EFFICIENT WATER QUALITY ANALYSIS & PREDICTION USING MACHINE LEARNING

LITERATURE SURVEY

This research explores the methodologies that have been employed to help solve problems related to water quality. Typically, conventional lab analysis and statistical analysis are used in research to aid in determining water quality, while some analyses employ machine learning methodologies to assist in finding an optimized solution for the water quality problem. Local research employing lab analysis helped us gain a greater insight into the water quality problem in Pakistan. In one such research study, Daud et al. [5] gathered water samples from different areas of Pakistan and tested them against different parameters using a manual lab analysis and found a high presence of E. coli and fecal coliform due to industrial and sewerage waste. Alamgir et al. [6] tested 46 different samples from Orangi town, Karachi, using manual lab analysis and found them to be high in sulphates and total fecal coliform count. After getting familiar with the water quality research concerning Pakistan, we explored research employing machine learning methodologies in the realm of water quality. When it comes to estimating water quality using machine learning, Shafi et al. [7] estimated water quality using classical machine learning algorithms namely, Support Vector Machines (SVM), Neural Networks (NN), Deep Neural Networks (Deep NN) and k Nearest Neighbors (kNN), with the highest accuracy of 93% with Deep NN. The estimated water quality in their work is based on only three parameters: turbidity, temperature and pH, which are tested according to World Health Organization (WHO) standards (Available online at URL https://www.who.int/airpollution/guidelines/en/). Using only three parameters and comparing them to standardized values is quite a limitation when predicting water quality. Ahmad et al. [8] employed single feed forward neural networks and a combination of multiple neural networks toestimate the WQI. They used 25 water quality parameters as the input. Using a combination of backward elimination and forward selection selective combination methods, they achieved an R2 and MSE of 0.9270, 0.9390 and 0.1200, 0.1158, respectively. The use of 25 parameters makes their solution a little immoderate in terms of an inexpensive real time system, given the price of the parameter sensors. Sakizadeh [9] predicted the WQI using 16 water quality parameters and ANN with Bayesian regularization. His study yielded correlation coefficients between the observed and predicted values of

0.94 and 0.77, respectively. Abyaneh [10] predicted the chemical oxygen demand (COD) and the biochemical oxygen demand (BOD) using two conventional machine learning methodologies namely, ANN and multivariate linear regression. They used four parameters, namely pH, temperature, total suspended solids (TSS) and total suspended (TS) to predict the COD and BOD. Ali and Qamar [11] used the unsupervised technique of the average linkage (within groups) method of hierarchical clustering to classify samples into water quality classes. However, they ignored the major parameters associated with WQI during the learning process and they did not use any standardized water quality index to evaluate their predictions. Gazzaz et al. [4] used ANN to predict the WQI with a model explaining almost 99.5% of variation in the data. They used 23 parameters to predict the WQI, which turns out to be quite expensive if one is to use it for an IoT system, given the prices of the sensors. Rankovic et al. [12] predicted the dissolved oxygen (DO) using a feedforward neural network (FNN). They used 10 parameters to predict the DO, which again defeats the purpose if it has to be used for a real-time WQI estimation with an IoT system. Most of the research either employed manual lab analysis, not estimating the water quality index standard, or used too many parameters to be efficient enough. The proposed methodology improves on these notions and the methodology being followed is depicted in Figure 1. Water 2019, 11, x FOR PEER REVIEW 3 of 14 three parameters and comparing them to standardized values is quite a limitation when predicting water quality. Ahmad et al. [8] employed single feed forward neural networks and a combination of multiple neural networks to estimate the WQI. They used 25 water quality parameters as the input. 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Most of the research either employed manual lab analysis, not estimating the water quality index standard, or used too many parameters to be efficient enough. The proposed methodology. Ahmed et al. [4] have used the supervised machine learning algorithms in order to assess the water quality index (WQI), where an individual index was used to summarize the overall quality of water, and water quality class (WQC). Their suggested techniques and the gradient boosting with a learning rate of 0.1 and polynomial regression with a degree of 2 has predicted the WQI most effectively, and that WQI was subsequently determined with a mean absolute error (MAE) of 1.9642 and 2.7273. In this instance, the MLP, which has the configuration of (3, 7), has the highest classification accuracy of 85.07%. Wang et al. [6] have proposed a two-layered model stacking approach for predictive modeling of beach water quality. The five most frequently used methods (partial least square, sparse partial least square, random forest, Bayesian network, akhand linear regression) are integrated into a machine learning model that is then used to generate the final forecast. In this case, the model stacking technique was applied to three different beaches around eastern Lake Erie, New York, USA, and compared to all five basis models. After analysis, the model stacking strategy performed better than all of the base models. Year-over-year, stacking model accuracy scores were constantly at or near the top of the rankings, with a year-on-year accuracy average of 78%, 81%, and 82.3% at the three tested beaches. Sillberg et al. [7] have developed a machine learning-based approach integrating attribute-realization (AR) and support vector machine (SVM) algorithm to classify the Chao Phraya River's water quality. The AR has determined the most significant factors to improve the river's quality using the linear function. In the categorization, the most contributing characteristics were: NH3 -N, TCB, FCB, BOD, DO, and Sal, boosting the contributed values in the range of 0.80–0.98, vs 0.25–0.64 for TDS, Turb, TN, SS, NO3-N, and Cond. The SVM linear method has enabled the best classification results represented as the accuracy of 0.94, a precision average of 0.84, recall average of 0.84, and F1-score average of 0.84. The validation showed that AR-SVM was a powerful method to identify river water quality with 0.86–0.95 accuracy when applied to three to six characteristics. Yilma et al. [8] have used an artificial neural network to simulate the Akaki River's WQI. The twelve water quality indicators from 27 dry and wet season sample locations were utilized to calculate the index. Except for one upstream location, all forecast results have shown low water quality. Here, the number of hidden layers (2–20), hidden layer neurons (5, 10, 15, 20, 25), transfer, training, and learning functions were used to train and verify the neural network model through 12 inputs and one output. Their study has revealed that an artificial neural network with eight hidden layers and 15 hidden neurons accurately predicted the WQI with an accuracy of 0.93. Bui et al. [9] have developed a random tree and bagging (BA-RT) hybrid machine learning method. Their research has tested four standalone (RF, M5P, RT, and REPT) and 12 hybrid data-mining algorithms (hybrids of the standalone with bagging, CVPS, and RFC) for forecasting monthly WQI in a humid climate in northern Iran. To forecast IRAQIs, they found that fecal coliform and total solids had the largest and least impact. Here, the optimal input combinations have differed across algorithms but the variables with poor correlations have performed worse. The Hybrid algorithms have improved their prediction power of several of the standalone models, but not all, and the Hybrid BA-RT has outperformed the other models by achieving R^2 0.941 using a 10-fold cross-validation technique, outdoing 15 standalone and hybrid algorithms. Ding et al. [10] have designed a hybrid intelligent method that combines Principal Component Analysis (PCA), Genetic Algorithm (GA), and Back Propagation Neural Network (BPNN) techniques for predicting river water quality. In this study, 23 different water quality indicator variables were utilized, each of which has a complicated non-linear connection to water quality. In this case, PCA has significantly increased the training speed of follow-up algorithms, while GA has optimized the parameters of BPNN. The average prediction rates for non-polluted and polluted water quality were 88.9% and 93.1% respectively, while the worldwide prediction rate was around 91%, according to the results. Azad et al. [11] have utilized the three evolutionary algorithms including, GA, DE, and

ACO_R in order to optimize the performance of adaptive neuro-fuzzy inference system (ANFIS) for water quality metrics prediction. These algorithms have been integrated with the ANFIS to predict the EC, SAR, and THE water quality metrics. Based on their research, the ANFIS-DE model, with an R^2 of 0.98 and an RMSE of 73.03, as well as a MAPE of 5.16, was the most accurate in predicting EC and TH in the test stage. Furthermore, the ANFIS-DE and ANFIS-GA models have shown the greatest performance in SAR (R^2 = 0.95, 0.91; RMSE = 0.43, 0.37; MAPE = 13.43, 13.72) prediction in a test stage. It has been shown that ANFIS is capable of producing the best results in the training stage with respect to water quality indicators. Zhang et al. [12] have improved a hybrid artificial neural network (HANN) model by the genetic algorithm (GA) for the prediction of drinking water treatment plants in china. The model has trained, validated, and has been continually validated using monthly data from 45 DWTPs across China that comprises eleven input variables for water quality and operational performance. The HANN model has shown better ability and consistency in forecasting the total water output of DWTPs in combination with the water quality and operational factors. Their prediction shows that the HANN model has improved its performance from 0.71 to 0.93 (R^2) by increasing the training data provided, as shown by the fact that the model has the ability to grow to the greatest level of performance.Hydraulic fracturing, pumping of a mixture of water, sand and additives under high pressure into a shale formation allowing the natural gas to flow out of the shale, is the other component that makes recovery of shale gas viable. The casing and cement that is installed during the drilling process provides protection for groundwater sources during the hydraulic fracturing process. Plus, several hundred to several thousand feet separate the top of the fracture zone of the Marcellus and the bottom of the deepest freshwater aquifer layer making it improbable for hydraulic fracturing fluids to reach groundwater used as a source of drinking water. Sustainable development of shale gas in the Marcellus requires the management of large volumes of water necessary for the drilling and hydraulic fracturing process to unleash the gas from the formation. Challenges associated with the development of shale gas involve the management of water – transportation, storage and disposal of the water and waste streams created during all stages of well development - in a manner that does not present a threat to human health and the surrounding environment. Exploration of the Marcellus Shale may pose water resource and water supply challenges to the gas industry operating in the Appalachian Basin (4). Water used for drilling and hydraulic fracturing normally comes from surface waters, groundwater, municipal potable water supplies, or reuse of flowback waters, or from some other water source. Surface Water Currently, the preferred source of hydraulic fracturing water is surface water which may be transported to the site by pipeline or truck (9). On average, for each horizontal well drilled in the Marcellus, three to five million gallons of water are needed to drill and hydraulically fracture the well. Only about 10% to 40% of this water is recovered and it typically contains high concentrations of total dissolved solids (TDS). The remaining water stays in the formation. Due to the amount of water loss, large amounts of new makeup water are required to develop each new gas well. Depending on the number of horizontal wells that may be drilled and hydraulically fractured in any given basin, water demand may become a critical issue particularly during the latter half of the year when stream levels are lowest. The Ohio River Basin is located within southwestern New York, western Pennsylvania, and much of West Virginia. It comprises all the major rivers and streams that make up the Ohio River. The Marcellus Shale region underlies approximately 10% of the Ohio River Basin (10). The Ohio River Basin and its major tributaries – the Monongahela and Allegheny Rivers, may be seen as less challenged from a water resource perspective when compared to the other river basins within the Marcellus Shale area. However, recent evaluations conducted by the West Virginia Water Use Survey and Pennsylvania State Water Plan highlight the Ohio River watershed may face some significant water resource challenges (4). With many streams and aquifers affected by acid mine drainage, supplies of potable water are often limited (4). When comparing shale gas development water use with other activities and practices such as agriculture, power generation, recreation and municipal consumption, shale gas water use accounts for a very small portion of overall general basin use, usually less than 1% (3). Besides quantity issues, concerns about the ecological impacts to aquatic resources from water withdrawals have been raised throughout the Marcellus Shale region (11).Groundwater in West Virginia is generally of good quality with 42% of the state's population relying on groundwater as the source of their domestic water supply; but, a recent comprehensive study by the United States Geological Survey (USGS) raises concerns based on iron, manganese and radon levels found in water samples taken from 300 wells around the state. Developing a groundwater well near an active Marcellus Shale development area would have to be able to provide sufficient yield and not have any impact on nearby drinking water supply wells or surface waters (9). To ensure this does not happen, a hydrological study of the area would need to be conducted prior to drilling the groundwater well.Municipal water suppliers are another option to provide a source for freshwater to drilling and hydraulic fracturing operations. To the extent that capacity exists to provide water for ratepaying customers as well as shale gas operators, the municipality may agree to provide water for hydraulic fracturing Recycling of flowback and produced water reduces the demand on freshwater supplies and the volume of water that requires treatment or disposal. It is unknown if reusing untreated flowback waters for hydraulically fracturing new wells would impede gas production. Therefore, most shale gas operators treat flowback waters to some degree. Many technical solutions exist to treat flowback waters. These technologies are discussed under the Best Available Practices section of this report. Other Sources Another option may be to use treated acid mine drainage (AMD). AMD is water that has been contaminated by contact with pyrite in strip-mine operations, refuse piles or abandoned deep mines that results in the formation of sulfuric acid and iron (9). Treatment typically involves neutralization and removal of metals such as iron. Common in many areas underlain by the Marcellus Shale, treated AMD may be a plausible substitution for surface water. Scaling by divalent and trivalent ions is an issue when considering the use of AMD. Some suggest treatment to reduce total hardness to 2,500 mg/L (12). A study in 2009 conducted by ProChem Tech International, Inc. found that treated AMD was a suitable substitute for freshwater for the hydraulic fracturing process of a shale gas well. It required a simpler treatment process compared to treatment of return flowback water and allowed an alternative use for AMD other than treatment and surface discharge. Using their unique chemical process with no addition of calcium hydroxide and inclined plate clarifiers to remove iron below 20 mg/L and keep calcium well below 350 mg/L, treated AMD was used in a successful operation in Pennsylvania (12). The use of AMD water in Marcellus Shale development may provide a win-win solution for coal and natural gas industries along with the regulatory agencies that are tasked to oversee activities of both industries by providing a use for the AMD instead of treatment and monitoring required for discharge. Several members of the Marcellus shale industry volunteered to participate in a study to develop an information base on the nature and composition of influent water and flowback waters associated with completions of

Marcellus shale gas wells (13). Nineteen well sites were identified throughout Pennsylvania and West Virginia where hydraulic fracturing would take place. Samples were taken of the: supply water prior to blending of additives, influent water following blending with additives but before the addition of sand, flowback samples at varying time lapses after hydraulic fracturing, and water from each producing well 90 days after completion. Results show influent water usually contains moderate to low concentrations of salts. Refer to Table 1 (13). The concentration of TDS in flowback increased with time while the flow rate decreased with time. Samples showing moderate TDS values in the influent water indicateimplementation of water reuse practices meaning those companies use flowback water in part to make up hydraulic fracturing fluid for subsequent fracturing. Oil and grease, and total organic carbon (TOC) concentrations in these samples indicate blending of flowback water with freshwater. General characteristics of the flowback and produced water are consistent with literature values. Typically the dissolved solids in flowback and produced waters from Marcellus wells consist of sodium, chloride, calcium and to a lesser extent, strontium, barium and bromide. Heavy metals of toxicological concern that are often associated with urban industrial activity were at very low levels compared to what is typically reported in sludge from municipal wastewater facilities. Among the volatile organic constituents tested, nearly 96% were found at non-detectable levels and 0.5% was above 1 mg/L. Constituents in produced waters that exceeded 100 parts per billion (ppb) included components commonly present in produced waters from natural gas operations: benzene, toluene, ethylbenzene and xylene (BTEX); naphthalene; several methylated benzene compounds and an alkylated toluene; however, few determinations of these compounds exceeded 2 parts per million (ppm; 13). Nearly all halogenated organic compounds were at non-detect levels strongly suggesting additives blended with makeup waters do not contain concentrations of organic chemicals of concern. The results of this shale gas water characterization effort indicate that PCBs, pesticides, and a large fraction of volatile organic compounds (VOCs) and semi-volatile organic compounds (SVOCs) should be considered unnecessary for the sampling and analysis of flowback waters in the future (13).In another research work, Physico-Chemical characteristics of Khadakwasla reservoir near Pune were monitored for Physico-Chemical parameters like temperature, pH, electric conductivity, Sodium, Potassium, Calcium, Magnesium, Silica, Iron, Bicarbonate, Chloride, Sulphate, Nitrate, Phosphate, dissolved Oxygen, biological Oxygen demand & chemical Oxygen demand. These parameters were analyzed by collecting water samples at 4 different locations of reservoir from July-2005 to Jan-2006. From this study, it is observed that there is a seasonal variation in concentration of Physico-Chemical parameters & some of parameters are beyond permissible limit, which shows degradation of water quality due to pollution (2). A study of geochemical effect on the Physico chemical properties of different sources of water in Nagpur Municipal area of Maharastra, Shivankar V.M. reveals the facts that in the present investigation, 3 different water sources samples of Nagpur area were collected & various chemical parameters were studied from the results & discussion. It is concluded that in the same Nagpur municipal area, when compared the results in case of bore water, lake water and well water, lake water was found to be more suitable for human beings for all purposes (3) In the present study 130 water samples in clean poly— bottles from different sources Viz. hand pumps, open wells, tube wells, water supply were taken & preserved according to standard methods, A titrimetri (complex metric) method prescribed by American public health association (APHA7) was followed for estimation. Calcium hardness (Ca-H) ranged from 50 to 480 mg/l, minimum Ca-H was observed from Inderpura village where as maximum Ca-H was reported from Badoli Village. Ca-H was found to be within the limit in 48%. Villages, where as 42% villages are higher. (4). In the study of, using an innovative technique for removal of fluoride from drinking water, researcher, analyzed that for sorption studies, contact time is on of the most important parameter as it decides the efficiency of the system. The study on the contact time revealed as the contact time increases, % removal increases rapidly, but gradually approaches to constant value exhibiting the attainment of equilibrium (5). In another research study work, the evaluation of water quality index around WCL, KoleraPimpari coal mines. Objectives of this work is to provide information on the ground & surface water Pimpari area in order to appreciate the impacts of mining activities on the quality of water and to discuss its suitability for human consumption from the water quality index values. Water quality of Pimpari village which is very near to open cast coal mines (WCL Kolera Pimpari) were calculated by considering 8 parameters namely pH, totalhardness, TDS, Chloride, Nitrate, Sulphate & Sodium. Study revealed that water quality is poor at naalha & unfit for human consumption without treatment, where as river & ground water is acceptable. (6) Research work carried on the drinking water quality of coal mine surrounded lime industry area, by Sunanda.A, revealed that most of the parameters are within the permissible range of WHO & IS-10500. The seasonal variation for pH, temperature , fluoride nitrate, total hardness, chloride, turbidity, electrical conductivity, alkalinity, total dissolved solids, sulphate, phosphate etc, are low in summer. The TDS, alkalinity as expected are high in summer. The above investigation suggest that a detailed survey & study of air, water & soil in the area is required especially the air pollution (7) According to the research topic, pollution analysis of water in lime industry area by Shaskikant R, Reveals the facts that lime is used in industrial & mining, waste water treatment. It neutralizes acid waste, adjusting pH, removes Phosphorous, fluorine, Magnesium & organic matter & it precipitates heavy metals. In fact lime treats potable & industrial water supplies including drinking water which disinfects bacteria. Because of above characteristics of lime though it is polluting the atmosphere still its natural presence in the area on the other hand must be blessing for purification of water (8) Another study was done on ground water samples of Sangamner area, Ahmednagar district, Maharashtra, to evaluate the chemistry of ground water. The Physico chemical analysis of 53 open wells water was carried out by standard methods. The study reveals that intensive irrigation has serious effect on the quality of water. P. J. Puri , M. K. N. Yenkie, et al [01] have studied water quality index (WQI) has been calculated for different surface water resources especially lakes, in Nagpur city, Maharashtra (India), for the session January to December 2008; comprising of three seasons, summer, winter and rainy season. Sampling points were selected on the basis of their importance. Water quality index was calculated using water quality index calculator given by National Sanitation Foundation (NSF) information system. The calculated (WQI) for various studied lakes showed fair water quality in monsoon season which then changed to medium in winter and poor for summer season. Gorewada lake showed medium water quality rating in all season except monsoon season. Futala, Ambazari and Gandhisagar lake has also declined in aesthetic quality over past decade following invasion of aquatic weeds such as hydrilla and water primrose, so the reasons to import water quality change and measures to be taken up in terms of surface water (lakes) quality management are required B. N. Tandel, Dr. J. Macwan, C. K. Soni [02] have studied, the water quality index is a single number that expresses the quality of water by integrating the water quality variables. Its purpose is to provide a simple and concise method for expressing the water quality for different usage. The present work deals with the monitoring of variation of seasonal water quality index of some strategically selected surface water bodies. The index improves the comprehension of general water quality issues, communicates water quality status and illustrates the need for and the effectiveness of protective practices. It is found that in all cases the change in WQI value follow a similar trend throughout the study period. The lake water is found of good quality (WQI - 67.7 to 78.5) during both seasons. However, it is found that water quality of lake deteriorates slightly from winter to summer season on account of the increase in microbial activity as well as increase in pollutants concentration due to water evaporation. S. Chandra, A. Singh and P. K. Tomar [03] have described, lake water is a source of drinking and domestic use water for rural and urban population of India. The main goal of the present study was to assess drinking water quality of various lakes i.e. Porur lake Chennai, Hussain Sager Hydrabad Vihar lake Mumbai in India. For this, lakes water samples were collected from six different sites and composite sample prepared were analyzed for pH, turbidity, electrical conductivity (EC), total dissolved solids (TDS), total alkalinity (TA), total hardness (TH)and calcium hardness (Ca-H), chemical oxygen demand(COD), biochemical oxygen demand (BOD), dissolved oxygen (D.O.), sulphate (as SO4 2-), nitrate (as NO3) and chloride (Cl-) levels .Some heavy metals like Iron, Zinc, Cadmium, Mercury, Nickel and Chromium were also analyzed in these samples. There were variations for EC (141-1041 "#$%&), turbidity (2-9 NTU), TDS (107.1–935.8 mg/L), SO4 2- (4–8 mg/L), TA (42–410 mg/L), TH (41-280 mg/L), Ca–H (14- 10 mg/L), BOD (5-9mg/L), COD (4–32 mg/L) NO3(1.1-3.6 mg/L) and Cl- (49-167 mg/L) levels at different sites. Water pollution indicates that these parameters were manifold higher than the prescribed limit by the WHO & BIS standard. Wu-Seng Lung, A. M. Asce [04] has studied, a twolayer time-variable model is developed to quantify seasonal variations of pH and alkalinity levels in acidic lakes. The model incorporates the CO2/ HCOJ/ CO5 equilibria with internal sources and sinks of alkalinity and acidity in the water column. External alkalinity and C02 acidity loadings are also incorporated. The modeling framework is applied to the Bickford Reservoir in Massachusetts and to Woods Lake and Panther Lake in Adirondack Park, New York. In general, in-lake alkalinity generation by reduction processes in the Bickford Reservoir during the summer months is simulated by the model. The observed response to snowpack release in Woods Lake and Panther Lake during the spring months is also reproduced by the model. All three model applications are efficiently run on a personalm computer system. T. M. Heidtke, A. M. Asce and W. C. Sonzogni [05] have studied, results from a study of water quality planning and management alternatives for the Great Lakes are used to identify cost-effective pollution control strategies. Mathematical models and other systems analysis techniques are applied to estimate pollutional loadings, specific water quality problem areas, costs and pollutant reductions offered through alternative management strategies. A determination of how these alternatives may be expected to achieve water quality objectives for the Great Lakes is made. Data from a diversity of Great Lakes research efforts are compiled, integrated, and used to project local and lake wide water quality conditions over the next twenty years. A set of management tools, including a near shore water quality index and a series of environmental quality maps, are developed to promote communication and interpretation of Great Lakes water quality data among technical and nontechnical interests. Findings from the study support a staged approach to pollution control, whereby the most cost effective programs are implemented and their results assessed before more expensive control measures are undertaken. V. Pradhan, M. Mohsin, B. H. Gaikwad [06] have studied, water quality of Chilika Lake was determined during the month of January 2012. It was observed that all the parameters are above permissible limit except at the sample site S2. The results are discussed in the light of findings of other workers. Dr. M. K. Mahesh, B. R. Sushmitha, H. R. Uma [07] have explained, a water quality index (WQI) developed by the Canadian Council of Ministers of the Environment (CCME) was applied to Hebbal lake of Mysore, Karnataka State, India, to study its impact on aquatic life, livestock and to know whether it is suitable for recreation, irrigation and drinking. The index of the lake is rated as poor with respect to drinking, recreation and livestock, marginal with respect to Aquatic life and excellent for irrigation purpose. The overall water quality is rated as poor. The water quality is almost always endangered or deteriorated and the conditions often deviate from natural levels. Anabaena and Microcystis aeruginosa form blooms, Phacus pleuronectes is also recorded and the lake water is unsuitable to protect aquatic life. Incidence of Fish kill occurred in 2011 due to contamination of water. S. Hussaina, V. Maneb, et al. [10] have studied, In the present work we are reported the Physico chemical properties like pH, conductivity, Turbidity, TDS, DO, fluoride, chloride, Sodium, Sulphate, etc. and the values are compared for treated and untreated water samples. The samples were collected from treatment plant of Ahmedpur, Dist Latur. The values changes apparently after the treatment of water. R. W. Gaikwad, V. V. Sasane [11] has explained, the present work is aimed at assessing the water quality of the groundwater in and around Lonar Lake. Water quality has been determined by collecting groundwater samples and subjecting the samples to a comprehensive physiochemical analysis. For assessing water quality, pH, total hardness, calcium, magnesium, bicarbonate, chloride, nitrate, sulphate, total dissolved solids, iron, manganese and fluorides have been considered. The higher values has been found to be mainly for Iron, Total hardness, chloride, fluoride, calcium and magnesium, many literature shown that groundwater quality in Lonar Taluka has been badly affected by nitrate contamination. The analysis reveals that the groundwater of the area needs some degree of treatment before consumption, and it also needs to be protected from the perils of contamination. Many different options are now in progress for treatment of water locally. Various community based programs have been tried in the past, but only few of these purely community run plants are successful. The future lies in providing safe drinking water in rural areas with a mixture of these options so that the objectives of providing safe water at low cost for sustaining over a long time and reaching to maximum number of people is achieved. water quality of Tirupati Area, A.Naraju, Z. Sharifi, E. Balaji. The multivariate statistical analysis, hydro geochemical modelling using visual MINTEQ software, indices of base exchange and Gibbs ratio were simultaneously applied to groundwater hydro chemical data of the Tirupati area. These techniques were applied to know the principal processes controlling the water chemistry. Fifty groundwater samples were analysed for pH, electrical conductivity (EC), Ca, Mg, Na, K,HCO3, CO3, Cl, and SO4. The results showed that the abundance of the major ions in the water samples is in following order: Na > Ca > Mg > K and HCO3 > Cl > SO4 > CO3 > F. Physico chemical analysis of ground water quality in different wards of south zone of Bhuswal Tehsil, Bhusawal was studied. Samples are collected from 7 different wards of sampling points of the south zone of Bhusawal, Jalgaon district of Maharashtra in December 2009. Analysis results obtained in this study show that the ground water quality is rather good, there is no fear of water quality problem & related health in near future to the consumer. This study shows that as water quality problem arising in big cities but south zone of Bhusal district Jalgaon, Maharashtra is still safe as ground water quality is concerned.