Water Level Prediction Techniques-A Review

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Abstract- The significance of groundwater for the existence of human society can't be overemphasized. Groundwater is the primary source of drinking water in both urban and rural areas of India. Besides, it is an vital source of water for the agricultural and the industrial sector. Being an essential and integral part of the hydrological cycle, its availability depends on the rainfall and recharge patterns. Till recently it had been considered as a reliable source of uncontaminated water. The continuously increasing demand for water has led to water scarcity. The condition is aggravated by the problem of water pollution and contamination. In this paper we will analyze various techniques which have been used for water level prediction.

1. Introduction:

In a watershed basin, the seasonal modelling of ground water fluctuations is very useful in planning and management of both the surface water and ground water resources. This is important in regions where there is depleting surface water resources and increase in water demand due to industrialization and urbanization. Further change in climatic trends results in the variation of rainfall quantities. Thus, ground water resources are becoming an alternate solution to meet the increase in demands. In case of Indian subcontinent, where rainfall patterns are changing due to change in climatic conditions, the over exploitation of ground water has become inevitable. The major source of ground water in most of the watersheds in India is through recharge from rainfall. The groundwater prediction models can be divided into two groups, namely, i) physical and ii) system theoretic. The main drawback of the physical model is the complexity of the models, which increases with increase in model parameters. Further, the development of these models is based on understanding of the physical processes in the system. On the other hand, the system theoretic model is based on data driven techniques, where the mapping or learning of the models is done through data itself. Here, the understanding of the physical process in model building is avoided to a large extent. In recent years, the system theoretic models have gained recognition in the field of surface as well as subsurface hydrology. Among the data driven models, Artificial Neural Network (ANN) model has been successfully applied to a wide variety of hydrologic problems. The application of a more promising data driven technique, the Fuzzy Inference System (FIS), has recently been increasing in hydrology. Further, in recent years many advancements of ANN, which includes, Radial Basis Function (RBF), Generalized Regression Neural Network (GRNN) And Adaptive Neuro-Fuzzy Inference Systems (ANFIS) has been adapted to hydrologic problems. The combination of ANN and FIS into the adaptive Neuro-fuzzy inference system (ANFIS) has advantages in a computational framework. The learning capability of ANN can be used effectively for automatic fuzzy if-then rule generation and parameter optimization. Several researchers have used ANFIS in hydrology.

2. Related Work:

Holger R. Maier, Graeme C. Dandy, (2000) [3] illustrated Artificial Neural Networks (ANNs) are being used increasingly to predict and forecast water resources variables. Hence in this paper, the steps that should be used in the development of such models are given. These are the choice of performance criteria, the division and pre-processing of the available data, the determination of appropriate model inputs and network architecture, optimisation of the connection weights (training) and model validation. The choices available to scientists at each of these steps are discussed and the issues that should be considered are discussed. A review of 43 papers dealing with the use of neural network models for the prediction and forecasting of water resources variables is undertaken in terms of the modelling process adopted. The vast majority of these networks are trained using the back-propagation algorithm.

Purna C. Nayak, Y. R. Satyaji Rao and K. P. Sudheer, (2006) [4] illustrated a research study that investigates the potential of artificial neural network technique in forecasting the groundwater level fluctuations in an unconfined coastal aquifer in India. The most appropriate set of input variables to the model are selected through a combination of domain knowledge and statistical analysis of the available data series. Several ANN models are developed that forecasts the water level of two observation wells. The results suggest that the model predictions are reasonably accurate as evaluated by various statistical indices. In general, the results suggest that the ANN models are able to forecast the water levels up to 4 months in advance reasonably well. Such forecasts may be useful in conjunctive use planning of ground water and surface water in the coastal areas that help maintain the natural water table gradient to protect seawater intrusion or water logging condition.

Shaoyuan Feng, Shaozhong Kang, Zailin Huo, Shaojun Chen, and Xiaomin Mao, (2008) [5] illustrated artificial neural networks (ANNs) and applied to investigate the effects of these factors on ground water levels in the Minqin oasis, located in the lower reach of Shiyang River Basin, in Northwest China. Using data spanning 1980 through 1997, two ANNs were developed to model and simulate dynamic ground water levels for the two sub-regions of Xinhe and Xiqu. The ANN models achieved high predictive accuracy. Sensitivity analyses were conducted with the models demonstrating that agricultural ground water extraction for irrigation is the predominant factor responsible for declining ground water levels exacerbated by a reduction in regional surface water inflows.

Edvin Aldrian and Yudha Setiawan Djamil, (2008) [6] illustrated the use of multi variable Adaptive Neuro Fuzzy Inference System (ANFIS) in predicting daily rainfall using several surface weather parameters as predictors. It was seen that relative humidity is the best predictor with a stable performance regardless of training data size and low RMSE amount especially in comparison to those from other predictors. Other predictors showed no consistent performances with different training data size. Performances of ANFIS reach a slightly above 0.6 in correlation values for daily rainfall data without any filtering for up to 100 data in a time series.

Fernando Castellanos, Nickel James, (2009) [7] adopts a new approach using Adaptive Neuro-Fuzzy Inference Systems (ANFIS) to forecast the average hourly wind speed. To determine the characteristics of ANFIS that best suited the target wind speed forecasting system, several ANFIS models were trained, tested and compared. Different types and number of inputs, training and checking sizes, type and number of membership functions and techniques to generate the initial Fuzzy Inference Systems (FIS) were analyzed. Comparisons of the different models were performed and the results showed that the 4 inputs models generated by grid partitioning and the 6 inputs models generated by subtractive clustering provided the smallest errors with the models using wind speed and air pressure as inputs having the best forecasting accuracy.

Mehmet Tektaş, (2010) [8] presents a comparative study of statistical and neuro-fuzzy network models for forecasting the weather of Goztepe, Istanbul, Turkey. For developing the models, nine-year data (2000-2008) comprising daily average temperature (dry-wet), air pressure, and wind-speed were used. Adaptive Network Based Fuzzy Inference System (ANFIS) and Auto Regressive Moving Average (ARIMA) models were applied. To ensure the effectiveness of ARIMA and ANFIS techniques, different models employing a different training and test data set have been tested. The performance comparisons of ANFIS and ARIMA models due to Moving Average Error, Root-Mean-Square error criteria, indicate that ANFIS yields better results.

Amutha R and Porchelvan P, (2011) [9] carried out research in Malattar sub-watershed, located in Vellore district, Tamilnadu, India. The results showed that both the models were able to predict the seasonal ground water levels with sufficient accuracy. However, it is observed that the ANFIS model is able to capture the dynamics of the surface water and ground water interactions better when compared to RBF and thus able to predict the seasonal ground water levels accurately.

Jawad S. Alagha, MdAzlinMd Said, YunesMogheir, (2012) [10] illustrated an introductory review of application of two AI techniques namely, artificial neural networks (ANNs) and support vector machine (SVM) in various hydrological applications. Here, ANNs and SVM theoretical background together with their strength points that make them suitable for hydrological modeling were briefly described. Moreover, various examples of successful applications of ANNs and SVM for modeling different hydrological processes were also provided.

Hadi Galavi and Lee TeangShui, (2012) [11] illustrated the application of ANFIS in water resources context and reviews the common architecture of ANFIS models been used in this area of research. The aim is to make the researchers aware of the ANFIS application process in water resources studies.

Riccardo Taormina et al. (2012) [12] illustrated Artificial Neural Networks (ANNs) have been successfully employed for predicting and forecasting groundwater levels up to sometime steps ahead. In this paper, we present an application of feed forward neural networks (FFNs) for long period simulations of hourly groundwater levels in a coastal unconfined aquifer sited in the Lagoon of Venice, Italy. After initializing the model with groundwater elevations observed at a given time, the developed FNN should able to reproduce water level variations using only the external input variables, which have been identified as rainfall and evapotranspiration. To achieve this purpose, the models are first calibrated on a training dataset to perform 1-hour ahead predictions of future groundwater levels using past observed groundwater levels and external inputs. Simulations are then produced on another data set by iteratively feeding back the predicted groundwater levels, along with real external data. The results show that the developed FNN can accurately reproduce groundwater depths of the shallow aquifer for several months. The study suggests that such network can be used as a viable alternative to physical-based models to simulate the responses of the aquifer under plausible future scenarios or to reconstruct long periods of missing observations provided past data for the influencing variables is available.

Hong Ding et al. (2012) [13] illustrated a nonlinear forecasting model is proposed in order to obtain accurate prediction results and ameliorate forecasting performances. In the model, the genetic algorithm (GA) is coupled with simulated annealing (SA) algorithms to evolve a back-propagation neural network (BPNN) algorithm, called GASANN. The new model's performance is compared with three individual forecasting models, namely weighting moving average (WMA), stepwise regression (SR) and autoregressive integrated moving average (ARIMA) models by forecasting yearly water level of Liujiang River, which is a watershed from Guangxi of China. The results show that the new model outperforms than the other models presented in this study in terms of the same evaluation measurements. Therefore, the nonlinear model proposed here can be used as an alternative forecasting tool for water level to achieve greater forecasting accuracy and improve prediction quality further.

Sanjeev Kumar, Ajay Indian, Zubair Khan, (2013) [14] illustrated an attempt for more accurate prediction of groundwater levels with the data of shorter period for the observation wells located in Delhi (India). Feed Forward network trained with training algorithm 'Levenberg Marquardt' and found very effective to predict the ground water levels quarterly.

Majid Heydari, Ehsan Olyaie, Hamid Mohebzadeh and Ozgiir Kisi, (2013) [15], illustrated artificial neural networks (ANN) to derive and to develop models for prediction the monthly values of dissolved oxygen and specific conductance as two water quality parameters of Delaware River at a station located at Pennsylvania site of the U.S. by using the monthly values of the other existing water quality parameters as input variables. The monthly data of four water quality parameters and discharge, for the time period 1995-2006 were selected for this analysis. In developing the ANN model for prediction of dissolved oxygen (DO) and specific conductance (SC), configuration 4-5-1 and 4-6-1 yielded optimal with 5 and 6 neurons in hidden layer respectively.

P. Abbasi Maedeh, N. Mehrdadi, G.R. Nabi Bidhendi and H. Zare Abyaneh, (2013) [16], illustrated to examine groundwater quality in Tehran with respect to the consumption pattern in the last ten years, five distinct neural network scenarios of different total dissolved solids (TDS) input and output parameters were set up. It is observed that, in order to forecast with a great deal of trial and error, the tangent algorithms with the momentum-training algorithm turns out to be less erroneous in contrast to the sigmoid algorithms with Levenberg-Marquet.

Manouchehr Chitsazan, Gholamreza Rahmani, Ahmad Neyamadpour, (2013) [17] illustrated the Artificial Neural Network (ANN) approach for forecasting groundwater level fluctuation in Aghili plain, southwest Iran. An optimal design is completed for the two hidden layers with four different algorithms: gradient descent with momentum (GDM), levenbergmarquardt (LM), resilient back propagation (RP), and scaled conjugate gradient (SCG). FFN-LM algorithm has shown best result in the present study for all three hydrogeological groups. At last, to evaluate applied division, a unit network with all data and using LM algorithm was trained. Validation of the network shows that dividing the piezometers into different groups of data and designing distinct networks gives more focus on simulating groundwater level in the plain.

M. Rezaeianzadeh, H. Tabari, A. ArabiYazdi, (2013) [18] illustrated on the use of artificial neural networks (ANN), adaptive neuro-fuzzy inference systems (ANFIS), multiple linear regression (MLR) and multiple nonlinear regression (MNLR) for forecasting maximum daily flow at the outlet of the KhosrowShirin watershed, located in the Fars Province of Iran. Precipitation data from four meteorological stations were used to develop a multilayer perception topology model. The results showed that the area weighted precipitation as an input to ANNs and MNLR and the spatially distributed precipitation input to ANFIS and MLR lead to more accurate predictions.

Vahid Nourani, (2014) [19], illustrated that employing Artificial Neural Network (ANN) for modeling suspended sediment load leads to acceptable results, but in past few years more attentions have been paid to apply hybrid models. Genetic Programming (GP) also eventuates applicable results, but most of studies show that ANN is more powerful tool than GP. Employing Support Vector Machine (SVM), showed accurate results than other approaches; especially, when using selected kernels. No coincidence, application of hybrid models leads to better results in comparison with sole AI-based models. Pre-processing of data and handling non-stationary data are the main reasons of such results.

Jignesh Patel, Dr.Falguni Parekh, (2014) [20] illustrated the development of an efficient model to forecast monthly monsoon rainfall for Gandhinagar station using Adaptive Neuro Fuzzy Inference System (ANFIS). Eight models were developed using various membership functions and climatic parameters as inputs. In this study, the generalized bell-shaped built-in membership function has been used as a membership function in both Hybrid and Back propagation method for ANFIS. The four evaluation parameters Root mean square error, Correlation Coefficient, Coefficient of Determination and Discrepancy ratio were used to evaluate the developed model. The study revealed that hybrid Model with seven membership functions and using three inputs, temperature, relative humidity and wind speed gives best result to forecast rainfall for study area.

Faramarz Keshvari and Seyed Amir Shamsnia, (2014) [21] illustrated evaluation of the system for predicting the flow of the QAREAGHAJ river has been given. For this purpose, gauging, rainfall, temperature, evaporation and monthly discharge of the BANDE BAHMAN station on QAREAGHAJ River in 30-year period (October 1982 to October 2012) were used for the model. The results showed that the artificial neural network can predict monthly discharge of the river with solidarity coefficient of 75.0.

Samarjit Kara, Sujit Dasb, Pijush Kanti Ghosh, (2014) [22] illustrated neuro fuzzy systems (NFS) development using classification and literature review of articles for the last decade (2002–2012) to explore how various NFS methodologies have been developed during this period. Based on the selected journals of different NFS applications and different online database of NFS, this article surveys and classifies NFS applications into ten different categories such as student modeling system, medical system, economic system, electrical and electronics system, traffic control, image processing and feature extraction, manufacturing and system modeling, forecasting and predictions, NFS enhancements and social sciences. For each of these categories, this paper mentions a brief future outline. This review work indicates mainly three types of future development directions for NFS methodologies, domains and article types: (1) NFS methodologies are tending to be developed toward expertise orientation. (2) It is suggested that different social science methodologies could be implemented using NFS as another kind of expert methodology. (3) The ability to continually change and learning capability is the driving power of NFS methodologies and will be the key for future intelligent applications.

Naser Almanaseer, A. Sankarasubramanian, M. Jerad Bales, (2014) [23] illustrated and analyses the potential in developing 6-month-ahead groundwater-level forecasts based on the precipitation forecasts from ECHAM 4.5 General Circulation Model Forced with Sea Surface Temperature forecasts. Ten groundwater wells and nine stream gauges from the USGS Groundwater Climate Response Network and Hydro-Climatic Data Network were selected to represent groundwater and surface water flows, respectively, having minimal anthropogenic influences within the Flint River Basin in Georgia, United States. Two low-dimensional models [principle component regression (PCR) and canonical correlation analysis (CCA)] for predicting groundwater and stream flow at both seasonal and monthly timescales were employed. Results from the work showed that using precipitation forecasts in climate models improves the ability to predict the inter annual variability of winter and spring stream flow and groundwater levels over the basin.

Shahaboddin Shamshirband, Member IEEE et al. (2015) [24] illustrated an investigation of the accuracy of soft-computing techniques in precipitation estimation. The monthly precipitation data from 29 synoptic stations in Serbia from 1946 to 2012 are used as a case study. Despite a number of mathematical functions having been proposed for modeling precipitation estimation, the models still have disadvantages such as being very demanding in terms of calculation time. Soft computing can be used as an alternative to the analytical approach, as it offers advantages such as no required knowledge of internal system parameters, compact solutions for multivariable problems, and fast calculation. Because precipitation prediction is a crucial problem, a process which simulates precipitation with two soft-computing techniques was constructed and presented in this paper, namely, Adaptive Neuro-fuzzy Inference (ANFIS) and support vector regression (SVR). In the current study, polynomial, linear, and radial basis function (RBF) are applied as the kernel function of the SVR to estimate the probability of precipitation. The performance of the proposed optimizers is confirmed with the simulation results. The SVR results are also compared with the ANFIS results. According to the experimental results, enhanced predictive accuracy and capability of generalization can be achieved with the ANFIS approach compared to SVR estimation. The simulation results verify the effectiveness of the proposed optimization strategies.

3. Conclusion:

This review paper discusses various strategies and techniques used for water level prediction. India's rapidly rising population and changing lifestyles has also increased the domestic need for water. The water requirement for the industry also shows an overall increase. Intense competition among users — agriculture, industry, and domestic sectors is driving the groundwater table lower. Thus, constant monitoring of the ground water levels is extremely important. The water levels if properly predicted well in advance can help the administration to plan better ground water utilization.

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