CASE STUDIES ON THE NEED FOR MONITORING OF WATER QUALITY IN THE UK

Ahmed Moustafa, Ashraf El-Hamalawi and Andrew Wheatley

Civil & Building Engineering Department, Loughborough University, Loughborough, LE11 3TU, England (UK)

ABSTRACT

The advanced monitoring of water quality and performing a real-time hazard analysis prior to entering Water Treatment Works (WTW) is very much a necessity nowadays in order to give warning of any contamination and avoid downtime of the WTW. Two case studies from the UK were examined; one being a groundwater WTW and the other a river WTW. Measured data from both sites were analysed. The results showed that no good correlation existed between the controlling parameters measured at the river WTW, but showed a good correlation for the groundwater WTW. The case studies highlighted the need for a new non-invasive type of measurement and for water companies to invest in their information technology infrastructure.

Keywords: Groundwater, Water Quality Analysis, Water Monitoring, Sensors, Turbidity.

1. INTRODUCTION

The objective of a water treatment works is to produce an adequate and continuous supply of water that is chemically, bacteriologically and aesthetically pleasing. More specifically, water treatment works must produce water that is (American Waterworks Association [1], EU Drink Water Directive [2]):

a) Palatable with no unpleasant taste,
b) Safe; does not contain pathogens or chemicals harmful to the consumer,
c) Clear; free from suspended solids and turbidity,
d) Colourless and odourless; aesthetic to drink,
e) Reasonably soft; allows consumers to wash clothes, dishes, themselves, without use of excessive quantities of detergents or soap,
f) Non-corrosive; to protect pipework and prevent leaching of metals from tanks or pipes,
g) Low organic content (high organic content results in unwanted biological growth in pipes and storage tanks that often affects quality).

A water treatment works must be able to produce a finished product of consistently high quality regardless of how great the demand might be. Like waste-water treatment, water treatment consists of a range of unit processes, usually used in series and this provides some design and operational flexibility to achieve this. The treatment required by water prior to being delivered to consumers will depend upon its initial quality, which is normally related to its source. In other words, the cleaner the raw water, the fewer treatment steps that are required, and hence the overall cost of water is less (Hughes, [3]).

The most expensive operations in conventional treatment are sedimentation and filtration, while water softening can also be very expensive. Groundwater is generally much cleaner than surface water and thus does not require the same degree of treatment, apart from aeration and disinfection before supply. Naturally occurring substances that may need to be reduced or removed in groundwater include iron, hardness (if > 300 mgl^{-1} as $CaCO_3$) and carbon dioxide. Compounds originating from urban activity are becoming increasingly common in groundwater and those requiring treatment include nitrates, pathogens and trace organics such as pesticides. Surface water requires more complex treatment due to its complex nature, although the quality of surface water can be very high, for example upland reservoir (Geldreich, [4]; Reasoner, [5]).

Monitoring and assessing the quality of waters in streams, reservoirs, lakes, and estuaries is critical to improve water quality. Current techniques for measuring water quality involve *insitu* measurements and/or the collection of water samples for subsequent laboratory analyses. While these technologies provide accurate measurements for a point in time and space, they are expensive, and do not provide either the spatial or temporal view of water quality needed for monitoring, assessing, or managing water quality for an individual water body or for multiple water bodies across the landscape (Ritchie & Cooper, [6]).

In 2004, 375 sites were monitored for compliance with the Surface Water Abstraction Directive (75/440/EEC) in England and Wales. Of these, 155 sites failed to comply with the Directive. However, over 90% of these 'failures' were due to insufficient sampling. These sampling shortfalls occur for a number of reasons, such as abstractions not being operated at the time of sampling, problems at the laboratory, and sampling error. The quality of abstracted water generally improved since 1993. It was found that levels of coloration, nitrate and polycylic aromatic hydrocarbons (PAHs) most commonly exceeded the Directive's standards in 2004 (Environment Agency, [7]).

Major water pollutants are suspended sediments (turbidity), pathogens, nutrients, metals, dissolved organic matter (DOM), pesticides, chlorophylls (algae, plants), temperature, and oils. Remote sensing applications to determine water quality are limited to measuring those substances or conditions that influence and change optical and/or thermal characteristics of the surface water properties (Ritchie & Cooper, [6]). Suspended sediments, chlorophylls, DOM, temperature, and oil are water quality indicators that can change the spectral and thermal properties of surface waters and are most readily measured by remote non-invasive sensing techniques. Substances (i.e., nutrients, metals) that do not change the optical and/or thermal characteristics of surface waters can only be inferred by measuring surrogate properties (i.e., chlorophylls) which may have responded to an input of chemicals. These remote sensing techniques should improve our abilities to monitor changes in the water topography and contents (Martinez et al, [8], Jane et al [9]).

The decision to look at case studies was made in order to find out how the water industry is coping with the flux of data that is being generated by sensors and to see what sort of improvements and/or recommendations can be made based on these studies (Dolgonosov & Korchagin, [10]).

CASE STUDIES

Two case studies were investigated. The sites chosen were based on two completely different types of water sources. One site, which can be referred to as the groundwater site, has its main water source from boreholes. The second site investigated was a lowland river of 30-100m^3/s flow rate.

This combination of ground and surface water WTW would enable us to set the benchmark on the reliability of sensors used in both cases and also examine hypothesis concluded from each site if applicable to the other. The hypotheses are based on the possible combination of sensors that would make it possible to operate the processes of the WTW or find alternative types of sensors.

1. Groundwater WTW

The project was initially aimed at resolving problems that were hampering the continuous operation at the groundwater WTW. The problems were caused by the shutdown of the WTW and the reporting of false alarms. This needed continuous intervention by the operating company to resolve these problems.

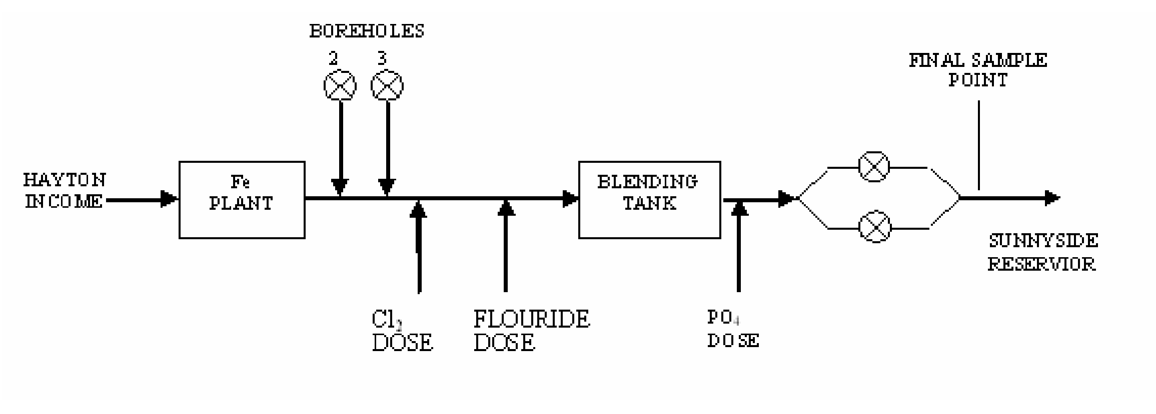

Figure 1: Groundwater WTW process diagram

1.1 Data Stored

The WTW operating system is configured to store several types of data that go through it and all causes of alarms raised. Some of the data stored were Fluoride & Phosphate levels, Borehole Flow 1, Borehole Flow 2, Incoming Flow, No.2 Borehole Flow, Total Borehole Flow, Booster Pump No.1 Delivery Pressure, and Booster Pumps Total Outflow. Other readings were also stored by the system indicating the cause of alarms or failures, e.g. power failure, maintenance worker on site, intruder alert, etc

After careful examination of the data retrieved from the site in text format, it was noticed that there was not much qualitative monitored data from the boreholes. The only two parameters that were stored were Fluoride and Phosphate dosage levels. This raises the question of what can be considered as minimum in terms of water monitoring WTW processes. It also highlights the issues involving legal requirements by the operating company to ensure operational standards are being met.

Table 1 illustrates the correlation coefficients found between the parameters. The correlation coefficient is a measure of the extent to which two measurement variables “vary together”. The correlation coefficient is scaled so that its value is independent of the units in which the two measurement variables are expressed. The value of any correlation coefficient must be between -1 and +1 inclusive. If positive correlation is found, it implies that large values of one variable tend to be associated with large values of the other; if negative correlation, then small values of one variable tends to be associated with large values of the other; and if correlation is near zero, then value of both variables tend to be unrelated.

From Table 1, a number of operational remarks can be made:

1. The Borehole Flow 2 with Incoming Flow are very much correlated, which suggests that they measure the same flow.
2. No. 2 Borehole Flow with Borehole Flow 1 and the Total Borehole Flow indicate that the major contributor to the groundwater WTW is actually Borehole 2. This could help the operator in determining the optimum location of water quality monitoring sensors that would yield the best possible operational gain.
3. Booster Pumps Total Outflow correlations indicate that its operational mode is very much dependent on the Incoming Flow more than on its outgoing one.
4. The flow rate is not connected to the Fluoride or the Phosphate levels. This could simply be caused by failure of the dosage sensor or an outside controller that adjusts the dosage levels.
5. Borehole Flow 1 is very much dependent on three main contributors to its readings, No 2 Borehole Flow, Total Borehole Flow and Booster Pumps Total Outflow.

Table 1: Correlation coefficients between measured parameters at the surface water WTW

	Borehole Flow 1	**Borehole Flow 2**	**Incoming Flow**	**No.2 Borehole Flow**	**Total Borehole Flow**	**Booster Pump No.1 Delivery Pressure**	**Fluoride Level**	**Phosphate Level**	**Booster Pumps Total Outflow**
Borehole Flow 1	1.00								
Borehole Flow 2	0.47	1.00							
Incoming Flow	0.46	**0.98**	1.00						
No.2 Borehole Flow	**0.85**	0.39	0.39	1.00					
Total Borehole Flow	**0.93**	0.50	0.50	**0.86**	1.00				
Booster Pump No.1 Delivery Pressure	0.38	0.51	0.51	0.33	0.40	1.00			
Fluoride Level	0.12	0.14	0.14	0.05	0.12	0.13	1.00		
Phosphate Level	-0.18	0.00	-0.01	-0.13	-0.03	-0.03	-0.10	1.00	
Booster Pumps Total Outflow	**0.74**	**0.83**	**0.84**	0.65	**0.77**	0.56	0.15	-0.04	1.00

Following on from the last operational remark made, it was decided to try and reprocess the data measured, using the Partial-Least Squares method. Three modelled equations were extracted for the Borehole Flow 1. Figure 2 below illustrates the results of the three models, with the measured flow versus the calculated flow in mega litres per day.

Partial least squares (PLS) is a method for constructing predictive models when the factors are many and highly collinear. PLS was developed in the 1960's by Herman Wold as an econometric technique, but some of its most avid proponents are chemical engineers and chemometricians. PLS has been applied to monitoring and controlling industrial processes; a large process can easily have hundreds of controllable variables and dozens of outputs (Dijkstra, [11]; Geladi & Kowalski, [12]; Stone & Brooks, [13]).

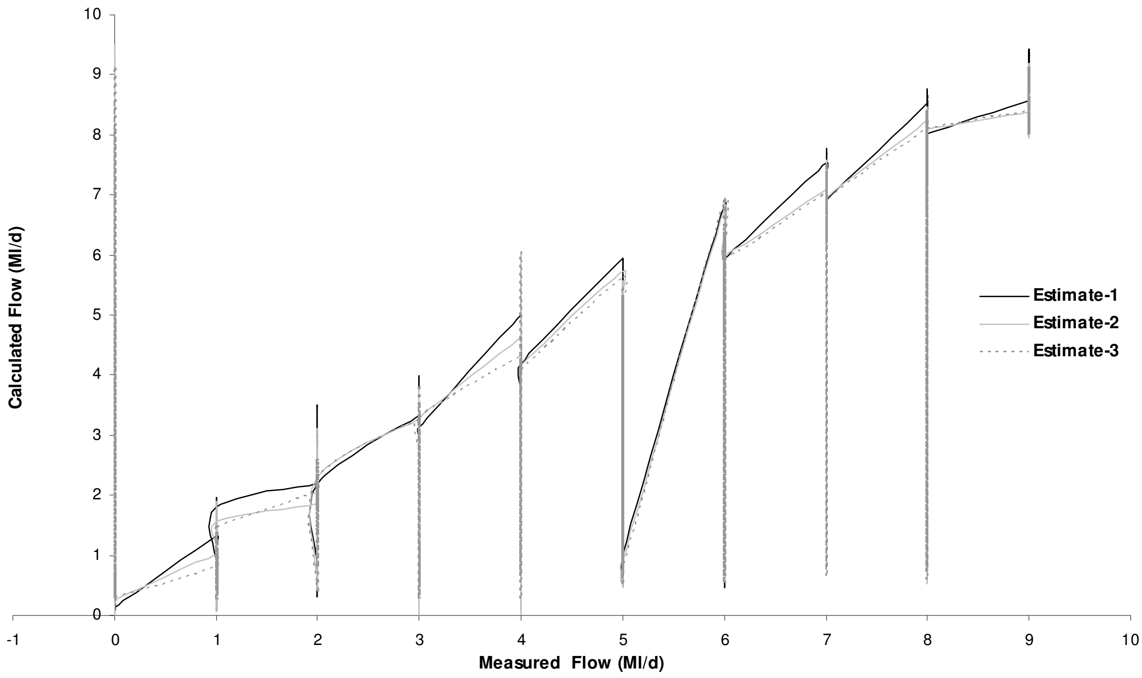

Figure 2: Illustration of the three models for Groundwater Borehole Flow

The graphs drawn out are highly similar in response. Estimate-1 is a calculated response for Borehole Flow 1 using all of the measured readings in table 1 as dependent factors. Estimate-2 is calculated using only the highly positive correlations associated with Borehole Flow 1, which are Borehole Flow 2, No. 2 Borehole Flow, Total Borehole Flow and Booster Pumps Total Outflow. Estimate-3 was drawn out from only No. 2 Borehole Flow, Total Borehole Flow and Booster Pumps Total Outflow which have a correlation level of 0.75 or over.

The three graphs showed a strong coherence and indicated the possible use of computations to predict the total outflow from the WTW. It can also help cut the maintenance cost of the plant by computing the output and discarding the other flow meters under normal operational conditions. The sudden drops in the three graphs were accredited to the downtime the WTW faced during the period when the flow data was measured.

Figure 2 highlights the relevance reliability of the measured flow at the groundwater WTW and the need to further enhance the capabilities of interpreting this data to run the site and be able to, as a key parameter, audit its operations, whether raised by alarms or detection in faulty sensors. The other recorded data were the Fluoride and Phosphate dosage levels. Figure 3 shows the two measurements for comparisons.

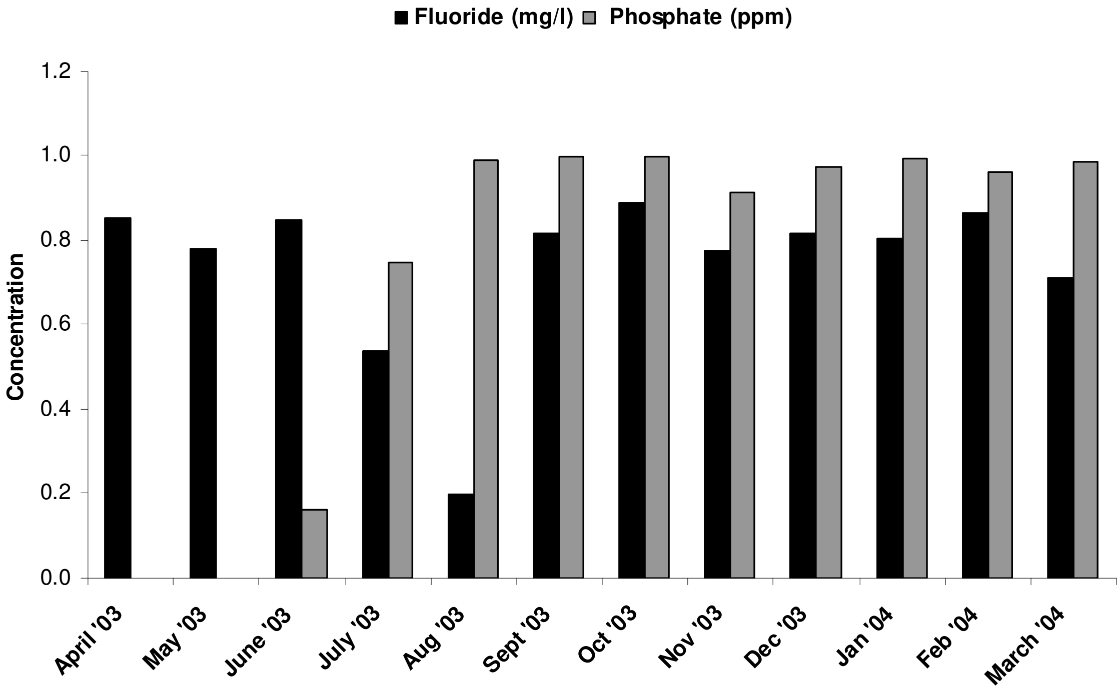

Figure 3: Fluoride and Phosphate dosage levels measured.

The measured dosage levels lead to a number of conclusions. Firstly at the start of April '03 and May '03, there was no evidence of Phosphate and this would in turn raise the question of when the legal maximum limit of around 1ppm was being met by the WTW and of when the equipment might have been installed. Secondly, a drop in Fluoride dosage was noticeable during the two month period of July '03 and Aug '03. There was no clear explanation that could have caused this drop in dosage levels. Despite comparing the data with the flow rate of the plant, still no explanation was given by the operator. It is clearly visible that the dosage method is almost in continuous sympathy with the flow.

Based on these conclusions drawn out from the graphs, it can be said that the data is still insufficient to run the WTW. The data is also insufficient and/or missing to confirm compliance; water quality measurements are not available to determine the efficiency of the WTW processes. The inaccuracy and discrepancies in the data caused by down time in the WTW is hampering the processes work and increases cost and time. No link with the SCADA (surveillance control and data acquisition) system can be drawn, except an indication that the chemical dosage levels are controlled from outside the plant works system.

2. River Water

Part of the objectives of the project was to improve the operational running of the SCADA system of the WTW through the use of an advanced sensors network and automated processes. A second case of surface water WTW was therefore chosen. This was to ensure that findings and obstacles faced with the first case study were very much real and unnoticed. The WTW is a river abstraction of around 100ML/day.

2.1 Data Stored

The site monitors Turbidity, Colour, pH, Conductivity, Ammonia & Temperature. These parameters were chosen on the basis of their availability and also their relevance to each other. Using this data, a statistical analysis was performed to try and correlate these data together.

A deterministic value of how much correlation existed between the different parameters, the covariance value between each parameter was calculated (Table 2).

The covariance tool is used to examine each pair of measurement parameters to determine whether the two measurement parameters tend to move collectively— that is, whether large values of one parameter tend to be associated with large values of the other (positive covariance), whether small values of one variable tend to be associated with large values of the other (negative covariance), or whether values of both variables tend to be unrelated (covariance near zero).

Table 2: Covariance coefficients between the parameters monitored

	Turbidity	Colour	pH	Conductivity	Ammonia	Temperature
Turbidity						
Colour	**81.223**					
pH	-0.532	-0.483				
Conductivity	**-362.84**	**-388.41**	4.068			
Ammonia	0.334	0.105	-0.002	-0.004		
Temperature	-5.748	-10.514	0.007	17.486	-0.002	

It is clear from the table that the most obvious positive link exists between turbidity & colour. This is acceptable as turbidity contributes largely to the colouring in the water as a result of sediments floating in the water. Figure 4 shows the Turbidity & Colour readings changing with time. The higher the covariance coefficients between the parameters monitored, the stronger the correlation between these parameters. It is also clear that the temperature has some effect on the conductivity readings. This sounds logical, as it would be anticipated that temperature would affect solubility of contaminants and therefore conductivity.

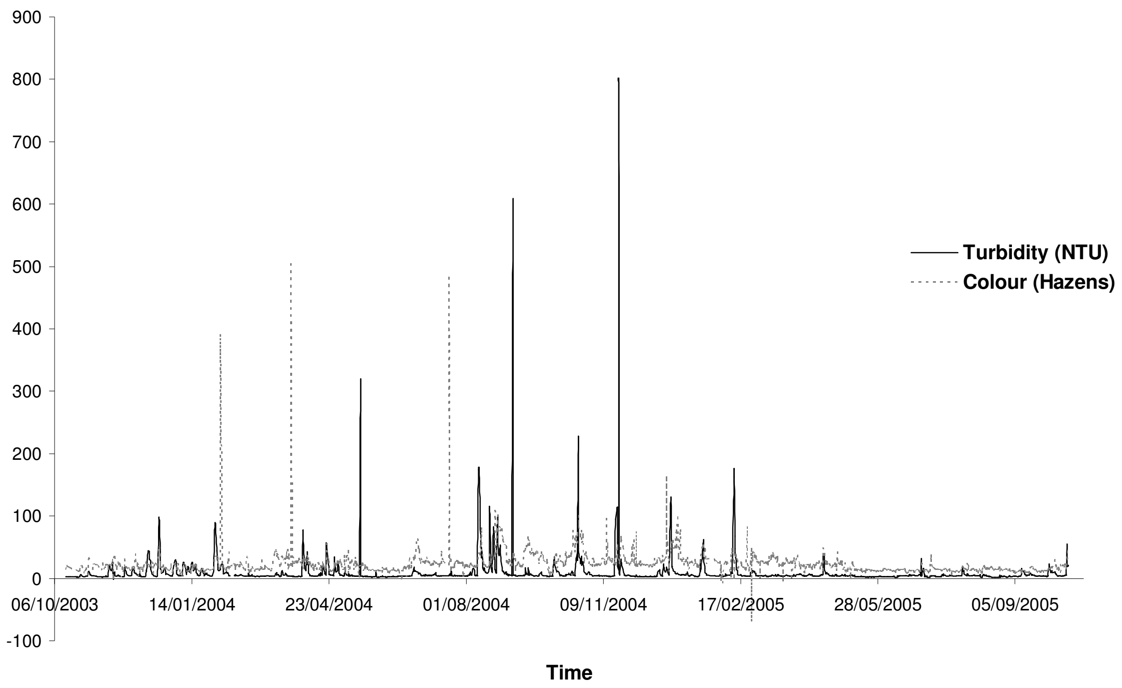

Figure 4: Changes of Turbidity & Colour with Time.

It is also noticeable from Table 2 that the covariance between turbidity & colour at one end, and conductivity at the other end. As stated before, negative covariance's imply small values of one variable tend to be associated with large values of the other. In other words, a decrease in turbidity & colour increases conductivity. Figure 5 illustrates these findings.

Figure 5 reveals the distinct characteristics of the river. The river conductivity reading mainly lies between 250 and 650 (umho/cm). These readings are circumstantial depending on other factors, like river flow, rain fall, etc. Salts, minerals, and even dissolved gases contribute to the conductivity of a given solution. This means that the conductivity can be used as an indicator of the amount of dissolved materials in a solution, thus how reliable an indicator of other parameters is.

Since the covariance analysis cannot be taken as a conclusive result, because it does not account for the different dimensionality of the parameters, another statistical analysis was used to double check the findings. This time the correlation coefficient was used (Table 3).

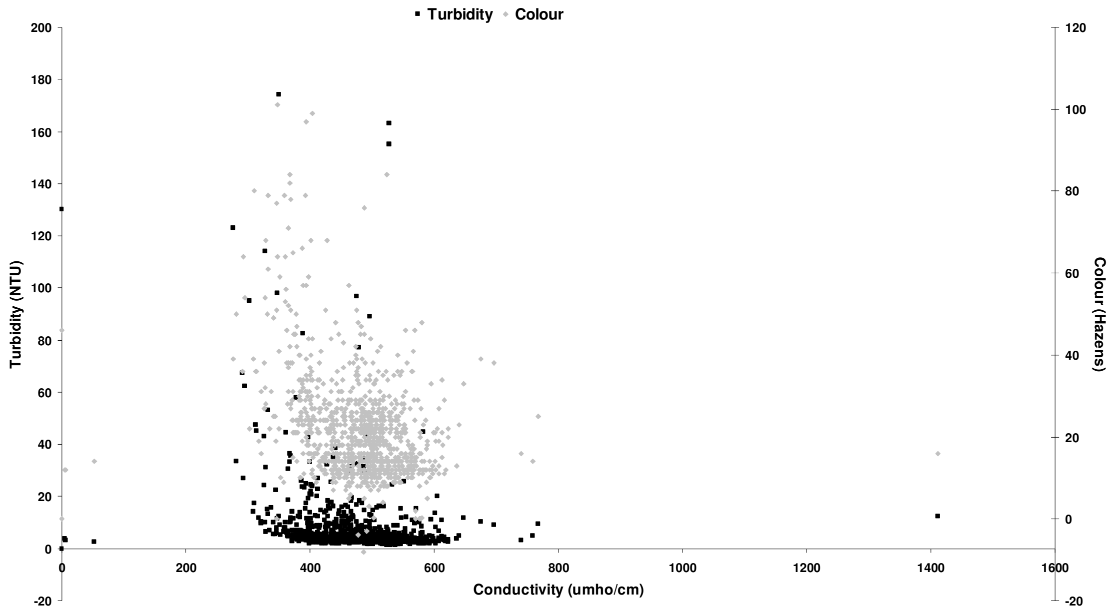

Figure 5: Conductivity readings with changes in Turbidity & Colour

Table 3: Correlation coefficient between the parameters monitored

	Turbidity	Colour	pH	Conductivity	Ammonia	Temperature
Turbidity	1.000					
Colour	**0.117**	1.000				
pH	-0.067	-0.084	1.000			
Conductivity	-0.146	-0.218	**0.199**	1.000		
Ammonia	**0.229**	0.100	-0.127	0.000	1.000	
Temperature	-0.041	-0.191	0.006	0.055	-0.010	1.000

The correlation coefficients calculated for the measured parameters at the river WTW have very small significance. This is an indication that all the parameters measured are not related to each other and cannot be interpolated from other types of sensors. The only explanation that can be noted from the correlation is that the relationship between Turbidity and Ammonia can be attributed to the rainfall effect on farmlands adjacent to the river. The rain is expected to wash some of the fertilizers into the river stream and causing the turbidity to rise at the same time.

From the above, it can be concluded that the data is not reliable enough to run the plant; each parameter measured is very much independent on its own of other types of parameters and their sensors. Sensors are clearly not really used fully; the interrelationship between sensors should be established to crosscheck the other sensor performance. Data also does not show how it benefits SCADA or how it links with it. Finally, data from sensors are disregarded as valuable information, since data used in the analysis were measured, not monitored.

CONCLUSION

Two case studies were looked at to examine the reliability and confidence of the sensors readings on the running of Water Treatment Works. Groundwater and surface water sites were both taken as a first step in analysing their measurements taken. The data represented by the two sites showed the lack of use, which is currently widespread in the water industry, for the full potential of an alternative measuring and monitoring techniques that can be implemented within the industry. It also emphasised the issue of backup monitoring and self adjusting automation processes that are needed within the industry to face the huge rise in power consumption. The study also showed that a relationship is needed to be found between the different types of sensors and/or measured parameters in order to cross check the sensors performance and be used as a guide of when maintenance procedures are needed. Operating procedures within the WTWs are also required to be improved to cut costs; for example, the use of artificial neural network would enhance the work rate of the site simply by detecting when it needs to reset itself without the support of an external operator.

ACKNOWLEDGEMENT

The authors would like to thank the Engineering & Physical Sciences Research Council (EPSRC) in the UK and Myriad Vision Ltd for their support and funding of this project. A special appreciation is also in place for Severn Trent Plc for the support given in accessing and gathering of the data for the two sites.

REFERENCES

[1] American Water Works Association, Water Quality and Treatment: A Handbook of Community Water Supplies, McGraw-Hill, New York, 1990.

[2] http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=CELEX:31998L0083:EN:HTML

[3] Hughes, G. Standardising Control for the Water Industry. The IEE Computing and Control Journal, 2004.

[4] Geldreich, E.E., Microbial Quality of Water Supply in Distribution Systems, Lewis Publishers, Bocta Raton, Fl, USA, 1996.

[5] Reasoner, D., Pathogens in Drinking Water – Are there any new ones? US Environmental Protection Agency, Washington, D.C, USA, 1992.

[6] Ritchie, J.C. and Cooper, C.M. Remote sensing for determining water quality: Application to TMDL, pp. 367-375. In: TMDL Science Issues Conference, Water Environment Federation, Alexandria, VA, USA, 2001.

[7] Environment Agency, 2004. http:// www.environment-agency.gov.uk/.

[8] Martinez, K, Hart, J. K. and Ong, R. Environmental Sensor Networks. Computer, vol. 37, no. 8, pp. 50-56. 2004

[9] Jane, K.H., and Martinez, K, *Environmental sensor networks*, Eos, Volume 86(16) page 162, 2005.

[10] Dolgonosov, B. M., and Korchagin, K. A. Statistical assessment of relationships between water flow in a river and water turbidity in water intakes. Water Resources, vol. 32, no. 2, pp. 175-182.

[11] Dijkstra, T. Some comments on maximum likelihood and partial least squares methods. Journal of Econometrics, 22, 67-90, 1983.

[12] Geladi, P, and Kowalski, B. Partial least squares regression: A tutorial. Analytical Chimica Acta, 185, 1-17, 1986.

[13] Stone, M. and Brooks, R. Continuum regression: Cross-validated sequentially constructed prediction embracing ordinary least squares, partial least squares, and principal components regression. Journal of the Royal Statistical Society, Series B, 52(2), 237-269, 1990.