2004

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Publication Details

Mi, X., Sivakumar, M. & Hagare, D. (2004). A general review of applications of artificial neural network to water industry. In M. Mowlaei, A. Rose & J. Lamborn (Eds.), Environmental Sustainability through Multidisciplinary Integration (pp. 234-243). Australia: Environmental Engineering Research Event.

A GENERAL REVIEW OF APPLICATIONS OF ARTIFICIAL NEURAL NETWORK TO WATER INDUSTRY

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SUMMARY: This paper presents case studies of applications of artificial neural network (ANN) to water industry including water treatment, water quality and water consumption. Overall, ANN was found to be superior to time series and multiple regression analysis for most applications. At the same time, however, ANN is a data driven model, so care has to be taken in preparing data for ANN models. Limitations of the current ANN study to coagulant dosages in water treatment plants are presented and further ANN improvements in this field are in progress.

1. INTRODUCTION

Numerous researchers have studied various mathematical methods to develop predictive models for the water and chemical industries, and provide accurate and efficient forecasting methods. The main motivation behind this research is the desire and need to improve the forecasting accuracy. These methods mainly include time series analysis, multiple regression analysis and artificial neural network (ANN) model. Neural computing is one of the fastest growing areas of artificial intelligence. Neural nets are inherently parallel and they hold great promise because of their ability to "learn" non-linear relationships. Over time the practical application of ANN in the fields of hydrology, water resources engineering, water, wastewater treatment, and water quality has increased significantly. Almost all literatures in the field of ANN suggested that it is a more efficient predicting tool than any other. The performance of the application of ANN and other predicting models in water industry are reviewed in this paper by means of selected case studies.

2. CASE STUDIES

2.1 General review

ANN has been widely studied and applied to a variety of areas. One of these areas is forecasting time series. Tang et al. (1991) compared ANN and Box-Jenkins methodologies (time series analysis). They concluded that ANN models are robust and provide good long-term forecasting. These models represent a promising alternative approach to forecasting, but there are problems determining the optimal topology and parameters for efficient learning. Mirsepassi (1997) undertook comparison between ANN and Box-Jenkins model for predicting chemical dosing in a water treatment plant. The results indicated that the ANN models provided more accurate estimates for the alum and polymer dosages for 1 to 7 days ahead predictions than Box-Jenkins model. However, in the case of the polymer dosage, ANN performance deteriorated considerably for 6 and 7 days ahead forecasts. He concluded that this might be attributed to the very low numerical values obtained for polymer dosage.

Teodosiu et al. (2000) undertook research on neural network modelling for ultrafiltration and backwashing. Their studies present the development and exploitation of mathematical models based on artificial neural networks, trained with experimental data obtained in a laboratory scale ultrafiltration system. Two neural networks models were constructed to predict the flux at any time instant during ultrafiltration and after backwashing for arbitrary cycles, within the ultrafiltration-backwashing process. Based on the results obtained it was concluded that the artificial neural networks were trained to accurately describe both flux evolution during the ultrafiltration on hollow fibre membranes and to predict the initial permeate flux after the backwashing. The advantage of the models besides an accurate description of the global process, is that they may be adapted for very different operating of backwashing conditions, and influent qualities, provided that a sufficient number of relevant experimental tests are available for the training procedure. A very good prediction of flux at any time instant can be achieved using the ANN and this aspect is proved by the very small values of the relative errors obtained after training for both ultrafiltration and backwashing.

Patel (2000) applied the back-propagation ANN models to a water treatment plant in order to predict the coagulant dosage. Sensitivity analysis determined the most sensitive inputs for the models. The results showed improvement in the prediction after using the most sensitive inputs to prepare the models. The overall conclusion of this study is that the ANN is exceptionally good in predicting the coagulant polyaluminiumchloride (PACl) and polymer dosage.

This paper focuses on ANN applications review in the field of water treatment, water quality and water consumption industry. Although the results presented in this paper are for a particular case study, they provide a valuable guide for engineers and scientists who are currently using, or intend to use ANN models for the predictions or forecasting of environmental variables.

2.2 Water treatment case studies

Yu, et al. (2000) studied the application of ANN to control the coagulant dosing in a full-scale water treatment plant in Taipei city, Taiwan. They studied the feasibility of applying the ANN to automatically control the coagulant dosing in the water treatment plant. Five on-line monitoring variables including turbidity (NTU_{in}), pH (pH_{in}) and conductivity (Con_{in}) in raw water, effluent turbidity (NTUout) of settling tank and alum dosage (Dos) were collected every 15 minutes during the period of one year from this plant to build the coagulant dosing prediction model. Three types of model including regression model, time series model and ANN model were used to predict alum dosage. According to the results of this study, all the regression models produced a poor prediction on coagulant dosage. Both time series and ANN models produced good prediction results of the dosage. The ANN model using previously known coagulant dosage performed the best prediction of alum dosage with a R^2 of 0.97 and a very low average predicted error of 0.75 mg/L of alum. Table 1 shows the prediction results of ANN model using previously known coagulant dosage. It was found that all ANN models produced good results. High correlation coefficients with over 0.9 between predicted and observed coagulant dosages were found, which are little higher than those predicted by time-series models. Some multi-parameter ANN models were also developed to improve the accuracy of prediction of coagulant dosing. The ANN model A13 with multi-parameter of four-step-previous coagulant dosages, turbidity of raw water and turbidity of effluent performed the highest R^2 of 0.97 (Table1).

Table 1 - Predictions of coagulant dosing by ANN with previous coagulant dosages (Yu et al., 2000)

Model	Input layer	Training RMSE	Testing RMSE	R^2
A5	$Dos_{(t-1)}$	0.030	0.028	0.90
A6	$Dos_{(t-1,\ t-2)}$	0.027	0.027	0.91
A7	$Dos_{(t-1\ to\ t-4)}$	0.027	0.026	0.92
A8	$Dos_{(t-1\ to\ t-8)}$	0.028	0.027	0.91
A9	$Dos_{(t-1\ to\ t-16)}$	0.030	0.029	0.90
A10	NTU_{in}, $Dos_{(t-1\ to\ t-4)}$	0.027	0.026	0.93
A11	NTU_{in}, NTU_{out}, $Dos_{(t-1,\ t-2)}$	0.025	0.024	0.94
A12	NTU_{in}, NTU_{out}, $Dos_{(t-1\ to\ t-4)}$	0.026	0.022	0.95
A13	$NTU_{in\ (t-1\ to\ t-4)}$, $NTU_{out\ (t-1\ to\ t-4)}$, $Dos_{(t-1\ to\ t-4)}$	0.020	0.016	0.97

where: 1) "$Dos_{(t-1\ to\ t-4)}$" refers the alum dosage 15, 30, 45, 60 minutes before.
2) Therefore, model A13 has 12 input nodes in input layer.

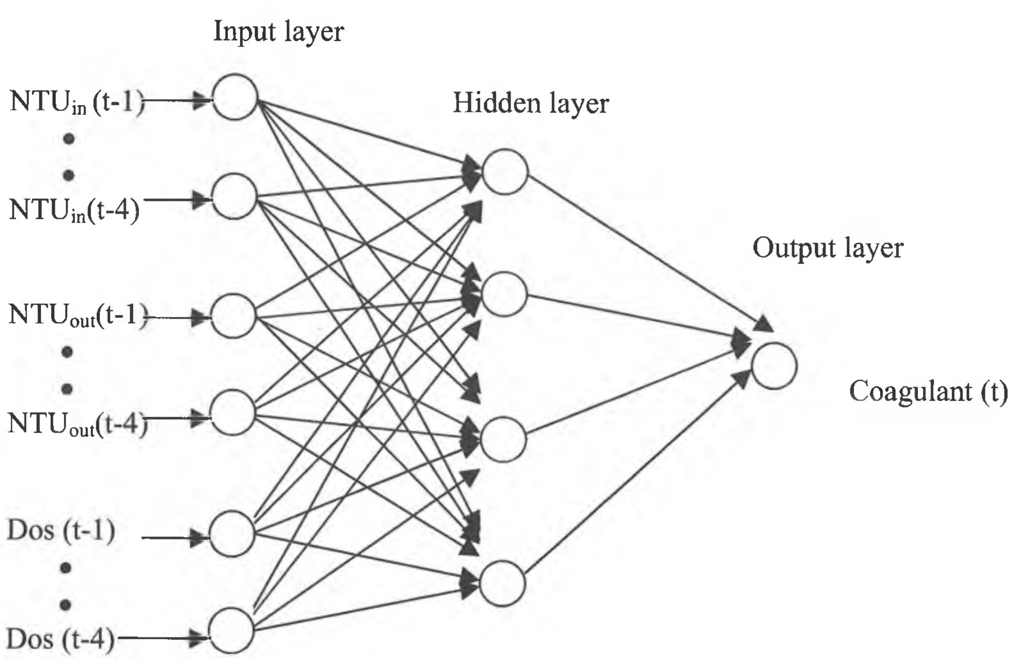

Figure 1. Architecture of the BPN model 13 (Yu et al., 2000)

The back-propagation network (BPN) was used in this study and demonstrated in Figure 1, which consists of three layers: one input layer, one hidden layer and one output layer. In this BPN model, the generalized delta learning rule was used as the training algorithm for network learning, and the gradient descent method was used to minimize the errors. Sigmoid function was used as activation function. Root mean square error (RMSE) was used to evaluate the performance of training and testing procedures.

Comparison of observed and predicted coagulant dosing by ANN model A13 is shown in Figure 2. Most of the coagulant dosages in this plant, approximately 97% are less than 30 mg/L of alum, and the predicted errors by model A13 are less than 1.2 mg/L of alum in this dosing range. In the range of below 15 mg/L, the predicted errors are less than 0.5 mg/L.

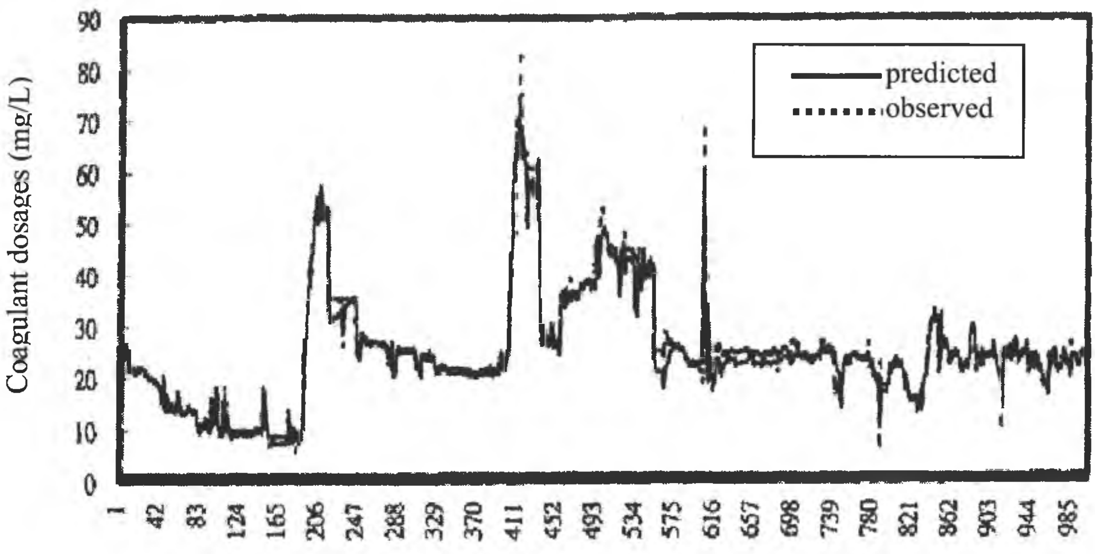

Figure 2. Comparison of observed and predicted coagulant dosing by ANN model A13 (Yu et al., 2000)

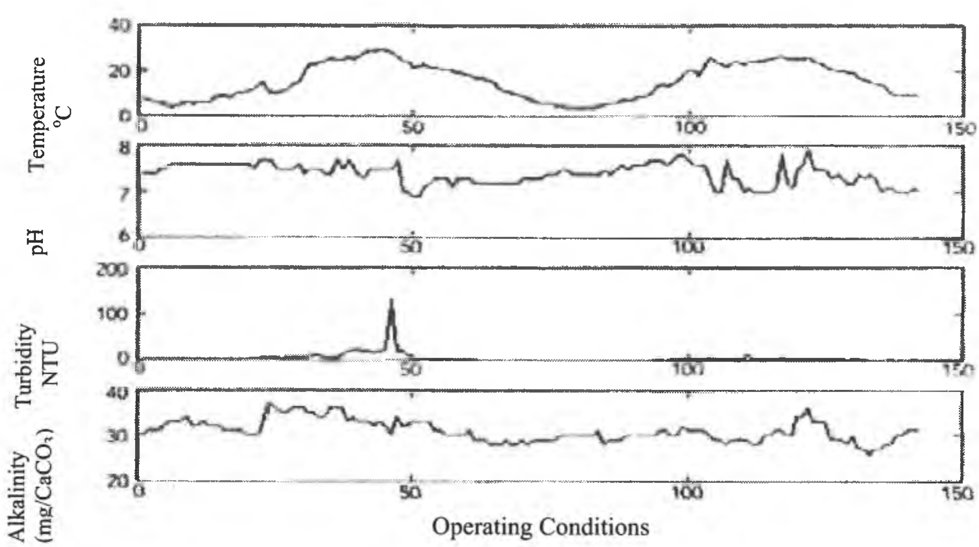

Figure 3. The water quality parameter changes of the learning data (Joo et al., 2000)

For promptly predicting required coagulant doses in response to water quality changes, a number of researchers have attempted to use the multi-variable regression (MVR) approach. However, the prediction capability of the MVR approach has not been satisfactory. Joo, et al. (2000) has attempted to predict the optimal coagulant dosing rate accurately and quickly using a widely-used ANN model called back-propagation network (BPN). As learning data for the ANN, two years' operating data of a water treatment plant were used. This plant has a capacity of 250ML/d and its raw water comes from a reservoir where the water quality undergoes seasonal changes. The learning data included one operational factor coagulant injection rate, and four raw water quality parameters such as temperature, pH, turbidity and alkalinity. From the historical 2-year data, 142 units of learning data were selected to represent the seasonal changes of temperature and drastic fluctuation of turbidity on rainy days (Figure 3). Another set of 72 units of data was used to verify the prediction capability of the developed ANN (Figure 4).

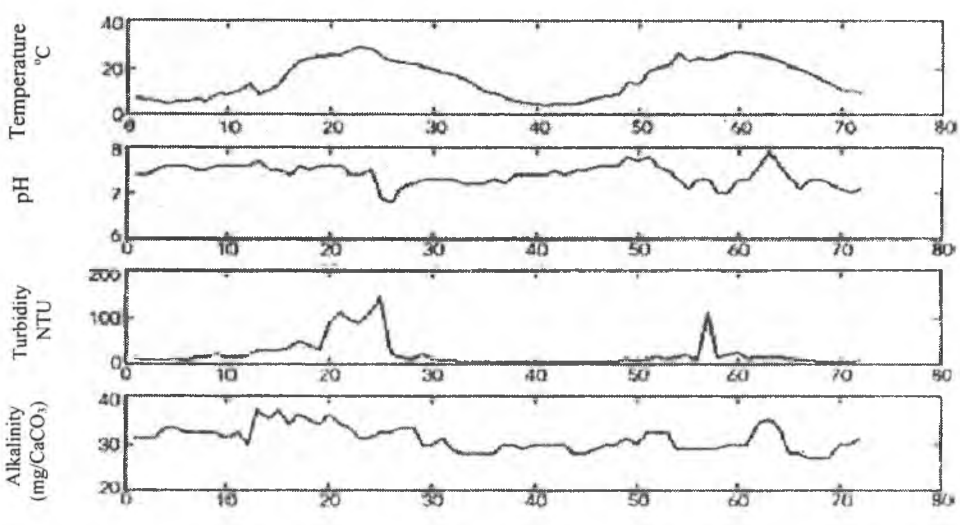

Figure 4. The water quality parameter changes of the computation phase (Joo et al., 2000)

To confirm the enhancement of the prediction capability of the ANN, MVR was conducted using the same historical data. The statistical program used for the MVR was MINITAB. The ANN used in this study is composed of three layers, one input layer, one hidden layer, one output layer. The number of artificial neurons in each layer is 5-10-1. The ANN was trained with learning data. The data not used in the training were then used to verify the performance of the trained ANN. The simulation was carried out by an ANN program coded in 'C' language at a workstation. A root-mean-square error (RMSE) was used as performance index to compare the prediction capability of the MVR equation and the ANN. The MVR equation which expressed relation between the coagulant dosing rate and the raw water quality parameters is as follows:

$$\text{Coagulant dosing rate} = -0.242 - 0.00708 * \text{temperature} - 0.0824 * \text{pH} + 0.00237 * \text{turbidity} + 0.0488 * \text{alkalinity} \quad (1)$$

The equation shows that turbidity and alkalinity have a positive effect of increasing the coagulant dosing rate; temperature and pH have a negative effect of decreasing the coagulant dosing rate. Figure 5 (top) represents the comparison of the real coagulant dosing rate and the predicted value calculated by MVR model. Figure 5 (bottom) shows the residual, which is equivalent to the real coagulant dosing rate (RCDR) minus the predicted value. The RMSE calculated from the real coagulation dosing rate and predicted value of MVR is 0.0143.

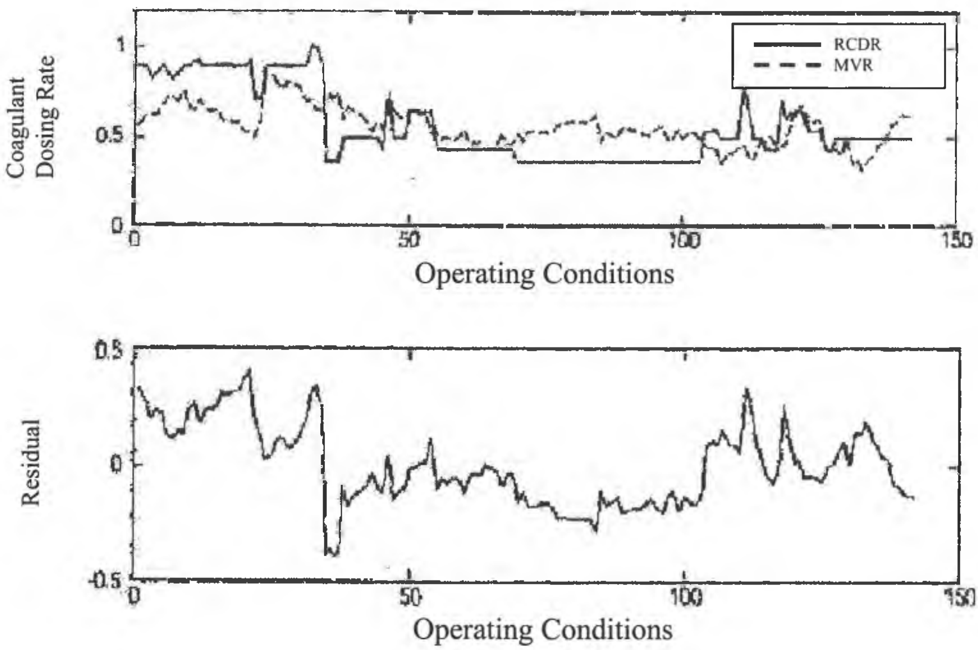

Figure 5. Comparison of predicted (MVR) and real coagulant dosing rate (RCDR) (top) and the residual (bottom) of multi-variable regression for data used (Joo et al., 2000)

The comparison result of the ANN for the real coagulant dosing rate and the predicted value of the ANN is shown in Figure 6 (top). Figure 6 (bottom) represents the residual of the real coagulant dosing rate and the predicted value of the ANN. The RMSE calculated from the real coagulant dosing rate and the predicted value of ANN is 0.0058. The RMSE for the two cases are summarized in Table 2.

As shown in Figures 5-6 and Table 2, the ANN has better prediction capability than the MVR from the viewpoint of RMSE value and residual range. When comparing the RMSE value, the ANN reduces the RMSE by 59% for the learning data. The prediction capability of the ANN is better than the MVR even during the period of a drastic change in the coagulant dosing rate. Therefore, this study concludes that ANN can be used for predicting optimum coagulant dosage when the feed-forward control algorithm is applied to cope with the raw water quality and operating condition changes. However, since ANN cannot reveal the direct mechanistic relationship between water quality parameters and required coagulant dosages, the training data must be prepared correctly in advance to derive a reliable ANN prediction.

From the above review of water treatment case studies we can see that ANN can play significant role in improving the performance of the water treatment plant as well as the quality of the water. At the same time, however, ANN is a data driven model, so care has to be taken in preparing data for ANN models.

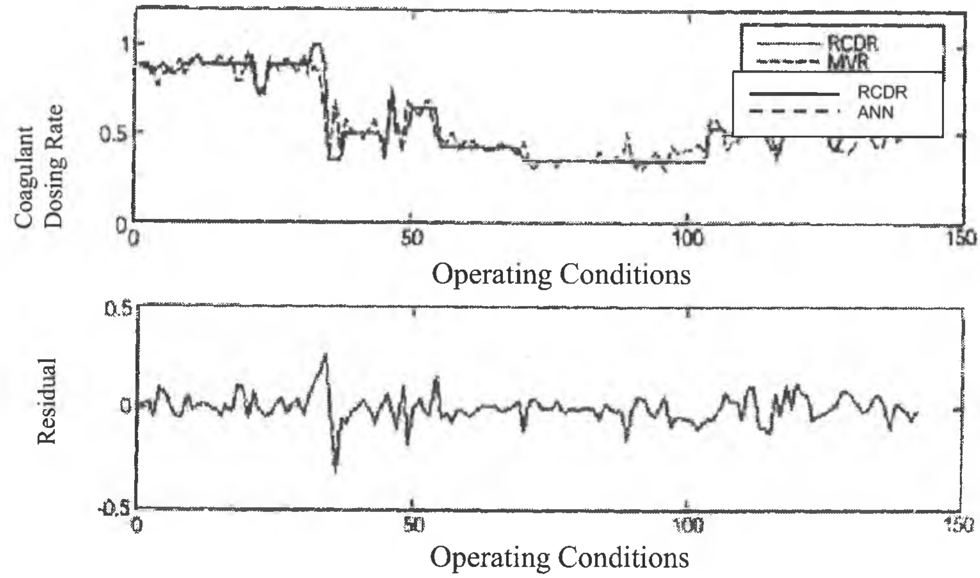

Figure 6. Comparison of predicted (ANN) and real coagulant dosing rate (RCDR)(top) and the residual (bottom) of the ANN for data used in the ANN training (Joo et al., 2000)

Table 2 RMSE and residual coagulant dosage of each prediction model in mg/L (Joo et al., 2000)

Prediction model	RMSE	Residual range
MVR (for the training data)	0.0143	(0.399, -0.388)
ANN (for the training data)	0.0058	(0.268, -0.326)

2.3 Water quality case studies

Maier and Dandy (1993) used a back-propagation network (BPN) to predict the salinity of the Murray River at Murray Bridge 14 days in advance. The data used included 5.5 years (1987-1992) of daily salinity, flow and water level readings at 12 locations. The ANN were trained with 4.5 years of data and tested using the remaining 1-year of data. Four different ANN models based on different training sets were used to predict the salinity for different years (1988, 1989, 1990 and 1991). Significance testing was first carried out to determine the significant inputs, which resulted in reducing the number of inputs, thereby speeding up training. The number of inputs was reduced from 141 to 51 and the number of outputs was 7. The performance of ANN was found to be very good. Predicted average absolute percentage error (AAPE) ranged from 4.7 % to 8.3 %. The ANN was able to forecast all major variations in the salinity as well as major sharp peaks, but had some difficulty predicting minor sharp peaks.

Maier and Dandy (1994,1995) used two procedures to determine the significant inputs to predict salinity in the River Murray at Murray Bridge. In the first method, the cross-correlation between the residuals of the output time series (salinity) and other component time series (water level and flow) were used. In the second method, the ANN models were developed using different training and testing data sets for the significance test. Both methods were used to obtain the inputs for an ANN model which in turn was used to predict salinity 14 days in advance. The results showed that both methods were suitable for obtaining the inputs to multivariate time series models without any prior knowledge regarding the time series. However, the method based on the ANN approach appears to be the most promising, as it is simpler, quicker to use and also has the ability to identify the critical inputs.

Moreover, BPN and ARIMA (Auto-Regressive Integrated Moving Average) models were developed by Maier and Dandy (1994,1995) to predict the salinity of the River Murray at Murray Bridge 1 and 14 days in advance. The AAPE for ANN and ARIMA models to predict 1 and 14 days in advance are shown in Table 3.

Table 3 Comparison of ANN and ARIMA models for AAPE (%) (Maier and Dandy, 1994,1995)

Model	1 Day in advance	14 Days in advance
ANN	2.3	10.9
ARIMA	1.1	12.1

The results indicated that the ANN performed worse than the ARIMA model for one day ahead forecasting but produced the better 14-day forecast. Moreover, the ANN model was simpler to operate, quicker to develop and the data did not need to be preprocessed by transforming it into stationary data. The ANN was also less sensitive to noise.

2.4 Water consumption case studies

An ANN was developed by Daniell (1991) in order to estimate water consumption for Canberra. Four input parameters, the monthly rainfall, the number of rainy days in a month, the monthly evaporation and the monthly average temperature were used to predict the average daily per capita water consumption for 1 month in advance. The ANN was trained using 10 years of data from 1975-1984 and tested for the years 1985 and 1986. The ANN and regression model results were compared. The results indicated that the ANN model performed considerably better than the regression model. Error estimates were not reported in the reference detailing this study.

Daniell (1991) also used an ANN model to estimate the magnitude of regional floods for the Australian Capital Territory (ACT) and compared the results with the regression method developed by Knee et al (1988). Ten catchment parameters which included area, slope, length, fall, precipitation, fractions of catchment under each land use (urban, rural and forest), annual series skew and partial series skew, were used as inputs to train a back-propagation network. The comparison between the two methods showed that the ANN average absolute percentage error (AAPE) value 3.9% was less than that obtained with the regression method (12.9%).

Forecasting models using ANN, multiple linear regression and time series methods were developed by Fleming (1993) to predict monthly water consumption in the Northern Adelaide Plains. Over 14 years of data was used for model training and testing, and included variables such as the month, rainfall in the current and previous months, monthly evaporation and number of days of rainfall during the month, and the price of water. The results indicated that the ANN provided more accurate and reliable per capita consumption prediction than both multiple and ARIMA models. The ANN and regression models demonstrated the ability to predict sudden changes in consumption whereas the ARIMA model could not predict sharp changes. The mean square errors for the ANN, multiple regression and ARIMA models were 1.29, 2.62 and 2.49 respectively. The seasonal patterns were predicted equally well by all three methods. However, ANN demonstrated an ability to provide improved forecasts with fewer input variables.

ANN in conjunction with the Box–Jenkins (BJ) approach has been demonstrated to model the monthly water consumption in Kuwait by BuHamra et al. (2003). The BJ approach was first used to predict the missing values of the monthly water consumption data from May 1990 to

December 1991 due to the Iraqi invasion of Kuwait. Once the unrecorded monthly water consumption was predicted, BJ approach was then used with the task of discovering the appropriate lagged variables or input nodes in the input layer of the neural networks. A supervised feedforward back-propagation neural network was then designed, trained and tested to model and predict water consumption from January 1980 to December 1999. It is interesting to note that the lagged or delayed variables obtained from the BJ approach and used in neural networks provide a better ANN model than the one obtained either blindly in blackbox mode as has been suggested or from traditional known methods, the average relative error for the training and testing data sets are reduced by 24%.

Domestic water use is generally the most important component of urban water consumption. Liu et al. (2003) applied ANN to model and forecast the water demand in urban areas. Results indicate that the WDF-ANN (water demand forecast using ANN) model offers an effective way to formulate domestic water demand in Weinan City in China. The model evaluation shows that the correlation coefficients are more than 90% both for the training data and the testing data.

3. CONCLUSIONS

A number of general conclusions can be drawn from ANN application case studies presented:

- Overall, ANN was found to be superior to time series and multiple regression for most applications.
- Consequently the application of ANN model to control the coagulant dosing is feasible in water treatment. Moreover, the ANN model is easy to develop and operate by comparison with time-series models.
- ANN structure plays an important role in determining the accuracy of predictions.
- ANN is relatively insensitive to data noise.

However, limitations of studies surveyed in this paper that are specific to coagulant dosages control in water treatment plants show that:

- Optimisation of the network structure has not been investigated.
- There is a lack of a more comprehensive analysis of these input parameters, which are critical to the coagulant dosages.
- None of the ANN models previously developed has used genetic algorithm (GA) to determine the significant input parameters for optimisation of ANN.
- The sensitivity of the particle count as a water quality parameter to coagulant dosages has not been investigated.

ACKNOWLEDGEMENTS

The financial support from Sustainable Earth Research Centre (SERC) of the University of Wollongong is gratefully acknowledged.

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