Advances in Geosciences
Vol. 17: Hydrological Science (2008)
Eds. Namsik Park *et al.*

RAINGAUGE-BASED RAINFALL NOWCASTING WITH ARTIFICIAL NEURAL NETWORK

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Rainfall forecasting and nowcasting are of great importance, for instance, in real-time flood early warning systems. Long term rainfall forecasting demands global climate, land, and sea data, thus, large computing power and storage capacity are required. Rainfall nowcasting's computing requirement, on the other hand, is much less. Rainfall nowcasting may use data captured by radar and/or weather stations. This paper presents the application of Artificial Neural Network (ANN) on rainfall nowcasting using data observed at weather and/or rainfall stations. The study focuses on the North-East monsoon period (December, January and February) in Singapore. Rainfall and weather data from ten stations, between 2000 and 2006, were selected and divided into three groups for training, over-fitting test and validation of the ANN. Several neural network architectures were tried in the study. Two architectures, Backpropagation ANN and Group Method of Data Handling ANN, yielded better rainfall nowcasting, up to two hours, than the other architectures. The obtained rainfall nowcasts were then used by a catchment model to forecast catchment runoff. The results of runoff forecast are encouraging and promising. With ANN's high computational speed, the proposed approach may be deliverable for creating the real-time flood early warning system.

1. Introduction

Rainfall forecasting can be obtained by long-term forecast, and short-term forecast, namely nowcasting. Numerical weather prediction models have been used for long term forecasting. However, their ability to provide accurate rainfall forecasts at the temporal and spatial resolutions still requires more improvement for many hydrologic applications (Brath, 1999); this is particularly crucial for catchments with small/medium sizes.

A number of approaches are available for rainfall nowcasting. For examples, there are (1) linear stochastic auto-regressive moving-average models (ARMA), which express the future rainfall as a linear function of past data, (2) the use of remote sensing observations (radar data and satellite images), which nowcasts rainfall based on the extrapolation of current weather conditions, (3) adaptive-network-based fuzzy inference system (ANFIS) proposed by Jang(1992), which can construct an input-output mapping based on both human knowledge (in the form of fuzzy if-then rules) and stipulated input-output data pairs, and (4) artificial neural network (ANN), which belongs to the non-linear, data-driven approaches. ANN depends on the available data for 'learning' without any priori hypothesis about the kind of relationship. One application described by Kuligowski and Barros (1998) showed that the ANN performance was superior to that of a multi-linear regression model at least for heavy rain events. Another study (Chau *et al.*, 2005) investigated two hybrid models based on ANN and ANFIS; the models were employed for flood forecasting in a channel reach of the Yangtze River in China. The ANFIS model was found to be optimal, but it entailed a large number of parameters. The performance of the ANN-GA model was shown to be good as well, yet it required longer computation time and additional modeling parameters.

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, proneness to over-fitting, and the empirical nature of model development.

The scope of this paper is to explore the nowcasting skill with artificial neural network using the observations from the rainfall/meteorological stations in Singapore. The proposed approach is then demonstrated on a relatively small urban catchment characterized by runoff with a short time of concentration.

2. Methodology

2.1. *Artificial neural network*

Artificial Neural Network (ANN) excels at problem diagnosis, decision making, and prediction. In this study, ANN is applied to train rainfall data set, learn the patterns, and develop the ability to reasonably classify new patterns or to make forecasts and predictions.

The basic building block of neural network technology is the simulated neurons. The network processes a number of inputs to produce an output,

ADVANCES IN GEOSCIENCES (A 6-Volume Set) - Volume 17: Hydrological Science (HS)

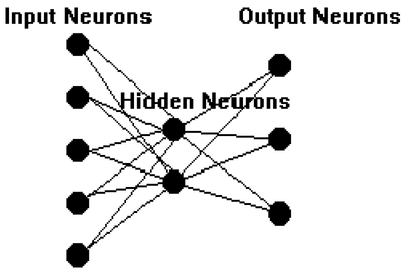


Fig. 1. Network structure.

the network's classifications or predictions. The neurons are connected by weights (depicted as lines as shown in Fig. 1) which are applied to values passed from one neuron to the next.

The network "learns" by adjusting the interconnection weights between layers. The network will be producing answer and repeatedly compared with the measured data, and each time the connecting weights are adjusted slightly in the direction of the measured data. As a result, the problem can be learnt, and a stable set of weights adaptively evolves and will produce a good prediction model.

In order to build up a successful neural network, it is important to know when to stop training. If the training is not sufficient, the net will not be able to learn the pattern; if the network is over trained, the network will memorize the training set thus it is unable to give a good answer on unseen data.

In this study a multilayer perceptron (MLP) with backpropagation (Bishop, 1995; Reed and Marks, 1999; Fausett, 1994; Rumelhart *et al.*, 1986) ANN is presented.

2.2. *Case study*

Singapore lies just north of the Equator near Latitude 1.5°N and Longitude 104°E. Because of its geographical location, maritime exposure and size, its climate is characterized by rather uniform temperature and pressure, high humidity, and abundant rainfall. The climate of Singapore can mainly be divided into two main seasons, the Northeast Monsoon and the Southwest Monsoon, separated by two relatively short inter-monsoon periods.

As shown from Fig. 2, five meteorological and five rainfall stations are considered in the study. They are spread quite throughout Singapore. The

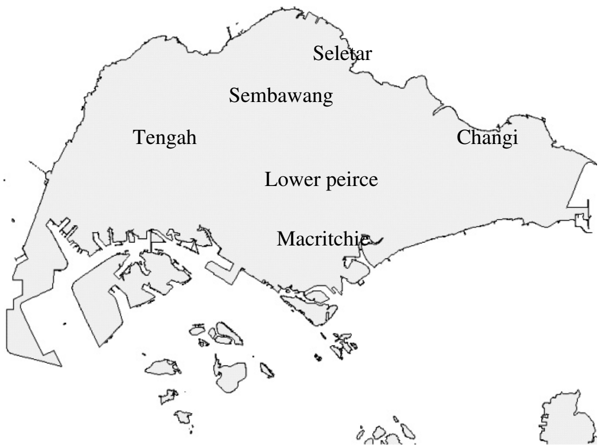


Fig. 2. Meteorological and rainfall stations considered.

five meteorological stations are Changi, Sembawang, Tengah, Seletar and Paya Lebar; hourly time series of meteorological data such as pressure, dry bulb temperature, wet bulb temperature, low cloud coverage, wind speed, WX (two figure numeric code representing the weather. E.g. 10 for mist; 60–65 for rain;), wind direction and rainfall are extracted from these five stations. The five rainguage stations are MacRitchie Reservoir, Lower Pierce Reservoir, Upper Seletar, Chestnut and Upper Pierce Reservoir; only hourly rainfall time series are considered for the current work. Table 1 summarizes the ANN input variables used for different forecast horizons.

To estimate rainfall at forecast horizons $(t + 1\Delta t)$ and $(t + 2\Delta t)$ where Δt is the incremental time step of 1 hour, the current and the past two hour weather variables (i.e. at times t, $t - 1\Delta t$, and $t - 2\Delta t$) are used. Table 1 shows the weather variables used at different time steps extracted from the five meteorological stations while at the other rainfall stations only rainfall data from times $(t - 1\Delta t)$ and $(t - 2\Delta t)$ are used as input variables.

In the study, 7 out of the 10 stations (Changi, Sembawang, Tengah, MacRitchie, Chestnut, Upper Seletar and Chestnut) are used as training stations while the remaining 3 stations are used for validation. Data considered as the training data set is from December–February of Years 2001 to 2005, and data from 17th to 19th Dec. 2006. We trained ANN with these data to later validate the trained ANN with the rainfall events from the period of 19th–21st December 2006. It should be noted that rainfall events in Dec 2006 were the third highest event ever recorded.

Table 1. Weather parameters used in the study as input variables.

parameters	$t-2\Delta t$	$t-1\Delta t$	t
Pressure	√	√	√
Dry-20	√	√	√
Cloud Coverage	√	√	√
Wind Speed	√	√	√
WX	√	√	√
Web Bulb Depression	√	√	√
Wind x-direction	√	√	√
Wind y-direction	√	√	√
Rainfall	√	√	NOT USED
Change in Pressure in the last 2 hours	—	—	√
Change in dry bulb temperature in the last 2 hours	—	—	√
change in wet bulb depression in the last 2 hours	—	—	√
Change in low cloud amount in the last 2 hours	—	—	√

Table 2. Rainfall prediction at forecast horizons $(t+1\Delta t)$, $(t+2\Delta t)$.

	Stations	Correlation Coefficient (CC) for time $(t+1\Delta t)$	Correlation Coefficient (CC) for time $(t+2\Delta t)$
Training	7 stations	0.6529	0.5639
Validation (19–21 December 2006)	Changi	0.6132	0.4630
	Sembawang	0.6877	0.4323
	Tengah	0.7386	0.5531
	MacRitchie	0.9540	0.7772
	Chestnut	0.9367	0.7330
	Upper Seletar	0.9114	0.6700
	Upper Pierce	0.9086	0.6952
	Paya Lebar	0.8003	0.6489
	Seletar	0.8541	0.5951
	Lower Pierce	0.9663	0.7290

The results are shown in Table 2. It can be seen that the performance indicator is reasonably good since the average goodness-of-fit for even $t+2\Delta t$ is around 0.6. It should be noted that the task of rainfall nowcasting is very difficult since the growth and decay of the rain storm is a very complicated process.

Figure 2 clearly shows the location situation of all the stations used. As MacRitchie station is the closest station to the Singapore River which is used later for the runoff simulation, the result of Neural Network for MacRitchie is presented in Fig. 3 and imported into rainfall-runoff model as rainfall input. It can be shown that the performance indicator is reasonably good since the correlation coefficient for even $(t + 2)$ is 0.7772.

3. Runoff Simulation

The nowcasted rainfall for times $(t + 1\Delta t)$ and $(t + 2\Delta t)$ are then used as input to a catchment runoff model, SOBEK (Introduction to SOBEK, 2004), to simulate the runoff from an urban catchment of about 12 km^2 area and characterized with a very short time of concentration about 20–30 minutes.

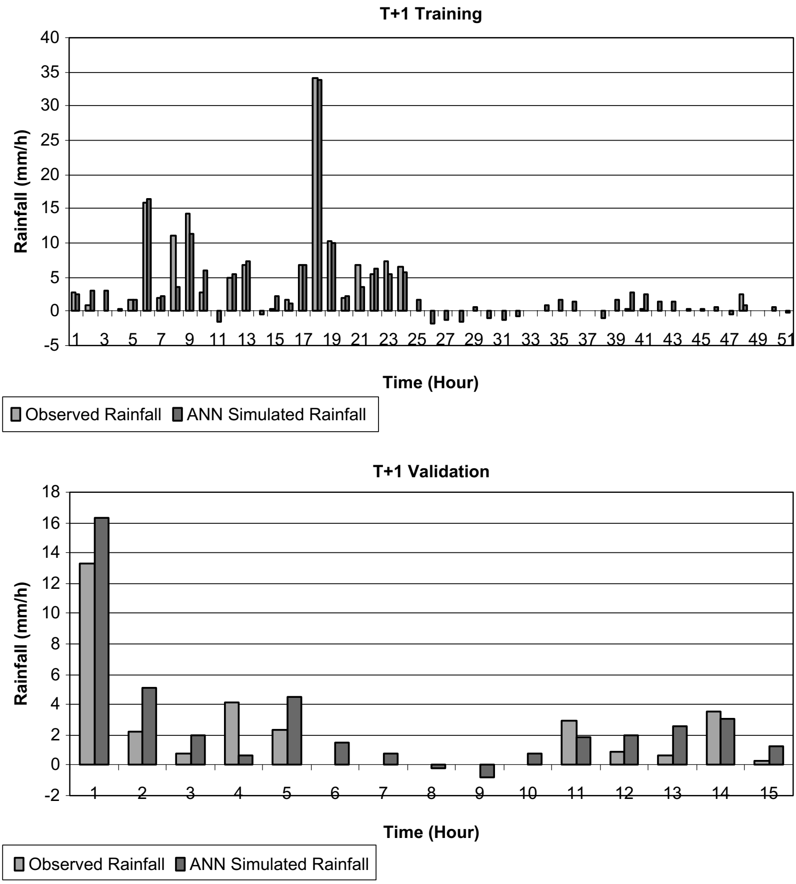
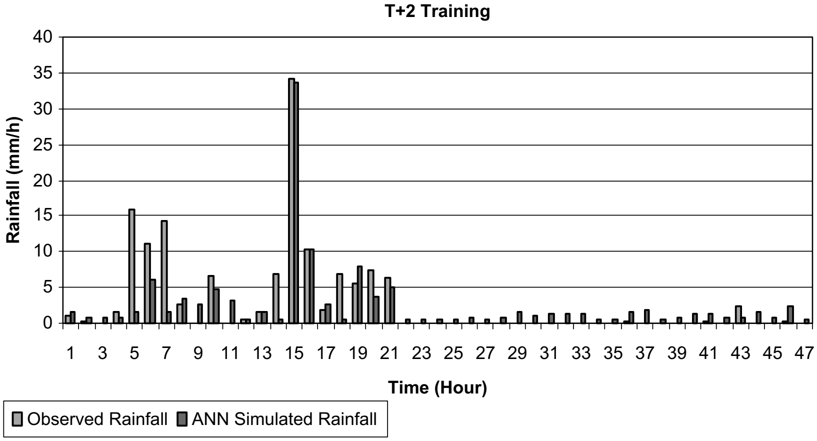


Fig. 3. Comparison of Macritchie rainfalls resulting from ANN and raingauges.



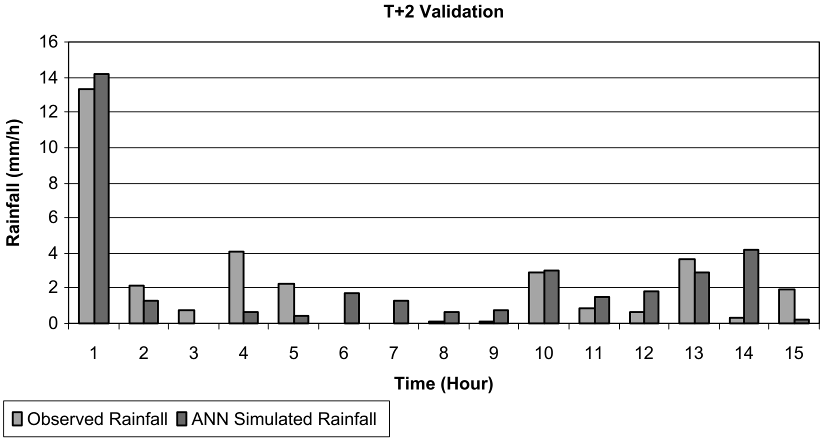


Fig. 3. (*Continued*)

Since the final target is the flow at the catchment outlet, the simulated flow obtained from ANN rainfall input is in reasonably good agreement with the flow obtained from measured rainfall as can be seen in Fig. 4 and Table 3. (Negative flow in Fig. 4 refers to tide impact.)

4. Conclusions

This paper presented a promising rainfall observation based rainfall nowcasting approach using Artificial Neural Network. Hourly meteorological and rainfall data were used to forecast rainfall quantities,

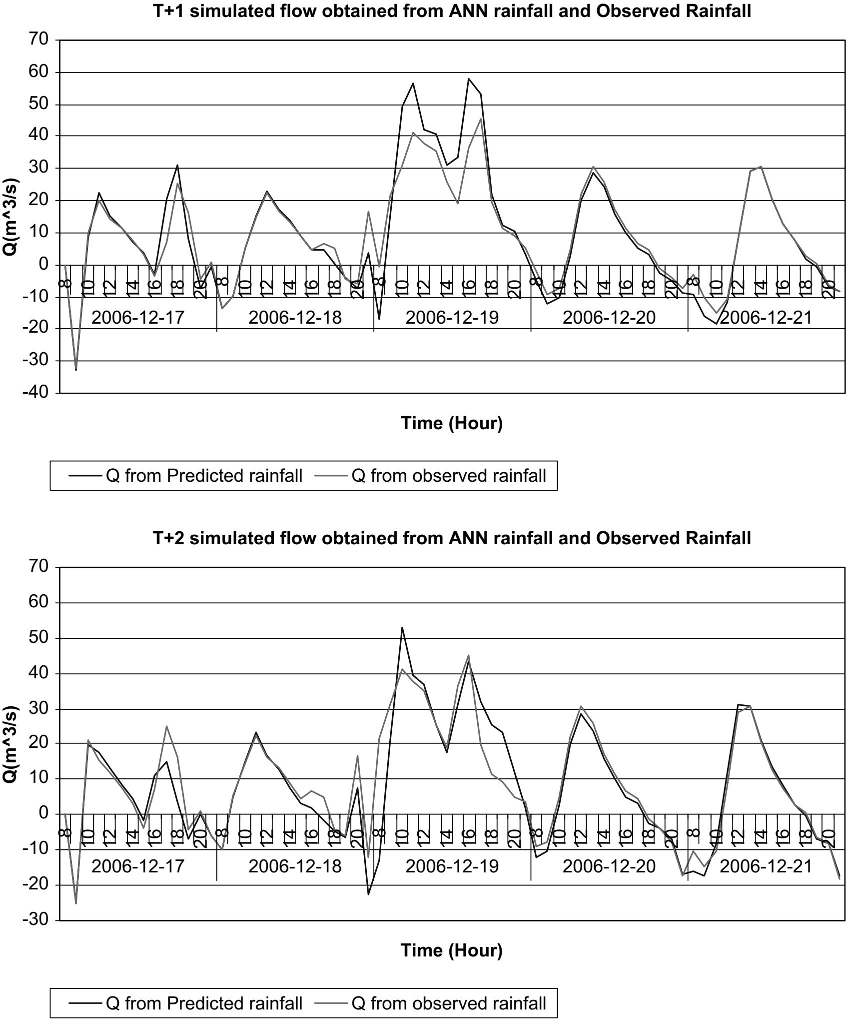


Fig. 4. Forecast flow results: (a) $t + 1\Delta t$; (b) $t + 2\Delta t$.

in this study, up to forecast horizons of 2 hours. The final rainfall forecast data were then demonstrated to simulate runoff from an urban catchment in Singapore.

The results, presented in terms of visual comparison of observed and simulated hydrographs and goodness-of-fit measures, indicate that the proposed approach is able to capture the peak discharges quite accurately.

Table 3. Result for flow forecast.

Correlation Coefficient	Lead time	
	$t + 1\Delta t$	$t + 2\Delta t$
Period (8:00 17/12/06–21:00 21/12/06)	0.9609	0.8828

The ability of the proposed approach to forecast rainfall and runoff may be considered necessarily needed for its application in the real time flood early warning systems.

Acknowledgment

The authors thank Executive Meteorological Officer Mr. K.H. CHEW from Meteorological Services Division for suggesting important weather parameters for ANN input.

References

1. C. M. Bishop, *Neural Networks for Pattern Recognition* (Oxford: Oxford University Press, 1995).
2. A. Brath, On the role of numerical weather prediction models in real-time flood forecasting, *Proceedings of the International Workshop on River Basin Modeling: Management and Flood Mitigation*, September 25–26, 1997, Monselice, Italy, 1999, pp. 249–259.
3. K. W. Chau, C. L. Wu and Y. S. Li, Comparison of several Flood Forecasting Models in Yangtze River. *J. Hydrologic Engrg.* **10**(6) (2005) 485–491.
4. M. N. French, W. F. Krajewski and R. R. Cuykendall, Rainfall forecasting in space and time using a neural network. *J. Hydrol.* **137** (1992) 1–31.
5. J. S. R. Jang, ANFIS: Adaptive-network-based fuzzy inference systems, *IEEE Trans. On Systems, Man, and Cybernetics*, 1992.
6. R. Krzysztofowicz, Recent advances associated with flood forecast and warning systems, US National Report to IUGG, 1991–1994, *Rev. Geophys.* 33 (Part 2, Suppl. S), (1995) 1139–1147.
7. R. Kuligowski and A. P. Barros, Localized precipitation forecasts from a numerical weather prediction model using artificial neural networks, *Weather and Forecasting* **13**, (1998) 1195–1205.
8. NHWC, Use and benefits of the National Weather Service river and flood forecasts. National Hydrologic Warning Council, USA. 21 pp (2002).
9. W. Yeh, L. Becker and R. Zettlemaoyer, Worth of inflow forecast for reservoir operation, *Journal of Water Resources Planning and Management* **108** (1982) 257–269.
10. Introduction to SOBEK, SOBEK manual with SOBEK version 2.09, WL | Delft Hydraulics, The Netherlands (2004).