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Backpropagation of error modelling applied to the River Ouse dataset

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Neurocomputing is an emergent technology concerned with the application of artificial neural networks - in this paper for modelling systems within a hydrological context. The most popular training algorithm for such networks is 'backpropagation of error' (Rumelhart *et al*., 1986; Tveter, 2004). This optimisation procedure provides an efficient computational mechanism for evaluating the derivatives of the network performance function with respect to a given set of network parameters. It corresponds to a propagation of errors backwards through the network. The term has also been adopted to describe feed forward multi-layered networks trained with the back propagation algorithm. Networks of this type have emerged as major workhorses in various areas of business and commerce; it is also the most common type of neural network that has been used to perform hydrological modelling operations (Maier & Dandy, 2000). Indeed, for most explorations, the standard backpropagation neural network is the first point-of-call and will often produce acceptable results. As such, the use of more complex solutions will seldom, if ever, need to be investigated. Thus fresh developments in neural network modelling should always be compared to standard backpropoagation models in order to establish the potential advantages that are on offer. Following the neural network procedures described in Dawson & Wilby (2001), this paper reports on the construction and application of a standard backpropagation neural network solution developed on the competition River Ouse Dataset. The selection of modelling inputs was based on a statistical consideration of raw inputs and

moving averages. Trial and error was used to determine an optimal number of hidden units. Early stopping, based on the use of a cross-validation dataset, was required to prevent over fitting. The results are compared to multiple linear regression outputs developed on identical inputs.

Dawson, C.W. and Wilby, R.L. (2001) Hydrological modelling using artificial neural networks. *Progress in Physical Geography* 25(1): 80 - 108.

Maier, H.R. and Dandy, G.C. (2000) Neural networks for the prediction of water resources variables: a review of modelling issues and applications. *Environmental Modelling and Software* 15(1): 101-124.

Rumelhart, D.E., Hinton, G.E. and Williams, R.J. (1986) Learning internal representations by error propagations. In: Rumelhart, D.E. and McClelland, J.L. Eds. *Parallel Distributed Processing: Explorations in the Microstructures of Cognition*, Vol. 1, 318-362. Cambridge, MA: MIT Press.