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IMPROVING GROUNDWATER LEVEL PREDICTION ACCURACY WITH A HYBRID ANN AND GENETIC ALGORITHM MODEL

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ABSTRACT:
The economy's expansion in recent years has resulted in a greater exploitation of groundwater and water resources. Groundwater is becoming more and more important due to excessive abstraction, both now and in the future. Reliable groundwater level estimations are important for enhancing groundwater resource exploitation decision support systems. This study examines how effectively a hybrid model of genetic algorithms (GA) and artificial neural networks (ANN) can forecast groundwater levels in an observation well from the Udupi area. The model is trained using rainfall data and ground water level data over a ten-year period. The prediction job is carried out using a conventional feed forward network. An artificial neural network is used to create a forecasting model for groundwater levels. The optimal weights for ANN are found using the Genetic Algorithm. According to this study, groundwater levels in observation wells may be accurately predicted using the ANN-GA model. Furthermore, a comparison analysis shows that the ANN-GA hybrid model outperforms the conventional ANN back-propagation technique.

I. INTRODUCTION

One of the main supplies for residential, commercial, and agricultural uses is groundwater. Groundwater level estimation is crucial for aquifer management and hydrogeology research. Variations in groundwater levels have frequently caused engineered constructions to sustain damage [1]. Appropriate choices about hydrogeology, water quality, and its management may be made with significant volumes of these changes [2]. It is crucial for this that the groundwater levels are continuously monitored. Administrators can more effectively plan the use of groundwater if the water levels are predicted well in advance. For any simulation model to be used effectively for water management and general development, a constant forecast of groundwater levels is necessary [1]. Aquifer modelling with a reasonable level of accuracy requires a quick and economical approach, which is crucial in this context. Numerous researchers, including Coulibaly et al., Daliakopoulos et al., Lallahem et al., Dogan et al., Nourani et al., Yang et al., and Sreekanth et al., have employed intelligent systems to achieve this aim [5,8,6,9,10,11,2]. These researchers modelled aquifers across a range of basins using artificial neural networks.

The way organic nervous systems, like the brain, process information served as the model for the information-processing paradigm known as artificial neural networks (ANN). Through a network of interconnecting nodes that are adjusted by connecting weights based on the training samples, it ascertains the relationship between the inputs and outputs of physical systems. It also extracts patterns and detects trends that are too intricate for humans or other computational techniques to notice [3]. Compared to traditional computers, neural networks approach problem solving differently. Its capacity to learn and extract meaning from complex and inaccurate data is astounding. It may pick up new information and use it based on training data or firsthand 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.

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 hourly groundwater levels in a coastal aquifer system. They confirmed that the developed feedforward neural network (FNN) can accurately reproduce groundwater depths

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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).

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
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

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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 ANALYSIS

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

PROPOSED SYSTEM

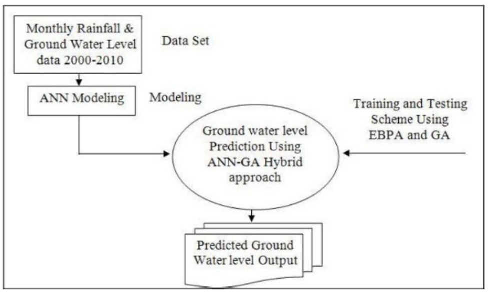
The proposed prediction model starts with the collection of hydro-meteorological data as shown in Figure 1. The ground water and rainfall data used for analysis are collected from geological department, Government of Karnataka, Udupi district. An observation well from a small town of Parkala, Udupi district 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

IV. SYSTEM DESIGN

System Architecture



V. SYSTEM IMPLEMENTATION

MODULES

Modules Description

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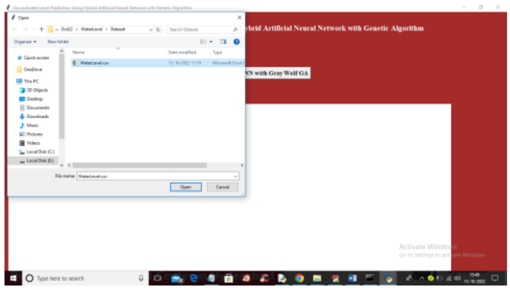
To implement this project we have designed following modules

1) **Upload Ground Water Level Dataset:** using this module we will upload dataset to application
2) **Preprocess Dataset**: using this module we will read dataset and then remove missing values and make processed dataset ready
3) **Run ANN with Crow Search GA:** processed dataset will be feed into this module to train water level prediction model and calculate MSE
4) **Run ANN with Grey Wolf GA:** processed dataset will be feed into this module to train water level prediction model and calculate MSE
5) **MSE Comparison Graph:** using this module we will plot error graph between both algorithms. Less error algorithm will be consider as best

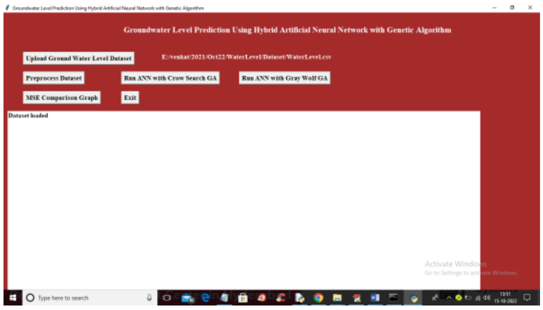
VI. SCREEN SHOTS

To run project double click on 'run.bat' file to get below screen

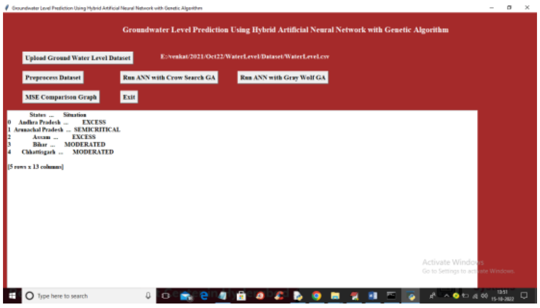
In above screen click on 'Upload Ground Water Level Dataset' button to upload dataset and get below output



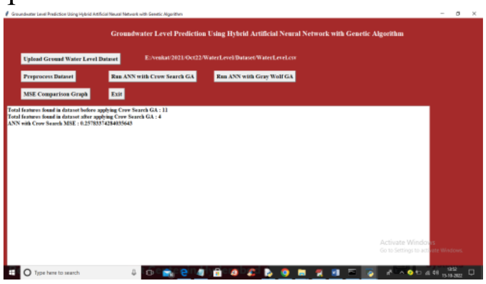
In above screen selecting and uploading 'WaterLevel.csv' dataset file and then click on 'Open' button to load dataset and get below output



In above screen dataset loaded and now click on "Preprocess Dataset" button to read and clean dataset and get below output



In above screen showing some values from the dataset and now click on 'Run ANN with Crow Search GA' button to optimize features and train with ANN to get below output



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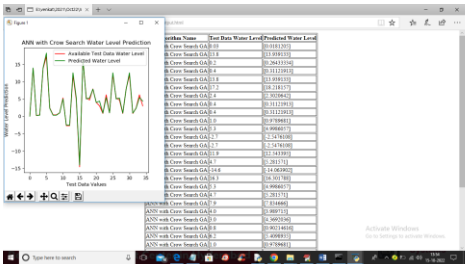
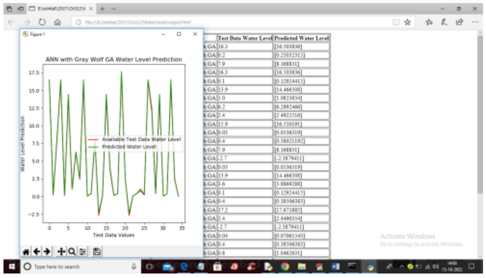
In above screen in first line we can see dataset contains 11 features and after optimization with Crow and GA we got 4 attributes and then training with ANN got 0.25 as the MSE error and below is the prediction output on test data

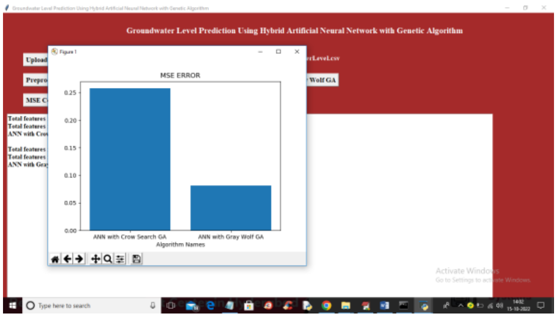


In above screen in tabular output first column contains Algorithm Name and second column contains TEST data water level and 3rd column contains predicted water level and in above table we can see there is minor difference between TEST value and predicted values and in graph also X-axis represents number of test data and y-axis represents Water Level and red line represents TEST water level and green line represents predicted water level and in above graph we can see both lines are fully overlapping so there is only minor difference between predicted and test values and now close above graph and then click on 'Run ANN with Gray Wolf GA' button to train ANN with Grey wolf and GA and get below output

In above screen with Grey wolf also 4 features selected and its MSE is 0.08 and below is the prediction output



In above screen we can see test and predicted water level in tabular output for Grey wolf and in graph we can see both lines are completely overlap so Grey wolf is giving close prediction so it's better than crow search and now click on 'MSE Comparison Graph' button to get below output



In above graph x-axis represents algorithm names and y-axis represents MSE error and in both algorithms Grey Wolf with GA ANN got less error rate

VII. CONCLUSION AND FUTURE ENHANCEMENT

Two soft computing techniques have been developed in this study to forecast the groundwater level in an observation well located in the Udupi area. In order to estimate groundwater level, ANN modelling was first done using a feed forward neural network design. Water level data and monthly rainfall records over a ten-year period served as the ANN model's inputs. The ANN gradient descent approach is used to compare the outcomes of the hybrid ANN-GA model. The ANN

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and ANN-GA algorithms' performance was assessed. It has been noted that the ANN-GA model performs better than the ANN model. Therefore, the research area's ground water levels may be predicted using the ANN-GA hybrid method. To get an accurate statement, more field-generated data analysis is required for groundwater level predictions.

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

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www.ijasem.org
Vol 18, Issue 4, 2024
https://doi.org/10.5281/zenodo.14066141
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.