A Real-Time Water Quality Information Acquisition System for Wastewater Source Control

Huijun Zhao[1], Roger O'Halloran[2], Melissa Winnel[1,3], Shanqing Zhang[1], Trang Nguyen[1], Peter Toscas[3] and Nigel Goodman[2]

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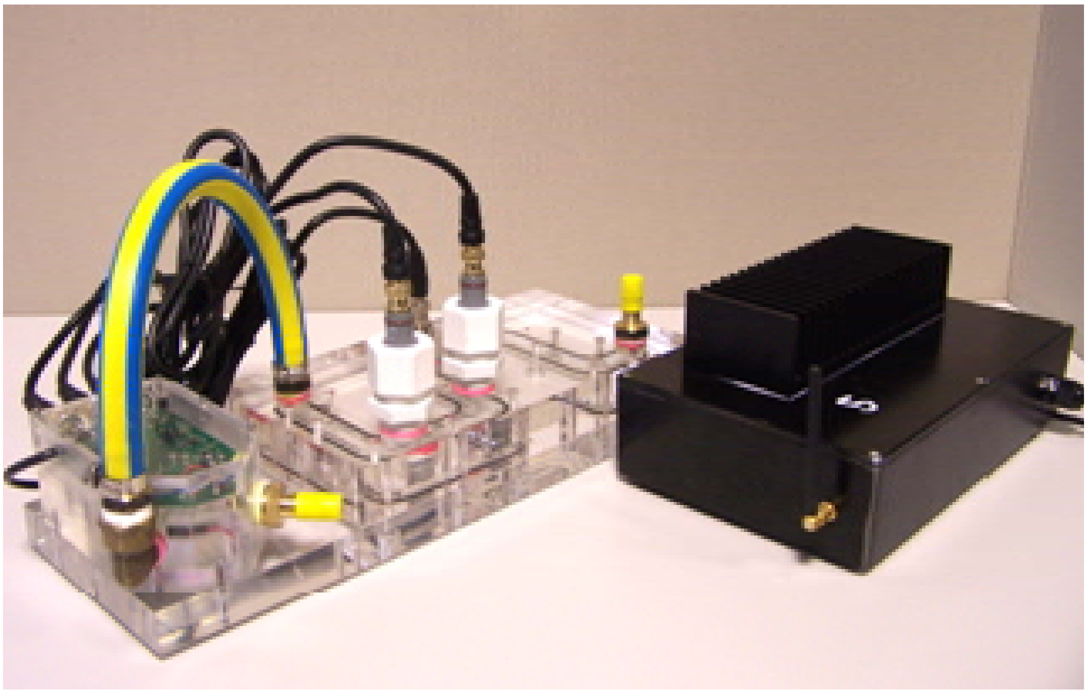

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The Urban Water Security Research Alliance (UWSRA) is a $50 million partnership over five years between the Queensland Government, CSIRO's Water for a Healthy Country Flagship, Griffith University and The University of Queensland. The Alliance has been formed to address South East Queensland's emerging urban water issues with a focus on water security and recycling. The program will bring new research capacity to South East Queensland tailored to tackling existing and anticipated future issues to inform the implementation of the Water Strategy.

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Enquiries should be addressed to:

The Urban Water Security Research Alliance
PO Box 15087
CITY EAST QLD 4002

Ph: 07-3247 3005
Email: Sharon.Wakem@qwc.qld.gov.au

Project Leader – Huijun Zhao
Griffith University
GOLD COAST QLD 9726

Ph: 07-5552 8261
Email: h.zhao@griffith.edu.au

Authors:
1 - Centre for Clear Environment and Energy, Gold Coast Campus, Griffith University, Queensland 4222.
2 - CSIRO Land and Water, Clayton South, VIC 3169.
3 - CSIRO Mathematics, Informatics and Statistics, Clayton South, VIC 3169.

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Cover Photograph:

Description: Connections between the sensor control electronics and sensors housing on the U-shaped flow cell.
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FOREWORD

Water is fundamental to our quality of life, to economic growth and to the environment. With its booming economy and growing population, Australia's South East Queensland (SEQ) region faces increasing pressure on its water resources. These pressures are compounded by the impact of climate variability and accelerating climate change.

The Urban Water Security Research Alliance, through targeted, multidisciplinary research initiatives, has been formed to address the region’s emerging urban water issues.

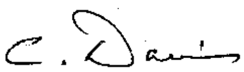
As the largest regionally focused urban water research program in Australia, the Alliance is focused on water security and recycling, but will align research where appropriate with other water research programs such as those of other SEQ water agencies, CSIRO’s Water for a Healthy Country National Research Flagship, Water Quality Research Australia, eWater CRC and the Water Services Association of Australia (WSAA).

The Alliance is a partnership between the Queensland Government, CSIRO’s Water for a Healthy Country National Research Flagship, The University of Queensland and Griffith University. It brings new research capacity to SEQ, tailored to tackling existing and anticipated future risks, assumptions and uncertainties facing water supply strategy. It is a $50 million partnership over five years.

Alliance research is examining fundamental issues necessary to deliver the region's water needs, including:

- ensuring the reliability and safety of recycled water systems.
- advising on infrastructure and technology for the recycling of wastewater and stormwater.
- building scientific knowledge into the management of health and safety risks in the water supply system.
- increasing community confidence in the future of water supply.

This report is part of a series summarising the output from the Urban Water Security Research Alliance. All reports and additional information about the Alliance can be found at http://www.urbanwateralliance.org.au/about.html.



Chris Davis
Chair, Urban Water Security Research Alliance

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EXECUTIVE SUMMARY

With the introduction of purified recycled water (PRW) in South East Queensland (SEQ), a closed water loop has been established in which PRW can be fed into Wivenhoe Dam, and ultimately the water supply system, when the combined level of the drinking water dams in SEQ falls below 40%. This gives rise to potential water quality risks from possible contaminants in the treated wastewaters. Consequently, new legislation governing PRW operation has been framed to minimise the human health impact, which means that a more stringent water monitoring regime is required.

In a three-stage project undertaken over five years, an integrated real-time Water Quality Information Acquisition System (WQIAS) was developed, and field trials were undertaken which demonstrated that it is the ideal basis for an effective management tool for wastewater source control. This is of particular relevance for the PRW system in SEQ, where continuous production of optimally treated wastewater is required to ensure reliable operation of the subsequent water purification stages.

In previous Stage 1 research, an in-depth understanding was gained of the issues and risks involved with closed water loop operation. It was determined that no effective real-time monitoring systems were in place at Barriers 1 and 2 of the PRW system (source control and the wastewater treatment plant), and that current sensor technologies could not perform reliably in the raw sewage environment. In Stage 2 of the project, a novel WQIAS sensing system with integrated real-time event detection was developed to operate effectively in raw sewage and treated effluent. The system has four main components that allow it to function for extended periods without calibration or maintenance:

- A new characterisation method based on recognising abnormal events with a univariate mathematical model, which does not rely on the accuracy of sensor signals;
- Robust sensors that can tolerate the harsh wastewater matrix;
- A compact flow manifold with unique hydrodynamics optimised to produce high shear zones where sensors are located to minimise biofouling; and
- Integrated software and hardware to implement this new technology in a reliable package.

In Stage 3 of the project, long-term field trials of the WQIAS real-time event detection system were undertaken at Barriers 1 and 2 at the Bundamba WWTP. Two independent units were deployed at each barrier to confirm the validity of any water quality changes observed. The trials showed that the system control hardware/electronics, including the sensing platform, performed as expected, and a number of significant events were detected. These included catchment overflows after heavy storms, several major industrial waste dumps, and one clarifier failure. Some of the waste dumps were shown to compromise WWTP performance, as they caused significant changes in dissolved oxygen and pH levels in the treated effluent discharge at Barrier 2.

The project has delivered a functioning WQIAS system that is an ideal basis to develop a sophisticated catchment management system. It has provided the springboard for an ARC Linkage project between Griffith University, Melbourne Water and Sydney Water to further develop the technology. CSIRO has also further refined the fouling resistant flow manifold, and is currently preparing a provisional patent application to protect the unique hydrodynamic design. It is anticipated that both these developments will result in significant advances in online monitoring technology applicable to harsh fouling environments such as wastewater.

1. INTRODUCTION

Uncertain global climatic conditions, ever increasing population growth and rapid industrialisation have placed enormous pressure on traditional freshwater sources. To address this situation, recently developed water security strategies have considered purified recycled wastewater (PRW) as a reliable source to increase the water supply capacity, especially in large cities.[1-3] Over the period 1997–2010, a large part of Australia experienced the most severe drought conditions on record - the Millennium drought. As a result, many Australian water utilities are now required to incorporate water reuse targets as a part of their water security strategies. This has led to multibillion dollar investments in new water infrastructure in major Australian cities, aiming to utilise alternative water sources (e.g., stormwater, desalinated seawater and PRW) to maximise the water supply capacity.

The Millennium drought seriously threatened the water supply in South East Queensland (SEQ), especially the broader Brisbane region. By July 2007, Wivenhoe Dam was at only 17% of capacity. In responding to the drought conditions and to secure the water supply in SEQ, the Queensland government invested substantial resources to establish a SEQ Water Grid, an important component being the Western Corridor Recycled Water Scheme for the production of PRW. The PRW scheme is one of the world's largest, consisting of a number of key treatment barriers including sewage treatment, advanced water treatment, surface water return to storages, and potable water treatment and distribution. The safety, reliability and efficiency of the treatment barriers are prime attributes for the successful operation of such a large scale PRW system, which relies heavily on guaranteeing the quality of PRW introduced into the water supply system.

Traditionally, wastewater management was focused on disposal of treated effluent while meeting environmental discharge targets. Under such circumstances, the potable water quality was relatively independent of the quality of wastewaters. With the introduction of a closed loop water cycle through increasing use of recycled water, wastewater is now seen as a part of source water. Furthermore, in order to be able to consider potable recycled water as a servicing option, the recycled water and drinking water supplies need to be cohesively managed to ensure risks to public health are minimised.

To this end, effective wastewater source control and management are crucial to mitigate potential risks at the earliest stage. The Australian Guidelines for Water Recycling requires thorough characterisation of source water quality to reduce any potential health risks, in particular the inputs from trade waste discharges.[4] In practice, state regulators require comprehensive recycled water management plans to mitigate risks, including implementing adequate monitoring practices to manage wastewater sources.[5]

There is, however, a major shortfall in the water quality monitoring techniques used to adequately address such regulatory requirements. Current monitoring regimes typically rely on taking discrete samples which lack the resolution to adequately describe wastewater quality in space or time, to capture illegal discharges, or to detect industry spill events. In other words, the introduction of recycled water, both potable and non-potable, dramatically changes the traditional means of wastewater control, as what was once a waste stream is now a part of the source water. This gives rise to potential water quality risks from possible contaminants in PRW. In this regard, source water characterisation and effective control of inputs are vitally important for safeguarding the recycled water infrastructure, water product, and ultimately public health.

In order to strategically address the shift required in the approach to wastewater management and quality control to ensure the integrity of PRW system, the project team undertook a wide consultation with SEQ water utilities, regulatory bodies and state governmental agencies to identify the technologies needed. The outcome was a consensus that there was a current need to develop a new management tool for effective wastewater source control and management. It was recommended that a new system should be developed that would be capable of alerting operators in real-time to anomalous changes (events) in wastewater quality that could potentially impact health and safety, sewer assets, downstream operations and recycled water quality. The system should also provide operators with a rapid response capability to mitigate risks in an operationally relevant timeframe, to dramatically enhance the capability of operators to safeguard system operation. Therefore, the primary aim of the project was determined to be the development of an effectively integrated real-time Water Quality Information Acquisition System (WQIAS) to safeguard PRW system operation and maintain the barriers' integrity by reducing the associated risks via an early warning mechanism (real-time event detection).

In order to effectively achieve such a project aim, a three-stage delivery plan was defined:

Stage 1 of the project was designed to set up a sound foundation for the subsequent stages. During this stage of the investigation, an in-depth understanding of the issues and risks involved with closed water loop operation was gained, and the key research activities required for future stages of the project were clearly identified. The investigation provided answers to important issues such as:

- The adequacy of existing data and data collection methods in maintaining the PRW barrier integrity;
- How on-line data can be collected for identifying potential risks that are introduced by the closed water loop;
- Targeted gaps and data short-falls at each treatment barrier;
- Currently available water quality monitoring techniques and their suitability for the PRW system; and
- Development of sensing methodologies.

By the end of this stage, an effective water quality information collection strategy was outlined, including options for real-time water quality data acquisition, protocols, transformation and use for relevant barriers. This was the subject of Technical Report #10 that was completed and delivered to the UWSRA management in 2009.

Stage 2 of the project was designed to develop new sensors/sensing technologies identified during Stage 1, along with a real-time event detection system. The aims of Stage 2 were:

- To develop and validate the system control hardware/electronics, including sensing platform;
- To develop and validate system control software, especially the event detection mathematical models suitable for Barriers 1 and 2; and
- To demonstrate the feasibility and applicability of the developed sensing system at for Barriers 1 and 2.

Stage 3 of the project was then designed to fully validate and demonstrate the applicability and reliability of the developed sensing system at Barriers 1 and 2 by a long-term on-site trial.

This report will summarise the findings from Stages 2 and 3, including:

- System hardware (including control electronics, sensor, flow cells, etc);
- System software (including system control software, mathematical models for establish sensing signal reference-line and event detection); and
- Validation and performance evaluation of the integrated system.

2. SYSTEM OVERVIEW

The primary aim of this project was to develop a WQIAS to safeguard operation of the PRW system and maintain barrier integrity by reducing the associated risks *via* an early warning mechanism, ie, real-time event detection. The WQIAS was specifically designed to enable reliable analytical determination in wastewater environments and thereby provide critically important wastewater quality data and determine abnormal events in real-time. The WQIAS has two key functional sections (Figure 1). The first is the Real-time Water Quality Data Acquisition Platform (RWQDAP) that consists of a specially designed sensing platform to host all required sensors, integrated control electronics and the interface to the on-board computing system. RWQDAP is capable of acquiring real-time water quality data and must function reliably over the long-term in wastewater environments without the need for maintenance. The other functional section is the on-board Computing/Communication Platform (CCP) that consists of a purpose built computing and communication system, along with an interface to the RWQDAP and central control computer(s).

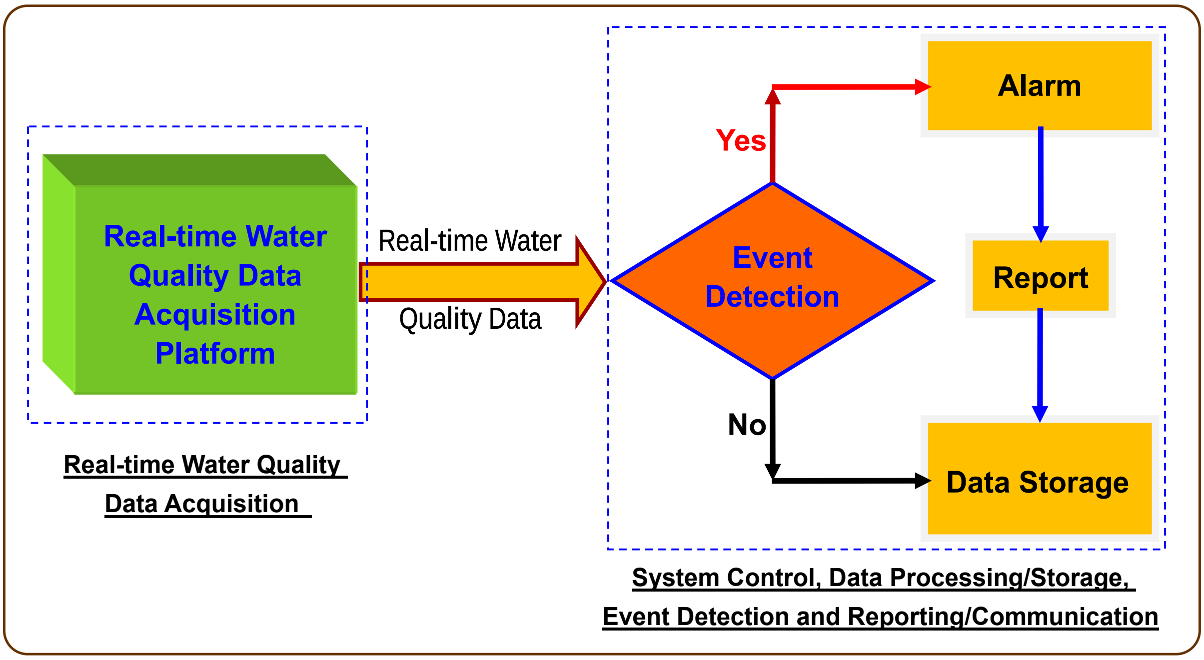


Figure 1. Schematic diagram of the Water Quality Information Acquisition System.

The CCP controls the operation of the RWQDAP processes and analyses the water quality data in real-time, detects any abnormal water quality changes (events), and handles data management/storage. The CCP uses wireless communication to report a detected event and raise an alarm in real-time, and also carries out the commands assigned by the central control computer. The CCP is operated by software that consists of a task management component, a data acquisition/processing/analysing component, a data management/storage component, an event detection component, and a communication component for alarm, reporting and communicating with the central computer.

The WQIAS can be deployed as an individual unit within any selected location of a sewer catchment. The WQIAS could also be deployed in groups at strategically import locations or critical control points of a sewer catchment and at the interface between the barriers (eg, between Barriers 1 and 2) to form a sensing network, as illustrated in Figure 2. The use of WQIAS units to build a sensing network within a catchment and at the interface between the barriers can significantly enhance the operators' ability and capability to predict the impact of an abnormal event and allow more time to mitigate potential risks.

In this work, for system development, proof of concept and demonstration purposes, the WQIAS units were deployed at the end of a sewer catchment (the entry to a wastewater treatment plant, WWTP) and at secondary effluent output point, the interface between Barriers 1 (WWTP) and 2 (Advanced Water Treatment Plant, AWTP), as shown in Figure 2.

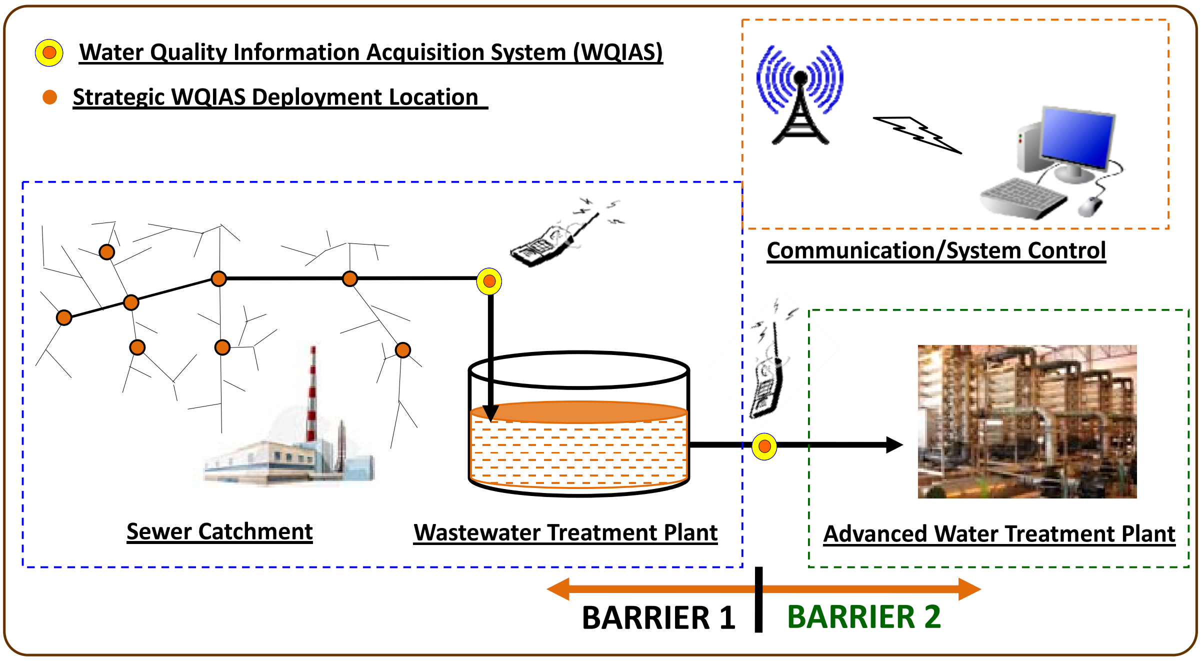


Figure 2. **Schematic diagram of WQIAS deployment within a sewer catchment.**

3. WQIAS HARDWARE DEVELOPMENT

Current wastewater monitoring practices rely on lab-based analysis of discrete samples[6,7]. Such an approach is incapable of precisely describing wastewater quality in space or time, or capturing anomalous changes that may adversely affect the wastewater operations and recycled water quality. This is mainly due to the lack of an effective continuous online wastewater monitoring system. The composition of raw sewage is highly diversified and presents as one of the most difficult analytical environments that challenges the limit of existing sensing technologies. Unlike well-controlled laboratory environments, the ever-present threats of blockage, surface contamination and biofouling are fatal problems causing sensor failure in wastewaters. Because of the limited availability of suitable sensors, current online sensing systems for wastewaters typically incorporate one or more of the following sensors: temperature (T); pH; conductivity (EC); turbidity (TB); dissolved oxygen (DO); and total organic carbon (TOC)[7,8]. Nevertheless, continuous functioning for sustained periods of even the most simple surrogate sensors (eg, pH, EC and TB) in raw sewage remains a serious challenge. A recent study conducted by the Water Environment Research Foundation in USA compared over 50 commercially available online sensors and revealed that only one met specified wastewater monitoring criteria[7].

In addition, the vast majority of sensors used for online monitoring applications are based on the direct adoption of classical lab-based analytical principles. This approach exhibits an intrinsic flaw of requiring strictly-defined measurement conditions. They may work well in laboratory environments where sample manipulation is allowed, but become problematic for field-based online applications where circumstances do not allow the sample to be artificially manipulated before assay[7].

For this project, two general strategies could be used to overcome this issue. One is to purposely develop new sensors/sensing technologies to suit the needs of wastewater environments, and the other is the innovative use of readily available sensors. The first strategy to develop new wastewater sensors is not only scientifically challenging but requires considerable time and resources without any guarantee of success. Considering the urgent need of this project, we decided to pursue the second strategy – developing a new approach to innovatively use readily available sensors for wastewater monitoring.

This section of the report summarises the research findings related to development of the WQIAS hardware system including hardware configuration, sensor selection/evaluation, design of a new flow-cell that innovatively uses hydrodynamic conditions to overcome biofouling, and the development of integrated electronics, on-board computer and communication function.

3.1. WQIAS Components

According to the designed functionality, the WQIAS consists of five functional components (see Figure 3):

(i) A pump for sample delivery;

(ii) A flow-cell to host required sensors;

(iii) An integrated control electronics circuit board for all sensor electronics and interfaced with the on-board computer;

(iv) An on-board computer interfaced with the control electronics and the communication device; and

(v) A wireless communication device.

The RWQDAP consists of components (ii) and (iii) to effect real-time water quality data acquisition. The CCP consists of components (iv) and (v), controlling the RWQDAP operation, water quality data processing/analysis/management/storage, abnormal event detection/alarm/reporting, and carrying out the central computer/operators' commands.

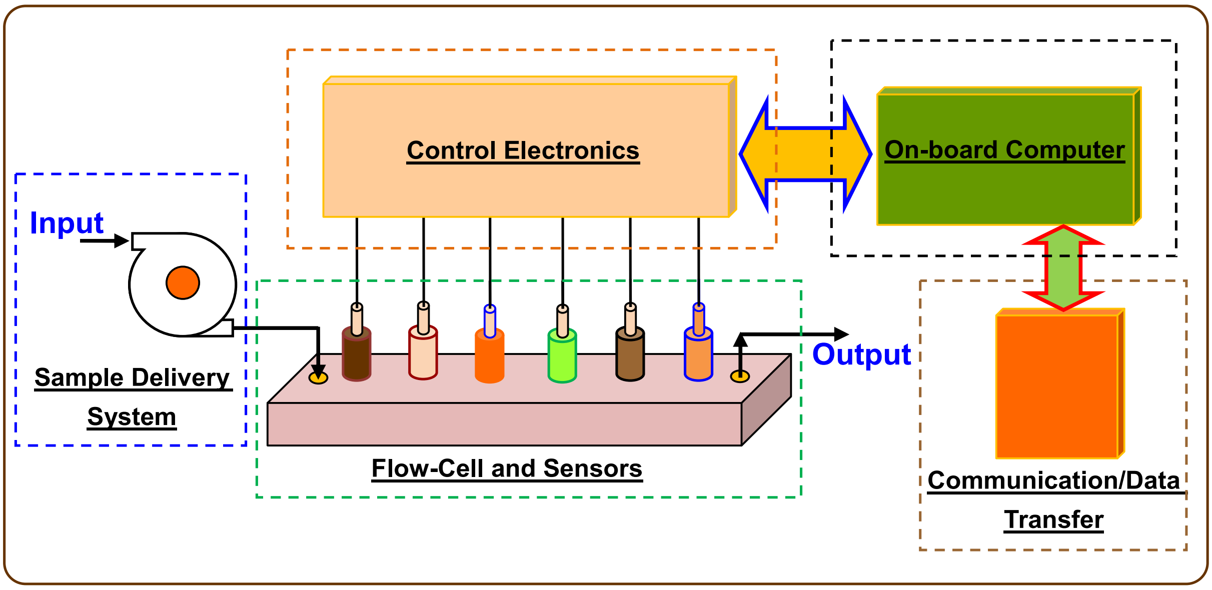


Figure 3. **Schematic diagram of WQIAS hardware components.**

3.2. Selection and Evaluation of Sensors

In this work, we have developed a new analytical approach to innovatively use commercially available surrogate sensors to acquire real-time water quality data and detect abnormal wastewater quality changes (see later for details). This approach requires the use of a group of surrogate sensors including temperature (T), pH, conductivity (EC), turbidity (TB), dissolved oxygen (DO) and redox potential (ORP) sensors. It is well known that raw sewage presents a very harsh and challenging analytical environment. Therefore, any sensor to be used for this project must meet some basic criteria, including:

(i) The sensor must be able to physically tolerate the raw sewage environment for a long period of time (eg, few years);

(ii) The sensor structure must be designed to minimise surface contamination, blockage and biofouling;

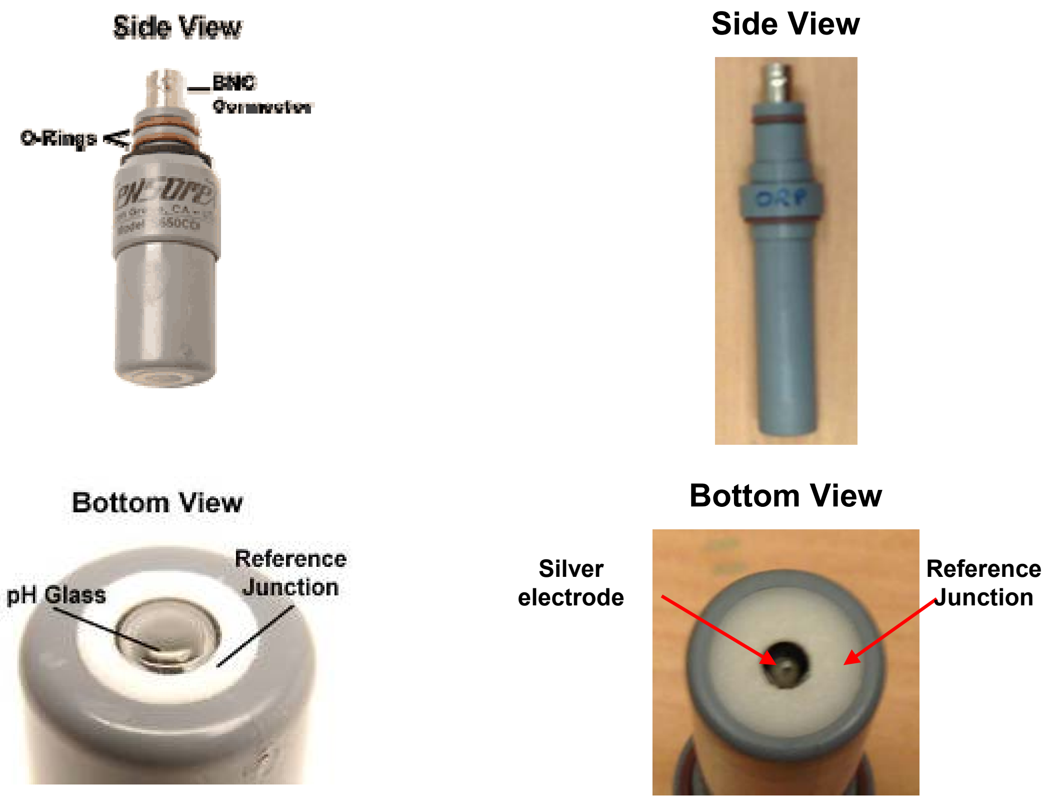
(iii) The sensor geometrical dimensions and shape need to be suitable for installation into the flow-cell (ie, flat sensing surface and less than 2 cm cross-section);

(iv) The sensor must have a reasonable response rate (ie, <1 s) and be able to operate continuously for extended periods; and

(v) The sensor should be a low power design.

A broad commercial sensor search and systematic evaluation was conducted and the results reported in our April-June Quarterly Report in 2009. The search results indicate that the temperature sensor is readily available. However, no suitable commercial EC and TB sensor were found, and only a limited number of commercially available pH, DO and ORP sensors meet the above criteria, but all would require modification before they could be installed into the flow-cells.

The pH 660CD (see Figure 4a) and ORP 660CD-ORP sensors (see Figure 4b) were sourced from Sensorex, who pioneered development of flat pH glass electrodes over 20 years ago. Both these electrodes are combination pH/Reference (or ORP/Reference) electrodes with double reference junction for added protection against contamination. They are easy maintenance, cartridge-type with quick disconnect BNC connectors. Electrode installation and removal can be done in just a few seconds and no tools are needed. Built into the electrode's body is a sealed, gel-filled double junction reference half-cell. This design provides an extra barrier against reference side contamination. Also, it allows the electrodes to be used in applications where sulphides, mercaptans, heavy metal ions, and similar materials are present (eg, sewage).



(a) pH probe

(b) ORP probe

Figure 4. Side and bottom views pH and ORP probes.

In the centre of the measuring surface is the pH-responsive flat glass surface. This surface is surrounded by the flat porous reference junction. The large area of this porous junction has thousands of pores that provide excellent sample contact.

The junction is enclosed by the electrode body. At the top of the electrode body is the quarter- turn, quick disconnect BNC connector and the leak-tight O-ring seals. The flat sensing surface is rugged, abrasion resistant, and self-cleaning. In both coating and abrasive applications, these cartridge-type electrodes can improve measurement accuracy, reduce maintenance, prolong electrode life and virtually eliminate breakage.

3.3 Self Cleaning Operation

This simple, but effective system has no moving parts and requires no power. When the electrode's flat measuring surface is exposed to turbulent flow, the resulting scrubbing action provides a self-cleaning effect in most applications. For the typical spherical electrode, the downstream side is shielded from the flow; coating forms on this dead flow area, causing sluggish and drifting signals.

3.4 Abrasion Free Operation

Particles sweep by the electrode's flat, non-protruding surface without impinging on or abrading it, extending electrode life. The non-protruding design virtually eliminates electrode breakage. Particles impinge on the upstream side of the spherical bulb, causing abrasion, calibration shift, and short life.

The Evita OXY 1100 50 µm membrane cartridge (085G0022) DO electrode (see Figure 5) was sourced from HACH. It has a pre-assembled anode, cathode, electrolyte, and membrane, and the sealed design eliminates the potential for leaks. It has a large gold anode and electrolyte volume (See Figure 5) and is designed to operate in raw sewage. The standard 50 µm cartridge has an operating range of 0-20 ppm and can last up to two years.

The DO electrode surface is almost flat and can be readily mounted in our custom designed flat top flow manifold.

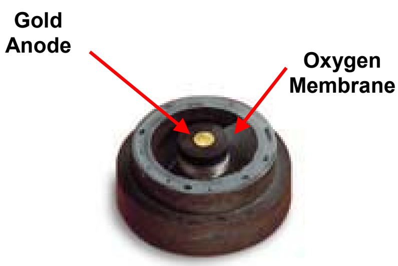


Figure 5. Bottom view of the dissolved oxygen (DO) probe.

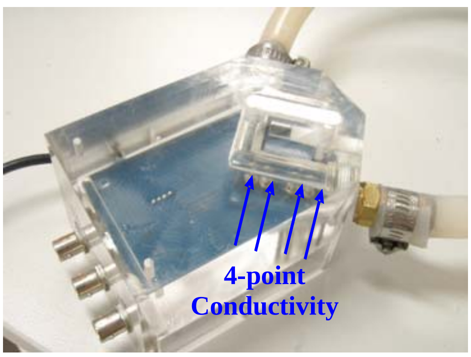
In light of the situation, we had no option but develop our own EC and TB sensors. The main problems with the commercial EC sensor are two-fold:

(i) Their geometries are unfit for the flow-cell and can easily be contaminated; and

(ii) These commercial EC sensors are relatively expensive and can only be operated and controlled by the original manufacturer instrument/electronics, which make them difficult to be integrated into our system.

After a detailed investigation and performance evaluation, a four-point conductivity sensor developed by CSIRO was employed for this project. This EC sensor employs four stainless steel bolts (cost less than $0.50) as the electrodes. The first generation EC sensor developed by CSIRO directly mounts four stainless steel bolts around a cross-section of the flow cell (Figure 6a). Importantly, the distribution of the four electrodes can be flexibly arranged to fit different geometric shapes of the flow-cells. This was further developed into the new generation EC sensor as shown in Figure 6b. The onsite evaluation demonstrated that such stainless steel four-electrode conductivity probes can be continuously operated in raw sewage for a period of three years without the need for replacement.

(a)



(b)

Figure 6. Photos of the initial (a) and newly-designed (b) 4-point conductivity probes.

The evaluation of commercially available TB sensors revealed a number of problems for use in this project:

(i) Their geometries are unfit for the flow-cell and are easily contaminated;

(ii) These commercial TB sensors are relatively expensive and can only be operated and controlled by the original manufacturers instrument/electronics, which make them difficult to be integrated into our system; and

(iii) More critically, these commercial TB sensors are unreliable in raw sewage, especially under flow conditions.

Initially, the project adapted a flow TB sensor developed by CSIRO as it can be readily installed into the flow cell and functions well under flow conditions. However, the onsite trial revealed that this CSIRO flow TB sensor had inadequate sensitivity for the secondary effluent at Barrier 2 and it required frequent maintenance due to the unsuitable configuration.

Hence, a new low turbidity sensor was developed (Figure 7). The sensor was designed with a near IR LED light source to avoid the interference of coloured species. It employs two photo diode detectors, one located at the opposite of the light input to measure the absorption and another set at 90^{o} to the input light to detect the scattered light for turbidity measurement. A unique feature of this dual detector configuration is that the effect of input light intensity change caused by the matrix can be corrected in the turbidity calculation. This makes the sensor highly reliable for wastewater turbidity measurement. The sensor has been continuously used in raw sewage TB monitoring at Barrier 1 for over two years without failure. This configuration also has high sensitivity, so that it is suitable for TB monitoring at Barrier 2 for the secondary effluent. The sensor was subsequently integrated into a specially designed flow cell that also accommodates a temperature sensor and a pH sensor (see later for details).

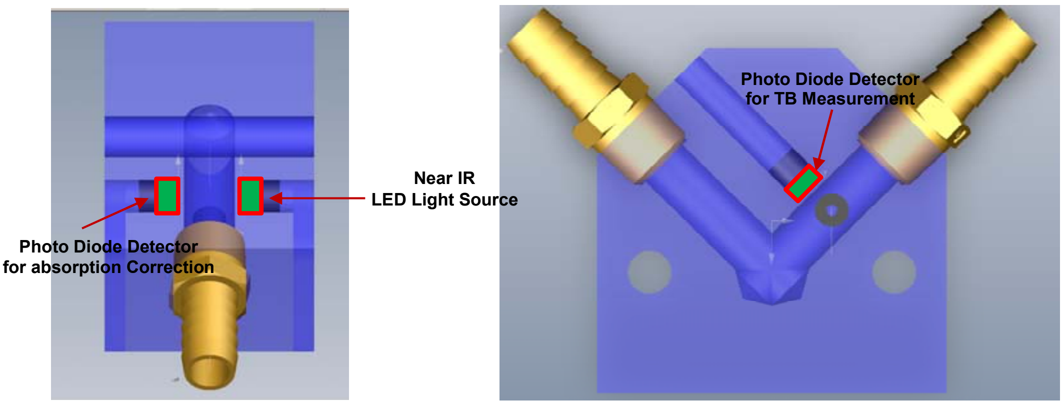


Figure 7. Dual-detector turbidity flow sensor.

3.5. Flow-Cell Design and Antifouling

As mentioned previously, raw sewage represents one of the harshest analytical environments. The failures of an online analytical system in raw sewage are often due to surface contamination, blockage and biofouling of sensors[7]. For such reasons, there has not been a real-time online water quality monitoring system reported that could function reliably over a period of weeks or even days without the need for maintenance. In fact, an online system must have a self-cleaning function to prevent surface contamination, blockage and biofouling before it can function continuously in the raw sewage environment for a considerable period (ie, weeks or months) without the need for maintenance.

Initial trials undertaken in a flow cell using the normal range of flow rate (ie, millilitres per minute) failed badly (Figures 8 to 10). Figure 8 shows a set of time series data from two pH sensors (hosted in a flow cell) deployed at the same location over the same time domain. Under such conditions, the sensing signals obtained from the two pH sensors should match each other if they are functioning normally. However, the data shows that the two sensors behaved very differently in terms of absolute value and the trend of changes, suggesting that one or both were not providing true pH reading(s). A detailed investigation found that both sensors were not in good working order because of surface contamination/biofouling (Figure 8 c). Similar failures were observed in trials using dissolved oxygen sensors (Figure 9). For turbidity, both sensors failed after 24 hours, when turbidity readings increased due to the formation of biofilm on the sensor surface (Figure 10).

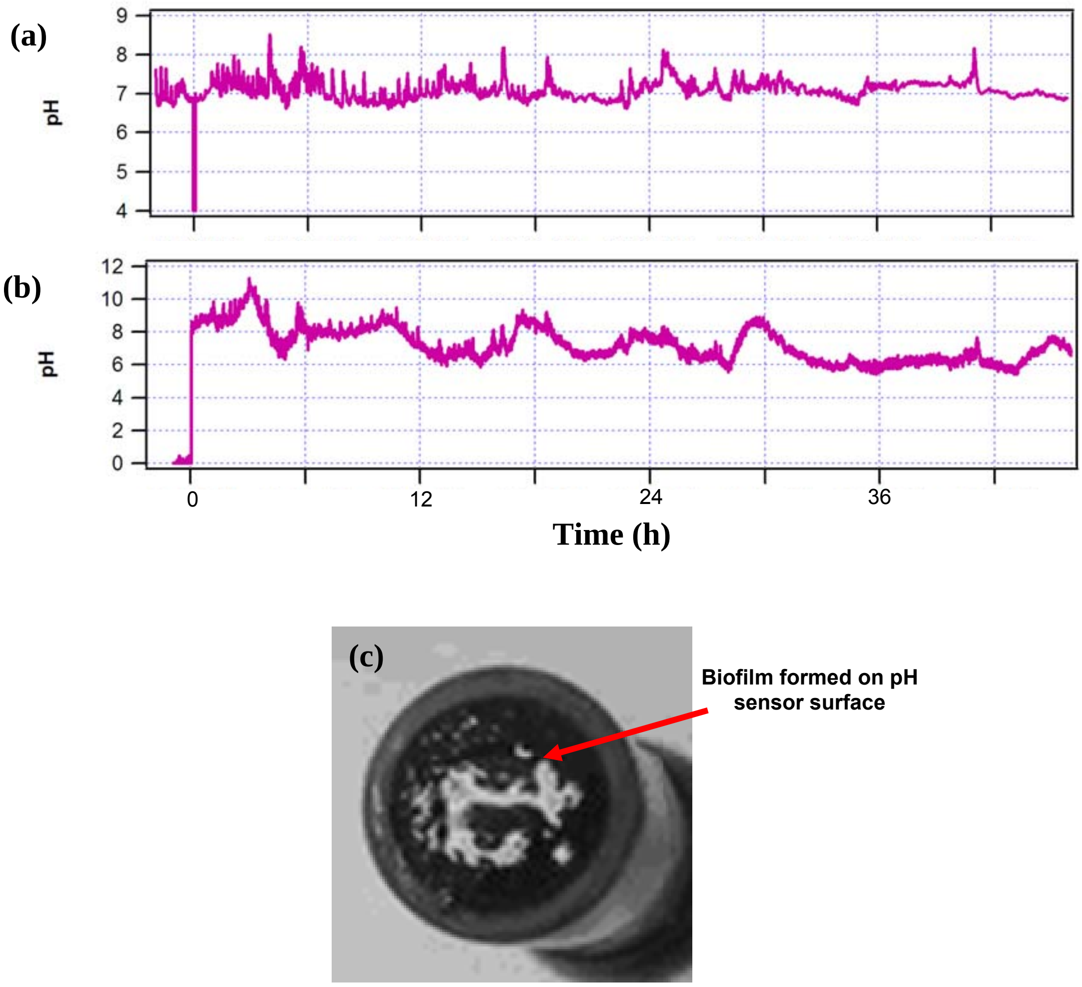


Figure 8. Time series data for pH obtained from: (a) sensor 1 and (b) sensor2; (c) pH sensor after 7 days use in raw sewage.

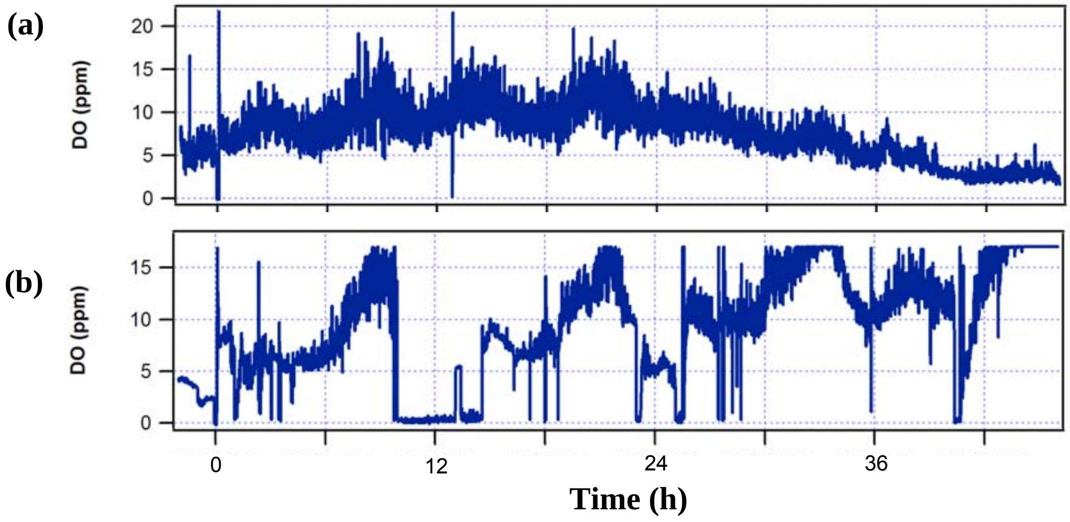


Figure 9. **Time series data for dissolved oxygen obtained from (a) sensor 1 and (b) sensor2.**

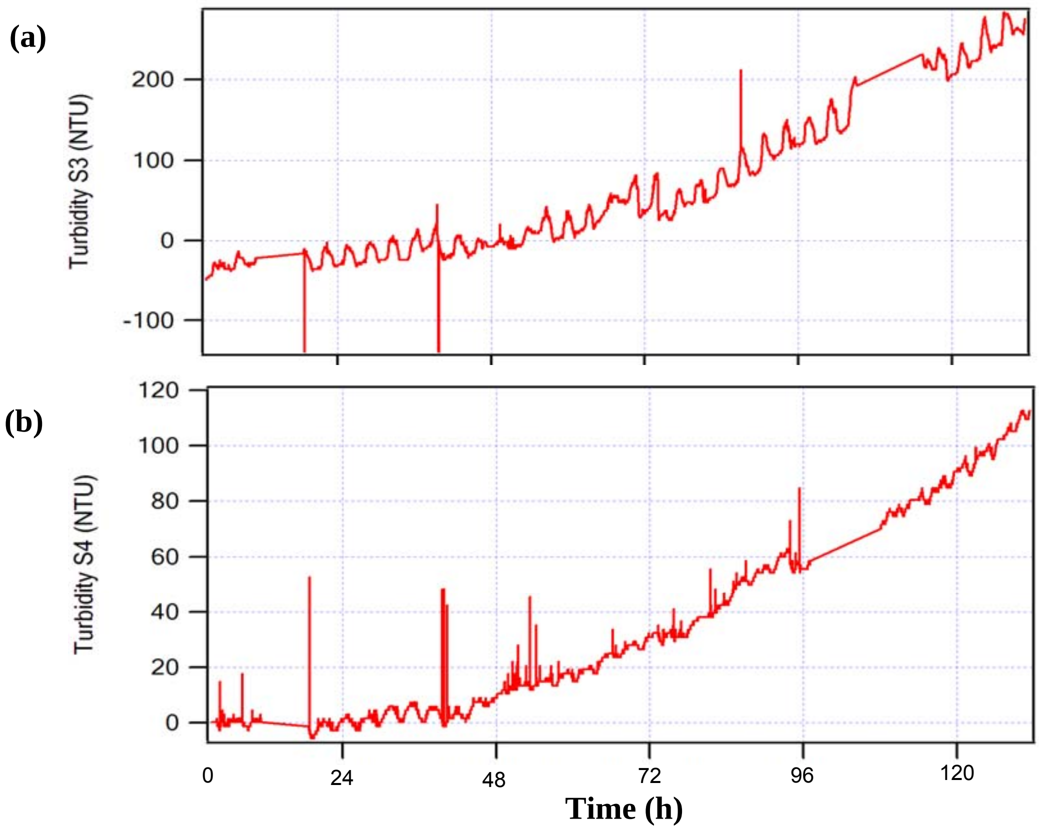


Figure 10. **Time series data for turbidity obtained from (a) sensor 1 and (b) sensor 2.**

In order to overcome the issue, we developed a new flow system that employs a specially designed flow-cell and unorthodox hydrodynamic flow conditions (up to 100 L/min) to achieve self-cleaning without the need for human intervention. The underlying principle is that all sewage contains solid particles and these solid particles can be used as the self-cleaning agent under high hydrodynamic flow conditions.

A tubular flow cell was initially designed to allow high flow rate up to 100 L/min (Figure 11a). The cell consists of multiple components that each hosts one sensor. Each component can be individually assembled in any sequence in the cell. Onsite trials at Bundamba WWTP revealed that the flow cell can allow a high flow rate and is capable of reliably providing real-time analytical signals for all the sensors. However, as shown in Figure 11b, after two months of continuous operation at Barrier 1 (raw sewage), the biofilm formation and surface contamination start to affect the sensing signal quality. Figure 11c shows the flow cells after two months use at Barrier 2 (secondary effluent). The biofilm formation and surface contamination was found to be more severe than that observed at Barrier 1, due to the fact that less solid particles are present in the secondary effluent than in the raw sewage. At this stage, the quality of the analytical signals was badly compromised. In addition, the turbidity sensor failed a number of times during the trial because the assembly gradually changed its position trapping air bubbles in the light pathway.

In order to further improve the system performance, a totally new flow cell was designed. The new design takes into account the drawbacks in the tubular flow cell. The new design is aimed to not only utilise the mechanical force of the solid particles under high flow conditions but also consider the cell's geometry to maximise the self-cleaning effect. Additionally, the new design considers system integration, allowing the control electronics to be directly mounted onto the flow cell to minimise electrical noise, ensuring a high quality analytical signal.

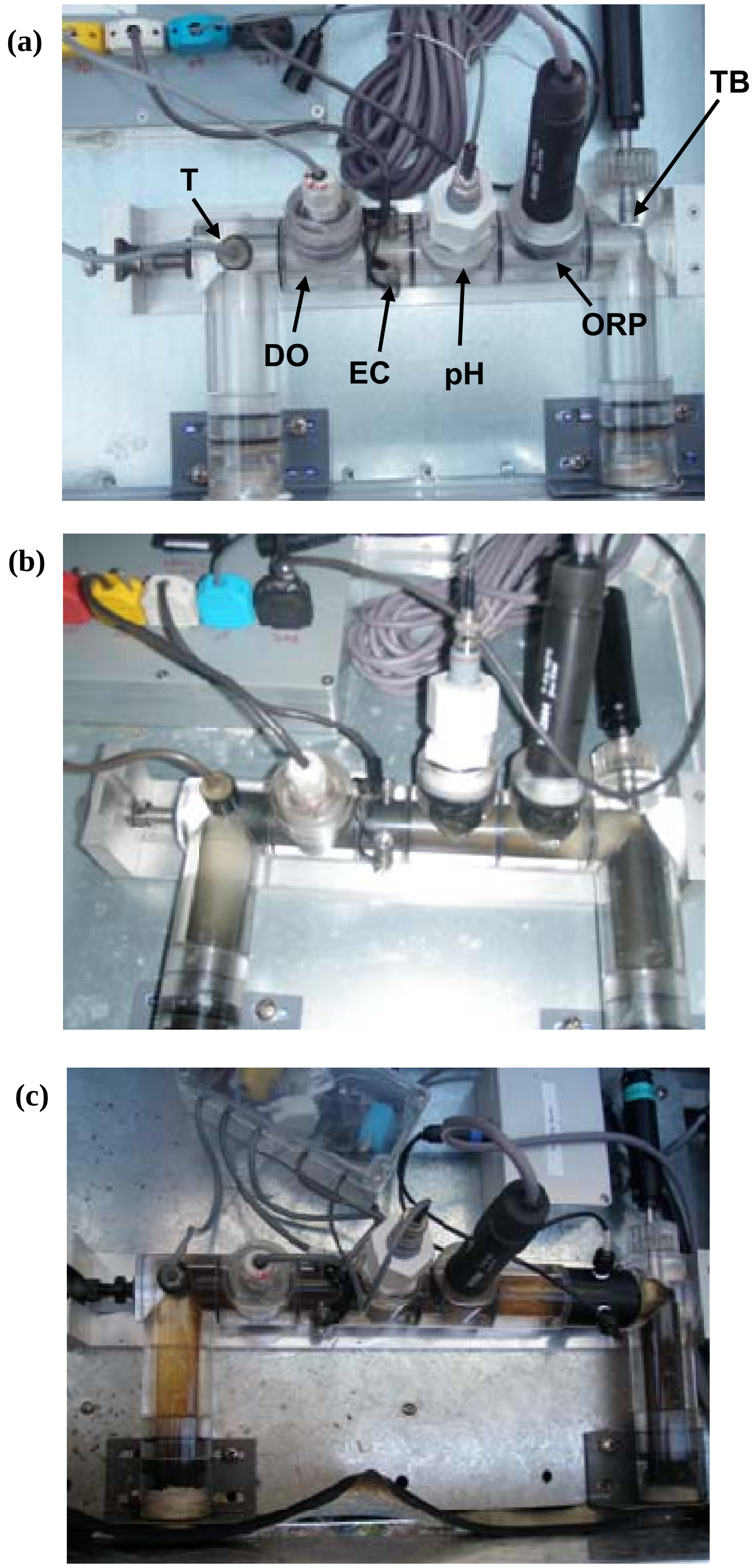


Figure 11. **(a) Tubular flow cell with individual assembled sensors; (b) after two months use in raw sewage (Barrier 1); (c) after two moths use in secondary effluent (Barrier 2).**

Figure 12 shows a novel wall-jetted flow-cell designed to house a temperature sensor, the in-house four probe conductivity sensor, along with the dual-detector turbidity sensor. The flow-cell injects wastewater flow at 45^{o} to the sensor surface using a 70 L/min flow rate. All sensors have been reliably operated over a 12-month period without the need for calibration and maintenance. With this design, all sensing electronics (for T, EC, TB, pH, DO and ORP) are mounted directly on the back of the flow cell to minimise electrical interference. This is critically important for an analytical system to operate in a WWTP environment for a sustainable period of time because the environment of any WWTP contains highly corrosive liquid and gases (eg, H_2S). These highly corrosive substances cause rapid corrosion of the electronics and other parts of the analytical system. In our initial work, we used an unsealed electronics design and found the electronic circuit board was severely damaged by corrosion within three months of use. With this new design, all electronics are fully sealed for corrosion protection (see later section for details).

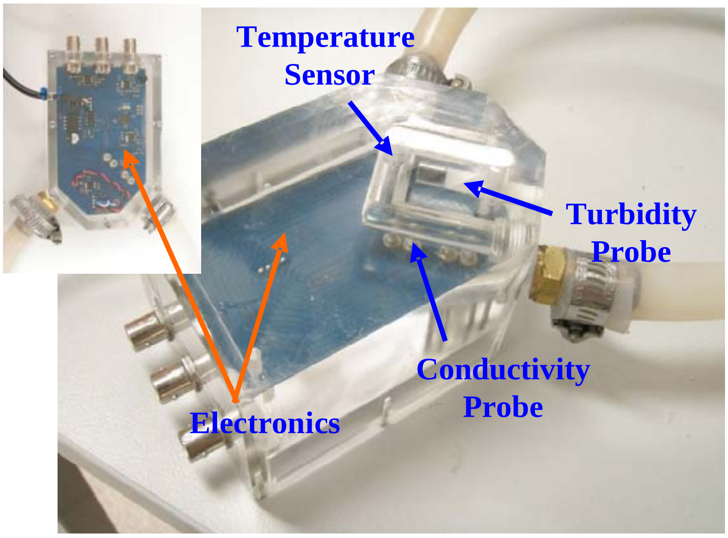


Figure 12. A wall-jetted flow-cell housing T, EC and TB sensors.

For the flow cell used to house the pH, DO and ORP sensors, detailed hydrodynamic flow modelling and experimental tests were conducted to optimise the *in situ* self-cleaning effect derived from sensor positioning within the flow cell, high fluid velocities and the presence of solid particles (used as the cleaning reagent) in wastewater. It was found that biofilm formation in particular parts of a U-shaped flow cell can be inhibited to a great extent (indicated by the circles in Figure 13). These locations can be utilised to house the sensors to minimise the effects of surface contamination and biofouling.

Hence, a U-shaped flow cell was designed in accordance with our modelling and experimental test results as shown in Figure 14a. The flow cell was then trialled in raw sewage over a 12-month period. All sensors functioned reliably over the 12-month test period without the need for calibration and maintenance, confirming the superior performance of the flow cell in the raw sewage environment. Figure 14b shows a pH sensor housed in the U-shaped flow cell after two months use in raw sewage. In stark contrast to the same type pH sensor housed in a conventional flow-cell with cross-sectional (180^{o} to sensor surface) flow rate of 10 ml/min after only one week of use in raw sewage at the same location (see Figure 8c), no obvious surface contamination or biofilm formation was observed, confirming the effectiveness of the self-cleaning U-shaped cell.

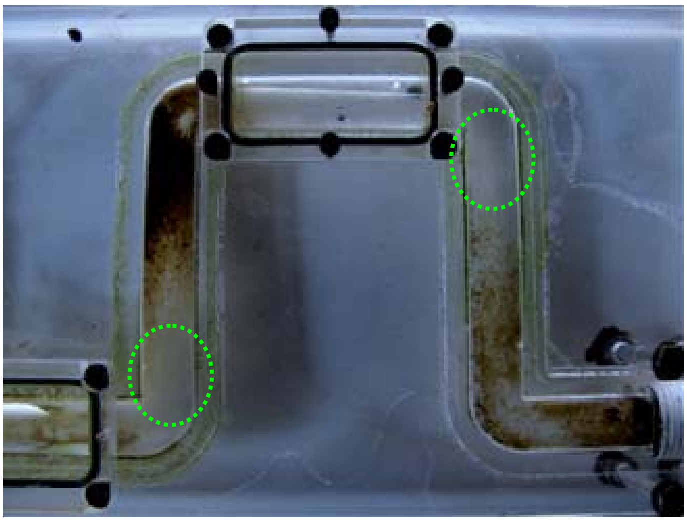


Figure 13. **U-shaped flow cell design.**

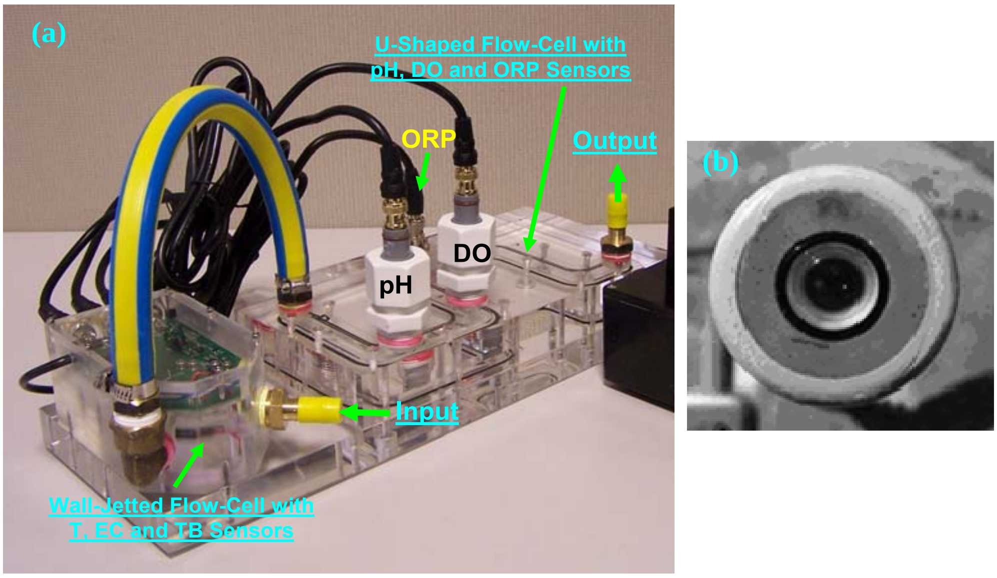


Figure 14. **(a) New generation flow cell combines a wall-jetted cell and a U-shaped flow cell; (b) pH sensor after two moths use in raw sewage.**

3.6. Control Electronics, On-board Computer and Communication

In order to quickly obtain real-time wastewater quality data during the initial stage of the project to allow development of the event detection mathematical model, the sensor control electronics developed previously by CSIRO were used (Figure 15). This system comprised two key components. One consists of sensor control units (each sensor is controlled by an individual electronic circuit board) and the other consists of a data logger and wireless communication device. The outputs of the sensor control units are analogue signals that input into the data logger and converted into digital signals. The digital signals can be sent via the on-board wireless communication device to an office computer. This system is only capable of recording real-time wastewater quality data. It is not capable of data processing, analysis or event detection. Because it does not have an on-board computer, all operations have to be manually set beforehand. Although this earlier system served the purpose of collecting real-time wastewater quality data for the event detection mathematical model development, it has a number of drawbacks:

- The analogue signal output and connection cables to the data logger make the system vulnerable to electrical interference;
- The individual sensor control circuit board is not compatible and cannot be integrated;
- The unsealed electronic circuits are vulnerable to the corrosive environment; and
- It does not have an on-board computer, which is necessary to enable remote control of system operation, real-time data processing/analysis/storage/transfer, and event detection.

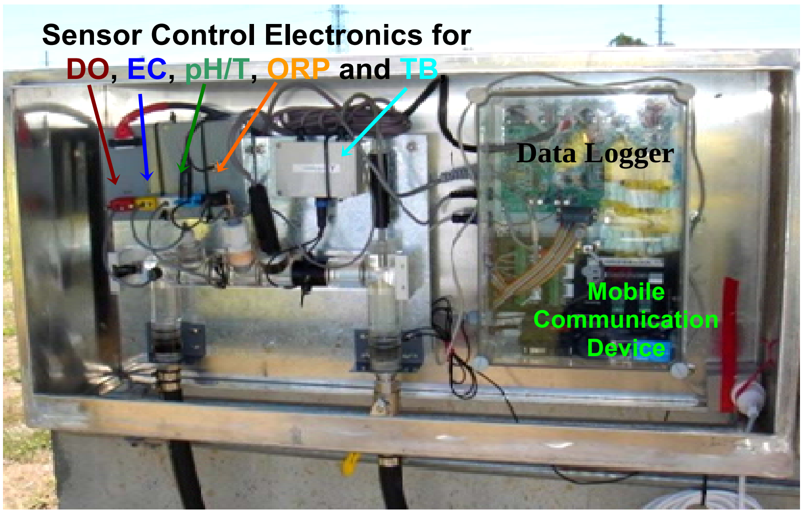


Figure 15. The sensor control electronics used for the initial stage of the project.

The 1st generation control electronics were hence designed to meet the project needs (Figure 16). The system integrated all sensor control electronics, the on-board computer and communication device onto a single circuit board. The data logger was removed because the outputs of all sensor-control units are digital signals that can be directly input into the on-board computer. However, field trials showed that the system was unstable in summer when the daytime temperature was high, due to overheating caused by the on-board computer components. Also, cable connections to the EC and TB sensors were subject to electrical interference from the pumps and other electrical equipment in the WWTP.

Figure 16. The 1st generation integrated sensor control electronics with on-board computer.

Therefore, new generation control electronics were developed to overcome the issues encountered in the 1st generation system (Figure 17). The new generation system consists of two components, the first comprises all the sensor control electronics (Figure 17a) and the second consists of an on-board computer and wireless communication device (Figure 17c). The sensor control electronics integrated all the sensors control electronics onto a single circuit board directly mounted and sealed onto the back of the wall-jetted flow cell (Figure 17a). This configuration enables direct connection to the EC electrodes and the TB sensor output without the need for cable connections, so that electrical interference is minimised. The inputs from pH, DO and ORP sensors are through sealed connectors (Figure 17b). The output sensing signals from all sensors are in digital format that can be directly input into the on-board computer (Figure 17c) via a single USB port (Figure 17d). Through the USB port, the on-board computer and control software can manage: (i) real-time control of all sensors; (ii) real-time acquisition, processing and analysis of wastewater quality data; and (iii) real-time detection, alarming and reporting of any abnormal wastewater quality change (event). Reporting of alarms, abnormal events, and all data transfer is managed via the communication unit. It should be mentioned that separation of the on-board computer and communication unit from the sensor control component not only enables direct connection to EC electrodes and TB output but also enables better heat management to improve the system reliability. As shown in Figure 17c, the on-board computer is directly mounted onto the metal box connected to a large heat-sink (Figure 17d). All electronic components are fully sealed and all connectors are also water and gas-sealed to prevent corrosion. Four systems were trialled in Bundamba WWTP for over 18 months, and there were no failures of the electronics system, apart from power blackouts.

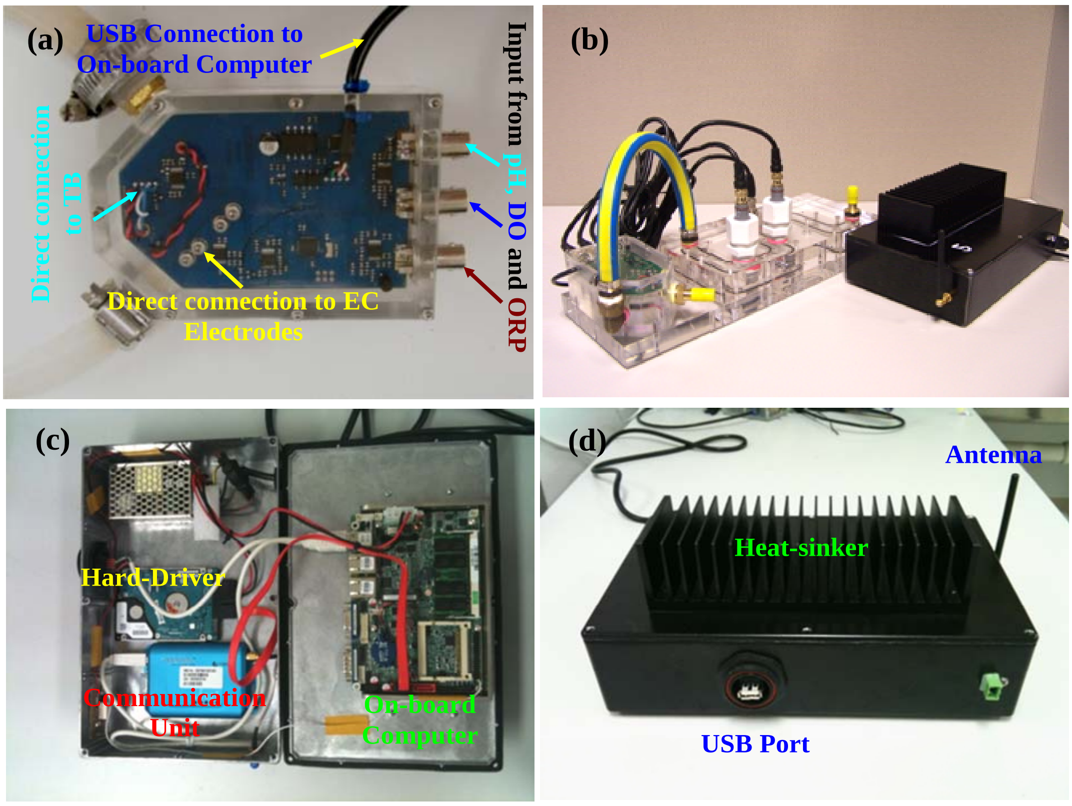


Figure 17. The integrated sensor control electronics, on-board computer and communication components. (a) the sensor control electronics directly mounted and fully sealed on the back of the wall-jetted flow cell; (b) the connections between the sensor control electronics and sensors housing on the U-shaped flow cell; (c) and (d) on-board computer and wireless communication unit.

4. WQIAS SOFTWARE DEVELOPMENT

Form an operational viewpoint, the WQIAS software consists of a high level task management component and a package of enabling software for different functions/tasks. The Task Management component is responsible for the overall control of the WQIAS operation. All enabling software for different functions/tasks is operated under the command of the Task Management.

There are four enabling software routines incorporated in the system for WQIAS: sensor hardware operational control; real-time water quality data acquisition; real-time water quality data processing, storage and abnormal event detection; and communication with office computer and operators to receive command, raise alarm and send report/recorded water quality data (Figure 18).

The sensor hardware operational control is a simple enabling component to control the sensor system hardware operation. It functions based on pre-determined commands or in response to commands sent by operators at any given time.

The real-time water quality data acquisition enables real-time reading of the water quality data output from all sensors and then feeds the data to the real-time water quality data processing, storage and abnormal event detection component. It functions using pre-determined commands such as the sensor reading sequence and the frequency of reading from each sensor.

The real-time water quality data processing, storage and abnormal event detection component is the most important enabling component since it is responsible for data processing and storage, and most importantly the detection of abnormal water quality changes (events). Data processing converts and normalises the water quality data of all sensors from the real-time water quality data acquisition component to a 'common form and scale' suitable for the mathematical model to detect an event. Event detection is implemented using a mathematical model that establishes a reference baseline (that represents normal water quality) and then determines if a significant event (abnormal water quality change) has occurred. An alarm will be incidentally raised through the communication reporting to the operator when an event is detected. This is the heart of this component and will be discussed in detail later.

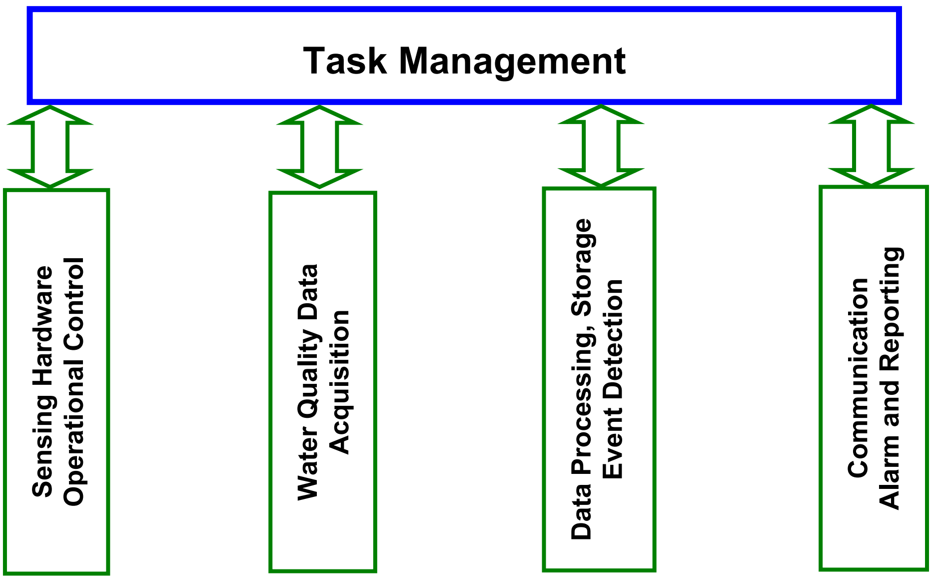


Figure 18. WQIAS software structure and functionality.

4.1. Brief Overview of Methodology of Mathematical Event Detection Model Development

Improved treatment system operational control and management using near real-time evidence-based decision making is the ultimate goal of abnormal wastewater quality event detection. In recent years, event detection systems (EDS) have been developed to improve the operational management of drinking water distribution systems[7,9]. These EDS utilise event detection algorithms to analyse online sensor data and simultaneously identify anomalous water quality changes based on one or a combination of discrimination, clustering and statistical analysis techniques[9c-e]. An ideal EDS should precisely determine all predefined events without false alarms. Nevertheless, all reported EDS to date are limited to drinking water distribution systems. Despite drinking water being a simpler matrix compared to wastewaters, the false alarm ratio is high. The high false alarm ratio is often caused by two major factors. One is the efficiency of the event detection algorithm used in the system and the other is the reliability and quality of input sensing data. The current practical algorithms recognise events according to the absolute values of single water quality parameter inputs[9c, d]. Data acquired this way can deviate significantly from the true values because measurement conditions required by classic quantitative methods (eg, sample manipulation and calibration prior to analysis) are not satisfied when monitoring continuously and online[7]. It was envisaged that the false alarm ratio could be dramatically reduced by developing a new approach capable of collectively utilising multiple water quality parameters to detect events, which is a key task of this project.

In this work, we have developed two new mathematical models for event detection. One is based on a unique multivariate mathematical model to detect anomalous events using collective input data of a spectrum of wastewater quality parameters generated in real-time from multiple sensors. The other is based on a novel univariate mathematical model using input data of individual sensors. The univariate model outputs for every sensor are then collectively input into a reasoning based decision making system to determine if an abnormal event has occurred.

4.2. Real-Time Event Detection Analytical Principle

Traditionally, quantitative analysis serves the sole purpose of determining the quantity of a known substance. However, for end users, the measured analytical values serve the purpose of allowing decision making concerning the measured event. For example, water quality parameters measured on the discharge effluent from a WWTP are used to make decisions such as: Does the effluent produced meet the regulation requirements? Can it be discharged? Is the plant fully functional and operating within the desirable control limits?

For end users, the ultimate purpose of an analytical measurement is to predict an ‘event’. To serve such an ultimate purpose, we do not have to accurately measure each parameter as long as precise event prediction can be achieved. That is, we need to know if the system is operating normally or abnormally. In fact, to accurately acquire field measurements of even simple water quality parameters in a continuous long-term fashion has proven to be difficult, especially for a complex water matrix such as raw sewage. Therefore, it is highly desirable to develop a new analytical principle that can precisely predict/detect an event without the need to fully rely on the accuracy of the measured sensing signal.

The proposed analytical principle detects ‘events’ based on real-time measurement of water matrix changes. To achieve this, the sensing system should meet the following requirements:

- A sensing platform incorporating multiple sensors;
- Selected sensors must be able to physically tolerate the applied matrix conditions. Ideally, the sensors should have a self-contained configuration, and require no additional chemical reagent to generate a response;
- Each selected sensor should respond to one or more physical/chemical aspects of sample matrix change;

- Required matrix change information for event detection can be collectively represented by the analytical signals obtained from incorporated sensors;
- Analytical signal of all sensors must be simultaneously acquired in a continuous real-time fashion; and
- Intelligent software (based on effective mathematical models) must be capable of real-time clustering the input analytical sensor signals into normal water matrix changes (reference-baseline) and anomalous matrix changes (events).

Commercially available sensors can measure almost all required water quality parameters under controlled environment/conditions (ie, in a laboratory environment). These parameters are more than adequate to represent all key aspects of a measured sample matrix (collective water quality parameters represent sample composition-matrix). An effective sensing platform can be built to suitably embody these purposely selected sensors, providing adequate matrix information for event detection.

The basis of the proposed event detection analytical concept is that the measured signals from all sensors represent different characteristics (parameters) of the same sample, in the same time domain, under the same physical/chemical conditions. Therefore, these measured parameters are not independent but are inherently interrelated. The quantitative relationships can be readily established depending on the types of sensors selected. For example, the interrelationship between temperature and pH can be given as:

$$E_{cell} = K - \frac{2.303RT}{nF} pH = K - 1.98 \times 10^{-4} (T)(pH)$$

In theory, a significant event must accompany significant water matrix (composition) changes. That is:

$$\{Matrix\ Changes\} \subset \{Event\}$$

Such significant matrix changes will lead to collective changes in the measured sensor signals:

$$\{\mathrm{CollectiveSignal}\,Changes\} \subset \{Matrix\,Changes\}$$

This means that a significant event can be detected by simply determining the sensor signal changes, which is readily achievable using existing sensor probes without the need to accurately determine the analytical values of each parameter (real-time, continuous, accurate determination of analytical values of each parameter has proven to be difficult). The applicability of such a principle may be illustrated by a real event recorded from Bundamba WWTP by a basic sensing system (see Figure 19).

Sudden and significant changes of the measured analytical signals from all sensors were observed on Sunday 22nd of July 2008 starting at approximately 7:30am, indicating that significant matrix changes had occurred (water quality/water sample composition changes). The analytical signals for pH and conductivity shown in Figure 19 have been corrected for temperature to confirm the observed pH and conductivity changes were caused by matrix changes. By applying the matrix change recognition principle, it can be seen that these changes are consistent with a waste dumping event. The quantity of the wastes dumped was large, as the impact on the quality of the sewage lasted for more than an hour. The observed increase in the temperature indicates the water quality parameter changes were caused by a sample source other than normal sewage sources. The decrease in pH indicates the new source added to the sewage contained a high concentration of acidic species (probably inorganic acids). The dramatic increase in conductivity indicates the new source also contained extremely high concentrations of ionic species other than acids, possibly salt or heavy metal ions (the effect of pH change on the conductivity can be estimated/corrected according to $\Delta[H^+]$). The new source also contained a high concentration of suspended solids as suggested by the increased turbidity.

The above decision making process is involved two key elements:

(i) Sensor data was identified and clustered as 'normal water' matrix data and used as the reference-baseline. The data variability in this baseline was considered as normal water matrix (water quality) changes; and

(ii) A set of rules/criteria based on regulatory requirements or operational limits was used to discriminate anomalous water matrix changes (events) from normal water matrix changes (reference-baseline).

Event detection mathematical models were subsequently developed based on the above analytical principle.

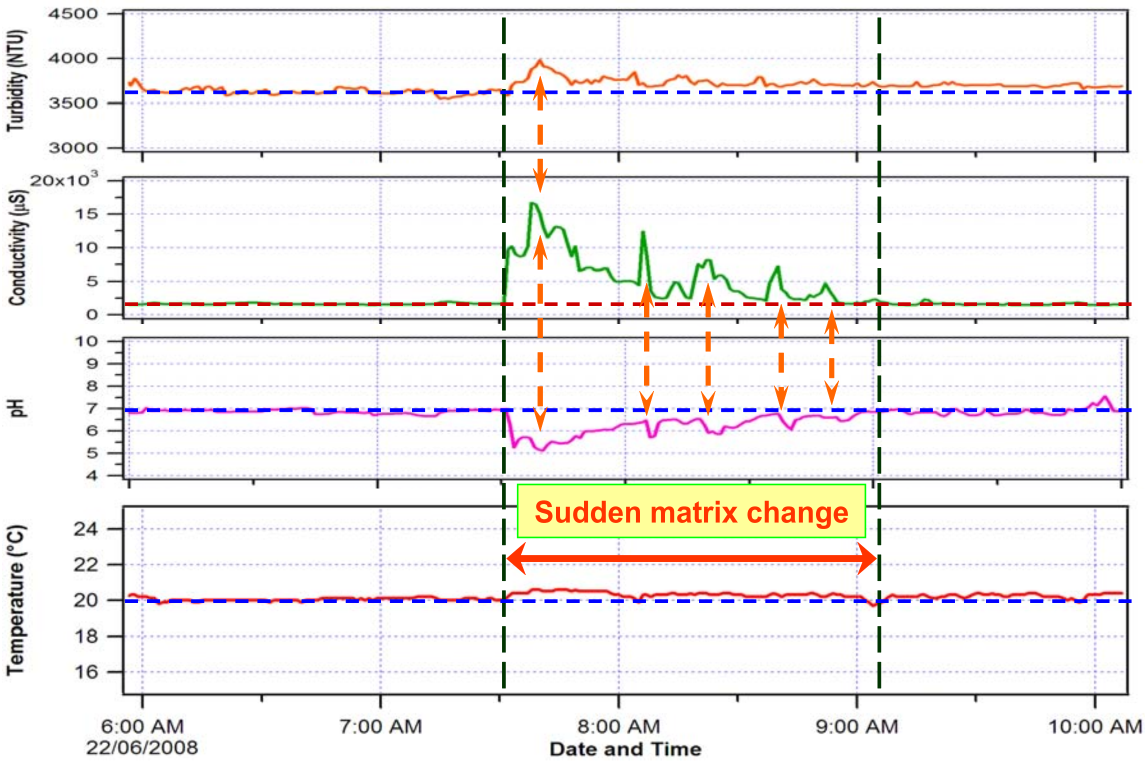


Figure 19. **A set of typical simultaneously acquired real-time sensor signal outputs.**

4.3. Brief Description of Multivariate Event Detection Mathematical Model

According to the above analytical principle, the event detection mathematical model has to be able to recognise the abnormal from the normal. Therefore real-time determination of the water quality reference-baseline (normal matrix variations) must be achieved to allow automatic clustering and comparison to the reference-baseline to determine if the input sensor data are anomalous (event). To achieve real-time event detection, the mathematical model must be capable of establishing the reference-baseline and determining if the input sensor data are abnormal in real-time. In this work, a multivariate event detection mathematical model was first developed using a robust time-delaying multivariate filter to establish the reference-baseline while simultaneously detecting the abnormal events by a multivariate statistical test.

A Robust Time-delaying Multivariate Filter was developed for real-time establishment of the reference-baseline. The method adopts a non-parametric filtering approach that aims to estimate the true signal and is robust to single outliers or small patches of outlying input data. The method relies on repeated median regression along with the assumption that within a local neighbourhood or small window width the underlying data can be estimated linearly, thus making it quick and suitable for real-time monitoring applications. By allowing the window width of the repeated median regression to vary, it can achieve a better modelling of the underlying data, and thus better estimation of trends in the data while still remaining robust (due to using median regression) to single or small patches of outlying data input. Based on the estimated underlying signal, if the data exceeds pre-specified critical bounds (could be both upper and lower bounds) a signal is issued to say that the data are outside these bounds. Otherwise, the data are deemed to be not anomalous, and the input data are used to renew the reference-baseline. In such a way, a precise reference-baseline can be developed in real-time and used as the reference to cluster (determine) anomalous data input.

A simplified mathematical description of the method is given below:

The robust filter clusters input data using a moving window approach. Assume that the current window of n observations ($X_{i,n,t}$) for variable i can be presented as:

$$\mathbf{x}_{t,n,i} = \begin{pmatrix} x_{t-n+1,i} \\ \vdots \\ x_{t,i} \end{pmatrix}$$

Where:

$x_{i,t}$ is the most recent observation for variable i.

The value for variable i at time t is calculated according to:

$$y_{t,i} = \operatorname*{median}_{j=1,\ldots,n} \left\{ x_{t-n+j} + (n-j)\,\beta_{t,i} \right\}$$

Where:

$$\beta_{t,i} = \operatorname*{median}_{j=1,\ldots,n} \left\{ \operatorname*{median}_{j \neq k} \left\{ \frac{x_{t-n+j} - x_{t-n+k}}{j-k} \right\} \right\}$$

The median referred to is the median of the current window.

The equation for the calculation of $y_{t,i}$ by assuming the data at time t for variable j is linear to allow rapid computation. $\beta_{t,i}$ is the slope for the linear relationship used to calculate $y_{t,i}$. Note that there is a slight delay in the detection of a change in the reference-baseline trend because at least half the observations in the window have to display the new trend. This time interval of delay can be adjusted based of the frequency of input data trend changes. For this reason, $y_{t,i}$ and $\beta_{t,i}$ are calculated using medians, thus making them robust to small numbers of outlying observations.

For a new set of input data, the *Multivariate Statistical Test* is simultaneously carried out while the input data are clustered using the robust filer.

Anomalous events can take on many forms. One example could be that one of the sensors suddenly gives an unusually high or low output. In other instances the anomaly may be more subtle and involve changes in a number of variables, which individually may not trigger any warnings, but taken together they may mean an anomalous event. A test statistic is needed that incorporates the information from different variables when deciding if a new observation is anomalous, and it needs to do this in real-time. A simplified mathematical description of the method is given below.

Assume that p variables (number of sensors/types of input data) are sampled at each time point. Then the input data values at times $t = m+1,\ldots,m+n$, given by the robust filter in accordance with Equation 6 can be presented as:

$$\mathbf{Y} = \begin{pmatrix} \mathbf{y}_{m+1} \\ \vdots \\ \mathbf{y}_{m+n} \end{pmatrix}$$

Where:

$$\mathbf{y}_i = \begin{pmatrix} y_{i1} \\ \vdots \\ y_{ip} \end{pmatrix}$$

represents the p univariate input at time i.

Let:

$$\mathbf{y}_{m+n+1} = \begin{pmatrix} y_{m+n+1,1} \\ \vdots \\ y_{m+n+1,p} \end{pmatrix}$$

represents the p input data from the robust filter at time $m+n+1$, and then the following multivariate test can be used to determine if the input data at time $m+n+1$ are anomalous relative to the input data from the previous n time points (reference-baseline):

$$\left(\mathbf{y}_{m+n+1} - \overline{\mathbf{y}}\right)' \mathbf{S}^{-1} \left(\mathbf{y}_{m+n+1} - \overline{\mathbf{y}}\right) > \chi^2_{\alpha,p}$$

Where:

n is the window width, $\chi^2_{\alpha,p}$ comes from the chi-square distribution with p degrees of freedom (covering the matrix of all input sensor data at any given time) and is determined as $P\left(\chi^2 > \chi^2_{\alpha,p}\right) = \alpha$ (**P** is the probability of inputted data rejection and α is a small value determined by the historical reference-baseline variation and the discrimination rules/values). $\overline{y}$ is the mean of the median values and can be presented as:

$$\overline{\mathbf{y}} = \begin{pmatrix} \dfrac{\sum_{i=m+1}^{m+n} y_{i,1}}{n} \\ \vdots \\ \dfrac{\sum_{i=m+1}^{m+n} y_{i,p}}{n} \end{pmatrix} = \begin{pmatrix} \overline{y}_1 \\ \vdots \\ \overline{y}_p \end{pmatrix}$$

S gives the sample (collective data input from all sensors) mean and covariance matrices from the p input data of the previous n time points ($\mathbf{Y}$):

$$\mathbf{S} = \begin{pmatrix} \frac{\sum_{i=m+1}^{m+n}(y_{i,1}-\overline{y}_1)^2}{n-1} & \frac{\sum_{i=m+1}^{m+n}(y_{i,1}-\overline{y}_1)(y_{i,2}-\overline{y}_2)}{n-1} & \cdots & \frac{\sum_{i=m+1}^{m+n}(y_{i,1}-\overline{y}_1)(y_{i,p}-\overline{y}_p)}{n-1} \\ \frac{\sum_{i=m+1}^{m+n}(y_{i,1}-\overline{y}_1)(y_{i,2}-\overline{y}_2)}{n-1} & \frac{\sum_{i=m+1}^{m+n}(y_{i,2}-\overline{y}_2)^2}{n-1} & \cdots & \frac{\sum_{i=m+1}^{m+n}(y_{i,2}-\overline{y}_2)(y_{i,p}-\overline{y}_p)}{n-1} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\sum_{i=m+1}^{m+n}(y_{i,1}-\overline{y}_1)(y_{i,p}-\overline{y}_p)}{n-1} & \frac{\sum_{i=m+1}^{m+n}(y_{i,2}-\overline{y}_2)(y_{i,p}-\overline{y}_p)}{n-1} & \cdots & \frac{\sum_{i=m+1}^{m+n}(y_{i,p}-\overline{y}_p)^2}{n-1} \end{pmatrix}$$

The event detection is achieved by real-time comparison of the statistically calculated value ($(\mathbf{y}_{m+n+1}-\overline{\mathbf{y}})' \mathbf{S}^{-1} (\mathbf{y}_{m+n+1}-\overline{\mathbf{y}}) > \chi^2_{\alpha,p}$) with the reference-baseline values and trend, and the imposed discrimination rules. If this statistically calculated value exceeds the allowed range, the input data at time $m+n+1$ is flagged as potentially anomalous (triggering an alert state and displayed as yellow symbols in the graphs below). $(\mathbf{y}_{m+n+1}-\overline{\mathbf{y}})' \mathbf{S}^{-1} (\mathbf{y}_{m+n+1}-\overline{\mathbf{y}}) > \chi^2_{\alpha,p}$ determines multivariate location shifts or shifts from the reference-baseline calculated from the previous n time points. This means that the input data from all sensors are evaluated collectively and considered during the decision making process. If the calculated values of the input data at $m+n+1$ show a continuously increasing or decreasing trend exceeding the predefined criteria (discrimination rules) and duration (define by the frequency variations in the reference-baseline) then the input data are deemed to be anomalous and clustered as an event to trigger an alarm (the alert state will be upgraded to an alarm state and yellow will be changed to red in the graphs below). Under such circumstances, the reference-baseline for time $m+n+2$ is based on the signals at times $t = m+1,\ldots,m+n$. That is, the reference-baseline for time $m+n+2$ is the same as that for time $m+n+1$. On the other hand, if the calculated values show that the trend no longer exceeds the predefined criteria, then for time $m+n+2$ the reference-baseline is renewed according to the input data at times of $t = m+2,\ldots,m+n+1$. That is, the oldest time point in the reference-baseline is deleted and the input data at time $m+n+1$ are included.

Software was developed to enable the implementation of the multivariate event detection mathematical model. The model has been tested by both pre-collected data and by an on-site trial at a WWTP. The results confirm that the model is capable of relatively reliably detection of abnormal events. However, it has drawbacks. The model is statistically based, so it involves large calculation tasks that requires significant computer power to ensure real-time completion of the tasks. The model will fail if any sensor in the system fails because it relies on the collective sensing signal input of all sensors. Also, the model can only be used with a specified sensing hardware system with a specified number/type of sensors. The model must be modified or re-developed if there is any change in the sensing hardware.

4.4. Brief Description of Univariate Event Detection Mathematical Model

In this work, a univariate event detection mathematical model was developed to overcome the drawbacks of the multivariate event detection mathematical model described in section 4.3. This mathematical model achieves real-time event detection by a simultaneous two-stage approach (see Figure 20). During the first stage, the newly developed robust baseline and univariate event detection models are used to establish a real-time reference baseline and simultaneously detect abnormal events for individual sensors. The outputs of the univariate event detection for individual sensors are collectively input into a reasoning unit to determine if the measured water matrix changes for the individual sensors are deemed to be an event.

4.4.1. Univariate Model

The univariate approach developed for this work can be described as a running median reference baseline with event bridging function. It is designed to mimic the processes that a trained human observer applies when evaluating the online data. The first thing done is to determine the scale and perspective from which to view the data. For example, we have observed that for the given flux, an event of less than about 30 minutes duration rarely has a significant impact on the performance of the treatment plant. If features with this time scale are of interest, then an observation window of only a few hours will be chosen. If gradual drifts or long-term trends are desired, then an observation window of days, weeks, months or even years will be required. Once the evaluation perspective has been selected, then the data is scaled to an appropriate window, and the observer will visually interpolate a reference baseline by running their eye across the data set. Spikes and other transitory features are ignored when setting the baseline; and the eye also continues the baseline underneath large features. Such a feature is of prime importance in eliminating false alarms. Rather than based purely on the statistics, the above empirical approach was adopted for the model and software development. It should be noted that where is necessary, the appropriate statistical tests are also employed.

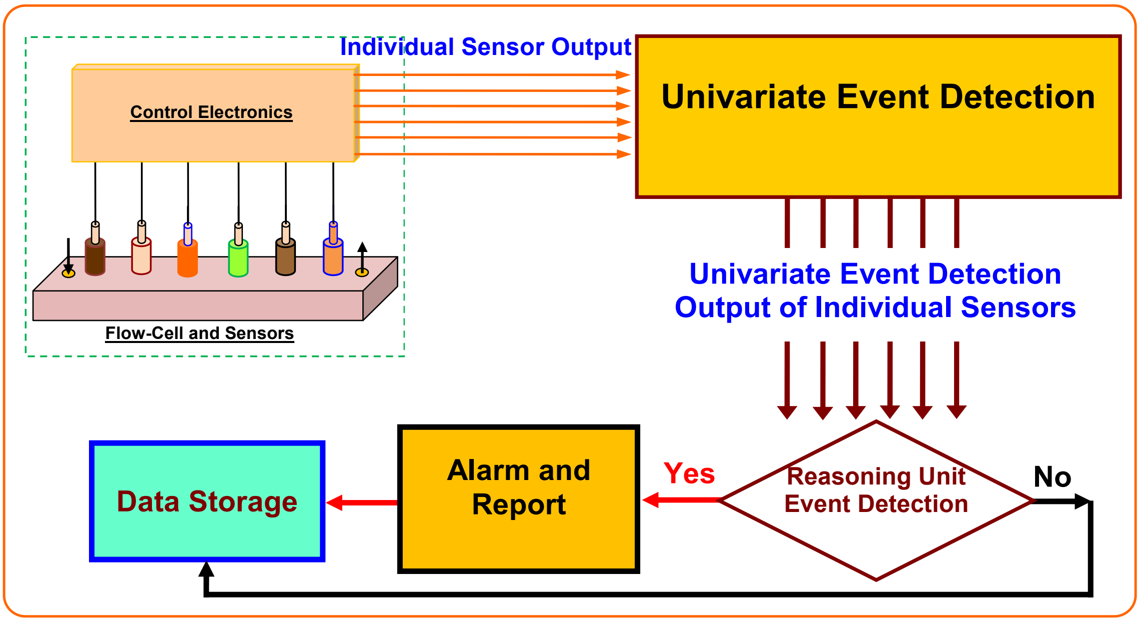


Figure 20. Schematic diagram of the univariate event detection mathematical model.

The univariate event detection mathematical model involves:

(i) establishing the real-time reference baseline for each variable (sensor) separately using a running median modified to bridge large deviations (occurs during a possible event);

(ii) a univariate statistical test is simultaneously applied to each variable (sensor) to determine if the readings observed at time t are anomalous relative to their reference baseline.

Real-time Reference Baselines for Individual Sensors

The first task is to construct a reference baseline which accurately reflects the underlying trend in the time-series data of individual sensors. The sewage monitoring data collected from the WWTP exhibits a great deal of short duration measurement noise that can cause problems by triggering multiple false alarms in the event detection routine. Since significant events in the raw sewage will generally be of long duration, we have developed a method that employs a running median with event bridging to remove this noise from the baseline, while at the same time preserving larger events that may represent potential threats to the treatment system.

The median is the middle point of a sample sorted in ascending order. It is a better estimate of the typical value than the mean when there are large outliers in the sample.

The median ν of a sample $z[i]$, $i = 1, \ldots, n$ can be defined as follows:

Let Z[i] be the sequence obtained by sorting z[i] in ascending order;

and Z[1] < Z[2] < … Z[n].

Then ν =median({z[1], z[2],…, z[n]})

=Z[(n+1)/2] (n odd), (Z[n/2]+Z[n/2+1])/2 (n even).

However, in the present case the data collected are real-time series which can be represented by the sequence:

x[k], k = 0, 1, 2, …, N-1.

For such real-time sequences, a running median (the median of a window of M data points continuously updated as each new data point arrives) can be used to estimate the trend:

y[k] = median({x[k], x[k + 1],…, x[k + M - 1] }), k = 0, 1, … , N - M.

The results of the running median calculated using various window widths for pH data collected from the raw sewage influent at the WWTP during November 2008 are shown in Figure . It can be seen that the extent of noise rejection and smoothing increases as the window width *M* increases.

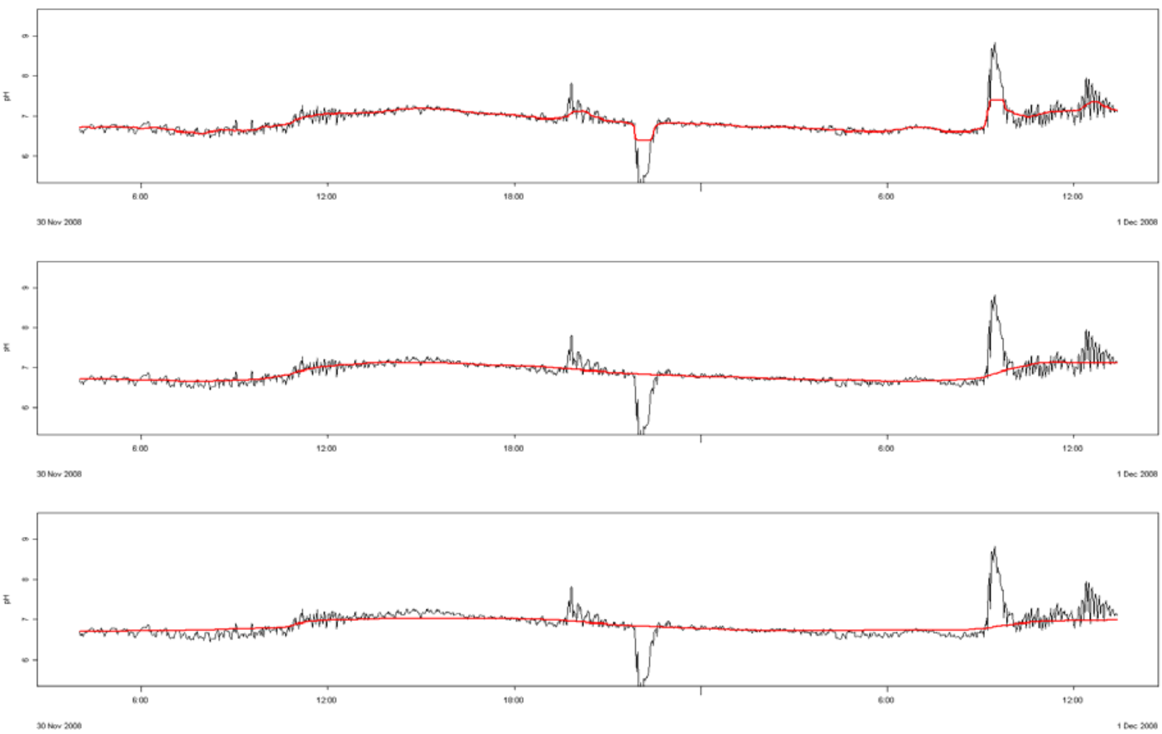


Figure 21. Running median pH data from a WWTP, window width (top to bottom) 1h, 5h, 12h.

The baseline computed using a 1 h window width rejected noise spikes and followed the shape of the data closely, but was also significantly affected by events. The 12 h window provided too much smoothing, and the resulting baseline showed a significant departure from the original data. The best result was found using $M = 5$ h.

For the purposes of this report, and given the observed events shown in WWTP data, we chose 2 h as the cut-off duration for events of interest when using the running median to set the reference baseline. However, we can further fine tune the event cut-off point by varying the value of *M*.

We have found that the optimum reference baseline for the WWTP data was generally found to result using a window width of 4-6 hours. The plots in Figure demonstrate how the trend line followed the general shape of the data without being unduly influenced by possible events or clusters of outliers.

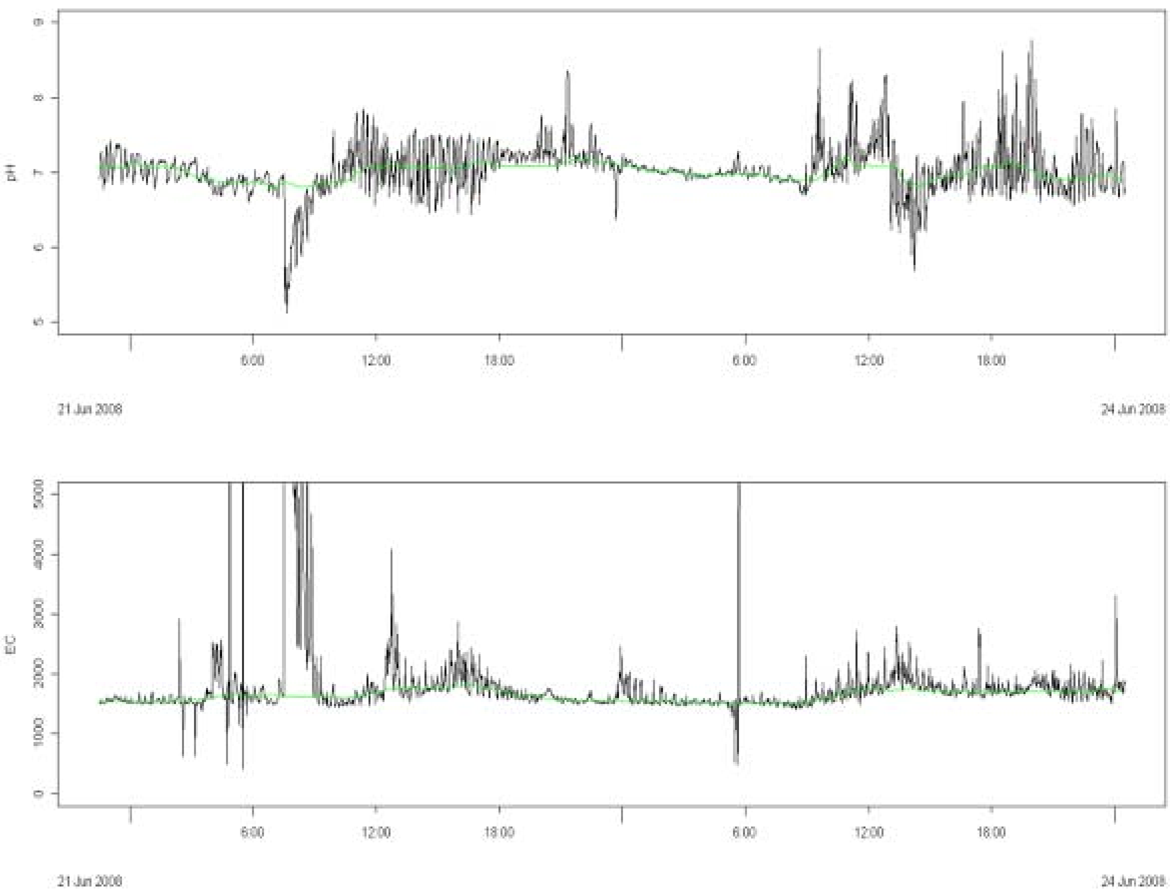


Figure 22. Baseline calculated for pH (top) and EC (bottom) data from a WWTP with running median, window 4h. Black (–) raw data, green (–) baseline.

Although the running median can eliminate short duration events (ie, <2 hours), an additional strategy is required to produce a functional trend line in the presence of longer events. Simply increasing *M* was not effective as it causes significant deviations for normal data (eg, see Figure). Consequently, we devised an event bridging method, in which the baseline is not updated during large deviations (which are possible events) but simply remains at its previous value. Updating is resumed once the underlying trend in the data is found to be returning to the pre-event median.

The following tests were applied to determine if the current data was part of a possible event. Let the current variable be ***Y*** and the current time point ***i***. If the trend in the data sample Y_i has been unidirectional for ***n*** time points then we are in a possible event situation and therefore would stop updating the baseline from position ***i-n***. An example of a unidirectional decreasing trend would be:

$$y_{d-m:d|0.5} \geq Y = \{y_{i-d}, y_{i-d-1}, y_{i-d-2}, \ldots y_i\}$$, for all values in the set ***Y***

Here ***d*** is the point at which the data was observed to first deviate from the baseline, ***m*** is the window width of the running median, and ***n*** is the minimum number of data points - sampled at 1 minute intervals - chosen to determine when there is a possible event. The ***n*** value was determined from the average time taken for the data to change direction, which for the Bundamba data set was measured at 25 minutes (i.e. ***n*** = 25).

To determine when to resume updating the baseline, we have used the criterion that the data must return to within the **{0.30, 0.70}** confidence interval of the baseline estimated previously. We take the mean of the previous ***p*** data points, where ***p*** is a small number (we used ***p***=5 for our data set), and compare this to the **{0.30, 0.70}** confidence interval at the departure point ***d*** from the baseline. We resume updating the baseline if it is within the bounds of the interval:

$$y_{d-m:d|0.7} \geq mean\{y_{i-p}, y_{i-p-1}, y_{i-p-2}, \ldots y_i\}$$, when above the baseline

$$y_{d-m:d|0.3} \leq mean\{y_{i-p}, y_{i-p-1}, y_{i-p-2}, \ldots y_i\}$$, when below the baseline.

Using this technique produces a robust reference baseline that more closely conforms to the visual estimation, and is suitable for event detection.

To speed up the runtime of the code whilst in the development environment, the trend was calculated first and then in a second run through the dataset, possible event points were removed and replaced by the trend values at the beginning of the possible event. This approach causes a jump in the baseline when emerging from event bridging, as evident in Figure 23. However, this does not happen when the code is run in real time, because updating resumes with the stationary baseline values included in the running median window, which results in a smoother transition (see Figure 24).

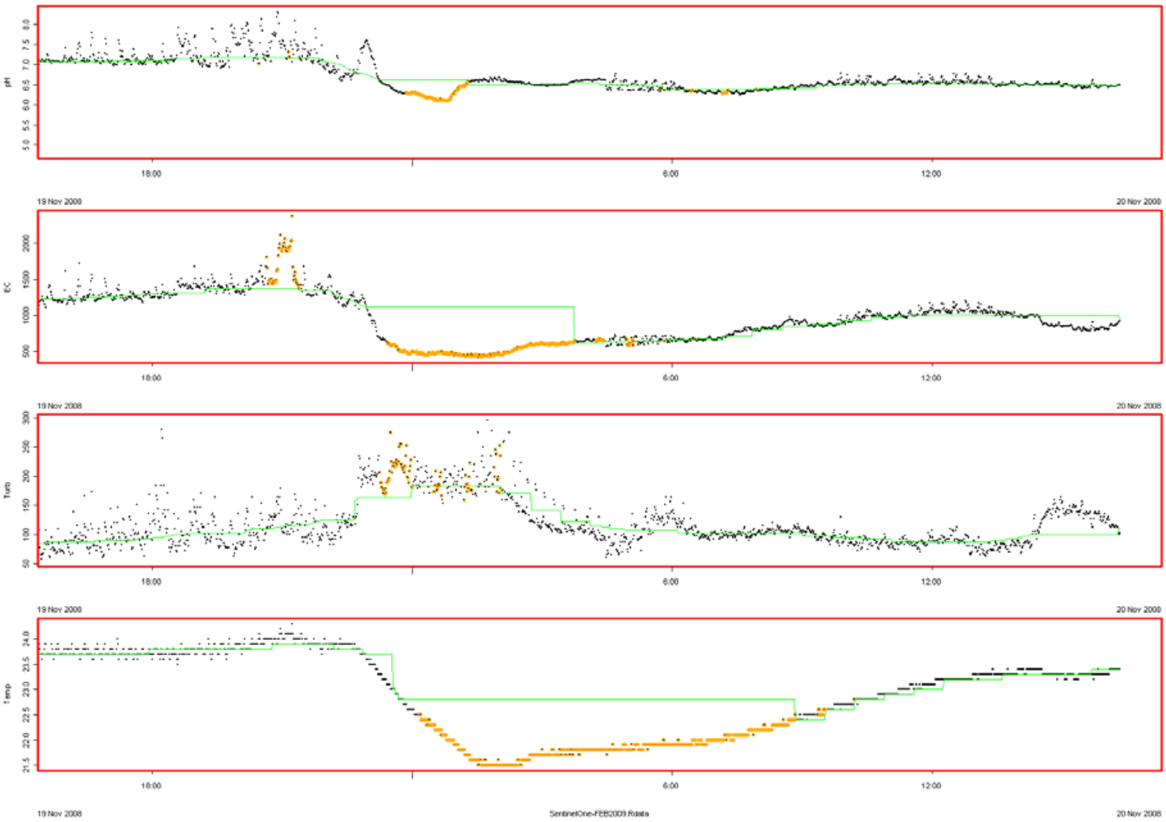


Figure 23. A detected catchment overflow event at a WWTP, showing artefacts from multi-step event bridging code. (—) raw data, (—) robust baseline, o: event alarm.

To initialise the baseline, two days data for a given data set is needed without any events so that the code can set the statistical parameters for the running median under normal operating conditions. This provides a sound initial basis for the baseline and event detection. Subsequently, these parameters are continuously updated, and will adapt to any changes in the characteristics of the input data.

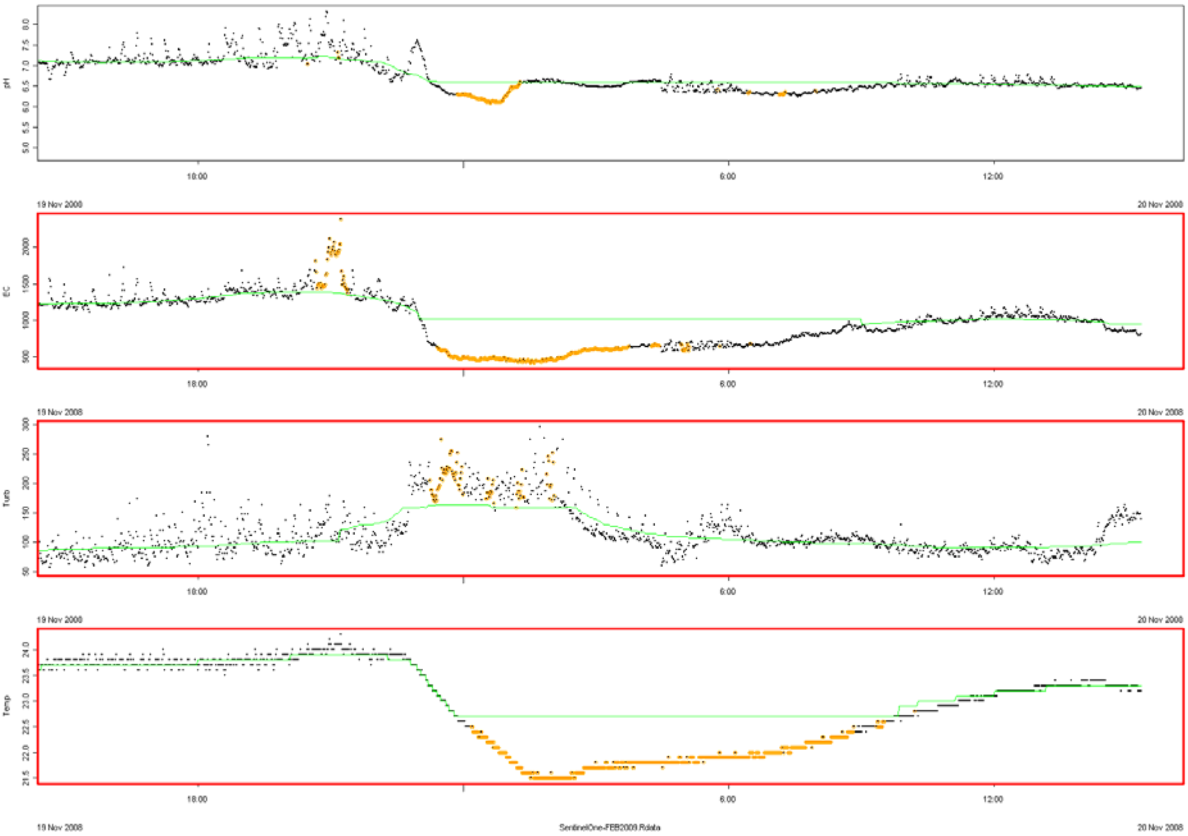


Figure 24. Real time resumption of updating for event bridging. Dataset and legend are as for Figure 23.

Using a running median with event bridging has a number of advantages over other methods: it eliminates almost all extreme values and clusters of outliers representative of noisy data, and it is not very sensitive to shifts in trend and instead follows more closely the baseline interpolated by eye, which is the key to determining what is an anomalous event with respect to what has been seen in the previous ***m*** time points (see Figures 23 and 24).

Univariate Detection of Possible Event of Individual Sensors

Different wastewater treatment plants may measure one or more parameters, so a test statistic is needed that can identify a change in a single variable that is significant enough to be considered an event by itself. The following describes the methodology used for a univariate statistic that will identify such a change in a measured variable p.

As mentioned previously, during the establishment of reference baseline, a possible event for individual sensors can be determined according to:

$$y_{d-m:d|0.5} \geq Y = \{y_{i-d}, y_{i-d-1}, y_{i-d-2}, \ldots y_i\}$$, for all values in the set Y

$$y_{d-m:d|0.7} \geq mean\{y_{i-p}, y_{i-p-1}, y_{i-p-2}, \ldots y_i\}$$, when above the baseline

$$y_{d-m:d|0.3} \leq mean\{y_{i-p}, y_{i-p-1}, y_{i-p-2}, \ldots y_i\}$$, when below the baseline.

Once a possible event for an individual sensor is detected, some empirical rule-based tests are applied to determine whether the event for a water quality parameter measured by an individual sensor should be classified as an alert (ie, the data is unusual) or an event (ie, the data is extremely unusual or likely to harm the treatment plant).

Classification of an alert (Figure) is done by comparing the Yn:n+1 samples to the 90% confidence interval ***w*** calculated from the previous two days data. In other words, if the current ***n*** data points are outside 90% of the observed data from the previous two days, then we consider this to be abnormal and flag an alert. It should be kept in mind that using this approach, the data must first have deviated unidirectionally from the robust baseline for a minimum of ***n*** time points before any comparison of these ***n*** data points to the previous two days data is required.

$$y_{i-w:i|0.90} \le Y = \{y_{i-n}, y_{i-n-1}, y_{i-n-2}, \ldots y_i\}$$

To upgrade this alert to an alarm, the data needs to continue either above or below the baseline and be outside the previous two days 99% confidence interval.

$$y_{i-w:i|0.99} \le Y = \{y_{i-n}, y_{i-n-1}, y_{i-n-2}, \ldots y_i\}$$

A further set of boundary conditions based on safe operating limits for the parameters are also used to determine if an alarm is flagged. If a variable is observed to exceed this boundary during a possible event situation then an event is automatically assumed.

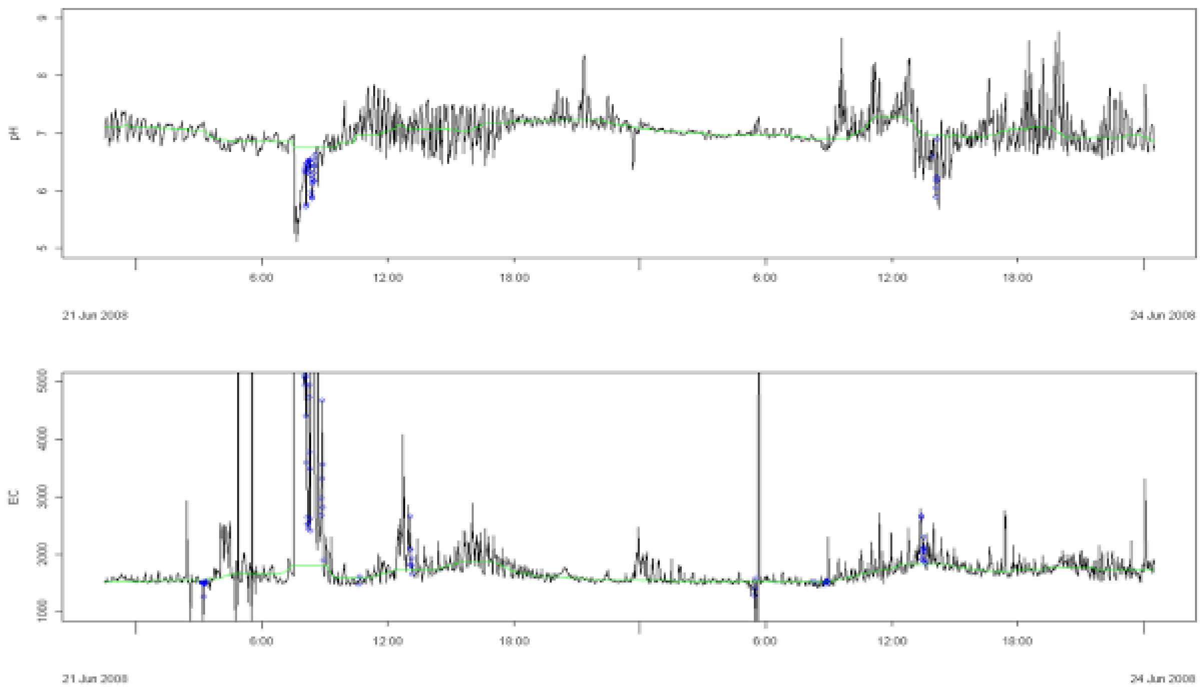


Figure 25. Event detection (alerts only), single variable (pH, EC), (–) raw data, (–) robust baseline, (o) alert CI (.05, .95).

Once an event for a water quality parameter (eg, pH) measured by an individual sensor (ie, pH sensor) is assumed, and/or simultaneous multiple events for more than one water quality parameters measured by different individual sensors are assumed by the Univariate Detection Model, the outputs will be used as the inputs into the reasoning unit to determine if the detected event is deemed to be a reportable event and an alarm should be raised.

4.4.2. Reasoning Unit

The reasoning-based decision making unit makes the final decision based on the inputs from the univariate event detection mathematical model (see Figure 20), and is designed to further minimise false alarms, and report to the operator with detailed characteristics of the detected event.

In practice, the output from the univariate event detection mathematical model could indicate one or more water quality parameters from multiple sensors are abnormal. Also, the degree of the assumed event by the univariate model can be varied for a given parameter (sensor) and amongst different parameters (sensors). In order to further minimise false alarms and provide a report to the operator with event details, the unit makes decisions by reasoning using the inputs from the univariate model and information in the 'database'. The 'database' attached to the unit contains all possible univariate detection outputs and their combinations. The possible changes in water quality characteristics and potential impact to the WWTP associated with each possibility are also incorporated in the 'database'. If the outcome of reasoning finds a match in the set of assumed events to the univariate detection mathematical model, an alarm will be raised and a report will be sent to the operator to specify the possible changes of water quality parameters and potential cause of the event.

4.4.3. Comments

Fully functional software was developed to enable implementation of the univariate event detection mathematical model. This model has been tested using both pre-collected data during the development phase and by long term on-site trials at a WWTP. The evaluation results confirmed (see Section 5.3 for details) that the model is capable of reliably detecting different types of abnormal events (eg, industrial dumping and catchment overflow events) without false alarms. The notable advantages of this new system include:

(i) In contrast to the multivariate event detection mathematical model, the univariate model employs a combined empirical-statistical approach that involves relatively less calculation tasks so requires only moderate computer power to enable real-time completion of the tasks.

(ii) Unlike the multivariate event detection mathematical model, the univariate model does not need a specified hardware system with specified number and type of sensors because the model determines an event for an individual water quality parameter based on the signal input from that individual sensor.

(iii) In the case of the multivariate event detection mathematical model, the system will fail if any sensor fails. The univariate model has the decided advantage that it employs a reasoning decision making mechanism that is capable of detecting events even if a sensor has failed.

(iv) The use of a reasoning decision making mechanism greatly reduced the false alarm ratio and improved the system reliability.

5. VALIDATION AND SYSTEM PERFORMANCE

The hardware and software of the WQIAS, including the event detection mathematical models, have been systematically evaluated for their validity and performance. The performance of WQIAS hardware has been evaluated and experimentally validated as detailed in Section 3 of this report. Therefore, this section will focus on the validation and performance evaluation of system software (including the mathematical model).

5.1. Validation of Sensing Signal

Acquiring reliable data based on classical analytical principles requires a strictly controlled measurement environment and frequent calibrations, which are virtually impossible for online real-time wastewater quality monitoring[7,10]. In order to automatically cluster and determine the input sensors' data as anomalous (event) in real-time, the model must first be capable of real-time determination of the reference-baseline (normal matrix variations). To do so, we have to firstly ensure the measured sensing signals and changes are due purely to the wastewater quality changes. For a laboratory based analytical system, confirmation of the relationship between the analytical signal and the concentration changes of a known analyte can be readily achieved by a standard calibration process. However, such an approach cannot be directly adopted to identify/confirm the causes of sensing signal changes for a real-time, *in situ* sensing system. This is because the compositions of wastewaters are highly complex and change dynamically with time due to extremely diversified sources. As a result, the measured sensing signals will vary irregularly with time in a highly volatile fashion (Figure 26). In this regard, prime consideration must be given to identifying if the input sensing signal changes are caused by compositional changes of the measured wastewater.

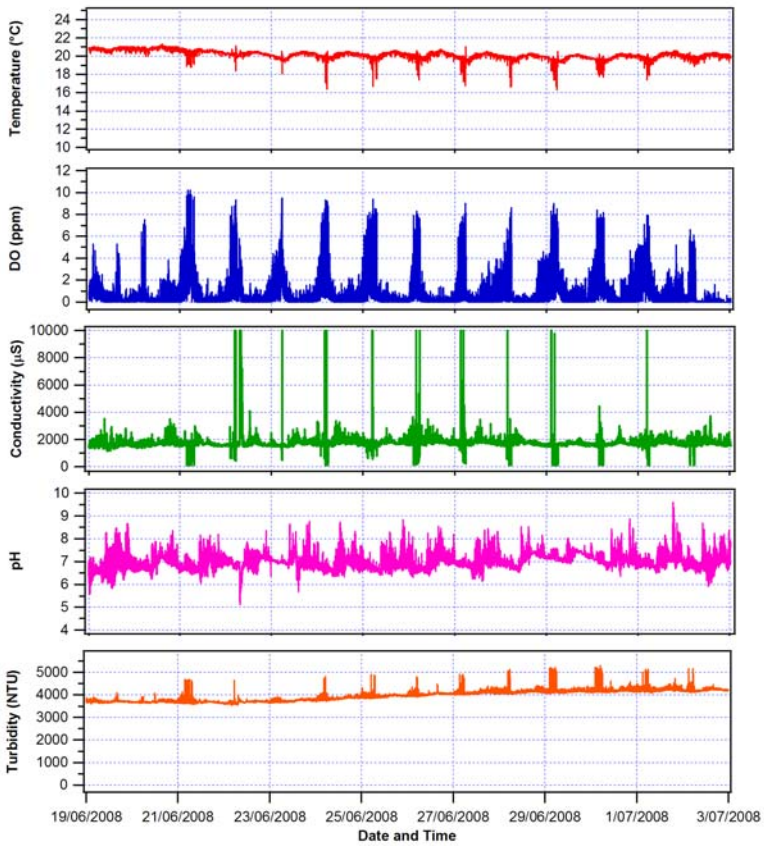


Figure 26. Real-time raw sewage data recorded by a WQIAS at Barrier 1.

A new approach using two identical but independent WQIAS units to validate each other is therefore proposed to confirm the causes of the sensing signal changes. Figure 27 shows the WQIAS deployed at Barriers 1 and 2 at the Bundamba WWTP. Two identical but independent WQIAS units were deployed at each barrier at the same location. The basis of such an approach is that if the sensor signals obtained from the two independent sensing units deployed at the same location correspond to each other in the same time domain and with similar response profiles, then the signal changes are most likely to be caused by water quality changes because the probability of all sensors in both sensing units giving false signals in a highly correlated manner is very low.

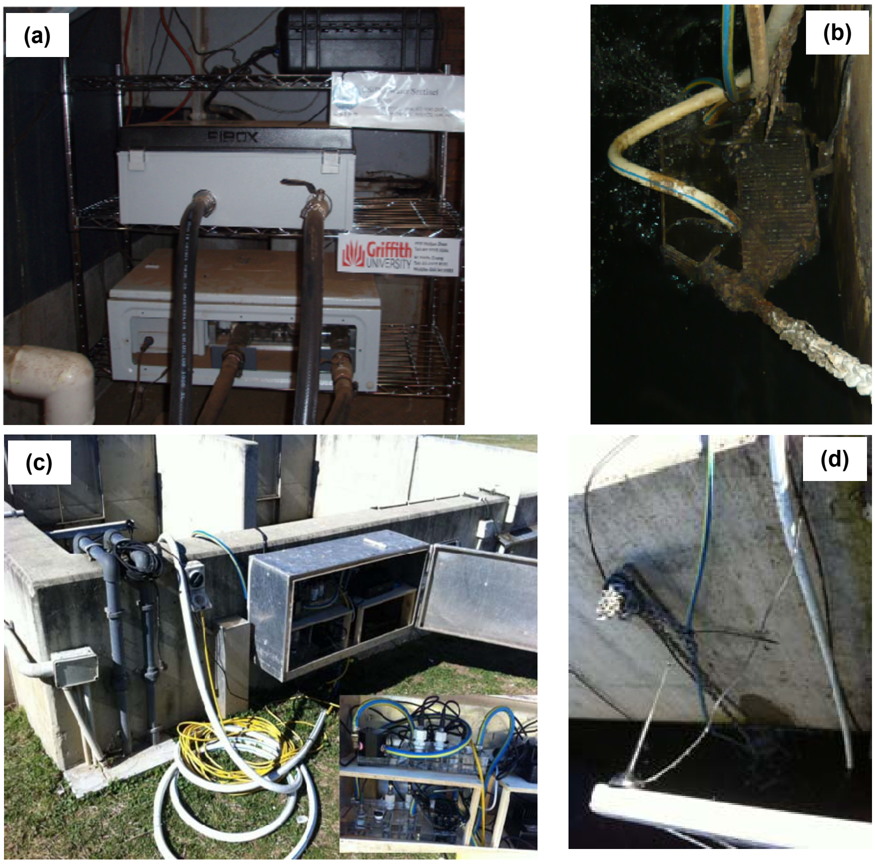


Figure 27. WQIAS deployment at Barrier 1 (a) and (b), and Barrier 2 (c) and (d) at the Bundamba WWTP.

Figure 28 shows two sets of typical input sensing data clustered as normal water matrix changes (falling within the reference-baseline) obtained from the two independent WQIAS units, during the same period, from the same water source and at the same sampling location. Despite the differences in the absolute analytical values of the two WQIAS units, the trend, magnitude and frequency of analytical signal changes are almost identical and highly correlated over a seven–hour sampling period. These confirm that the sensors were functioning reliably and the measured analytical signal changes were caused by wastewater quality changes rather than random noise. This 'calibration' approach provides us with a practical means to confirm the originality and reliability of the sensing signal in sewage. This also inspires us to develop a reliable data acquisition method based on relative analytical signal inputs using an established reference-baseline in real-time as a reference without the need for on-going calibration.

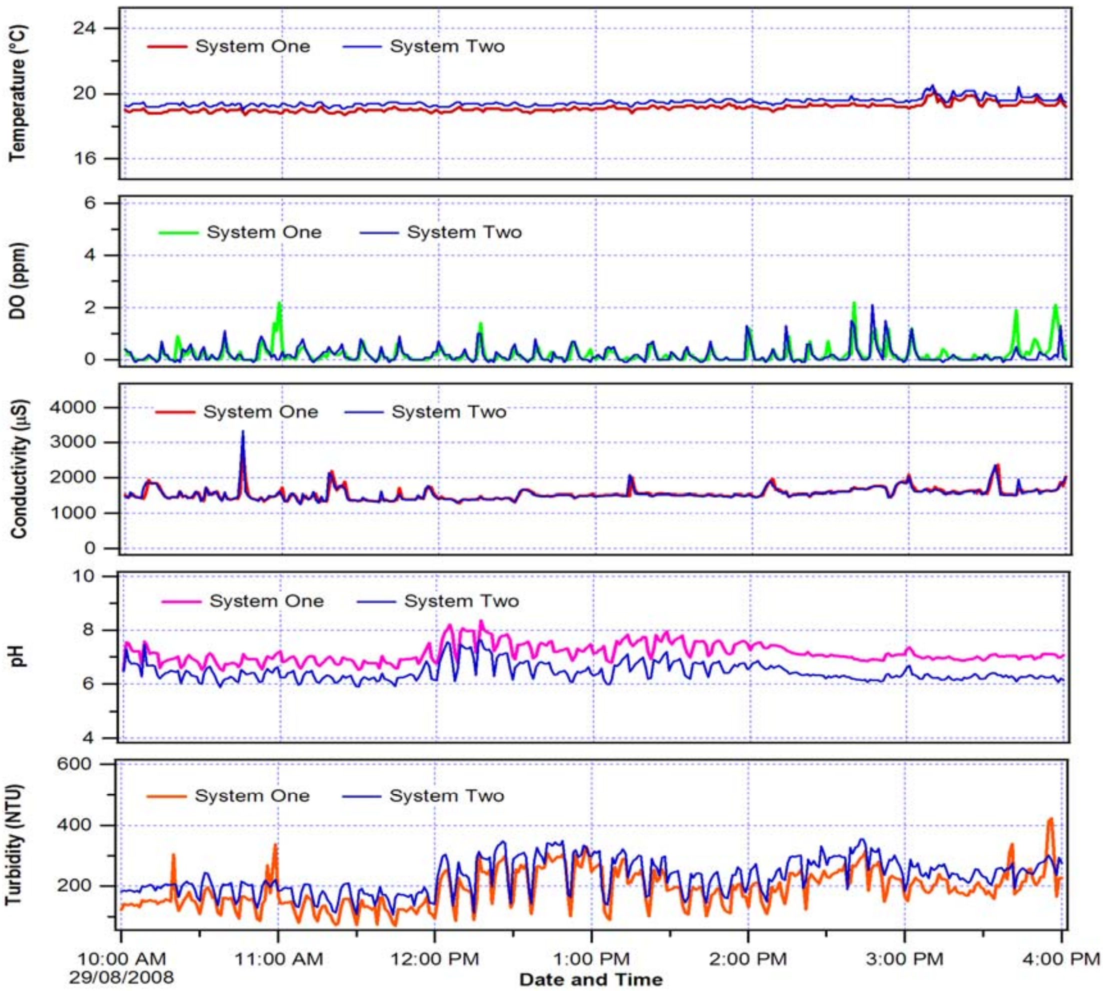


Figure 28. Two sets of real-time raw sewage data recorded by two identical but independent WQIAS units deployed at Barrier 1.

5.2. Event Simulation

In this work, systematic event simulation experiments were conducted to provide information and knowledge needed for development of the event detection mathematical model. Such simulation experiments also allow us to better understand the characteristics of the WQIAS in responding to changes of water quality parameters, and the characteristics of events generated by different sorts of sources including power and pump failures. The information obtained was also used to form part of a 'database' for the event detection reasoning unit (see Section 4.4.2) for final decision making.

All event simulation experiments were conducted on site at a WWTP. The simulations were carried out in two different modes – steady mode (Figure 29) and dynamic mode (Figure 30). The steady mode simulates an event superimposed on a steady 'background' while a dynamic mode simulates an event superimposed on a dynamically changing 'background', where the 'background' is referred to as the raw sewage (at Barrier 1) or secondary effluent (at Barrier 2).

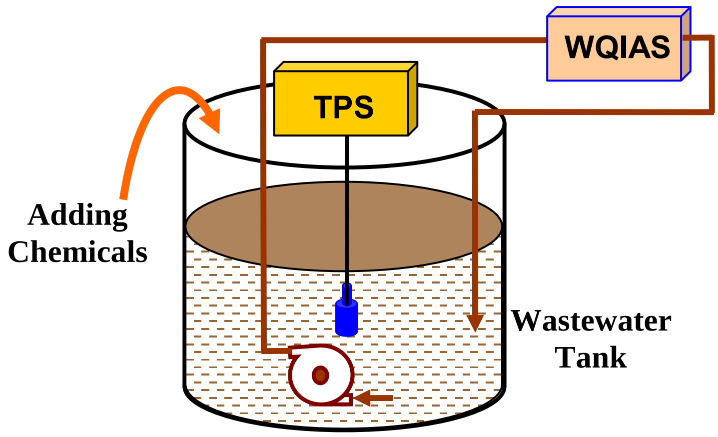


Figure 29. Experimental setup for steady mode event simulations.

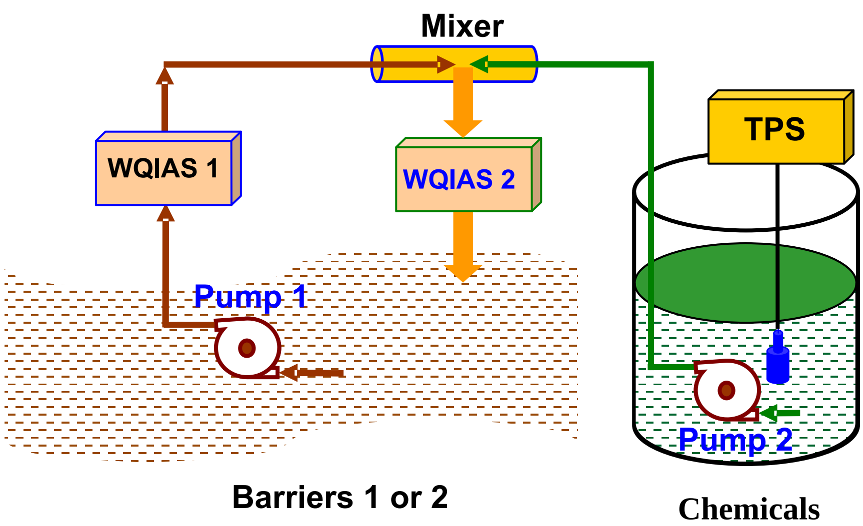


Figure 30. Experimental setup for dynamic mode event simulations.

5.2.1. Steady Mode Event Simulation

The steady mode event simulation experiments were carried out as illustrated in Figure 29. A 2.5 m^3 tank was used as the wastewater tank for the event simulation experiments. The procedure used for steady mode event simulation experiments was as follows:

(i) Pump 2 m3 wastewater from Barrier 1 or 2 into the wastewater tank as the 'background' water;

(ii) Circulate the 'background' water through the WQIAS to obtain stable readings from both WQIASs and the in situ TPS meter; and

(iii) 'Events' were generated by adding chemicals representing waste dumps (such as salt, acid, base, milk, and organics) into the tank, or other actions (such as pump or power off) to obtain stable reading from both the WQIAS and TPS meter.

The test system used a TPS meter to confirm the readings from the WQIAS. Figure 31 shows a set of typical simulation responses resulting from actions in a time sequence of the circulation pump on and off, pumping air into the wastewater tank (increasing dissolved oxygen), adding salt solution into the wastewater tank (increasing conductivity), adding acid solutions into the wastewater tank (decreasing pH), adding basic solutions into the wastewater tank (increasing pH), adding milk into the wastewater tank (increasing turbidity).

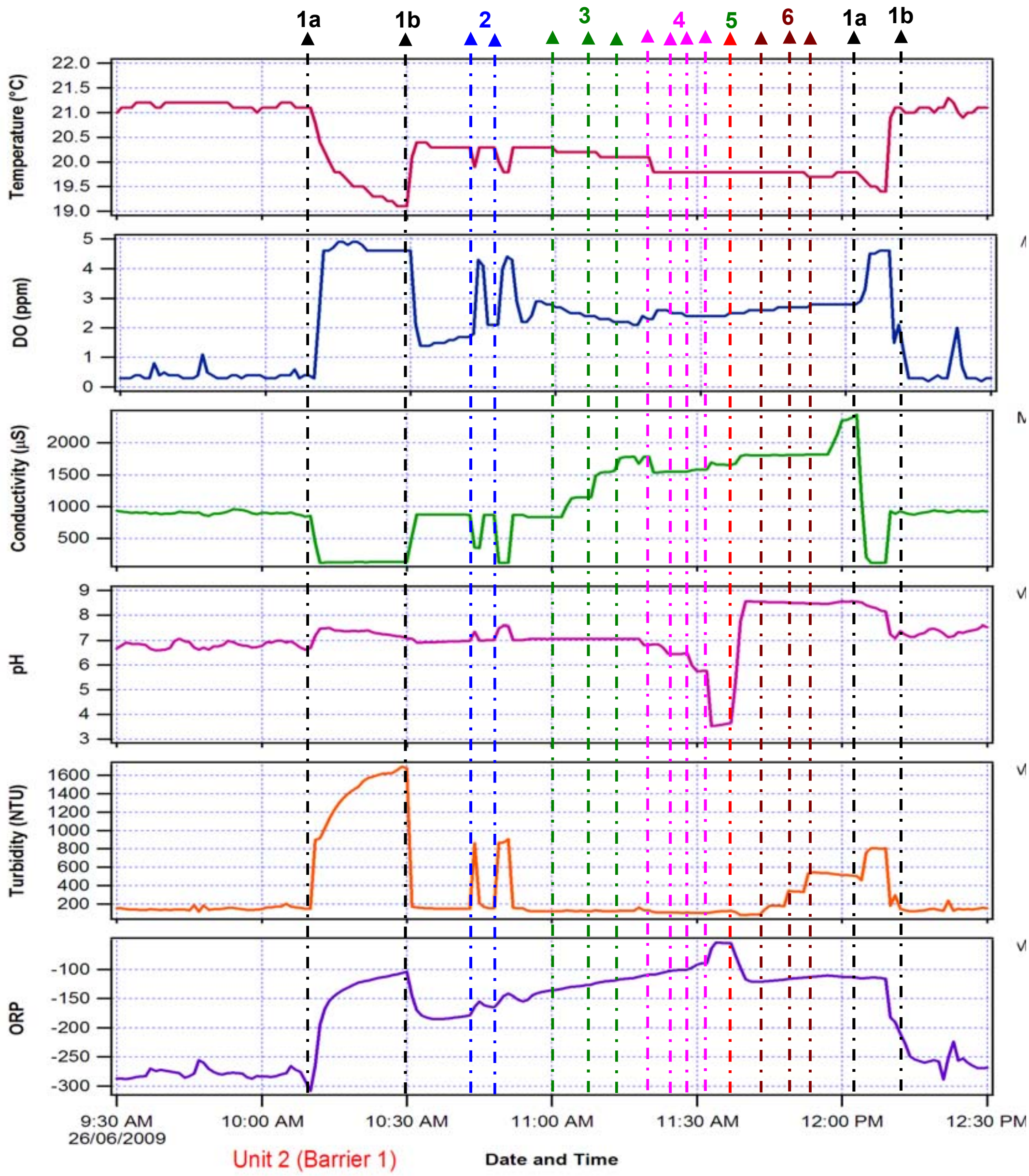


Figure 31. Steady mode event simulations. 1a and 1b: circulation pump on and off; 2: pumping air; 3: adding salt; 4: adding acid; 5: adding base; 6: adding milk.

5.2.2. Dynamic Mode Event Simulation

In practice, the background wastewater characteristics always change with time. Therefore, the event simulation should be carried out under a dynamically changing background. In this regard, the dynamic mode should allow a more realistic event simulation. The dynamic event simulation can be used to effectively and rapidly accumulate the characteristics of the WQIAS responding to different forms of 'events' for developing and validation of event detection mathematical models.

The dynamic mode event simulation experiments were carried out as illustrated in Figure 30. The event generating solutions used to generate 'events' were prepared by mixing the chemicals/solutions with the 'background' wastewater from Barrier 1 (raw sewage) or Barrier 2 (secondary effluent) in a storage tank. The characteristics of the chemical solutions were monitored by a TPS meter installed in the storage tank (see Figure 30). In order to measure and confirm an artificially generated 'event' in real-time dynamic mode, the system employed two identically built WQIAS units, one (WQIAS 1) was installed in the wastewater intake pipeline (from raw sewage at Barrier 1 or secondary effluent at Barrier 2), measuring the dynamically changing background water quality, and the other (WQIAS 2) was installed in the pipeline after the intake wastewater was mixed with event generating solutions to measuring the resulting changes (Figure 30). The procedure used for dynamic mode event simulation experiments was as follows:

(i) Switch on pump 1 and WQIAS 1 and 2 to obtain the dynamic background of the wastewater stream at Barrier 1 or the effluent stream at Barrier 2;

(ii) Switch on the storage tank TPS meter to measure the characteristics of the event generating solution containing representative chemicals (eg, salt, acid, base, milk, and organics, etc.);

(iii) Switch on pump 2 to inject the event generating solution from the storage tank into the mixer via a 3-way valve.

The composition of event generating solution and the ratio of the flow rates between pumps 1 and 2 could be used to control the 'event' generation. Figure 32 shows a typical set of data obtained during dynamic event generation when the flow rates of pump 1 and pump 2 were set at 10 and 3.4 L/min. These results demonstrated that the dynamic event simulation can be used to rapidly accumulate knowledge of different types of events for development and validation of the mathematical model. The dynamic event simulation experiments were performance systematically and all results were analysed for their characteristics and incorporated into the 'database' for the reasoning unit (see section 4.4.2). The experimental results demonstrated that the WQIAS is capable of responding to dynamic changes caused by a variety of different sources (e.g., changes in chemical composition/water quality) in a real-time fashion.

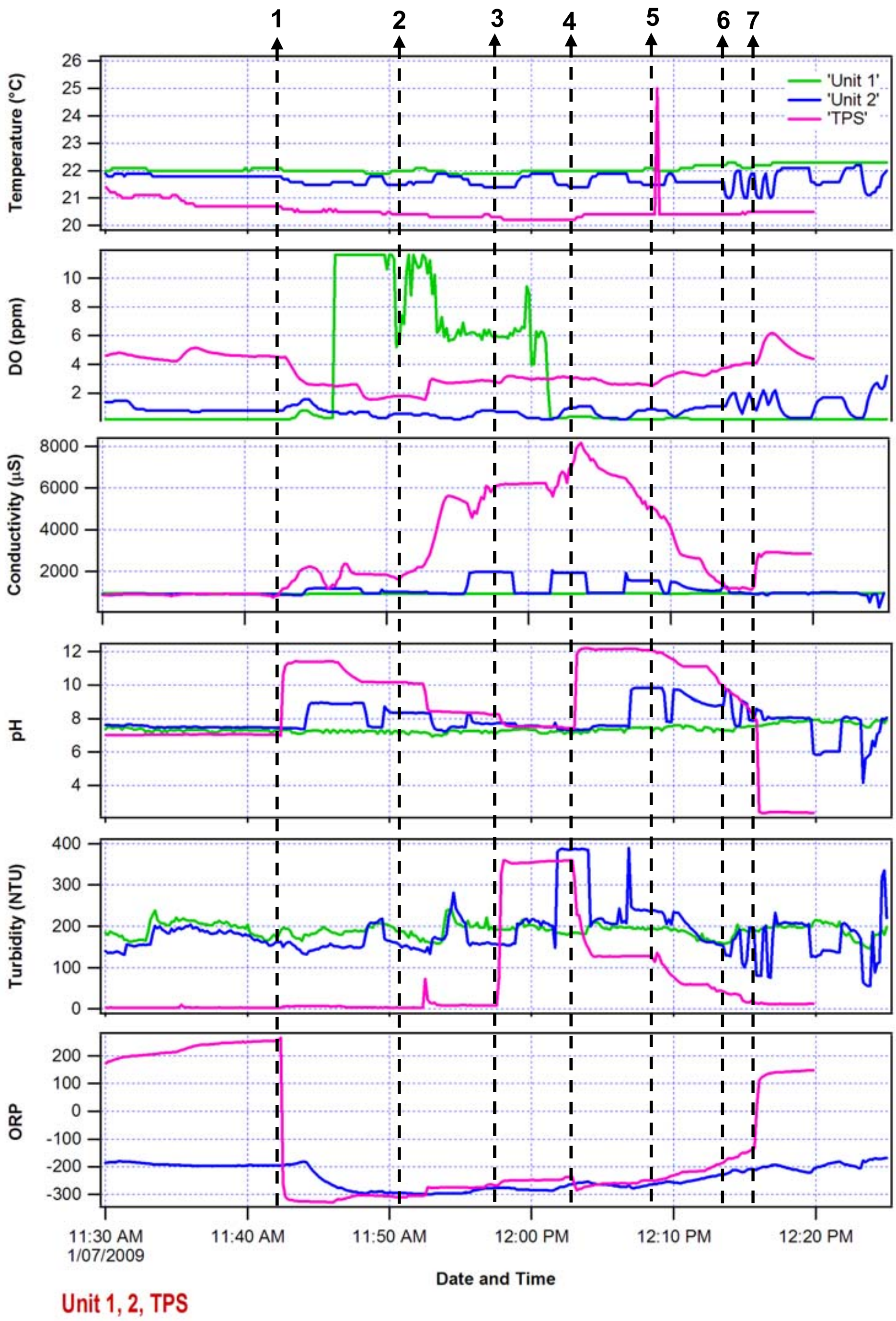


Figure 32. Dynamic mode event simulations by injecting event generating solution from the storage tank: 1: Na2S; 2: soy sauce; 3: milk; 4: base; 5: tap water; 6: fast flow rate; 7: acid.

5.3. Event Detection

Real-time detection of abnormal wastewater quality change events is the main objective of this project. In this regard, the ability to detect different forms of events relies largely on the effectiveness of the embodied event detection mathematical model. In this project, we have developed two different mathematical models for event detection. A Multivariate Event Detection Mathematical Model was developed in the earlier stage of the project. Although it demonstrated the capability to detect abnormal wastewater quality change events, it had a number of drawbacks (see Section 4.3). Therefore, a Univariate Event Detection Mathematical Model was developed to overcome those drawbacks encountered by the Multivariate Model (see Section 4.4). It should be noted that over a period of four years from 2008-2011, the WQIAS recorded/detected over 60 events from the WWTP trial that were deemed to have an impact on plant operation. According to the causes of the event, these detected events could be classified into four different categories:

(i) Wastewater composition/quality changes at Barrier 1 (raw sewage) caused by industrial waste discharge;

(ii) Wastewater composition/quality changes (raw sewage) caused by a natural event (eg, heavy rainfall);

(iii) Effluent composition/quality changes caused by significant composition/quality changes of raw sewage; and

(iv) Effluent composition/quality changes caused by failure of the WWTP.

This report will demonstrate typical examples of detected events of each category and implications of event detection for operational control and management.

It should be mentioned that all events reported here were detected using the final version of Univariate Event Detection Mathematical Model. The earlier events (before 2009) reported here were originally detected by the Multivariate Event Detection Mathematical Model, but were reprocessed by the Univariate Event Detection Mathematical Model using original data input into the model. It should be also mentioned that no false alarm was raised by the Univariate Event Detection Mathematical Model over the final six-month deployment period between June and December 2011.

5.3.1. Long-Term Stability

The system stability, especially over the long-term, was evaluated by deploying the WQIAS units at both Barriers 1 and 2. Because performance of the hardware, including the flow cell and sensors, has previously been evaluated (Section 3.3.), this section will only focus on the long-term software stability. The long-term stability experiments were carried out simultaneously at both barriers over a six-month period.

Over the experimental period, the WQIAS units installed at Barrier 1 were offline on several occasions due to power failure, major flooding, and earthworks for flood recovery. Other than power off and forced shutdown events, the systems functioned well during the entire test period. Figure 33a shows the plots of sensing data from a WQIAS unit installed at Barrier 1 over a five-week period.

Over the experimental period, the WQIAS units installed at Barrier 2 were also interrupted a number of times for the same reasons experienced at Barrier 1. Other than power off and forced shutdown events, the systems functioned well during the entire test period. Figure 33b shows the plots of sensing data from a WQIAS unit installed at Barrier 2 over a four-month period. It also experienced a plant malfunction due a clarifier failure, which will be discussed in a later section.

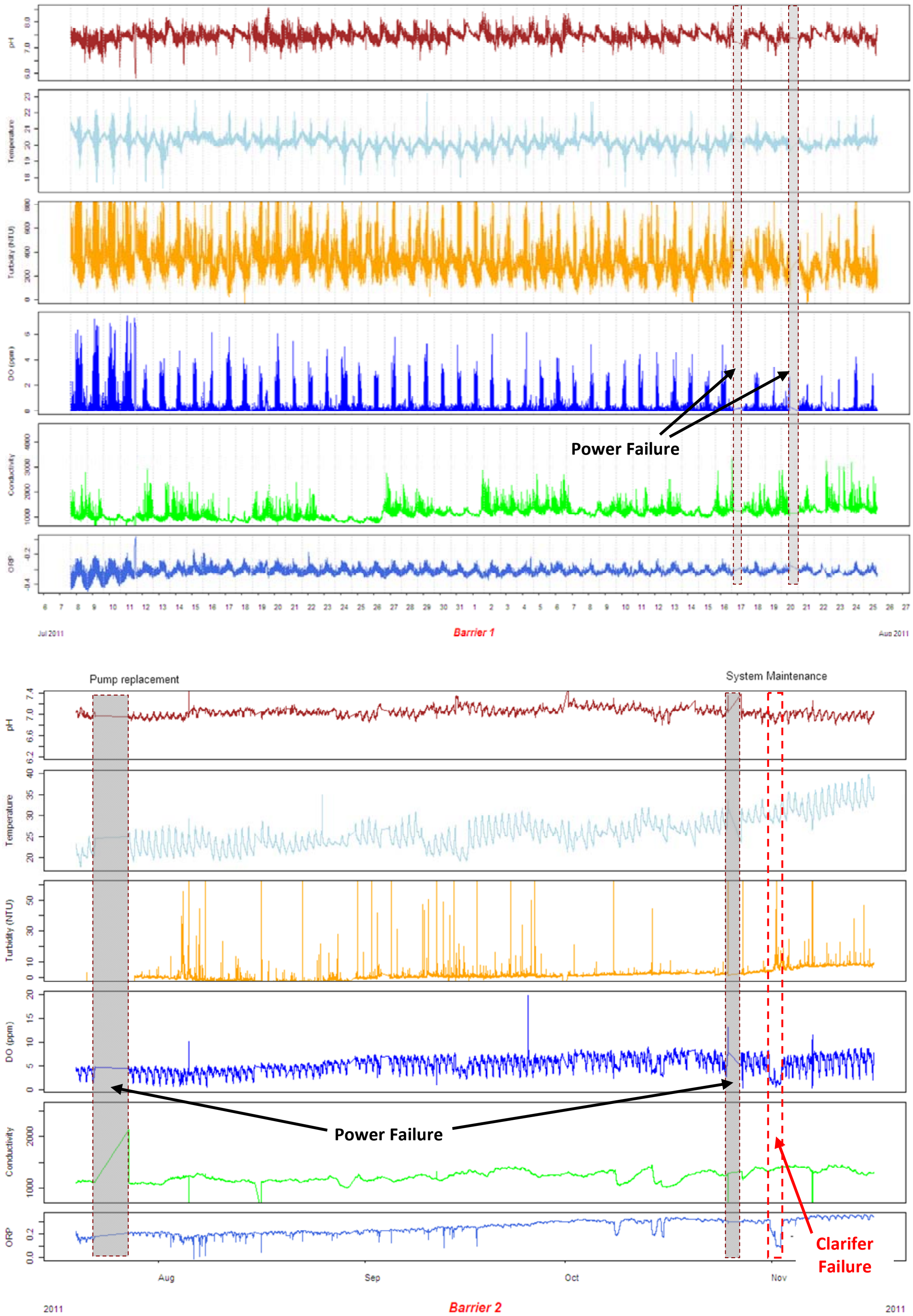


Figure 33. Real-time wastewater data recorded from WQIAS units deployed at Barrier 1 (top) and Barrier 2 (bottom).

5.3.2. Detected Event at Barrier 1 Due to Industrial Waste Discharge

Over the period of four years that the WQIAS was trialled at a WWTP, we have detected over 60 significant events that have had an impact on the WWTP operation to a certain degree. Amongst these events, 80% of them were due to irregular industrial discharge/dumping actions. A number of examples are presented in this report to demonstrate the capabilities of the WQIAS to detect events caused by irregular industrial discharge/dumping. Figure 34 shows two events detected at Barrier 1 of a WWTP on 28th and 30th of November 2008.

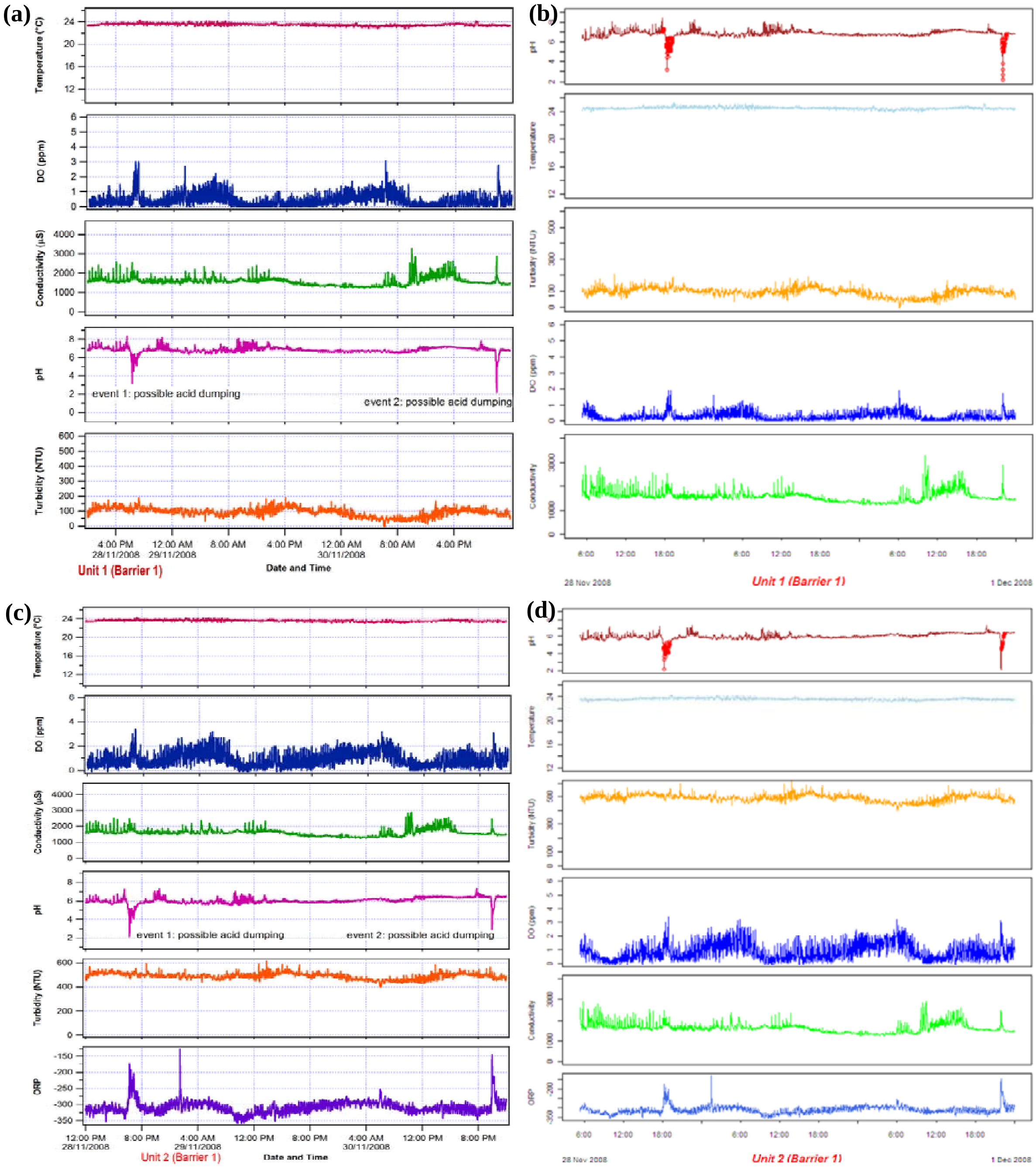


Figure 34. Typical irregular industrial wastes discharge/dumping events. (a) and (c): original real-time wastewater quality data recorded by WQIAS 1 (a) and WQIAS 2 (b) deployed at the same location at Barrier 1 of the WWTP; (b) and (d): Detected event over the same period of deployment from the original data acquired by WQIAS 1 (b) and WQIAS 2 (d).

The two identical but independent sensing units at Barrier 1 recorded both events in an almost identical manner (see Figures 34a and c), indicating the reliability of the system. Both events were detected and identified as near identical industrial acid discharge events (Figure 34 b and d). Alarms were raised on both occasions due to the abnormal change detected in pH as shown by the red dots in Figures 34 b and d.

Our interpretation of the two recorded events is that both were the result of irregular industrial waste discharges because of the sharp decrease to pH 2, as normal discharges would be highly unlikely to have such a low pH. In addition, the increase in the measured conductivities indicated the discharged waste contained ionic species. The increase in the measured DO suggests a low organic content. The sharp increased in ORP measured by Unit 2 combined with the measured changes in conductivity and pH value implies the sample may contain significant amount of high oxidation state heavy metal ions, which can be harmful for the bioactivity of the WWTP.

The first event on 28th of November 2008 lasted for ~1.5 hours, indicating a large discharge quantity. The second event lasted for ~40 minutes, suggesting less amount of wastes discharged in comparison to the first event. It should be noted that both measured events exhibited almost identical characteristics, indicating that they were probably from the same source. The major difference between the two events was the quantity/volume of the discharged wastes. The potential effect of these irregular discharge events on the performance of the WWTP will be discussed in section 5.3.4.

Figure 35 shows another example of an irregular industrial waste discharge event detected on 2nd September 2011. Both WQIAS units located at Barrier 1 raised an alarm at the same time for the same reasons because the pH and turbidity were deemed to be abnormal (pH 9.3 and TB >1600). The system classified and reported the event as an industrial base discharge event with a high concentration of suspended solid particles.

5.3.3. Detected Event at Barrier 1 Due to a Natural Event

The raw sewage quality change could also cause by a natural event, such as heavily rainfall or flooding. Over the period 2008 - 2011, we recorded/detected a number of events at Barrier 1 due to catchment overflow caused by heavy rainfall or flooding events. This category of events made up nearly 10% of the total events detected. Figure 36 shows two recorded natural events at Barrier 1 on 18th and 20th of November 2008, corresponding to two heavy storms recorded in the area. The events detected indicate that the catchment overflowed during that period. The event was identified because of the following characteristics:

- A drop in the measured temperature was recorded (the stormwater was cooler than domestic waste);
- A sharp increase in measured DO was recorded (the stormwater was saturated with air);
- A reduced conductivity was recorded (the stormwater contained lower concentrations of ionic species in comparison to the normal wastewater); and
- A slight decrease in pH was recorded (attributed to the stormwater being saturated with CO_2 from air).

The abnormal changes for temperature, EC and DO were simultaneously detected by the univariate event detection mathematical model in both WQIAS units, and the logic tests based on the above mentioned characteristics by the reasoning units classified these as overflow events. Two alarms were raised and reported as catchment overflow events.

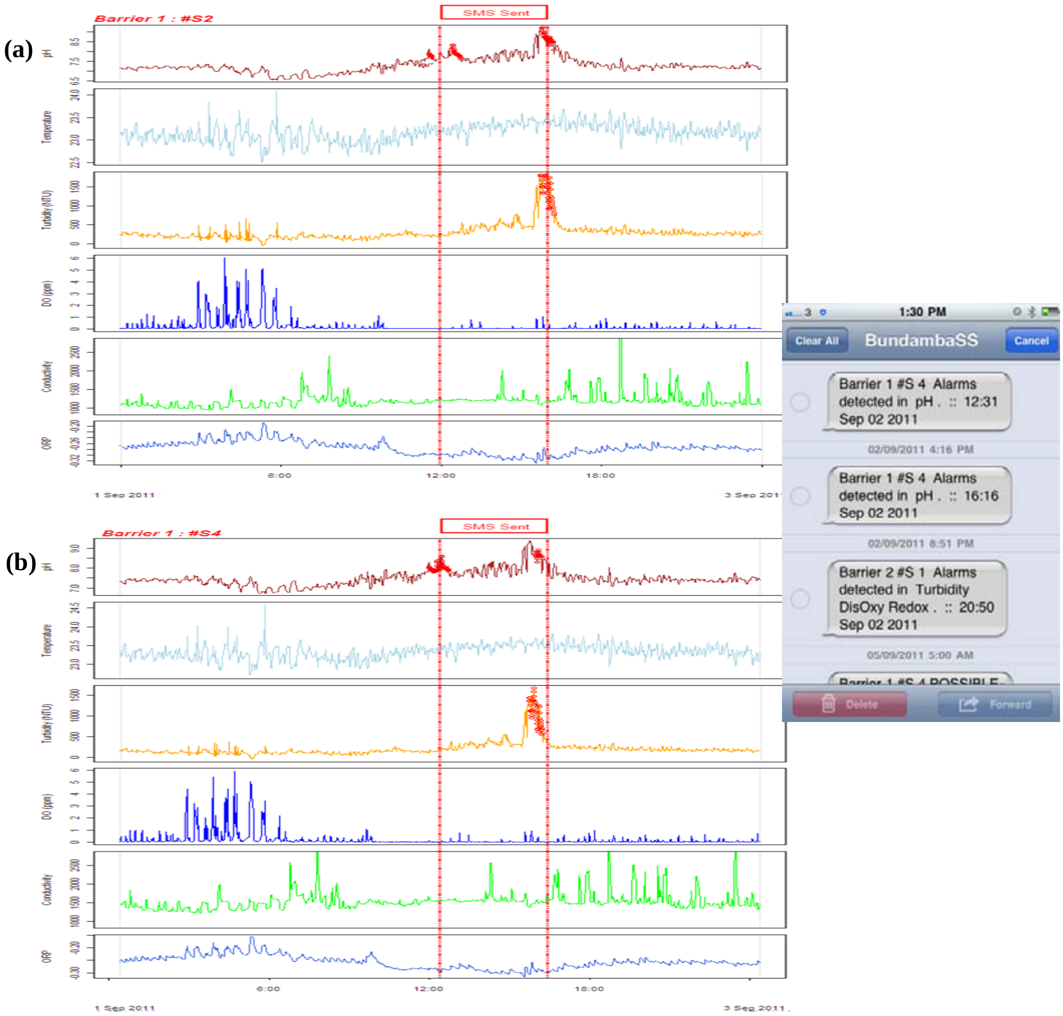


Figure 35. A typical irregular industrial waste discharge/dumping event detected by WQIAS 1 (a) and WQIAS 2 (b).

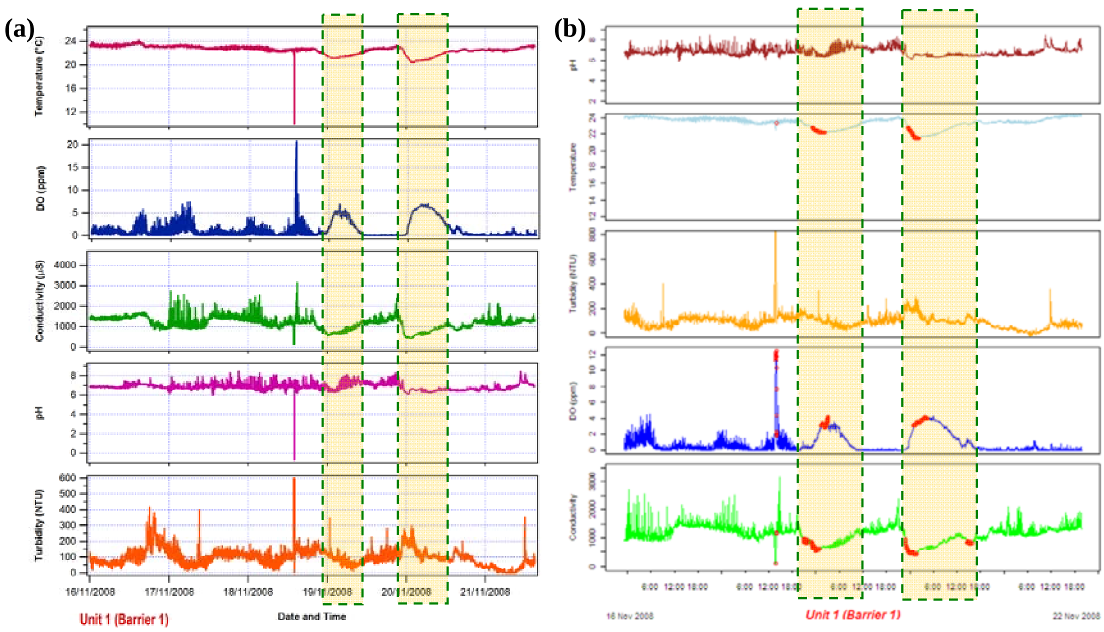


Figure 36. A typical catchment overflow event detected at Barrier 1.

5.3.4. Detected Event at Barrier 2

As mentioned previously, WQIAS units were installed at Barriers 1 and 2 over the entire deployment period. This enabled us to simultaneously collect real-time water quality data from these two consecutive barriers and detect any effect of events across the barriers. This is very important as it allows us to assess the impact of the input wastewater quality (raw sewage) on the quality of the treated effluent. The ability to collectively assess the input and output water quality can also be used to indicate the buffering capacity of a WWTP in respect to the input water quality changes, which can be further developed into a powerful tool assisting the grid operators/manager's decision making in responding to an emergency event to minimise/eliminate risks.

Generally, a WWTP is designed with the capacity to produce quality effluent from normal wastewaters feed under normal conditions. Its performance may be compromised (even totally malfunction) when an unlikely discharge event significantly changes the quality of the source water to an extent beyond the WWTP's buffering capacity. The risk and impact of an event to the WWTP can be greatly reduced if an event detection system is in place.

As described in Figure 34 in Section 5.3.2, two industrial acid discharge events were detected at 6:14 pm 28th and 10:15 pm 30th of November 2008 at Barrier 1 of a WWTP. These events were detected by the univariate event detection mathematical model, and the logic tests based on the event characteristics by the reasoning units classified both events as almost identical industrial acid discharge events (Figure 34). Although both measured events exhibit almost identical characteristics, the quantity of the discharges were different. The first event on 28th of November 2008 lasted for ~1.5 hours and the second event on 30th of November lasted for ~40 minutes, suggesting the quantity of the wastes discharged during first event was near three times of the second event. It took nearly 12 hours for these problematic acid discharges to go through the reactor and reach Barrier 2, as shown in Figure 37.

An abnormal pH decrease (pH<4) was detected at Barrier 2 at 6 am on the morning of 29th of November, which resulting from the first discharge event at Barrier 1 at 6:14 pm on 28th of November. The detected abnormal pH change was over three pH units below the normal reference baseline, which suggests the plant performance was compromised during the period when the problematic discharges were in the reactor. An abnormal oxygen depletion event was also detected prior to the pH event. This abnormal oxygen depletion of the secondary effluent was consistent with the biological stress caused by the acid discharges. Although the measured characteristics of both discharge events were similar (probably from the same source), the observed impacts on the WWTP were markedly different. The measured pH at Barrier 2 for the first event with the larger discharge quantity was found to be around pH 4, which is significantly lower than that of normal pH range (between pH 6 to 7.5), indicating such quality and quantity discharged wastewater had exceeded the buffering capacity of the WWTP. In fact, the effect of the first discharge event on the performance of the WWTP lasted for nearly 24 hours before the plant went back to normal.

In contrast, the smaller quantity of similar quality discharged waste generated very limited impact on the WWTP as suggested by the second event measured at Barrier 2 (see Figure 38). The measured pH only dropped slightly to pH 6.5 and quickly recovered to normal range over only three hours. As a result, the system did not detect any abnormal pH change resulting from the 2nd acid discharge event. However, two short periods of abnormal oxygen depletions were detected, suggesting the occurrence of biological stress caused by the 2nd acid discharge event.

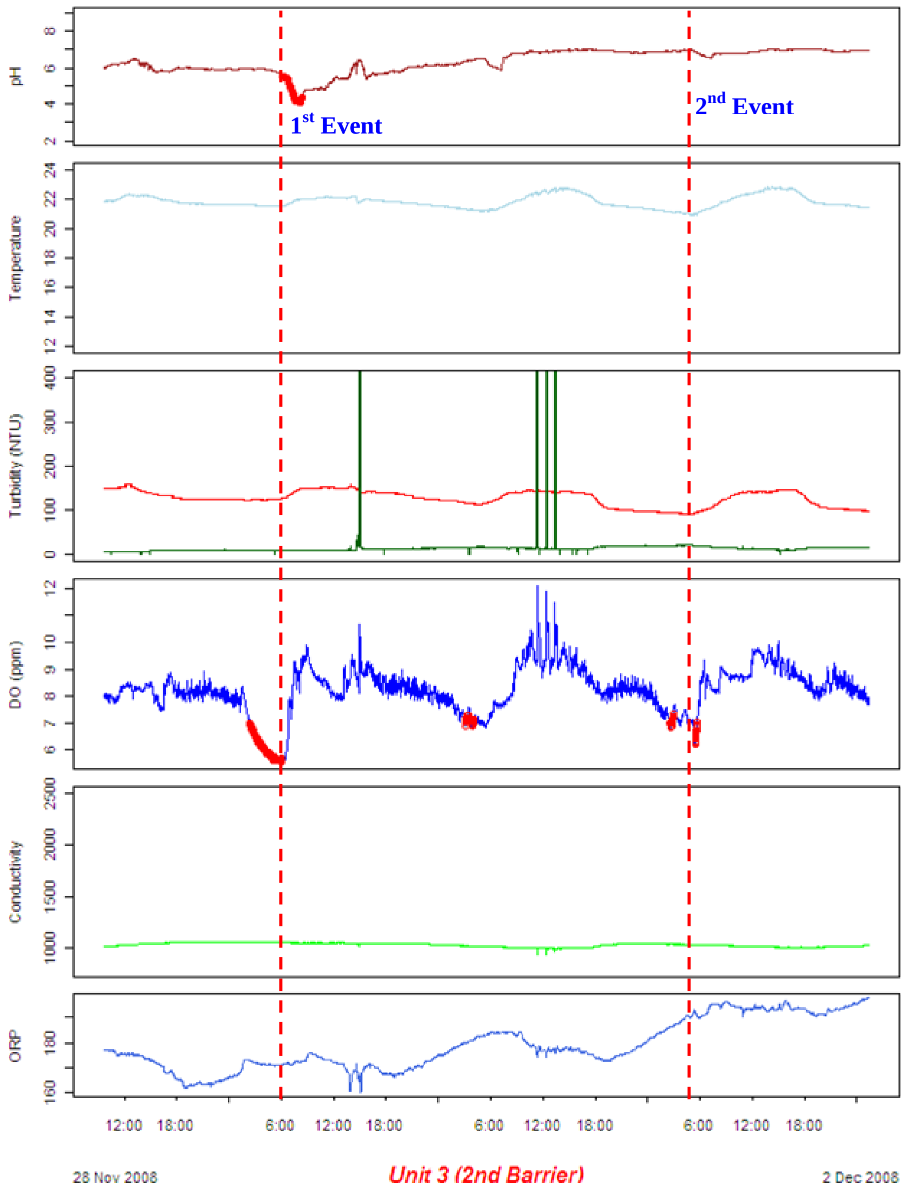


Figure 37. A detected event at Barrier 2 resulting from an irregular industrial discharge at Barrier 1.

Figure 38 shows another event detected by the two WQIAS units installed at Barrier 2. The event lasted for over three days and the abnormal turbidity, DO and ORP were detected by both WQIAS units. However, at the time the event was classified by both WQIAS units as an 'unknown event' because the reasoning unit could not determine the causes of the event as over the same week, no abnormal event was detected/reported by the WQIAS units installed at Barrier 1 (Figure 39). We reported the detected 'unknown' event to the WWTP operator to check if the plant was malfunctioning over the period the event was detected. The investigation confirmed that the clarifier of the plant was malfunctioning during the period the event was detected. This explains the detected abnormal water quality parameters. The abnormally high turbidity was because less solid particles were removed by the failed clarifier. The abnormally low DO and negative ORP values were cause by the higher concentration of organics in the effluent because of the failed clarifier. An event with such characteristics has now been incorporated into the reasoning units.

In summary, the developed WQIAS has been demonstrated capable of detecting different categories of abnormal events at both Barriers 1 and 2.

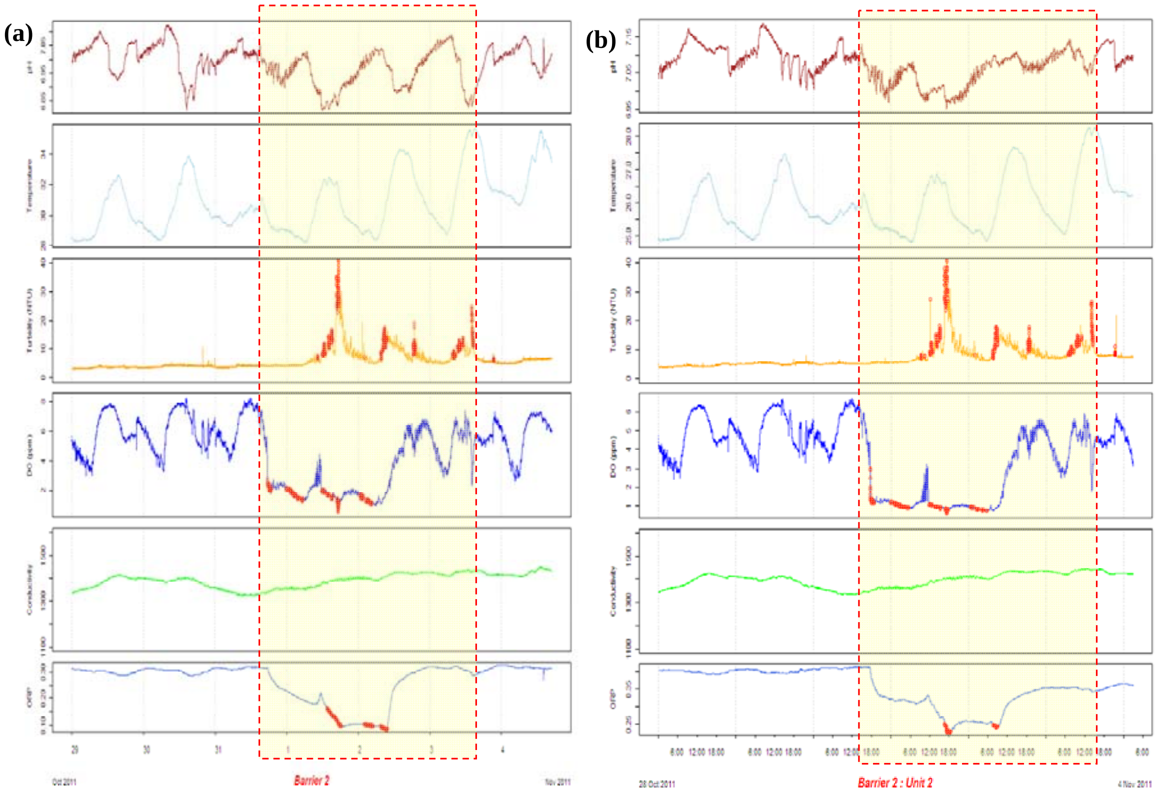


Figure 38. A detected event due to the failure of the clarifier in the WWTP.

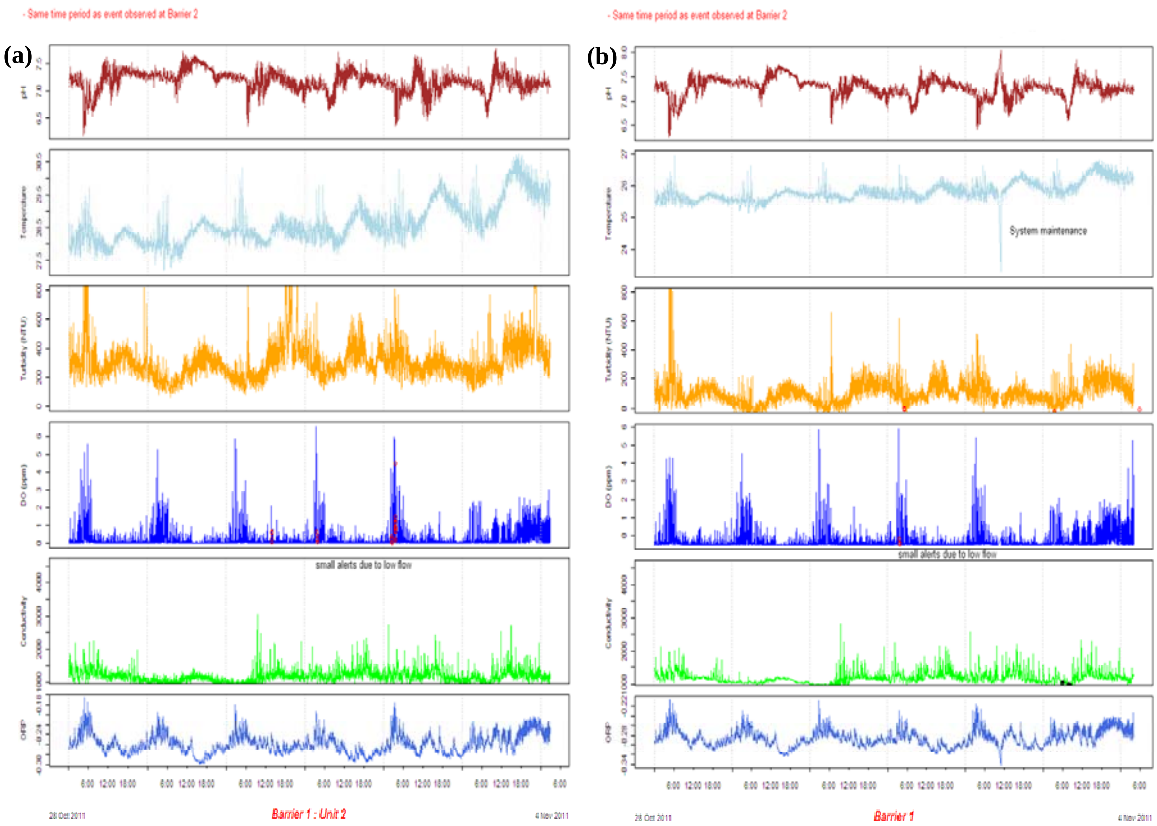


Figure 39. Plot of sensing data from Barrier 1 during the clarifier failure at Barrier 2.

6. CONCLUSIONS

In a three-stage project undertaken over five years, an integrated real-time Water Quality Information Acquisition System (WQIAS) was successfully developed, and field trials were undertaken which demonstrated that it can form the basis of a robust and effective management tool for wastewater source control. This is of particular relevance for the PRW system in SEQ, where continuous production of optimally treated wastewater is required to ensure reliable operation of the subsequent water purification stages.

In previous Stage 1 research, an in-depth study was undertaken of the issues and risks involved with closed water loop operation, and the key research activities required for future stages of the project were clearly identified. It was determined that no effective monitoring systems were in place at treatment Barriers 1 and 2 and, furthermore, that current sensor technologies could not perform reliably in the raw sewage environment. An effective water quality information collection strategy was outlined, including options for real-time water quality data acquisition, protocols, transformation and use for the relevant barriers.

Consequently, in Stage 2 of the project, a novel WQIAS with integrated real-time event detection has been developed to operate effectively in raw sewage and treated effluent. The WQIAS is based on a novel analytical principle in which ‘events’ are detected based on real-time measurement of water matrix changes. This is used to determine if the wastewater is ‘abnormal’ based on the changes observed relative to a ‘normal’ reference baseline. Unlike conventional chemical analysis, this protocol can work even if the sensor calibrations have drifted, since it relies on changes and trends in the data rather than absolute values.

The WQIAS has four main features that allow it to function for extended periods in a range of wastewaters without calibration or maintenance:

- A novel characterisation method based on recognising abnormal events in continuous online data from a set of robust water quality sensors;
- A compact flow manifold with unique hydrodynamics optimised to produce high shear zones where sensors are located to minimise biofouling;
- An effective mathematical model that can reliably detect events in noisy raw sewage data; and
- Integrated software and hardware to implement this new technology in a reliable package.

A specialised data collection platform was designed to meet these requirements. The system was based around a novel flow manifold with high-shear wall-jet hydrodynamics, replaceable pH, ORP and DO sensors, and integrated temperature, 4-electrode EC and dual detector turbidity sensor. The sensor electronics control board was integrated into the flow cell to minimise electrical noise. A dedicated single board computer, hard drive and 3G modem were sealed into a finned enclosure to host the data processing and real-time event software. Alarm functionality including the ability to send text alerts and operate an autosampler was also incorporated.

Two new real-time mathematical models were devised to implement event detection. Data collected from an operating WWTP was used to test the performance of both models. The first model was based on a unique multivariate mathematical model using the collective input data from the six wastewater quality parameters. However, the multivariate model was quite restrictive, as any change to the sensors required the model to be re-calibrated. We therefore developed an alternative univariate mathematical model to evaluate the data from individual sensors. It can be described as a running median reference baseline with event bridging function. It is designed to mimic the processes that a trained human observer applies when evaluating the online data. The univariate model outputs for every sensor collectively are then input into a reasoning based decision making system to determine if an abnormal event has occurred.

In Stage 3, a six-month field trial of the WQIAS real-time event detection system was undertaken at Barriers 1 (raw sewage influent) and 2 (treated effluent) at the Bundamba WWTP. Two independent units were deployed at each barrier to confirm the validity of any water quality changes observed. The system control hardware/electronics, flow manifold, sensors and real-time event detection software all performed as expected. Most importantly, no false alarms were generated during the trial, and a number of significant events were detected. These included catchment overflow after heavy storms, several major industrial waste dumps, and one clarifier failure. Some of the waste dumps were shown to compromise WWTP performance, as they caused significant changes in dissolved oxygen and pH levels in the treated effluent discharge at Barrier 2.

The project has successfully delivered a functioning WQIAS system that is an ideal basis to develop a sophisticated catchment management system. It has provided the springboard for a new ARC Linkage project between Griffith University, Melbourne Water and Sydney Water to further develop the WQIAS technology. CSIRO have further refined the fouling resistant flow manifold, and are currently preparing a provisional patent application to protect the unique hydrodynamic design. It is anticipated that both these developments will result in significant advances in online monitoring technology applicable to harsh fouling environments such as wastewater.

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