Journal of Network and Innovative Computing
ISSN 2160-2174, Volume 1 (2013) pp. 320-331

Computational Intelligence in Weather Forecasting: A Review

Nazim Osman Bushara [1] and Ajith Abraham [2]

[1]Faculty of computer science and information technology, Sudan University for Science and Technology (SUST), Khartoum, Sudan
nazim_ob@yahoo.com

[2]Machine Intelligence Research Labs (MIR Labs), Scientific Network for Innovation and Research Excellence, WA, USA
ajith.abraham@ieee.org

***Abstract*: Since 1990s, computational intelligence models have been widely used in several applications of weather forecasting. Thanks to their ability to have powerful pattern classification and pattern recognition capabilities. This paper presents an overview of using the various computational intelligence tools in weather forecasting, describing the main contributions on this field and providing taxonomy of the existing proposals according to the type of tools used.**

***Keywords*:** Weather Forecasting, Computational Intelligence**.**

I. Introduction

Weather forecasting is the application of science and technology to predict the state of the atmosphere for a future time and a given location. Human kind has attempted to predict the weather since ancient times.

The problem of generating predictions of meteorological events is more complex than that of generating predictions of planetary orbits [1]. This is because the atmosphere is unstable and the systems responsible for the events are the culmination of the instabilities and involve nonlinear interaction between different spatial scales from kilometers to hundreds of kilometers. The chaotic nature of the atmosphere limits the validity of deterministic forecasts [2]. The increasing economic cost of adverse weather events provides a strong reason to generate more accurate and updated weather forecasts [3]. Today, weather forecasts are made by collecting quantitative data about the current state of the atmosphere and using scientific understanding of atmospheric processes to project how the atmosphere will evolve. The traditional weather forecasting approaches like:

(a) The empirical approach

(b) The dynamical approach

The first approach is based upon the occurrence of analogues and is often referred to by meteorologists as analogue forecasting. This approach is useful for predicting local-scale weather if recorded cases are plentiful. The second approach is based upon the equations and forward simulations of the atmosphere, and is often referred to as computer modeling. Because of the grid Coarseness, the dynamical approach is only useful for modeling large-scale weather phenomena and may not predict short-term weather efficiently.

Weather forecasting (particularly rainfall prediction) is one of the most imperatives, important and demanding operational tasks and challenge made by meteorological services around the world. It is a complicated procedure that includes numerous specialized fields of knowledge. The task is complicated because in the field of meteorology all decisions are to be taken with a degree of uncertainty, because the chaotic nature of the atmosphere limits the validity of deterministic forecasts [2].

Rainfall prediction is very important for countries whose economy depends mainly on agriculture, like many of the third World countries [4]. In general, considered climatic phenomena and the precipitation of non-linear phenomena in nature, leading to what is known as the "butterfly effect". Required parameters to predict rainfall, extremely complicated and unclear so that the uncertainty in the prediction using all these criteria enormous even for a short period.

The most prevalent techniques [5] used to predict rainfall is numerical and statistical methods. Although research in these areas takes place for a long time, the successes of these models is rarely concrete because these models have been found to be very accurate in calculation, but not in prediction as they cannot adapt to the irregularly varying patterns of data which can neither be written in form of a function, or deduced from a formula. Numerical weather prediction uses current weather conditions, as input into mathematical models of the atmosphere there is a limited success in forecasting weather parameters using numerical models. The accuracy of the models depends on the initial conditions, which are inherently incomplete. These systems are not able to achieve satisfactory results in domestic cases, short-term, as well as the weak performance in order to predict the long-term seasonal rain even for a large spatial scale. However, the atmospheric circulation is quite sensitive to initial conditions [6]. Because of this characteristic, predictability by the numerical weather forecast is limited within, say, 1 week at present. We have no idea how to handle the chaotic behaviors of the atmosphere and make a long-range forecast by the numerical weather prediction yet.

Statistical models analyze historical data and identify relationships between precursors and consequences. They are distinct from dynamical models in their lack of use of any physical equations. In a statistical approach, certain variables are typically designated as predictors, while others need to be predicted. Two main drawbacks of the statistical models are:

1. Statistical models are not useful to study the highly nonlinear relationships between rainfall and its predictors, even if one considers models like power regression.

2. There is no ultimate end in finding the best predictors. It will never be possible to get different sets of regional and global predictors to explain the variability of the two neighboring regions having distinguished rainfall features.

In this paper, we attempt to provide a comprehensive review and current state-of-the-art of using various computational intelligence tools for weather forecasting in particular rainfall prediction.

The paper is organized as follows. Section 2, discussed a comprehensive review of different contributions. Section 3 illustrates the methodology that has been used and taxonomy is illustrated. Analysis of the review is presented in Section 4. Finally, conclusions and directions of future research are discussed in Section 5.

II. Literature review

Soft computing techniques and machine learning approaches have been widely used in several applications of weather forecasting, for example they have been applied in rain fall prediction, temperature forecasting, rainfall runoff modeling, flood forecasting and wind forecasting. The results proved that they are better than conventional approaches.

In the nineties, Young et al. [7] have proved that radial basis function (RBF) networks produced good prediction and better than the linear models which produced poor prediction for Rainfall Prediction.

Hsieh, et al. [8] applied various artificial neural network (ANN) models for prediction and analysis in meteorology and oceanography data and they have found ANN technique is very useful. In the study of rainfall runoff modeling, Christian et al. [9] illustrated the ability of ANN to cope with missing data and to “learn” from the event currently being forecast in real time makes it better choice than conventional lumped or semi distributed flood forecasting models.

In a similar research, Trigo and Palutikof [10] used ANN for simulation of daily temperature for climate change over Portugal. And they have compared the performances of linear models and ANN model using a set of rigorous validation techniques. Finally, they concluded that the non-linear ANN model is more efficient than the linear models. In a comparative study of short-term rainfall prediction models for real time flood forecasting, Toth et al. [11] founded that the time series analysis technique based on ANN provides significant improvement in the flood forecasting accuracy in comparison to the use of simple rainfall prediction approaches.

Luk et al. [12] have implemented and compared three types of ANNs suitable for rainfall prediction i.e. multilayer feed forward neural network, Elman partial recurrent neural network and time delay neural network. During a study of radial basis function neural network (RBFNN) for rainfall runoff model, Chang et al. [13] concluded that RBFNN is a good technique for a rainfall runoff model for three hours ahead floods forecasting. Michaelides et al. [14] proved that ANN is a suitable technique for the study of the medium and long-term climatic variability. The ANN models trained were capable of detecting even minor features and discrimination between various classes. In comparative study Maqsood et al., [15] illustrated that Hopfield Model (HFM) for weather forecasting in southern Saskatchewan, Canada is relatively less accurate and RBFN is relatively more reliable for the weather forecasting problems and in comparison the ensembles of neural networks produced the most accurate forecast. Cannon and Whitfield [16] introduced in their climate change studies the bagging (or bootstrap aggregation) method as an ensemble neural network (ENN) approach and showed the suitability of ENNs for downscaling techniques. Combining outputs of several member models can significantly improve generalization performance, because the generalization error of the final predictive model is controlled.

Jeong and Oh [17] developed new rainfall-runoff models that can be used for ensemble stream flow prediction. The new models used two types of artificial neural networks, i.e. single neural network (SNN) and ensemble neural network (ENN). Both ANN models used the early stopping method to optimize generalization performance during training. The bagging method was used in that study for the ENN to control the generalization error better than the SNN. The ANN models were applied to make 1-month ahead probabilistic forecasts for inflows to the Daecheong multipurpose dam in Korea. The calibrated ANN models were compared with each other first. The results illustrated that the ENN is less sensitive to the input variable selection and the number of hidden nodes than the SNN is, and the ENN, in general, produced smaller RMSEs than the corresponding SNN, which implies that the ENN can reduce the generalization error more efficiently than the SNN can. Comparing the SNN and ANN with a rainfall-runoff model TANK, which has been widely used in Korea, with respect to their simulation accuracy, this study found that the new ANN models performed better than TANK for 9 out of 10 test cases. Finally, the study tested TANK and the ENN using some probabilistic forecasting accuracy measures and showed of the test months from 1996 to 2001, the skills of the ENN were better than those of TANK. During the dry season in particular, the ENN improved its ESP performance considerably better than that of TANK. Therefore, the study concluded that an ENN should be substituted for the existing rainfall-runoff model, TANK, for the ESP probabilistic forecasting system for the Daecheong dam inflows in Korea.

Somvanshi et al. [18] illustrated that ANN model can be used as a suitable forecasting tool to predict the rainfall, which out performs the ARIMA (Autoregressive Integrated

Moving Average) model. Nagesh et al. [19] implemented artificial intelligence techniques for forecasting regional rainfall and they found that this technique shows reasonably good performance for monthly and seasonal rainfall forecasting. Bustami et al. [20] used ANN for rainfall and water level prediction and the empirical results illustrate that ANN is an effective method in forecasting both missing precipitation and water level data. Hayati, and Mohebi [21] used ANN for short-term temperature forecasting (STTF) and founded that MLP network has the minimum forecasting error and can be considered as a good method to model the STTF systems.

In a comparative study between Artificial Intelligence and Artificial Neural Network for rainfall runoff modeling, Aytek et al. [22] illustrated that genetic programming (GP) formulation performs quite well compared to results obtained by ANNs and is quite practical for use. It is concluded from the results that GP can be proposed as an alternative to ANN models. Hocaoglu et al. [23] developed adaptive neuro-fuzzy inference system for missing wind data forecasting. In a Case Study on Jarahi Watershed, Solaimani, [24] studied Rainfall-runoff Prediction located in a semiarid region of Iran Based on Artificial Neural Network and founded that Artificial Neural Network method is more appropriate and efficient to predict the river runoff than the classical regression model. Shamseldin [25] examined the effectiveness of rainfall-runoff modeling with ANNs by comparing their results with the Simple Linear Model (SLM), the seasonally based Linear Perturbation Model (LPM) and the Nearest Neighbor Linear Perturbation Model (NNLPM) and concluded that ANNs could provide more accurate discharge forecasts than some of the traditional models.

Nayak et al. [26] have offered an application of an adaptive neuro-fuzzy inference system (ANFIS) to hydrologic time series modeling, and it was observed that the ANFIS model preserves the potential of the ANN approach fully, and eases the model building process.

Exploring the new concept, soft computing models based on ANNs and an Evolving Fuzzy Neural Network (EFuNN) for predicting the rainfall time series, Abraham and Philip [27] have analyzed 87 years of rainfall data in Kerala state, the southern part of Indian Peninsula. Authors ttempted to train 5 soft computing based prediction models with 40 years of rainfall data. Also in the same context Maqsood et al., [28] have applied a soft computing model based on a RBFN for 24-h weather forecasting of southern Saskatchewan, Canada. The model is trained and tested using hourly weather data of temperature, wind speed and relative humidity in 2001. The performance of the RBFN is compared with those of multi-layered perceptron (MLP) network, Elman recurrent neural network (ERNN) and Hopfield model (HFM) to examine their applicability for weather analysis. Reliabilities of the models are then evaluated by a number of statistical measures. The results indicate that the RBFN produces the most accurate forecasts compared to the MLP, ERNN and HFM.

Luenam et al., [29] presented a Neuro-Fuzzy approach for daily rainfall prediction, and their experimental results show that overall classification accuracy of the neuro-fuzzy classifier is satisfactory. Vamsidhar et al., [30] have used the back propagation neural network model for predicting the rainfall, basis on humidity, dew point and pressure in India. In the training phase, authors obtained 99.79% of accuracy and 94.28% in the testing phase. From these results they have concluded that rainfall can be predicted in the future using the same method. Patil and Ghatol [31] used various ANN models such as radial basis functions and multilayer perceptron with Levenberg Marquardt and momentum learning rules for predicting rainfall using local parameters and they found the models fit for the same task.

Joshi and Patel [32] studied Rainfall-Runoff modeling using ANN, in the that study they have compared three neural network techniques, Feed Forward Back Propagation (FFBP), Radial Basis Function (RBF) and Generalized Regression Neural Network (GRNN) and they have seen that GRNN flow estimation performances were close to those of the FFBP, RBF and MLR. The theoretical basis of the RBF approach lies in the field of interpolation of multivariate functions. The solution of exact interpolating RBF mapping passes through every data point. Different number of hidden layer neurons and spread constants were tried in study.

As we have observed that many of the researchers have used ANN models and soft computing models for forecasting Rainfall, Temperature, Wind and Flood etc., El-Shafie et al. [33] have studied and compared Dynamic versus Static neural network models for rainfall forecasting, they have developed soft computing models using Multi-Layer Perceptron Neural Networks (MLPNN), RBFNN and Adaptive Neuron-Fuzzy Inference Systems (ANFIS), finally they concluded that the dynamic neural network namely IDNN could be suitable for modeling the temporal dimension of the rainfall pattern, thus, provides better forecasting accuracy. Sawaitul et al. [34] presented an approach for classification and prediction of future weather using back propagation algorithm, and discussed different models which were used in the past for weather forecasting, finally the study concludes that the new technology of wireless medium can be used for weather forecasting process.

Nelson et al. [35] discussed the issue of whether ANNs can learn seasonal patterns in a time series. They trained networks with both de-seasonalized and the raw data, and evaluated them using 68 monthly time series from the M-competition. Their results indicate that the ANNs are unable to adequately learn seasonality and that prior de-seasonalization of seasonal time series is beneficial to forecast accuracy. However, Sharda and Patil [36] concluded that the seasonality of the time series does not affect the performance of ANNs and ANNs are able implicitly to incorporate seasonality.

Several empirical studies find that ANNs seem to be better in forecasting monthly and quarterly time series Kang, [37]; Hill et al. [38], [39]) than in forecasting yearly data. This may be due to the fact that monthly and quarterly data usually contain more irregularities (seasonality, cyclicity, nonlinearity, noise) than the yearly data, and ANNs are good at detecting the underlying pattern masked by noisy factors in a complex system.

III. Taxonomy Based on Computational Intelligence Methodology Used

A. Artificial Neural networks (ANNs)

Abhishek et al. [40] used Feed Forward Network for predicting the rainfall. In the study, monthly rainfall was used as input data for training and testing model. The authors analyzed 50 years of rainfall data for seasonal monsoon (8 months) in Udupi, Karnataka. The empirical results showed that Multi-layer Algorithm is better than Single-layer algorithm terms of performance and Back Propagation is the best algorithm comparing with Layer Recurrent and Cascaded feed Forward back Propagation. They concluded that the results of their study were fairly good and high degree of accuracy was obtained. However they obtained large MSE (0.44) because their input data is not quit enough to train the neural network so Larger the amount of input data, lower is the MSE after training. Also they employed only two of the rainfall predictors (Humidity and the average Wind Speed) and there are other predictors such as temperature, wind direction, sunshine, pressure …etc have not be taken in the consideration.

Mohammad [41] designed artificial neural network to predict two weather temperatures (average high and average low) for one month ahead in Baghdad, Iraq. Author used feed-forward neural network with back propagation learning algorithm. For network's training and testing, the author used meteorological daily data for three years (2007-2010). Empirical results suggested that the ANN model has good performance, and low cost of implementation. However the change in weather because of solstice has been effected in training of ANN, these increasing epochs to reach a validation, to reach a validation for September the network needed (235 epochs).

De and Debnath [42] proposed ANN model to forecast the mean monthly surface temperature in the monsoon months (June, July and August) over India. Authors developed multilayer feed forward neural network used back propagation algorithm. Three models are generated for both maximum and minimum temperature each model for one of the monsoon months. Data of these three months for the period 1901-2003 were used. The results obtained from the study showed that the Artificial Neural Network has been found to produce a forecast with small prediction error, also he has established that the third model (for the month of August) is the best predictive model over the other two models with the percentage of prediction error = 0.00995147 below than 5% in both maximum and minimum temperature. However the prediction error for the others two models is still high for the month of June = 0.019704765 and for the month of July = 0.016191574.

Hayati et al. [21] designed short-term temperature forecasting (STTF) Systems for one day ahead for Kermanshah city, west of Iran. Authors used back propagation as the learning algorithm. As back propagation training algorithms are often too slow for practical problems they tried to accelerate the convergence by used several high performance algorithms and they found scaled conjugate gradient was suitable for that purpose. Authors used MLP to train and test using ten years (1996-2006) meteorological data. For accuracy of prediction, they split data into four seasons and then for each seasons one network is presented. The global set of patterns is divided into two randomly selected groups, the training group, corresponding to 67% of the patterns, and the test group, corresponding to 33% of patterns. Two random days in each season are selected as unseen data, which have not been used in training. MSE is used to measure the performance. Tan-sig is used as activation function at each hidden layers and pure-linear is used at each layer. The empirical results showed that MLP network is best suited for this research, it has a good performance and reasonable prediction accuracy was achieved for this model.

Baboo and Shereef [43] used back propagation neural network for predicting the temperature based on the training set provided to the neural network. The ANN is trained and tested using real training data set. Authors used complete daily one year weather data. Through the implementation of this system, it is illustrated, how an intelligent system can be efficiently integrated with a neural network prediction model to predict the temperature. The results shows that when iteration count goes below 1000 the RMSE is more and when it reaches 5000 the error value is up to 0. There are various parameters like the no. of layers, epochs, no. of neurons at each layer etc. and ANN is trained with 200 data and tested for unseen data the result varies with 2.16% errors. The research illustrates a Min RMSE of 0.0079 and Max error of 1.2916.

Devi et al., [44] studied how neural networks are useful in forecasting the weather. Three-layered neural network was designed and trained with the existing dataset and obtained a relationship between the existing non-linear parameters of weather. So many parameters are taken and their relationships are taken into consideration those factors for the temperature forecasting. Like temperature, humidity, dew point, visibility, atmospheric pressure, sea level, wind speed, wind direction. The data is normalized using min-max normalization to scale the dataset into the range of 0 to 1. Authors compared the performance between feed forward network and Radial basis function network to check which is better for the temperature forecasting. The Results indicated that Propagation feed forward network had the best performance and taken for further development for prediction of temperature.

Mayilvaganan, and Naidu [45] tried to forecast groundwater level of a watershed using ANN and Fuzzy Logic. They have developed three-layer feed-forward ANN using the sigmoid function and the back propagation algorithm. Authors concluded that ANNs perform significantly better than Fuzzy Logic.

El-Shafie et al. [46] attempted to use neural network and regression technique for rainfall-runoff prediction and the empirical results illustrated that the feed forward ANN can describe the behavior of rainfall-runoff relation more accurately than the classical regression model.

Lekkas et al., [47] developed a multilayer back propagation network and found that BPN does not always find the correct weight and biases fort the optimum solution, whereas their results supported the hypothesis that ANNs can produce qualitative forecast.

Luk et.al [12] developed three alternative types of ANNs, namely multilayer feed forward neural network (MLFN), Elman partial recurrent neural networks, and time delay neural network (TDNN) and the models provided reasonable predictions of the rainfall depth one time-step in advance.

Geetha and Samuel [48] predicted Rainfall in Chennai, India using back propagation neural network model, by their research the mean monthly rainfall is predicted and the results illustrated that the model can perform well both in training and independent periods.

Naik and Pathan [49] proposed new method of weather forecasting using Feed forward ANN with Levenberg Back Propagation Algorithm for training. The results showed that FFNN is appropriate for weather forecasting.

Tiron and Gosav [50] proposed a feed forward neural network approach for short-term prediction of the rainfall field from radar data from the province of Moldova, Romania. The reflectivity data sets extend over July 2008. The ANN system with reflectivity values as input variables was trained to predict the rain rate on the ground. The ANN network was trained with the learning algorithm based on the back-propagation of errors. The results of the study indicated that the use of artificial neural network as a rainfall forecasting system is feasible and efficient.

Dombayc and Golcu [51] tried to predict daily mean ambient temperatures by use of an ANN model in Denizli, South-Western Turkey. They used the meteorological data of the years 2003- 2005 and 2006 as the training and testing data respectively. They analyzed different ANN networks and selected a feed-forward back propagation algorithms consists of 3 inputs, 6 hidden neurons and 1 output.

Afzali et al. [52] developed an artificial neural network for ambient air temperature prediction in Kerman city located in the south east of Iran. The mean, minimum and maximum ambient air temperature during the year 1961-2004 was used as the input parameter in Feed Forward Network (FNN) and Elman Network. The output of the models is composed of one day and one-month ahead air temperature prediction. The experiments illustrated that ANN approach is a desirable model in ambient air temperature prediction, while the results from Elman network are more precise than FNN network.

Perea et al. [53] analyzed an energy consumption predictor for greenhouses using a multi-layer perceptron (MLP) artificial neural network (ANN) trained by means of the Levenbergh-Marquardt back propagation algorithm. The predictor uses cascade architecture, where the outputs of a temperature and relative humidity model are used as inputs for the predictor, in addition to time and energy consumption. The performance of the predictor was evaluated using real data obtained from a greenhouse located at the Queretaro State University, Mexico. This study shows the advantages of the ANN with a focus through analysis of variance (ANOVA). Energy consumption values estimated with an ANN were compared with regression-estimated and actual values using ANOVA and mean comparison procedures. Results show that the selected ANN model gave a better estimation of energy consumption with a 95% significant level. The study resents an algorithm based in ANOVA procedures and ANN models to predict energy consumption in greenhouses.

Paras et al. [54] used feed forward artificial neural networks with back propagation for supervised learning using the data recorded at Pantnagar station situated in Tarai region of Uttarakhand state, India since April 1996 to March 1999 and is available as weekly average. The trained ANN was used to predict the future weather conditions. The results are very encouraging and it is found that the feature based forecasting model can make predictions with high degree of accuracy. The model can be suitably adapted for making forecasts over larger geographical areas.

Chang et al. [13] tried RBFN to develop a rainfall–runoff model for three-hour-ahead flood forecasting. They have used dataset of the Lanyoung River collected during typhoons for training, testing and validating the network. After the study they found that that the RBF NN can be considered as an appropriate technique for predicting flood flow.

Maqsood et al. [15] projected ensemble model performance is contrasted with multi-layered perceptron network (MLPN), Elman recurrent neural network (ERNN), RBFN, Hopfield model (HFM) predictive models and regression techniques. They have used dataset of temperature, wind speed and relative humidity to train and test the different models. With each model, 24-h-ahead forecasts are prepared for the winter, spring, summer and fall seasons. Furthermore, the performance and reliability of the seven models are then evaluated by a number of statistical measures. Among the direct approaches employed, empirical results indicate that HFM is relatively less accurate and RBFN is relatively more reliable for the weather forecasting problem. In comparison, the ensemble of neural networks and RBFN produced the most accurate forecasts.

In a comparative study Maqsood et al. [28] applied a soft computing model based on a RBFN for 24-h weather forecasting of southern Saskatchewan, Canada. The model is trained and tested using hourly weather data of temperature, wind speed and relative humidity. The performance of the RBFN is compared with those of multi-layered perceptron (MLP) network, Elman recurrent neural network (ERNN) and Hopfield model (HFM) to examine their applicability for weather analysis. Reliabilities of the models are then evaluated by a number of statistical measures. The results indicate that the RBFN produces the most accurate forecasts compared to the MLP, ERNN and HFM.

Santhanam et al. [55] developed two neural network models for weather forecasting, based on various factors obtained from meteorological experts such as temperature, air pressure, humidity, cloudiness, precipitation, wind direction and wind speed. Authors evaluated the performance of Radial Basis Function (RBF) with Back Propagation (BPN) neural network. The back propagation neural network and radial basis function neural network were used to test the performance in order to investigate effective forecasting technique. The Results showed that the prediction accuracy of RBF was 88.49% while the prediction accuracy of BPN was 81.99. The results indicated that proposed radial basis function neural network is better than back propagation neural network.

Abdul–Kader [56] evaluated the use of two different artificial neural network models namely, RBF and back propagation neural networks to forecast temperature in some Egyptian towns. The gained simulated results showed that the popular feed-forward neural network, which trained by differential evolution algorithm (DE) is the most accurate model to use as a temperature predicator. Especially in the uniform temperature distribution (minimum or maximum temperature) which can be considered the most suitable technique for temperature forecasting.

Maqsood et al., [57] presented a comparative study of different neural network models for forecasting the weather of Vancouver, British Columbia, Canada. For developing the models, they used one year's data comprising of daily maximum and minimum temperature, and wind-speed. They used Multi-Layered Perceptron (MLP) and an Elman Recurrent Neural Network (ERNN), which were trained using the one-step-secant and Levenberg- Marquardt algorithms. To ensure the effectiveness of neurocomputing techniques, they also tested the different connectionist models using a different training and test data set. Their goal is to develop an accurate and reliable predictive model for weather analysis. Radial Basis Function Network (RBFN) exhibits a good universal approximation capability and high learning convergence rate of weights in the hidden and output layers. Experimental results obtained have shown RBFN produced the most accurate forecast model as compared to ERNN and MLP networks.

Awchi [58] investigated the potential of Radial Basis Function (RBF) neural networks for the prediction of reference Evapotranspiration (ETo). The study utilized daily climatic data of temperature, relative humidity, sunshine hours, wind speed, and rainfall for five years collected from Mosul meteorological station, north of Iraq. Thirteen RBF networks each using varied input combination of climatic variables have been trained and tested. The network output is compared with estimated daily Penman-Monteith ETo values. To evaluate the performance of RBF networks, the same networks in the studied cases were re-trained using the well known feed forward-back propagation (FF-BP) networks. In addition, the effect of including a time index within the inputs of considered networks is investigated. The study showed that the RBF network is seen to emulate the FF-BP in its performance and can be effectively used for ETo prediction. Besides, it is much easier to built and much faster to train. It is noticed that the networks' output are very highly correlated to estimated ETo, especially when concerning all the climatic parameters. The study results reveal that adding a time index to the inputs highly improves the ETo prediction of the studied cases.

Lin and Chen [59] used radial basis function network (RBFN) to construct a rainfall-runoff model for the Fei–Tsui Reservoir Watershed in northern Taiwan for predicting real time stream flows. The fully supervised learning algorithm has been presented for the parametric estimation of the network. The results showed that the RBFN could be successfully applied to build the relationship between rainfall and runoff. Moreover, the proposed network trained using the fully supervised learning algorithm provides better training and testing accuracy than the network trained using the hybrid-learning algorithm does. The proposed network also gives better forecasts.

Chow and Cho [60] have developed recurrent Sigma-Pi neural network for rainfall forecasting system in Hong Kong. The results were very promising, and the neural-based rainfall forecasting system is capable of providing a rainstorm-warning signal one hour ahead. They have concluded that the neural network based now casting system is capable of providing a reliable rainfall now casting.

In comparative study of Jordan and Elman networks for rainfall-runoff modeling for the upper area of Wardha River in India, Deshmukh and Ghatol [61] have developed the models by processing online data over time using recurrent connections. The prediction results of the Jordan network indicated a satisfactory performance in the three hours ahead of time prediction. The conclusions also indicated that the Jordan network is more versatile than Elman model and can be considered as an alternate and practical tool for predicting short term flood flow.

Gong et al., [62] have tried Elman neural network models for wind power forecasting. The relevant data sequences provided by numerical weather prediction are decomposed into different frequency bands by using the wavelet decomposition for wind power forecasting. The Elman neural networks models are established at different frequency bands respectively, then the output of different networks are combined to get the eventual prediction result. For comparison, Elman neutral network and BP neutral network are used to predict wind power directly. Several error indicators are given to evaluate prediction results of the three methods. The simulation results showed that the Elman neural network can achieve good results and that prediction accuracy can be further improved by using the wavelet decomposition simultaneously.

Meng and Wu [63] proposed a novel hybrid Radial Basis Function Neural Network (RBF–NN) ensemble model is proposed for rainfall forecasting based on Kernel Partial Least Squares Regression (K–PLSR). In the process of ensemble modeling, the first stage the initial data set is divided into different training sets by used Bagging and Boosting technology. In the second stage, these training sets are input to the RBF–NN models of different kernel function, and then various single RBF–NN predictors are produced. Finally, K–PLSR is used for ensemble of the prediction purpose. Their findings reveal that the K–PLSR ensemble model can be used as an alternative forecasting tool for a Meteorological application in achieving greater forecasting accuracy.

B. Fuzzy Expert Systems

Özelkan et al., [64] compared the performance of regression analysis and fuzzy logic in studying the relationship between monthly atmospheric circulation patterns and precipitation. Liu and Chandrasekar [65] developed a Fuzzy Logic and Neuro-Fuzzy system for classification of a hydrometeor type based on polarimetric radar measurements where fuzzy logic was used to infer a hydrometeor type, and the neural network-learning algorithm was used for automatic adjustment of the parameters of the fuzzy sets in the fuzzy logic system according to the prior knowledge. Luenam et al. [29] presented a Neuro-Fuzzy approach for daily rainfall prediction, and their experimental results show that overall classification accuracy of the neuro-fuzzy classifier is satisfactory.

Mahabir et al. [66] investigated the applicability of fuzzy logic modeling techniques for forecasting water supply for the Lodge Creek and Middle Creek basins, located in southeastern Alberta, Canada. By applying fuzzy logic, a water supply forecast was created that classified potential runoff into three forecast zones: 'low', 'average' and 'high'.

Spring runoff forecasts from the fuzzy expert systems were found to be considerably more reliable than the regression models in forecasting the appropriate runoff zone, especially in terms of identifying low or average runoff years. Based on the modeling results in these two basins, it is concluded that fuzzy logic has a promising potential for providing reliable water supply forecasts.

Bae et al. [67] have developed Adaptive Neuro-Fuzzy Inference System (ANFIS) to predict the optimal dam inflow. The model used dataset of rainfall, inflow, temperature, relative humidity observation data and monthly weather forecasts. The subtractive clustering algorithm was adopted to enhance the performance of the ANFIS model and the hybrid-learning algorithm was adopted to enhance model performance. The ANFIS model for monthly dam inflow forecasts was tested in cases with and without weather forecasting information. The results demonstrated that a neuro-fuzzy system is appropriate for dam inflow forecasts. The model gave better performances where the various field data were available.

Abraham and Philip [27] have attempted to train 5 soft computing based prediction models with 40 years of rainfall data. For performance evaluation, network predicted outputs were compared with the actual rainfall data. Simulation results reveal that soft computing techniques are promising and efficient. They used an artificial neural network using back propagation (variable learning rate), adaptive basis function neural network, neural network using scaled conjugate gradient algorithm and an Evolving Fuzzy Neural Network (EFuNN) for predicting the rainfall time series. The test results given by EFuNN algorithm were the best. Lowest RMSE was obtained using EFuNN (0.090) and it was 0.095, 0.094, 0.092 and 0.093 for BP, BP-VLR and SCG and ABF neural networks respectively. Also they found EFuNN adopts a one-pass (one epoch) training technique, which is highly suitable for online learning. Hence online training can incorporate further knowledge very easily. Compared to pure BP and BP-VLR, ABFNN and SCGA converged much faster. Finally they concluded that EFuNN outperformed neurocomputing techniques with the lowest RMSE test error and performance time.

Aliev et al. [68] proposed, fuzzy recurrent neural network (FRNN) based time series forecasting method for solving forecasting problems, and they found that the performance of the proposed method for forecasting fuzzy time series shows its high efficiency and effectiveness for a wide domain of application areas ranging from weather forecasting to planning in economics and business.

C. Evolutionary Algorithms

Aytek et al. [22] have found that genetic programming (GP) formulation performs quite well compared to results obtained by ANNs and is quite practical for use. It is concluded from the results that GP can be proposed as an alternative to ANN models.

Jiang and Wu [69] investigated the effectiveness of the hybrid Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) evolved neural network for rainfall forecasting and its application to predict the monthly rainfall in a catchment located in a subtropical monsoon climate in Guilin of China. They adopted a hybrid Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) for the automatic design of NN by evolving to the optimal network configuration(s) within an architecture space, namely PSOGA–NN. The PSO is carried out as a main frame of this hybrid algorithm while GA is used as a local search strategy to help PSO jump out of local optima and avoid sinking into the local optimal solution early. The proposed technique is applied over rainfall forecasting to test its generalization capability as well as to make comparative evaluations with the several competing techniques, such as GA–NN, PSO–NN and NN. The experimental results showed that the GAPSO–NN evolves to optimum or near–optimum networks in general and has a superior generalization capability with the lowest prediction error values in rainfall forecasting. Finally they concluded that the predictions using the GAPSO–NN approach can significantly improve the rainfall forecasting accuracy.

Riley and Venayagamoorthy [70] used a recurrent neural network (RNN) for Photovoltaic (PV) system modeling. They used particle swarm optimization (PSO) for modifying the network weights to train the network and minimize the sum of the mean absolute error (MAE). Also they have compared a traditional modeling approach using the Sandia Photovoltaic Array Performance Model to a new method of characterization using a recurrent neural network (RNN). The results showed that modeling and characterizing an existing PV system with a recurrent neural network may provide adequate results for existing PV systems, although in this case, the RNN model did not perform as well as the component-based model. Thus, it seems that in the case where component parameters are known, a traditional PV modeling approach may yield more accurate model results. Also The RNN model correctly learned the relationships between the weather data and performance data.

D. Machine learning approaches

Zhao and Wang [71] developed a neural network technique, support vector regression (SVR), to monthly rainfall forecasting. Authors used particle swarm optimization (PSO) algorithms, which searches for SVR's optimal parameters, and then adopts the optimal parameters to construct the SVR models. The monthly rainfalls in Guangxi of China during 1985–2001 were employed as the data set. Authors compared the new neural network technique with back–propagation neural networks (BPNN) and the autoregressive integrated moving average (ARIMA) model. The experimental results demonstrated that SVR outperformed the BPNN and ARIMA models based on the normalized mean square error (NMSE) and mean absolute percentage error (MAPE).

Young et al., [7] studied the predicting the daily rainfall at 367 locations based on the daily rainfall at nearby 100 locations in Switzerland. The whole area is divided into four sub-areas and each is modeled with a different way. Predictions in two larger areas were prepared by RBF networks based on the location information only. Predictions in two smaller were made using a simple linear regression model based on the elevation information only. They have concluded that the RBF networks produced good prediction while the linear models poor prediction.

Shamseldin [25] examined the effectiveness of rainfall-runoff modeling with ANNs by comparing their results with the Simple Linear Model (SLM), the seasonally based Linear Perturbation Model (LPM) and the Nearest Neighbor Linear Perturbation Model (NNLPM) and concluded that ANNs could provide more accurate discharge forecasts than some of the traditional models.

Isa et al. [72] tried to predict daily weather conditions based on various measured parameters gained from the Photovoltaic (PV) system. In that work, Multiple Multilayer Perceptron (MMLP) network with majority voting technique was used and trained using Levenberg Marquardt (LM) algorithm. Different techniques of voting are used such as majority rules, decision making, consensus democracy, consensus government and supermajority. The way of the voting technique is different depending on the problem involved. Majority voting technique was applied in the study so that the performance of MMLP can be approved as compared to single MLP network. The proposed work has been used to classify four weather conditions; rain, cloudy, dry day and storm. The system can be used to represent a warning system for likely adverse conditions. Experimental results demonstrate that the applied technique gives better performance than the conventional ANN concept of choosing an MLP with least number of hidden neurons.

On the other hand Lunagariya et al. [73] made an effort to verify the weather forecast from NCMRWF. Analysis was carried out weekly, seasonal as well as yearly basis using various numerical verification techniques like ratio score, usability analysis and correlation approach during July 2006 and September 2008-09. The forecasts were found within usability range for some parameters but for other parameter improvement is still possible.

David [74] explained that the purpose of statistical inference is to make sequential probability forecast for future observation rather than to express information about parameters. Therefore, there is a need of an approach, which is better than the statistical inference method. However, Glahn and Lowry [75] have proved that Model Output Statistics (MOS) technique is an objective weather forecasting technique, which consists of determining a statistical relationship between a predict and variable forecast by a numerical model at some projection time. It is the determination of the “weather related” statistics of a numerical model. They applied this technique, together with screening regression to the predication of surface wind, probability of precipitation, maximum temperature, cloud amount and conditional probability of frozen precipitation. The obtained results are compared with the national weather system over Teletype and facsimile. Results illustrate that MOS is a useful technique in objective weather forecasting. Therefore, in the proposed research statistical regression as multidimensional response surface tool is applied to forecast local monsoonal precipitation.

Su et al. [76] proposed an approach that can incorporate both types of prediction (global prediction and local prediction.) to increase prediction accuracy. The proposed Markov–Fourier gray model (MFGM) prediction approach uses a gray model to roughly predict the next datum from a set of the most recent data and a Fourier series to fit the residual errors produced by the gray model. Finally, Markov state transition matrices are employed to recode the global information generated also by the residual errors. By combining a local predicted value obtained by a Fourier series and a global estimated error obtained by the Markov forecasting method, the approach can predict the future weather more accurately.

IV. Review Analysis

We presented a review of the use of different computational intelligence tools for weather forecasting and found the unique characteristics of ANNs: adaptability, nonlinearity and arbitrary function mapping ability make them quite suitable and useful for weather forecasting tasks. Overall, ANNs give satisfactory performance in weather forecasting and they surpassed the traditional models. Gorr et al. [77] believe that ANNs can be more appropriate for the following situations:

(1) Large data sets
(2) Problems with nonlinear structure
(3) The multivariate time series forecasting problems

After the review of a wide range of ANN architectures for weather forecasting, it is 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, wind, and found significant results using the same architectures. Most of the scientists have concluded that BPNN and RBFN are the appropriate method to predict weather phenomenon. However there are some limitations of neural networks models such as:

1- ANNs are black-box methods. There is no explicit form to explain and analyze the relationship between inputs and outputs. This causes difficulty in interpreting results from the networks. Also no formal statistical testing methods can be used for ANNs.
2- ANNs are prone to have over fitting problems due to their typical, large parameter set to be estimated.
3- There are no structured methods today to identify what network structure can best approximate the function, mapping the inputs to outputs. Hence, the tedious experiments and trial-and-error procedures are often used.
4- ANNs usually require more data and computer time for training.

Liong and He [78] explained that Neural networks offer a number of advantages, including requiring less formal statistical training, ability to implicitly detect complex nonlinear relationships between dependent and independent variables, ability to detect all possible interactions between predictor variables and the availability of multiple training algorithms. Disadvantages include its “black box” nature, greater computational burden, and proneness to over fitting and the empirical nature of model development. Table 1 summarizes the previous related works, it shows the advantages, limitations and the technologies have been used for weather forecasting.

Technology	Advantages	Limitations
Neural networks	• Handle nonlinearity. • Does not required pre knowledge about domain. • Requires less data preparation. • Ability to learn and (generalization). • Decrease Complexity of mathematical computing increase accuracy.	• Does not show the relation between the i and the output. • Require more data and computer time training. • There are no structured methods to identify network structure can best approximate the func
Fuzzy logic	• 1 -Simplify knowledge acquisition and representation. • 2- Solution to nonlinear problems. It allows heu decision-making strategies to be formulated by natural lang rules rather than mathematical models.	• Require more fine-tuning and simulation b operational. • Highly dependent on domain ex knowledge, the knowledge extraction proce crucial as the whole fuzzy system is dependent o domain expert knowledge. • They usually use heuristic or trial and approach in selecting the types of membe functions, inference engine and defuzzific methods. This approach is time-consuming.
Evolutionary algorithms	• Hybridization with Other Methods: They can be us optimize the performance of neural networks, fuzzy syst production systems, and wireless systems. • Parallelism, The evaluation of each solution can be ha in parallel. • Conceptual Simplicity: The evolutionary algorithm co of initialization, iterative variation and selection in light performance index. Pre-knowledge is not required.	• No guarantee for finding optimal solution finite amount of time. • Parameter tuning mostly by trial-and-error.
Machine Learning	• Deal with numerical or categorical variables. • Copes with noise. • Gives expected error rate. • Good predictive power.	• Can generate large trees that require pruni • Harder to classify > 2 classes. • Poor at handling irrelevant attributes. • Can be affected by noise.
Statistical models	• Good skill for long rage forecasts. • Use of multiple predictors. • Shows explicit correlations between observations of ti • series.	• Not useful to study the highly nonlinear relationships between rainfall and its predictors. • There is no ultimate end in finding the predictors.
Numerical models	• Suitable to short-range weather prediction (used to generate either short-term weather forecasts or longer-term climate predictions). • Achieve very high-resolution simulation of severe weather precipitation systems.	• The accuracy of the models depends on the initial conditions, which are inherently incomplete. • Are not able to achieve satisfactory results in domestic cases. • Weak performance in order to predict the long-term seasonal rain even for a large spatial scale. • Needs high performance computing and memory space to get more accuracy. • Common method to forecast weather, which involves a complex of mathematical computing.

Table 1. Comparative analysis of techniques in Meteorological forecasting.

V. Conclusions

This paper presented an overview of using the various computational intelligence tools in weather forecasting, describing the main contributions on this field and providing taxonomy of the existing proposals according to the type of tools used. We focused on the capabilities of neural networks in the prediction of several weather phenomena such as rainfall, temperature, flood and tidal level etc. In the comparative study among various neural network techniques, feed forward networks and radial basis function networks are found as appropriate solutions for the prediction of long-range weather forecasting. The study of feed forward network and radial basis function networks for long range meteorological parameters pattern recognition over smaller scale geographical region illustrate a good performance and reasonable prediction accuracy.

References

[1] J. R. Holton, “An Introduction to Dynamic Meteorology”, Academic Press, San Diego, USA. 1972.

[2] P. Lynch, “The origins of computer weather prediction and climate modeling”, Journal of Computational Physics 227, 3431–3444, 2008.

[3] N. Anbarci, J. Boyd III, E. Floehr, J. Lee and J. J. Song, “Population and income sensitivity of private and public weather forecasting”, Regional Science and Urban Economics 41, 124–133, 2011.

[4] A. Abraham, N. S. Philip and K. B. Joseph, “Will we have a wet summer? Long-term rain forecasting using soft computing” models, modeling and simulation 2001, in: Proceedings of the 15th European Simulation Multi Conference on Society for Computer Simulation International, Prague, Czech Republic, pp. 1044–1048, 2001.

[5] G. Shrivastava, S. Karmakar and M. K. Kowar, “Application of Artificial Neural Networks in Weather Forecasting: A Comprehensive Literature Review”, International Journal of Computer Applications (0975 – 8887) Volume 51– No.18, 2012.

[6] R. Kimura, “Numerical weather prediction”, Journal of Wind Engineering and Industrial Aerodynamics 90, pp. 1403–1414, 2002.

[7] L.S. young, C. Sungzoon, P.M. Wong, “Rainfall Prediction Using Artificial Neural Networks”, Journal of Geographic Information and Decision Analysis, vol. 2, no. 2, pp. 233 – 242, 1998.

[8] W.H. Hsieh, and B. Tang, “Applying Neural Network Models to Prediction and Analysis in Meteorology and Oceanography”, Bull. Amer. Met. Soc., 79, pp. 855-1870, 1998.

[9] W. D. Christian and W Robert, “An artificial neural network approach to rainfall runoff modeling”, Hydrological Sciences—Journal, 43(1), pp. 47-66, 1998.

[10] R. M. Trigo and J. P. Palutikof, 1999, “Simulation of Daily Temperatures for Climate Change Scenarios over Portugal: A Neural Network Model Approach”, University of East Anglia, Norwich, NR4 7TJ, United Kingdom, climate research (Clim., Res.), 13,pp. 45–59, 1999.

[11] E. Toth , A.Brath and A. Montanari, “Comparison of short-term rainfall prediction models for real-time flood forecasting”, Journal of Hydrology, Elsevier, 239, pp. 132-147, 2000.

[12] K. C.Luk, J. E. Ball AND A. Sharma, “An Application of Artificial Neural Networks for Rainfall Forecasting”, Mathematical and Computer Modelling 33, pp. 883-699, 2001.

[13] F. J. Chang, J. M. Liang, and Y. C. Chen, “Flood Forecasting Using Radial Basis Function Neural Networks”, IEEE Transactions On Systems, Man, And Cybernetics, vol. 31, no. 4, pp. 530-535, 2001.

[14] S. C. Michaelides, C. S. Pattichis and G. Kleovoulou, “Classification of rainfall variability by using artificial neural networks”, International Journal Of Climatology, pp. 1401–1414, 2001.

[15] I. Maqsood, Riaz M. Khan and A. Abraham, “Weather Forecasting Models Using Ensembles of Neural Networks”, Neural Comput & Applic, 13, pp. 112–122, 2004.

[16] A. J. Cannon and P. H. Whitfield, “Downscaling recent stream flow conditions in British Columbia, Canada using ensemble neural network models”, Journal of Hydrology, 259: 136–151, 2002.

[17] D. Jeong and Y. Kim,” Rainfall-runoff models using artificial neural networks for ensemble streamflow prediction”, Hydrol. Process. 19, 3819–3835, 2005.

[18] K. V. Somvanshi, P. O. Pandey, K. P. Agrawal, V. N. Kalanker1, Ravi .M.Prakash and R. Chand, “Modelling and prediction of rainfall using artificial neural network and ARIMA techniques”, J. Ind. Geophys. Union, Vol.10, No.2, pp.141-151, 2006.

[19] Kumar D. Nagesh, Reddy M. Janga and Maity Rajib, “Regional Rainfall Forecasting using Large Scale Climate Teleconnections and Artificial Intelligence Techniques”, Journal of Intelligent Systems, Vol. 16, No.4, pp. 307-322, 2006.

[20] R. Bustami, N. Bessaih, C. Bong and S. Suhaili, “Artificial Neural Network for Precipitation and Water Level Predictions of Bedup River”, International Journal of Computer Science, vol 34:2, 2007.

[21] M. Hayati, and Z. Mohebi,” Application of Artificial Neural Networks for Temperature Forecasting”, World Academy of Science, Engineering and Technology, 28 , pp. 275-279, 2007.

[22] A. Aytek, M. Asce and M. Alp, “An application of artificial intelligence for rainfall–runoff modeling”, J. Earth Syst. Sci., vol. 117, No. 2, pp. 145–155, 2008.

[23] O. F. Hocaoglu, Y. Oysal and M. Kurban, “Missing wind data forecasting with adaptive neuro-fuzzy inference system”, Springer-Verlag London, vol. 18, pp. 207–212, 2009.

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

[25] A.Y.Shamseldin, “Application of a neuralnetwork technique to rainfall-runoff modeling”, Journal of Hydrology, vol. 199, pp. 272-294, 1997.

[26] P.C. Nayak, K.P Sudheerb, D.M.Ranganc and K.S. Ramasastrid, “A neuro-fuzzy computing technique for modeling hydrological time series”, Journal of Hydrology, Elsevier, 291, pp. 52–66, 2004.

[27] A. Abraham and N. S. Philip, “Soft Computing Models for Weather Forecasting”, Journal of applied science and computations, vol. 11, pp. 106-117, 2004.

[28] I. Maqsood, R. M. Khan, H.G. Huang and R. Abdalla, “Application of soft computing models to hourly weather analysis in southern Saskatchewan, Canada”, Elsevier, vol. 18, pp. 115–125, 2005.

[29] P. Luenam, S. Ingsriswang, L. Ingsrisawang, P. Aungsuratana, and W. Khantiyanan, 2010, “A Neuro-Fuzzy Approach for Daily Rainfall Prediction over the Central Region of Thailand”, Proceedings of the International Multiconferance of Engineers and Computer Scientists 2010, vol. 1, March 17-19, 2010, Hong Kong.

[30] E. Vamsidhar, K.V.S.R.P. Varma, P. S. Rao and R. satapati, “Prediction of Rainfall Using Backpropagation Neural Network Model”, International Journal on Computer Science and Engineering, Vol. 02, No. 04, pp. 1119-1121, 2010.

[31] C. Y. Patil and A. A. Ghatol, “Rainfall forecasting using local parameters over a meteorological station: an artificial neural network approach”, International Journal of Engineering Research & Industrial Applications, Vol.3, No. II, pp 341-356, 2010.

[32] J. Joshi and V. M. Patel, “Rainfall-Runoff Modeling Using Artificial Neural Network (A Literature Review)”, National Conference on Recent Trends in Engineering & Technology, B.V.M. Engineering College, V.V.Nagar,Gujarat,India, 13-14, May 2011.

[33] A. El-Shafie, A. Noureldin, M. R.Taha, and A.Hussain, “Dynamic versus static neural network model for rainfall forecasting at Klang River Basin, Malaysia”, Hydrology and Earth System Sciences, vol. 8, pp. 6489–6532, 2011.

[34] D. S. Sawaitul, K. P. Wagh, P. N. Chatur, “Classification and Prediction of Future Weather by using Back Propagation Algorithm-An Approach”, International Journal of Emerging Technology and Advanced Engineering, Volume 2, Issue 1, pp. 110-113, 2012.

[35] M.Nelson, T.Hill, B. Remus and M. O’Connor,” Can neural networks be applied to time series forecasting and learn seasonal patterns: An empirical investigation”, In: Proceedings of the Twenty seventh Annual Hawaii International Conference on System Sciences, pp. 649–655, 1994.

[36] R. Sharda and R. B. Patil, “Connectionist approach to time series prediction: An empirical test”, Journal of Intelligent Manufacturing, 3, pp.317–323, 1992.

[37] S.Kang, “An Investigation of the Use of Feedforward Neural Networks for Forecasting”, Ph.D. Thesis, Kent State University, 1991.

[38] T.Hill, L.Marquez, M. O’Connor and W. Remus, “Artificial neural networks for forecasting and decision making”, International Journal of Forecasting 10, pp5–15, 1994.

[39] T.Hill, M. O’Connor and W. Remus, “Neural network models for time series forecasts”, Management Sciences, vol. 42, issue. (7), pp1082– 1092, 1996.

[40] K. Abhishek, A. Kumar, R. Ranjan and S. Kumar, “A Rainfall Prediction Model using Artificial Neural Network”, IEEE Control and System Graduate Research Colloquium. pp. 82-87, 2012.

[41] A. S. Mohammad, “Weather Temperature Forecasting Using Artificial Neural Network”, Journal of Engineering and Development, Vol. 15, No. 2, June (2011) ISSN 1813-7822.

[42] S. S. De and A. Debnath, “Artificial Neural Network Based Prediction of Maximum and Minimum Temperature in the Summer Monsoon Months over India”, Applied Physics Research, Vol. 1, No. 2, Nonember 2009.

[43] S. S. Baboo and I. K. Shereef, “An Efficient Weather Forecasting System using Artificial Neural Network”, International Journal of Environmental Science and Development, Vol. 1, No. 4, October 2010 ISSN: 2010-0264.

[44] C.J. Devi, B.S.P. Reddy, K.V. Kumar, B.M. Reddy and N.R. Nayak, “ANN Approach for Weather Prediction using Back propagation ”, International Journal of Engineering Trends and Technology, Volume 3, Issue 1, 2012, ISSN: 2231- 5381.

[45] K. M. Mayilvaganan and K.B Naidu, “ANN and Fuzzy Logic Models for the Prediction of groundwater level of a watershed”, International Journal on Computer Science and Engineering, Vol. 3 No. 6, pp. 2523-2530, 2011.

[46] A. El-Shafie, M. Mukhlisin, A.A. Najah and M.R. Taha, “Performance of artificial neural network and regression techniques for rainfall-runoff prediction”, International Journal of the Physical Sciences, Vol. 6 No 8, pp. 1997-2003, 2011.

[47] D.F. Lekkas, C. Onof, M.J. Lee and E.A. Baltas, “Application of artificial neural networks for flood forecasting”, Global Nest Journal, Vol 6, No 3, pp 205-211, 2004.

[48] G.Geetha, S. R Samuel, “Prediction of monthly rainfall in Chennai using back propagation neural network model”, International Journal of Engineering Science and Technology, Vol. 3 No. 1, pp. 211-213, 2011.

[49] A.R. Naik and S.K.Pathan, “Weather Classification and forecasting using Back Propagation Feed-forward Neural Network”, International Journal of Scientific and Research Publications, Volume 2, Issue 12, December 2012, ISSN 2250-3153.

[50] G. Tiron and S. Gosav, “The July 2008 Rainfall Estimation From Barnova WSR-98 D Radar Using Artificial Neural Network”, Romanian Reports in Physics, Vol. 62, No. 2, P. 405–413, 2010.

[51] O. A. Dombayc, and M. Golcu, “Daily means ambient temperature prediction using artificial neural network method: A case study of Turkey”, Renewable Energy, 34: pp.1158-1161, 2009.

[52] M. Afzali, A. Afzali and G. Zahedi, “Ambient Air Temperature Forecasting Using Artificial Neural

Network Approach", International Conference on Environmental and Computer Science IPCBEE vol.19(2011), IACSIT Press, Singapore, pp.176-180, 2011.

[53] M.T. Perea, G.H. Ruiz, J.R. Moreno, R.C. Miranda and E.R. Araiza, "Greenhouse Energy Consumption Prediction using Neural Networks Models", International Journal of Agriculture & Biology, Vol. 11, No. 1, pp. 1-6, 2009.

[54] S.M. Paras, A. Kumar, and M. Chandra, "A Feature Based Neural Network Model for Weather Forecasting", World Academy of Science, Engineering and Technology, vol. 10, pp.10-22, 2007.

[55] T. Santhanam and A.C. Subhajini, "An Efficient Weather Forecasting System using Radial Basis Function Neural Network", Journal of Computer Science Volume 7, Issue 7, pp.962-966, 2011.

[56] H. M. Abdul–Kader, "Neural Networks Training Based on Differential Evolution Algorithm Compared with Other Architectures for Weather Forecasting", International Journal of Computer Science and Network Security, VOL.9 No.3, pp.92-99, March 2009.

[57] I Maqsood, M.R. Khan and A. Abraham, "Intelligent Weather Monitoring Systems Using Connectionist Models", Neural, Parallel & Scientific Computations, Vol. 10, pp.157-178, 2002.

[58] T.A. Awchi, "Application of Radial Basis Function Neural Networks for Reference Evapotranspiration Prediction", Al-Rafidain Engineering Vol.16, No.1,pp. 117-130, 2008.

[59] G. Lin and L, Chen, "A non-linear rainfall-runoff model using radial basis function network", Journal of Hydrology 289, pp.1–8, 2004.

[60] T. W. S. Chow and S. Y. Cho, "Development of a recurrent Sigma-Pi neural network rainfall forecasting system in Hong Kong", Neural Computing & Applications, Volume 5, Issue 2, pp. 66-75,1997.

[61] R.P. Deshmukh and A.A. Ghatol, "Comparative study of Jorden and Elman model of neural network for short term flood forecasting", 3rd IEEE International Conference on Computer Science and Information Technology (ICCSIT), 2010, vol. 9, pp.400 – 404, 9-11 July 2010.

[62] X.L. Gong, Z.J. Hu, M.L. Zhang and H. Wang, "Wind Power Forecasting Using Wavelet Decomposition and Elman Neural Network", Advanced Materials Research, Vol. 608-609 ,pp 628-632, 2013.

[63] C. Meng and J. Wu, "A Novel Nonlinear Neural Network Ensemble Model Using K-PLSR for Rainfall Forecasting", Bio-Inspired Computing and Applications: Lecture Notes in Computer Science Volume 6840, pp 41-48, 2012.

[64] E.C. Özelkan, F. Ni, and L. Duckstein, "Relationship between monthly atmospheric circulation patterns and precipitation: Fuzzy logic and regression approaches", Water Resources Research, Volume 32, Issue 7, pp.2097–2103, 1996.

[65] H. Liu and V. Chandrasekar, "Classification of Hydrometeor Type Based on Multiparameter Radar Measurements: Development of a Fuzzy Logic and Neuro Fuzzy Systems and In-situ Verification", J. Atmos. Ocean Tech., Vol. 17, pp.140-164, 2000.

[66] C. Mahabir, F.E. Hicks and A. R. Fayek, "Application of fuzzy logic to forecast seasonal runoff", Hydrological Processes. Vol.17, pp.3749–3762, 2003.

[67] D.H. Bae, D.M. Jeong and G. Kim, "Monthly dam inflow forecasts using weather forecasting information and neuro-fuzzy technique", Hydrological Sciences Journal, vol.52, No.1, 2007.

[68] R. A. Aliev, B. Fazlollahi, R. R. Aliev and B. Guirimov, "Linguistic time series forecasting using fuzzy recurrent neural network", Soft Comput, vol. 12,Issue 2, pp. 183–190, 2008.

[69] L. Jiang and J. Wu, "Hybrid PSO and GA for Neural Network Evolutionary in Monthly Rainfall Forecasting", Intelligent Information and Database Systems: Lecture Notes in Computer Science Volume 7802, pp 79-88, 2013.

[70] D.M. Riley, and G.K. Venayagamoorthy, "Comparison of a recurrent neural network PV system model with a traditional component-based PVsystem model", 37th IEEE Photovoltaic Specialists Conference, Seattle, WA, pp. 2426 – 2431, June 2011.

[71] S. Zhao and L. Wang, "The Model of Rainfall Forecasting by Support Vector Regression Based on Particle Swarm Optimization Algorithms", Life System Modeling and Intelligent Computing: Lecture Notes in Computer Science, Volume 6329, pp. 110-119, 2010.

[72] I.S. Isa, S. Omar, Z. Saad, N.M. Noor and M.K. Osman, "Weather Forecasting Using Photovoltaic System and Neural Network", 2nd International Conference on Computational Intelligence, Communication Systems and Networks, Liverpool, United Kingdom, pp.96-100, July 28-July 30, 2010.

[73] M.M. Lunagariya, S. K. Mishra and V. Pandey "Verification and usability of medium range weather forecast for Anand region" Journal of Agrometeorology, vol.11, Special Issue, pp. 228-233, 2009.

[74] A. P. Dawid, "Present position and potential developments: some personal views. Statistical theory. The prequential approach", Journal Roy. Statist. Society Association, pp. 278-292, 1984.

[75] H.R. Glahn, and D.A. Lowry, "The Use of Model Output Statistics (MOS) in Objective Weather Forecasting", Journal of Applied Meteorology, vol. 11,Issue 8, pp. 1203–1211, 1972.

[76] S.F. Su, C.B. Lin, and Y.T. Hsu, "A High Precision Global Prediction Approach Based on Local Prediction Approaches", IEEE Transactions on Systems,MAN, and Cybernetic— Part C:Applications And Reviews, VOL.32, NO. 4, pp.416-425, November 2002.

[77] W.L. Gorr, D. Nagin and J. Szczypula, "Comparative study of artificial neural network and statistical models for predicting student grade point averages", International Journal of Forecasting,Vol 10, pp 17–34, 1994.

[78] S.Y. Liong and S. He, "Rain gauge-Based Rainfall Nowcasting with Artificial Neural Network", Advances in Geosciences, vol. 17: Hydrological Science (HS), pp.1-9, 2008.