Simulation of urban wastewater systems using artificial neural networks: embedding urban areas in integrated catchment modelling

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ABSTRACT

The urban wastewater system is an important part of integrated water management at the catchment level, yet, more often than not, inclusion of the system and its interaction with the surrounding catchment is either oversimplified or totally ignored in catchment modelling. Reasons of complexity and computational burden are mostly at the heart of this modelling gap. This paper proposes to use artificial neural networks (ANN) as a surrogate for the simulation of the urban wastewater system, allowing for a more realistic representation of the urban component to be incorporated into catchment models within a broad scale modelling framework. As a proof of concept, an integrated urban wastewater model is developed and its response in terms of both quantity and quality in combined sewer overflow (CSO) discharges and treatment plant effluent are captured and used to train a feedforward back-propagation ANN. The comparative results of the integrated urban water model and the ANN show good agreement for both water quantity and quality parameters. The resulting trained network is then embedded into a MIKE BASIN catchment model. It is suggested that ANN models greatly improve the level at which broad scale catchment models can accurately take into account urban–rural interactions.

Key words | artificial neural network, catchment scale model, integrated catchment management, integrated modelling, urban wastewater system, water quality modelling

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INTRODUCTION

Integrated catchment management has increasingly been recognised and practised as an important way to achieve and maintain environmental and sustainable regional development objectives (Jakeman & Letcher 2003). In the EU, the Water Framework Directive (WFD) (CEC 2000) requires water management in all Member States to be implemented on the basis of the catchment scale, rather than on administrative or political boundaries. This has brought new challenges not only to institutions, policy and legislation, but also to the research community. For the implementation of the WFD, developing appropriate simulation models plays an essential role in the formulation of river basin management plans, able to identify objectives

and assess strategies to achieve good ecological and chemical water quality status on a catchment-wide basis (McIntyre et al. 2003).

Catchment-wide models are constructed to simulate hydrological processes and point and non-point source pollution in surface runoff, river and groundwater flow in a river basin. Therefore, these models are generally used to predict water quality and quantity responses to extreme climatic or incidental events, management options and interventions. Urban areas affect the natural water cycle, at a catchment scale, in two ways: abstraction of water from the natural cycle for water supply to support life and then return of wastewater after use, and the covering of land with

impermeable surfaces that divert rainwater away from the local natural drainage system (Butler & Davies 2004). Catchment models have to consider the impact of urban areas both on water quality and quantity: however, most of the popular models, such as SWAT (Arnold *et al.* 1998) and MIKE BASIN (DHI 2003), lack a realistic urban component and thus are unable to model pollutant transport and transformation within urban wastewater systems.

The urban wastewater system itself consists of several subcomponents, including the sewer and drainage systems and the wastewater treatment plant(s), which interact both between themselves and with the surrounding environment. In terms of subsystems' interaction, even conventional urban water modelling usually treats the subsystems as separate while the interactions between the entire urban water system and the surrounding catchment are mostly ignored in "standard" catchment models (Butler & Schütze 2005). Reasons of complexity and computational burden are mostly at the heart of these modelling gaps.

The aim of this paper is to present the development of an ANN model able to simulate urban wastewater systems and predict both CSO discharges and treatment effluent characteristics, based on a truly integrated urban wastewater model. The ANN model is then embedded into the MIKE BASIN catchment model and the resulting integrated catchment model's functionality is demonstrated on the semi-hypothetical case study of the Vrbas catchment in Bosnia-Herzegovina.

METHODS AND MODELS

The proposed approach for modelling urban areas in a river catchment framework is shown in Figure 1. The term "integrated", as used in this schematic figure and this paper, refers to two levels of integration. A first level of integration takes place at the urban scale, where an "integrated" urban wastewater model, comprising of sewer/drainage system with CSOs and treatment plants, is constructed to generate a sequence of training data, which is then used to define a surrogate data-driven model, in the form of an ANN (training phase). A second level of integration takes place at the catchment level where the surrogate model is embedded into a catchment model (here MIKE BASIN by
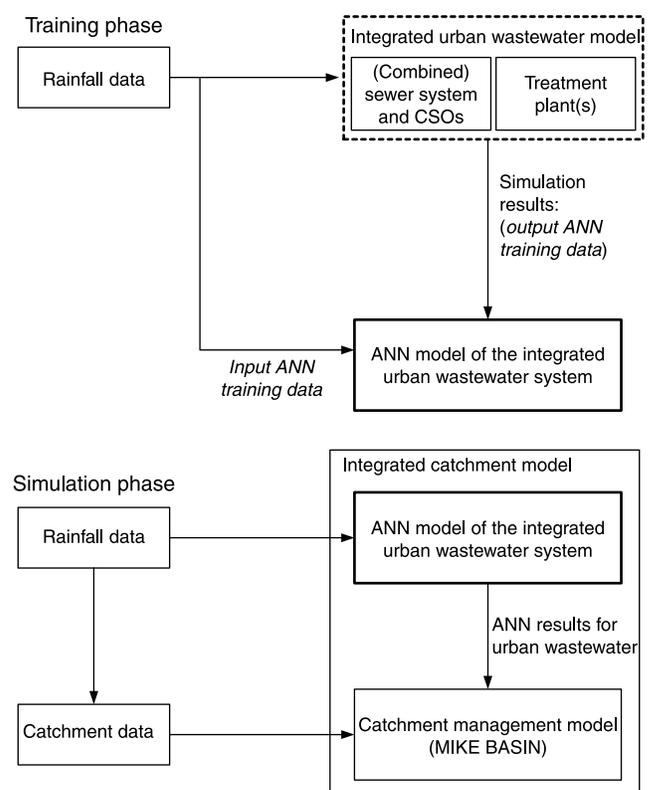

Figure 1 | Scheme of the proposed approach for modelling urban areas in a catchment scale model.

DHI) to consider the impacts of the urban wastewater system at the catchment (simulation phase).

The integrated urban wastewater model

Developing an integrated urban wastewater model to simulate the sewer system and treatment plant as a whole began to gain increased attention in the 1990s, although this idea was first proposed and discussed several decades ago (see also Butler & Schütze (2005) for a more extended discussion and review on, and development of, real-time control for the integrated urban wastewater system). Since then, several simulation tools and methods have been developed to assess the integrated urban wastewater system performance (Rauch *et al.* 2002). Some approaches attempt to link existing models of each subsystem together, and this usually involves adaptation of existing models and the development of interfaces to handle the inputs and outputs of each subsystem. This type of model normally runs sequentially, although it can be developed for synchronous

simulation (for example, using the OpenMI standard (http://www.openmi.org/)), which requires an extra computational demand because of intensive data exchange between the sub-models. Meanwhile, the functionality of the integrated model will be subject to existing models and thus has less flexibility to fit the actual modelling needs. Another approach is to develop an integrated model in a common platform, which allows fully dynamic simulation of the urban wastewater system. Examples of such a platform include SIMBA (IFAK 2005) and WEST (Vanhooren *et al.* 2003).

In this study, the SIMBA tool is used to construct an integrated model for the integrated urban wastewater system. SIMBA provides a general simulation environment in MATLAB/Simulink (http://www.mathworks.com/products/simulink/, developed by Mathworks) for simulating the water quantity and quality processes in sewer systems and treatment plants, and also allows users to develop their own modules for their specific needs. In the integrated urban wastewater model, the sewer system is modelled using the KOSIM method (ITWH 1995), and the treatment plant consists of a storm tank, primary clarifier and activated sludge reactor and secondary clarifier. A widely used sludge model, Activated Sludge Model No.1 (ASM1), is applied to model the biochemical processes in the reactor (Henze *et al.* 1986).

The catchment model

MIKE BASIN is a GIS-based water resources management tool (http://www.dhigroup.com/Software/WaterResources/MIKEBASIN.aspx, developed by DHI). It can be used in water availability analysis, water supply allocation, management and infrastructure planning, pollution discharge allocation, environmental impact analysis and many other fields (DHI 2003).

For hydrologic simulations, MIKE BASIN builds a network of branches and nodes. Branches represent individual stream sections and nodes are point locations, where it is assumed that water enters or leaves the network through extractions, return flow and runoff. These may be confluences, diversions, locations where certain water activities occur (such as water abstraction points for irrigation or water supply) or important locations where model results are required.

MIKE BASIN can simulate pollutant transport in the river system, taking account of various biochemical processes. Substances that can be modelled include dissolved oxygen (DO), biochemical oxygen demand (BOD_5), chemical oxygen demand (COD), ammonia/ammonium, nitrate and total phosphorus. Pollution from point and non-point sources can be modelled. Point sources are related to nodes, using for example different effluent water quality levels to represent different wastewater treatment types. This approach is, however, too simplified to allow for a proper representation of the complexity of the urban wastewater system.

Neural networks

An ANN is a network of simple computational elements, which can exhibit complex global behaviour, defined by the connections between neurons and neuron parameters. In theory, the neural network has the capacity to approximate any (arbitrarily complex) function without having to know or specify its form, so it has been widely used as a data-driven modelling tool in environmental and water resources engineering (ASCE Task Committee 2000; Maier & Dandy 2000; Rao & Alvarruiz 2007).

Since sewer systems and treatment plants involve various complex physical, chemical and biological processes, which exhibit nonlinear behaviour, the ANN demonstrates an advantage over physically based models as it does not require an explicit formulation of the underlying processes. Application of ANN to the sewer system and treatment plant has been explored widely, for example, within the context of urban rainfall runoff modelling (Giustolisi 2000), treatment plant influent prediction (El-Din & Smith 2002), rehabilitation (Makropoulos & Butler 2005), sewer system optimal control (Darsono & Labadie 2007) and treatment plant performance prediction (Mjalli *et al.* 2007; Raduly *et al.* 2007). In this paper an ANN model is developed to predict water flow and water quality discharged from an integrated urban wastewater system, which includes a sewer system with CSOs and a treatment plant. These outflows represent one of the main important interactions of the system with its surrounding catchment and also have a significant impact on water quality of receiving water bodies during storm events.

DEVELOPMENT OF THE ANN

Input and output

The neural network was built to model the quantity and quality of wastewater that enters the river during storm events from the urban areas. In the UK, about 70% by length of the sewer systems are combined, with wastewater and storm-water flowing together in the same pipe, a situation not unusual in many other developed countries (Butler & Davies 2004). Thus, such a combined sewer system is assumed for the example application in this paper. CSO discharges are typically activated during rainfall periods when the flow in the sewer system is above a certain level constrained by the capacity of downstream wastewater treatment plants. CSO discharges have a significant impact on river water quality because these flows are untreated and discharged into the river directly. Based on the above discussion as to the important components of the urban water system, the inputs to the ANN are rainfall and dry weather flow and outputs are both CSO discharges (flow rate, COD and ammonium concentrations) and treatment plant effluent (flow rate, BOD_5 and ammonium concentrations).

The SIMBA-based integrated wastewater model was used to generate output data for ANN training. The operation of the urban wastewater system was initially optimised against a series of quality objectives, including CSO volumes and maximum concentrations in treatment plant effluent to derive an optimal control strategy (Fu *et al.* 2008). Using rainfall and dry weather flow as input parameters, this "optimal" system was then used to generate water quantity and quality variables in CSO discharges and treatment plant effluent. This data was subsequently used to train and test the ANN model.

Before the data can be used to train and validate the network, it has to be preprocessed by scaling to a specified range. The neural network toolbox of MATLAB 7.0, which was used to develop the ANN model in this research, provides a transformation function to normalize the dataset so that the inputs and targets will have means of 0 and standard deviations of 1.

ANN architecture

The feedforward back-propagation ANN was chosen because it is the most widely used network in environmental and water engineering (ASCE Task Committee 2000; Maier & Dandy 2000). The network consists of one input layer, one output layer and at least one hidden layer. Each layer has a number of neurons, which are connected to the neurons of another layer with weights, but not to neurons in the same layer. Each neuron converts the weighted inputs from the previous layer to an output signal, which acts as an input to the neurons in the following layer.

The number of input neurons in our ANN was determined by the combination of rainfall and dry weather flow. To present the rainfall data to the network, a moving window of past records must be used to capture time delays in the input–output relationship. As the window size increases, so does the number of inputs and the complexity of the network, having a significant impact on the network performance (Bowden *et al.* 2005). Thus it is necessary to find an optimal window size to achieve the best perfomance. For the case study introduced in the next section, a range of different sizes from 5 to 24 h, based on the sub-catchment's concentration time, were tested to find the appropriate lag for the rainfall series. The size of 15 h was chosen beyond which the lagged time series has no significant effect on the network performance. The predictability of the output variables was not affected by the lag of dry weather flows, so no past information was used. Thus, a total of 16 neurons was used in the input layer, including the rainfall series, its 14 lags and dry weather flows.

The number of hidden layers and relevant neurons are problem-dependent and usually determined by a trial-and-error procedure (Maier & Dandy 2000). Through preliminary tests, one hidden layer with 15 neurons was used in this study as this proved sufficient to provide accurate predictions. The neurons in the hidden layers usually employ nonlinear transfer functions: in this case the log-sigmoid function was used. The linear output neurons allow the outputs to take on any value, rather than be restrained to a specific range in contrast to outputs from the log-sigmoid function, which fall into the 0 to 1 range.

The number of output neurons is dependent on the ANN model used, which could be either a single-output network or a multiple-output network. Using the former means that several networks should be constructed in order to predict each of the output variables separately. Preliminary tests showed single-output networks do not improve

prediction accuracy to a significant extent. For the purpose of simplicity, a multiple-output network was used in this work, which means that the network has six output neurons, generating all the outputs simultaneously, i.e. flow rate, COD and ammonium concentrations for CSO discharges, and flow rate, BOD_5 and ammonium concentrations for treatment plant effluent.

ANN training

Network training is a process whereby connection weights and biases of the ANN are adjusted using pre-computed input–output training pairs and the ANN's performance in simulating the "correct" outputs is monitored by means of an error function, between simulated and pre-computed outputs for the same inputs. In this study, a root mean square of errors (RMSE) is used, which measures the generalised standard deviation between observed data and simulated network responses. It is expressed as

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(O_i - S_i)^2}$$

where O_i and S_i are observed and simulated data, respectively, and N is the total number of data. A RMSE of 0 represents a perfect match, with the performance of the network decreasing as RMSE increases.

The neural network toolbox in MATLAB 7.0 provides a series of alternative back-propagation algorithms, including the Levenberg-Marquardt algorithm, the conjugate gradient algorithm and the quasi-Newton algorithm. These algorithms were tested for the purposes of our work and the Levenberg-Marquardt algorithm was selected as the one that provides the best performance in terms of prediction of wastewater quantity and quality for the urban system. The learning rate and momentum constant in the case study were set as 0.01 and 0.9, respectively.

An important problem that the network may suffer from during the training process is underfitting or overfitting. The former indicates that the network had failed to fully detect the signal in the dataset and may result from too few hidden layers or neurons in the hidden layers. The network configuration should be adjusted to improve its performance. On the other hand, when the latter occurs,

the network is in effect trained to fit the noise as well as the signal and therefore its capacity to generalize when new data is presented is diminished. To prevent overfitting, an "early stopping" technique was used in this study. In this technique, the available data was divided into three subsets: training, validating and testing, in a ratio of 3:1:1, respectively. Each of the subsets was defined to fully represent the modelling domain, covering various rainfall events in terms of the total amount and maximum intensity. When training the network using the training subset, the error on the validating subset is monitored. The training stops when the validation error begins to increase. This is taken as an indication that the network begins to overfit the training data.

For the early stopping technique, it is important to ensure that the training algorithm does not converge too rapidly. The convergence of the Levenberg-Marquardt algorithm is controlled by several parameters: the Marquardt adjustment parameter mu, decrease factor mu_dec and increase factor mu_inc. When mu is large, the algorithm becomes gradient descent with a small step size. When mu is zero, it becomes Newton's method that is faster. During iteration, the value mu is multiplied by mu_dec when the ANN performance is reduced by a step and is multiplied by mu_inc whenever a step would increase the performance function. The algorithm is stopped if mu becomes larger than a specified maximum value. The following parameter settings were used in this research so that the convergence is relatively slow: $mu = 1$; $mu\_dec = 0.8$ and $mu\_inc = 1.5$ (Han *et al.* 2007).

RESULTS AND DISCUSSION

The method is demonstrated by a semi-hypothetical case study of the Vrbas catchment in Bosnia-Herzegovina. The river Vrbas is a tributary of the river Sava, which is the biggest tributary of the Danube. Vrbas drains a part of the northern slopes of Mount Dinara and its source is on the southern slope of Mount Varnica, at around 1,530 m above sea level. The river is approximately 235 km long and the catchment is 70 km wide and 150 km long, with an area of 6385 km^2. Figure 2 shows the location of the Vrbas
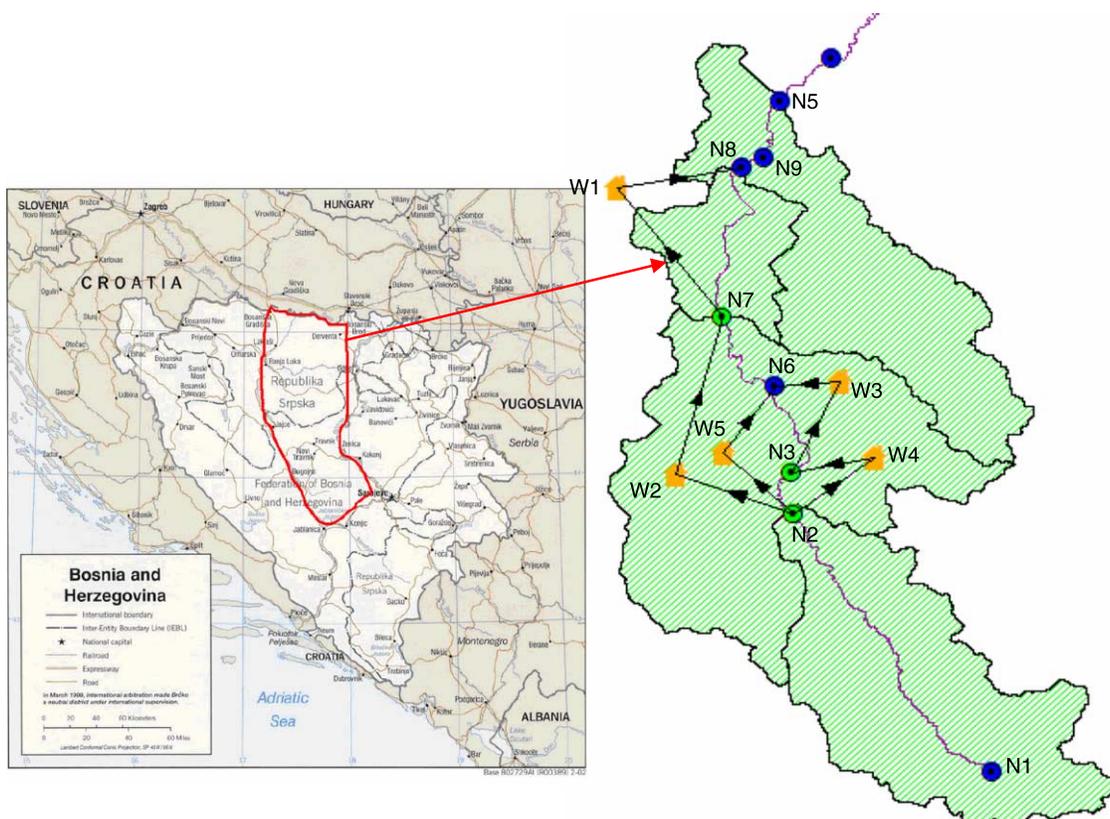
Figure 2 │ The Vrbas catchment: W1–W5 represent cities and N1–N9 river nodes where inflow or outflow occurs or parameters are measured.

catchment and its schematic representation, used in the MIKE BASIN catchment model.

The catchment has five major cities, one of which (W4) was chosen to demonstrate the approach discussed in this paper. Due to a lack of urban wastewater data for the specific city, an urban area originally adapted from the example of ATV (1992) and Schütze *et al.* (2002) was assumed to represent the city node W4. This city has an area of $7.5\,km^2$, which accounts for about 0.5% of the sub-catchment in which the city is located. A full catchment model has been developed and calibrated within a previous study (Ireson *et al.* 2006) and was used as a basis for embedding the surrogate urban wastewater model.

A two-year rainfall dataset, covering a wide range of seasonal variations, was available for network training, validating and testing. The time step in the record was originally 5 min and was aggregated to 1 h in order to save training time. The rainfall series include 120 rain events in total, which differed significantly in both the total rainfall amount and average/maximum intensity. About 75% of the

rainfall events had less than 9 mm in total amount, with a range of 1–25 mm, and about 75% of the rainfall events had less than 10 mm/h in maximum intensity within a range of 0.8–67.2 mm/h. Effort was made to ensure that the training subset covered the full range of total amount and maximum intensity.

The training process was stopped with a RMSE of 0.0122 when the validation error started to rise. The prediction results for the testing data subset are shown in Figure 3, in terms of two output variables: flow rate and ammonium concentration of treatment plant effluent. ANN predictions are in good agreement with the integrated model outputs in terms of treatment plant effluent flow. The prediction of ammonium concentration is slightly poorer at the beginning of the sequence, and this may result from the complexity and slow reactions in the underlying chemical and biological processes. This accuracy is, however, sufficient for applications within catchment models.

A linear regression analysis between the ANN predictions and SIMBA outputs was conducted to evaluate the
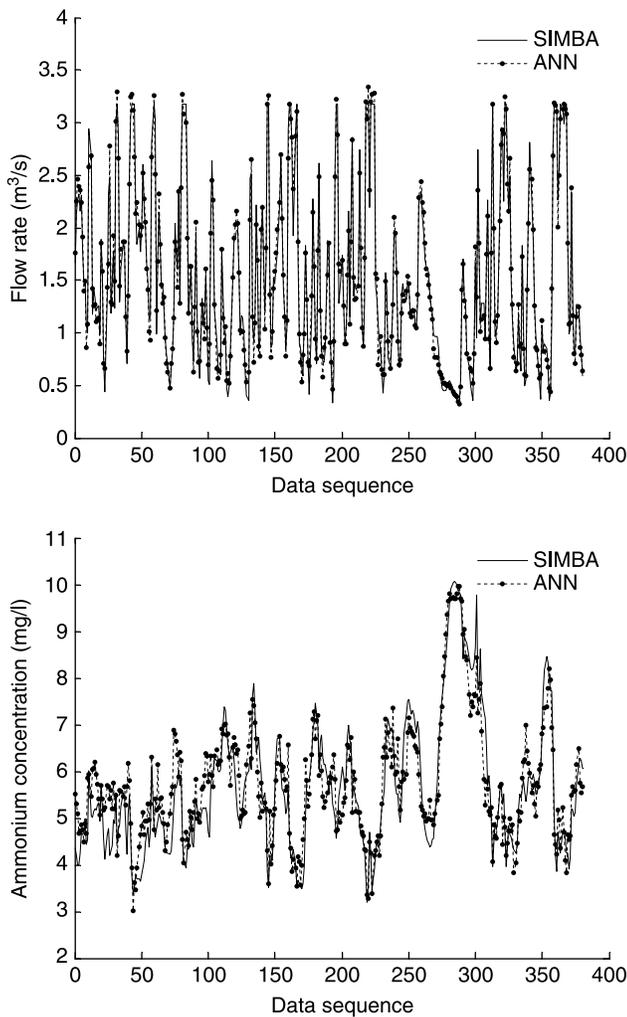
Figure 3 | ANN predictions of treatment plant effluent.

Figure 4 | Correlation between ANN predictions and SIMBA model outputs. Dotted line represents the perfect fit, i.e. ANN predictions (A) equal to targets (T).

ANN model performance, and the correlation coefficient (R) was calculated, as shown in Figure 4. The ANN model can provide an accurate prediction for the CSO flow and BOD_5 concentration of treatment plant effluent, with correlation coefficients R of 0.98 and 0.97, respectively. For comparison, Figure 4 also shows the perfect fit line, which would have been achieved if the predictions matched the targets exactly.

To incorporate the urban component into a catchment model, one important factor is the computational time required. The simulation was run on a P4 CPU 2.40 GHz PC. To run the validation dataset, the integrated model requires about 30 min: however, the ANN needs only 0.1 s. Considering the time required for ANN training, the total time for the ANN training and validation is about 2 min,
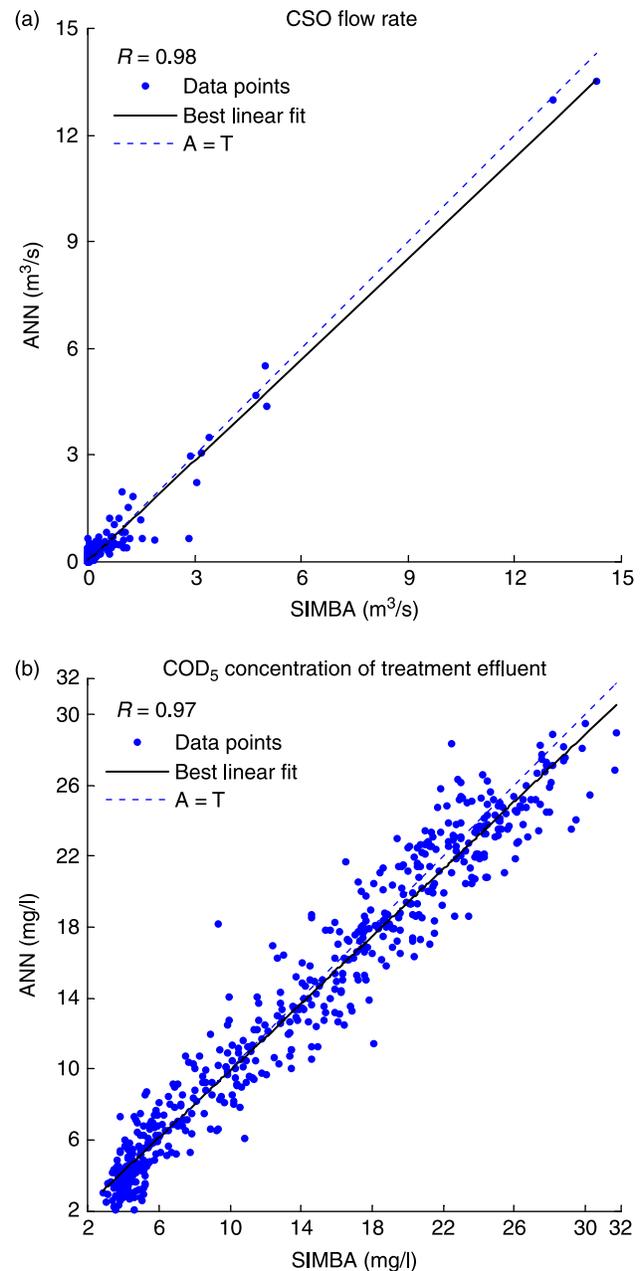
15 times faster than the integrated model run. It shows that the ANN has a great advantage over the physically based model and can improve computational efficiency significantly when linked to a catchment model.

The advantage of this computational edge of ANN would be more significant when multiple cities were to be simultaneously represented. In that situation, the ANN can

be trained using each city's historical dataset, and then used to embed that city in the catchment model, reducing the need to develop a different physically based model for each city. This has implications not only for computational time, but also for time associated with model development. It should be noted, however, that this last suggestion is only valid where the system itself (e.g. the infrastructure) does not change between the training and modelling periods and most importantly where adequate historical data exists to drive a comprehensive training process. Further, the ANN, like other empirical and statistical methods, has difficulties in extrapolation beyond the range of training data (Maier & Dandy 2000). Thus, its prediction efficiency can be reduced considerably when potential future situations are out of the range of historical data.

EMBEDDING THE ANN

To facilitate data exchange and synchronization between the ANN model and MIKE BASIN, an integrating interface was developed using Visual Basic for Applications (VBA) in the Microsoft Excel environment. The neural network model was implemented by using the ANN toolbox within MATLAB 7.0. Both MATLAB and MIKE BASIN provide an Excel link, allowing access to the models developed in these two environments from the Excel environment, which was used in this work as a user interface.

The main features of the graphical user interface are shown in Figure 5. The interface is divided into three sections: parameter setting, model run and results display. The parameter setting allows users to input the dataset for the ANN training and prediction, and to choose different training methods and window sizes for network training. Users can also decide which city to model and incorporated into the MIKE BASIN model simulation. For the multiple-cities case, the ANN should be trained and implemented for each city and the prediction results for all cities are then input into the MIKE BASIN model. A runoff parameter is used here to consider 'double counting' of runoff from urban areas, which would result from the drainage component of the integrated urban wastewater model and the runoff component of the catchment model both calculating runoff for the surface occupied by the urban
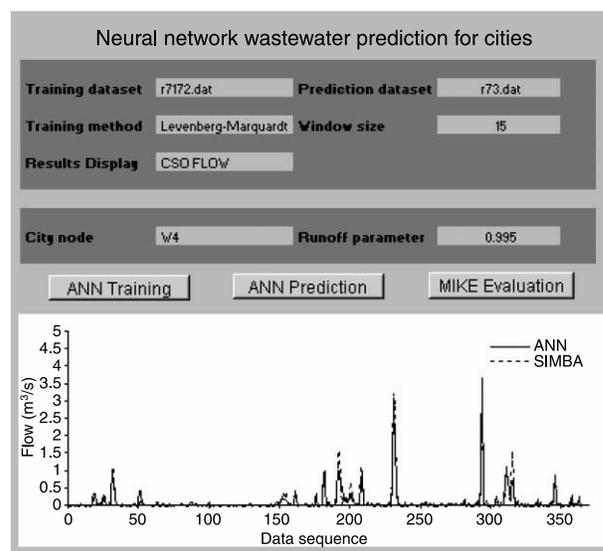

Figure 5 | Graphical user interface of the ANN predictions for city nodes.

area. This parameter may be interpreted as the ratio of the urban area to the sub-catchment, in which the city lies. The parameter is applied to the MIKE BASIN catchment model to deduct the runoff from urban areas. Three buttons are provided for ANN training, prediction and MIKE BASIN simulation, respectively. The results of ANN prediction are automatically displayed at the bottom of this interface upon the selection of an output variable.

The underlying information flow is feedforward, i.e. the predictive flow and pollutants from the ANN model are fed into MIKE BASIN to calculate water quantity and quality in the river, and no information is passed back to the ANN. The errors propagated to the catchment model are well constrained as the ANN has a high predictive accuracy. To compare this integrated approach with the original MIKE BASIN approach, the MIKE BASIN model was run using a rough approximation of an N removal treatment process associated with the city node (Makropoulos et al. 2006). The results were then compared with those of the MIKE BASIN/ANN integrated model. The same rainfall time series was used to drive both modelling set-ups.

Figure 6 shows a comparison of the results obtained for flow and DO concentration at Node N5 (see Figure 2) downstream of city W4. The flow rates at Node N5 from the two methods are almost the same. This is probably because the city outflow is not significant with regard to the runoff from the whole catchment and the river base flow
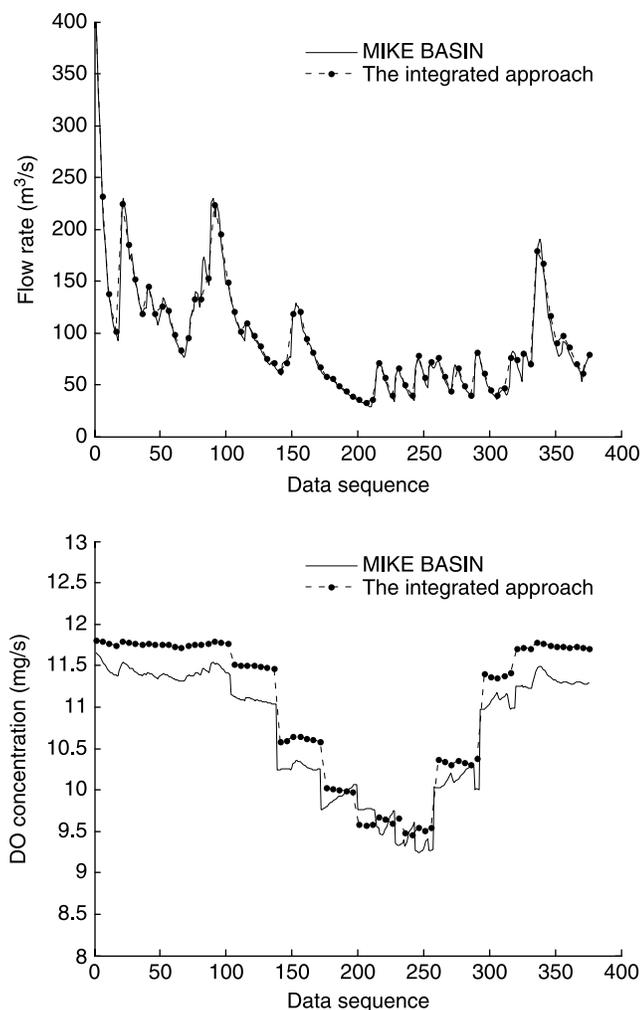
Figure 6 | Comparison results of flow and DO concentrations at downstream node N5.

(the city area is only 0.5% of the modelled sub-catchment). However, a clear difference is shown for DO concentration levels. In the original MIKE BASIN model, enhanced by the DSS reported in Makropoulos *et al.* (2006), only domestic wastewater is considered as "treated" and stormwater going into combined sewer systems is not taken into account. In the integrated approach, most of the stormwater flows into the treatment plant and only overflows (through the CSOs) when the treatment capacity is reached. Meanwhile, a "real" treatment is simulated, as opposed to some arbitrary reduction assumptions used in the original MIKE BASIN model, also contributing to a better water quality at Node N5. The DO concentrations from the integrated approach are smoother due to the effect of storage in the treatment

plant. Compared with the MIKE BASIN model, the proposed approach more accurately represent the characteristics of urban wastewater system outflow and thus improves simulation accuracy in the river.

CONCLUSIONS

Catchment-wide water management models usually lack a realistic urban component able to capture (some of the) complexities of the urban wastewater system. However, it is not practical to link a real integrated urban wastewater model to a catchment model due to high computational demands, particularly in long-term simulation or optimization situations. In this paper, an ANN model was developed to address this problem and was incorporated into a catchment model to allow for a better integration of the urban areas within a broad-scale modelling framework.

A feedforward back-propagation network was trained on the input–output data generated by an integrated urban wastewater model. The inputs include rainfall and dry weather flow, and the outputs considered are the quantity and quality in both CSO discharges and treatment plant effluent. Comparison of results between the integrated model and the ANN shows good agreement for both water quantity and quality parameters. Furthermore, the ANN proved to be much more efficient computationally, facilitating its incorporation into catchment models, in contrast to physically based urban wastewater models, even when ANN training time is taken into account.

An integrating interface was developed to link the ANN model with a MIKE BASIN catchment model and initial results are promising. It is suggested that ANN approaches have the necessary efficiency, accuracy and simplicity, which make them potentially useful for "embedding" urban wastewater systems and more accurately representing their characteristics within a truly integrated catchment modelling framework.

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