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Drought Forecasting, using Artificial Neural Network (ANN) and Predict Values of Drought Condition Derived using Rainfall Data

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Abstract: This paper focuses on drought forecasting, using Artificial Neural Network (ANN) and predicts the values of drought condition derived using Rainfall data of Indore (M.P). We have used the Rainfall data as input data of ANN model for drought forecasting, and determine Standardized Precipitation Index (SPI). Artificial Neural networks operate on the principle of learning from a training set. There is a large variety of neural network models and learning procedures. Two classes of neural networks that are usually used for prediction applications are feed-forward networks and recurrent networks. They often train both of these networks using back-propagation algorithm.

Keywords: Artificial Neural Networks (ANNs), SPI.

I. INTRODUCTION

Artificial intelligence (AI) is a growing trend in computer automation systems. Several types of artificial intelligence technology are available. These include robotics, voice-recognition systems, and many smart computer systems. Artificial intelligence refers to any computer system that uses a logical process to learn and improve, based on the surrounding environment and prior mistakes. This technology is undergoing a great evolution, but is still far short of the capacity of the human brain. It may take several decades before computers will can actually use logic to determine the best approach for problem solving. The current AI systems can learn, but in a limited spectrum. This is because the human brain processes thousands of variables to solve a specific problem.

II. ARTIFICIAL NEURAL NETWORK

Neural networks provide a method for extracting patterns from noisy data. We have applied them to a wide variety of problems, including cloud classification (Bankert,[2], 1994) and tornado warnings (Marzban and Stumpf,[3], 1996) in a meteorological context. We discuss the advantages and disadvantages of neural networks in comparison to other statistical techniques for pattern extraction in (Marzban and Stumpf,[3] (1996)). We can find more detail about the construction of neural networks in (Marzban and Stumpf,[3] (1996)) and (Müller and Reinhardt,[4] (1991)) and references therein. The standard procedure for use of a neural network involves ''training'' the network with a large sample of representative data. The network has some number of input and output ''nodes'' representing the predictor and predict and variables, respectively. In between, there are a number of hidden nodes arranged in layers. The number of hidden nodes and layers is usually determined empirically to optimize performance for the particular situation. Each connection between nodes on a particular layer and the layer above it can be represented by a weight, viz. that indicates the importance of that connection between the i^{th} and j^{th} nodes. The training phase of the neural network is designed to optimize the weights so that the mean-squared error of the output is minimized. For each node at a particular layer, the input node values from the previous layer are multiplied by the weight of the connections between the nodes and then all of the different connections are summed to produce the value at that node. This process is repeated for all nodes and then for each layer. The network then can be used to make predictions based on new input values.

III. USE OF ARTIFICIAL NEURAL NETWORKS (ANNs) FOR FORECASTING DROUGHT CONDITION.

In recent decades artificial neural networks (ANNs) have shown exceptional ability in modelling and forecasting non-linear and non-stationary time series and in most of the cases especially in prediction of phenomena have showed excellent performance.

This discussion presents the application of artificial neural networks to predict drought in meteorological station Indore (M.P). In this paper, different architectures of artificial neural networks in Rainfall Data have been used as inputs of the models. According to the results taken from this research, dynamic structures of artificial neural networks, including Recurrent Network (RN) and Time Lag Recurrent Network (TLRN) showed better performance for this application (because of higher accuracy of its outputs). Finally, TLRN network with only one hidden layer and hyperbolic tangent transfer function was the most appropriate model structure to predict drought for the next year. In fact, by a prediction of the Drought before its occurrence, it is possible to evaluate drought characteristics in advance. It was found that ANN is an efficient tool to model and predict drought events.

Artificial Neural networks operate on the principle of learning from a training set. Two classes of neural networks that are usually used for prediction applications are feed-forward networks and recurrent networks. We often train both of these networks using the backpropagation algorithm. An advantage of backpropagation is that it is simple. Prediction networks usually take the historical measured data, and after some processing stages, future condition is simulated. In this research, after evaluation and testing of different ANN Structures, TLRN and RN we selected networks because of their higher performance, and then between these two, TLRN network showed slightly higher abilities. Therefore, TLRN was the final selected ANN type for drought prediction in this study.

IV. STUDY AREA AND DATA SOURCE

Indore:

Fig. 1

The geographical location of Indore is 22.2 - 23.05o North Latitude and 75.25 - 76.16o East Longitude. It is the largest city of the Central-Indian state of Madhya Pradesh; with an area of 3898 sq km, and is situated on the Malwa Plateau. The location of Indore makes it central to the Indian subcontinent. The city once used to serve as the summer capital of the former state of Madhya Bharat. The location of Indore is just south of the Satpura range, at an altitude of 553 meters above sea level.

The strategic location of Indore on the western fringes of the state of Madhya Pradesh has been instrumental in determining the climatic conditions of the city. Summer in Indore spans between the months of April and June and the temperatures soar as high as 45 degrees Celsius during the month of May. Summer temperatures in Indore usually vary between 35 degrees to 40 degrees centigrade. However, an interesting feature about the Indore summer is that although the summer days are scorching hot, the evenings are much cooler and pleasant. Indore, being located on the southern extremity of the Malwa Plateau is subject to the bracing wind of the Shab-e- Malwa during the early evening. Rainfall in Indore is quite sparse and the city receives 35 to 40 inches .i.e. approximately 80 cm rainfall annually from the southwest monsoon downpours. Winters are fairly cold with the average night temperature being around 10 degrees centigrade. Often during winter, the mercury dips as low as 2 degrees centigrade, the lowest mark ever being 1.5 degrees Celsius

V. STANDARDIZED PRECIPITATION INDEX (SPI)

The SPI is an index developed by McKee,[5] et al. (1993) based on the probability of rainfall for the time scale of interest and is relatively less complex to compute. The time scale reflects the impact of drought on the availability of the different water resources. Soil moisture conditions respond to rainfall anomalies on a relatively short scale. Groundwater, stream flow, and reservoir storage reflect the longer-term rainfall anomalies. For the calculation of SPI for any location long time series of rainfall for the desired period (monsoon season for this study) is used. This long time series of rainfall is fitted to a probability distribution, which is then transformed into a standardized normal distribution so that the mean SPI for the location and desired period is zero. Positive SPI values indicate greater than median rainfall and negative values indicate less than median rainfall. The classification of the drought intensities based on the SPI value is as follows;

Table.1. SPI V/s Drought

Table for SPI	
2.0 +	Extremely Wet
1.5 to 1.99	Very Wet
1.0 to 1.49	Moderately Wet

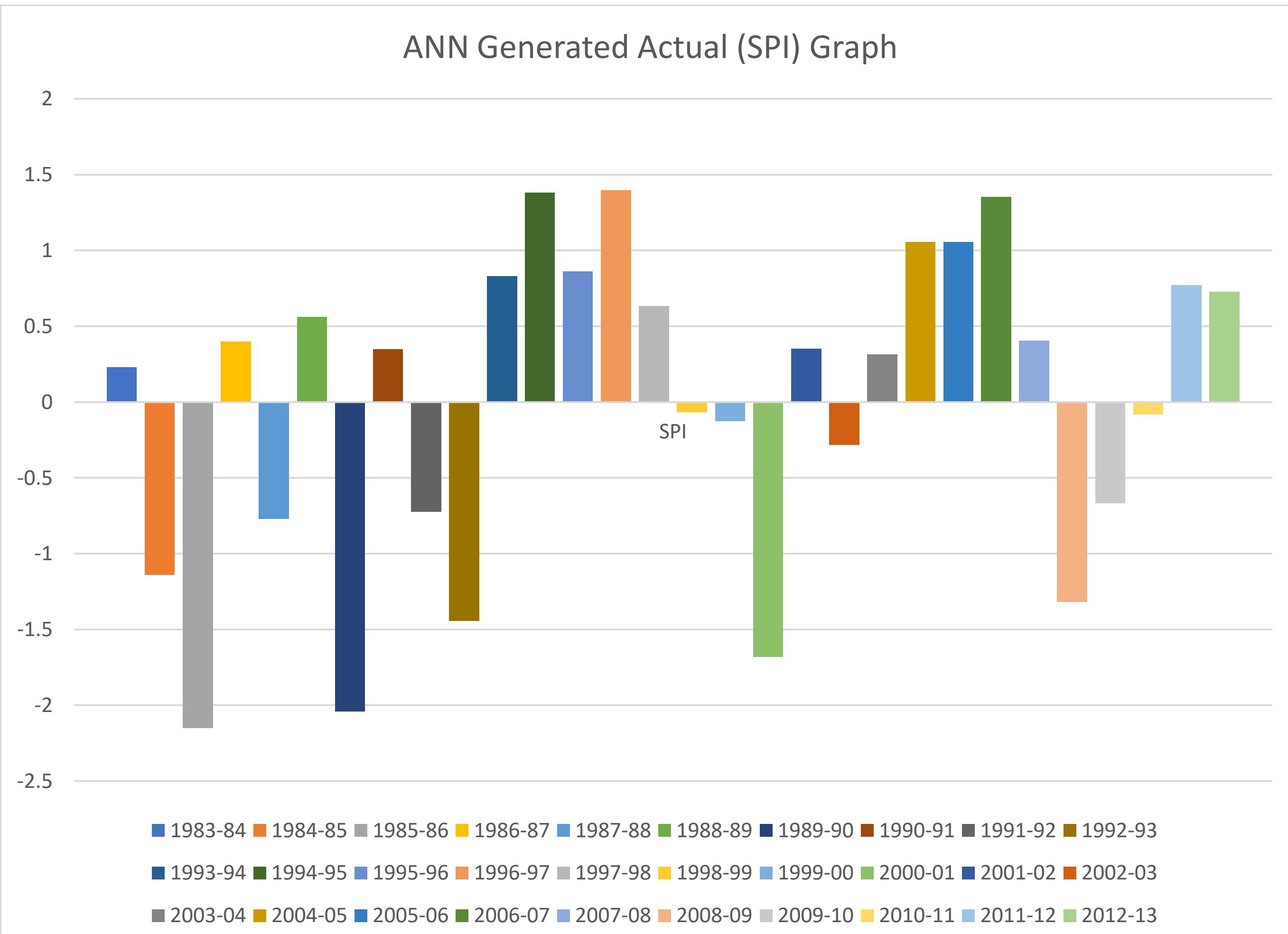
-.99 to .99	Near Normal
-1.0 to -1.49	Moderately Dry
-1.5 to -1.99	Severely Dry
-2 and less	Extremely Dry

The SPI is an index developed by McKee,[5], et al. (1993) based on the probability of rainfall for the time scale of interest and is relatively less complex to compute. The time scale reflects the impact of drought on the availability of the different water resources. The SPI is calculated using the following equation, written as

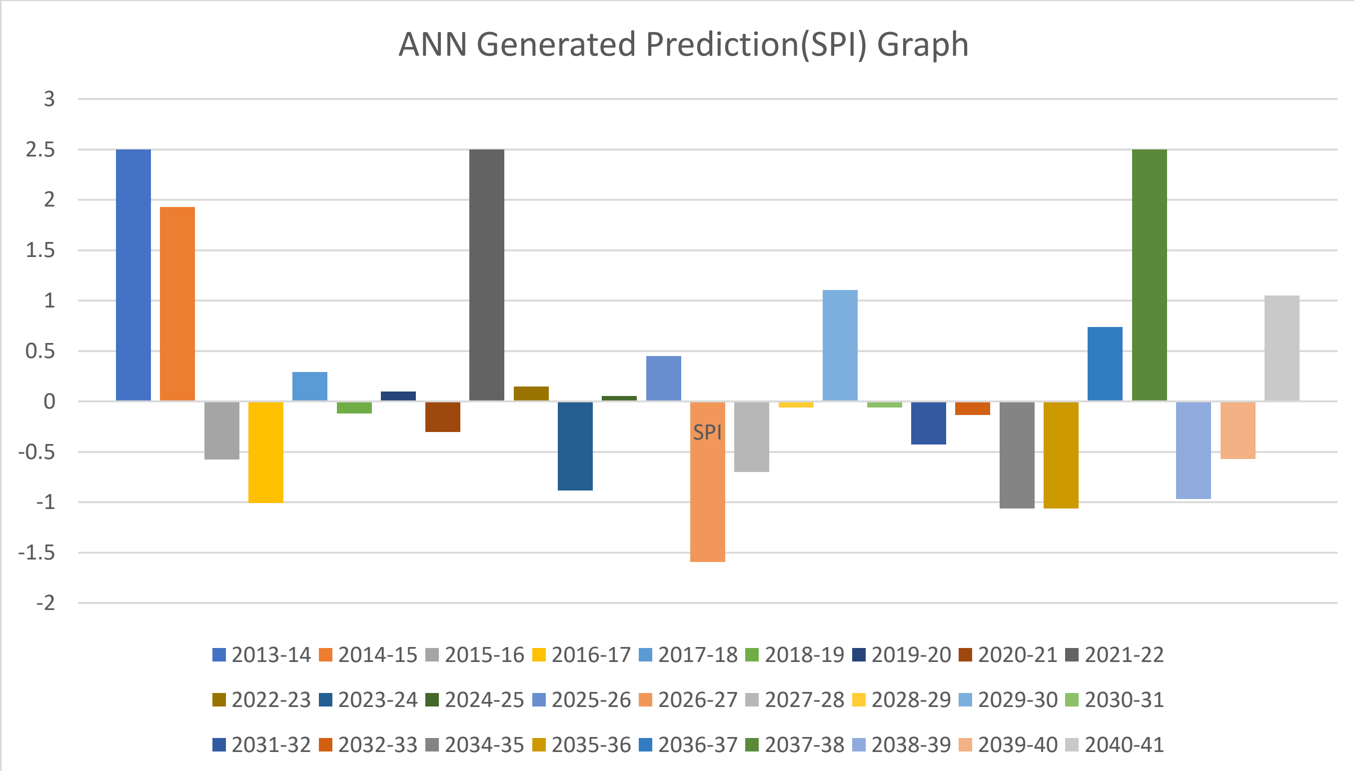
$$\mathbf{SPI}= \frac{Xij - Xim}{\sigma}$$

Where, *Xij* is the seasonal precipitation at the ith rain-gauge station and jth observation, *Xim* is its long-term seasonal mean and σ is its standard deviation. Although McKee,[6], *et al.*, (1995) in the original classification scheme proposed 'mild drought' for SPI values less than 0.00, in the modified SPI classification scheme of Agnew,[1],(1999), there is a straight jump from 'no drought' to 'moderate drought'. In the present study, SPI maps have been classified using the modified scheme of Agnew,[1],(1999) to represent various hydro-meteorological drought intensities, however, 'mild drought' has been recognized corresponding to the SPI values less than -0.50, which has a probability of occurrence 0.309 (Agnew,[1],1999). Seasonal normal's of 30 years (1982-2012) have been used for calculation of SPI. Instead of averaging anomalies for the entire terrain, SPI has been computed separately for each of the rain-gauge stations falling within and around the study area.

VI. ANN GENERATED (SPI) GRAPH



Graph.1. ANN Generated Actual (SPI) Graph



Graph.2. ANN Generated Prediction (SPI) Graph

VII. CONCLUSION

Initially, the ANN model has been conducted on the whole dataset. We have performed graphical visualization in order to make it easier to understand the data itself graph 1and 2 shows it.

The SPI graph generates by ANN model indicate that meteorological drought appears in the Indore region in a random fashion. From graph 1 the negative bars in years 1985-86, 1989-90 , show over all extreme drought condition in these years, while 1988-89 depict severely dry condition and remaining years show mild meteorological drought occurrence. The positive bars in years 1994-95, 1996-97, 2006-07 show that good rainfall condition. Higher positive values indicate to good rainfall.

Similarly, from prediction graph 2 the negative bars in years 2026-27 show extremely dry condition, while 2034-35, 2035-36 show moderately dry condition occurrence in these years. The positive bars in years 2013-14, 2021-22, 2037-38 show that good rainfall condition. It is observed that the actual result is very close to the predicted result in concerned area.

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