

## Application of Artificial Neural Networks for Rainfall Modelling

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### ABSTRACT

Artificial Neural Networks (ANNs) have been tried by researchers for rainfall forecasting in different parts of the world. In this paper, three categories of model are tried for rainfall forecasting of Pratapgarh district by varying number of inputs. In the first model (Model-A), rainfall of same week of previous three years and rainfall of three preceding weeks of same year used as input. In the second model (Model-B), rainfall of same week of previous four years and rainfall of four preceding weeks of same year used as input. While, in the third model (Model-C), rainfall of same week of previous five years and rainfall of five preceding weeks of same year used as input. The number of hidden layer neurons varied from 1 to 20. The performance of models was tested by using statistical indices such as R, RMSE and MAE. The obtained results of the models showed that, increasing number of inputs significantly improved the performance of models. It was concluded that, the model performance was not significantly affected by increase in number of neurons in hidden layer.

**Keywords:** Rainfall, Modelling, Artificial Neural Network.

### INTRODUCTION

Rainfall is a random event and therefore its prediction is a very difficult and cumbersome. Rainfall variation will be one of the important factors for determination of overall impacts of climate change (Roy & Mazumdar, 2013). The studies of extreme rainfall events have great relevance and importance for water resources management. The incident of extended dry period or heavy rain at the critical stages of the crop growth and development may lead to noteworthy reduction in the crop yield and hence significantly affect the economy of the country (Venkateswarlu, 2011). The

knowledge about rainfall patterns for agriculture is primarily needed for crop planning in rainfed agriculture. Rainfed agriculture is highly vulnerable due to rainfall variability, which is often devastating to agriculture (Radhika et al., 2011). Rainfall in the many parts of India is unevenly distributed and erratic (Manoj & Kumar, 2013). If better predictions of rainfall were available three to six months ahead of time, it may be possible to modify decisions to minimize unwanted impacts and to take advantage of expected favourable conditions (Sharma, 2012).

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Most hydrological data, which plays important role in rainfall forecasting, is non-linear in nature (Belayneh & Adamowski, 2012). Various conventional models such as regression models have drawback that they assume data as linear and stationary. Such models does not deal with nonlinearities in the data (Mishra & Desai, 2006). Artificial neural network (ANN) is a computer program designed to simulate the way in which the human brain processes the information. It is formed from hundreds of single units or artificial neurons, connected with coefficients, which constitutes a neural structure and organised in a layer. The complex nonlinear relationship between input and output data sets can be easily identified through ANN, which may too difficult to conventional mathematical equations (French et al., 1992). Due to its high nonlinear functional characteristic, ANN application has provided many advantages in rainfall forecasting, rainfall-runoff modelling and sediment forecasting. They are in use as forecasting models from past two decades in various scientific areas (Cutore et al., 2009). The complexity and non-linearity makes it attractive to try the artificial neural network approach, which is inherently suited to problems that are mathematically difficult to describe.

Artificial Neural Networks have been used for rainfall forecasting in many parts of the world including Australia (Abbot & Marohasy, 2014, Mekanik et al., 2013, Luk et al., 2001), Greece (Nastos et al., 2011), Taiwan (Lin & Wu, 2009), Iran (Hosseini & Mahjouri, 2015, Araghinejad et al., 2011, Kashiwao et al., 2017), Japan (Kashiwao et al., 2017), Brazil (Ramirez et al., 2005), USA (Silverman, & Dracup, 2000, Kuligowski & Barros, 1998), Italy (Toth et al., 2000), Ireland (Shamseldin, 1997) and India (Mishra et al., 2018, Sojitra et al., 2016, Gupta et al., 2014, Mandal & Jothiprakash, 2012, Sudheer et al., 2002). The present study applies ANN models for generating more practical rainfall forecasts

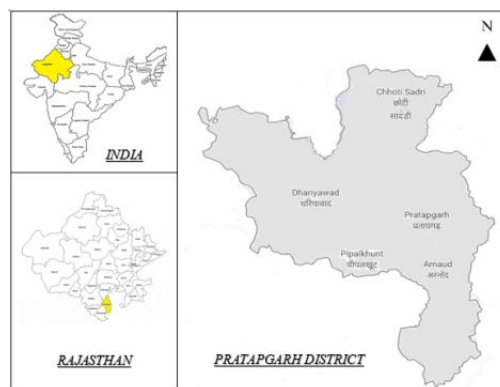
for Pratapgarh district than forecasts based on simple regression or statistical models.

## MATERIALS AND METHODS

ANN is a flexible mathematical structure that is capable of identifying complex non-linear relationships between input and output data sets (French et al., 1992). An ANN architecture is designed by weights between neurons, a transfer function that controls the generation of output in a neuron and learning laws that defines the relative importance of weights for input to a neuron. The incoming signals are multiplied by respective weights through which they are propagated towards the neurons or node. They are aggregated there and the net input is passed through the activation function or transfer function to produce the output. The simplest types of neural network are multilayer perceptrons (MLPs), where the input-output relationship depends only on the present input (Abbot & Marohasy, 2014). There is no fixed or systematic method to establish a suitable architecture and it is basically problem specific. Thus, a trial and error method using different number of neurons is still being preferred choice of most users (Ouhmad & Halimi, 2014). The choice of input variables in ANN is an important issue. The number of neurons in the output layer depends on the number of target variables.

### Study area:

Pratapgarh is an important district of Rajasthan state located at 24.03°N 74.78°E with average elevation of 580 metres above mean sea level. It is situated at the junction of Aravali mountain ranges and the Malwa Plateau. The geographical area of Prtapgarh is 4117 square kilometre. The average annual rainfall is 856 mm. Pratapgarh district comprises 5 subdivisions, viz. Arnod, Chhotisadri, Dhariawad, PipalKhunt and Pratapgarh. The study area comes under IV B agroclimatic zone (Hussain, 2015).



**Fig. 1: Location map of the study area**

### Data:

The weekly rainfall data of 50 years (1967-2016) from Water Resources Department Rajasthan was used to develop ANN models for rainfall forecasting of 5 stations in the study area. ANN models were created by using MATLAB (R.2014a) ANN toolbox.

### MATERIALS AND METHODS

There is no general rule for selection of input variables of ANN and it is rather problem dependent. Therefore, trial and error method was used to choose input variables to ANN models in this study. Due to lack of available data on the necessary temporal and spatial scales, previous rainfall values are used as inputs to ANN. Three different categories of ANN models were developed for rainfall forecasting using historical data based on varying inputs. These models are:

1. ANN model A with six neurons in the input layer (i.e. rainfall of same week of previous three years and rainfall of three preceding weeks of same year).
2. ANN model B with eight neurons in the input layer (i.e. rainfall of same week of previous four years and rainfall of four preceding weeks of same year).
3. ANN model A with ten neurons in the input layer (i.e. rainfall of same week of previous five years and rainfall of five preceding weeks of same year).

According to Fletcher and Goss (1993), the number of neurons in hidden layer should be  $(2n+1)$ , where  $n$  is the number of input neurons. In the present study, one hidden layer was used and number of neurons in hidden

layer were varied from 1 to 20. Here, rainfall of particular week was the target variable and hence one output layer was used in neural network architecture. The logsigmoid and purline transfer functions were used in model development and Levenberg-Marquardt (LM) algorithm also denoted by *trainlm* was used as learning algorithm. All neural network architectures were optimised for 1000 epochs or with a goal of mean square error 0.01.

The weekly rainfall data of 50 years (1967-2016) was divided into three subsets *viz.* training dataset, testing dataset and validation dataset in 70:15:15 proportion (Shamseldin, 1997). The data was normalised (in the range of 0 to 1) to transform input features of data into same range of values, which minimised the bias within ANN. The performance of formulated ANN models was evaluated using statistical indices such as correlation coefficient (R), root mean square error (RMSE) and mean absolute error (MAE). The models having higher values of correlation coefficient and lower values of mean absolute error and root mean square error were considered as the best-fit model for the particular station.

### RESULTS AND DISCUSSION

Performance of ANN models for varying inputs:

The data pertaining to the performance indices of best-fitted models from all three categories for different stations in Pratapgarh district are given in Table 1. The graphical representation of actual and forecasted rainfall using best fit ANN architecture during testing

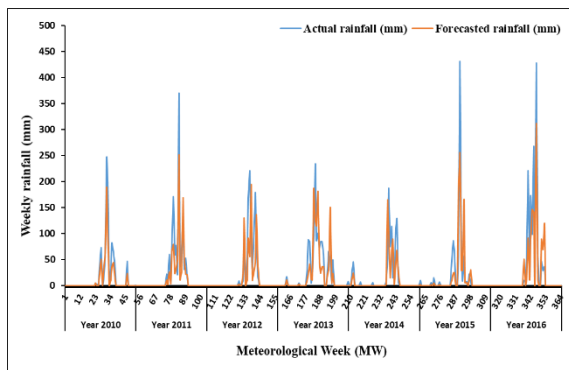
phase (on unseen data) for different selected stations is shown in Fig. 1 (a to e).

**Table 1: The best ANN models for different stations in the study area**

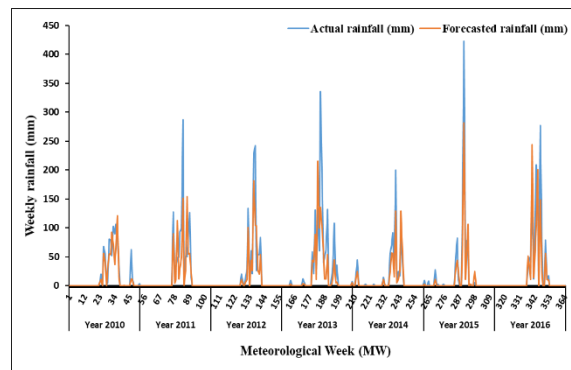
Sr. No.	Station	ANN Models	Performance indices								
			Training			Testing			Validation		
			R	RMSE	MAE	R	RMSE	MAE	R	RMSE	MAE
1.	Arnod	10-19-1	0.82	4.89	1.20	0.82	4.77	1.19	0.82	4.99	1.21
2.	Chhotisadri	8-20-1	0.85	3.22	1.15	0.86	3.02	1.12	0.85	3.30	1.15
3.	Dhariawad	10-18-1	0.88	2.66	1.08	0.87	2.893	1.10	0.87	2.81	1.10
4.	PipalKhunt	10-13-1	0.86	3.20	1.12	0.87	2.74	1.10	0.86	3.10	1.11
5.	Pratapgarh	10-13-1	0.87	2.64	1.10	0.89	2.34	1.00	0.88	2.46	1.01

It was noted that, Model C with ten neurons in input layer was best fitted for 4 stations while Model B best fitted for only Chhotisadri station. Model A was not found best for any of stations in the study area on the basis of

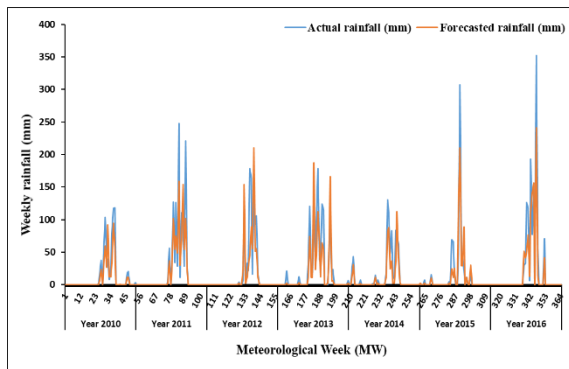
performance evaluation parameters. Therefore, increased number of inputs significantly improved the performance of models. Tokar & Johnson (1999) and Luk et al., (2001). reported the similar results.



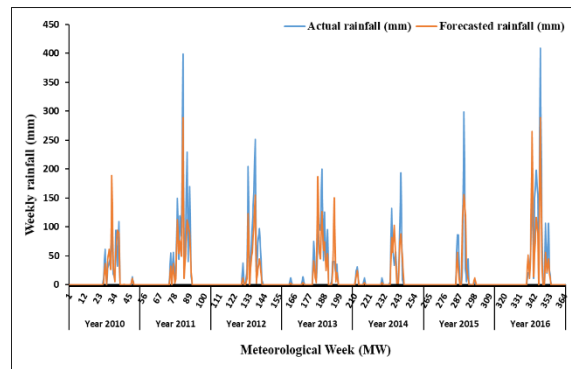
**a. Actual and forecasted rainfall using ANN architecture 10-19-1 (Model C) for Arnod station**



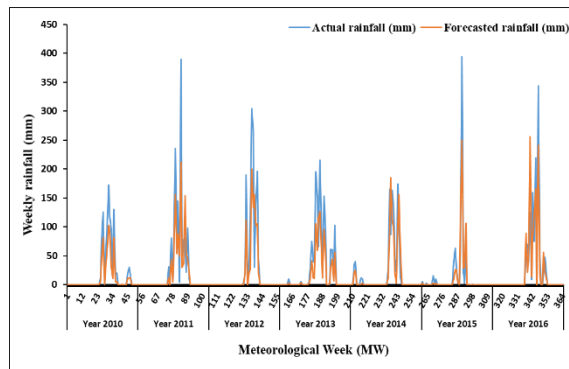
**b. Actual and forecasted rainfall using ANN architecture 8-20-1 (Model B) for Chhotisadri station**



**c. Actual and forecasted rainfall using ANN architecture 10-18-1 (Model C) for Dhariawad station**



**d. Actual and forecasted rainfall using ANN architecture 10-13-1 (Model C) for Pipal Khunt station**

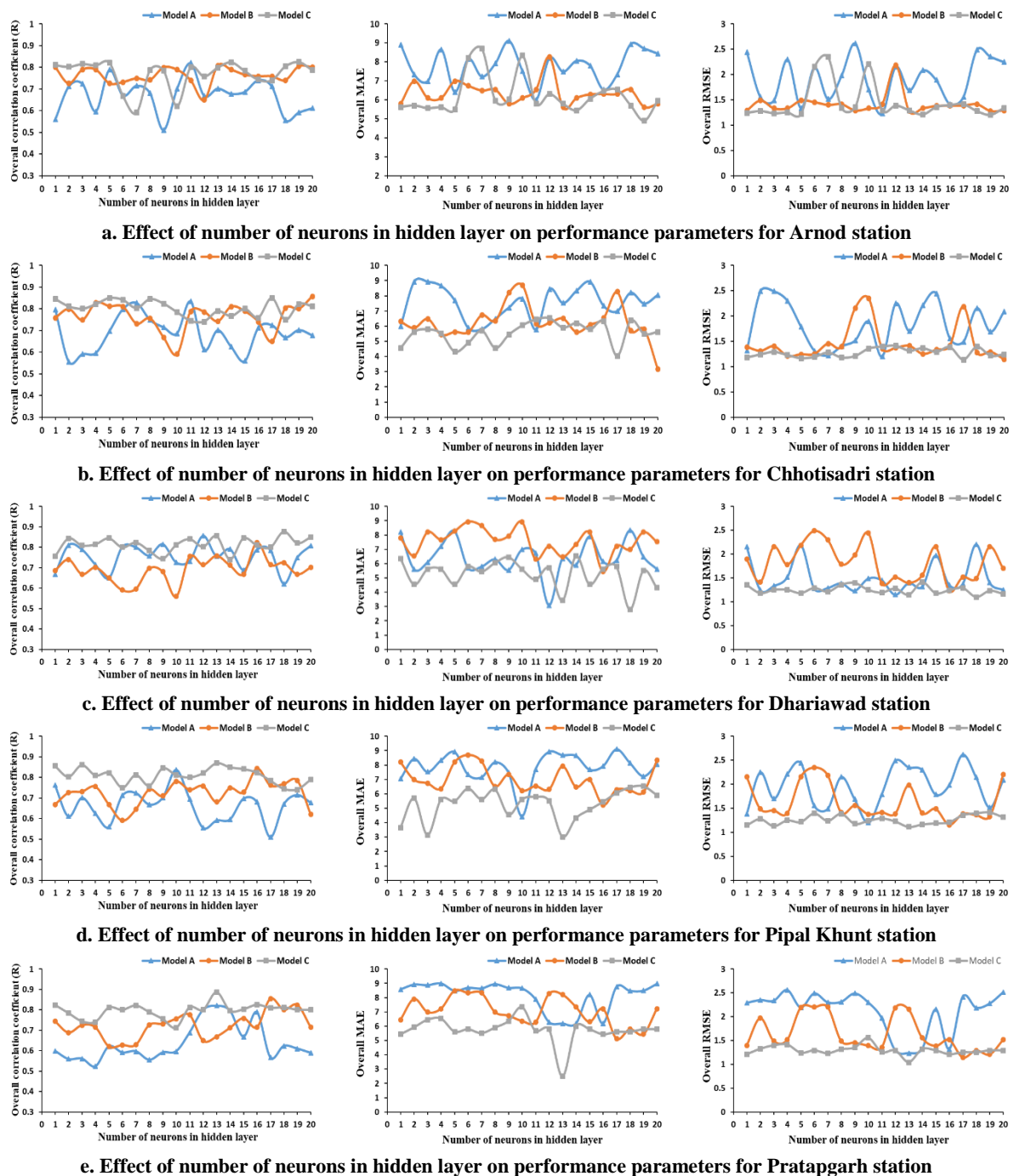


**e. Actual and forecasted rainfall using ANN architecture 10-13-1 (Model C) for Pratapgarh station**

**Fig. 1: Actual and forecasted rainfall using best ANN architecture for different stations in the study area**  
**Performance of ANN models for varying neurons in hidden layer:**

Three ANN model categories with varying number of inputs were evaluated for different number of neurons (1 to 20) in hidden layer. The graphical representation of change in overall value of performance indices with varying number of neurons in hidden layer for best-fitted models are presented in Fig. 2 (a to e). It was observed that, the change in number of neurons in hidden layer not significantly affected the performance of models. R values

in training, validation and testing phase changed with the change in the number of neurons in hidden layers for all categories of models. The performance of models was not significantly affected by increase in number of neurons in hidden layer upto 10. However, between 10 to 20 neurons their performances improved in the form of R, MAE and RMSE for most of the selected stations. Dubey (2015) and Mishra et al. (2018) reported the similar results.



**Fig. 2: Effect of number of neurons in hidden layer on performance parameters for different stations in the study area**

**CONCLUSION**

Rainfall is produced by a complex combination of various processes operating over a large extent of space and time, previous rainfall values are often used as input to ANN models. In this study, three different categories of ANN models were developed for rainfall forecasting of Pratapgarh district using historical data based on varying inputs. In general, Model-C with ten neurons in input layer was best fitted for most of the selected stations. Increased number of inputs significantly improved the performance of models in most of the stations. The change in number of neurons in hidden layer not significantly affected the performance of models. The performance of ANN models was not significantly affected by increase in number of neurons in hidden layer upto  $(2n+1)$ , where n is number of input neurons. This is supported by findings of Fletcher and Goss (1993). Generally, a black box model such as ANN underestimates the peak values in time series due to sudden imposition of extreme inputs, such as in case of heavy rainfall. Therefore, the models which uses only current and some previous time steps such as WANN (wavelet-ANN), ANFIS etc. which have long term periodicity memory and uses stored data of extreme events that occurred in past can forecasts peak values more accurately.

**REFERENCES**

- Abbot, J., & Marohasy, J. (2014). Input selection and optimisation for monthly rainfall forecasting in Queensland, Australia, using artificial neural networks. *Atmospheric Research*, 138, 166-178.
- Araghinejad, S., Azmi, M., & Kholghi, M. (2011). Application of artificial neural network ensembles in probabilistic hydrological forecasting. *Journal of Hydrology*, 407, 94-104.
- Belayneh, A., & Adamowski, J. (2012). Standard precipitation index drought forecasting using neural networks, wavelet neural networks and support vector regression. *Applied Computational Intelligence and Soft Computing*, 6, 1-13.
- Cutore, P., Mauro, G. D., & Cancelliere, A. (2009). Forecasting palmer index using neural networks and climatic indexes. *Journal of Hydrologic Engineering*, 14, 588-595.
- Dubey, A. D. (2015). Artificial neural network models for rainfall prediction in Pondicherry. *International Journal of Computer Applications*, 120, 30-35.
- Fletcher, D. S., & Goss, E. (1993). Forecasting with neural network: An application using bankruptcy data. *Information Management*, 24, 159-167.
- French, M. N., Krajewski, W. F., & Cuykendall, R. R. (1992). Rainfall forecasting in space and time using a neural network. *Journal of Hydrology*, 137, 1-31.
- Gupta, P., Mishra, S., & Pandey, S. K. (2014). Time series data mining in rainfall forecasting using artificial neural network. *International Journal of Scientific Engineering and Technology*, 3, 1060-1065.
- Hosseini, S. M., & Mahjouri, N. (2015). Integrating support vector regression and a geomorphologic artificial neural network for daily rainfall-runoff modelling. *Applied Soft Computing*.
- Hussain, M. (2015). Agro-Climatic zones and economic development of Rajasthan. *International Journal of Humanities and Social Science Invention*, 4, 50-57.
- Kashiwao, T., Nakayama, K., Ando, S., Ikeda, K., Lee, M., & Bahadori, A. (2017). A neural network-based local rainfall prediction system using meteorological data on the Internet: A case study using data from the Japan Meteorological Agency. *Applied Soft Computing*, 56, 317-330.
- Kuligowski, R. J., & Barros, A. P. (1998). Localized precipitation forecasts from a numerical weather prediction model using artificial neural networks.

- Weather and Forecasting*, 13, 1194-1204.
- Lin, G. F., & Wu, M. C. (2009). A hybrid neural network model for typhoon-rainfall forecasting. *Journal of Hydrology*, 375, 450-458.
- Luk, K. C., Ball, J. E., & Sharma, A. (2001). An application of artificial neural networks for rainfall forecasting. *Mathematical and Computer Modelling*, 33, 683-693.
- Mandal, T., & Jothiprakash, V. (2012). Short-term rainfall prediction using ANN and MT techniques. *ISH Journal of Hydraulic Engineering*, 18, 28-37.
- Manoj, K., & Kumar, P. P. (2013). Climate change, water resources and food production: some highlights from India's standpoint. *International Research Journal of Environment Sciences*, 2, 79-87.
- Mekanik, F., Imteaz, M. A., Trinidad, S. G., & Elmahdi, A. (2013). Multiple regression and artificial neural network for long-term rainfall forecasting using large scale climate modes. *Journal of Hydrology*, 503, 11-21.
- Mishra, A. K., & Desai, V. R. (2006). Drought forecasting using feed forward recursive neural network. *Ecological Modelling*, 198, 127-138.
- Mishra, N., Soni, H. K., Sharma, S., & Upadhyay, A. K. (2018). Development and analysis of artificial neural network models for rainfall prediction by using time-series data. *International Journal of Intelligent Systems and Applications*, 1, 16-23.
- Nastos, P. T., Moustris, K. P., Larissi, I. K., & Paliatsos, A. G. (2011). Rain intensity forecast using artificial neural networks in Athens, Greece. *Atmospheric Research*, 10, 1-8.
- Nourani, V., Kisi, O., & Komasi, M. (2011). Two hybrid artificial intelligence approaches for modelling rainfall-runoff process. *Journal of Hydrology*, 402, 41-59.
- Ouhmad, S., & Halimi, A. (2014). The impact of number of neurons in the hidden layer on the performance of MLP neural network: Application to the fast identification of toxic gases. *International Journal of Computer and Information Engineering*, 8, 2060-2064.
- Radhika, C., Vanaja, M., & Bali, S. K. (2011). Climate change and rainfed agriculture: rural development perspectives. *Journal of Rural Development*, 30, 411-419.
- Ramirez, M. V., Velho, H. F., & Ferreira, N. J. (2005). Artificial neural network technique for rainfall forecasting applied to the Sao Paulo region. *Journal of Hydrology*, 301, 146-162.
- Roy, P. K., & Mazumdar, A. (2013). Water resources in India under changed climate scenario. *International Journal of Engineering Research and Applications*, 3, 954-961.
- Shamseldin, A. Y. (1997). Application of neural network technique to rainfall-runoff modelling. *Journal of Hydrology*, 199, 272-294.
- Sharma, V. S. (2012). Extractive resource development in a changing climate: Learning the lessons from extreme weather events in Queensland, Australia. National Climate Change Adaptation Research Facility, Gold Coast 110.
- Silverman, D., & Dracup, J. A. (2000). Artificial neural networks and long-range precipitation prediction in California. *Journal of Applied Meteorology*, 39, 57-66.
- Sojitra, M., Purohit, R. C., Pandya, P., & Kyada, P. (2016). Short duration rainfall forecasting modelling through ANNs. *Scientific Journal of Agricultural Engineering*, 4, 11-20.
- Sudheer, K. P., Gosain, A. K., & Ramasastri, K. S. (2002). A data-driven algorithm for constructing artificial neural network rainfall-runoff models.

- Paradkar et al.** *Ind. J. Pure App. Biosci.* (2019) 7(5), 105-112 ISSN: 2582 – 2845  
*Hydrological Processes*, 16, 1325-1330.
- Tokar, A. S., & Johnson, P. A. (1999). Rainfall-runoff modelling using artificial neural networks. *Journal of Hydrologic Engineering*, 4, 232-239.
- Toth, E., Brath, A., & Montanari, A. (2000). Comparison of short-term rainfall prediction models for real-time flood forecasting. *Journal of Hydrology*, 239, 132-147.
- Venkateswarlu, B. (2011). Rainfed agriculture: strategies for livelihood enhancement. ICAR sponsored training course on sustainable agriculture production through innovative approaches for enhanced livelihoods, 2-15<sup>th</sup> Sept.