Water Quality and Sediment Behaviour of the Future: Predictions for the 21st Century (Proceedings of Symposium HS2005 at IUGG2007, Perugia, July 2007). IAHS Publ. 314, 2007.

Neuroevolution methodologies applied to sediment forecasting

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Abstract Sediment forecasting represents a significant modelling challenge. This is due to the combined effects of suspended sediment transfer and throughput being source limited and subject to hysteresis effects. Recent approaches to modelling and forecasting have involved the use of neural networks. Despite yielding good results, this method has its own set of limitations, for example lack of guidance in parameter setting and the potential to overtrain. This paper reports on the application of a neuroevolutionary toolbox, JavaSANE. This toolbox is applied to two catchments in Puerto Rico that have been previously studied by Kisi (2005), who used a range of different methods including a neuro-fuzzy approach and neural networks to model suspended sediment in these catchments. These experiments are replicated using JavaSANE and compared to the results reported in Kisi (2005). These results show that JavaSANE produces estimates that are better or comparable to those of Kisi (2005).

Key words genetic algorithm; JavaSANE; neural network; neuroevolution; Puerto Rico; sediment

INTRODUCTION

The last decade has witnessed an escalation in the demand for better sediment modelling methodologies (Horowitz, 2003; White, 2005). This has been a consequence of the need to obtain accurate estimations of suspended sediment for watershed management operations (e.g. reservoir sedimentation) and environmental impact assessment, such as contaminant transport and water quality trends (De Vries & Klavers, 1994; Horowitz, 1995; Horowitz *et al*., 2001). However, suspended sediment prediction presents a significant modelling challenge with two fundamental problems: suspended sediment transfer and throughput is source limited and it is subject to hysteresis effects. Previous modelling attempts have focused on the use of conceptual models that have tried to capture the physical processes in a catchment. More recently, research has focused on exploiting the use of neural networks (NNs). For example, Abrahart & White (2001) applied NNs to a series of four small experimental catchments in Malawi while Jain (2001) used NN to model the sediment-rating curve at two sites on the Mississippi River. Nagy *et al*. (2002) used a NN trained with backpropagation to estimate the total sediment concentration. The model was verified with a large number of data points from several rivers and the results showed that the NNs compared well to conventional methods. More recent studies include that of Agarwal *et al*. (2005), who used backpropagation NNs to model suspended sediment of the River Varsadhara in India. Kisi (2005) used a combination of techniques including neuro-fuzzy, backpropagation NNs, multiple linear regression models and sediment rate curves to predict suspended sediment for two catchments in Puerto Rico. Finally, Cigizoglu & Kisi (2006) used a range dependent network to model sediment of the River Schuylkill River in the USA.

The majority of these examples use a NN trained with backpropagation. This approach, however, has several disadvantages such as long training times, lack of guidance on architecture and parameter settings, and the potential to overtrain. In response to this, researchers have begun to explore the potential of neuroevolutionary methods. Neuroevolution (NE) is the application of a genetic algorithm to the development of NNs. There are no backpropagation training parameters to specify, training is fast and a cross-validation data set or stopping criteria are not required. NE also allows the use of alternative objective functions other than the standard sum of errors squared used by conventional NNs, which has been recently demonstrated by Dawson *et al*. (2006). This paper uses a customised version of the NE software package JavaSANE (Moriarty & Miikkulainen, 1998) to develop NNs for sediment prediction. The models are developed for the two catchments in Puerto Rico used by Kisi (2005); comparisons with Kisi's work will be undertaken and discussed. Further planned experiments are also discussed.

STUDY AREA

The flow-sediment time series data used within this paper are from stations in Puerto Rico (Fig. 1). Quebrada Blanca station (henceforth referred to as QB) is situated near Jagual (USGS Station no. 50051150, latitude 18°09′40″, longitude 65°58'58"). The second station, Rio Valenciano (RV), is located at Juncos (USGS Station no. 50056400, latitude 18°12′58″, longitude 65°55′34″). Quebrada Blanca has a drainage area of 43.57 km^2 with a gauge datum of 130 m. The drainage area of Rio Valenciano is 8.63 km^2 with a gauge datum of 98 m. Daily time series data of river flow and sediment concentration were downloaded directly from the US Geological Survey (USGS) website: http://webserver.cr.usgs.gov/sediment. For each station, the 1994 water year (consisting of 365 daily values from October 1993 to September 1994) was

Fig. 1 Location of study sites.

used for training JavaSANE. The 1995 water year (Oct 1994–Sep 1995) was used to test the models. An assessment of the statistical parameters of the data by Kisi (2005) showed a highly skewed distribution in the sediment and flow data at both stations.

THE JavaSANE MODELLING ENVIRONMENT

JavaSANE is based on the concept of "cooperative coevolution" (Horn *et al.*, 1994; Potter, 1997). Essentially, this involves the evolution of a population of hidden neurons, rather than the traditional approach of evolving a population of working networks. Each neuron cooperates with other neurons with the aim of finding the optimal solution (see Dawson *et al.*, 2006, for further details). The cooperative coevolution algorithm has been incorporated into two software packages that are designed to produce neural network models using Symbiotic Adaptive Neuro-Evolution (SANE; Moriarty & Miikkulainen, 1998): SANE-C "research code" and JavaSANE "platform independent code that requires minimum effort to implement novel applications in fresh domains". The original source code, documentation and research papers can be found at: http://nn.cs.utexas.edu/pages/software/software.html. The basic steps of the algorithm are given in Fig. 2.

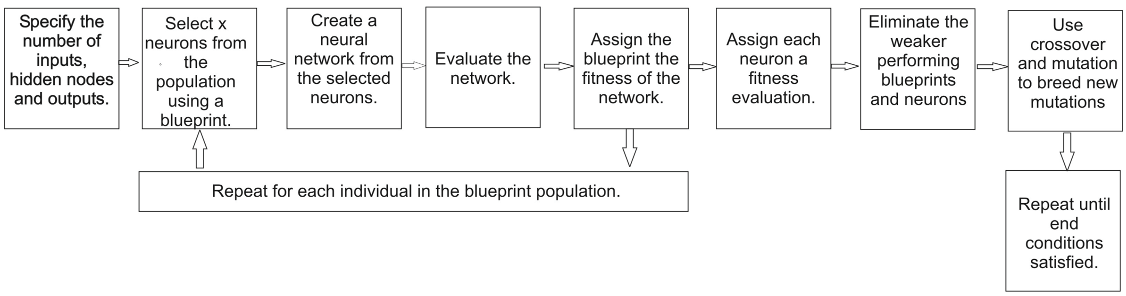

Fig. 2 The algorithm used by JavaSANE.

EXPERIMENTAL SET-UP

In his work on Puerto Rico, Kisi (2005) developed several models and performed comparisons on how well these performed. This included a neuro-fuzzy approach, a feedforward network trained with backpropagation, a multi-linear regression model and sediment rating curve developed on the water year 1994 (see Kisi, 2005, for full details of the model architectures). Kisi also developed several other models (e.g. pure fuzzy logic models) that are not provided in this paper. The model inputs and network architectures of Kisi (2005) are provided in Table 1 for both QB and RV. All experiments are designed to predict S_t or the suspended sediment in mg/L on day t. Experiments D1 and D2 are attempts to predict the sediment using only flow data (Q_t and Q_{t-1}), while D1S and D2S add sediment from the previous day (S_{t-1}) as an additional input.

JavaSANE was used to evolve neural network solutions for the two stations and the four experiments using the same architectures of Kisi (2005) in Table 1. RMSE was

Table 1 NN inputs and architectures tested at RV and QB.

Experiment	Model inputs	Neural network architecture (input: hidden:output) RV	QB
D1	Q_t	1:1:1	1:2:1
D2	Q_t and Q_{t-1}	2:2:1	2:2:1
D1S	Q_t and S_{t-1}	2:2:1	2:2:1
D2S	Q_t, Q_{t-1} and S_{t-1}	3:2:1	3:2:1

used as the objective function and 50 different solutions per experiment and station generated. The best model was selected on the basis of the lowest RMSE in training conditions. This model was then used to make predictions for the test data set. Model performance on the test data set was evaluated using a combination of R-squared (R^2), root mean squared error (RMSE) and relative error of the total sediment load to facilitate comparison with Kisi (2005).

RESULTS

The results of Kisi (2005) and the JSNN (JavaSANE) models for RV and QB are provided in Tables 2 and 3, respectively. For both RV and QB, the neuro-fuzzy, neural network and JSNN models outperform both linear regression and the sediment rating curve. For RV, the JSNN models perform slightly worse but comparable to the neuro-fuzzy and neural network models of Kisi (2005). However, there is no pattern to which experiment produces the best result. The simplest model (D1) using only current flow data as input yielded the best performing model using a neuro-fuzzy approach while a model using flow and sediment produced the best results for the BPNN and JSNN models.

For QB the JSNN model produced the best performing model, with the neuro-fuzzy model only marginally worse. As with RV, the best neuro-fuzzy model was D1, the BPNN was a combination of D2 and D2S while the JSNN was a mixture of D1S and D2S (depending upon which error metric is chosen).

Table 2 RV statistical results for test period (water year 1995).

Exp.	Neuro-fuzzy NFNN RMSE	R^2	Neural BPNN RMSE	R^2	JSNN RMSE	R^2	Linear SRC1 RMSE	R^2	MLR1 RMSE	R^2
D1	51.97	0.876	54.64	0.867	62.99	0.863	58.46	0.85	74.51	0.84
D2	60.18	0.839	52.35	0.874	53.07	0.870	-	-	76.42	0.84
D1S	61.52	0.829	95.14	0.702	55.17	0.871	-	-	76.99	0.85
D2S	70.31	0.775	52.16	0.876	61.65	0.848	-	-	73.55	0.85
Best model	D1 51.97	D1 0.876	D2S 52.16	D2S 0.876	D2 53.07	D2 0.870	D1 58.46	D1 0.85	D2S 73.55	D1S 0.85

NFNN = neuro-fuzzy model; BPNN = backpropagation neural network; JSNN = JavaSANE neural network; SRC1 = sediment rating curve model developed on a single annual data set; MLR1 = multiple linear regression model developed on a single annual data set. The original values of Kisi (2005) were presented as MRSE, for comparison with the JSNN results; they have been converted into RMSE.

Table 3 QB statistical results for test period (water year 1995).

Exp.	Neuro-fuzzy NFNN RMSE	R^2	Neural BPNN RMSE	R^2	JSNN RMSE	R^2	Linear SRC1 RMSE	R^2	MLR1 RMSE	R^2
D1	17.96	0.929	27.32	0.821	18.36	0.920	53.11	0.816	29.99	0.894
D2	21.40	0.887	21.40	0.865	22.51	0.908	-	-	29.99	0.894
D1S	19.68	0.907	36.30	0.754	17.72	0.925	-	-	29.80	0.891
D2S	21.97	0.883	21.59	0.888	21.20	0.930	-	-	29.80	0.890
Best model	D1 17.96	D1 0.929	D2 21.40	D2S 0.888	D1S 17.72	D2S 0.930	D1 53.11	D1 0.816	D1S/D2S 29.80	D1/D2 0.894

NFNN = neuro-fuzzy model; BPNN = backpropagation neural network; JSNN = JavaSANE neural network; SRC1 = sediment rating curve model developed on a single annual data set; MLR1 = multiple linear regression model developed on a single annual data set.

Table 4 Comparison of the relative error in the total estimated sediment loads for the test period (water year 1995).

Location	Neuro-fuzzy NFNN	Neural BPNN	JSNN	Linear SRC1	MLR1
QB	10.9 (D1)	9.2 (D2)	7.3 (D1S)	–83.0 (D1)	–31.0 (D1S/D2S)
RV	–1.8 (D1)	–2.0 (D2S)	–1.1 (D2)	–7.4 (D1)	–29.0 (D2S)

Table 4 contains the relative error in the total sediment load for the test data set produced by each best performing model for QB and RV. This model is listed in brackets beside the relative error. The results show that the relative errors are much smaller for the neuro-fuzzy and neural network models compared to the sediment rating curve and the multiple linear regression model. The JSNN models also had the smallest relative error of all the models for both catchments.

Figures 3 and 4 contain the best performing JSNN models for RV and QB. The graphs show that the models are able to predict sediment relatively well on the test data, with some problems occurring at the peaks. There is a tendency to underestimate some of the larger peaks in both catchments, a problem also encountered by Kisi (2005). This is probably a result of a combination of a small number of peak events in the training data set and the use of global models. It is possible to address both of these problems through techniques such as booting and the application of local modelling techniques (Anctil & Lauzon, 2004).

CONCLUSIONS AND FURTHER WORK

This paper has compared an evolutionary neural network approach embedded in JavaSANE with a range of other approaches reported in Kisi (2005) including neuro-fuzzy, neural networks trained with backpropagation, multiple linear regression and sediment rating curves. The results show that the models produced using JavaSANE outperformed the other models for the Quebrada Blanca catchment and were comparable in performance to the neuro-fuzzy and neural network models of Kisi (2005) for the Rio Valencia catchment. The JavaSANE models also outperformed all approaches in terms of relative error of the total sediment load. In addition to performance

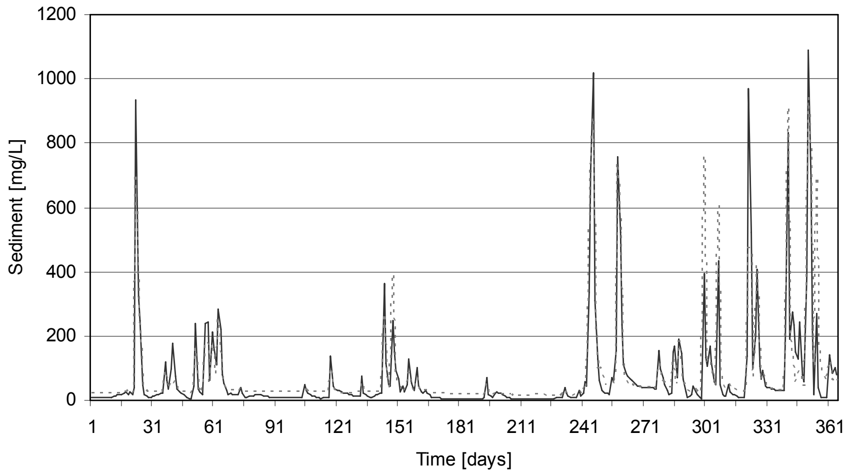

Fig. 3 Model predictions for JSNN D1S for the test data set at RV. The solid black line is actual sediment values while the dotted grey line is predicted.

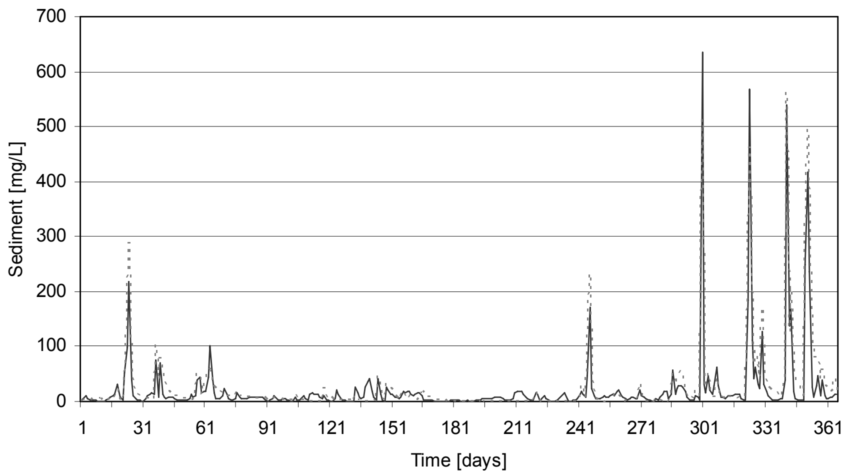

Fig. 4 Model predictions for JSNN D2 for the test data set at QB. The solid black line is actual sediment values while the dotted grey line is predicted.

improvements, there are other advantages of an evolutionary neural network approach. These include ease of use in terms of training the neural network, reducing the tendency for overfitting and the need for stopping criteria, and the ability to use a range of different objective functions.

Both this paper and Kisi (2005) used RMSE as the objective function for minimisation. Which objective function to use, and whether a single objective function is sufficient to produce the best performing model, is open for discussion. Some preliminary experimentation was undertaken where the relative error of the total sediment load was used to select the best performing model in training mode. In at least two cases, a better JSNN model was produced but this was not consistent across all experiments. Further work could therefore look at: (a) choosing an alternative and more meaningful objective function than RMSE such as relative error, and (b) choosing more than one objective function such as a combination of RMSE and RE.

For QB the JSNN models as well as the models of Kisi (2005) produced negative sediment. One method for further investigation is to penalise models that produce negative sediment when evolving neural network solutions with JavaSANE to avoid negative model predictions. This constraint would be simple to implement by adjusting the objective function. A similar exercise has been undertaken by Abrahart *et al.* (2007) in rainfall–runoff modelling. Other improvements will focus on better peak predictions through the use of techniques such as boosting and committee approaches.

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