RUNOFF PREDICTION WITH ARTIFICIAL NEURAL NETWORK

THESIS

Submitted to
Dr. Panjabrao Deshmukh Krishi Vidyapeeth, Akola
in partial fulfilment of the requirements
for the Degree of

MASTER OF TECHNOLOGY

IN

AGRICULTURAL ENGINEERING

(SOIL AND WATER CONSERVATION ENGINEERING)

By

PUNDLIK ANUJA DINANATH

DEPARTMENT OF SOIL AND WATER CONSERVATION ENGINEERING,
POST GRADUATE INSTITUTE, AKOLA

DR. PANJABRAO DESHMUKH KRISHI VIDYAPEETH
KRISHINAGAR PO, AKOLA (MS) 444104

Enrolment Number - EE-964

2014

DECLARATION OF STUDENT

I hereby declare that the experimental work and its interpretation of the thesis entitled **"RUNOFF PREDICTION WITH ARTIFICIAL NEURAL NETWORK"** or part thereof has neither been submitted for any other degree or diploma of any University, nor the data have been derived from any thesis / publication of any University or Scientific Organization. The sources of material used and all assistance received during the course of investigation have been duly acknowledged.

30/06/2014

Place: Akola.

Date : 30 / 06 /2014

(Pundlik Anuja Dinanath)

Enrolment No. EE-964

CERTIFICATE

This is to certify that the thesis entitled **"RUNOFF PREDICTION WITH ARTIFICIAL NEURAL NETWORK"** submitted in partial fulfillment of the requirement for the degree of "**Master of Technology In Agricultural Engineering (Soil and Water Conservation Engineering)"** of Dr. Panjabrao Deshmukh Krishi Vidyapeeth, Akola is a record of bonafide research work carried out by **Pundlik Anuja Dinanath** under my guidance and supervision.

The subject of thesis has been approved by the Student's Advisory Committee.

Place : Akola
Date : 30/06/2014

Dr. S. M. Taley
Chairman,
Advisory Committee

Countersigned

Associate Dean,
Post Graduate Institute
Dr. Panjabrao Deshmukh Krishi Vidyapeeth, Akola.

THESIS APPROVED BY THE STUDENT'S ADVISORY COMMITTEE
INCLUDING EXTERNAL EXAMINER (AFTER VIVA–VOCE)

1. Chairman	Dr. S. M. Taley	
2. Member	Shri. M. U. Kale	
3. Member	Shri. A.R. Mhaske	Absent
4. Member	Shri. G. R . Atal	
5. External Member	(Dr. G. U. Satpute)	

ACKNOWLEDGEMENT

Gratitude can't be seen or expressed, it can only be felt deep in heart and is beyond description. With the grace of Almighty, I am able to carve another milestone in my academic journey. It is my great privilege and immense pleasure to acknowledge all persons who have been helpful during the entire course of investigation.

I allied this present opportunity to express my deep sense of gratitude and obligation to my esteemed Major Advisor, Dr. S. M. Taley, Head, Deptt. of SWCE and Director of Agro-Ecology and Environment Centre, Dr.PDKV., Akola, for his valuable and sustaining guidance, continuous encouragement, sublime suggestions, constructive criticism with care and magnanimous help during the course of investigation.

Diction is not enough to express my deep and profound sense of gratitude and indebtedness, reverence and heartfelt thanks to my Advisory committee member Er. M. U. Kale, Assistant Professor, Deptt. of Irrigation & Drainage Engineering, Dr. PDKV, Akola for his meticulous guidance, transcendent suggestions, constructive counsel, critical appreciation and his relentless efforts during the entire research work inspiring guidance at every step, constant supervision, which not only moulded my research work in a right form. I accord my sincere appreciation and heartfelt respect to him.

I am equally indebted to the members of my Advisory committee Er. A.R. Mhaske, Asso. Prof. and Er. G. R. Atal, Asst. Prof., Deptt. of SWCE, Dr. PDKV, Akola, for their timely help.

It is my privilege to accord the sincere thanks to Prof. Dr. G. U. Satpute, Deptt. of SWCE, Dr. PDKV, Akola with deep sense of gratitude and great pleasure.

I am very thankful to Dr. D. M. Mankar, Associate Dean, PGI, Dr. PDKV, Akola, for providing me the necessary facilities to complete my research work in stipulated time.

I sincerely special thanks to Mr. K. A. Jadhav, (RA), Mr. V. P. Ubarhande, (RA), Ms. S. C. Vilhekar, (SRF), Ms. S. M. Pongde,(SRF),NAE-RWMRA, Dr. PDKV, Akola.

I wish my cordial thanks to Shri. G. T. Sawale, Shri. Rathod, Shri. Khandare for their timely help.

I reward my affection to my beloved friends Shital, Chippy, Aditika, Mangesh, to my Junior Ashwini, Supriya, Pranali, Priyanka, Rani and to all who had directly and indirectly supported me.

It is time to surface out genuflect love and affection and gratitude to my father Mr. Dinanath Pundlik and mother Mrs. Deepa Pundlik for their blessings, support and affectionate love to educate me to this level and whose encouragement brings out the best in every one of my endeavors. No appropriate words could be traced to convey my respect, love and thanks for intellectual stimulation, affectionate and rejuvenating support of my elder brothers Amogh and Ambarish. I would like to express my deep feelings of love to my sister in law Aditi.

At last, I remember the Almighty who gave me strength, courage and perseverance to achieve this goal.

Date : Akola
Place : 30/06/2014

(Pundlik Anuja Dinanath)
Enrolment No. EE-964

Table of Contents

(A) List of Tables

(B) List of Figures

(D) Abbreviations

%	:	Per cent
AEEC	:	Agro- Ecology and Environment Centre
Agril.	:	Agricultural
ANN	:	Artifial Nural Network
BPANN		Back Propagation Artificial Neural Network
C.A.E.T.	:	College of Agriculture Engineering and Technology
Deptt.	:	Department
Dr.PDKV	:	Dr. Punjabrao Deshmukh Krishi Vidyapeeth
E	:	East
Engg.	:	Engineering
et al.	:	And others
Fig.	:	Figure
Ha	:	Hectare
I.A.R.I.	:	Indian Agriculture Research Institute
i.e.	:	That is
Ltd.	:	Limited
L-M		Levenberg-Marquardt
MLP	:	Multilayer Perceptron
mm	:	Mille meter
MS	:	Maharashtra State
MISO	:	Multiple-Input Single-Output
PI	:	Persistence Index
RBF	:	Redial basis Function
R^2_{NS}	:	Nash-Sutcliffe coefficient of efficiency
R-R	:	Rainfall – Runoff
Sci	:	Science
Soc.	:	Society
T1	:	Treatment 1
T2	:	Treatment 2
T3	:	Treatment 3
viz.	:	Namely

(F) Thesis Abstract

a)	**Title of the thesis**	:	**"RUNOFF PREDICTION WITH ARTIFICIAL NEURAL NETWORK"**
b)	**Full name of student**	:	**Pundlik Anuja Dinanath**
c)	**Name and address of Major Advisor**	:	**Dr. S. M. Taley** Head, Dept. Soil and Water Conservation Engineering and Director, Agro Ecology and Environment Center, Dr. P.D.K.V., Akola (M.S.) - 444104.
d)	**Degree to be awarded**	:	M.Tech. (Soil and Water Conservation Engg.)
e)	**Year of award of degree**	:	2014
f)	**Major subject**	:	Soil and Water Conservation Engineering
g)	**Total number of pages in the thesis**	:	52
h)	**Number of words in the abstract**	:	170
i)	**Signature of the student**	:	
j)	**Signature, name and address of forwarding authority**	:	

Head,
Department of Soil and Water Conservation Engineering,
Post Graduate Institute,
Dr. Panjabrao Deshmukh Krishi Vidyapeeth,
Akola (M.S.).

ABSTRACT

Radial Basis Function ANN models with Levenberg-Marquardt (L-M) and momentum algorithm were formulated to predict simulated runoff from watershed. Best architecture of RBF ANN model to predict simulated runoff from watershed was determined on the basis of statistical performance measures. The model 5 predicted simulated runoff better than other models,

with Nash-Sutcliffe coefficient of efficiency and persistence index for treatment T1 as 0.86 and 0.92, for treatment T2 as 0.93 and 0.96 and for treatment T3 as 0.89 and 0.93 respectively. Therefore model 5 having inputs as current day rainfall, one day ahead rainfall, two day ahead rainfall, one day ahead runoff, two day ahead runoff should be used to predict simulated runoff from watershed for all three treatments. The study also confirmed that the number of processing elements in hidden layer and epochs did not have any consistent impact on the performance of RBF ANN models. Thus it is concluded that number of nodes in the hidden layer and epochs during training should be optimized by trial and error method.

CHAPTER I
INTRODUCTION

1.1 Background information

Most of the watersheds in India are operated in isolation and often the managers of 'watershed system rely on empirical methods, their experience, and judgment for taking decisions. Obviously, these procedures have their own disadvantages and may result in non-optimal utilization of water. The advancement in the field of system engineering and the modern computer facilities available now could be effectively utilized for integrated planning and management of water resources in optimal way. With increase in population and overall economic development in the country, demand for water has increased considerably. The utilization of water resources are finite in extent and cannot be expanded to meet the growing demands. The various uses of water for irrigation, power generation, industrial and municipal water supply with concurrent flood protection are not only competing but also conflicting sometimes. Due to this, the water resources planners and managers are facing a challenging task of managing the limited water resources of various river basins in the country.

A rainfall-runoff model is a mathematical model describing the rainfall - runoff relations of a catchment area, drainage basin or watershed. More precisely, it produces surface runoff hydrograph as a response to rainfall hydrograph as input. In other words, the model calculates the conversion of rainfall into runoff. A rainfall runoff model can be really helpful calculating the discharge from a basin. The transformation of rainfall into runoff over a catchment is very complex hydrological phenomenon, as this process is highly nonlinear, time-varying and spatially distributed. Over the years researchers have developed many models to simulate this process. Based on the problem statement and on the complexities involved, these models are categorized as empirical, black-box, conceptual or physically-based distributed models. Physically based distributed models are very complex and required too many data and tedious for the application purpose. The conceptual models attempt to represent the known physical process occurring in the rainfall-runoff transformation in a simplified manner by way of linear or nonlinear mathematical formulations but their implementation and calibration is complicated and time consuming. While black-box models, which establish a relationship between input and the output functions without considering the complex physical laws governing the natural process such as rainfall-runoff transformation.

One of the main research challenges in hydrology is the development of computational models that are able to accurately simulate a catchment's response to rainfall. Such models are capable of forecasting future river discharge values, which are needed for hydrologic and hydraulic engineering design and water management purposes. However, simulating the real-world relationships using these Rainfall- Runoff (R-R) models is difficult task since the various interacting processes that involve the transformation of rainfall into discharge are complex and variable. Hydrologists have attempted to address this modelling issue from two different points of view: using knowledge-driven modelling and data-driven modelling. Knowledge-driven RR modelling aims to reproduce the real-world hydrological system and its behavior in a physically realistic manner. This way of R-R modelling is therefore based on detailed descriptions of the system and the processes involved in producing runoff. The best examples of knowledge driven modelling are so-called physically-based model approaches, which generally use a mathematical framework based on mass, momentum and energy conservation equations in a spatially distributed model domain, and parameter values that are directly related to catchment characteristics. These models require input of initial and boundary conditions since flow processes are described by differential equations (Rientjes, 2004). Examples of physically-based R-R modelling are the System Hydrologique European (SHE) (Abbott *et al.*, 1986a, b) and the Representative Elementary Watershed (REW) (Reggiani *et al.*, 2000; Reggiani and Rientjes, 2005) model approaches.

A data-driven technique that has gained significant attention in recent years is Artificial Neural Network (ANN) modelling. In many fields, ANNs have proven to be good in simulating complex, non-linear systems. This awareness inspired hydrologists to carry out the earliest experiments using ANNs in the first half of the 1990s. Their promising results led to the first studies on the specific topic of ANNs for R-R modelling (Halff *et al.*, 1993; Hjemfelt and Wang, 1993; Karunanithi *et al.*, 1994; Hsu *et al.*, 1995; Smith and Eli, 1995; Minns and Hall, 1996). The ASCE Task Committee on Application of Artificial Neural Networks in Hydrology (2000) and Dawson and Wilby (2001) give good state-of the- art reviews on ANN modelling in hydrology. The majority of studies have proven that ANNs are able to outperform traditional statistical R-R techniques (Hsu *et al.*, 1995; Shamseldin, 1997; Sajikumar and Thandaveswara, 1999; Tokar and Johnson, 1999; Thirumalaiah and Deo, 2000; Toth *et al.*, 2000) and to produce comparable results to conceptual R-R models (Hsu *et al.*, 1995; Tokar and Markus, 2000; Dibike and Solómatine, 2001). The field of R-R modeling using ANNs is nevertheless still in an early stage of development and remains a topic of ongoing research (Anctil *et al.*, 2004; Jain and Srinivasulu, 2004; Rajurkar *et al.*, 2004).

ANN, Fuzzy logic, decision tree algorithms have been used to model the rainfall-runoff process (Maier and Dandy (2000); ASCE, 2000b; Dawson *et al.*, 2001) to avoid the requirement of large volume of data. The soft computing techniques model the physical process better than the conceptual and empirical models without understanding the elements of physical process. The complexity and non-linearity involved in rainfall-runoff process, makes it attractive to try the Artificial Neural Network (ANN) approach, which is inherently suited to problems that are mathematically difficult to describe.

1.2 Importance and need of study:

On the basis of amount of water provided by the catchment to the water bodies, crop management practices as well as irrigation scheduling on the downstream side will be planned. It is therefore vital to predict accurate runoff to the water bodies for optimization of water resources in command area so as to increase yield and income per unit drop of water. Considering the above discussion a study entitled **'Runoff prediction with Artificial Neural Network'** was undertaken with following objectives:

1.3 Objectives of the study

I. To formulate ANN models to estimate runoff of watershed of Agro-Ecology Environment Center, Dr. P.D.K.V., Akola, Dist.-Akola.

II. To calibrate and validate the ANN models to estimate runoff of watershed of Agro-Ecology Environment Center, Dr.P.D.K.V., Akola, Dist.-Akola.

III. To predict runoff using simulated results.

1.4 Hypothesis

Present study was formulated to predict runoff from watershed area using ANN. The different ANN models were tested using the most efficient tool like ANN, so as to have best model for prediction of runoff with minimum data.

1.5 Scope and limitations

There is a need to double annual food grain production from the present about 210 million tonnes to 420 million tonnes within next 10 years. Since land and water is a shrinking resource for agriculture, the pathway for achieving this goal has to be higher productivity per unit of arable land and water. As such, the question of restricting the runoff in view to avoid soil, water and nutrient loss assumes a great significance in perspective water resource planning.

CHAPTER II

REVIEW OF LITERATURE

This chapter presents the brief literature survey in the field of R-R modelling using ANN.

Rajurkar *et al.* (2002) applied ANN methodology for modelling daily flows during monsoon flood events for a large size catchment of the Narmada river in Madhya Pradesh (India). The spatial variation of rainfall was accounted by subdividing the catchment and treating the average rainfall of each sub-catchment as a parallel and separate lumped input to the model. 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. The present model provided a systematic approach for runoff estimation and represented the improvement in prediction accuracy over the other models studied herein.

Zhang and Govindaraju (2003) used modular neural network structure to handle complex sets of rainfall-runoff data. Different modules within the network were trained to learn subsets of the input space in an expert fashion. A gating network was used to mediate the response of all the experts. The three modular architectures used in the study represent the low, medium and high runoff events. Bayesian concepts were utilized in deriving the training algorithm. Average monthly rainfall of current and previous months and average monthly temperatures were treated as network inputs, and monthly runoff was treated as output. The performance of modular networks in predicting runoff over three medium sized catchments was examined.

Sudheer *et al.* (2003) developed a technique to improve the peak flow estimation in river flow models. They used appropriate data transformation to reduce the local variation in the function being mapped. They concluded that the model built on the transformed data outperformed the model built on raw data. The peak flow estimates were improved by data transformation.

Harun *et al.* (2003) described the application of multilayer perceptrons (MLP) and radial basis function (RBF) to predict daily runoff as a function of daily rainfall for the Sungai Lui, Sungai Klang, Sungai Bekok, Sungai Slim and Sungai Ketil catchments area. The performance of ANN was evaluated based on the efficiency and the error. The study concluded that ANN has a potential for successful application to the problem of runoff prediction.

Agrawal and Singh (2004) developed multilayer Back Propagation Artificial Neural Network (BPANN) models to simulate rainfall-runoff process for two sub-basins of Narmada River (India) viz. Banjar up to Hridaynagar and Narmada up to Manot considering three time scales viz. weekly, ten-daily and monthly with variable and uncertain data sets. The BPANN runoff models were developed using gradient descent optimization technique and were generalized through cross-validation. In almost all cases, the BPANN developed with the data having relatively high variability and uncertainty learned in less number of iterations, with high generalization.

Jain and Srinivasulu (2004) presented the results of a new approach employing real-coded genetic algorithms (GAs) to train ANN techniques for hydrologic modelling. Many standard statistical measures were employed to assess and compare various models investigated. The results obtained in this study demonstrate that ANN rainfall-runoff models trained using real-coded GA are able to predict daily flow more accurately than the ANN rainfall-runoff models trained using BP method. The proposed approach of training ANN models using real-coded GA can significantly improve the estimation accuracy of the low-magnitude flows. It was found that the gray box models that are capable of exploiting the advantages of both deterministic and ANN techniques performed better than the purely black box type ANN rainfall-runoff models. A partitioning analysis of results was needed to evaluate the performance of various models in terms of their efficiency in modelling and effectiveness in accurately predicting varying magnitude flows (low, medium, and high flows).

Jareanpon *et al.* (2004) proposed a method that uses an Adaptive Radial Basis Function neural network model with a specially designed Genetic Algorithm (GA) to obtain the optimal model parameters. A significant feature of the Adaptive Radial Basis Function network is that it is to able crack new hidden units and solve the spread factor problem using a genetic algorithm. It was found that the evolved parameter values improved the model performance.

Nagesh Kumar *et al.* (2004) developed recurrent neural networks for forecasting river flow for Hemavati River in India. A feed forward neural network was also developed and applied to the same river. The training of recurrent neural network was done by using the method of ordered partial derivatives. The feed forward neural network was trained by improved back propagation algorithm. They found that recurrent neural network models gave better results than the feed forward neural network for single step and multi step ahead forecasting.

Lekkas *et al.* (2004) assessed the relative performance of existing models in comparison to ANN. Ali Efenti, a sub-catchment of the river Pinions (Greece), was examined and the results supported the hypothesis that ANNs can produce qualitative forecasts. A 7-hour ahead forecast in particular proved to be of fairly high precision, especially when an error prediction technique was introduce to the ANN models.

Antar *et al.* (2005) developed a rainfall-runoff model for the Blue Nile catchment. The best geometry of the ANN rainfall-runoff model in terms of number of hidden layer and nodes was identified through a sensitivity analysis. The Blue Nile catchment (about 300,000km^2) in the Nile basin was selected as a case study. The catchment was classified into seven sub-catchments and the mean areal precipitation over sub-catchment was computed as a main input to the ANN model. The available daily data (1992-99) were divided into two sets for model calibration (1992-96) and for validation (1997-99). The results of the ANN model were compared with one of physical distributed rainfall-runoff models that apply hydraulic and hydrologic fundamental equations in a grid base. The results over the case study are and the comparative analysis with the physically based distributed model showed that the ANN technique had great potential in simulating the rainfall-runoff process adequately. Because the available record used in the calibration of the ANN model was too short, the ANN model was biased compared with the distributed model, especially for high flows.

Jeong and Kim (2005) used two types of an ANN, viz. Single Neural Network (SNN) and Ensemble Neural Network (ENN), to provide better rainfall-runoff simulation capability than TANK (the existing rainfall-runoff model), which had been used with the ensemble stream flow prediction (ESP) system for forecasting monthly inflows to the Daecheong multipurpose dam in Korea. Using the bagging method, the ENN combined the outputs of member networks so that it could control the generalization error better than SNN. This study compared two ANN models with TANK in respect to the relative bias and the root-mean-square-error. The overall results showed that the ENN performed the best among the three rainfall-runoff models. The ENN also considerably improved the probabilistic forecasting accuracy, measured in terms of average hit score, half-Brier score and hit rate, of the present ESP system that used TANK. Therefore, this study concluded that the ENN would be more effective for ESP rainfall-runoff modeling than TANK or an SNN.

Rajurkar and Ojha (2005) applied ANN model for daily rainfall-runoff modelling over a large size catchment of the Godavari river in the state of Maharashtra (India). The study illustrated the application of the Error Back Propagation (EBP) type of ANN model for simulating the rainfall-runoff process. The inputs to the ANN consisted of combinations of variable like current and past rainfall and runoff values. The data for daily rainfall and runoff were collected for monsoon season as high flows are expected during this period and modeled for flood forecasting, design and operation of water resources structures etc. the antecedent runoff was used to the ANN for bringing soil moisture state of the catchment in the ANN based rainfall-runoff modelling. Different input combinations were applied to the ANN and the best configuration evolved for each input combination was presented. The performance of the models was evaluated based on various statistical and graphical criteria, which were indicative of the model performance. The performance of the ANN model applied was satisfactory. The EBP model had improved with respect to both E2 and R2 criteria with increase in number of input combinations as low cost and efficient methodology.

Parasuraman *et al.* (2006) proposed spiking modular neural network (SMNN) to model the stream flow and compared its result with the regular feed forward neural networks (FFNN) with case study of a basin in Canada. It was concluded that the SMNNs were effective in discretizing the complex mapping space into simpler domains that could be learnt with relative ease.

Anctil *et al.* (2007) tested ANNs for thee output updating of one day ahead streamflow forecasts derived from three lumped conceptual rainfall-runoff (R-R) models: the GR4J, the IHAC, and the TOPMO. ANN output updating proved superior to a parameter updating scheme and to the 'simple' output updating scheme, which always replicated the last observed forecast error. In fact, ANN output updating was able to compensate for large differences in the initial performance of the three updating approaches were not able to achieve. This was done mainly by incorporating input vectors usually exploited for ANN R-R modelling such as previous observed error. For one-day-ahead forecasts, the performance of all three lumped conceptual R-R models, used in conjunction with ANN output updating, was equivalent to the ANN R-R model. For three-day-ahead forecasts, the performance of the ANN-output-updated conceptual models was even superior to that of the ANN R-R model, revealing that the conceptual models were probably performing some tasks that the ANN R-R model cannot map.

Gabitsinashvili *et al.* (2007) described river runoff forecasting as one of the most complex areas of research in hydrology because of the uncertainty of hydrological and hydrology because of adequate records. He forecasted daily river flow using two ANN models: a Multi Layer Perceptrons (MLP) network and a Radial Basis Function (RBF) Network. The ANN technique was applied to predict runoff in three mountain rivers in Georgia. The results showed that ANNs could be successfully applied to forecast runoff using rainfall time series for the studied sub-catchments. A comparative study of both networks indicates that RBF models require little background knowledge of ANNs and less time for development.

Ismail (2007) employed two artificial neural network (ANN) approaches for the reservoir management and operation purpose. At first the monthly inflow data of a given reservoir were forecasted for the future. The ANN methods employed in the study are Radial Basis Networks (RBN). The remaining data were used for testing. The results of the artificial neural network were compared with those of the reservoir operation programs that were commonly used by the General Directorate of State Hydraulic Works (DSI) of Turkey.

Kerem *et al.* (2007) employed Feed Forward Back Propagation (FFBP), Radial Basis Function (RBF) and Generalized Regression Neural network (GRNN) for rainfall-runoff modelling of Turkish hydro-metrological data. The daily rainfall and daily mean flow data were coupled to form the basis of rainfall-flow modelling using different ANN configuration. It was seen that all three different ANN algorithms compared well with conventional.

Kisi (2007) developed four different ANN models with training algorithms such as back propagation, conjugate gradient, cascade correlation and Levenberg-Marquart to forecast daily stream flow of North Platte River in the United States. The results from the different algorithms were compared with each other.

Toth and Brath (2007) investigated the real-time forecasting ability of a conceptual and a neural network model, comparing the performances obtainable for increasing lead-times and analyzing the influence of the amount of the calibration data over two real-data case studies. Neural networks proved to be an excellent tool for the real time rainfall-runoff simulation of continuous periods (including low, average and peak flows), provided that an extensive set of hydro-meteorological data is available for calibration purposes. On the other hand, the comparison highlights that a conceptual formulation may allow a significant forecasting improvement in comparison with the data driven approach when focusing on the prediction of flood events and especially in case of a limited availability of calibration data.

Kalteh (2008) developed a rainfall-runoff model using an ANN approach, and secondly describe different approaches including Neural Interpretation Diagram, Garson's algorithm, and randomization approach to understand the relationship learned by the ANN model. The results indicate that ANNs are promising tools not only in accurate modelling of complex processes but also in providing insight from the learned relationship, which would assist the model in understanding of the process under investigation as well as in evaluation of the model.

Mutlu *et al.* (2008) evaluated the use of Artificial Neural Network (ANN) models to forecast daily flows at multiple gauging stations in Eucha Watershed, an agricultural watershed located in north-east Oklahoma. Two different neural network models, the Multi-Layers Perceptrons (MLP) and the Radial Basis neural Network (RBFNN), were developed and their abilities to predict stream flow at four gauging stations were compared. Different scenarios using various lags were developed and compared for their ability to make flow predictions at four gauging stations. The input vector selection for both models involved quantification of the statistical properties such as cross, auto, and partial autocorrelation of the data series that best represented the hydrologic response of the watershed. Measured data with 739 patterns of input-output vector were divided into two sets: 492 patterns for training and the remaining 247 patterns for testing. The best performance based on the RMSE, R2 and Coefficient of Efficiency (CE) was achieved by the MLP model with current and antecedent precipitation and antecedent flow as model inputs. Both models performed satisfactory for flow prediction at multiple gauging stations; however, the MLP model outperformed the RBFNN. The RBFNN uses a fuzzy min-max network to perform the clustering to construct the neural network which takes considerably less time than the MLP model. Results show that ANN models are useful tools for forecasting the hydrologic response at multiple points of interest in agricultural watersheds.

Fong Lin *et al.* (2009) proposed a Radial Basis Function (RBF)-based model with an information processor for more accurate forecasts of hourly reservoir inflow. Firstly, based on the Multi-Layer Perceptron neural (MLP) network, an information processor was developed to pre-process the typhoon information (namely, typhoon characteristics and rainfall) and to produce forecasts of rainfall. The forecasted rainfall and the observed inflow were then used as input to the RBF-based model, which was a nonlinear function approximate, to produce forecasts of hourly inflow. For parameter estimation of the RBF-based model, the fully-supervised learning algorithm was used. Actual applications of the proposed model were performed to yield 1- to 6-h ahead forecasts of inflow. To assess the improvement due to the use of the typhoon information processor, models without the typhoon information processor were constructed and compared with the proposed model. The result showed that the proposed model performed the best and was capable of providing improved forecasts of hourly inflow, especially for long lead-time. They concluded that proposed model with a typhoon information processor can extract useful information from typhoon characteristics and rainfall, and consequently improve the forecasting performance.

Kisi (2009) has proposed the application of a conjunction model (neuro-wavelet) for forecasting daily intermittent stream flow. The neuro-wavelet conjunction model is improved by combining two methods, discrete wavelet transform and artificial neural network (ANN), for 1 day ahead stream flow forecasting and results are compared with those of the single ANN model. The comparison result revealed that the suggested model could significantly increase the forecast accuracy of single ANN in forecasting daily intermittent stream flows.

Modarres (2009) applied 17 global statistics and 3 additional non-parametric tests to evaluate the ANNs for rainfall-runoff modelling. The weakness of global statistics for validation of ANN is demonstrated by rainfall-runoff modeling of the Plasjan Basin in the western region of the Zayandehrud watershed, Iran. Although the global statistics showed that the multi layer perceptron with 4 hidden layers (MLP4) is the best ANN for the basin comparing with other MLP networks and empirical regression model. The non-parametric tests illustrated that neither the ANNs nor the regression model are able to reproduce the probability distribution of observed runoff in validation phase. However, the MLP 4 network was the best network to reproduce the mean and variance of the observed runoff based on non-parametric tests. The performance of ANNs and empirical model was also demonstrated for low, medium and high flows. Although the MLP 4 network gave the best performance among ANNs for low, medium and high flows based on different statistics, the empirical model showed better results. However, none of the models was able to simulate the frequency distribution of low, medium and high flows according to non-parametric tests.

Prada-Sarmiento and Obregon-Neira (2009) have indicated that fewer studies were carried out to understand the physics behind ANN models and their applicability in solving day to day engineering problems even though their successful application in civil engineering have been reported for the past 15 years. This work explores the possibility of linking the weights of simple multilayer perceptrons with some physical characteristics of watersheds, by means of statistical regressions

Jain and Kumar (2009) presented the results of a study aimed at a systematic dissection of the massively parallel architectures of trained ANN hydrologic models to determine if they learn the underlying physical sub processes during training and it had been achieved using simple qualitative and quantitative techniques. The data derived from three contrasting catchments at two different time scales were employed to develop ANN models and test the methodologies employed for knowledge extraction. The results obtained in this study indicated that the number of hidden neurons determined during training for a particular data set correspond to certain sub processes of the overall physical process being modelled. It was found that the time scale of the data employed had an effect on optimum ANN architecture and knowledge extracted.

Solaimani (2009) presented in the study aims to utilize an Artificial Neural Network (ANN) to modeling the rainfall runoff relationship in a catchment area located in a semiarid region of Iran. The paper illustrates the applications of the feed forward back propagation for the rainfall forecasting with various algorithms with performance of multi-layer perceptions. The monthly stream of Jarahi Watershed was analyzed in order to calibrate the given models. The research explored the capabilities of ANNs and the performance this tool would be compared to the conventional approaches used for stream flow forecast. Efficiencies of the gradient descent (GDX), conjugate gradient and Levenberg-Marquardt (L-M) training algorithms are compared to improve the computed performances. The monthly hydrometric and climatic data in ANN were ranged from 1969 to 2000. The results extracted from the comparative study indicated that the Artificial Neural Network method is more appropriate and efficient to predict the river runoff than classical regression model.

Birinci (2010) compared MLR (Multivariate Linear Regression), ARIMA (Autoregressive Integrated Moving Average) and RBFNN (Radial Basis Function Neural Network) to predict and model daily mean flow. The daily mean flow data of Anamur River between the years 1989 and 2003 were processed. RBFNN model provided more reliable results than others.

Fernando and Shamseldin (2010) conducted study using the data of a stream to illustrate that the hidden neurons in an ANN modelling tool, indeed, do have roles to play in representing the various processes involved in the hydrological phenomenon. The study highlighted sheds light on the role of the hidden neurons in a Radial Basis Function (RBF) type ANN used to forecast the streamflows using the antecedent daily flow data. It was shown that (a) the modeler can determine the level to which the hydrograph is decomposed and, therefore, the complexity of the neural network, (b) each node in the hidden layer of neurons plays a role in reconstructing the hydrograph from its components, and that (c) the contributions from the hidden layer neurons are representative of the components that make up the flow hydrograph both quantitatively and qualitatively. They further suggested that numerical experiments with varying catchment characteristics be carried out to make conclusive remarks regarding the shapes of the composition hydrographs and ascertain if they mimic any of the traditional flow separation techniques.

Goyal *et al.* (2010) focused on a concept of using dimensionless variables as input and output to Artificial Neural Network (ANN) and discusses the improvement in the results in terms of various performance criteria as well as simplification of ANN structure for modeling rainfall-runoff process in certain Indian catchments. In the present work, runoff was taken as the response (output) variable while rainfall, slope, area of catchment and forest cover are taken as input parameters. The data used in this study were taken from six drainage basins in the Indian provinces of Madhya Pradesh, Bihar, Rajasthan, West Bengal and Tamil Nadu, located in the different hydro-climatic zones. A standard statistical performance evaluation measures such as root mean square (RMSE), Nash–Sutcliffe efficiency and Correlation coefficient were employed to evaluate the performances of various models developed. The results obtained in this study indicate that ANN model using dimensionless variables were able to provide a better representation of rainfall–runoff process in comparison with the ANN models using process variables investigated in this study.

Kari *et al.* (2010) developed a workable forecasting system for downstream catchment. Instead of taking the flow time series only concurrent flood peaks of 12 years of base and forecasting stations, along with its corresponding travel time were considered for analysis. Both statistical method and ANN based approach were considered for finding the peak to reach at delta head with its corresponding travel time. The travel time was finalized adopting clustering techniques, there by differentiating high, medium and low peaks. The method was simple and it did not take into consideration the rainfall and other factors in the intercepted catchment. A comparison between both methods were tested and it was found that the ANN methods are better beyond the calibration range over statistical method and the efficiency of either methods reduced as the prediction reached was extended. However, it was able to give the peak discharge at delta head before 24 hour to 37 hour for high to low peaks.

Fong Lin (2011) stated that in the construction of a Radial Basis Function (RBF) network, the key learning strategy was to identify the configuration (i.e. to determine the parameters of radial basis functions), which has significant influence on model performance. To improve the performance of RBF network, a two-step learning algorithm was proposed. In a supervised manner, the optimal configuration of RBF network was determined. For evaluating the performance of the RBF-based model two-step learning algorithm was proposed. An actual application was performed to forecast hourly inflow during typhoons. The results showed that the proposed model can successfully yield one- to six-hour ahead forecasts of inflow. For comparison, two other neural networks, the well known Back-Propagation Neural (BPN) network and the RBF network with the existing conventional learning algorithm, were also adopted to construct the hourly inflow forecasting models. The cross-validation results demonstrated that the proposed model provides more reliable and accurate inflow forecasts than the two other models. He concluded that the proposed model is useful to improve the forecasts of inflow to the reservoir.

Joshi (2011) employed three neural network methods i.e. Feed Forward Back Propagation (FFBP), Radial Basis Function (RBF) and Generalized Regression Neural Network (GRNN) for rainfall-runoff modelling of Maleshri hydrometeorologic data. It was seen that all three different ANN algorithms compared well with conventional Multi Linear Regression (MLR) technique. It was seen that only GRNN technique did not provide negative flow estimations for some observations. The rainfall-runoff correlograms was successfully used in determination of the input layer node number.

Jothiprakash and Kote (2011) studied the effect of data pre-processing while developing artificial intelligence (AI) based data-driven techniques, such as Artificial Neural Networks (ANN), Model Trees (MT) and Linear Genetic Programming (LGP), for Pawana Reservoir in Maharashtra, India. The daily one-step-ahead inflow forecasts are compared with flows generated from a univariate autoregressive integrated moving average (ARIMA) model. For full-year data series, a large error was found mainly due to the occurrence of zero values, since the reservoir was located in an intermittent river. The relevant range of inputs for each category was selected based on autocorrelation and partial autocorrelation analyzed of the inflow series. Conventional pre-processing methods, such as transformation and/or normalization of data, did not perform well because of the large variation in magnitudes, as well as the many zero values (65% of the full-year data series). The results indicated that AI methods are powerful tools for modeling the daily flow time series with appropriate data pre-processing, in spite of the presence of many zero values. The Time-Lagged Recurrent Network (TLRN) ANN modeling technique applied in this study mapped the inflow forecasting in a better way than the standard Multi-Layer Perceptron (MLP) neural networks, especially in the case of the seasonal data series. The MT technique performed equally well for low and medium inflows, but failed to predict the peak inflows. However, LGP outperformed the other AI models, and also the ARIMA model, for all inflow magnitudes. In the LGP model, the daily full-year data series with more zero inflow values performed better than the daily seasonal models.

Lohani *et al.* (2011) compared artificial neural network (ANN), fuzzy logic (FL) and linear transfer function (LTF)-based approaches for daily rainfall-runoff modelling. The study investigated the potential of Takagi-Sugeno (TS) fuzzy model and the impact of antecedent soil moisture conditions in the performance of the daily rainfall-runoff models. Eleven different input vectors under four classes, i.e. (i) rainfall, (ii) rainfall and antecedent moisture content, (iii) rainfall and runoff and (iv) rainfall, runoff and antecedent moisture content were considered for examining the effects of input data vector on rainfall-runoff modelling. Using the rainfall-runoff data of the upper Narmada basin, Central India, a suitable modelling technique with appropriate model input structure was suggested on the basis of various model performance indices. The results of models indicated that the fuzzy modelling approach was uniformly outperforming the LTF and also always superior to the ANN-based models.

Othman and Naseri (2011) studied Artificial Neural Network (ANN) approach for forecasting of long term reservoir inflow using monthly inflow available data. A Levenberg-Marquardt Back Propagation (LMBP) algorithm was used to develop the ANN models. In developing the ANN models, different networks with different numbers of neuron hidden layers were evaluated. A total of 21 years of historical data were used to train and test the networks. The optimum ANN network with 4 inputs, 5 neurons in hidden layer and one output was selected. To evaluate the accuracy of the proposed model, the Mean Squared Error (MSE) and the Correlation Coefficient (CC) were employed. The network was trained and converged at MSE = 0.0188 by using training data subjected to early stopping approach. The network could forecast the testing data set with the accuracy of MSE = 0.0283. Training and testing process showed the correlation coefficient of 0.7282 and 0.7228 respectively.

Bowden *et al.* (2012) presented a novel detection system for identifying uncharacteristic data patterns by which, the warning with forecast of the flow could be issued. This approach combined a self-organizing map (SOM), to partition the data set, with nonparametric kernel density estimators to calculate local density estimates (LDE). The SOM-LDE method determined the degree to which a new input pattern could be considered to be contained within the domain of the calibration set. If a new pattern was found to be uncharacteristic, a warning could be issued with the forecast, and the ANN model retrained to include the new pattern. This approach of selectively retraining the model was compared to no retraining and the more computationally onerous case of retraining the model after each new sample. These three approaches were applied to forecast flow in the Kentucky River, USA, using multilayer perceptron (MLP) models. The results demonstrate that there is a significant advantage in retraining an ANN that has been deployed as a real-time, operational model, and that the SOM-LDE classifier is an effective approach for identifying the model's range of applicability and assessing the usefulness of the forecast.

Mittal *et al.* (2012) developed a dual (combined and paralleled) artificial neural network (D-ANN), which aims to improve the models performance, especially in terms of extreme values. The performance of the proposed dual-ANN model is compared with that of feed forward ANN (FF-ANN) model. The later being the most common ANN model used in hydrologic literature. The forecasting exercise is carried out for hourly river flow data of Kolar Basin, India. The results of the comparison indicate that the D-ANN model performs better than the FF-ANN model.

Sarkar and Kumar (2012) examined the applicability of model for the event-based rainfall-runoff process. A case study has been done for Ajay river basin to develop event-based rainfall-runoff model for the basin to simulate the hourly runoff at Sarath gauging site. The results demonstrate that ANN models are able to provide a good representation of an event-based rainfall-runoff process. The two important parameters, when predicting a flood hydrograph, are the magnitude of the peak discharge and the time to peak discharge. The developed ANN models have been able to predict this information with great accuracy. This shows that ANNs can be very efficient in modeling an event-based rainfall-runoff process for determining the peak discharge and time to the peak discharge very accurately.

Lalozaee *et al.* (2013) compared the efficiency of artificial neural networks (ANN) in rainfall-runoff process simulation with Identification of Hydrographs and Components from Rainfall, Evaporation and Stream (IHACRES) model in northeast of Iran, then the results of these models was compare with daily observed values. In the IHACRES model, the parameters chosen as input data were daily rainfall, daily temperature and daily discharge. As a first step, with using daily values the IHACRES model was calibrated for 6-year period (1996-2002) in the basin. Then, model for a 4-year period (2002-2006) was validated. In the ANN model, daily rainfall and temperature as input data and daily observed discharge as output data were used. Then, with daily temperature eliminating, daily rainfall and discharge were used in simulation. In the research, three criteria, namely, Correlation Coefficient (R2), Nash-Sutcliffe Efficiency (NSE) and Root Mean Square Error (RMSE) were used to assess the performance of the models. The comparison results show that the ANN has better performances in Simulation of Rainfall-Runoff process from IHACRES model.

CHAPTER III

MATERIAL AND METHODS

This chapter describes the description of study area, data collection, input data preparation and model setup procedures for rainfall-runoff model using ANN technique.

3.1 Study area and data collection

The watershed of Agro-Ecology and Environment Center (AEEC) of Dr. Panjabrao Deshmukh Krishi Vidyapeeth, Akola was considered for study. The study area is located at 22^0 41' latitude and 77^0 22' E longitudes and is depicted in Fig. 3.1. The maximum slope of watershed is 5%, while average slope is 1.6%. Soils in the watershed are clay, sandy, and sandy loam. The various types of crops and orchard grown in the watershed are custard apple, lemon, mango etc. Watershed comprises eight farm ponds and total area of watershed is about 32.5 ha. Watershed is divided into two sub watersheds and six micro watersheds. The slope of most of the fields ranges from 0.5 to 2.5%. The entire area of watershed is treated with various land treatments *viz.* sowing along slope cultivation with opening of tied furrows (T1), contour cultivation with opening of alternate furrow (T2) and contour cultivation with opening of ridge and furrow (T3) and utilized under plantation of Agro-horticulture, Silvi-pasture systems and experimental monitoring plots.

The climatic condition of the region can be broadly described as semi-arid type. Rains are mostly received from South-West monsoon through June to October with mean annual precipitation of 750 mm, which is generally received in 41 rainy days. Winter rains are uncertain but has an average of 86.9 mm during October to January. Total rainy days ranges in between 30 to 55.

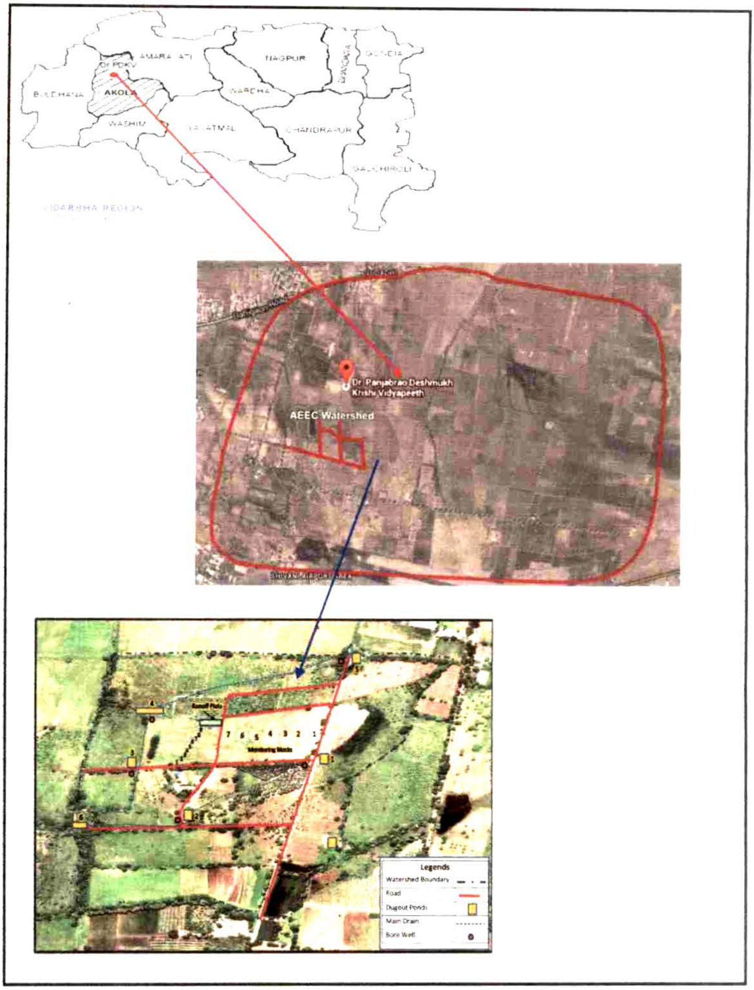

Fig. 3.1 Location of AEEC watershed

3.2 Data collection and input data preparation

The daily rainfall and runoff values for the study area were obtained for three treatments *viz.* sowing along slope cultivation with opening of tied furrows (T1), contour cultivation with opening of alternate furrow (T2) and contour cultivation with opening of ridge and furrow (T3) from the office of Director, Agro Ecology and Environment Center, Dr. PDKV, Akola for the period from 2000 to 2012. The area under T1, T2 and T3 is 0.4, 0.35 and 0.34 ha, respectively. The crop on the watershed is cotton. Rainfall and runoff data was transformed into excel sheet as required by the model.

3.3 Development of ANN models

Artificial neural network are effective tool to model non-linear system. It has certain performance characteristics resembling biological neural networks of the human brain. It is capable of representing arbitrarily complex non-linear processes that relate the inputs and outputs of any system. The fundamental processing element of a neural network is a neuron. It works like a biological neuron, which receives inputs from other sources, combines them in some way, performs a generally nonlinear operation of the result, and then output the final result.

ANN consists of three main layers (Fig.3.2): input layer, connecting input information to network (not carrying out any computation); one or more hidden layers, acting as intermediate computational layers; and an output layer, producing final output.

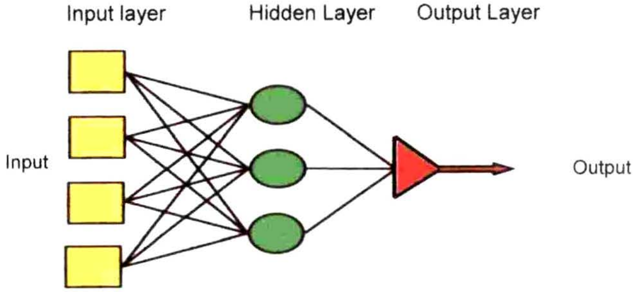

Fig 3.2 General ANN architecture

Radial Basis Function (RBF) ANN is mostly used type of ANN in hydrological modeling (Harun *et al.*, 2003; Karem *et al.*, 2007; Fernando and Shamseldin, 2007; Joshi and Patel, 2011) and so is adopted in this research to predict runoff. RBFs are feed-forward networks with one or more hidden layers. RBF ANN model is formulated by determining/selecting optimum number of hidden layers, number of processing elements in hidden layer, training algorithm, activation function, stop criteria and input parameters. These parameters were fixed as follows.

3.3.1 Number of hidden layers

The major concern of ANN structure is to determine appropriate number of hidden layers and number of neurons in each layer. There is no systematic way to establish suitable architecture, and selection of appropriate number of neurons is basically problem specific. Hornik *et al.* (1989) proved that a single hidden layer network containing sufficiently large number of neurons can be used to approximate any measurable functional relationship between input data and output variable to any desired accuracy. Dawson and Wilby (2001) stated that an ANN with only one hidden layer is enough to represent the nonlinear relationship between rainfall and corresponding runoff or inflow to reservoir. Considering the recommendations of above studies, a single hidden layer was used in this study.

3.3.2 Number of processing elements in hidden layer

Performance of ANN depends on number of nodes or processing elements in hidden layer. There are some algorithms, including 'Pruning and Constructive Algorithms', to determine an 'optimum' number of neurons in hidden layer(s) during training. However, trial and error procedure using different number of neurons is still being preferred choice of most users (Shamseldin, 1997; Zealand *et al.*, 1999; Abrahart and See, 2000). As no specific guidelines exist for choosing the optimum number of hidden nodes for a given problem, this network parameter was optimized using trial and error procedure, in this study.

3.3.3 Selection of training algorithm

ANN training is fundamentally a problem of non-linear optimization, which minimizes error between network output and target output by repeatedly changing the values of ANN's connection weights according to a predetermined algorithm. The most common learning rule (supervised learning) for RBF is back propagation algorithm. Among various algorithms reported in literature Levenberg-Marquardt (L-M) algorithm is much more robust and outperformed other algorithms in literature. Therefore it was used in this study. Also momentum algorithm was selected for judging its ability to predict runoff.

3.3.4 Selection of activation function

Activation functions are needed for introducing non linearity into network and it is non-linearity that makes multi-layer networks so powerful. Various transfer functions reported in literature are sigmoidal types, hard limit transfer functions (bounded to 0 or 1), linear, polynomial, rational function (ratios of polynomial) and fourier series (sum of cosines). In literature, most commonly used transfer functions for R-R modeling are sigmoidal type transfer functions in hidden layers and linear transfer functions in output layer due to its advantage in extrapolation beyond the range of training data (Zealand *et al.*, 1999; Calvoa and Portelab, 2007). Therefore, sigmoid and linear tanaxon transfer functions, in hidden and output layer, respectively, are used in this study.

3.3.5 Selection of stop criteria

The simple ideas of capping the number of iterations or of letting the system train until a predetermined error value is not obtained. The reason is that ANN has to perform well in test set data *i.e.* ANN should perform well in data it never saw before (good *generalization*) (Bishop, 1995). The weights are changed during training, according to optimization of some performance measure (in this study, mean squared error), which a measure for degree is of fit (or difference) between network estimates and output values. Alteration of network parameters in training phase is commonly stopped before the training optimum is found, because network will start learning noise in training data and lose its generalization capability (overtraining). However, stopping too early means ANN has not yet learnt all information from training data (under training). Both situations are likely to result in sub-optimal operational performance of ANN model. For this reason, available data are often split in three separate data sets (split-sampling method): (1) training set, (2) cross-validation set, and (3) validation set. The first set provides data on which ANN is trained. The second set is used during training phase to reduce the chance of overtraining of network. Minimization of training error is stopped as soon as cross-validation error starts to increase. This point is considered to lie between undertraining and overtraining. The later of three data sets is used to validate the performance of trained ANN. This is also called as early stopping approach. Considering advantages of early stopping approach, it was used in this research work.

3.3.6 Selection of input parameters

There is no general theory to choose input parameters to ANN model, rather it is problem dependent. Generally, trial and error procedure is used to finalize the input variables to ANN model.

As hydrological state for a great part determines catchment's response to a rainfall event, it is critical as input to ANN model. Previous runoff values are therefore often used as ANN inputs, since these are indirectly indicative for hydrological state (ASCE, 2000). Based on this line of work, basically five models were formulated as follows using current and previous day's rainfall and runoff as inputs and desirable output is one-day later runoff, for treatment T1.

Model 1 $R_{t+1} = f((P_t,)(R_t))$ ..... (3.1)

Model 2 $R_{t+1} = f((P_t, P_{t-1})(R_t))$ ..... (3.2)

Model 3 $R_{t+1} = f((P_t, P_{t-1})(R_t, R_{t-1}))$ ..... (3.3)

Model 4 $R_{t+1} = f((P_t, P_{t-1}, P_{t-2})(R_t, R_{t-1}))$ ..... (3.4)

Model 5 $R_{t+1} = f((P_t, P_{t-1}, P_{t-2})(R_t, R_{t-1}, R_{t-2}))$ ..... (3.5) where,

P_t = Current day rainfall;

P_{t-n} = Rainfall of n^{th} days before current day;

R_t = Current day runoff;

R_{t-n} = runoff 'n' days before current day;

R_{t+1} = One day later runoff;

t = Current day;

n = 1, 2, 3..... N^{th} day;

Firstly the performance of these formulated models was tested with Levenberg Marquardt algorithm at 100 epochs. Later on, the best model, in terms of statistical parameters, among these formulated models, was tested with Momentum algorithm for 50, 100, 200, 250 and 300 epochs.

The best ANN model found for treatment T1 was further tested for treatment T2 and T3 by varying 1-10 nodes in the hidden layer.

3.3.7 Calibration and validation of ANN model

To avoid overtraining and undertraining, split sampling method was used. As more than 90 per cent rainfall as well as runoff was received during monsoon months *i.e.* June to September, the data of rainfall and runoff from watershed only for monsoon months for the period 2000 to 2010 was considered for ANN modeling.

The available data was split into three separate data sets: (1) training set, (2) cross-validation set, and (3) validation set. These data sets were then used for respective operation. The size of training, cross validation and testing set was 803 (60%), 268 (20%) and 268 (20%) exemplars, respectively.

3.3.7.1 Training

Training of ANN was achieved by adjusting (determining) weights and biases of neurons through an iterative algorithm that minimizes error between network predicted outputs and actual data.

3.3.7.2 Cross Validation

The cross validation is carried out to avoid possibility of overtraining of network. It is for evaluating the weights and biases, and for deciding when to stop the training. The stopping criterion used in this study was early stopping approach.

3.3.7.3 Testing

Third data set was used to validate weights and biases, to verify the effectiveness of stopping criterion and to estimate the expected network operation on new data sets.

The ANN model implementation was carried out using Neuro Solutions for Excel version V.

3.3.8 Model performance

As suggested by ASCE Task Committee (ASCE, 2000) on application of ANNs in hydrology, Nash-Sutcliffe coefficient was used as performance indicator along with Persistence Index, a dimensionless statistical performance criterion. While during training and cross validation the software uses mean squared error, a built in statistical performance criterion. These performance measures are described below.

a) Nash-Sutcliffe coefficient of efficiency

Nash-Sutcliffe coefficient of efficiency (R^2_{NS}) is used to assess predictive power of hydrological models (Nash and Sutcliffe, 1970). R^2_{NS} is described by following relationship

$$R^2_{NS} = 1 - \frac{\Sigma(Q_O - Q_S)^2}{\Sigma(Q_O - Q_{av})^2} \qquad ..... (3.6)$$

Where,

Q_O = observed runoff;

Q_S = simulated runoff; and

Q_{av} = mean of observed runoff.

Nash-Sutcliffe coefficient of efficiency can range from 0 to 1. R^2_{NS} value of 1 therefore indicates perfect fit. An efficiency of zero indicates that the model predictions are as accurate as the mean of observed data. Closer the model efficiency to 1, more accurate is the model. Model efficiency less than 0.7 correspond to a very poor fit (Coulibaly *et al.*, 2000).

b) Persistence index

Persistence index (PI) was generally used to evaluate the performance of model (Kitanidis and Bras, 1980). PI index is especially useful when previous discharge values are used as input to ANN model since it evaluates model in comparison to a persistence model, which is a model that presents the last observation as a prediction (Anctil *et al.*, 2004b; Vos and Rientjes, 2005b). This basically means that the model variance is compared with variance of a very simple model that takes the last observation as a prediction. PI index is described mathematically as follows.

$$PI = 1 - \frac{\sum_{k=1}^{N}(Q_O - Q_P)^2}{\sum_{k=1}^{N}(Q_O - Q_{O-1})^2} \qquad \text{..... (3.7)}$$

Where,

Q_O = discharge at time k;

Q_{O-1} = discharge at time k-1; and

Q_P = predicted discharge

PI = 1 indicates a perfect fit between estimated and observed values. On the other hand, PI = 0 is equivalent to saying that the model provides previously observed values as prediction, which is known as naive model. A negative PI value means the model is altering the original information, performing worse than a naive model (Anctil and Rat, 2005).

c) Mean Square Error

MSE is measures the averages of squares of error. It is risk function, corresponding to the expected value of the squared error loss or quadratic loss.MSE was calculated by using following equation

$$MSE=\frac{1}{N}\sum_{i=1}^{N}(P_i - Q_i)^2 \qquad ..... (3.8)$$

Where,

N = number of observations,

P_i = simulated runoff,

O_i = observed runoff.

CHAPTER IV

RESULTS AND DISCUSSION

This chapter deals with the training; cross validation and test results of data driven model *i.e.* RBF ANN, formulated to predict runoff from watershed of Agro Ecology and Environment Center (AEEC), Dr. PDKV, Akola.

4.1 Performance of formulated ANN models during training, cross validation and testing

For real time prediction of runoff, one day ahead forecast of runoff from watershed is chosen and accordingly five RBF ANN models were formulated with varying input parameters. Accurate forecast of runoff in monsoon season (June to September) is of particular interest. To identify an appropriate RBF ANN model, number of nodes in hidden layer was optimized by trial and error procedure. The number of nodes in hidden layer was varied over 1-10 and performance of best model was checked. Performance of each model was evaluated on test data set. The best ANN architecture for each of all models were determined and presented in Table 4.1, whereas detailed results for various architectures of different models are presented in Annexure A.

From Table 4.1, it is cleared that Model 5 gives the best performance among all models in terms of R^2_{NS} and PI. The performance of five models *i.e.* with Levenberg- Marquardt (L-M) algorithm is comparable with each other though at varying number of nodes in hidden layer. Performance of models with momentum algorithm except for Model 7 is below the minimum criteria for statistical measures. The model 7 (5-2-1, for 100 epochs) performed better with R^2_{NS} and PI values as 0.986 and 0.675, respectively. But the value of PI is below the minimum criteria i.e. 0.7 and thus it is not considered for prediction of runoff from watershed. Therefore, it is cleared from the Table 4.1 that the RBF ANN models with momentum algorithm could not quantify the runoff from the watershed to the accuracy.

Table 4.1 Statistical evaluation of best neural network architecture of each ANN model on test data set for treatment T1

Particular \ Model No.	1	2	3	4	5	6	7	8	9	10
ANN architecture	1-10-1	2-5-1	3-2-1	4-4-1	5-10-1	5-5-1	5-2-1	5-5-1	5-8-1	5-9-1
Inputs	P_t	P_t, R_t	P_t, P_{t-1}, R_t	P_t, P_{t-1}, R_t, R_{t-1}	P_t, P_{t-1}, P_{t-2}, R_t, R_{t-1}	P_t, P_{t-1}, P_{t-2}, R_t, R_{t-1}	P_t, P_{t-1}, P_{t-2}, R_t, R_{t-1}	P_t, P_{t-1}, P_{t-2}, R_t, R_{t-1}	P_t, P_{t-1}, P_{t-2}, R_t, R_{t-1}	P_t, P_{t-1}, P_{t-2}, R_t, R_{t-1}
Input layer	1	2	3	4	5	5	5	5	5	5
Hidden layer	1	1	1	1	1	1	1	1	1	1
Output layer	1	1	1	1	1	1	1	1	1	1
Nodes in hidden layer	10	5	2	4	10	5	2	5	8	9
Epochs	100	100	100	100	100	50	100	200	250	300
Algorithm	LM	LM	LM	LM	LM	Moment	Moment	Moment	Moment	Moment
Transfer function										
Hidden layer	Sigmoid	Sigmoid	Sigmoid	Sigmoid	Sigmoid	Sigmoid	Sigmoid	Sigmoid	Sigmoid	Sigmoid
Output layer	Linear tanaxon	Linear tanaxon	Linear tanaxon	Linear tanaxon	Linear tanaxon	Linear tanaxon	Linear tanaxon	Linear tanaxon	Linear tanaxon	Linear tanaxon
R^2_{NS}	0.771	0.826	0.859	0.818	0.862	0.112	0.986	0.217	0.242	0.274
PI	0.869	0.887	0.908	0.895	0.921	0.434	0.675	0.501	0.517	0.537

P_t = current day rainfall, R_t = current day runoff; t = current day, t-n = n day before current day; n = 1, 2, 3.........N

The performance of model 5 was found best for the architecture 5-10-1 *i.e.* five inputs, ten processing elements in the hidden layer and one output at 100 epochs with Levenberg – Marquadt (L-M) algorithm and Radial basis function (RBF). The inputs used were current day rainfall, one day ahead rainfall, two day ahead rainfall, one day ahead runoff, two day ahead runoff and current day runoff from the watershed. It performed best in terms of statistical parameters such as Nash-Sutcliffe coefficient of efficiency as 0.86 and persistence index as 0.92. Therefore, performance of Model 5 is discussed in the following sections.

4.1.1 Performance of model 5 during training and cross validation

The performance of Model 5 in terms of MSE during training and cross validation with respect to epochs as given by software is depicted in Fig. 4.1.

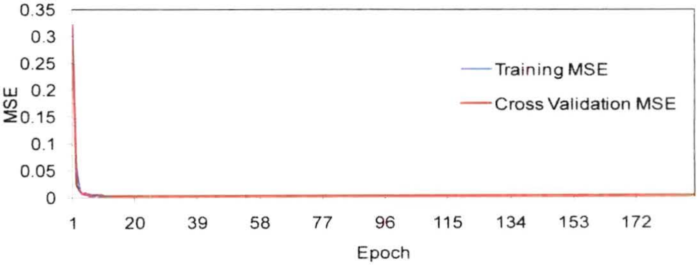

Fig. 4.1 Performance of model during training and cross validation for treatment T1

Fig. 4.1 shows that the minimum MSE during training was 0.001607 for 100 epochs, while during cross validation the MSE started increasing after 26 epochs. The minimum MSE during cross validation was 0.0018818 while final MSE was 0.0019140.

4.1.2 Performance of model 5 during testing

The temporal variation of rainfall, observed runoff and simulated runoff from watershed with Model 5 over test period is shown in Fig. 4.2, while Fig 4.3 depicts scatter plot.

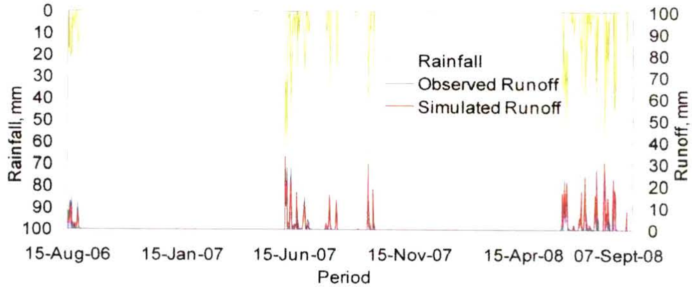

Fig. 4.2 Performance of model for treatment T1 during testing

It is cleared from Fig. 4.2 that the observed and simulated runoff is in good agreement with each other. All runoff events small as well as large are well simulated by the model. It is also cleared from the figure that the model 5 underestimated the moderate peak flow. Every rainfall event is resulted in runoff. It might be due to small size of field under observation.

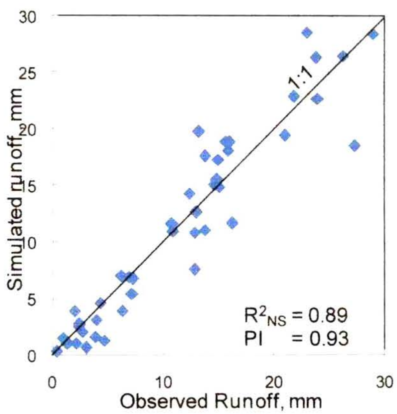

Fig. 4.3 Scatter diagram of simulated and observed runoff from watershed for treatment T1

The scatter plot clears that the runoff from watershed lies on both sides of 1:1 line, which shows that there is no consistent over or under estimation. Nash-Sutcliffe coefficient of efficiency close to 1 indicates that the Model 5 predicts runoff from watershed with accuracy. Value of Persistence index as 0.92 also confirms satisfactory agreement between simulated and observed runoff.

4.1.3 Performance of model 5 for treatment T2

The model 5 was tested for treatment T2, as its performance was found best. The performance of model 5 was judged by varying 1-10 nodes in the hidden layer and is presented in Table 4.2

Table 4.2: Statistical performance of model for treatment T2

No. of nodes in hidden layer	R^2_{NS}	PI
1	-1.00	-0.17
2	0.84	0.91
3	0.77	0.87
4	0.87	0.92
5	**0.93**	**0.96**
6	0.11	0.48
7	0.68	0.81
8	0.28	0.58
9	0.87	0.93
10	0.91	0.95

From Table 4.2, it is cleared that model 5 performed best for the architecture 5-5-1for the architecture 5-5-1 *i.e.* five inputs, five processing elements in the hidden layer and one output at 100 epochs. The performance of model 5 for this architecture is discussed in following section. The performance of Model 5 for treatment T2 in terms of MSE during training and cross validation with respect to epochs is depicted in Fig. 4.4, while Fig. 4.5 and 4.6 shows temporal variation of runoff and scatter plot for testing period, respectively.

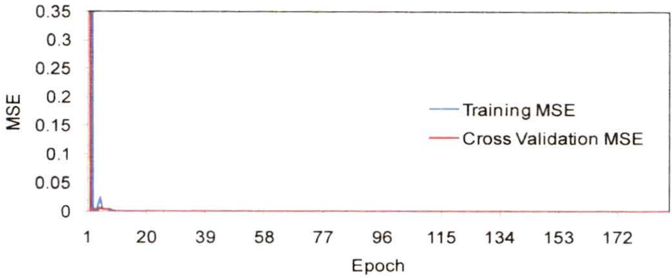

Fig. 4.4 Performance of model during training and cross validation for treatment T2

The figure showed that the minimum MSE during training was 0.0011348 for 100 epochs, while during cross validation the MSE started increasing after 18 epochs. The minimum MSE during cross validation was 0.000959 while final MSE was 0.000960.

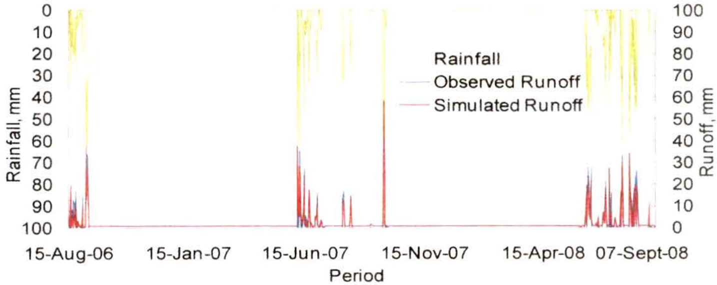

Fig. 4.5 Performance of model for treatment T2 during testing

From Fig.4.5, it is cleared that the observed and simulated runoff is in good agreement. The model 5 underestimated the moderate peak flow. All runoff events small as well as large are well simulated by the model.

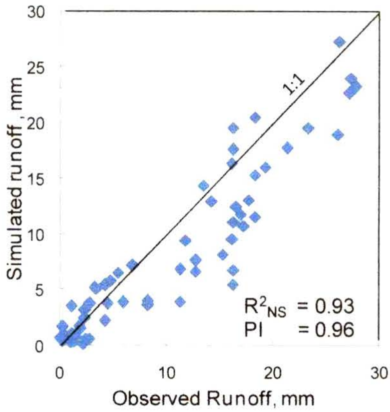

Fig. 4.6 Scatter diagram of simulated and observed runoff from watershed for treatment T2

The scatter plot clears that the runoff from watershed lies on both sides of 1:1 line, which shows that there is no consistent over or under estimation. High values of statistical performance measures confirm good agreement between simulated and observed runoff.

4.1.4 Performance of model for treatment T 3

The model 5, was also tested for treatment T3 by varying nodes 1-10 in hidden layer. The performance of model 5 for varying nodes in hidden layer *i.e.* 1-10, is presented Table 4.3.

Table 4.3: Statistical performance of model for treatment T3

No. of nodes in hidden layer	R^2_{NS}	PI
1	-0.96	-0.16
2	0.68	0.81
3	0.89	0.93
4	0.00	0.40
5	**0.89**	**0.93**
6	0.86	0.91
7	0.79	0.88
8	-0.95	-0.16
9	0.87	0.92
10	0.77	0.86

The model 5 gives best performance for the architecture 5-5-1 *i.e.* five inputs, five processing elements in the hidden layer and one output at 100 epochs. The inputs used were current day rainfall, one day ahead rainfall, two day ahead rainfall, one day ahead runoff, two day ahead runoff and current day runoff from watershed.

The performance of Model 5 for treatment T3 in terms of MSE during training and cross validation with respect to epochs is depicted in Fig. 4.7, while Fig. 4.8 and 4.9 shows temporal variation of runoff and scatter plot for testing period, respectively.

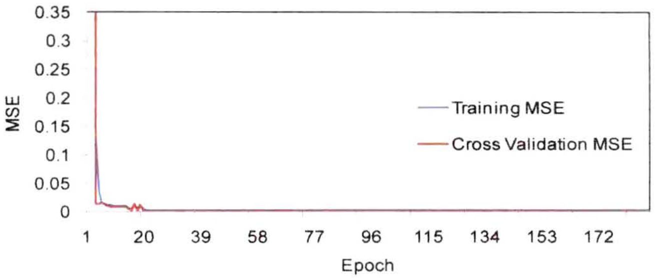

Fig. 4.7 Performance of model during training and cross validation for treatment T3

The figure cleared that the minimum MSE during training was 0.002783 for 100 epochs, while during cross validation the MSE started increasing after 31 epochs. The minimum MSE during cross validation was 0.001250 while final MSE was 0.001272.

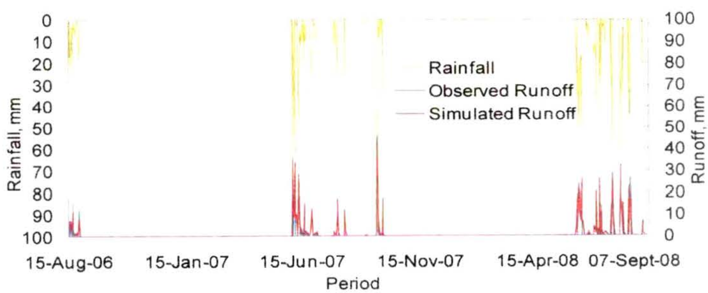

Fig. 4.8 Performance of model for treatment T3 during testing

From Fig.4.8, it is cleared that the observed and simulated runoff are in good agreement. It is also cleared from figure that the model 5 underestimated the moderate peak flow. All runoff events small as well as large are well simulated by the model.

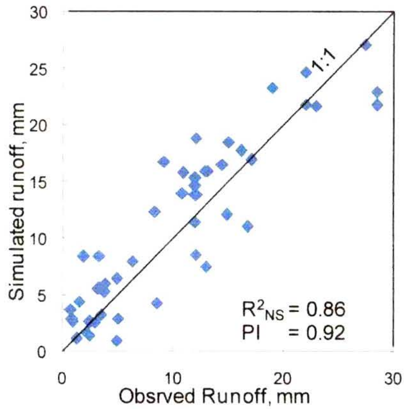

Fig. 4.9 Scatter diagram of simulated and observed runoff from watershed for treatment T3

The scatter plot clears that the runoff from watershed lies on both sides of 1:1 line, which shows that there is no consistent over or under estimation. The performance of Model 5 (5-5-1) in terms of statistical measures confirms good agreement between simulated and observed runoff.

4.2 Prediction of runoff using simulated results

The validated RBF ANN model 5 was used to predict the runoff from the watershed for the period 2011-2012. The results are presented below.

4.2.1 Prediction of runoff for treatment T1 using validated model 5

The runoff was predicted using validated model 5 (*i.e.* 5-10-1) for treatment T1. The statistical performance of model is presented in Table 4.4.

Table 4.4 Statistical performance for prediction of model for treatment T1

No. of nodes in hidden layer	R^2_{NS}	PI
10	0.91	0.95

The model 5 (5-10-1) predicts the runoff with high accuracy in terms of Nash-Sutcliffe coefficient of efficiency as 0.91 and persistence index as 0.95. The temporal variation of runoff against rainfall is depicted in Fig.4.10, while Fig.4.11 shows the scatter plot.

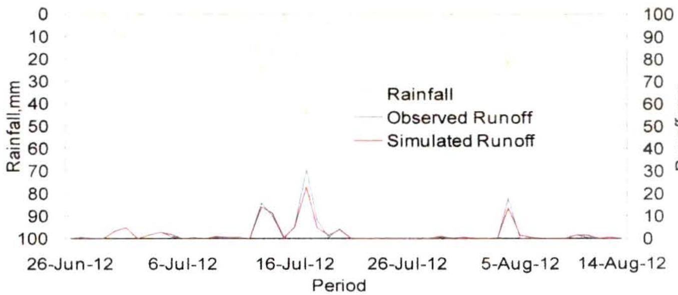

Fig. 4.10 Performance of model for prediction for treatment T1 during testing

The figure confirmed that the observed runoff and simulated runoff are in close agreement.

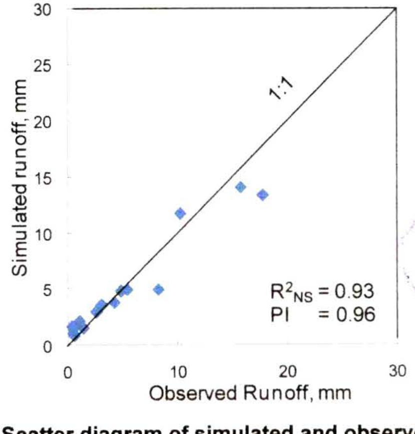

Fig. 4.11 Scatter diagram of simulated and observed runoff from watershed for treatment T1 for prediction

The scatter plot clears that there is no consistent over or under estimation.

4.2.2 Prediction of runoff for treatment T2 using validated model 5

The runoff was predicted using validated model 5 (*i.e.* 5-5-1) for treatment T2. The statistical performance of model 5 (*i.e.* 5-5-1) is presented in Table 4.5.

Table 4.5 Statistical performance for prediction of model for treatment T2

No. of nodes in hidden layer	R^2_{NS}	PI
5	0.96	0.97

The model 5 (5-5-1) predicts the runoff with high accuracy in terms of Nash-Sutcliffe coefficient of efficiency as 0.96 and persistence index as 0.97. The temporal variation of runoff against rainfall is depicted in Fig.4.12, while Fig.4.13 shows the scatter plot.

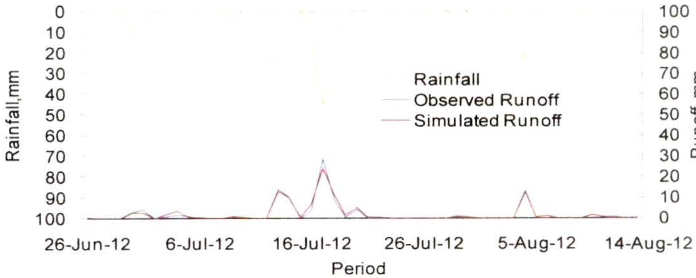

Fig. 4.12 Performance of model for prediction for treatment T2 during testing

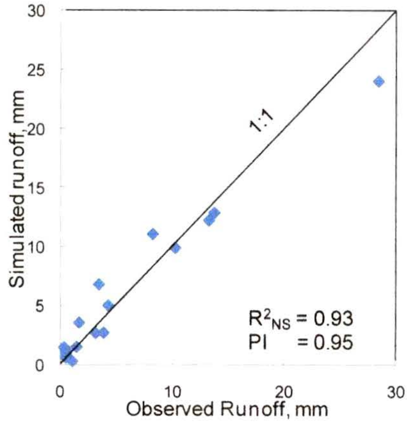

Fig. 4.13 Scatter diagram of simulated and observed runoff from watershed for treatment T2 for prediction

The Fig. 4.12 confirmed that the observed runoff and simulated runoff are in close agreement. The scatter plot clears that there is no consistent over or under estimation.

4.2.3 Prediction for treatment T3 using validated model 5

The runoff was predicted using validated model 5 (*i.e.* 5-5-1) for treatment T3. The statistical performance of model is presented in Table 4.6.

Table 4.6 Statistical performance for prediction of model 5 for treatment T3

No. of nodes in hidden layer	R^2_{NS}	PI
5	0.89	0.93

The model 5 (5-5-1) predicts the runoff with high accuracy in terms of Nash-Sutcliffe coefficient of efficiency as 0.89 and persistence index as 0.93. The temporal variation of runoff against rainfall is depicted in Fig.4.14, while Fig.4.15 shows the scatter plot.

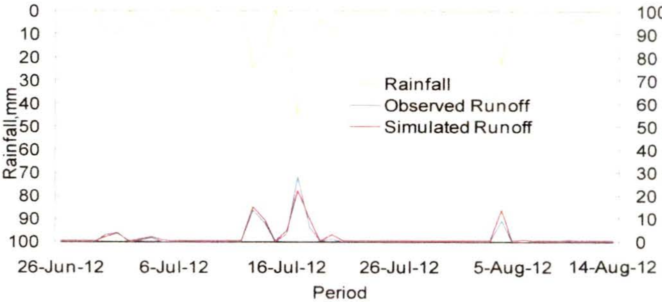

Fig. 4.14 Performance of model for prediction for treatment T3 during testing

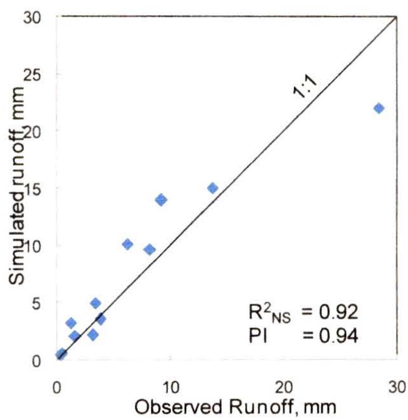

Fig. 4.15 Scatter diagram of simulated and observed runoff from watershed for treatment T3 for prediction

The Fig. 4.15 confirmed that the observed runoff and simulated runoff are in close agreement. The scatter plot clears that there is no consistent over or under estimation.

CHAPTER V

SUMMARY AND CONCLUSIONS

For real time management of watershed one day ahead prediction of simulated runoff was chosen as desired output and accordingly five RBF ANN models were formulated with varying input parameters with single hidden layer for treatment T1. The performance of these formulated models was tested with Levenberg Marquardt algorithm at 100 epochs. Later on, the best model, in terms of statistical parameters, among formulated models was tested with momentum algorithm for 50, 100, 200, 250 and 300 epochs. Sigmoid and linear tanaxon were used as transfer function, in hidden and output layer, respectively. The early stopping criterion was used to cap the number of iterations. Split sampling method was employed with splitting of data in 60:20:20 proportions for training, cross validation and testing, respectively. The required data was collected from the office of Director, Agro Ecology and Environment Center, Dr. PDKV, Akola for the period from 2000 to 2012. The tested ANN model was used to predict the runoff from rainfall for the period 2011-2012. The ANN model implementation was carried out using Neuro Solutions for Excel version V.

The performance of all ten models on test data set for their best architecture was compared to find out the best model for prediction of runoff from watershed. Model 5 (5-10-1) shows better performance as compared to other models, in terms of statistical parameters such as Nash-Sutcliffe coefficient of efficiency (R^2_{NS}) and Persistence index (PI). The best ANN model found for treatment T1 was further tested for treatment T2 and T3. Model 5 with 5-5-1 architecture was found best for treatment T2 and T3. During this study following specific conclusions are drawn.

i) The model 5 with architecture 5-10-1 *i.e.* five inputs (current day rainfall, one day ahead rainfall, two day ahead rainfall, one day ahead runoff and two day ahead runoff from the watershed), ten processing elements in the hidden layer and one output at 100 epochs with Levenberg – Marquadt (L-M) algorithm and Radial basis function (RBF) performed best in terms of statistical parameters such as Nash-Sutcliffe coefficient of efficiency as

0.86 and persistence index as 0.92 for treatment T1. Therefore ANN RBF model should be used for prediction of runoff from for cotton crop sowing along slope cultivation with opening of tide furrows on AEEC watershed of Dr. PDKV, Akola.

ii) The model 5 with architecture 5-5-1 *i.e.* five inputs (current day rainfall, one day ahead rainfall, two day ahead rainfall, one day ahead runoff, two day ahead runoff and current day runoff from the watershed), five processing elements in the hidden layer and one output at 100 epochs with Levenberg – Marquadt (L-M) algorithm and Radial basis function (RBF) performed best in terms of statistical parameters such as Nash-Sutcliffe coefficient of efficiency as 0.93 and persistence index as 0.96 for treatment T2. Therefore it should be used for cotton on contour cultivation with opening of alternate furrow on this watershed area. Therefore this ANN RBF model should be used for prediction of runoff from cotton crop on contour cultivation with opening of alternate furrow on AEEC watershed of Dr. PDKV, Akola.

iii) The model 5 with architecture 5-5-1 *i.e.* five inputs (current day rainfall, one day ahead rainfall, two day ahead rainfall, one day ahead runoff, two day ahead runoff and current day runoff from the watershed), five processing elements in the hidden layer and one output at 100 epochs with Levenberg – Marquadt (L-M) algorithm and Radial basis function (RBF) performed best in terms of statistical parameters such as Nash-Sutcliffe coefficient of efficiency as 0.89 and persistence index as 0.93 for treatment T3. Therefore this ANN RBF model should be used for prediction of runoff from cotton crop on contour cultivation with opening of ridge and furrow on AEEC watershed of Dr. PDKV, Akola.

iv) It is cleared that the RBF ANN models with momentum algorithm could not quantify the runoff from the watershed to the accuracy.

v) The study also confirmed that the number of processing elements in hidden layer and epochs did not have any consistent impact on the performance of RBF ANN models. Thus it is concluded that number of nodes in the hidden layer and epochs during training should be optimized by trial and error method.

CHAPTER VI

LITERATURE CITED

Abbott, M. B., Bathurst, J. C., Cunge, J. A., O'Connell, P. E. and Rasmussen, J. (1986).: An introduction to the european hydrological system – Syst`eme Hydrologique Europ´een, 'SHE', 1: History and philosophy of a physically-based, distributed modelling system, *J. Hydrol.*, 87, 45–59.

Abrahart, R. J., and See, L. (2000). Comparing neural network and autoregressive moving average techniques for provision of continuous river flow forecasts in two contrasting catchments. *Hydrol. Process.*, 14, 2157-2172.

Agrawal, A. and Singh, R. D. (2004). Runoff modelling through back propagation artificial neural network with variable rainfall-runoff data. *J. Water Resources Management,* 18(3):285-300.

Anctil, F., Michel, C., Perrin, C., and Andrassian, V. (2004). A soil moisture index as an auxiliary ANN input for streamflow forecasting, *J. Hydrol.*, 286, 155–167.

Anctil, F. and Rat, A. (2005). Evaluation of neural network stream flow forecasting on 47 watersheds. *J. Hydrologic Engg.*, 10: 85-88.

Anctil, F., Charles, P. and Vazken, A. (2007). ANN output updating of lumped conceptual rainfall forecasting models. *JAWRA J. American Water Resources Association.*39 (5):pp 1269-1279.

Antar, M.A., Ibrahim, E. and Allam, M.N. (2005). Rainfall-runoff modeling using artificial neural network technique: a Blue Nile catchment case study. *J. Hydrol. Processes*, 20(5):201-1216.

ASCE Task Committee on Application of Artificial Neural Networks in Hydrology. (2000b). "Artificial neural networks in hydrology-II: Hydrologic applications." *J. Hydrol. Engrg.*, 5(2): 124-137.

Birinci, V. and Aky,O. (2010). A Study on modeling daily mean flow with MLR, ARIMA and RBFNN. *BALWOIS* - Ohrid, Republic of Macedonia.

Bishop, C. (1995). Neural networks for pattern recognition. Oxford University Press, New York.

Bowden, G.J., Maier, H.R. and Dandy, G.C. (2012). Real-time deployment of artificial neural network forecasting models: Understanding the range of applicability. 48(10), <http://onlinelibrary.wiley.com/doi/10.1029/2012WR011984/abstract>.

Calvoa, I. and Portelab, M. (2007). Application of neural approaches to one step daily flow forecasting in Portuguese watersheds. *J. Hydrol.*, 332(1-2): 1-15.

Coulibaly, P., Anctil, F. and Bobee, B. (2000). Daily reservoir inflow forecasting using artificial neural networks with stopped training approach. *J. Hydrol.*, 230: 244-257.

Dawson, C.W. and Wilby, R.L. (2001). Hydrological modelling using artificial neural networks. *Prog. Phys. Geog.*, 25:8-108.

Dibike, Y.B. and Solomatine, D.P. (2001). River flow forecasting using artificial neural networks, *Phys. Chem. Earth* (B), 26 (1),1–7.

Fernando, A.K. and Shamseldin, A. (2007). Role of hidden neurons in RBF type ANN in stream flow forecasting. Oxley L, and Kulasari D, (Eds), CD Rom. MODISIM 2007 International Congress on Modelling and Simulation. Land, Water and environmental management: Integrated systems for sustainability IMODISIM 2007 *International Congress*, Pp. :6-16.

Fong, G.L., Wu, M.C., Chen, G.R., and Tsai, F.Y. (2009). An RBF-based model with an information processor for forecasting hourly reservoir inflow during typhoons. Article, 23(25): 3598-3609.

Fong, G.L. and Wu, M.C. (2011). An RBF network with a two-step learning algorithm for developing a reservoir inflow forecasting model. *J. of Hydrology*, vol. 2 Pp: 42.

Gabitsinashvili, G.D., Namgaladze, and Bertacchi, U. (2007).Evaluation of artificial neural network techniques for river flow forecasting. *Environmental Engineering and Management J*, 6(1): 37-43.

Goyal, M.K., Ojha, C.P. (2010): Analysis of Mean Monthly Rainfall Runoff Data of Indian Catchments Using Dimensionless Variables by Neural Network, *J.l of Environmental Protection*,1,155-171.

Halff, A.H., Halff, H.M. and Azmoodeh, M. (1993). Predicting from rainfall using neural networks, *ASCE Proceedings of Engineering Hydrology*, 760–765.

Harun, S., Nor, I.A. and Kassim, A.H. (2003). Rainfall-Runoff Modelling Using Artificial Neural Network. M. Sc. Thesis, Kolej Universiti Tenkologi Tun Hussein Onn.Pp:45-67.

Hjemfelt, A.T. and Wang, M. (1993). Artificial neural networks as unit hydrograph applications, *ASCE Proceedings of Engineering Hydrology*, 754–759.

Hornik, K., Stinchcombe, M. and White, H. (1989). Multilayer feed forward networks are universal approximators. *Neural Networks*, 2: 359-366.

Hsu, K.L., Gupta, H.V., and Sorooshian, S. (1995). Artificial neural network modeling of the rainfall-runoff process,*Water Resour. Res.*, 31 (10), 2517–2530.

Ismail, K. and Kerem, C. (2007). Reservoir Management Using Artificial Neural Networks. 14th Reg. Directorate of DSI, Istanbul.

Jain, A. and Srinivasulu, S. (2004). "Development of effective and efficient rainfall-runoff models using integration of deterministic, real-coded genetic algorithms and artificial neural network techniques." *Water Resour. Res.*, 40, W04302, 1-12.

Jain, A. and Kumar, S. (2009). "Dissection of trained neural network hydrologic model architectures for knowledge extraction." *Wat. Resour. Res*, 45(7), W07420, doi:10.1029/2008WR007194.

Jareanpon, C.W., Pensuwon, R.J., Frank and Davey, N. (2004). An Adaptive RBF Network optimized using an Genetic Algorithm applied to Rainfall Forecasting Proceed international Symposium on Commutation and Information Technologies (ISCK 2004) Sapporo, Japan, October 26-29.

Jeong, D. and Kim, Y. (2005). Rainfall-runoff models using artificial neural networks for ensemble streamflow prediction. *J. Hydrol Processes*, 19(19), 3819-3835.

Joshi, J. (2011). Rainfall-Runoff Modeling Using Artificial Neural Network (A Literature Review). National Conference on Recent Trends in Engineering & Technology .12(6):1787-1800.

Jothiprakash, V. and Kote, A.S. (2011). Improving the performance of data-driven techniques through data pre-processing for modelling daily reservoir inflow. pp: 168-186.

Kari, A.K., Lahani, A.K., Goel, N.K. and Roy, G.P. (2010). Development of Flood Forecasting System Using Statistical and ANN Techniques in the Downstream Catchment of Mahanadi Basin, India. *J. Water Resource and Protection*. 2:880-887.

Karunanithi, N., Grenney, W.J., Whitley, D., and Bovee, K. (1994). Neural network for river flow prediction, *J. Comput. Civil Eng.*, 8 (2), 201–220.

Kalteh, A.M. (2008). Rainfall-runoff modelling using artificial neural networks (ANNs): modelling and understanding, Caspian *J. Env. Sci.* Vol. 6 No.1 pp. 53-58.

Kerem, H.P., Ahmet and Omer, A. (2007). Artificial neural network models in rainfall-runoff modellling of Turkish rivers.

Kisi, O. (2007). "Streamflow forecasting using different artificial neural network *J. of Hydrologic Engineering,*12.

Kisi, O. (2009). "Neural Networks and Wavelet Conjunction Model for Intermittent Stream flow Forecasting." *J. of Hydrologic Engineering*, 14(8), 773–782.

Kitanidis, P.K. and Bras, R.L. (1980). Real-time forecasting with a conceptual hydrologic model, 2, applications and results, *Water Resour. Res.*, 16(6): 1034-1044.

Lekkas, D.P., Onof, C., Lee, M.J. and Baltas, E.A. (2004). Application of Artificial neural network for flood forecasting. Global Nest: the Int. J. Vol. 6, No.3,pp 204-210.

Lohani, A.K., Goel, N.K. and Bhatia, K.K.S. (2011). "Comparative study of neural network, fuzzy logic and lineartransfer function techniques in daily rainfall-runoff modelling under different input domains."*Hydrol. Process*. 25, 175–193.

Lalozaee, A., Pahlavanravi, A., Bahreini, F., Ebrahimi, H. and Iezadi, H. (2013). Efficiency comparison of IHACRES model and Artificial Neural networks (ANN) in rainfall-runoff process simulation Inkameh watershed, *Inter journal of agriculture*: research and review. Vol., 3 (4), 900-907.

Maier, H.R. and Dandy, G.C. (2000). "Neural networks for the prediction and forecasting of water resources variables: A review of modelling Issues and applications." *Environmental Modelling & Software*, 15, 101-124.

Minns, A.W. and Hall, M.J. (1996). Artificial neural networks as rainfallrunoff models, *Hydrolog. Sci. J.*, 41 (3), 399–417.

Mittal, P., Chowdhury, S., Roy, S., Bhatia, N. and Srivastav, R. (2012). Dual Artificial Neural Network for Rainfall-Runoff Forecasting: *J of Water Resource and Protection*, 2012, 4, 1024-1028.

Mutlu, E.I., Chaubey, H., Hexmoor and Bajwa, S.G. (2008). Comparison of artificial neural network models for hydrologic predictions at multiple gauging stations in an agricultural watershed. *J.Hydrological processes*.22(26),5097-5106.

Modarres, R. (2009). Multi-criteria validation of artificial neural network rainfall-runoff modeling. *Hydrology Earth system sciences*. 13:441-421.

Nagesh, K.D., Srinivasa, R.K. and Sathish, T. (2004). "River Flow Forecasting using Recurrent Neural Networks", *Water Resour. Manage.*, 18(2), 143-161.

Nash, J.E. and Sutcliffe, J.V. (1970). River flow forecasting through conceptual models part 1 - a discussion of principles. *J. Hydrol.*, 10: 282–290.

Othman, F. and Naseri, M. (2011). Reservoir inflow forecasting using artificial neural network. *Inter Journal of the Physical Sciences*. 6(3):434-440.

Parasuraman, K., Elshorbagy, A. and Carey, S.K. (2006). "Spiking modular neural networks: A neural network modeling approach for hydrological processes." *Water Resour. Res.* 42, W05412, 1-14.

Prada-Sarmiento, F. and Obregon-Neira, N. (2009). "Forecasting of monthly streamflows based on Artificial Neural Networks." *J. Hydrol. Engrg.*, 14(12), 1390-1395.

Rajurkar, M.P., Kothari, U.C. and Chaube, U.C. (2002). Artificial neural network for daily rainfall-runoff modelling. *Hydrological Science J*, 47(6):885-877.

Rajurkar, M.P., Kothyari, U.C. and Chaube, U.C. (2004). Modeling of the daily rainfall-runoff relationship with artificial neural network, *J. Hydrol.*, 285, 96–113.

Rajurkar, M.P. and Ojha, S. (2005). Application of ANN for daily rainfall runoff modeling. *Geophysical Research* Abstracts, 7.

Reggiani, P. and Rientjes, T.H.M. (2005). Flux parameterization in the representative elementary watershed approach: Application to a natural basin, *Water Resour. Res.*, 41 (4), W04013.

Reggiani, P., Sivapalan, M. and Hassanizadeh, S.M. (2000). Conservation equations governing hillslope responses: exploring the physical basis of water balance, *Water Resour. Res.*, 36 (7), 1845–1863.

Rientjes, T.H.M.(2004). Inverse modelling of the rainfall-runoff relation; a multi objective model calibration approach, Ph.D. thesis, Delft University of Technology, Delft, The Netherlands.

Sarkar, A. and Kumar, R. (2012). Artificial Neural Networks for Event Based Rainfall-Runoff Modeling, *J. of Water Resource and Protection*, 4: 891-897.

Solaimani, K. (2009). Rainfall-runoff Prediction Based on Artificial Neural Network (A Case Study: Jarahi Watershed), *American-Eurasian J. Agric. & Environ. Sci.*, 5 (6): 856-865.

Sudheer, K.P., Nayak, P.C. and Ramasastri, K.S. (2003). "Improving peak flow networks: A neural network modeling approach for hydrological processes." *Water Resour. Res.* 42, W05412, 1-14.

Smith, J. and Eli, R.N. (1995). Neural-network models of rainfall-runoff process, *J. Water Resour. Plng. Mgmt.*, 121 (6), 499–508.

Sajikumar, N. and Thandaveswara, B.S. (1999). A non-linear rainfallrunoff model using an artificial neural network, *J. Hydrol.*, 216,32–55.

Shamseldin, A.Y. (1997). Application of a neural network technique to rainfall-runoff modelling, *J. Hydrol.*, 199, 272–294.

Thirumalaiah, K. and Deo, M.C. (2000). Hydrological forecasting using neural networks, *J. Hydrol. Eng.*, 5 (2), 180–189.

Tokar, A.S. and Johnson, P.A. (1999). Rainfall-runoff modeling using artificial neural networks, *J. Hydrol. Eng.*, 4 (3), 232–239.

Tokar, A.S. and Markus, M. (2000). Precipitation-runoff modeling using artificial neural networks and conceptual models, *J. Hydrol. Eng.*, 5 (2), 156–160.

Toth, E., Brath, A. and Montanari, A. (2000). Comparison of short-term rainfall prediction models for real-time flood forecasting, *J. Hydrol.*, 239, 132–147.

Toth, E. and Brath, A. (2007). "Multistep ahead streamflow forecasting: Role of calibration data in conceptual and neural network modelling." *Water Resour. Res.*, 43(11), W11405, doi:10.1029/2006WR005383.

Vos, N.J. and Rientjes, T.H.M. (2005). Constraints of artificial neural networks for rainfall-runoff modelling: trade-offs in hydrological state representation and model evaluation. *Hydrology and Earth System Sciences*, 9: 111-126.

Zealand, C.M., Burn, D.H., and Simonovic, S.P. (1999). Short term streamflow forecasting using artificial neural networks. *J. Hydrol.*, 214(1-4), 32-48.

Zhang, B. and Govindaraju, R.S. (2000). "Prediction of watershed runoff using Bayesian concepts and modular neural networks." *Water Resour. Res.*, 36(3), 753-762.

VITA

1. Name of student : **Pundlik Anuja Dinanath**
2. Date of birth : 20/10/1988
3. Name of the college : PGI, Dr. PDKV, Akola
4. Residential address : At post, Tal.:Jalgaon (Jamod).
   Dist.: Buldana.
   State: Maharashtra, 443402.
5. Academic qualifications :

Sr. No.	Name of degrees awarded	Year in which obtained	Division/ class	Name of awarding university	Subjects
1	B.Tech. (Agril. Engg.)	2010	First	Dr. P.D.K.V., Akola	Agriculture Engineering

6. Research papers published /
   Popular articles (if any) : Two.
   Field of interest : Research and development.

7. E-mail - : aanujapundlik@gmail.com

Signature of student

Place: Akola

Date: 30 / 06/ 2014

(Pundlik Anuja Dinanath)

APPENDIX A

Performance of all RBF ANN models for treatment T1

Following parameters are common in five basic ANN models.

Algorithm : RBF, LM   Trg :CV: Tset : 60-20-20

Output : Simulated Runoff   Epoch: 100

Transfer function: Hidden layer – Sigmoid;   Output layer – Linear Tanaxon

Table A1: Statistical performance of Model 1

Inputs: Current day rainfall

No. of nodes in hidden layer	R^2_{NS}	PI
1	0.751	0.858
2	0.503	0.717
3	0.009	0.436
4	0.435	0.679
5	0.447	0.686
6	0.032	0.450
7	-0.700	0.033
8	0.739	0.857
9	0.600	0.773
10	**0.771**	**0.869**

Table A2: Statistical performance of Model 2

Inputs: Current day rainfall, one day ahead runoff

No. of nodes in hidden layer	R^2_{NS}	PI
1	-0.585	-0.029
2	0.784	0.86
3	-0.538	0.0009
4	-0.851	-0.202
5	**0.826**	**0.887**
6	0.647	0.771
7	0.510	0.682
8	0.767	0.867
9	-0.065	0.393
10	0.794	0.883

Table A3: Statistical performance of Model 3

Inputs: Current day rainfall, one day ahead rainfall, one day ahead runoff

No. of nodes in hidden layer	R^2_{NS}	PI
1	0.158	0.453
2	**0.859**	**0.908**
3	-0.292	0.161
4	0.953	-0.046
5	0.983	0.632
6	0.994	0.883
7	-0.609	-0.044
8	0.527	0.693
9	-0.792	-0.163
10	-0.186	0.229

Table A4: Statistical performance of Model 4

Inputs: Current day rainfall, one day ahead rainfall, two day ahead rainfall, one day ahead runoff

No. of nodes in hidden layer	R^2_{NS}	PI
1	-0.836	-0.056
2	0.247	0.566
3	-0.647	-0.075
4	**0.818**	**0.895**
5	-0.127	0.351
6	0.590	0.764
7	0.763	0.864
8	0.818	0.895
9	0.500	0.712
10	0.704	0.829

Table A5: Statistical performance of Model 5

Inputs: Current day rainfall, one day ahead rainfall, two day ahead rainfall, one day ahead runoff, two day ahead runoff

No. of nodes in hidden layer	R^2_{NS}	PI
1	0.729	0.846
2	0.546	0.742
3	0.496	0.713
4	0.580	0.761
5	-0.787	-0.015
6	0.770	0.869
7	0.701	0.830
8	0.205	0.548
9	0.689	0.823
10	**0.862**	**0.921**

Following parameters are common in five ANN models.

Algorithm : RBF, Momentum Trg :CV: Tset – 60-20-20

Output : Simulated Runoff

Transfer function: Hidden layer – Sigmoid; Output layer – Linear Tanaxon

Table A6: Statistical performance of Model 6

Inputs: Current day rainfall, one day ahead rainfall, two day ahead rainfall, one day ahead runoff, two day ahead runoff

Epoch: 50

No. of nodes in hidden layer	R^2_{NS}	PI
1	-0.031	0.342
2	0.087	0.418
3	-0.069	0.318
4	**0.112**	**0.434**
5	0.046	0.392
6	-0.010	0.356
7	0.054	0.397
8	-0.411	0.100
9	-0.138	0.274
10	-0.100	0.298

Table A7: Statistical performance of Model 7

Inputs: Current day rainfall, one day ahead rainfall, two day ahead rainfall, one day ahead runoff, two day ahead runoff

Epoch: 100

No. of nodes in hidden layer	R^2_{NS}	PI
1	0.099	0.426
2	**0.986**	**0.675**
3	0.111	0.433
4	0.162	0.466
5	0.165	0.468
6	0.054	0.397
7	0.110	0.433
8	-0.910	-0.277
9	0.060	0.401
10	0.065	0.404

Table A8: Statistical performance of Model 8

Inputs: Current day rainfall, one day ahead rainfall, two day ahead rainfall, one day ahead runoff, two day ahead runoff

Epoch: 200

No. of nodes in hidden layer	R^2_{NS}	PI
1	0.014	0.371
2	0.037	0.387
3	0.066	0.405
4	0.103	0.428
5	**0.217**	**0.501**
6	0.0006	0.363
7	0.095	0.423
8	-0.407	0.103
9	0.053	0.397
10	-0.043	0.335

Table A9: Statistical performance of Model 9

Inputs: Current day rainfall, one day ahead rainfall, two day ahead rainfall, one day ahead runoff, two day ahead runoff

Epoch: 250

No. of nodes in hidden layer	R^2_{NS}	PI
1	0.107	0.431
2	0.024	0.378
3	-0.194	0.239
4	-0.013	0.354
5	0.041	0.389
6	-0.015	0.352
7	-0.082	0.310
8	**0.242**	**0.517**
9	0.213	0.498
10	-0.703	-0.085

Table A10: Statistical performance of Model 10

Inputs: Current day rainfall, one day ahead rainfall, two day ahead rainfall, one day ahead runoff, two day ahead runoff

Epoch: 300

No. of nodes in hidden layer	R^2_{NS}	PI
1	0.088	0.419
2	0.022	0.377
3	0.182	0.479
4	-0.043	0.335
5	0.067	0.406
6	0.044	0.391
7	0.096	0.424
8	-0.521	0.030
9	**0.274**	**0.537**
10	-0.411	0.100

Table A11: Statistical performance of Model 11

Performance of RBF ANN models for treatment T2

Following parameters are ANN model.

Algorithm : RBF, LM Trg :CV: Tset – 60-20-20

Output : Simulated Runoff Epoch: 100

Transfer function: Hidden layer – Sigmoid; Output layer – Linear Tanaxon

Inputs: Current day rainfall, one day ahead rainfall, two day ahead rainfall, one day ahead runoff, two day ahead runoff

No. of nodes in hidden layer	R^2_{NS}	PI
1	-1.00	-0.17
2	0.84	0.91
3	0.77	0.87
4	0.87	0.92
5	0.93	0.96
6	0.11	0.48
7	0.68	0.81
8	0.28	0.58
9	0.87	0.93
10	**0.91**	**0.95**

Table A12: Statistical performance of Model 12

Performance of RBF ANN models for treatment T3

Following parameters are ANN model.

Algorithm : RBF, LM Trg :CV: Tset – 60-20-20

Output : Simulated Runoff Epoch: 100

Transfer function: Hidden layer – Sigmoid; Output layer – Linear Tanaxon

Inputs: Current day rainfall, one day ahead rainfall, two day ahead rainfall, one day ahead runoff, two day ahead runoff

No. of nodes in hidden layer	R^2_{NS}	PI
1	-0.96	-0.16
2	0.68	0.81
3	0.89	0.93
4	0.00	0.40
5	**0.89**	**0.93**
6	0.86	0.91
7	0.79	0.88
8	-0.95	-0.16
9	0.87	0.92
10	0.77	0.86