Proceedings of the 2001 IEEE
International Symposium on Intelligent Control
September 5—7, 2001 • México City, México

ANN-based Sensing and Control Developments in the Water Industry: A Decade of Innovation

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Abstract-- Compared to other process industries, the technology employed by the water industry is of a relatively low level, although this deficit has been reduced in recent years mainly due to the increased competitiveness in the privatised market place. In general, however, methods of process regulation are far from ideal, leading to inefficient plant operation , occurrence of unnecessary costs and in some cases low water quality. Improvements in control and supervision methods have been recognised as one means of achieving higher water quality and efficiency objectives in the potable water industry. The lack of research in this application area is evident from the paucity of published literature, especially when compared to wastewater treatment control.

Attempts to improve the performance of water treatment works through the application of improved control and measurement have had variable success. The most quoted reason for this is that the individual dynamic operations defining the treatment cycle are complex, highly non–linear and poorly understood. These problems are compounded by the use of faulty or badly maintained sensors. The efficient and robust operation of any industrial system is critically dependent on the quality of the measurements made. Also, the structure of the control policy and choice of the individual controller parameters are important decisions to the economic operation.

Because of their ability to capture non–linear information very efficiently, artificial neural networks (ANNs) have found great popularity amongst the 'control community' and other disciplines. This paper discusses a recent application of ANNs at surface water treatment works. The study is used to describe how the introduction of ANNs has resulted in more reliable system measurement and consequently improved coagulation control

Index Terms-- Water treatment, coagulation control, artificial neural networks, process control, sensor failure detection, inferential estimation, neuro control

I. INTRODUCTION

The majority of the drinking water consumed in the UK is treated at surface water treatment works where raw water is abstracted from rivers and reservoirs. The type of treatment it then undergoes depends on the source and the quality of its water. In general, the poorer the qualities of the raw water the more expensive it is to treat.

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Prior to privatisation the majority of water treatment processes were under manual control. Since privatisation, the water industry has been seeking ways, especially via the increased use of automatic control [Bevan, 1999], to produce high quality water at reduced cost whilst at the same time 'down–sizing' its work force. The water treatment process consists of a complex group of interconnected physical and chemical systems. It is not immediately obvious how each one relates with its neighbour, however, it is well known that a problem with one process, if not addressed, will quickly result in a much larger problem in one or more of the subsequent stages.

The addition of chemicals to the water is arguably the most critical process within a surface water treatment works. Water quality legislation dictates maximum concentrations for chemical elements in drinking water and so the control of the amount of chemicals added to the water and the process of monitoring its quality are very important. The key unit operation is chemical coagulation. Successful control of this clarification process is invariably followed by problem–free operation of the secondary and tertiary treatment processes.

The key to efficient coagulation control is the addition of just sufficient coagulant chemical to the process. Too much coagulant will ensure treatment targets are achieved but at great cost, both in chemical consumed and extra sludge waste produced. Too little coagulant will result in poor treatment performances and problems in subsequent processes such as filtration.

II. WATER TREATMENT AND THE CLARIFICATION PROCESS

Two main types of water source are used for providing potable water supplies: these being surface water (rivers and reservoirs) and ground water (bore holes). Each type has different raw water characteristics and invariably place different emphases on specific treatment processes. For example, ground water sources tend to be of much higher quality than surface water sources and consequently need much less processing, chlorination often being sufficient. Bore hole and reservoir sources have cheaper running costs but limited availability of suitable sites and capital cost of developing them make river abstraction sites a necessity to supply the region's demands.

The purification of water for domestic consumption involves several stages of treatment of the raw water to remove suspended solids, colour and bacteria before entering the distribution network. The individual treatment processes include clarification, disinfection, pH adjustment, filtration and taste and odour removal, see Figure 1.

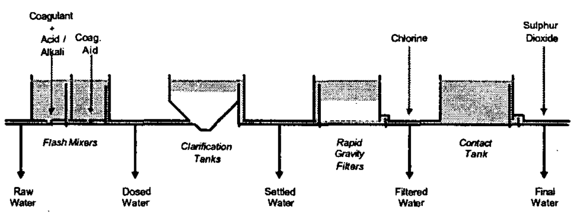

Figure 1: Potable water treatment processing units.

Clarification can be roughly divided into a two-stage process, comprising of coagulation and flocculation (see Figure 2). In the coagulation stage, a coagulant chemical (a salt of a highly charged metal ion) is added to the water in a mixing vessel, often with mechanical agitation to ensure uniform distribution of the chemical. The highly charged metal ion destabilises the negatively charged impurities in the water. The species combine together to form larger particles called flocs. Flocculation involves the combination, by collision, of small particles, under natural turbulence, into larger particles. A flocculation aid (usually a natural starch or a polymer solution) may also be added to assist floc formation. The final stage of the clarification process is the separation of the large flocs formed by coagulation and flocculation from the water, usually by settlement.

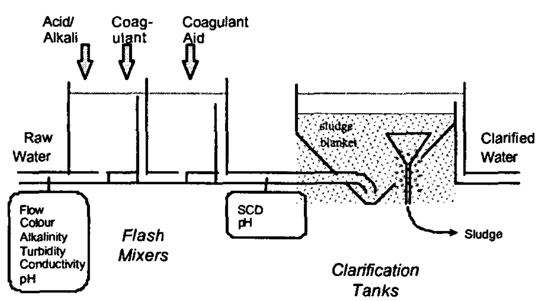

Figure 2: Schematic cross–section of the clarification unit in potable water treatment processes.

The next stage is filtration, where the particles passing through the previous stages or precipitating later are removed. The water is passed through a bed of sand at low speed and the suspended solids are removed. The filters are backwashed periodically to remove the collected matter. Note that backwashing is energy intensive and is required more regularly if the clarification stage is not performing well.

The final stages in the process are commonly chlorination and pH adjustment. The former finely adjusts the chlorination dose for disinfection purposes and the latter raises pH sufficiently to reduce corrosion in the distribution network.

III. Overview of Artificial Neural Networks

Neural networks are a relatively new application in process control and their uses have been found to be wide ranging in many industries. The water industry has been slower than most to investigate the full potential of these methods.

Neural networks may only give a model of a process and it is this model which must be incorporated with some other technique to provide control strategies. (Examples include feed–forward control, internal model control and closed–loop linearisation.)

The important features of artificial neural networks are their ability to model (learning from past process data) the complex non–linearities of a process and their capacity to accommodate multi–input multi–output (MIMO) systems. The artificial neural networks are in no way reliant on any understanding of the process but will produce a model based solely on the previous behaviour of the inputs and outputs of the plant [Thodberg, 1993]. This makes the application of artificial neural networks very suitable to water treatment processes.

IV. Automating the Clarification Process

A. *Manual Control*

This was the original philosophy for many plant operated today. To aid the operator in deciding the correct coagulant dose, the works chemist can carry out a series of jar tests. This involves taking sample of raw water and splitting this into 5 or 6 separate samples. These are then each dosed with chemicals used in the actual plant prior to the clarification stage (e.g. acid/lime.) A suitable range of coagulant dose is then injected to the samples. The samples are then stirred in a certain manner (typically rapid stirring to start followed by more gentle stirring) to simulate conditions in the plant. This is invariably done by a special piece of laboratory equipment. When the stirring has ended the chemist will leave the samples for a short time before visually deciding which coagulant dose has produced the best floc. Based on this finding, a recommended coagulant dose is prescribed and the agreed value is introduced into the process by the plant operator. Only under extremely differing conditions and under the advice of the chemist would this dose be altered before a new set of jar tests was carried out.

Numerous factors combined to ensure that manual control was the method used for many water treatment plants in the past. The processes were even less well understood than today, control hardware and instrumentation was much less advanced and more expensive and finally there was not the stringent economic and regulatory pressures on the industry which now exist. There has been a lot of recent research into the study of feed–forward algorithms for coagulation control. In these schemes the amount of chemical coagulant required is assumed to be directly related to raw water parameters [Nahm et al, 1996].

B. *Feed–forward Coagulation Control*

After a period of operation, sufficient data were collected from the process to allow the development of a feed–forward law to automatically determine the optimum coagulant dose [Boucher *et al*, 1990]. The model inputs originally used were based on the raw water parameters of colour and turbidity. This law was originally developed via linear regression techniques, but has since been extended to a neural network solution. It was thought that the complex, non–linear structure of these models could provide more accurate models which took into account a wider range of raw water parameters.

The approach taken in this research was to examine a data set of nearly 500 data samples, representing over one years' worth of 'jar test' results from a single treatment works. The data consisted of six variables that together classified the raw water quality, namely: colour, pH, turbidity, conductivity, alkalinity and temperature. The data were pre–processed using techniques to improve the statistical quality of the data, such as allowing for seasonal variations in water quality, by having different models for different seasons and removing examples of poor control performance from training data sets intended for human operator mimicking.

The estimation performance of the neural network is impressive, as shown in Figure 3. By basing treatment decisions on such accurate models of previous successful treatment operation, plant efficiency will be improved since automatic and consistent control actions can be made.

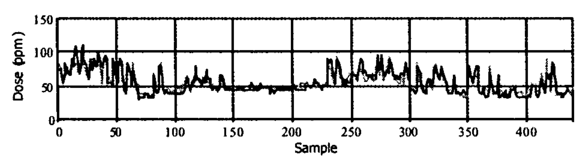

Figure 3: Estimation of optimum coagulant dose using an artificial neural network approach.

C. *Inferential Estimation using Artificial Neural Networks*

The requirements to find future cost savings has resulted in more detailed analysis of even those schemes deemed to be successful, like the simple automatic dosing system described in the previous section. Such an analysis revealed that under conditions of high turbidity the colour meter reading was consistently higher than the laboratory reading taken by the chemist [Cox *et al*, 1995] as seen in Figure 4. Since no unused chemical recovery strategy is in use, this was obviously causing chemical wastage thus costing the company money.

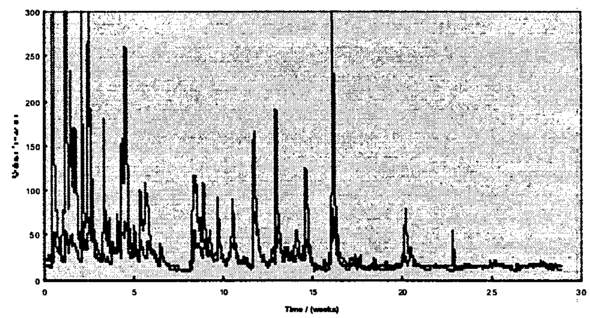

Figure 4: Time–series plot of measured colour and true colour.

When analysing the treatment plant's records it was fairly obvious from the data that turbidity and colour were related but quantifying the relationship was difficult. This is partly due to the complex, non–linear relationship but mainly due to a lack of theoretical knowledge of the natural processes occurring at molecular and particle level. It was postulated that a possible way forward would be to use an ANN to estimate true colour based on plant raw water data. It was decided to use the raw water parameters of colour (the corrupted meter reading) and turbidity to predict a more accurate colour reading. From earlier studies on plant data using the Principal Component Analysis technique, it had been found that conductivity and temperature were also important variables. Hence, an assortment of structures, using various combinations of process parameters as inputs to the model for true colour prediction, were evaluated.

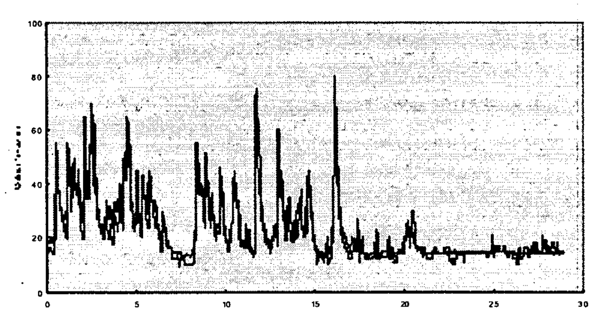

Figure 5: Time–series plot of true colour and ANN estimated colour.

Various network topologies were tested on a training data set covering about three months of plant operation. Eventually a 3-3-3-1 multi–layer perceptron network (MLP) was used. The raw water input variables were colour (the visible colour of the water), turbidity (number of suspended particles in the water) and conductivity (ionic strength of the water). Figure 5 illustrates the performance of the MLP on the validation section of the data.

V. Neural Self–Tuning Control

The drive towards efficiency, quality and safety has meant that plant automation has become a necessity. This is particular so within the water treatment industry where the behaviour of the various chemical, physical and biological relations are both not fully understood and highly non–linear in nature. Conventionally this is achieved using fixed term PID controllers in the majority of applications, however, in these cases alternative controller structures are required in order to provide the necessary performance. Within this section some ANN alternatives are considered.

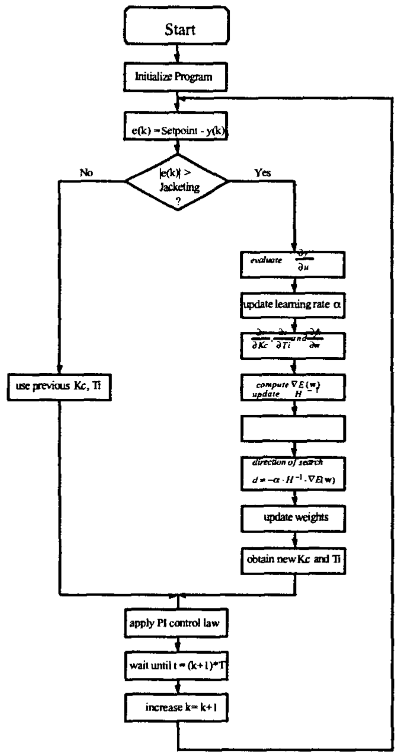

Figure 6: Self-tuner computational flow diagram

The automation of non–linear systems is typically undertaken by some adaptive control strategy which is generally model based in order to adapt the controller parameters to compensate for the change in process behaviour. Here a Neuro Self–tuning PI strategy is considered, along with a flow control example based upon a laboratory water flow rig where it was used to simulate coagulant dosing control (see Figure 7, [Fletcher *et al*, 2000]). Regulation of the flow of water into a treatment works is essential if the plant is to operate effectively. Changes in flow can deeply unsettle the clarification process causing disruption of the sludge blanket and subsequent blockage of the primary filtration system.

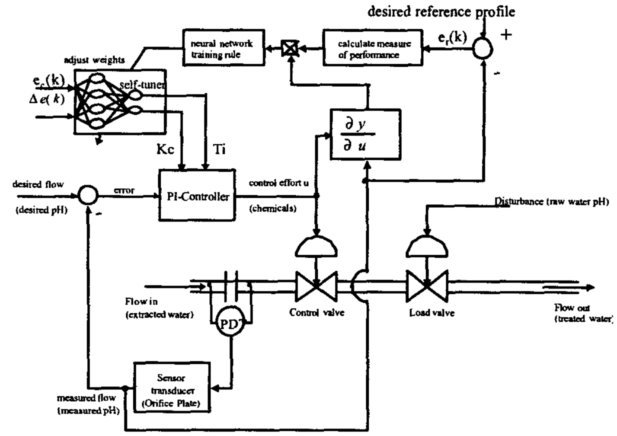

Figure 7: Structure of the water flow rig system.

The performance of the neuro self–tuning PI controller was assessed by introducing disturbances (via the load valve) at the system output to emulate variable consumer demand. In addition, a variable dead time was introduced artificially, as the length of the pipe was not sufficiently long to demonstrate actual system behaviour, i.e. $pipe\,length \le dead\,time \le pipe\,length + 1.5\,\mathrm{sec}$. The actual transport delay of the pipe being only 0.45 sec. The following results illustrate load rejection performance at a set point of 6V to randomly generated load demands where it consistently out performed fixed–term PI control [Fletcher et al, 2000].

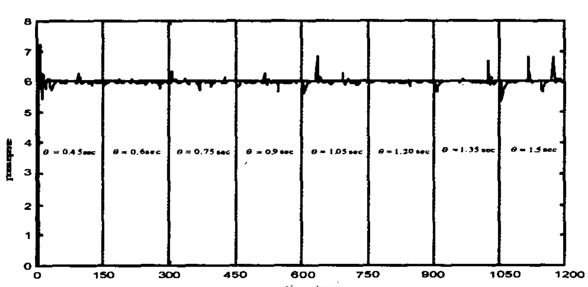

Figure 8: Performance under process disturbances and with varying system dead–time.

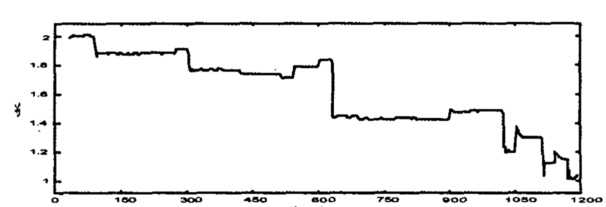

Figure 9: Adaptation of the Kc parameter.

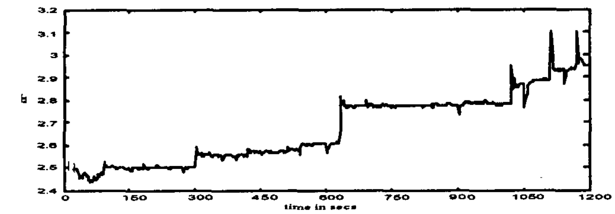

Figure 10: Adaptation of the T_i parameter.

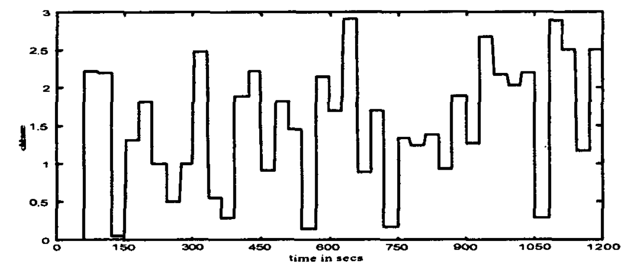

Figure 11: Disturbance profile on load valve

VI. CONCLUSIONS

The introduction of increasingly stringent regulations at water treatment works emphasises the need for a high degree of reliability in the operation of the individual unit operations. The response of the industry has been the establishment of a range of quality or conformance standards since their satisfaction offers potential benefits in terms of production consistency, reduced operational costs and improved safety. However, these improvements can only be realised if the process control and plant management policies are well structured and designed. This paper has identified several situations where an ANN has been used to help provide a solution that has contributed to an improvement in the overall plant performance.

Modelling of the complex relationships between the process variables involved in the water treatment process is possible using the flexible non–linear format of ANNs. In this way feed–forward control strategies may be directly applied.

Inferential estimation can prove to be a cost effective means of determining plant measurements for variables which are expensive or impractical to measure. It may also be possible by this means to speed up the sampling time of a measured variable for more accurate control.

Finally, an ANN was used to provide the mechanism to allow the adaptation of fixed term controller parameters in response to the to adapt to the non–linear behaviour of the process.

Other work [Fletcher et al, 2000] using an auto–associative neural network to identify sensor failure and aid signal reconstruction has been developed. The results suggest that the validation technique is able to adequately identify sensor failure whilst also providing reasonable estimates of 'corrupted measurements' for monitoring and control purposes. Some of these techniques have been proven on a small–scale pilot plant sited at one of the larger works. These new methods are presently being investigated at five different sites owned by Northumbrian Lyonnaise.

VII. ACKNOWLEDGEMENTS

The authors would like to thank both Northumbrian–Lyonnaise and the University of Sunderland for technical and financial support of this work.

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