SURVEY ON FLOOD FORECASTING METHODS

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Abstract: Artificial intelligent models (AIMs) have been successfully adopted in hydrological forecasting in a plenty of literatures. However, the comprehensive comparison of their applicability in particular short-term (i.e. hourly) water level prediction under heavy rainfall events was rarely discussed. Therefore, in this study, the artificial neural networks (ANN), Intelligent multi agent approach, Markov Chain Monte Carlo (MCMC) were selected for comparison. Through analyzing main affecting factors of the artificial neural network model, the optimization model is established and the optimization parameters is obtain based on the method of momentum and self-adaptive of learn rate, This optimize artificial neural network is not only set up with the limited training samples, but also can improve the operating speed and study efficiency.

Key Words: *Flash flood forecasting, Intelligent multi agent approach, Markov Chain Monte Carlo (MCMC).*

1. INTRODUCTION:

Flood forecasting is the use of forecasted precipitation and streamflow data in rainfall-runoff and streamflow routing models to **forecast** flow rates and water levels for periods ranging from a few hours to days ahead, depending on the size of the watershed or river basin. Two types of real time flood forecasting models include simple trigger flood forecasting and more sophisticated catchment-wide integrated hydrological and hydrodynamic models.

Approximately five million people, in two million properties, live in flood risk areas in England and Wales. Autumn 2000 saw some of the worst floods ever recorded in the UK and raised public awareness of potential flood risks. It is now well recognized that flood risks can be reduced but can never be completely eliminated. Hence in recent years there has been a significant move from a strategy of flood defense to one of flood risk management; therefore it is important to provide an effective and reliable flood warning service as part of the flood risk management process. Flood warnings must be provided with an adequate lead time for the public and the emergency services to take actions to minimize flood damages.

Real time flood forecasting is an important and integral part of a flood warning service, and can help to provide more accurate and timely warnings. Depending on catchment characteristics and catchment response to rainfall, various types of flood forecasting models, including correlations, simple trigger flood forecasting, and more sophisticated real time catchment-wide integrated hydrological and hydrodynamic models may be adopted. These models provide flow and level forecasts at the selected key locations known as Forecast Points, which are usually located along major rivers or on streams near urban areas that have a history of flooding.

2. ARTIFICIAL NEURAL NETWORK:

ANN consists of a large number of parallel processing neuros, working independently and connecting to each other by weighted links. It is capable of simulating complex nonlinear system due to its ability of self-learning, self adaption and generalization. The feed forward neural network (FFNN), with one input layer, one or more hidden layer and one output layer, is employed in this study. BP algorithm, firstly introduced by Rumelhart, is employed for training. The global error could be calculated as:

$$E= 1/2N \sum_{l=1}^{N} \sum_{j=1}^{M} (s^l_j - t^l_j)^2$$

where *M* is the number of output variables, *N* is the number of training patterns, *s* are simulated values, *t* are observed values, *j* are neurons in the output layer, and *l* are training patterns. In
backward propagation of error signal, the weights and biases are adjusted accordingly and automatically.

$$V_{i+1} = V_i – r_i g_i$$

where **v** are vectors of weights and biases, **r** are vectors of learning rate, **g** are vectors of gradient, and *i* is the time step of training.[1][5]

3. INTELLIGENT MULTI AGENT APPROACH:

Intelligent multi-agent approach for flood disaster forecasting based on case based reasoning. Firstly, the proposed framework is constructed by three main modules, which are “Front end user computer”, “Back end server” and “Flood disaster forecasting servers”. Particularly, the proposed flood disaster forecasting system is made of several agents, in which each agent is designed to implement a particular functional unit. Secondly, the flood disaster
forecasting algorithm is illustrated. In our algorithm, each agent has its own case base and can not visit the case base of other agents directly, and each case is made up of a problem part and a solution part. Finally, experiments are conduct to make performance evaluation based on the “Active Archive of Large Floods.[2]

3.1 SYSTEM FRAMEWORK:

Multi-agent systems can be utilized to tackle problems which are difficult or impossible for an individual agent or a monolithic system to solve. Intelligence may include some methodic, functional, procedural or algorithmic search, find and processing approach . The framework of the proposed flood disaster forecasting system in advance. In the proposed framework, the user terminal can be connected to back end server through all kinds of browsers. This framework is made up of three main modules:

- Front end user computer,
- Back end server and
- The flood disaster forecasting servers on the web.

Particularly, the system has a lot of agents, among them each agent is designed to implement a particular functional unit. The back end server is installed with a case based reasoning database, different from the task manager agent and mobile information agent. Afterwards, information can be connected from users to agent servers through back end server. Furthermore, agent servers are constructed by task agents, interface agent and case based reasoning module.

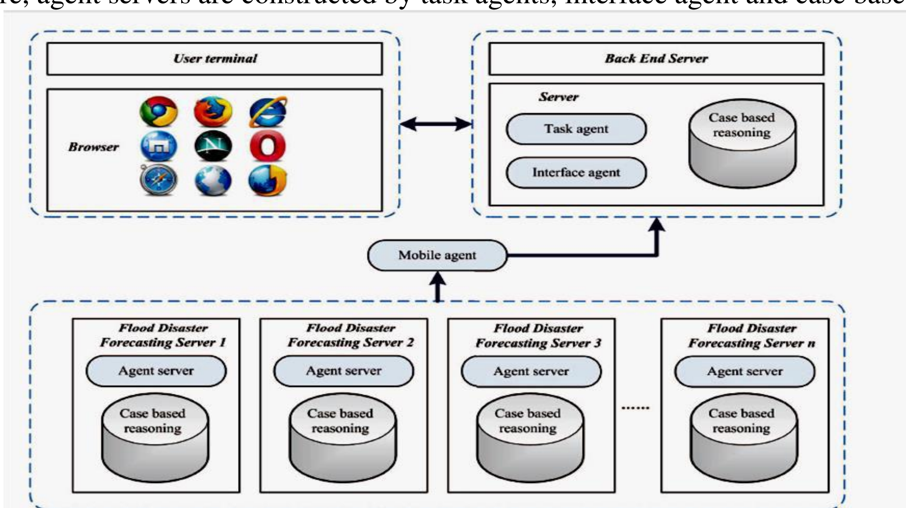


Figure 1. *Framework of the proposed flood disaster forecasting system*

Forecasting the flood disaster for a long period time can be implemented through an iterative arrangement time model. Furthermore, the forecast period is limited in the available data of rainfall forecasts. In this experiment, we divide a large areas into several small areas.[2]

4. MARKOV CHAIN MONTE CARLO ALGORITHM:

As a numerical simulation method, MCMC has been used in several fields such as physics, astronomy, meteorology, communication. The key of MCMC is how to choose a transfer distribution to make sampling more effective. Generally sampling methods are Metropolis-Hastings (M-H), Gibbs and Adaptive Metropolis (AM). Among these methods, only AM dose not depend on a specified transfer distribution in advance and has a faster convergence speed. AM was one of sampling methods of MCMC, which was put forward.

Compared with M-H and Gibbs, a specified transfer distribution of AM depends on covariance of initial samples and the present sample. For AM, the transfer distribution is defined as a multi-dimension normal distribution in parameter’s space, and the initial covariance is determined by prior information. During the course of sampling, the transfer density (covariance matrix) is updated adaptively according to samples information, so the calculation speed and the convergence rate of MCMC are improved. The initial samples play an important part in sampling ability of AM, so RAGA was taken to optimize the initial samples.[3]

5. BAYESIAN FORECASTING SYSTEM:

The Bayesian Forecasting System (BFS) was a general theoretical framework for probabilistic forecasting via any deterministic hydrologic model. A linear perturbation model was used to describe likelihood function and autoregressive model was used to describe prior distribution in BFS, and the complexity of solution of Bayesian posterior distribution was decreased in some extent.

The complexity was further decreased by using the Artificial Neural Network (ANN) to describe prior distribution and likelihood function. But there were still two disadvantages:

(i) the convergence rate of traditional ANN, related to initial weights and bias, was usually slower. (ii) A certain distribution and sample interval of parameters were specified in traditional Metropolis-Hasting algorithm,

which did not ensure ergodicity and rapid convergence.The Markov Chain Monte Carlo based on Adaptive Metropolis algorithm (AM-MCMC) and the Back Propagation (BP) ANN based on Real-coded Accelerated Genetic Algorithm (RAGA) were used in BFS to research the probabilistic flood forecast. The RAGA was used to optimize weights and bias of BP ANN improve BP training converged rapidly. The AM-MCMC didn't depend on a specified distribution and prior intervals of parameters, which ensured ergodicity and fast sampling efficiency of MCMC.

Table 1. Results of forecast of flood discharge by BFS based on BP and AM-MCMC

Flood code	Empirical discharge (m^3/s)	Forecast discharge (m^3/s)		Confidence interval of 80%	Error of flood peak (%)		Deterministic coefficient		Peak delay-time (h)	
		XAJ	BP	BP	XAJ	BP	XAJ	BP	XA	BP
840612	632	524	606	(588, 626)	-17.1	-4.06	0.88	0.98	-1	0
840723	1060	990	992	(731, 1010)	-6.65	-6.44	0.94	0.97	0	1
850603	235	257	256	(234, 278)	9.32	8.87	0.76	0.98	-4	-4
850621	476	499	517	(496, 538)	4.81	8.63	0.93	0.99	-1	-1
860714	227	233	246	(224, 268)	2.9	8.5	0.74	0.96	-1	-1
860909	844	848	883	(861, 907)	0.51	4.69	0.95	0.99	0	0
870511	341	251	406	(384, 428)	-26.4	0.19	0.86	0.95	-1	0
870622	316	398	431	(409, 453)	25.89	36.43	0.60	0.81	-1	1
870627	367	288	453	(431, 475)	-21.4	23.5	0.86	0.96	0	0
870719	819	945	903	(879, 926)	15.4	10.2	0.92	0.98	1	1
870821	556	388	545	(523, 567)	-30.2	-1.9	0.79	0.96	0	1

Shown as table 1, the accuracy of forecast flood peak, the deterministic coefficient and the flood peak delay-time of floods forecasted by BFS were higher than that of floods forecasted.

The errors of flood peaks were less than 10% except the only three floods (870622, 870627, 870719); the deterministic coefficients were greater than 90% except the only one flood (870622). The cause for the forecasts of floods 870622 and 870627 were little worse than that of Xin'anjiang Model might result from the poor posterior information provided by forecasts of Xin'anjiang Model, which proved the posterior information was important to forecast of BFS. It is to say that BFS might expand affection of posterior information on flood predicted.[3]

6. STANDARD NETWORK TRAINING USING GRADIENT DESCENT METHOD:

Multiple-layer neural network using back propagation training algorithm is popular in neural network modeling because of its ability to recognize the pattern and relationship between non-linear signals. The term of back propagation usually refers to the manner in which the gradients of weights are computed for non-linear multi- layer networks. A neural network must be trained to determine the values of the weights that will produce the correct outputs. The standard or basic training method is called 'Gradient Descent Method'; in which weight changes move the weights in the direction where the error declines most quickly.

Training is carried out by assigning random initial weights to each of the neurons (usually between 0.1 to 1.0), and then presenting sets of known input and target (output) values to the network. The network estimates the output value from the inputs, compares the model predicted output to the target value, and then adjusts the weights in order to reduce the mean squared difference between the network output and the target values. The complete input-output sets are often run through the network for several iterations (or epochs) until either the mean square error is reduced to a given level or reaches a minimum, or until the network has been trained for a given number of iterations. The results given by the applications are given below:

1) The neural network model can be used to predict long-term historic water level data for the analysis of storm surges in many locations along Florida coastal lines, estuaries, bays, and coastal waterways. Water level data derived from

the ANN model can be used as ocean boundary conditions to support hurricane storm surge hydrodynamic modeling for inland waters.

2) Long-term water level data derived from ANN model for the large number of local stations in estuaries and coastal waters can be further used to validate the performance of traditional storm surge models in complex coastal environments.[4]

7. BOLAM AND MOLOCH MODELS:

The LAPS system has been recently implemented to initialize the two meteorological models developed at CNR-ISAC, BOLAM and MOLOCH. BOLAM is a hydrostatic limited area model, appropriate for grid spacing of the order of 10 km . MOLOCH is a nonhydrostatic model that allows an explicit representation of atmospheric deep convection (“convection permitting model”) and is appropriate for simulations with grid spacing of the order of 1 km [10]–[12].

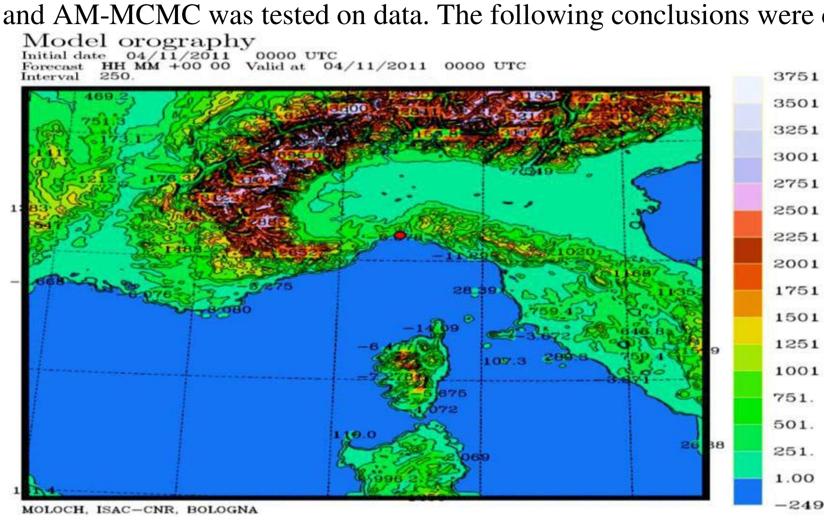
In the configuration implemented at ISAC, BOLAM forecasts are used to provide initial and boundary conditions (IC/BC) to MOLOCH, so as to bridge the gap between coarse time-space scales of global analyses/forecasts and a convection-resolving grid. In this paper, LAPS analyses, exploiting mesoscale data assimilation, are used to provide initial conditions to both BOLAM and MOLOCH models. The assimilation and forecasting experiments presented here are based on a heavy rain episode. The amount of precipitation of this event exceeded 500 mm in 24 h.[4]

7.1 STAGES IN BOLAM AND MOLOCH

1) LAPS Interfaces With BOLAM and MOLOCH
2) Data Sources
   A) Surface Observation Data
   B) Sounding Data
   C) Satellite Data
   D) Radar Reflectivity Data

8. CONCLUSION:

A Bayesian probabilistic flood forecasting model based on BP ANN and AM-MCMC has been presented. The purpose of use of AM-MCMC is to obtain posterior distribution of hydrologic variate (discharge). BP ANN was used to construct a prior density and a likelihood function of discharge in BFS. The Bayesian probabilistic flood forecasting model based on BP ANN and AM-MCMC was tested on data. The following conclusions were drawn:



Domain and topography (contour interval 250 m) of the high-resolution model MOLOCH characterized by the steep orography due to the Alps and the Apennines.

(i) The BP ANN can capture the nonlinear reflection of hydrologic process well. The BP based on GA can make the speed of convergence of prior density and likelihood function more faster, and GA made the efficiency of BP improved.

(ii) A transfer distribution for parameters is not needed to be specified in advance in AM algorithm, The AM-MCMC could obtain the posterior mean process of flood discharge as forecast process. On the whole, the precise of probabilistic forecast is higher than that of Xin’anjing Model .

(iii) Not only mean of forecast discharge but also variance of forecast discharge at each moment is given by the Bayesian probabilistic flood forecasting model. And the variance of prediction can be used to estimate the uncertainty of flood forecast, which is helpful to consider the risk of flood control determination.[5]

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