ARTIFICIAL NEURAL NETWORK MODEL FOR GROUNDWATER LEVEL PREDICTION

By

Ananya.M.M (2017-02-005)

Dilsha.C (2017-02-020)

Gargi.A (2017-02-023)

PROJECT REPORT

Submitted in partial fulfillment of the requirement for the degree of

BACHELOR OF TECHNOLOGY

IN

AGRICULTURAL ENGINEERING

Faculty of Agricultural Engineering and Technology

Kerala Agricultural University

DEPARTMENT OF IRRIGATION AND DRAINAGE ENGINEERING

KELAPPAJI COLLEGE OF AGRICULTURAL ENGINEERING AND TECHNOLOGY

TAVANUR P.O.-679573

KERALA, INDIA

2020

DECLARATION

We hereby declare that this project report entitled **"Artificial neural network model for Groundwater level prediction"** is a bonafide record of project work done by us during the course of project and that the report has not previously formed the basis for the award to us of any degree, diploma, associate ship, fellowship or other similar title of any other university or society.

Place: Tavanur

Date: **13-3-2021**

Ananya.M.M

(2017-02-005)

Dilsha.C

(2017-02-020)

Gargi.A

(2017-02-023)

CERTIFICATE

Certified that this project report entitled **“Artificial neural network model for Groundwater Level Prediction”** is a record of project work done jointly by **Ananya.M.M (2017-02-005), Dilsha.C(2017-02-020) and Gargi.A (2017-02-023)** under my guidance and supervision and that it has not previously formed the basis for the award of any degree, diploma, fellowship or associate ship to them.

Place: Tavanur

Date: 13-03-2021

Guide:

Dr.Asha Joseph
Professor
Department of IDE
Kelappaji College of
Agricultural Engineering
&Technology, Tavanur

Co-guide:

Er.Praveena.K.K
Assistant Professor
Department of IDE
Kelappaji College of
Agricultural Engineering
&Technology, Tavanur

ACKNOWLEDGEMENT

Presentation inspiration and motivation have always played a key role in success of any venture.

First and foremost, we would like to thank the "God almighty", for his infinite grace and help without which this project would not have reached its completion, also being able to complete this project with success.

On the very outset of this report, it's our privilege to extend our sincere and heartfelt obligation to our supervising teacher ***Dr. Asha Joseph*** *(Professor, Department of Irrigation and Drainage Engineering, KCAET, Tavanur) who have helped us in this endeavour for her active guidance, profound suggestion, constant backing, help, co-operation and encouragement, so that we have made headway in the project.*

We would like to pay our deep sense of gratitude to ***Dr.Sathian K.K*** *(Dean, KCAET, Tavanur, Faculty of Agricultural Engineering and Technology) for his support and unfailing guidance that he offered during the completion of this project.*

I feel to acknowledge my indebtedness to ***Dr. D.Sasikala*** *(Head of department, Department of Irrigation and drainage engineering, KCAET, Tavanur) for giving advice and playing valuable role to make this project a success.*

We would like to specially thank ***Dr.Roshni*** *and* ***Dr. Anu Varughese*** *for showing interest and giving kind advices which helped our project to be a fruitful one.*

We are also thankful to ***Er.Praveena.K.K****, our co-guide for the untiring commitment in correcting us through mistakes and leading the way.*

Above all, we are very thankful to our parents for being an inspiration, without them preparation of this manuscript would have been not possible.

Finally we would also like to thank each and every one who directly or indirectly helped us to get this work done.

Ananya.M.M (2017-02-005)

Dilsha.C (2017-02-020)

Gargi.A (2017-02-023)

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SYMBOLS AND ABBREVIATIONS

%	: Percentage
º	: Degree
′	: Apostrophe
&	: And
3D	: Three Dimension
amsl	: Above Mean Sea Level
ANN	: Artificial Neural Network
ArcGIS	: Geographic Information System
ARIMA	: Autoregressive Integrated Moving Average
ASCE	: American Society of Civil Engineers
BMDA	: Barind Multipurpose Development Authority
CGWB	: Central Ground Water Board
CNN	: Convolutional Neural Network
COC	: Correlation Coefficient
Con-ANN	: Conventional Artificial Neural Network
CSSRI	: Central Soil Research Institute
CWC	: Central Water Commission
CWFT	: Continuous Wavelet Fast Fourier Transform

CWT	: Continuous Wavelet
CWTFT-ANN	: Continuous Wavelet Fast Fourier Transform-Artificial Neural Network
E	: East
et al	: and others
Etc.	: Etcetera
FFN-LM	: Feed Forward Network - Levenberg Marquardt
Fig	: Figure
FNN	: Feed Forward back propagation Neural Network
GDM	: Gradient Descent with Momentum
GUI	: Graphic User Interface
GW	: Ground Water
GWLs	: Ground Water Levels
HPA	: High Plains Aquifer
IWM	: Integrated Waste Management
KNN-RF	: A hybrid K-Nearest Neighbour-Random Forest
LBRB	: Lower Bhavani River Basin
LM	: Levenberg Marquardt
LMS	: Least Mean Square

LOGSIG	: Log sigmoid Transfer function
m	: Metre
MAE	: Mean Absolute Error
MAPE	: Mean Absolute Percentage Error
MATLAB	: MATrix LABoratory
MISO	: Multiple Input Single Output
MLR	: Multivariable Logistic Regression
mm	: Milli Metre
MRVA	: Mississippi River Valley Alluvial Aquifer
MSE	: Mean Square Error
N	: North
NF	: Neuro Fizzy
No.	: Number
NSE	: Nash - Sutcliffe
PE	: Processing Elements
R	: Correlation coefficient
R^2	: Coefficient of Determination
RARS	: Regional Agriculture Research Station
RMSE	: Root Mean Square
RP	: Resilient back propagation
SCG	: Scaled Conjugate Gradient
SOM-NARX	: Self- Organizing Map- Non linear Autoregressive exogenous inputs

SVM	: Support Vector Machines
TANSIG	: Tan sigmoid Transfer function
Traingd	: Gradient Descent back propagation
Traingdm	: Gradient Descent with Momentum back Training Algorithms
Traingdx	: Variable Learning Rate Gradient Descent
Trainlm	: Levenberg Marquardt back propagation Training Algorithms
Trainrp	: Resilient Back propagation training Algorithms
TSA	: Time Series Analysis
Xm	: Normalized value
Xmax	: Maximum value of total data considered for normalization
Xmin	: Minimum value of total data considered for normalization
Viz	: Namely
WT	: Wavelet Transform

INTRODUCTION

CHAPTER 1
INTRODUCTION

Groundwater is an important natural resource for human survival system and is one of the major sources of irrigation. It is the most critical source of fresh water that serves about one-third of the world's water demands. Socio-economic development is closely linked with the availability and accessibility of groundwater resources (Robins, 2014). For instance, 36% of the domestic freshwater supply, 42% of water for agriculture, and 27% of the industrial water demand comes from groundwater (Khosravi, *et al*., 2018). While the world's water demand is expected to rise significantly in the future (Healy, 2019) recent studies report an intensive drop in groundwater levels in many parts of the world (Castellazzi, *et al*., 2016).Human behaviour and the impact of climate change are considered to be the root cause of this. Due to increased population and decreased groundwater recharge, the demand increases and it may not be feasible to check the draft of groundwater resources. In India, groundwater meets the 65% irrigation and 85% of drinking demand. However, surface water share has declined in irrigation from 60% in 1950 to 30% in the first decade of the twenty-first century (CGWB 2010).

Groundwater level is an indicator of groundwater availability, groundwater flow, and the physical characteristics of an aquifer or groundwater system (Srihan, 2010).Any phenomenon, which produces pressure change within an aquifer, results into the change of ground water level (Dogan, *et al*., 2012). These changes in ground water level can be a result of changes in storage, amount of discharge and recharge, variation of stream stages and evaporation. Where a stream channel is in indirect contact with an unconfined aquifer, the stream may recharge the ground water, or receive discharge from the ground water. The general consideration is that due to any reason if the aquifer pressure rises above the atmospheric pressure an up levelling in ground water level results and vice versa. The crop productivity and soil quality also depends on water used for irrigation. The poor quality water used for irrigation may reduce the crop yield and also affects soil quality (Ayers and Westcot, 1994).

The shallow water table depths have significant impacts on crop growth, vegetation development and contaminant transport. Furthermore, depletion of groundwater supplies, conflicts between groundwater users and surface water users, potential for ground water contamination are concerns that will become increasingly important as further aquifer development takes place in any basin. The consequences of aquifer depletion can lead to local water rationing, excessive reductions in yields etc.

The groundwater quality is deteriorating day by day due to overexploitation of groundwater, surplus use of chemical fertilizers and pesticides which percolate into aquifer in many parts of the country (Goyal *et al*.,2010; Jangam *et al*., 2015).Nevertheless, the levels of the water tables may also fluctuate seasonally due to the amount of evapotranspiration extracts, hydraulic properties, and other natural events (Rathay, *et al*., 2018). Also, diminished precipitation and high temperature can also lead to reduced groundwater levels during dry periods. The increased dependence on groundwater, spatial-temporal variation, and discrepancies of groundwater resources have also impacted ground water levels (Uhlemann, 2016). The only available option is to increase the recharge rate to the aquifer by suitable means. Therefore it is necessary to quantify the present rate of groundwater recharge, monitor the change in water table depth and then predict the future trend of water table depth before any intervention.

In developed countries, water management planning usually, indeed almost always, proceeds through the use of one or more computer simulation models. These models, which may be very simple or highly complex, based on observed data or theoretical principles, stochastically or deterministically driven, provide a framework for decision-making that is endorsed by the community of water users and water regulators. To date, a wide variety of models have been developed and applied for groundwater table depth forecasting. These models can be categorized into empirical time series model and physical descriptive model.

The empirical time series models have been widely used for water table depth modelling. The major disadvantage of empirical approach is that they are not adequate for forecasting when the dynamical behaviour of the hydrological system changes with time (Bierkens, 1998). In a water table aquifer, relationship between precipitation, canal releases, and the groundwater level are likely nonlinear rather than linear, and the models that approximate the processes in linear form fail to represent the processes effectively. Owing to the difficulties associated with non-linear model structure identification and parameter estimation, very few truly non-linear empirical models such as stochastic differential equation and threshold autoregressive self-extracting open-loop models have been reported for shallow water table modelling (Bierkens, 1998). In recent years, artificial neural networks (ANNs) have been used for forecasting in many areas of science and engineering. ANNs have been proven to be effective in modelling virtually any nonlinear function to an arbitrary degree of accuracy. The main advantage of this approach over traditional methods is that it does not require the complex nature of the underlying process under consideration to be explicitly described in mathematical form. This makes ANN an attractive tool for modelling water table fluctuations.

ANN is the most popular tool for groundwater prediction. An ANN can be defined as data processing system consisting large number of simple highly interconnected processing elements (PEs or artificial neurons) in architecture analogous to cerebral cortex of brain in which inputs and outputs are connected to each other by a set of weights. It takes number of inputs weight them, sums them up, adds a bias and uses a results as the argument for singular valued function, the transfer function, which results in the neurons output (Strik *et al.*, 2005). In the ANN model three layers are used first one is input variables, then hidden neurons and the output. The input variables are processed with some weight and the predicted output is delivered. Neural networks have flexible nonlinear function mapping capability that can approximate any continuous measurable function with arbitrarily desired accuracy, whereas most of the commonly used empirical models do not have this property. Second, being nonparametric and data-driven, neural networks impose few prior assumptions on the underlying process from which data are generated. Also, high computation rate, learning ability through pattern presentation, prediction of unknown patterns, and flexibility affronts for noisy patterns are other advantages of using ANNs.

There are a wide variety of network architectures and learning methods that can be combined to produce neural networks with different computational abilities. ANNs are most robust than any computational methods or modelling techniques in hydrology because of their ability to handle large variations of parameters. The ANN modelling and evaluation use the software, MATLAB (ver. 7.10.0.324 (R2010a)) as the source code program. MATLAB is a high-level language and interactive environment for numerical computation, visualization and programming; it is used extensively by control engineers for analysis of design. MATLAB can be used to analyse data, develop algorithms and to create models and applications. An application of MATLAB includes signal processing, 3 control systems, test and measurement, computational finance and computational biology. Initially, it was simply a Matrix Laboratory. However, today it is much more powerful. It was designed to group large amounts of data in arrays and to perform mathematical operations on this data as individual arrays rather than as groups of data. This makes it very easy to apply complicated operations to the data, and it makes it very difficult to do it wrong.

In view of all the above facts, a research entitiled **"Grounwater level prediction using ANN"** was conducted in Pattambi region with the following objectives;

i. To study Artificial Neural Network (ANN) modelling and develop ANN model for groundwater level fluctuation.
ii. To evaluate the performance of ANN model for groundwater level prediction.
iii. To develop a one month ahead prediction model for groundwater level forcasting.

REVIEW OF LITERATURE

CHAPTER-II

REVIEW OF LITERATURE

A computer based software model, MATLAB (ver. 7.10.0.324 (R2010a)) using Artificial Neural Network will be able to predict the groundwater level based given input parameters like rainfall, maximum and minimum temperature, relative humidity, evaporation etc. ANNs are most robust than any computational methods or modelling techniques in hydrology because of their ability to handle large variations of parameters. Hence our study created a model for predicting groundwater level with the above mentioned parameters at Pattambi region.

The review has been organized objective wise under the following subheads.

a) Groundwater level estimation
b) Factors affecting groundwater level fluctuation
c) Groundwater level prediction using ANN.
d) Other applications of ANN.

2.1 GROUNDWATER LEVEL ESTIMATION

In the research conducted by Huang and Tian (2016), the ability and accuracy of the three data driven models are investigated by applying them to forecast groundwater level in the Shule river basin situated in Gansu province, China. Data-driven methods have proven their applicability in modelling complex and nonlinear hydrological processes. The focus of this study is the application and comparison of three data-driven models for forecasting short-term groundwater levels. The purpose is to develop a new data-based method for highly accurate groundwater level forecasting that can be used to help water managers, engineers, and stake-holders manage groundwater in a more effective and sustainable manner. A set of popular datadriven models are evaluated and compared, including Artificial Neuron Networks (ANNs), Support Vector

Machines (SVMs), and M5 Model Tree. The feasibility and capability of these models are demonstrated through a case study of forecasting fivedays ahead groundwater level in an arid and semi-arid basin located in north-western China. The encouraging simulation results show that the methodologies can simplify and improve the procedure of groundwater level forecast.

Sahoo and Russo (2016) developed a new ensemble modelling framework based on spectral analysis, machine learning, and uncertainty analysis, as an alternative to complex and computationally expensive physical models. This study had two main objectives: (1) to quantify the relative influence of climate variability, crop irrigation demand, and stream flow on groundwater level change and (2) to develop an empirical (data-driven) model of the hydrologic system. They used simulated crop irrigation demand as a model input in lieu of unavailable groundwater pumping data. They applied and evaluated this new approach in the context of two aquifer systems supporting agricultural production in the United States: the High Plains aquifer (HPA) and the Mississippi River Valley alluvial aquifer (MRVA). They selected input data sets by using a combination of mutual information, genetic algorithms, and lag analysis, and then use the selected data sets in a Multilayer Perceptron network architecture to simulate seasonal groundwater level change. As expected, model results suggest that irrigation demand has the highest influence on groundwater level change for a majority of the wells. Their method employs concepts from mutual information theory to capture nonlinear dependencies between explanatory variables by using their joint and marginal probability instead of a linear correlation. However, it has the disadvantage that even if a predictor has a strong connection with the model output, this information might be redundant if the same information is already provided by another predictor.

Chang and Chang (2016) explored the characteristics of regional groundwater level fluctuations with surface water interaction mechanisms based on long-term monitoring data sets through soft-computing techniques. They proposed a novel hybrid SOM-NARX model to predict the monthly spatial distribution of groundwater levels for the Zhuoshui River basin in Central Taiwan. The core idea was to classify the regional groundwater level maps in the SOM and then update the best matched map (a neuron in the SOM) using the forecasted average regional groundwater level obtained from the NARX model. The proposed method offers a milestone in modelling regional (two-dimensional) environmental issues and presents a new insightful methodology in realizing the complex relationship between groundwater and surface water for predicting reliable monthly regional groundwater level maps. The Zhuoshui River basin in Taiwan was the study case, and its monthly data sets collected from 203 groundwater stations, 32 rainfall stations and 6 flow stations during 2000 and 2013 were used for modelling purpose.

Singh *et al.* (2018) predicted the groundwater levels of different areas in Delhi with respect to various parameters that affect the groundwater levels in the environment. To find the best machine learning technique to perform the prediction of groundwater, they initially performed a comparative analysis of four machine learning techniques: Support vector machine, Artificial Neural Networks, Random forests and Linear regression models. They proceeded with the models that give satisfactory results. They perform forecasting using the ARIMA model to predict the parameters that affect groundwater levels across the next ten years. The forecasting of parameters resulted in increasing the database by two times, hence they performed the prediction of the water table using the models Support vector machine, Artificial neural networks and Linear regression models. Thus, concluded that the Artificial Neural Networks model performs better than the Support vector machine and Linear regression models.

As a part of literary survey and research in Turkey, Kaya *et al*. (2018) compared Artificial neural network model with a M5 tree model to find the best fit for groundwater prediction. Both models gave similar accuracy and it was also observed that the M5 tree model that is usually used for classification gives comparable results to ANN. Even though the mean absolute error of ANN was less than that of the SVM model, SVM gave more accurate results.

Another system for the prediction of groundwater was built by Jinglin *et al.* (2017) using support vector machines and particle optimization algorithms and was concluded to be a good technique.

2.2 FACTORS AFFECTING GROUNDWATER LEVEL FLUCTUATION

Vitola *et al*. (2012) clarified about the seasonal effects of precipitation and temperature on groundwater level changes in monitoring stations of the Latvia University of Agriculture. Using mathematical statistics and graphic-analytic methods it was concluded that autumn and winter precipitation had the dominant impact on groundwater level fluctuations, whereas spring and summer season fluctuations were more dependent on the air temperature. As a result of the study, the predominant impact of meteorological conditions (air temperature and amount of precipitation) on the fluctuations of the level of groundwater by the season had been proven, using the graphic-analytical method and the method of mathematical statistical analysis.

Dammo *et al*. (2017) evaluated the climate variability using a simple approach, which considered variability as the difference between the mean monthly values of climatic elements and depth to water table within the times. The investigation used 30 years (1982-2012) record of hydro-meteorological data. The result of these findings, show mean monthly rainfall, maximum temperature, relative humidity and depth to water table ranged between 195.2 - 0.1mm, 1404.5 - 1012.20C, 76.9 - 14.1% and 22.7 - 6.2m respectively. In order to reduce their effects on groundwater level, more trees should be planted so that the amount of solar radiation reaching the earth surface will be reduced.

Hasan *et al*. (2013) conducted their study in five Upazilas under Chapai Nawabgonj district from 2007 to 2011 and found out the effect of rainfall on groundwater level fluctuation. Rainfall and groundwater fluctuation data were collected from BMDA, Rajshahi and evapotranspiration data were collected from IWM, Dhaka. The data were analysed to show the rainfall variations, runoff, infiltration and groundwater fluctuation levels in different years. This study illustrates that there were no significant change in rainfall and infiltration patterns during the study period, but the overall ground water table was declining day by day due to over withdrawal of groundwater for irrigation purpose.

Abdullahi and Garba (2015) examined the effect of rainfall on groundwater level fluctuation using the rainfall, Evapotranspiration and groundwater level fluctuation data from 2001 to 2013 in Terengganu Malaysia. This was done due to the increasing water demand with the increase in population growth and socioeconomic development. These data were analysed to show the rainfall variations, runoff, infiltration and groundwater fluctuation levels in different years. The analysis also illustrated that, the rainfall is influencing the groundwater level of the study area as the rain usually started in September and ended in December.

The main objective of the study conducted by Narjary *et al.* (2014) was to assess the trends as well as variability of rainfall and groundwater levels to understand the response of groundwater systems to climatic stresses in Karnal district of Haryana and to study the scope of artificial groundwater recharge structures for mitigating the adverse impact of rainfall variability on groundwater. Climatic data for 38 years (1972–2010) was collected from the agro-meteorological observatory located at Central Soil Salinity Research Institute (CSSRI), Karnal (29°43′N, 75°58′E, altitude of 245 m amsl) in the Indo-Gangetic alluvial plains. The climate of Karnal district is influenced in a major way by the southwest monsoon occurring during June to September.

Kotchoni *et al*. (2018) analysed long-term (19–25 years) records of groundwater levels and rainfall are used to explore the relationships between rainfall and recharge in three hydrogeological environments common to the humid tropics of Benin and other parts of West Africa: Quaternary sands, Mio-Pliocene sandstone, and crystalline rocks. Recharge is estimated from groundwater-level fluctuations and employs values of specific yield derived from magnetic resonance soundings. Inter-annual changes in groundwater storage correlate well to inter-annual rainfall variability. However, recharge varies substantially depending upon the geological environment: annual recharge to shallow aquifers of Quaternary sands amounts to as much as 40% of annual rainfall, whereas in deeper aquifers of Mio-Pliocene sandstone and weathered crystalline rocks, annual fractions of rainfall generating recharge are 13 and 4%, respectively.

2.3 GROUNDWATER LEVEL PREDICTION USING ANN

Jalalkamali *et al*. (2011) investigated the abilities of neurofuzzy (NF) and artificial neural network (ANN) techniques to predict the groundwater levels. Two different NF and ANN models comprise various combinations of monthly variabilities, that is, air temperature, rainfall and groundwater levels in neighbouring wells. . In addition, the effect of input combination on model performance was also investigated. The result suggested that the NF and ANN techniques are a good choice for the prediction of groundwater levels in individual wells. The methods used to predict the groundwater level in the Kerman plain in Iran and their performances were evaluated by using RMSE, MAPE and R2. It was found that the NF computing technique could successfully be employed in modelling the groundwater level from the available groundwater data.

The purpose of the study of Chitsazan *et al*. (2015) was to apply feed forward back propagation neural network (FNN) to predict groundwater level of Aghili plain, which is located in south-western Iran. An optimal design was completed for the two hidden layers with four different algorithms: descent with momentum (GDM), Levenberg Marquardt (LM), resilient back propagation (RP), and scaled conjugate gradient (SCG). Statistical analysis in terms of Mean-Square-Error (MSE) and correlation coefficient (R) was used to investigate the prediction performance of ANN. FFN-LM algorithm had shown best result in the present study for all three hydrogeological groups. The achieved results of ANN model in contrast with results of finite difference model showed very high accuracy of artificial neural network in predicting groundwater level. The results showed that LM algorithm has the best performance for training all three hydrogeological groups.

The potentiality of neural computing techniques for forecasting groundwater levels was analysed by Nayak *et al*. (2006), by developing ANN models for a shallow aquifer of Central Godavari Delta System in India .The results from ANN model in general indicate that ANN is an effective tool for monthly groundwater levels forecasting. 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 results suggest that the model predictions are reasonably accurate as evaluated by various statistical indices.

The principle objective of the study conducted by Van Ty *et al*. (2018) was to predict groundwater levels (GWLs) under different impact factors using Artificial Neural Network (ANN) for a case study in TraNoc Industrial Zone, Can Tho City, Vietnam. The results showed that GWLs in the study area had been found to reduce rapidly from 2000 to 2015, due to the over-withdrawals from the enterprises for production purposes. The calibrated ANN structures have successfully demonstrated that the GWLs can be predicted considering different impact factors.

Kaya *et al*. (2018) observed groundwater level (GWL) using artificial neural networks (ANN), M5tree (M5T) approaches in Reyhanlı region in Turkey. In their study, monthly total rainfall, monthly mean temperature and monthly groundwater level data of Reyhanlı region were used for the groundwater level prediction. Groundwater level measured in the previous years belonging to the Reyhanlı region was performed using Artificial Neural Networks (ANN), M5Tree (M5T) methods. The results showed that (ANN) and M5tree (M5T) models were found to be very close to each other. Comparisons revealed that the ANN and M5T model had the closer accuracy in the groundwater level and both method can be used to predict groundwater level.

In the work done by Kombo *et al*. (2020), a hybrid K-Nearest Neighbor-Random Forest (KNN-RF) was used for the prediction of variations in groundwater levels (L) of an aquifer with the groundwater relatively close to the surface. The study intended to examine the capacity of the KNN-RF ensemble model for the characterization of seasonal responses of the groundwater levels of a permeable fractured aquifer in eastern Rwanda utilizing limited site-data. Potential predictors were: the observed daily mean temperature (T), precipitation (P), and daily maximum solar radiation (S). Previous day's precipitation P (t − 1), solar radiation S (t), temperature T (t), and groundwater level L (t) showed the highest variation in the fluctuations of the groundwater tables. Experimental results have confirmed the high performance of the proposed model in terms of root mean square error (RMSE), mean absolute error (MAE), Nash–Sutcliffe (NSE), and coefficient of determination (R).

Nair and Sindhu (2016) developed ANN models using different sets of combinations of the input parameters and the best combination was selected based on the performance parameters. Factor analysis and ANN gave same set of input combinations for groundwater level forecasting during monsoon and non-monsoon season. The factors that influence and control the groundwater level fluctuation were determined to develop a forecasting model and examine its potential in predicting groundwater level. Models for prediction of water table depth were developed based on Artificial Neural Networks (ANN) with different combinations of hydrological parameters. The best combination was confirmed with factor analysis. The input parameters for groundwater level forecasting were derived using Time Series Analysis (TSA). Mamom river basin in Trivandrum district was chosen as the study area.

Shamsuddin *et al.* (2017) illustrates the development and application of artificial neural networks (ANNs) to predict groundwater tables in two vertical wells located in confined aquifer adjacent to the Langat River. ANN model was used in this study is based on the long period forecasting of daily groundwater tables. The performance of different models structure of the ANN is used to identify the fluctuation of the groundwater table and provide acceptable predictions. The results clearly showed that accurate predictions can be achieved with time series 1-day ahead of forecasting groundwater table and the interaction between river and aquifer can be examine. The findings of the study can be used to assist policy marker to manage groundwater resources by using RBI method.

Vetrivel and Elangovan (2016) researched to find the optimum model of ANN technique through various pre-processing technique in the process of groundwater level prediction in Lower Bhavani River Basin (LBRB). Hybrid Con-ANN (Conventional Artificial Neural Network) model with WT (Wavelet Transform), CWT (Continuous Wavelet) and CWFT (Continuous Wavelet Fast Fourier Transform) pre-processing techniques were performed. Based on the prediction performance, CWTFT-ANN was found to be the best model by comparing with the other models through statistical indices RMSE, R-Squared, COC, MSE and MAS measurement.

The study carried out by Sahoo and Madan (2015) examined the potential of two data-driven approaches, MLR and ANN, for simulating/ predicting transient groundwater levels over a groundwater basin using relevant real-world data. MLR and ANN modelling was carried out at 17 sites in Japan, considering all significant inputs: rainfall, ambient temperature, river stage, 11 seasonal dummy variables, and influential lags of rainfall, ambient temperature, river stage and groundwater level. The performance of the models was evaluated using statistical and graphical indicators. , it was concluded that the ANN technique was superior to the MLR technique in predicting spatial-temporal distribution of groundwater levels in a basin.

Wagh *et al*. (2016) presented an artificial neural network (ANN) model for predicting values of sodium adsorption ratio (SAR), residual sodium carbonate, magnesium adsorption ratio, Kellys ratio and percent sodium (%Na) in the groundwater of Nanded tehsil.The spatial distribution maps of measured and predicted values of irrigation indices were prepared using ArcGIS software. The result confirmed that the ANN model was an applied tool to predict the groundwater suitability for irrigation purpose in Nanded tehsil.

2.4. OTHER APPLICATIONS OF ANN

Sveucilista *et al*. (2009) conducted a study which deals with the application of artificial neural network to inventory classification which uses four input variables (four criteria) and three output variables. Artificial intelligence methods like neural networks, fuzzy logic and genetic algorithms are applied. By comparing the results of neural network inventory classification with the original data, they concluded that neural network model predicted classes with acceptable accuracy.

A condensed review of the use of artificial neural networks in decision support systems for a wide range of application areas were given by Delen and Sharda (2015). A fairly comprehensive (but less technical) explanation of artificial neural networks was given. Compared to the normative techniques such as optimization with linear programming, ANN is a relatively more complex modelling technique that often leads to a non-optimal solution (because it is a heuristic modelling technique).

Basheer and Hajmeer (2000) familiarized ANN-based computing (neuro-computing). The history of the evolution of neuro-computing and its relation to the field of neurobiology was briefly discussed. ANNs were compared to both expert systems and statistical regression and their advantages and limitations were outlined. The objective was to provide a preliminary understanding of ANNs and answer the why and when these computational tools are needed, the motivation behind their development, and their relation to biological systems and other modelling methodologies, the various learning rules and ANN types, computations involved, design considerations, application to real-world problems, and advantages and limitations

Malik *et al*. (2005) presented a survey of the research and explosive developments of many ANN-related applications. A brief overview of the ANN theory, models and applications was presented. Potential areas of applications were identified and future trend was discussed

In the study by Ghumman *et al*. (2011), the rainfall–runoff model based on Artificial Neural Networks (ANNs) was developed and applied on a watershed in Pakistan. The results of ANN models were compared with a mathematical conceptual model. The cross validation approach was adopted for the generalization of ANN models. . The results confirmed that ANN model is an important alternative to conceptual models and it can be used when the range of collected dataset is short and data is of low standard.

Rajurkar *et al.* (2002) pointed out the application of artificial neural network (ANN) methodology for modelling daily flows during monsoon flood events for a large size catchment of the Narmada River in Madhya Pradesh (India). A linear multiple-input single-output (MISO) model coupled with the ANN was shown to provide a better representation of the rainfall-runoff relationship in such large size catchments compared with linear and nonlinear MISO models. It was observed that coupling of the ANN with a multiple-input single-output model predicted the daily runoff values with high accuracy, both in the training and the validation periods.

MATERIALS AND METHODS

CHAPTER –III

MATERIALS AND METHODS

This chapter includes the various methods used in the study, description of the study area and collection of data. The basics of Artificial Neural Network (ANN) and the methods used to predict groundwater level using certain input parameters are explained in detail. The correlation between predicted values and the observed groundwater level were made. Also, one month ahead prediction models were created and best model was selected. Each of these parts are detailed in the following subheads.

3.1 STUDY AREA

The groundwater level which was considered as the output parameter were taken from the observation well, number 159 of Srikrishnapuram region, near Pattambi .The climate data for the present study collected from RARS Pattambi, and streamflow data from Pulamanthole gauging station, Bhrathappuzha basin located in Palakkad district of Kerala state in India were considered as input parameters for predicting groundwater level.

Pattambi is located at western end of Palakkad district of the state of Kerala, South India which is at 10.76ºN latitude and 76.57ºE longitude (Fig.3.1). The entire region is at an elevation of 63m above the mean sea level.

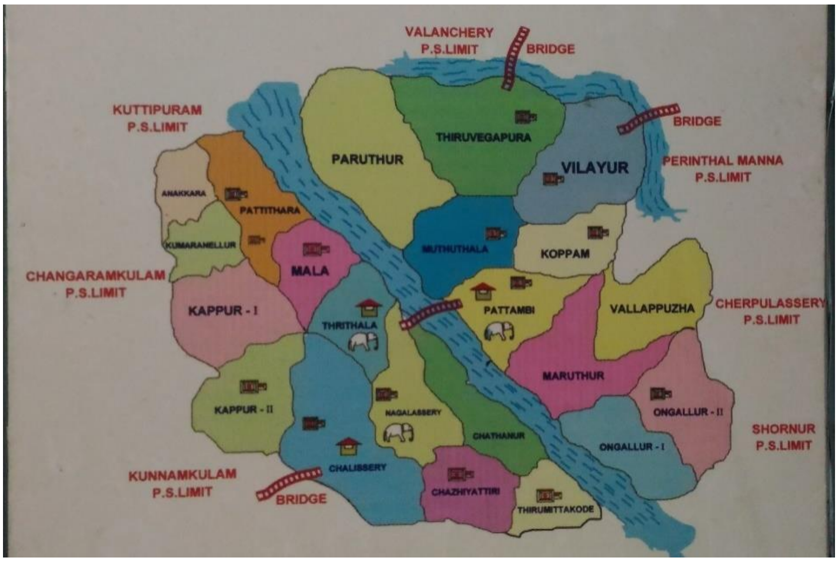


Fig .3.1 Pattambi region

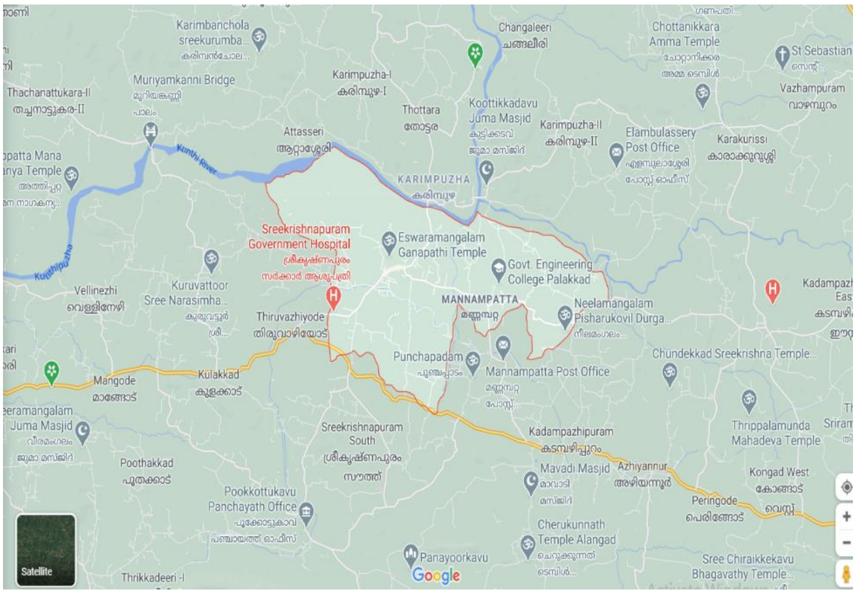


Fig. 3.2 Sreekrishnapuram block

3.2 DATA COLLECTION

A total of seven parameters were taken into consideration for this study viz., Maximum and minimum temperatures, maximum and minimum relative humidity, pan evaporation, streamflow and rainfall. The climate data were collected from RARS Pattambi and streamflow data from Pulamanthole gauging station. The groundwater level which is considered as the output parameter were taken from CGWC department. We selected the observation well no: 159 of Srikrishnapuram region, Pattambi. The data was collected for a period of 20 years from 1999- 2019. For monthly analysis, the daily data were converted into average monthly values.

3.3 STUDY OF ARTIFICIAL NEURAL NETWORKS

Neural networks and deep learning are vast topics in the technology industry, they currently provide the best solutions to many problems in image recognition, speech recognition and natural language processing. Recently many papers have been published featuring AI that can learn to paint, build 3D Models, create user interfaces (pix2code), some create images given a sentence and there are many more incredible things being done every day using neural networks. Dr. Robert Hecht-Nielsen, one of the first inventor of neuro-computers, defines a neural network as “a computing system made up of a number of simple, highly interconnected processing elements, which process information by their dynamic state response to external inputs.” Artificial Neural Network is simply a computational model that is inspired by the way biological neural networks in the human brain process information.

3.3.1 History of ANN

Since the early nineties, ANNs have been successfully used in hydrology related areas such as rainfall-runoff modelling, stream flow forecasting, groundwater modelling, water quality, water management policy, rainfall forecasting, hydrologic time series and reservoir operations (ASCE, 2000). Usually in hydrology the problems are not clearly understood or are too ill-defined for a meaningful analysis using physically based methods; in such conditions ANN appear more attractive.

Moreover, ANN routinely model the nonlinearity of the underlying process without having to solve complex partial differential equations. Unlike regression-based techniques, there is no necessity to make assumptions about the mathematical form of relationship between input and output. Because existence of noise in the inputs and outputs are handled by an ANN without severe loss of accuracy because of distributed processing within the network. This truly enhances the capabilities of ANN and make them desirable for a large class of problems in hydrology.

3.3.2. Biological motivation and connections

The basic computational unit of brain is a neuron. Approximately 86 billion neurons can be found in the human nervous system and they are connected with approximately10^{14} — 10^{15} synapses. The diagram below shows a drawing of biological neuron (left) and a common mathematical model (right). The basic unit of computation in a neural network is the neuron, often called a node or unit. It receives input from some other nodes, or from an external source and computes an output. Each input has an associated weight (w), which is assigned on the basis of its relative importance to other inputs. The node applies a function to the weighted sum of its inputs. The idea is that the synaptic strengths (the weights w) are learnable and control the strength of influence and its direction: excitory (positive weight) or inhibitory (negative weight) of one neuron on another. In the basic model, the dendrites carry the signal to the cell body where they all get summed. If the final sum is above a certain threshold, the neuron can fire, sending a spike along its axon. In the computational model, we assume that the precise timings of the spikes do not matter, and that only the frequency of the firing communicates information. We model the firing rate of the neuron with an activation function (e.g. sigmoid function), which represents the frequency of the spikes along the axon. (Fig 3.3).

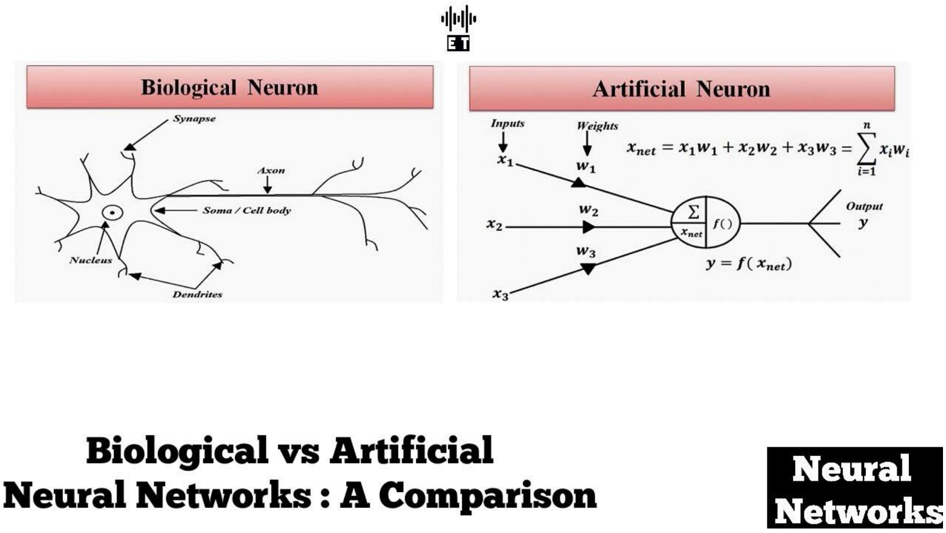


Fig 3.3 Biological neuron and artificial neural network

3.3.3 Components of ANN

- Input Nodes (input layer): No computation is done here within this layer, they just pass the information to the next layer (hidden layer most of the time). A block of nodes is also called layer.

- Hidden nodes (hidden layer): In Hidden layers where intermediate processing or computation is done, they perform computations and then transfer the weights (signals or information) from the input layer to the following layer (another hidden layer or to the output layer). It is possible to have a neural network without a hidden layer.

- Output Nodes (output layer): Here we finally use an activation function that maps to the desired output format (e.g. softmax for classification).

- Connections and weights: The network consists of connections, each connection transferring the output of a neuron I to the input of a neuron j. In this sense I is the predecessor of j and j is the successor of I, Each connection is assigned a weight Wij.

- Bias: It is an additional parameter in the neural network which is used to adjust the output along with the weighted sum of the inputs to the neuron.

•Activation function: the activation function of a node defines the output of that node given an input or set of inputs. A standard computer chip circuit can be seen as a digital network of activation functions that can be “ON” (1) or “OFF” (0), depending on input. This is similar to the behaviour of the linear perceptron in neural networks. However, it is the nonlinear activation function that allows such networks to compute nontrivial problems using only a small number of nodes. In artificial neural networks this function is also called the transfer function.

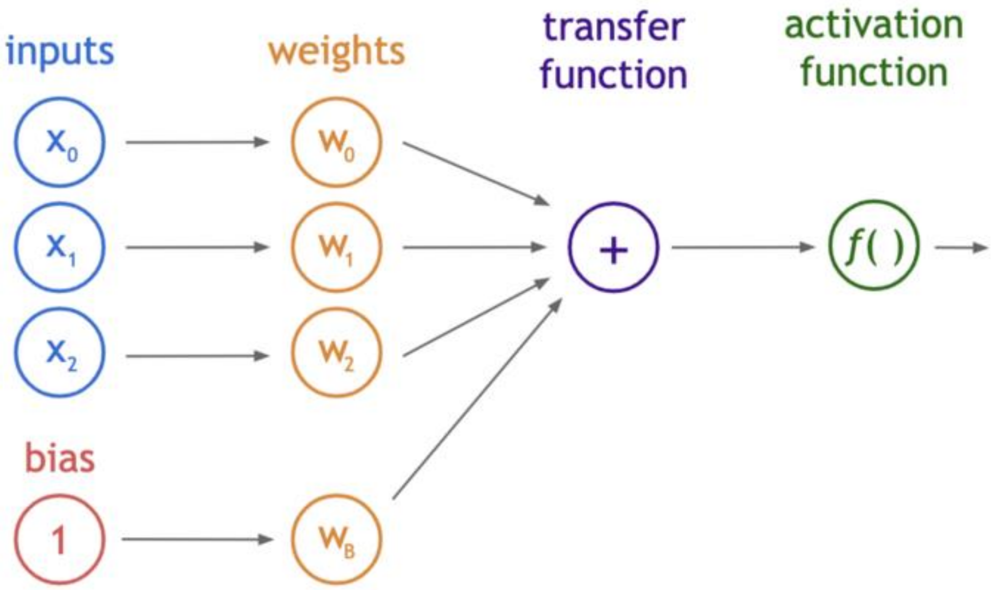


Fig 3.4 Components of ANN

3.3.4 Layers in ann

An input layer, one or more hidden layers of computation nodes and an output layer of computation nodes are the layers of a Multilayer Feed forward Network (MFFN). The input signal propagated through the network in a forward direction. In this study, we changed the numbers of hidden layers to get maximum accurate output.

3.3.4.1 Selection of Neurons and connection of Layers

A neuron is an information processing unit which is fundamental to the operation of a neural network. Input neurons are essential part of network models whose purpose is to feed the input to the next layer of neurons. In some network every neuron is connected to every other neuron in the same layer whereas in some other networks, neurons within the same layer are not connected. Thus the type of layout for the network neurons and the type of connections between the neurons constitute the architecture of the particular model of the neural network. All input transmitted through a connection was multiplied by the weight. Weight assignment on the connection indicates the strength of the signal that was fed for aggregation and the type of interaction between two neurons. Weighted input was the only argument of the transfer function, which produces an output. Initially randomly distributed weights were present in the network architecture. An externally applied bias is also included in the connection process. Depending on whether the transfer function is positive or negative the bias has the effect of increasing or decreasing. Fig 3.5 shows the input, hidden and output layers together with their connections. Initial weights were assigned at the time of neurons selection in neural network toolbox.

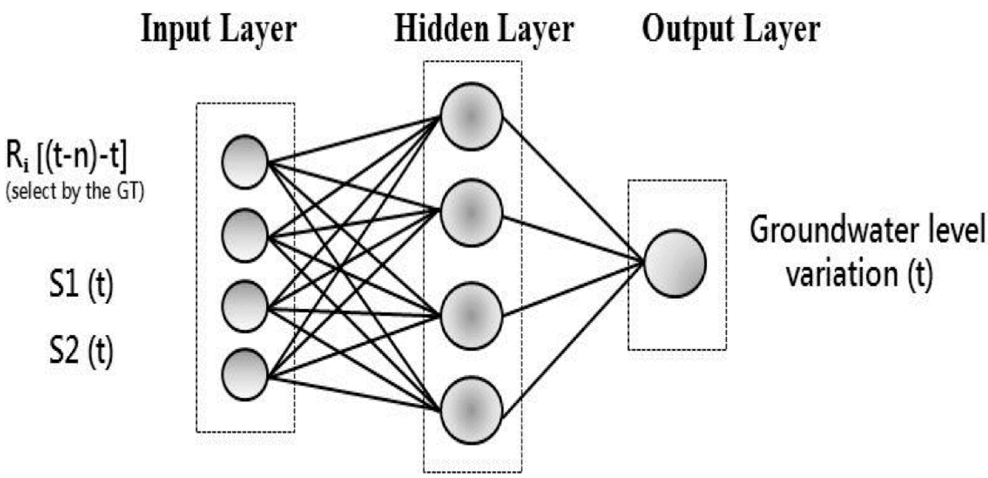


Fig. 3.5. Inputs, Hidden and Output Layers and their Connections

3.3.5 Network architecture

Several aspects of the architecture of neural networks that focus on the prediction of variables associated with hydrology are covered by Maier and Dandy (2000). Their suggestions were followed in the development of the current model. The structure of the network is determined by trial and error. The size of the input and hidden layer of the network has been variable depending on the prediction horizon, whereas the output layer has a single node. The number of nodes in the hidden layer and the stopping criteria were optimized in terms of obtaining precise and accurate output. Finally, the transfer function used in the hidden layer were hyperbolic tangent sigmoid function and log sigmoid function to compare their performance. It is noteworthy that there is no well-established direct method for selecting the number of hidden nodes for an ANN model for a given problem. Thus the common trial-and-error approach remains the most widely used method.

3.3.5.1 Types of neural networks

Neural networks are massive parallel processors comprised of single artificial neurons. Fig. 3.6 shows a typical single neuron with a sigmoid activation function, three input synapses and one output synapse. Synapses represent the structure where weight values are stored.

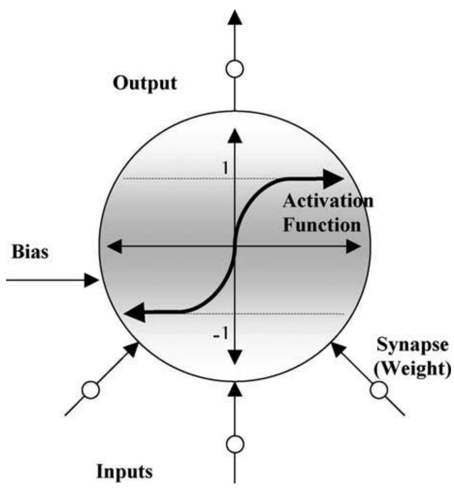


Fig. 3.6 Typical Artificial neuron

3.3.5.1.1 Feedforward neural network (FNN)

Feedforward neural networks have been applied successfully in many different problems since the advent of the error back propagation learning algorithm. This network architecture and the corresponding learning algorithm can be viewed as a generalization of the popular least-mean-square (LMS) algorithm (Haykin, 1999). A multilayer perceptron network consists of an input layer, one or more hidden layers of computation nodes, and an output layer. Fig. 3.7 shows a typical feedforward network with one hidden layer consisting of three nodes, four input neurons and one output. The input signal propagates through the network in a forward direction, layer by layer. Their main advantage is that they are easy to handle, and can approximate any input/output map (Hornik *et al*., 1989). The key disadvantages are that they train slowly, and require lots of training data (typically three times more training samples than network weights).

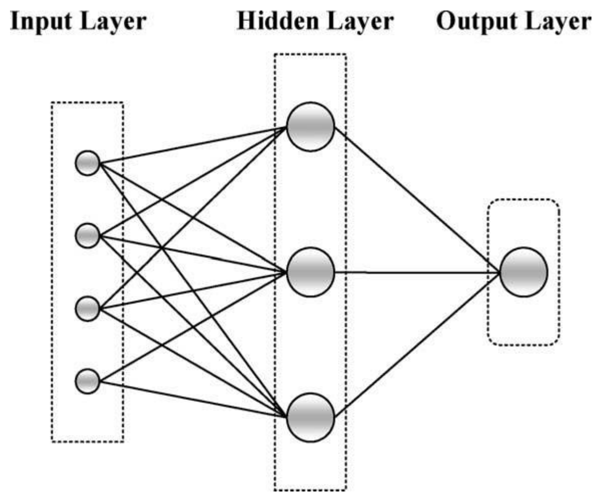


Fig.3.7 Typical Feedforward neural network

There are three types of feedforward neural networks:

- Single-layer Perceptron: This is the simplest feedforward neural Network and does not contain any hidden layer, which means it only consists of a single layer of output nodes. This is said to be single because when we count the layers we do not include the input layer, because at the input layer no computations is done, the inputs are fed directly to the outputs via a series of weights.

- Multi-layer perceptron (MLP): This class of networks consists of multiple layers of computational units, usually interconnected in a feedforward way. Each neuron in one layer has directed connections to the neurons of the subsequent layer. In many applications the units of these networks apply a sigmoid function as an activation function. MLP are very more useful and one good reason is that, they are able to learn non-linear representations (most of the cases the data presented to us is not linearly separable).

- Convolutional Neural Network (CNN): Convolutional Neural Networks are very similar to ordinary Neural Networks, they are made up of neurons that have learnable weights and biases. In convolutional neural network (CNN, or ConvNet or shift invariant or space invariant) the unit connectivity pattern is inspired by the organization of the visual cortex, Units respond to stimuli in a restricted region of space known as the receptive field. Receptive fields partially overlap, over-covering the entire visual field. Unit response can be approximated mathematically by a convolution operation. They are variations of multilayer perceptrons that use minimal pre-processing. Their wide applications is in image and video recognition, recommender systems and natural language processing. CNNs requires large data to train on.

3.3.5.1.2 Elman or recurrent neural network (RNN)

Fully recurrent networks, introduced by Elman (1990), feed the outputs of the hidden layer back to itself. Partially recurrent networks start with a fully recurrent net and add a feed forward connection that bypasses the recurrence, effectively treating the recurrent part as a state memory. Fig. 3.8 shows a typical recurrent network consisting of four input nodes, a hidden layer with 3 nodes and one output. A context layer is interconnected with the hidden layer and plays the role of the network memory. These recurrent networks can have an infinite memory depth and thus find relationships through time as well as through the instantaneous input space (Haykin, 1999). Most real-world data contains information in its time structure. Recurrent networks are the state of the art in nonlinear time series prediction, system identification, and temporal pattern classification (Zhang *et al*., 1998).

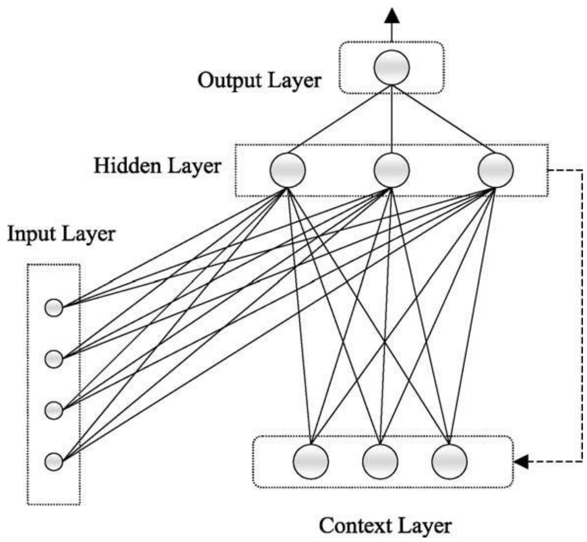


Fig. 3.8 Typical recurrent neural network

3.3.5.1.3 Radial basis function network (RBF)

Radial basis function (RBF) networks are nonlinear hybrid networks typically containing a single hidden layer of computation nodes. This layer uses Gaussian transfer functions, rather than the standard sigmoidal functions employed by a FNN. Fig.3.9 shows a typical radial basis function consisting of a hidden layer of four nodes, four inputs and three outputs. The centers and widths of the Gaussians are set by unsupervised learning rules, and supervised learning is applied to the output layer (Haykin, 1999). Radial basis function networks tend to learn much faster than a FNN.

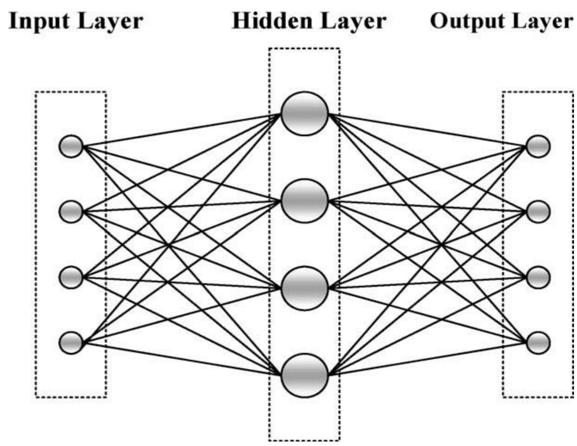


Fig .3.9 Typical radial basis function

3.3.5.2 Training algorithms

It is a step by step procedure for adjusting the connection weights of an artificial neural network. Three different algorithms are being used in order to identify the one which trains a given network more efficiently.

3.3.5.2.1 Gradient descent with momentum and adaptive learning rate back propagation (GDX)

This method uses back propagation to calculate derivatives of performance cost function with respect to the weight and bias variables of the network. Each variable is adjusted according to the gradient descent with momentum. For each step of the optimization, if performance decreases the learning rate is increased. This is probably the simplest and most common way to train a network (Haykin, 1999).

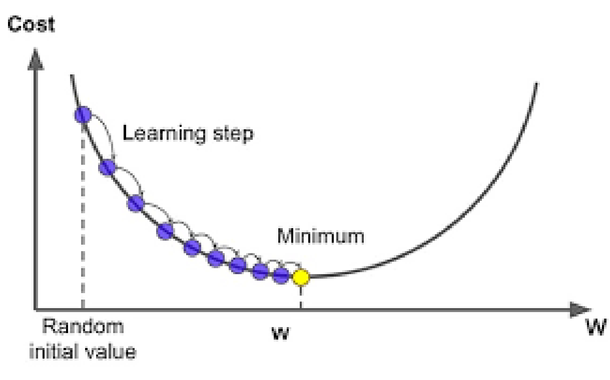


Fig. 3.10 Gradient descent Algorithm

3.3.5.2.2. Levenberg–Marquardt (LM)

The Levenberg–Marquardt method is a modification of the classic Newton algorithm for finding an optimum solution to a minimization problem. It uses an approximation to the Hessian matrix in the following Newton-like weight update

$$\boldsymbol{x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T e}$$

where ,

x =Weights of neural network

J= Jacobian matrix of the performance criteria to be minimized

μ=A scalar that controls the learning process

e= residual error vector.

When the scalar *m* is zero, the above equation is just the Newton's method, using the approximate Hessian matrix. When *m* is large, then it becomes gradient descent with a small step size. Newton's method is faster and more accurate near an error minimum, so the aim is to shift towards Newton's method as quickly as possible.

Levenberg–Marquardt has great computational and memory requirements and thus it can only be used in small networks (Maier and Dandy, 1998). Nevertheless, many researchers have been successfully using it (Anctil *et al*., 2004). The Levenberg–Marquardt algorithm is often characterized as more stable and efficient. Also, both Coulibaly *et al*. (2000); Toth *et al*. (2000) point out that it is faster and less easily trapped in local minima than other optimization algorithms.

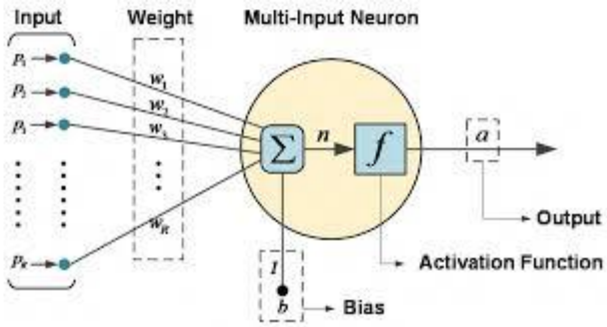


Fig 3.11 Levenberg-Marquardt Algorithm

3.3.5.2.3 Bayesian regularization (BR)

The Bayesian regularization is an algorithm that automatically sets optimum values for the parameters of the objective function. In the approach used, the weights and biases of the network are assumed to be random variables with specified distributions. In order to estimate regularization parameters, which are related to the unknown variances, statistical techniques are being used. The advantage of this algorithm is that whatever the size of the network, the function won't be over-fitted. Bayesian regularization has been effectively used in literature (Anctil*et al*., 2004; Coulibaly *et al*., 2001a,b,c; Porter *et al*., 2000).

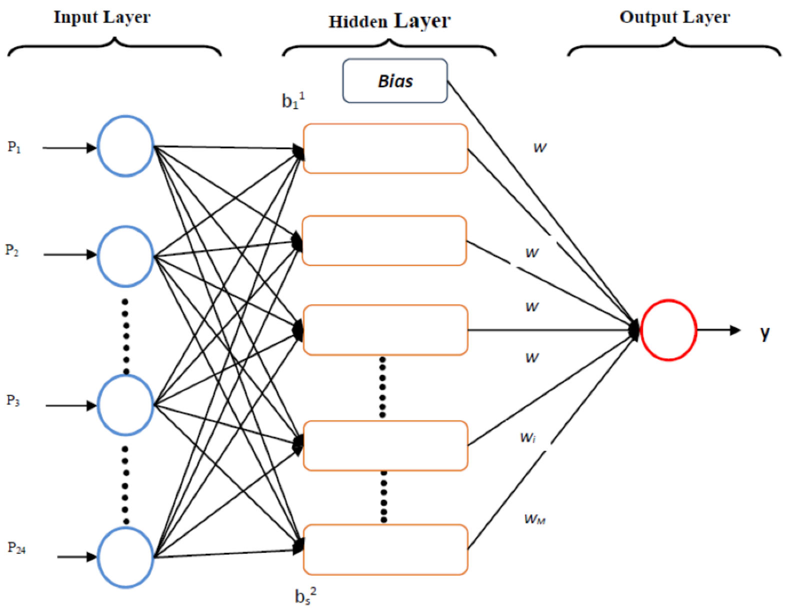


Fig 3.12 Bayesian Regularization

3.3.5.3 Training functions

Several different back propagation training algorithms are there, which have variety of different computation and storage requirements. No single algorithm could be found that was best suited for all conditions and locations. In the neural network toolbox, the different training functions included were traingd, traingdm, traingdx, trainlm, trainrp etc. In this work trainlm i.e. Levenberg Marquardt algorithm was used.

Table 3.1 Different training functions and training algorithms

Function Name in MATLAB	Training Algorithm
trainlm	Levenberg-Marquardt back-propagation
trainbr	Bayesian Regularization back-propagation
trainbfg	BFGS Quasi-Newton back-propagation
trainrp	Resilient Back propagation back-propagation
trainscg	Scaled Conjugate Gradient back-propagation
traincgb	Conjugate Gradient with Powell/Beale Restarts back-propagation
traincgf	Fletcher-Powell Conjugate Gradient back-propagation
traincgp	Polak-Ribiére Conjugate Gradient back-propagation
trainoss	One Step Secant back-propagation
traingdx	Variable Learning Rate Gradient Descent back-propagation
traingdm	Gradient Descent with Momentum back-propagation
traingd	Gradient Descent back-propagation

3.3.5.4 Learning function

Learning is a process by means of which a neural network adapts itself to a stimulus by making proper parameter adjustments, resulting in the production of desired response. Here two learning functions are mentioned in create new network window LEARNGD and LEARNGDM.

Table 3.2 Learning function according to training function

Training Function	Learning Function
trainlm	learngdm
trainlm	learngdm
traincgf	learngdm
trainlm	learngd
traincgf	learngdm
trainlm	learngdm
trainlm	**learngdm**

Table 3.3 Learning functions and their performance index

Adaption learning function	Performance functio
LearnGDM	MSE[1]
LearnGD	MSE
LearnGDM	MSEREG[2]
LearnGD	SSE[3]
LearnGDM	MSEREG
LearnGD	SSE
LearnGDM	MSEREG
LearnGDM	MSEREG
LearnGDM	MSEREG
LearnGDM	MSEREG

This ANN modelling work was done by using LEARNGDM learning function, which means Gradient descent with momentum weight and bias learning function.

3.3.5.5 Transfer function

It is a mathematical representation, in terms of spatial or temporal frequency, of the relation between the input and output of a system. Using this function neurons or layers net output were mapped to its actual output. Here, three types of transfer functions are explained, which are mentioned below:-

3.3.5.5.1 Log Sigmoid Transfer Function

The sigmoid functions are widely used in back-propagation network because of the relationship between the value of function at a point and the value of the derivative at that point which reduces the computational burden during training. The graph, symbol and algorithm of function which was used in the following format (Fig 3.13).

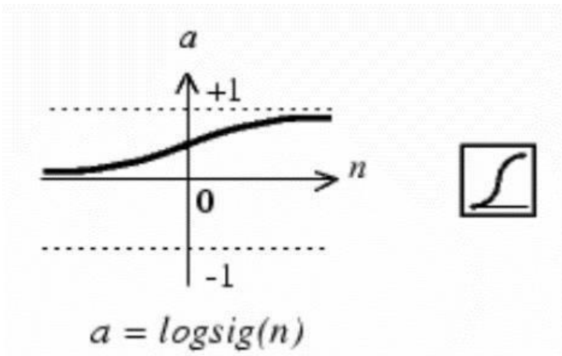
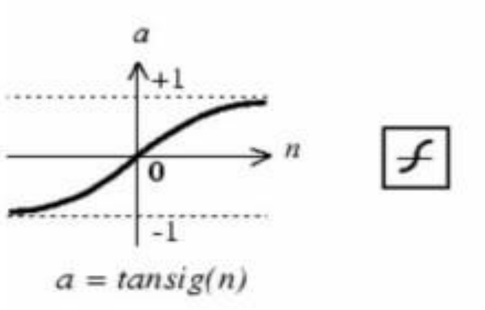


Fig 3.13 Log Sigmoid Transfer function

3.3.5.5.2 Tan sigmoid Transfer Function

Tan sigmoid transfer function is also known as 'hyperbolic tangent sigmoid transfer function'. For neural networks where speed is important, this function is best. The tan sigmoid function range is between -1 and +1. The graph, symbol and algorithm of function which was used in the following format (Fig 3.14).



$$tansig\ (n) = 2 / (1+exp\ (-2*n)) - 1$$

Figure 3.14 Tan Sigmoid Transfer function Transfer function

3.3.5.5.3 Pure Linear Transfer Function

The pure linear function range is between -1 and +1. The graph, symbol and algorithm of function that was used had the following format as shown in Fig 3.15.

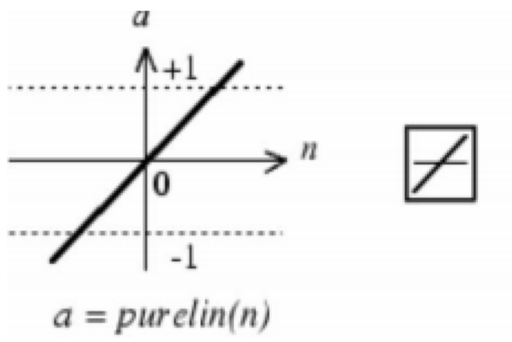


Fig. 3.15 Pure Linear Transfer function

3.3.6 Advantages of ANN

- The application of ANN does not need a prior knowledge of the process because they have black box properties
- ANN have inbuilt property of nonlinearity since neurons activate a nonlinear filter cold & activation function.

- ANN could have multiple input having different characteristics, so they are able to represent the time-space variability.
- ANN have flexibility to represent change of problem environments
- Massive parallelism, distributed representation and learning and generalization ability.
- Fault tolerance
- They are able to recognize the relation between input and output variables without explicit physical considerations.
- They work well even when the training sets contain noise and measurement errors.
- They are able to adapt to solutions over time to compensate for changing circumstances.
- They possess other inherent information- processing characteristics and once trained are easy to use.
- They have the ability of pattern classification, clustering or categorization, function approximation prediction or forecasting, optimization, content-addressable memory control.

3.3.7 Disadvantages of ANN

The success of an ANN application depends on both quality and quantity of data available. This condition could not be easily met, as many hydrologic records do not go back far enough. Even when long historic records are available, it is not certain that conditions remained homogenous over this time span. Therefore, datasets recorded over a system that is relatively stable and unaffected by human activities are desirable. Representing temporal variations is often achieved by including past inputs or outputs as current inputs. However, it is not immediately clear how far back one must go in the past to include temporal effects. This makes the resulting ANN structure more complicated.

3.4 DEVELOPMENT OF ANN MODELS

In the development of ANN models, an appropriate set of inputs were selected by correlation method, which may be the most popular technique for selecting appropriate inputs in hydrology. This was utilized to calculate the strength of the relationship between each potential input with the output. Training and validation was done to get the more accurate model for groundwater level predictions. Performance of each model was studied under the performance criteria of Root Mean Square Error (RMSE) and Coefficient of Correlation(R). The output of each model was compared with observed groundwater level. The observed groundwater level was taken from well 159 Sreekrishnapuram. Outputs of ANN model were compared statistically and the best architecture was selected.

3.4.1 Software used

For this study we were used MATLAB 7.0 for the development of Artificial Neural Network model. MATLAB is a proprietary multi-paradigm programming language and numeric computing environment developed by Mathematical Works. It allows matrix manipulations, plotting functions and data, implementation of algorithm, creation of user interfaces, and interfacing with programs written in other languages.

MATLAB integrates computation, visualization, and programming in an easy-to-use environment where problems and solutions are expressed in familiar mathematical notation. MATLAB has different toolbox for different fields of functions, like bioinformatics toolbox, curve fitting toolbox, database toolbox, fuzzy logic toolbox, neural network toolbox, optimization toolbox etc. For this work MATLAB neural network toolbox was used. The network manager consists of all operations of importing inputs, target, creation of new network, outputs, network errors etc. For importing the data in network manager, it is necessary to have those variables either in workspace or disc in mat file format. The view of the MATLAB work windows can be shown in Fig. 3.16 to Fig. 3.20. After importing all the input and target files from workspace to network manager the next step was the creation of new network.

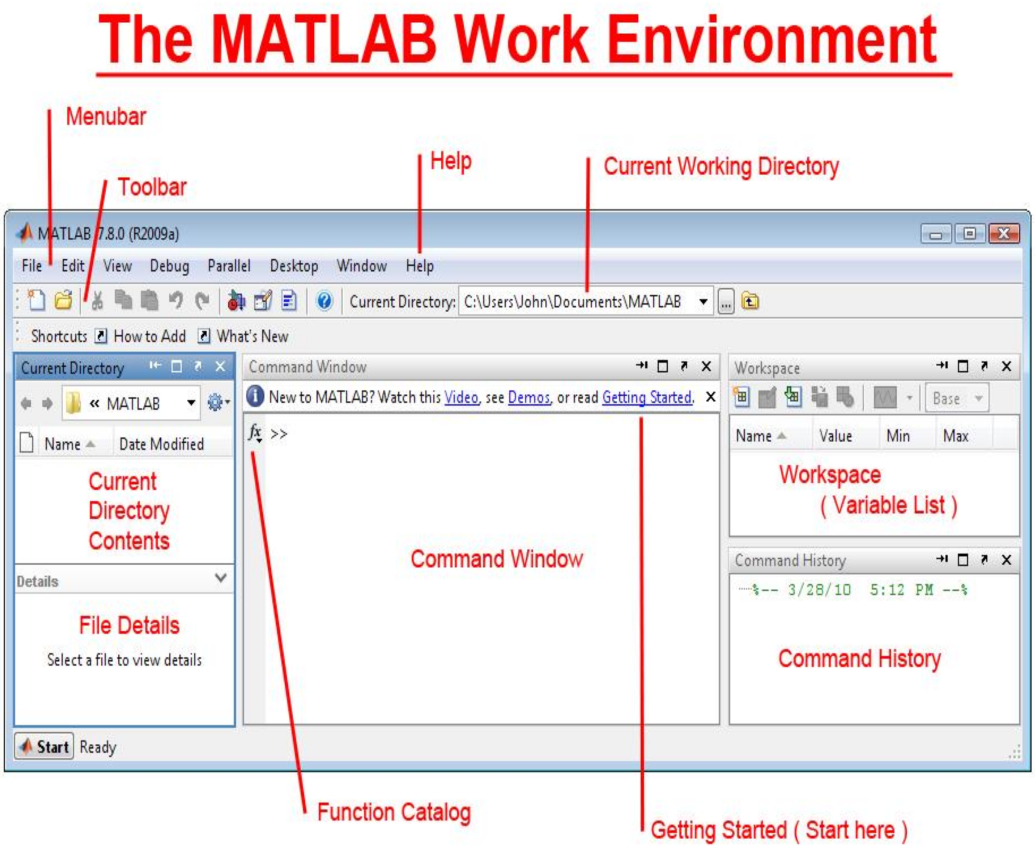


Fig 3.16 The MATLAB work environment

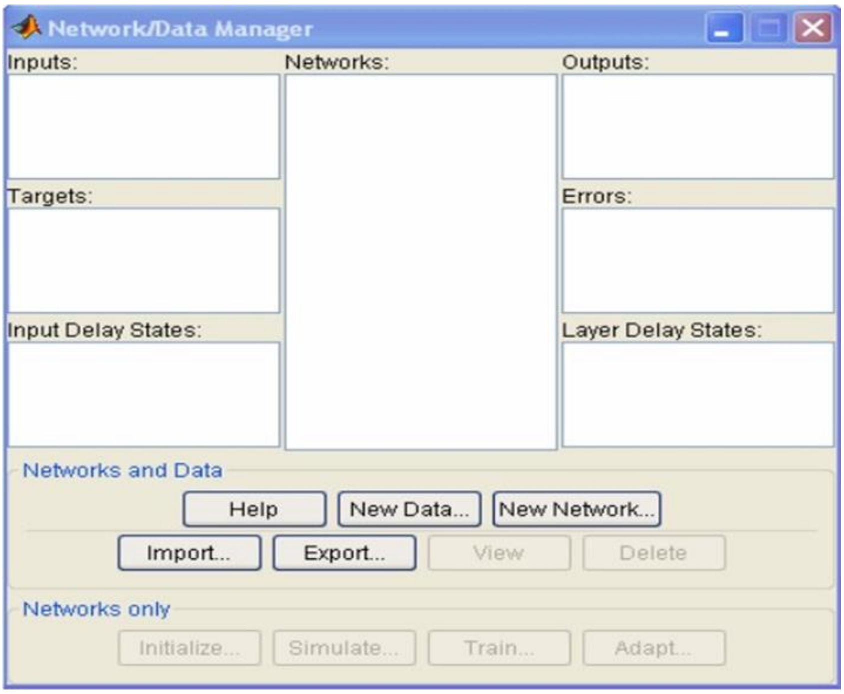


Fig 3.17 Neural network toolbox of MATLAB 7.0

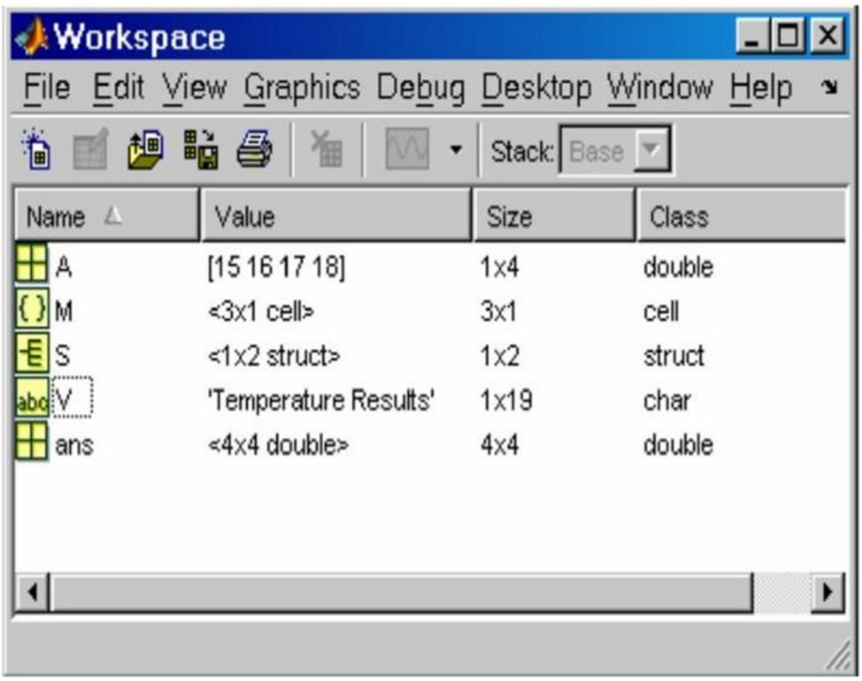


Fig 3.18 Workspace Window

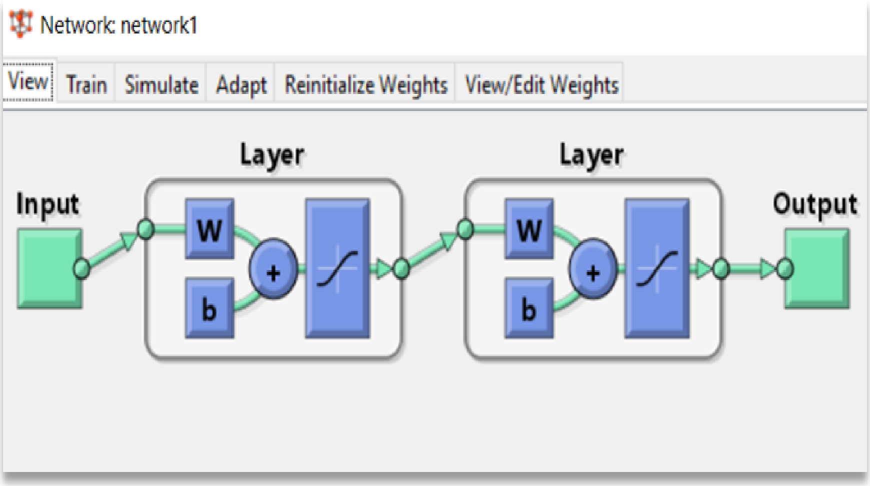


Fig 3.19 Neural Network

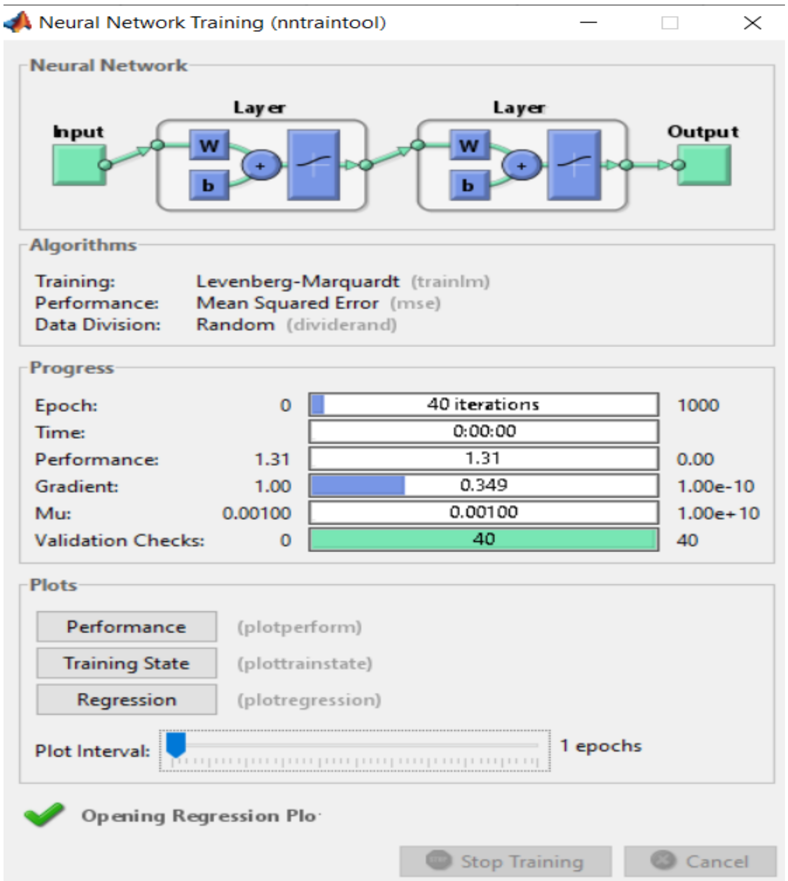
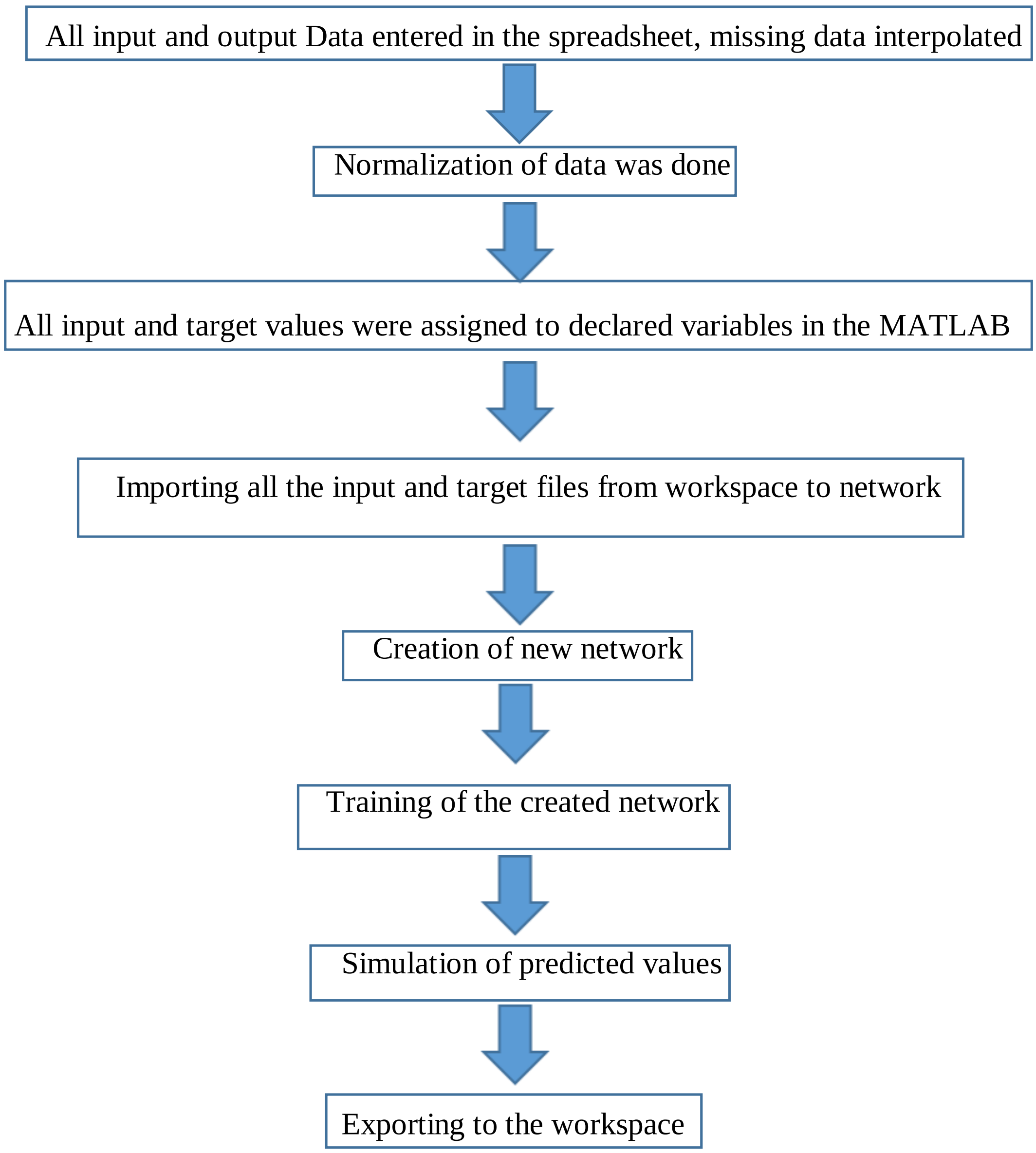


Fig.3.20 Neural Network Training

3.4.2 Steps in ANN modelling:



3.4.3. Data Analysis

The collected data from RARS Pattambi, CGWB and Pulamanthole gauging station were analyzed before using it for ANN modelling.

3.4.3.1 Correlation Analysis

Correlation analysis was done after entering the acquired data in MS Excel spreadsheet format. Correlation between observed groundwater level and each parameter was determined separately. The results showed the significance of the variables in predicting groundwater level. Even though, some variables sowed negative correlation with the groundwater level, they were also taken into consideration. It was then used for deciding further modelling strategies. Different modelling strategies were formulated by changing the transfer functions.

3.4.4 Data partitioning

Data used for this study was from January 1999 to December 2019. The total number of datasets used were 252.The two basic processes that take place in the model development are model training and simulation. According to this concept the data was divided into two part i.e., for training and simulation. Out of 252 datasets, 189 were taken for model training and 63 were taken for simulation.

3.4.5 Data normalization procedure

Neural network training can be done more efficiently if certain pre-processing steps like data normalization are performed on the network input and target. Data normalization scales the input and target so that they fall within a specific range. This process removes the cyclicity of the data and help in quick training of network. Data normalization was done in our present study using equation;

$$\boldsymbol{x_m = \frac{x_i - x_{min}}{x_{max} - x_{min}}}$$

Where,

Xm = Normalized value

Xi = Selected data value

Xmin= Minimum value of total data considered for normalization

Xmax= Maximum value of total data considered for normalization

Above formula scales data inputs and target in the range of 0 and 1.

All these normalized input and target values were then assigned to the declared variables in the MATLAB. Then, importing of all the files separately from MATLAB workspace to the ANN network manager, where the creation of models with different modelling strategies were done.

3.4.6 Creation of models in MATLAB

Different models were created with different modelling strategies in MATLAB software using ANN toolbox which have a particular set of ANN neural architecture. Table 3.4 shows the neural architecture used for our study.

Table 3.4 Neural Architecture used for the study

Components	Type
Neural Network	Feed Forward Neural Network
Training algorithm	Levenberg-Marquardt (LM)
Training function	TRAINLM
Learning function	LEARNGDM
Transfer function	Tan sigmoid, Log sigmoid function

By maintaining all components of neural architecture same except the transfer functions, a total of 14 models were created. Out of this, 7 models were created with tansigmoid transfer function and the remaining 7 models were created with logsigmoid transfer function each of which varies in their number of hidden layers (5, 10, 15, 20, 25 and 30). Training parameters like maximum fail, epochs and goals were adjusted. The maximum fail value were increased to 100. Goal was set to zero. Maximum epochs were provided as 1000. Best model was selected on the basis of R and RMSE value.

3.5 EVALUATION OF PERFORMANCE OF MODEL

3.5.1 Root Mean Square Error (RMSE)

It is the square root of the MSE. Advantage of using RMSE is that, RMSE has same units as that of variables involved in computation. It is defined in the following equation

$$\textbf{RMSE} = \sqrt{|MSE|}$$

3.5.2 Coefficient of Correlation (R)

It is the measure of the accuracy of a hydrologic modelling, is generally used for comparisons of alternative models. A high R implies a good model performance. The perfect match between the calculated and observed GW values would give R=1.0. It can be calculated using following equation.

$$\boldsymbol{R = \frac{\frac{1}{N}\sum_{i=1}^{N}(GW\ obs - GW\ pred)(GW\ pred - UGW\ pred)}{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(GW\ obs - GW\ pred)\hat{}2}\sqrt{\frac{1}{N}\sum_{i=1}^{N}(GW\ pred - UGW\ pred)\hat{}2}}}$$

Where,

UGW obs = Mean of observed groundwater level, mm

UGW pred = Mean of predicted groundwater level, mm

3.6 CREATION OF ONE MONTH AHEAD PREDICTION MODEL

One month ahead prediction models were created, for which the input data were shifted one month ahead keeping the observed output to be same. Four models were created by changing the number of hidden layers as 5, 10, 15, and 20. The training parameters were adjusted accordingly.The best model was arrived on the basis of RMSE and R value.

RESULTS AND DISCUSSION

CHAPTER IV

RESULTS AND DISCUSSION

Groundwater is reserved in the subsurface in a geologic system called aquifer. Groundwater level is an indicator of groundwater availability, groundwater flow and the physical characteristics of an aquifer or groundwater system (Nair and Sindhu, 2016). A decrease in groundwater levels can trigger a number of eco-environmental problems capable of seriously affecting both local agricultural production and economic development (Li *et al*. 2019).The increased dependence on groundwater, spatial-temporal variation etc have impacted groundwater levels. So it is necessary to quantify the present rate of recharge, monitor the changes in water table depths and predict the future trend. A groundwater model provides a quantitative framework for synthesizing field information and for conceptualizing hydrogeologic processes. An understanding of groundwater dynamics with the application of computer and mathematical tools can be used to predict groundwater flow and level fluctuation (Mao *et al*. 2002). ANN in particular, ANNs have been found useful in the area of groundwater modelling. Keeping this points in view modelling of groundwater levels were done using ANN .

In this chapter, the results of correlation analysis, Analysis of different models, Comparison of models in terms of correlation coefficient and RMSE value and selection of best model are discussed in the following subheads.

4.1. CORRELATION ANALYSIS

Correlation analysis was performed between observed groundwater levels and each meteorological parameter separately.

Table 4.1 Correlation of meteorological parameter with observed Evapotranspiration

Sr. No	Meteorological parameters	Coefficient of correlation (GW)
1.	Max temp	0.4681036
2.	Min temp	0.023229
3.	RF	-0.3621
4.	Evaporation	0.40664
5.	RH1	-0.10803
6.	RH2	-0.237599
7.	Stream flow	-0.6187

Correlation results showed the significance of each variable with respect to observed groundwater level, which was further used in deciding modelling strategies. Though a few variables showed negative correlation with GW, in the correlation matrix, yet these variables were included in the model development because they are known to affect the groundwater level fluctuations and they are within the range of correlation coefficient (i.e, 1 to -1). Fig.4.1 shows the variation of available groundwater levels and input variables during the period July 1998-June 2020.

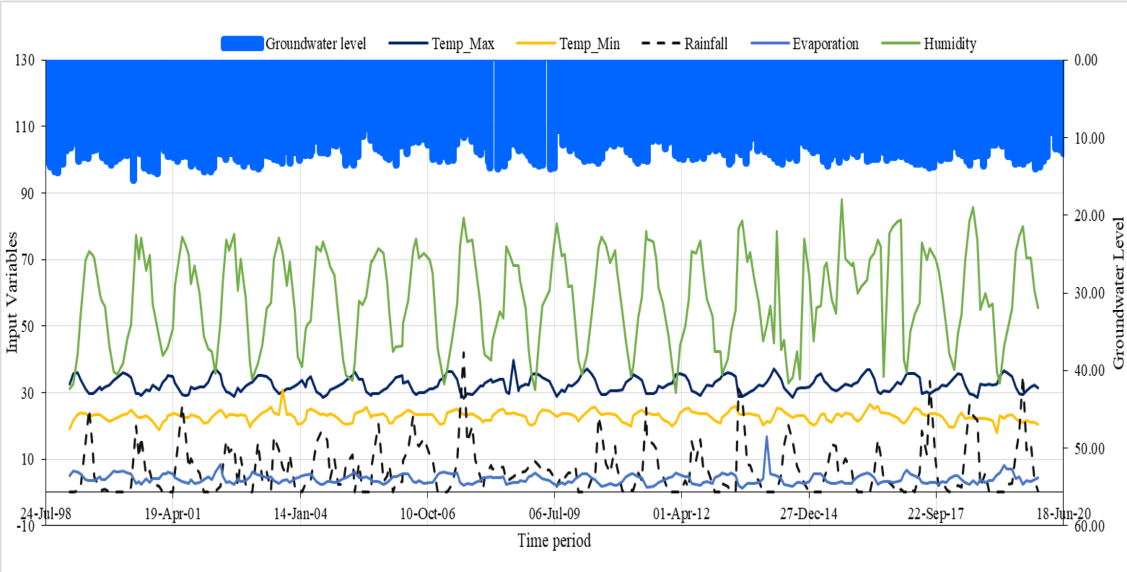


Fig 4.1 Variation of available groundwater levels and input variables during the period Jul 98-Jun 20

4.2 MODEL STRATEGY

ANN model architect consists of different number of hidden layers, hidden neurons and transfer functions etc. There are no fixed rules for developing an ANN model, even though a general framework can be followed based on previous successful applications. In this study Feed Forward Back Propagation (FFBP) model architecture was used and two different transfer functions were used.

4.2.1 ANN models for groundwater level fluctuation

Two modelling strategies were adopted; one with TANSIG Function and the other with LOGSIG Function. In each of these strategies, 7 models were developed by changing the number of hidden layers (5, 10, 15, 20, 25, 30). Models obtained by both strategies were compared and the best was selected. Table 4.2 shows the different modelling strategies used in development of ANN models.

Table 4.2 Different modelling strategies used in development of ANN models.

Strategy 1(TANSIG Function)		Strategy 2(LOGSIG FUNCTION)		
Model No	No of hidden layers	Model No	No of hidden layers	Model names
1	5	1	5	7-5-1 FFN LM
2	10	2	10	7-10-1 FFN LM
3	15	3	15	7-15-1 FFN LM
4	20	4	20	7-20-1 FFN LM
5	25	5	25	7-25-1 FFN LM
6	30	6	30	7-30-1 FFN LM
7	35	7	35	7-35-1 FFN LM

In the model names of different models for both TANSIG and LOGSIG functions, as in Table 4.2,

- 7 indicates number of input variables
- Middle number indicate the number of hidden layers
- 1 indicates the number of output layer
- FFN indicates the neural network used
- LM indicated the training algorithm used.

4.2.1.1 Network Architecture

The network architecture of different ANN models created using tansigmoid and logsigmoid functions are shown in Table 4.3 and Table 4.4 respectively.

Table 4.3 Network architecture for Tansigmoid function

Model No	No. of hidden layers	Neural network	Learning function	Transfer function	Training algorith m	Training function	Max fail	Epoch
1	5	**FFN**	**LEARNGDM**	**Tansig**	**LM**	**trainlm**	**25**	**1000**
2	10	**FFN**	**LEARNGDM**	**Tansig**	**LM**	**trainlm**	**30**	**1000**
3	15	**FFN**	**LEARNGDM**	**Tansig**	**LM**	**trainlm**	**68**	**1000**
4	20	**FFN**	**LEARNGDM**	**Tansig**	**LM**	**trainlm**	**58**	**1000**
5	25	**FFN**	**LEARNGDM**	**Tansig**	**LM**	**trainlm**	**50**	**1000**
6	30	**FFN**	**LEARNGDM**	**Tansig**	**LM**	**trainlm**	**100**	**1000**
7	35	**FFN**	**LEARNGDM**	**Tansig**	**LM**	**trainlm**	**100**	**1000**

Table 4.4 Network architecture for Logsigmoid function

Model No	No of hidden layers	Neural Network	Learning Function	Transfer function	Training algorithm	Training function	Max fail	Epoch
1	5	**FFN**	**LEARNGDM**	**Logsig**	**LM**	**trainlm**	**50**	**1000**
2	10	**FFN**	**LEARNGDM**	**Logsig**	**LM**	**trainlm**	**100**	**1000**
3	15	**FFN**	**LEARNGDM**	**Logsig**	**LM**	**trainlm**	**25**	**1000**
4	20	**FFN**	**LEARNGDM**	**Logsig**	**LM**	**trainlm**	**65**	**1000**
5	25	**FFN**	**LEARNGDM**	**Logsig**	**LM**	**trainlm**	**50**	**1000**
6	30	**FFN**	**LEARNGDM**	**Logsig**	**LM**	**trainlm**	**100**	**1000**
7	35	**FFN**	**LEARNGDM**	**Logsig**	**LM**	**trainlm**	**100**	**1000**

4.2.2 ANN models for one month ahead prediction models

Once a network is trained it may be used to produce forecasts. One month ahead prediction models were created, for which the input data is shifted one month ahead, keeping the observed output same. Four models were created by changing the number of hidden layers as 5, 10, 15 and 20. The training parameters were adjusted accordingly.The best model was arrived on the basis of RMSE and R value.

For creating one month ahead prediction model, a feed-forward network with Levenberg-Marquardt training algorithms was used. The trained network with minimum error was saved and can be used for forecasting future groundwater level. The neural network of each model producing minimum value of RMSE and maximum value of R was selected as best model and can be further used in one-month-ahead water level forecasting of groundwater. Table 4.5 shows the details of four different models for one month ahead prediction.

Table 4.5 Models for one month ahead prediction model

Model no.	No of hidden layers	Neural network	Learning function	Transfer function	Training algorithm	Training function	Max. fail	Epoch	Model name
1	5	FFN	LEARNG DM	tansig	LM	traintm	25	1000	7-5-1
2	10	FFN	LEARNG DM	tansig	LM	trainlm	30	1000	7-10-1
3	15	FFN	LEARNG DM	tansig	LM	trainlm	68	1000	7-15-1
4	20	FFN	LEARNG DM	tansig	LM	trainlm	58	1000	7-20-1

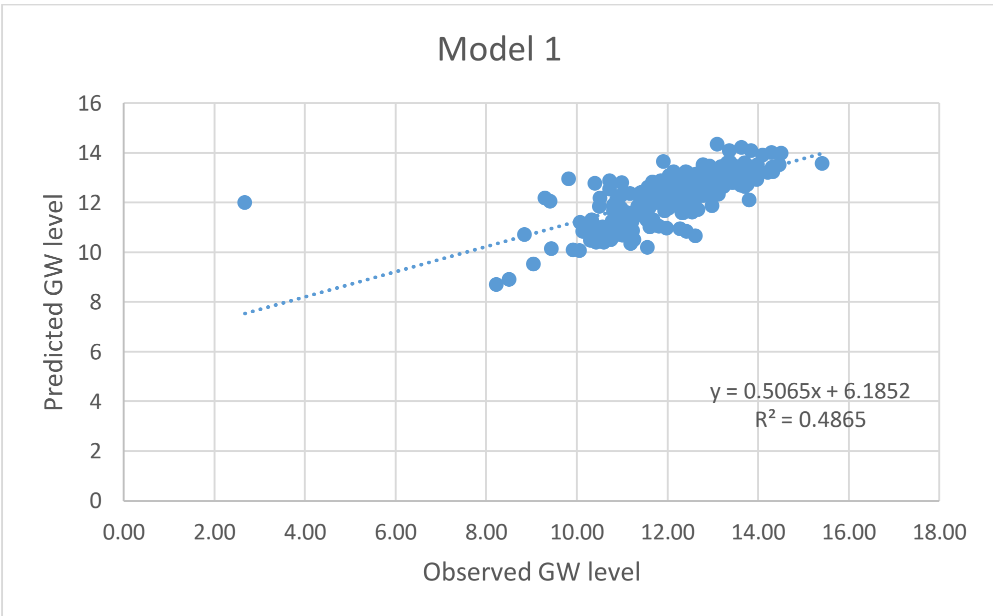
4.3. PERFORMANCE OF MODEL

All the network models were tested for performance criteria of root mean square error (RMSE) and coefficient of correlation(R) and then the values are compared to select the best model.

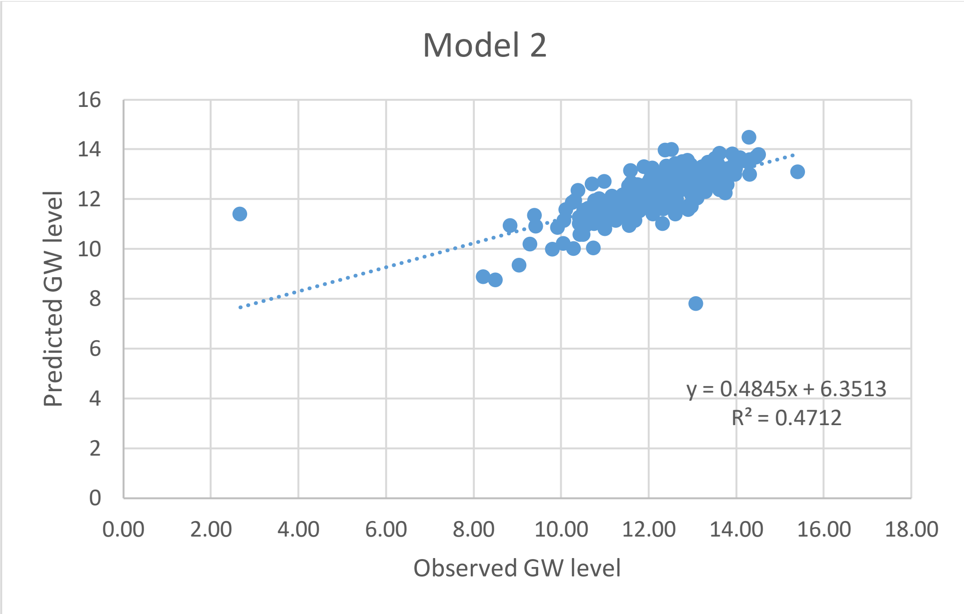
4.3.1 Comparison of ANN models for groundwater level fluctuation

Performance criteria RMSE and R were used for selection of best artificial neural network from 14 neural networks that were studied. Seven models have network with feed forward back propagation architecture and tan sigmoid transfer function and the other seven have log sigmoid transfer function. All involves seven Input parameters with TRAINLM training function, LEARNGDM learning function and varying number of layers as 5, 10, 20 etc.

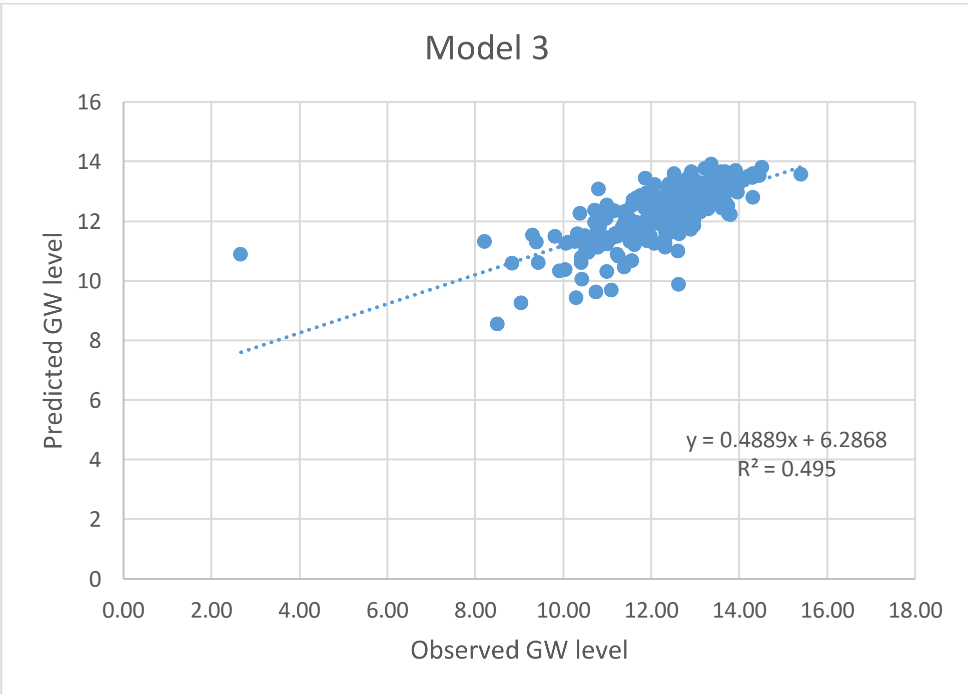
4.3.1.1 Models used tan sigmoid function



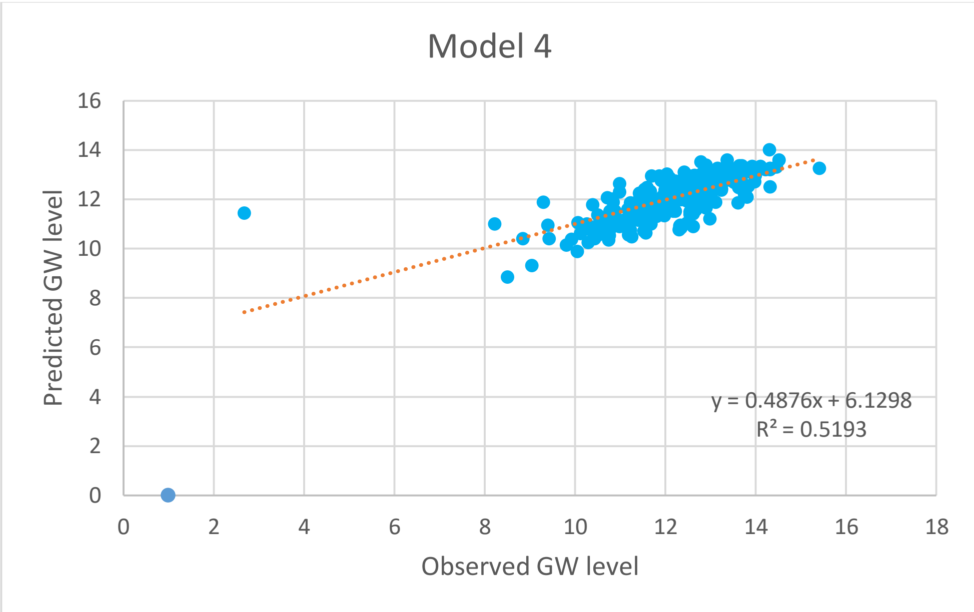
(a)


Model 2
Predicted GW level
Observed GW level
0
2
4
6
8
10
12
14
16
0.00
2.00
4.00
6.00
8.00
10.00
12.00
14.00
16.00
18.00
y = 0.4845x + 6.3513
R² = 0.4712

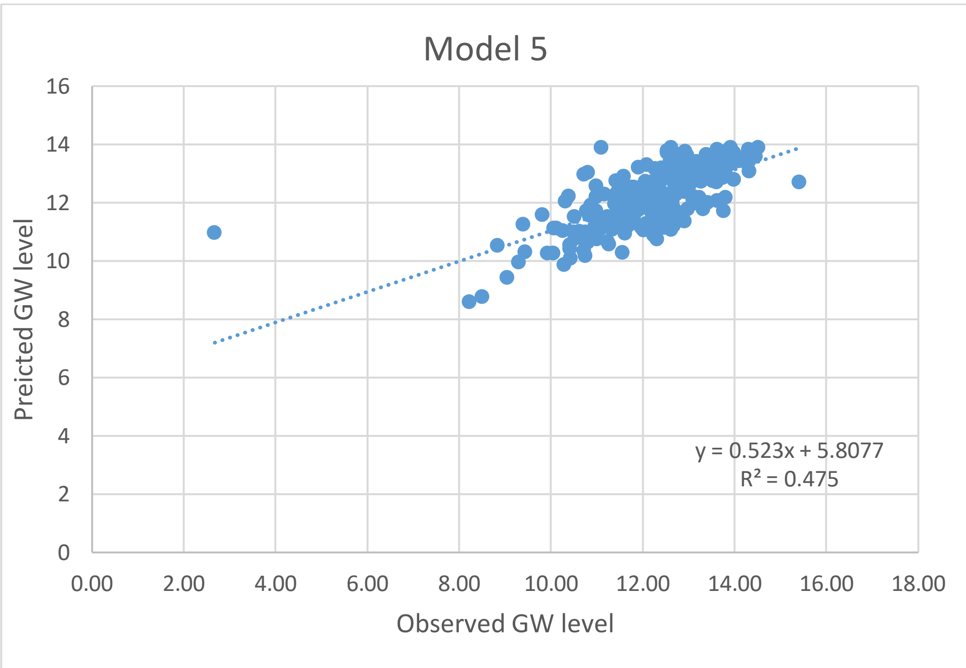
(b)


Model 3
Predicted GW level
Observed GW level
0
2
4
6
8
10
12
14
16
0.00
2.00
4.00
6.00
8.00
10.00
12.00
14.00
16.00
18.00
y = 0.4889x + 6.2868
R² = 0.495

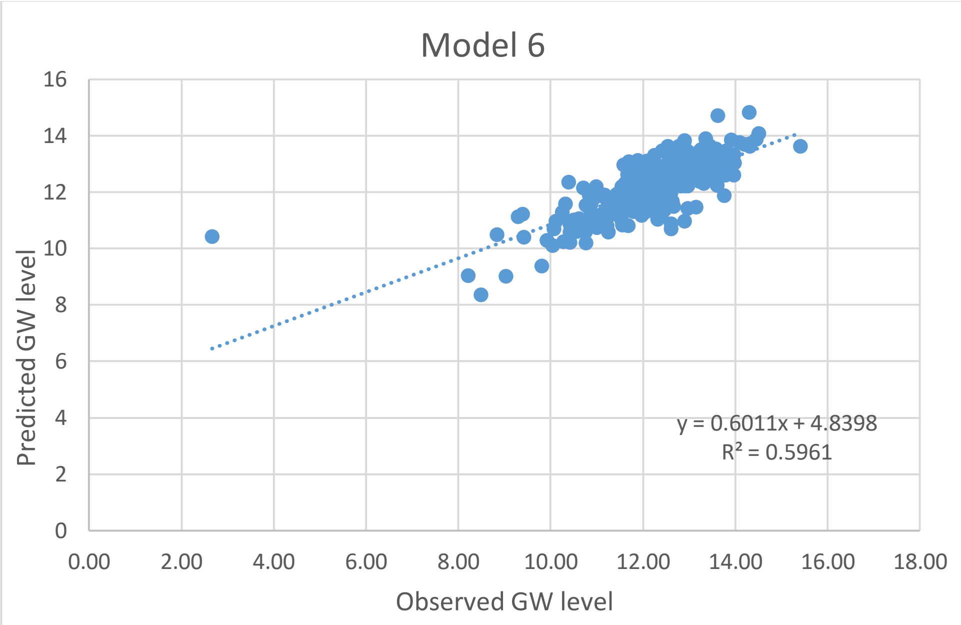
(c)


Model 4
Predicted GW level
Observed GW level
y = 0.4876x + 6.1298
R² = 0.5193
0
2
4
6
8
10
12
14
16
18

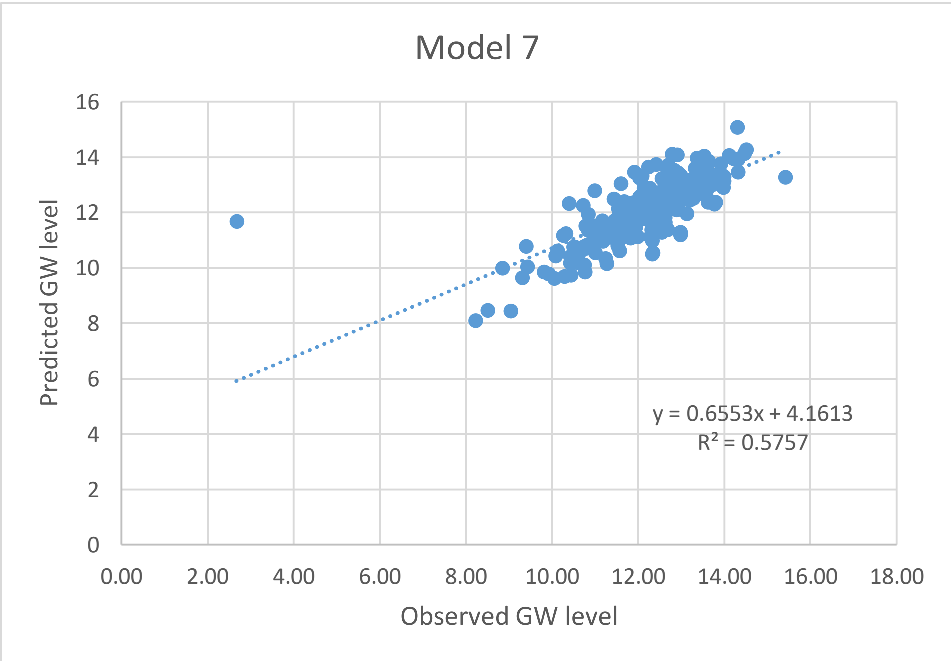
(d)


Model 5
Preicted GW level
Observed GW level
y = 0.523x + 5.8077
R² = 0.475
0.00
2.00
4.00
6.00
8.00
10.00
12.00
14.00
16.00
18.00

(e)



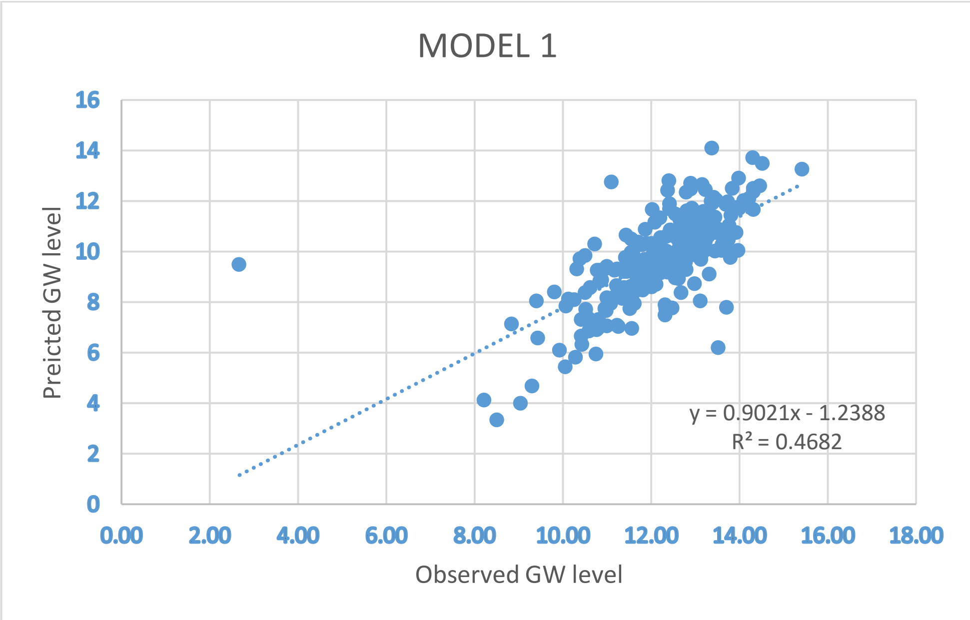
(f)



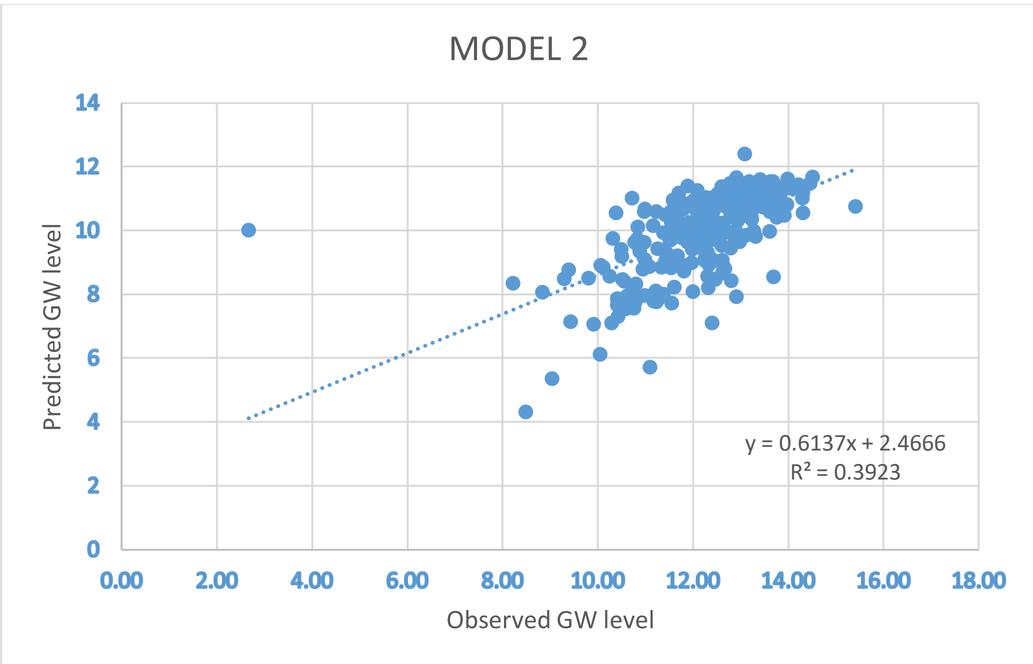
(g)

Fig 4.2. Model plots for tan sigmoid function

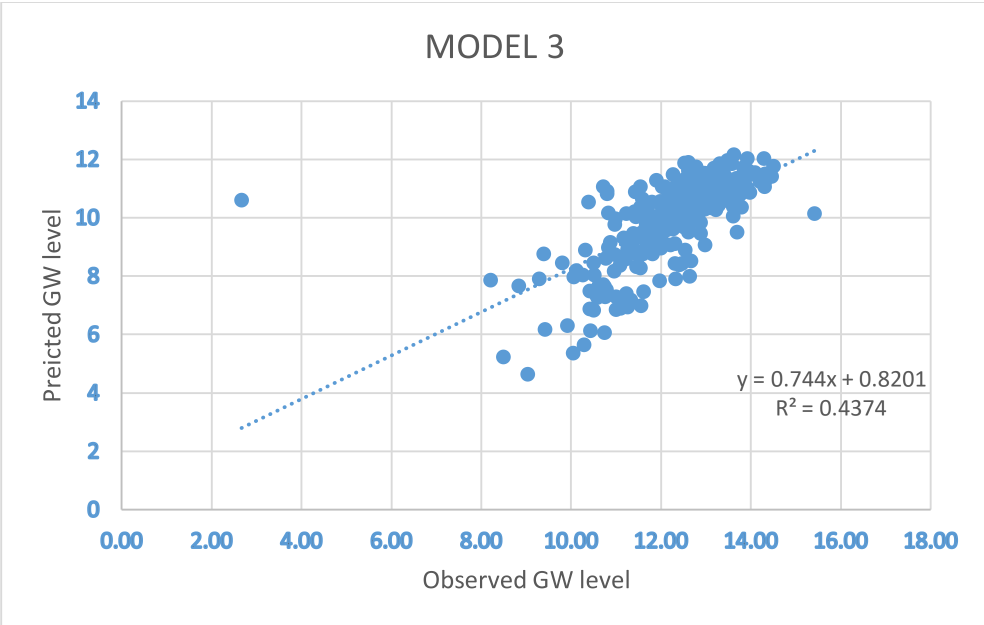
4.3.1.2 Models used log sigmoid function



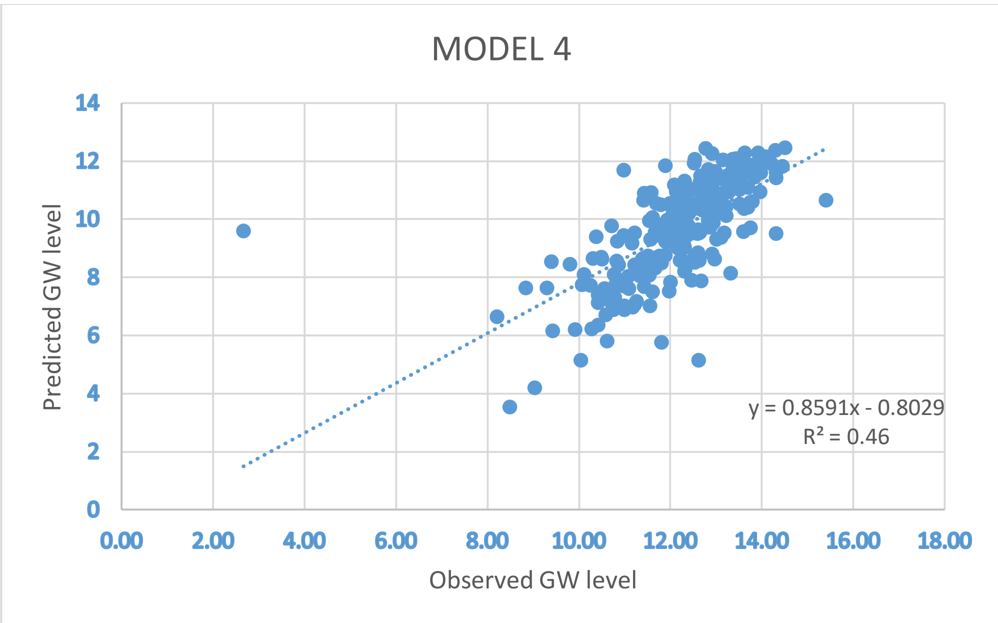
(a)



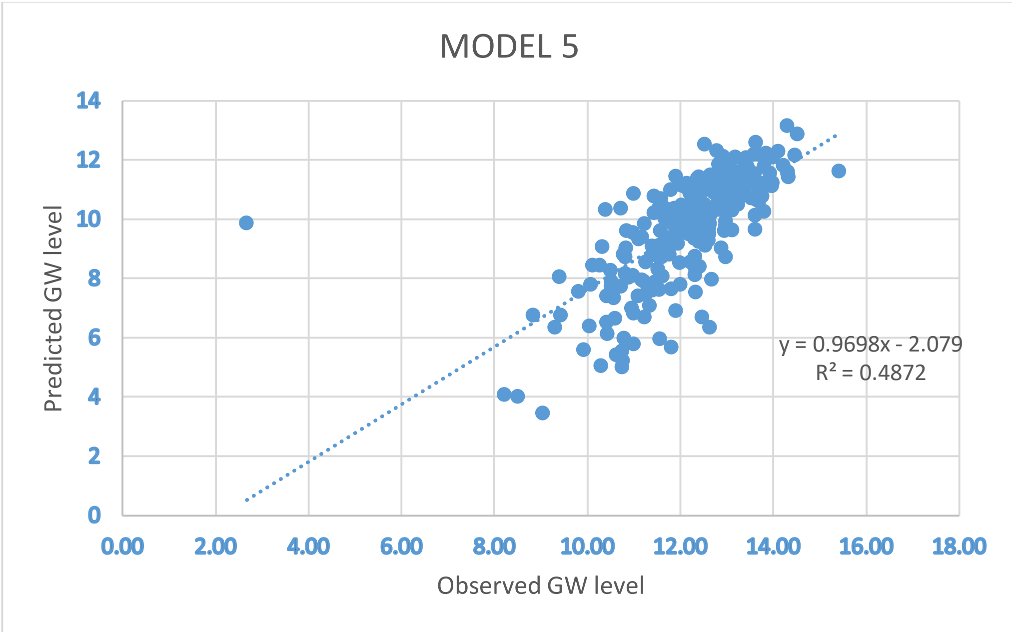
(b)


MODEL 3
Preicted GW level
Observed GW level
y = 0.744x + 0.8201
R^2 = 0.4374
0
2
4
6
8
10
12
14
0.00
2.00
4.00
6.00
8.00
10.00
12.00
14.00
16.00
18.00

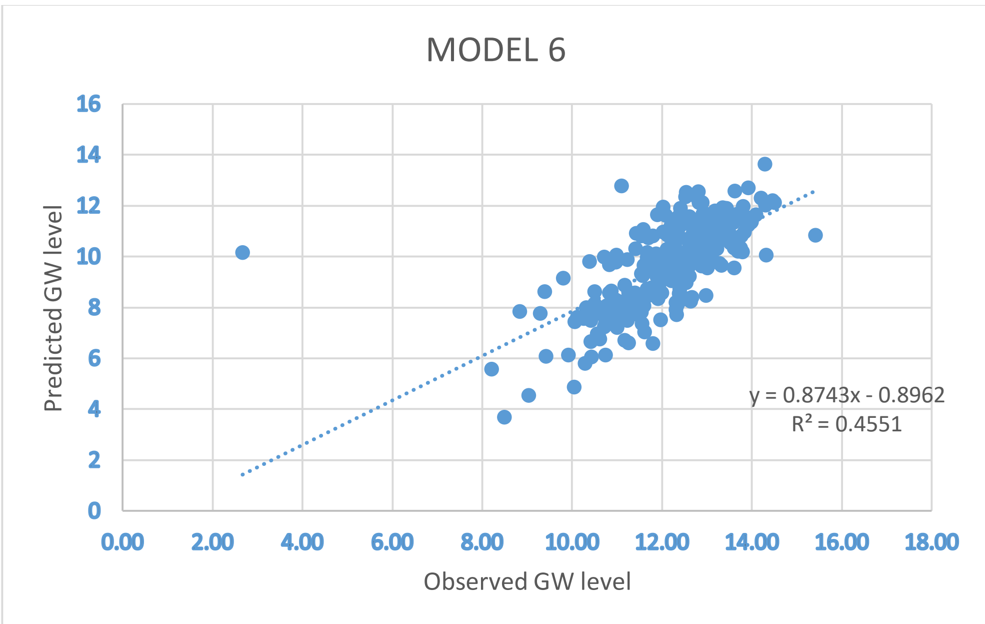
(c)


MODEL 4
Predicted GW level
Observed GW level
y = 0.8591x - 0.8029
R^2 = 0.46
0
2
4
6
8
10
12
14
0.00
2.00
4.00
6.00
8.00
10.00
12.00
14.00
16.00
18.00

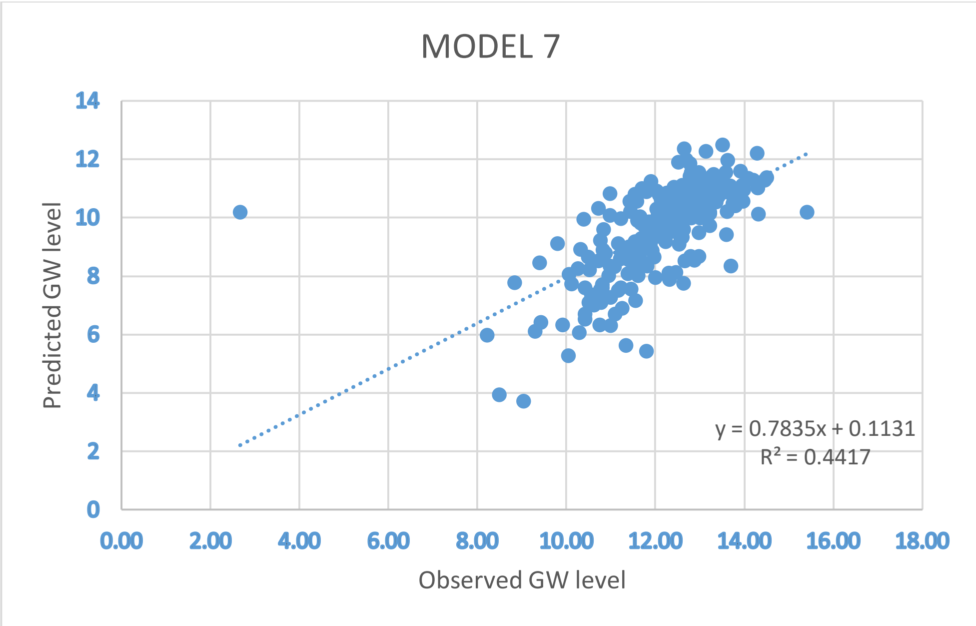
(d)


MODEL 5
Predicted GW level
14
12
10
8
6
4
2
0
0.00
2.00
4.00
6.00
8.00
10.00
12.00
14.00
16.00
18.00
Observed GW level
y = 0.9698x - 2.079
R² = 0.4872

(e)


MODEL 6
Predicted GW level
16
14
12
10
8
6
4
2
0
0.00
2.00
4.00
6.00
8.00
10.00
12.00
14.00
16.00
18.00
Observed GW level
y = 0.8743x - 0.8962
R² = 0.4551

(f)

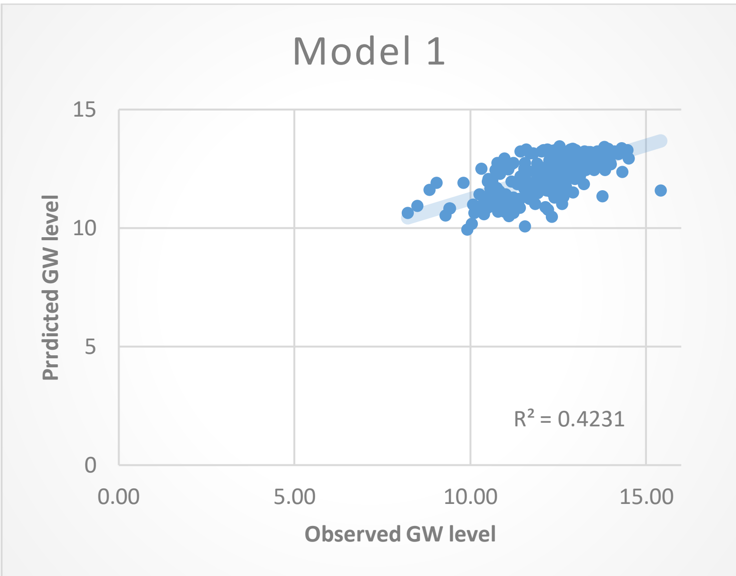


(g)

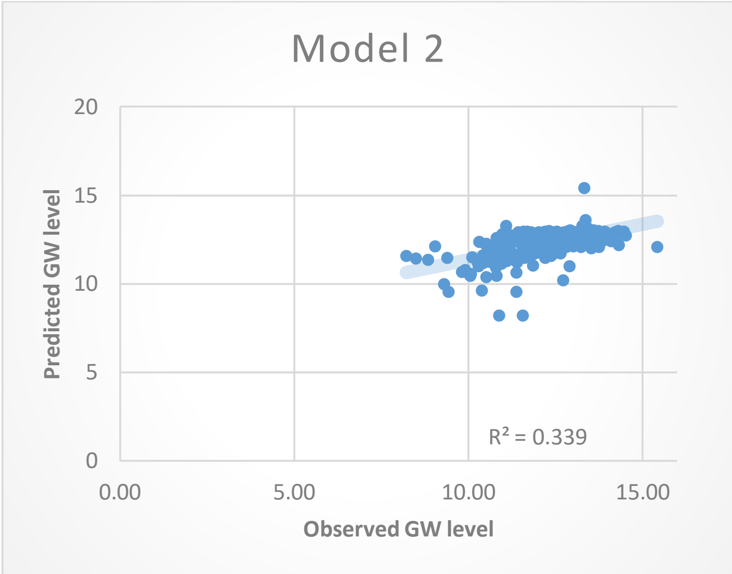
Fig 4.3. Model plots for log sigmoid function

4.3.2 Comparison of ANN models for one month ahead prediction

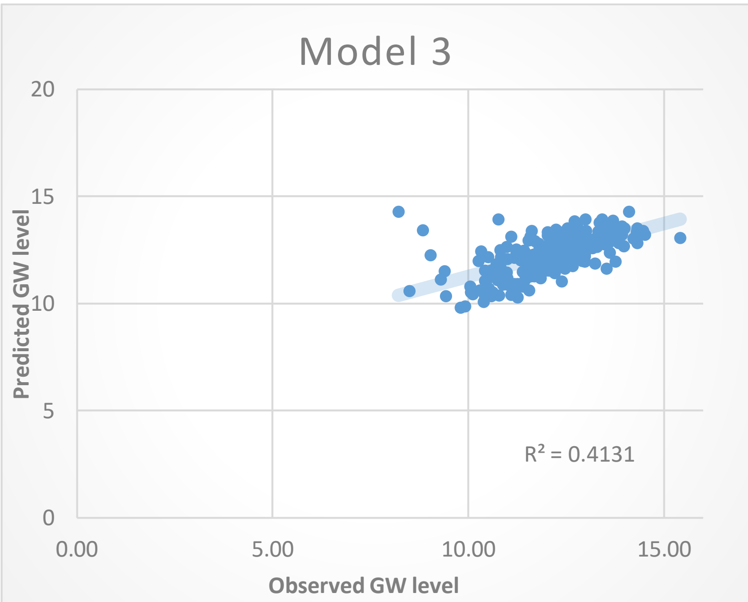
4.3.2.1 Models for one month ahead prediction



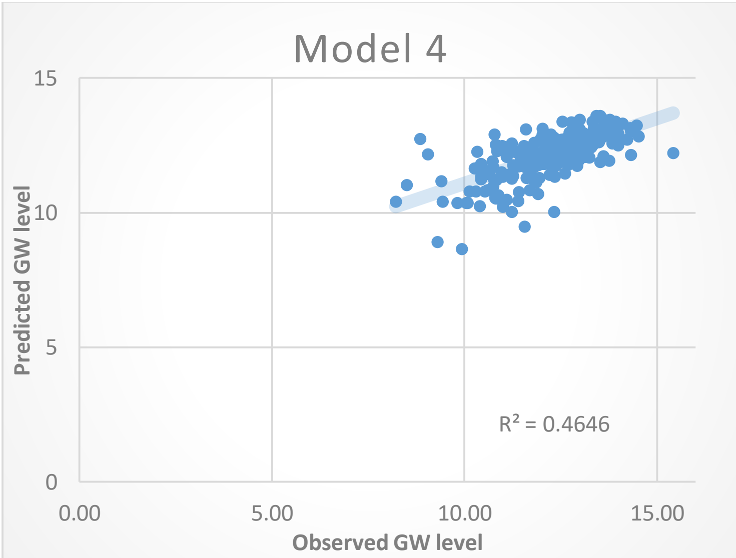
(a)


Model 2
Predicted GW level
20
15
10
5
0
0.00
5.00
10.00
15.00
Observed GW level
R² = 0.339

(b)


Model 3
Predicted GW level
20
15
10
5
0
0.00
5.00
10.00
15.00
Observed GW level
R² = 0.4131

(c)



(d)

Fig 4.4. Model plots for one month ahead prediction

4.4 SELECTION OF BEST MODEL

Best model is selected such that it have maximum R value and least RMSE value.

4.4.1 Selection of best ANN model for groundwater level fluctuation

4.4.1.1 For Tan sigmoid fuction

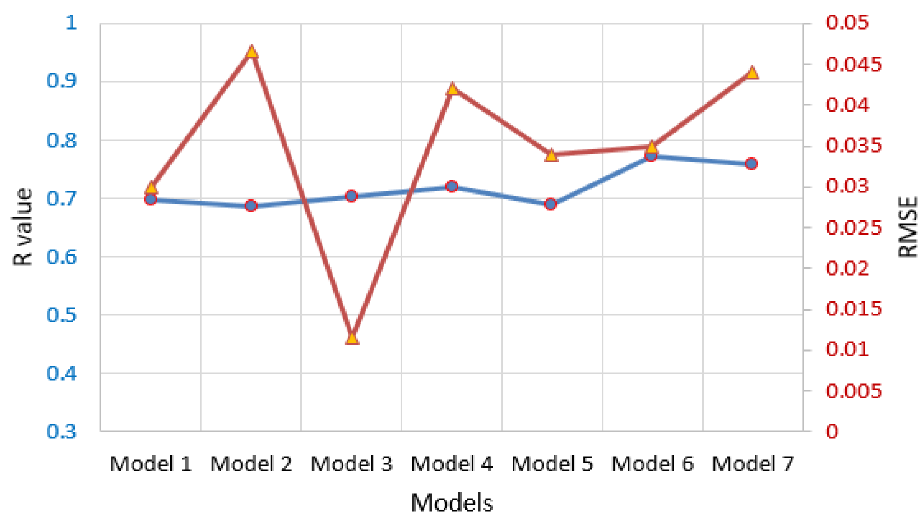


Fig 4.5 Comparison of models for tan sigmoid

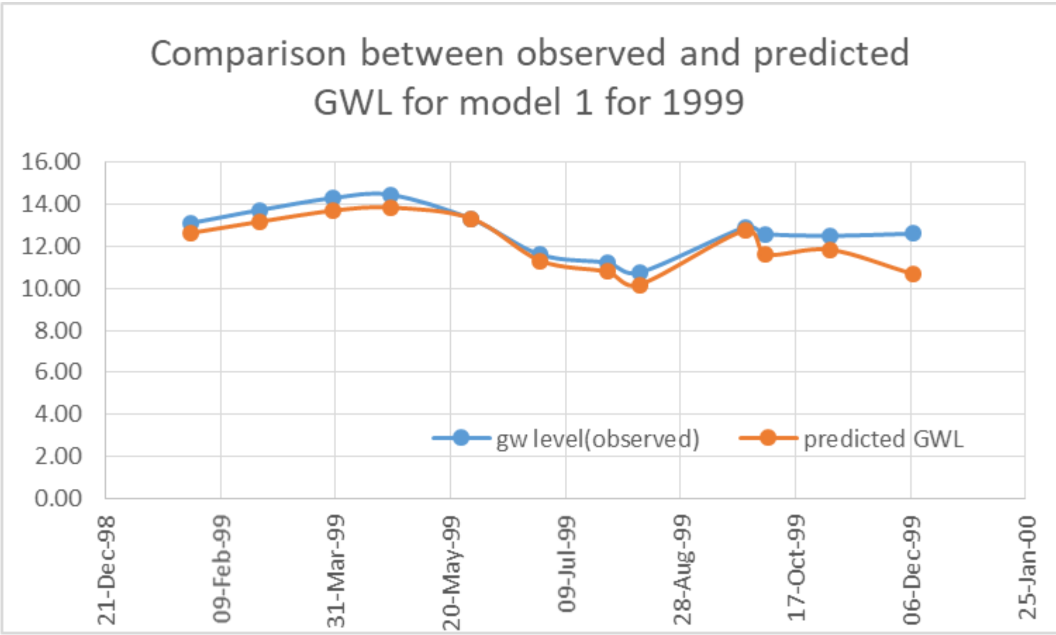
Best model is selected with maximum R value and minimum RMSE value. However, from the graph two models; MODEL 1 and MODEL 6 is found to be better performing.

For MODEL1, R =0.7

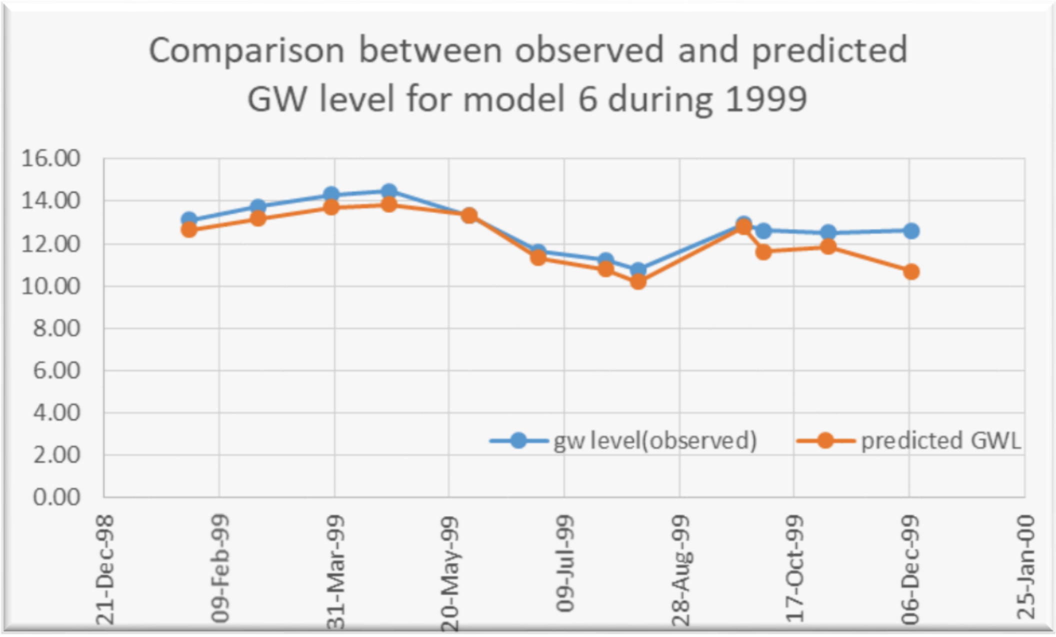
RMSE =0.03

For MODEL6, R =0.78

RMSE =0.035



(a) MODEL 1 (7-5-1 FFN LM)



(b) MODEL 6 (7-30-1 FFN LM)

Fig 4.6. (a) & (b) Comparison of observed and predicted groundwater levels for MODEL 1 and 6 for year 1999

Fig 4.6 shows a graphical comparison between the observed and predicted groundwater levels for both the models 1 and 6. From this figure, models 1 and 6 both shows a close predicted values with the observed groundwater values. So, we compared them in terms of R and RMSE values.

RMSE value of both the models are almost same. But the R value for MODEL 6 is slightly more than MODEL 1. Hence MODEL6 with R=0.78 can be selected as the best model. Fig 4.7, 4.8, 4.9, 4.10 shows the regression plot, progress and algorithm, neural network and training parameters for model 6.

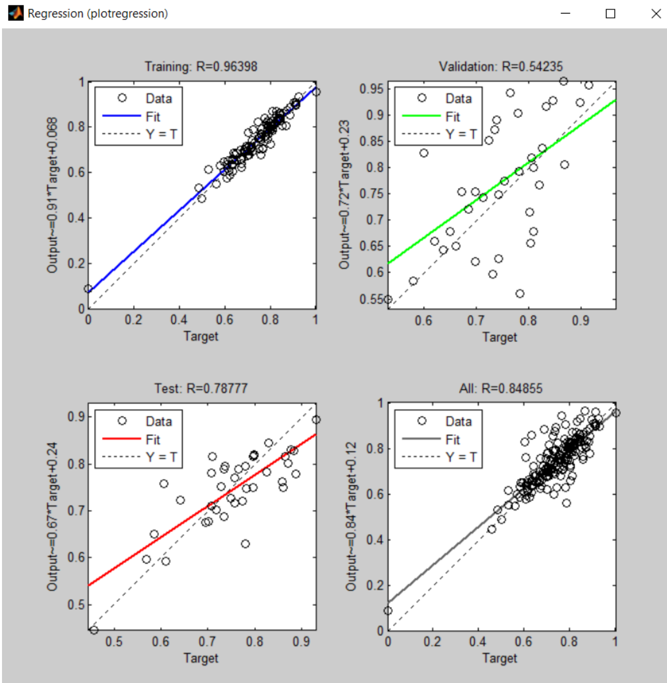


Fig 4.7. Regression plot for model6

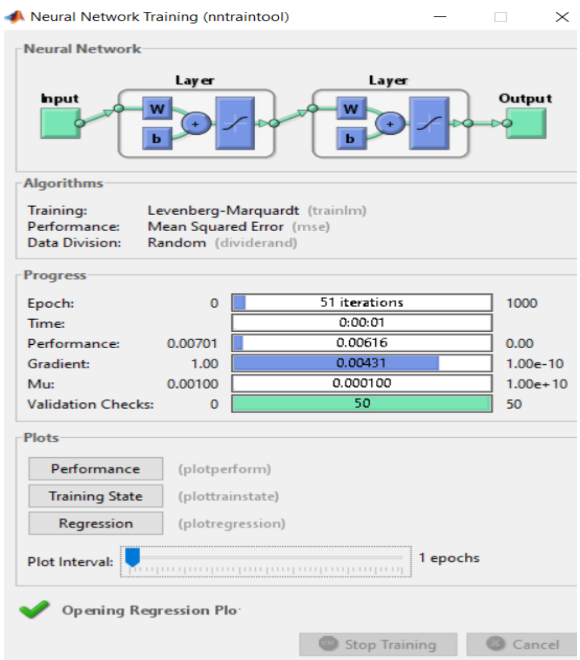


Fig 4.8. Progress and algorithms for model 6

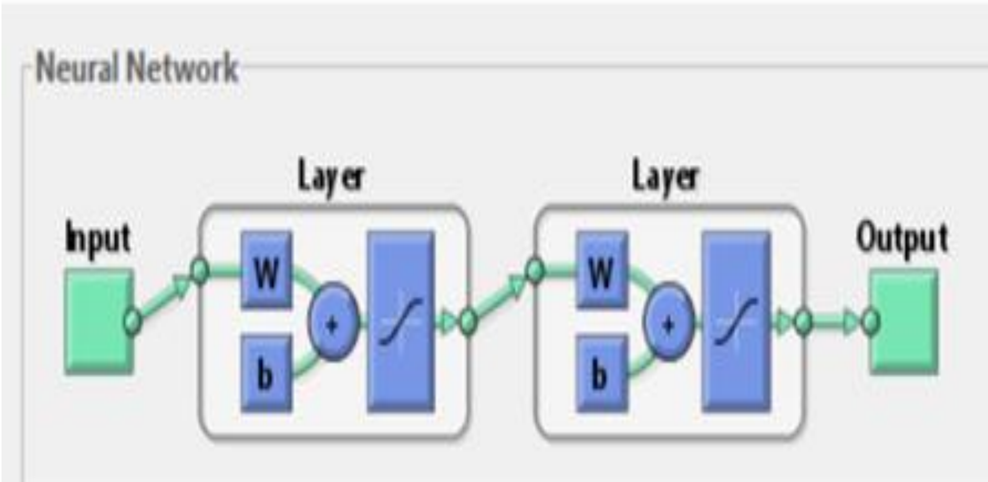


Fig 4.9. Neural network for model 6

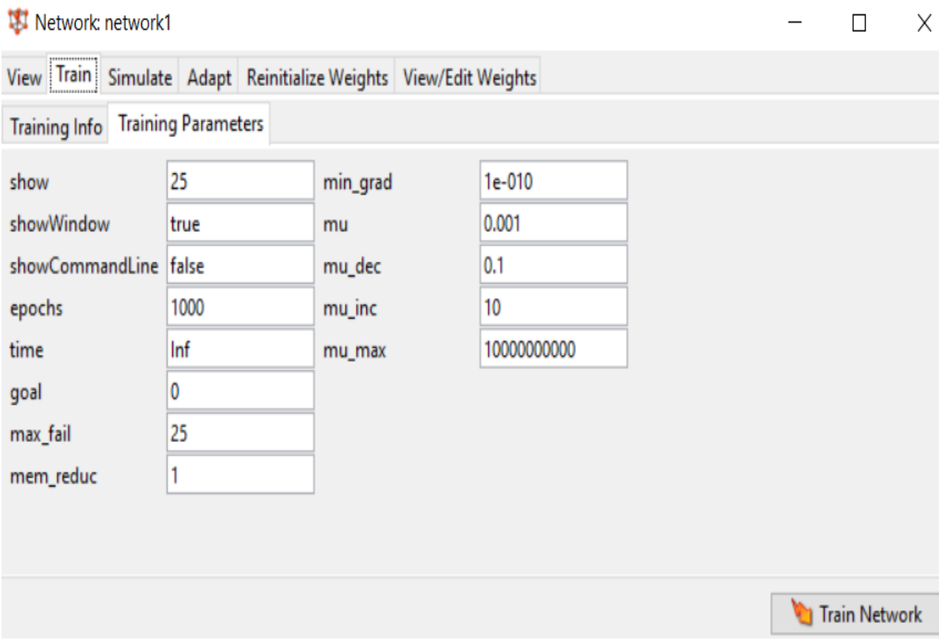


Fig 4.10. Training parameters for model 6

4.4.1.2. For log sigmoid function

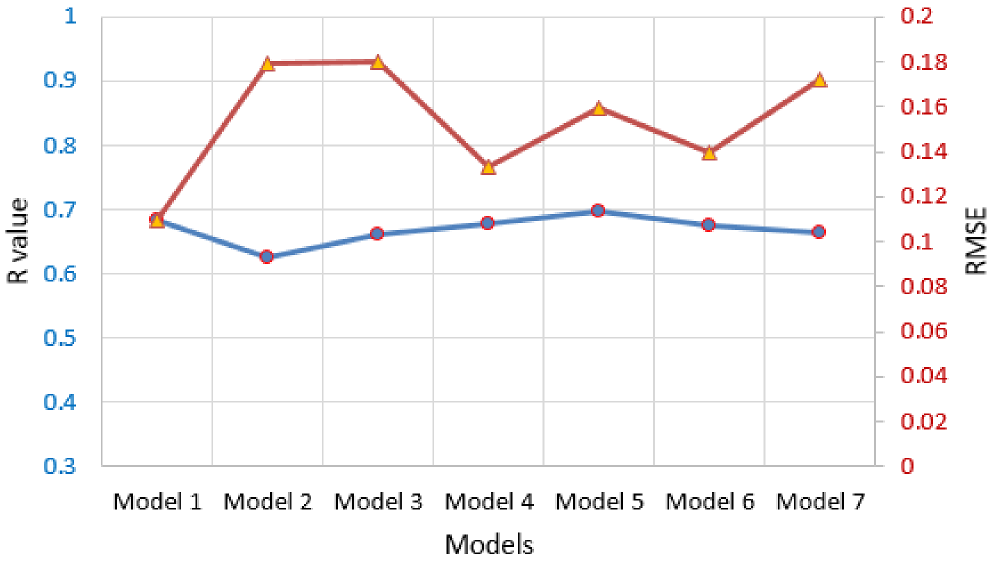


Fig 4.11. Comparison of models of log sigmoid function

Here, models with log sigmoid function were analysed and a graph is plotted comparing the different models with their R and RMSE values as shown in the Fig.4.10. From the graph it is found that the MODEL 1 performed better with R=0.684 and RMSE=0.109.

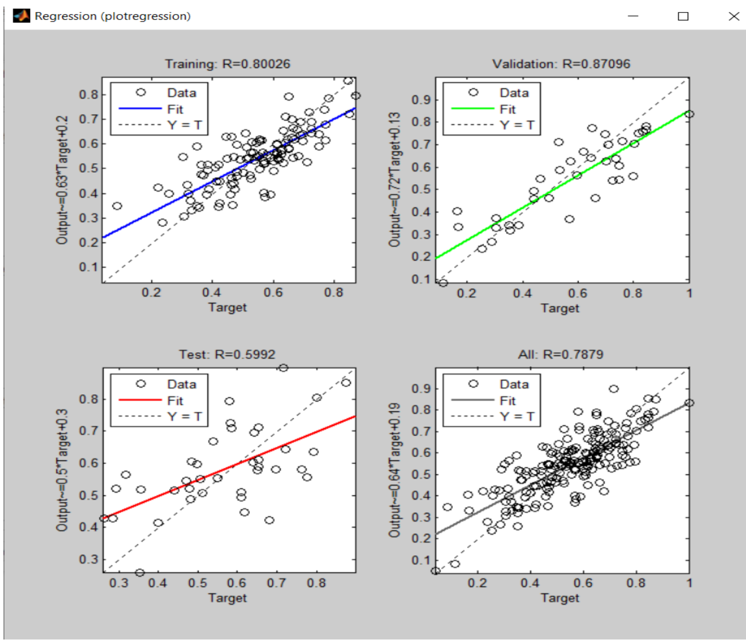


Fig 4.12. Regression plot for model 1

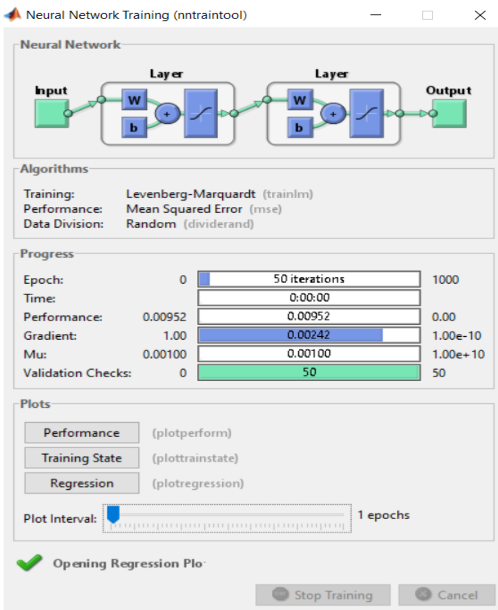


Fig 4.13. Progress and algorithms for model 1

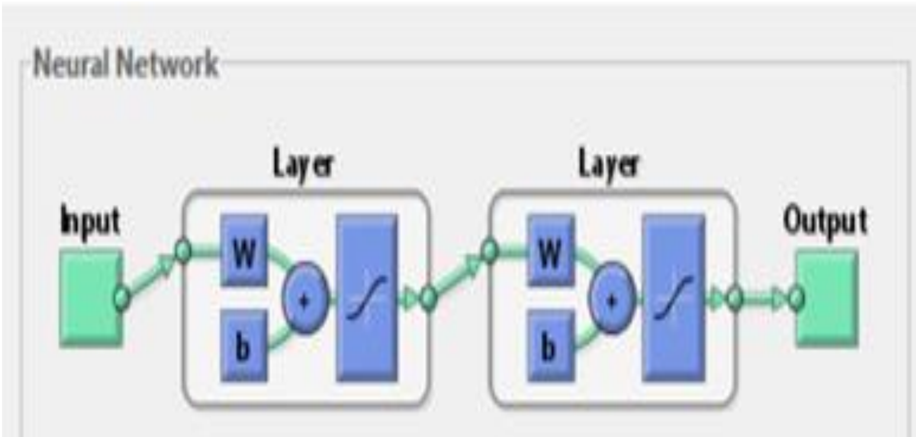


Fig 4.14. Neural network for model 1

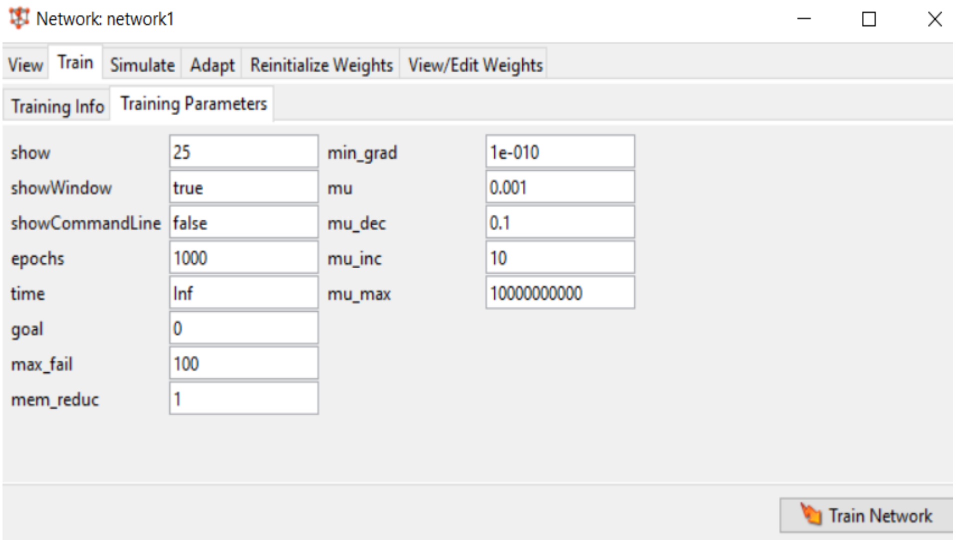


Fig 4.15. Training parameters for model 1

4.4.2.3 Findings from created models

The results of comparison of Tan sigmoid and log sigmoid transfer function is shown in the Table 4.6.

Table 4.6. R and RMSE values for Tan and Log sigmoid transfer function

Models	**Tan sigmoid function**			**Log sigmoid function**		
	R^2	R	RMSE	R^2	R	RMSE
1	0.4865	0.7	0.03	0.4682	0.684	0.109
2	0.4712	0.68	0.046	0.3923	0.626	0.179
3	0.495	0.71	0.01	0.4374	0.661	0.180
4	0.5193	0.73	0.042	0.46	0.678	0.134
5	0.475	0.69	0.034	0.4872	0.697	0.159
6	0.5961	0.78	0.035	0.4551	0.674	0.139
7	0.5757	0.76	0.044	0.4417	0.664	0.172

4.4.2.1 For Tan sigmoid transfer function

- In MODEL 1and 6, two values of observed and predicted groundwater level was found very close to each other for the year 1999.
- The remaining predicted values for both models were little bit underestimated.
- Model 6 is very close to regression line with better regression coefficient.
- Hence **MODEL 6 (7-30-1 FFN LM)** with maximum R value=0.78 and RMSE value=0.035 can be considered as the best model in Tansig function.

4.4.2.2 For Log sigmoid transfer function

- Four values of the observed and predicted groundwater level were found in close agreement, whereas the other values were little bit underestimated.
- The difference between the observed and predicted values were less in MODEL 1 compare to other models and the deviation was also less.
- Hence, MODEL1 was found to be the best in log sigmoid function with R=0.684 and RMSE=0.109.

Sreekanth.P.D., *et al* (2009) conducted similar study to forecast the groundwater level using ANN in Maheshwaram Watershed. They randomized the data into different sets by changing the number of layers and concluded that FFNN-LMB (16-30-9) is the best fit model for predicting groundwater level with an accuracy of 93%. They obtained a RMSE value of 3.13 which is comparable with the RMSE value obtained with our model.

The observed and predicted values of the best fit model for Maheshwaram Watershed is shown in the Fig 4.16.

Fig 4.16. Overall mean trend of observed and predicted values (FFNN-LBM model)

The trend followed in the graph is similar to the graphical representation of observed and predicted values by MODEL 6. It shows the accuracy of the network.

4.4.2 Selection of best ANN model for one month ahead prediction

Once a network is trained with a set of suitable input parameters, it can be used to forecast the future ground water fluctuations. Table 4.7 shows the R and RMSE values of four different models for one month ahead prediction. A model is selected in such a way that it have maximum R value and minimum RMSE value. Fig.4.17 shows comparison of observed and predicted values by different models.

Table 4.7. R and RMSE values for one month ahead prediction models

Model no.	**R**	**RMSE**
1	0.65046	0.893
2	0.582237	0.9639
3	0.642729	0.92248
4	0.681616	0.863407

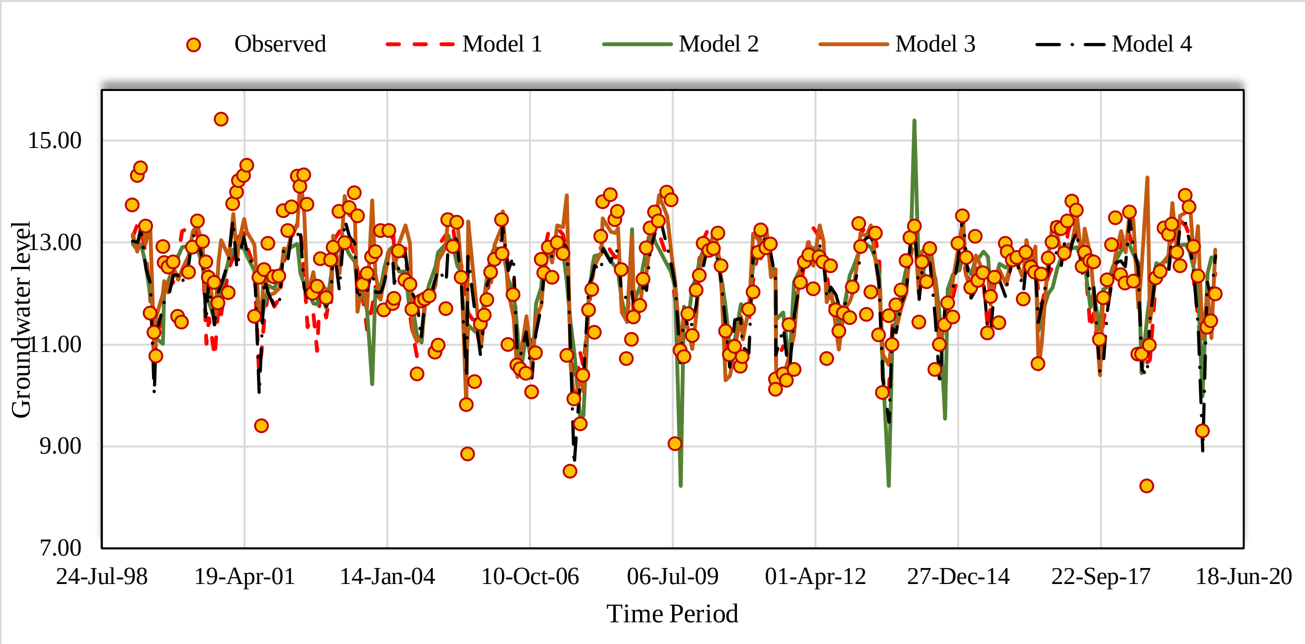


Fig.4.17. Comparison of observed and predicted values by different models

Four models were created for one month ahead prediction. From the Fig 4.17., predicted groundwater values of MODEL 4 is more close to the observed ones. So, MODEL 4 (7-20-1 FFN LM) with R=0.681616 and RMSE=0.86307 was found the best model. Its model plot is shown in Fig.4.18. Since R is greater than 0.5, this can be used for further one month lead predictions.

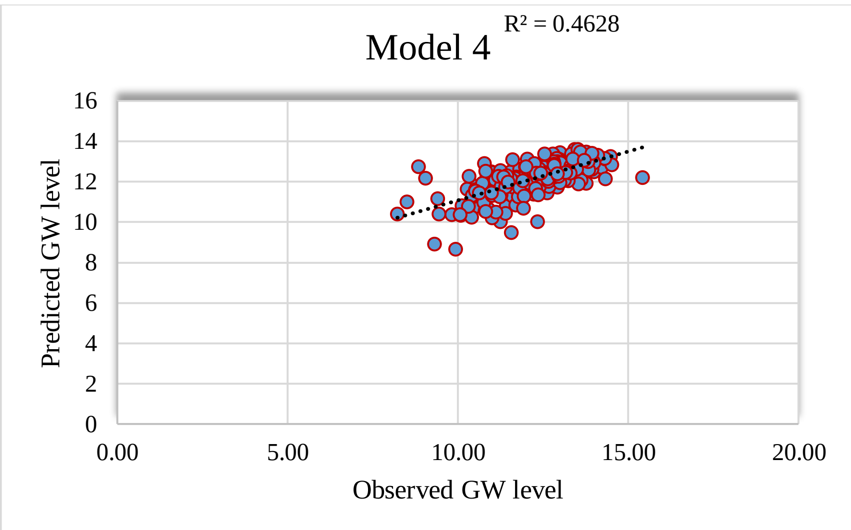


Fig 4.18. Model plot of MODEL 4

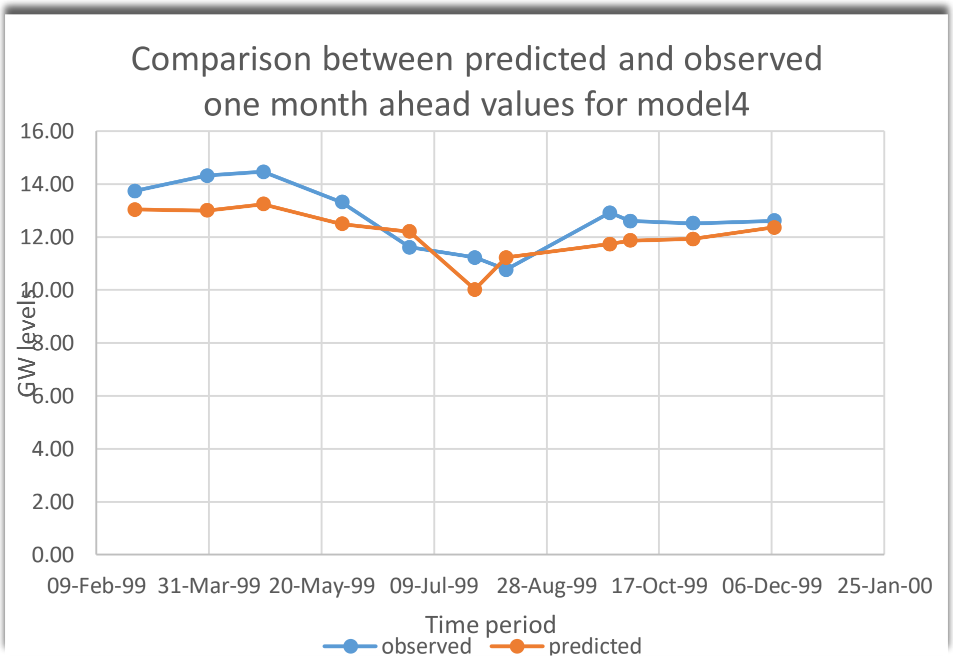


Fig 4.19. Comparison of observed and predicted values of MODEL 4

Fig 4.19 shows the comparison between the observed and predicted groundwater level for MODEL 4. This shows how much the values are close to each other.

A similar study was conducted by Zhang et al. (1998) on ground water prediction under different impact factors using ANN for a case study in Tra noc industrial zone of Vietnam. They developed different ANN models using different sets of combinations of input parameters and selected the best model based on performance statistics. The data of ground water levels (GWLs) was first used to initialize the ANN model with observed GWLs at a given time to reproduce water level variations using input variables (rainfall, river water levels and withdrawal discharge from pumping) and calibrated the selected ANN structures via trial and error on a training dataset to perform 1-, 2-, 3- month ahead predictions of future GWLs using past observed GWLs and input variables. By changing the number of hidden neurons through trial and error method, the two structures 14-15-1 and 12-15-1 were selected for 1-, 2-, 3- month ahead predictions at QT08 and QT16 stations respectively. The best fit between observed and predicted values showed high values of R efficiency (R2) and lower RMSE values. R 2 values were greater than 90% and variation in RMSE statistics lies between 0.06 and 0.22 which is very less than MODEL 4 (7-20- 1 FFN LM) in our study and it shows similarities in graphical representation in comparison between observed and predicted values. So in comparable with these 14-15-1 and 12-15-1 structures, MODEL 4 can be used for predicting the GWLs at one month ahead prediction.

4.4.3 General findings

- Models created using TANSIG function showed better R value and lesser RMSE value than that created using LOGSIG functions for groundwater level predictions.
- Among the Tansig models MODEL 6 (7-30-1 FFN LM) was found to be the best model with R=0.78 and RMSE =0.035
- Among the Log sig models MODEL 1 (7-5-1 FFN LM) was found to be the best model with R=0.684 and RMSE=0.109
- Hence among all the models created for groundwater fluctuation, MODEL 6 in tansig function showed better R value and least RMSE value. So, MODEL 6 can be used for monthly groundwater level prediction.
- From the four models created for the one month ahead prediction, MODEL 4 was found to be the best model and can be further be used for future one month ahead prediction.

SUMMARY AND CONCLUSIONS

CHAPTER V

SUMMARY AND CONCLUSIONS

Groundwater is the water found underground in the cracks and spaces in soil, sand and rock. It is an important natural resource for human survival system and major source of irrigation. Groundwater quality is deteriorating day by day due to its over exploitation. The increased dependence on ground water, spatial-temporal variation etc. have impacted groundwater levels. So it is necessary to quantify the present rate of recharge, monitor the changes in water table depths and predict the future trend. A groundwater model provides a quantitative framework for synthesizing field information and for conceptualizing hydrogeologic processes.

Wide variety of models have been developed and applied for groundwater table depth forecasting. These models can be categorized into empirical time series model and physical descriptive model. Empirical approach are not adequate for forecasting when dynamical behaviour of hydrological system changes with time. Artificial Neural Network (ANN) have been proven to be effective in modelling virtually any nonlinear function to an arbitary degree of accuracy. Robust than any computational or modelling techniques in hydrology because of their ability to handle large variations of parameters. ANN is defined as data processing system consisting large number of simple highly interconnected processing elements (PEs or artificial neurons) in architecture analogous to cerebral cortex of brain. ANN has three layers, first one is input variables, then hidden neurons and output. The input variables are processed with some weight and the predicted output is delivered. ANN modelling and evaluation using MATLAB (ver. 7.10.0.324 (R2010a)) software is now widely used for groundwater level prediction. Proprietary multi-paradigm programming language and numeric computing environment developed by Math Works. MATLAB allows matrix manipulations, plotting of functions and data, implementation of algorithm, creation of user interfaces, and interfacing with programs written in other languages. It has different toolbox for different fields of functions, like bioinformatics toolbox, curve fitting toolbox, database toolbox, fuzzy logic toolbox, neural network toolbox, optimization toolbox etc. We used MATLAB 7.0 version for the development of Artificial Neural Network model using neural network toolbox.

In this study, the potential of neural network computing technique for forecasting groundwater level was investigated by developing ANN models. The result indicates that the capability of neural network models in modelling of monthly groundwater level. Correlation analysis was done to observe the significance of different parameters used. Seven models were created for Tan sigmoid and Log sigmoid function with difference in their number of layers. Out of the models created, Model 6 (R=0.78 ,RMSE=0.035) was best for Tan sigmoid function and Model 1(R=0.684, RMSE=0.169) was best for Log sigmoid function. Tan sigmoid was best with high value of R (0.78) as compared to Log sigmoid function.

Once the network trained with a set of suitable input parameters, it was used to forecast the future ground water fluctuations. For this, one month a head prediction models were created, for which the input data is shifted one month ahead by keeping the observed output same. Four models were created in feed-forward network with Levenberg-Marquardt training algorithm by changing the number of hidden layers and training parameters. MODEL 4 (7-20-1 FFN LM) with R=0.681616 and RMSE=0.86307 was found to be the best model for one month lead prediction of ground water. Comparison of observed and predicted values of MODEL 4 was graphically represented and most of the predicted and observed points were seemed as very closely. So MODEL 4 was selected with its maximum R value and minimum RMSE value for future forecasting of ground water level.

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ABSTRACT

ABSTRACT

Groundwater level is an indicator of groundwater availability, groundwater flow and the physical characteristics of the groundwater system. It is an important natural resource for human survival system and major sources of irrigation. Groundwater quality is deteriorating day by day. So the measurement and analysis of groundwater level is needed for maintaining groundwater availability. The accurate prediction of groundwater levels is essential for sustainable utilization and management of vital groundwater resources. For management of groundwater level a model is required which can predict the groundwater level in future with the current available information. The Artificial Neural Network (ANN) technique has been found to be very much suited to the modelling of non-linear and dynamic systems such as water resources systems. The main advantage of the ANN technique over traditional methods is that it does not require the complex nature of underlying processes to be explicitly described in mathematical form. After proper training, ANN models can yield satisfactory results for many prediction problems in the field of hydrology. In this study different ANN models are developed to evaluate the groundwater level fluctuations. One month ahead prediction models were also developed to extend the possibility of forecasting groundwater levels in coming future. Models were developed with different combinations of transfer function and number of hidden layers. All these were developed using MATLAB 7.0 software which is a multi-paradigm programming language and numeric computing environment developed by MathWorks. The best model for predicting groundwater levels were selected on the basis of coefficient of correlation(R) and RMSE value. Models with higher R value and lesser RMSE value is found to be the best performing one. Sreekrishnapuram region near Pattambi was selected as the study

region. Input parameters for groundwater level fluctuations were identified and the monthly data of the same were collected for a period of 20 years from Jan 1999- Dec 2019. The model was trained, validated and tested for randomly chosen parameters. The developed ANN models for predicting groundwater level fluctuations shows good correlation coefficient ranging from 0.6-0.78. And the developed ANN models for one month ahead prediction also showed better values of R with an R value of 0.68 for the best model. All the models developed showed comparatively lesser RMSE value. Thus it can be determined that ANN provides a feasible method in predicting groundwater levels.