Data Fusion and Neural Networks for Disaster Forecasting: Flood Prediction Case

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ABSTRACT

A model of Adaptive Data Fusion Reservoir Inflow Forecasting using Concurrent Neural Networks (ADAFIFCON) is presented. It uses a fusion of previous rainfall and reservoir inflow data. The system consists of three backpropagation neural networks. Each neural module is trained to estimate a specific class of data dynamics: low, medium and high gradients. The decision fusion module uses a concurrent strategy. The model is applied to forecast the reservoir inflow for St-Jean Lake, Quebec, Canada. The method may be applied for disaster prediction and management for NATO (Science for Peace) Projects.

1.0 INTRODUCTION

Multisensor data fusion is an emerging technology drawn from artificial intelligence, pattern recognition, statistical estimation, and other areas. Fusion multisensor data has significant advantages over simple source data, obtaining a more accurate estimate of a physical phenomenon. Data fusion provides new modelling opportunities in other areas of the physical and social sciences, which includes geographical and environmental research.

In hydrological research, a significant effort has been concentrated to river flow prediction task. Flash floods are dangerous phenomena, which have produced in the past important economic losses and in some cases, life losses. A flood warning systems is a technical way to reduce such risks. If the hydrological system includes a dam equipped with control gates, improved criteria for gates operation during the flood can be assessed. There have been many recent papers and contributions regarding the applications of backpropagation neural networks (BPNN) for river discharge (or reservoir inflow) forecasting.

We further present a model of **A**daptive **Da**ta **F**usion Reservoir **I**nflow **F**orecasting using **Co**ncurrent **N**eural **N**etworks (ADAFIFCON). It uses a fusion of rainfall and inflow data (previous samples of rainfall and reservoir inflow data). This multi-system consists of a set of three concurrent backpropagation neural networks, corresponding to the three classes of rainfall sample gradients: low, medium and high. The model is applied for the reservoir of St-Jean Lake, Quebec, Canada.

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2.0 ADAPTIVE DATA FUSION RESERVOIR INFLOW FORECASTING WITH CONCURRENT NEURAL NETWORKS (ADAFIFCON)

We propose the data fusion system for reservoir inflow forecasting (ADAFIFCON) shown in Figure 1. It consists of a set of three concurrent backpropagation neural networks. Each neural module is designed to estimate a specific class of data dynamics: low, medium and respectively high gradients.

The input data which are amalgamated by the data fusion system corresponds to:

- the previous samples of the reservoir inflow:

  y[n-1], y[n-2], y[n-3], … y[n-q]

- the previous rainfall samples:

  x [n-1], x [n-2], … x [n-p]

The training set (consisting of rainfall data and corresponding inflow data) is divided before training into three time domains : D_L, D_M and D_H, The classification of a given sample pair { x[n] , y[n] } is given by the following decision rule based on the gradient of the rainfall adjacent samples :

$$0 < | x[n] - x[n-1] | \le \alpha \quad \Rightarrow \quad \{x[n], y[n]\} \in D_L$$

$$\alpha < | x[n] - x[n-1] | \le \beta \quad \Rightarrow \quad \{x[n], y[n]\} \in D_M$$

$$\beta < | x[n] - x[n-1] | \quad \Rightarrow \quad \{x[n], y[n]\} \in D_H \qquad (\text{with } 0< \alpha <\beta),$$

where D_L, D_M and D_H are the time domains corresponding to the labels ***low***, ***medium*** and ***high***. Each neural network (L, M, or H) is trained using the samples of the corresponding domain (subset), characterized by its rainfall dynamics (D_L, D_M or D_H).

After training, the three neural modules (Figure 1) estimate in parallel the output task (reservoir inflow). The decision fusion module uses a concurrent strategy by choosing at each step the best fitting neural module. Namely, at each forecasting step one chooses the neural network which obtained the best estimation accuracy at the previous step.

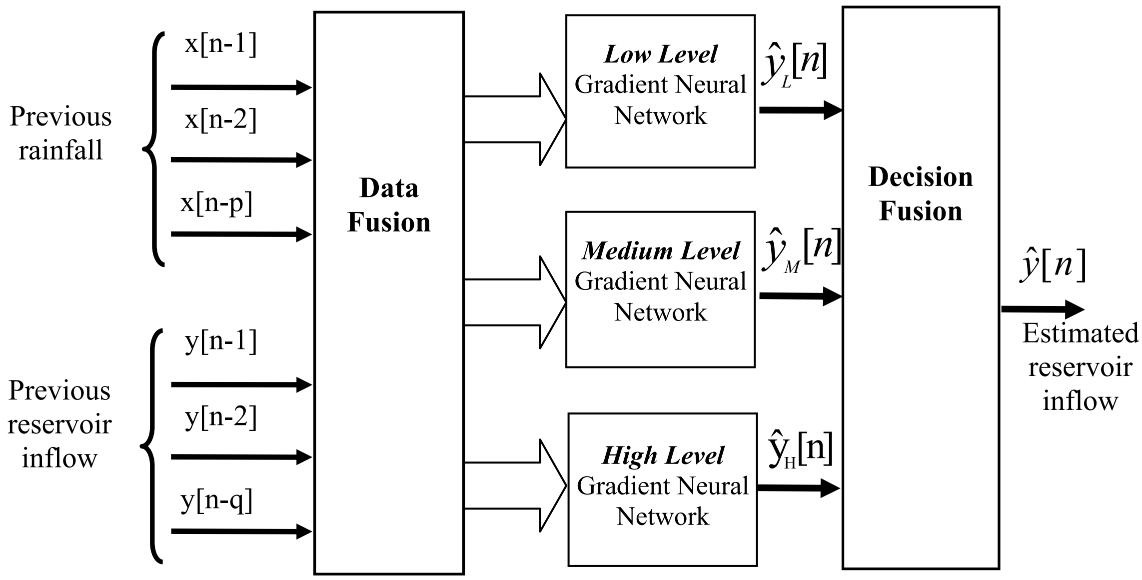

Figure 1: Adaptive data fusion reservoir inflow forecasting with concurrent neural networks (ADAFIFCON)

3.0 EXPERIMENTAL RESULTS

3.1 Hydrological and meteorological datasets

We considered the quarter monthly inflows data as well as corresponding rainfall data for the St-Jean Lake reservoir, Quebec, Canada. The data covered the period of the years 1953-1982.

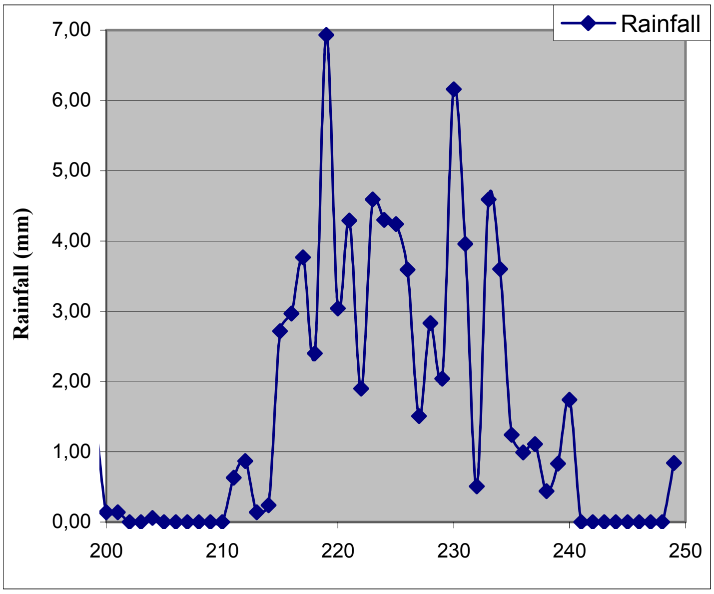

Figure 2: Observed rainfall

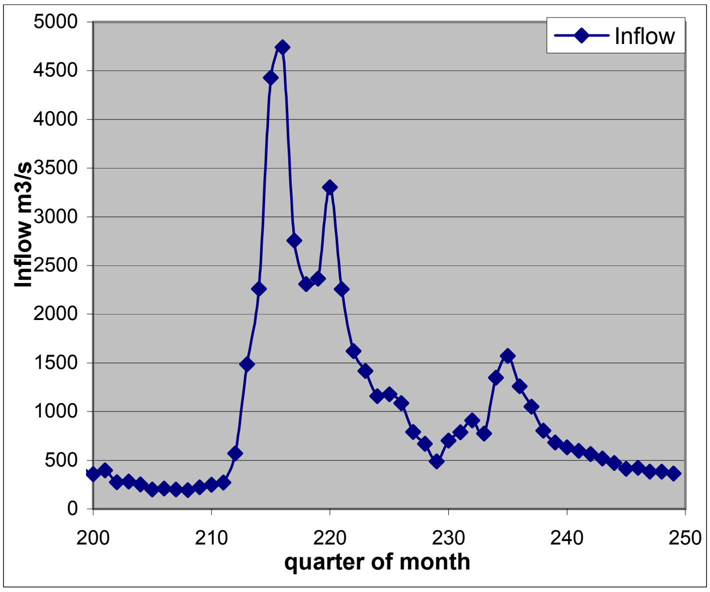

Figure 3: Observed reservoir inflow

In Figures 2 and 3 one can see an example of the observed rain-fall and the corresponding St-Jean Lake reservoir inflow. The sampling period is equal to a quarter of month.

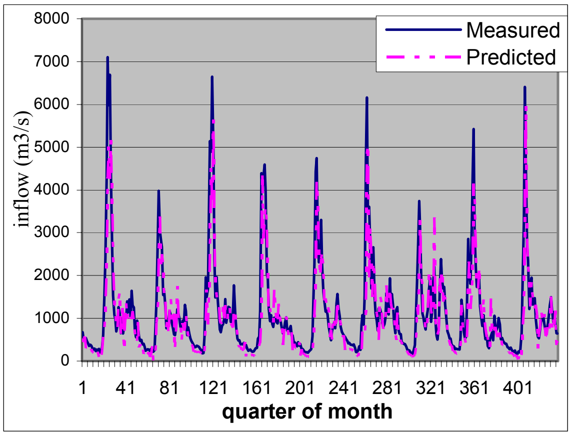

Figure 4: Measured vs. Predicted Inflows (m^3/s)

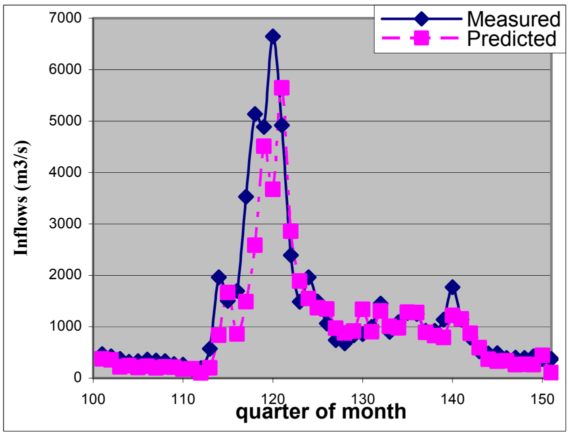

Figure 5: Measured vs. Predicted Inflows (m^3/s)

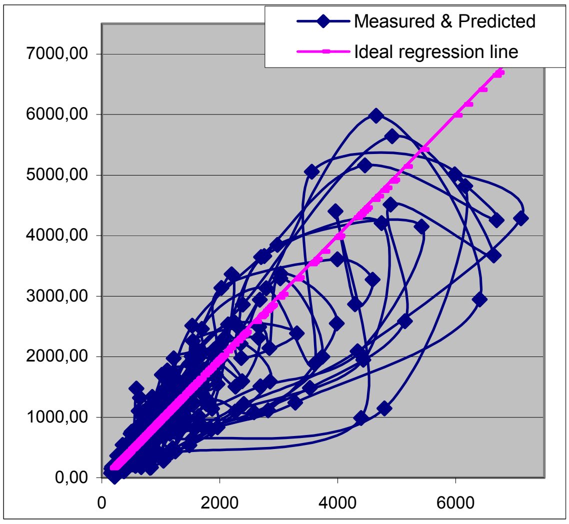

Figure 6: Measured and Predicted Inflows (in m^3/s)

3.2 Model evaluation

Each backpropagation neural module has a feedforward architecture with the following dimensions :

- number of input neurons equals the number of input data
- number of hidden neurons = 4
- one output neuron

We used a number of 100 training epochs. For performance evaluation, we consider the following measures:

- the root mean square error (Rmse) between the ideal and the forecasted reservoir inflow data
- the correlation coefficients of the ideal inflow sequence and the estimated one.

The experimental results are given in Table 1 and Figures 4-6.

Table 1: Performance evaluation of the ADAFIFCON model

	Inputs		Rmse (m^3/s)	Correlation
	Reservoir Inflow	Rainfall	Test.	Test.
ADAFIFCON (Multi-system) (3-nets)	y[n-1], y[n-2], y[n-3]	x[n], x[n-1], x[n-2]	0.596	0.8552
	y[n-1], y[n-2], y[n-3]	none	0.627	0.8532
	y[n-1], y[n-2], y[n-3]	x[n-1], x[n-2]	0.588	0.8585
	y[n-1], y[n-2]	x[n], x[n-1]	0.591	0.8558
	y[n-1], y[n-2]	x[n-1], x[n-2]	0.580	0.8629
	y[n-1], y[n-2]	none	0.616	0.8536
	y[n-1], y[n-2]	x[n-1]	0.592	0.8479
Mono-system (single net)	y[n-1], y[n-2], y[n-3]	x[n], x[n-1], x[n-2]	0.669	0.8506
	y[n-1], y[n-2], y[n-3]	none	0.626	0.8539
	y[n-1], y[n-2], y[n-3]	x[n-1], x[n-2]	0.661	0.8560
	y[n-1], y[n-2]	x[n], x[n-1]	0.679	0.8556
	y[n-1], y[n-2]	x[n-1], x[n-2]	0.648	0.8576
	y[n-1], y[n-2]	x[n-1]	0.653	0.8581
	y[n-1], y[n-2]	none	0.627	0.8560
Naive	y[n-1]	none	0.628	0.8570

The best result corresponds to the case of using 4 inputs: 2 previous rainfall samples {x[n-1], x [n-2]} and 2 previous inflow samples {y [n-1], y [n-2]}. The advantage of using the proposed multiple network system over a single network system is obvious. The case of naïve prediction is also considered for comparison.

The method may be applied for disaster prediction and management in NATO Science for Peace Projects.

4.0 REFERENCES

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