Estimation of Daily Groundwater Table Using Backpropagation Neural Network Model by Assessing Training Algorithm

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Abstract

The Onça stream is a Brazilian waterway, a canal on the left bank of the Rio das Velhas and a tributary of the São Francisco River. Although it plays an important role in the management of groundwater levels in the Ribeirao Preto region, the final groundwater capacity is declining in many parts of Brazil in response to abstraction. Predicting and forecasting stream water level using simple but effective methods can provide a reliable tool for future management of groundwater. In the present study, the daily water level of a particular well from the year 2004 to 2014 was considered as the dataset. The adopted database was segregated as 70% for training the above-mentioned models and the remaining 30% data was utilized for model testing. One of the soft computing methods, Backpropagation Neural Network was utilized for the prediction of daily groundwater table. In this, BPNN model, various training algorithm were utilized and compared based on the value of coefficient of correlation (R)and the time taken. The model also assessed by various statistical parameters like root means square error (RMSE), mean total error (MAE), determination coefficient (R^2), Normalized mean biased error (NMBE). The results depicted that the developed model have good forecasting ability.

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1. Introduction

The weather condition variations, water pollution are the certain factors which elevates the water requirement across the globe. One of the most important sources of freshwater is the groundwater, however, the abstraction and climate changes diminish the groundwater level**[3][21**]. Groundwater research is extremely important because surface water is scarce in arid and semi-arid countries. These naturally filtered liquids are sometimes mistaken for good drinking and flowing water. The importance of multivariate modelling occurred in the planning, construction and operation of Meteorological and hydrological systems are frequently used in water resource systems.(for example, precipitation, flow, and temperature) **[19][17][12]**. Artificial Intelligence approaches including Genetic Programming (GP), Adaptive Neuro Fuzzy Inference System (ANFIS), Artificial Neural Networks (ANN), and M5tree (M5T) have been understood in recent years: that it was used ANNs to estimate monthly groundwater level variations**[22][20].**ANN was used to estimate subsurface water levels; A hybrid ANN-numerical model for groundwater problems**[1][5].**ANN model was used to solve a challenging problem, In New Jersey, there is a real-world subsurface water management challenge**.[2][4][6**].ANN to estimate groundwater levels in China's West Jilin Province. ANN was used to investigate the effects of human activities on regional groundwater levels. ANNs were developed by et al. (2005) to predict potentiometric surface elevations accurately. **[19][11][9]**The primitive dispute in the water resource management is the meticulous prediction of groundwater level **[8].** As urban areas extend across the world, governments and organizers search for approaches to precisely anticipate the groundwater level so they can ensure the water request is met as the populace development continues to increment and furthermore as a vital factor when planning new urban areas**.[13][15].** The groundwater table has been estimated by using various modelling techniques [Artificial Neural Network is one of the supervised learning inspired from human brain's architecture. During the early 1970's the Backpropagation neural network was established but the fame of the BPNN was escalated by Rumelhart (1986). The shortage of water assets has driven cultivators to improve their water system procedures to give crops their accurate water prerequisites. The external climatic conditions were utilized in order to predict the leaf area index for a greenhouse transpiration model by adopting the BPNN model **[14][23].** The spatial evolution of sea ice of the Liaodong Bay was predicted with précised accuracy by the BP neural network model**[10]**. Ground source heat pump (GHSP) systems have been broadly utilized in private and business structures all through the world because of their elite and ecological kind disposition. The prediction of GHSP was carried out by adopting the BP model and the output was promising with higher accuracy**[18]**. The BP model was utilized as an evolutionary soft computing model for numerous real time problem **[7][16]**.In this study, the goal is to evaluate the different training algorithm in BP model in order to predict the daily groundwater table in the Rio das Velhas region in Brazil. The evaluation of this model was carried out by different statistical indices such as Root mean square error (RMSE), Mean Absolute error (MAE), Coefficient of determination (R^2), Normalized mean bias error (NMBE), Performance Index (PI), Nash–Sutclie coefficient (NS). In order to construct the BPNN model, MATLAB was utilized.

2. Study area & Data assemblage

The Ribeirão das Posses watershed is located in the south of Minas Gerais State, Brazil, and extends between geographic coordinates from 22°49'46" to 22°53'21" south and from 46°13'24" to 46°15'08" west. The study area is depicted in the following figure 1.The daily groundwater table for a particular well in the above-mentioned location was observed from the year 2004 till 2014.

In order to model the nonlinear hydrological process, the selection of possible input variable was one of the disputes. In this study, the various input fusions were adopted to resolve this hydrological modelling issue. The observed data from the year 2004-2014 was calibrated. This model, utilized 70% of the data for training and 30% of the data for the testing, as there is no universal rule for the segregation of data (Taheri et al., 2019; Pham et al., 2019; Chen et al., 2019; Khosravi et al., 2019; Khozani et al., 2019). The data was normalized between 0 and 1 by using the following equation (1)

$$\text{normalized value} = \frac{\text{value} - \text{min.value}}{\text{max.value} - \text{min.value}} \quad (1)$$

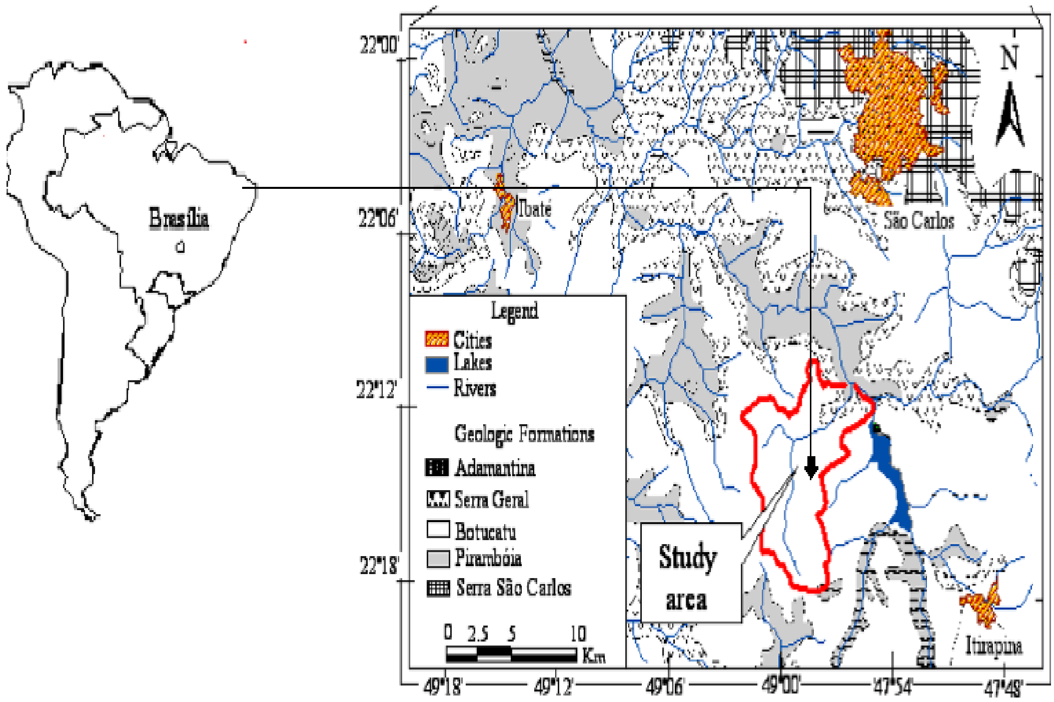


Figure 1: Location of the study area.

3. Methodology

Artificial neural networks (ANNs) are one of the computing techniques and systems that can derive new information by learning from the properties of the human brain's ability to create and discover new information. They were developed with the help of the human brain's ability to create and discover new information.The goal is to be able to execute without assistance. Inspired by artificial neural networks, the human brain is the consequence of learning process mathematical modelling.The feed-forward-backpropagation ANN methodology, which works on the idea of backpropagation, is the most extensively used ANN method. An ANN model has three layers: input, hidden, and output.

Standard patterns are required in ANN in order to build an essential relationship between the data pair of inputs and outputs. Additionally, the predictability of a skilled ANN should also be examined for the situations which were not the part of the neural network training.

The ANN models generally used to build up prescient models in light of its self-learning, nonlinearity, and self-assertive capacity estimation capacity. The BPNN model is one of the subsets of the ANN, which has typically input, hidden and the output layer. The main pro of this BP model was the reverse transmission of signals and errors. The typical architecture of the BPNN model was depicted in the following figure 2.

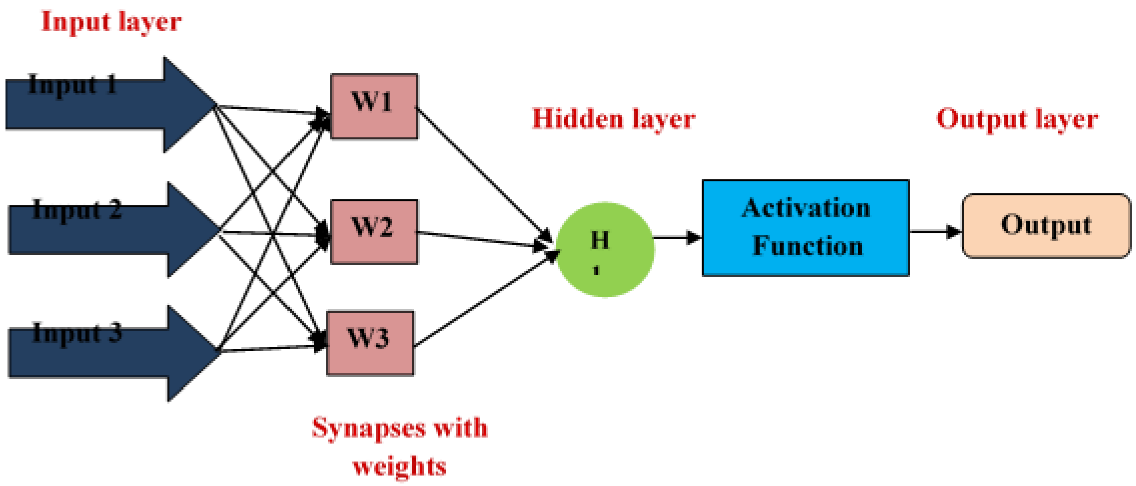


Figure 2: Typical architecture of BPNN model.

In the back propagation model, the preliminary weights were set arbitrarily and later it was altered as per the disparities between the training and the output data. The standard BP neural network utilizes an algorithm of descent gradient, and the network weights are changed contrarily along the gradient of the function. Consequently, the anticipated values continue to draw nearer to the observed value (Feng et al., 2020). In the initial stage, the BPNN model, promulgate the inputs forward and the yield of the various layers can be computed by using the following equation (2) (Jana et al., 2018).

$$G^{n+1} = f^{n+1}(w^{n+1}.G^{n+1} + b^{n+1}) \tag{2}$$

where G- is the output, f is the transfer function, w is referred as the weight matrix for various layers; n=0, 1…,M-1, M is the number of layers; and b is termed as the bias matrix for the considered layers.,The next stage in BP is to disseminate the sensitivities backward through the network initiating from the final layer.

$$s^M = 2K^M(x)^M(t - S) \tag{3}$$

where, s is the sensitivity, x is the net input and t is considered to be the target

$$K^M = [f^n(x_1^n) \ \ldots \ 0 \ \vdots \ f^n(x_2^n) \ \vdots \ 0 \ 0 \ f^M(x_{sn}^n) \quad]$$

Then the last layer of the sensitivities is then back propagated to the initial layer by the and it can be expressed as per the following equation (4)

$$s^n = F^n(x^n)(W^{n+1})^T . s^{n+1} \tag{4}$$

The biases and the weights will be upgraded in the concluding step by adopting the steepest descent rule which are as follows in the following equations (5) and (6)

$$W^n(k+1) = W^n(k) - \alpha s^n (G^{n-1})^T \tag{5}$$

$$b^n(k+1) = b^n(k) - \alpha s^n \tag{6}$$

where, α is the learning rate.

The BPNN model was developed in the software MATLAB and the training dataset which is 70% of the total dataset was utilized to develop the model and the remaining 30% of the model was adopted to assess the trained model.One of systems which can learn adaptively is DENFIS. This system can able to change dynamically every model to particular output for each input. If a relationship which is complex must be modelled, then DENFIS is trust worth approach. A experimented has conducted where DENFIS has given a model with 2 inputs to estimate ET for minimum and maximum temperatures. ANFIS is Adaptive Neural Fuzzy Inference Systems is similar software but Advaned version of it is DENFIS. Neuro-fuzzy models has been used by ANFIS for input and output to build a relationship called predictor-predictand. The drawback of ANFIS is because of stationary structure its arduous to adapt for the inputs which are new. In addition, ANFIS produces NF models which grows exponentially as per the numerous inputs given, which turns hard for solving high dimensional inputs. The DENFIS system uses rising clustering functions with many steps are taken to predict the cluster centers. This cluster data generates NF models. The massive noise in the data can be managed by the algorithms which are clustered in DENFIS makes the system model efficiently. There are two ways to develop the DENFIS system; Offline and online learning system. DENFIS develops a function, which is modified many times by Least-Square adopting method. If the process is offline, a better accuracy can be achieved using best learning algorithm for the dynamic evolution of NF models. (Jitter plot).In the study , the structure used is feed forward neural network and method is described as follows:This method mainly contains 2 phases. They are forward and backward computing.

In first case, which is forward computing, every layer has a weight matrix which has a connection with one behind layer and also to the upcoming layer. The weight matrix of the hidden layer is W_{ij} with f^1 as the activation function. Then the output layer also has the activation function f^2 and the weight matrix is W_{jm} Then the input vector of network is x belongs to R^{nx1} and the response vector which is output vector is y belongs to R^{nx1} .

The relation between them is written as follows

$$y_m = f^{(2)}\left\{\sum_{j=1}^{m}\left[f^{(1)}\left(\sum_{i=1}^{n}x_i W_{ij} + b_j\right)\right]W_{jm} + b_m\right\}$$

In this study, most used three transfer functions are Log-sigmoid, liner and tangent sigmoid and examined in experiments.Backward computing which is after forward computing, relay on the algorithms to settle the weights. This method of normalizing the weights to reduce the differences among desired and actual outputs is known as network learning or training. In a case where the errors are higher then the expected results, then the errors are repeated through and through backward in the network till minimized. In terms of ANN this stage is also known as algorithm of Back-propagation.

According the methods used to train the models of ANN(feed-forward neural networks), variety of back-propagation algorithms are generated and adopted. In a study, one of the algorithms of back-propagation called Levenberg-Marquadt, which is faster and second order nonlinear optimization method is used. This algorithm uses a newton method which is simplified and applied for adoption. The process of training should be considered a set of inevitable weights that reduce error (ep) for all samples in the group.Human brain's learning skills inspires for information processing methods of ANN. To establish the present patterns among input and output data sets, ANN requires samples to adopt accordingly. Also it is must examine the ability of ANN when given the input the DATA from outside of the sample given. To conduct entire process, including testing and training, the data we have should be randomized and divided accordingly. Approximately, the data for training the ANN is 70% and for testing only 30%, which is divided equally into sets for testing and validation.

To train the ANN, the data from 70% is used, which higher than the testing as ANN requires mode data to establish and understand the relationship between the data pairs of input and output updating the work weights of neural network systematically and BO algorithm. While training is going on, there is a chance for ANN to over-learn of over-fit the sample patterns given while training. This can be resulted for the low generalization of the network when given new data.

To over come the over fitting the ANN work, the data from Validation can also be used but indirectly So that this helps to reduce the errors during validation. Once the training is finished successfully then the testing of ANN start in second phase from the remaining data. The ANN has to predict the results using the training algorithms for rest of the input given from the data with as less as errors possible.

4. Results and Discussion

There are no norms for modifying the number of hidden neurons, a hit and trial approach were utilized for determining the optimum number of hidden neurons (Naik et al., 2014). In the upcoming table (1) the syntax for the various training functions and their corresponding algorithm type has been shown.

Table 1: BPNN model's training functions and their corresponding algorithm.

S.No	Type of Algorithm	Syntax of the training function
1	Scaled Conjugate Gradient	trainscg
2	Levenberg-Marquardt	trainlm
3	Fletcher-Reeves Conjugate Gradient	traincgf
4	BFGS quasi-Newton backpropagation	trainbfg
5	Gradient Descent with Momentum and Adaptive Learning Rate	traingdx
6	Bayesian Regularisation	trainbr
7	Polak-Ribiére Conjugate Gradient	traincgp
8	Conjugate Gradient with Powell/Beale Restarts	traincgb

The tuning parameters such as training algorithms, hidden transfer function, output transfer function and number of hidden neurons were determined by trial-and-error approach. The table (1) shows the utilization of various training algorithm that the BPNN model can adopt. The transfer functions such as "tansig" "logsig" and "purelin" were utilized.

According to the above-mentioned table, maximum of 2 hidden neurons were adopted in order to obtain the best result. The epochs are nothing but the iterations, which exposed that the number of iterations took place at lease mean squared error and the time taken to achieve the iteration with best possible coefficient of correlation value.

The above table 1 depicts that, the model number M4 and M6 with the training algorithm 'trainbgf' and 'trainbr' with the same transfer functions 'logsig' and 'tansig' were providing the best coefficient of correlation (R) value with minimal error.

The following table 2 depicts the neural architecture and the design parameters for the BP model.

Table 2: Neural structure and the design parameters of the BPNN model.

Trial Model No	**Training Algorithm**	**Hidden transfer function**	**Output Transfer function**	**Neuronal architecture (input-hidden-output)**	**Epochs**	**Time (sec)**	**MSE**	**Validation**	
								Training (R)	**Testing (R)**
M1	trainscg	tansig	logsig	3-2-1	300	5	0.000289	0.9968	0.9889
M2	trainlm	tansig	logsig	3-1-1	300	10	0.000223	0.9970	0.9894
M3	traincgf	purelin	logsig	3-1-1	19	1	0.000248	0.9968	0.9915
M4	trainbgf	logsig	Tansig	3-1-1	76	2	0.00008585	0.9988	0.9934
M5	traingdx	logsig	Logsig	3-1-1	140	3	0.0006883	0.9914	0.9769
M6	trainbr	logsig	Tansig	3-1-1	150	5	0.000062	0.9991	0.9945
M7	traincgp	purelin	Tansig	3-1-1	21	1	0.000714	0.9906	0.9884
M8	traincgb	tansig	Tansig	3-1-1	53	2	0.000128	0.9983	0.9926

. The performance of the model M4 and M6 can be depicted in the upcoming figure 3 and 4.

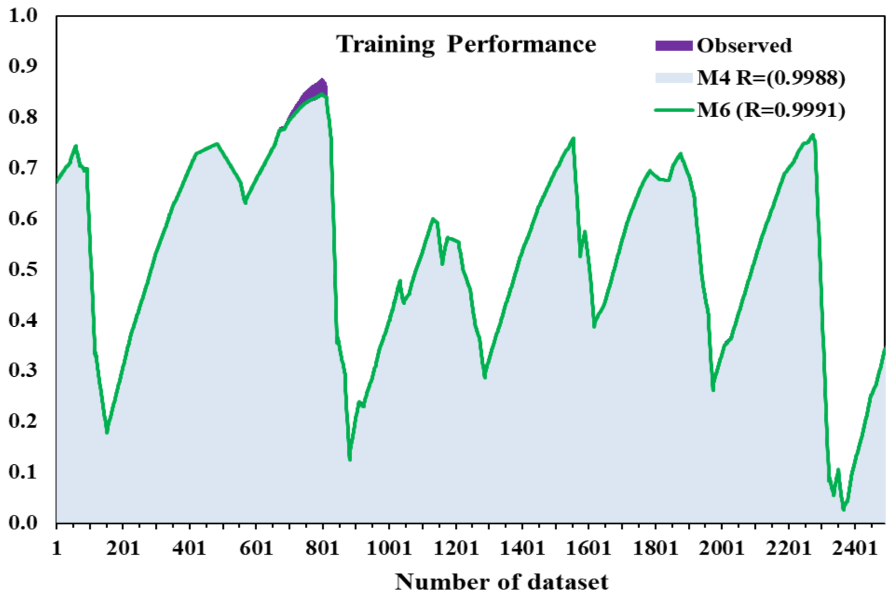


Figure 3: Training Performance of the BPNN model of M4 and M6.

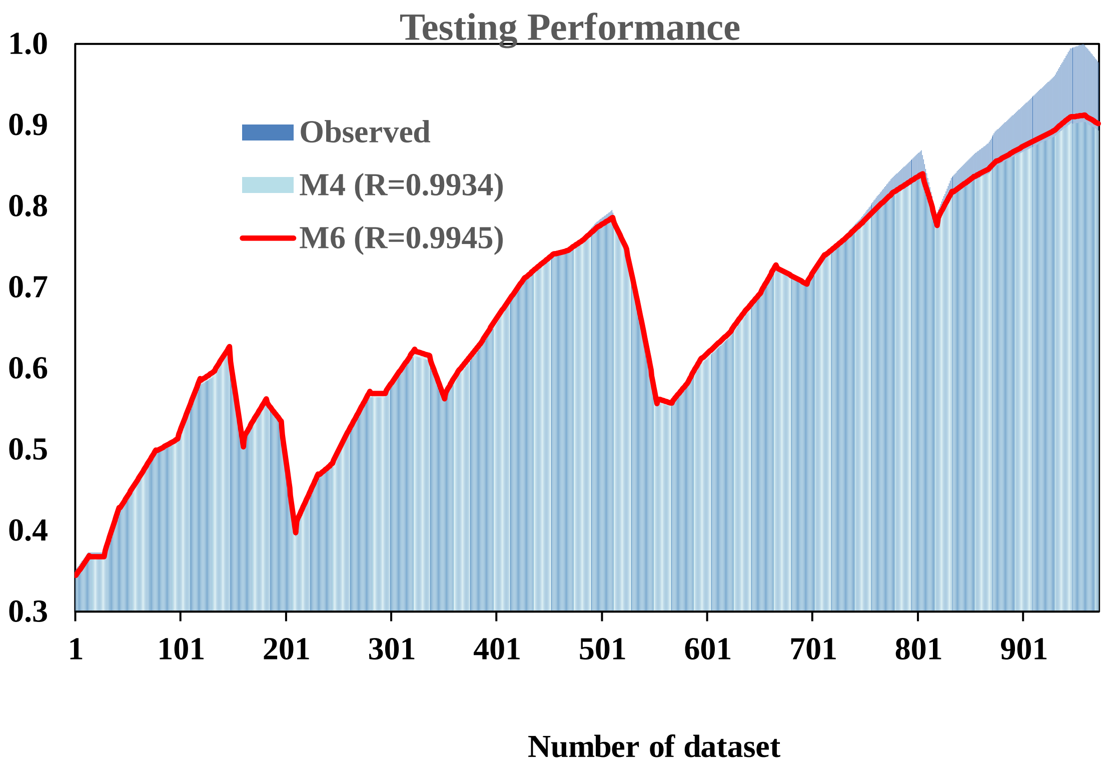


Figure 4: Testing Performance of the BPNN model of M4 and M6.

The above figure depicted that the models M4 and M6 performs well in determining the daily groundwater table, however the model M6 outperforms the other models. The upcoming figure (4) explains compares the potential of the various adopted training algorithm with respect to their coefficient of correlation (R) and the time taken for forecasting the groundwater level. The figure (4) explains that, the model M6 outperforms other BPNN models.

There are other various statistical parameters such as Root mean squared error (RMSE), Mean absolute error (MAE), Coefficient of determination (R^2), Normalized mean bias error (NMBE), Variance account factor (VAF), Nash Sutcliffe efficiency (NS), Performance Index (PI) and adjusted determination coefficient (Adj.R^2) are utilized in order to assess the capability of the developed BPNN model

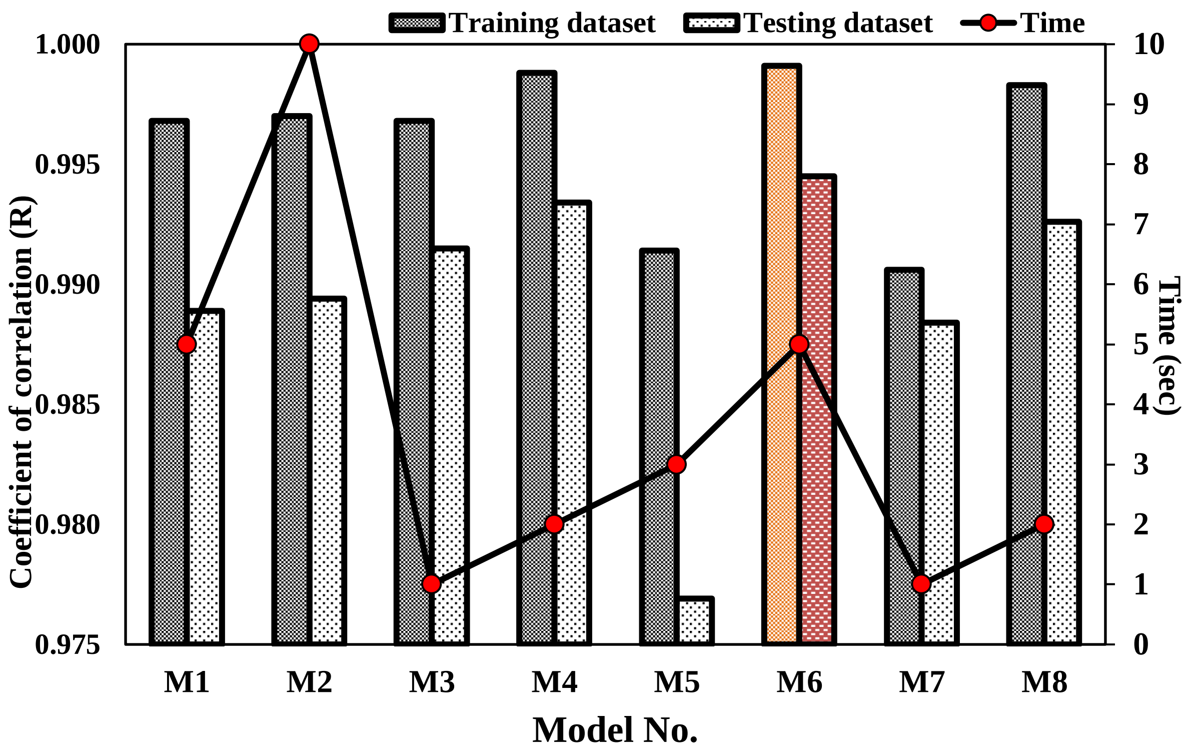


Figure 5.Comparison of performance of various training algorithms.

. The statistical values for the M4 and M6 models are depicted in the following table 3.

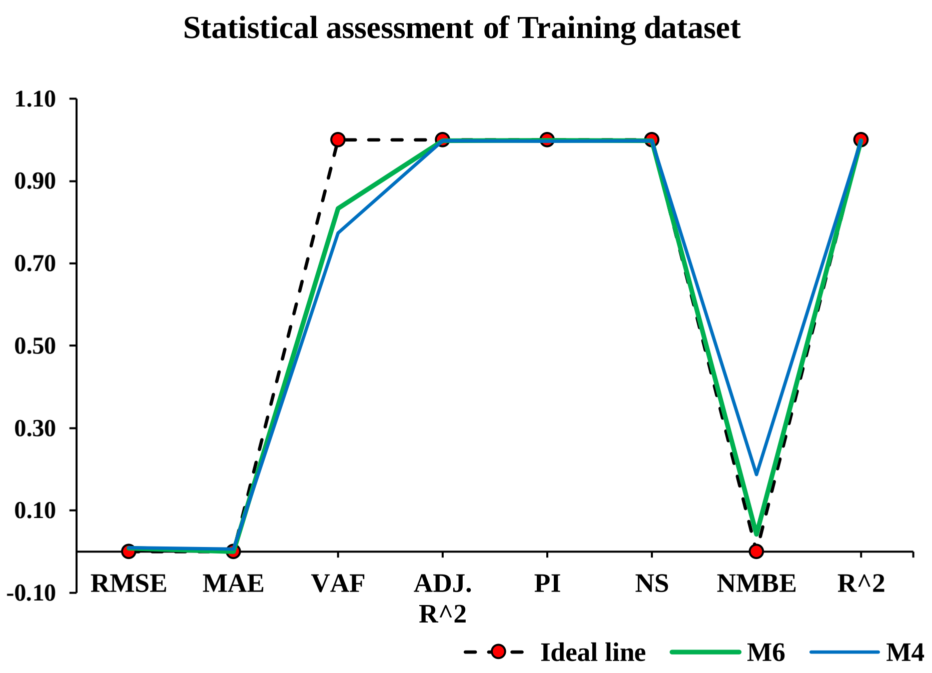
Table 3: Statistical assessment of the models M4 and M6.

STATISTICAL PARAMETER	M4		M6	
	Training	Testing	Training	Testing
RMSE	0.00927	0.02557	0.00786	0.00021
MAE	0.00636	0.01387	0.00000	0.00001
VAF	0.77380	-1.29526	0.83399	0.69525
ADJ. R^2	0.99760	0.98682	0.99820	0.98901
PI	0.99607	0.94829	0.99868	0.99575

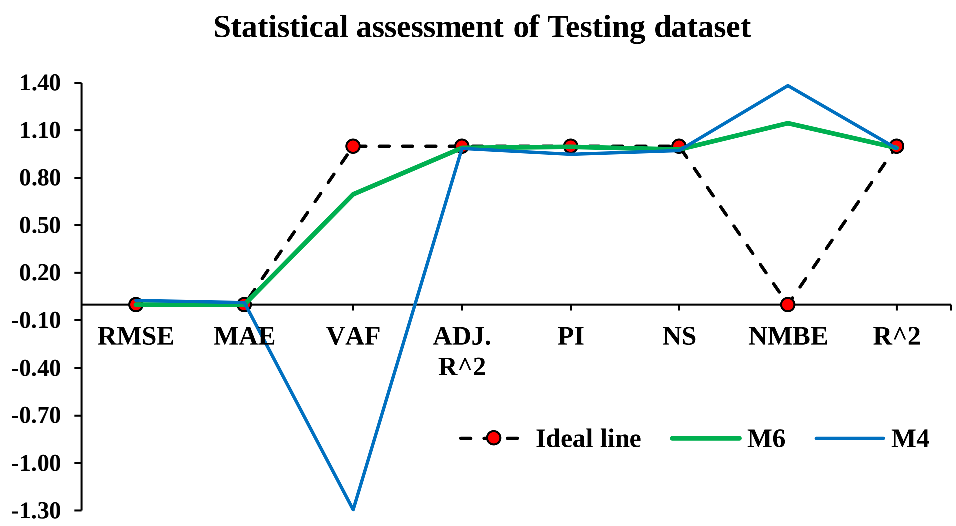
NS	0.99771	0.97360	0.99835	0.97873
NMBE	0.18683	1.38263	0.04245	1.14537
R^2	0.99760	0.98684	0.99820	0.98903

The above table 3 depicted that the errors such as RMSE and MAE for both M4 and M6 are less, however, the M6 model has less error than the M4 model. If the value of NMBE is positive then it represents the over prediction and vice versa as under prediction. From the above table 3, the value of NMBE for M6 model is more efficient than the M4 model.

Almost in most of the statistical parameters, the M6 model which has the training algorithm "trainbr" outperforms the other adopted training algorithms for predicting the daily groundwater table. The following figure (5a) and (5b) depicts the pictorial representation of the statistical assessment by comparing the M4 and M6 models.



6(a)



6(b)

Figure6(a) and 5(b) compares the statistical values of the developed M4 and M6 BPNN model.

5. Conclusion

The precise determination of the groundwater table can assist to guide the sustainable development and management of water usage. This study adopted one of the machine learning technique, BPNN in order to forecast the daily groundwater table variations for the specific location in Brazil. The capability of BPNN model by utilizing various training algorithm has been depicted in this study, however the method Bayesian regularization backpropagation with the syntax of “trainbr” with 1 hidden neuron and the transfer functions are logsig and tansig provided the best optimized output. The statistical performances of M6 model were compared with the other M4 model and hence the Bayesian regularization backpropagation method provided the best result. The adopted M6 model, when compared with the other models clearly depicted the accuracy and greater performance in every criterion.

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