SENSOR FAILURE DETECTION IN WATER QUALITY MONITORING

G Waterworth

School of Engineering, Faculty of Information and Engineering Systems, Leeds Metropolitan University,
Central Site, Leeds LS1 3HE
Email: g.waterworth@lmu.ac.uk

Abstract: in the treatment of raw water, to make it suitable for use as drinking water, it is necessary to monitor and control key parameters such as colour, pH and turbidity. Signal condition monitoring is essential when the automatic control of one or more parameters is dependent on the quality of the measurements made. Operational failure of process plant instrumentation can lead to reduced production and plant shutdown. This paper considers a number of possible methods of identifying faulty sensors including multiple regression, and artificial neural networks, and also methods of estimating values to allow for continued plant operation. *Copyright ©2000 IFAC*

Keywords: Sensor fault detection, water pollution, neural networks, regression analysis, fuzzy modelling.

1. INTRODUCTION

In a plant such as a water treatment works, it is essential for public safety that errors in the measurement of water quality are detected early. Failure of process plant instrumentation can lead to inferior water quality, reduced output or even plant shutdown. In the move towards more automated control of plants, it is necessary that signals fed to the computer are reliable.

Decisions on dosing levels for the various added chemicals are often based on measurements taken on-line of raw water parameters. In water treatment works, a large amount of data is collected for both monitoring and control, and the integrity of the instrument readings is essential.

For various reasons, sensor hardware redundancy may not be an appropriate solution to data integrity. The cost and size of additional instrumentation may be prohibitive, and a redundancy scheme could require a triplicate system using majority voting, with increased overload on the computer acquiring the data. It is therefore necessary to investigate other techniques for the identifying of faulty sensors.

The problem of sensor validation is the detection, identification and possible reconstruction of faulty sensors using known models or a priori knowledge to examine the sensor signals. Fault detection can often be achieved by the use of process models of one form or another. These models may be based on statistical techniques such as multivariate modelling, Kalman, or principal component analysis. Increasingly, research is considering more advanced models using various forms of artificial neural network, which can also, in certain situations, reconstruct an estimate of the faulty sensor reading. They have good functional approximation and classification abilities, and find use in non-linear system identification and estimation. These properties make them useful for use in fault detection and isolation.

This paper reviews a number of these methods and gives the results of a neuro-fuzzy technique of sensor failure detection applied to data obtained from an actual plant.

2. WATER TREATMENT

Modern water treatment plants need to meet UK and EC standards of quality. Moorland areas that draw on water from upland sources acquire high levels of colour and turbidity through contact with peat, together with suspended matter and dissolved metals. The colour and dissolved metals are removed during a three-stage chemical treatment process.

In a typical treatment plant, water entering the site is mixed with a coagulant such as ferric or aluminium sulphate to make any impurities stick together. The pH value is also adjusted at this point. The water then passes to flocculation tanks where a sediment known as 'floc' is formed. This can be removed by a sludge scraper. It then passes through the first stage rapid gravity filters where lime is added and any remaining colour or suspended matter is removed. Lime and a solution of chlorine are added to remove manganese and kill the bacteria, after which the water is pumped to the second stage rapid gravity filters. The treated water is then dosed with chlorine for disinfection and phosphate to control the plumbosolvency in the water mains system. It then flows to the contact tank which provides sufficient time for the chlorine to achieve complete disinfection.

The quality is continually monitored at every stage of the process using sensors to measure quality parameters such as colour, pH, turbidity, temperature and conductivity. The treatment process is controlled by a series of programmable logic controllers, and monitors are linked to a supervisory computer control and data acquisition system. Typical variations of these water quality variables are shown in **Figure 1**.

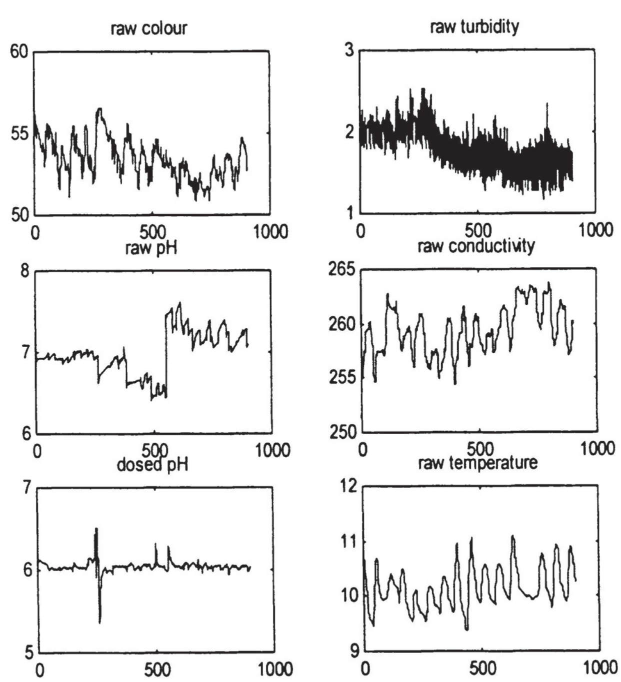

***Figure 1** Water quality variables over 15 day period*

They show the wide range of raw water conditions that can exist, with rapid changes often taking place in some of the variables. Because the water fed to the treatment works is derived from a number of different sources, abrupt changes in these variables can take place. Also, variables can drift considerably over longer periods with changes being seasonal as well as stochastic.

3. FAULT DETECTION AND ISOLATION

3.1 Classical Methods

The types of error that occur in sensor instrumentation depends, to some extent, on the variable being measured and on the associated electronics and data transmission method. Faults such as sensors going off-line or signals exceeding a threshold level are easy to identify and take appropriate action. Other faults such as bias error, noise error and slow drift in the sensor output are more difficult. Also sensors may become blocked with dirt or instruments go out of calibration.

Many approaches to fault detection and isolation have been developed, with most of them using model based strategies (Upadhyaya and Skorska, 1984; Yung and Clarke, 1989; Ray, Desai and Deyst, 1983; Gentler, 1988; Turkey, 1989; Frank, 1990; O'Reilly, 1998). Possible techniques may use either univariate or multivariate statistical models. In a model based scheme, the model generates an estimate of the sensor output, and this is compared to the actual output with the analysis of the residuals being the means of identifying faults. The residuals will be in the form of noise, which in a normal system will be approximately Gaussian with a known covariance. A sensor fault will manifest itself by some change in the statistical characteristics of the residual, indicating a deviation from expected behaviour.

Kalman filtering is an effective technique in multi sensor fault detection. It is a well tried, and well known state estimation method. It does place a high computational load on the already heavily used computer system. It also has the disadvantages in the detection of sensor faults in water quality monitoring in that it requires a state-space representation of the process model, which is difficult to achieve. The generalised likelihood ratio (GLR) method is an improvement, but is computationally demanding.

Observers based on process models are difficult to implement in water treatment plant since many of the operations are not well understood. They generally make use of knowledge of the process being measured, and hence their implementation tends to be specific to a particular system, making it difficult to transfer to another system.

Classical statistical techniques are not suitable for analysing sensor data which is corrupted by noise and where the variables exhibit colinear behaviour. Multivariate principal component analysis (PCA) overcomes some of these difficulties by projecting the multivariate data on to a lower dimensional space. The use of PCA for sensor fault identification via reconstruction is discussed by several authors (Dunia, et al., 1996; Kramer, 1991). A signal analysis technique allows for the reduction of false alarms and for the identification of different types of sensor fault. Due to the various sensor outputs being well correlated, only a few principle components are needed to establish the data variance.

A non-linear PCA technique for multivariate data analysis is discussed by several authors (Kramer, 1991).

Martin and Morris (1995) discuss a statistical approach to the monitoring of process signals and the detection of sensor faults based on statistical process control (SPC). Typically a univariate statistical analysis is used, but this multivariate projection technique considers all the data simultaneously to extract information on the 'directionality' of the process variations, that is the behaviour of one variable relative to another.

Upadhyana (1985) outlines several sensor failure detection and estimation methods including analytical redundancy, generalised liklihood ratio approach, parity space representation, data driven representation and verification by using correlation from independent instruments.

Isermann (1994) suggests the integration of different fault detection and diagnosis process model based methods using parameter estimation, state estimation, and parity equation approaches.

Willsky (1976) gives an excellent survey of failure detection in dynamic systems.

3.2 Neural Network Methods

Artificial neural networks (ANN) have good functional approximation and classification abilities. They find use in non-linear system identification and estimation. These properties make them appropriate for use in fault detection and isolation (Mourot et al., 1983; Adgar et al., 1995; Fletcher et al., 1995; Yu Gomm and Williams, 1998; Adgar and Cox 1999).

Zhang et al. (1998) discusses a neural network based non-linear observer for sensor fault diagnosis. The technique uses a deconvolution method and a B-spline neural network as a non-linear observer. Sensor faults are then detected from the residual of the observer.

Once the fault has been detected, it is appropriate to identify which is the faulty sensor. This is done by a further stage of data analysis such as the use of contribution plots (Miller at al., 1993). It may also be appropriate to consider sensor data reconstruction (Dunia et al 1996; Bohme et al 1998)

Bohme Fletcher and Cox (1998) describe a method which uses a neural network to identify sensor malfunction and provide sufficient knowledge to allow signal reconstruction. If there is analytical redundancy between the sensory measurements, and if the relationships between the sensors is known, it is possible to reconstruct an estimate of one or more of the corrupted sensor measurements. The method uses a dimensionality reduction techniques, but using an auto associative neural network, in which the output vectors match the input vectors under normal operation.

The fact that there are many sensors in water treatment plants increases the probability of sensor faults, but also provides redundancy for fault detection since sensor measurements are highly correlated under normal conditions. The use of redundancy for sensor failure detection in colour monitoring is considered in the next section.

4. COLOUR ESTIMATION IN WATER QUALITY MONITORING

In the measurement of raw water parameters, it is often difficult to obtain an accurate reading for colour under conditions of high turbidity. This occurs when the river source is subject to large and rapid variations in quality. It is thus found necessary to develop a method of colour sensor failure detection, and to provide an indication of any fault conditions. An appropriate method of modelling raw water colour is to use other sensor outputs. Using regression analysis it is found that raw water colour can be modelled using inputs from raw water turbidity and raw water pH. Three methods are considered to identify the model, these being regression, subtractive fuzzy clustering and ANNs.

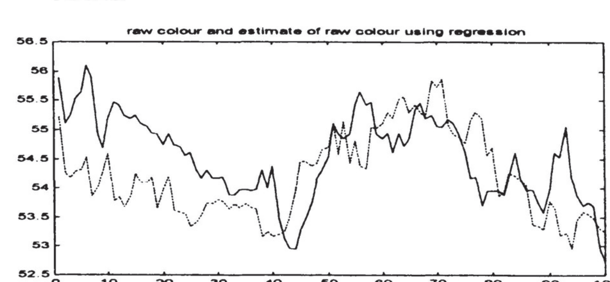

***Figure 2** Comparison of estimated vs. measured raw water colour using regression*

A regression model is first developed as a means of providing an estimate of raw water colour. The comparison graph of estimated vs. measured raw water colour for this model is shown in **Figure 2**.

The next method that is considered uses the technique of subtractive fuzzy clustering. Clustering of numerical data forms the basis of many classification and system modelling algorithms. The purpose is to distill natural groupings of data from a large data set. We first estimate the number of clusters, and then fit the data to the cluster groups.

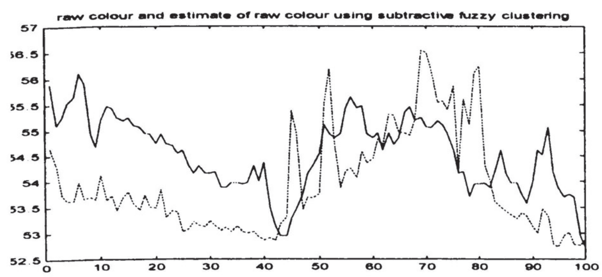

Figure 3 *Comparison of estimated vs. measured raw water colour using subtractive fuzzy clustering*

Due to non-linearity of the colour sensor characteristics, the modelling of raw water colour is better performed using a neural network. This has better estimation abilities, particularly in cases of signal fault detection with unknown non-linearities. A conventional multi-layer perceptron model is found to give satisfactory modelling performance. A graph of the estimated vs. measured raw water colour using this ANN is shown in **Figure 4**. A graph of the residual of the estimate with actual colour is shown in **Figure 5**.

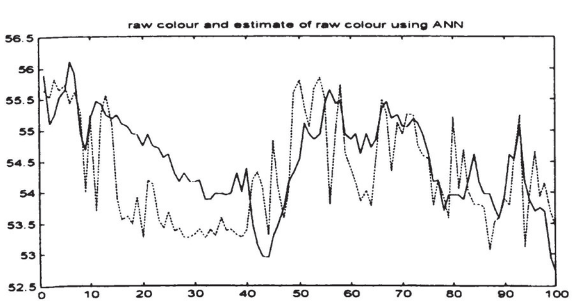

Figure 4 *Comparison of estimated vs. measured raw water colour using neural network*

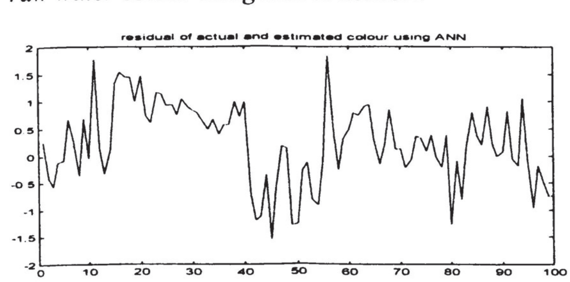

Figure 5 *Residual of actual and estimated raw water colour using ANN*

5. RESULTS

Two sensor faults are considered, these being probably the most common. **Figure 6** shows a gradual drift in the colour sensor output, with the associated residual increasing beyond some specified limit.

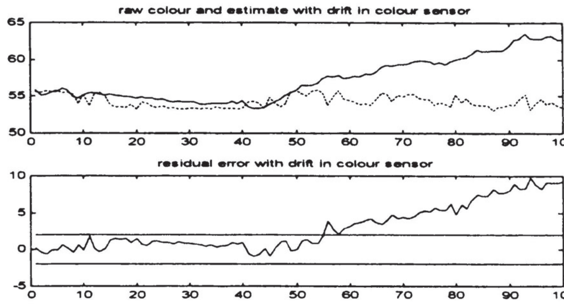

Figure 6 *Identification of drift in colour sensor*

Figure 7 shows the addition of noise on the sensor output, with the corresponding variance rising above some specified limit.

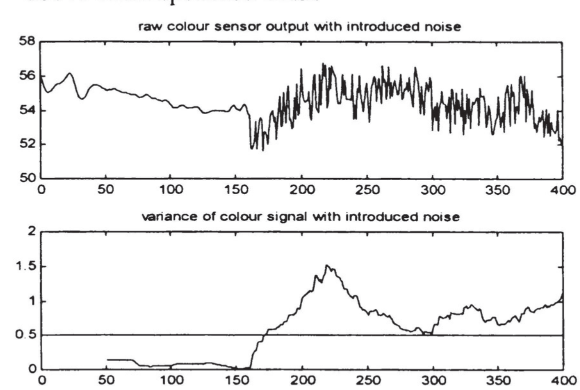

Figure 7 *Identification of noise in colour sensor*

6. CONCLUSIONS

Various sensor validation schemes have been considered including both traditional and modern methods. The paper has reviewed some of the available literature on the subject, including that specific to the water treatment industry. The use of a multivariate model for estimating raw water colour has shown that there is not a lot of difference between the conventional statistical approach, and neuro-fuzzy methods. It has been shown that analytical redundancy can be used to detect certain sensor faults, whilst other faults may be best identified using some statistical fault signature such as variance.

REFERENCES

Adgar A., et al (1995) Improved measurement and control philosophies for water treatment plant using artificial neural networks, *Water and Wastewater Treatment, Mech Eng Pub Ltd.*

Adgar A., and Cox C.S., (1999) Fault detection and automatic control compensation using a model switching strategy. *COMADEM '99, Sunderland, UK.*

Boehme T.J., Fletcher I., and Cox C.S., (1998) Sensor failure detection and signal reconstruction using autoassociative neural networks, *Int. ICSC/IFAC Symp. On Neural Computation '98, Technical University of Vienna, Austria*

Dunia R. et al (1996) Use of principal component analysis for sensor fault identification, *Computer chem. Eng.*, **20**, S713-S718

Frank P.M., (1990) Fault diagnosis in dynamic systems using analytical and knowledge-based redundancy - a survey and some new results, *Automatica,* **26**, 459-474

Fletcher et al (1997) Process fault detection and signal reconstruction using statistical and advanced techniques within the water industry *Int. Conf. Systems Eng., Coventry, UK*

Gertler J.J., (1988) Survey of model-based failure detection and isolation in complex plants, *IEEE Control Systems Magazine,* 3-11

Isermann R. (1994) Integration of fault detection and diagnosis methods, *IFAC Symposium Safe Processes '94,* 597-612

Kramer M.A., (1991) Nonlinear principal component analysis using autoassociative neural networks, *AIChE Journal,* **37**, 2, 233-243

Martin E.B., and Morris A.J., (1995) Multivariate statistics and neural networks in process fault detection, *IEE Collq. Quality and Qualitative Modelling,*711-718

Mirabadi A. et al (1998) Fault detection and isolation in multisensor train navigation systems, *UKACC Int. Conf. on Control '98,* **455**, 969-974

Mourot G et al, (1993) Sensor fault detection using fuzzy logic and neural networks, *IEEE Int. Conf. on Systems Man.* 369-374

O'Reilly P.G. (1998) Local sensor fault detection using Bayesian decision theory. *UKACC Int. Conf. on Control '98,* **455**,247-251

Ray A., Desai M., and Deyst J., (1983) Fault detection and isolation in a nuclear reactor, *J. Energy,* **7**, 79-85

Turkey A.A., (1989) Practical statistical algorithm for sensor validation in discrete dynamic systems, *Fourth Int. Conf. on CAD, CAM, Robotics and Factories of Future,* 1-15

Upadhyaya B.R, and Skorska M. (1984) Sensor fault analysis using decision theory and data-driven modeling of pressurised water reactor subsystems. *Nuclear Technology,* **64**,70-77

Upadhyaya B.R., (1985) Sensor failure detection and estimation, *Nuclear Safety,* **26**, 32-43

Willsky A.S., A survey of design methods for failure detection in dynamic systems, *Automatica,* **12**, 601-611

Yu D.L., Gomm J.B. and Williams D., (1999) Sensor fault diagnisis in a chemical process via RBF neural networks, *Control Engineering Practice,* **7**, 49-55

Yung S.K. and Clarke D.W. (1989) Local sensor validation. *Measurement and Control,* **22**, 132-141

Zhang H.Y. et al ((1998) Sensor fault diagnosisfor systems with unknown nonlinearity using neural network based nonlinear observers, *UKACC Int. Conf. on Control '98,* **455**, 981-986