An Hybrid Neural Network Based System for Optimization of Coagulant Dosing in a Water Treatment Plant

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Abstract

Artificial Neural Network (ANN) techniques are applied to the control of coagulant dosing in a drinking water treatment plant. Coagulant dosing rate is non-linearly correlated to raw water parameters such as turbidity, conductivity, pH, temperature, etc. An important requirement of the application is robustness of the system against erroneous sensor measurements or unusual water characteristics. The hybrid system developed includes raw data validation and reconstruction based on a Kohonen self-organizing feature map, and prediction of coagulant dosage using multilayer perceptrons. A key feature of the system is its ability to take into account various sources of uncertainty, such as atypical input data, measurement errors and limited information content of the training set. Experimental results with real data are presented.

Introduction

The water industry is striving to produce higher quality water at a lower cost due to increased regulatory standards. Improved process control through the introduction of new technologies has increased the operational efficiency of chemical process plants. Coagulation process is one of the most important stages in surface water treatment, allowing the removal of colloidal particles. The main difficulty is to determine the optimum chemical coagulant dosage related to the influent of raw water. Good coagulation control is essential for maintenance of satisfactory treated water quality and economic plant operation. Poor control leads to wastage of expensive chemicals, failure to meet the water quality targets, and less efficient operation of sedimentation and filtration processes. Good control can reduce manpower and chemical costs and improve compliance with treated water quality targets. Traditional methods of controlling coagulant dose rely heavily upon manual intervention. These include manual methods such as jar-tests and automatic control ensured mainly by streaming current detector (SCD) [1-2]. Jar testing involves taking a raw water sample and applying different quantities of coagulant to each sample. After a short period of time each sample is assessed for water quality and the dosage that produces the optimal result is used as a set point. Operators change the dose and make a new jar test if the quality of treated water changes. Disadvantages associated with jar testing are the necessity to perform manual intervention, and the limitation to feedback control. In opposition, SCD systems measure the net residual charge surrounding turbidity and colloidal particles in water [3-4]. These instruments require a set point to be entered which represents an optimum water-quality standard. Streaming-current values above the set point indicate an excess of coagulant, while values below the set point indicate insufficient coagulant for full flocculation to occur. A jar test must then be carried out to determine the set point. Disadvantages associated with the SCD are its operation cost and its lack of adaptation to all types of raw water quality.

This paper addresses the problem of automatic coagulation control based on the raw water characteristics such as turbidity, conductivity, pH, temperature, etc. Some previous studies [5-6] have shown the potential effectiveness of such an approach based on ANN's. The

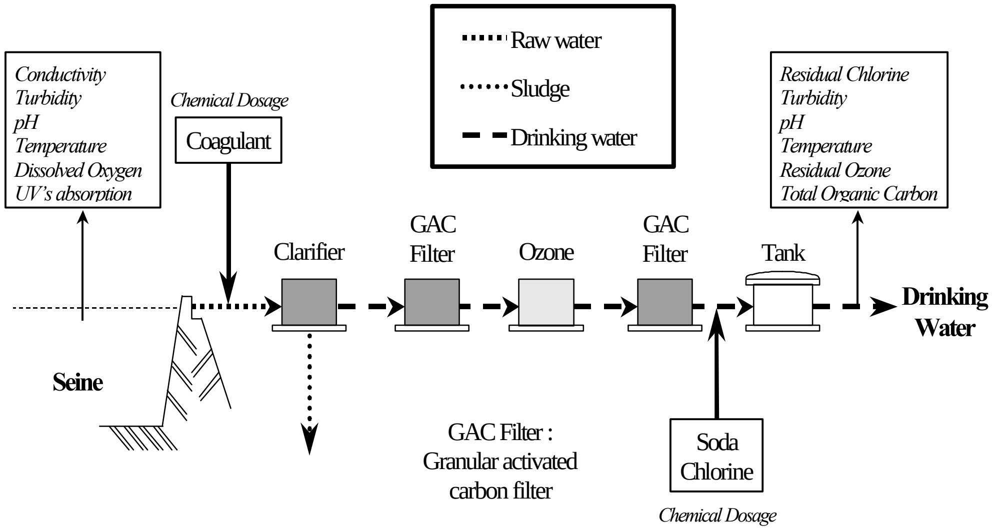

Figure 1 - Simplified synopsis of the water treatment plant.

innovative aspect of this work resides in the integration of various techniques in a global system including data validation and reconstruction, automatic control of coagulation, and analysis of uncertainties.

Given the high variability of the inputs and the low reliability of available sensors, an important requirement of the application is *robustness* of the system, running without human supervision, against erroneous sensor measurements or unusual water characteristics, due to accidental pollution for instance. Special attention also has to be paid to the automatic design and training of such a system from learning data (including the phases of data validation, input selection and model choice), which should allow the portability of the system at low cost from one site to another.

A brief description of the water treatment process is first provided in Section II. The methodology used to build the hybrid system for the automatic control of coagulation is then described in Section III. Finally, experimental results are presented and discussed in Section IV.

Water treatment operation

Water treatment involves physical, chemical and biological processes that transform raw water into drinking water. However, contrary to most industrial processes, for which the quality of the input raw material is under control, the quality of the given raw water source may fluctuate due to natural perturbation or occasional pollution. The Viry-Chatillon water treatment plant, which was used as an application site for this study, provides water to more than 300,000 inhabitants and has a nominal capacity to process 120,000 m^3 of water per day. Figure 1 presents a schematic overview of the various operations necessary to treat the water, the available measurements, and the coagulant dosing point. Raw water is abstracted from the river Seine and pumped to the treatment works. Water treatment plants invariably include two main process units, clarification and filtration. Other units may be required depending of the quality of the water source. The coagulation process is brought about by adding a highly ionic salt (aluminum sulfate) to the water. A bulky precipitate is formed which electrochemically attracts solids and colloidal particles. The solid precipitate is removed by allowing it to settle to the bottom of the tank and then periodically removing it as sludge. The coagulation process accounts for the removal of most of the undesirable substances from the raw water and hence tight monitoring and control of this process is essential. The next stage is filtration, where the particles passing trough the previous stages are removed.
Filtered water is also treated by ozonation to eliminate the last micro-pollutant. The final stages in the process are chlorination and pH adjustment. The water is then stored in a tank and ready to be transported through the water supply network.

Methodology

The system developed for optimization of the coagulant process was divided into three modules: single-parameter data validation, multi-parameter data validation and reconstruction, and determination of coagulant dosage. Figure 2 illustrates the structure of the system.

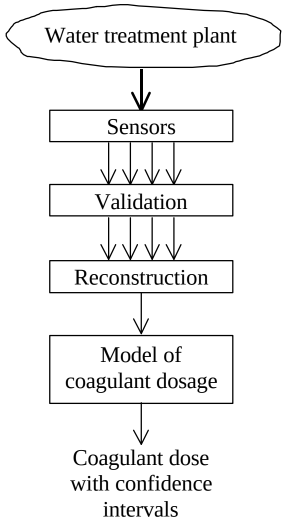

Figure 2 - Structure of the system for prediction of coagulant dosage.

Single-parameter data validation

As the system has to operate on-line with unreliable input data coming from a real process, the *data validation* step is fundamental. The objective of this first step, referred to as single-parameter sensor data validation, is to associate a confidence level to each raw data item. Confidence is measured by a real number belonging to [0,1]. A zero confidence means "no confidence, the data is invalid" while a confidence equal to one means "the data is perfectly valid". At this stage, the validation procedure is quite simple and is based on a comparison of each signal and its derivative to a range of values typically obtained in the absence of erroneous measurements. Raw data whose confidence level is less than a given threshold are declared as invalid data. Although this simple approaches proves to be sufficient in most cases, the detection of inconsistencies in the data involving more than one parameter requires the use of more sophisticated techniques such as Kohonen maps.

Multi-parameter data validation and reconstruction

We propose an approach based on the use of a Self-Organizing Map (SOM) [7] for multi-parameter data validation and reconstruction of input data. The process in which the SOM is formed is an unsupervised learning process. The SOM defines a mapping from the input data space $\Re^n$ (raw water quality parameters) onto a regular two-dimensional array of nodes. A reference vector, or prototype, $m_i \in \Re^n$ is associated to each node i. Each input vector $x \in \Re^n$ is compared with the m_i, and the best match defines the winning prototype. The input is then mapped onto the corresponding location on the grid.

With this technique, the evolution of raw water quality can be visualized in two dimensions, and atypical data or outliers can be detected by measuring the distance between each input vector and its closest reference vector. More precisely, the activation of unit *i* for input *x* was defined using a Gaussian kernel:

$$K(i) = \exp\left(\frac{-1}{2 s_i^2} \left\| x - m_i \right\|^2 \right),$$

where σ^2_i is a parameter defining the size of the influence region of unit *i*. If the activation of the winning prototype is smaller than a specified threshold, the current sample is considered as invalid. The contributions of each of the components of vector x to the distance $\|x - m_i\|$ are then examined to determine more precisely which sensors should be declared as faulty. These sensor measurements are then disconnected to compute a new winning prototype with only valid parameters. For reconstruction, each missing value of a given input variable is estimated by the value of the corresponding component in the winning prototype. In order to improve the reconstruction accuracy we use a combination of the k nearest nodes. Each missing or invalid value j is estimated by a combination of the corresponding component in the k nearest prototypes:

$$\hat{x}(j) = \frac{\sum_{i=1}^{k} K(i)\ m_i(j)}{\sum_{i=1}^{k} K(i)},$$

where $m_i(j)$ denotes component j of prototype i.

At this stage, the pre-processing phase is terminated and the data is ready to be processed by the coagulant dosage model.

Modeling of coagulant dosage

For the modeling of coagulant dosage, a multilayer perceptron (MLP) with sigmoidal activation functions was trained using the Optimal Brain Damage (OBD) [8] learning and pruning algorithm. This approach is based on the following general procedure.

First, a relatively large network (Figure 3) is trained using the back-propagation algorithm. The network is then examined to assess the relative importance of the weights, and the least important are deleted.

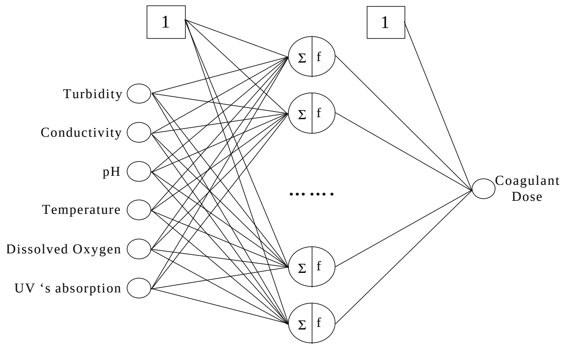

Figure 3 - Initial network.

The implementation of this technique consists of the following steps (Figure 4):

1. Choose a relatively large initial network architecture.
2. Train the network using a back-propagation algorithm applied to a sum of squares error function.
3. Compute the second derivatives H_{ii} for each of weights and evaluate the saliencies.
4. Sort the weights by saliency and delete some of the low-saliency weights.
5. Go to step 2 and repeat until some overall stopping criterion is reached.

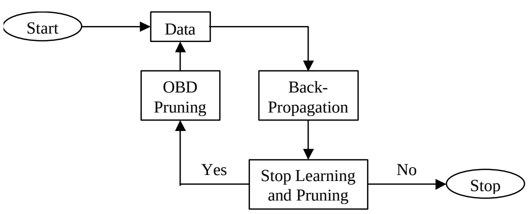

Figure 4 - Learning and pruning algorithm.

For practical use, a software system to predict the optimal coagulant dosing rate should not only provide point estimates but also confidence intervals. Bootstrap sampling [9] was used to generate confidence intervals for the system outputs [10]. As shown in Figure 5, 50 bootstrap sets of training data were created from the original data training data by resampling with replacement. These bootstrap training sets were used to train 50 bootstrap MLP models using the same architecture and training procedure described previously. Lower and upper limit confidence bounds for any input were obtained by sorting these outputs and selecting the 10% and 90% cumulative levels. The confidence interval provides upper and lower limits on the prediction.

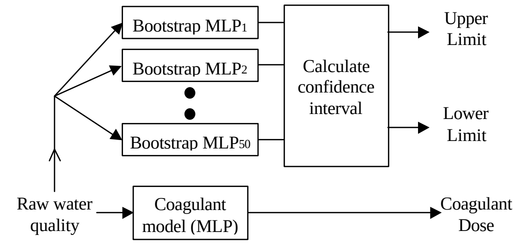

Figure 5 - Bootstrap sampling to generate confidence interval.

Results

The water treatment plant of Viry-Chatillon has been well instrumented for several years. Various process variables (see Figure 1) such as conductivity, turbidity, pH, temperature, dissolved oxygen, UV absorption of raw water and coagulant dosage are available. The raw database is made of 100,000 measurements of each variable during a period of 12 month (November 97 – November 98) sampled every 5 minutes. Many sensor faults were detected and only 1600 measurements of each parameters were available for training.

We used 70% of the data set to develop the model, find the best structure of the ANN and estimate the prediction accuracy by bootstrap. The other part of the data set was used to validate the resulting model. The prediction accuracy and confidence interval of the ANN are shown in Figure 6 on the validation set.

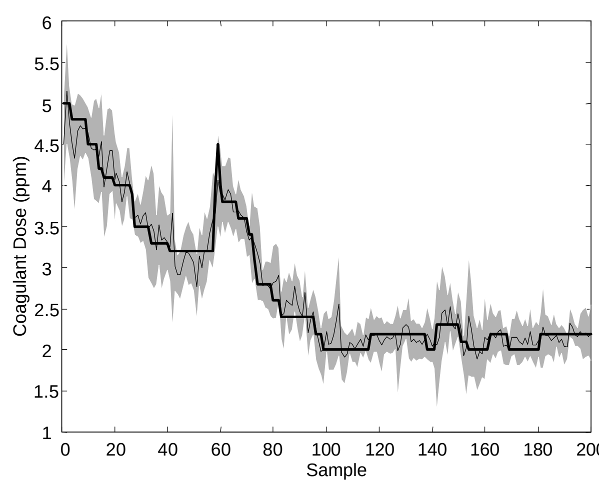

Figure 6 - Actual (thick line) versus predicted (thin line) coagulant dosage with ANN model on test data and confidence interval (shaded region).

In order to assess the robustness of the system, an off-line simulation study was performed on the original raw water parameters, with faults introduced at certain time steps. In the simulation process we used two weeks of real data sampled every 5 minutes from 24th June 1998 to 9th July 1998. The dissolved oxygen was simulated to be degraded with a rising ramp of 0.005 mg/l per samples (every 5 minutes). The faults occurs on the 1st July at 8:00 at sample 2017 as shown in figure 7.

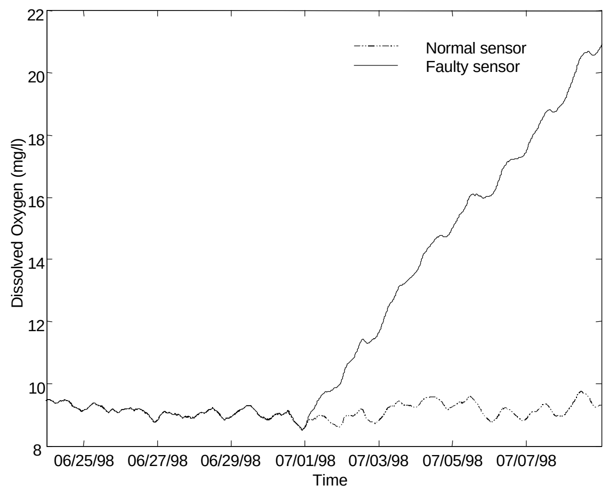

Figure 7 - Degraded dissolved oxygen sensor.

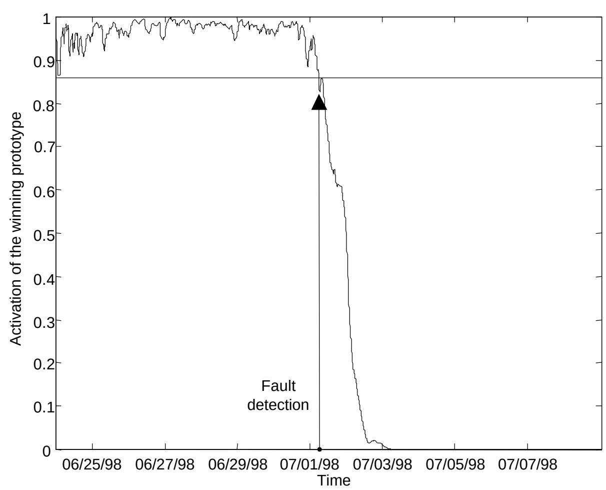

Figure 8 - Activation of the winning prototype.

Using the Kohonen net, the fault was detected 72 samples (6 hours) later at 1st July 14:00 (Figure 8), and the dissolved oxygen variable was correctly identified as being the faulty parameter. Figure 9 shows the reconstruction of dissolved oxygen using the Kohonen net approach.

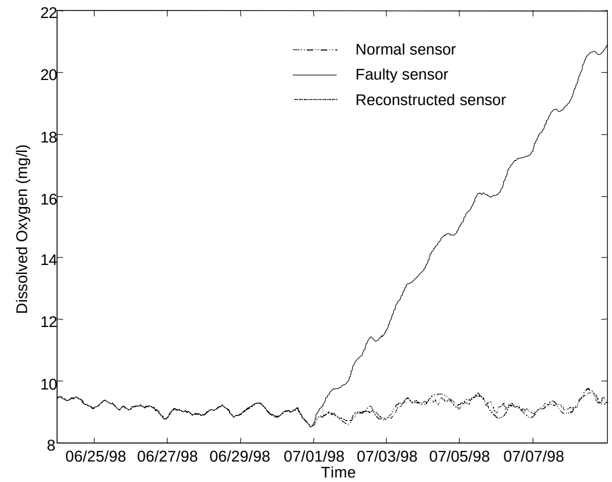

Figure 9 - Reconstruction of dissolved oxygen.

After this pre-processing phase the data is ready to be processed by the coagulant dosage model. The prediction accuracy and confidence interval of the ANN are shown in Figure 10 for the pre-processed data. This is to be compared with the prediction results without pre-processing as shown in Figure 11. These results clearly demonstrate the robustness induced by the preprocessing module in our system.

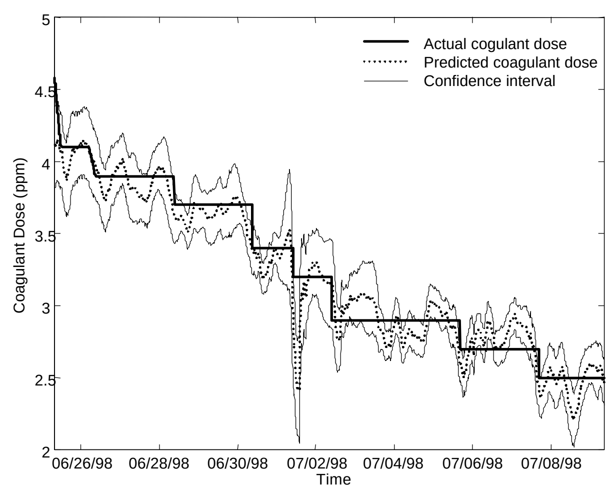

Figure 10 - Actual (thick line) versus predicted (doted line) coagulant dosage with ANN model and confidence interval (thin line)

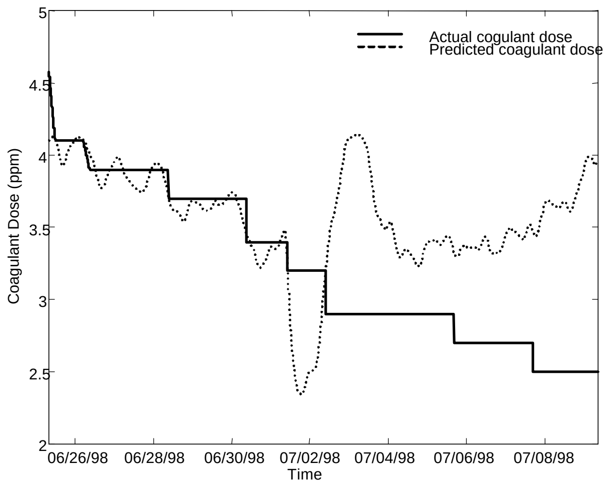

Figure 11 - Actual (thick line) versus predicted (doted line) coagulant dosage with ANN model without pre-processing.

Conclusions

An integrated coagulant dosing system based on unsupervised and supervised neural network models, as well as various statistical techniques, has been described. Experimental results using real data have demonstrated the efficiency and soundness of this approach. Field testing is currently underway to fully validate the system before its widespread dissemination to other sites. The main observed benefits have been treated water of a more consistent high quality, together with improved security of service, as the system will respond reliably and effectively over long periods. Significant savings in coagulant usage can be obtained in certain cases.

The performance of the network is obviously dependent on the quality and completeness of data provided for system training. Consequently, continuous updating of training data during operational use is expected to improve the performance of the system. This model, however, is only based on the previous behavior of operators and jar-test results. Further work is needed to develop a model taking into account the dynamics of the process, and to predict treated water parameters (mainly turbidity) at the output of the clarification process.

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