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Project Report

On

RAINFALL-RAINOFF MODELLING USING ARTIFICIAL NEURAL NETWORK

आपो हि ष्ठा मयोभुवः

Conducted at National Institute of Hydrology, Roorkee

Uttarakhand

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CERTIFICATE

This is to certify that **Miss. Priyanka Gaurav** has undergone a project work on "**Rainfall-Runoff modelling by using ANN**" from 1stnovember, 2014 to 30thapril, 2016 as a six months training submitted to the Research Management and Outreach Division, National Institute of Hydrology, Roorkee,in partial fulfillment of the requirement for the award of degree of "**Master of Technology"** in **Civil Engineering** specialization in **Environmental Engineering** is the original work carried out by her under our supervision and guidance.

A. R. Senthilkumar 02/05/16

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My diction would be ina[illegible]uate to express my deepest sense of gratitude and heartfelt thanks to my guide [illegible] ***Shobha*** [illegible]***,*** *for* his support and *for spending out his precious and valuable time and consistently guiding me throughout my training period.* suggestion and blessings.

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[illegible]

ABSTRACT

The runoff means the draining or flowing off of precipitation from a catchment area through a surface channel. There are three types of runoff namely direct runoff, baseflow runoff, and natural flow runoff. The relationship between rainfall-runoff is one of the most complex hydrological phenomena to comprehend the spatial and temporal variability of watershed characteristics and precipitation patterns and also to the number of variable involved in the modelling of the physical process. By ANN modelers the problem of rainfall runoff modelling has received maximum attention.In this report, the application of Artificial Neural Network model (ANN) and a model combining the multiple layer regression (MLR) is investigated to make the ANN model using rainfall-runoff data of Hamp river, Chattisgarh. The rainfall in the catchment area Chirapani, Bodla, and Panadariya and the hourly discharge data is used to carry out this research work. The duration of data used is from 1881 to 2009. The RMSE of ANN model during calibration and validation was found to be 0.9721 and 0.9896 respectively, whereas for the MLR model, RMSE value during calibration and validation was 0.9628 and 0.9648 respectively, and also the ANN model efficiency during calibration and validation was 0.9449 and 0.9794 respectively, whereas the MLR model efficiency during calibration and validation was 0.9271 and 0.9307 respectively, indicates a substantial improvement in the model performance.In addition, comparison of the scatter plots of ANN model are more precise than those found by the MLR.

CONCLUSION

The relationship between rainfall-runoff is one of the most complex hydrological phenomena to comprehend the spatial and temporal variability of watershed characteristics and precipitation patterns and also to the number of variable involved in the modelling of the physical process. In this study,the ANN model has been developed to predict the rainfall runoff. The rainfall in the catchment area Chirapani, Bodla, and Panadariya and the hourly discharge data is used to carry out this research work. The duration of data used is from 1881 to 2009.

The MLR model is developed by using decomposed signals of rainfall, runoff and as input data. The statistical indices such as coefficient of correlation, root mean squared error (RMSE) and model efficiency have been used to evaluate the performance of the both the models.

The analysis of the performance of the both ANN and MLR models clearly indicate that the application of ANN helps in the better prediction of rainfall runoff. Moreover, MLR when combined with ANN was able to substantially enhance the performance of the model. A comparison of results obtained by the ANN model.

The RMSE of ANN model during calibration and validation was found to be 0.9721 and 0.9896 respectively, whereas for the MLR model, RMSE value during calibration and validation was 0.9628 and 0.9648 respectively, and also the ANN model efficiency during calibration and validation was 0.9449 and 0.9794 respectively, whereas the MLR model efficiency during calibration and validation was 0.9271 and 0.9307 respectively, indicates a substantial improvement in the model performance. In addition, comparison of the scatter plots of ANN model are more precise than those found by the MLR.

CONTENTS

CHAPTER 1

INTRODUCTION

1.1.BACKGROUND OF ARTIFICIAL NEURAL NETWORKS

In 1943 the first step towards ANN came by Warren Mcculloch a neurologist. He showed that even a simple type of neural networks could compute any arithmetic or logical function. Hebb was a researcher he wrote a book in 1949 entitled "The organisation of behaviour" which pursued the idea classical psychological conditioning is ubiquitous in animals which is the properties of individual neurons. Hebb took this idea further than anyone before. In the 1940s and early 1950s so many other peoples were examining the issues surrounding the neuro computing. In 1957 and 1958 the first successful neuro computer was developed by frank Rosenblatt, Charles Wightman and others. The Rosenblatt is known as the founder of neuro computing. During 1970s, so many leaders began to publish their work including Amari, Fukushima, Grossberg and klopf and Gose. They were those who put the field of neural network on a firm footing. many neuro computing researcher became bold enough to begin submitting proposals in early 1980s to explore the development of neuro computers and of neural network applications. John Hopfield (in the 1983-1986) was an physicist of worldwide reputation. He had become interested in neural network a few years earlier.

1.2 Analogy between ANNs and nervous systems:-

From our best guesses of working of the nervous system of human and animals the ANN techniques are developed. Operation of ANNs and a nervous system like brain is resemble to each other. From the different locations in the networks the information could be received b the biological neural networks like nervous systems. When the neural networks senses the information, then this information is start to move from neuron ton neuron through the networks and after the reaching the information the proper response is generated. By releasing chemicals the biological neurons passes the information to each other and it's causes a connecton between neurons. (ref N.J.DE.VOS 2003)

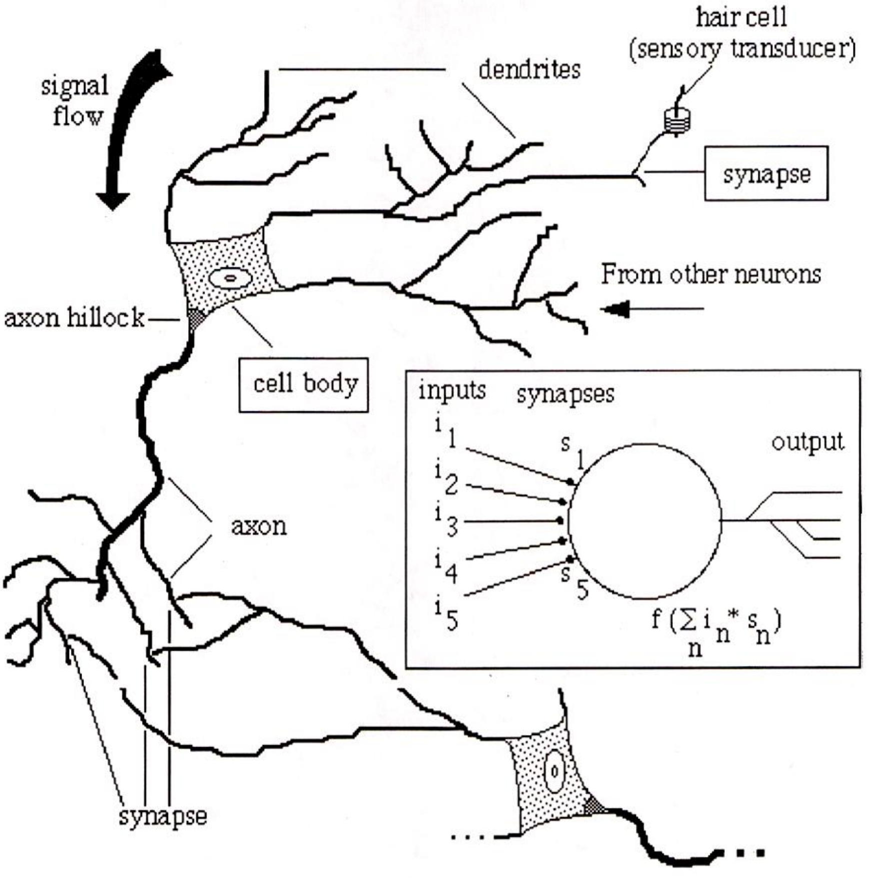


Fig.1.1:- analogy b/w nervous sytem an ANN(ref. google images)

1.3. ABOUT ARTIFICIAL NEURAL NETWORK

A family of models inspired by biological neural networks is called an artificial neural network. ANN are used to estimate that can depend on a large number of input and inputs are generally unknown. As neurons are exchanging the message between each other in our body, the role of ANN is same as neurons which are generally presented as systems of interconnected 'neurons'. The connection in ANN models have numeric weight that can be tuned based on experience. In recent years, an artificial neural network has been used in many areas for forecasting in science and engineering. The main advantage to choose the ANN over the traditional methods of modelling is that there is no requirement of complex nature of the underlying process under consideration to be explicitly described in mathematical terms. So many applications are use multilayer perceptron (MLP) type ANNs with the error back propagation(BP) techniques which leads to MLP/ BP MODELS that are non-linear in the parameters. The backpropagation is a gradient descent search technique that may descend to a suboptimal solution to the problem. In the transfer function of its hidden layer nodes the radial basis functions (RBF) network has the non-linearity embedded. For real situation the RBF networks based model have been developed to make the prediction of flow. The approach of artificial neural network (ANN) are differ from the traditional approaches in stochastic hydrology in the sense that it is belongs to a class of the data-driven approaches as opposed to traditional model driven approaches. The neural network was developed by using the generalized delta rule for a semi-linear feed forward net with error back propagation. The code of program was written in C in UNIX environment. The neural network model was treated as a Black Box, and relationships between the physical components of the catchment were not to be fed. The number of input nodes, N, and the number of output nodes, M, in an ANN are dependent on the problem to which the network is being applied. Unfortunately, there are no fixed rules as to how many nodes should be included in the hidden layer. If there are too few nodes in the hidden layer the network may have difficulty generalizing to problems it has never encountered before. On the other hand, if there are too many nodes in the hidden layer, the network may take an unacceptably long time to learn anything of any value. Different numbers of hidden nodes were used in the networks developed in this study for rainfall-runoff modelling. The best results are presented later.

1.3.1. Standard Feedforward

Most mapping networks can be designated standard feedforward networks. The number of variations of these ANNs is vast. The most important characteristic of standard feedforward networks is that the only types of connections during the operational phase are feedforward connections. Note that during the learning phase feedback connections do exist to propagate output errors back into the ANN .A standard feedforward network may be built up from any number of hidden layers, or there may only be input units and an output layer. The training algorithm used can be any kind of supervised learning algorithm. All other ANN architecture parameters (number of neurons in each layer, activation function, use of a neuron bias, et cetera) may vary.

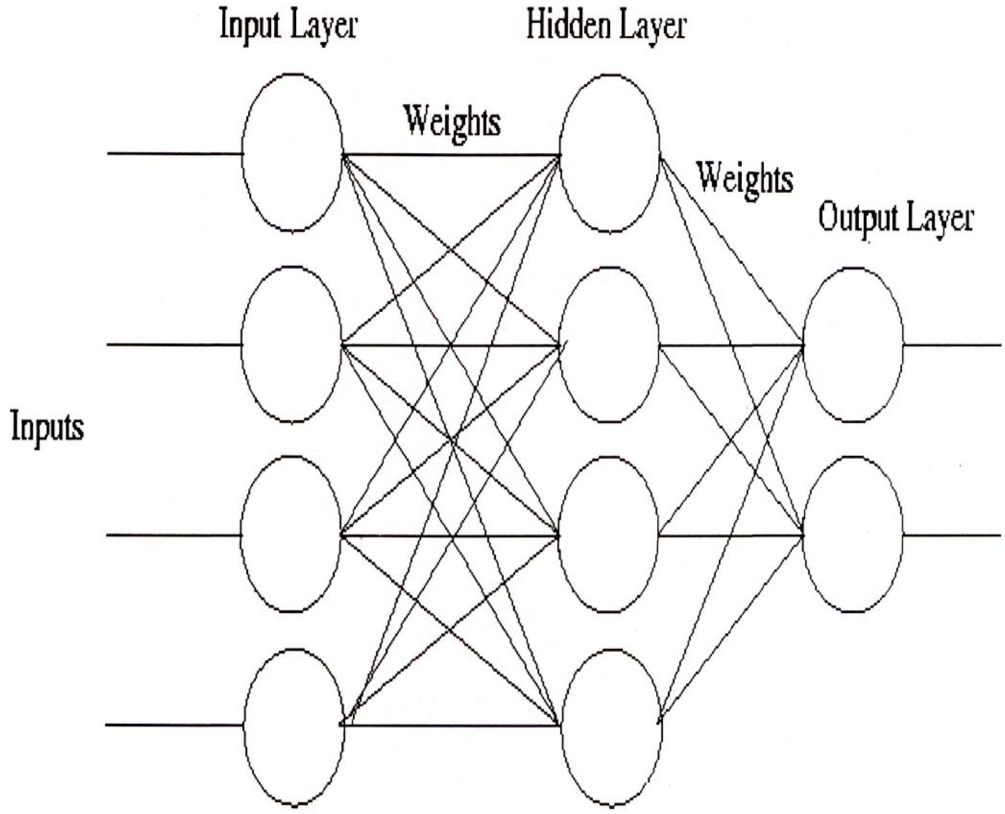


Fig:1.2. standard feed foreward(google image)

1.3.2. Multilayer Perceptron

Feedforward networks with one or more hidden layers are often addressed in literature as multilayer perceptron (MLPs).This name suggests that these networks consist of Perceptron (named after the Perceptron neurocomputer developed in the 1950's,.The classic Perceptron is a neuron that is able to separate two classes based on certain attributes of the neuron input. Combining more than one perceptron results in a network that is able to make more complex classifications. This ability to classify is partially based on the use of a hard limiter activation function .The activation function of neurons in feedforward networks, however, is not limited to just hard limiter functions; sigmoid or linear functions are often used too. And there are often other differences between perceptron and other types of neurons. From this we can conclude that the name MLP for multilayer feedforward networks consisting of regular neurons (not perceptron, which are neurons with specific properties) is therefore basically incorrect. To avoid misunderstandings, the author will not use the term MLP for a standard feedforward networks with one or more hidden layers.

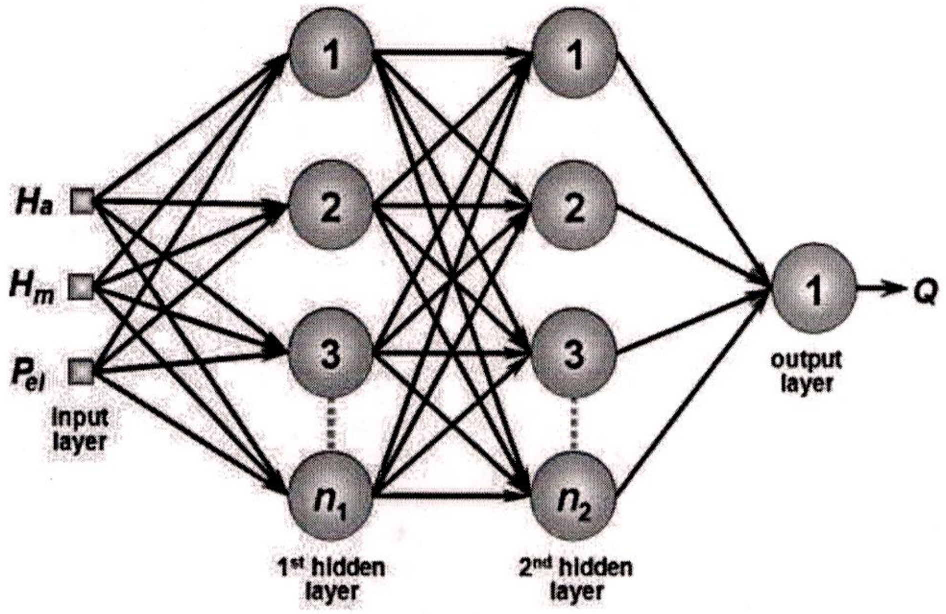


Fig:1.3. multilayer perceptron(MLP)

1.3.3. Backpropagation Algorithm

Feedforward networks are sometimes referred to with a name that is derived from the employed training algorithm. The most common learning rule is the backpropagation algorithm. An ANN that uses this learning algorithm is consequently referred to as a backpropagation network (BPN).One must bear in mind, however, that different types of ANNs (other than feedforward networks) can also be trained using the backpropagation algorithm. These networks should never be referred to as backpropagation networks, for the sake of clarity. It is for the same reason, that the author will not use a term such as 'backpropagation network' in this report, but will refer to such an ANN by its proper name: backpropagation-trained feedforward network.

1.3.4. The Radial Basis Function

The Radial Basis Function (RBF) network is a variant of the standard feedforward network. It can be considered as a two-layer feedforward network in which the hidden layer performs a fixed non-linear transformation with no adjustable internal parameters. The output layer, which contains the only adjustable weights in the network, then linearly combines the outputs of the hidden neurons.The RBF network is trained by determining the connection weights between the hidden and output layer through a performance training algorithm.The hidden layer consists of a number of neurons and internal parameter vectors called 'centres', which can be considered the weight vectors of the hidden neurons. A neuron (and thus a centre) is added to the network for each training sample presented to the network. The input for each neuron in this layer is equal to the Euclidean distance between an input vector and its weight vector (centre), multiplied by the neuron bias. The transfer function of the radial basis neurons typically has a Gaussian shape. This means that if the vector distance between input and centre decreases, the neuron's output increases (with a maximum of 1). In contrast, radial basis neurons with weight vectors that are quite different from the input vector have outputs near zero. These small outputs only have a negligible effect on the linear output neurons.

1.4. RAINFALL-RUNOFF MODELLING USING ANN

The runoff means the draining or flowing off of precipitation from a catchment area through a surface channel. There are three types of runoff namely direct runoff, base flow runoff, and natural flow runoff. The relationship between rainfall-runoff is one of the most complex hydrological phenomena to comprehend the spatial and temporal variability of watershed characteristics and precipitation patterns and also to the number of variable involved in the modelling of the physical process. There are lots of models are designed to overcome the problems of rainfall runoff modelling but their predictions gives more error and unsatisfactory results, out of these other models the ANN has received maximum attention because the ANN gives less error and satisfactory results. Since the mid of 19th century was the last decade when the ANN models have been applied to the rainfall-runoff modelling. Existing methods used to estimate runoff from rainfall are frequently classified into two groups viz., Black Box model and Process model (Todini, 1988). In the black box modelling approach, empirical relations are used to relate runoff and rainfall, and only the input (rainfall) and the output (runoff) have physical meanings. Simple mathematical equations, time-series methods and neural networks methods fall into this category. Process models attempt to simulate the hydrological processes in catchments and involve the use of many partial differential equations governing various physical processes and equations of continuity for surface and soil water flow. Conceptual rainfall-runoff models (Chiew et.al., 1993) can be considered as a third group of modelling approach.

1.5. APPLICATIONS OF ANN

The following applications of ANN are:-

- By usin simple hand motion-lean back the ANN cn skip tracks or control volume on media player.
- Function approximation or regression analysis, including time series prediction or modelling.
- Call control, for example 'answer an incoming call with a wave of the hand while driving or working.
- Data processing, including filtering, clustering, blind signal separation and compression.
- Classification, including pattern and sequence recognition, novelty detection and sequential decision making.
- Scroll Web Pages, or within an eBook with simple left and right hand gestures, this is ideal when touching the device is a barrier such as wet hands are wet, with gloves, dirty etc. 7. Application areas of ANNs include system identification and control (vehicle control, process control), game-playing and decision making (backgammon, chess, racing), pattern recognition (radar systems, face identification, object recognition, etc.), sequence recognition (gesture, speech, handwritten text recognition), medical diagnosis, financial applications, data mining (or knowledge discovery in databases, "KDD").
- Another interesting use case is when using the Smartphone as a media hub, a user can dock the device to the TV and watch content from the device- while controlling the content in a touch-free manner from afar.
- If your hands are dirty or a person hates smudges, touch-free controls are a benefit.

1.6. ADVANTAGES OF ANN:-

- Adaptive learning: An ANN has the ability to do work based on the given data for training.
- Self-Organisation: Can prepare its own organisation of the information which received during learning time.
- Real Time Operation: The ANN computations can be done in parallel, and special hardware devices are manufactured and designed which take the advantages of red time operation capability.

- For generalizing and harnessing the information in the data, the pattern recognization is a powerful technique. Neural networks learn how to recognize the pattern that exist in the data set.
- Neural networks systems are developed by learning rather than programming.
- In a changing environment the neural networks are flexible so that, they are excellent to learn a sudden changes.
- Whenever conventional approaches get fail then the neural networks can build informative models. The neural networks can manage the complex interaction so that they can model the data easily, which is so difficult to model with traditional approaches like inferential statics or programming logic.
- The neural networks perform better as compared to classical statistical modelling, and it is better on most problems.

CHAPTER -2

LITERATURE REVIEW

2.1 INTRODUCTION

The rainfall-runoff relationship is highly nonlinear and complex process and it is very important to determine the rainfall-runoff relationship for hydrologic engineering design and management purposes. It is dependent on number of factors such as initial soil mixture, land use, watershed geomorphology, evaporation of rainfall etc. rainfall-runoff models like empirical, lumped and distributed models have been developed and used for the streamflow simulation at the catchment outlet. A family of models inspired by biological neural networks is called an artificial neural network. ANN are used to estimate that can depend on a large number of input and inputs are generally unknown. As neurons are exchanging the message between each other in our body, the role of ANN is same as neurons which are generally presented as systems of interconnected 'neurons'. The connection in ANN models have numeric weight that can be tuned based on experience. In recent years, an artificial neural network has been used in many areas for forecasting in science and engineering. The main advantage to choose the ANN over the traditional methods of modelling is that there is no requirement of complex nature of the underlying process under consideration to be explicitly described in mathematical terms. So many applications are use multilayer perceptron (MLP) type ANNs with the error back propagation(BP) techniques which leads to MLP/ BP MODELS that are non-linear in the parameters. The current study is designed for modelling of rainfall-runoff hourly data of HAMP river which is located in Chattisgarh. In this chapter some review papers are listed so that we can know about past research on ANN and also about development of ANN models. After read some research papers I am became to know the further scope of ANN modelling and development.

2.2 REVIEW

Tokar and Johnson (1999) An artificial neural network methodology was applied to forecast daily runoff as a function of daily precipitation, temperature and snowmelt for the little Patuxent river watershed on Maryland. The content and length of training data was investigated to predict the sensitivity of accuracy. The rainfall-runoff model of artificial neural networks was compared favourably with results which were obtained by using existing techniques like statistical regression and a simple conceptual model. This comparison shows that an ANN model provided higher training and testing accuracy for little Patuxent river, when it was compared with the regression and simple conceptual models.

Tokar^{-1}and Momcilo(2000) In this study, The Artificial neural network models are compared with traditional conceptual models so that it can predict the watershed runoff as a function of rainfall, temperature and snow water . The ANN technique was applied on the Fraser River in Colorado, Raccoon creek in Iowo, and little Patuxent River in Maryland with different climatic and physiographic characteristics. In Fraser River the ANN was used to model monthly streamflow and it was compared with water balance model. In the Raccoon river watershed, to model the daily rainfall-runoff process the ANN techniques was used and then it was compared with the Scromento soil moisture accounting model. In the Patuxent river the daily rainfall-runoff process was modelled using the ANN technique, so that the testing results and training were compared to the all simple conceptual models which are used in comparison of Fraser river and Raccoon river watershed. The artificial neural network model provided higher accuracy in all comparison cases of these three basins. Fraser River provided more accurate monthly streamflow for the Raccoon River, provided reasonably calibrate accuracy. But at the end in the Patuxent river basin the ANN model provides higher accuracy.

Elshorbagy et al. (2000) In the Red river valley in southern Monitoba the spring runoff prediction has been done, because of the devastating effect of the flood in southern Monitoba. The spring runoff prediction is an important issue. In this case the ANN technique is used and then it was compared to linear and nonlinear regression techniques. In this study, the advantage and disadvantage of the three modelling techniques were discussed. After the comparison of ANN technique to the NRA model, the ANN models shows better results than NRA models even the LRA models may prove suitable candidates for consideration.

Jain and Indurthy (2003) In this paper, the investigation of suitability of some deterministic and statistical techniques along with the artificial neural network has been done to made an event based rainfall-runoff process. In this study it has been found that the ANN model is an outer formed conventional models, it provides a good representation of an event-based rainfall-runoff process. The investigation includes the deterministic unit hydrograph theory, static regression and the ANN. The result obtained that the ANN models have been able to predict this information with higher accuracy.

Tokar (1999) The ANN designs perform differently for the effects of seasonal variation of rainfall and runoff and this seasonal variation were investigated for monthly rainfall runoff simulation on 815km^2 water shed in central Oklahoma. The seasonal variation of explicit representation was achieved by using a separate ANN for each month. In this study it is concluded that the way in which the effects of seasonal climate and runoff variations were incorporated in the ANN was the main difference between three designs.

Senthil et al. (2004) developed a model for rainfall-runoff modelling of two Indian River basins by comprehensive evaluation of the performance of MLP and RBF type neural network models. The comparison was made between RBF and MLP type neural networks. the model prediction accuracy was based on the choice of the type of networks after a long trial and procedure. The optimum number of hidden neuron is to be fixed for MLP whereas the OLS algorithm was fixed for RBF networks. When comparison was made the RBF networks shows the poor generalised properties than those of MLPs in rainfall-runoff models.

Sudheer et al. (2000) the purpose of this paper study was to present an ANN models for rainfall-runoff process for one of Indian basin. Also this paper ia showing the comparison of the performance of back propagation(BP) and radial basis function (RBF) type neural networks for representing the complex rainfall-runoff process. These two ANN models (BP and RBF) were developed for Baitrani River basin and each model were compared with each other. They conclude that the already popular

ANN model have a viable alternative RBF network for rainfall-runoff process which uses the back propagation algorithm for training. Model provided higher training and testing accuracy for little Patuxent river, when it was compared with the regression and simple conceptual models.

Smith and Eli (1995) The Neural-network models hold the possibility of circumventing these difficulties by training the network to map rainfall patterns into the measures of runoff that could be of interest. To investigate the potential of this approach, a very simple 5 x 5 grid cell synthetic watershed is used to generate runoff from stochastically generated rainfall patterns. The performance of the training network and testing using a single rainfall pattern time of peak and to predict the discharge peak of the resulting runoff hydrographs was in the range of expected value. The unexpected exceptional performance demonstrated by the networks' ability to predict the resulting Fourier coefficients, but confirmed the earlier hypothesis concerning information content in the output.

Karim solaimani(2009) The aim of the study is to utilize the artificial neural network to modelling the relationship of rainfall runoff in catchment area are located in a semiarid region of Iran. This paper illustrate the application of the feedforward back propagation with various algorithm with performance of MLP for the rainfall forecasting. In this research paper the research explored the capabilities of ANNs and the ANN tool's performance that would be compared to the conventional approaches which is used for stream flow forecast. After this performance the ANN models shows the appropriate capability to model hydrological process. It is concluded that the ANN tools are very useful and powerful tools to handle the various complex problems as compared to other traditional models. The result shows that the ANNs has the capability to modelling the rainfall runoff relationship in the arid and semiarid region where the rainfall and runoff are very irregular.

Hsu et ol.(1995) to identiying the structure and the parameters of three layered feed forward ANN models and to demonstrated the potential of ANN models for the nonlinear hydrologic behaviour of watersheds simulation the linear least square simplex(LLSSIM) procedure is used. In this study it was shown that the non-linear ANN hydrologic model gives better performance than linear ARMAX (autoregressive moving average with exogenous input) time series approach and the conceptual SAC-SMMA(sacramento soil moisture accounting)model. It was concluded that, in any catchment where the modelling of the physical process was not so important the ANN approach could be used as substitute of conceptual model.

Raman and Sunil kumar(1995)they used artificial neural network for the synthesis of inflows to Mangalam and Pothundy reservoirs located in the Bharathapuzha, Kerala. In this paper the real observations were used to feed forward network training and testing. To model the ANN the feed forward structure was used and the backpropagation algorihm was used to train the data set. It was shown that the neural network provided a very good fit with the data. The ANN model's results were compared with AR model. It was concluded that the ANN model could be used to water resources time series modelling in place of multivariate modelling.

Minns and Hall(1996) they developed the artificial neural network model to runoff simulation from rainfall and they also compared with conceptual hydrological model consisting single linear reservoir. It was concluded that the increase of hidden layer neuron did not give better results as compared o the one with less number of neurons.

Dawson and Wilby(1998) In this paper the rainfall runoff modelling is to be done by using ANN approach in two flood prone catchment area in UK with real hydrometric data. The ANN performance was compared with the conventional flood forecasting system. To model the flood forecasting system the multi-layered feed forward network structure was used and for training the network combination, the back propagation algorithm was used. It was concluded that there was considerable scope for development of ANN flood forecasting systems.

Sajikumar and Thandeveswara(1999) developed the mothly rainfall-runoff model by using temporal back propagation neural network(TBPNN) and also compared the model with the results of Volterra type functional series model. It was found that the TBPNN performed better than the other model and the model was applied to Thuthapuzh river in Kerala, India and Lee river in UK.

Elshorbogy et al.(2000) To predict spring runoff in the Red River valley(southern Manitoba,Canada)by using ANN they used feed forward neural network structure and to model the spring runoff the feed forward neural network structure was used. To train the network the back propagation training algorithm was used and also the linear and non-linear regression models were constructed. They were concluded that the

ANN models demonstrated superiority in most cases and also concluded that the performance of the other two techniques was comparable.

Raghuwanshi et al(2006) ANN model were developed for predicting runoff for a small catchment in INDIA on daily and weekly basis. LevenbergMarquart back propagation algorithm were used to train the Artificial neural network models. Developed the regression models and also compared with the performance of ANN models. It is concluded that the ANN models were performed better than linear regression model.

Jurgen D.Garbrecht(2006) Investigate the seasonal rainfall and runoff variation for monthly rainfall-runoff simulation on an 815km^2 watershed in central OKLAHOMA,wiyh the performance of three artificial neural network (ANN) designs for monthly rainfall-runoff simulation. Explicit representation of seasonal variations was achieved by use of a separate ANN for each calendar month. The results shows that the ANN designs that accounted explicity for seasonal variations of rainfall and runoff performed best by all performance measured. It was concluded that comparision of three different ANN designs for monthly rainfall-runoff simulation was correction of the simulated runoff could be applied to further enhance runoff simulation performance.

Ms. Sonali. B. Maind and Ms. Priyanka Wankar (2014) In this study they gives the overview of training and working of ANN. This paper gives the advantages and applications of ANN . An ANN is inspired by the biological nervous system such as the human brain. It was concluded that the ANN is the quick and relatively easily phenomena so, that an ANN can capture many kinds of relationships and it is also proved that this kind of technologies will works in future.

Rahul P. Deshmukh(2010) Used time lagged and general recurrent neural network for rainfall-runoff modelling for Wardha River, India. For generating the model the processing of online data over time is done using general recurrent connections. The comparison was made between both the short term runoff prediction. It was concluded that the performance of time lagged recurrent neural network is satisfactory for 3-h lead time. they also concluded that For short time runoff time lagged recurrent neural network is a good tool.

Gurjeet singh et. Al(2015) In this study the modelling of daily runoff from small agricultural watershed Kapigari in Eastern INDIA having drainage area of 973ha by using artificial neural network with resampling techniques was reported. By the use of ANN technique an attempt was made in eastern INDIA to relate the continuously monitored runoff data from sub watersheds and the whole watersheds for the rainfall. To find the optimum number of neuron in the hidden layers A 10-fold Cross validation techniques was used. By using a 10-fold cv method the results shows that the artificial neural networks models were stablished with shorter length of training data set neglect the neural network over fitting during the training process and also the biasness was investigated by using the bootstrap resampling technique based ANN(BANN) for short length of training data set. It was also concluded that the BANN gives more efficiency in solving the over-fitting and under-fitting problems.

Kumar et al(2007) For seasonal rainfall prediction and individual months rainfall prediction they adopted ANN by using climate indices as predictor variables.

Karamouz et al(2009) In this paper the comparison between ANN and statistical down-scaling model(SDSM) has been done so that they predict the rainfall. After the comparison they conclude that the SDSM gives the better performance than ANN , and it is also conclude that the SDSM is more intensive in comparison to ANN.

Sahai et al.(2000) The ANN was used to predict the monsoon river of seasonal and monthly mean summer over the INDIA. They used only rainfall time series as input.

Fernando and Jayawardena(1998) The ANN rainfall-runoff model was developed by Fernando and Jayawardena, they used hourly data of rainfall and runoff for an catchment area in Kamhonsa in JAPAN. To decide on the input vector they presented a qualitative examination of the cross-correlation between the rainfall and runoff.

Hsieh et al(2003) To predict the seasonal volume of the Columbia river Hsieh et al used the Multiple layer regression(MLR) model and feed forward(FF) ANN models using the principal components of large-scale climatic indices. The prediction of MLR and ANN were identical, It was implying that, in the short sample size the detectable relationships were lin.

CHAPTER-3

AREA AND DATA USED

3.1. STUDY AREA

3.1.1. MAHANADI BASIN:-

The major river in East central INDIA is Mahanadi which drains an area of about 141,600 square kilometeres (54,700sq mi.). It has a total course of 858 kilometeres (533mi). The Mahanadi flows through Chattisgarh and Odisha. The Mahanadi word comes from two Odia words 'maha' and 'nadi' which means 'The great river', Mahanadi rises from Raipur and the Raipur is the district of Chattisgarh. Mahanadi rises from Sihawa mountain of Chattisgarh province and debouched into the Bay of Bengal in Orissa province (Pradeep sea port). The starting point of Mahanadi is near Sihawa in the Amarkantaka mountains of chattisgarh. The Mahanadi changes the course from southeast to south near boudh town while after passing few killometeres it takes a southeastern course again. The total length of river since its origin is 832km out of which only 77kms crosses on southwest periphery. The main tributaries of Mahanadi are Tndula, Kharum, Amner, Surhi, Hamp, Arpa and Lilagar etc.

Length= 858km

Discharge= 2,119 m^3/s

Basin area= 141,600km^2

Source= sihawa

Country= India

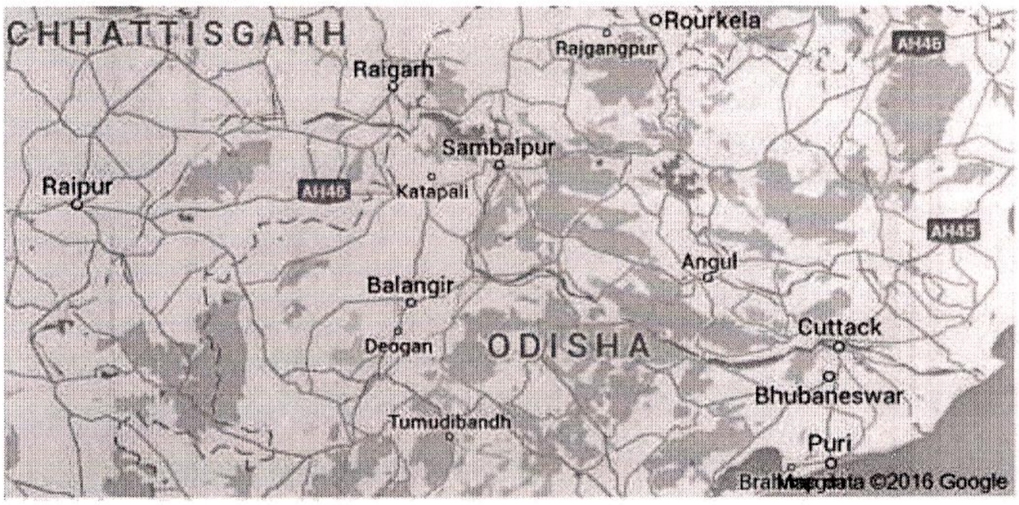
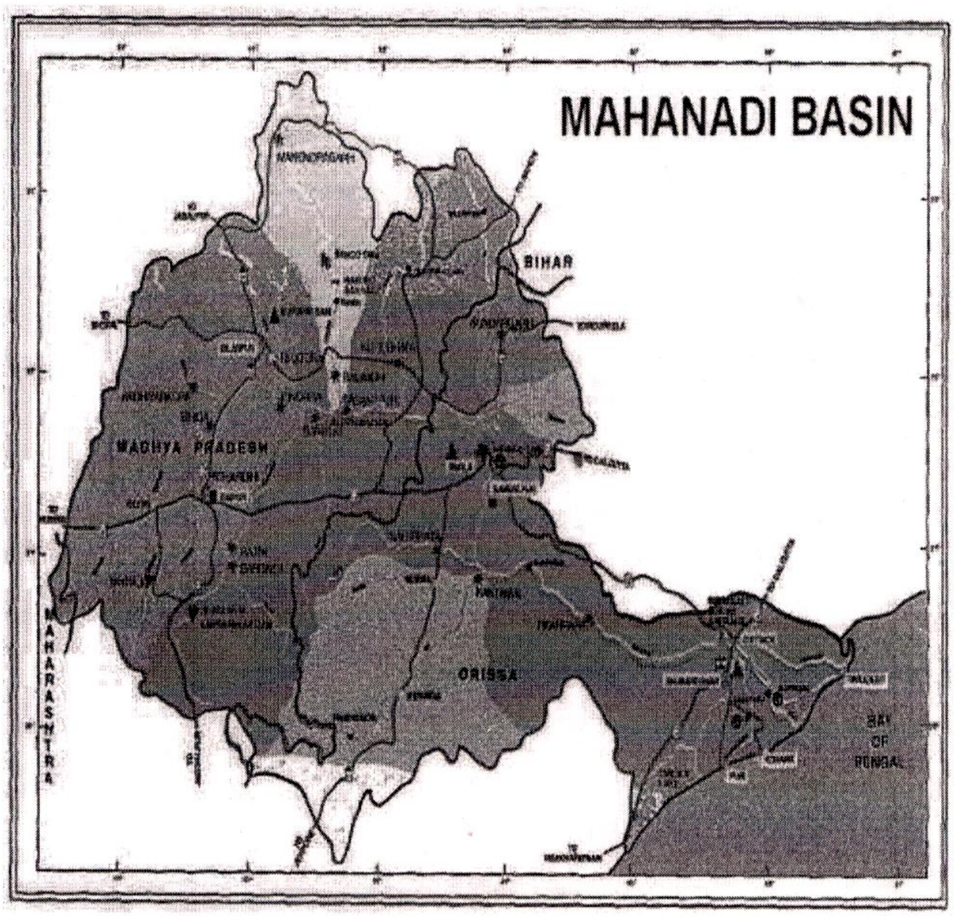


Fig:3.1 chattisgarh map (ref. GOOGLE images)



PROJECTS :Existing, Ongoing, Under Consideration

OBSERVATION SITES :Gauge(G), Gauge Discharge(GD), Gauge Discharge Sediment(GDS), Gauge Discharge Water Quality (GWQ), Gauge Discharge Sediment Water Quality(GDSQ), Flood Forecasting(FF)

STATE CAPITALS :

Fig:3.2 Mahanadi basin (ref. GOOGLE images)

During the monsoon season the Mahanadi basins receives the 90% of its rainfall. Because of cyclones the formation of depression takes place in Bay of Bengal which results the heavy rainfall, floods and destruction. Around the Mahanadi basins, there are about 149IMD raingauge stations. In the Mahanadi basin the coldest and hottest months are may and December. 42.7°C temperature was recorded at Titlagarh in May which was the highest monthly mean maximum temperature and the 84°C temperature was recorded at Ambikapur and this temperature was the lowest monthly mean minimum temperature. Total drainage area of Mahanadi basin is 141,589km^2, the maximum drainage area is Chattisgarh is around 75,136km^2. In Mahanadi, the main soil types are found namely red soil and yellow soil. Lateriate soil, black soil, alluvial soils , mixed red soil and black soils are the other soils are found in Mahanadi river. In this basin , the flood is the very big problem which has been observed, particularly in delta areas.

3.1.1. SEONATH RIVER(sub-basin of Mahanadi)

Seonath river rise from Panabaras village in Rajnand gaon district. Te latitude of the basin is located between 200 16' N to 22041'N and the longitude is located between 80025'E to 82035'E. The area is 30,860sqkm. The length of river traverse is 380Km. Tendula, Kharum, Arpa, HAMP, Agar and Maniyari ar the main tributaries of Seonath river. The variation of mean annual rainfall in the basin from 1005mm to 1255mm.

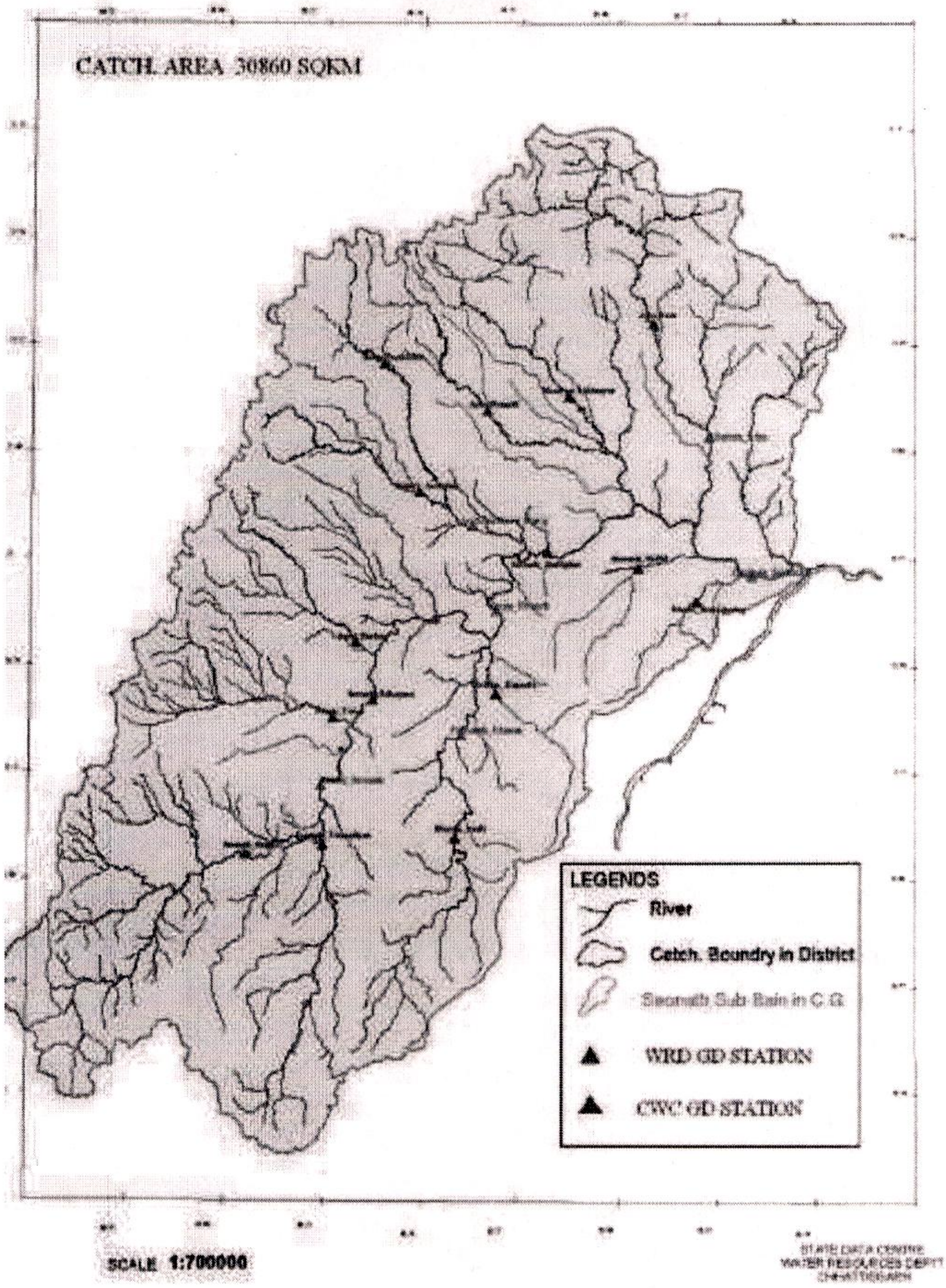


Fig:3.3.gauge and discharge of seonath basin of Mahanadi(ref. GOOGLE images)

3.2.DATA USED :

3.2.1 Three catchments of rainfall –runoff data is used

1. Pandariya
2. Bodla
3. Chirapani

(a) **Pandariya :-** pandariya is a village of Chattisgarh and also a nagar panchayat in Kabirdham district of Chattisgarh. The location of pandariya in Chattisgarh, India is at 22.23^0 N 81.42^0 E. The average elevation of Pandariya is 348m(1,142ft). Total population in Pandariya is about 12453 from which the percentage of males are 51% and females are 49% and the literacy rate of males are greater than females , maes literacy rate is 69% and females literacy rate is 48% .

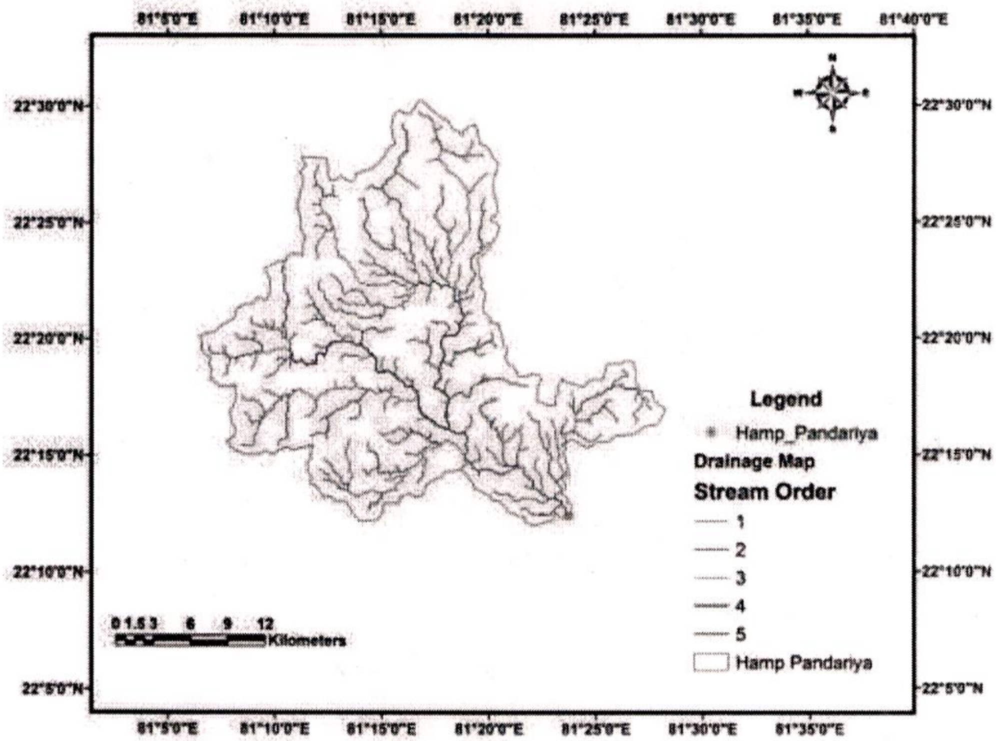


Fig:3.4. layout of Hamp-pandariya

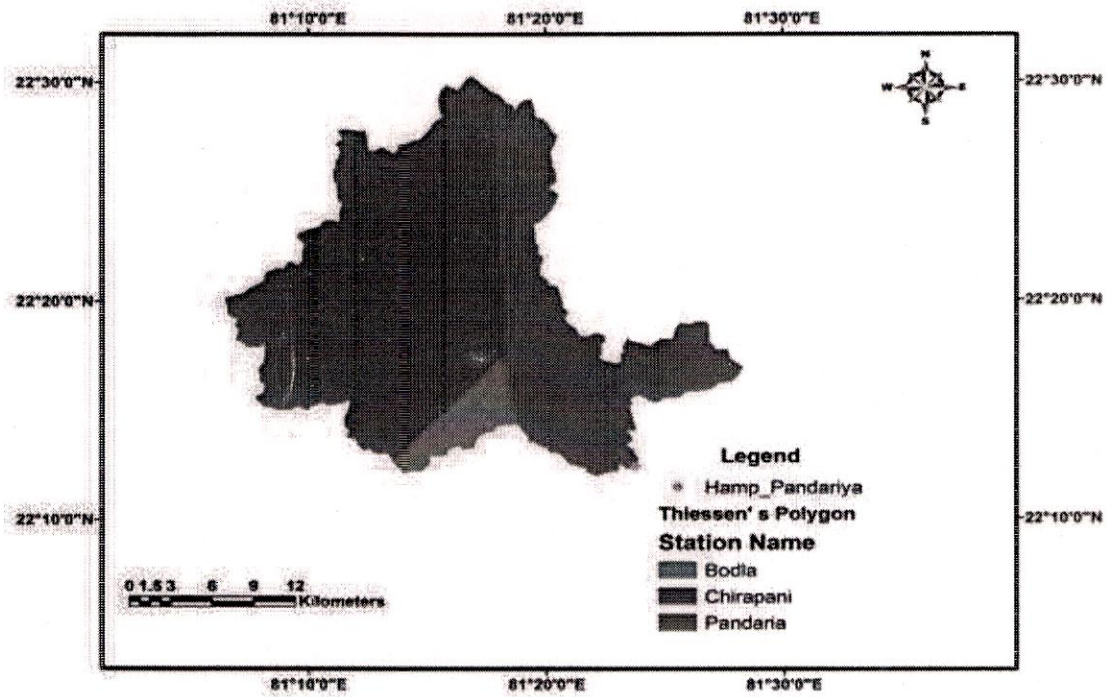


Fig:3.5 Thesssen's polygon (hamp- pandariya)

(b) BODLA:- Bodla is also a small village of Chattisgarh , Kabirdham district. Bodla is also known as as village panchayat, the local language of Bodla is Punjabi. The location of Bodla village is in UTC 5.30 time zone. The latitude and the longitude of the Bodla is 26.05 and 74.02. Bodla has total population is about 5689.

3.3 The data used is of 1981-2009(30 years)

The observed discharge used in ANN is shown below :-

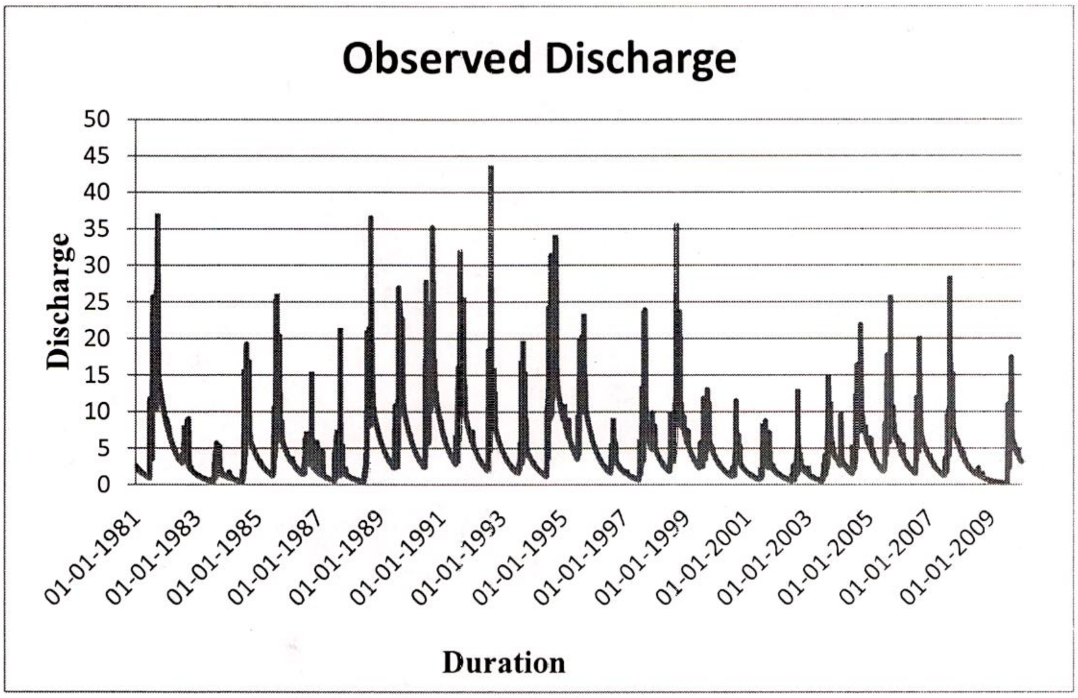


Fig:3.6 The observed rainfall data used in ANN

The observed rainfall data used in ANN is shown below :-

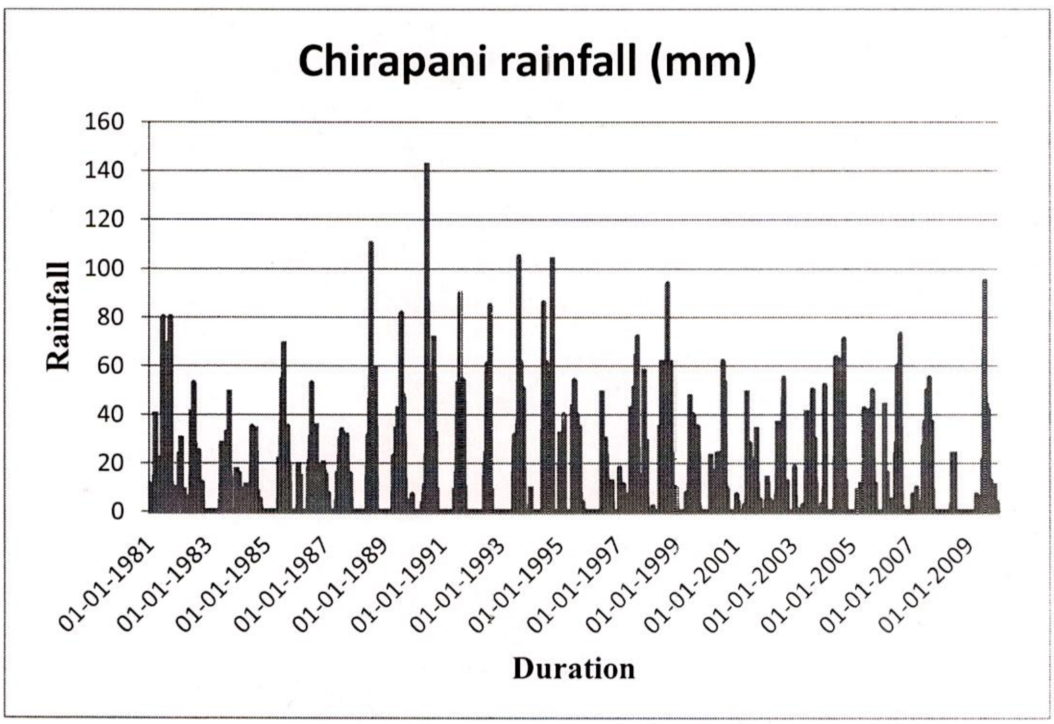


Fig:3.7 The observed rainfall data used in ANN

The observed rainfall used in ANN is shown below :-

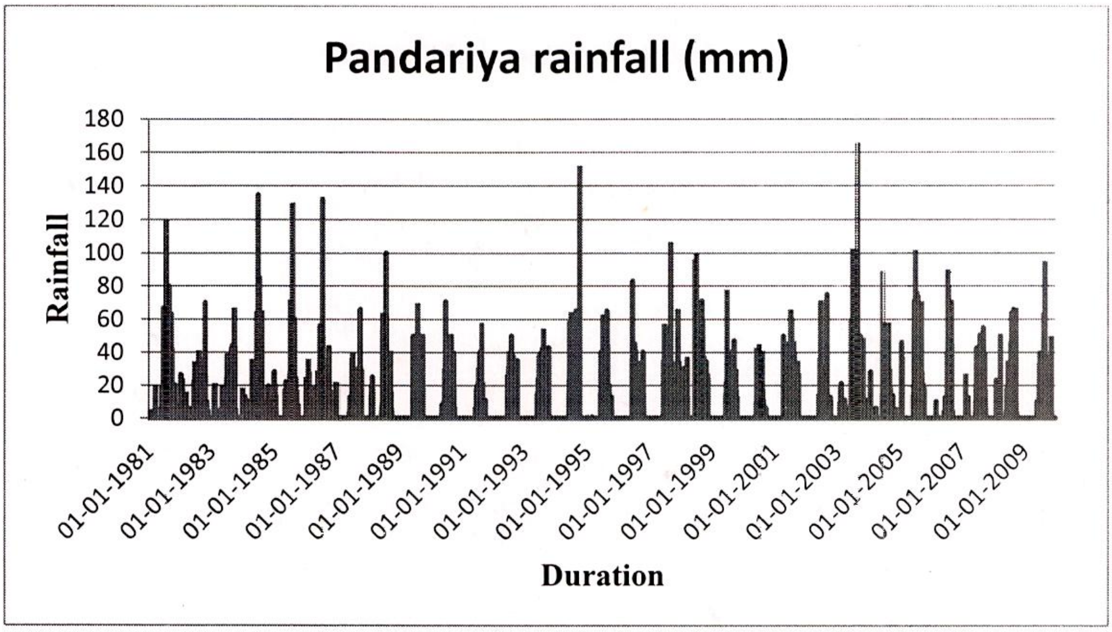


Fig:3.8 The observed rainfall data used in ANN

The observed rainfall used in ANN is shown below :-

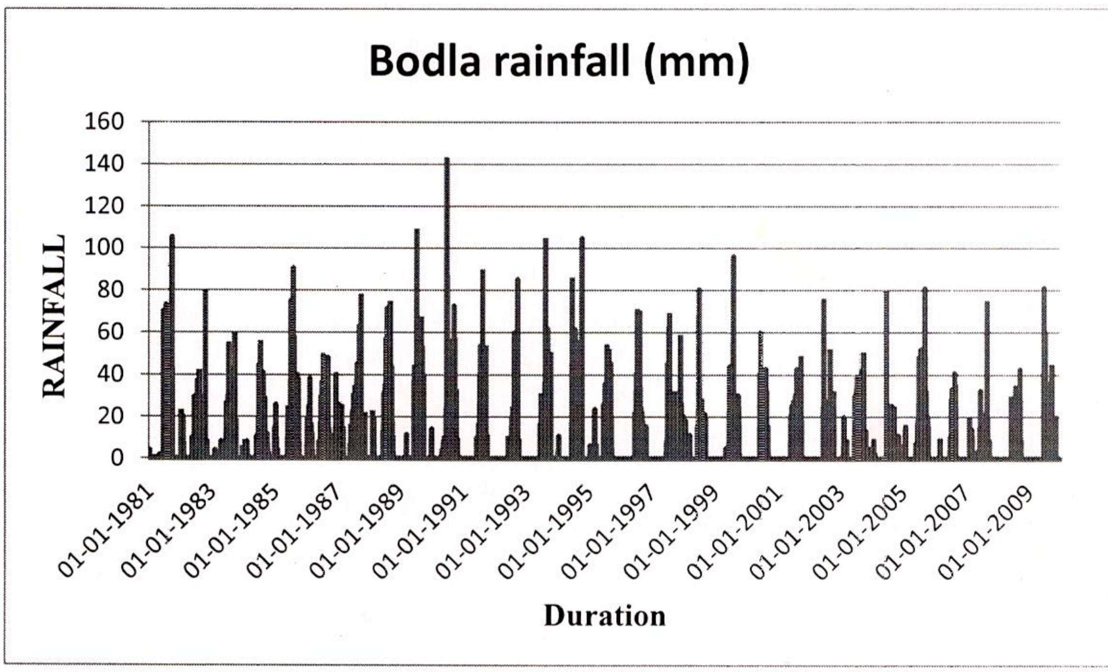


Fig:3.9 The observed rainfall data used in ANN

CHAPTER-4

MODELLING OF RAINFALL RUNOFF USING ANN

4.1 INTRODUCTION

4.2. UNDERSTANDING OF ARTIFICIAL NEURAL NETWORK

A family of models inspired by biological neural networks is called an artificial neural network. ANN are used to estimate that can depend on a large number of input and inputs are generally unknown. As neurons are exchanging the message between each other in our body, the role of ANN is same as neurons which are generally presented as systems of interconnected 'neurons'. The connection in ANN models have numeric weight that can be tuned based on experience. In recent years, an artificial neural network has been used in many areas for forecasting in science and engineering. The main advantage to choose the ANN over the traditional methods of modelling is that there is no requirement of complex nature of the underlying process under consideration to be explicitly described in mathematical terms. So many applications are use multilayer perceptron (MLP) type ANNs with the error back propagation(BP) techniques which leads to MLP/ BP MODELS that are non-linear in the parameters. The backpropagation is a gradient descent search technique that may descend to a suboptimal solution to the problem. In the transfer function of its hidden layer nodes the radial basis functions (RBF) network has the non-linearity embedded. For real situation the RBF networks based model have been developed to make the prediction of flow. The approach of artificial neural network (ANN) are differ from the traditional approaches in stochastic hydrology in the sense that it is belongs to a class of the data-driven approaches as opposed to traditional model driven approaches. The neural network was developed by using the generalized delta rule for a semi-linear feed forward net with error back propagation. The code of program was written in C in UNIX environment. The neural network model was treated as a Black Box, and relationships between the physical components of the catchment were not to be fed. The number of input nodes, N, and the number of output nodes, M, in an ANN are dependent on the problem to which the network is being applied. Unfortunately, there are no fixed rules as to how many nodes should be included in the hidden layer. If there are too few nodes in the hidden layer the network may have difficulty generalizing to problems it has never encountered before. On the other hand, if there are too many nodes in the hidden layer, the network may take an unacceptably long time to learn anything of any value. Different numbers of hidden nodes were used in the networks developed in this study for rainfall-runoff modelling. The best results are presented later. The runoff means the draining or flowing off of precipitation from a catchment area through a surface channel. There are three types of runoff namely direct runoff, base flow runoff, and natural flow runoff. The relationship between rainfall-runoff is one of the most complex hydrological phenomena to comprehend the spatial and temporal variability of watershed characteristics and precipitation patterns and also to the number of variable involved in the modelling of the physical process. By ANN modelers the problem of rainfall runoff modelling has received maximum attention. Since the mid of 19th century was the last decade when the ANN models have been applied to the rainfall-runoff modelling. Existing methods used to estimate runoff from rainfall are frequently classified into two groups viz., Black Box model and Process model (Todini, 1988). In the black box modelling approach, empirical relations are used to relate runoff and rainfall, and only the input (rainfall) and the output (runoff) have physical meanings. Simple mathematical equations, time-series methods and neural networks methods fall into this category. Process models attempt to simulate the hydrological processes in catchments and involve the use of many partial differential equations governing various physical processes and equations of continuity for surface and soil water flow. Conceptual rainfall-runoff models (Chiew et.al., 1993) can be considered as a third group of modelling approach.

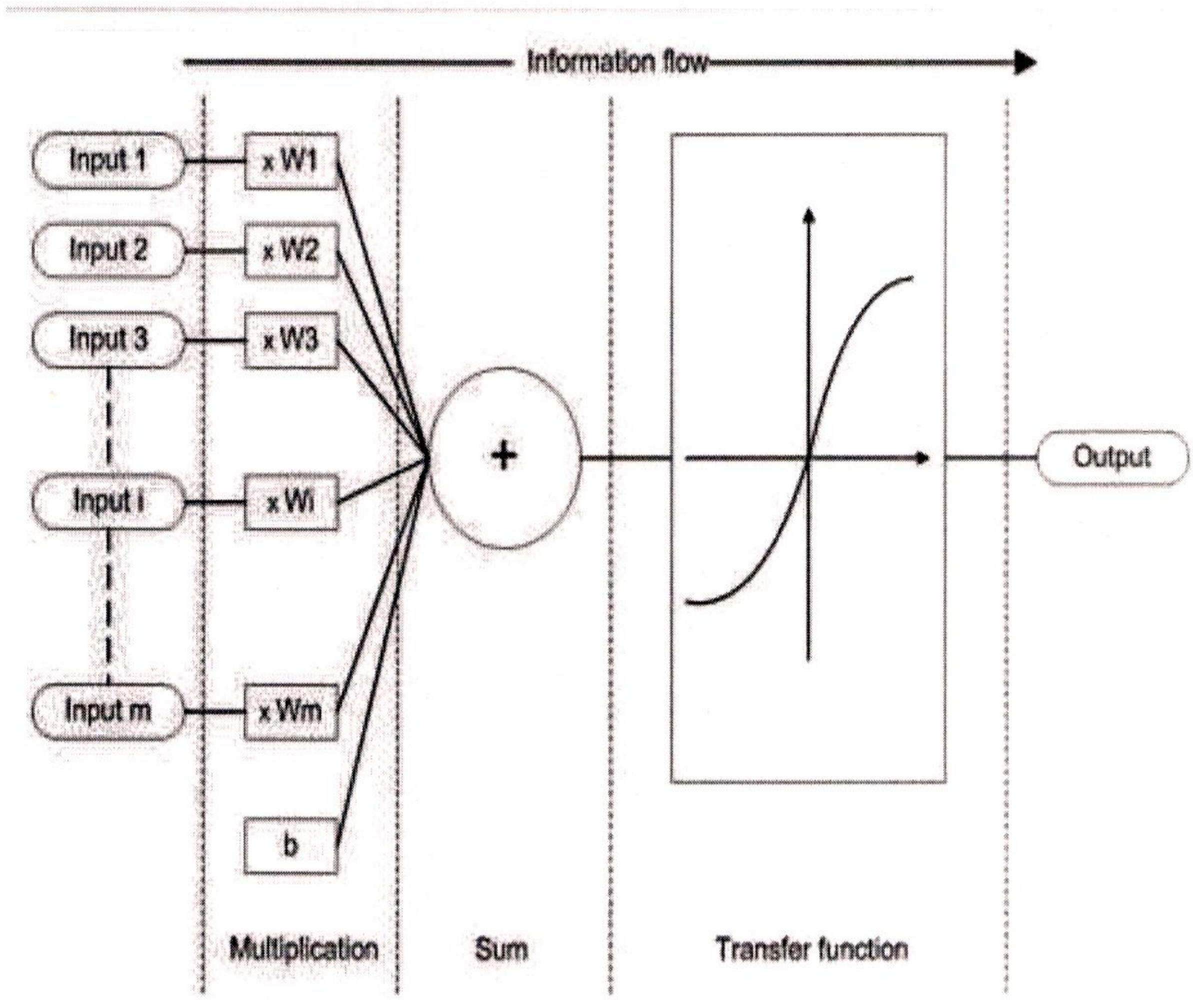


Fig:4.1. working of artificial neural network (Kenji Suzuki 2011)

4.3. GROWING INTREST IN ANN DUE TO SOME BENEFITS ARE:-

An ANN has the ability to do work based on the given data for training, the ANN Can prepare its own organisation of the information which received during learning time, The ANN computations can be done in parallel, and special hardware devices are manufactured and designed which take the advantages of red time operation capability, Neural networks systems are developed by learning rather than programming, In a changing environment the neural networks are flexible so that, they are excellent to learn a sudden changes, Whenever conventional approaches get fail then the neural networks can build informative models. The neural networks can manage the complex interaction so that they can model the data easily, which is so difficult to model with traditional approaches like inferential statics or programming logic,The neural networks perform better as compared to classical statistical modelling, and it is better on most problems.

4.4. Introduction to ANN design tool modify in MATLAB

The software is a tool in the MATLAB environment that was used during the course of investigation- the so called CT 5960ANN Tool. This ANN tool is a costomized ANN design tool and the ANN design tool is based on an existing tool. The CT5960ANN Tool was developed by a group of civil engineering of the Delft university of technology.

4.5. FLOW CHART OF MODELLING BY ANN

To represent the Algorithm we can use the Flow chart. The modelling by using ANN is very simple but with the help of a flow chart we can understand the process of modelling in ANN easily. It is a simplest process to understand or taking the overview of the work. This flow chart is showing the framework of ANN.

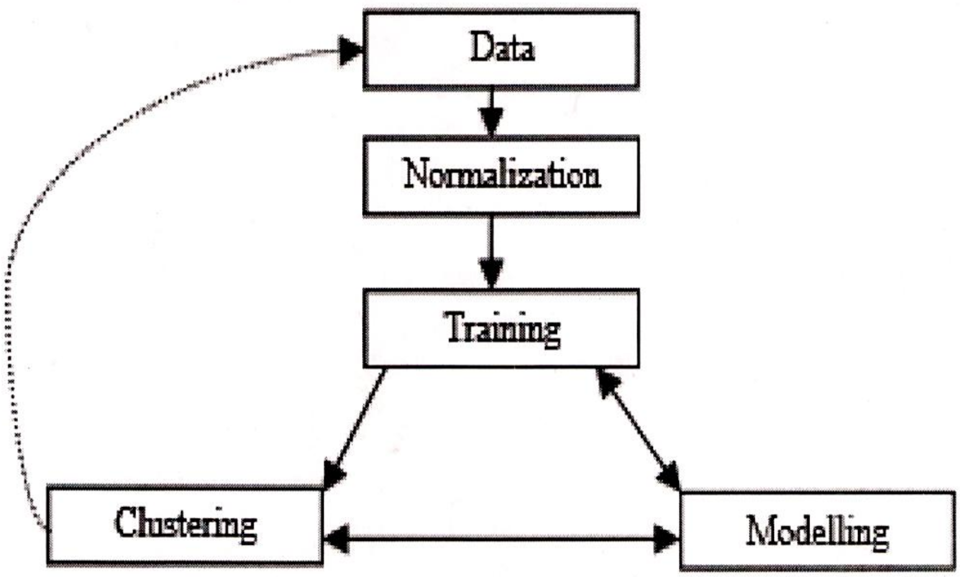


Fig:4.2.flow chart of ann modelling (ref.AMAN mohammad kalteh)

4.6. Mathods and Algorithm Used in Modelling:-

4.6.1. Back Propagation Algorithm

Feed forward networks are sometimes referred to with a name that is derived from the employed training algorithm. The most common learning rule in training is the back propagation algorithm. An ANN that uses this learning algorithm is consequently referred to as a back propagation network (BPN).One must bear in mind, however, that different types of ANNs (other than feed forward networks) can also be trained using the back propagation algorithm. These networks should never be referred to as back propagation networks, for the sake of clarity.

The back propagation algorithm is the best known algorithm for training artificial neural networks. The algorithm is convergent linearly. Basically, in Back propagation algorithm each input pattern of the training data set is passes through a feed forward network from input units to output layers. The comparison between the network output and the desired target output is to be done and an error is computed based on an error function. After the error computation the error is propagated backward through to each neuron, and the connection weights are adjusted correspondingly.

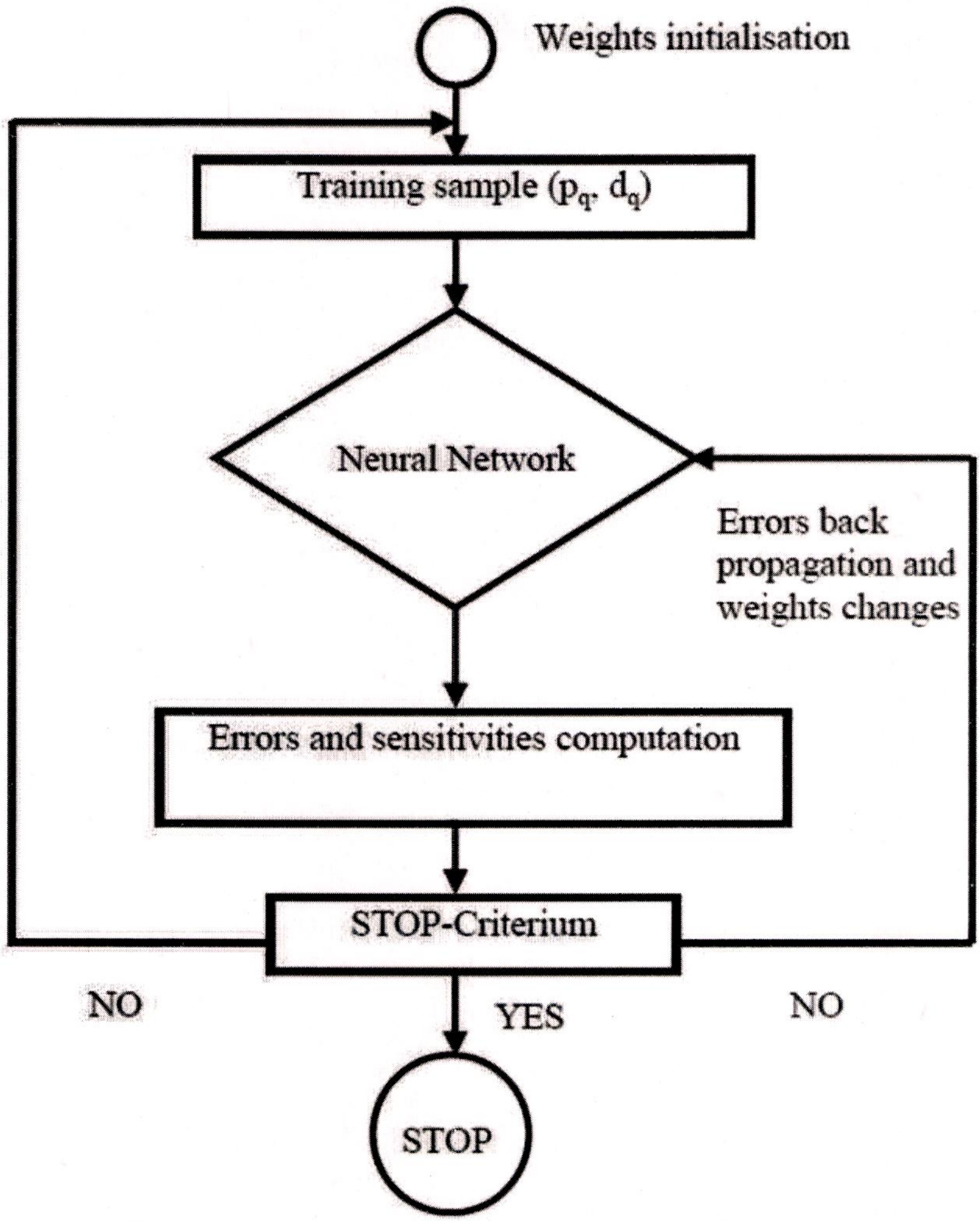


Fig:4.3 flow chart showing the performance of back propagation (google images)

4.6.2. multy layer perceptron Feedforward networks with one or more hidden layers are often addressed in literature as multilayer perceptron (MLPs).This name suggests that these networks consist of Perceptron (named after the Perceptron neurocomputer developed in the 1950's,.The classic Perceptron is a neuron that is able to separate two classes based on certain attributes of the neuron input. Combining more than one perceptron results in a network that is able to make more complex classifications. This ability to classify is partially based on the use of a hard limiter activation function .The activation function of neurons in feedforward networks, however, is not limited to just hard limiter functions; sigmoid or linear functions are often used too. And there are often other differences between perceptron and other types of neurons. From this we can conclude that the name MLP for multilayer feedforward networks consisting of regular neurons (not perceptron, which are neurons with specific properties) is therefore basically incorrect. To avoid misunderstandings, the author will not use the term MLP for a standard feedforward networks with one or more hidden layers.

4.6.2.1 Applications of MLP :-

- The standard algorithm is the back propagation algorithm and the multy layer perceptron are use the back propagation algorithm for any supervised learning pattern process and in parallel distributed processing.
- The multy layer perceptron has the ability to solve the problems stochastically.
- The multy layer perceptron gives the approximate solution of complex problems. (ref. Wikipedia)

4.6.3. Standard feed forward artificial neural network The Artificial neural network is called feedforward artificial neural network when the Artifiacial neural network is work as feed forward topology. This is called feed forward artificial neural network in only one condition if the information is flowing from input to output in only one direction and there is no back loops. In this process the number of layers, types of transfer function or number of connections between individual artificial neurons are unlimited. The simplest feed forward artificial neural networks consist of single perceptron so that, it has the capability of the linear separable problems. For purpose of analytical description of simple multilayer feed forward artificial neural network is shown on figure below:

N1=f1(w1x1+b1)

n1=f2(w2x2+b2)

n3=f3(w3x3+b3)

m1=f4(q1n1+q2n2+b4)

m2=f5(q3n3+q4n4+b5)

y=f6(r1m1+r2m2+b6)

y=f6{r1(f4[q1f1(w1x1+b1)+q2f2(w2x2+b2)+b4)+...........+r2(f5[q3f2(w2x2+b2)+q4 f3[w3x3+b3]+b5))+b6}

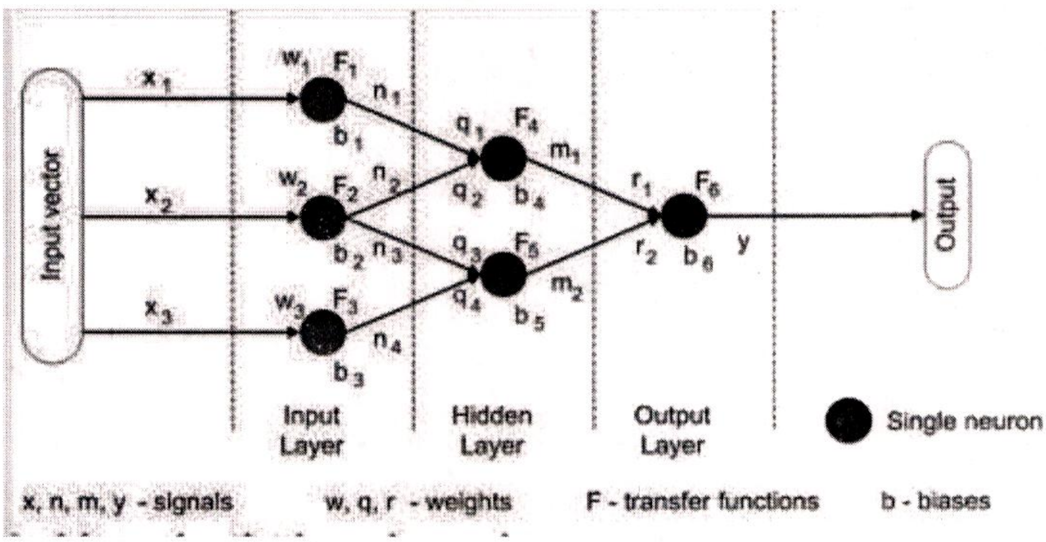


Fig:4.4 feed forward ANNs (Kenji Suzuki 2011)

where artificial neural networks' parameters optimization problem solving by hand is impractical the simple feed-forward artificial neural network can led to relatively long mathematical descriptions. Although analytical description can be used on any complex artificial neural network in practise we use computers and specialised software that can help us build, mathematically describe and optimise any type of artificial neural network.

4.6.4. Multiple layer regression:-

There are two types of regression models first is linear multiple regression structure model and another is non-linear regression structure model, but the only multiple linear regression model is to be described in this chapter. The MATLAB which is a mathematical computer software is used to coputer the regression of all regression models. In the modelling of multiple layer regression model the runoff at time (t) is regressed against the rainfall and runoff in the past. To model an event-based rainfall-runoff process the input variable are needed. The MLR model can be represented as follows :-

$$R_t = \beta_0 + \beta_1 P_t + \beta_2 P_{t-1} + \beta_3 P_{t-2} \text{ ------------ } \beta_9 P_{t-8} + \beta_{10-t-9}$$

Where β is showing the regression coefficient are to determined and R is showing the runoff of P is showing the precipitation (rainfall) and the t is representing the time.

4.7. HOW TO LEARN A NEURAL NETWORK

The training of the artificial neural network is to determine the best values of all the weights. The actual output of a neural network is compared with the desired output during the learning mode. In the beginning the weights are randomly set and are then adjusted so that the closer match between the desired and the actual output is produce by the next iteration. There are various methods of learning are used for weight adjustments and try to minimize the difference or error between observed and computed output data. A lot of time is consumed in training phase. When the ANN reaches a user-defined performance level then we can consider that it is completed. The network has achieved the desired statistical accuracy at this level, as it produces the required outputs for a given sequence of inputs.The resulting weights are typically fixed for the application when no further learning is judged necessary.

4.8. FORMULATION FOR SOLVING THE PROBLEMS

On the two statistical properties of the time series such as mean and standard deviation, the whole data length is devided from which one is used for calibration(training) and another is used for validation of ANN model. By performance indices such as root mean square error(RMSE) model efficiency(EFF) and coefficient of correlation (CORR) the performance during calibration and validation is to be evaluated.

Root mean squared error (RMSE) $=\sqrt{\frac{\sum_{k=1}^{K}(t-y)^2}{K}}$

Efficiency (EFF) $=1-\frac{\Sigma(t-y)^2}{\Sigma(t-\bar{t})^2}$

Coefficient of Correlation (CORR) $=\frac{\Sigma TY}{\sqrt{\Sigma T^2 \Sigma Y^2}}$

where K= is the number of observations;

t =observed data;

y = computed data;

$T = t - \bar{t}$ in which $\bar{t}$ is the mean of the observed data;

and $Y = y - \bar{y}$ in which $\bar{y}$ is the mean of the computed data.

4.9. STATE OF ACTIVATION OF THE NEURONS

The state of activation of the neurons of networks represent the state of the system. The state of a system can be represented by the N vector real number a(t). if we let the N is the number of neurons and the vector of N real number a(t), is specifies the state of activation of the neurons in a network. The activation value can be any of mathematical type depends on ANN models.

4.9.1. Activation rule:-

The activation rule is can be also called Transfer function. The new Activation values can be determine, and the activation values of a neuron are based on the input. If we let the function F, and the F takes a(t) and vector **net**, for each different types of connection the function F will takes a(t) and the net vector, which will develop of new state of activation.

From the simple identify function to linear or non linear function the function F can vary like sigmoid function, so that a(t+1)= net (t)= W-o(t)

The most common transfer functions are ;-

1. **Linear activation rule.**

a (t+1) = F_{lin} (**net** (t)) = alfa- **net** (t)

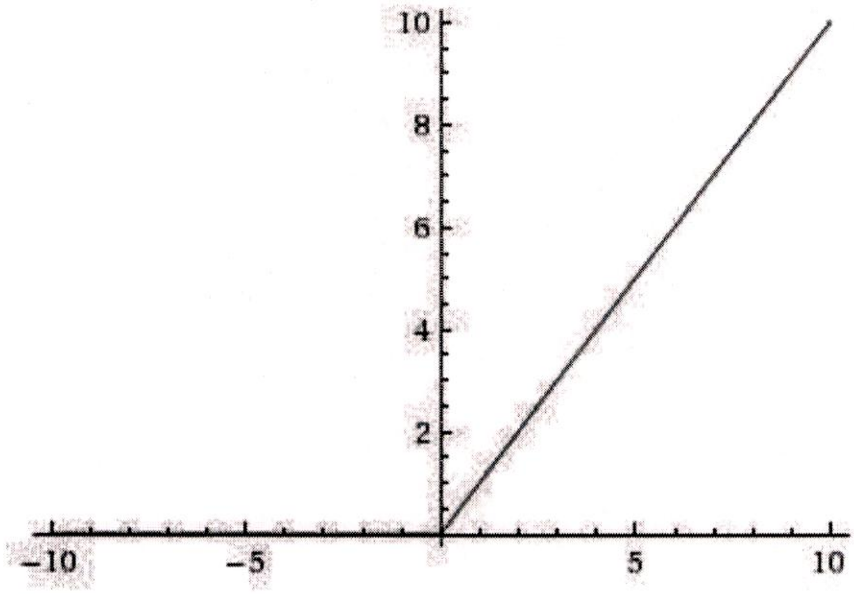


Fig: 4.5 Linear activation function (ref. google images)

2. **Hard limiter activation rule** .

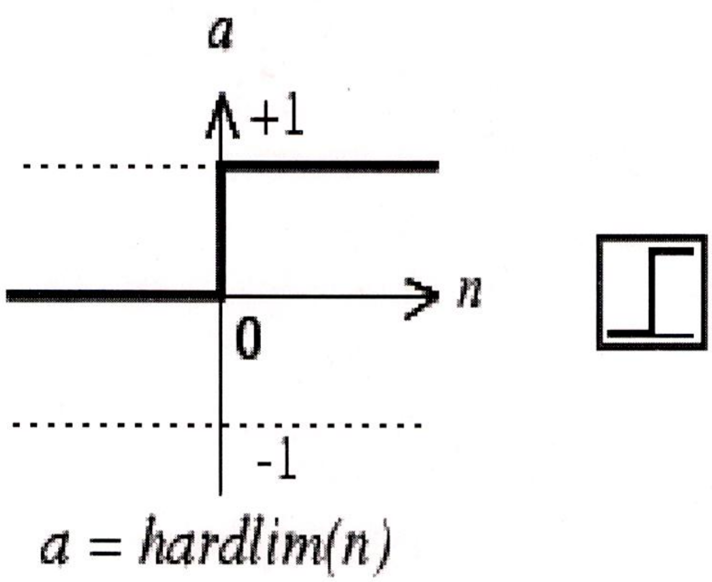


Fig:4.6 Hard limiter activation function (ref. google images)

3. Saturating linear activation rule.

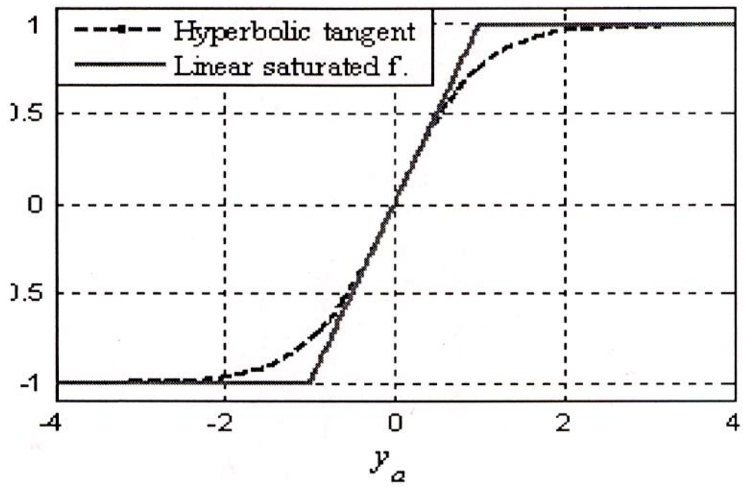


Fig:4.7 saturated linear activation rule (ref. google images)

4. Gussain activation rule.

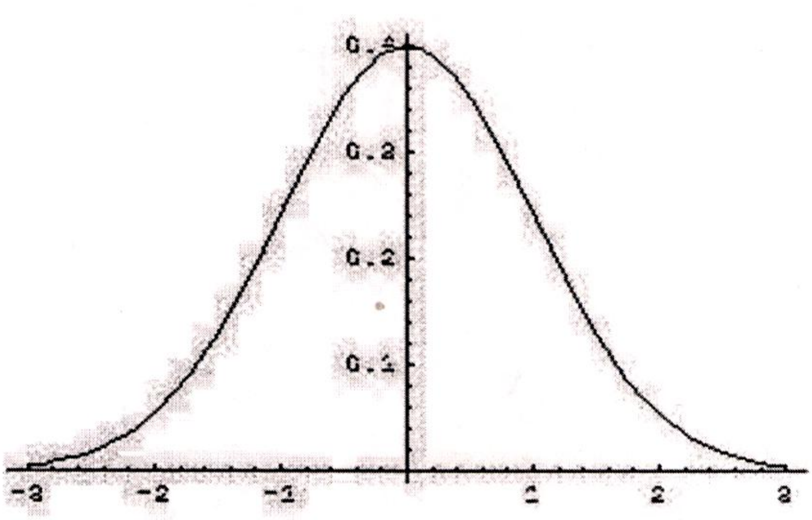


Fig:4.8 Gussain activation function rule(ref. google images)

5. **Binary sigmoid activation rule.**

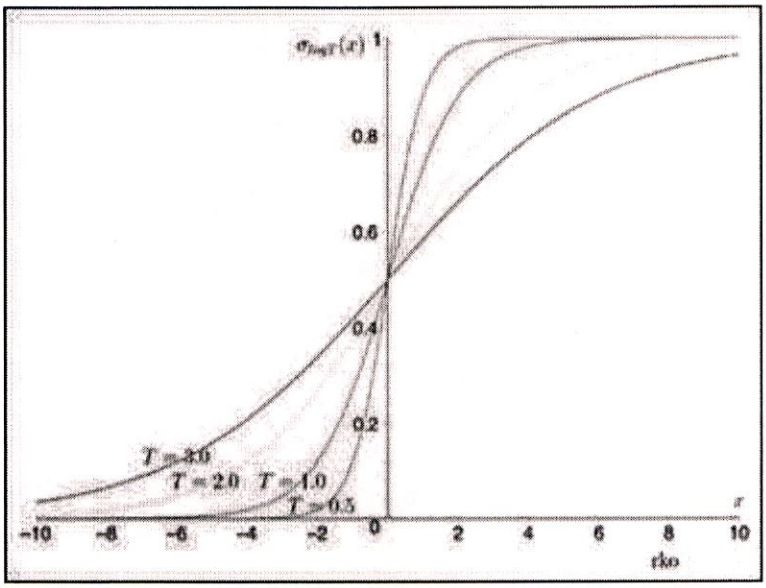


Fig:4.9 Binary sigmoid activation function rulr(ref. google images)

6. **Hyperbolic tangent activation function rule**

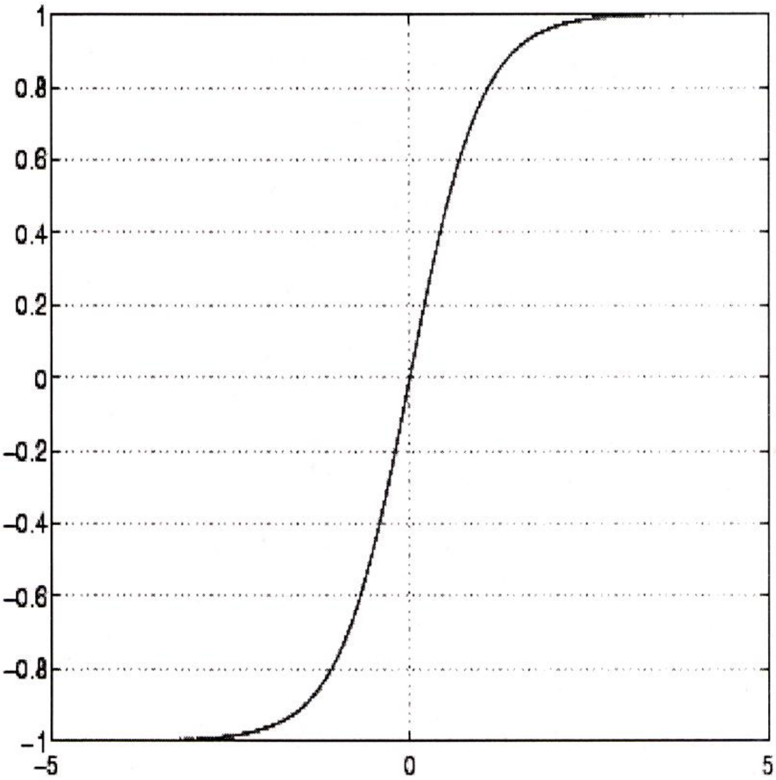


Fig:4.10 hyperbolic tangent activation function rule(ref. google)

4.10. CLASSIFICATION OF TRAINING ALGORITHM:-

The training algorithm or learning algorithm can be classified as supervised algorithm and unsupervised algorithm.

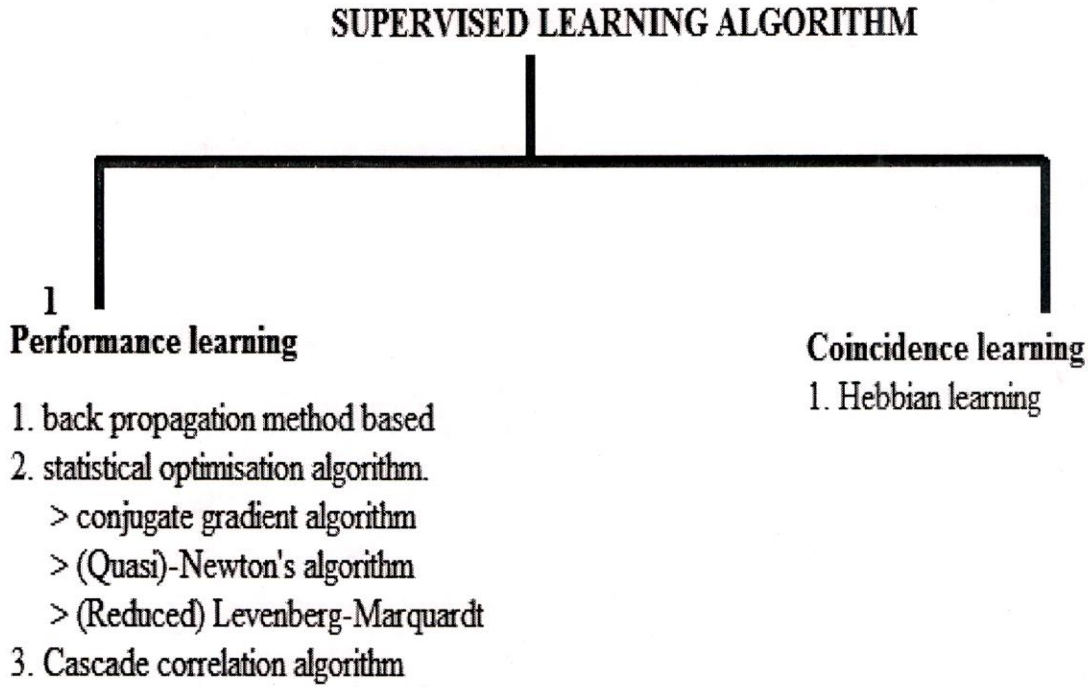


Fig:4.11. Flow chart of supervised learning algorithm

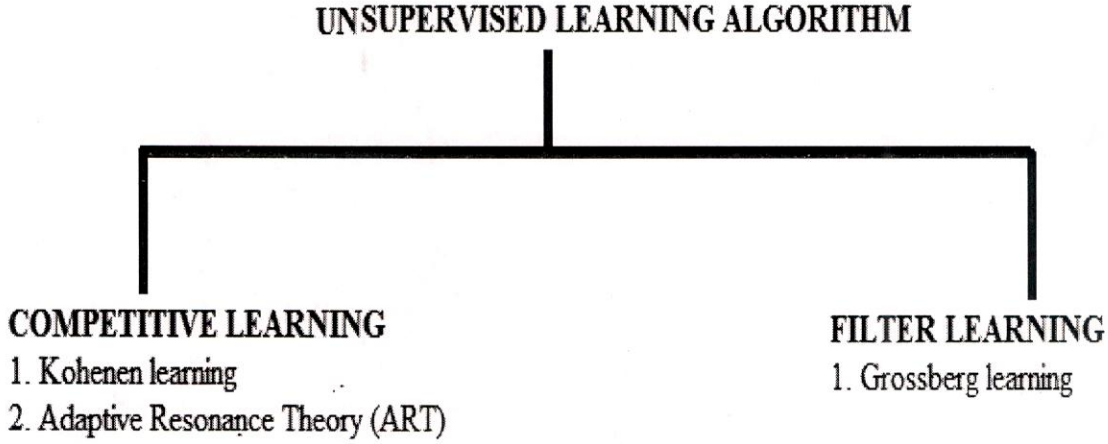


Fig:4.12. flow chart of unsupervised learning algorithm

CHAPTER- 5

RESULTS AND CONCLUSSION

5.1. INTRODUCTION:-

5.2. DEVELOPMENT OF ANN MODEL

The feedforward ANN model architecture has been considered to modeling of rainfall runoff using, using hourly total rainfall, hourly total runoff data as the input to the model. ANN models with different hidden neuron structure have been developed and the best ANN model has been selected based on the performance evaluation criteria.

5.3. TRAINING ALGORITHM:-

The training of the artificial neural network is to determine the best values of all the weights. The actual output of a neural network is compared with the desired output during the learning mode. In the beginning the weights are randomly set and are then adjusted so that the closer match between the desired and the actual output is produce by the next iteration. There are various methods of learning are used for weight adjustments and try to minimize the difference or error between observed and computed output data. A lot of time is consumed in training phase. When the ANN reaches a user-defined performance level then we can consider that it is completed. The network has achieved the desired statistical accuracy at this level, as it produces the required outputs for a given sequence of inputs. the resulting weights are typically fixed for the application when no further learning is judged necessary.

5.4. INPUT VECTOR SELECTION:-

The determination of significant input variables is the one of the important step in the development of a model. Generally, the potential input variables are not equally informative since, some may be correlated and some have no significant relationship with the output vectors being modelled. An analytical technique, such as cross-correlation is often employed when the relationship to be modelled is not well understood. The cross correlation is only able to linear dependence detectation between two variables, and this the major disadvantage of cross correlation. Therefore the cross correlation is not able to adopt any non-linear dependence that may exist between input and output and may also gives the possible results in the omission of important input and the inputs are related to output in a non-linear fashion. A combination of a priori knowledge and analytical approaches are the preffered approaches, and these approaches are preferred to determine the appropriate inputs and lags of inputs. Generally, the significant lags of input variable are found out by trial and error. But, Sudheer et al. (2002) have suggested a statistical procedure that avoids the trial and error procedure. They have reported that the statistical parameters such as auto-correlation function (ACF), partial auto-correlation function (PACF) and cross-correlation function (CCF) could be used to find out the significant lag values of input variables. The current study has been designed for rainfall runoff modelling using ANN with rainfall-runoff hourly data of HAMP river, Chattisgarh.

The auto-correlation coefficient (Salas *et al.*, 1980) is given as

$$r_k = \frac{\sum_{t=1}^{N-k}(x_t - \overline{x_t})(x_{t+k} - \overline{x_{t+k}})}{\left[\sum_{t=1}^{N-k}\left(x_t - \overline{x_t}\right)^2 \sum_{t=1}^{N-k}\left(x_{t+k} - \overline{x_{t+k}}\right)^2\right]^{1/2}}$$

(5.1)

Where r_k is called the *lag-k* correlation coefficient, the serial correlation coefficient or the auto-correlation function (ACF), x_t is the time series for $t = 1,..,N$, x_{t+K} is the lagged time series for $t = 1,..., N\text{-}k$, $\overline{x_t}$ is the sample mean for $t = 1,....N$, $\overline{x_{t+k}}$ is the sample mean *for* $t = 1,...,N\text{-}k$, N is the sample size. The partial auto-correlation coefficient may be obtained by given equation below (Salas *et al.*, 1980)

$$\phi_1(1) = \rho_1, \phi_1(2) = \frac{\rho_1(1-\rho_2)}{(1-\rho_1^2)}, \phi_2(2) = \frac{\rho_2 - \rho_1^2}{(1-\rho_1^2)}$$

$$\phi_k(k) = \frac{\rho_k - \sum_{j=1}^{k-1}\phi_j(k-1)\rho_{k-j}}{1 - \sum_{j=1}^{k-1}\phi_j(k-1)\rho_j}$$

$$\phi_j(k) = \phi_j(k-1) - \phi_k(k)\phi_{k-j}(k-1)$$
(5.2)

To determine the partial auto-correlation function from a sample series $x_1,\ldots, x_N$, the sample autocorrelation the *ρ's* are replaced by *r's*. *ρ's* are auto-regression coefficients. The cross-correlation coefficient is given as (Salas *et al.*, 1980)

$$r_k^{ij} = \frac{\sum_{t=1}^{N-k}\left(x_t^{(i)} - \overline{x_t^{(i)}}\right)\left(x_{t+k}^{(j)} - \overline{x_{t+k}^{(j)}}\right)}{\left[\sum_{t=1}^{N-k}\left(x_t^{(i)} - \overline{x_t^{(i)}}\right)^2 \sum_{t=1}^{N-k}\left(x_{t+k}^{(j)} - \overline{x_{t+k}^{(j)}}\right)^2\right]^2}$$
(5.3)

where r_k^{ij} is the lag-k cross-correlation coefficient, $x_t^{(i)}$ is the time series values of series *i*, $x_t^{(j)}$ is the time series values of series *j*, $\overline{x_t^{(i)}}$ is the mean of the first N-k values of series *i*, and $\overline{x_{t+k}^{(j)}}$ is the mean of the last N-k values of series *j*.

The ACF and PACF of rainfall and discharge at Hamp are presented in Figures 5.1 and 5.2 respectively. The CCF between discharge and rainfall values at Chirapani, Bodla, and Pandariya are presented in Figures from 5.3 to 5.5 respectively. The PACF of the rainfall and discharge at Hamp with 95 % confidence levels and CCF of discharge values at Hamp between rainfall of all stations Chirapani, Bodla, and Pandariya suggest the most valuable input vector for ANN modeling for real time flood forecasting.

The auto-correlation function shows the smooth curve which indicate that the rainfall discharge value at Hamp is autoregressive. The partial auto correlation coefficient (PACC) of time series helps in determining the order of the auto-regression.

The partial auto-correlation coefficient of discharge value at Hamp for lag 1 is 0.94. The partial auto-correlation coefficient values for other lags are less than 0.12. The cross-correlation coefficients of discharge at Hamp with rainfall at Chirapani, Bodla and Pandariya for lag 0 are 0.36, 0.24 and 0.18 respectively. The cross-correlation coefficient of discharge at Hamp for rainfall at Chirapani for lag 0 that is 0.36 is higher than all other lagged cross-correlation coefficient values of other lags so for Chirapani input value selected is (t) whereas, for Bodla and Panadariya the cross-correlation for lag 1 is 0.25 and 0.21 which is higher than all other lagged cross-correlation coefficient values so the input variable selected is (t-1).

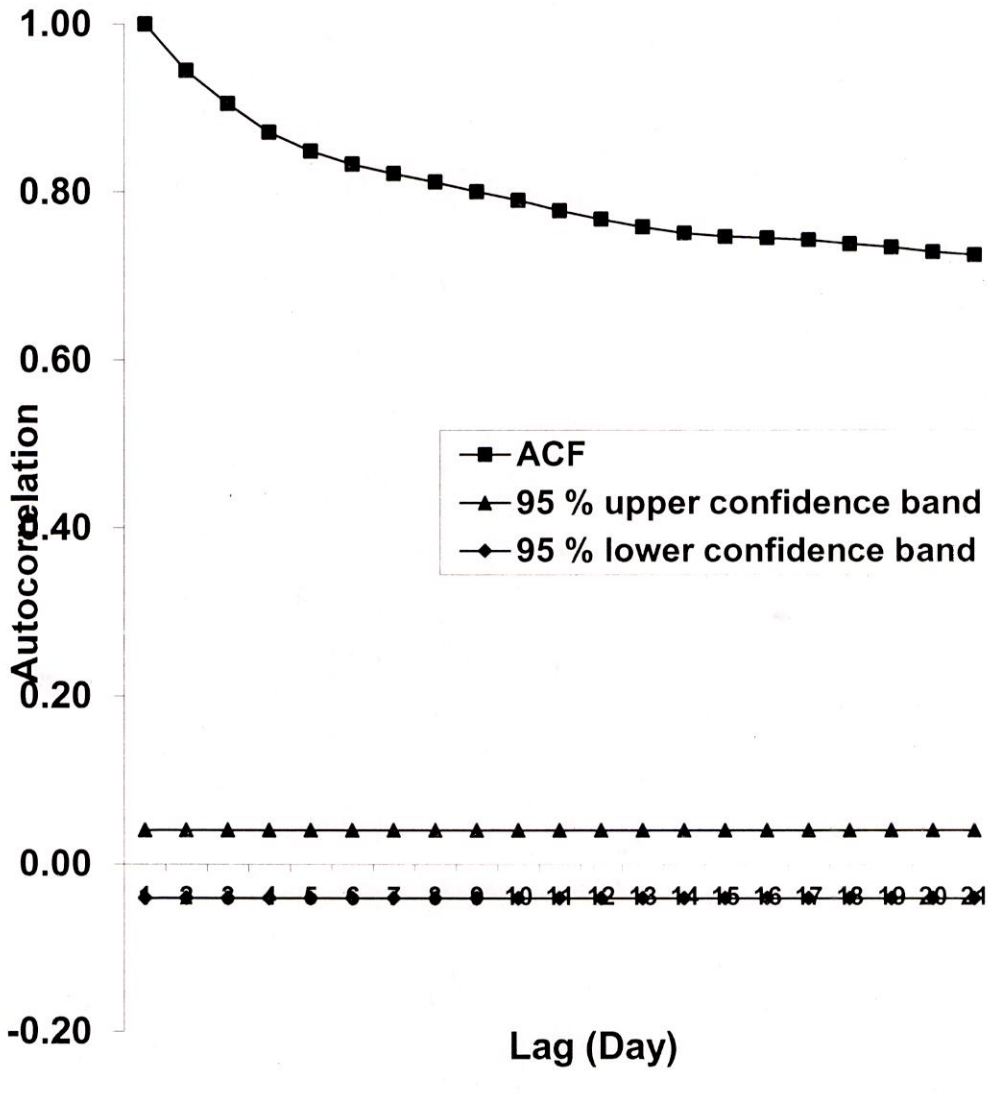


Fig 5.1. The autocorrelation of the discharge value at Pandariya

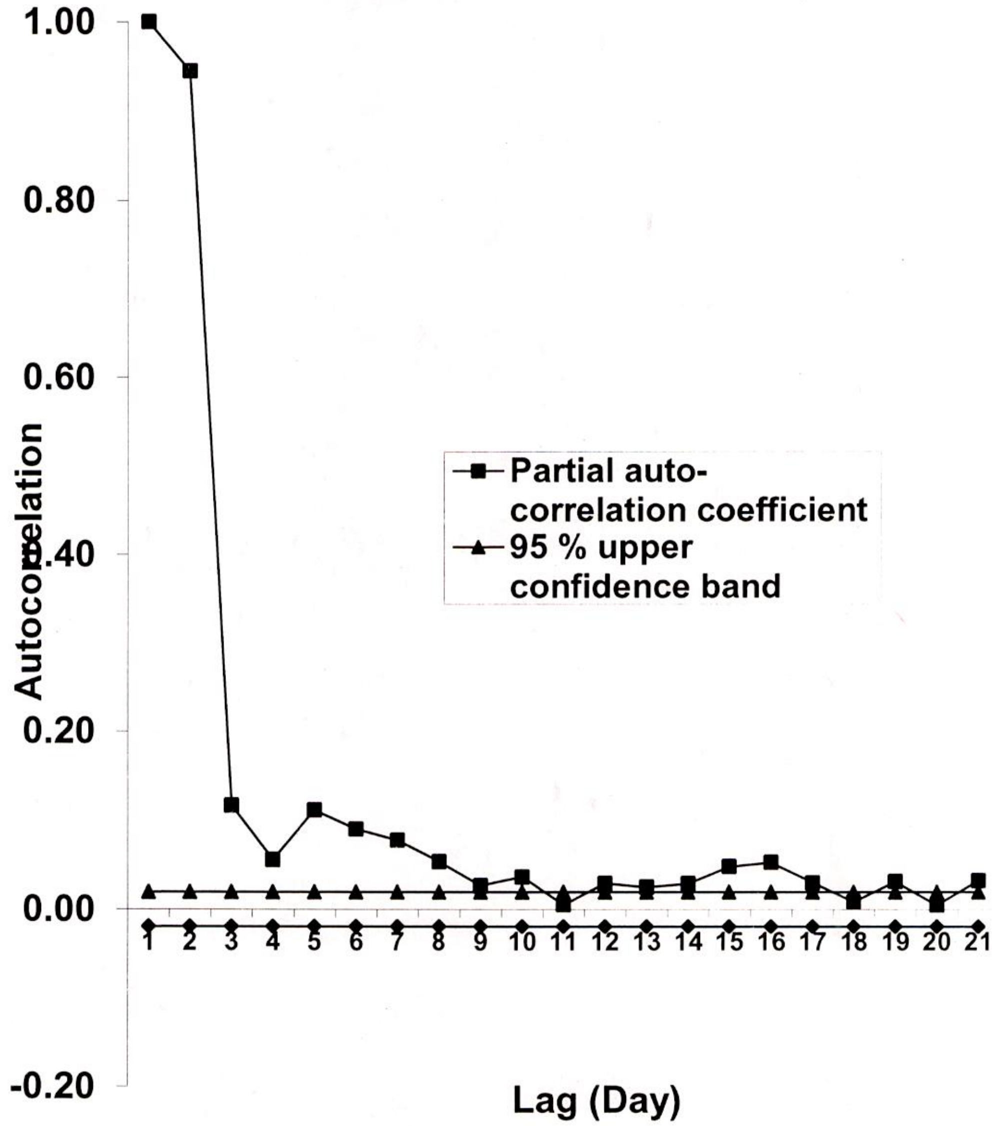


Fig:5.2.The partial autocorrelation of the discharge value at Pandariya

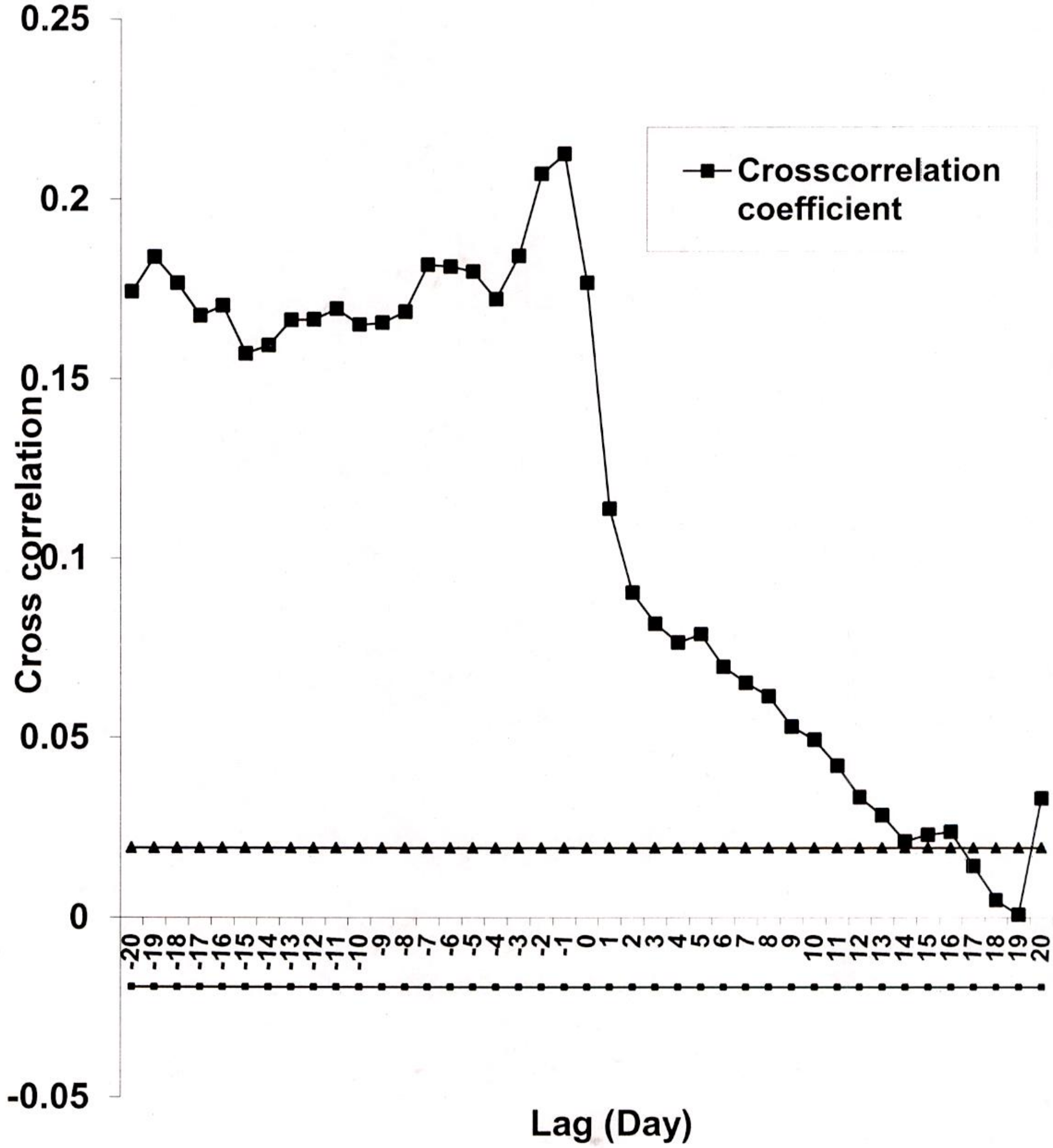


Fig:5.3. The cross-correlation of discharge at Boadla

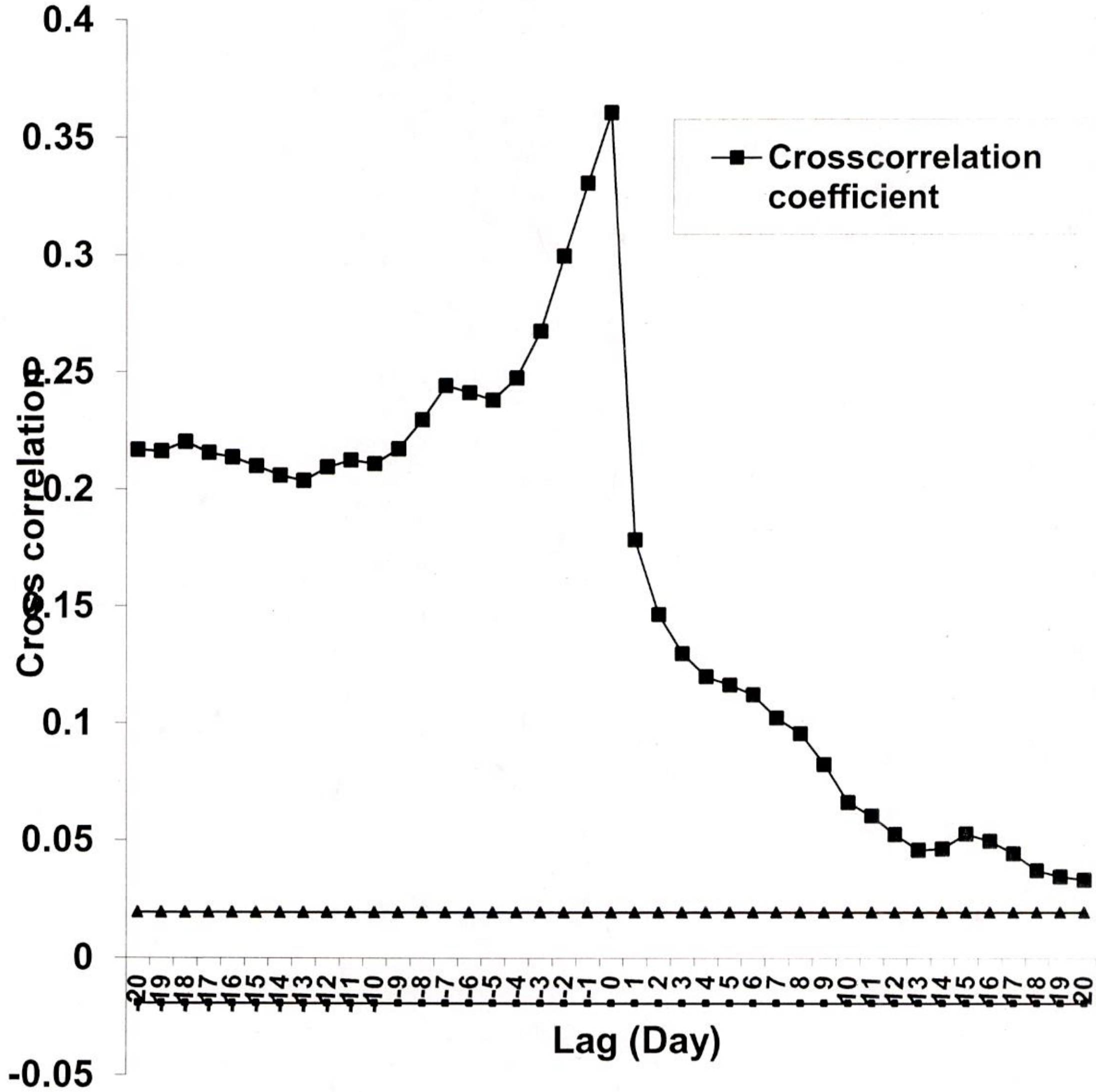


Fig :5.4 The cross-correlation of discharge at Chirapani

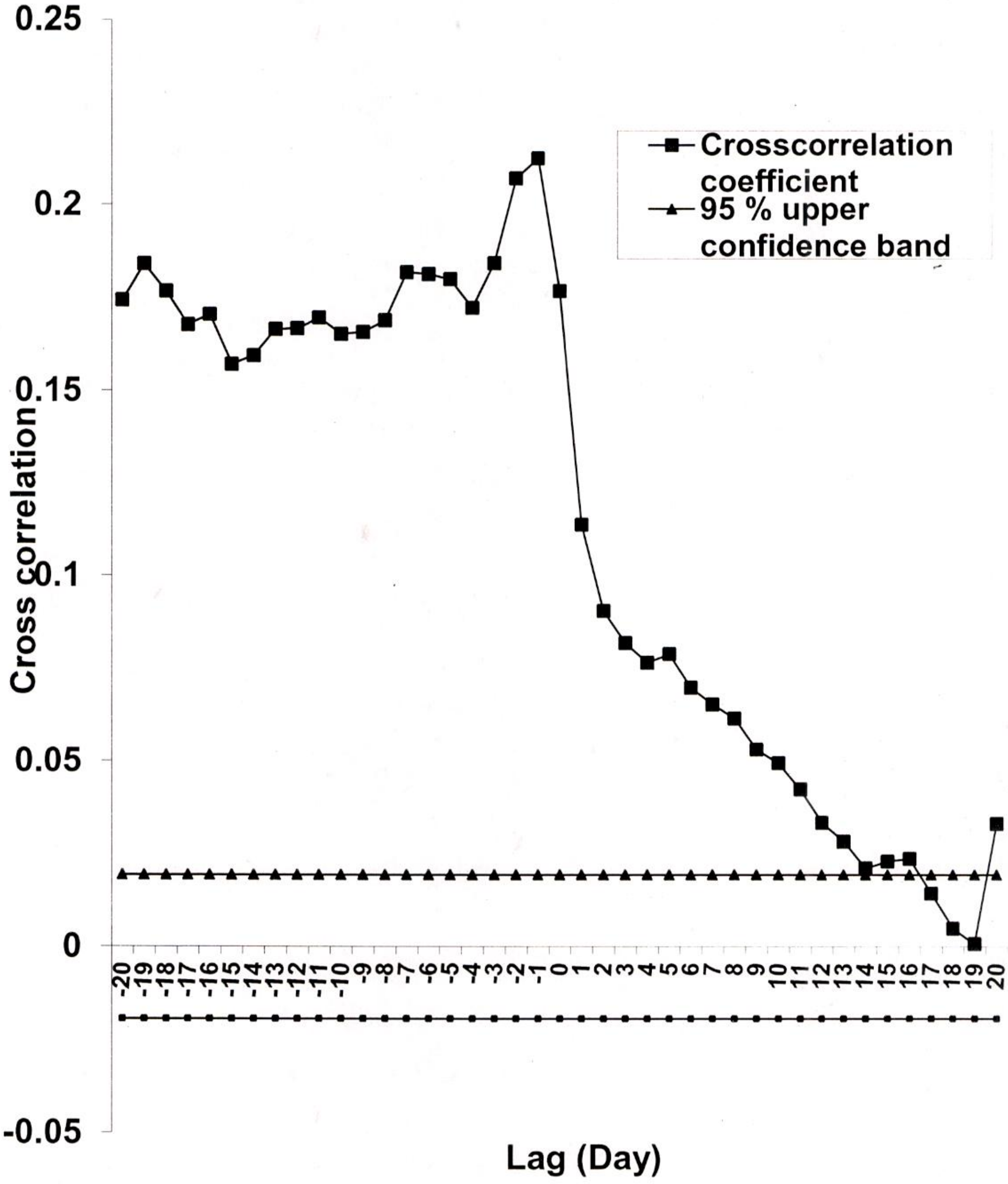


Fig :5.5 The cross-correlation of discharge at Pandariya

5.5. RESULTS FOR ANN:-

Equation for ANN :-

Data(t-1,:)=[rchi(t) rpan(t-1) rbod(t-1) dis(t-1) dis(t)]

Model No	ANN Structure	Calibration			Validation		
		CORR	RMSE	EFF%	CORR	RMSE	EFF%
DIS1	4-1-1	0.9527	1.3322	0.9073	0.9664	0.8394	0.9333
DIS2	4-2-1	0.9531	1.3263	0.9081	0.9670	0.83.03	0.9347
DIS3	4-3-1	0.9693	1.0773	0.9394	0.9888	0.4849	0.9777
DIS4	4-4-1	0.9696	1.0727	0.9399	0.9892	0.4757	0.9786
DIS5	4-5-1	0.9715	1.0384	0.9437	0.9896	0.4682	0.9792
DIS6	4-6-1	0.9721	1.0270	0.9449	0.9896	0.4669	0.9794
DIS7	4-7-1	0.9711	1.0454	0.9429	0.9888	0.4869	0.9776
DIS8	4-8-1	0.9727	1.0167	0.9460	0.9897	0.4690	0.9792
DIS9	4-9-1	0.9731	1.0091	0.9468	0.9894	0.4741	0.9787
DIS10	4-10-1	0.9735	1.0020	0.9475	0.9897	0.4687	0.9792
DIS11	4-11-1	0.9737	0.9985	0.9479	0.9893	0.4765	0.9785
DIS12	4-12-1	0.9740	0.9923	0.9486	0.9881	0.5025	0.9761
DIS13	4-13-1	0.9742	0.9886	0.9489	0.9891	0.4812	0.9781
DIS14	4-14-1	0.9740	0.9935	0.9484	0.9892	0.4800	0.9782
DIS15	4-15-1	0.9742	0.9895	0.9488	0.9887	0.4913	0.9771

Table5.1 Results of ANN model during calibration and validation

CALIBRATION GRAPH FOR ANN:-

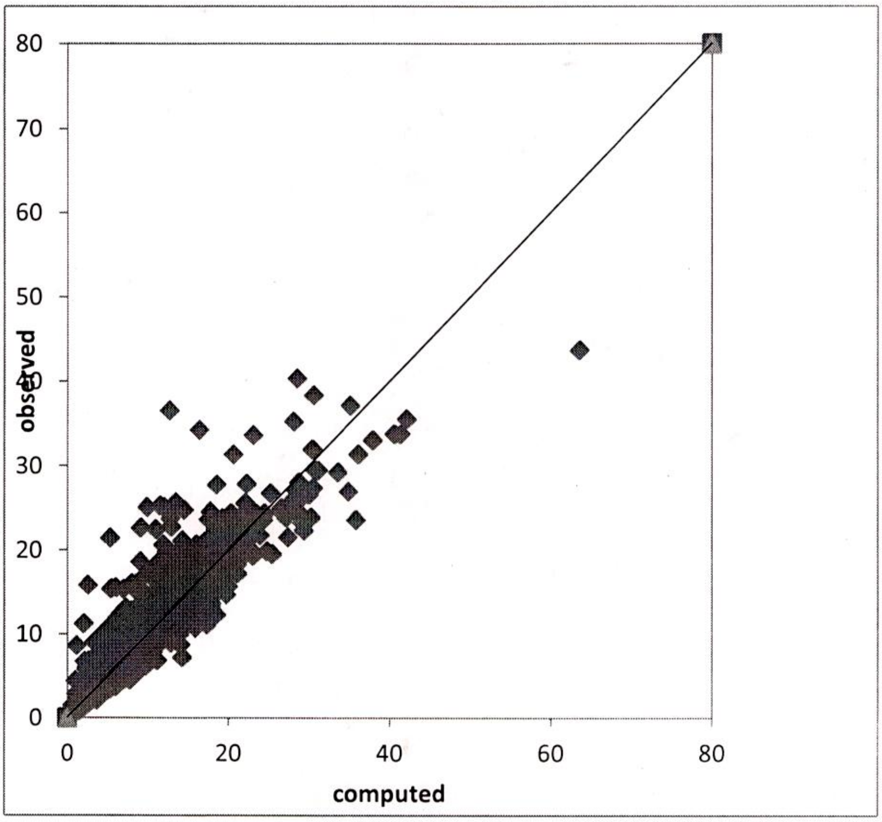


Fig:- 5.6 The performance of ANN model during calibration

VALIDATION GRAPH FOR ANN:-

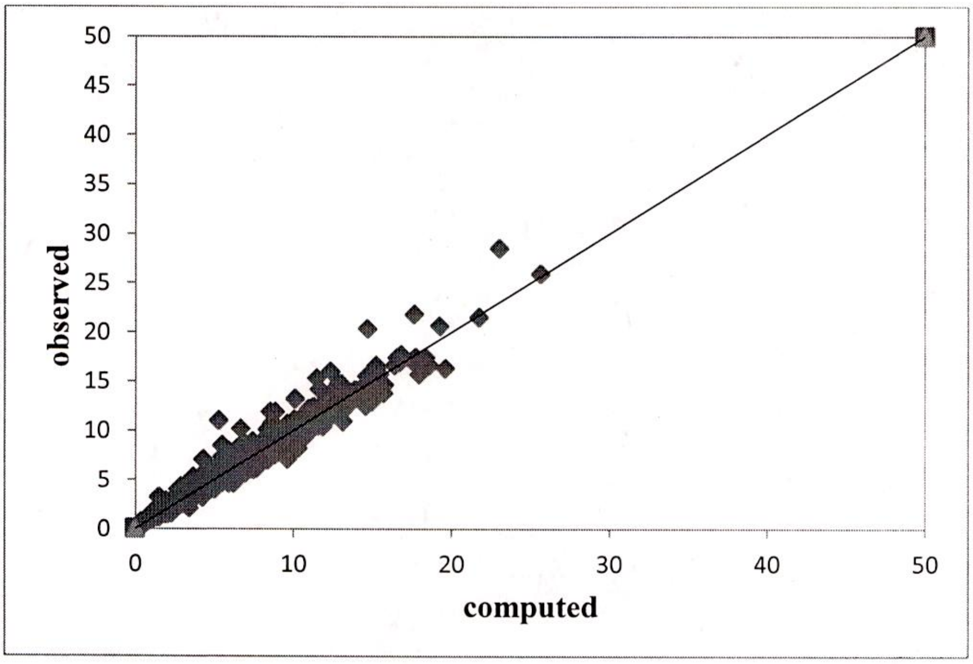


Fig:-5.7 The performance of ANN model during validation

RESULTS FOR MLR:-

MLR

Multiple linear regression is the most common form of linear regression analysis. As a predictive analysis, the multiple linear regression is used to explain the relationship between one continuous dependent variable from two or more independent variables.

MLR Equation:-

$RQ_{hamp} = 0.1154_{chirapani,t} - 0.0023_{pandariya,t-1} - 0.0205_{bodla,t-1} + 0.9153DIS_{hamp,t-1} + 0.1850$

Calibration and validation:-

CALIBRATION GRAPH FOR MLR:-

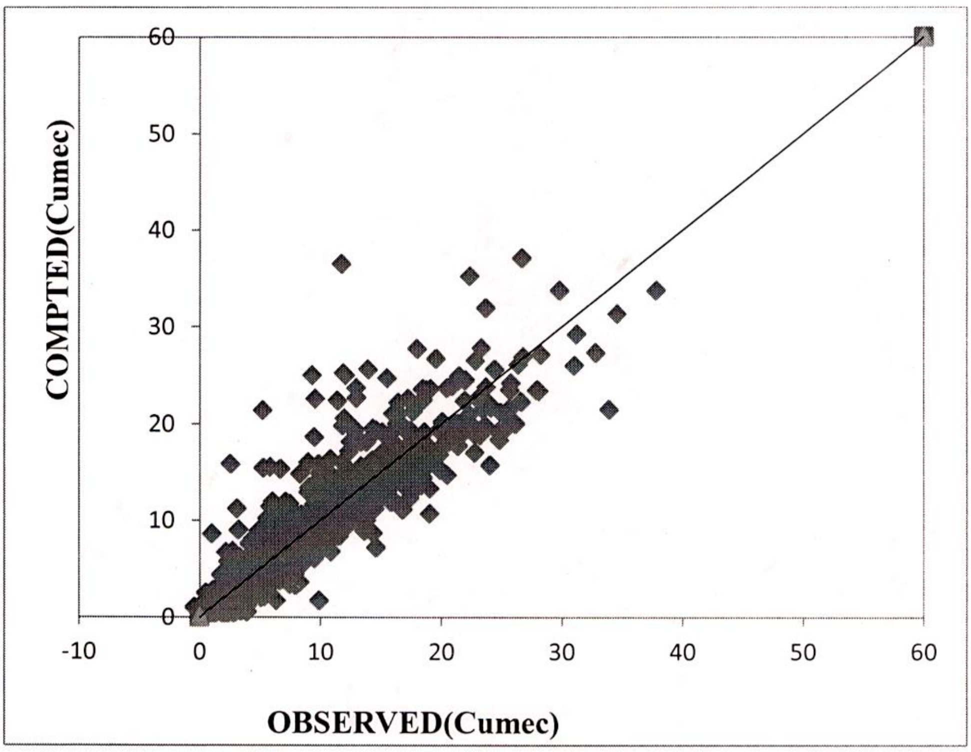


Fig :-5.8 The performance of MLR model during calibration

VALIDATION GRAPH FOR MLR:-

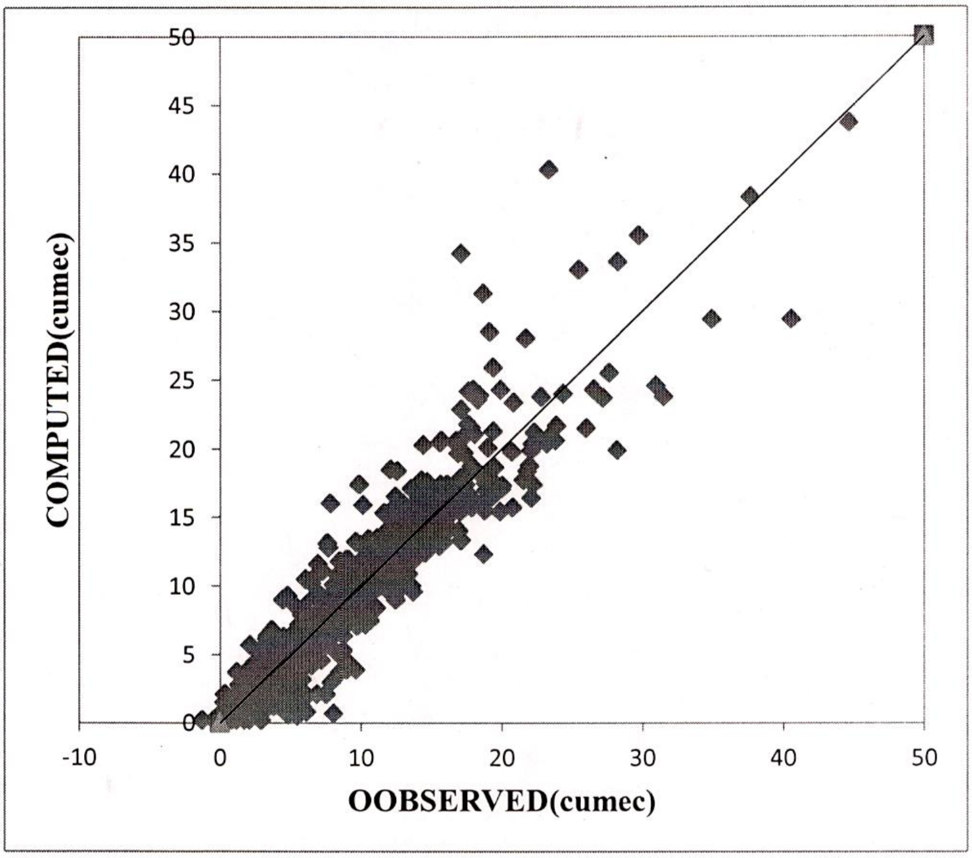


Fig:-5.9 The performance of ANN model during validation

Table 5.2 Comparison of results between best ANN and MLR models

	ANN model		MLR model	
	Calibration	**Validation**	**Calibration**	**Validation**
Coefficient of Correlation	0.9721	0.9896	0.9628	0.9648
RMSE	1.0270	0.4669	1.1809	1.0970
Model efficiency	0.9449	0.9794	0.9271	0.9307
Percentage error in peak streamflow estimation	-45.44	10	-1.9407	-2.1967

CONCLUSION

The relationship between rainfall-runoff is one of the most complex hydrological phenomena to comprehend the spatial and temporal variability of watershed characteristics and precipitation patterns and also to the number of variable involved in the modelling of the physical process. In this study,the ANN model has been developed to simulate the runoff from rainfall. The rainfall in the catchment area at Chirapani, Bodla, and Panadariya and the hourly discharge data is used to carry out this research work. The duration of data used is from 1981 to 2009.

The MLR model is developed by using rainfall, runoff as input data. The statistical indices such as coefficient of correlation, root mean squared error (RMSE) and model efficiency have been used to evaluate the performance of the both the models.

The analysis of the performance of the both ANN and MLR models clearly indicate that the application of ANN helps in the better prediction of rainfall runoff. A comparison of results of ANN and MLR was obtained.

The RMSE of ANN model during calibration and validation was found to be 0.9721 and 0.9896 respectively, whereas for the MLR model, RMSE value during calibration and validation was 0.9628 and 0.9648 respectively, and also the ANN model efficiency during calibration and validation was 0.9449 and 0.9794 respectively, whereas the MLR model efficiency during calibration and validation was 0.9271 and 0.9307 respectively, indicates a substantial improvement in the model performance. In addition, comparison of the scatter plots of ANN model are more precise than those found by the MLR.

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