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An Evolutionary-based Real-time Updating Technique for an Operational Rainfall-Runoff Forecasting Model

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Abstract: Error-correction is widely known to be one of the effective methods of real-time updating and tends to be the easiest method to implement and couple with existing simulation models. Methods such as autoregressive (AR) or autoregressive integrated moving average (ARIMA) have been widely used but the main disadvantage of such approaches is the prior assumption of the form of error correlation. Genetic programming (GP), a relatively new evolutionary-based technique, can be used to generate a suitable expression linking the observations, simulation model results and the error in the simulation for the purpose of error correction. In this study, GP functions as an error correction scheme to complement runoff forecasting model used by the UK Environment Agency (Southwest region) known as WRIP. WRIP is a transfer function-based operational forecasting software which uses radar rainfall as input. The proposed method is tested on a flashy catchment in Devon, UK. Hourly runoff forecasts of different updating intervals are performed for forecast horizons of up to six hours. The results show that the proposed updating scheme is able to forecast the runoff quite accurately for all updating intervals considered and particularly for those updating intervals not exceeding the time of concentration of the catchment. These results formed part of an ongoing feasibility studies by the UK Environment Agency and the proposed method will be tested on other catchments in the future.

Keywords: genetic programming; real-time updating; rainfall-runoff; artificial neural network; forecasting

1. INTRODUCTION

A catchment flood forecasting system is a system that takes information on the past and current states of meteorological conditions and those of the catchment, as inputs to it, and forecasts the catchment's response into the future. In real-time forecasting, however, the originally forecast values may be updated or modified as measured data become available and, thus, prediction errors can be determined and used for forecasting. In real-time runoff forecasting with rainfall runoff simulation models, rainfall time series up to the desired runoff forecast horizon must be available. The required rainfall time series within the runoff forecast horizon may be estimated with, for example, a non-linear prediction method. In this study, the measured rainfall time series, at any runoff forecast horizon, is made available to evaluate the performance of the proposed evolutionary algorithm-based error updating scheme.

In the Environment Agency (especially for the Southwest region), a key element of the flood forecasting strategy is to use rainfall-runoff modelling in order to increase the lead time for key flood forecasting sites, and to allow the flood duty officer to assess the severity of a flood event. Historically, rainfall-runoff modelling has been done by predicting river flow from total rainfall. This approach was based on an assumption that the only significant floods occur when the catchment is saturated. In reality, how wet the catchment is determines what proportion of rainfall is effective, ie makes its way to the river. More recently, the concept of effective rainfall has been used for flood forecasting with some success.

A recent UK Environment Agency R&D report (Environment Agency, 2003) on real-time modelling of flood discussed several issues on real-time updating. They are:
(i) Updating often improves the accuracy of forecast and hence should be adopted unless there is a good reason not to (e.g. poor data quality);
(ii) Updating should not be used to account for or compensate the use of a poorly structured or inappropriate model;
(iii) Since most updating procedure cannot account for timing error, model calibration can play an important role in adjusting for time lag; and
(iv) In cases where backwater effects predominate the flow (hence rating), it may be necessary to apply updating over a limited flow or level ranges only.

All the above issues highlighted by the R&D report are relevant to MATH/ WRIP model used in this study and, hence, shall be taken into account and addressed in turn:

The aims of this study are to: (1) compare the forecasts of a calibrated rainfall-runoff model, WRIP, with and without the evolutionary-based real-time error updating scheme; (2) evaluate the effectiveness of using total and effective rainfall flood forecasting in conjunction with the proposed evolutionary-based error updating scheme; and (3) suggest how far in the future, i.e. the maximum forecast horizon, the proposed error updating scheme can be used with confidence.

2. AUTOMATIC ERROR UPDATING

Real-time updating algorithms can be grouped into four categories: (i) input updating; (ii) state updating; (iii) parameter updating, and (iv) error updating. Figure 1 shows a schematic diagram of a generic real-time updating system for a computer simulation model (WMO, 1992). It can be seen that all the above updating algorithms rely on or attempt to improve forecasts results by examining previous forecast performance and allowing for adjustments in either (i) input variables (such as precipitation or air temperature); (ii) state variables (state updating); or (iii) model parameters (parameter updating); or (iv) model output values (error correction).

2.1 Previous studies

In 1992, the World Meteorological Organisation conducted a real-time intercomparison study which compared 14 rainfall-runoff models with different updating schemes (WMO, 1992). They found that for small catchments, the Kalman filter approach seemed to perform better than other schemes.

Toth et al. (1999) proposed the used of ARMA and ARIMA models update the results of a conceptual rainfall-runoff model. Their scheme was to model the differences between the measured and simulated runoff from the R-R model, and using the forecasted differences to adjust the simulated runoff. They found that the ARMA(1,1) scheme seemed to be able to improve the forecasted runoff best. Brath et al. (2002) later examined the used of neural networks and non-parametric methods and found that neural networks provided great improvements in the discharge forecast.

The concept of error updating using evolutionary-based methods was first proposed by Khu et al. (2001). In their work, genetic symbolic regression was used to update the MIKE11/NAM model and the results were found to be better than the auto-regressive or Kalman filter method proposed in the WMO intercomparison report (WMO, 1992).

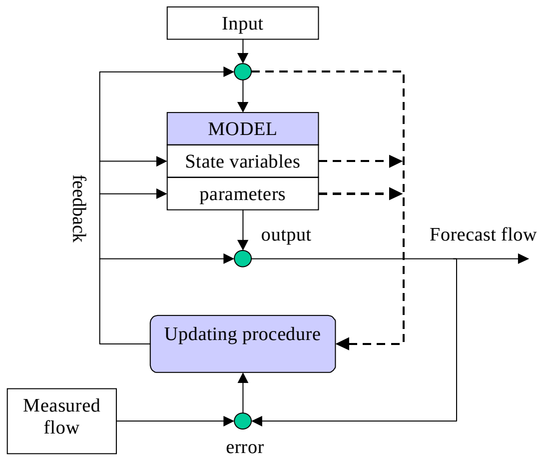

Figure 1: Schematic diagram of different updating modes (adapted from WMO, 1992)

2.2 Genetic Programming approach

Genetic Programming (GP) is a relatively new domain-independent method for evolving computer programs to solve, or approximately solve, problems (Koza, 1992). In engineering applications, GP is frequently applied to model structure identification problems. In such applications, GP is used to infer the underlying structure of either a natural or experimental process in order to model the process numerically. GP inferred models have the advantages of (1) generating simple parsimonious expressions and

(2) offering some possible interpretations to the underlying process.

GP belongs to a class of probabilistic search procedures known as Evolutionary Algorithms (EAs) which includes Genetic Algorithms (GA) (Holland, 1975), Evolutionary Programming (EP) (Fogel et al., 1966) and Evolutionary Strategy (ES) (Schwefel, 1981). These techniques use computational models of natural evolutionary process for the development of computer based problem-solving systems. All evolutionary algorithms function by simulating the evolution of individual structures via processes of reproductive variation and fitness based selection. The techniques have become extremely popular due to their success at searching complex non-linear spaces and their robustness in practical applications.

One successful application of GP in automatic program discovery is that of symbolic regression, instead of the traditional numerical regression. In traditional numerical regression, one pre-determines the functional form, either linear or higher order, and the task is to determine the coefficients. In symbolic regression, the task is to both find a suitable functional form and determine the coefficients. Hence, GP involves finding a mathematical expression, in symbolic form, relating a finite sampling of values of a set of independent variables (x_i) and a set of dependent variables (y_j).

GP can be viewed as an extension of Genetic Algorithm (GA) in terms of the basic principles of operations. Like GA, GP works with a number of solution sets, known collectively as a population, rather than a single solution at any one time. With a large number of solution sets, it gives both techniques the advantage of avoiding the possibility of getting trapped in the local optima.

There are, however, two major differences between GP and GA. They are:
(i) GP works with two sets of variables, instead of one set of variables as in GA. One set of variables, known as the terminal set, contains the independent variables and constants, $\{x_i\}$, similar to GA. The other set, known as the functional set, contains the basic operators used to form the function, *f( )*. For example, the function set may contain the following operators { +, -, *, /, ^, log, sin, tanh, exp, ….} depending on the perceived degree of complexity of the regression. Thus, the symbolic regression is performed using these two variable sets and it is possible to derive a large number of possible functional relationships to fit the data.
(ii) In most EAs, the length of the solution set is normally fixed. In GP, however, the length is allowed to vary from one solution set to another. This variation in length is due to the two genetic operators, crossover and mutation. The flexibility in the structure length increases the search space significantly.

The solution sets in each iteration are collectively known as a generation. In GPs, the size of a population does not have to be the same from one generation to the next. The solutions of the very first generation are usually generated through a random process. However, those of the subsequent generations are generated through genetic operations. Each possible solution set can be represented and visualized in either parse tree form or in Polish notation (Lukasiewicz, 1957). As the population evolves, new solution sets replace the older ones and are supposed to perform better. The solution sets in a population associated with the best fit individuals will, on average, be reproduced more often than the less-fit solution sets. This is known as the Darwinian principle of the "survival of the fittest".

The basic procedure of GP can be described as follows:
1. generate the set of initial population;
2. evaluate each parse tree and assign the fitness;
3. form the temporary population by selecting candidates according to their fitness. This temporary population is called the mating pool. Candidates with higher fitness are given greater probabilities to mate and hence, to produce children or offspring;
4. choose pairs of parse tree from the temporary mating pool randomly for mating and apply the genetic operator called crossover. Crossover is the exchange of genetic material (such as fitness, composition) between two selected candidates;
5. select a crossover site where the material will be exchanged randomly, thereby resulting in the creation of offspring;
6. apply another genetic operator known as mutation which randomly changes the genetic information of the candidate;
7. copy the resultant chromosomes into the new population;
8. evaluate the performance of the new population;
9. repeat steps 3-8 until a predetermined criterion is reached.

3. OPERATIONAL R-R MODEL

The operational rainfall-runoff model used in this study is the WRIP (Weather Radar Information Processor) system originally developed for the southwest regional office, UK Environment Agency. WRIP is a conceptual model that utilises the concept of transfer functions and physical realisable transfer function (PRTF) (Han, 1991) to model the relationship between rainfall and runoff from a catchment. The PRTF model is linear and time-invariant, and accommodates the non-linear time-variant nature of rainfall-runoff process by three parameters (shape, volume and timing). The transformation of these parameters into basic transfer function parameters guarantees stability. The simulated flow can then be merged with the telemetered flow data to produce the predicted hydrograph.

WRIP's main source of error (apart from rainfall forecast) is that the transfer function coefficients are determined based on calibrated events and hence, the model is essentially deterministic. The calibrated model should forecast well if an event similar to the calibration event occur, but not for "dissimilar" events. Hence, there is a need to adjust the model performance based on dynamic simulation.

4 PROPOSED SCHEME

4.1 Linking GP with WRIP

A GP toolkit was developed to facilitate the integration of the updating scheme with the operational flood forecasting model, WRIP. Since WRIP is used in real-time, the computational efficiency of the updating scheme is of primary importance. The standard forecasting interval for the Environment Agency is 1 hour, with lead times of up to 6 hours depending on catchments, hence, the forecasting period is not of a major constraint.

WRIP has a real-time link-up with radar information direct from the UK Meteorological Office which provides radar rainfall information at 5 minutes intervals. In other words, the flood duty officer can change their flood forecasting model once they receive the latest radar rainfall information. In practice, WRIP is usually configured to update the model forecast at 15 minutes intervals.

Two different forms of automatic error updating algorithm are investigated. They are genetic programming (GP) and artificial neural networks (ANN). A genetic programming toolkit was developed to facilitate the analysis and details of the genetic programming method used have been reported in Khu *et al.* (2001).

The procedure of application of GP for real-time updating can be expressed as follows and shown in Fig. 2. The WRIP model is first used to simulate the discharge, *QSIM*, for the whole period of interest based on the rainfall data, *R*. The proposed procedure is then used to compute the prediction error, ε, by comparing the simulated discharge, *QSIM*, with the observed discharge, *QOBS*, for time, *t*. The new simulated or improved discharge, $QIMP_t$, is computed by adjusting $QSIM_t$ for each forecast lead-time within the forecast horizon.

Mathematically, the measured discharge, $QOBS_t$, at time *t*, can be expressed as:

$$QOBS_t = QSIM_t + \varepsilon_t \qquad (1a)$$

or

$$\varepsilon_t = QOBS_t - QSIM_t \qquad (1b)$$

GP is used to infer the functional relationship, *F( )*, between the simulated discharges and the past simulation errors, and the present simulation error. For lead time of 1 hour, the functional relationship for GSR prediction error, $\hat{\varepsilon}_{t+1}$, may be expressed as follows:

$$\hat{\varepsilon}_{t+1} = F\{QSIM_{t+1},\ QSIM_t,\ .\ QSIM_{t-4},\ \varepsilon_t,\ \varepsilon_{t-1}\ ..\ \varepsilon_{t-4}\} \qquad (2a)$$

and the forecast improved discharge, $QIMP_{t+1}$, can be obtained from:

$$QIMP_{t+1} = QSIM_{t+1} + \hat{\varepsilon}_{t+1} \qquad (2b)$$

For lead time of 2, 3,…, α hours, the recursive form of Eq. (2) can be written as:

$$\hat{\varepsilon}_{t+\alpha} = F\{QSIM_{t+\alpha}\ ,.,\ QSIM_{t+\alpha-4}\ ,\ \hat{\varepsilon}_{t+\alpha-1}\ ,.,\ \hat{\varepsilon}_{t+\alpha-4}\} \qquad (3a)$$

$$QIMP_{t+\alpha} = QSIM_{t+\alpha} + \hat{\varepsilon}_{t+\alpha} \qquad (3b)$$

It should be noted that the values of $\hat{\varepsilon}_{t+\alpha}$ in Eq. (3a) may be either the actual errors at instances when measured data are available or GP derived errors.

4.2 Application

The proposed evolutionary-based updating method is applied to simulate flow for Bishops Hull, River Tone, a rural catchment upstream of Taunton. It is important to get reliable flood forecasts at Bishops Hull as Taunton has come close to flooding on several occasions in the past few years. Predictions of the timing, shape and scale of the flood response are superior using effective rainfall instead of total rainfall. Improved flood predictions are possible using total rainfall, but extra care is needed in adjusting the volume runoff to initial catchment wetness index. Use of total rainfall will not improve the prediction of the timing and shape of the flood hydrograph, and will cancel out any benefits due to real-time updating of predicted flows using observed flows.

A series of experiments was conduct to investigate the suitability of real-time error updating/ correction. Since error correction can be used in conjunction with either total rainfall predicted flow or effective rainfall predicted flow, the effectiveness on both types of flow was investigated. Table 1 show the results of applying GP and ANN error updating on both total and effective rainfall for the period December 1999 (calibration). It can be seen that the error updating results using GP are comparable to that using ANN. Similar good results can be obtained from validating the algorithm for an unseen rainfall-runoff period (Apr 2000).

From the results in Table 1, it can be seen that both GP and ANN can effectively improve the forecast runoff for up to 5 time-steps ahead, using total rainfall forecasting mode. If the effective rainfall mode is used, although the un-corrected WRIP's forecast was better than that of using total rainfall, the results of error correction can only be effective up to 4 time-steps ahead.

5 CONCLUSIONS

This paper discusses a novel technique of coupling a conceptual rainfall-runoff model with an evolutionary-based error correction/ updating technique. The results showed that with the addition of a suitable error updating/ correction such as genetic programming (GP) or artificial neural networks (ANN), the results of WRIP had improved significantly. This applies for both calibration and validation data set of the catchment under investigation.

It is shown that the proposed error correction scheme, when applied on WRIP, is more effective for forecast using total rainfall. Both GP and ANN were able to provide good forecast for up to 5 time-steps (i.e. 5 hours) ahead.

The resultant formula (not shown here due to space limitation) from the GP error updating is transparent to the flood warning engineers and can be interpreted as an advanced form of auto-regressive formulation (Khu et al., 2001). Any over or under prediction by the WRIP software will be captured via the simulated flow terms. Moreover, an error in the correction terms from the previous time-step will be automatically adjusted by the error terms. In this sense, the updating technique using GP and ANN are actually learning from the mistaks of previous WRIP prediction and GP error correction.

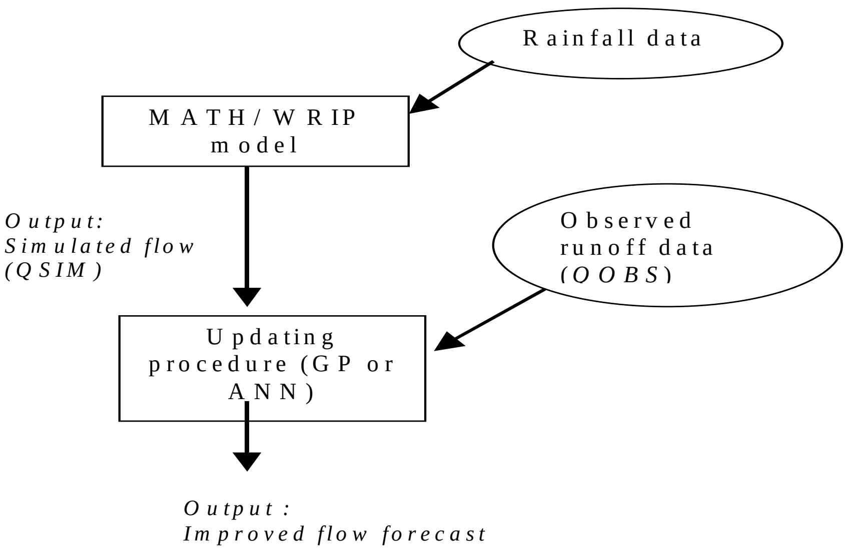

Figure 2: Flowchart of error correction in WRIP model

Table 1: Root Mean Square Error for Different Prediction Lead-times for GP and ANN

		Root Mean Square Error, RMSE (m^3/s)					
		Using Total rainfall			Using Effective Rainfall		
	Lead-time (hours)	WRIP	Calibration	Validation	WRIP	Calibration	Validation
GP	1	8.54* / 4.53**	0.90	0.63	6.34* / 2.59**	0.96	0.73
	2	----	1.25	1.15	----	1.49	0.67
	3	----	1.76	1.47	----	2.52	1.42
	4	----	2.68	1.90	----	3.68	3.21
	5	----	3.26	2.35	----	3.70	3.11
ANN	1	8.54* / 4.53**	0.61	0.63	6.34* / 2.59**	0.90	0.61
	2	----	2.00	0.96	----	1.25	1.24
	3	----	3.09	1.96	----	1.76	1.94
	4	----	5.70	3.34	----	2.68	2.49
	5	----	6.79	3.31	----	3.26	3.33

Note: Under WRIP column – "" applies to calibration data set; "**" applies to validation data set.*

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