The water quality monitoring system is to find the quality of the drinking water at low cost. This system monitors the water quality in real time and in-pipe. The implementation is at low cost and it is light weight, the in-pipe electrochemical and optical sensors are employed in the main sensor node. The algorithms are validated and evaluated by the experiments for examining intentional contamination events of various concentrations of Escherichia Coli bacteria and heavy metals. From the results obtained it indicates this system is inexpensive and is capable of detecting the high impact contaminants at fairly low concentrations.

Keywords: Electrochemical, Escherichia Coli bacteria, Contamination event

INTRODUCTION

Clean drinking water is a critical resource, important for the health and well-being of all humans. The consumption of water services are fronting new challenges in their real-time process due to partial water resources, demanding expensive requirements, emergent inhabitants, ageing structure, stringent procedures and improved consideration towards conservation of water provisions from inadvertent or cautious pollution. There is a requirement for better on-line water observing systems given that prevailing laboratory-grounded methods are too slow to extend effective reaction and does not afford a level of communal health defense in real time. Rapid detection (and response) to instances of contamination is critical due to the potentially severe consequences to human health. Traditional methods of water quality control involve the manual collection of water samples at various locations and at different times, followed by laboratory analytical techniques in order to characterize the water quality. Such approaches are no longer considered efficient. Although, the current methodology allows a thorough analysis including chemical and biological agents, there is a clear need for continuous on-line water quality monitoring with efficient spatio-temporal resolution [3]. Us Environmental Protection Agency (USEPA) has carried out an extensive experimental evaluation [4] of water quality sensors to assess their performance on several contaminations. The main conclusion was that many of the chemical and biological contaminants...
used have an effect on many water parameters monitored including Turbidity (TU), Oxidation Reduction Potential (ORP), Electrical Conductivity (EC) and pH. Thus, it is feasible to monitor and infer the water quality by detecting changes in such parameters. Given the absence of reliable, in-line, continuous and inexpensive sensors for monitoring all possible biological and chemical contaminants, our approach is to measure physicochemical water parameters that can be reliably monitored with low cost sensors and develop low cost networked embedded systems (sensor nodes) as well as contamination detection algorithms to fuse these Multi-sensor data in order to infer possible contamination events. Even though this approach may suffer from some false alarms, it can be compensated/eliminated by the large scale deployment and the possibility of correlating the decisions from various sensor nodes which is the topic of our future work. The current monitoring paradigm and this [1] paper proposes the idea of monitoring the quality of water delivered to consumers, using low cost, low power and tiny in-pipe sensors. The main contribution of this paper is the design and development of a low cost system that can be used at the premises of consumers to continuously monitor qualitative water parameters and fuse Multi-parametric sensor response in order to assess the water consumption risk. In particular, the contributions regarding the low cost system is the design and development of low cost networked embedded systems as well as optical sensors (turbidity) for water quality monitoring, the development of event detection algorithms using

**PROPOSED SYSTEM**

Traditional methods of water quality control involve the manual collection of water samples at various locations and at different times, followed by laboratory analytical techniques in order to characterize the water quality. Such approaches are no longer considered efficient. The proposed system uses event detection algorithm for detection of contamination in water.

**Cerebellar model articulation controller**

A neural network is a computational model based on the neuron cell structure of the biological nervous system. The neural network can learn through a training set of data using a learning algorithm. The neural network forms a mapping between inputs and desired outputs from the training set by altering weights by means of the learning algorithm. The operation of the Albus CMAC can simply be defined in terms of a huge set of overlying, Multi-dimensional receptive fields with finite boundaries. The response of the CMAC neural network to a given input is the average of the responses of the receptive fields excited by that input, and is not affected by the other receptive fields. The adjustable weight of the excited receptive fields is affected by neural network training for input vector, but does not affect the weights of the remaining majority of receptive fields.

Therefore, if a receptive field is excited, its response is equal to the magnitude of a single adjustable weight specific to that receptive field. If a receptive field is not excited, there will not be a response from it, i.e., each receptive field is assumed to be an off/on type of entity. The CMAC output is the average of the adjustable weights from all the excited receptive fields. If nearby points in the input space excite the same receptive fields, they produce the same output value adjusting weights according to the Least Mean
Square adaptation rule. In this rule the learning rate is a defined constant between 0 and 1.

For a large rate, the learning speed will improve but there will be error due to gradient noise. A smaller learning rate will result in smaller adjustments to the look up table and thus slow training the relationship between the learning error and learning speed for a variety of learning rate constants of the algorithm considered for the detection of drinking water quality.

a. CMAC accepts real inputs and gives real outputs.

b. CMAC has a built-in local generalization, meaning that input vectors that are “close” in the input (state) space will give outputs that are close, even if the input has not been trained on.

c. CMAC has the property that large networks can be used and trained in practical time.

d. CMAC uses the LMS adaptation rule of Widrow and Hoff (Widrow et al. 1960).

e. CMAC can learn a wide variety of functions.

f. CMAC obeys superposition in the output space.

g. CMAC has a practical hardware realization

### B. Event Detection Algorithms

Two event detection algorithms were developed to fuse on-line Multi-sensor measurements in order to assess the water contamination risk when anomalies are detected. An event detection algorithm enables the system to act as an “early warning system” for possible potable water quality deterioration at the point of installation (e.g. homes). Both algorithms are based on normalized sensor outputs given by

\[ N_i = \text{where } S_i \text{ is the current measurement of parameter } i \{ \text{fTU; ORP; pH; EC}_{gi}, \} i, i \text{ are the mean and standard deviation over a moving time window } w \text{ and } i \text{ is a sensor based parameter associated with measurement accuracy of each parameter } i. \text{ Normalized sensor outputs } N_i \text{ are used to filter baseline (i.e mean) fluctuations. The objective of the event detection algorithms is to activate an alarm when normalized sensor outputs exhibit sudden and significant changes, given that these changes are bounded within the quality ranges suggested by drinking water quality standards (see Table 1, quality range). The detection of water quality changes that are outside the expected quality ranges (min/max violations) } \]

![Figure 1: CMAC Controller](image1)

![Figure 2: Quantization vs Initialization](image2)
is easier and can be done by a weighted Multi-parameter cost function in the form of
\[ RO = \sum w_i \cdot J_i \]
where \( J_i \) are binary variables that indicate whether parameter \( i \) has been violated and \( w_i \) are non-negative weights which imply the significance of the violation of each parameter \( i \). If \( RO = 0 \) no violation is assumed, however as \( RO > 0 \) increases the water contamination risk is also increases. As previously indicated, the objective in this paper is to detect anomalies when water quality changes are inside the expected quality ranges by fusing the Multi-sensor data. Therefore a risk indicator \( RI \) function is defined that takes a value \( RI = 1 \) if a contamination event is detected or \( RI = 0 \) otherwise. The first event detection algorithm is denoted as Vector Distance Algorithm (VDA) and the risk indicator \( RV_{DAI} \) function used in this algorithm is estimated based on the Euclidean distance between the normalized sensor signal vector \( N \) and the normalized control signal vector \( N_0 \) of pure (clean) water.

Therefore, the risk indicator \( RV_{DAI} \) is given by
\[ RV_{DAI} = \begin{cases} 1 & \text{if } ||N-N_0|| > d \\ 0 & \text{otherwise} \end{cases} \]
Note that VDA algorithm requires the normalized control signal vector \( N_0 \) as well as a calibration threshold \( d \) (obtained from a learning phase) to execute. The second event detection algorithm is denoted as Polygon Area Algorithm (PAA) and the risk indicator \( RP_{AAI} \) function used in this algorithm is estimated based on the ratio of the polygon area \( A_N \) formed by the \( N \) vector components (when projected (displayed) on a two-dimensional spider graph with four (TU, ORP, pH, EC) axes starting from the same point) to the polygon area \( A_1 \) formed by the 1 ones vector components (i.e \( 1 = [1111]^T \)). Therefore, the risk indicator \( RP_{AAI} \) is given by
\[ RP_{AAI} = \begin{cases} 1 & \text{if } A_N/A_1 > 1 \\ 0 & \text{otherwise} \end{cases} \]
Note that PAA algorithm does not require any further information to execute.

C. System and Sensors Development and Integration

The overall system architecture under discussion in presented and is comprised of the following three subsystems: a central measurement node (PIC32 MCU based board) that collects water quality measurements from sensors, implements the algorithm to assess water quality and transmits data to other nodes, a control node (ARM/Linux based platform) that stores measurement data received from the central measurement node in a local database and provides gateway to the internet, visualize data (charts), and sends email/sms alerts and finally a tiny notification node(s) (PIC MCU based board) that receives information from the central measurement node through an interconnected Zigbee RF transceiver and provides local near-tap notifications to the user (water consumer) via several interfaced peripherals (LED, LCD, Buzzer). It should be noted that the central measurement node serves as the sensor node.

The idea is to install these sensor nodes in many consumer sites in a spatially-distributed manner to form a WSN that will monitor the drinking water quality in the water distribution system from the source to the tap. The central measurement node is interfaced to Multi-parameter sensor array comprised of Turbidity (TU), ORP, pH, Electrical Conductivity(EC) and Temperature(T) sensors. The in-pipe Turbidity sensor is constructed from scratch based on our previous work [1] while the other sensor probes obtained from Sensor-ex Corpr. The pH sensor embeds an RTD sensor which is used for temperature sensing and temperature compensation of pH and EC measurements. TU, ORP, pH and toroidal EC sensors have flat measuring surfaces for cost effective self-

Note: This article can be downloaded from [http://www.ijerst.com/International-Conference-on-ICARSM-2015.php#1](http://www.ijerst.com/International-Conference-on-ICARSM-2015.php#1)
cleaning. The complete system photo, with TU, ORP, pH, EC and T sensors as well as a rotor-flow sensor mounted in a plastic pipe.

1. Turbidity Sensor Development

Although there is plenty of turbidity measuring instruments available on the market at the moment, most of them are expensive and not directly compatible with in-pipe, in-line requirements as well as WSNs technology. Therefore, the goal is to develop a low cost, easy to use and accurate enough turbidity sensor for continuous in pipe turbidity monitoring in water distribution systems using commercial off-the self-components. The turbidity sensor development was based on the ratio turbidimeter design (see Figure 3(a)) where both transmitted and scattered light intensities are measured to eliminate errors (interferences) due to IR emitter intensity drift and sample absorption characteristics. An infrared (860 nm) narrow beam LED emits light through an optical gap to the water sample and two IR photodiodes separated around 1cm from the emitter receive simultaneously the 90° scattered and 0° transmitted light. The photodiodes spectral sensitivity are selected to fit with that of the IR light source.

The instrumentation and analog signal conditioning of the sensor is as follows: The IR emitter is pulsed at 1kHz with a square wave signal and the photodiodes convert the light directly into electrical current, then a high-gain, low-noise CMOS(Complementary metal-oxide-semiconductor) trans impedance amplifier with background light rejection is used to convert the each photo current to voltage output. The ac output of each trans impedance amplifier is then converted to a dc signal using a precision active peak detector. Finally the 90° scattered dc signal is further conditioned by an instrumentation amplifier for 0 NTU offset nulling and additional amplification. The conditioned voltage outputs are

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Measurement Principle</th>
<th>Units</th>
<th>Range</th>
<th>Resolution</th>
<th>Accuracy</th>
<th>Quality Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Turbidity</td>
<td>Optical/infrared scattering</td>
<td>NTU</td>
<td>0-100</td>
<td>0.1</td>
<td>±0.5</td>
<td>0-5</td>
</tr>
<tr>
<td>ORP</td>
<td>Galvanic cell/platinum electrode</td>
<td>mV</td>
<td>-200-200</td>
<td>2</td>
<td>±10</td>
<td>600-800</td>
</tr>
<tr>
<td>pH</td>
<td>Galvanic cell/glass electrode</td>
<td>pH</td>
<td>0-14</td>
<td>0.05</td>
<td>±0.1</td>
<td>6.5-8.5</td>
</tr>
<tr>
<td>Conductivity</td>
<td>Conductive cell</td>
<td>ìS/cm</td>
<td>100-2000</td>
<td>10</td>
<td>5%</td>
<td>500-1000</td>
</tr>
<tr>
<td>Conductivity</td>
<td>Inductive cell</td>
<td>ìS/cm</td>
<td>200-300</td>
<td>10</td>
<td>5%</td>
<td>500-1000</td>
</tr>
<tr>
<td>Temperature</td>
<td>RTD resistance</td>
<td>°C</td>
<td>-5-100</td>
<td>0.1</td>
<td>±0.1</td>
<td>-</td>
</tr>
<tr>
<td>Flow</td>
<td>Magnetic rotor, hall effect sensor</td>
<td>L/min</td>
<td>1-115</td>
<td>0.0015</td>
<td>15%</td>
<td>-</td>
</tr>
</tbody>
</table>
then sampled by a 10 bit A/D converter with reference voltage of 1.1V and the sensor output voltage $V = V_{90\degree}c:V_{0\degree}$ is given as the signal ratio of the scattered $V_{90\degree}$ to the transmitted $V_{0\degree}$ voltage, $c$ is calibration coefficient. An indirect method for the sensor calibration was employed, in order to avoid the use of the carcinogen and expensive chemical formazin solutions. Therefore, a number of samples were created and the turbidity of each sample is measured both by the turbidity sensor under calibration and by a laboratory turbidimeter (Lutron TU-2016) used as reference. Then the relationship between turbidity (in NTU) and the voltage output (in mV) of the turbidity sensor is extracted and given by $TU = 0.1035V, 0.292$. The sensor generates an output voltage proportional to the turbidity or suspended particles and has a linear response in the range of 0-100 NTU with 0.1 NTU resolution. Finally, as shown in Fig. 3 the turbidity sensor probe was mounted in a flat surface PTFE (teflon) housing and sealed in a hydraulic Tee fitting for inline installation.

**RESULT AND DESCRIPTION**

In this section, we present the results of the experimental performed to validate the behavior and evaluate the performance of the developed hardware and algorithms on intentional contamination events. The experimental setup consists of the sensor node (central measurement node) that takes samples every 5s from potable water flowing through a flow cell. Intentional contamination of two important contaminants (Escherichia coli bacteria and arsenic) of various concentrations was injected at discrete time intervals and the performance of the event detection algorithms is evaluated on real time. Escherichia coli bacteria and arsenic contamination in drinking water is very severe problem causing serious poisoning to large numbers of people all over the world.

**A. Microbiologically (E.coli) contaminated drinking water**

The first experiment considers the case of microbiologically (E.coli) contaminated drinking water. Most E. coli strains are in general harmless to humans, but some types can cause serious food and water poisoning. However, the presence of E.coli is used to indicate that other pathogenic organisms may be present (often of fecal origin). According to WHO guidelines & EU Drinking Water Directive E.coli parametric value is 0 CFU/100mL.

**B. Chemically (Arsenic) contaminated drinking water**

The second experiment considers the case of chemically (Arsenic) contaminated drinking water. Water contamination by toxic heavy metals and especially arsenic contamination is a common problem encountered in many countries due to undue deposition of mining, agricultural, industrial and urban wastes in water resources. Arsenic is known to affect negatively the mental and central nervous system function, to damage the blood composition, lungs, kidneys, liver, and other vital organs, as well as it contributes to certain neurological degenerative processes and causes skin cancer. According to WHO guidelines & EU Drinking Water Directive Arsenic parametric value is 10 g/L.

**CONCLUSION**

In this article, the design and development of a low cost sensor node for real time observation of drinking water quality at end user sites is presented. The proposed sensor node consists
of several in-pipe water quality sensors with flat measuring probes. Unlike commercially available analyzers, the developed system is low cost, low power, lightweight and capable to process, log, and remotely present data. Moreover, contamination event detection algorithms have been developed and validated to enable these sensor nodes to make decisions and trigger alarms when anomalies are detected. Such execution is appropriate for large deployments supporting sensor network approach for providing temporally rich data to water consumers, water enterprises and consultants. In the future, we plan to investigate the performance of the event detection algorithms on other types of contaminants (e.g. nitrates) and install the system in several locations of the water distribution network to characterize system/sensors response and wireless communication performance in real field deployments.

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