Proceedings of ERAD (2004): 115–119 © Copernicus GmbH 2004

ERAD 2004

Combining and comparing rainfall observing systems in hydrological modelling of a rural catchment

G. L. Robbins[1], **M. Grum**[2], **and C. G. Collier**[1]

[1]School of Environmental & Life Sciences, Peel Building, University of Salford, Salford, Greater Manchester, M5 4WT, UK
[2]PH-Consult, Ordruphojveg 4, DK 2920 Charlottenlund, Denmark

Abstract. Rainfall can be measured by several different techniques at the same time. Each technique possesses different characteristics with respect to accurately representing the intensity and variability of a rainfall event. A stochastic state space modelling approach has been developed to combine the rainfall measurements of several observing systems (including radar and river flow gauges) to maximise the knowledge of rainfall intensity over an area. A Kalman filter technique considers estimates of the likely errors present in both the model and observations. Model predictions are then updated using knowledge of these errors and the observed values. This technique is used in conjunction with a catchment model of a river system, to determine the most appropriate rainfall field given the available rainfall and flow observations.

The River Croal catchment (143 km^2) in North West England is observed by a network of sixteen tipping bucket rain gauges, three dual frequency microwave links and a C-band weather radar. A simple rainfall runoff model of the Irwell catchment is constructed using an arrangement of fast and slow linear reservoirs for each subcatchment. A flow gauge placed near to the catchment outlets provides regular flow measurements. The stochastic state space modelling technique, outlined above is applied to measurements made by the complete hydrometeorological network, and its ability to provide model input for successful flow prediction is demonstrated. Ongoing research to assess the usefulness of various combinations of observing systems is also demonstrated. This will help determine a relationship between the number and distribution of different rainfall measurement techniques within a catchment and the quality of flow predictions a model such as this can provide.

Correspondence to: G. L. Robbins
(g.l.robbins@salford.ac.uk)

1 Introduction

The representation of high spatial variability in the rainfall structure over a catchment is often critical to the success of real time flood prevention and monitoring. The point measurements by rain gauge networks have proved to be very accurate in terms of depth but offer a limited description of the spatial structure. Weather radar covers this spatial variation well but has proven to provide relatively poor depth coverage (Collier, 1996). The recent development of rainfall measurement from the attenuation caused by rainfall to dual-frequency microwave links (Rahimi et al., 2002) now enables estimates of the mean intensity of rainfall to be made between two points. This new technique is a compromise between the good depth measurement of the rain gauge network and the good spatial coverage of the weather radar, as depicted by Fig. 1.

A stochastic state-space modeling approach, described more fully in Sect. 2, has been developed for the combined exploitation of the information content in several different types of rainfall and hydrological measurement. This not only promises to provide the optimal rain plane given the set of measurements but will also update the system state using flow measurements. A sub catchment upstream of a flow or level gauge could also be considered a rain gauge assuming that one is able to give a fair description of the lumping and delay that takes place. This implies that model predictions of a hydrograph may continue to be improved even after the rain has stopped falling.

In this study we look at flow predictions using a simple model of the River Croal catchment, a tributary of the River Irwell in North West England. This catchment has a dense hydrometeorological network comprising rain gauges, microwave links and a weather radar. This study aims to consider the performance of the model using several combinations of these instruments.

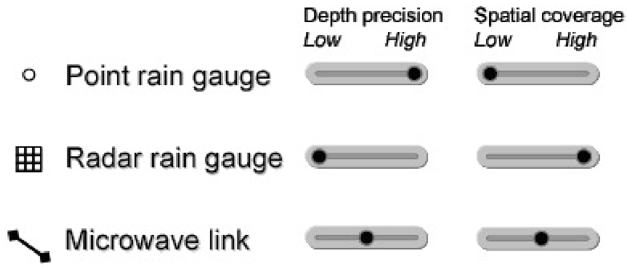
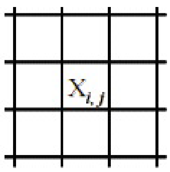


Fig. 1. Rainfall measurements relative strengths. Point rainfall measurement with high depth precision, radar with good spatial coverage and microwave link which maybe somewhere in between.



$$X_{i,j}(t)=\sum_{k=-1}^{1}\sum_{l=-1}^{1}\alpha_{k,l}\cdot X_{i+k,j+l}(t-\Delta t)$$

where the coefficients $\alpha_{k,l}$ are given by the table

i \ j	-1	0	+1
-1	0.05	0.05	0.05
0	0.05	0.60	0.05
+1	0.05	0.05	0.05

or $\alpha_{k,l}=f$ (wind speed, wind direction)

Fig. 2. A very simple model which, one step ahead, predicts the rainfall intensity to be a weighting of its own current value with its immediate neighbours.

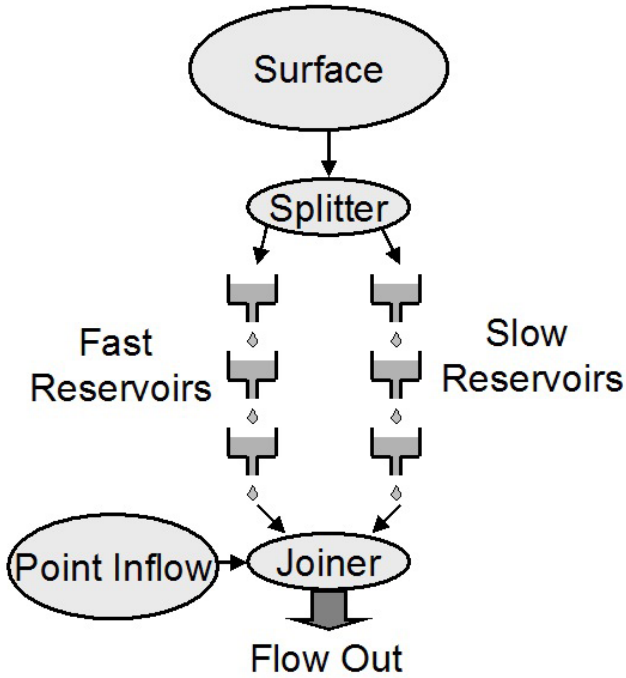


Fig. 3. Schematic diagram of a simple catchment model based on a series of three slow and a second series of three fast linear reservoirs flowing parallel to each other.

The stochastic modelling technique applied in this study has been presented theoretically by Grum et al. (2002). The approach is described briefly, in section 2, with a focus on the application to the presented case.

2 The stochastic state-space modelling approach

The potential of combining several types of rainfall measurements is noted in Sect. 1. This is achieved by constructing a model of the rainfall plane and the hydrological system. All measured data is considered to be different ways of looking at the same thing. On the presence of any observations, the state of the rain plane and the hydrological system is updated by weighting between what the model has predicted and the available observations. The weighting is done, using a Kalman filter, based on the uncertainties of the predictions and observations respectively.

A simple model predicts the rainfall intensities one step ahead for each pixel of the rain plane and is based on the notion that the rainfall in a particular pixel, $X_{i,j}$ at time-step t-1 will probably be like that at time-step t (Fig. 2). Therefore at every time-step the rainfall model predicts the rainfall intensity based on knowledge from the previous time-step. This is achieved by weighting a pixel's own current value with those of its immediate neighbour pixels. A dampening coefficient, β, is incorporated with a value of just under 1.0, to introduce an exponential decay of the intensity.

A simple rainfall-runoff model is also constructed using a two series linear reservoirs running parallel to each other, one to represent the fast and the other to represent the slow flows through the system (Fig. 3). The proportion of water flowing into the slow reservoir series is exponentially inversely proportional to the volume of water present in the reservoirs. At any given moment, the state of the runoff system is defined by the volume of water present in each of the reservoirs.

To apply the Kalman filter a prediction is needed not only of the state variables themselves but also a prediction of their variances. The model also serves to calculate the propagation of the state's covariance matrix. The complexity and structure of the model is not important so long as it adheres to the following general discrete time non linear form;

$$\underline{X}_t=\underline{f}\left(\underline{X}_{t-1},\underline{u}_{t-1}\right)+\underline{e}_{1,t},\qquad(1)$$

where X is a vector of the state variables, $f(\ldots)$ is the set of functions transforming the state variable and known input variables at time $t-1$ to the state variables at time t, and e_1 is a vector of the model error.

The observation equation defines how one is observing the state of the system and is of the form;

$$\underline{Y}_t=\underline{h}\left(\underline{X}_t\right)+\underline{e}_{2,t},\qquad(2)$$

where Y is a vector of the observations , $h(\ldots)$ is the set of functions defining how the state variables, X, are observed and e_2 is a vector of the observation error.

Table 1. Microwave link properties.

Link	Length (km)	Frequencies (GHz)
Winter Hill (WH) – Clarkes Hill (CH)	14.0	12.8/17.6
Cow Lane (CL) – Height Barn (HB)	8.9	13.9/22.9
Hameldon Hill (HH) – Clarkes Hill (CH)	23.0	12.8/17.6

Table 2. Hydrometeorological networks used.

Network	Constituent
Full Network	All rain recording devices
Radar & RG	Radar and all rain gauges
5 RG	Five Rain gauges; LR WS HW RD CG (Fig. 4)
MW	All microwave links
MW & RG	All microwave links and all rain gauges
All RG	All rain gauges
Radar	Radar alone
Radar & MW	Radar and all microwave links

It is difficult to estimate the variances of the magnitude of event as the observation errors have little to do with, for example, the measurement errors related to the sample analysis. However, based up on a given set of parameter and variance values, the likelihood of actually obtaining the observed values may be calculated. The best set of parameters and variabilities can be selected as those that have the highest likelihood. This is achieved using an off-line optimisation procedure based on this maximum likelihood criterion.

3 Methodology

Rainfall measurements from a variety of hydrometeorological networks are assimilated into the stochastic state-space model. Estimates of the error variances associated with each measurement technique and with the model have been predetermined. Flow predictions are provided at regular intervals (in this case 50 time-step intervals) from the start of the event, and these are then compared to the observed flow at the catchment outlet. The flow predictions are compared using three techniques; a comparison of the peak flow magnitude, the time of peak flow and the modelling efficiency (Nash and Sutcliffe, 1970).

4 Case Study

The Croal drains approximately 143 km^2 of the West Pennine Moors, joining the River Irwell on the South East edge of the industrial town of Bolton, North West England. Rainfall over the area is measured by a dense hydrometeorological network shown by Fig. 4. Sixteen 0.2 mm tipping bucket rain gauges are used. However these are mostly located over

Table 3. Observation and state error standard deviations.

Observation/State	Error standard deviation
Fast reservoir water volume state	1960 m^3
Slow reservoir water volume state	600 m^3
Flow gauge observation	2.73 $\mathrm{m}^3\mathrm{s}^{-1}$
Rain gauge observation	0.909 $\mathrm{mm\,hr}^{-1}$
Microwave link observation	1.00 $\mathrm{mm\,hr}^{-1}$
Radar observation	0.933 $\mathrm{mm\,hr}^{-1}$

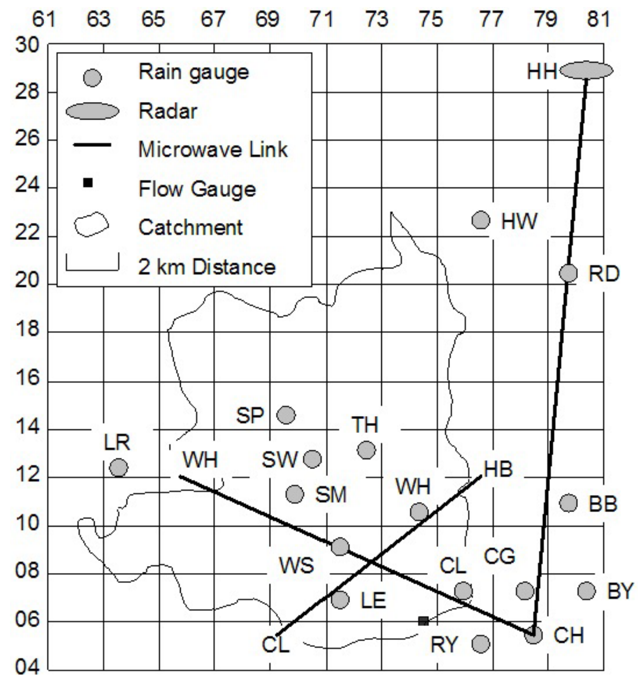


Fig. 4. Plan of the Croal catchment and its hydrometeorological network.

the southern half of the catchment leaving the northern half very sparsely covered. Two dual frequency microwave links also cover the southern half of the catchment with a third aligned North – South along the entire length of the catchment albeit several kilometers to the East. The microwave link properties are shown on Table 1. A C-Band weather radar providing data on a 300 s time-step at 2 km×2 km resolution is located at Hameldon Hill with the pixels indicated by the grid (Fig. 4). Flow measurements, at 15 min intervals, are made at Farnworth weir, just before the confluence with the River Irwell (Fig. 4).

Several rain planes are constructed for the various hydrometeorological networks used and these are described in Table 2. The chosen rainfall event is frontal with embedded convection and occurs on 12–13 September 2001 (Fig. 5). Initially stochastic model optimisations, noted in Sect. 2, were run to determine appropriate error standard deviations for the observation and model states (Table 3).

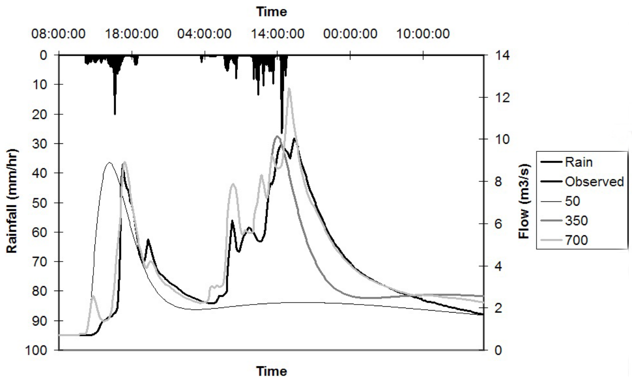


Fig. 5. Rainfall, observed river flow and forecast hydrographs after various time-steps.

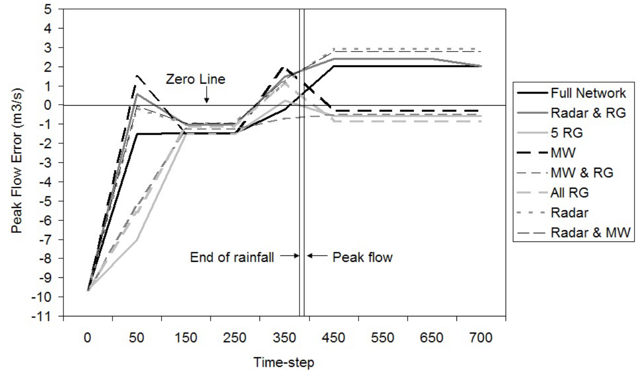


Fig. 7. Peak flow error for forecasts at various time-steps.

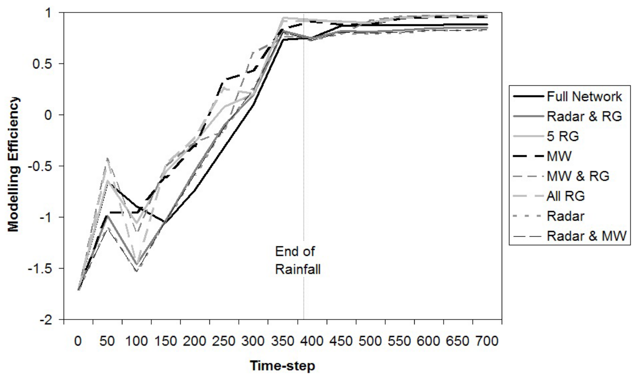


Fig. 6. Nash and Sutcliffe modelling efficiency for flow forecasts at various time-steps.

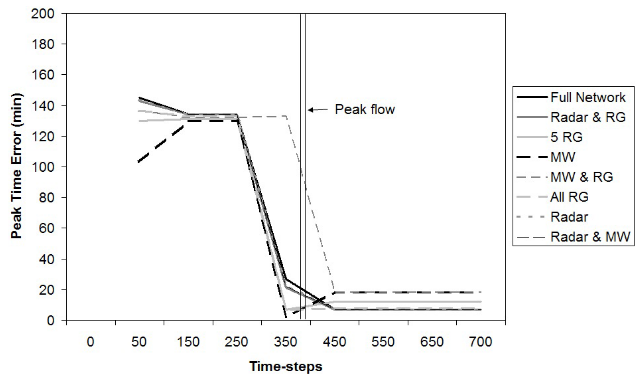


Fig. 8. Error in peak time for forecasts at various time-steps.

5 Discussion of Results

Hydrographs showing flow predictions made after various time-steps form the start of the event are shown on Fig. 5. Graphs showing the Nash and Sutcliffe modeling efficiency, the peak magnitude error and the time to peak error are shown as Figs. 6, 7 and 8 respectively.

The predictions using each hydrometeorological network provide a closer match to the observations the later they are made after the onset of the rainfall (Fig. 5). The flow reconstructions continue to improve after it has ceased to rain (13/09/2001 16:00; time-step 385) due to information from the flow measurements updating the system states (Fig. 6). Increases in performance of all networks at the 50 and 350 time-step forecasts illustrates the rain plane model's ability to predict the subsequent rise in flow. In the forecast made at time-step 350 (175 min before the end of the rainfall and 200 min before the flow peak), each network, except for the rain gauge and microwave combination, predicts the peak flow magnitude within 20%, and the time of peak flow within 30 time-steps (150 min) of the observations (Figs. 7 and 8). Forecasts made after time-step 350 are split between those networks including the radar and those that do not. This suggests that for this case, the models ability to predict may be better than its ability to update.

Generally the microwave links, the rain gauges and the combination of these two techniques produce good flow reconstructions. Close estimates of the peak flow magnitude ($10.35\,\mathrm{m}^3\mathrm{s}^{-1}$) are predicted at the 350 time-step forecast. The microwave link and rain gauge combination fails to predict the time of peak flow until after the end of the rainfall in this particular example only because predictions of the first rainfall peak are higher than those of the second. This second peak has a higher magnitude according to the observed flow. There is no advantage of having sixteen rain gauges instead of the five used in the limited rain gauge network.

The radar is one of the poorer performers in terms of the peak flow magnitude prediction, however the predicted time is very close. The overestimations in peak flow magnitude made using the radar based networks are 2–3 times the magnitude of the underestimations made by the other networks. This illustrates spatial structure within the rainfall is well represented by the radar although the actual depth of rainfall is not estimated so well.

The radar tends to dominate the rain depth estimations since the radar combination with either the microwave links or the rain gauges fails to provide a peak flow magnitude prediction that is closer to the observations than those by the radar operating alone. The combination of the full hydrometeorological network only slightly improves this flow prediction. Hydrometeorological networks not including the radar produce peak flow predictions that are close to the observations and provide hydrographs that generally provide closer matches to the flow observations.

6 Summary and conclusions

This novel technique of flow prediction achieves its objective to a certain degree of success by providing reasonable flow forecasts some 200 min before the peak flows occur. The results suggest that the microwave links and rain gauges produce the better flow reconstructions in this particular rainplane and model configuration. The radar does not perform so well and this has an effect on predictions using the full hydrometeorological network and combinations of the radar with the rain gauges or the microwave links. There is no evidence to suggest that improved flow predictions are achieved by using sixteen rain gauges instead of five that are distributed evenly around the catchment.

These results are limited and based on the study of a single event over a particular catchment. They only serve to demonstrate the possible performance a stochastic state space modeling technique such as this may achieve. Future work will apply this technique to a multitude of rainfall events. The entire Irwell catchment (554 km^2) will also be considered by combining similar model of all five subcatchments to form a semi-distributed model of the larger river system.

Acknowledgement. This work is part of the EU Framework V MANTISSA project. Thanks go to all the project partners for their support.

References

Collier, C. G.: Applications of weather radar systems, John Wiley & Sons, Chichester, 1996.

Grum, M., Harremoes, P., and Linde, J. J.: Assimilating a multitude of rainfall and runoff data using a stochastic state space modelling approach, 91CUD, Portland, Oregon, 2002.

Nash, J. E. and Sutcliffe, J. V.: River flow forecasting through conceptual models. Part 1 – a discussion of principals, Journal of Hydrology, 10, 282–290, 1970.

Rahimi, A. R., Holt, A. R., Upton, G. J. G, and Cummings, R. J.: The use of dual-frequency microwave links for measuring path averaged rainfall, Accepted Journal of Geophysical research: Atmospheres.