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Review Article

Rainfall Forecasting using Artificial Neural Networks (ANNs): A Comprehensive Literature Review

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ABSTRACT

Weather forecasting is important for people. It helps to make more informed daily decisions and to keep out of danger. Accurate weather forecasting has been one of the most challenging problems around the world. Unlike traditional methods, modern weather forecasting involves a combination of computer models, observation and knowledge of trends and patterns. To recognize the application of Artificial Neural Networks (ANNs) in weather forecasting, especially in rainfall forecasts a comprehensive literature review from 1997 to 2019 is done and presented in this paper. It is observed that architectures of ANN such as BPN, MLP, and FFNN is best established to be forecast chaotic behaviour and have efficient enough to forecast rainfall.

Keywords: *Artificial Neural Networks (ANN), BPN, MLP, FFNN, Rainfall forecasting*

INTRODUCTION

Rainfall is an extremely complex, non-linear and dynamic process that is not clearly understood. The rainfall depends on many climatic variables such as temperature, relative humidity, wind speed and direction, atmospheric pressure in addition to its value in the past. The various influencing variables mentioned above are highly inter-related among each other in a complex and non-linear manner (Ganti, 2014). Rainfall forecasting is part of weather forecasting and is crucial for various sectors, such as agriculture, water resource management, flood management as well as transportation. Rainfall prediction is useful to warn about a natural disaster such as floods and to plan activities such as cropping pattern schedule. Rainfall forecasting still becomes a challenging task due to the uncertainty of natural phenomena (Purnomo et al., 2017). Many studies have been conducted on rainfall forecasting; however, the success model of rainfall forecasting is rarely visible. Researchers have used different soft computing techniques like the Genetic Algorithm (GA), ANN, and Fuzzy logic for rainfall forecasting.

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However, many researchers preferred to use of ANN for rainfall forecasting because, 1. ANNs are data-driven model and do not require restrictive assumptions about the form of the basic model. 2. ANN can also predict the pattern which is not provided during training. 3. ANN is efficient at training large-size of samples due to its parallel processing capability. 4. ANN can implicitly detect complex nonlinear relationships between dependent and independent variables (Darji et al., 2015). Traditional methods make an assumption based on time series data but ANN does not require restrictive assumptions based on time series data. Therefore, nowadays Artificial Neural Networks more popular for rainfall forecasting and prediction.

The aim of this study is to be categorized ANNs in Rainfall forecasting and their applicability without any scientific controversy. The objectives of this study are to identify all methods including ANNs for Rainfall forecasting up to date and their performances and evaluate the performance of ANNs. These objectives are considered via a comprehensive review of literature from 1997 to 2019. It is observed that several methods are used including ANNs for rainfall forecasting. Although, ANNs are found suitable without any controversy. However, detail of discussion concerning the architecture of ANN for the same is rarely visible in the literature; while various applications of ANN are available. In the present study, the review of these contributions is accomplished and tried to identify that a neural network is adequately suitable for modelling of chaotic data sets. This paper has been constructed with the sections. The comprehensive review of worldwide contribution from 1997 to 2019. Artificial neural networks techniques for climatic data are unquestionably accepted and scientific disagreements are not discussed. A Table of different modelling techniques and finally conclusions of the study are described.

COMPREHENSIVE LITERATURE REVIEW

The significant and north worthy contributions in the field of rainfall forecasting from 1997 to 2019 are reviewed and identified fundamental with their vital methodologies. The major contributions are discussed in this section. The primary objective of this research is to develop a model for rainfall forecasting using a neural network. In the initial years of 1997 Shamseldin stated that The comparison of the results of the neural network forms corresponding to each of the four external input scenarios with those of the SLM, the LPM, and NNLPM showed that, in calibration, one or other form of neural network has substantially higher R^2 model efficiency values than other three models in the case of all of the six test catchments. The outcomes reflected that the neural network showed considerable potential in rainfall-runoff modelling.

In the year 1998 Kuligowski and Barros found that the overall accuracy of the forecasts as measured by root mean square error (RMSE) and correlation coefficient (R) was slightly lower than that obtained using linear regression. The neural network approach provided significant improvements for moderate to high precipitation amounts, which were the most important conditions for operational hydrology. Dawson and Wilby (1998) found that ANNs are like conventional hydrological models in that different attributes of the hydrograph simulated to varying degrees of success. The optimization criteria used here (MSRE) was unbiased, whereas an in the statistic or the RMSE would have simulated peaks better than low flows.

In the year 1999 Tokar and Johnson said that the ANN rainfall-runoff model was compared favourably with the results obtained using existing techniques such as statistical regression and a simple conceptual model. The ANN model provided a more systematic approach, reduced the length of calibration data, and shortened the time spent in the calibration of the models. At the same time, it represented an improvement in the prediction accuracy and flexibility of current methods. Palmer (1999) said that weather and climate have greater potential economic value than corresponding single deterministic forecasts with uncertain accuracy.

In the year 2000 Luk et al., found that the ANNs provided the most accurate predictions when an optimum number of spatial inputs was included in the network and that the network with lower lag consistently produced better performance. Toth et al. (2000) concluded that how the considered time-series analysis techniques, and especially those based on the use of ANN, provided a significant improvement in the flood forecasting accuracy in comparison to the use of simple rainfall prediction approaches of heuristic type, which were often applied in hydrological practice.

In the year 2001 Luk et al., developed and compared three types of ANNs suitable for rainfall prediction therefore, a multilayer feed-forward neural network, Elman partial recurrent neural network and time delay neural network. Michaelides et al. (2001) found that ANN is a suitable tool for the study of the medium- and long-term climatic variability. The ANN models trained were capable of detecting even minor characteristics and differentiating between various classes. After a study of RBFNN, Chang et al. (2001) found that RBFNN is a suitable technique for a rainfall-runoff model for three hours ahead of floods forecasting.

In the year 2002 Sudheer et al., concluded that the outcomes were highly promising and indicated that it could significantly reduce the effort and computational time required in developing an ANN model. The proposed algorithm would easily lead to a more compact network, thus avoiding a long trial and error procedure. Successful implementation of the methodology presented could lead to certain automation procedures in model development. Taylor and Buizza (2002) found that there is strong potential for the use of weather collective predictions in NN load forecasting.

In the year 2003 Wilby et al., concluded that neural network outputs associated with each hidden node, produced from the output node after all other hidden nodes had been deleted, then compared with state variables and internal fluxes of the conceptual model. Correlation analysis suggested that hidden nodes in the neural network correspond to dominant processes within the conceptual model.

In the year 2004 Rajurkar et al., stated that the approach adopted herein for modelling produces reasonably satisfactory results for data of catchments from different geographical locations, which thus proved its versatility. Most importantly, the substitution of the previous day’s runoff by a term that represents the runoff estimated from a linear model and coupling the simple linear model with the ANN proved to be very much useful in modelling the rainfall-runoff relationship in the non-updating mode.

In the year 2005 Ramirez et al., found that ANN forecasts were superior to the ones obtained by the linear regression model. Lekkas (2005) presented that in real-time applications, like flow regulation and flood forecasting where the precision and modelling speed is crucial, black-box models and signal processing techniques need to be implemented.

In the year 2006 Somvanshi et al., revealed that the ANN is a more appropriate ten AIRMA model in long term prediction. Leng et al. (2006) evident that the GA-based pruning method, as a global search tool, is superior to the OBS-based pruning method to identify the significance of the existing EBF neurons. Gooijer et al. (2006) reviewed the progress on time series forecasting.

In the year 2007 Hayati and Mohebi stated that the forecasting reliability was evaluated by computing the mean absolute error between the exact and predicted value. Kumar et al. (2007) predicted that ANNs are suitable for seasonal Rainfall prediction and forecasting. Joorabchi et al. (2007) concluded that the feed forward Back-propagation learning algorithm could predict flood events very accurately.

In the year 2008 Hung et al. stated that results were highly satisfactory for rainfall forecast 1 to 3 h ahead. Sensitivity analysis indicated that the most important input parameter besides rainfall itself was the wet-bulb temperature in forecasting rainfall. Qi and Zhang (2008) found that the most effective way to model and forecast trend time series with NNs, a recent popular nonlinear modelling tool.

In the year 2009 Ghalhary et al., concluded that artificial neural network method was very successful in predicting rainfall and in more than 70 % of years could predict rainfall within acceptable precision. The root mean square error of the model was found to be 41 mm which was considered negligible at a yearly level and it was expected that by increasing the number of years of statistical data the precision of the model would increase. Gholizadeh and Darand (2009) found that high feasibility in the prediction of month rainfall precipitation. Combination neural networks with genetic algorithms showed better results. Hung et al. (2009) concluded that a generalized feed-forward ANN model using a hyperbolic tangent transfer function achieved the best generalization of rainfall. Especially, the use of a combination of meteorological parameters. ANN forecasts had superiority over the ones obtained by the persistent model. Lin and Wu (2009) found that the proposed model could forecast more precisely than the model developed by the conventional neural network approach.

In the year 2010 Baboo and Shereef (2010) found that Backpropagation neural network approach for temperature forecasting is capable of giving good results and can be considered as a substitute for traditional meteorological approaches. Wu et al. 2010 have attempted to seek a relatively optimal data-driven model for rainfall time series forecasting using modular artificial neural networks, they found that the normal mode indicates MANN performs the best among all four models, but the advantage of MANN over ANN is not significant in monthly rainfall series forecasting. To predict the intensity of rainfall using artificial neural networks.

In the year 2011 Khalili et al., (2011) found that perform statistical analysis of the obtained models showed the best-chosen model of daily forecasting. The correlation coefficient (R), Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) were 0.89, 0.14 (mm) and 1.15 (mm) for March, 0.85, 0.14 (mm) and 1.16 (mm) for May and 0.86, 0.15 (mm) and 1.17 (mm) for December, respectively which presented the effectiveness of the proposed models.

In the year 2012 Shrivastava et al., found that architectures of ANN such as BPN, RBFN was best established to be forecast chaotic behaviour and have efficient enough to forecast monsoon rainfall as well as other weather parameter prediction phenomenon over the smaller geographical region. Shafie et al., (2012) concluded that the RBF neural network model showed significantly better stability than the MR model.

In the year 2013 Mekanik et al., investigated an application of Artificial Neural Network (ANN) and Multiple Regression (MR) analysis to forecast long term seasonal spring rainfall. The MR models that not violated the limits of statistical significance were selected for future spring rainfall forecast. The ANN was developed in the form of multilayer perceptron using the L-M algorithm. Both MR and ANN models were evaluated statistically using Mean Square Error (MSE), Mean Absolute Error (MAE), Pearson correlation (r) and Willmott index of agreement (d). The MR models showed very poor generalization ability for east Victoria with correlation coefficients of -0.99 to -0.90 compared to ANN with correlation coefficients of 0.42 to 0.93; ANN models also showed better generalization ability for central and west Victoria with correlation coefficients of 0.68 to 0.85 and 0.58 to 0.97 respectively. The errors of the testing sets for ANN models were generally lower compared to multiple regression models. Sinha et al., (2013) found that rainfall-runoff modelling using multilayer perceptron techniques. The MLP ANN was found suitable for the rainfall-runoff nonlinear transformation process. Results suggested that the performance of MLP ANN was better for rainfall-runoff modelling.

In the year 2014 Ganti evaluated monthly monsoon rainfall forecasting using artificial neural networks. Artificial neural networks (ANNs) was proposed as efficient tools for modelling and forecasting. The results showed that forecasting monsoon rainfalls using ANNs was encouraging. India's economy and agricultural activities was effectively managed with the help of the availability of accurate monsoon rainfall forecasts. Gupta et al., (2014) developed an artificial neural network (ANN) based model for rainfall time series forecasting. The proposed model used a Multilayer perceptron (MLP) network with backpropagation algorithm for training. It was found that multilayer perceptron network predicted more accurate than other traditional models. Nastos et al., (2014) evaluated artificial neural networks modelling for forecasting the maximum daily total precipitation. The results showed that a quite satisfactory relationship (R^2 = 0.482, IA = 0.817, RMSE = 16.4 mm and MBE = +5.2 mm) appears between the forecasted and the respective observed maximum daily precipitation.

In the year 2015 Darji et al., (2015) concluded that FFNN (feed-forward neural network), RNN (recurrent neural network) and TDNN (time-delay neural network) were suitable to predict rainfall than other forecasting techniques such as statistical and numerical methods. FFNN performs was better for forecasting of monthly rainfall data, TDNN performs better for forecasting of yearly rainfall data. Moreover, it was observed that the forecasting accuracy of ANN could be improved by considering other meteorological parameters (evaporation, mean temperature, humidity, and soil temperature) as inputs. Dubey (2015) found 12 different ANN models, which were trained and tested using different combinations of the training algorithms, training functions and adaptive learning functions. Sharma and Nijhawan (2015) found that the three-layer model was used for training and studying different attributes of the hidden neurons in the network. The back-propagation was best out of the three networks. An increase in number of neurons of the network showed a decrease in mean square error and TRAINLM showed best results in training, testing and validation of data.

In the year 2016 Rasel et al., found that the superiority of multivariate non-linear ANN over traditional linear MR methods for seasonal rainfall forecasting by considering the effects of climate variables. Li et al., (2016) proposed a novel time series prediction method, MANNP model. This model can successfully predict the time-series by providing it with data on the relevant factors. It could be concluded that, prediction made by MANNP can be used as an effective time series analysis and prediction tools.

In the year 2017 Purnomo et al., (2017) developed an artificial neural network for monthly rainfall rate prediction. Two neural network models were proposed for monthly rainfall rate forecasting. The experiment results showed that the accuracy of the first model was much better than the accuracy of the second model. Its average accuracy is just above 98 %, while the accuracy of the second model was approximately 75%. Also, both models tend to perform better when the fluctuation of rainfall was low. Srivastava et al., (2017) developed artificial intelligence-based models using an artificial neural network (ANN) for daily rainfall prediction for 4-month duration. The performances of the models were evaluated qualitatively by visual observation and quantitatively. The sensitivity analysis indicated that the most important input parameter besides rainfall itself was the vapour pressure in rainfall forecasting for the study area.

In the year 2018 Chattopadhyay and Goutami demonstrated a neurocomputing based predictive model for forecasting average rainfall in India during the summer monsoon. Backpropagation method with conjugate gradient descent algorithm was implemented to develop the neurocomputing model and it was learned thrice to reach an error minimized through supervised learning. After three runs of the model, it was found that developed model gave a high prediction yield. Then, Shannon-Fano coding was implemented and the coding efficiency was measured by dividing the error percentage of prediction into various classes. The efficiency of conjugate gradient descent algorithm for multilayer ANN was finally established through Shannon-Fano coding. Kyada et al. (2018) developed rainfall forecasting using artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS) models. ANN model (4-6-4-1) was the best for the prediction of rainfall among all the models. ANN models showed better performance than the ANFIS models in rainfall forecasting. The sensitivity analysis revealed that vapour pressure was the most a sensitive parameter in rainfall prediction. Mishra et al. (2018) used an artificial neural network (ANN) technique to develop one-month and two-month ahead forecasting models for rainfall prediction using monthly rainfall data. In these models, feed-forward neural network (FFNN) using backpropagation algorithm and Levenberg-Marquardt training function was used. The performance of both the models was assessed based on regression analysis in terms of mean square error (MSE) and magnitude of relative error (MRE). The proposed ANN model showed optimistic results for both the forecasting models and one-month ahead forecasting model found to perform better than two months ahead forecasting model.

Table 1: Identified methods of modelling in the literature (1997-2019)

Sr. No.	Year	Methods	Contributors
1	1997	Artificial Neural Networks-ANN, SLM, LPM, NNLPM	Shamseldin
2	1998	Back Propagation Neural Network	Kuligowski and Barros
3		Artificial Neural Networks-ANN	Dawson and Wilby
4	1999	Artificial Neural Networks-ANN	Tokar and Johnson
5		Decision-Model Analysis	Palmer
6	2000	Artificial Neural Networks-ANN	Luk et al.
7		Artificial Neural Networks-ANN, ARMA	Toth et al.
8	2001	Artificial Neural Networks-ANN, MLFN, TDNN	Luk et al.
9		Artificial Neural Networks-ANN	Michaelides et al.
10		Artificial Neural Networks-ANN, RBFNN	Chang et al.
11	2002	Artificial Neural Networks-ANN	Sudheer et al.
12		Neural Networks-NN	Taylor and Buizza
13	2003	Artificial Neural Networks-ANN	Wilby et al.
14	2004	Artificial Neural Networks-ANN	Rajurkar et al.
15	2005	Feed-Forward Neural-Network	Ramirez et al.
16		Black Box Models and Signal Processing Techniques	Lekkas
17	2006	AIRMA Model	Somvanshik et al.
18		GA-Based Pruning Method	Leng et al.
19		Time Series Forecasting	Gooijer et al.
20	2007	Artificial Neural Networks-ANN, MLP	Hayati and Mohebi
21		Artificial Neural Networks-ANN	Kumar
22		Feed-Forward Back-Propagation	Joorabchi et al.
23	2008	Artificial Neural Networks-ANN, FFTN	Hung et al.
24		Time Series with NNs	Qi and Zhang
25	2009	Artificial Neural Networks-ANN	Ghalhary et al.
26		Artificial Neural Networks-ANN, MLPN	Gholizadeh and Darand
27		Artificial Neural Networks-ANN	Hung et al.
28		Artificial Neural Networks-ANN, MLPN	Lin and Wu
29	2010	Back Propagation Neural Network	Baboo and Shereef
30		Modular Artificial Neural Networks	Wu et al.

31	2011	Feed-Forward Perceptron Network	Khalili et al.
32	2012	Artificial Neural Networks-ANN, BPN, RBFN	Shrivastava et al.
33		Radial Basis Function Neural Networks	Shafie et al.
34	2013	Artificial Neural Network-ANN, Multiple Regression	Mekanik et al.
35		Artificial Neural Networks-ANN, MLP	Sinha et al.
36	2014	Artificial Neural Networks-ANN	Ganti
37		Artificial Neural Networks-ANN, MLP	Gupta et al.
38		Artificial Neural Networks-ANN	Nastos et al.
39	2015	Feed Forward Neural Network, RNN, TDNN	Darji et al.
40		Artificial Neural Networks-ANN	Dubey
41		Back Propagation Neural Network	Sharma and Nijhawan
42	2016	Artificial Neural Networks-ANN, MR	Rasel et al.
43		Feed-Forward Neural Networks	Li et al.
44	2017	Artificial Neural Networks-ANN	Purnomo et al.
45		Artificial Neural Networks-ANN	Srivastava et al.
46	2018	Multilayer Artificial Neural Networks	Chattopadhyay and Goutami
47		Artificial Neural Networks-ANN, ANFIS	Kyada et al.
48		Feed-Forward Neural Networks	Mishra et al.
49	2019	Multilayer Perceptron Neural Network	Velasco et al.

In the year 2019 Velasco et al., developed Multilayer Perceptron Neural Network (MLPNN) for week head rainfall forecasting. The MLPNN architecture was a supervised feed-forward neural network having 11 input neurons consisting of different weather variables along with various hidden neurons and 7 output neurons representing the week-ahead forecast. The MLPNN models which were SCG-Tangent and SCG-Sigmoid produced a MAE of 0.01297 and 0.1388 and RMSE of 0.01512 and 0.01557, respectively. The viable implementation of MLPNN in rainfall forecasting hopes to provided organizations and individuals with lead-time for the strategic and tactical planning of activities and courses of action related to rainfall.

RESULTS AND DISCUSSIONS

After review of a wide range of ANN architectures for rainfall forecasting, it has been observed that most of the researchers have used BPN and RBFN techniques for forecasting various weather phenomenon e.g. rainfall, temperature, flood, rainfall-runoff etc, and found significant results using the same architectures. Hence in the literature review of moreover 23 years of researches. Most of the scientists have concluded that Back Propagation Neural Network (BPNN), Multilayer Perceptron Neural Network (MLP) and Feed Forward Neural Network (FFNN) are the appropriate method to predict weather phenomenon. Since rainfall forecasting is a dynamic and non-linear process so ANN can be used for prediction of rainfall. From the research, it is also found that ANN is the best approach than Numerical and traditional methods. On the contrary, Feed Forward Neural Networks is the best algorithm to use the neural network for weather forecasting.

Recently, Khalili et al., in 2011 have presented ANN modelling for daily rainfall forecasting in Mashhad synoptic station. The ANN model is used as a black-box model, and it was found that the hidden dynamics of rainfall through the past information of the system. The obtained results of the validation phase are shown in Table 2 that include Correlation Coefficient (R), Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) for daily prediction using GS531 and GS651.

Table: 2 Results of used superior ANNs structures (Khalili et al. 2011)

ANN Structure	R	RMSE (mm)	MAE
GS531 (March)	0.83	0.17	1.20
GS651 (March)	0.89	0.14	1.15
GS521 (May)	0.82	0.19	1.22
GS681 (May)	0.85	0.14	1.16
GS571 (December)	0.82	0.20	1.24
GS631 (December)	0.86	0.15	1.17

The above prediction values proved that the ANN model gave satisfactory prediction performance. Mishra et al., (2018) shown that those networks are useful in forecasting rainfall and the working of the most powerful forecasting algorithm called feed-forward neural networks. During an intense study of applications of various architectures of ANN, it has been found that the BPN, MLP and FFNN are the methods that have been used by most of the researchers and the result of their experiment found to be satisfactory without any scientific controversy. In general, it has been observed that out of various forecasting techniques such as statistical and numerical modelling, over the meteorological data, ANN is proved to be an appropriate technique undoubtedly for forecasting various weather phenomenons.

CONCLUSIONS

This study concentrates on the capabilities of ANN in the forecasting of several weather phenomena such as rainfall, temperature, flood and tidal level etc. finally it has been concluded that the major architectures therefore BPN, MLP and FFNN are sufficiently suitable to forecast and prediction weather phenomenon. In the comparative study among various ANN techniques, BPN and FFNN are found as appropriate solutions for prediction of long-range weather forecasting. The study of BPN and FFNN for long-range meteorological parameters pattern recognition over smaller scale geographical region shows good performance and sensible prediction accuracy. However, concluded that the neural network is the most suitable to predict weather forecasting.

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