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Forecasting of Rainfall and Flood Situation: A Literature Review

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Abstract: *Forecasts of water inflow into major reservoirs of different rivers are needed for the operational planning over periods ranging from a few hours to several months ahead. Medium-range forecasts of the order of a few days to two week shave usually been obtained by simple ARMA-type models, which do not utilize information on observed or forecast precipitation, nor stream flow observations from upstream gauging stations. Recently, several different hydrological models have been tested to assess the potential improvements in forecasts that could be obtained by using observed and forecast precipitation as additional inputs. In this paper we have carried out a review of different techniques used for forecasting the water flow into various rivers and fore casting the flood situation.*

I. Introduction

The incorporation of quantitative precipitation forecasting (QPF) in flood warning systems has been acknowledged to play a key role, allowing for an extension of the lead-time of the river flow forecast ,which may enable a more timely implementation of flood control [1] (Brath et al., 1988). The QPF integration is particularly needed in small and medium-sized mountainous basins where, given the short response time of the watershed, a precipitation forecast is necessary for an extension of the lead-time of the flood warning. It is widely recognized that obtaining a reliable QPF is not an easy task, rainfall being one of the most difficult elements of the hydrological cycle to forecast (e.g. French et al., 1992), and great uncertainties still affect the performances of both stochastic and deterministic rainfall prediction models.

River flow forecasts are required to provide basic information for reservoir management in a multipurpose water system optimization framework. An accurate prediction of flow rates in tributary streams is crucial to optimize the management of water resources considering extended time horizons. Moreover, runoff prediction is crucial in protection from water shortage and possible flood damages.

The rainfall-runoff, process represents a complex nonlinear problem and there are several approaches to solve it. Traditionally, hydrological simulation modeling systems are classified into three main groups, namely, empirical black box, lumped conceptual, and distributed physically-based models [3, 2].

Flooding leads to numerous hazards, with consequences including risk to human life, disturbance of transport and communication networks, damage to buildings and infrastructure, and the loss of agricultural crops. Therefore, prevention and protection policies are required that aim to reduce the vulnerability of people and public and private property. Many solutions for flood mitigation and prevention have been suggested however, a vast amount of data and knowledge are required about the causes and influencing factors of floods and their resulting damage. Flood forecasting and prediction capabilities evolved slowly during the 1970s and 1980s. However, recent technological advances have had a major impact on forecasting methodologies. For instance, hydrological models use physical detection systems to forecast flood conditions based on predicted and/or measured parameters [2]. River flow models are used as components in actual flood forecasting schemes, where forecasts are required to issue warnings and to permit the evacuation of populations threatened by rising water levels. The basis of such forecasts is invariably observation and/or predictions of rainfall in the upper catchment area and/or river flows at upstream points along main rivers or tributaries. Forecasts about the discharge are obtained in real-time, by using the model to transform the input functions into a corresponding discharge function time [3].

II. Literature review

The methods of flood routing are broadly classified a empirical, hydraulic, and hydrological (Fread, 1981). A number of soft computing related techniques were used for flood forecasting in addition to Muskingum method. A brief literature review is presented to provide an overview.

Preliminary concepts and numerous applications of Artificial Neural Networks (ANN) to hydrology are available (ASCE, 2000a,b; Fernando and Jayawardena, 1998). Cheng and Chau (2001), Cheng and Chau (2002) proposed fuzzy iteration methodology and three-person multi-objective conflict decision model respectively for reservoir flood control operation for a case study of Fengman Reservoir, China. Chau et al. (2005) employed the Genetic Algorithm based Artificial Neural Network (ANN-GA) and the Adaptive Network based Fuzzy

Inference System (ANFIS), for flood forecasting in a reach of the Yangtze River in China. Similar studies are reported by Cheng et al. (2002, 2008a,b).

Muskingum method is a hydrological flood routing technique (Chow et al., 1988) which was modified by many researchers. In the two parameter Muskingum method, there are number of ways for finding the two parameters, K (travel time) and x (weighing factor for prism and wedge storage of routing reach). These methods were discussed in detail by Singh and McCann (1980) and applied to a set of data to assess their relative efficacy. Gill (1978) proposed segmented curve method, in which least square method was used to find out the parameters of nonlinear form of Muskingum method. Stephenson (1979) demonstrated the way to calculate directly the coefficients of Muskingum method, C0, C1, and C2 using Linear Programming instead of calculating the parameters, K and x.

O'Donnell (1985) considered the lateral flow factor in Muskingum two parameter model of single input single output (si-so) nature, which was converted into a three parameter model. The parameters are K, x, a (a shows the fraction of lateral flow in comparison with inflow to the reach). The least square technique is used to find out these parameters in the routing reach automatically. Khan (1993) extended the si-so flood routing model to include lateral flow to form a multi input single output (mi-so) model with lateral flow.

Tung (1985) developed state variable modeling technique for solving the nonlinear form of Muskingum method. The parameters of the model were found out by four methods of curve fitting. Yoon and Padmanabhan (1993) developed software, MUPERS, where both linear and nonlinear relationships were dealt with. Kshirsagar et al. (1995) found parameters by a constrained, nonlinear (successive quadratic) programming. In this work, the Muskingum equation was used for routing the upstream hydrograph and the intermediate un gauged lateral inflow. The lateral inflow was calculated by an impulse response function approach. Mohan (1997) used genetic algorithm for parameter estimation of nonlinear Muskingum method and compared its performance with the approach by Yoon and Padmanabhan (1993).

Samani and Jebelifard (2003) applied multi linear Muskingum method for hydrologic routing through circular conduits. Das (2004) developed a methodology for parameter estimation for the Muskingum model of stream flow routing. Al-Humond and Esen (2006) presented two approximate methods for estimating Muskingum flood routing parameters. Geem (2006) introduced the Broydene Fletchere Goldfarbe Shanno (BFGS) technique, which searches the solution area based on gradients for estimation of Muskingum parameters.

Choudhury (2007) proposed a multiple inflows Muskingum model. This model appropriately extended the Muskingum philosophy to multiple inflows routing, expressed in a single in flow single out flow form. The model performance is compared with the nonlinear kinematic wave model. He applied the model to the flood events in Narmada Basin, India. Das (2007) developed a chance constrained optimization based model, for Muskingum model parameter estimation. Das (2009) developed a methodology for Muskingum model's parameter estimation for reverse stream flow routing for which a fresh calibration was found necessary. Chu (2009) applied Fuzzy Inference System (FIS) and Muskingum model in flood routing where rules of FIS were incorporated with the Muskingum formula.

III. Comparing different Rain fall and Flood forecasting Techniques:

A) Artificial Neural Network:

An alternative approach to flow forecasting has been developed in the recent years, which is based on the ANN [3]. Recent studies have reported that ANN may offer a promising alternative for the hydrological forecasting of stream flow [7]. The ANN is a computer program that is designed to model the human brain and its ability to learn tasks [4]. An ANN differs to other forms of computer intelligence in that it is not rule based, as in an expert system. An ANN is trained to recognize and generalize the relationship between a set of inputs and outputs. Early artificial neural networks were inspired by perceptions of how the human brain operates. In the recent years, ANN technological developments have made it more of an applied mathematical technique with some similarities to the human brain. ANNs retain two characteristics of the brain as primary features: the ability to (1) 'learn' and (2) generalize from limited information [5]. Both biological and artificial neural networks employ massive, interconnected simple processing elements, or neurons. The knowledge stored as the strength of the interconnecting weights (a numeric parameter) in ANNs is modified through a process called learning, using a learning algorithm. This algorithmic function, in conjunction with a learning rule, (i.e., back-propagation) is used to modify the weights in the network in an orderly fashion. Unlike most computer applications, an ANN is not ''programmed,'' rather it is ''taught'' to give an acceptable answer to a particular problem. Input and output values are sent to the ANN, initial weights to the connections in the architecture of the ANN are assigned, and the ANN repeatedly adjusts these interconnecting weights until it successfully produces output values that match the original values. This weighted matrix of interconnections allows the neural network to learn and remember [10]. When using an ANN to solve a problem, the first step is to train the ANN to ''learn'' the relationship between the input and outputs. This action is accomplished by presenting the network with examples of known inputs and outputs, in conjunction with a learning rule. The ANN maps the relationship between the inputs and outputs, and then modifies its internal functions to determine the best relationship that is be represented by the ANN.

The inner workings and processing of an ANN are often thought of as a ‘‘black box’’ with inputs and outputs. One use-ful analogy that helps to understand the mechanism occurring inside the black box is to consider the neural network as a super-form of multiple regressions. Like linear regression, which finds the relationship that {y} = f{x}, the neural network finds some function f{x} when trained. However, the neural network is not limited to linear functions. It finds its own best function to the best of its ability, given the complexity used in the network, and without the constraint of linearity (Hewitson and Crane [5]). The most common type of artificial neural network consists of three groups, or layers, of units: (1) a layer of ‘‘input’’ units are connected to (2) a layer of ‘‘hidden’’ units, which are connected to (3) a layer of ‘‘output’’ units (Fig. 1)The activity of the input units represents the raw information that is fed into the network. The activity of each hidden unit is determined by the activities of the input units and the weights on the connections between the input units and the hidden units. The behavior of the output units depends on the activity of the hidden units and the weights between the hidden units and output units [12].

B) The MGB-IPH hydrological model

Many hydrological models can be used to make stream flow forecasts based on predicted rainfall, and the comparative study developed in Brazil by ONS also included lumped rainfall–runoff models, more complex distributed hydrological models, and black-box models based on neural networks. The question whether a distributed rainfall–runoff model performs better than simpler models has been posed repeatedly in the past. It has been argued that distributed models would perform better where distributed input data were available, such as rainfall estimated by radar. But a recent study – the Distributed Model Inter comparison Project – showed that lumped models performed comparatively well even using radar rainfall data, although in one basin with elongated shape (Blue River), distributed models outperformed lumped models (Reed et al., 2004). Distributed models also appear to perform better when uncertainties in input data and parameter values are considered (Carpenterand Georgakakos, 2006). It can also be argued that distributed or semi-distributed models should be used in large basins where spatial variability in rainfall and runoff generation processes may play a larger role, and the results presented in this paper were all obtained using the distributed large-scale hydrological model MGH-IPH (Collischonn et al., 2007; Collischonn and Tucci, 2001). This is a large-scale distributed hydrological model developed for use in large South American basins, where densities of hydrological instrument networks are relatively low and records are commonly short. Using the classification proposed by Beven (2001), the model can be classified as a hydrological response unit model. It uses input data derived from Geographical Information Systems giving information on basin characteristics such as land use, topography, vegetation cover and soil types, which guide the calibration of parameter values. The MGB-IPH model was developed from the LARSIM (Bremicker, 1998) and VIC (Liang et al., 1994; Nijssem et al., 1997) models, with some changes in the evapotranspiration, percolation and stream flow propagation modules. It has modules for calculating the soil water budget; evapotranspiration; flow propagation within a cell, and flow routing through the drainage network. The drainage basin is divided into elements of area – normally on aMedium-range reservoir inflow predictions based on quantitative precipitation forecasts 113 square grid of 10 · 10 km – connected by channels, with vegetation and land use within each element categorized into one or more classes, the number of vegetation and land-use types being at the choice of the user. The Grouped Response Unit (GRU) (Kouwen et al., 1993) approach is used for hydrological classification of all areas with a similar combination of soil and land cover without consideration of their exact locality within the grid (or cell). A cell contains a limited number of distinct GRUs. Soil water budget is computed for each GRU, and runoff generated from the different GRUs in the cell is then summed and routed through the river network. This approach has been used in other large-scale hydrological models, such as VIC (Wood et al., 1992; Liang et al., 1994; Nijssem et al., 1997) and WATFLOOD (Kouwen and Mousavi, 2002; Soulis et al., 2004).

The soil water balance is computed independently for each GRU of each cell, using components describing canopy interception, evapotranspiration, infiltration, surface runoff, sub-surface flow, base flow and soil water storage. Rainfall values are interpolated spatially and at each time step to give an estimate at the center of each grid cell using inverse-distance-squared interpolation. Flow generated within each cell is routed to the stream network using three linear reservoirs (baseflow, sub-surface flow and surface flow). Stream flow is propagated through the river network using the Muskingum–Cunge method. A more comprehensive description of the model, including results from aproxy-basin test, is given by Collischonn et al. (2007) and further applications are presented by All asia et al. (2006), Collischonn et al. (2005) and Tucci et al. (2003).

C) **1ARMA model application:**

The application of low-order ARMA processes to model short-term precipitation values is consideredhere, following the modeling framework proposed by Brath et al. (1988) and Burlando et al. (1993).

The application of ARMA models requires the data to be stationary and this is often not the case for hourly rainfall observations, whose statistical properties may vary with the season. Nonetheless, the limited number of rainfall events in the observation period prevented us, in the split-sample calibration, from grouping the events in monthly periods, as it is usually done in hydrology to circumvent non-stationary. In the adaptive calibration application, non-stationary is accounted for by allowing the model parameters to vary with time since the calibration is performed solely on the progress of the current event. We preferred not to perform any preliminary transformation of the data in order to make them as close to Gaussian as possible. In fact, Gaussian data are not required for the forecast application of ARMAmodels, since they provide the best linear prediction even in the non-Gaussian case (Brockwell and Davis,1987).

The selection of the model orders, p and q, was driven by some results available in literature. Obeysekera et al. (1987) determined an equivalence between the correlation structure of an ARMA(1,1) model and some point process models, like the Poisson rectangular pulses and the Neyman–Scott white noise models (see Rodriguez-Iturbe et al.,1984). On the other hand, the Neyman–Scott rectangular pulses model, which has proved to represent the stochastic structure of rainfall better (Rodriguez-Iturbe et al., 1987), has a correlation structure equivalent to that of an ARMA(2,2) process. In the adaptive calibration, the parameters are estimated in correspondence with each forecast instant, on the basis of the last values measured in real-time. The number of past observations to be used for each calibration was chosen on the basis of the results of a previous study (Brath et al. 1998). The estimation of the parameters was performed there with a number w of observations xt immediately preceding each forecast instant, with w varying from 7 to 100, aiming at identifying the value of w that provides the best forecasting performances. The results showed that for increasing w, the efficiency of the forecast improved moderately for short lead times (1–3 h), but a longer set of past data (more than3 days of previous hourly observations) provided a much better performance for lead-times longer than4 h. Thus, we set the moving window of past rainfall observations to be used in each adaptive calibration equal to the 100 last measured hourly observations (that is, w = 100).

IV. Conclusion and Future Work

Given the important role of flood forecasting and that so much has been written on the subject, this paper aims to provide comprehensive coverage of the status of the research work carried out by different researchers. Taking a utilitarian viewpoint, we believe that the success of a forecasting model lies in its out-of-sample forecasting power. It is impossible, in practice, to perform tests on all flood forecasting models on a large number of data sets and over many different periods. The contribution of this review is to provide a bird's-eye view of the whole forecasting literature and to provide some recommendations for the practice and future research.

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