Drinking water quality and treatment: the use of artificial neural networks

C.W. Baxter, Q. Zhang, S.J. Stanley, R. Shariff, R-R.T. Tupas, and H.L. Stark

Abstract: To improve drinking water quality while reducing operating costs, many drinking water utilities are investing in advanced process control and automation technologies. The use of artificial intelligence technologies, specifically artificial neural networks, is increasing in the drinking water treatment industry as they allow for the development of robust nonlinear models of complex unit processes. This paper highlights the utility of artificial neural networks in water quality modelling as well as drinking water treatment process modelling and control through the presentation of several case studies at two large-scale water treatment plants in Edmonton, Alberta.

Key words: artificial neural networks, water treatment process control, water treatment modelling.

Résumé : Afin d'améliorer la qualité de l'eau potable tout en réduisant les coûts d'opération, plusieurs services d'eau potable sont en train d'investiguer dans le domaine des contrôles avancées de procédés et des technologies d'automatisation. L'utilisation de technologies basées sur l'intelligence artificielle, plus spécifiquement de réseaux neuronaux artificiels, augmentent dans l'industrie du traitement de l'eau potable puisqu'ils permettent le développement de robustes modèles non linéaires d'unités de procédés complexes. Cet article met en lumière l'utilité des réseaux neuronaux artificiels pour la modélisation de la qualité de l'eau de même que pour la modélisation et le contrôle des procédés de traitement de l'eau potable, et ce par le biais de plusieurs études de cas à deux usines de traitement de l'eau à large échelle à Edmonton, Alberta.

Mots clés : réseaux neuronaux artificiels, contrôle de procédés de traitement de l'eau, modélisation du traitement de l'eau.

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Introduction

The use of artificial neural networks for process modelling and control in the drinking water treatment industry is currently on the rise and is considered to be a key area of research. Over the past few years, joint efforts between researchers at the University of Alberta and EPCOR Water Services, the utility that provides drinking water for the City of Edmonton and surrounding communities, have produced a number of successful water quality and treatment process models and applications.

The purpose of this paper is to highlight the utility of artificial neural networks in water quality modelling as well as drinking water treatment process modelling and control through a review of these models and applications. More specifically, models for raw water colour, water demand, turbidity and colour removal through enhanced coagulation, water softening, and filtration performance will be reviewed.

Overview of artificial neural network modelling

General characteristics

The artificial neural network (ANN) technique is an artificial intelligence technique that attempts to mimic the human brain's problem solving capabilities. Artificial neural networks are capable of self-organization and learning; patterns and concepts can be extracted directly from historical data (Baxter et al. 1999). In general, artificial neural networks can be applied to the following types of problems: pattern classification, clustering and categorization, function approximation, prediction and forecasting, optimization, associative memory, and process control (Jain et al. 1996). When presented with data patterns, sets of historical input and output data that describe the problem to be modelled, ANNs map the cause-and-effect relationships between the model input data and output data. This mapping of input and output relationships in the ANN model architecture allows developed models to be used to predict the value of the model output parameter, given any reasonable combination of model input data, with satisfactory accuracy.

When applied to the drinking water treatment industry, the ANN technique holds several advantages over conventional modelling methods. With respect to data processing, the type of relationship between the input and output data is determined purely from the information presented, with no presumptions from the network (Harvey and Harvey 1998). In

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C.W. Baxter,[1] Q. Zhang, S.J. Stanley, R. Shariff, R-R.T. Tupas, and H.L. Stark. Department of Civil and Environmental Engineering, University of Alberta, Edmonton, AB T6G 2M8, Canada.
S.J. Stanley and R. Shariff. EPCOR Water Services, Inc., 10065 Jasper Avenue, Edmonton, AB T5J 3B1, Canada.

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[1] Corresponding author (e-mail: cwbaxter@ualberta.ca).

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addition, the ANN technique is fault-tolerant both in model development and in subsequent applications; discontinuities in the data, different levels of data precision, noise, and data scatter are easily accommodated (Foody and Aurora 1997). The technique is also extremely fast and flexible; advances in computing power have minimized the time required to develop models, as well as the time required to re-train models to incorporate new data and to reflect process modifications. In drinking water treatment, where process modifications can occur frequently, the ability to quickly modify process models is key. Artificial neural network process models can be developed without quantifying the micro-scale interactions that occur. In drinking water treatment, such interactions are often poorly understood, making it impossible to develop useful mechanistic process models. Finally, since ANN models are developed using full-scale operational data, the scale-up concerns commonly associated with bench-scale and pilot-scale empirical models are eliminated.

With respect to the disadvantages of the ANN modelling technique, many researchers consider the developed models to be “black-box” models, as ANNs do not yield explicit mathematical formulae (Harvey and Harvey 1998). In addition, little is known about the applicability of the models to data that lie outside the domain on which the models were trained. No set protocol for developing ANN models exists; each modeller may incorporate different modelling techniques. Finally, the ANN technique is data intensive and is best suited to problems where large data sets exist (Zhang and Stanley 1997). Current research efforts are aimed at eliminating or reducing the effects of these disadvantages to encourage the more widespread use of the ANN technique.

Components of artificial neural network models

There are seven major components to an ANN model, which are collectively known as the ANN architecture: (1) processing units or neurons; (2) a state of activation; (3) an output function for each neuron; (4) a pattern of connectivity or weights between units; (5) a propagation rule for propagating patterns of activities through the weights; (6) an activation function for combining the inputs impinging on a unit with the current state of that unit to produce a new level of activation for that unit; (7) a learning rule whereby weights are modified by experience (Rumelhart et al. 1986). Depending on the ANN software employed, some or all of these components may be adjusted or modified by the model developer.

Artificial neural network models are generally grouped into two broad categories, feed-forward networks and feed-backward networks, according to the pattern of flow of model input information within the architecture. In feed-forward networks, model input data is processed forward through the network in sequential fashion independent of previous input data. The network prediction error information may, however, be propagated in a backward direction through the network, as will be discussed. In feed-backward networks, recurrent loops exist within the architecture that permit the network to retain a short-term memory with respect to previous input information. Such information is incorporated into the current information processing, making feed-backward networks particularly useful for time-series modelling.

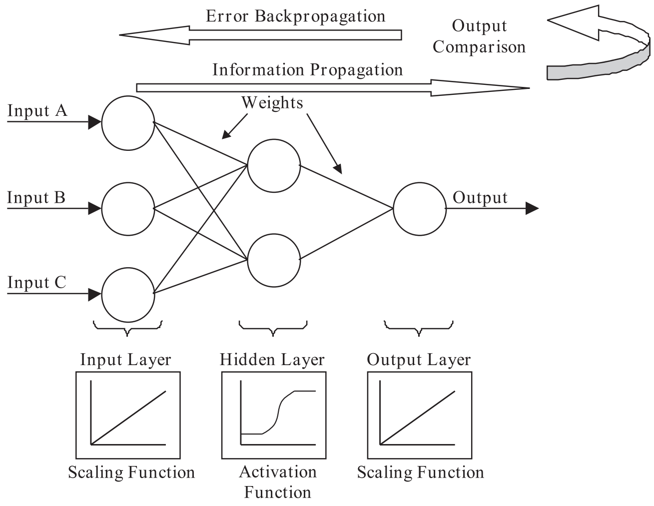
Artificial neural network learning

The ANN learning process for drinking water treatment process models, where one output parameter is being modelled, is a multiple-input single-output nonlinear optimization process. Artificial neural networks learn by reorganizing their internal structure according to a learning rule or algorithm to minimize the error between the actual output value and the model-predicted output value for the entire set of data patterns. A more complete description of the ANN learning process can be made by referring to Fig. 1, which depicts a three-layer feed-forward network with error back-propagation. This network, commonly referred to as a three-layer back-propagation network, is among the most often used architectures in process modelling. For the purposes of the current discussion, each data pattern consists of three input parameters and a single output parameter. Initially, input parameter information is scaled in the input layer, which has one neuron per input, according to a scaling function. Typical scaling functions are linear and scale the values of all the input parameters to a common range, generally 0 to 1. Each input layer neuron is connected to each of the hidden layer neurons by a connection weight. Weights are mathematical constructs that assign a numerical value to the weight or importance of the connection between neurons. The output from each input neuron is multiplied by the appropriate connection weight and the resulting products are transferred to the hidden layer neurons. In the hidden layer, each neuron sums the value of the incoming products and processes the sum through a predefined activation function, which defines the neuron’s state of activity. While many activation functions are possible, the logistic activation function generally produces the best results for process modelling applications. The logistic function is nonlinear and scales data to a range of 0 to 1. Output values from each of the hidden layer neurons are multiplied by the appropriate weights, as before, and the resulting products are transferred to the output layer. In the output layer, which has one neuron for each output parameter, each neuron sums the value of incoming products and maps the sum into an output value according to a predefined scaling function. The resulting model predicted value of the output is compared with the actual value of the model output parameter from the data pattern. The output units then backpropagate the prediction error back to the hidden layer according to a learning algorithm. Finally, the hidden layer units modify their incoming connection weights according to the learning algorithm to reduce the prediction error. The entire process is repeated for each data pattern in sequence until the ANN produces a sufficiently small error, as determined by the user, on a separate data set.

Applications of artificial neural network modelling in civil and environmental engineering

The first recorded use of ANN modelling in the field of civil and environmental engineering occurred in the early 1980s, when the technique was applied to the optimization of construction tasks (Flood and Kartam 1997). Since then, the number and diversity of applications has increased to include groundwater remediation (Garrett et al. 1992), hydrology and water resources engineering (Daniell 1991), wastewater treatment (Cote et al. 1994; Boger 1997), and air quality monitoring (Hasham et al. 1998). As suggested earlier, the

Fig. 1. Components of a simple back-propagation artificial neural network.



use of ANNs in the drinking water treatment industry is also on the rise. Applications other than those discussed in subsequent sections include trihalomethane formation and speciation (Hutton et al. 1996), alum and polymer dose forecasting in coagulation (Mirsepassi et al. 1995), source water salinity forecasting (DeSilets et al. 1992), and the prediction of residual chlorine in the distribution system (Rodriguez et al. 1997).

Model integration and process control

In water treatment plants, the completed models can be integrated into supervisory control and data acquisition (SCADA) systems through a number of proprietary Visual Basic and Microsoft Excel interfaces. These ANN interfaces serve as essential links between the ANN models and the SCADA system, process control and optimization applications, and end-users. Each online interface receives model input data, measured by online instruments, in real-time from the main SCADA computer. The model input data is processed through the ANN software's run-time module, which subsequently returns a model-predicted output value to the interface.

The numerous ANN interfaces can be classified into two groups according to their intended application: process optimization interfaces and virtual laboratory interfaces. The process optimization interfaces allow plant operators to optimize chemical costs and chemical doses online in real-time according to variations in influent water quality. The virtual laboratory interfaces are typically offline applications that use historical data and allow operators and other personnel to conduct virtual full-scale experiments to gain important insight into the factors affecting the unit processes. Alternatively, the virtual laboratory interfaces can be used for historical scenario analysis and in the training of new operators.

With respect to process control applications, ANNs can be incorporated into an internal model control scheme in either a direct or an indirect method (Psichogios and Ungar 1991). In the indirect method, the model is a process model trained to predict the output of the process, as previously discussed. As such, given the values of the process inputs and process control parameters, the model predicts the expected value of the process output. In the direct method, a process-inverse model is trained to predict the value of a process control parameter required to reach a target value of the process output. As such, given the values of the process inputs, the values of all but one of the process control parameters, and a desired value of the process output parameter, the model predicts the optimal value of a process parameter. Both the direct and indirect methods can be combined to develop a reliable automated process control system. In the context of water treatment process control, a desired value of the process output is selected and the process-inverse model is used to select the optimal dosing conditions required to meet the target. The process model is used to provide feedback error between the actual process output and the predicted value of the process output.

Water treatment plant description

EPCOR Water Services operates two surface water treatment plants (WTPs), E.L. Smith WTP and Rossdale WTP, with a total capacity of 520 $\mathrm{ML \cdot d^{-1}}$ to serve a population of 815 000 in Edmonton, Alberta and the surrounding communities. Both plants use conventional treatment and softening was practiced until May 2000. The E.L. Smith WTP is located on the western fringe of Edmonton, while the Rossdale WTP facility is located in the heart of the city, approximately 15 km downstream. Both plants use water from the North Saskatchewan River, which has its source in the Canadian Rocky Mountains and flows for approximately 500 km through aspen forest and agricultural land prior to reaching Edmonton. Due to substantial seasonal variations, in the North Saskatchewan River flow and ambient air temperature, the river water quality varies considerably. Raw water daily average turbidities range from approximately 2 NTU (nephelometric turbidity units) in winter, when the river is under ice cover, to over 1400 NTU during spring thaw. Similarly, raw water colour ranges from approximately 2 TCU (true colour units) to 80 TCU throughout the year.

Methodology

As was previously discussed, there is no standard protocol for the development of ANN models and applications. Each researcher approaches the model development stage in a slightly different fashion. The remainder of this section discusses the key and common aspects of model development, as determined collectively through the authors' modelling experiences.

Data requirements

Artificial neural network models are initially developed and trained using historical data. As previously mentioned, the ANN technique is data intensive; the quality of the developed models is highly dependent on the source data used. The main criteria used to specify the boundaries of a source data set is that it must be fully representative of the full spectrum of possible conditions to which the model will be applied. In modelling water treatment processes for plants that treat surface waters in temperate locales for example, the source data set should be selected to encompass at least one full year of data to ensure that the cyclical nature of the influent water quality is fully described.

Model development and evaluation

For the vast majority of the ANN models and applications discussed herein, a three-stage model development and evaluation methodology was employed. The source data analysis stage involves a statistical analysis of the data to be used in modelling. In the model development stage, candidate ANN architectures are first developed and then evaluated using a historical data set. Finally, where possible, the models are integrated into plant SCADA system to evaluate performance on a real time basis.

Source data analysis

To select the best data for modelling, a thorough analysis of the data must be performed. For each potential input or output parameter, the data accuracy and frequency is ascertained. A descriptive statistical analysis is also used to identify the mean, standard deviation, distribution, and range of the data, as well as variations on a daily or seasonal basis.

Model development

Successful model development involves the optimization of a multitude of modelling parameters. Whereas the number of parameters and optimization routines vary according to the model developer, the following are generally considered to be the most important; selection of model input data and output data, selection of appropriate data patterns, organization of data patterns into multiple data sets, determination of the internal network architecture, and evaluation of candidate models. A complete description of each of these modelling parameters is presented by Stanley et al. (2000).

Online model evaluation

Once the best candidate historical model has been selected, its performance can be evaluated online in real-time through integration with the plant SCADA system. As previously discussed, Visual Basic and Microsoft Excel interfaces receive model input data, measured by online instruments, in real-time from the main SCADA computer. The model input data is processed through the ANN model's run-time module, which subsequently returns a model-predicted output value to the interface. By comparing the model predicted value to the actual process output online in real-time over a set period of time, the suitability of the model for process control applications can be determined.

Data handling and software

All models were developed using historical data obtained from the EPCOR Water Services SCADA historian. Pentium-class PCs with Windows NT v4.0 operating systems were used to run the NeuroShell 2 ANN software from Ward Systems Group, Inc. of Frederick, Maryland, U.S.A.

Discussion of developed models and applications

Water quality and demand models

Colour in the North Saskatchewan River

In 1995, an ANN model was developed to predict the colour in the North Saskatchewan River, the source water for both of EPCOR Water Services' water treatment plants, 24 h in advance. Changes in the quality of the North Saskatchewan River, both on a daily and a seasonal basis, greatly impact conventional treatment processes. During summer storm events, as well as during spring thaw, the influent water quality parameters such as colour can vary by several orders of magnitude in a single day. The goal of the model was to provide plant operators with an early warning system for raw water quality changes and, therefore, improve treatment efficiency during quality fluctuations. A complete description of the project is presented in (Zhang and Stanley 1997).

A total of five years of daily average data, from 1990 to 1994, were used to develop and evaluate the model. The best model was developed using eleven input parameters, as listed in Table 1.

The raw water quality parameters are used to identify current river water quality conditions. The time series parameters, consisting both of lag parameters and rate of change parameters, are used to represent the time-series correlation between successive colour measurements. The lag parameters measure the difference in the value of a parameter over a defined time span; lag-2 parameters, for example, measure the difference between the current value and that of 2 days ago. The environmental parameters are those that measure rainfall and the cumulative number of temperature degrees above the freezing threshold since the beginning of the year. Both of these parameters assist the model in determining colour contributions due to spring thaw and runoff. Finally, the index parameters allow the model to establish a seasonal baseline. Each index parameter can have a value of either 0 or 1. During springtime, when river water colour is due primarily to runoff, the spring index will have a value of 1 whereas the summer index has a value of 0. In the summer, when river water colour is due primarily to rainfall and subsequent runoff, the summer index will have a value of 1 and the spring index will have a value of 0.

When applied to the 1994 data set, which was reserved for model evaluation and was not used in model development, the trained model forecasted raw water colour at the Rossdale WTP intake 24 h in advance with a mean absolute error of 0.62 TCU and an r^2 value of 0.94. Since development, the model has been successfully used to forecast raw water quality at Rossdale WTP. Operators are better able to anticipate large fluctuations in source water quality and are able to adjust process operations accordingly.

Water demand forecasting

In 1999, An ANN model was developed to predict daily and 12-day water demands for the City of Edmonton. A 24-h profile prediction method was also developed, which was accomplished by normalizing the data. In the water treatment industry, the cost of electricity for the pumping of water in distribution systems accounts for a large portion of the operating budgets of many water utilities. In Alberta and many other locations in North America, there is currently a move toward the deregulation of the power industry. This will lead to changes in rate structures that potentially could affect water utilities. As a result, there is a need for water utilities to better understand their power usage and pumping requirements, which are primarily based on demand. This understanding can be used to optimize power usage by taking advantage of the rate structure to reduce power costs.

Table 1. Model input parameters for the prediction of raw water colour.

Parameter	Classification
River flow rate ($m^3 \cdot s^{-1}$)	Raw water quality parameter
Colour at Rossdale WTP intake (TCU)	Raw water quality parameter
Lag-1 river flow rate ($m^3 \cdot s^{-1}$)	Time series parameter
Lag-1 colour at Rossdale WTP intake (TCU)	Time series parameter
Colour change rate ($TCU \cdot d^{-1}$)	Time series parameter
Lag-1 turbidity at Rossdale WTP intake (NTU)	Time series parameter
Lag-2 turbidity at Rossdale WTP intake (NTU)	Time series parameter
Rain precipitation (mm)	Environmental parameter
Temperature degree day (°C, 0°C threshold)	Environmental parameter
Spring index	Index parameter
Summer index	Index parameter

Note: abbreviations: NTU, nephelometric turbidity unit(s); TCU, true colour units(s); WTP, water treatment plant.

Table 2. Model input parameters for water demand forecasting models.

Daily water demand	Twelve-day water demand
Minimum daily temperature (°C)	Minimum daily temperature (°C)
Maximum daily temperature (°C)	Maximum daily temperature (°C)
Previous day of rainfall (mm)	Previous day of rainfall (mm)
Previous 5 days of rainfall (mm)	Previous 5 days of rainfall (mm)
Previous 30 days of rainfall (mm)	Previous 30 days of rainfall (mm)
Summer index	Summer index
Weekday or weekend index	Weekday or weekend index
Water demand from 9:00 to 10:00 a.m.	

The daily and 12-day water demand models were developed using 27 months of hourly and daily data. The model inputs consist of meteorological parameters and index parameters (Table 2). The input parameters were chosen based on the availability of forecasted meteorological parameters and the significance of the parameter as it pertains to water demand. To account for seasonal and weekly fluctuations in demand, summer index and weekday or weekend index parameters were included in model development. In the daily water demand model, the water demand from 9:00 to 10:00 a.m. was included to set a demand baseline prior to the development of the daily pumping schedule, which is produced daily at 10:30 a.m. by EPCOR Water Services.

The 24-h water demand model was developed by normalizing the data and grouping similar demand profiles into categories, based on the value of water demand. The appropriate 24-h demand profile is then superimposed on the predicted daily water demand to obtain the hourly water demand.

The daily model was tested on an independent data set, reserved for model evaluation, that had a mean water demand of 324 $ML \cdot d^{-1}$. The 3-layer back-propagation model yielded an r^2 value of 0.90 and a mean absolute error of 8.1 $ML \cdot d^{-1}$. These results are represented graphically in Fig. 2. The 12-day model was tested using all 27 months of water demand data and 30 year averaged meteorological data as the input values. An r^2 value of 0.49 and a mean absolute error of 16.5 $ML \cdot d^{-1}$ were achieved. It is expected that the 12-day model performance will improve when used in conjunction with actual weather forecasts for the first 5 days, which is currently being verified. The 30 year averaged meteorological data will continue to be used for the last 7 days.

The water demand models were developed for EPCOR Water Services to be used as an aid to the operators in setting up a pump schedule. The forecasts will also be used for predicting the quantity of water that will need to be treated in the near future and for scheduling regular maintenance.

Process models

Colour removal through coagulation

In 1998, ANN models for the removal of colour by enhanced coagulation at the Rossdale WTP and E.L. Smith WTP were developed. Colour is used by EPCOR Water services as a surrogate for natural organic matter, the prime precursor for the formation of disinfection by-products. As more stringent requirements for the removal of disinfection by-products are developed, plant operators will need more advanced tools to achieve disinfection by-product reductions. The main goal of this project was to provide such a tool to the operators at both treatment facilities. The project is described in-depth by Stanley et al. (2000).

The models were developed using three years of full-scale water treatment plant data. The model inputs, of which there are twelve, are listed in Table 3. The input data consist of raw water quality, operational, and time-series data. Input parameters were selected based on data availability as well as the likelihood of there being a cause-effect relationship between the candidate input and the model output, clarifier effluent colour.

When the completed models were applied to previously unseen data, they predicted the clarifier effluent colour with a mean absolute error <0.32 TCU. This result is less than the error associated with the instrument used to measure colour in the clarifiers. The models were also tested online during a spring thaw in 1998, when model predictions were compared with actual clarifier effluent colour on an hourly basis. For both facilities, mean absolute errors <0.35 TCU were obtained.

The models are used by the plant operators as tools for indirect process control. Multiple-parameter graphical and tabular applications that use model-generated data allow for an iterative determination of the appropriate doses of alum, powdered activated carbon, and polymer, as well as the appropriate operating conditions required to achieve a desired effluent quality for the entire spectrum of influent water quality conditions without using bench scale tests. In addition to process control applications, the completed models

Fig. 2. Model results for daily water demand model.

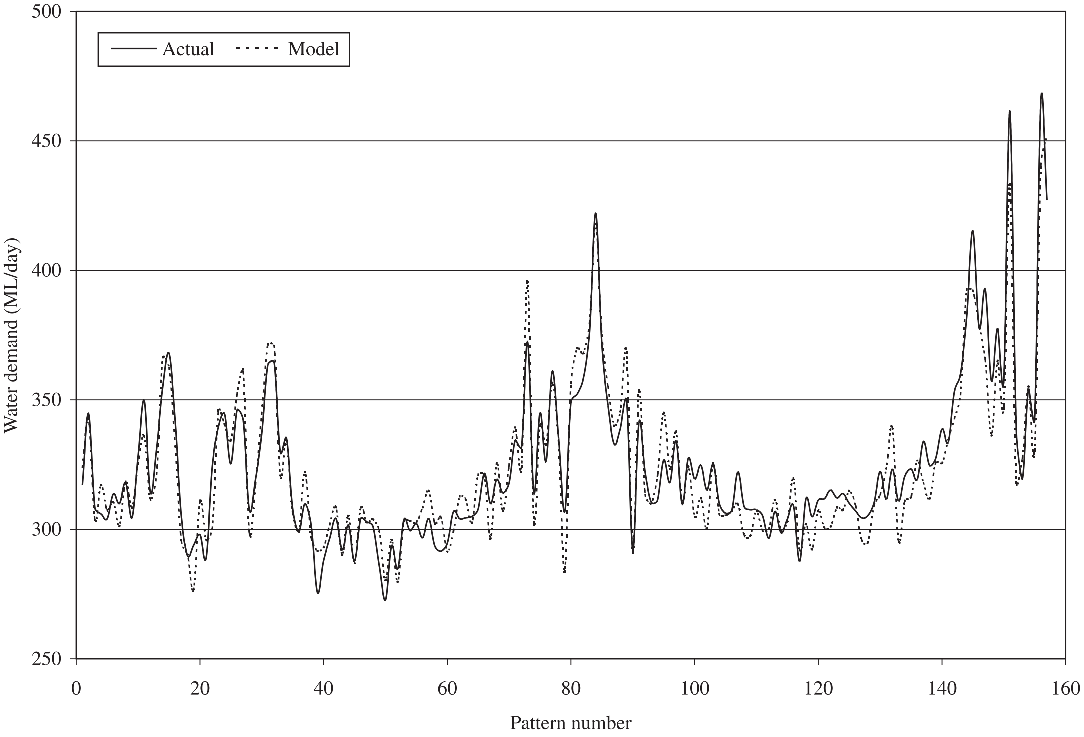


Table 3. Model input parameters for colour removal by coagulation.

Parameter	Classification
Influent pH	Raw water quality parameter
Influent turbidity (NTU)	Raw water quality parameter
Influent water temperature (°C)	Raw water quality parameter
Influent colour (TCU)	Raw water quality parameter
Influent hardness (mg·L^{-1} as $CaCO_3$)	Raw water quality parameter
Influent alkalinity (mg·L^{-1})	Raw water quality parameter
Alum dose (mg·L^{-1})	Process parameter
PAC dose (mg·L^{-1})	Process parameter
Polymer dose (mg·L^{-1})	Process parameter
Overflow rate (m^3·d^{-1})	Process parameter
Lag-1 influent turbidity (NTU)	Time-series parameter
Lag-1 influent colour (TCU)	Time-series parameter

Note: abbreviations: NTU, nephelometric turbidity unit(s); PAC, powdered activated carbon; TCU, true colour units(s).

can be used as a virtual full-scale laboratory to provide insight into the enhanced coagulation process. The effects of simultaneously changing multiple input parameters on the removal of natural organic matter can be assessed without the added costs and scale-up concerns associated with bench-scale and pilot-scale experiments.

Turbidity removal through coagulation

In conjunction with the models for the removal of colour through coagulation, models were developed for the removal of turbidity at the Rossdale WTP and E.L. Smith WTP in 1998. The goal of this project was to develop tools that could be used by plant operators to predict both the clarifier effluent turbidity for a given combination of raw water quality and operations information, as well as predict the appropriate alum dose required to produce a given quality of effluent. As such, both process models and inverse process models were developed. A complete description of the project is presented by Stanley et al. (2000).

All models were developed using three years of daily average data from the EPCOR Water Systems SCADA historian. The input parameters used for each of the model types are presented in Table 4. The input data for the process model, which predicts clarifier effluent turbidity, are similar

Table 4. Model input parameters for turbidity process and inverse process models.

Inputs for process models	Inputs for inverse process models
Influent pH	Influent pH
Influent turbidity (NTU)	Influent turbidity (NTU)
Influent water temperature (°C)	Influent water temperature (°C)
Influent colour (TCU)	Influent colour (TCU)
Influent alkalinity (mg·L^{-1})	Influent alkalinity (mg·L^{-1})
Lag-1 influent colour (TCU)	Lag-1 influent colour (TCU)
Lag-1 influent turbidity (NTU)	Lag-1 influent turbidity (NTU)
Lag-1 influent alkalinity (mg·L^{-1})	Lag-1 influent alkalinity (mg·L^{-1})
Alum dose (mg·L^{-1})	PAC dose (mg·L^{-1})
PAC dose (mg·L^{-1})	Overflow rate (m^3·d^{-1})
Overflow rate (m^3·d^{-1})	Clarifier effluent turbidity

Note: abbreviations: NTU, nephelometric turbidity unit(s); PAC, powdered activated carbon; TCU, true colour units(s).

Table 5. Model input parameters for softening models.

Clarifier effluent total hardness model	Lime dose model
Raw water temperature (°C)	Raw water temperature (°C)
Raw water pH	Raw water pH
Raw water total hardness ($mg{\cdot}L^{-1}$ as $CaCO_3$)	Raw water total hardness ($mg{\cdot}L^{-1}$ as $CaCO_3$)
Raw water alkalinity ($mg{\cdot}L^{-1}$)	Raw water alkalinity ($mg{\cdot}L^{-1}$)
Plant flow rate ($ML{\cdot}d^{-1}$)	Plant flow rate ($ML{\cdot}d^{-1}$)
Alum dose ($mg{\cdot}L^{-1}$)	Alum dose ($mg{\cdot}L^{-1}$)
Lime dose ($mg{\cdot}L^{-1}$)	Effluent total hardness ($mg{\cdot}L^{-1}$ as $CaCO_3$)
Softening clarifier effluent pH	Softening clarifier effluent pH

Fig. 3. Model results for softening process inverse model.

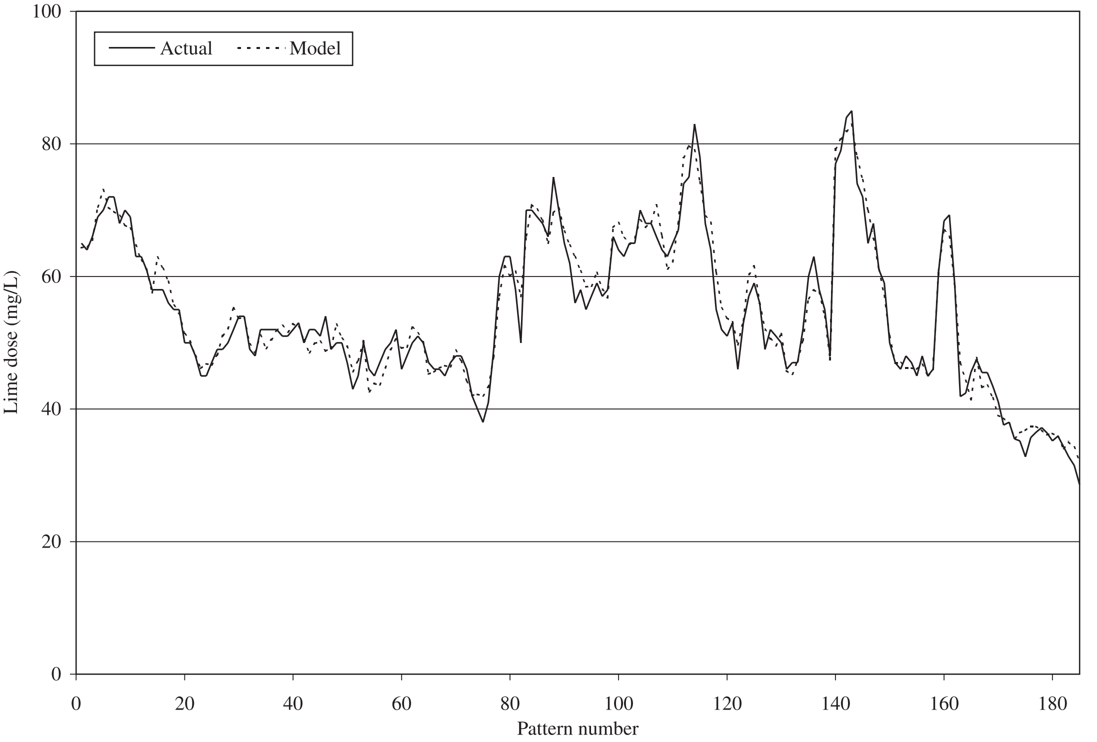


Table 6. Model input parameters for filter effluent particle count models.

Inputs for Process Models	Classification
Influent pH	Raw water quality parameter
Influent turbidity (NTU)	Raw water quality parameter
Influent water temperature (°C)	Raw water quality parameter
Influent alkalinity ($mg{\cdot}L^{-1}$)	Raw water quality parameter
Influent hardness ($mg{\cdot}L^{-1}$ as $CaCO_3$)	Raw water quality parameter
Plant flow ($ML{\cdot}d^{-1}$)	Process parameter
Alum dose ($mg{\cdot}L^{-1}$)	Process parameter
Polymer dose ($mg{\cdot}L^{-1}$)	Process parameter
PAC dose ($mg{\cdot}L^{-1}$)	Process parameter
Lime dose ($mg{\cdot}L^{-1}$)	Process parameter

Note: abbreviation: NTU, nephelometric turbidity unit(s); PAC, powdered activated carbon.

to those used for the colour models and include raw water quality parameters, operational parameters, and time series parameters. For the inverse process model, the clarifier effluent turbidity becomes an input parameter and the alum dosage becomes the sole output parameter.

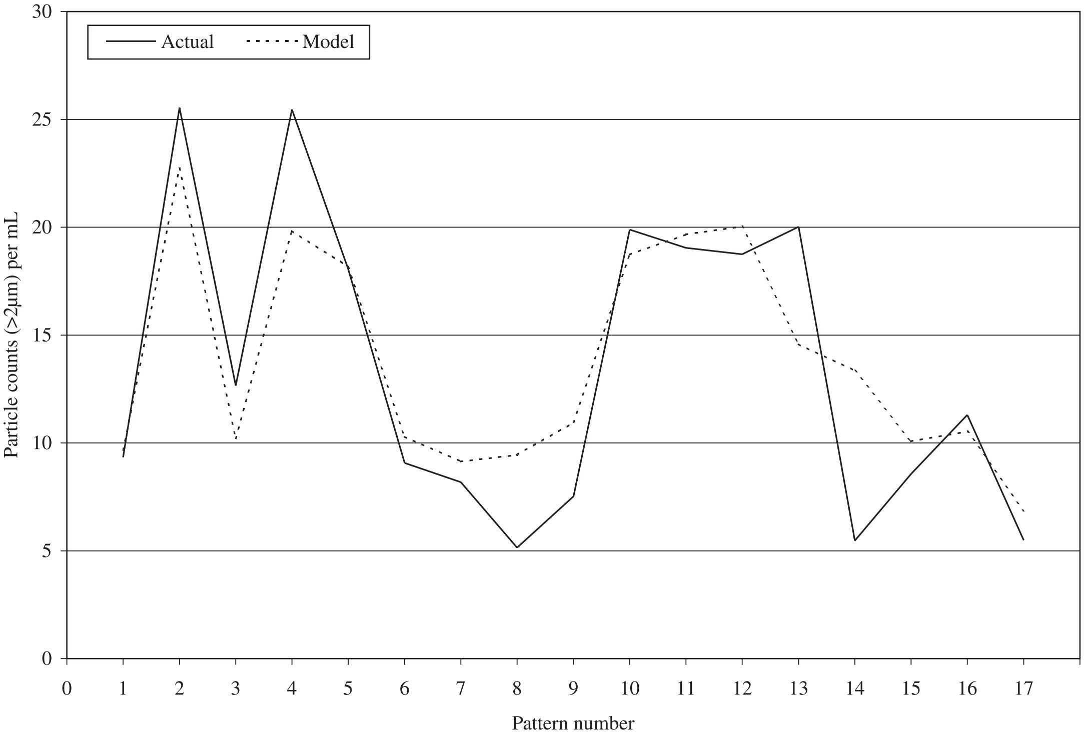
When applied to previously unseen data, the completed process models predicted clarifier effluent turbidity with a mean absolute error <0.77 NTU. The inverse plant model, used to predict the alum dose required to achieve a desired value for clarifier effluent turbidity, predicted the alum dose with a mean absolute error <1.8 $mg{\cdot}L^{-1}$. Once again, the developed models are currently being used online to supplement the results of bench-scale tests for the selection of operational characteristics. The models are also being used to provide greater insight into particulate removal by enhanced coagulation through virtual experimentation.

Softening

In 1997, ANN models were developed for the softening process at Rossdale WTP. The specific goals of the models were to estimate the total hardness in the softening clarifier effluent as well as the softening lime dose requirements.

At the Rossdale WTP, partial softening was carried out in the second cross-flow clarifier of each plant where slaked

Fig. 4. Model results for filter effluent particle counts model.



lime slurry as well as an anioinic polymer was injected upstream of the tapered flocculation section of the clarifier. The process incorporated solids recycling, as it greatly improved both the efficiency of the reaction and the effluent turbidity. Typically, the goal of the softening process was to maintain a mean effluent hardness of 135 mg·L^{-1} (as $CaCO_3$).

Two separate ANN models were developed to meet the project needs previously outlined; a process model that predicts clarifier effluent total hardness, and a process inverse model to predict an appropriate lime dose. A list of the input parameters for each model is presented in Table 5.

For each model, the input data consisted of raw water parameters, process parameters, and process effluent parameters. The raw water parameters, such as pH and alkalinity, serve to describe the quality of the plant influent. The process parameters, such as plant flow and lime dose, are those which can be adjusted by plant operators to improve process efficiency. The process effluent parameters provide information concerning the level of treatment provided by the clarifier. Models were developed using over 8 months of daily average historical operational data, spanning January to August 1997. This time-frame was selected to encompass the full range of operational conditions at the Rossdale WTP facility.

When applied to a previously unseen data set, the feedforward process model predicted clarifier effluent total hardness with a mean absolute error of 2.7 mg·L^{-1} (as $CaCO_3$) and an r^2 value of 0.84. The process inverse model predicted the lime dose with a mean absolute error of 2.0 mg·L^{-1} and an r^2 value of 0.95. The results for the process inverse model are depicted graphically in Fig. 3.

The completed models were used in scenario analysis and for monitoring softening in real-time on the Rossdale WTP SCADA system. Process operators could use the process inverse model to determine the optimal lime dose given any combination of raw water conditions and a target softening clarifier effluent total hardness.

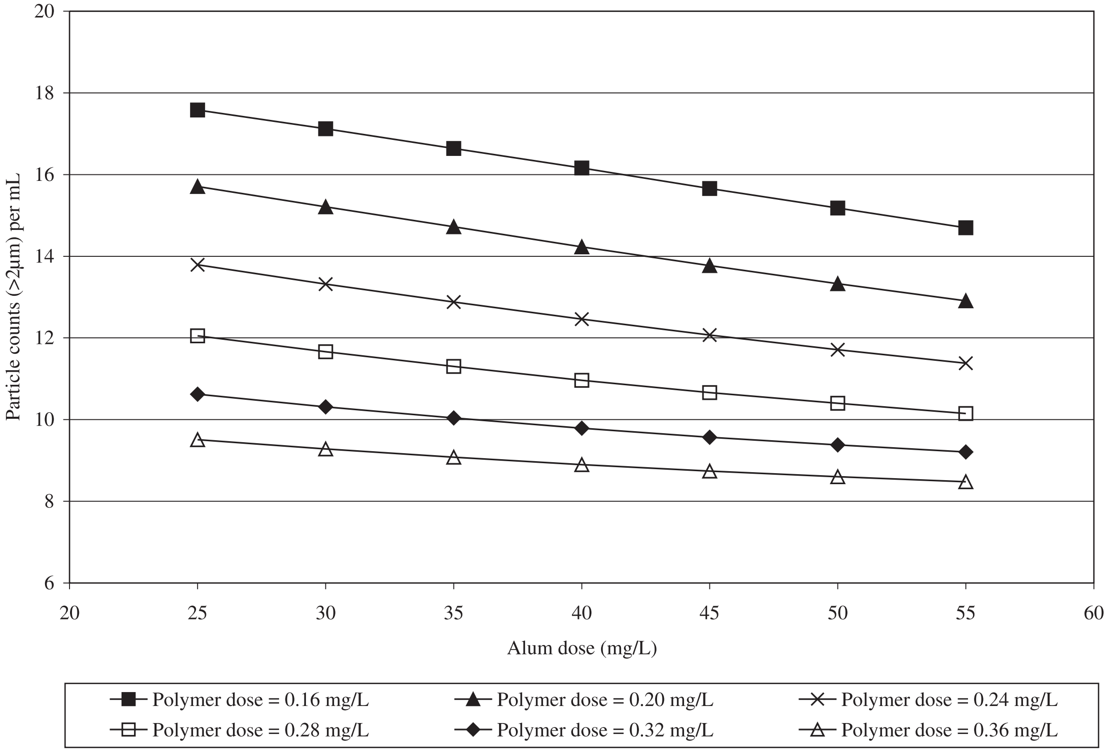
Filtration performance

In 1999, an ANN model for the prediction of filter effluent particle counts (>2 μm·L^{-1}) at E.L. Smith WTP was developed. One of the main goals in water treatment is the removal of particulate matter in that it is related to removal of water-borne pathogens, and this is largely achieved through filtration. Turbidity removal is a standard indirect measure of particulate removal and filtration performance. Particle count measurements in filter effluent allow for a direct measure of particulate removal and are more sensitive to changes in filtration performance. There is currently a weak understanding of relationships among particle count removal, chemical usage, and raw water quality, since the relationships are complex and nonlinear. The goal of this project was to use ANN modelling as a powerful analysis tool to further plant operators' understanding of particle count reduction through filtration.

The model was developed using one year of full-scale data from the E.L. Smith WTP. Model inputs, presented in Table 6, were selected based on data availability and significance of effect on filtration performance, as suggested by recent literature.

When applied to previously unseen data, the model predicted filter effluent particle counts with a mean absolute error of 2.3 particle counts·mL^{-1} and an r^2 value of 0.79. The model results are presented graphically in Fig. 4. As particle counters were only installed at E.L. Smith WTP in March 1998, a relatively small data set exists and only 17 data points are presented in Fig. 4. Nevertheless, the model dem-

Fig. 5. Model analysis of effect of alum dose and polymer dose on particle counts.



onstrated excellent predictive capacity on previously unseen data.

As with previously discussed models, the completed particle count model can be used for the iterative determination of optimal dosing strategies. The model also serves as a powerful research tool for examining the effects of various parameters on measured particle counts. Instead of performing standard jar tests in a wet laboratory, the model can serve as a virtual laboratory for testing effects of chemical doses and other parameters. The effect of alum dose and polymer dose on particle counts during winter conditions, using the ANN model as a virtual laboratory, is presented graphically in Fig. 5. As can be seen in Fig. 5, incremental increases in polymer dose can achieve more substantial particle count reductions than comparatively large increases in alum dose. Such information gives plant operators a better understanding of particle count behaviour, and thus allows for better control of filtration performance.

Conclusions

In conclusion, the ANN modelling technique has been successfully applied to a number of unit processes at EPCOR Water Services' two Edmonton water treatment facilities. The technique is able to capture the nonlinear characteristics of processes where the micro-scale interactions are often poorly understood. In so doing, the ANN technique provides water treatment plant operators with viable alternatives to bench scale experiments for determining optimal process operating characteristics.

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