Development of Hydro-Environment Model for Maintaining a Reservoir using Artificial Intelligence

Rohit Anumarlapudi, Naga Chaitanya Kavuri

Abstract:Forecasting and maintenance plays an important role for optimal reservoir operations. Present study mainly refers in developing an Artificial Intelligence (AI) model which helps in maintaining reservoir and amplify the decision making scientifically. In this development process, multi-layer perceptron, a method which can give the regression and correlate the parameters that influence the inflow of reservoir is used. Parameters like rainfall (mm), temperature (°C), land-use land-cover and relative humidity (Rh %) data is gathered from Andhra Pradesh State Disaster Management Authority (APSDMA). To obtain this correlation, 8years of data is collected with reference to Prakasam barrage upstream up to pulichintala project, Krishna district, Andhra Pradesh, India. These collected data are shaped into matrix form and tested using different training algorithms like Levenberg–Marquardt, Bayesian regularization and scaled conjugate gradient algorithms. From theabove-mentionedmodels Levenberg–Marquardtand Bayesian regularizationalgorithms exhibits better performance and accuracy compared to scaled conjugate gradient algorithm

Index Terms: Artificial Intelligence, Hydro-Environment,Forecasting, Multi-Layer Perceptron

I. INTRODUCTION

Reservoirs play significant role in water management. Reservoirs are constructed for several purposes like flood control, hydropower generation, irrigation, water supplyand other purposes. Though they serve common purposes there are some conflicts during floods and drought seasons.To come through these conflicts, decision making for inflow and storage capacity of particular reservoir should be done more scientifically for optimal utilization of water.Accordingly, efforts should be doubled to intensify the effectiveness and operational efficiency to obtain beneficial results from reservoirs.Forecasting the inflow of reservoir helps in maintaining storage capacity, decision making at the time of floods and droughts etc. Forecasting is a very hard approach as these water systems are dynamic with variable inputs and outputs and non-linear responses [1]. It is always a challenging task for exact prediction of stream flow [2].Long term forecasting of streamflow plays major role in flawless management of water resources [3]. Streamflow is influenced by various parameters like temperature, rainfall, humidity, evaporation, transpiration etc. and other unknown factors [4]. Water resource management also involves political and economic measures like marketing and water pricing [5]. Number of methods has been used to find the non-linear relationship between rainfall and runoff such asempirical, conceptual, physically and data driven. Thesemodels have been used in different fields of water resources with interesting results [6].Forecasting is usedto manage floods, droughts, water supply for domestic, industrial and agricultural purposes, power generation etc. [7]. ANN leads to plenty of studies on usage of neural networking in reservoir inflow forecasting [8].As conventional methods i.e., autoregressivemoving average (ARMA), autoregressive (AR), linear regression (LR), multi-linear regression (MLR),autoregressive integrated moving average (ARIMA) are not capable of finding non linearity, studies have done to overcome the drawbacks and limitations of classical methods [9].ANN can be processed by, the information processing that exists at multiple single elements namely neurons also called as nodes through transfer of signals between neurons by connection links [10]. As these links represent its intensity it contains certain strength and every node of ANN applies non-linear transformation that determines output signals from input signals.

II. RESEARCH SIGNIFICANCE

The present work explores the capability of ANN in finding out the nonlinear relationships between theparameters influencing the inflow of a reservoir and its water reserve. For this purpose, prakasam Barrage, located in Vijayawada of Krishna District in Andhra Pradesh, India has been chosen. In this development process, multi-layer perceptron, a method which can give the regression and correlate the parameters that influence the inflow of reservoir is used.Also, comparison is done between three training algorithms namely Levenberg–Marquardt, Bayesian regularization and scaled conjugate gradient algorithms, which helps in identifying the best model for complex problems. Parameters like rainfall (mm), temperature (°C), land-use land-cover and relative humidity (Rh %) data is gathered from Andhra Pradesh State Disaster Management Authority (APSDMA) are considered as samples and tested among algorithms.

III. METHODOLOGY

A. Study area

Study area (Figure 1) selected for present work is Prakasam barrage which stretches 1223.5m on river Krishna connecting two districts namely, Krishna and Guntur. Located at 16°30'22"North latitudes and 80°36'18" East longitudes.

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Rohit Anumarlapudi, Department of Civil Engineering, Koneru Lakshmaiah Educational Foundation (Deemed to be University), Guntur, India.

Dr. K. NagachaitanyaKavuri, Department of Civil Engineering, Koneru Lakshmaiah Educational Foundation (Deemed to be University), Guntur, India.

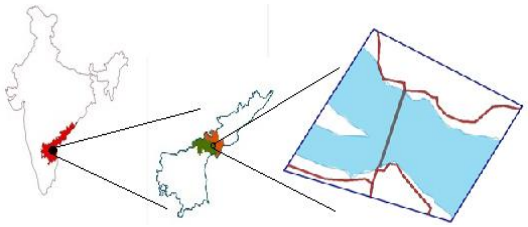

Figure 1: study area

B. Dataset used

Monthly data of rainfall, temperature and relative humidity in and around Prakasam barrage are collected from Andhra Pradesh State Disaster Management Authority (APSDMA), Vijayawada, Krishna district, Andhra Pradesh, India. Total of 8 years data is collected i.e., 01January 2008 to 31 December 2015. From this accessible data, 5 years of data (01 jan 2008 to 31 dec 2012) is used for training and developing a model, 2013 and 2014 data used for cross validation and 2015 data for evaluating the model which is developed from ANN.

C. Artificial Neural Networking (ANN)

Artificial neural networking is a complex mathematical approach representing our human brain with a network of nodes containing an input layer, output layer and hidden layers[11]. ANN is a very fast and efficient method used in finding the complexes in non-linearity and helps in processing the problem with multiple variables. It is stated that due to its efficiency it can be used in time prediction series[12].

D. Single layer perceptron

A single processor neuron receiving inputs and generates output is considered as a perceptron. This process is carried when, inputs received by processor contains some weight which it processes through activation function to estimate the output value. Where this activation function allows to confirm the desired range of expected output. These weights of input values should be optimal to estimate the best results that is with least amount of errors. Perceptron process is shown in Figure 2.

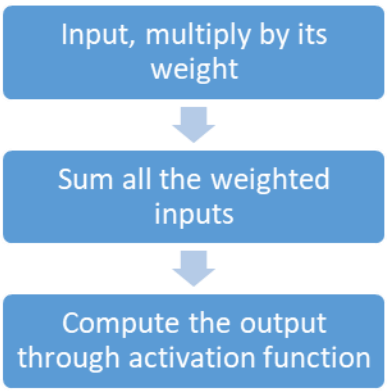

Figure 2: Perceptron processing

But pointed that a single perceptron can only solve linearly seperable problems stating, it cannot solve multiple complex problems. Hence a new mode, multi layer perceptron came into act to solve these complexed problems.

E. Multilayer perceptron

Linking of single perceptron to one another to form multiple layers is known as multilayer perceptron. More complex problems that are not linearly separable can be solved by chaining these single perceptron's. Hidden layers play a prominent role in producing estimated outputs. These are the processors present in-between the input and output layers where all the process takes place. It is like a data frame receives input, compute all the functions and delivering the output. More the inputs and hidden layers, more complexity takes place in output generation.

IV. DISCUSSION AND RESULTS

A. Raw sample

Selected parameters data collected from APSDMA is managed to arrange in matrix form. This matrix is taken into neural networking in matlab software to run the analysis. Three different training algorithms are used to compare the results. Software divides the given samples among training, validation, testing and result.

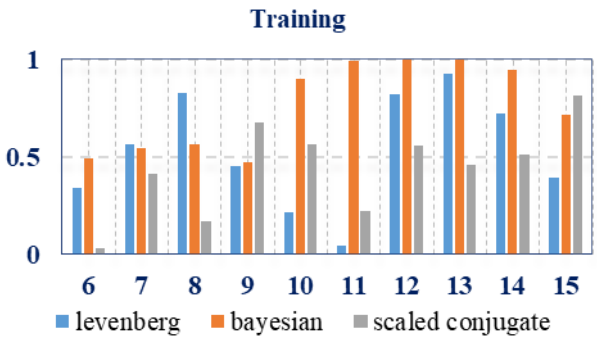

Figure 3: comparison of training samples

Training samples are analyzed with different hidden layers among Levenberg–Marquardt, Bayesian regularization and scaled conjugate gradient algorithms. Figure 3is drawn between hidden layers and regression values. From the fig it shows that maximum regression values occur at 13 layers for Levenberg–Marquardt and Bayesian regularization and 15 layers for scaled conjugate gradient.

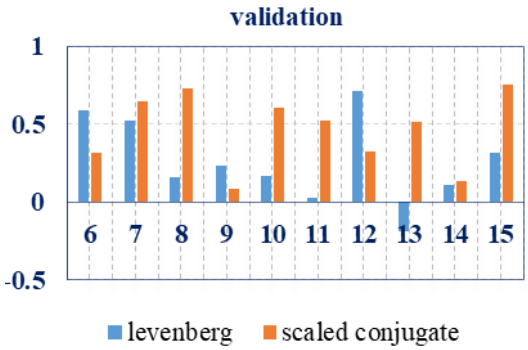

Figure 4: comparison of validation samples

Figure 4 is drawn by comparing the validation values of training algorithms, Levenberg–Marquardt and scaled conjugate gradient. Different hidden layer combinations are used and observed that Levenberg–Marquardt algorithm shows maximum regression value at 12 hidden layers and scaled conjugate gradient at 15 layers.

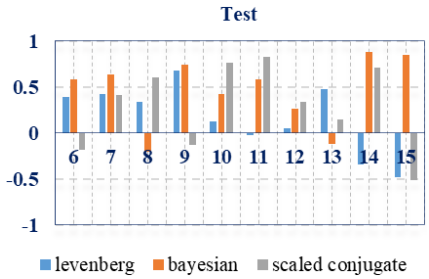

Figure 5:comparison of test samples

Figure 5 shows the comparison between three training algorithms of test samples. Regression value can be achieved high at 7 layers for Levenberg–Marquardt, 14 layers for Bayesian regularization and 11 layers for scaled conjugate gradient.

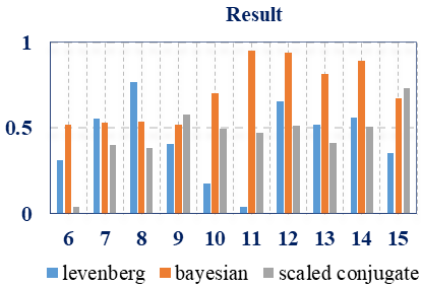

Figure 6:comparison of result samples

All the samples are considered in analyzing the result comparison between algorithms. From figure 6 we can observe that maximum regression value for Levenberg–Marquardt is at 8 layers, 11 hidden layers for Bayesian regularization and 15 layers for scaled conjugate gradient.

B. Normalized sample

To decrease the variations among the selected samples, collected samples are subjected to normalization. These normalized values are taken in form of matrix and used in neural networking.

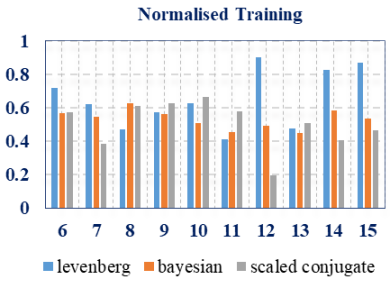

Figure 7:comparison of normalized training samples

Figure 7 is drawn between normalized samples among three training algorithms. When compared to raw samples, we observe variation for regression value i.e., at 12 layers for Levenberg–Marquardt, 8 layers for Bayesian regularization and 10 layers for scaled conjugate gradient.

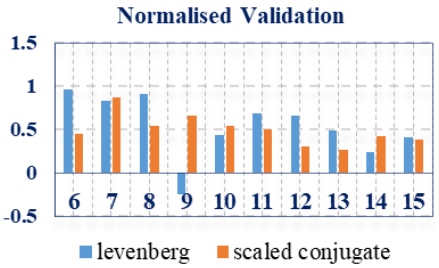

Figure 8:comparison of normalized validation samples

Figure 8 is drawn by taking normalized validation samples among algorithms. In validation, samples show maximum variation that optimum regression value is observed at 6 layers for Levenberg–Marquardt algorithm and at 7 layers for scaled conjugate gradient algorithm. Bayesian regularization algorithm cannot consider validation samples.

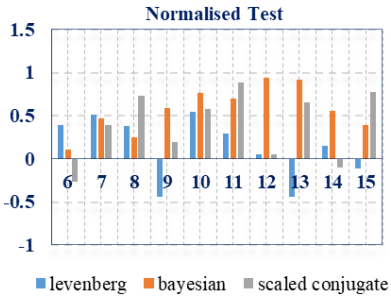

Figure 9:comparison of normalized test samples

Test samples show variation among Levenberg–Marquardt and Bayesian regularization algorithms but not for scaled conjugate gradient algorithm when compared to raw samples. From figure 9, Levenberg–Marquardt observes maximum regression at 10 layers, Bayesian regularization algorithm at 12 layers and scaled conjugate gradient at 11 hidden layers.

From figure 10 variation between raw samples and normalized samples is not much observed in Levenberg–Marquardt and Bayesian regularization algorithms maximum regression is obtained at 6 and 12 layers for Levenberg–Marquardt, at 8 and 9 layers for Bayesian regularization and 10 &11 layers for scaled conjugate gradient algorithm.

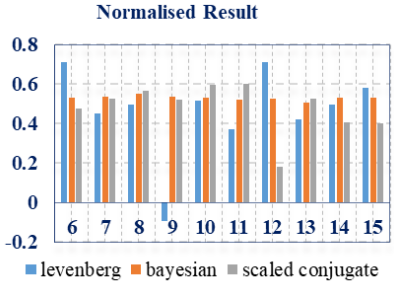

Figure 10:comparison of normalized result samples

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V. CONCLUSION

From the above graphs and results we can conclude that hidden layers play important role in obtaining good regression value. It is observed that variations are less in normalized samples when compared to raw sample. For raw sample data, Levenberg–Marquardt algorithm experienced optimum regression value and Bayesian regularization algorithm obtained optimum values for normalized data samples. This is due to Bayesian's ability to identify the complexity of problem and produce robust solution. We observe training process cannot be done during analysis due to, when iterations reach maximum, acceptable performance level and when estimation error is observed below the target.

Aforesaid model may fail due to unavailability of required data, drastic change in climate and weather conditions which effects the values of selected parameters, change in the inflow parameter due to construction of new capital regionnear the selected study area and outflow variations from Pulichintala project.

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AUTHORS PROFILE

Rohit Anumarlapudiis pursuing M. Tech degree in Construction Technology Management from KL Deemed to be University, Guntur, Andhra Pradesh, India.HereceivedB.Tech Degree in Civil Engineering from KallamHaranadhareddy Institute of Technology (KHIT), Chowdavaram, Andhra Pradesh, India in 2017. He also published a paper on Geo-polymer concrete in seventh sense research international journal in his graduation period.He attended 2 international conference and actively participated in workshops and seminars in and around the University.

Dr. Naga ChaitanyaKavuri, working as an Assistant Professor in Department of Civil Engineering and dean of Waste and Water Management at K L University. He completed his B. Tech in Bio-Technology from Godavari Institute of Engineering and Technology, Andhra Pradesh, M. Tech in Chemical Engineering from National Institute of Technology Rourkela and PhD in Civil Engineering from National institute of Technology Rourkela. He published 15International and 1 National referred Journals. He is a man of interest on various fields. His main area of Interest is in "Air pollution modeling, Environmental Engineering.