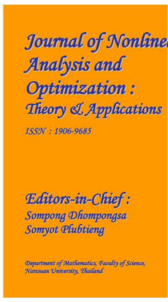
Journal of **N**onlinear **A**nalysis and **O**ptimization
Vol. 15, Issue. 1, No.15 : 2024
ISSN : **1906-9685**



PREDICTING GROUNDWATER LEVELS WITH A HYBRID ANN-GENETIC ALGORITHM APPROACH

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ABSTRACT

The economy's expansion in recent years has resulted in a greater use of groundwater and water resources. Groundwater abstraction has increased, making it more important than ever for both current and future needs. Precise assessments of the level of groundwater play a crucial role in enhancing decision-support platforms for the extraction of groundwater resources. This study looks at how effectively a hybrid model comprising a genetic algorithm (GA) and artificial neural network (ANN) can forecast the levels of groundwater in an observation well in the Udupi area. The model is trained using rainfall data collected over a ten-year period and ground water level data. The prediction job is carried out using a typical feed forward network. An artificial neural network is used to construct a forecasting model for groundwater levels. The ideal weights for ANN are found using the Genetic Algorithm. According to this research, groundwater levels of observation wells may be reliably predicted using the ANN-GA model. Furthermore, a comparison analysis shows that the conventional ANN back-propagation method is outperformed by the ANN-GA hybrid model.

I. INTRODUCTION

1.1 About the project

Groundwater is one of the major sources of supply for domestic, industrial and agricultural purposes. Estimation of groundwater level is very important in hydrogeology studies and aquifer management. In many cases, groundwater level fluctuations have resulted in damage to engineering structures [1]. With considerable amounts of these fluctuations, appropriate decisions can be presented in terms of hydrogeology, water quality and its management [2]. For this, a constant monitoring of the groundwater levels is extremely important. The water levels, if forecast well in advance, helps administrators to better plan the groundwater utilization. A continuous forecast of groundwater levels is required to effective use of any simulation model for water management and overall development [1]. In this regard, it is important to develop a fast and cost-effective method for aquifer simulation with an acceptable accuracy. Towards this goal, many researchers have used intelligent systems including, Coulibaly et al., Daliakopoulos et al., Lallahem et al., Dogan et al., Nourani et al, Yang et al., Sreekanth et al. [5,8,6,9,10,11,2 These researchers used ANN for aquifer modelling in a variety of basins.

ANN is an information-processing paradigm, that is inspired by the way biological nervous systems, such as the brain, processes information. It determines the relationship between inputs and outputs of physical systems by a network of interconnecting nodes adjusted by connecting weights based on the training samples, and extracts patterns and detects trends that are too complex to be noticed by either humans or other computational techniques [3]. Neural networks take a different approach to problem solving than that of conventional computers. It has remarkability to learn and derive meanings from complicated and imprecise data. It has an ability to learn and apply the knowledge based on the data given for training or initial experience.

Problem Statement:

Groundwater is a critical natural resource, and accurate prediction of groundwater levels is essential for sustainable water resource management. Existing methods for groundwater level prediction often rely on traditional hydrological models, which may struggle to capture the complex and nonlinear relationships between various influencing factors. Moreover, the presence of uncertainties, nonlinearity, and the dynamic nature of groundwater systems poses a significant challenge in achieving precise and reliable predictions. To address these limitations, there is a need for advanced and adaptive modeling techniques. The current problem lies in the inadequacy of conventional methods for groundwater level prediction, particularly in the face of dynamic environmental conditions and the intricate interactions among hydrological variables. Traditional models may not fully exploit the potential of artificial intelligence and machine learning techniques to handle the complexities associated with groundwater dynamics.

Developing a robust and accurate groundwater level prediction model demands a hybrid approach that combines the strengths of artificial neural networks (ANNs) and optimization techniques, such as genetic algorithms. The challenge involves designing a hybrid model that can effectively learn from historical data, adapt to changing conditions, and optimize its parameters to enhance prediction accuracy. Addressing this problem is crucial for optimizing water resource management strategies, preventing over-extraction, and ensuring the sustainability of groundwater utilization.

Objectives:

1. Data Collection and Preprocessing:
 - Gather comprehensive historical groundwater level data, including relevant hydrological variables, and preprocess the data to ensure cleanliness, consistency, and suitability for model training.
2. Hybrid Model Architecture Design:
 - Develop a hybrid artificial neural network (ANN) model integrated with a genetic algorithm (GA) for optimizing model parameters. Design the architecture to effectively capture nonlinear relationships and adapt to changing groundwater dynamics.
3. Feature Selection and Dimensionality Reduction:
 - Implement techniques for feature selection and dimensionality reduction to identify the most influential variables affecting groundwater levels, enhancing the model's efficiency and interpretability.
4. Genetic Algorithm Optimization:
 - Apply genetic algorithms to optimize the weights, biases, and architecture of the artificial neural network, enabling the model to adapt and evolve over time for improved accuracy in groundwater level predictions.
5. Time Series Analysis:
 - Incorporate time series analysis techniques to capture temporal patterns and seasonality in groundwater level data, ensuring the model's ability to handle dynamic changes over different time intervals.

6. Model Training and Validation:
- Train the hybrid model on historical data and validate its performance using an independent dataset. Utilize proper cross-validation techniques to ensure robustness and generalization capability.

1.2 Existing System

The back-propagation algorithm (BP) is the most popular in the domain of neural networks, which is utilized in the most frequently mentioned studies for aquifers simulation. BP is the standard of the Gradient Descent algorithm (GDA). The gradient descent method, its algorithms, easily become stuck in local Minimum and often need a longer training time. Chau et al [7] showed the stochastic optimization method (GA) to train a FNN; therefore, numerical weights of neuron connections and biases represent the solution components of the optimization problem. In fact, a combination of genetic algorithm to adjust the neural network weights was proposed in several researches on artificial intelligence

Disadvantage

1) Takes more time to train algorithm

1.3 Proposed System

The proposed prediction model starts with the collection of hydro-meteorological data as shown in Figure 1. The ground water and rainfall data used for analysis are collected from geological department, Government of Karnataka, Udupi district. An observation well from a small town of Parkala, Udupi district was identified as study area. The ground water variation for a period of 10 years (2000-2010) with rainfall data for same period is used to train the model. The 70% of the data is set as a training set, 15% of the data is used for validation and another 15% for testing the data. The Feed forward Neural Network was used in this work, which consists of two input layers, 4 hidden layers and an output layer. The data for 9 years was taken and the network was trained to forecast the ground water level of the 10th year and compared it with the desired data for the 10th year.

Advantages

1) Overcome the drawback of error back propagation algorithm

2) Trains Model with speed.

II. LITERATURE SURVEY

A detailed review of artificial neural network applications can be found in Maier et al. [12]. They reviewed forty-three papers dealing with the use of neural network models for the prediction of water resources variables. In recent years, Nourani et al. [13] evaluate a hybrid of the ANN-Geostatic methodology for spatiotemporal prediction of groundwater levels in a coastal aquifer system. Jalalkamali and Jalalkamali [14] employed a hybrid model of Artificial Neural Network and Genetic Algorithm (ANN-GA) for forecasting groundwater levels in an individual well. The hybrid ANN-GA model was designed to find an optimal number of neutrons for hidden layers. Their research admitted the superiority of the ANN-GA model in prediction of groundwater levels. Taormina et al. [15] employed an ANN for simulation of hourlygroundwater levels in a coastal aquifer system. They confirmed that the developed feedforward neural network (FNN) can accurately reproduce groundwater depths of the shallow aquifer for several months. Moreover, a combined method of discrete wavelet transform method and different mother wavelets with ANN (WANN) was proposed by Nakhaei and Saberi Naser[16] for the prediction of groundwater level fluctuations. Furthermore, a hybrid model of Neuro Fuzzy Inference System with Wavelet (Wavelet-ANFIS) was proposed by Moosavi et al. [17] for groundwater level forecasting in different prediction periods. These studies demonstrated that the wavelet transform can improve accuracy of groundwater level forecasting.

The back-propagation algorithm (BP) is the most popular in the domain of neural networks, which is utilized in the most frequently mentioned studies for aquifers simulation. BP is the standard of the Gradient Descent algorithm (GDA). The gradient descent method, its algorithms, easily become stuck in local minimum and often need a longer training time. Chau et al [7] showed the stochastic optimization method (GA) to train a FNN; therefore, numerical weights of neuron connections and biases represent the solution components of the optimization problem. In fact, a combination of genetic algorithm to adjust the neural network weights was proposed in several researches on artificial intelligence (Belew et al.; Liang et al.; Montana) [20,21,22].

Genetic Algorithm is one type of stochastic algorithms that is capable of solving multi-dimensional complex problems, especially non-smooth, noncontiguous, non-differentiable objective function to find the global optimum, to escape the local optima and acquire a global optima solution. This combination would be an efficient method of training neural networks because, it takes advantage of the strengths of genetic algorithms and back propagation (the fast initial convergence of stochastic algorithms and the powerful local search of back propagation), and circumvents the weaknesses of the two methods (the weak fine-tuning capability of stochastic algorithms and a flat spot in back propagation).

Nasseri et al. [4] developed a Feed forward Neural Network coupled with Genetic Algorithm to simulate the rainfall field. The technique implemented to forecast rainfall for a number of times using hyetograph of recording rain gauges. The results showed that when Feed forward neural network coupled with Genetic Algorithm, the model performed better compared to similar work of using ANN alone. ANN applications in hydrology vary, from real time to event based modelling. They have been used for groundwater modelling, level estimation (Coulibaly et al.; Nourani et al) [5,10]. A comprehensive review of the applications of ANNs in hydrology can be found in the ASCE Task Committee report (ASCE, 2000a,b)[19]. Sreekanth et al. [1] have systematically appraised the feat of the ANN model and the standard FNN trained with Levenberg algorithm, was tested for predicting groundwater level at Maheshwaram watershed, Hyderabad, India. The model competence and correctness were estimated according to the Root Mean Square Error (RMSE) and regression coefficient (R2). The model furnished the best fit and the forecast trend was hand in glove with the experiential data. Kostas et al. [18] have competently conceived a technique to predict the monthly maximum, minimum, mean and cumulative precipitation totals within a period of the next four successive months, by means of ANNs. The precipitation datasets represent monthly totals recorded at four meteorological stations in Greece. For the appraisal of the outcomes and the competencies of the designed prognostic methods, suitable statistical indexes like the coefficient of determination (R2), the index of agreement (IA) and the RMSE were employed. The observations from this appraisal demonstrated that the technique of ANN furnishes ample precipitation totals in four successive months and these outcomes emerge as superior ones in relation to those gathered by means of traditional statistical methods.

III. .SYSTEM DESIGN

System Architecture

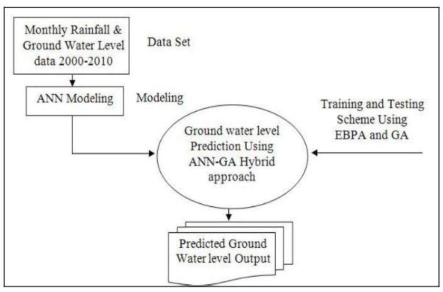


Fig:1 System Architecture

BLOCK DIAGRAM

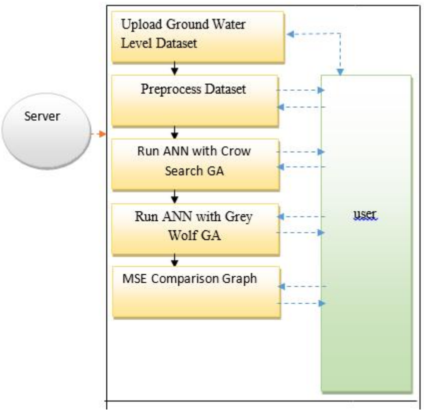


Fig:2 Block Diagram

IV. MODULE IMPLEMENTATION

Upload Ground Water Level Dataset: using this module we will upload dataset to application

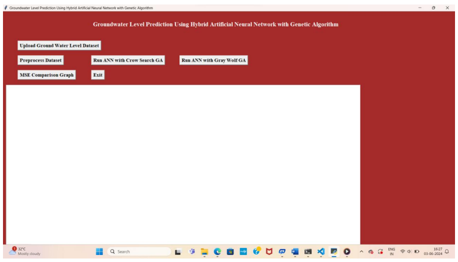
Preprocess Dataset: using this module we will read dataset and then remove missing values and make processed dataset ready

Run ANN with Crow Search GA: processed dataset will be feed into this module to train water level prediction model and calculate MSE

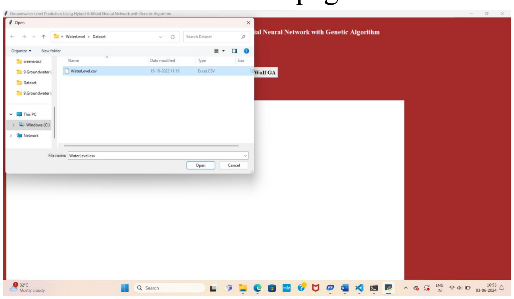
Run ANN with Grey Wolf GA: processed dataset will be feed into this module to train water level prediction model and calculate MSE

MSE Comparison Graph: using this module we will plot error graph between both algorithms. Less error algorithm will be consider as best

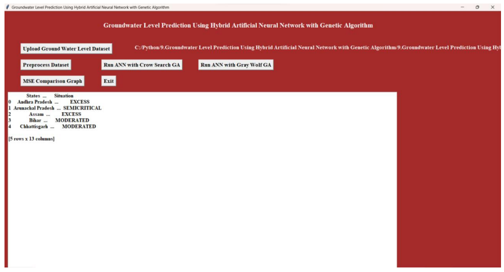
V. SCREEN SHOTS



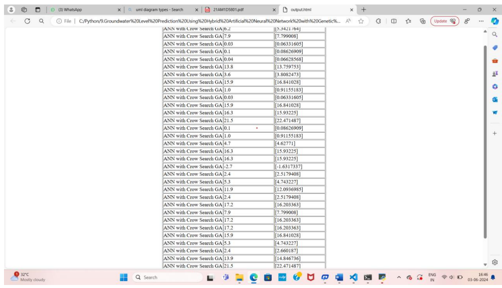
SS:1 Homepage



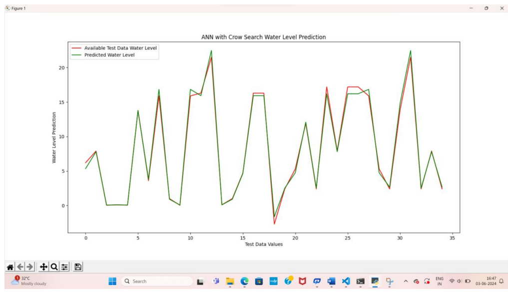
SS:2 Dataset



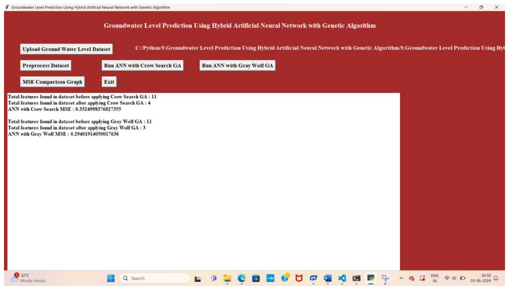
Ss:3 Process Data



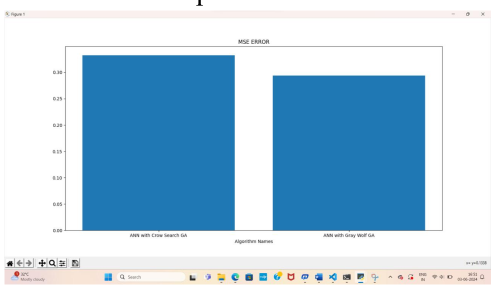
SS:4 Run ANN with Crow Search Ga



Ss:5 Output



SS:6 ANN With Crow Search Water level prediction



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S:6 MSE Comparison Graph

VI. CONCLUSION AND FUTURE ENHANCEMENT

In this paper, two approaches of soft computing have been developed for predicting groundwater level in an observation well identified in Udupi district. Initially ANN modelling was carried out using feed forward neural network architecture to predict groundwater level. The inputs of the ANN model were monthly rainfall record and water level for period of 10 years. The hybrid ANN-GA model was developed and the results are compared with the ANN gradient descent algorithm. The performance of ANN and ANN-GA algorithms was evaluated. It is observed that the performance of ANN-GA is considered superior than ANN model. Thus, ANN-GA hybrid algorithm can be used for predicting ground water levels over the study area. Further, more investigations needed on the field generated data in groundwater level forecasting to have a precise statement.

REFERENCES

[1] Sreekanth P.D., Geethanjali N., Sreedevi P.D, Shakeel Ahmed, Ravi Kumar N. and Kamala Jayanthi P.D., Forecasting groundwater level using artificial neural networks., Journal of Current Science, Vol. 96, No. 7, 2009.

[2] Hosseini Z. and Nakhaei M., Estimation of ground water level using a hybrid genetic algorithm Neural network., Journal of pollution, Vol 1(1), Winter , pp.9-12, 2015.

[3] Banerjee P., Prasad R.K. and Singh V.S., Forecasting of groundwater level in hard rock region using artificial neural network., Journal of Environmetal Geology, 58(6),pp 1239-1246, 2009.

[4] M.Nasseri, K.Asghari and M.J.Abedini, ,Optimized scenario for rainfall forecasting using GA coupled with artificial neural network, Science direct, Elsevier, Vol 35, pp. 1415-1421,2008.

[5] Coulibaly P, Anctil F, Aravena R, Bobee B., Artificial neural network modeling of water table depth fluctuations, Water Resources Research, 37(4): 885-896,2001.

[6] Lallahem, S., and Mania, J., Evaluation and forecasting of daily groundwater inflow in a small chalky watershed., Hydrological Process., 17(8), 1561- 1577,2003.

[7] Chau, K. W., Application of a PSO-based neural network in analysis of outcomes of construction claims. Automation in Constructions. 16(5), 642 646, 2007.

[8] Daliakopoulos, I., Coulibaly, P., and Tsanis, I. K., Groundwater level forecasting using artificial neural networks., Journal of Hydrology ., 309, pp.229-240,2005.

[9] Dogan, A., Demirpence, H., and Cobaner, M., Prediction of groundwater levels from lake levels and climate data using ANN approach., Water SA., 34, 199-205,2008.

[10] Nourani, V., Moghaddam, A. A., and Nadiri, A, An ANN-based model for spatiotemporal groundwater level forecasting. Hydrological Process. 22, 5054-5066, 2008.

[11] Yang, Z. P., Lu, W. X., Long, Y. Q., and Li, P., Application and comparison of two prediction models for groundwater levels: A case study in Western Jiilin Province, China., Journal of Arid Environment, 73, 487-492,2009.

[12] Maier, H. R., Jain, A., Dandy, G. C., and Sudheer, K. P., Methods used for the development of neural networks for the prediction of water resource variables in river systems: current status and future directions, Environmental Modelling and Software. 25(8), 891-909, 2010.

[13] Nourani, V., Ejlali, R. G., and Alami, M. T. ,Spatiotemporal groundwater level forecasting in coastal aquifers by hybrid artificial neural network geostatistics model: A case study., Environmental. Engineering. Science. 28(3), 217-228,2011.

[14] Jalalkamali, A., and Jalalkamali, N., ,Groundwater modeling using hybrid of artificial neural network with genetic algorithm., African Journal of

Agricultural Research. 6(26), 5775-5784,2011.

[15] Taormina, R., Chau, K., and Sethi, R., Artificial Neural Network simulation of hourly groundwater levels in a coastal aquifer system of the Venice lagoon., Engineering Application of Artificial Intelligence , 25(8), 1670-1676,2012.

[16] Nakhaei, M., and Saberi Naser, A. , A combined Wavelet-Artificial Neural Network model and its application to the prediction of groundwater level fluctuations, Journal of Geopersia., 2(2), 77- 91,2012.

[17] Moosavi, V., Vafakhah, M., Shirmohammadi, B., and Behnia, N.A. ,Wavelet-ANFIS Hybrid Model for Groundwater Level Forecasting for Different Prediction Periods.,Water Resource. Management., 27(5), 1301-1321,2013.

[18] Kostas P Moustris ,Loanna K Larissi and Panagiotis T Nastos,, Rainfall Intensity forecast using Artificial Neural Networks in Athens, Elsevier ,pp.1 -8,2014.

[19] ASCE Task Committee on Application of Artificial Neural Networks in Hydrology, Artificial neural networks in hydrology, parts I and II. J. Hydrological Engineering. 5(2), 115-137,2000.

[20] Belew, R. K., McInerney, J., and Schraudolph, N. N., Evolving networks: using the genetic algorithm with connectionist learning. (In C.G. Langton (Eds.) Artificial Life II., USA: Addison-Wesley), (pp. 511-547), 1991.

[21] Liang, H., Lin, Z., and McCallum, R. W., Application of combined genetic algorithms with cascade correlation to diagnosis of delayed gastric emptying from electrogastrograms, Medical Eng. Phys., 22, 229-234, 2000.