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Artificial Neural Network Technique for Groundwater Modelling of Jaspura Block

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ABSTRACT

As a result of economic development and climatic change, arid and semi-arid areas are confronted with significant difficulties in the management of limited freshwater resources. For the most part, groundwater is the most significant water supply in these regions. Groundwater level prediction is a critical component of appropriate sustainable development and must be done correctly. The use of physical-based models is often used in the modelling and prediction of groundwater. However, owing to data shortages in many arid and semi-arid regions, they are not relevant in these areas. The usefulness of data-driven techniques in modelling complicated and nonlinear hydrological processes has been shown in many studies. It is the implementation and comparison of four algorithm-based models for forecasting groundwater levels that is the focal point of this research.This article compares the different Artificial Neural Network method and applies to the Jaspura Block of Banda Districts which is part of the Yamuna River Basin. For the forecast of groundwater levels four distinct algorithms Levenberg Marquardt, Gradient Descent, Scaled Conjugate Gradient and Bayesian regularization are used for optimal design. The ANN training data for input is collected from Recharge and Discharge data while groundwater level data for output layer were being used. The best algorithm comes to the Levenberg Marquardt algorithm in comparison with the other algorithms.

Key words : *Modelling, Artificial neural network, Recharge, Discharge*

Introduction

Ground water makes the most significant contribution to water, and it is primarily used for human survival and socioeconomic improvement. Thus water has a special position whether viewed within the framework of a developing economy or within that of a developed region. The economic development has been harshly in an substandard position by the dearth of water. In developing countries, the agriculture is also acknowledged as strength of economy which has been also defenseless badly due to the non accessibility of water. The necessity of water has been increased in the midst of time to meet the necessity of increasing demand of food and industries. India which is currently having adequate fresh water supply also facing problems on account of rising demand due to population pressure, over exploitation of the assets and rapid growth in agriculture and industry. Growing crisis of ground water scarcity and alarming declines in ground water levels in various developing countries indicate that ground water policy in most of the countries are failing to protect life's most vital resources. In last decades due to meet out the various demand the pressure on ground water increases and it results as depletion of groundwater.So, prediction of water table which is declining day by day in the areas

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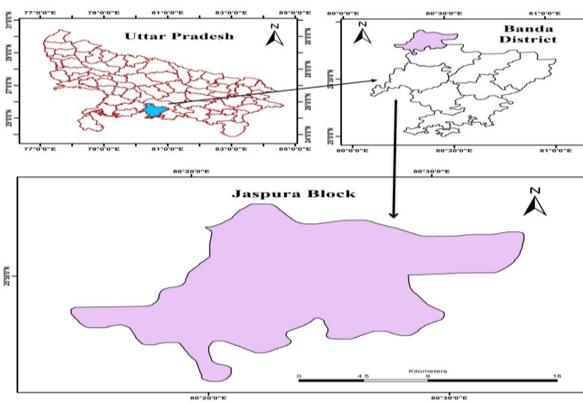
which are suffering from over operation of ground water has become an urgent need to harness the available water resources by the proper execution, optimal utilization and a stable water development projects. For the reason that surface water is inadequate in arid and semi-arid areas, groundwater research is very beneficial. These waters, which have been organically filtered, are often found to be of high quality for drinking and running water. Multiple variables are taken into consideration while planning, designing, and operating water resources systems since climatic and hydrological variables are often considered (precipitation, flow, temperature, etc.) (Pegram, 1972). Recent years have seen the application of Artificial Intelligence techniques such as Genetic Programming (GP), Adaptive Neuro Fuzzy Inference System (ANFIS), and Artificial Neural Networks (ANN): (Unes *et al.* (2015a, 2015b); Tasar *et al.* (2017); Demirci *et al.* (2017)) Coulibaly *et al.* (2001). During the last decade, the Artificial Neural Network (ANNs) model has become accepted in hydrological modeling and forecasting. Humans are able to do difficult tasks like perception, pattern detection, or reasoning much more competently and also able to learn from examples and neural systems of human brain are to some extent mistake tolerant. The advantage of ANN over other methods have been discussed by French *et al.* (1992). ANN is especially useful if nonlnonlinearity occur in a problematic domain (Taslloti, 2004). Research and development in Artificial Neural Networks (ANNs) started with an effort to model the bio-physiology of the human brain, create models which would be capable of mimic processes characteristics of human on a computational level. Neural networks are often seen as an optional method for dealing with huge volumes of dynamic, non-linear and noisy data, especially in circumstances that do not completely ignore the basic physical interactions. Water supplies for human activity include all the lakes, rivers, and waterways which flow into the seas in the ultimate section. These fluids are consumed in the hydrological cycle by evapotranspiration and replenished by precipitation. Due to the drought, the levels of the lake have decreased, impacting the fish and fauna of the lakes in recent years. In the region, the supply of drinking water is obtained from the groundwater; thus, there is a public awareness of the precise link between groundwater pumping, lake levels, precipitation and the evapotranspiration. The three fundamental sustainable development principles according to O'Riordan (2000) are maintenance and protection of critical ecosystems, use of renewable resources to a cautious level and cost the livelihoods based on natural burdens and social disturbances. How strong are these principles applied to the resources of groundwater?

Study area



Jaspura Block Map

Bundelkhand region consists of seven districts of UP, Jhansi, Jalauan, Lalitpur, Hamirpur, Banda, Chitrakoot. A Banda district is drained by Baghain, Yamuna, Ken Rivers. Jaspura blocks consists Fine loam soil, Coarse loamy calcareous soil. Japura lie under moderate category of distribution of forest. For study consideration, two wells were taken. Recharge and Discharge were taken according to CGWB norms. In Recharge and Discharge all the factors were included.

Methodology

Ground Water Balance Equation

$$R_c + R_i + R_r+R_c+S_i+I_g+E_t+T_p+S_e+O_g+\Delta S \quad .. (1)$$

Where,

R = Rainfall Recharge;

R_c = Canal seepage Recharge;

Rr = Field irrigation Recharge; Rt = Recharge from pond storage

I_g = inflow from blocks; Et = Evapo-transpiration;

T_p = Groundwater discharge from tubewell;

S_i, S_e = influent and effluent seepage from rivers; Og = outflow to other blocks; and

ΔS = change in ground water storage.

All these parameters are calculated by Central Groundwater norms.

Block Name	Well Name	Longitude	Latitude	Area (sqkm)
Jaspura	Pailani	80.42	25.76	161.98
	Bhitari ka Dera	80.34	25.83	182.98

For Bhitari ka Dera well

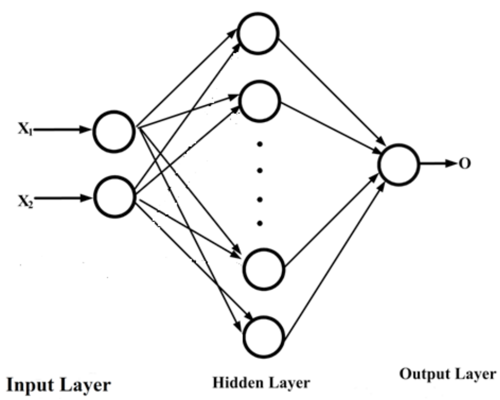
Year	Recharge in ha-m	Discharge in h a-m	GWL in mbgl
1995	1540.046579	260.0509189	22.15
1996	2595.699767	273.3558105	20.68
1997	1171.098903	853.9247841	19.55
1998	1132.557523	313.894474	19.65
1999	1217.498154	314.2505965	21.68
2000	3227.424772	355.8779854	19.2
2001	2461.279388	360.3810871	2.4
2002	1252.660569	365.318004	24.25
2003	2251.876162	347.2915695	23.54
2004	1584.825472	388.1943369	21.9
2005	1952.508691	413.4459176	4.36
2006	1977.295566	419.3298961	5.71
2007	738.3347182	425.1870501	7.8
2008	2032.24963	431.2799293	10.1
2009	1558.170605	437.6954362	16.81
2010	1081.687623	441.0007087	21.55
2011	2538.045971	443.2692364	20.15
2012	1879.983007	446.350098	20.83
2013	2753.395246	459.4512102	19.87
2014	928.4236876	462.3176496	20.21
2015	1591.541113	465.184089	23.23
2016	2463.317144	468.0505284	22

For Well Pailani

Year	Recharge in Ha-m	Discharge in Ha-m	GWL in mbgl
1995	1421.581	240.047	21.3
1996	2396.031	252.3284	20.2
1997	1081.014	788.2383	19.61
1998	1045.438	289.7487	21.4
1999	1123.844	290.0775	20.2
2000	2979.161	328.5028	20.61
2001	2271.95	332.6595	17.3
2002	1156.302	337.2166	21.3
2003	2078.655	320.5768	22.2
2004	1462.916	358.3332	21.94
2005	1802.316	381.6424	21.69
2006	1825.196	387.0738	21.35
2007	681.5397	392.4804	18.81
2008	1875.923	398.1046	21.74
2009	1438.311	404.0266	22.5
2010	998.4809	407.0776	21.23
2011	2342.812	409.1716	20.82
2012	1735.369	412.0155	19.9
2013	2541.596	424.1088	19.98
2014	857.0065	426.7548	21.4
2015	1469.115	429.4007	22.7
2016	2273.831	432.0466	22.67

Design of ANN Based Model

In the current research, water table dependence was developed using the ANN technique, which is an information processing system generated using training data to memorize and generalize its characteristics. Neural networks consist of several linked layers which lead to a multi-layer forward feeding network. The ANN allows describing the interdependence of specific physical amounts and of the unexpected whose value must at a time be anticipated. The input layer contains the input value or the physical amounts that impact the predictable variable. It generally has no other purpose than the input signals received and buffered. The network outputs are produced through the output layer. The input layer is called a hidden layer; each layer of the output layer is an internal network layer, which doesn't touch the external environment. 0 or more hidden layers can be included to ANN. If each output from one layer is connected to the next layer node, a network is said to be completely connected. For this research a single-layer supply network was established, which generated predictions of water table.



ANN ARCHITECTURE

Gradient Descent algorithm: The most straightforward training algorithm is also known as the steepest descent. The data from the provided gradient vector is necessary, and hence the approach is called first order. The approach starts from the beginning and proceeds step by step in the direction of training until the target condition is satisfied.

Levenberg-Marquardt algorithm: Levenberg-Marquardt algorithm gives a numerical solution to the problem for minimizing the nonlinear functions. It is the fast with stable convergence. In the field of artificial neural network, this algorithm suitably find for training small and medium size problems. It is intended to approx. the second order training rate without computing the Hessian Matrix. This algorithm can be applied only when the loss function has the form of a sum of squares because the error estimated is as the mean square error or the normalized error. It needs to compute the gradient and the Jacobian Matrix of the loss.

Bayesian Regularization (BR)

The Bayesian regularization is a mechanical technique that sets optimal standards in support of the point function parameter. A random variable with a given circulation is defined as the weight and bias of the network. The advantage of using Bayesian Regularization is that whatsoever the size of the network the function won't be over fitted. Bayesian regularization have been efficiently used in literature (Anctil *et al.,* 2004).

Scaled Conjugate Gradient (SCG)

The algorithm of SCG (Moller, 1993) determines the computation of a quadratic error in the area. This hypothetical basis work was demonstrated by Moller (1993) as being the main order approach of the primary derivatives such as regular back propagation and an important manner for the secondary derivative to get the local lowest order technique. SCG is a mixture of gradient algorithms in the second order that helps decrease a multi dimensional target function. SCG is a simple and scalable technique that keeps the search from the time expensive line via the information iteration (Karmokar *et al.,* 2012). The SCG method shows supra linear convergence in large problems, according to Moller (1993).

Criteria for Evaluation

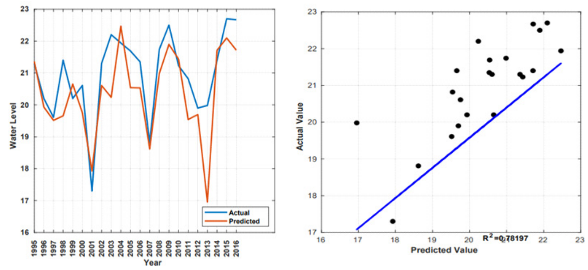
The following statistical indices such as (R^2) efficiency criteria, root mean square error (RMSE), Mean Square Error (MSE) were used to evaluate the performance.

Results and Discussion

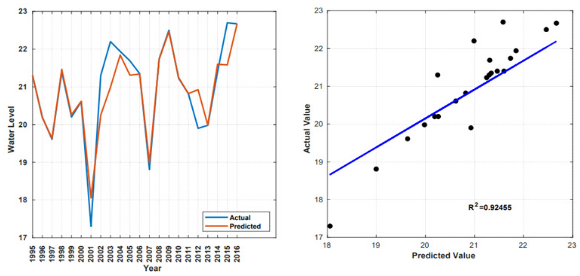
Determination of groundwater level of Pailani well of Jaspura block in monsoon season

The ANN models are trained, tested and validated using the recharge and discharge parameters to obtain the groundwater level of Pailani well of Jaspura block. The inputs and output for training the respective ANN models are taken for the period of 1995 to 2016 from the Pailani well region and trained using different training algorithms. The model is trained using a trail approach for every training algorithm for achieving the optimal network. Here, the model trained with Levenberg Marquardt algorithm is found to be optimal with least mean square error (MSE). The performance plots of R^2 for training, testing and validating data are shown in the Figures 3.

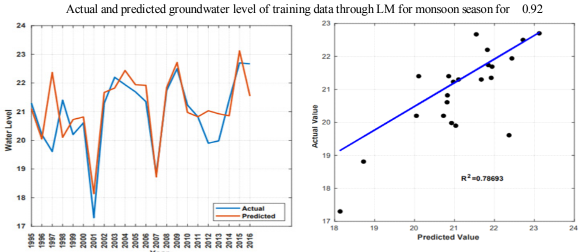
The scattering diagrams of actual and predicted groundwater levels for training, testing and validation data are also shown in the The value of R^2 is close to 1 that finds a linear fit between the actual and predicted values of groundwater level. The performance of the developed models trained with different training algorithms is listed. This performance is characterized by various parameters like MSE, RMSE and R^2 values of training, testing and validation data.



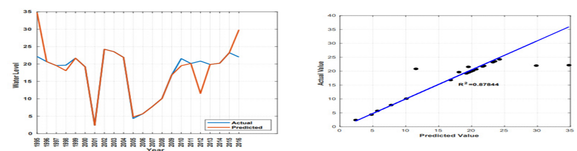
. Actual and predicted groundwater level of training data through LM for monsoon season for 0.78



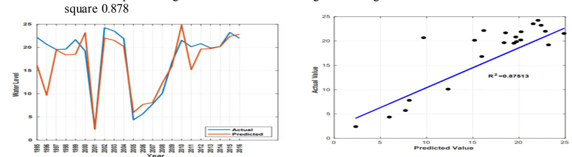
Actual and predicted groundwater level of training data through LM for monsoon season for 0.92



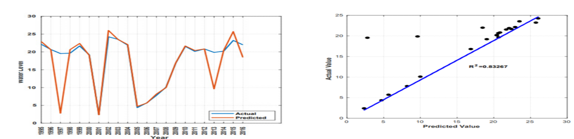
Actual and predicted groundwater level of training data through LM for monsoon season for 0.76



Actual and predicted groundwater level of training data through LM for monsoon season for R square 0.878



Actual and predicted groundwater level of training data through LM for monsoon season for R square 0.875



Actual and predicted groundwater level of training data through LM for monsoon season For R square 0.83

Table 9. Performance of ANN models developed with different training algorithms for Pailani well of Jaspura block during monsoon season

Criteria of Evaluation	Gradient Descent			Bayesian Regularization			Levenberg Marquardt			Scaled Conjugate Gradient		
	MSE	RMSE	R^2	MSE	RMSE	R^2	MSE	RMSE	R^2	MSE	RMSE	R^2
Training	102.7	10.13	0.50	3.44	1.8	0.92	**0.43**	1.05	0.92	1.10	0.65	0.89
Testing	75.59	8.69	0.41	42.47	6.51	0.43	**0.25**	0.50	0.78	0.60	0.77	0.87
Validation	189.1	13.75	0.36	0.25	0.50	0.004	**0.38**	0.83	0.72	0.69	0.61	0.80
Epoch	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000

Criteria of Evaluation	Gradient Descent			Bayesian Regularization			Levenberg Marquardt			Scaled Conjugate Gradient		
	MSE	RMSE	R^2	MSE	RMSE	R^2	MSE	RMSE	R^2	MSE	RMSE	R^2
Training	246.4	5.43	0.69	6.23	0.83	0.85	**0.42**	0.85	0.87	0.86	0.81	0.84
Testing	303.2	16,37	0.68	54.76	0.79	0.84	**0.66**	0.85	0.87	0.96	0.94	0.76
Validation	146.8	9.34	0.68	1.82	0.94	0.73	**0.37**	0.94	0.83	0.92	0.96	0.82
Epoch	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000

Performance of ANN models developed with different training algorithms for Bhitari well of Jaspura block during monsoon season

Determination of groundwater level of Bhitarika dreawell of Jaspura block in monsoon season

The ANN models for Bhitari ka dera well of Jaspura block during the monsoon period are obtained following the same implementation technique, i.e., using the trial approach to have an optimal ANN model. The inputs to the model are Recharging and Discharging parameters that is taken for the Bhitari ka dera well region during the monsoon period of 1995-2016. Utilizing the same scheme of network modelling, different ANN models have been developed and trained with different learning algorithms. The models are trained, tested and validated using appropriate data and the optimal network has been achieved.

Conclusion

Although the ANN is a very good hydrological tool, it has several limitations over a physical hydrological model. When contemplating future simulation scenarios that include adding new model factors like groundwater loss, land use change and irrigation patterns, etc., it can never replace a physically based model. The purpose of the artificial neural network in this research was prediction of groundwater. The data for input and output are separated into hydrogeological groups of wells and for each layer of wells, LM, SCG, BR and GD have been trained. The results show directly that for all four wells the LM algorithm operates quite well. Results show that the ANN model can anticipate the complicated behaviour of the virtual physical structure. One of the main advantages of this ANN method is that it may offer accurate forecasts with groundwater data constraints.

Declarations

Conflict of interest: No conflict of interest.
Consent for Publication: Upon acceptance, we give the consent to publish the article.

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