Proceedings of the Second Science Symposium – August, 2004
Faculty of Science, University of Ruhuna, Matara, Sri Lanka
2:29-36

Development of a rainfall forecasting model for Sri Lanka using artificial feed-forward neural network

Dharmaratna, W.G.D. and Premarathna, L. D.

Department of Physics, University of Ruhuna, Matara, Sri Lanka.
correspondence: *dharma@phy.ruh.ac.lk*

Abstract

A rainfall forecasting model for Sri Lanka is constructed using artificial feed-forward back-propagation neural network. The data obtained from meteorological station in Colombo is used. The rainfall data with the humidity and atmospheric pressure measurements taken at the ground level are used to train the network. The preliminary results indicate that the model is successful in predicting rainy days one day ahead in Colombo area with the accuracy of 67%. The possibilities for further improvement of the model are discussed.

Introduction

Neural network models, more accurately Artificial Neural Network (ANN) computational models, are algorithms used for cognitive tasks, such as learning and optimization. They are based on concepts derived from research on the nature of the human brain, in general description.

In human brain, a biological neuron collects signals from other neurons through a host of fine structures called dendrites. The neuron sends spikes of electrical activity through a long, thin strand known as an axon, which further splits into thousands of branches. At the end of each branch, a structure called synapse converts the activity from the axon into electrical effects that inhibit or excite activity in the connected neuron. When a neuron receives excitatory input that is sufficiently large compared with its inhibitory input, it sends a spike of electrical activity down its axon. Learning occurs by changing the effectiveness of the synapses as the influence of one neuron on another changes.

Like in a human brain, neural networks also consist of processing units or nodes (artificial neurons) and connections (weights) between them. The processing units transport incoming information through their outgoing connections to other units. The "electrical" information is simulated with specific values stored in those weights that

make the networks have the capacity to learn, memorize and create relationships amongst data.
Among many different networks, the most widely used are the multi-layer feed-forward neural networks, which are capable of representing non-liner functional mappings between inputs and outputs and are hailed as "Universal Approximators". Moreover, it is a "multi variable analysis tool" that can be used in almost any task or job which requires computing power, such as, Forecasting, Image processing, Pattern Recognition, and Function approximation. These networks can be trained with a powerful and computationally efficient error back-propagation method, which is the most commonly used method for training multi-layer feed-forward networks. This technique was popularized by Rumelhart, Hinton and Williams in 1986 (Rao and Rao 1994).

It is known that scientists have built forecasting models (Pankiewicz *et al.* 2001, Baratta 2003) successfully, in particular using upper atmospheric data, in other countries. The application of pattern recognition techniques (including neural networks) has been investigated with the aim of improving the use of satellite imagery in numerical weather prediction and in other quantitative forecasting systems given in Pankiewicz *et al.* (2001). The model of Baratta (2003) has predicted the rainfall intensities with RMS errors less than 3 mm of rain.

However, very few (Barr-Kumarakulasinghe and Pathiraja 1997, Punyawardena and Kulasiri 1997, Perera *et al.* 2002) attempts were made in numerical forecasting for Sri Lanka. Perera *et al.* (2002) have attempted to make a model based on Markov method using data from nine weather stations in Sri Lanka. A construction of a model based on feed-forward back-propagation neural network architecture is attempted to predict rainy days in near future on daily basis using ground level data on environmental parameters. Some preliminary results of the model are presented here for data collected at the meteorological station in Colombo (Longitude 79.87E, Latitude 6.09E and Altitude 7m).

Data Pre-processing

The most important step when using neural networks is the training of the net with correct data. Therefore, the selection of correct and relevant parameters and pre-processing the data in the most suitable format to the input of the net is very important. Firstly, we tried to investigate any direct correlation between the rainfall and the other relevant physical quantities by plotting rainfall with other parameters, individually. We were not able to identify any direct correlation clearly. Therefore, we started with parameters, rainfall, humidity, atmospheric pressure, average wind speed and the temperature. The data used in the analysis is obtained from the Colombo station of the Department of Meteorology.

Figure 1 shows the variation of raw data, atmospheric pressure (PM) (a), humidity (PM) (b) and rainfall (24-hour period from 09.00 AM) (c), throughout the year (1990). Pressure and humidity data were available for morning (AM, 09.00) and afternoon (PM, 18.00) separately. A significant difference has been seen between AM and PM data, in particular, for humidity. Therefore, both AM and PM data were used when available. The data fed to the input of the net is normalized according to the following formula.

$$\text{Normalized data} = \frac{\text{Raw data - Average}}{\text{Maximum}}$$

where, Average is the average of a given parameter for the period considered and Maximum is chosen to normalize the data between 1 and –1. Throughout our studies it was discovered that the performance of the net could be significantly improved by using a fuzzy classification, instead of a continuous variable, for the past rainfall as follows. In order to predict that whether or not the following day (Tomorrow) of any particular day would be a rainy day, the data of both the particular day (Today) and the day before (Yesterday) were used. A new parameter RAI is defined such that, RAI is +1 if both today and yesterday were rainy days, RAI is +0.5 if today is a rainy day but yesterday was non-rainy day, RAI = -0.5 if today is non-rainy day but yesterday was a rainy day, and RAI = -1.0 if both today and yesterday were non-rainy days. For other parameters, normalized today's data were used for the input. For the training purpose tomorrow's information on the rain is used as the output of the net. Therefore, the output for the training mode is 1 for rainy days and 0 for non-rainy days. For the training purpose it was considered that any day as a rainy day if the rainfall is greater than 0.3 mm and non-rainy day if there is no rain. A few days with tomorrow's rainfall between 0.0 and 0.3 mm were not used for the output in the training mode but these days were considered in the testing mode.

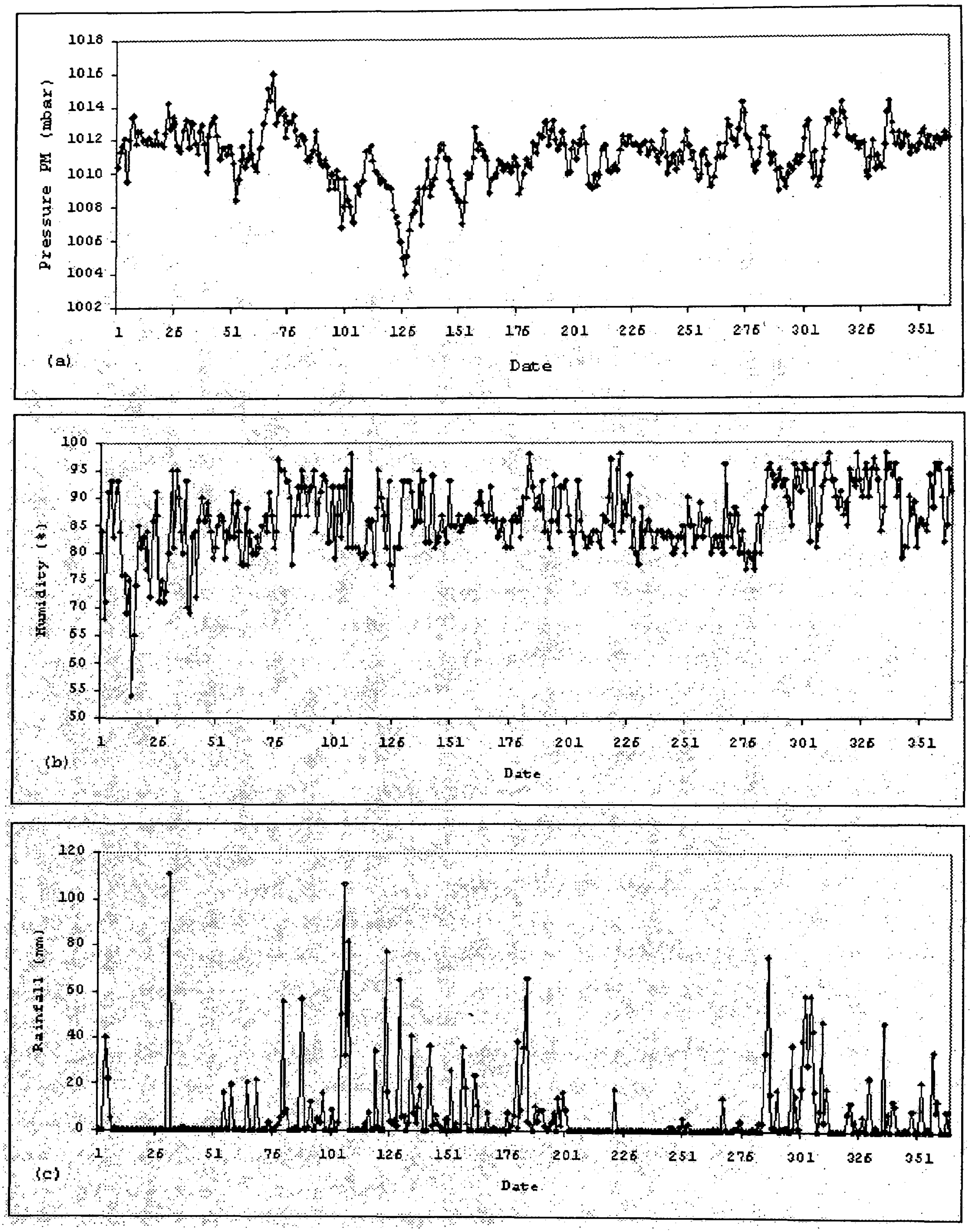

Figure 1. Variation of raw data throughout the year. (a) Atmospheric Pressure (b) Humidity (c) Rain fall

Network Architecture

Through our preliminary studies it was found that, out of the parameters mentioned earlier, temperature and wind speed did not improve the result when the other parameters were considered in this model. Therefore, we used only five parameters, RAI, humidity (AM & PM), and temperature (AM & PM) were used as the input node. These parameters define the input layer of the network. Obviously, there is only one output node, tomorrow's rain (0 or 1), which is the output layer of the network. In the network, there is a freedom to choose the number of hidden layers and the number of nodes in each hidden layer. Number of hidden layers and the number of nodes in a hidden layer have to be decided by training and testing with some test data sets. The network requires a sufficient number of hidden nodes to learn the general features of the relationship. Too many hidden nodes cause over fitting while too few leads to under fitting. The goal is to use as few nodes in the hidden layer as possible while retaining the network's ability to

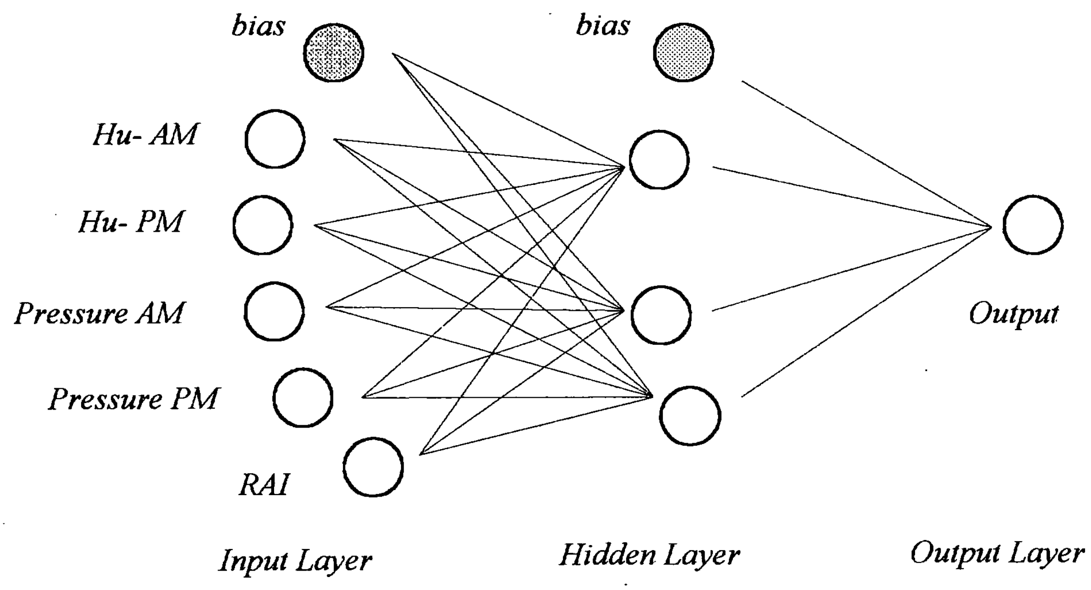

Figure 2. Network architecture of the model

learn the relationships among the data. Using known data, several attempts were made by changing these parameters by trial and error method. It was concluded that the performance of the net is best when a hidden layer of three nodes were included.

Figure 2 shows the schematic representation of the network architecture used in the final analysis. The bias term is set to 1.0. For the neural networks trained by back propagation method, sigmoid functions are commonly used as activation functions because of its differentiability. A bipolar sigmoid function was used in this case.

The basic network algorithm given in Roa and Rao (1994) is used for the analysis with some additional codes incorporated to preprocess the data. An object-oriented programme was developed in C^{++} and it was run on Linux operating system.

Results

It was mentioned earlier that out of the parameters considered only humidity, pressure and the past rainfall (defined as RAI) were important in this model. The network with one hidden layer with three hidden nodes performed well for these parameters. Furthermore, training of the network was done in different ways and the results were obtained when the network is trained using past 30 days and the prediction is made for the 31st day. This procedure was repeated, 30 days at a time for training, for one year of data. The histogram in figure 3 shows the output of the network for one year of data.

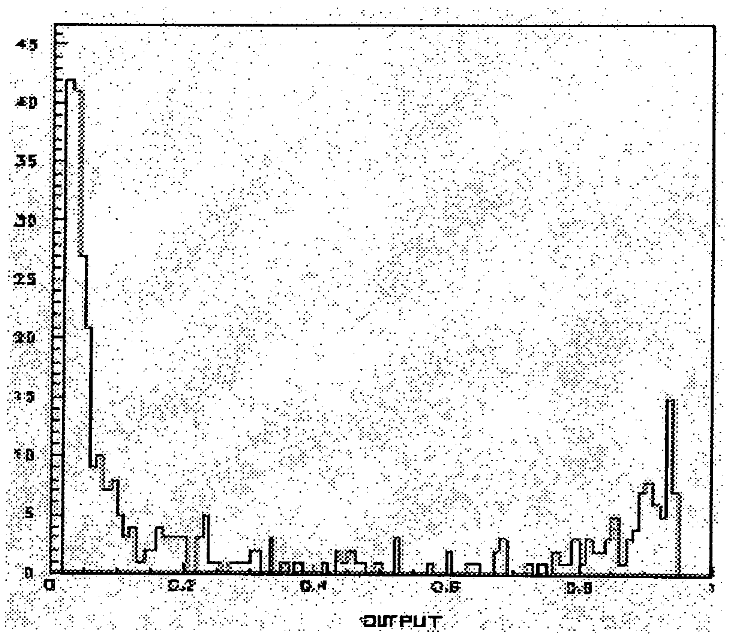

Figure 3. Output of the network for one year of data

The peak at the left close to 0 represents non-rainy days and the peak at the right close to 1 represents rainy days. The two peaks are well separated. The peak at the right has less data due to the fact that there were less rainy days during this year.

In this preliminary result, predictions were correct up to 69.3% days while the remaining dates the predictions were incorrect. The most important parameter was the RAI defined earlier using the information on rain during the immediate last two days. If any of the seven parameters considered here is used with the parameter RAI the predictability would be 61% or above. The optimum value is obtained with the five parameters RAI, humidity (AM & PM) and atmospheric pressure (AM & PM).

Discussion and Conclusion

In this preliminary result, the model has been successful in predicting rainy days, one day ahead, correctly for 69.3% times using a feed-forward back-propagation neural network with data collected at the ground level. It is interesting to note that the predictive power of the preliminary model constructed here is of the same order for as the result given in Perera *et al.* (2002) for the data collected at the same weather station. However, we believe that there are many possibilities to improve the predictability of this model. One important drawback is the less number of rainy days in a sample of 30-day data set, which is used to train the network. This could be easily overcome by combining the same 30-day period of the year for a number of (10 years for example) years for the training. This could be easily achieved by collecting last ten years of data. Furthermore, except for the rainfall, we have used only the today's values of the parameters for the prediction for tomorrow. Perhaps, by fuzzifying the other parameters using immediate last few days data, like the parameter RAI, the performance of the network could be improved. Only the data collected at the ground level was used in this model. Undoubtedly, by using relevant upper atmospheric data the performance of the model could be improved significantly.

Acknowledgements

Authors greatly appreciate the corporation of the Department of Meteorology, Sri Lanka, in providing all data used in this study. Valuable discussions with Dr. Janak Wedagedara, Department of Mathematics, University of Ruhuna and his help in setting up the required software are greatly appreciated.

References

Baratta D, Cicioni G, Masulli F and Studer L. 2003 Application of an ensemble technique based on singular spectrum analysis to daily rainfall forecasting. Neural Networks 16:375–387

Barr-Kumarakulasinghe SA and Pathiraja K. 1997 Automated Sri Lankan and South Indian Monsoonal Rainfall Prediction and Dissemination through the World Wide Web. Tenth Conference on Applied Climatology. Reno Nevada.

Pankiewicz GS, Johnson CJ and Harrison DL. 2001 Improving radar observations of precipitation with a Meteosat neural network classifier. Meteorol. Atmos. Phys. 76:9-22

Perera HKWI, Sonnadara DUJ and Jayewardene DR. 2002 Forecasting the occurrence of rainfall in selected weather stations in the wet and dry zones of Sri Lanka. Sri Lankan J. Phy. 3:39-53.

Punyawardena BVR and Kulasiri D. 1997 Development and comparison of Markov models for the rainfall in the dry zone of Sri Lanka. Proceedings of Joint International conference on Agricultural Engineering and Technology. Volume 1: 231-238.

Rao VB and Rao HV. 1994 Neural Network Computing, McGraw-Hill.