time and distance can be evident from Figure 4.3 for location 3. This location with catchment area of about 12 km^2 is surrounded by residential as well as industrial area and the river receives the industrial waste as well as the domestic waste without any treatment resulting in increased level of BOD and TP beyond the maximum permissible limit and low values of DO below the minimum permissible limit of 4 mg/L.The pH values were found to be in the acidic range during the monsoon season in August’04 with a value of 3.45 and with the values of 6.65 and 6.62 during the premonsoon showers in April’04 an April ’05 respectively. Alkalinity was observed to be very low in the monsoon season in August ’04 (11 mg/L) with a maximum concentration during the premonsoon shower in April ’04 (328 mg/L), which crossed the desirable level of 200 mg/L. Alkalinity is important for fish and aquatic life as it buffers against rapid pH changes. Minimum required buffering capacity for the protection of aquatic life is 20 mg/L. Location 3 did not meet this requirement in the month of August and the low alkalinity indicated corrosive water. Precipitation of $CaCO_3$, decomposition of plant materials and the acidic nature of rainfall caused by atmospheric carbon dioxide and

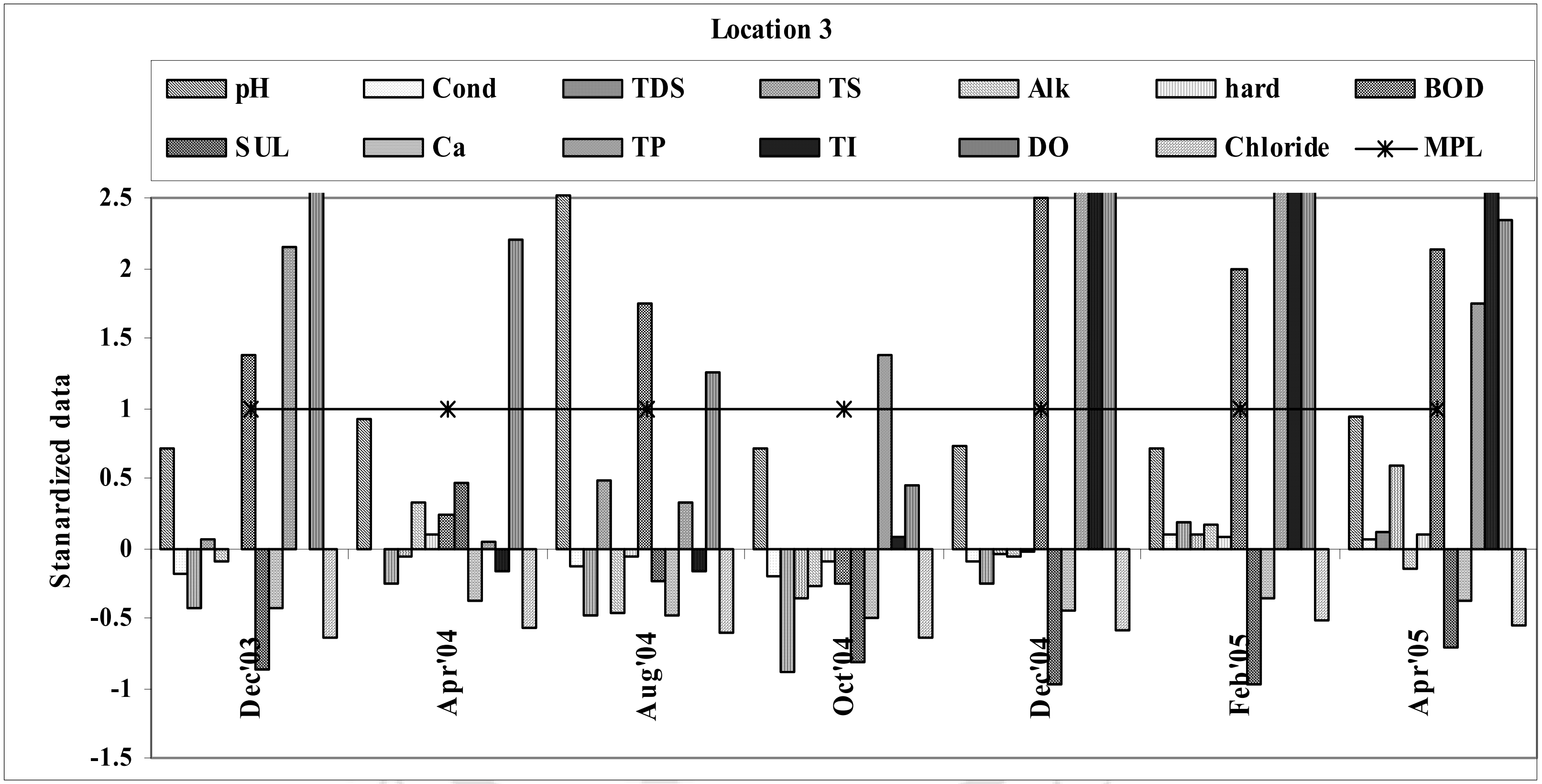


Figure 4.3 Pollution status of location 3 based on standardized value of concentration of different parameter [Cond - conductivity, TDS – total dissolved solids, TS – total solids, Alk – alkalinity, hard – hardness, BOD – biochemical oxygen demand, Cl – chloride, Ca- calcium, TP – total phosphorus, TI – total iron, DO – dissolved oxygen, MPL – maximum permissible level]

other airborne pollutants especially oxide gases of sulphur and nitrogen could be the causes of low alkalinity (Hairstone, 1995). In this case the low alkalinity accompanied by the drop in pH value confirms that the precipitation of $CaCO_3$ could be the cause. Maximum conductivity was observed during the dry season in February' 05 with a value of 909 μS/cm. Total dissolved solids showed the similar trend as conductivity with values ranging from 54 mg/l during October' 04 to dry 592mg/L during the season in February' 05 which indicates the presence of ion rich subsurface flow during low flow period. Total solids were least (136 mg/L) during the post monsoon season in February'05 and maximum (1093 mg/L) during the premonsoon shower in April' 05 which is the clear indication of presence suspended solids brought down by runoff. Values of hardness were found to be above the desirable limit of 100 mg/L during the summer seasons in April '04 and April '05 (140 mg/L each) and in February '05 (130 mg/L). Hardness was observed to be the least during the flood in October '04 with a concentration of 64 mg/L, which could be due to the natural attenuation. BOD was observed to be least in October '04 (2 mg/L) and for all other seasons it was observed to be high with concentrations ranging from 12 mg/l to 24 mg/l with highest concentration during the low flow period in December' 04.This indicates the presence of organic mater due to the domestic as well as industrial wastes. Concentration of chloride was below the desirable limit of 250 mg/L for all seasons with maximum value of 69 mg/L during the low flow period in February'05. This indicates lack of dilution during the low flow period. Sulphate was observed to surpass the desirable level of 200 mg/L during the premonsoon shower in April '04 with a value of 292 mg/L. Concentration was the least (6.52 mg/l) during the low flow period in December '04. Elevated levels of sulphates during the rain after the dry spell could be due to fertilizers and refuse leachates. Concentration of calcium was with in the desirable level of 75 mg/L for all the seasons with highest concentration 30 mg/L in the month of February '05 (low flow period). It was observed that concentrations of total phosphorus was above the desirable level of 0.2 mg/L for all seasons with maximum concentration of 3.8 mg/L in February '05 and minimum concentration of 0.23 mg/L in April '04. Runoffs besides the aquatic weeds are the source of higher concentration of total phosphorus during the flood. It was observed that after the flood, the concentrations of total iron increased above the maximum permissible limit with values of 390 μg/L in August '04, 15000 μg/L in October '04, 3400 μg/L in February '05 and 9000 μg/L in April '05. These elevated levels are likely to be due to ground water seepage. Water table rises after the flood and in winter the predominant natural source of water in the study area is the base flow. A rise in the concentration from 3400 μg/L in the month of February '05 to 9000 μg/L in April '05 was observed which could be due to the frequent earth cutting in the nearby area followed by pre monsoon shower. Concentration of sodium was observed to be within the safe limit of 50 mg/L in all seasons except during the dry season in February '05 when the concentration was 59.6 mg/L. Potassium was observed to be below the desirable limit with values ranging from 8.5 mg/L during the monsoon season in August '04 to 29 mg/L during the dry season in February '05. Dissolved oxygen didn't meet the requirement for minimum allowable level of 4 mg/L except in October '04 (5.1 mg/L) with values ranging from 0.1 mg/L in the month of December '04 to 3.5 mg/L in August '04.Although the reaeration could replenish the DO during the rainy season to some extent it could not bring it to a level more than 5.1 mg/L.

Similar to location 3, location 4(a) that receives the drainage from industries as well as residential developments showed concentrations above the maximum permissible limit for BOD, TP and TI while DO was below the minimum permissible limit (Figure 4.4) TP and DO showed concentration beyond the permissible level during the post monsoon season. pH value was in the acidic range during the monsoon (August '04) with a value of 5.9. For all other seasons, the pH values were within the desirable level with values ranging from 6.7 to 7.1. Conductivity values were with in the desirable level with a maximum value of 727 μS/cm in February '05. Total dissolved solids also lied within the desirable range of 500 mg/L with values ranging from 172 mg/L (October' 04) to 473 mg/L (February '05). Total solids were found to be the least (200 mg/L) during the post monsoon season in October '04 and highest (612 mg/L) during the pre monsoon shower in April'05. Maximum value of alkalinity (318 mg/L) was observed during the premonsoon shower in April '04,

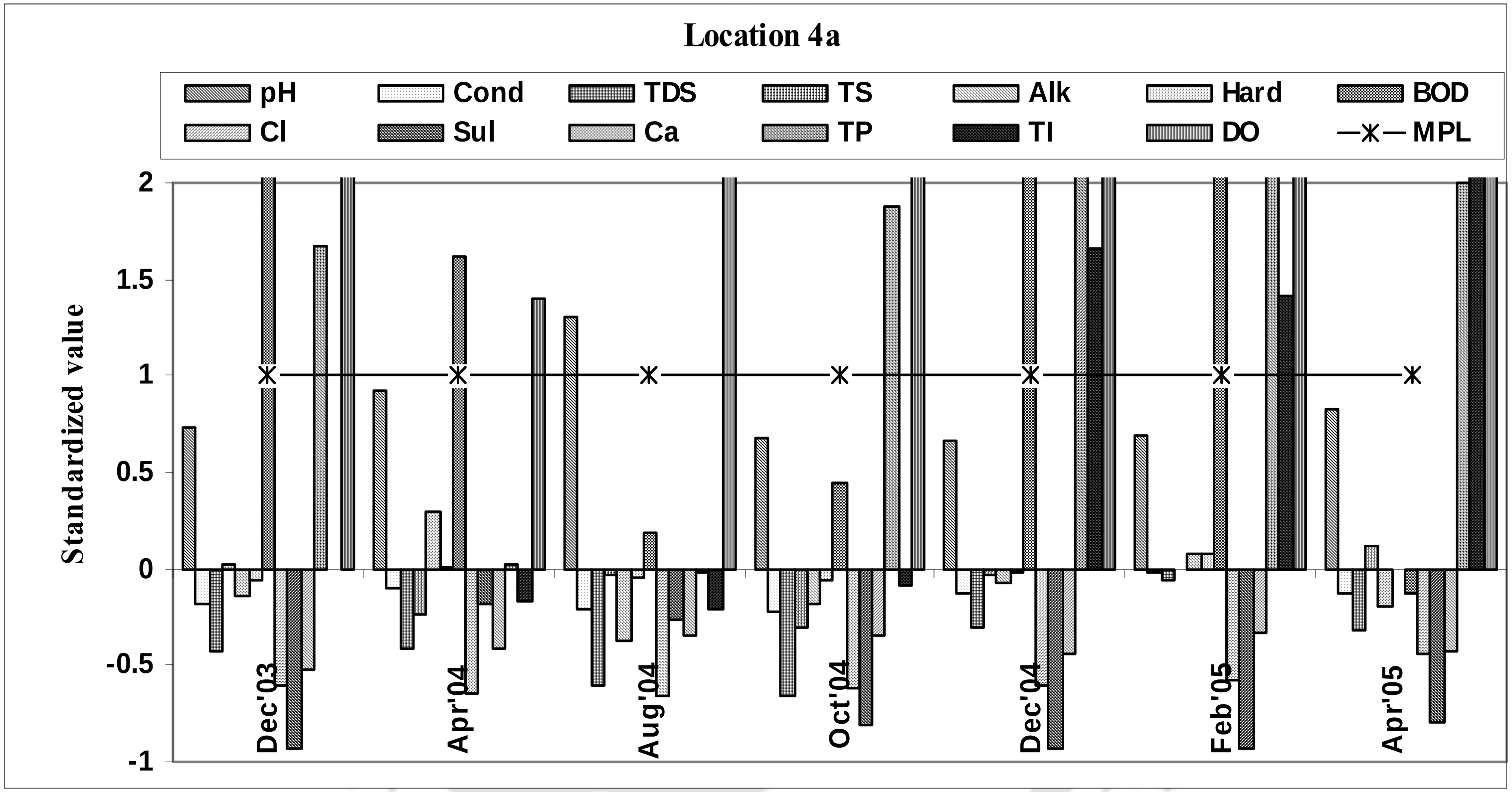


Figure 4.4 Pollution status of location 4a based on standardized value of concentration of different parameters [Cond - conductivity, TDS – total dissolved solids, TS – total solids, Alk – alkalinity, hard – hardness, BOD – biochemical oxygen demand, Cl – chloride, Ca- calcium, TP – total phosphorus, TI – total iron, DO – dissolved oxygen, MPL – maximum permissible level]

which crossed, the desirable level of 200 mg/L. Hardness was found to maximum value in February ’05 (130 mg/L). BOD was maximum values (23.2 mg/L) in December’ 04.concentrations beyond the permissible level, except during the premonsoon shower in April’05 with a concentration of 3 mg/L.Natural attenuation is observed to be the cause of reduction in BOD. Chloride concentrations were below the desirable level of 250 mg/L with values ranging from 21 mg/L during the monsoon in August ’04 to 94 mg/L in April ’05 which indicates that the sudden downpour during the summer season might have washed down the refuse leachates as the catchment area of the location is mainly residential. Sulphate also showed the same trend as chloride for this location maximum concentrations of 165 mg/L during the premonsoon shower in April’ 04. Calcium was also found to be below the desirable level with maximum concentration of 34 mg/L in February ’05 with out much seasonal variation in concentration. Concentrations of total phosphorus were above the desirable level and even above the maximum allowable level for all seasons except April ’04 (0.2 mg/L) and August ’04 (0.18 mg/L) with maximum value of 3.3 mg/L in February ‘05, which indicates the presence of aquatic weeds. Lower levels in the monsoon season is the clear indication that there is no contribution from catchment area and it is clear from the land use pattern that it is a residential area. The concentrations of total iron was observed to be 2294 μg/L in December ‘04, 2000 μg/L in February ’05 and 3800 μg/L in April ’05. Subsurface flow could be the source of increased level of total iron during the winter season in December and the dry season in February. Frequent hill cutting for the developmental activities also might have contributed to the elevated levels of total iron in the month of April in the summer season compared to the levels in December and February. Sodium was below the desirable limit for all seasons with maximum concentration of 44.5 mg/L in February ’05. Potassium was within the desirable limit with maximum 16.2 mg/L in February ’05. DO concentration didn’t meet the minimum allowable level for any of the seasons with values ranging from 0 mg/L in August ’04 3.2 mg/L in April ’04. As in the case of location 3 the runoff combined with the aquatic weeds might have increased the phosphorus concentration, which in turn increased the stress on the oxygen budget of the system, reducing the DO level beyond the minimum permissible level. Samples collected from Station 4(b), which is the drain carrying surface water from Guwahati refinery, was observed to have acceptable pH range with values ranging from 6.5 to 7.1 (Figure 4.5). Values of conductivity were also within the desirable level with a maximum value of 585 µS/cm during the post monsoon season in October'04 and a minimum value of 370 µS/cm during the pre monsoon shower in April '04. Elevated levels in the post monsoon season could be the contribution from the main river as the water gets mixed up with the drain water during high flow period. Total dissolved solids was maximum (326 mg/L) in the month of April '05 during the premonsoon shower, which is within the desirable level of 500 mg/L. Values of total solids were found to be above the desirable level during the premonsoon showers in April'04 (824 mg/L), and April'05 (704 mg/L). Alkalinity value crossed the desirable level only in the month of April '04 with a value of 215 mg/L. Values of hardness were in the range of 70 mg/L mg/L to 106 mg/L, highest during the premonsoon shower in April'05. Hence catchment area contributes to alkalinity and hardness. BOD values showed the same trend as the previous location 4(a) with slightly higher values. For all seasons the BOD values were above the desirable levels and during the low flow seasons the values crossed the maximum allowable level of 12 mg/L and the maximum observed was 27.2 mg/L in December' 04 and the minimum was 4.25 mg/L in April'04 during the pre monsoon shower. This indicates the presence of organic waste in the drain from the refinery and runoff from the catchments helps in reducing the BOD by dilution. As in the case of previous locations, concentrations of chloride were well below the desirable level with maximum value of 36 mg/L each during the post monsoon season in October '04 and pre monsoon shower in April '05, which indicates the contribution from the catchment area. Maximum concentration of sulphate was 127.5 mg/L (August'04) that could be from refuse leachate. Concentration of calcium was maximum in the month of August '04 with a value of 37.5 mg/L. Total phosphorus was found to be above the desirable level with values ranging from 0.52 mg/L (April '04) to 1.9 mg/L (December' 04). Elevated levels in the dry season confirm the presence of aquatic weeds in the location. Concentrations of Total iron were observed

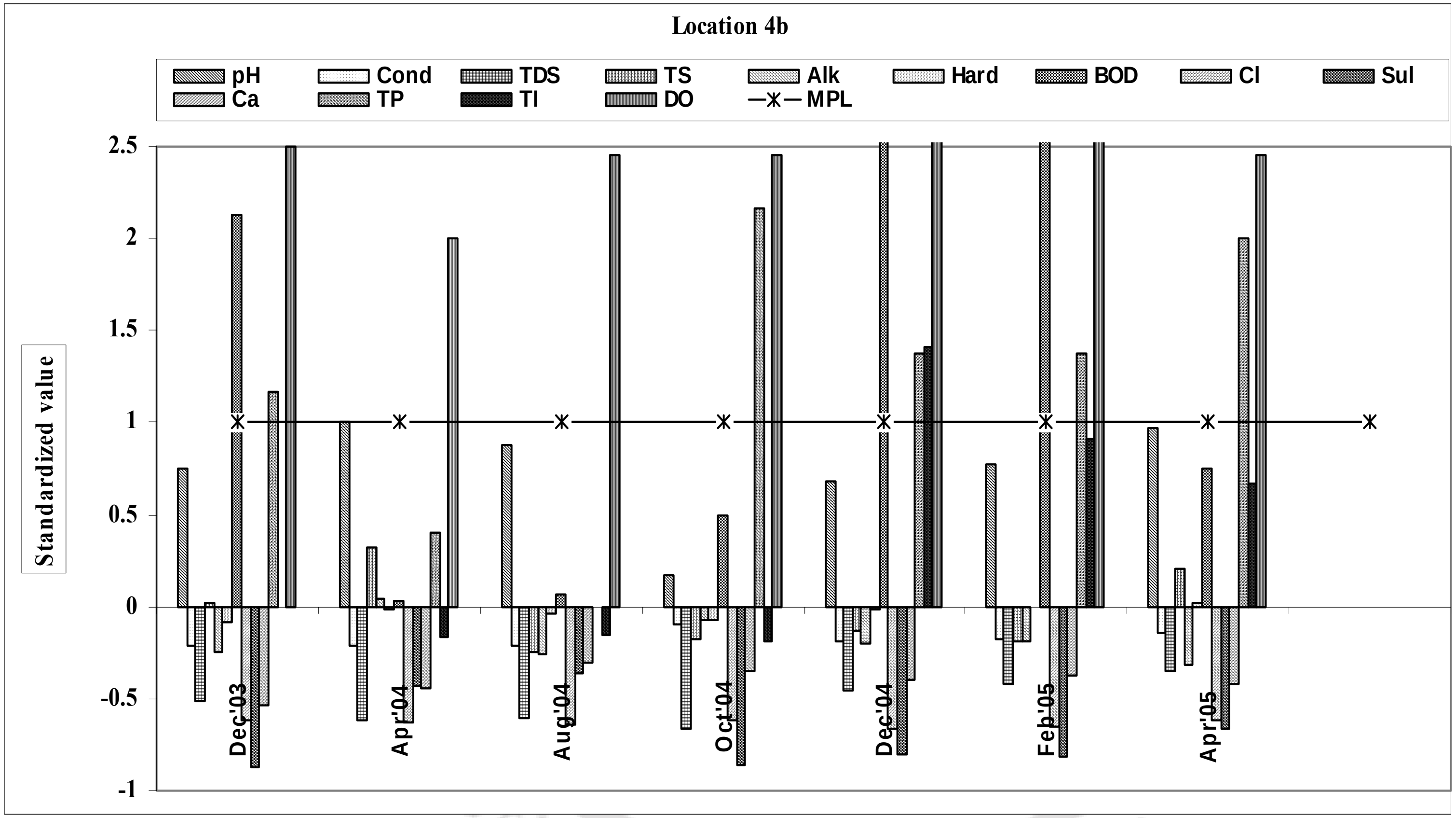


Figure 4.5 Pollution status of location 4b based on standardized value of concentration of different parameters [Cond - conductivity, TDS – total dissolved solids, TS – total solids, Alk – alkalinity, hard – hardness, BOD – biochemical oxygen demand, Cl – chloride, Ca- calcium, TP – total phosphorus, TI – total iron, DO – dissolved oxygen, MPL – maximum permissible level]

to have crossed the desirable level in December' 04 (1996 μg/L), February '05 (1400 μg/L) and April '05 (1100 μg/L). Elevated concentrations of iron indicate ground water seepage during the low flow season. But the concentrations are lower than that of the previous locations, which could be due to the dilution with iron free wastewater from the refinery. Very small concentrations of sodium and potassium were observed with a maximum value of 20.6 mg/L in August '04 and 11.9 mg/L in April '05 respectively. Very low concentration dissolved oxygen (0.1 mg/L to 1.1 mg/l) was observed. Presence of organic waste as well as the aquatic weeds increased the levels of BOD and the total phosphorus, which in turn reduced the concentration of DO.

Increase in waste load can be evident from the observations (Figure 4.6) for location 4m. Dissolved oxygen seemed to be below 4 mg/L throughout the year. Except during the monsoon and the post monsoon, concentrations of parameters like BOD, COD and TP were observed to be very high and found to be well above the maximum permissible limits.pH values were within the range 6.15 (August '04) to 7.25 (October '04). During the monsoon season pH seemed to be in the acidic range which could be due to the presence of humic substances. That indicates the dissolution of CO_2 of the atmosphere with the rainwater, which makes it acidic. Values of conductivity and total dissolved solids were observed to be below the permissible range with maximum values of 520 μS/cm and 338 mg/L in the month of April '05.here also contribution from the catchment area is evident. Total solids was observed to be above the desirable level in the months of December '03, August '04 and April, 05 with concentrations of 700 mg/L, 1206 mg/L and 744 mg/L respectively. For other seasons values were within the desirable level. Alkalinity was found to be below the desirable level for all seasons except in April '04 with a value of 233 mg/L, which is possibly from the catchment, minimum value of 65 mg/L being during the monsoon season in August '04, which could be due to dilution. Hardness was observed to be maximum (102 mg/L) during the low flow in February '04, which can be from subsurface flow as well as from the waste. BOD values were with in the range of 3.5 mg/L in the month of August '04 to 26.4 mg/L in the month of December '04 which is a clear indication of organic matter in the water samples.

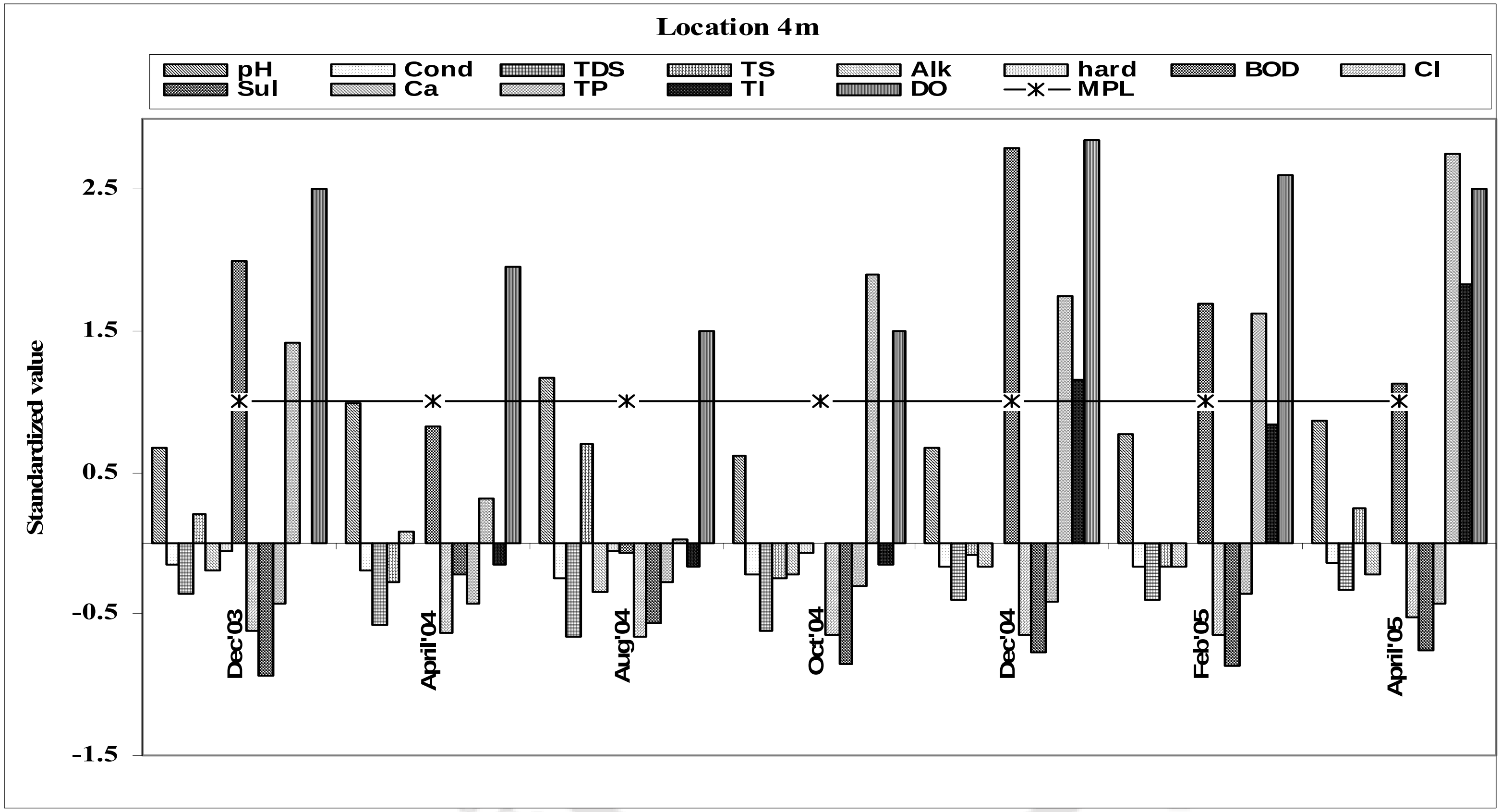


Figure 4.6 Pollution status of location 4m based on standardized value of concentration of different parameters [Cond - conductivity, TDS – total dissolved solids, TS – total solids, Alk – alkalinity, hard – hardness, BOD – biochemical oxygen demand, Cl – chloride, Ca- calcium, TP – total phosphorus, TI – total iron, DO – dissolved oxygen, MPL – maximum permissible level]

During the monsoon and the flood seasons the concentrations of BOD was observed to be below the permissible level, which could be due to the dilution with the runoff water. Concentrations of chloride, sulphate and calcium were well below the desirable limits with maximum values of 67 mg/L (April'05), 157 mg/L (April' 04) and 40 mg/L (august' 04) respectively. Total phosphorus values varied from 0.22 mg/L in August '04 to 1.7 mg/L in October '04. Total phosphorus was found to be very high during the post monsoon, which indicated the presence of excess amount of aquatic weeds. As in the case of previous locations total iron was observed to be above the desirable level during December '04 (1683 μg/L), February '05 (1300 μg/L) and April '05 (2500 μg/L). Here also effect of ground water seepage and the earth cutting activities for development areas could be observed. As in the previous locations concentrations of sodium and potassium were observed to be very small ranging from 2 mg/L to 26.6 mg/L and 7.5 mg/L to 13 mg/L respectively. Dissolved oxygen also showed the same status as that of the previous location with values ranging from 0.3 mg/L to 3 mg/L, which proved that the location is highly polluted with organic matter and needs proper consideration for land use pattern and waste management.

Figure 4.7 shows the pollution levels of location 5. This station also shows the similar behaviour as its upstream location. pH values ranged between 6.35 during the monsoon in August '04 to 7.36 after the flood in the month of October. Maximum value of conductivity was observed during the premonsoon shower in April' 05 with a value of 545 μS/cm. Same trend was observed in the case of total dissolved solids with maximum value of 354 mg/L in April'05. The total solids were observed to be above the desirable level during premonsoon showers in April' 04 (620 mg/L) and April' 05 (684 mg/L), minimum (196 mg/L) during the post monsoon season. Values of alkalinity were maximum and above the desirable limit during premonsoon shower in April '04 (225 mg/L as $CaCO_3$) and minimum during monsoon in August'04 (83 mg/L as $CaCO_3$). Hardness was observed to be maximum for the months April '04 with a value of 162 mg/L as $CaCO_3$ and minimum value (70 mg/L as $CaCO_3$) was observed during the post monsoon in October'04. These observations shows dissolved solids and suspended solids are contributed from the catchment area.

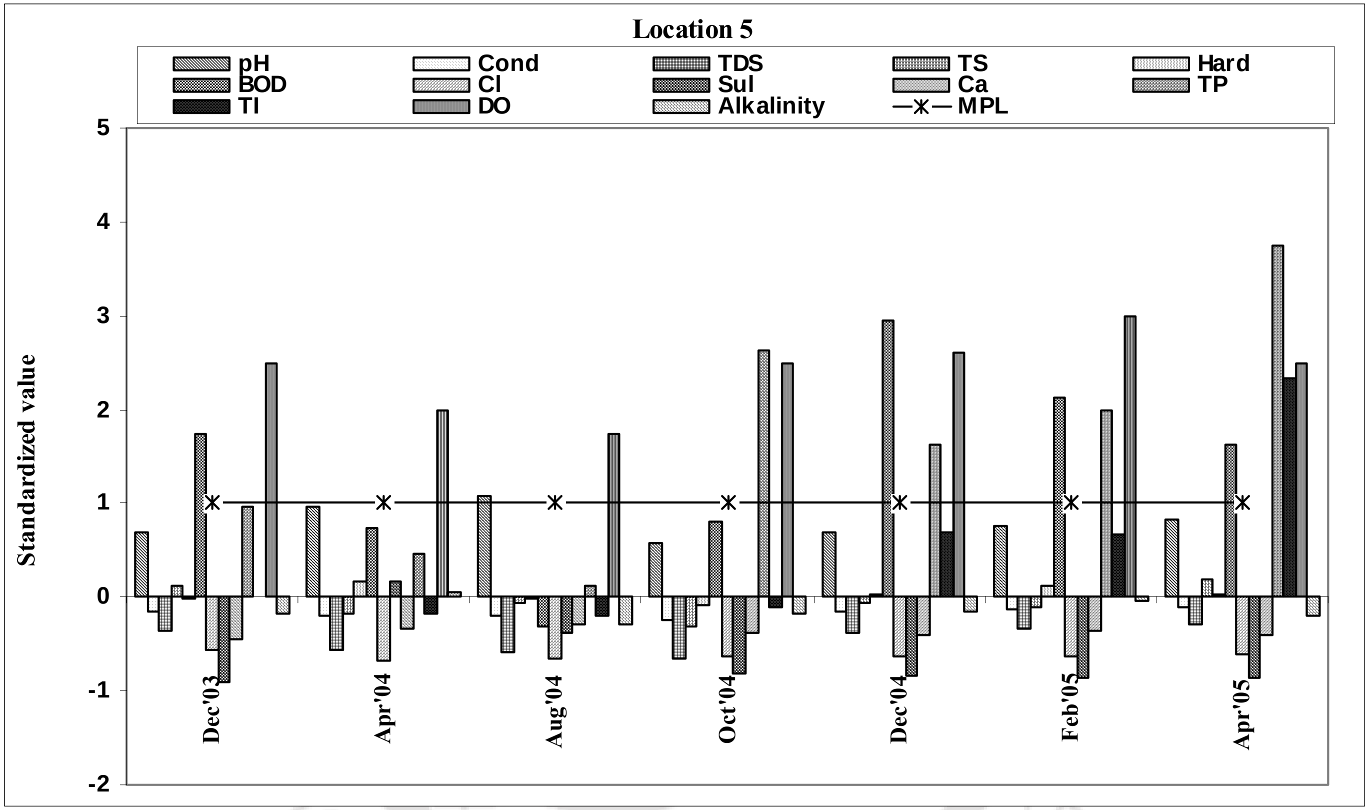


Figure 4.7 Pollution status of location 5 based on standardized value of concentration of different parameters [Cond - conductivity, TDS – total dissolved solids, TS – total solids, Alk – alkalinity, hard – hardness, BOD – biochemical oxygen demand, Cl – chloride, Ca- calcium, TP – total phosphorus, TI – total iron, DO – dissolved oxygen, MPL – maximum permissible level]

Maximum value of BOD (27.6 mg/L) was observed during December ’04 and minimum value of 1.5 mg/L during monsoon in August ’04 which indicates the presence of excess quantity of organic matter. Reduced levels during the wet seasons show the effect of dilution with the runoff. Maximum concentrations of chloride, sulphate and calcium were observed to be 53 mg/L (December ’03), 233 mg/L (April ‘04) and 39 mg/L (August ’04), respectively. Comparatively higher quantity chloride indicates the presence of domestic and industrial waste during low flow period. Total phosphorus was observed to be above the desirable limit for all seasons with a maximum value of 3.6 mg/L in December’04, which is a clear indication of aquatic weeds as well as the settled organic matter, which releases the nutrient to the water column. Total iron was also observed to be above the desirable limit during February ’05 (1100 μg/L) and above the maximum allowable limit during December ’04 (3518 μg/L) and April ’05 (3100 μg/L). Lowering of ground water level might have decreased the TI concentration to some extent but hill cutting for developmental activities should be the probable cause for rise in the concentration during premonsoon shower in April’ 05. As in the previous locations sodium and potassium were observed to be well below the desirable level with maximum 25.7 mg/L in February ‘05 and 14.2 mg/L in April ’05. There was very little dissolved oxygen within the range of 1.75 mg/L to 3 mg/L throughout the year which itself indicates the poor water quality.

In the case of location 6,concentration of parameters like BOD TP, DO crossed the maximum allowable limit (Figure 4.8) this indicates the presence of excessive organic wastes and aquatic weeds in the station throughout the year. Even the flood or the runoff did not help the system in attenuation of the waste. pH values were with in the range of 6.36 to 7.36. Conductivity was above the desirable value during low flow period and premonsoon shower with maximum concentration of 894 mg/L during February ’05. Same trend was observed for TDS with maximum value of 578 mg/L (February’ 05). Elevated levels of ionic concentration during low flow period could be an indication of contribution from the urban waste as well as from the surface flow, which could be rich in ionic concentration due to originally higher rock soil dissolution. Total solids were maximum during April ’05 (1089 mg/L) probably

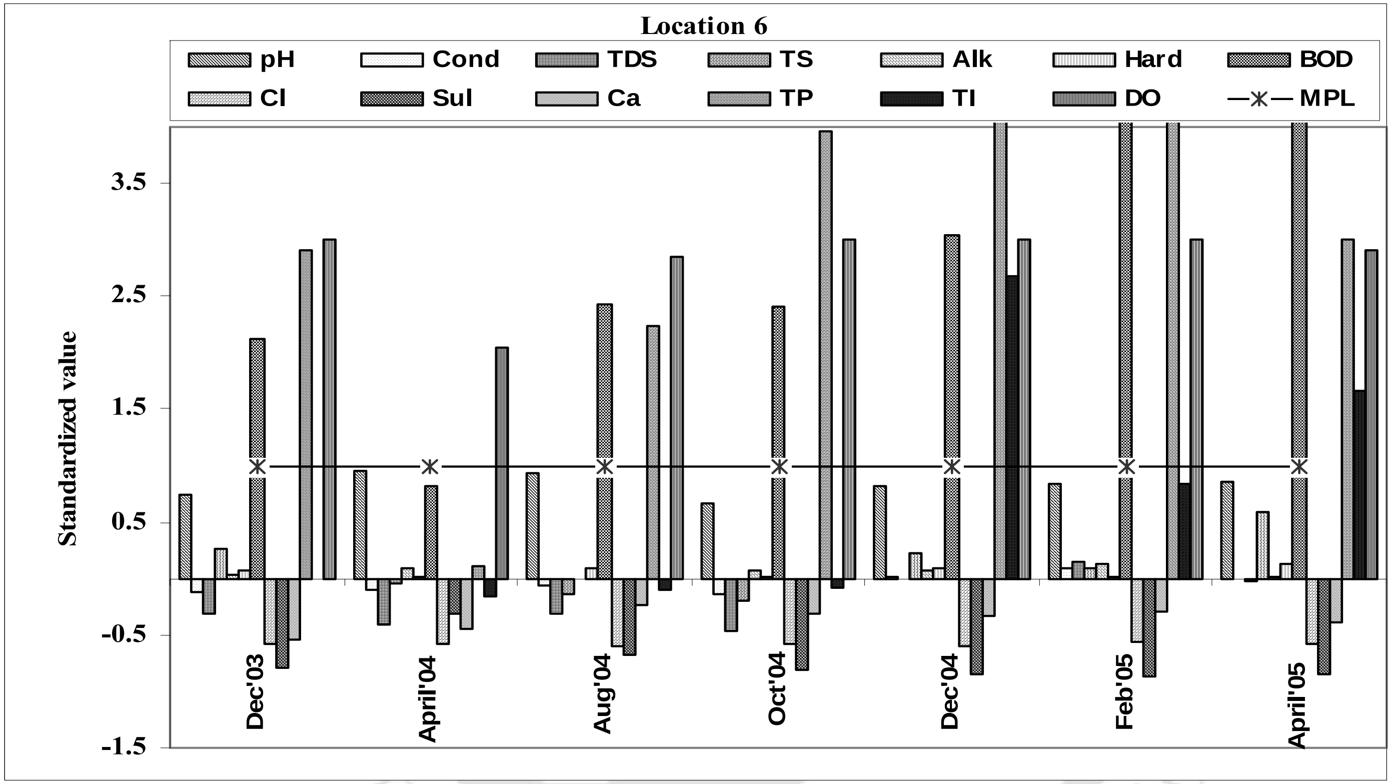


Figure 4.8 Pollution status of location 6 based on standardized value of concentration of different parameters [Cond - conductivity, TDS – total dissolved solids, TS – total solids, Alk – alkalinity, hard – hardness, BOD – biochemical oxygen demand, Cl – chloride, Ca- calcium, TP – total phosphorus, TI – total iron, DO – dissolved oxygen, MPL – maximum permissible level]

contributed from the catchment area. Alkalinity values were above the desirable level except during August ’04 (199 mg/L) with maximum concentration of 248 mg/L in February’ 05. Additional drainages from local industries and residential development without any treatment contribute to elevated levels in alkalinity during low flow period. Hardness values were above the desirable level for all seasons with maximum value of 152 mg/L (April ’05), which indicates the contribution from land. BOD was high throughout the seasons with values ranging from 10.5 mg/L (April’04) to 70 mg/L (February ’05). It was observed from land use pattern that location 6 is close to industrial and railway establishments surrounded by large swamps. Higher values of BOD in this location could be from the settled animal and human wastes carried by the urban runoff during rain from streets and side walks, nutrients from leaves and papers from residential areas, as well as the decayed organic matter. Maximum concentrations of chloride, sulphate and calcium were, 51 mg/L (February ’05), 136 mg/L (April ’04) and 46 mg/L (October ’04) respectively. There was not much seasonal variation for the concentration of chloride for this location. Increased pollution is apparent from the increased level of concentration compared to the previous stations. Higher concentration of sulphate during the premonsoon shower indicates the contribution from land. Total phosphorus was found to be above the maximum permissible level for all the seasons except during April ’04 (0.3 mg/L). The values ranged from 1.98 mg/L (August ‘04) to 4.4 mg/L (February ’05). Sources of elevated concentration could be the fertilizer runoff, human and animal waste, domestic wastes with the use of detergents and industrial wastes. Elevated level of TP during low flow indicates the presence of settled organic waste also due to the excess growth of aquatic weeds. Like the previous stations concentration of TI seemed to be very high during the low flow period in December’04 with a concentration of 3518 μg/L.During the low flow period in February’ 05 decrease in the concentration is noticed (1300 μg/L) followed by a raise in the concentration during the pre monsoon shower in April’05 (2300 μg/L). Here also the ground water seepage as well as the developmental activities could be the probable cause for the increased level of Total iron. Sodium and potassium were found to be below the desirable value with values with maximum values of 43.3 mg/L during the dry season and 17.4 mg/L during

April ’05 respectively. Dissolved oxygen was found to be nil during low flow period and very small quantities of dissolved oxygen were observed with values 1.9 mg/L during April ’04, 0.3 mg/L in August ’04 and 0.2 mg/L in April ’05 as a result of combined effect of aquatic weeds and organic matter.

Location 7(a) also showed the similar trend as station 6 for the parameters BOD DO, total Phosphorus, and total Iron (Figure 4.9). All other parameters were within the acceptable limit. Land use of this location covers partly agricultural lands, residential complexes and huge medical campus facilities. The pH was within the maximum allowable range with values varying from 6.73 (August ‘04) to 7.33 (April ’04). Maximum values of conductivity and TDS were 838 µS/cm (February ’05) and 546 mg/L (February ’04) respectively. Elevated levels during the low flow period settled increased quantity of settled wastes. Maximum alkalinity was found to be 593 mg/L (April ’04). Hardness values were above the desirable level with maximum value of 162 mg/L (April ’04). These observation shows that alkalinity and hardness were contribute by the catchment area. Low flow period in February’05 was observed to have highest BOD (51 mg/L), which is a clear indication of settle organic matter. elevated levels during December ’04, February ’05 and April ’05 with values of 1287.4 µg/L, 1300 µg/L and 3500 µg/L respectively. Sodium and potassium were within the allowable limit with maximum concentrations of 41.8 mg/L (February ’05) and 14.5 mg/L (April ’05). Dissolved oxygen was nil during December ’03, October’04, February ’05 and April ’05 with very low in concentration during April ’04 (1.7 mg/L), August ’04 (1.1 mg/L) and December ’04 (0.1 mg/L).

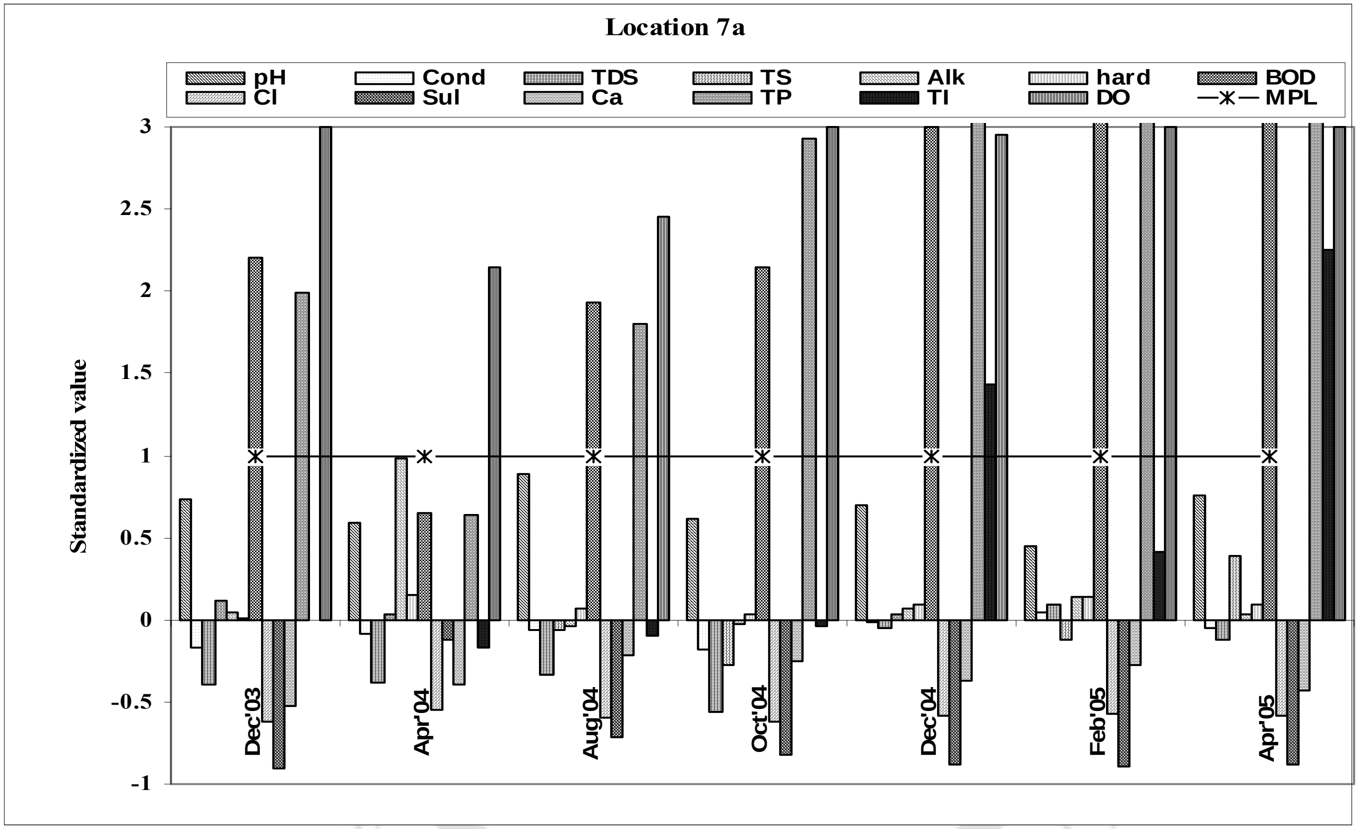


Figure 4.9 Pollution status of location 7a based on standardized value of concentration of different parameters [Cond - conductivity, TDS – total dissolved solids, TS – total solids, Alk – alkalinity, hard – hardness, BOD – biochemical oxygen demand, cl – chloride, Ca- calcium, TP – total phosphorus, TI – total iron, DO – dissolved oxygen, MPL – maximum permissible level]

Location 7(b) seemed to be the most polluted location where concentrations of all major parameters are well above the maximum permissible level (Figure 4.10). This sampling location in the channel is located across an input drain, which collected the wastewater from the concentrated urban settlement and business establishments. Sources of elevated concentrations could come from fertilizer runoff, human and animal wastes from failing septic system, sewage treatment plants, and domestic wastes with the use of detergents and industrial wastes. The pH of the samples were within the allowable range for all seasons and the range were 6.83 in the month of April ’04 to 7.16 in the month of October ’04. Conductivity varied from 590 µS/cm in the month of April ’04 to 1480 µS/cm in the month February ’05 TDS values were above the desirable limit with maximum value during the low flow period in February ’05 (962 mg/L). This observation indicates the presence of dissolved salts in elevated levels. Maximum concentration of total solids was observed to be 1438 mg/L during December ‘04, which indicates the presence of suspended solids apart from dissolved solids in high concentration. Alkalinity was observed to be high during the premonsoon shower in April ’04 with a concentration of 558 mg/L, which indicates that contribution from catchment also is prominent. It was observed that hardness value were above the desirable limit with maximum concentration of 230 mg/L during February ’05 indicates the contribution from subsurface flow apart from the polluted water. BOD values were in the range 8.8 mg/L in the month of April ’04 to 70 mg/L in the month of February’05 which indicates higher level of pollution in terms of organic matter both settled and dissolved. Maximum concentrations of chloride, sulphate and calcium 92 mg/L in February ‘05, 399 mg/L in April’04 and 53 mg/L in August’04 respectively. All were below their desirable limit except for sulphate. Concentration of total phosphorus were very high with values ranging from 0.7 mg/L during April ’04 to 8.5 mg/L during February ’05 which indicates the presence of aquatic weeds and settled organic matter. Concentrations of total iron were observed to be above the maximum permissible limit for the months December ’04 (2056 µg/L), February ’05 (1800 µg/L) and April ’05 (2200 µg/L), which indicate the presence of subsurface flow. Maximum concentrations of sodium and potassium were 67.6 mg/L during February ’05 and 21.5 mg/L in October ’04 respectively.

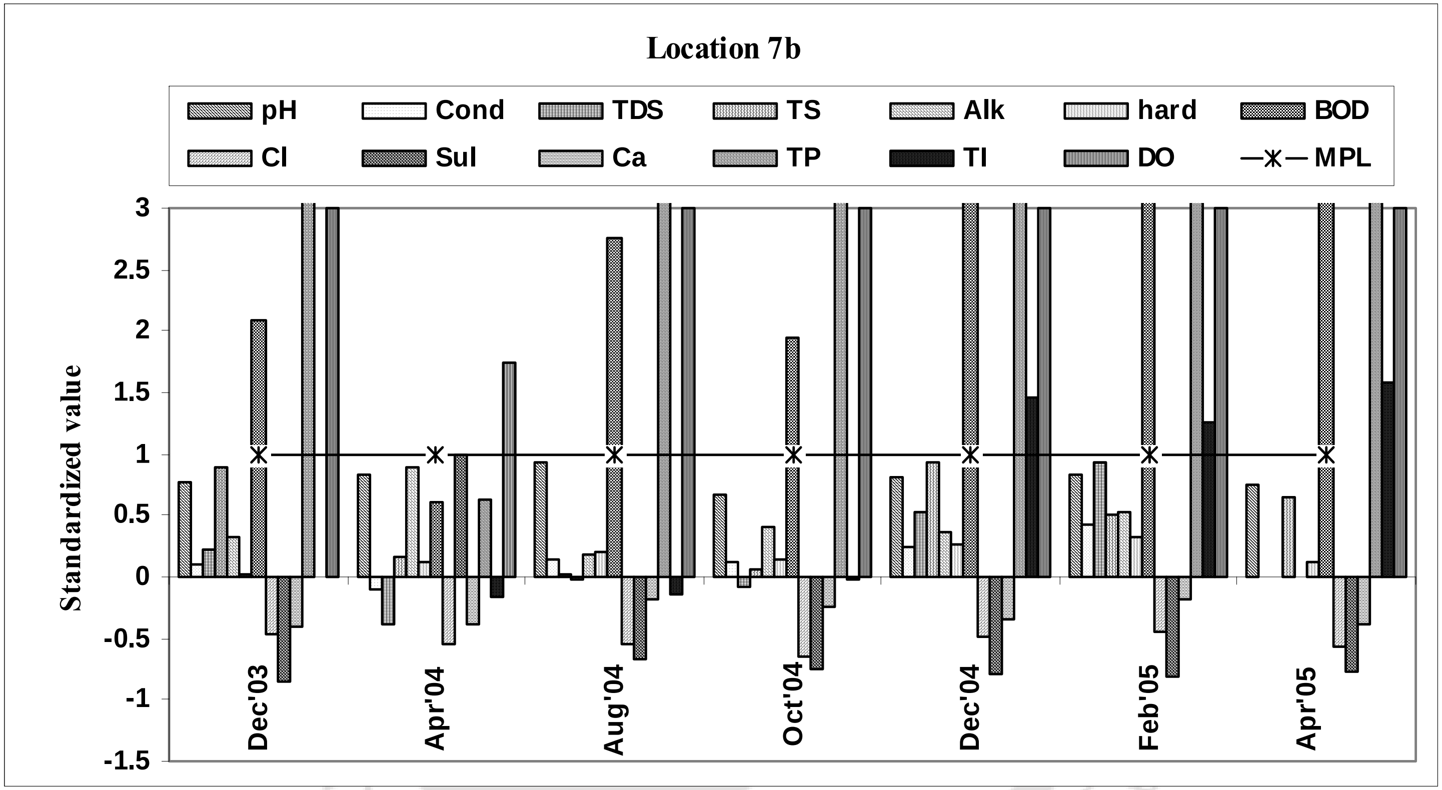


Figure 4.10. Pollution status of location 7b based on standardized value of concentration of different parameters [Cond - conductivity, TDS – total dissolved solids, TS – total solids, Alk – alkalinity, hard – hardness, BOD – biochemical oxygen demand, Cl – chloride, Ca- calcium, TP – total phosphorus, TI – total iron, DO – dissolved oxygen, MPL – maximum permissible level]

Dissolved oxygen were nil for all the seasons except during April ’04 with a concentration of 2.5 mg/L which is combined effect of excess growth of aquatic weeds as well as organic matter from domestic as well as industrial waste.

Location 7m shows the similar trend as location 7b in the concentration of the parameters (Figure 4.11). But concentrations of total iron seemed to be higher than that of station 7b during the dry season. Very high levels of BOD, TP and very low level of DO is a clear indication of excessive organic wastes, Aquatic weeds and untreated wastes from residential areas as it is the drainage confluence of 7a and 7b. The pH values were with in the range 6.46 during August ’04 to 7.31 during October’04. Conductivity values were with in the desirable limit with maximum value of 733 μS/cm in the month February ‘05. TDS values were below the desirable limit for all the seasons with maximum value of 477 mg/L in February ’05. Total solids were with in the range 250 mg/L during October ’04 to 790 mg/L during April ‘05. Alkalinity varied between 102 mg/L in the month of August ‘04 to 408 mg/L during April ’04. It was observed that maximum value of hardness was 148 mg/L during February ’05. BOD values were in the range 5 mg/L in the month of August ’05 to 35 mg/L in the month of February ’05. Maximum concentrations of chloride, sulphate and calcium were 76 mg/L in April’05, 150 mg/L in April’04 and 46.5 mg/L in August ’04 respectively. Concentration of total phosphorus were observed to be ranging from 0.09 mg/L during August ’04 to 4 mg/L during February ’05. Concentrations of total iron showed elevated levels for the months December ’04 (2755 μg/L), February ’05 (1600 μg/L) and April ’05 (3000 μg/L). Concentrations of sodium and potassium were in the range 4.2 mg/L during April ‘05 to 41.2 mg/L during February ’05 and 7.4 mg/L in the month of August ’04 to 14.7 mg/L in April ‘05 respectively. Dissolved oxygen was in the range 0 mg/L during October ’04 and February ’05 to 1.9 mg/L during August ’04.

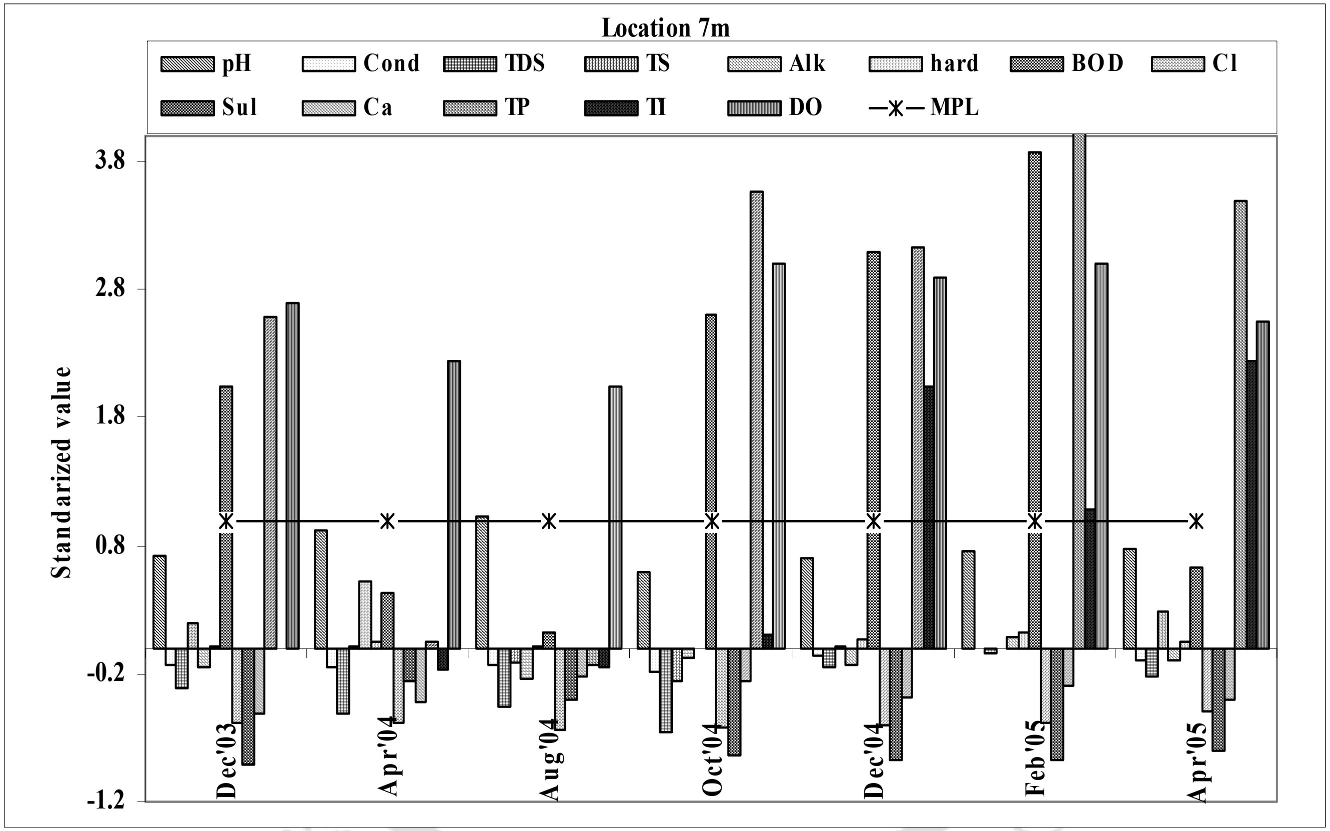


Figure 4.11 Pollution status of location 7m based on standardized value of concentration of different parameters

[Cond - conductivity, TDS – total dissolved solids, TS – total solids, Alk – alkalinity, hard – hardness, BOD – biochemical oxygen demand, Cl – chloride, Ca- calcium, TP – total phosphorus, TI – total iron, DO – dissolved oxygen, MPL – maximum permissible level]

Location 8, which is located near the sluice gate showed a different trend as shown in Figure 4.12. The organic waste and the aquatic weeds from the upstream stations as well as the input from the catchment area gets trapped near the sluice gate inducing higher BOD.The pH varied from 6.09 during the monsoon in August '04 to 7.1 during winter in December '04.Maximum value of conductivity was 815 μS/cm during February '05 and that of TDS was 509 mg/L in the month of February '05 which indicates the presence of settled waste. Maximum concentration of TS observed was 930 mg/L (April '05). Alkalinity and hardness were found to have maximum value during low flow period in February '05 with values of 254 mg/L and 146 mg/L respectively, which is the clear indication of the polluted wastewater and not from the catchment area. Values of BOD were in the range 3.4 mg/L (April '04) to 30.5 mg/L (February '05). Chloride, sulphate and calcium were observed to be well with in the desirable level maximum concentrations of 76 mg/L (April '05), 187.3 mg/L (April '04) and 68.4 mg/L (August '04). Total phosphorus also seemed to be high except during the premonsoon shower in April'04 and the monsoon season in August'04. The values were above the desirable limit for all the seasons with values ranging from 0.28 mg/L (August '04) to 3.9 mg/L (February '05), which indicates the presence of aquatic weeds. Dilution caused by the premonsoon shower during the month of April reduced the concentration of total Phosphorus while samples collected after 3 days of heavy rain during April'05 showed elevated levels of 3.2 mg/L which indicates that catchment area also contributed the total phosphorus in the location. Higher concentrations of 2.39 mg/L and 3.2 mg/L during the December '03 and December '04 respectively indicate the presence of excess aquatic weeds in station 8. Increase in the level from 0.277 mg/L in the monsoon season in August to 2.5 mg/L in the flood showed the contribution from the catchment area which probably have promoted the growth rate of aquatic weeds thereby causing further increase in the concentration of total phosphorus to 3.9 mg/L during the driest period in February. As in the case with the previous locations elevated levels of total iron were observed in December '04 (3318 μg/L), February '05 (1600 μg/L) and April '05 (3000 μg/L). Concentrations of sodium and potassium were well below the desirable

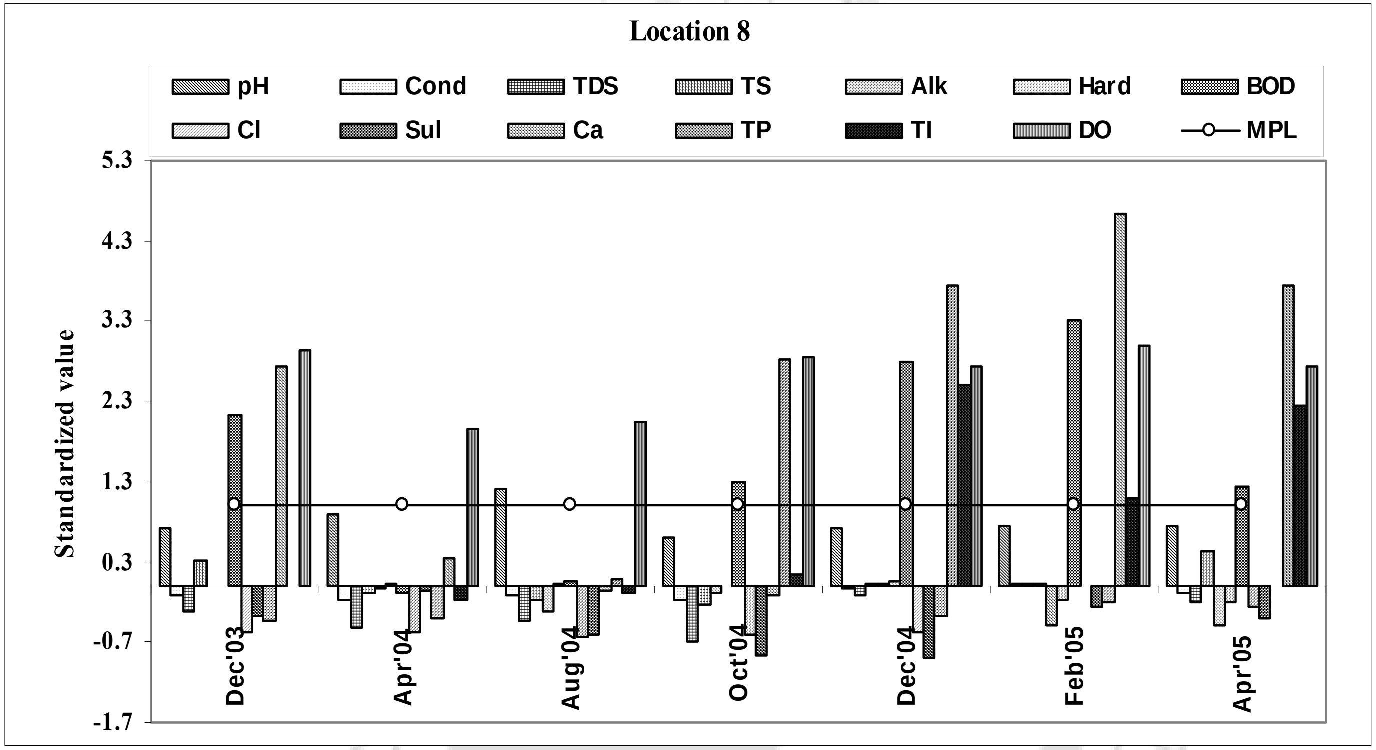


Figure 4.12 Pollution status of location 8 based on standardized value of concentration of different parameters [Cond - conductivity, TDS – total dissolved solids, TS – total solids, Alk – alkalinity, hard – hardness, BOD – biochemical oxygen demand, Cl – chloride, Ca- calcium, TP – total phosphorus, TI – total iron, DO – dissolved oxygen, MPL – maximum permissible level

limit with values ranging from 3.03 mg/L (December ’04) to 45.4 mg/L (February ’05) and 7.8 mg/L (August’ 04) to 15.1 mg/L (April’ 05) respectively. Concentrations of dissolved oxygen were observed to be very low with values ranging from 0 mg/L (February ‘05) to 2.1 mg/L (April ’04). Though the replenishment from atmosphere during the premonsoon shower and the monsoon season (1.9 mg/L) was observed, it did not meet even the minimum permissible level of 4 mg/L due to the excessive load of organic waste as well as the aquatic weeds during the previous seasons.

As shown in Figure 4.13, all the parameters except total phosphorus and total iron were found to be within the desirable level for location 9, which is the location in the river Brahmaputra just upstream of the confluence. Range of pH values were 7 (April ’04) to 7.86 (October ’04), Conductivity and TDS were observed to have maximum concentrations of 238 μS/cm in February ’05 and 150 mg/L (February ’05), alkalinity was observed to be maximum during the premonsoon shower in April’04 with a concentration of 135 mg/L and maximum concentration of hardness was observed to be 84 mg/L in December ’04 and BOD varied from 0.1 mg/L (April ’05) to 9 mg/L (December ’03). Chloride, sulphate and calcium were observed to have maximum values of 4.5 mg/L (December’03), 168 mg/L (April ’04) and to 83 mg/L (August ’04) respectively. Values of total phosphorus were in the range 0.17 mg/L (December ‘03) to 0.93 mg/L (October ’04). Total iron were observed to have crossed the desirable limit for the months December ’04 (322.2 μg/L), February ’04 (900 μg/L) and April ’05 (1000 μg/L) which is a clear indication that elevated levels in Bharalu had influenced the water quality of River Brahmaputra even in the upstream portion. Concentrations of sodium and potassium were observed to be very less compared to the other locations with maximum concentrations of 10.2 mg/L in August ’04 and 4.6 mg/L in February ’05 respectively. Concentrations of dissolved oxygen were above the desirable level with values ranging from 6.3 mg/L (April ‘04) to 8.6 mg/L (December ’03).

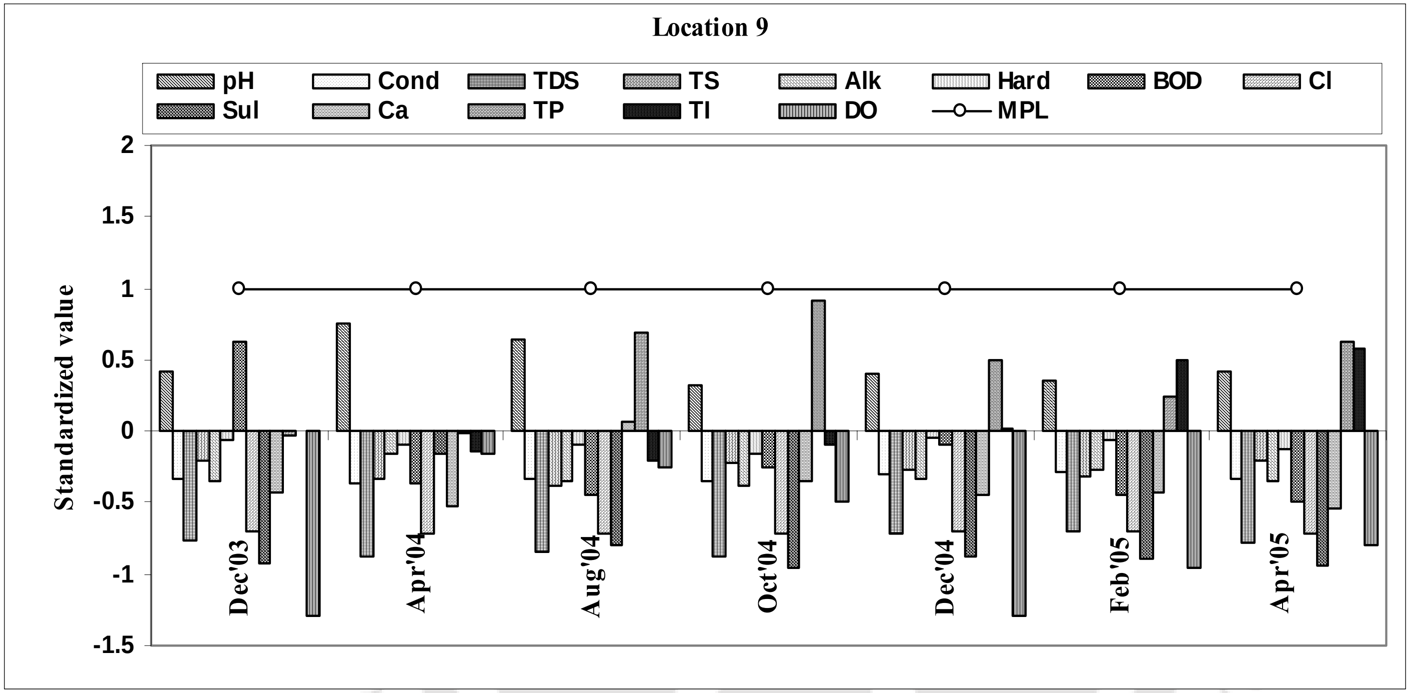


Figure 4.13 Pollution status of location 9based on standardized value of concentration of different parameters [Cond - conductivity, TDS – total dissolved solids, TS – total solids, Alk – alkalinity, hard – hardness, BOD – biochemical oxygen demand, Cl – chloride, Ca- calcium, TP – total phosphorus, TI – total iron, DO – dissolved oxygen, MPL – maximum permissible level]

Location 10 is the point on river Bharalu just before it meets River Brahmaputra near Bharalumukh .pH varied between 6.14 during August '04 and 7.26 during October '04 (Figure 4.14). Maximum value of conductivity was within the desirable level with a value of 733 μS/cm in the month of February '05. TDS and TS were in the range 208 mg/L (October '04) to 470.6 mg/L (December '04) and 248 mg/L (October '04) to 520 mg/L (December '03) respectively. Elevated levels during the low flow periods indicate the dissolved as well as suspended solids carried down from the upstream as well as the subsurface flow. Alkalinity values were higher than the desirable range with maximum value during April '04 (375 mg/L). Hardness was maximum in April' 04 (154 mg/L). This indicates that alkalinity and hardness were induced by the run off through the catchment. BOD were below the desirable value during April '04 with a value of 1.9 mg/L and for all other seasons values were above the desirable level with a maximum value of 32 mg/L during February '05 which indicates the settled organic waste. Maximum concentrations of Chloride, sulphate and calcium were observed to be 50 mg/L (February '05), 261 mg/L (April '04) and 54 mg/L (August '04) respectively. Chloride in comparatively higher concentration confirms the presence of settled wastes. All values were with in the desirable limit except for sulphate during April'04 and refuse leachates carried down by the surface run off could be the probable cause. Concentrations of total phosphorus and total iron varied from 0.04 mg/L (April '04) to 1.622 mg/L (October '04) and 0.83 μg/L (August '04) to 4607.8 μg/L (December '04) respectively. Elevated levels of total phosphorus indicate the excess growth of aquatic weeds in the location and that of total iron in the dry season is the clear indication that subsurface flow is prominent. Sodium and potassium were very low for all the seasons with maximum concentrations of 48.9 mg/L (February '05) and 12.8 mg/L (April '05) respectively. Dissolved oxygen is very low with values ranging from 0 mg/L (February '05) to 2 mg/L (August '04) which is the indication of excess aquatic weeds as well as organic wastes due to the pollution from land as well as water.

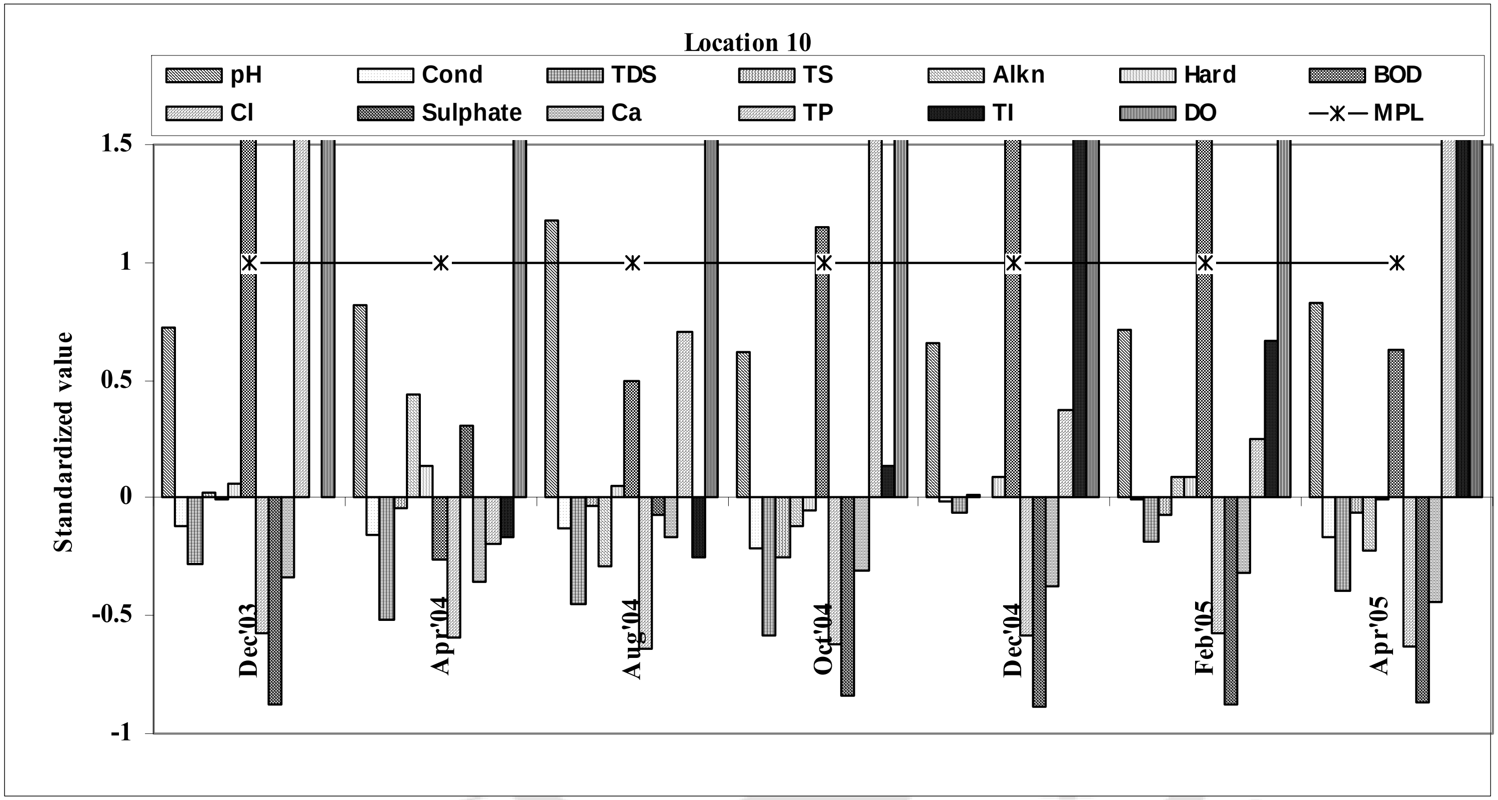


Figure 4.14 Pollution status of location 10 based on standardized value of concentration of different parameters [Cond - conductivity, TDS – total dissolved solids, TS – total solids, Alk – alkalinity, hard – hardness, BOD – biochemical oxygen demand, Cl – chloride, Ca- calcium, TP – total phosphorus, TI – total iron, DO – dissolved oxygen, MPL – maximum permissible level]

Location 11 is the location on River Brahmaputra about 1.5 kms down stream of the confluence. Sampling of this location was carried out to check whether there is any change in the quality compared to that of the location 9 of river Brahmaputra. pH values were in the range 6.44 (April ‘04) to 7.4 (February ’05), which is slightly less than that of location 9. Slight Increase in all other parameters was observed for this location (Figure 4.15). Conductivities were observed to have a maximum concentration of 306 μS/cm (October ’04). TDS also showed the same trend with maximum concentration of 198 mg/L (October ’04). Higher levels of dissolved salts in the post monsoon season indicate presence of settled wastes brought down to the river from the tributary during the monsoon season. Maximum values of alkalinity and hardness observed were 153 mg/L (April ’04) and 86 mg/L (December ’04) respectively that are with in the desirable levels. Elevated levels of alkalinity during the pre monsoon shower indicate the contribution from the adjoining land and subsurface flow and waste from the tributary is the probable source of hardness during the dry period. Maximum value of BOD (11.33 mg/L) during the winter season in December ’03 indicates the presence of settled organic waste. Chloride, sulphate and calcium were observed to have maximum concentration of 15.5 mg/L (October ’04), 161.3 mg/L (April ’04) and 51.6 mg/L (August ’04) respectively. Concentrations of total phosphorus varied from 0.03 mg/L (April ‘04) to 1.348 mg/L (October ’04) and that of total iron was in the range 0 μg/L (August ‘04) to 1800 μg/L (April ’05). These observations show that the pollutants were carried down from the polluted tributary to the main river. Sodium and potassium were observed to have maximum concentrations of 12.7 mg/L (October ’04) 6.1 mg/L (August ’04), respectively. Decline in dissolved oxygen was also observed for this location with concentration ranging from 3.6 mg/L (December ’03) to 7.3 mg/L (December ’04).

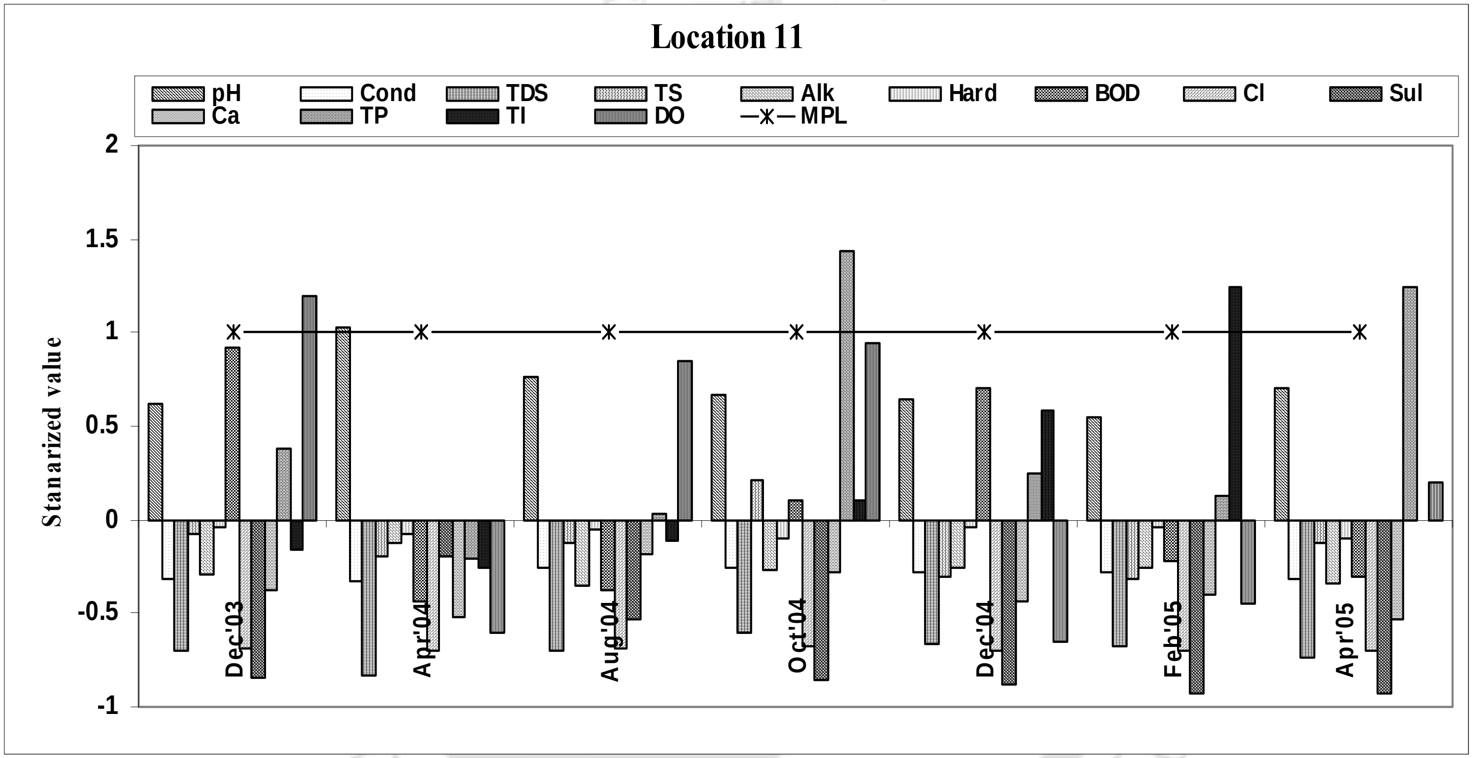


Figure 4.15 Pollution status of location 11 based on standardized value of concentration of different parameters [Cond - conductivity, TDS – total dissolved solids, TS – total solids, Alk – alkalinity, hard – hardness, BOD – biochemical oxygen demand, cl – chloride, Ca- calcium, TP – total phosphorus, TI – total iron, DO – dissolved oxygen, MPL – maximum permissible level].

4.2 Description of the most polluted location

Location 7b was observed to be the most polluted site. This sampling location in the channel is located across an input drain, which collects wastewater from concentrated urban settlements and business establishments. From the GIS plot it was inferred that this drain has a 15.53 km^2 urban catchment area and has about 11.2 km channel length. It is a sandy /marshy/rock outcrop terrain. Levels of BOD, TP and DO indicated the poor water quality. Drainage of the sub basin is not as much influenced by the soil factor as by the urban drainage.

On examining the analysis results it was understood that apart from biochemical oxygen demand, total phosphorus also plays an important role in reducing the oxygen budget of the study area. As shown in Figure 4.16, dissolved oxygen was observed to be least where concentrations of total phosphorus and biochemical oxygen demand are the highest. Studies conducted by Parr and Mason (2004) revealed that heterogeneity of a riverbed should be taken in to account when calculating the oxygen budget of the entire river. Eutrophication results in abundant growth of algae, which smothers submerged macrophytes during summer months, increasing organic loading and accumulating silts resulted in a breakdown of sediment water boundary layer, leading to release of nutrients previously locked up in the sediment. Large number of organic mud patches in the river, increased temperature, and high sediment oxygen demand, low DO at night due to respiration of a large biomass of macrophytes would add to the stress on a river (Barica, 1974). DO and total phosphorus indicated an identical trend. Sediment with particulate organics has a large impact on the ecology of the Bharalu River, impacting community composition. Muddy sediments can have a large oxygen demand, particularly at high temperature, since they support large bacteria than sand or gravel sediments (Parr & Mason, 2003). Both these factors were present in the case of Bharalu.

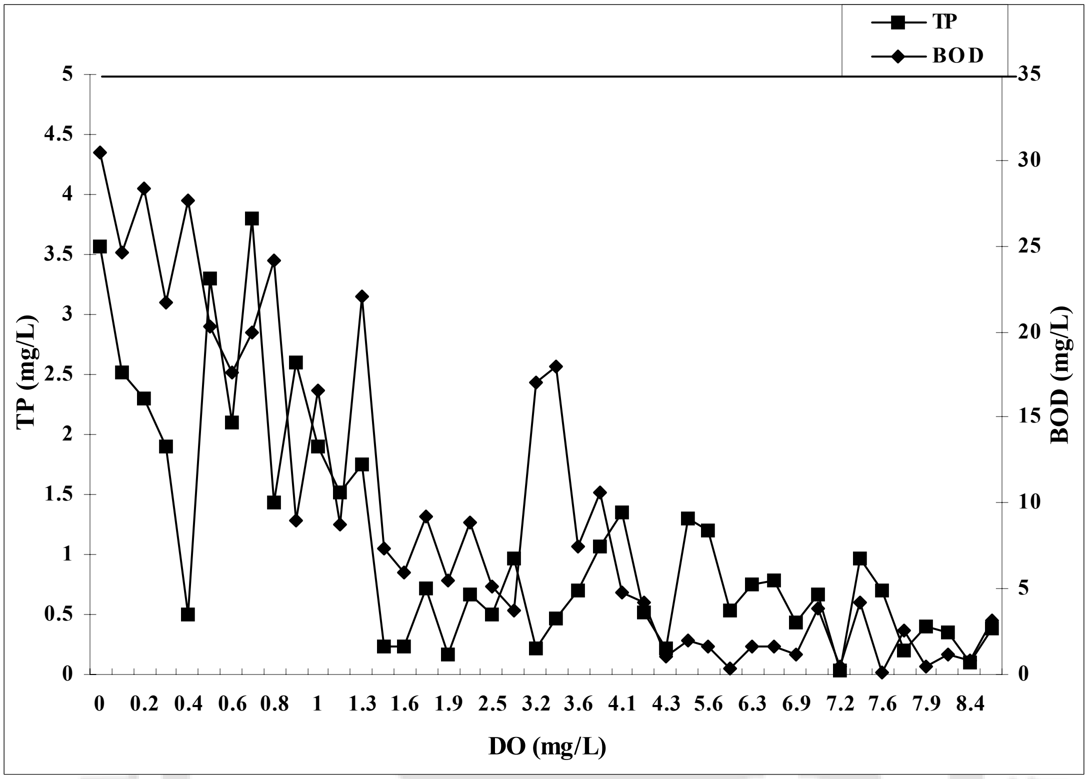


Figure 4.16 Variation of DO with respect to TP and BOD

4.3 CORRELATION COEFFICIENTS OF PARAMETERS

4.3.1 Correlation matrix

Correlation matrix for all the variables was generated and entered in Table 4.1. It can be seen from the correlation matrix that significant correlation occur between DO/BOD (-0.66), DO/TP (-0.55), DO/conductivity (-0.77), DO/TDS (-0.74), DO/hardness (-0.73), DO/chloride (-0.76), BOD/TP (0.7), BOD/conductivity (0.76), BOD/TDS (0.81), TP/conductivity (0.74), TP/TDS (0.76), alkalinity/conductivity (0.7), alkalinity/hardness (0.76), conductivity/TDS (0.97), conductivity/hardness (0.9), conductivity/chloride (0.85), TDS/hardness (0.87), TDS/chloride (0.8) and hardness/chloride (0.8).

As shown in Figure 4.17, it was observed that conductivity is having the highest correlation with dissolved oxygen with a value of -0.77 followed by Chloride (-0.755),

Table 4.1. Correlation matrix generated from the analysis results.

	DO	pH	BOD	TP	Alka	Cond	TS	TDS	TI	Sulp	Na	Ca	Hard	Chlo
DO	1	0.15	-0.66	-0.55	-0.52	-0.77	-0.49	-0.74	-0.12	0.01	-0.45	-0.44	-0.73	-0.76
pH	0.15	1	0.003	0.11	0.04	-0.13	-0.33	-0.1	0.05	-0.44	-0.14	-0.06	-0.12	-0.14
BOD	-0.66	0.003	1	0.7	0.45	0.76	0.44	0.81	0.19	-0.25	0.46	0.64	0.64	0.57
TP	-0.55	0.11	0.7	1	0.43	0.74	0.50	0.76	0.26	-0.35	0.44	0.28	0.56	0.62
Alkal	-0.52	0.04	0.45	0.43	1	0.7	0.37	0.63	-0.08	0.42	0.58	0.26	0.76	0.65
Cond	-0.77	0.04	0.76	0.74	0.7	1	0.64	0.97	0.14	0.03	0.56	0.47	0.9	0.85
TS	-0.49	-0.33	0.44	0.50	0.37	0.64	1	0.68	0.18	0.04	0.05	0.10	0.54	0.68
TDS	-0.74	-0.1	0.81	0.76	0.63	0.97	0.68	1	0.2	-0.1	0.5	0.4	0.87	0.8
TI	-0.12	0.05	0.19	0.26	-0.08	0.14	0.18	0.2	1	-0.33	-0.3	-0.25	-0.003	0.2
Sulp	0.01	-0.44	-0.25	-0.35	0.42	0.03	0.04	-0.1	-0.33	1	0.2	0.1	0.21	0.1
Na	-0.45	-0.14	0.46	0.44	0.58	0.56	0.05	0.5	-0.3	0.2	1	0.6	0.5	0.4
Ca	-0.44	-0.06	0.64	0.28	0.26	0.47	0.10	0.4	-0.25	0.1	0.6	1	0.5	0.3
Hard	-0.73	-0.12	0.64	0.56	0.76	0.9	0.54	0.87	-0.003	0.21	0.5	0.5	1	0.8
Chlo	-0.76	-0.14	0.57	0.62	0.65	0.85	0.68	0.8	0.2	0.1	0.4	0.3	0.8	1

total dissolved solids (-0.735), hardness (-0.731), potassium (-0.663), bio chemical oxygen demand (-0.656), total phosphorus (-0.554), alkalinity (-0.552), total solids (-0.486), sodium (-0.445), calcium (-0.435), pH (0.152), sulphate (0.013). Negative value for a parameter indicates that dissolved oxygen decreases with increase in concentration of that particular parameter and positive value indicates that dissolved oxygen increases with increase in the concentration of the parameter. Here all the parameters except pH and sulphate showed negative correlation.

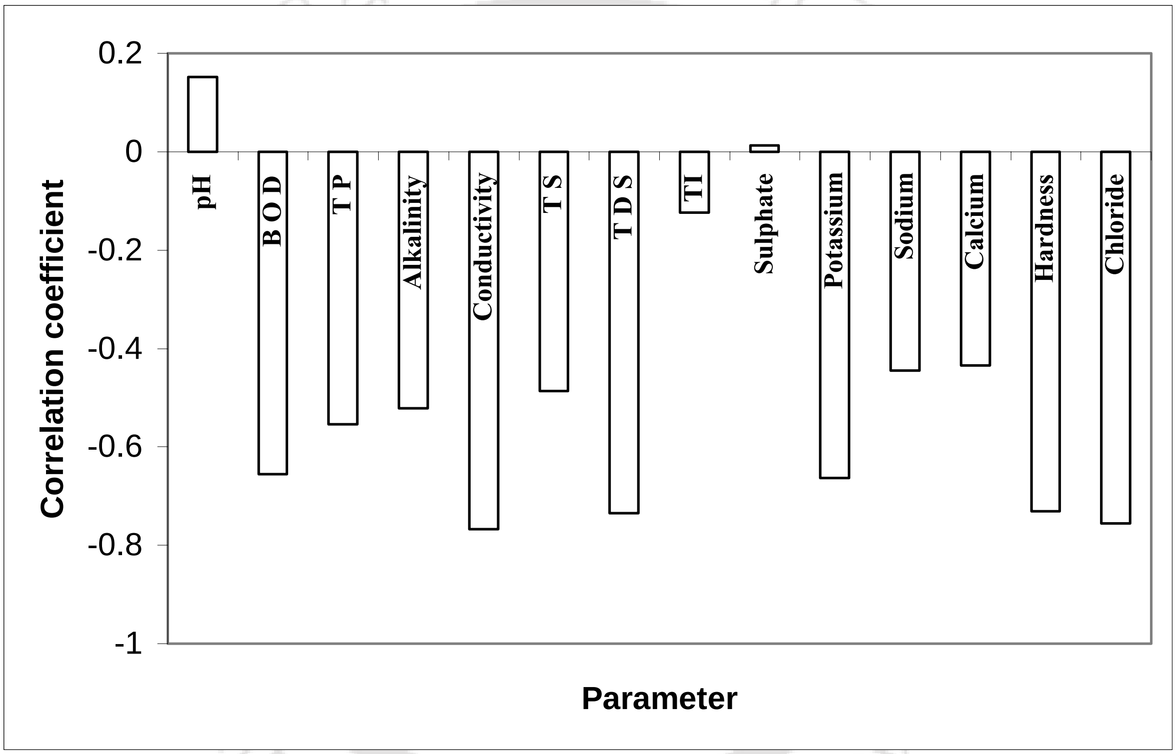


Figure 4.17. Correlation coefficients of parameters with respect to dissolved oxygen

The graphical representation of average concentrations of parameters with comparatively higher correlation (above 50%) with dissolved oxygen is shown in Figure 4.18. All the sampling stations except the origin at Basista and the location at River Brahmaputra were highly contaminated in terms of biochemical oxygen demand, total phosphorus and dissolved oxygen biochemical oxygen demand, total phosphorus, alkalinity, conductivity, total dissolved solids, potassium, hardness and chloride are having comparatively higher correlation coefficient (above 50%). Average concentrations of BOD varied from 3.9 mg/L to 31 mg/L, total phosphorus varied from 0.62 mg/L to 5.16 mg/L, alkalinity varied from 37.2 mg/L to 354 mg/L, conductivity varied from 63.3 μS/cm to 982 μS/cm, total dissolved solids from 36.5 mg/L to 587 mg/L, potassium from 2.7 mg/L to 16.7 mg/L, hardness from 17 mg/L to 169 mg/L and chloride from 1.8 mg/L to 64.4 mg/L. Among these parameters, the concentrations of potassium, hardness and chloride are well below the permissible limits of 100 mg/L, 500 mg/L, and 600 mg/L and even below the desirable limits of 100 mg/L, 200 mg/L and 200 mg/L, respectively. Concentration of total dissolved solids is well below the maximum permissible limit of 1500 mg/L but it was observed to be above the desirable level of 500 mg/L during the dry season. Maximum average value of conductivity was found to be above the desirable limit but concentrations were well below the maximum permissible limit of 2500 μS/cm. Same trend was observed for alkalinity also. Concentrations of biochemical oxygen demand as well as total phosphorus were observed to be very high. Dissolved oxygen was observed to be well below the maximum allowable level of 4 mg/L with average concentrations ranging from 0.34 mg/L to 7.7 mg/L. High level of biochemical oxygen demand as well as total phosphorus and low DO is the clear indication of excess quantity of organic wastes as well as aquatic weeds.

Chloride is found in most natural waters and is not of concern at low levels. Analysis results revealed that maximum concentration of chloride was 92 mg/L that is well below the desirable limit of 250 mg/L that was observed at 7b, the most contaminated location. Chloride ions (Cl^-) contribute to total salt content (electrical conductivity) of the water, which is also evident from the high correlation (0.85) between conductivity and chloride. Hardness is a measure of the amount of calcium, magnesium, and iron dissolved in water. Hardness showed strong correlations with alkalinity (0.76), conductivity (0.9) and total dissolved solids (0.87).

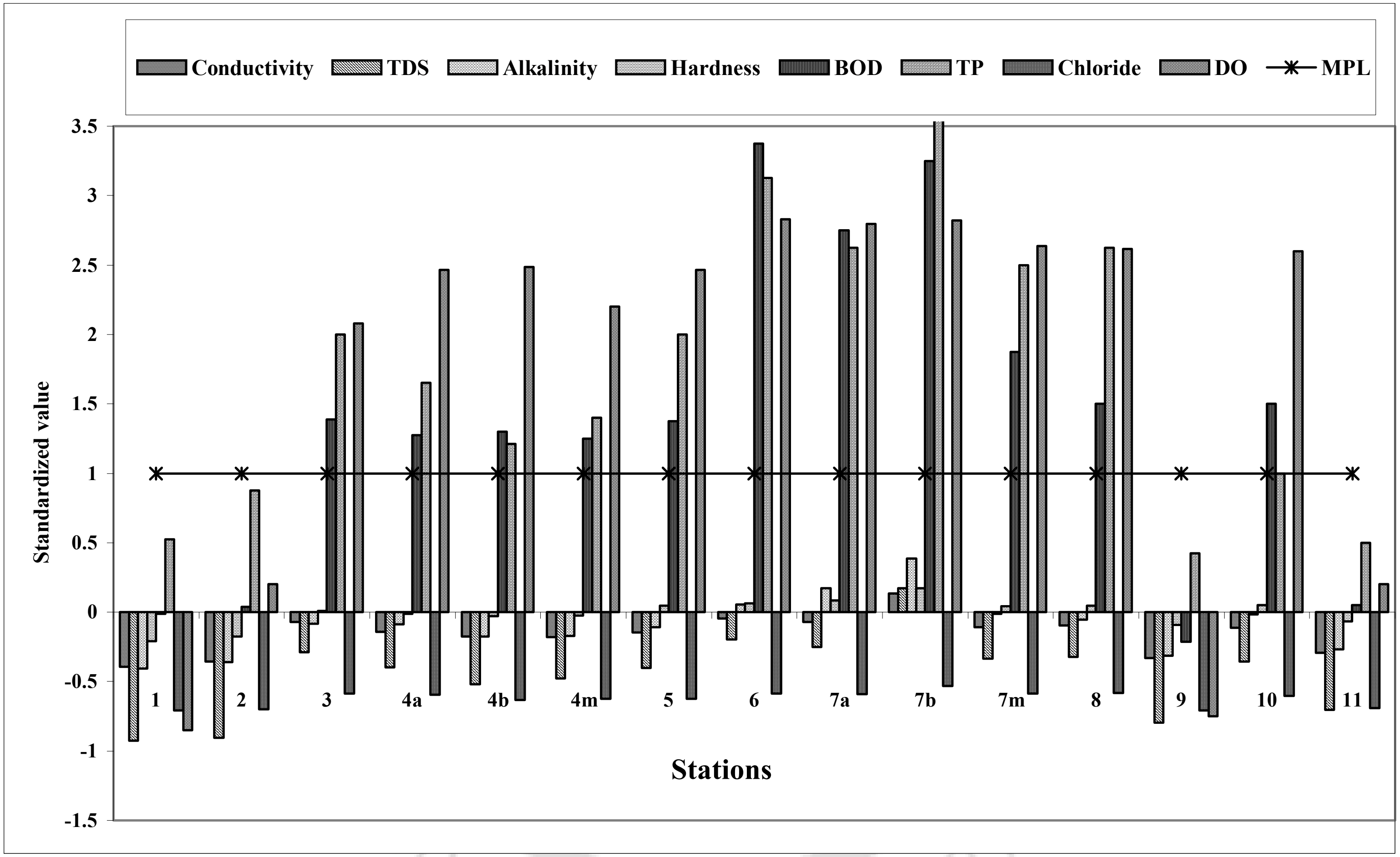


Figure 4.18 Average values of parameters having correlation coefficient above 5

4.4 CONCLUSIONS

For the Bharalu catchment and the stream, the water quality was found to be generally poor, with significant seasonal and spatial variations. Dissolved oxygen, which is a major water quality indicator, was observed to be either absent or very low in several locations irrespective of the season. Following conclusions can be drawn based on the water quality evaluation.

- Urban runoff was observed to have predominant influence on alkalinity. Maximum values of alkalinity were observed in all locations during the premonsoon shower. Maximum value of 592 mg/L was observed in location 7a with catchment area of 40 km^2, which covers agricultural land, residential complexes and a large medical campus. The premonsoon shower after a after a long spell of dry season was observed to increase the alkalinity which could be due to the contribution from the catchment area. But this increase in value is only for a short period as the observation obtained from the samples collected during the monsoon season indicated reduction in alkalinity due to dilution.
- Elevated levels of conductivity during the low flow period indicate the presence of subsurface flow in the middle reaches. Higher levels in the points of origin during premonsoon shower indicate the contribution from the catchment area, which is free from human interference.
- No significant seasonal variation was observed for chloride concentration. Increasing concentration towards the down stream is a clear indication of increasing pollution and comparatively higher concentration during the low flow period indicates the wastes getting concentrated due to lack of dilution as well as the presence of ion rich subsurface flow which is the case for conductivity also.
- Concentrations of sulphate showed pronounced seasonal variation, and elevated levels in the wet season indicate land use pattern plays a major role in sulphate concentration irrespective of the catchment area. This is evident from the observation in station 7b.
- Total phosphorus was high in all the locations promoting excessive growth of weeds and inducing more stress on DO of the water channel. Very high concentration of TP indicates the decayed organic waste in the bed apart from excess

growth of aquatic weeds which results in release of nutrients from the sediment water interface

- Combined effect of total phosphorus and organic matter brought down the DO well below the permissible level. The drains from the urban area and the market place carried dead water without any dissolved oxygen at all.
- BOD and total phosphorus were found to be the crucial parameters to be managed to improve the quality of the system studied.
- The locations in the middle reaches, especially location 7b, were the most affected location due to expanding urban growth. This underlines the need of a proper waste management scheme for the whole city and that of a treatment plant before the wastewater of the Bharalu tributary is discharged into the river Brahmaputra.

CHAPTER
FIVE

MODELING METHODOLOGY

5.1 INPUT AND OUTPUT VARIABLES

One of the main causes of oxygen depletion or sinks is the oxidation of organic matter and other reduced matter in the water column (Cox, 2003). Hence BOD was taken as one of the input parameters for modeling. Phosphorus and nitrogen are nutrients, which are most important for the growth of blue green algae that imparts discoloration, odor, and formation of unsightly, smelly scums on the water surface (Maier & Dandy, 1997). These were exactly the characteristics of the study area. Of the two nutrients nitrogen and phosphorus, phosphorus is regarded as the limiting nutrient. When there is too much phosphorus in water, eutrophication can be speeded up that result in depletion in dissolved oxygen. Phosphorus gets into water in both urban and agricultural settings and it tends to attach to soil particles and thus moves into surface water bodies from run off. Rapid growth of aquatic vegetation as a result of excess phosphorus lowers the dissolved oxygen as the vegetation dies and decays and uses up oxygen. Considering this fact and comparatively higher correlation coefficient obtained from the data generated from laboratory analysis, it was decided to take total phosphorus as the second input parameter. Experimental data showed that conductivity showed highest correlation with dissolved oxygen. Electrical conductivity estimates the amount of total dissolved salts. Bacterial metabolism in the nutrient rich river bed consumes oxygen and release CO_2.This CO_2 rapidly dissolves in water to form carbonic acid, bicarbonate ions and carbonate ions and the new ions increase the TDS and therefore the conductivity. Hence increase in conductivity can also be correlated to dissolved oxygen depletion. Hence it was selected as the third input parameter. Alkalinity was included as the fourth input parameter to simulate the chemical properties of the habitat. The input and output parameters are given in Table 5.1 with their minimum and maximum values.

Table 5.1. Input (p) and output (t) parameters for model studies.

Code	Parameter	Minimum	Maximum
P1	Biochemical Oxygen demand (mg/L)	0	70
P2	Total phosphorus (mg/L)	0.03	8.5
P3	Conductivity (μS/cm)	47	1480
P4	Alkalinity (mg/L)	22	412
t	Dissolved oxygen (mg/L)	0	8.8

5.2 FUZZY RULE BASED MODEL

It is a fact that ecological monitoring data bear a large uncertainty, which is mostly caused by measurement error and natural variation as well as vagueness. In most of the cases, the relationship between the ecosystem components are not exactly known and analytical models for establishing these relationships are not available. In such a case a model can be build based on expert knowledge and a fuzzy logic approach can be used for solving uncertainty problems. The basic concept of fuzzy set theory is a membership function, which represents numerically to what degree an element belongs to a set. In this theory an element can be a member of a particular set to a certain degree, which is called its membership degree. Fuzzy rules consist of two parts: an antecedent part stating conditions on the input variable(s) and a consequent part describing the corresponding values of the output variable(s). Usually, the case of single output variable is considered. Creating fuzzy expert system consists of four basic steps:

1.Defining membership function for input and output variables

2.Defining rules to relate the membership function of each variable to the output through a series of IF-THEN statements

3.Rules are mathematically evaluated and the results are combined

4.Resulting function is evaluated as a crisp number through defuzzification.

On examining the generated data, the domain of each input variable was partitioned into number of fuzzy sets or linguistic variables. A fuzzy rule base system was constructed that connects the input variables to the output variable by means of IF-THEN rules. Given particular values of the input variables degree of fulfillment of the rule is obtained by aggregating the membership degrees of these input values into the respective fuzzy sets. Fuzzy output was determined by the degrees of fulfillment and the consequent parts of the rules. In this study the famous Mamdani method with the help of math work's MATLAB fuzzy logic toolbox editor (version 6.0.0.88 Release 12) was used to develop the prediction model. According to this method, being the k^{th} crisp input variable defined as a_k, $A_{i, j, k,}$ its corresponding j^{th} fuzzy input number considered in the i^{th} rule $B_{i,l}$ is the lth fuzzy output number relevant to the ith rule , the Mamdani rule is

IF a_1 is $A_{i,j,1}$ AND a_2 is $A_{i,j,2}$ AND...AND a_K is A i,j,k THEN $B_{i,l}$

Fuzzy operator 'minimum' was applied as the variables are combined using 'AND' and the aggregation was performed with the 'maximum' function. The centrioid or center of gravity method was applied as a means of defuzzification of the output membership function to determine a crisp set.

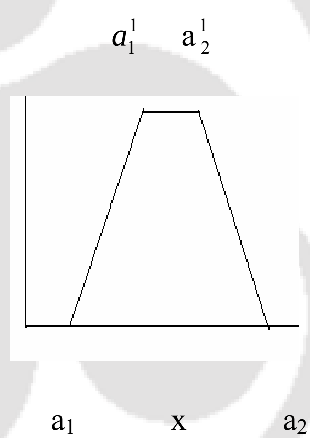
5.2.1 DESCRIPTION OF FUZZY REGIONS

Based on the correlation coefficients four sensitive parameters namely the biochemical oxygen demand (BOD), total phosphorus (TP), conductivity and alkalinity were selected as the input variables and dissolved oxygen as the output variables. Taking the experimental data into consideration these parameters were fuzzified into fuzzy subsets as shown in Tables 5.2 to 5.6 and Figures 5.1 to 5.5. Membership functions of input and output variables were created using fuzzy logic tool box editor.

Trapizoidal fuzzy number A is defined by the membership function

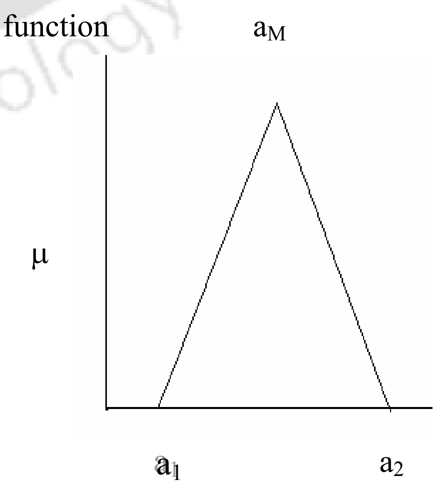
$$\mu = \begin{cases} \dfrac{x-a_1}{a_1^1-a_1} & \text{for } a_1 \le x \le a_1^1 \\ 1 & \text{for } a_1^1 \le x \le a_2^1 \\ \dfrac{x-a_2}{a_2^1-a_2} & \text{for } a_2^1 \le x \le a2 \\ 0 & \text{Otherwise,} \end{cases}$$

Where $[a_1, a_2]$ is the supporting interval and a_1^1 and a_2^1 are the values at the highest level of the trapezoidal region.



Triangular fuzzy number A is defined by the membership function

$$\mu = \begin{cases} \dfrac{x-a_1}{a_M-a_1} & \text{for } a_1 \le x \le a_M \\ \dfrac{x-a_2}{a_M-a_2} & \text{for } a_M \le x \le a_2 \\ 0 & \text{otherwise} \end{cases}$$



Where $[a_1, a_2]$ is the supporting interval and the point $(a_M, 1)$ is the peak.

FUZZY SUBSETS FOR BOD

For BOD, a trapezoidal membership function is created for values 0 mg/L to 3 mg/L as well as for values 10 mg/L to 70 mg/L. The values in between were assigned triangular membership functions. Seven fuzzy regions were defined for BOD as given in Table 5.2 and the fuzzy sets are shown in Figure 5.1

Table 5.2 Description of fuzzy sets for BOD.

Range in mg/L	**Description**	**Function used**
0 – 3	Excellent	Trapezoidal
1.5-4.5	Very good (VG)	Triangular
3 - 6	Good (G)	Triangular
4.5 –8.5	Very fair (V_F)	Triangular
6 - 10	Fair (F)	Triangular
8 -12	Acceptable (Acc)	Triangular
10 -70	Objectionable (Obj)	Trapezoidal

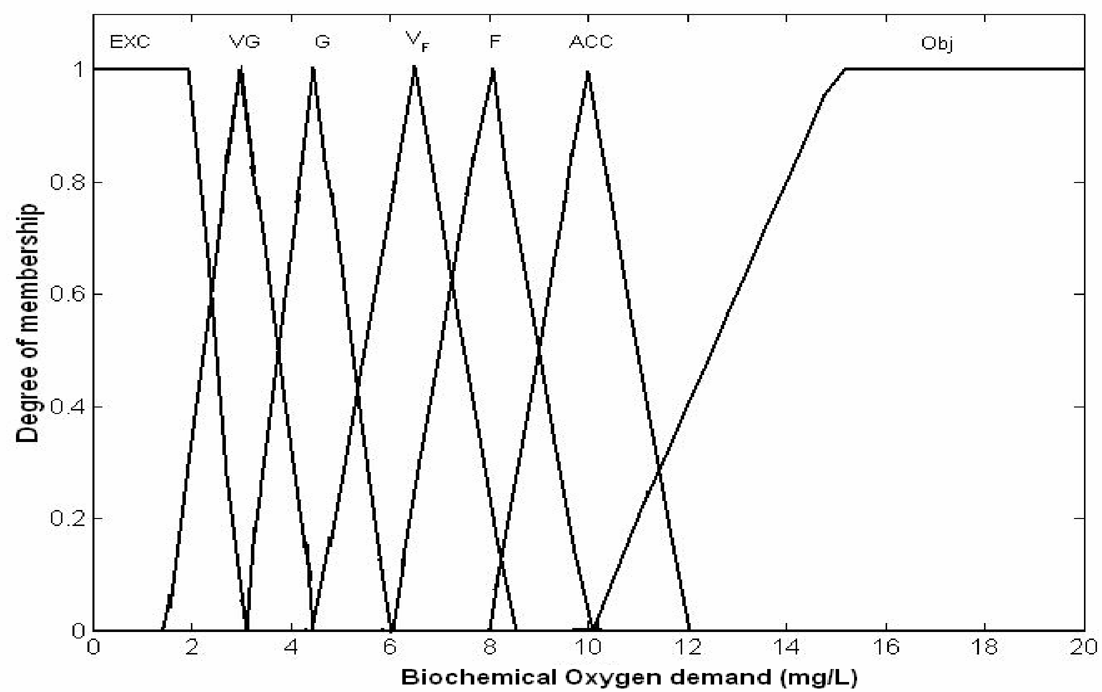


Figure 5.1 Fuzzy regions for BOD based on concentration

FUZZY SUBSETS FOR TOTAL PHOSPHORUS

Seven fuzzy regions were created for total phosphorus as shown in Table 5.3 and Figure 5.2. For the values from 0 mg/L to 1.5 mg/L triangular membership functions were created and from 1.2 mg/L to 9 mg/L trapezoidal membership functions were created.

Table 5.3 Description of Fuzzy sets for TP

Range in mg/L	**Description**	**Function used**
0- 0.3	Very good (VG)	Triangular
0.15 - 0.45	Good (G)	Triangular
0.3 – 0.9	Very Fair (VF)	Triangular
0.6 –1.2	Fair (F)	Triangular
0.9 – 1.5	Acceptable (ACC)	Triangular
1.2 – 9	Objectionable (Obj)	Trapezoidal

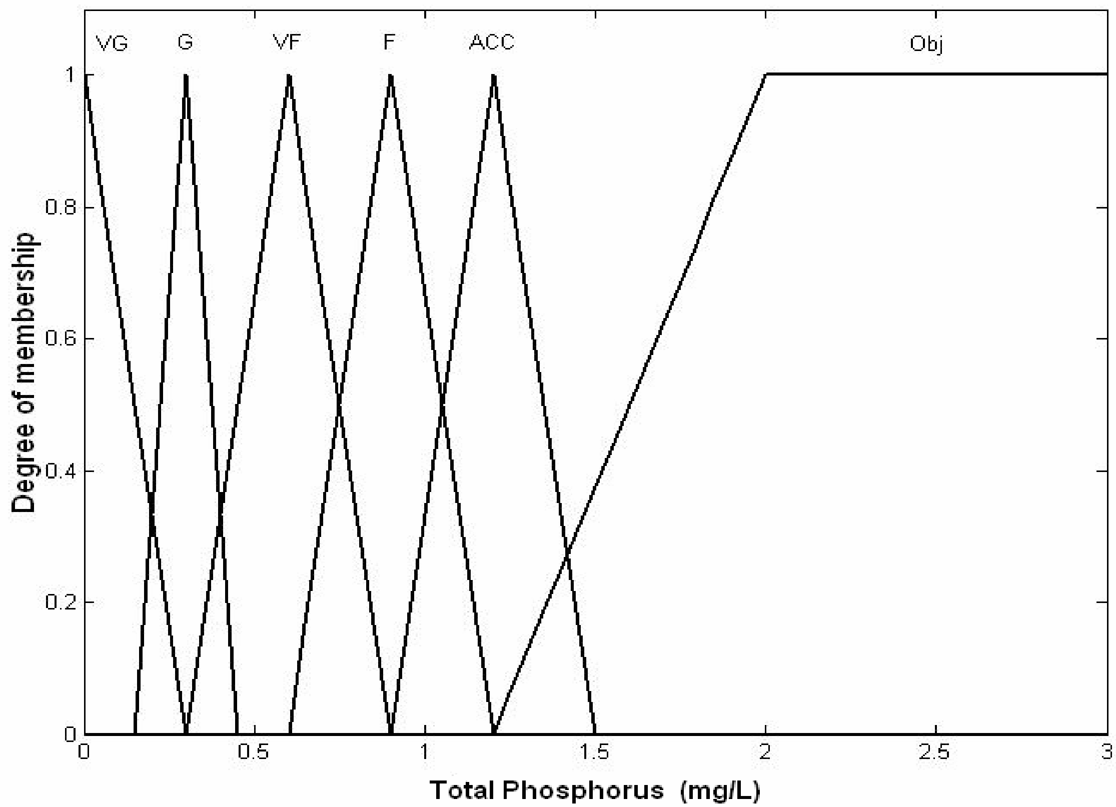


Figure 5.2. Fuzzy regions for total phosphorus based on concentration.

FUZZY SUBSETS FOR CONDUCTIVITY

Six fuzzy regions were developed for conductivity five triangular membership functions were provided up to the range of 850 μS/cm and trapezoidal membership function was assigned for the range above 700 μS/cm (Table 5.4 and Figure 5.3).

Table 5.4 Description of fuzzy sets for Conductivity.

Range in μS/cm	**Description**	**Function used**
0 –100	Excellent (Exc)	Triangular
50 – 250	Very good (VG)	Triangular
150 – 450	Good (G)	Triangular
300 – 600	Very fair (VF)	Triangular
450 – 850	High (H)	Triangular
700 – 2000	Very high (V H)	Trapezoidal

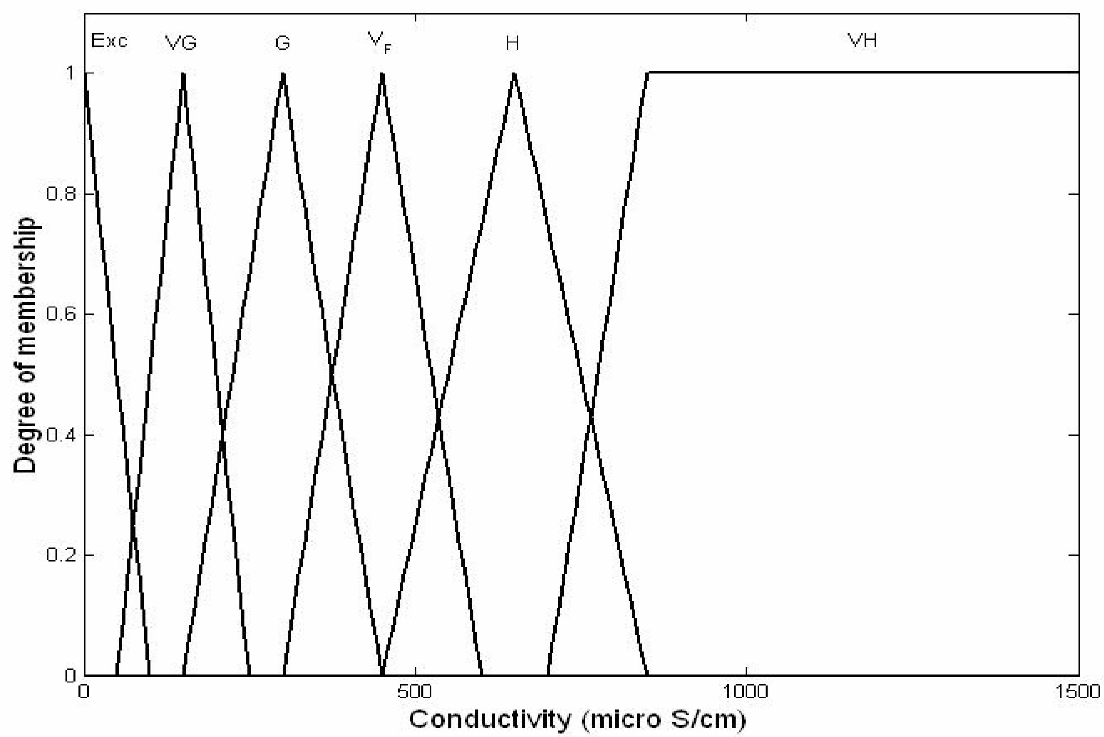


Figure 5.3.Fuzzy regions for conductivity based on concentration.

FUZZY SUBSETS FOR ALKALINITY

Trapezoidal membership functions were assigned for alkalinity ranging from 0 mg/L to 100 mg/L and for 400 mg/L to 600 mg/L. Triangular membership functions were assigned for the regions 50 mg/L to 150 mg/L, 100mg/L to 250 mg/L, 175 mg/L to 325 mg/L and 250- 450 mg/L (Table 5.5 and Figure 5.4).

Table 5.5 Description of fuzzy sets for Alkalinity

Range in mg/L	Description	Function used
0-20-80-100 mg/L	Excellent (exc)	Trapezoidal
50-150 mg/L	Very good (vg)	Triangular
100-250 mg/L	Good (g)	Triangular
175-325 mg/L	Fair (F)	Triangular
250-450 mg/L	High (H)	Triangular
400 - 600 mg/L	Very high (VH)	Trapezoidal

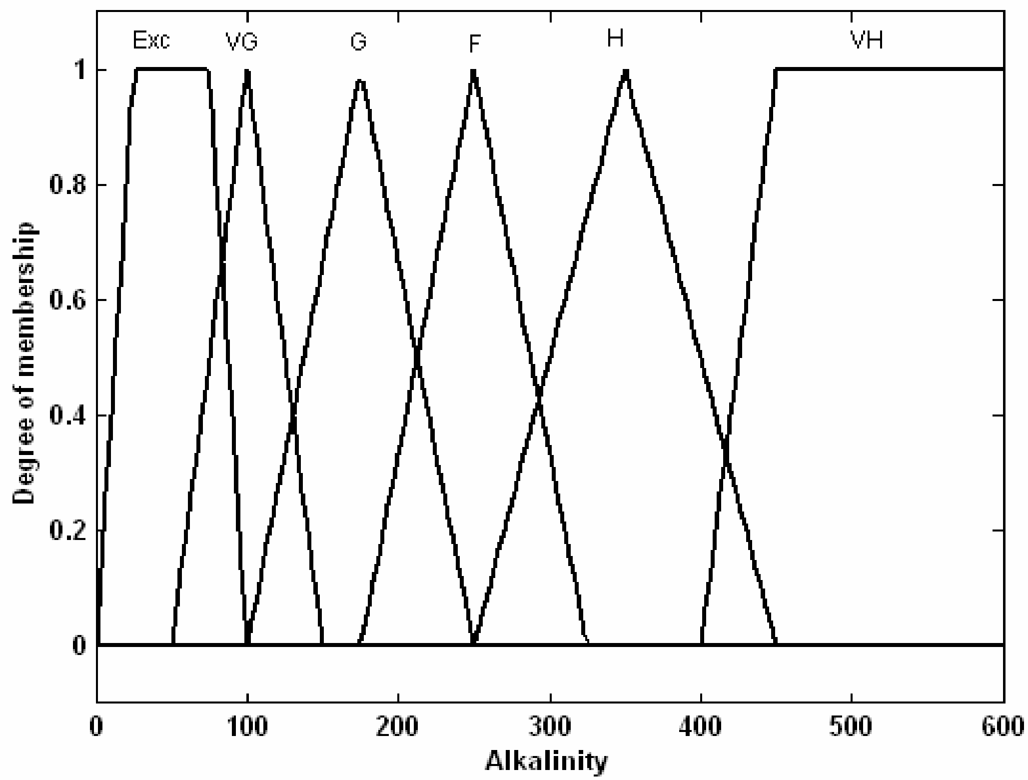


Figure 5.4 Fuzzy regions for alkalinity based on concentration

FUZZY SUBSETS FOR DISSOLVED OXYGEN

Dissolved oxygen which is the output variable is divided in to 7 fuzzy sets with trapezoidal membership functions for the range 0 mg/L to 2.5 mg/L and 7 mg/L to 9 mg/L and triangular functions for the values 2 mg/L to 4 mg/L, 3 mg/L to 5 mg/L, 4 mg/L to 6 mg/L, 5 mg/L to 7 mg/ L, 6 mg/L to 8 mg/L (Table 5.6 and Figure 5.5).

Table 5.6 Description of fuzzy sets for Dissolved oxygen

Range in mg/L	**Description**	**Function used**
0 – 2.5	Highly objectionable (H_Obj)	Trapezoidal
2 – 4	Objectionable (Obj)	Triangular
3 – 5	Bad (bad)	Triangular
4-6	Acceptable (Acc)	Triangular
5-7	Good (G)	Triangular
6-8	Very Good (VG)	Triangular
7-9 mg/L	Excellent (exc)	Trapezoidal

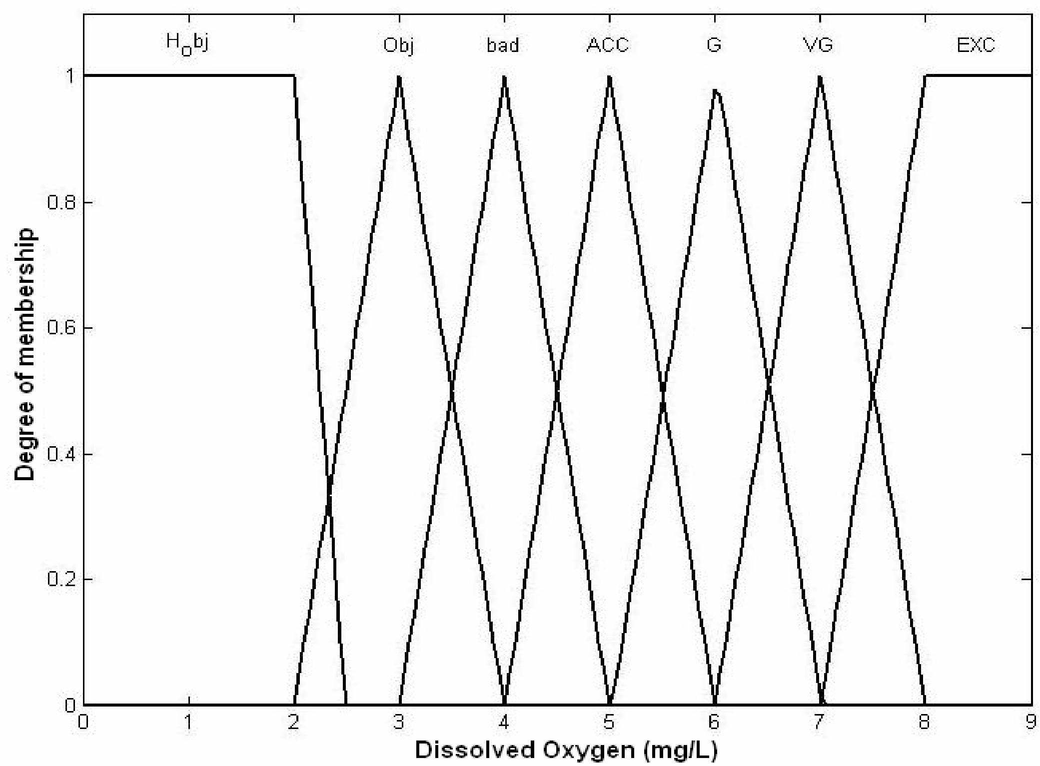


Figure 5.5 Fuzzy subsets for DO based on concentration

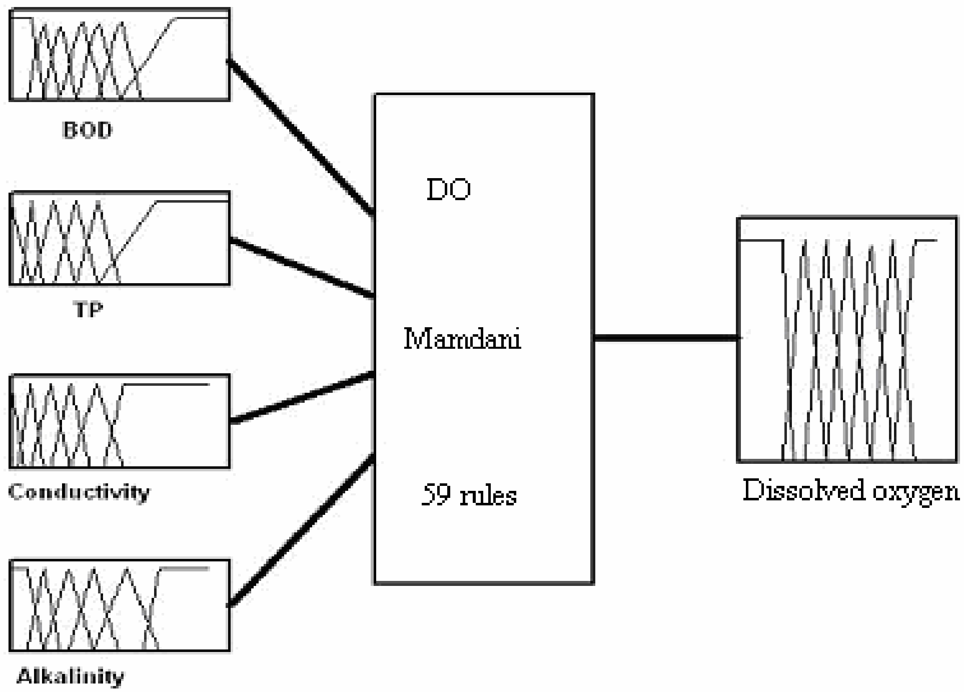


Figure 5.6. Fuzzy system with 4 inputs and 1 output used in the study

Table 5.7 summarizes the fuzzy rules that connected the input variables to the output variable by means of if- then rules. These rules were implemented in a fuzzy inference system of the Mamdani – Assilian rule that produces a crisp output. ‘And’ has been used as a conjunction operator in the fuzzy rule base. Total of 59 rules were extracted from the data sets and 46 data sets were used for validation. In the table ‘Exc’ stands for excellent, ‘VG’ for very good, ‘G’ for good, ‘VF’ for very fair, ‘F’ for fair, ‘ACC’ for acceptable, ‘Obj’ for objectionable and ‘H Obj’ for highly objectionable.

Table 5.7. Fuzzy rule base based on experimental data

	BOD	TP	COND	ALK	DO
1	Exc	VF	Exc	Exc	Exc
2	Exc	VG	Exc	VG	Exc
3	Exc	VG	Exc	Exc	Exc
4	Exc	VF	VG	Exc	Exc
5	Exc	VG	VG	G	VG
6	Exc	F	VG	EXC	VG
7	Exc	Obj	VG	Exc	VG
8	Exc	G	G	VG	VG
9	Exc	VG	VG	G	G
10	Exc	ACC	Exc	Exc	G
11	Exc	ACC	VF	VG	ACC
12	Exc	ACC	VG	Exc	ACC
13	Exc	VG	VF	H	H Obj
14	VG	Obj	VF	VG	H Obj
15	VG	VF	G	VG	Exc
16	VG	VF	VF	G	H OBJ
17	VG	G	G	EXC	Obj
18	VG	Obj	G	VG	Obj
19	G	VF	Exc	Exc	VG
20	G	G	VG	G	VG
21	G	VG	VF	VG	H_Obj
22	G	ACC	G	VG	Bad
23	G	VG	H	VG	H OBJ
24	VF	VG	VF	Exc	H OBJ
25	VF	G	H	H	H_Obj

26	F	VG	VG	EXC	EXC
27	F	G	VF	H	H_Obj
28	F	Obj	G	VG	H_Obj
29	F	VF	Vf	VG	H OBJ
30	F	OBJ	H	G	H_Obj
31	F	Obj	VF	G	H_Obj
32	F	Obj	VF	G	H_Obj
33	ACC	VF	G	VG	VG
34	ACC	VF	VG	VG	Obj
35	ACC	F	H	VH	H_Obj
36	ACC	VF	VF	F	H OBJ
37	ACC	Obj	VF	VG	H OBJ
38	ACC	Obj	G	VG	H OBJ
39	ACC	G	H	F	H_Obj
40	ACC	F	Exc	EXC	Bad
41	Obj	Obj	G	G	H_OBJ
42	Obj	Obj	H	G	H_OBJ
43	Obj	Obj	VF	G	H_OBJ
44	Obj	F	VF	G	H OBJ
45	Obj	Obj	VH	H	H_Obj
46	Obj	Obj	VF	G	H_OBJ
47	Obj	Obj	H	F	H_Obj
48	Obj	Obj	VF	G	H_OBJ
49	Obj	ACC	G	VG	H_OBJ
50	Obj	Obj	VF	F	H_OBJ
51	Obj	Obj	VF	G	H_OBJ
52	Obj	Acc	VF	VG	H_OBJ
53	Obj	VF	H	G	H_Obj
54	Obj	Obj	H	G	H_ OBJ
55	Obj	VF	H	F	H_OBJ
56	Obj	VF	VF	Exc	Obj
57	Obj	G	H	H	Obj
58	Obj	Obj	VH	F	H_Obj
59	Obj	Obj	VH	G	H_Obj

After defining the linguistic variables and rules, next step is the determination of the degree of membership of the input in the rule antecedents. In this model minimum – operator is employed for the implication 'and',

the degree of match of the rule 'r' is

$$\alpha_r = \min_{i=1,\ldots\ldots,n} \{ \mu_i^{ji}(x_i^{input}) \}$$

here 'i' indicates the linguistic variable, I = 1,……..n; 'j' indicates the term of the linguistic variable 'i', j = 1,………,m(i), and m(i) is the number of terms of the linguistic variable i. The results of the evaluation process is obtained by aggregation of all consequences using the maximum operator which is given by:

$$\mu^{conseq}(u) = \max_r \{ \mu_r^{conseq}(u) \}$$

where $\mu_r^{conseq}(u) = \min \{ \alpha_r , \mu^j(u) \}$

5.2.2 DEFUZZIFICATION

Defuzzification or decoding the outputs is the operation that produces a nonfuzzy control action, a single crisp value 'u' that adequately represents the membership function μ^{conseq} (u) of an aggregated fuzzy control action. The three often-used methods are center of area (COA), which is also called center of gravity (COG), center of sums (COS) and means of maxima (MOM) (Zimmermann 1996). Center of area method is the most widely used method of the defuzzification method and consists of selecting the value corresponding to the center of gravity of the solution set.

$$u = \frac{\int_u u.\mu^{conseq}(u)du}{\int_u \mu^{conseq}(u)du}$$

5.2.3 PERFORMANCE OF THE MODEL

In order to conduct quantitative comparison both the training datasets as well as the validation data sets were fed in to the model and the defuzzified crisp values were plotted with observations. RMSE (Root mean square error value), R^2 (coefficient of determination) value and E (Nash coefficient of efficiency) were used to evaluate the model performance. RMSE is given by,

$$RMSE = \sqrt{\frac{1}{n}(\sum_{1}^{n}(x_i - x_i^m)^2)},$$

Where x_i is the observed value of the i^{th} data set and

x_i^m is the respective model output.

The ideal value for RMSE is 0. Coefficient of determination is a statistical measure of how well the regression line approximates the real data points. An R^2 of 1 indicates that the regression line perfectly fits the data. When the RMSE is minimum and R^2 is high (> 0.8), a model can be judged as very good (Strik et.al, 2005). Nash efficiency is given by the expression,

$$E = 1- \frac{\sum_{i=1}^{n}(x_0^i - x_m^i)^2}{\sum_{i=1}^{n}(x_0^i - \overline{x}_0)^2}$$

Where x_o is the observed value , x_m is the modeled value ,x^i is the output of the i^{th} data set, $\overline{x}_0$ is the mean of the observations.The closer the model efficiency is to 1, the more accurate the model is (Nash and Sutcliffe ,1970).

5.3 ARTIFICIAL NEURAL NETWORK MODEL

In this study, a three- layer feed forward artificial neural network (ANN) model having four input neurons, one output neuron and seven hidden neurons was used as shown in Figure 4.8. Dissolved oxygen concentration in water bodies is influenced by a number of physical, chemical and biological factors. An attempt has been made to obtain a relationship connecting biochemical oxygen demand, total phosphorus, conductivity and alkalinity with dissolved oxygen concentration.

5.3.1 DATA NORMALIZATION

The input and output quantities were first normalized to a range of 0.1 to 0.9 with the following equations:

$$\mathbf{nP_i = 0.1 + 0.8 * (P_i - P_{min\ i})/(P_{max\ i} - P_{min\ i})}$$

$$\mathbf{nt = 0.1 + 0.8 * (t_i - t_{min\ i})/(t_{max} - t_{min})}$$

where nP_i is the normalized value, $P_{max\ i}$ and $P_{min\ i}$ are the maximum and minimum values of the ith node in the input layer and nt, t_{max}, t_{min} are the corresponding values in the output layer, respectively for all the feed data vectors. When the training was completed the simulation results were de-normalized by reversing the action.

5.3.2 TRAINING ALGORITHM USED

Tangent sigmoid function was selected between the input layer and the output layer and logarithmic sigmoid function was used between the hidden layer and the output layer. Levenberg- marquardt was the training method selected as it was reported to have fastest convergence for medium sized neural networks (Karul et.al, 2000., Math works, 2000).

The Levenberg–Marquardt algorithm is an iterative technique that locates a local minimum of a multivariate function that is expressed as a sum of squares of several non-linear real valued functions. It interpolates between the Gauss-newton algorithm (GNA) and the method of gradient descent (Lourakis and Argyros,2005). It uses an approximation to the Hessian matrix in the following Newton-like weight update

$$x_{k+1} = x_k - [J^TJ + \mu I]^{-1} J^T e.$$

Where x_k is the weights of neural network, J is the Jacobian matrix that contains network errors with respect to the weights and biases, μ is a scalar that controls the learning process and e the residual error vector. When the scalar μ is zero, the above equation is just the Newton's method, using the approximate Hessian matrix. When μ is large, the equation becomes gradient descent with a small step size. Newton's method is faster and more accurate near an error minimum, so the aim is to shift towards Newton's method as quickly as possible (Math works, 2000, Daliakopoulos et al, 2005). Thus, the value of μ is decreased after each successful step (reduction in performance function) and is increased only when a tentative step would increase the performance function. In this way, the performance function will always be reduced at each iteration of the algorithm.

The Neural Network Toolbox 6 and MATLAB release 12 (The math works Inc USA, 2000) were used for the development of the neural network models. A MATLAB code was written, which loaded the data file, trained, tested and validated the networks and the weights and bias matrices, and performances were saved in separate text files so that they can be used in Microsoft Excel as well as for further studies like sensitivity analysis and optimization.

5.3.3 GENERALIZATION

Out of the available data, 75 data sets were used for training, 15 for validation and 15 for testing. Performance of the neural network model was evaluated with the root mean square error (RMSE), coefficient of determination (R^2), and Nash efficiency (E) between the modeled output and measures of training and validation and testing data sets. The best fitting ANN model should give good prediction for training data, validation data as well as for testing data. A well-trained network should give the output with least error for training as well as validation data. Once that is done, its performance for a third set of data (testing data), which is not included in the training data or the validation data should be checked. If testing error also appears to be in the same manner as the training and validation data, it can be taken as the best-fit model (Engin et.al, 2005). An over fitted neural network typically imitates the data in the training set very successfully but generates a bad estimation for the data not included in the training. For a good generalization, over fitting should be prevented either by early stopping that involves stopping the training, when the errors for the validation set begin to rise or by regularization, which involves the modification of the performance function to assign only a minimum number of hidden layer neurons that is just sufficient for learning the system. (Karul et al, 2000., Moatar et al, 1999., Burien et al., 2001). The second method is used in this study to avoid over fitting. As there is no universal formula to fix the required number of hidden neurons, a trial and error approach was applied to select the best ANN architecture. The trial started with 4 hidden neurons and more neurons were gradually added during learning, until the optimal result was achieved in the validation data. This way, the neural network architecture with 7 hidden neurons and with tangent sigmoidal function (tansig) in the input layer and logarithmic sigmoidal function (logsig) in the output layer was finalized .the neural network topology used for dissolved oxygen prediction is shown in Figure 5.7.

Tansig(n) calculates the output according to :

$$\mathbf{n_h = 2/(1+exp(-2*n))-1,}$$

Where $\mathbf{n_h}$ is the output from the hidden layer, and $\mathbf{n = W_1 * P + b_1}$

where $\mathbf{W_1}$ is the weight matrix connecting input and the hidden layer,

$\mathbf{P}$ is the input matrix

$\mathbf{b_1}$ is the bias .

Final output can be expressed in the form:

$$\mathbf{t_m = logsig\ (W_{2*}n_h+b_2) = 1/(1+exp(-(W_{2*}(2/(1+exp(-2* (W_1*P + b_1)))-1)+b_2)),}$$

Where

$\mathbf{W_2}$ and $\mathbf{b_2}$ are the weight and bias matrices connecting the hidden layer and the output layer.

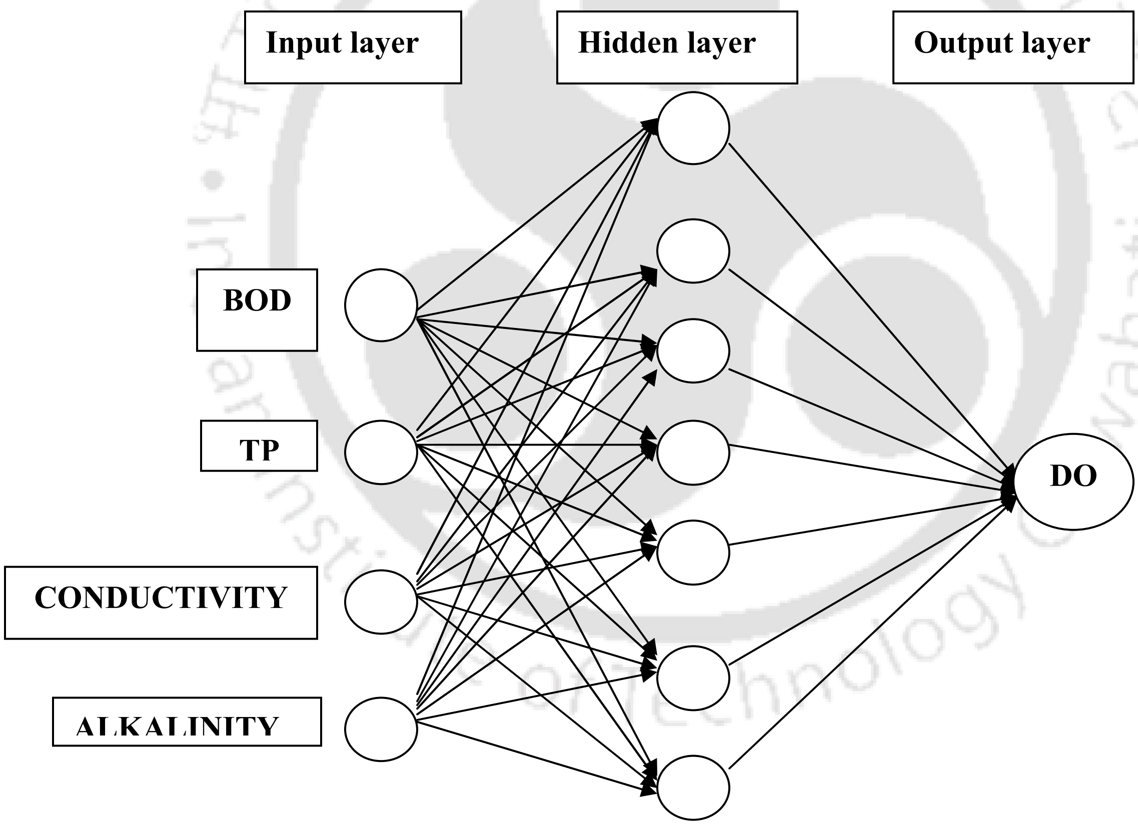


Figure 5.7 Neural network topology used in the study

5.4 MULTIPLE LINEAR REGRESSION MODEL

The empirical relation is derived on the basis of obtained experimental results for predicting dissolved oxygen in terms of BOD, TP, conductivity and alkalinity. Assuming the variables agrees with the linear model,

$Y=X\beta$, where

Y is the n-by-1 matrix of output parameter,

X is the n-by-p matrix of input parameter,

β is the p-by-1 matrix of coefficients

β and ε are evaluated and the output variable was calculated by resubstituting the values.

In the first trial the relationship tried was

$$t_n = K_1 + K_2 * p_{1n} + K_3 * p_{2n} + K_4 * p_{3n} + K_5 * p_{4n} \qquad (4)$$

where t_n is the output for the n^{th} data set,

P_{1n} , P_{2n} , P_{3n} & P_{4n} are the input variable for the n^{th} data set ,

K_2 , K_3 , K_4 & K_5 are the regression coefficients and

K_1 is the constant where the regression line intercepts the y axis representing the amount the dependant t_n will be when all the independent variables are zero.

It can be represented in the matrix form as

$Y=X\beta$

$$Y=\begin{Bmatrix} tr_1 \\ tr_2 \\ . \\ . \\ tr_n \end{Bmatrix} \quad X=\begin{Bmatrix} 1 & p_{11} & p_{21} & p_{31} & p_{41} \\ 1 & p_{12} & p_{22} & p_{32} & p_{42} \\ . & . & . & . & . \\ . & . & . & . & . \\ 1 & p_{1n} & p_{2n} & p_{3n} & p_{4n} \end{Bmatrix} \quad \beta=\begin{Bmatrix} K_1 \\ K_2 \\ K_3 \\ K_4 \\ K_5 \end{Bmatrix}$$

X is known as the sensitivity matrix. Using the least square method β can be estimated as

$$\beta = (X^T X)^{-1} X^T Y = V X^T Y.$$

R^2 value was checked after resubstituting the regression coefficients. In the next trial relation of the following form was used to check whether it could give better performance.

$t_r = K_1 * P_1^{K_2} * P_2^{K_3} * P_3^{K_4} * P4^{K_5}$, which was made into linear form by taking the logarithmic form as ,

$$\log t_r = \log K_1 + K_2 * \log P_1 + K_3 * \log P_2 + K_4 * \log P_3 + K_5 * \log P_4.$$

In this case,

$$Y = \begin{Bmatrix} \log(t_{r1}) \\ \log(t_{r2}) \\ . \\ . \\ \log(t_{rn}) \end{Bmatrix} \quad X = \begin{Bmatrix} 1 & \log(p_{11}) & \log(p_{21}) & \log(p_{31}) & \log(p_{41}) \\ 1 & \log(p_{12}) & \log(p_{22}) & \log(p_{32}) & \log(p_{42}) \\ . & . & . & . & . \\ . & . & . & . & . \\ 1 & \log(p_{1n}) & \log(p_{2n}) & \log(p_{3n}) & \log(p_{4n}) \end{Bmatrix} \quad \beta = \begin{Bmatrix} k_1 \\ k_2 \\ k_3 \\ k_4 \\ k_5 \end{Bmatrix}$$

The results were compared with the results of the ANN model in terms of R^2 value, RMSE value and Nash-Sutcliff model efficiency coefficient.

5.5 USE OF ANN FOR PARAMETRIC STUDIES

5.5.1 ASSESSMENT OF CONTRIBUTION OF INPUT VARIABLES

Convinced by the predictive quality of artificial neural network model in the present work, studies on their explanatory capacity were carried out. Influence of each variable in terms of its contribution to the output was first found out. Partial derivative method (PaD) was used to analyze the contribution of inputs. Algorithms were obtained from the study done by Gevrey et.al (2003). However in ecology relationships are the results of multivariate and nonlinear conditions and phenomena are rarely due to a simple cause or to a unique perturbation. Hence modification of PaD method, which uses the second order derivative suggested by Gevrey et.al (2006), was used to analyze the contribution of all possible pair-wise combinations of input variables, taking into account two-way interaction between variables.

For a network with ni inputs, one hidden layer with nh neurones, and one output, the partial derivatives of the output yj with respect to input xj (with j_ 1, . . ., N and N the total number of observations) are:

$$d_{ji} = D_j * (\sum_{nh=1}^{nh} (w_2(1, nh) * y_1(nh, j) * (1 - y_1(nh, j) * w_1(nh, i)))$$

Where Dj is the derivative of the output neuron with respect to its input and is given by,

D = y_2 (1-y_2) and

y_2 = response vector of the given data set.

y1 (nh, j) is the response of the h^{th} hidden neuron, w2 and w1 are the weights between the output neuron and h^{th} hidden neuron, and between the i^{th} input neuron and the h^{th} hidden neuron.

The relative contribution of the ANN output to the data set with respect to an input is calculated by a sum of the squared partial derivatives obtained per input variable:

$$SSD_i = \sum_{j=1}^{N} (d_{ji})^2$$

One SSD (Sum of Square Derivatives) value is obtained per input variable. The SSD values allow classification of the variables according to their increasing contribution to the output variable in the model. The input variable that has the highest SSD value is the variable, which influences the output variable most (Gevrey et.al 2003).

By considering two-way interactions, the PaD2 algorithm uses the computation of the partial derivatives of the ANN output with respect to the two inputs. Two types of results can be obtained. The first one is a profile of the output variation for small changes of two input variables, and the second is the relative contribution of a paired-input variable to the network output perturbations. For a network with ni inputs, one hidden layer with nh neurons, and one output, the partial derivatives of the output yi with respect to inputs x_{ij} and $x_{i+1\ j}$ (with j=1, . . . N and N the total number of observations and with x_i and x_{i+1} the two inputs which constitute the interaction studied) are:

$$d_j = \frac{D*((1-2y_2)*(\sum_{nh=1}^{nh}(w_2(1,nh)*y_1(nh)*(1-y_1(nh))*w_1(nh,i+1))+}{\sum_{nh=1}^{nh}(w_1(nh,i)*w_1(nh,i+1)*w_2(1,nh)*y_1(nh)*(1-y_1(nh))*(1-2*y_1(nh)))}$$

When D is the derivative of the output neuron with respect to its input, an is given by $D = y_2(1-y_2)$ and

y_2 = response vector of the given data set.

$y_1(nh)$ the response of the h^{th} hidden neuron, $w_2(1,nh)$ the weight between the output neuron and h^{th} hidden neuron, and w1 (nh, i) and w_1 (nh, i+1) are, respectively, the weights between the first studied input neuron and the h^{th} hidden neuron and between the second studied neuron and the h^{th} hidden neuron.

The relative contribution of the ANN output to the data set with respect to a pair of input is the sum of the squared partial derivatives obtained per pair of input variables:

$$ssd = \sum_{1}^{N}(d_j)^2$$

The value of sum of square derivatives (SSD) is obtained per pair of input variables. The SSD values allow the classification of the interactions according to their increasing contribution to the output variable in the model. The pair of input variables that has the highest SSD value is the pair that influences the output most (Gevrey et.al (2006). These calculations were done by writing the code in MATLAB environment by calling out the text file containing the weights and bias matrices of the optimized neural network.

5.5.2 VARIABLE OPTIMIZATION USING CONTOUR PLOTS

In this study contours were drawn by keeping the values of two parameters fixed (lower values in one trial and the higher values in the next trial) and giving some increment for other two parameters so as to cover the whole domain used for the study. Contour plots provide some clue for the decision makers about the range of input parameters to be maintained so that the output parameter can be maintained with in the safe or the desirable level. Maximum value was selected such that beyond which the system no longer can maintain the dissolved oxygen in the acceptable level. Four sets of contour plots were prepared.

1. Contour plots for DO concentrations vs TP and BOD, when

(a) Conductivity = 50 μS/cm and alkalinity = 25 mg/L,

(b) Conductivity = 300 μS /L and alkalinity =150 mg/L

2. Contour plots for DO concentration vs conductivity and alkalinity when

(a) BOD = 0 mg/L, TP = 0.03 mg/L (b) BOD =10 mg/L, TP= 1 mg/L.

3. Contour plots of DO concentration vs conductivity and BOD when

(a) alkalinity = 25 mg/L, TP = 0.04 mg/L. (b) alkalinity = 180 mg/L. TP = 1 mg/L.

4. Contour plots of DO concentration Vs conductivity and TP when

(a) BOD = 0 mg/L, alkalinity = 25 mg/L, (b). BOD = 8 mg/L, alkalinity = 200 mg/L.

After obtaining the contour plots for some specific values, original data sets with output values above the desirable level were selected to obtain contour plots. This was done to have a comparison and to check the reliability of the contour plots in parametric studies.

5.6 SUMMARY

Based on the correlation coefficient the variables that were strongly correlated with dissolved oxygen could be identified and those variables were selected as the input variables for developing models. Three data driven models namely the fuzzy rule based model, the artificial neural network model and the multiple linear regression model were developed. Tuning of fuzzy rule based model was carried out by adding more fuzzy sets and adding more rules to cover the entire pattern of the generated data sets. The ANN model was tuned by optimizing the number of neurons in the hidden layer and then assigning different transfer functions for the input layer and the output layer. The best-fit model was arrived at by comparing the RMSE and R^2 values obtained in each trial and selecting that which produced the least RMSE. The purpose of developing multiple linear regression models was to have a comparison with the artificial neural network. Nash efficiency coefficient was also found to assess the predictive power of the model. Parametric studies were carried out to identify the most influencing parameter and to find out the optimum range of each parameter to maintain the safe level of dissolved oxygen.

CHAPTER
SIX

RESULTS AND DISCUSSION ON MODEL PERFORMANCE

6.1 RESULTS OF FUZZY RULE BASED MODELING

Based on the correlation coefficients between different parameters four sensitive parameters, the BOD), (TP), conductivity and alkalinity were selected as input variables to predict DO for the environmental system under study to develop a fuzzy rule based model and an artificial neural net work model.

On examining the data sets 59 rules of different combinations were to be created to cover the complete domain of all the input parameters. Out of the generated data sets those used for creating the rule base for the fuzzy logic model were taken as training data and the remaining 46 data sets were taken as the testing data. Platform selected for the fuzzy logic expert system was MATLAB (version 6.0.0.88 Release 12) and Matlab's fuzzy logic toolbox. Variables were combined using the concept 'AND'. Fuzzy operator 'minimum' operator was applied as the 'AND' function to combine the variables. The results of the evaluation process were obtained by aggregation of all consequences using the maximum operator function. The centroid, or centre of gravity, method was applied as a means of defuzzification of the output membership functions to determine a crisp set.

Plots of the observed data and estimated values obtained from the fuzzy model are given in Figures 6.1 and 6.2 for training data and the testing data respectively. The predictive accuracy of the fuzzy model is very reasonable. Estimated DO values from the fuzzy logic model were found to be agreeing with the observed DO values with a coefficient of determination of 0.9446 and RMSE of 0.72 for the training data and a coefficient of determination of 0.9195 and RMSE of 0.97 for the testing data. Nash efficiency was observed to be 0.997 for training data and 0.91 for testing data. It was observed that accuracy of the model results depends mainly on the number of fuzzy regions and the fuzzy rules based on all possible combinations. In this study DO level of 0 mg/L to 2.5 mg/L is assigned a fuzzy region termed as 'highly objectionable' and 2 mg/L to 4 mg/L is assigned a fuzzy region termed as 'objectionable'.

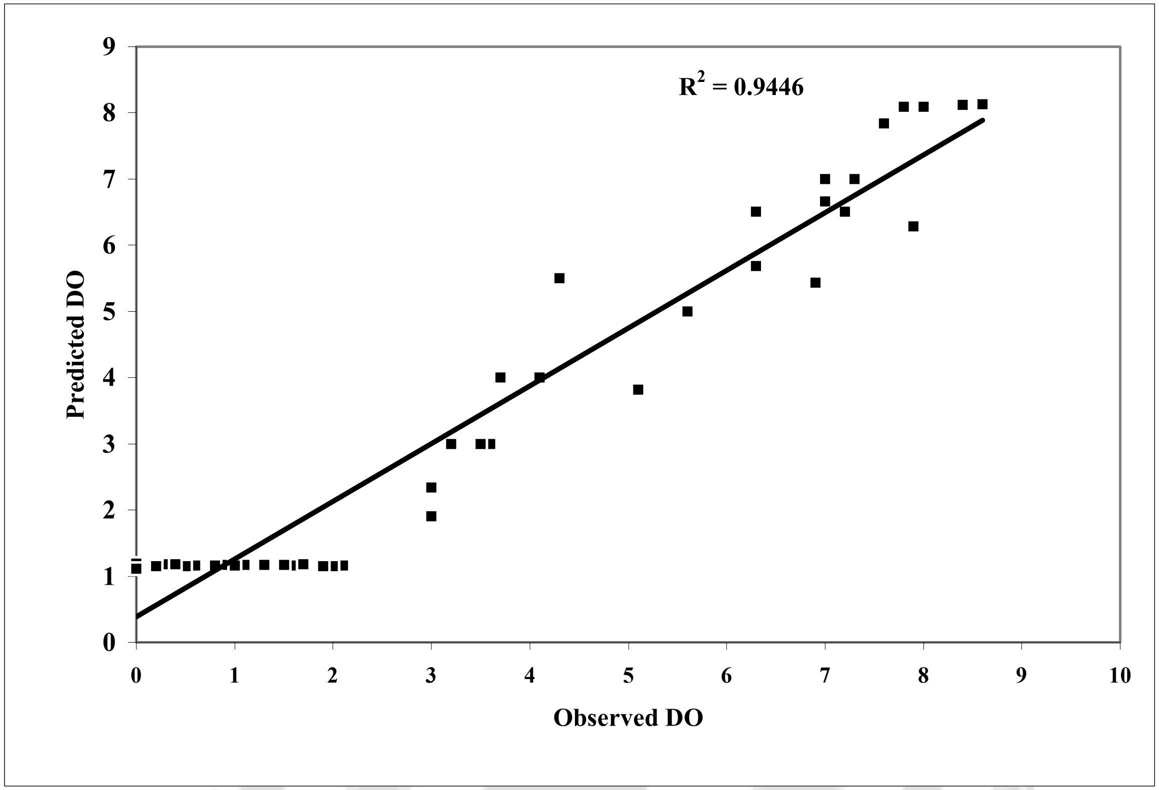


Figure 6.1. Results of fuzzy model for training data

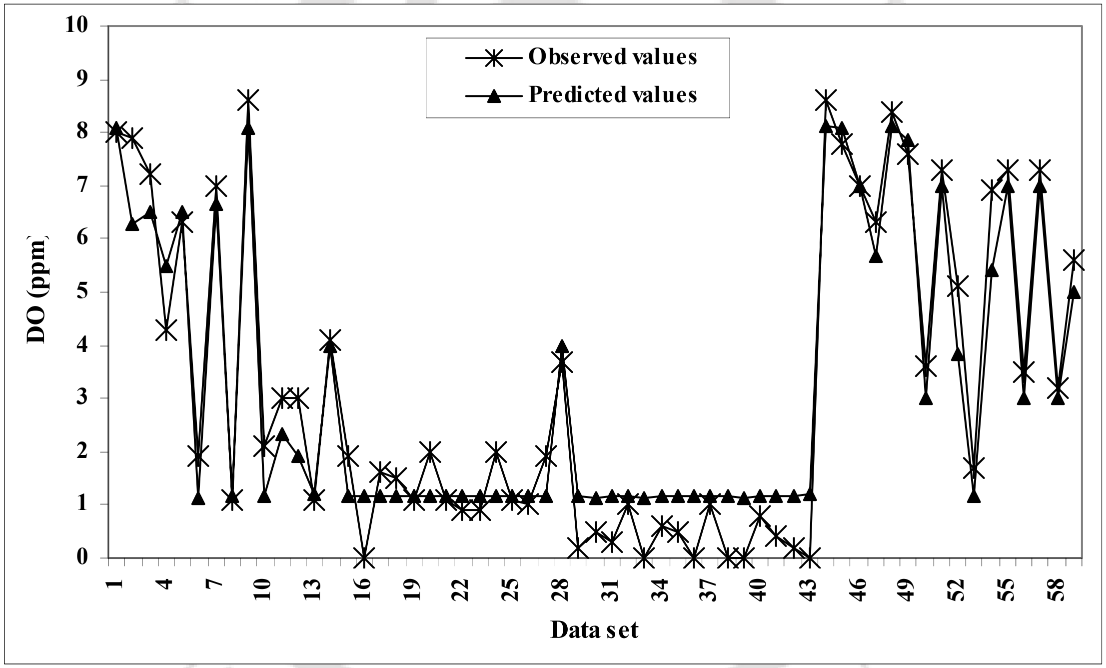


Figure 6.2. Performance of fuzzy model for training data

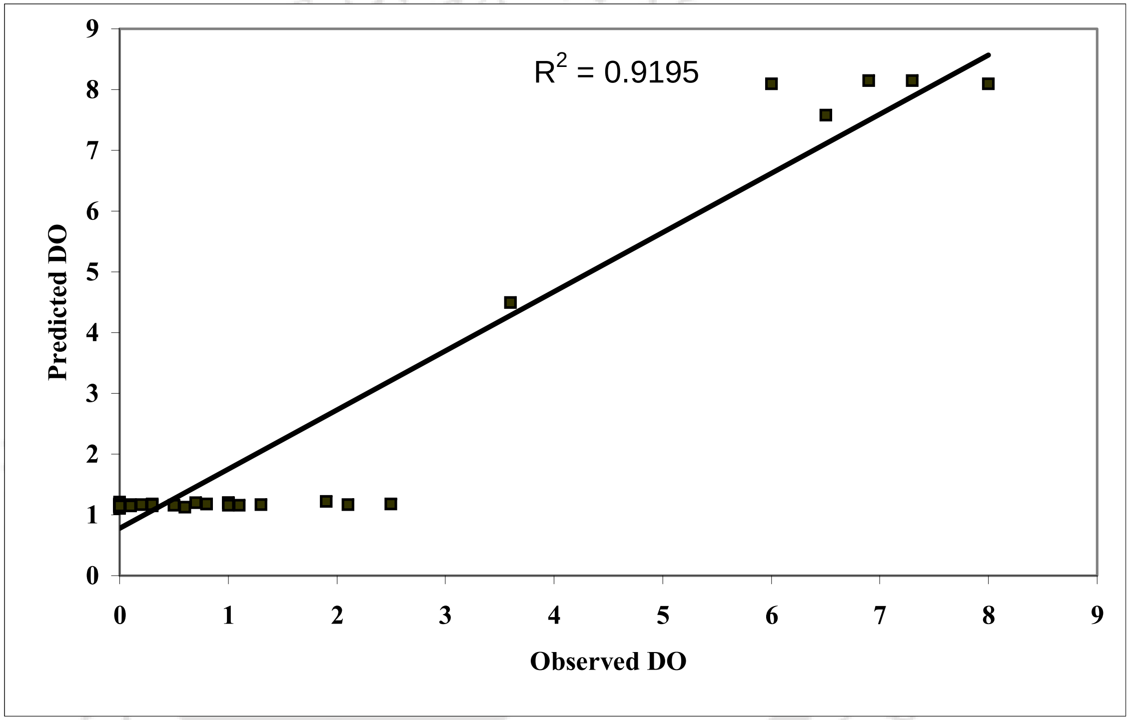


Figure 6.3 Results of fuzzy model for validation data.

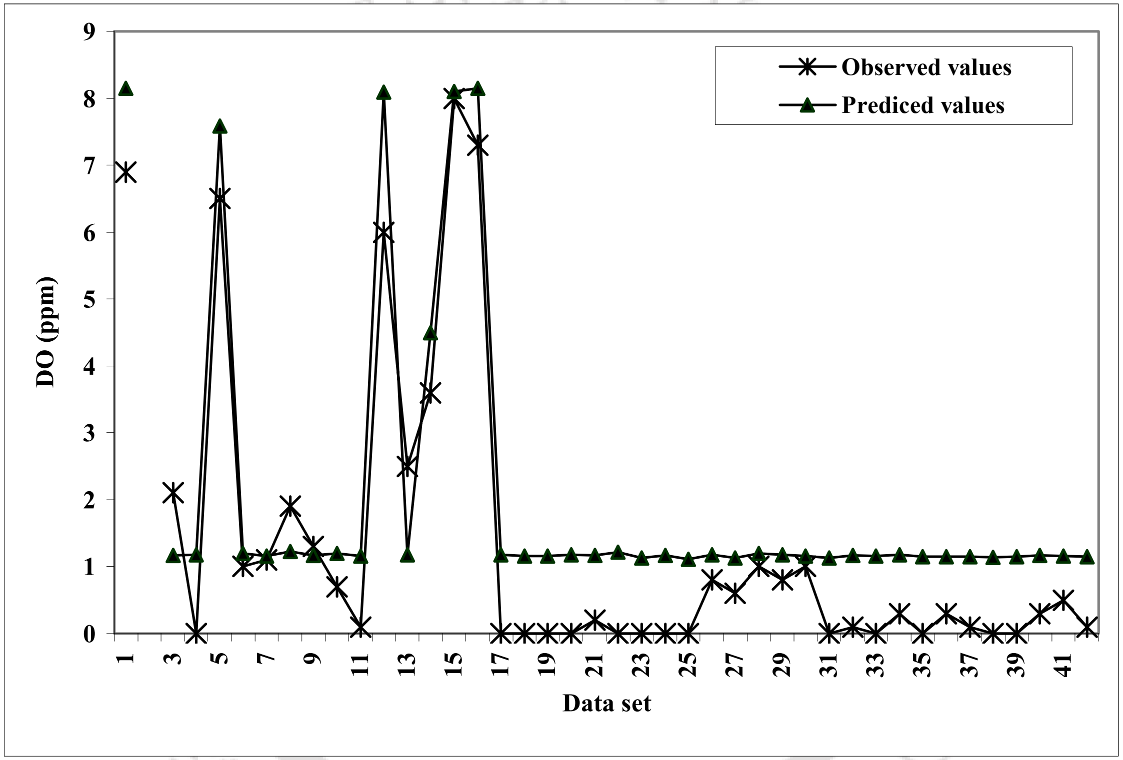


Figure 6.4 Performance of fuzzy model for validation data

Results would have been more accurate if more number of fuzzy regions could be included in between. But including fuzzy region for the DO levels below 4 mg/L was considered meaningless in the practical sense as the whole region between 0 mg/L and 4 mg/L is considered highly objectionable.

While creating rule base and validating the model, it was observed that fuzzy rule based models produce some unexpected failure. In particular, they are not able to predict the output for an input data pattern, which is unknown to the model. This concludes that the fuzzy rule based model is appropriate when it is possible introduce all the possibilities in the rule base, as in the case of some mechanical or electronic tool. But this is not the case with ecological modeling. When natural phenomena have to be dealt with, the number of possible combinations may be large and the drawback observed in this model will affect the prediction accuracy adversely.

6.1.1 CONCLUSIONS

Construction of a fuzzy rule based model is comparatively easy. The model is data driven and can be trained further with every new set of data. The linguistic structure of the model makes it transparent and easy to understand. The predictive accuracy of the fuzzy model is quite reasonable. It was observed that accuracy of the model results depends mainly on the number of fuzzy regions and the fuzzy rules based on all possible combinations.

Though fuzzy rule based models produced satisfactory results some drawbacks were observed while developing rule base. Accuracy of the results increases with increase in membership functions with in the regions. This model is not able to execute a forecast in some testing cases when the input vectors do not satisfy any “IF” condition of the trained/calibrated rules. This concludes that the fuzzy rule based model is certainly appropriate when it is possible introduce all the possibilities in the rule base, as in the case of some mechanical or electronic tool, but it may not be totally reliable when dealing with natural phenomenon where the number of possible combinations may be extremely large as the model can not produce results for the input combinations that was not considered in the training phase.

6.2 ARTIFICIAL NEURAL NETWORK MODEL PERFORMANCE.

In this study a three- layer feed forward artificial neural network (ANN) model having four input neurons, one output neuron and seven hidden neurons gave satisfactory results. As the number of hidden neurons in the hidden layer can vary, and will affect the quality of the ANN, an optimal number of hidden neurons were to be determined for the neural network to achieve the best performance. As there is no universal formula to fix the required number of hidden neurons, a trial and error approach was applied to select the best ANN architecture. The trial started with 4 hidden neurons and gradually added more during learning, until the optimal result was achieved in the validation data. Figure 5.23 shows the effect of hidden layer neurons on the performance of the ANN in the study. This way the neural network architecture with 7 hidden neurons and with tangent sigmoidal function in the input layer and logarithmic sigmoidal function in the out put layer was finalized.

The RMS errors for the predicted results were 0.3222, 0.4994 and 0.5657 with coefficients of determination of 0.9808, 0.9132 and 0.9563 and Nash efficiency coefficient of 0.981, 0.970 and 0.962 for training data, testing data and validation data respectively. Expression for output derived out from the ANN model is of the form,

$$\mathbf{t_m = logsig(W_2*nh+b_2) = 1/(1+exp(-(W_2*(2/(1+exp(-2*(W_1*P + b_1))) -1)+b_2)),}$$

Where W1 is the weight matrix connecting input and the hidden layer,

P is the input matrix

$\mathbf{b_1}$ is the bias .

$\mathbf{W_2}$ and $\mathbf{b_2}$ are the weight and bias matrices connecting the hidden layer and the output layer.

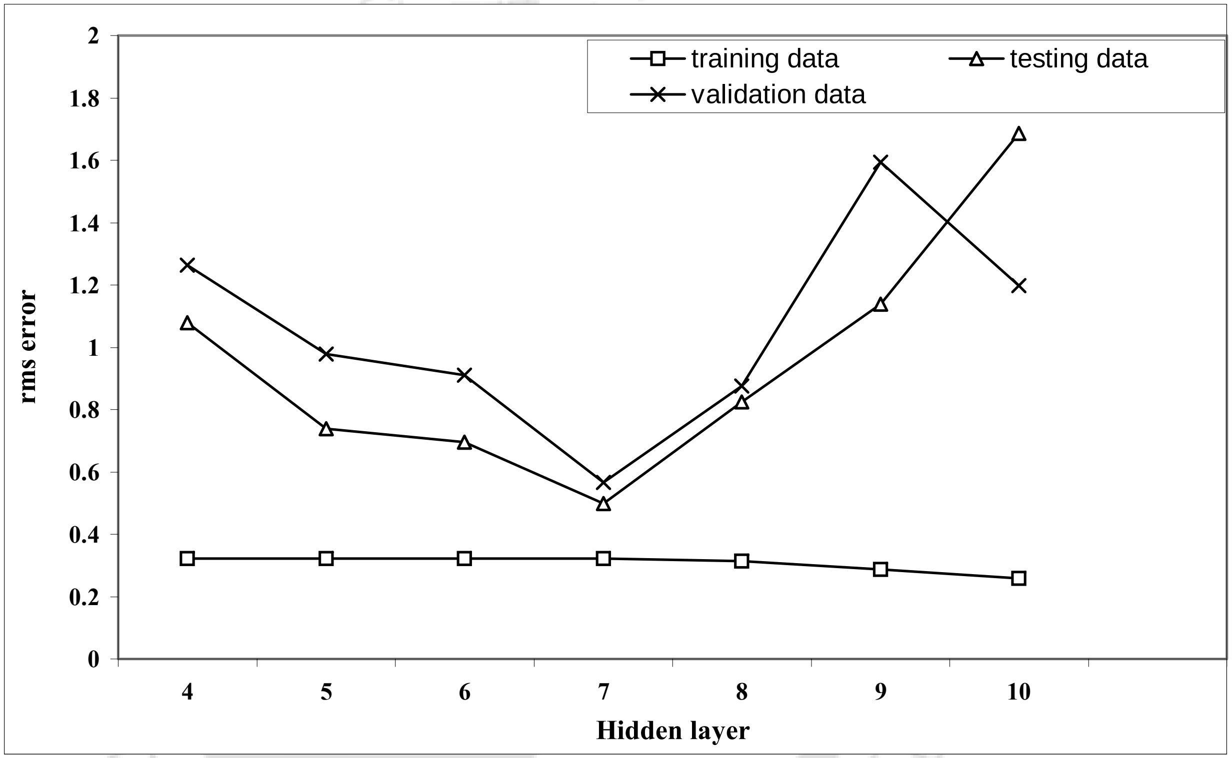


Figure 6.5 Plot of rms error against number of neurons in the hidden layer for ANN modelling

6.3 DO PREDICTION USING MULTIPLE LINEAR REGRESSION MODEL

In the first trial the assumed linear equation was,

$$\mathbf{t_n = K_1 + K_2 * P_{1n} + K_3 * P_{2n} + K_4 * P_{3n} + K_5 * P_{4n}}$$

where $\mathbf{t_n}$ is the output for the nth data set,

$\mathbf{P_{1n}}$, $\mathbf{P_{2n}}$, $\mathbf{P_{3n}}$ & $\mathbf{P_{4n}}$ are the input variable for the nth data set ,

$\mathbf{K_2}$, $\mathbf{K_3}$, $\mathbf{K_4}$ & $\mathbf{K_5}$ are the regression coefficients and

$\mathbf{K_1}$ is the constant where the regression line intercepts the y axis representing the amount the dependant $\mathbf{t_n}$ will be, when all the independent variables are zero.

The R-square value, which is the ratio of regression sum of squares to the total sum of squares was calculated and observed to be 0.4998 as shown in the Figure 6.6.

In the next trial relation of the following form is used:

$$\mathbf{t_r = K_1 * (P_1)^{K_2} * (P_2)^{K_3} * (P_3)^{K_4} * (p_4)^{K_5},}$$

which was made in to linear form by taking the logarithmic form as :

$$\mathbf{\log t_r = \log K_1 + K_2 * \log P_1 + K_3 * \log P_2 + K_4 * \log P_3 + K_5 * \log P_4}$$

Here, better prediction compared to the previous case was obtained with coefficient of determination (R^2) of 0.8371 and an RMS error value of 1.07, whereas for the ANN model, the R^2 value and RMS error were 0.9808 and 0.322 respectively. This justifies the use of ANN for the present study. Figures 6.7(i) and (ii) shows the training of the ANN model and MLR predictions, respectively. ANN model predicted the experimental DO values with a coefficient of determination (R^2) of 0.9808 and RMS value of 0.3222 showing better agreement than those of MLR with the coefficient of determination (R^2) of 0.8371, RMS error value of 1.07, and Nash efficiency coefficient of 0.789. Figure 6.8 (i) and (ii) shows the coefficients of determination (R^2) of 0.9716 and 0.9481 for the testing data for ANN and MLR model. The coefficients of determination of (R^2) of 0.9673 and 0.8855 were obtained for validation data for ANN model and MLR model respectively, as shown in Figure 6.9 (i) and (ii). RMS error values for the ANN and MLR model output for the testing data were 0.49 and 1.61 respectively and that for validation data were 0.56 and 1.84 respectively. The Nash efficiency coefficient for MLR model

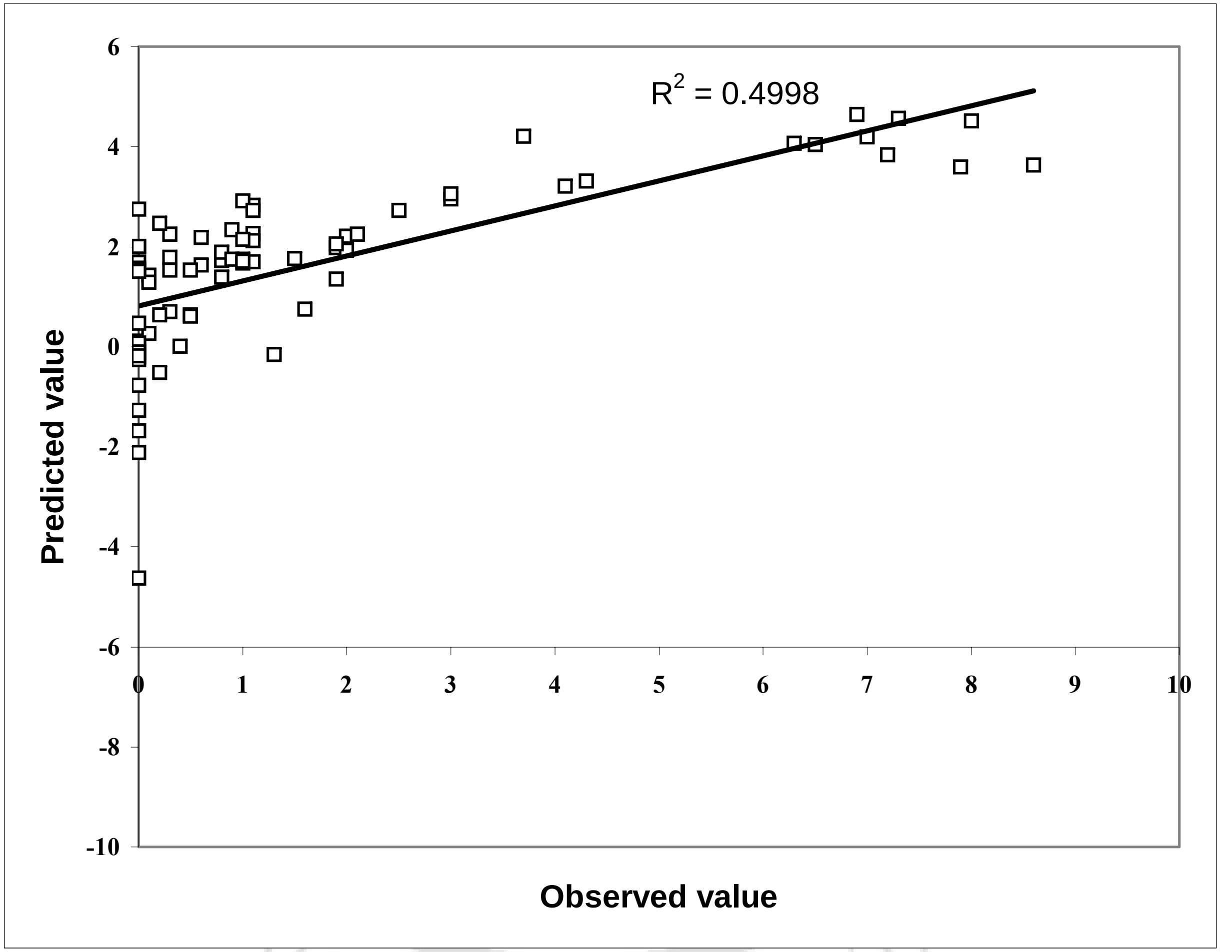


Figure 6.6 Results of MLR using simple linear equation for DO prediction

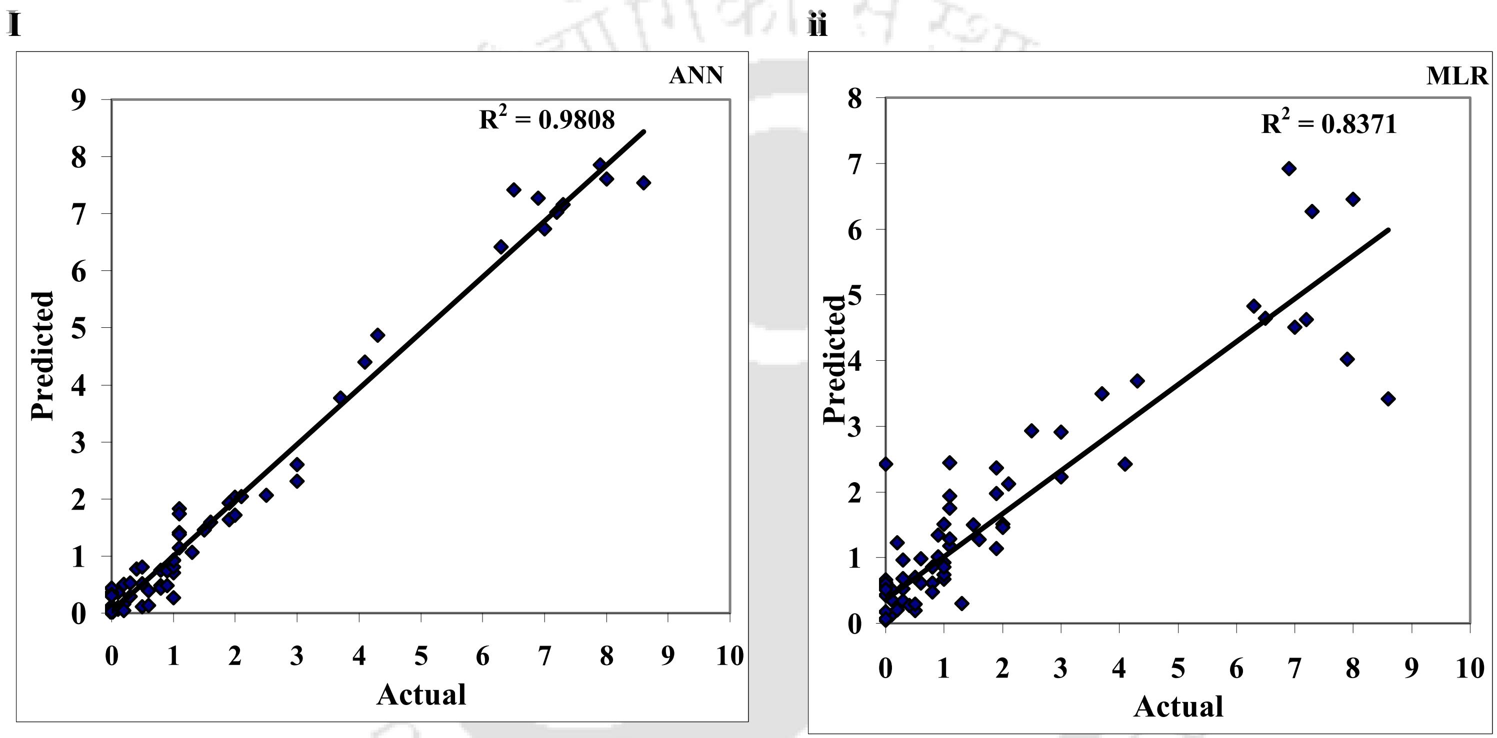


Figure 6.7 Results of (i) ANN simulations and (ii) MLR simulations of training data for DO prediction.

i. ii.

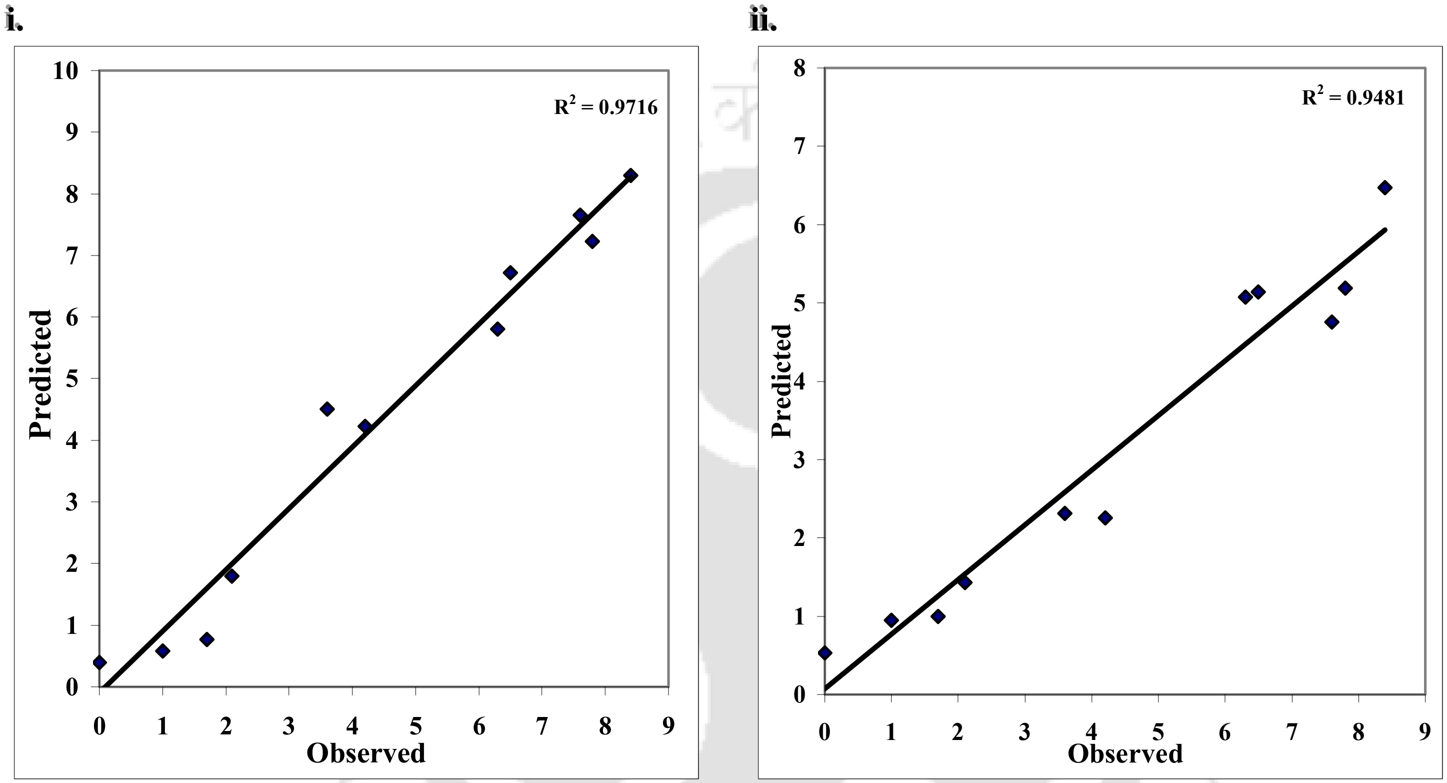


Figure 6.8 Results of (i) ANN simulations and (ii) MLR simulations of testing data for DO prediction.

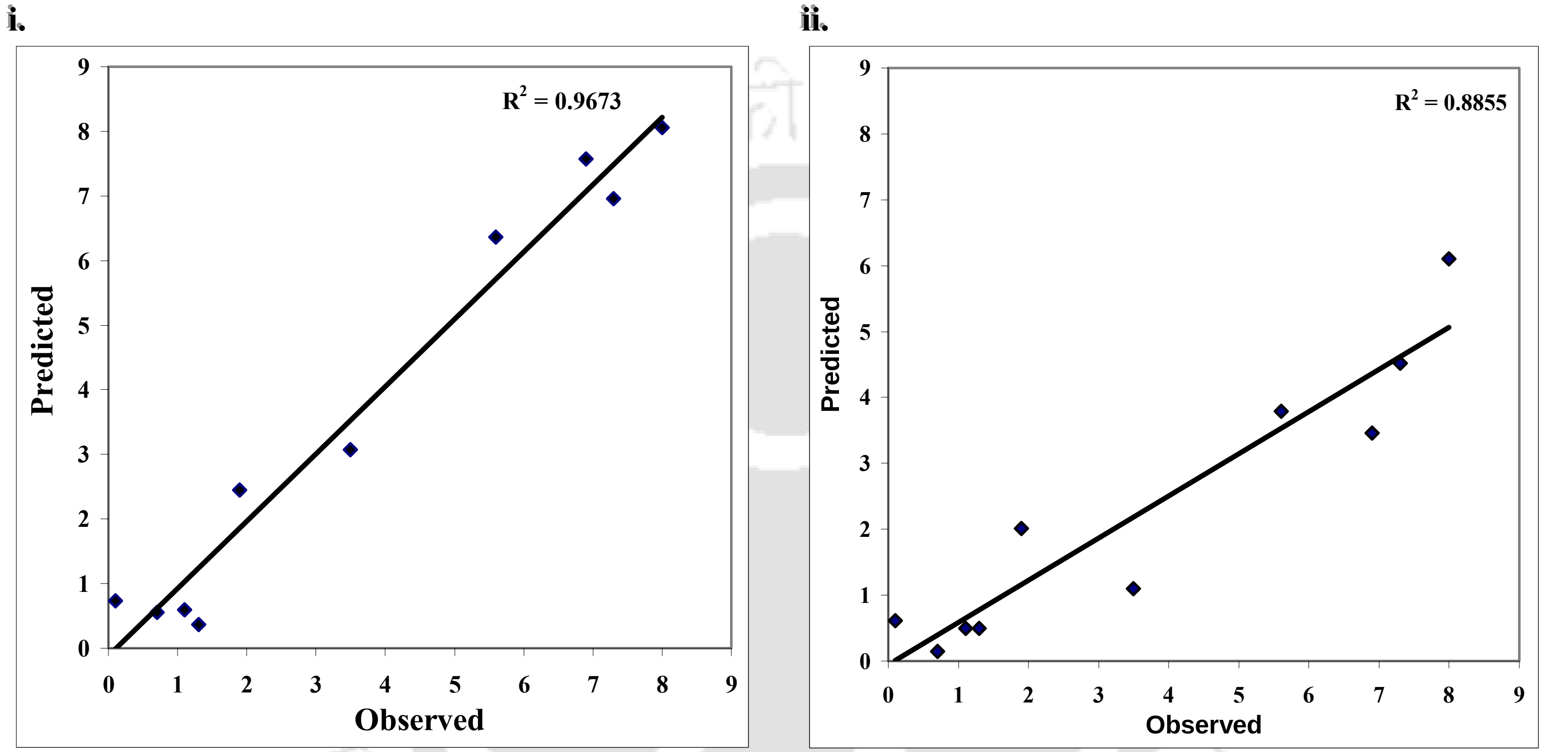


Figure 6.9 Results of (i) ANN simulations and (ii) MLR simulations of validation data for DO prediction

was found out to be 0.681 and 0.593 for testing data and validation data respectively. Thus, ANN model predictions were able to follow the trend better, as compared to those with MLR model prediction as shown in Figure 6.10.

The equation derived from MLR model is:

$$\mathbf{t_r = -3.2568*(P_1)^{-0.6167}*(P_2)^{-0.1083}*(p3)^{-0.5095}*(p4)^{-0.0750}}$$

Where $\mathbf{t_r}$ is the out put (dissolved oxygen)

$\mathbf{P_1}$, $\mathbf{P_2}$, $\mathbf{P_3}$ and $\mathbf{P_4}$ represents BOD, TP, Conductivity and Alkalinity respectively.

6.4 CONCLUSIONS ON MODEL PERFORMANCE

On comparing fuzzy rule based model and artificial neural network model the models considered present different levels of reliability. Fuzzy rule based model is not able to execute a forecast in some testing cases where the input vectors do not satisfy any "IF" condition of the trained/calibrated rules. This lack of response can suggest that the fuzzy logic approach is appropriate only when the enumeration of all the possibilities can be included, as in the case of some mechanical or electronic tool, but it may not be totally reliable when dealing with natural phenomenon where the number of possible combinations may be extremely large. The ANN model does not present this problem since, given its own architecture, for each input vector an output vector is always obtained through the transfer functions of the hidden and the output layers. The study indicates that ANN can provide satisfactory results for predicting DO as a function of BOD, TP, conductivity and alkalinity. The network, which performed best, was the one with 7 hidden neurons, tangent sigmoidal function in the hidden layer and logarithmic sigmoidal function in the output layer. A comparison study of ANN with MLR proved that ANN demonstrates better performance with a coefficient of determination of 0.9808, RMSE of 0.3222 and Nash efficiency coefficient of 0.981, whereas that for MLR, it was 0.8371, 1.07 and 0.681 respectively thus justifying the use of ANN for the present study. Though named as a black box, relationship connecting the input and the output parameters could be available from the best fit neural net work model by taking out its weights and bias matrix.

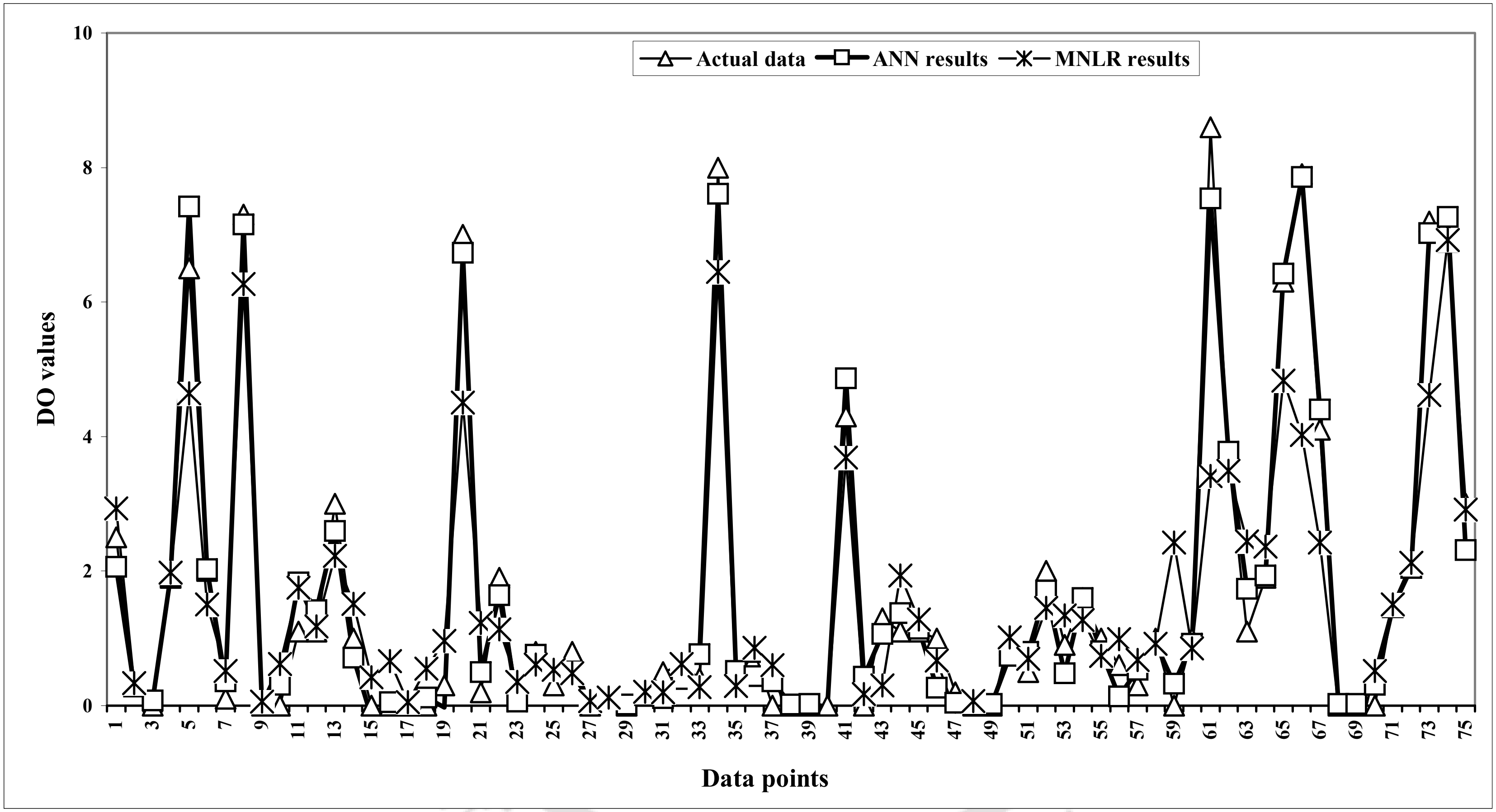


Figure 6.10 Comparison of ANN and MLR results

6.5 CONRIBUTION OF VARIABLES USING SIMULATED NEURAL NETWORK

For assessing the contribution of each input variable partial derivative method (PaD) suggested by Gevrey et al (2003) was adopted in the present study. By using partial derivative method, two results could be obtained. One is the profile of the output variation and second is the classification of relative contribution of each variable to the network output.

Figure 6.11 presents the derivative plots of PaD method. Partial derivative values of dissolved oxygen with respect to BOD were negative. This indicates that output variable decreases with increase in BOD.When microorganisms begin the process of breaking down the organic matter like dead plants, leaves manure, sewage and even food waste present in the water body, much of the available dissolved oxygen is consumed by aerobic bacteria, robbing other aquatic organisms of the oxygen they need to live. Hence higher quantity of BOD indicates large quantity of organic matter and decrease in dissolved oxygen in the water body, which is evident from the profile plot as well. Partial derivative values of DO with respect to TP are all positive and near zero at higher values. This means that dissolved oxygen increases with increase in TP but to a lesser extent for higher values. Though the ultimate effect of excess level of nutrients is the depletion of dissolved oxygen, this depletion is the result of algal crashes which ends up in high BOD and which in turn results in DO depletion. Immediate effect of algal and other submerged plant growth is the oxygen transfer into the water body during the day through photosynthesis. Partial derivative of DO with respect to conductivity are positive and negative without a precise direction. It may be due to its interaction with other variables. However the values for lower concentrations are negative. Partial derivative values for DO with respect to alkalinity are all positive which implies that an increase in alkalinity will lead to an increase of dissolved oxygen but to a lesser extent for the higher values of alkalinity. Partial derivative method showed that total phosphorus is the highest contributed variable followed by conductivity, alkalinity and BOD (Figure 6.12).

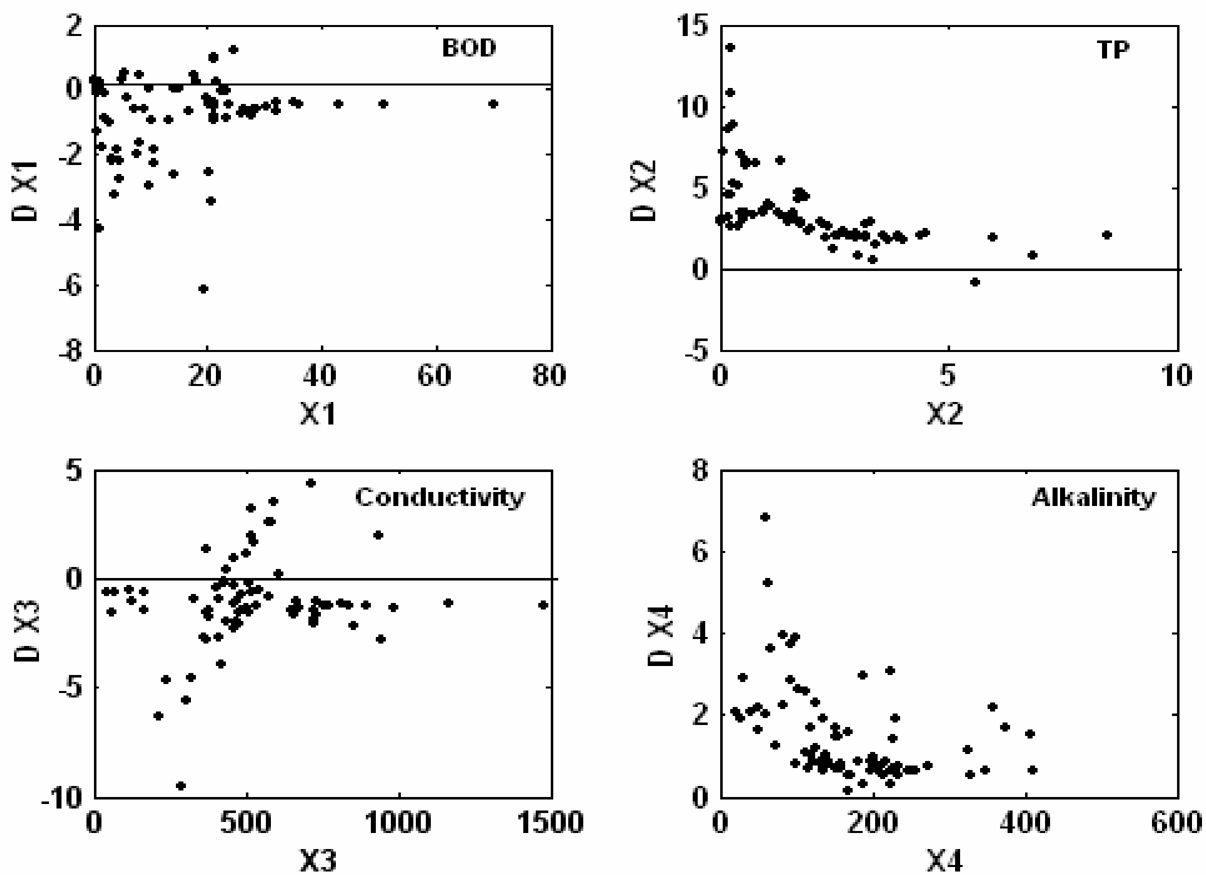


Figure 6.11 Partial derivatives of the ANN model response (DO) with respect to each independent variable.

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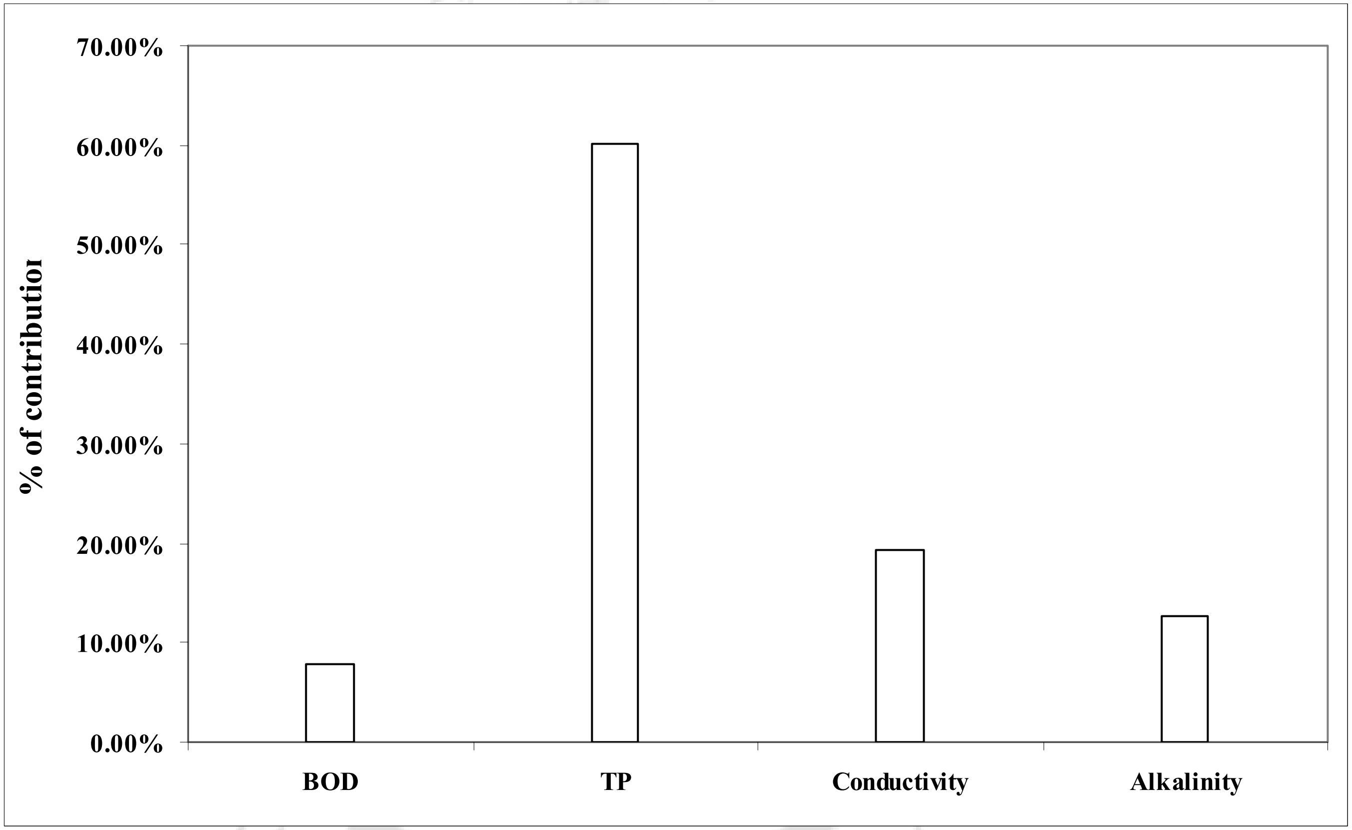


Figure 6.12. Results of partial derivative method showing relative contribution (%) of input variable

The graph of the partial derivative versus the paired variables is shown in Figure 6.13. The x and y axes represent the pair of input variables and z-axis represents the partial derivative of dissolved oxygen with respect to the paired inputs. It was observed that all partial derivatives of DO for BOD-TP interaction is almost negative. This indicates that DO decreases with increase in BOD and TP. In the case of BOD – Conductivity interaction, all partial derivative values of DO are negative for lower values of BOD and all values of conductivity, and positive for higher values of BOD and all values of conductivity, but the pattern remains stable after crossing the null value. Partial derivative values of DO are mainly negative for BOD-Alkalinity interaction and DO remains stable for higher values of BOD and alkalinity, which means dissolved oxygen decreases with increase in BOD and alkalinity. In the case of TP-conductivity interaction negative values were observed for all values of TP and high values of conductivity and with decrease in conductivity it was observed to be approaching null value. This also indicates that DO value decrease with increase in values of total phosphorus and conductivity. A clear-cut profile was not observed in the case of TP-alkalinity interaction. Negative values were observed in the case of conductivity – alkalinity interaction indicating decrease in DO for increase in the values of conductivity and alkalinity. Sum squared partial derivative values are obtained as $0.7303*10^{8}$, $4.5334*10^{8}$, $0.6206*10^{8}$, $4.3956*10^{8}$, $0.4291*10^{8}$, $1.8322*10^{8}$ respectively for BOD-TP , BOD-conductivity , BOD-alkalinity, TP-conductivity , TP-alkalinity, conductivity-alkalinity respectively. On examining the sum squared partial derivative values, it can be seen that BOD-conductivity and TP-conductivity are influencing dissolved oxygen in a similar way with former having slightly higher percentage of contribution than the latter and are the most influencing pair for the environmental system under study. Conductivity-alkalinity is the next contributing pair followed by BOD-TP, BOD-alkalinity and TP- alkalinity. Relative contribution in percentage obtained by PaD method is shown in Figure 6.14.

According to Olsen's classification on the basis of conductivity, waters with conductivity values between 250 μS/cm and 1000 μS/cm are rich in electrolyte and are characterized as eutrophic (Bellos and Sawidis, 2005). The values of conductivity used in this study belong to this range and hence the result obtained from this parametric study can be justified. Importance of TP-conductivity interaction and BOD-conductivity

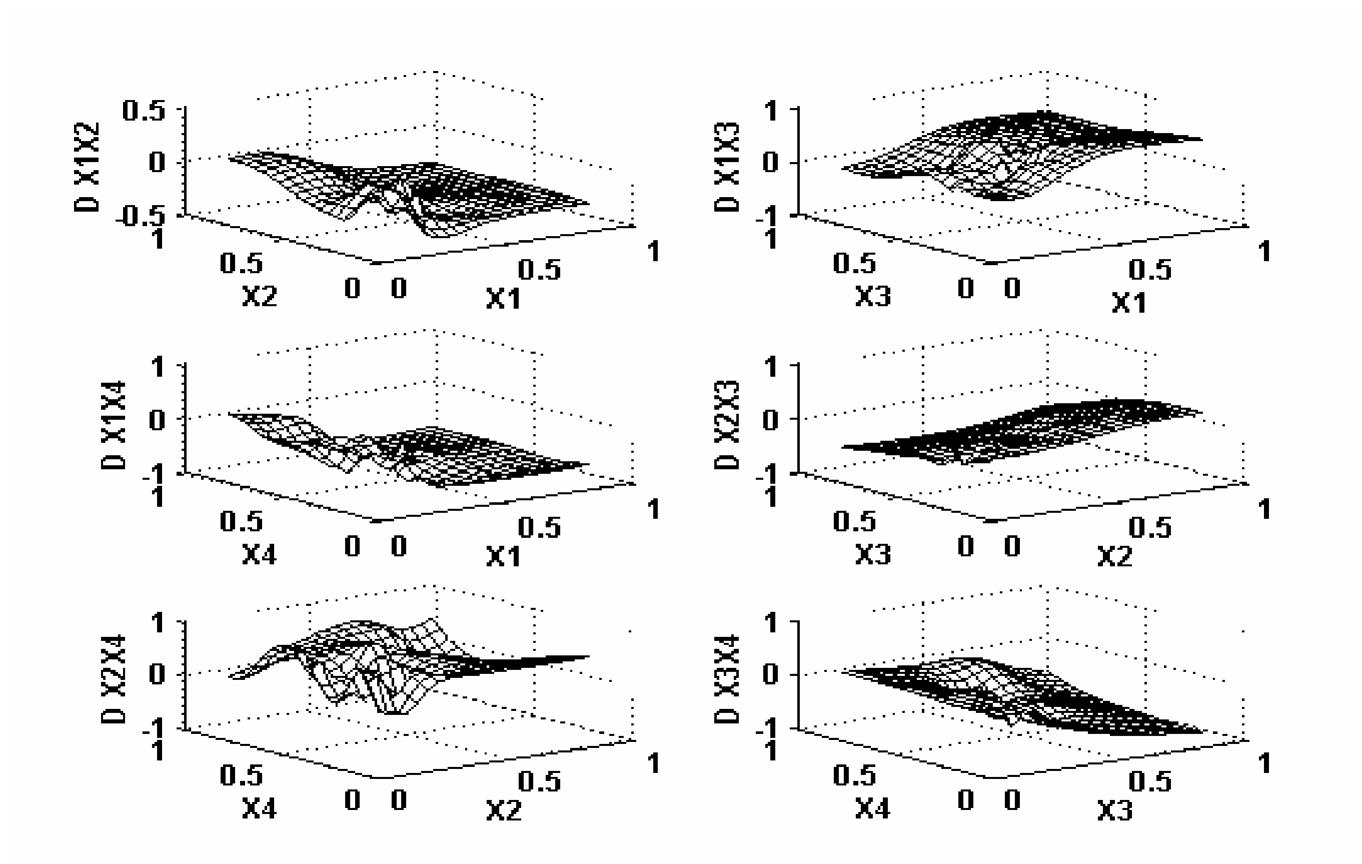


Figure 6.13 Partial derivative of DO 3D graph for two-way interaction

X1-BOD, X2-TP, X3-Conductivity, X4-Total alkalinity.

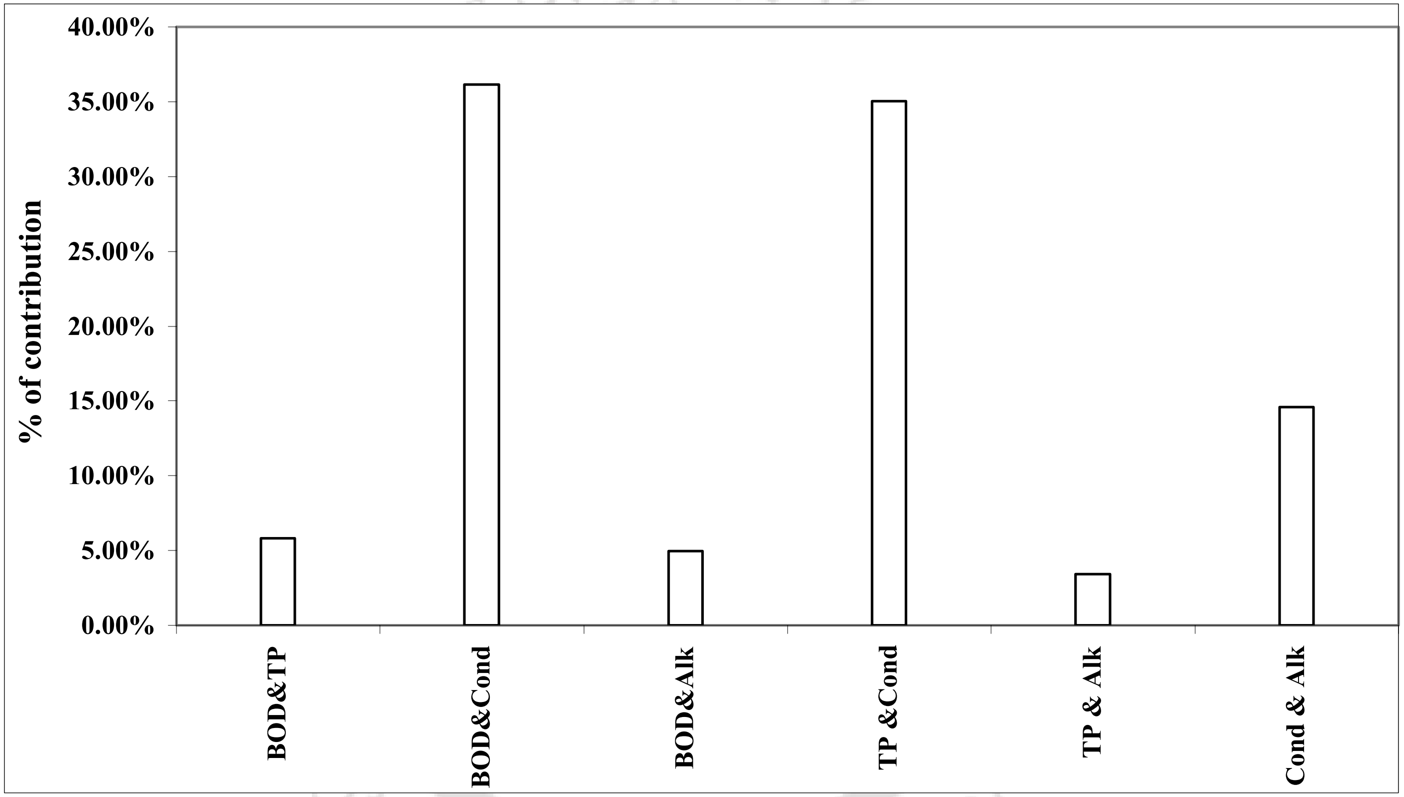


Figure 6.14. Results of partial derivative method for two-way interaction

interaction can hence be justified. Studies done by Gevrey et al (2003) and Olden et al (2004) proved that partial derivative method seemed to be the reliable methodology for assessing the contribution of input variables using simulated ANN model and this tempted to adopt partial derivative method in the present study. Another advantage of PaD method is that apart from obtaining the relative contribution of input variables, profile of the output variations for small changes of the input variables could also be obtained. It is possible to rank the inputs of the ANN one by one or by paired input combination in order of contribution.

6.5.1 CONCLUSIONS

It is clear from this study that in ecology, using a single variable sensitivity analysis may lead to misleading interpretation. In this study with single input sensitivity analysis BOD seemed to be the least contributing variable, but is having a major role with the interaction of conductivity. Hence it is evident that we must consider variable interaction since environment is composed of many characteristics acting together. Behaviour of the profile plots obtained from the two-way interaction also justifies the values of the correlation coefficient, which concludes that selection of input variable based on correlation coefficient is a reliable method.

6.6 OPTIMIZATION OF VARIABLES USING CONTOUR PLOTS

Figures 6.15, 6.16, 6.17, 6.18, 6.19, 6.20, 6.21 and 6.22 presents the contour plots of dissolved oxygen concentration as a function of BOD, TP, conductivity and alkalinity. These plots were drawn by simulating the best fit ANN model by assigning some values for two parameters and giving some increments for the other two.

Figures 6.15 and 6.16 indicate that an optimal region exists in which the dissolved oxygen concentrations can be maintained within the safe limits. BOD should be below 6 mg/L and TP should be below 1 mg/L, in order to maintain the DO above the desirable level of 6 mg/L when conductivity and alkalinity are 50 μS/cm and 25 mg/L respectively and TP values are low. BOD and TP should be below 11 mg/L and 1 mg/L respectively to maintain the DO above the minimum tolerable level of 4 mg/L. For a conductivity of 300 μS/cm and an alkalinity of 150 mg/L, DO will be within the desirable level for a BOD of 3 mg/L and TP of 0.4 mg/L. BOD should be below 8.5 mg/L and TP should be below 1.2 mg/L to maintain a DO level above the maximum tolerable level of 4mg/L.

Figures 6.17 and 6.18 indicate that an optimal region exists within which the dissolved oxygen concentration can be maintained below the safe limits. Conductivity should be below 275 µS/cm and alkalinity should be below 125 mg/L to maintain the DO level above 4 mg/L. To maintain DO concentration above 6 mg/L, conductivity should be below 225 µS/cm and alkalinity should be below 200 mg/L when BOD and TP values are the least. For values of BOD =10 mg/L and TP = 1mg/L, dissolved oxygen cannot be maintained above 6 mg/L. To maintain DO above 4 mg/L, conductivity should be below 150 µS/cm and alkalinity should be below 75 mg/L.

Figure 6.19 demonstrates that for least values of TP and alkalinity (0.04 mg/L and 25 mg/L respectively) DO can be maintained within the desirable limit by controlling the conductivity below 200 µS/cm and BOD values below 4 mg/L. BOD values can go up to 12 mg/L for conductivity values ranging from 50 µS/cm to 100 µS/cm, whereas Figure 6.20 shows that conductivity values in the range of 750 µS/cm to 1500 µS/cm and BOD values below 2 mg/L provides a safe domain of dissolved oxygen when alkalinity is 180 mg/L and total phosphorus of 1mg/L.This implies that for the range between 25 mg/L and 180 mg/L of alkalinity and total phosphorus between 0.04 mg/L to 1 mg/L, with BOD below 6 mg/L dissolved oxygen will be above the desirable range of 5 mg/L for conductivity values below 200 µS/cm and between 750 µS/cm and 900 µS/cm. Figure 6.21 shows that conductivity below 250 µS/cm and TP below 2 mg/L is the safe domain for DO for a value of BOD of 0 mg/L and alkalinity of 25 mg/L. However, BOD should be below 8 mg/L and alkalinity should be below 200 mg/L, conductivity should be between 225 µS/cm to 275 µS/cm and TP should be less than 0.2 mg/L for DO to be above the desirable level of 6 mg/L as shown in Figure 6.22.

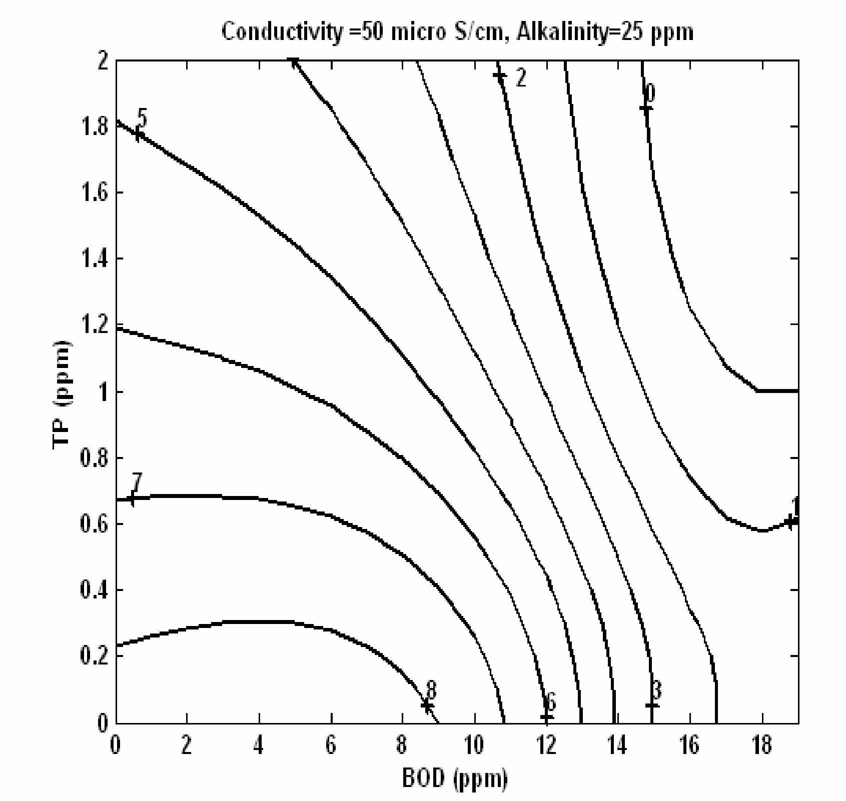


Figure 6.15 Contour plots for concentrations of DO vs TP and BOD, when conductivity =50 µS/cm & alkalinity = 25 mg/L.

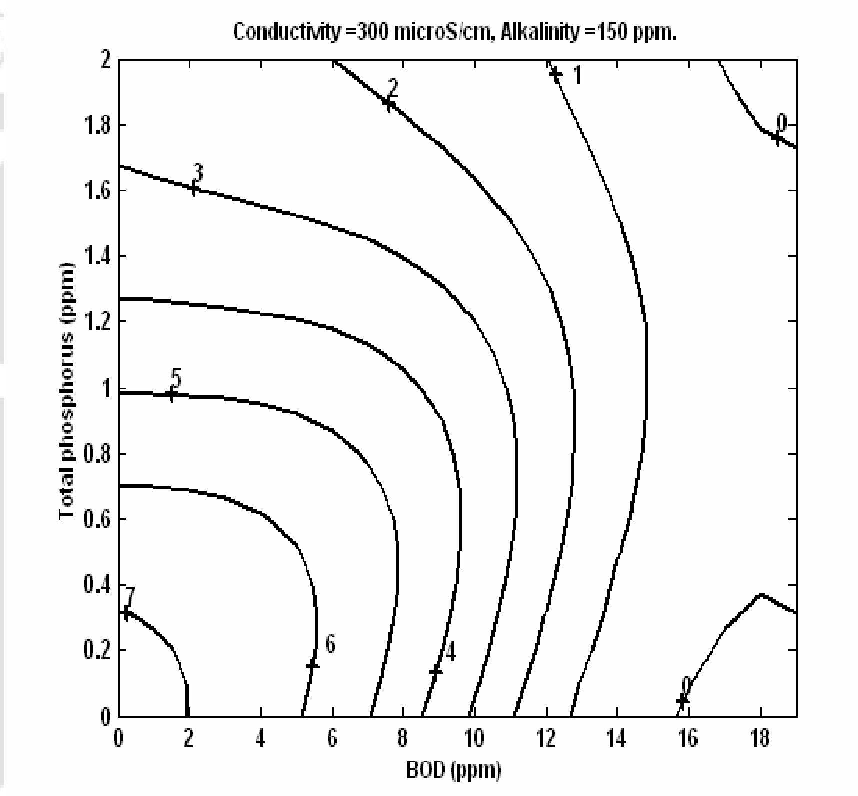


Figure 6.16 Contour plots for concentrations of DO vs TP and BOD, when Conductivity= 300 mg/L and alkalinity =150 mg/L.

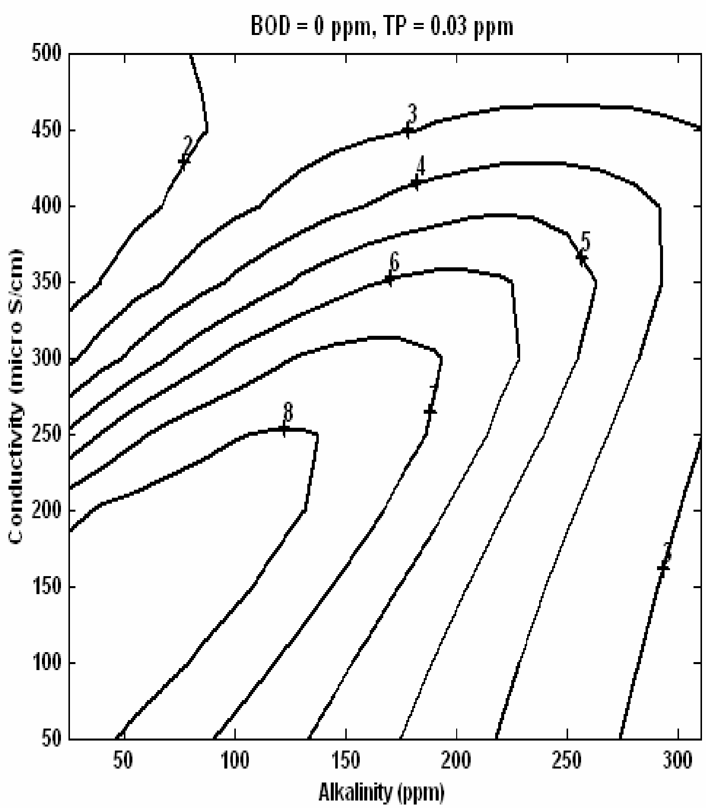


Figure 6.17 Contour plots for concentration of DO vs conductivity and alkalinity, when BOD = 0 mg/L, TP= 0.03mg/L

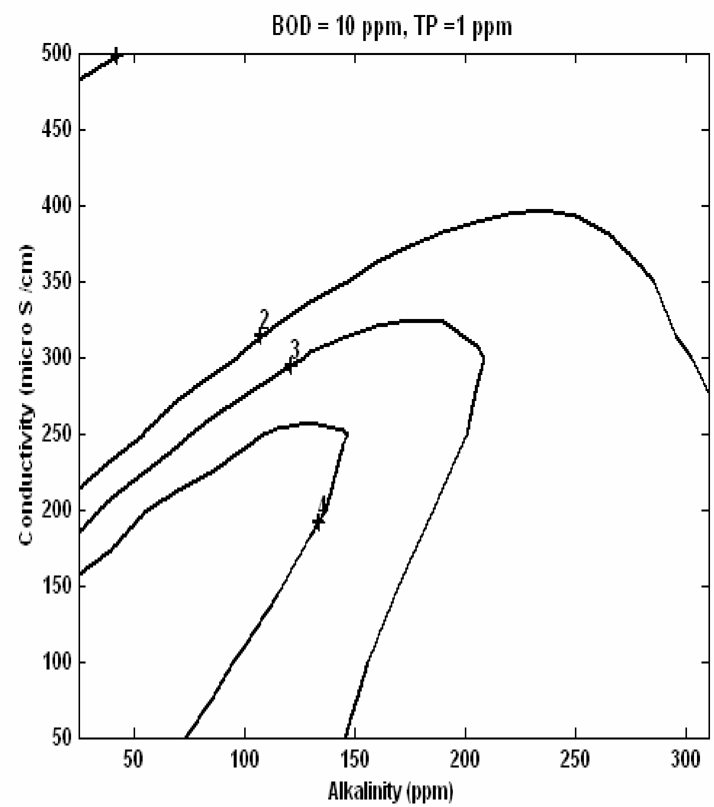


Figure 6.18 Contour plots for concentration of DO vs conductivity and alkalinity, when BOD =10 mg/L, TP=1mg/L.

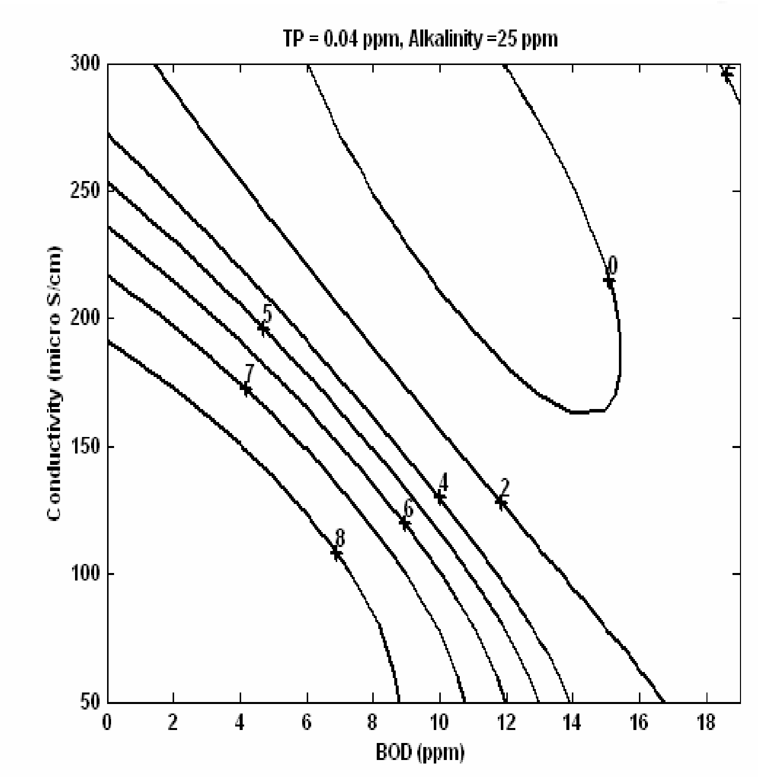


Figure 6.19 Contour plots of concentration of DO vs conductivity and BOD, when alkalinity = 25 mg/L, TP = 0.04 mg/L

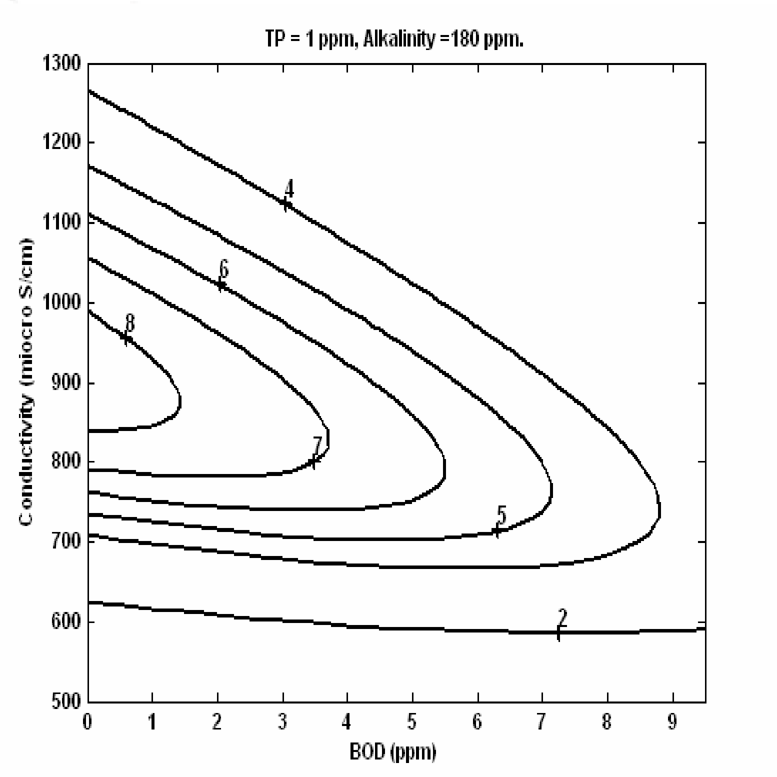
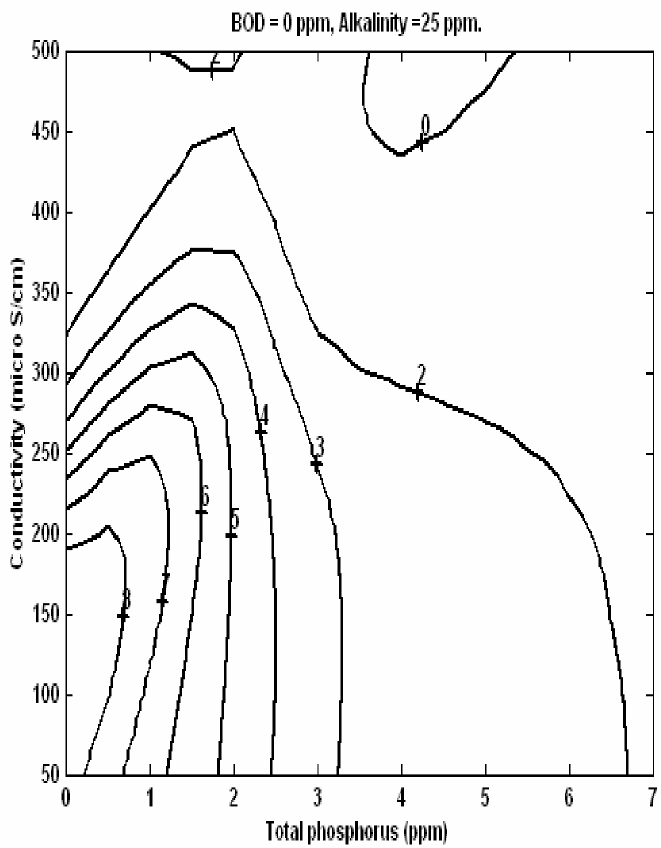


Figure 6.20 Contour plots of concentration of DO vs. conductivity and BOD, when alkalinity= 180 mg/L, TP= 1 mg/L.



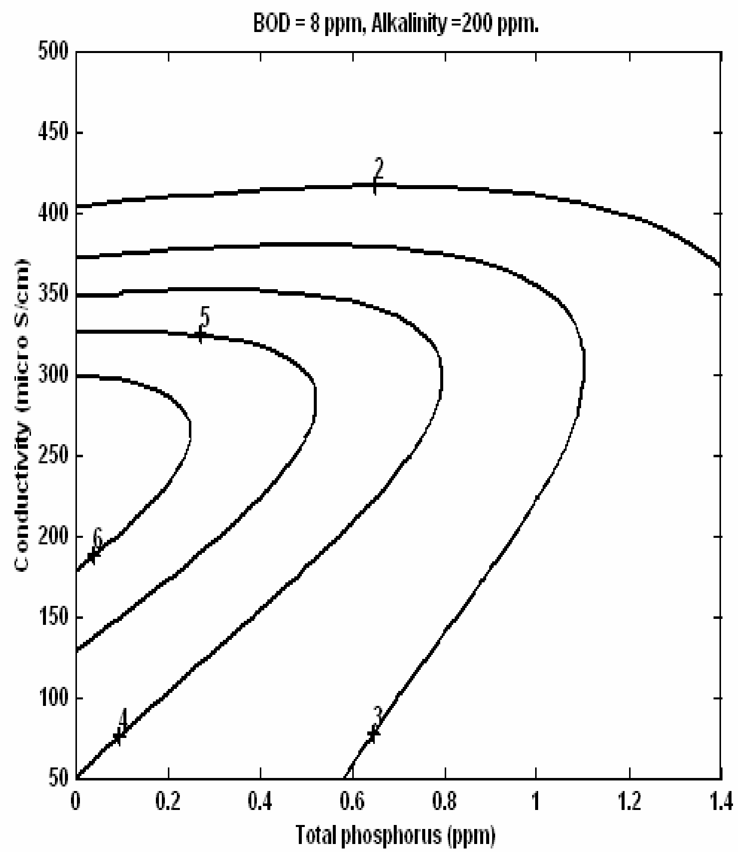


Figure 6.21 Contour plots of DO concentration Vs conductivity and TP, when BOD = 0 mg/L, alkalinity = 25 mg/L.

Figure 6.22. Contour plots of DO concentration Vs conductivity and TP, when BOD = 8 mg/L, alkalinity = 200 mg/L.

From the contour plots it can be concluded that for the environmental system under study there are certain ranges for input parameters to be maintained to bring the DO above the desirable level. Inference from the contour plots are briefed in Table 6.1 in which the values of parameters with which the system can maintain DO above the desirable level of DO of 6mg/L.

Table 6.1 Inference from the contour plots

BOD (mg/L)	**TP (mg/L)**	**Conductivity (μ S/cm)**	**Alkalinity (mg/L)**
<5	<1	50	25
<3	<0.4	300	150
0	0.03	<225	<125
10	1	------	-----
<6	0.04	<150	25
<3	1	Between 750 &1000	180
0	<1.2	<225	25
8	<0.2	Between 225 &300	200

6.6.1 COMPARISON OF INFERENCE OF THE CONTOUR PLOTS WITH EXPERIMENTAL DATA

Data combinations that provide the DO levels above the desirable level are listed in Table 6.2. Contour plots corresponding to the values in the table are drawn (Figures 6.23 to 6.33 and the results were compared. This was done to check the reliability of the contour plots in optimizing the variables.

Table 6.2 Data sets with DO above 6 mg/L

Data no:	BOD (mg/L)	TP (mg/L)	Conductivity (μ S/cm)	Alkalinity (mg/L)	DO (mg/L)
1	2.6	0.19	70	83	7.8
2	5.8	0.4	112	145	7
3	1.1	0.19	122	135	6.3
4	0.13	0.56	47	22	6.9
5	0.3	0.54	71	29	6
6	0.5	0.75	164	60	6.5
7	1.2	0.46	47	40	7.3
8	0.8	0.1	60	34	8
9	5.2	0.7	68	32	7.3
10	3.2	0.6	220	66	8.6
11	9.6	0.4	261	96	7.3
12	0.5	0.4	238	94	7.9
13	2.2	0.3	251	98	6.9
14	2.3	0.20	44	28	8
15	0.51	0.03	167	152.5	7.2
16	0.1	0.7	171	58	7.6
17	2.1	1.3	81	28	6.3
18	9	0.17	166	59	8.6
19	2	0.93	126	50	7
20	2.8	0.82	70	33	6.5

Figure 6.23 agrees with the output in the data set 1 where BOD=2.6 mg/L, TP = 0.19 mg/L, conductivity = 70.2 μ S/cm and alkalinity = 82.5 with the output DO = 7.8 mg/L.

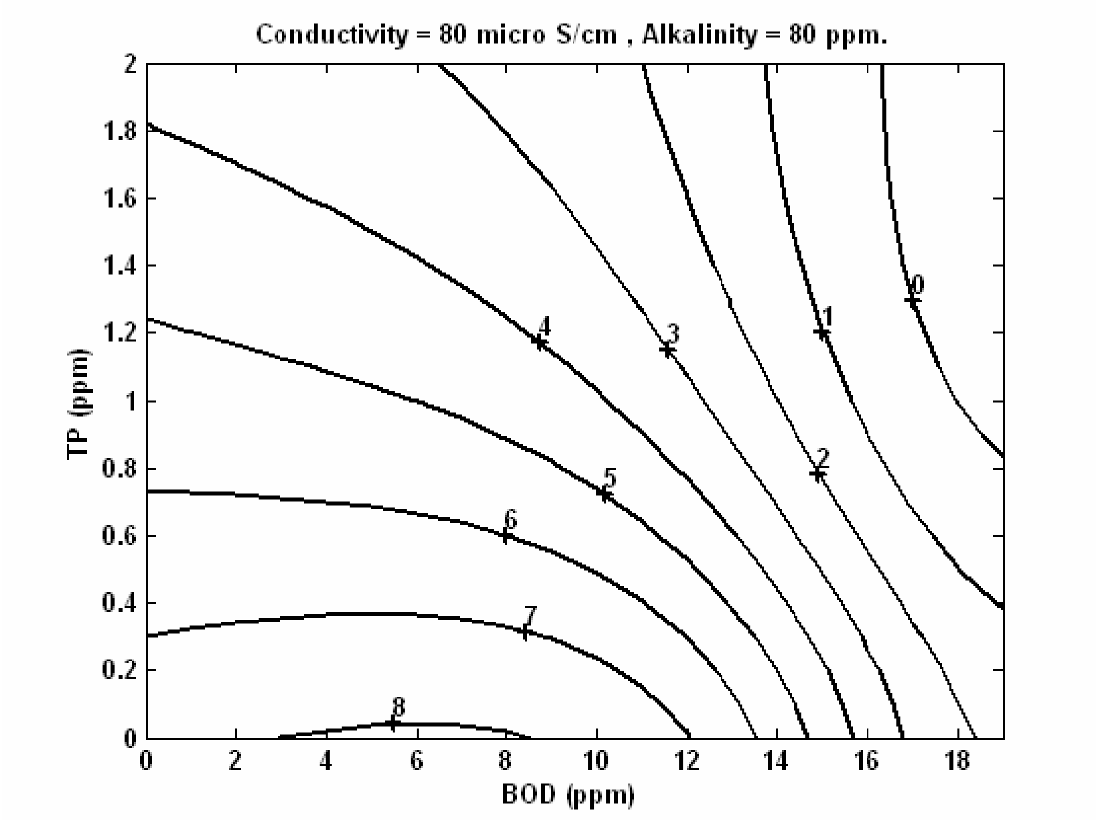


Figure 6.23. Contour plots of concentration of DO vs BOD and TP, when Conductivity = 80 µS/cm, alkalinity = 80 mg/L

Figure 6.24 shows the contour plots corresponding to the data set no 2 and no. 9. According to data set no.2, BOD = 5.8 mg/L, TP = 0.4 mg/L, Conductivity = 111.5 µ S/cm, alkalinity = 145 mg/L and DO = 7. In the contour plots drawn with BOD = 6 mg/L and TP = 0.5 mg/L, range of DO corresponding to conductivity of 111.5 and alkalinity of 145 mg/L were observed to be in between 5mg/L and 6 mg/L. In the data set 9, BOD =5.2 mg/L, TP= 0.7 mg/L, conductivity = 67.8 µ S/cm, alkalinity = 32 mg/L, DO = 7.3 mg/L. The value of DO in the contour plot corresponding to these data set lies in the region above 7 mg/L, which is close with the observed output.

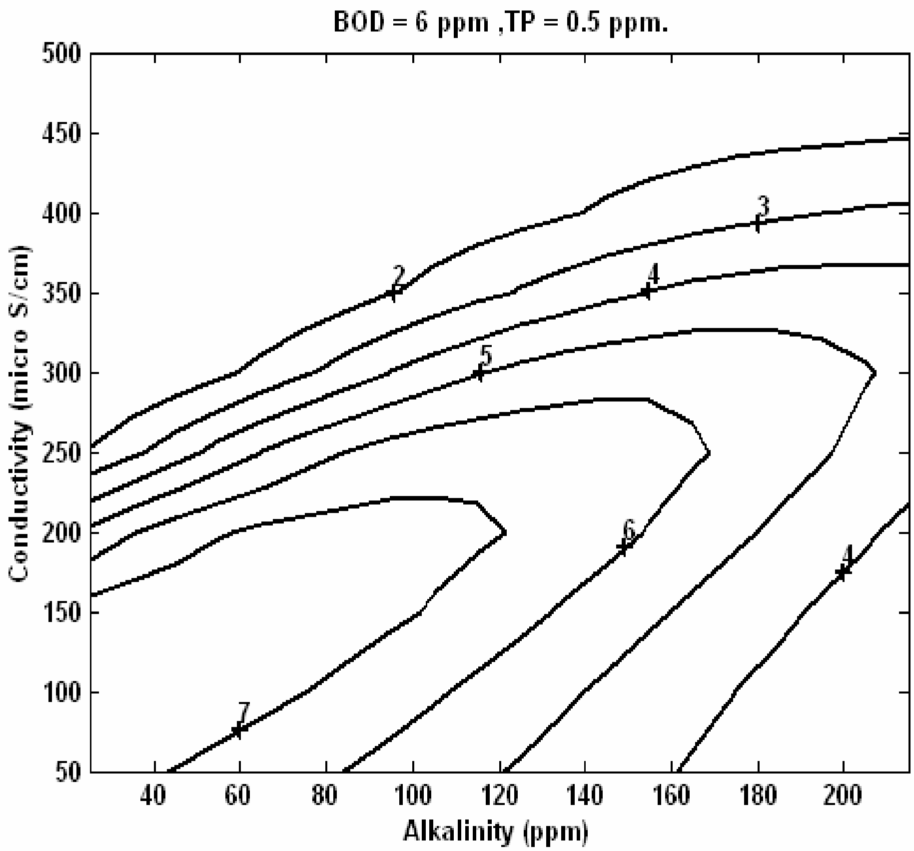


Figure 6.24. Contour plots of DO concentration Vs conductivity and alkalinity, when BOD = 6 mg/L and TP =0.5 mg/L.

Figure 6.25 shows the contour plots that is matching with the data set 15 where BOD = 0.51 mg/L, TP = 0.03 mg/L, conductivity = 167 μ S/cm, and alkalinity = 153. The observed DO value was 7.2 mg/L. For the contour plots drawn with conductivity value of 175 μ S/cm and alkalinity of 150 mg/L the DO value corresponding to the BOD of 0.51 mg/L and TP of 0.03 mg/L is above 7 mg/L, which matches the observed data.

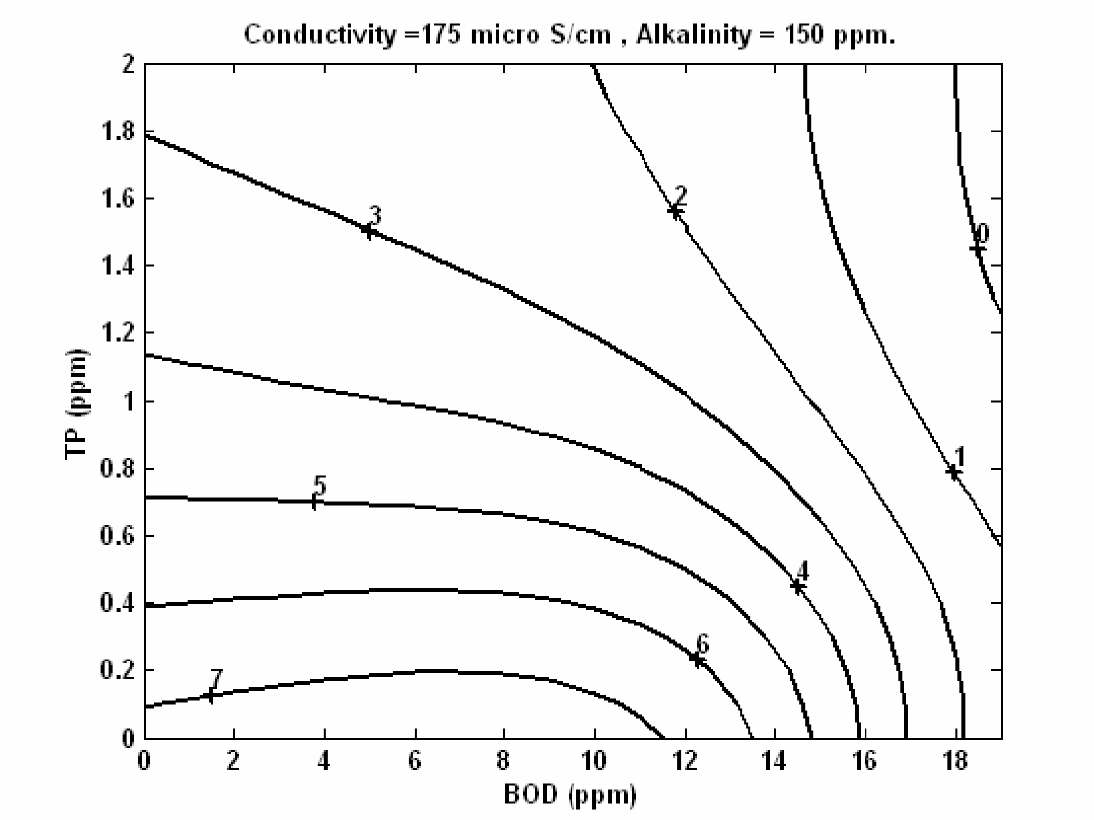


Figure 6.25 Contour plots of concentration of DO Vs BOD and TP, when conductivity=175 µS/cm and alkalinity =150 mg/L

Contour plots of DO against conductivity and alkalinity when BOD = 1 mg/L and TP = 0.2 mg/L are shown in figure 6.26. This was drawn to check the outputs of data sets 3 7 & 8. Corresponding to the conductivity of 122 µS/cm and alkalinity of 135 mg/L in data set 3, DO value in the contour plot is between 6 and 7 that agrees with the observed value of 6.3. For the conductivity of 47 µS/cm and alkalinity of 40 mg/L in the data set no.7 the DO value lies in the range between 7 mg/L and 8 mg/L where as the observed DO is 7.3 mg/L. In the case of data set 8 where conductivity = 60 µS/cm and alkalinity is 34 mg/L DO was observed to be 8 for a BOD of 0.8 mg/L and TP of 0.1 mg/L. Corresponding to the conductivity of 60 µS/cm and alkalinity of 34 mg/L in the contour plots with DO = 1 mg/L and TP= 0.2 mg/L, DO was found to be close to 8 mg/L which also agreed with the observed output.

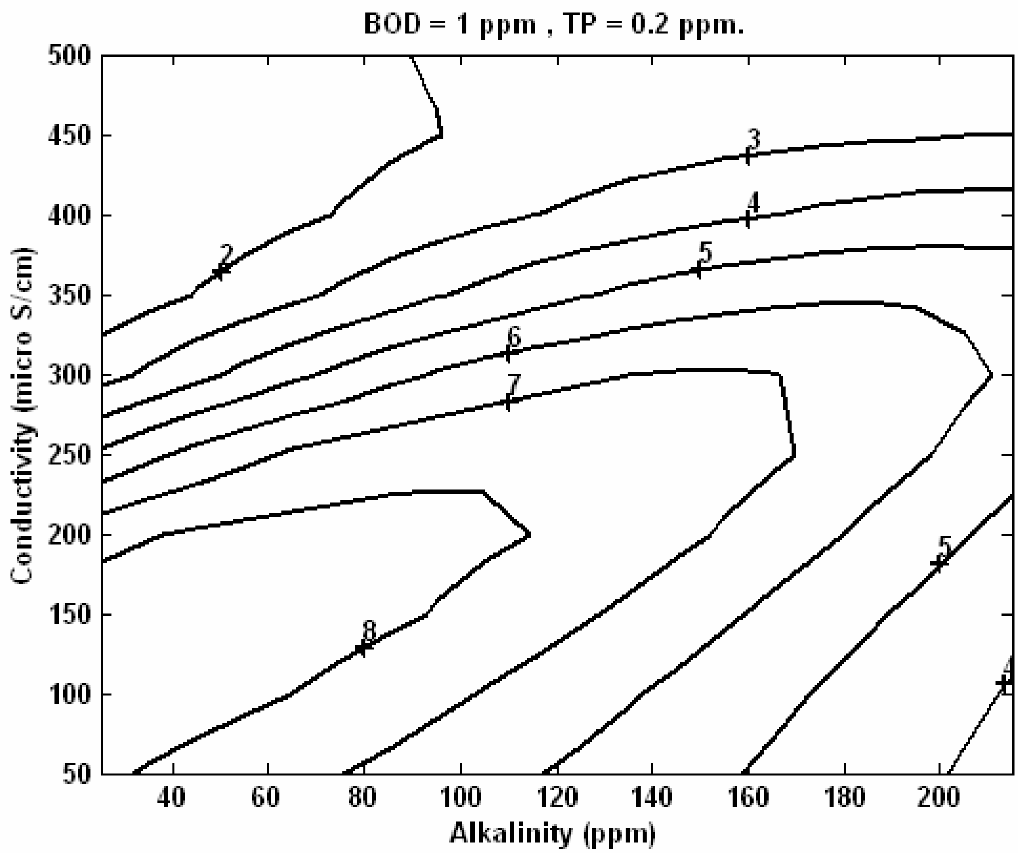


Figure 6.26 Contour plots of concentration of DO Vs conductivity and alkalinity, when BOD=1 mg/L, and TP = 0.2 mg/L

DO region corresponding to a conductivity of 47 µS/cm and alkalinity of 22 for a BOD of 0.2 mg/L and TP of 0.6 mg/L was very close to 7 mg/L (Figure 6.27) whereas the observed DO corresponding to BOD= 0.13 mg/L, TP = 0.6 mg/L, conductivity of 47 µS/cm and alkalinity of 22 mg/L in data set 4 was 6.9 mg/L. Here too a close agreement between the contour plot observation and the actual output was observed.

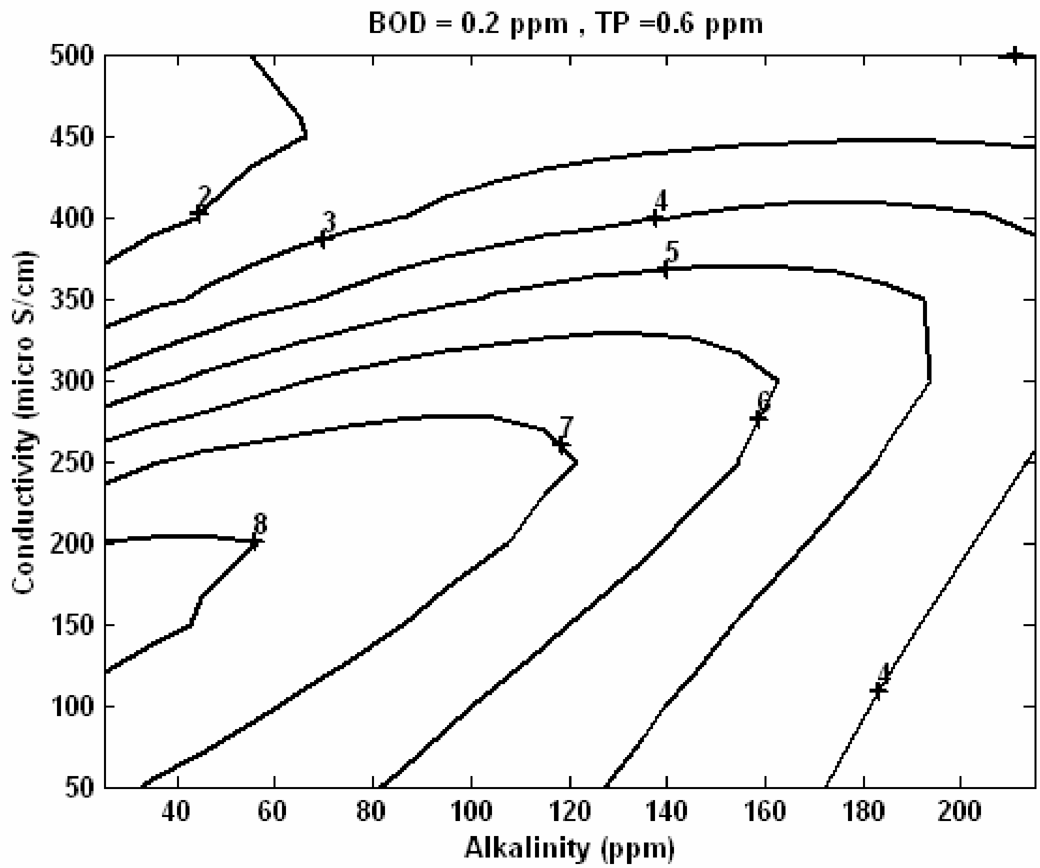


Figure 6.27. Contour plots of DO vs conductivity and alkalinity, when BOD =0.2 mg/L, TP = 0.6 mg/L.

Figure 6.28 shows that when BOD = 0.3 mg/L and TP = 0.54 mg/L for a conductivity of 80 μS/cm and alkalinity of 30 mg/L the DO value lies between 7 mg/L and 8 mg/L where as the observed value in the data set 5 for a BOD of 0.3 mg/L and TP of 0.54 mg/L, conductivity of 71 μS/cm and alkalinity of 29 mg/L was 6 mg/L which is a matching with tolerable difference. In the case of data set 17, observed DO was 6.3 for a BOD of 2.3 mg/L, TP = 1.3 mg/L, conductivity = 81 μS/cm and alkalinity = 28 mg/L whereas the contour plot shows a DO value very close to 6 mg/L.

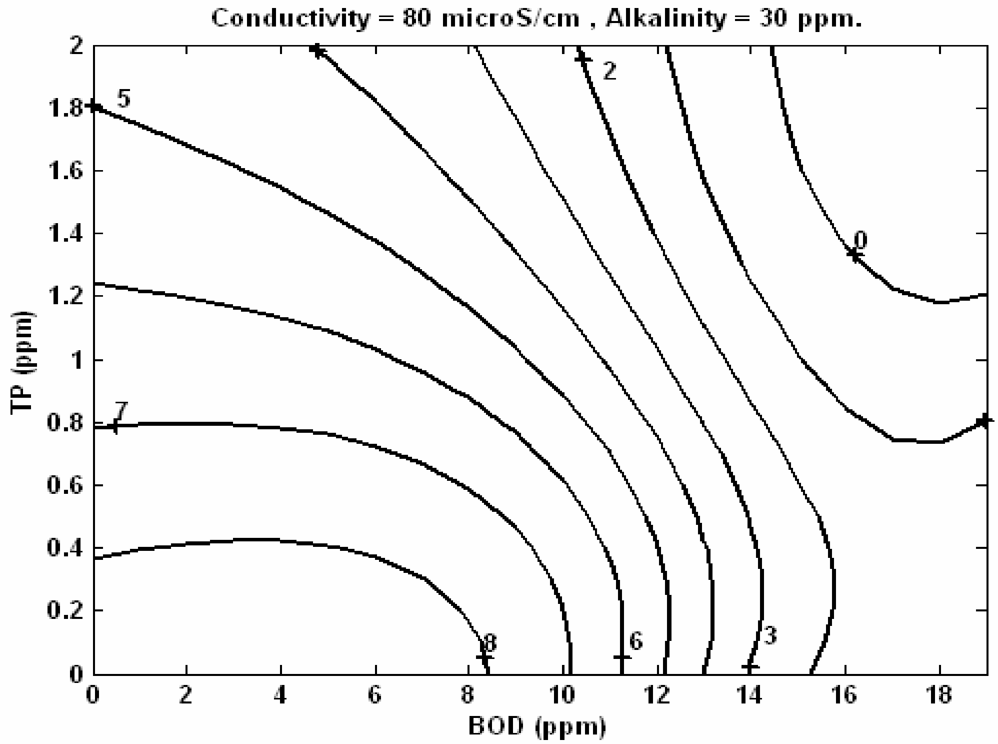


Figure 6.28. Contour plots of DO vs BOD and TP, when conductivity = 80 μS/cm, alkalinity = 30 mg/L.

Output of the data set 14 was observed to be matching with the contour plot drawn keeping conductivity 50 μS/cm and alkalinity 30 mg/L (Figure 6.29). When BOD = 2.3 mg/L, TP = 0.2 mg/L, conductivity 44 μS/cm and alkalinity = 28 mg/L, DO was observed to be 8 mg/L. In the contour plot for same values of BOD and TP and conductivity of 50 μS/cm and alkalinity of 30 mg/L the DO was observed to be 8 mg/L.

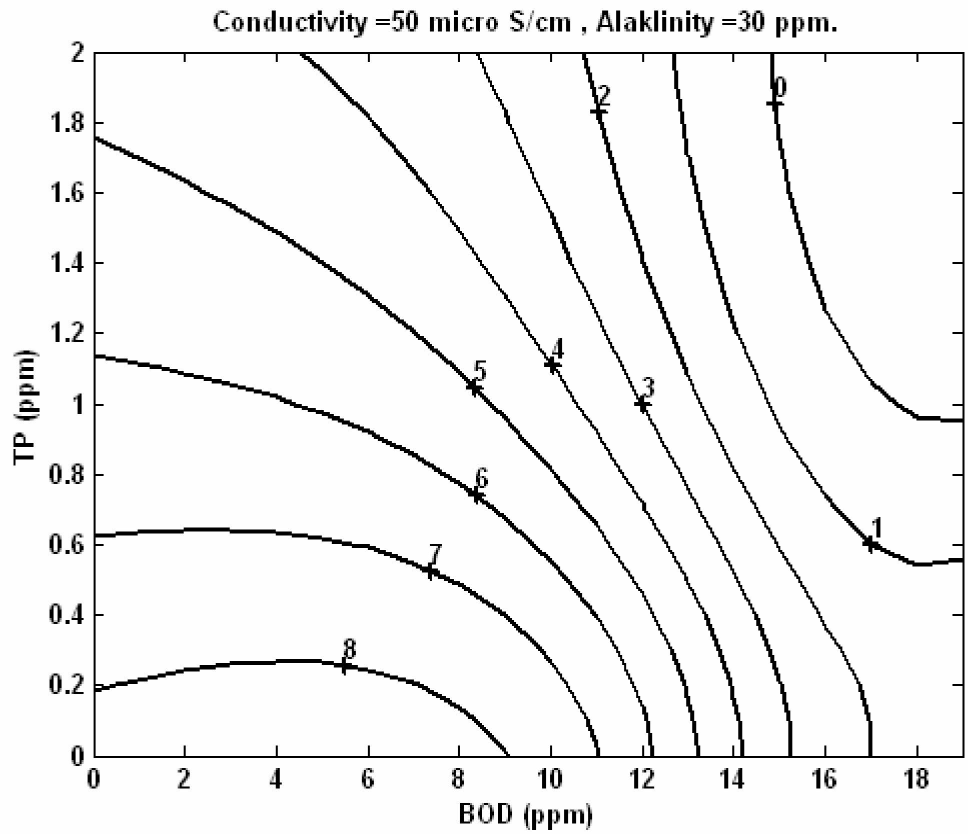


Figure 6.29. Contour plots of DO Vs TP and BOD, when conductivity = 50 µS/cm and alkalinity = 30 mg/L.

Outputs of the datasets 6 and 16 match with the observation in Figure 6.30 where for a conductivity of 175 µS/cm and an alkalinity of 75 mg/L, BOD of 0.5 mg/L and TP of 0.75 mg/L, DO in the contour plot was very close to 7 mg/L where as the observed DO was 6.5 mg/L for a conductivity and alkalinity of 164 µS/cm and 60 mg/L respectively (data set 6). In the case of data set 16, for BOD of 0.1mg/L, TP of 0.7 mg/L, conductivity of 171µS/cm and alkalinity of 78 mg/L, observed DO was 7.6 mg/L where as in the contour plot DO was observed to be between 7 mg/L and 8 mg/L .In the case of data set 18, contour plot gave a DO value between 6 mg/L and 7 mg/L for a combination of BOD = 9 mg/L, TP = 0.17 mg/L, conductivity = 175 µS/cm and alkalinity = 75 mg/L whereas the observed data when conductivity = 166 µS/cm and alkalinity = 59 mg/L was 8.6 mg/L which is in disagreement with the contour plot data. This data can be considered as spurious data as DO value of 8.6 mg/L can not be expected for a system with BOD of 9 mg/L.

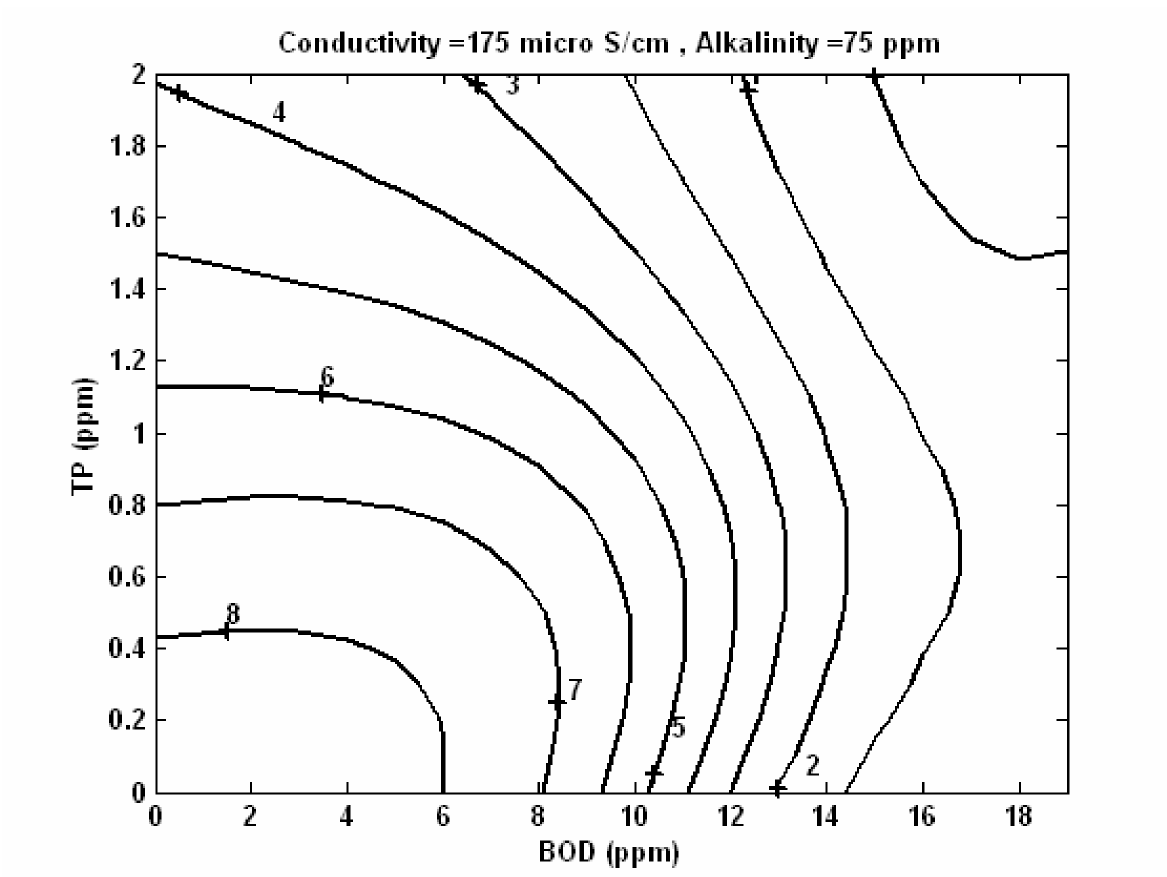


Figure 6.30 Contour plots of DO Vs TP and BOD, when conductivity = 175 μS/cm and alkalinity = 75 mg/L.

Contour plot shown in Figure 6.31 almost matches with the data set 10, where BOD = 3.2 mg/L, TP = 0.6 mg/L, conductivity = 220 μS/cm and alkalinity = 66 mg/L. The DO observed was 8.6 mg/L, where as in the contour plots for BOD = 3 mg/L and TP = 0.5 mg/L, DO showed a value between 7 mg/L and 8 mg/L. The difference can be accounted for any experimental error.

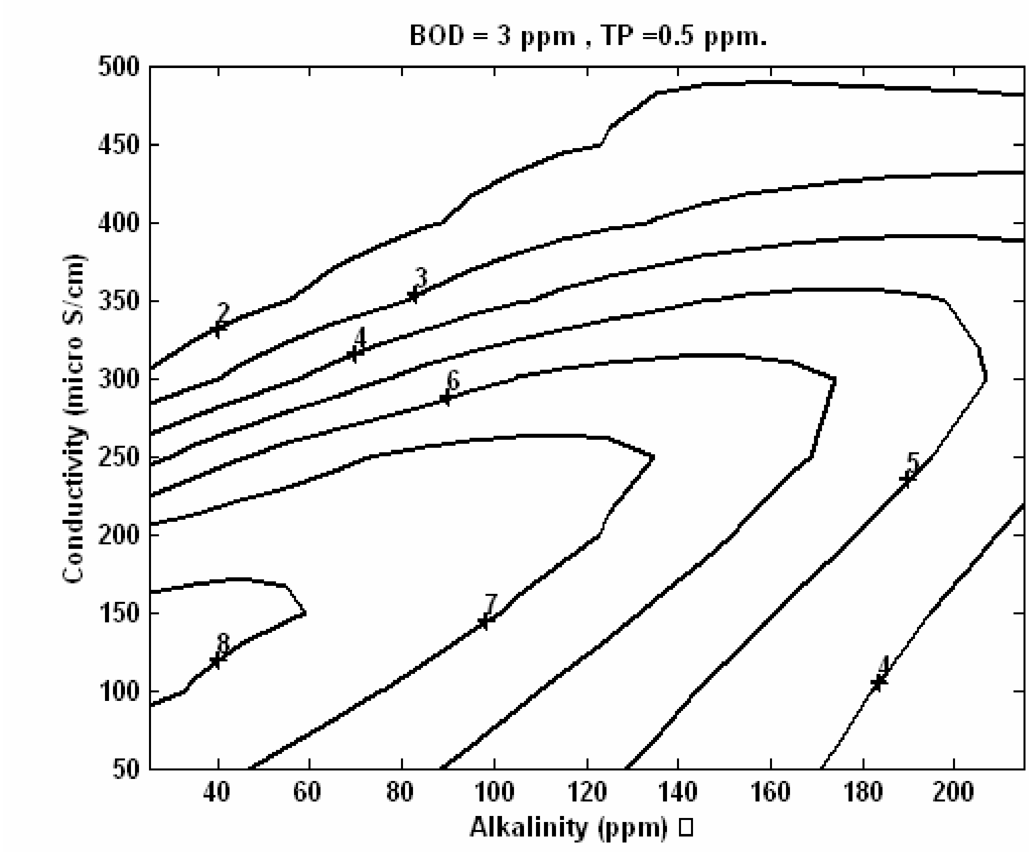


Figure 6.31 Contour plots of DO Vs conductivity and alkalinity, when BOD = 3mg/L, TP= 0.5 mg/L.

Outputs of data sets 12 and 13 exactly matches with the results of the contour plot as shown in figure 6.32, but in the case of data sets 11, where BOD = 9.6 mg/L, TP = 0.4 mg/L, conductivity = 261 µS/cm and alkalinity = 96 mg/L, the observed data was 7.3 mg/L whereas the value of DO corresponding to the input values from the contour plot was observed to be below 3 mg/L. This difference can also be accounted for any experimental error as for a BOD value of 9.6 mg/L and TP of 0.4 mg/L; a DO value above 6 mg/L is very unlikely.

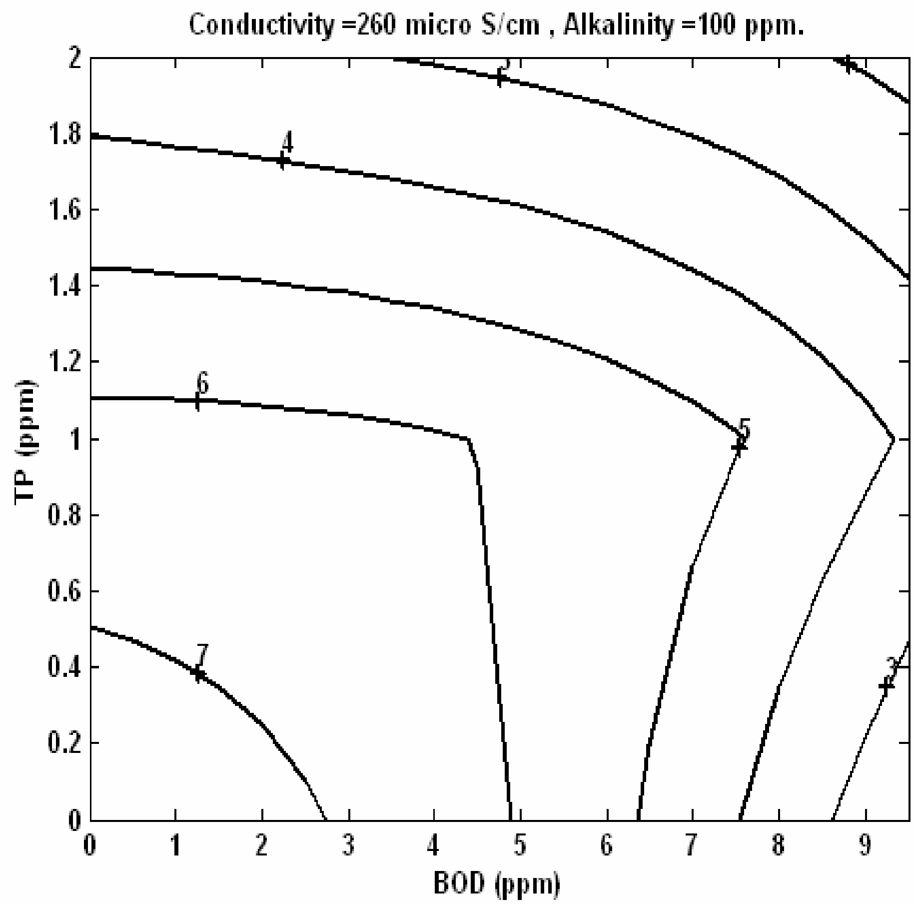


Figure 6.32 Contour plots of DO Vs TP and alkalinity, when conductivity =260 μS/cm, alkalinity = 100 mg/L.

Results of the contour plots shown in figure 6.33 illustrates that for a BOD of 3 mg/L and TP of 0.9 mg/L, DO value lies between 6 mg/L and 7 mg/L for the values of conductivity of 126 μS/cm and alkalinity of 50 mg/L, as well as for a conductivity of 69 μS/cm and alkalinity of 33 mg/L. This inference exactly matches with the data sets 19 and 20. Table 6.3 summarizes the results from the contour plots drawn with the actual data sets.

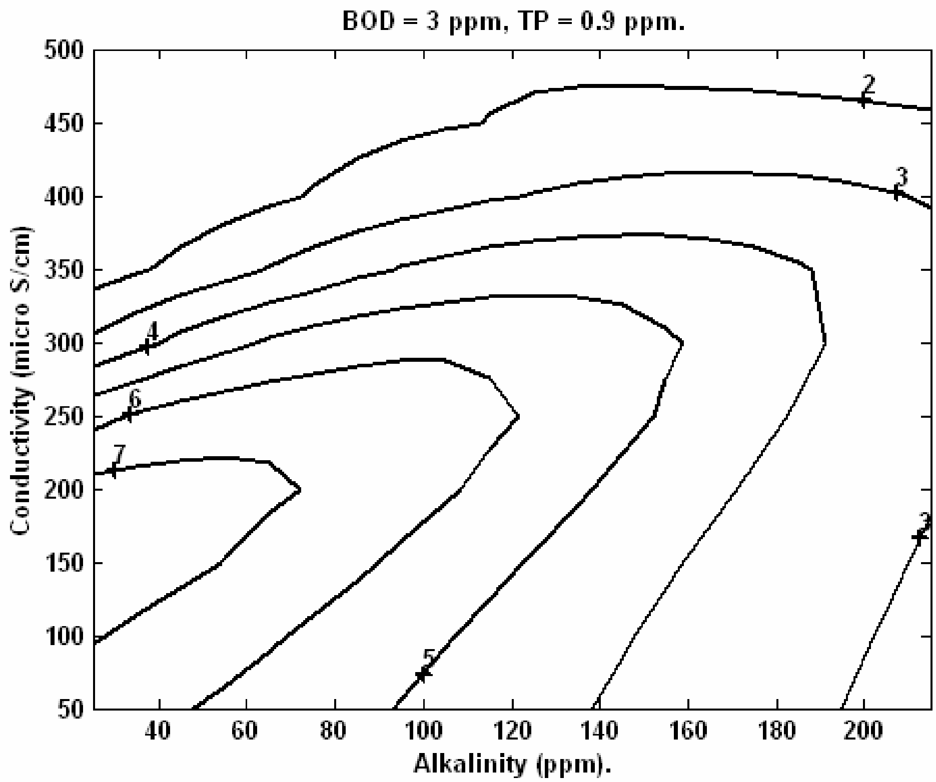


Figure 6.33 Contour plot of DO Vs conductivity and alkalinity, when BOD = 3 mg/L and TP = 0.9 mg/L.

Table 6.3 Comparison of the original data with contour plots.

Data no:	BOD (mg/L)	TP (mg/L)	Conductivity (μ S/cm)	Alkalinity (mg/L)	DO (mg/L) (observed)	DO from contour plots
1	2.6	0.19	70.2	82.5	7.8	Betwee7 &8
2	5.8	0.4	111.5	145	7	Close to 5
3	1.09	0.19	122.4	135	6.3	Between 6 &7
4	0.125	0.56	47.4	22	6.9	Close to 7
5	0.3	0.54	71	29	6	Between 7 & 8
6	0.5	0.75	164	60	6.5	Close to 7
7	1.2	0.46	46.7	40	7.3	Between 7 & 8
8	0.8	0.1	59.5	34	8	Close to 8
9	3.2	0.6	220	66	8.6	Between 7& 8
10	9.6	0.4	261	96	7.3	Below 3
11	0.5	0.4	238	94	7.9	Between 7 &8
12	2.2	0.3	251	98	6.9	7
13	2.33	0.202	43.7	28	8	8
14	0.506	0.03	166.65	152.5	7.2	Above 7
15	0.1	0.7	171.2	58	7.6	Between 7 & 8
16	2.1	1.3	81.1	28	6.3	Close to 6
17	9	0.17	166	59	8.6	Between 6 & 7
18	2	0.93	126	50	7	Close to 7
20	2.8	0.82	69.1	33	6.5	Between 6 & 7

6.6.2 CONCLUSION ON CONTOUR PLOTS

On comparing the experimental data and the results of the contour plots it is that contour plots prepared using parameters of the simulated neural network can successfully optimize the parameters for the environmental system studied. Contour plots can be used as an effective tool for the decision makers to get an idea about concentrations of parameters that can maintain the quality indicators of the system under study within the acceptable or the desirable level.

CHAPTER
SEVEN

MAJOR CONCLUSIONS

The generalized conclusions of the present work derived from chapter 4 and chapter 6 are as follows:

- From the three models studied *viz*: The fuzzy rule based model, multiple linear regression and the artificial neural network model, for prediction of dissolved oxygen, which is an important water quality indicator, artificial neural network model is found to be the most appropriate model.
- A relationship was developed connecting BOD, TP, conductivity and alkalinity with dissolved oxygen in the system studied using artificial neural network model. From this work, successful prediction of dissolved oxygen from a small set of physical chemical and biological measurements, by artificial neural network model is established.
- Selection of input variables for the ANN models based on the correlation coefficients proved to be a reliable method.
- Explanatory capacity of the ANN model, apart from its predictive quality in ecology, was proved by the satisfactory results obtained from the sensitivity analysis. As the environment is composed of many characteristics acting together, considering variable interaction proved to have meaning than finding the contribution of single variable. Thus by means of quantitative approach like partial derivative method it is possible to identify individual and interacting contributions of predictor variables in ANN model.
- Contour plots proved to be efficient tools for optimizing the parameters to maintain the system safe. For optimizing the variables of an ecosystem ranges of values are to be obtained. Successful optimization of the variables could be arrived at by making use of contour plots.
- Water quality of the Bharalu tributary was found to be generally poor, with significant seasonal and spatial variations. Dissolved oxygen, was observed to be either absent or very low in several locations irrespective of the season.

- Analysis results indicated the presence of excess amount of decomposed organic matter, leaching from phosphorus rich rock, human and animal waste, land and its vegetation along the middle reach of the system under study. Excess growth of aquatic weeds resulted in settled organic load and silt accumulation that could have resulted in high sediment oxygen demand and respiration by biomass in the nights adding to the stress on DO which made the system deficient in dissolved oxygen. Desilting followed by implementing proper land use management, drainage system and waste disposal are the effective remedial measures to be taken for the system studied.

SCOPE FOR FUTURE RESEARCH

- **INFLUENCE OF SOD ON DISSOLVED OXYGEN OF THE WATER COLUMN**

  It is understood from the study that Oxygen depletion in the river ecosystem can be attributed to a variable combination of biochemical oxygen demand, total phosphorus, conductivity and alkalinity. Combination of conductivity with total phosphorus and bio chemical oxygen demand was observed to be the most contributing. Sediment can provide important storage capacity for nutrients and there is a possibility that in nutrient rich shallow water bodies sediment oxygen demand can be substantial due to decayed aquatic weeds and other organic matter. Hence there is a scope for further studies in using data ANN model in the prediction of dissolved oxygen budget of a water body including sediment oxygen demand and study its influence.

- **INCLUSION OF HYDROLOGIC PARAMETERS**

  Inclusion of hydrologic parameters like discharge, depth, velocity, along with water quality variables as input parameters so as to get a complete picture of water quality prediction of a particular environmental system. Developing such a model makes it feasible to transfer the model to a different environmental system.

- **FORMULATION OF A FUZZY NEURAL NETWORK MODEL FOR WATER QUALITY PREDICTION**

  If the data sets are fuzzified and fed to the neural network instead of feeding as such as the input variable more better generalization can be expected and that seems to be a promising research in the future study.

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