

# Connected Sensors, Innovative Sensor Deployment and Intelligent Data Analysis for Online Water Quality Monitoring

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**Abstract**— The sensor technology for water quality monitoring (WQM) has improved during recent years. The cost-effective sensorised tools that can autonomously measure the essential physical-chemical and biological (PCB) variables are now readily available and are being deployed on buoys, boats and ships. Yet, there is a disconnect between the data quality, data gathering and data analysis due to the lack of standardized approaches for data collection and processing, spatio-temporal variation of key parameters in water bodies and new contaminants. Such gaps can be bridged with a network of multiparametric sensor systems deployed in water bodies using autonomous vehicles such as marine robots and aerial vehicles to broaden the data coverage in space and time. Further, intelligent algorithms (e. g. artificial intelligence (AI)) could be employed for standardised data analysis and forecasting. This paper presents a comprehensive review of the sensors, deployment and analysis technologies for WQM. A network of networked water bodies could enhance the global data intercomparability and enable WQM at global scale to address global challenges related to food (e.g., aqua/agriculture), drinking water, and health (e.g., water borne diseases).

**Index Terms**—Water quality monitoring, Internet of Things, Connected Sensors, Robotics, Sensor Deployment, Intelligent Data Analysis.

## I. INTRODUCTION

THE deterioration of water quality (WQ), caused by drivers such as climatic/seasonal changes, global warming, human activities or industrial waste is a major global concern. Since WQ directly impacts public health and economy, monitoring and assessing the quality and the causes of its degradation in water bodies has been a priority for governments all over the world [1-4]. Traditionally, the WQ is monitored by collecting discrete samples at weekly or monthly intervals and analysing in laboratory for physico-chemical-biological (PCB) parameters to reflect the changes in climatic, geochemical and geomorphological conditions and the properties of underlying aquifers in riverine systems [5-8]. As the rivers and large water bodies exhibit highly dynamic and often non-linear behaviour in both time and space, such low-frequency data collection makes it difficult to establish linkages between cause and effect and develop potential remedy or take timely decisions.

Additionally, the outcomes of traditional ‘sample collection and lab analysis’ methods could vary substantially due to the time gap between sampling and analysis.

Further, due to climatic changes and human and industrial activities, new determinants are regularly added in water system. As an example, in January 2014 the Elk River in Charleston, USA became contaminated by a leaking storage tank containing 4-Methylcyclohexanemethanol, a little-known coal-processing chemical, and the contaminated water drawn into city’s water supply system left over 300,000 people and area businesses without water for several weeks [9]. Researchers had little information on how the spilled chemicals moved through water, their stability or toxicity, or even how to measure them, because the published information was either limited or non-existent. So, many more chemical compounds are continually added to the list of parameters needed to be monitored than the current capability allows. More recently, the pandemic has presented similar situation due to the potential water-based transmission of coronavirus [10]. Robust strategies are required to bridge the knowledge gaps and to generate reliable estimates to develop appropriate mitigation measures.

Over the last decade, the WQ observing technology has risen to the challenge of scientists and has provided them with tools that identify poor WQ by autonomously measuring the essential PCB parameters [11-21]. Sensorised buoys and boats have been deployed for data collection and in situ-monitoring [22-28]. Likewise, the satellite imagery and time-averaged spatial analysis tools have been used for remote water quality monitoring (WQM) at regional levels [29]. Despite these options becoming more readily available, there is a gap between the technology and the end-user and a disconnect between data quality, data gathering by autonomous sensors and data analysis. The autonomous WQ observing technology could be advanced with network of sensors and geographical information systems (GIS) and suitable analysis methods to obtain water related information in real time [30]. With the impact of climate change, sole reliance on historical hydrologic patterns is no longer a viable route for forecast. Due to lack of standardized approaches for data analysis, and the gaps in the

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training of technicians and the approaches they use to analyse the data, it is also difficult to achieve the global data intercomparability. Such issues can be addressed by real-time WQM with suitable sensor networks [12, 19, 31-35].

Sensing in various water environments, particularly in large water bodies and underwater, is complex, expensive and challenging for a number of reasons. The environment is unforgiving for many sensing technologies; many modalities readily available in air cannot be used underwater and usually require specific packaging; or with limited range and sensitivities, the communications are severely affected. For instance, electromagnetic (EM) waves do not propagate well in water, especially salt-water; corrosion is prevalent, and biofouling can present as real challenge in shallow waters. As a result, the real-time WQM remains a challenge and methods that allow holistic water management, also considering the catchment management or the WQM at the source, need greater attention. The catchment management or the WQM at the source are important as the proportion of nutrients and sediments could vary significantly (e.g., during stormy events).

The sensor technologies that enable accuracy, repeatability, reliability and remote communication are vital to meet the growing challenges in the WQM. As new requirements for remote sensing emerge, there is need to develop multisensory systems to simultaneously measure multiple parameters, as well

their deployment strategies (e.g., using a mobile robots) to capture the spatio-temporal variations. The comprehensive discussion in this review paper focusses on these challenges and their solutions based on smart sensing technologies. It may be noted that the sensor based WQM has also been covered in some previous review articles [4, 36-45], where the discussion is restricted to a measuring a limited set of parameters and the real time monitoring using connected sensor network is generally not covered. For example, review focussing on graphene-based sensors (pH, disinfectants, mercury, lead, chromium, etc.) for WQM [44], various electrochemical sensors and mechanisms for monitoring pH and chlorine have been reported [46]. Likewise, biosensors for pathogens or chemical water contaminants (i.e. faecal pathogens, arsenic, and fluoride) [47] and the information and communications technology (ICT) [14] have been reviewed. Complementing the previous reviews, the holistic discussion in this comprehensive review covers the key topics related to connected sensors for real-time WQM, as summarised in Fig. 1. These include: (a) multiparametric sensory systems, (b) deployment of a network of multiparametric sensory systems in water bodies to broaden the data coverage in space and time (e. g., using autonomous marine robots and aerial vehicles,) and (c) using intelligent algorithms (e. g., artificial intelligence (AI)) for standardised data analysis and forecasting. By structuring the paper on above

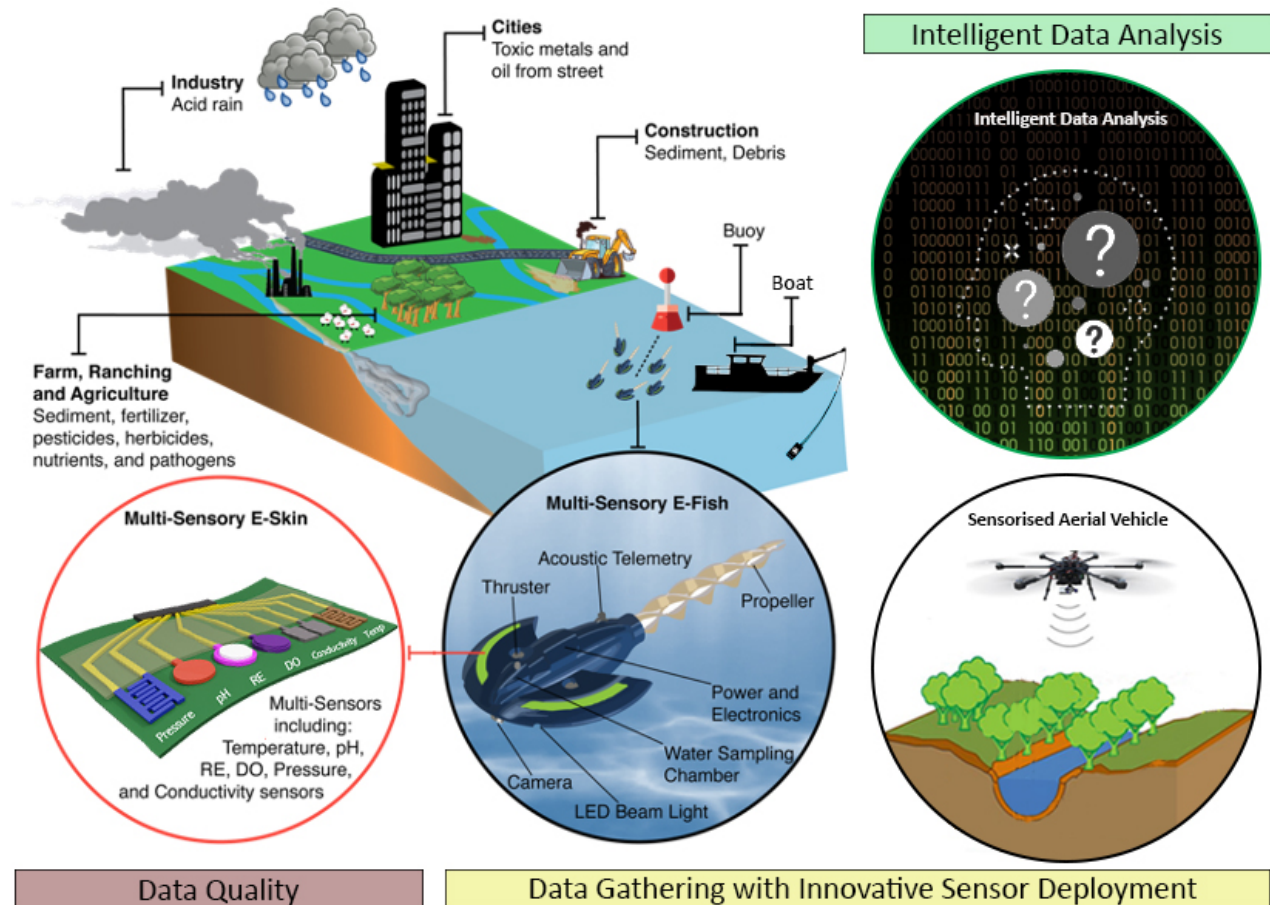


Fig. 1: (left) Various human activities contributing to the deterioration of water quality and the ways for its monitoring, including using multiparametric sensor patches or electronic skin (e-Skin), traditional methods of sensor deployment such as using sensorised buoys, and advanced deployment using underwater robots or multisensory e-Fish. (right) Key constituents of a holistic WQM system.

lines, it is hoped that the reader will be able to identify the disconnect between data quality, data gathering and data analysis and encouraged to explore innovative solutions. This is also a distinguishing feature of this review article.

This paper is organised as follows: Section II focuses on the ways to improve the data quality. To this end, various sensors and materials have been discussed. The data quality can also be improved by using suitable form factors and therefore flexible and disposable sensors are also discussed in section II. Various methods for sensor deployment in water bodies are discussed in Section III. These include sensor-instrumented buoys or moorings, as alternative to traditional ‘sample collection and lab analysis’ methods as well as advanced methods such as using underwater robots or autonomous aerial vehicles. These methods allow the high frequency collection of PCB properties of the water. Further, sensors interface with onboard electronics of robots and communication between them and the control station are also discussed in section III. The packaging methods employed for sensors and related components are also discussed in this section. Section IV briefly discusses the traditional methods data analysis as well as potential use for artificial intelligence (AI) in context with analysis and prediction of WQ. Future direction and perspectives are discussion in Section V, and this is followed by summary of conclusions in Section VI.

## II. IMPROVING THE DATA QUALITY

The WQM is carried out through a range of sensors that measure the basic PCB parameters. The quality of data collected by these sensors can be influenced by several factors such as (i) type of sensors (ii) functional materials used for the development of sensors and (iii) number of sensors etc. This section discusses these factors with a view to provide an insight into what it takes to improve the sensor data quality.

### A. Water Quality Parameters

A large number of PCB parameters that need to be monitored to ascertain the WQ are summarised in Table 1. The acceptable concentrations or range of these parameters depend on the end-use, for example drinking water (DW), bathing, aquaculture (freshwater fish directive or salmonid water regulations), ground water, or surface water (SW) for other uses etc. The most common parameters that are widely analysed to ascertain water quality are pH, dissolved oxygen (DO), Cl<sup>-</sup>, Na<sup>+</sup>, nitrate, and dissolved ions [4, 45, 48, 49]. Some of the parameters including pH, Cl<sup>-</sup> ions and temperature are also used for monitoring health, food quality or to monitor the quality of air [50-57]. For example, spatial variation can be expected in the values of pH and Cl<sup>-</sup> in an area [52] and the sensors that offer wide operating range (e.g. pH sensors in the range of 1.5-12) could be employed.

The biological, organic and inorganic toxic pollutants cause the variation of concentrations of various parameters in water or add new contaminants. For example, several human activities and products such as pharmaceuticals (antibiotics, hormones, non-steroidal anti-inflammatory drugs), personal care products (preservatives, bactericides/disinfectants, and

sunscreen UV filters), endocrine disruptors (pesticides, plasticizer and antimicrobial) herbicides, artificial sweetener, etc. add new water pollutants [4, 58, 59]. As discussed in previous section, there is always a possibility of the presence of new pollutants in water bodies [4, 60, 61]. As an example, micro plastics and pathogens need to be monitored to prevent loss of life or improve health and wellbeing [10, 61-66]. Few recent studies also indicate that presence of coronavirus in wastewater from the hospitals, quarantine centres and domestic households with positive cases [64, 65, 67, 68]. The potential transmission of SARS-CoV-2 within faecal contaminated rivers has been highlighted recently and a similar transmission risk is likely to exist from untreated or partially treated wastewater and drinking water in regions or countries with poor sanitation, especially if they are experiencing high infection rates [69]. Transmission may also be possible to and from susceptible riparian animals, or some cetaceans, that have fed from, lived around or within, or ingested faecal contaminated water [69]. The timely detection of such new contaminants can offer an opportunity to develop an early warning system. For example, by monitoring the wastewater coming from an area it is possible to identify the potential asymptomatic covid cases and prepare for the health requirements (e. g. readying the ventilators [70] or setting up temporary health centre etc.) in that area. The smart connected sensors-based approach is much needed for such cases. Further, using multisensory patches could help establish the linkages or dependencies between the various parameters.

TABLE I: GENERAL RANGE OF SOME IMPORTANT MARKERS WHICH NEEDS TO BE MONITORED FOR WATER QUALITY (SW – SURFACE WATER; DW – DRINKING WATER) [3].

Parameters	SW	DW
<b>Chemical Parameters</b>		
pH	5.5 - 9	6.5 – 9.5
Dissolved Oxygen (DO) in ppm	0.5 -10	--
Sulphate (mg. l <sup>-1</sup> SO <sub>4</sub> )	200	250
Phosphates (mg. l <sup>-1</sup> P <sub>2</sub> O <sub>5</sub> )	0.7	--
Sodium (mg. l <sup>-1</sup> Na)	--	200
Ammonia (mg. l <sup>-1</sup> NH <sub>4</sub> )	0.005-4	
Fluoride (mg. l <sup>-1</sup> F)	1.7	1.5
Iron (mg. l <sup>-1</sup> Fe)	2	1.5
Chloride (mg. l <sup>-1</sup> Cl)	250	250
Lead (mg. l <sup>-1</sup> Pb)	0.05	0.01
Nitrate (mg. l <sup>-1</sup> NO <sub>3</sub> )	50	50
Manganese (mg. l <sup>-1</sup> Mn)	2	0.05
Zinc (mg. l <sup>-1</sup> Zn)	5	5
Nickel (mg. l <sup>-1</sup> Ni)	--	0.02
Cyanide (mg. l <sup>-1</sup> CN)	0.05	0.05
Chromium (mg. l <sup>-1</sup> Cr)	0.05	0.05
Arsenic (mg. l <sup>-1</sup> As)	0.10	0.01
Benzene (mg. l <sup>-1</sup> compound)	--	0.01
Boron (mg. l <sup>-1</sup> B)	2	1
Cadmium (mg. l <sup>-1</sup> Cd)	0.005	0.05
Copper (mg. l <sup>-1</sup> Cu)	1	2
Mercury (mg. l <sup>-1</sup> Hg)	0.001	0.001
Selenium (mg. l <sup>-1</sup> Se)	0.01	0.01
Vinyl Chloride (µg. l <sup>-1</sup> )	--	0.50
<b>Biological Parameters</b>		
ECH	--	0.0001
E-Coli (no./100 ml)	10000	0
Epichlorohydrin (µg. l <sup>-1</sup> )	--	0.10
<b>Physical Parameters</b>		
Temperature (°C)	25	
Turbidity (ppm)	05-10	

### B. Materials for Sensors

The quality of data generated by the WQM sensors is evaluated through their sensitivity, response time, selectivity (interference to other ions), hysteresis, drift effect, lifetime, stability in various water conditions and biocompatibility etc. For example, the ideal sensitivity of potentiometric pH sensors should be close to Nernstian response 59.12 mV/pH. Further, these sensors have fast response (<1 minute) and negligible hysteresis, drift and interference effects. Few pH sensors that exhibit above mentioned properties include RuO<sub>2</sub> based pH sensors [34, 71-74]. As an example, in our previous work we observed the of sensitivity 56.11 mV/pH with response time <15 s [71]. A summary of the materials used for the fabrication of sensors such as pH, DO, ammonia, nitrate and ions etc. is included in Table II.

Recently, biocompatible and biodegradable materials have attracted significant interest [75-77]. The choice of materials and eventually the sensor performance, depends on their structural properties. For example, nanostructured materials exhibit high surface to volume ratio, and hence the fast response and high sensitivity [20, 78-80]. In addition, the shape or morphology of the nanomaterial could influence the sensor performance [81, 82]. The porosity, pore size and grain size of the crystals influence on the response time. For example, in a work involving the Cu<sub>2</sub>O-doped RuO<sub>2</sub> based pH sensitive electrode (SE), it has been shown that the pH sensitivity does not vary with the thickness of SE (from ~2.0 to ~5.0 μm) [78], but the response time does. The response time was found to improve from ~80–120 s (for SE thickness of 2.0 μm) to ~25 s (for SE thickness of 5.0 μm) as improved crystallization was possible for thicker SEs. Further, the inner active site in the SE and developed porosity led to sensors with improved performances [78]. A comparison of various influencers of the bulk, microstructural and nano-structural properties of the

TABLE II: PERFORMANCES OF WQM SENSORS

Sensor	Material	Sensitivity	Response time	Ref
pH	RuO <sub>2</sub>	58 mV/pH (2-13)	1-2 s at 23°C	[107]
DO	RuO <sub>2</sub>	41 mV/decade (0.6-8 ppm)	8-10 min at 9°C	[107]
pH	Bi <sub>2</sub> Ru <sub>2</sub> O <sub>7+x</sub> + RuO <sub>2</sub>	58 mV/pH (2-13)		[102]
DO	Bi <sub>2</sub> Ru <sub>2</sub> O <sub>7+x</sub> + RuO <sub>2</sub>	30.57 mV/decade (0.5-8 ppm)		[102]
pH	RuO <sub>2</sub> +SnO <sub>2</sub>	56.5mV/pH(2-12)	5-9 s	[103]
Nitrite	Au	0.98 coefficient mM range	0.5 - 8	[20]
Hg <sup>2+</sup>	MoS <sub>2</sub>	0.64 μA/ppb (0.1 - 100 ppb)	1.8 s	[21]

electrode is given in Fig. 2. Recently molecule-based sensors have also received attention for the fabrication of electrochemical and biosensors [83]. The miniaturized sensors with fast response have been realized using materials with nano or molecular structures [83]. The cost (of both material and fabrication), life- time, flexibility are other factors which also need to consider in the SE design. As discussed in the following sub-section, in a vast majority of the recently reported flexible sensors for WQM or other applications such as wearables for health monitoring, the micro or nanostructured materials have been utilized. With the functionalization of nanomaterials and nanoparticles, they could be used in biosensors as the recognition elements or the transducers, especially for pathogen detection in WQM [84, 85]. The selection of the nanomaterials for the fabrication of a biosensor depends on the properties of the nanomaterials and their application and as a result several types of nanomaterials have been used in the design of microbial biosensors [85], as discussed in the following subsection.

### C. Sensors for Water Quality Monitoring

The methodologies that have been employed for monitoring various PCB parameters in water include electrochemical, physical and optical sensing. Among these, the electrochemical sensing is preferred [49, 54] due to several advantages as noted in Fig. 3a. Electrochemical and bio sensors offer cost-effective route for simultaneous monitoring of PCB parameters using multi-sensory patch and are suitable for online monitoring of large water bodies such as reservoirs. In electrochemical sensing, the conventional glass-based sensors are of limited use for online monitoring and their response could be influenced by the prevailing pressure and temperature conditions. In this regard, the electrochemical solid-state sensors based on metal oxides (MO<sub>x</sub>), polymers or carbon-based materials (based on thick/thin film) technology are better and suitable to be used as part of wireless sensor networks [54, 83, 86-89]. The qualitative analysis of the features and th1/8/22e advantages of the solid state based physical, electrochemical and biosensors are summarized in Fig. 3b. This includes type of sensors (potentiometric, voltammetry, chemi-resistance, capacitive, ion sensitive field effect transistors (ISFETs)) and materials used for the fabrication. The performance parameters such as sensitivity, response time, selectivity may depend on the type of fabrication adopted for development of sensors including screen printing, chemical deposition, physical deposition, sol

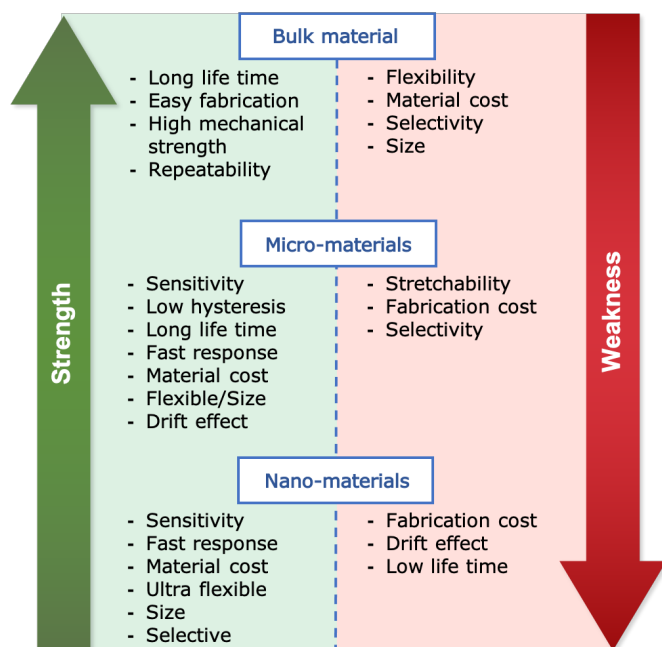


Fig. 2: Comparison (positive and negative) factors of materials for sensors fabrication.

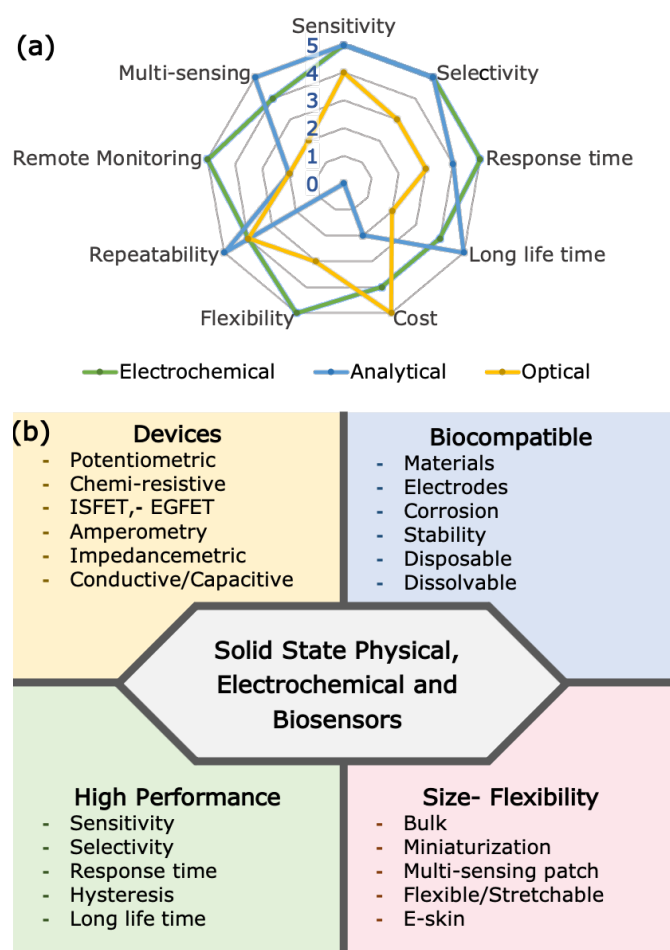


Fig. 3: Comparison of electrochemical, analytical and optical based sensors (b) general summary of solid-state sensors including various type of devices (sensors).

gel methods [90] and type of sensors.

#### 1) Potentiometric and Amperometric sensors:

It is essential to develop reliable sensors to measure individual parameters or multiparametric sensor systems for simultaneous detection of multiple analytes. Among different types of sensor configurations, the potentiometric sensors, as illustrated in Fig. 4a [54], are widely used for pH and DO monitoring. The potentiometric electrochemical sensors, consisting of sensitive and reference electrodes, offer simple and attractive approach with their sensitivity measured by Nernstian equations [18, 71]. Examples include sensors that use thick film Ag/AgCl/KCl based reference electrode (RE), showing excellent long-term stability comparable with glass RE and hence suitable for applications requiring data collection over long periods [71, 91-97]. Due to high sensitivity, chemical stability and long lifetime, the RuO<sub>2</sub> has been used as SE in many pH and DO sensors [54, 71, 97]. Using RuO<sub>2</sub>, the pH sensor (2-13 range; sensitivity 58 mV/pH at 23°C) and DO sensor (0.6 - 8.0 ppm log [O<sub>2</sub>]; -4.71 to -3.59 with sensitivity of -41 mV/decade at pH 8) have been developed with excellent performances [105, 117]. The response of these sensors is strongly influenced by the temperature of water. When the water temperature is low, the sensor shows slow responses. For example, at 9°C the pH sensor

shows response time of 8-10 min as compared to 1-2s at high temperature (23°C) [73, 98].

Silicon based thin film sensor have been used in several applications [52]. Due excellent response consistency, they could offer excellent opportunity for WQM. However, one of the major issues with these sensors is the lack of compatible RE. A vast majority of reported works based on thin film-based Ag/AgCl REs show drift [99, 100]. To solve this issue, solid-state Ag/AgCl electrode could be placed in a mini tank of KCl solution for better ion exchange, as done in the case of nitrite monitoring sensor [20], and the outcome was a stable potential with very small variation of 2 mV. The design of this sensor shows potential usefulness for monitoring of analytes such as phosphates and ammonium. With further modification of the working electrode (WE) it may also be possible to use this design for urea and ammonia monitoring. The array of RuO<sub>2</sub> based sensitive electrode has also been used for lower measurement errors in microfabricated sensors developed in ISFET technology [101]. These sensors show excellent performances with a sensitivity of 55.64 mV/pH and low drift rate 0.38 mV/h at pH 7 and the array of such sensors could be useful for monitoring parameters such as free chlorine, DO, dissolved ions, and heavy metals.

There are many dissolved metal ions in water which are also toxic and can cause health risks if their concentration is high, as listed in Table I. For example, toxic Hg<sup>2+</sup> (as per WHO it should be <1ppb) could cause acute poisoning, irreversible neurological damage, cancer, and motion disorders that can lead to death. Hg<sup>2+</sup> could be detected using a molybdenum disulfide (MoS<sub>2</sub>) functionalized AlGaN/GaN high electron mobility transistor (HEMT) sensor [21]. The sulphur atoms in MoS<sub>2</sub> attract the Hg<sup>2+</sup>, leading to the adsorption of these ions on the surface of the MoS<sub>2</sub> to form Hg-S complexation. The formation of Hg-S reduces the electrons from MoS<sub>2</sub> surface and

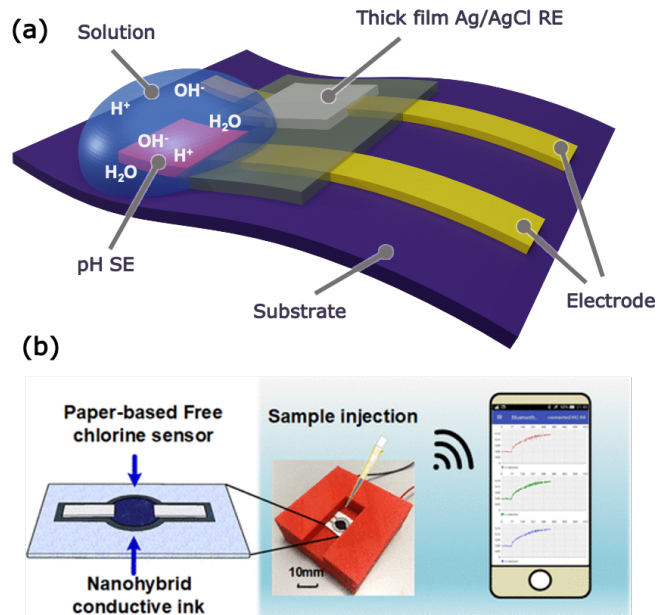


Fig. 4: (a) Schematic representation of a potentiometric pH sensors [54] (b) Image of a nanohybrid paper-based free chlorine monitoring sensor with 3D packing and readout 'Reprinted (adapted) with permission from [112]. Copyright (2020) Am. Chemical Soc.

hence increases the drain-source current of the transistor. This type of sensor could also be used for other heavy metal ions such as  $\text{Cd}^{2+}$ ,  $\text{Ni}^{2+}$ ,  $\text{Cu}^{2+}$ ,  $\text{Pb}^{2+}$ ,  $\text{Zn}^{2+}$ , and  $\text{Cr}^{3+}$  [21]. The heavy metal ions can also be monitored using potentiometric or amperometric method.

### 2) Interdigitated and chemi-resistive based sensor

To solve the RE related issue with potentiometric sensors, the interdigitated electrode (IDE) design has been used in conductive/capacitive/impedance and chemi-resistive (two electrode) based sensors. Several active electrode materials (metal oxides, polymers and carbon) are suitable to be used with electrode of IDE based sensors [104-106]. Such IDE based sensor are fabricated by using metal oxides, polymers, and carbon-based material [79, 107-109]. One the best IDE based sensors for WQM reported is the hydrogel (polymer), which is shows biocompatibility and low cost for materials and fabrication. The electrical properties including conductivity of hydrogels change during interaction with analytes [106, 110, 111]. The miniaturized pH sensor consist of an active electrode is hydrogel of polypyrrole and polyaniline. The major drawbacks of hydrogel-based sensor are their low mechanical strength and low lifetime.

The chemi-resistive sensing is another class of sensors which does not require a RE. An example of paper-based chemi-resistive sensor for real-time monitoring of free chlorine is shown in Fig. 4b [112]. This sensor uses nanohybrid ink based on graphene and PEDOT: PSS. The chemi-resistive pH sensors, with nanocomposites of single-wall carbon nanotubes (SWCNTs) and nafion used for SE, have also been explored for WQM using drones with wireless communication capability [113]. The nafion layer enhances the performance of the flexible sensor by reducing the degradation of electrical properties due to the cracking (even breaking) of the SE while bending. Further, the results from this type of sensor show that the sensitivity could be improved by increasing the number of printed layers of SE. Similar configuration could be used for online monitoring of conductivity, chloride ion detection and temperature sensors. Further, various forms of CNTs could be used for improved sensing performance [114].

### 3) Multi-sensors for WQM

As discussed in Section 2.1, multiple parameters need to be monitored in water. In this regard, multiparametric sensors on the same substrate is advantageous. As an example, multiparametric sensing platform (pH, DO, temperature, conductivity, and turbidity sensors) for online WQM [34, 74, 115]. The first printed multi-sensory patch (pH, DO, conductivity and temperature) for WQM showed continuous operation for several months in water with <5% and <10% errors for pH and DO sensors respectively[116]. A multi-sensory patch by thick film technology for pH, DO, temperature, turbidity and conductivity has also been developed with integrated data acquisition, and signal conditioning modules [72]. Another example highlighted the performances in Table II, is the integrated online monitoring system with pH, free chlorine and temperature sensors [86]. In another work, emerging pharmaceutical contaminants, and heavy metal were also detected, along with pH, chlorine temperature, using multi-

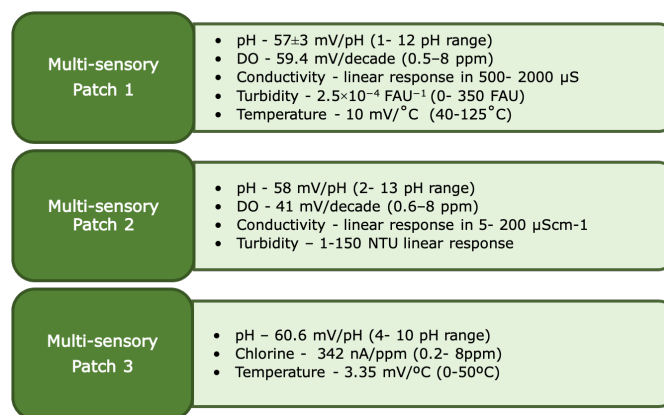


Fig. 5: Comparison of the performances of multi-sensory patches used for online WQM. Patch 1 [72], Patch 2 [98], Patch 3 [86].

sensory patch [12]. Comparison of the performances of few multi-sensory patches reported for WQM is given in Fig. 5.

### 4) Biosensor for pathogens monitoring

In addition to the chemical and dissolved metal ions, the detection of bacteria in water is another major challenge. The electrochemical transducer are most promising in this case also due to their selectivity, high sensitivity, measurability in complex and turbid samples, simple structure and miniaturization, rapid response, and low cost [137]. Electrochemical biosensors can be divided into major four categories: (a) impedimetric, (b) conductometric, (c) amperometric, and (d) potentiometric [10]. Table III summarizes the different electrochemical sensors-based detection method for food and waterborne bacteria. The nanomaterial based sensor approach is attractive in the case of bacteria detection due to rapid, inexpensive, and accurate measurement needed for food safety and environmental monitoring [138, 139]. The distinct physical, chemical, magnetic, sensing, catalytic, mechanical, and optical properties of nanomaterials due to high surface to volume ratio, reactivity, and high penetrability allow the use of variety of advanced nanomaterials to develop sensors for microbial detection with improved specificity and sensitivity [139, 140]. The gold nanomaterials, also known as gold sol (colloid in which solid particles are dispersed in continuous liquid phase) are widely used for bacterial detection owing to their distinct physicochemical, optical, and electronic features. Additionally, they are biocompatible, easy to synthesise and control the physicochemical properties, and easy to functionalize with various biological recognition elements [141, 142]. Due to similar reasons, the magnetic nanoparticles (MNPs) have also attracted considerable interest for application in bacteria detection [143, 144]. Other category of materials employed in the fabrication of biosensors are the conducting polymers (e.g. PEDOT: PSS, polypyrrole) [84, 145]. Different recognition elements such as antibodies, enzymes, etc. have been used to improve the magnetic, optical, and electronic properties of conducting polymers with an aim to design inexpensive, simple, sensitive and selective biosensors [84]. Due to the mechanical and electrical properties, surface area, low-cost, stability over longer periods, and the possibility for real-time applications, the carbon-based nanomaterials are also

TABLE III: SUMMARY OF THE REPORTED ELECTROCHEMICAL BASED BIOSENSORS FOR FOODBORNE AND WATERBORNE BACTERIA DETECTION

Transducer	Target	Material	Linear range	LOD	Ref.
Amperometric	<i>E. coli</i>	Au NPs	10–10 <sup>9</sup> CFU/mL	10 CFU/mL	[117]
Amperometric	<i>E. coli</i> O157:H7	3-aminopropyl triethoxysilane (APTES)	1 fM–10 μM	0.8 fM	[118]
Amperometric	<i>E. coli</i> O157:H7	core-shell magnetic beads and Au NPs	10 <sup>2</sup> –10 <sup>6</sup> CFU/mL	52 CFU/mL	[119]
Amperometric	<i>S. aureus</i>	SWCNT	10 <sup>2</sup> –10 <sup>5</sup> CFU/mL	10 <sup>2</sup> CFU/mL	[120]
Amperometric	<i>Listeria monocytogenes</i>	MWCNT Fibers	10 <sup>2</sup> to 10 <sup>3</sup> cfu/mL	1.7 × 10 <sup>2</sup> cfu/mL	[121]
Amperometric	<i>E. coli</i> O157:H7	Nickel oxide	10 <sup>1</sup> to 10 <sup>7</sup> cells/mL	1 cell/mL	[122]
Conductometric	<i>Bacillus subtilis</i>	SWCNTs	10 <sup>2</sup> –10 <sup>10</sup> CFU/mL	10 <sup>2</sup> CFU/mL	[123]
Conductometric	<i>Escherichia coli</i>	magnetic beads	2.5 × 10 <sup>3</sup> –2.5 × 10 <sup>8</sup> CFU·mL <sup>-1</sup>	2.3 × 10 <sup>4</sup> CFU·mL <sup>-1</sup>	[124]
Impedimetric	<i>E. coli</i> O157:H7	Gold nanofilm	50–500 CFU/mL	50 CFU/mL	[125]
Impedimetric	<i>E. coli</i>	Gold print	10–10 <sup>8</sup> CFU/mL	3 × 10 CFU/mL	[126]
Impedimetric	<i>E. coli</i> O157:H7	Au NPs	300–10 <sup>5</sup> CFU/mL	100 CFU/mL	[127]
Impedimetric	<i>E. coli</i>	Cu3(BTC)2/PANI	2–2 × 10 <sup>8</sup> CFU/mL	2 CFU/mL	[128]
Impedimetric	<i>E. coli</i> O157:H7	polypyrrole (PPy)	10 <sup>3</sup> –10 <sup>8</sup> CFU/mL	10 <sup>3</sup> CFU/mL	[129]
Impedimetric	<i>Bacillus cereus</i>	Au NPs	10 <sup>0</sup> –10 <sup>7</sup> CFU/mL	10 <sup>0</sup> CFU/mL	[130]
Impedimetric	<i>S. Typhimurium</i>	Au NPs	10–10 <sup>5</sup> CFU·mL <sup>-1</sup>	10 CFU·mL <sup>-1</sup>	[131]
Potentiometric	<i>Salmonella typhimurium</i>	PEDOT: PSS	1 - 1.28 × 10 <sup>5</sup> cells mL <sup>-1</sup>	5 cells mL <sup>-1</sup>	[132]
Potentiometric	<i>Vibrio alginolyticus</i>	Magnetic Beads	10–100 CFU mL <sup>-1</sup>	10 CFU mL <sup>-1</sup>	[133]
Potentiometric	<i>Bacillus cereus</i>	Polypyrrole	10 <sup>2</sup> –10 <sup>5</sup> CFU/mL	10 <sup>2</sup> CFU/mL	[134]
Potentiometric	<i>E. coli</i>	carbon quantum dots	2.9 cfu/mL to 2.9 × 10 <sup>6</sup> cfu/mL	0.66 cfu/mL	[135]
Potentiometric	<i>E. coli</i> O157:H7	ZnO Nanorod Arrays	10 CFU/mL to 10 <sup>5</sup> CFU/mL	1.0 × 10 <sup>2</sup> (CFUs)/mL	[136]

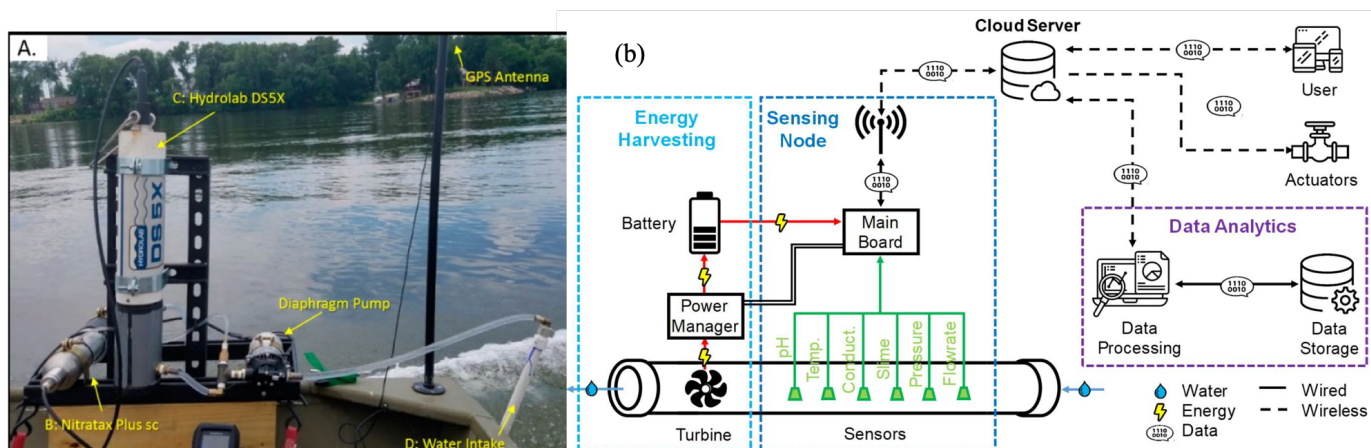


Fig. 6: (a) Nitrate monitoring sensors attached to the boat for real time monitoring in river [23]. (b) Architecture for monitoring physical-chemical parameters by kinetic energy harvesting and long-range radio links connection to a Cloud server, providing visualization, feedback control, and analytics [13].

widely used nanomaterials for biosensor. For example, graphene has received great attention via different variants such as Graphene quantum dots (GQDs), reduced graphene oxide (rGO), graphene oxide and graphene composites [146]. The carbon nanotubes (CNTs) (either multiple walls or single wall) and fullerenes, are other increasingly used nanomaterials for biosensors with enhanced performance due to their interesting catalytic, mechanical, and electrical properties [84, 147]. Taking the advantages of non-toxicity, biocompatibility, and high chemical and physical stability, the silica nanoparticles (SiNPS) have also been explored [148, 149]. For example, SiNPS with size range of 5–1000 nm have been used in electrochemical biosensors for microbial detection [141].

For rapid detection of water quality parameters, it is important to integrate the multiple sensors with readout electronics and wireless communication modules. An example of the reported architecture for monitoring physical and chemical parameters given in Fig. 6 [13]. More details about sensor deployment and communication are given in the following section.

### III. IMPROVING THE SENSOR DATA GATHERING

As discussed in Section I, the outcomes of traditional ‘sample collection and lab analysis’ methods could vary substantially due to the time gap between sampling and analysis, as well as due to the gaps in the training of technicians and the approaches they use for the data analysis. As a result, robust strategies have been sought from time to time to bridge the knowledge gaps and to generate reliable estimates to develop appropriate mitigation measures. In this regard, the different methods for deployment of autonomous sensors have been explored along with development of suitable interface electronics for real-time data transmission and communication. This section discusses these ways of placement of sensors in space and gathering their data at various times.

#### A. Sensor Deployment Methods

The deployment of autonomous sensors installed at select locations (based on experience) in the water body (e.g., using buoys) have been explored for in-situ analysis. In terms of

technology, instruments such as sensor-instrumented buoys or moorings have been considered recently to overcome traditional bottlenecks related to WQM shown in Fig. 1. These methods allow the high frequency collection of PCB properties of the water. Sensor-instrumented buoys in a water column can also allow the temporal variations in WQ to be characterised and the drivers of these changes in the WQ to be better understood. For example, information on biological production (via DO measurements) and water column stratification (via temperature and salinity measurements) can be easily collected. However, the deployment and operation of permanent scientific monitoring buoys, as used by national and international agencies and harbour authorities, are typically expensive (e.g., capital cost of > £0.5–1 million) and thus few of them exist. While they provide excellent temporal coverage, the sparse spatial coverage in the heterogeneous coastal zones is challenging and also this approach is cost prohibitive for small to medium sized businesses to purchase and operate [150-153]. Cost effective methods that allow capturing spatial and temporal variations in WQ are much needed. In this regard, sensor networks and advanced sensor deployment techniques such as using surface or underwater robotic vehicle or autonomous aerial vehicle namely drones, could be useful. Such methods have already advanced the monitoring activities in areas such as agriculture and given many similarities there is no reason why they cannot be tried to WQM. When presented

with the challenge of sensing in the underwater environment, one can envisage multiple requirements and scenarios, all requiring different approaches and deployment strategies: At one end of the spectrum is large scale, long term environment monitoring.

In this case, a large number of fixed sensors, able to measure environment parameters at regular intervals, when triggered by an external signal or based on changes in the environment is advisable [154]. For coastal water quality monitoring compact and low-cost autonomous sensors are now being used within low-cost moorings [155] enabling the potential for widespread deployment of such sensors. Fig. 6 shows an example of nitrate monitoring sensors attached to the boat to collect data in every 15s from Iowa and Cedar Rivers [23]. The addition of multi-sensory nodes on number of travelling or fisheries boats could for a network to provide rich information about water quality. The deployment of such networks and their retrieval is often costly, and some nodes can be lost or damaged.

The low-cost lightweight autonomous airborne drones or unmanned aerial vehicles (UAVs) (<2 kg take-off weight) hold great potential for WQM via remote sensing, sensor deployment and water sampling as shown in Fig. 1 and Fig. 7a. Their potential for environmental and ecological monitoring has been identified [156] and they are already being used for coastal monitoring [157], while some advances have been made with water sampling [158]. However, their routine use for the

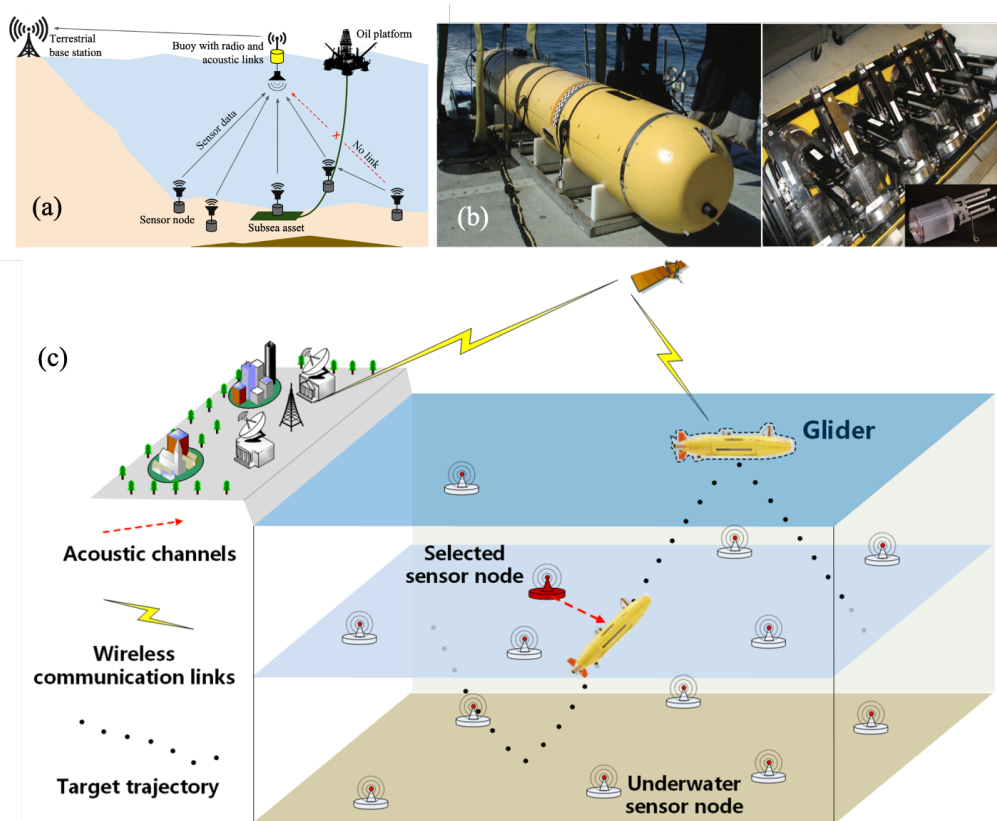


Fig. 7: (a) Sensor network deployment and data gathering (b) The Dorado AUV with an onboard water sample collection system consisting of 10 1.8 L “gulpers” that can be triggered by the onboard computer. Real-time measurements by the AUVs sensor suite can guide physical sample collection decisions (c) Example of coordination between a fixed and mobile sensor network for data gathering and harvesting.



remote sensing of the water and sensor deployment will require characterization of, and improvements in, the on-board geolocation accuracy and precision. This is needed to allow the drone to know its precise position (in all planes) for optical remote sensing and any deploy, return and retrieve applications in water regions where no-fixed points of reference exist. The relatively short flight times (e. g. due to battery and payloads limitations), and distances (often limited by country-specific flight rules) means that use of the lightweight drones for water quality monitoring will likely be limited to inland waters and near-shore estuarine and coastal environments.

At the other end is the opportunistic or event driven monitoring on-demand using a mobile asset such as mobile robots, which offer the opportunity to gather data where and when required. The sensors modules attached on the string of buoy, as mentioned earlier, could provide WQM at various depths in a water body but still the information is from a fixed location. On other hand, mobile assets such as autonomous underwater vehicles (AUVs) with sensory skin could provide frequent information from different areas. Getting the right data at the right time enables to respond quickly to emergency situation, adapt the sensing to the specific task at hand and complement environmental models requiring in-situ data to be calibrated and validated [159]. In this regard, the deployment of sensors by using AUVs, drifters and autonomous surface vehicles (ASVs) illustrated in Fig. 1 and Fig. 7b leading to a heterogeneous system of fixed and mobile sensor nodes [160], is an interesting direction. In this setup, the fixed network can be used for environment sensing as well as acoustic localization of the mobile assets shown in Fig. 7c. The mobile robot can be used to perform denser environmental sensing in specific areas of interest, track dynamics phenomena and fronts and be used as a 'data mule' to gather data from the fixed nodes using short range, high bandwidth acoustic or optical channels.

Equipped with multiple sensors and the interfacing electronics, these autonomous robotic nodes could possibly connect to the Cloud for real-time WQM. However, the remote monitoring in this way can be challenging due to issues such as poor connectivity, large power requirements and regular maintenance of large number of sensors nodes, as discussed in Section 3.3. Furthermore, the sensors nodes experience wide variation of ambient conditions (e.g., pressure, temperature) as the sensors need to be deployed at different depth levels (surface, mid and bottom) to analyse in wide area and this often leads to calibration issues, as discussed in Section 3.2. This requires designing sensors and electronics for wide operating ranges. Dedicated electronic circuit required for such sensors interface and is discussed in following.

### B. Electronic interfaces to the sensor

Distributed multi-sensory nodes/modules envisioned for WQM must be functional in adverse environmental condition for a long period of time. They can be even more effective if they are able to communicate amongst themselves as well as a base station. However, the primary operating condition for a sensor node is the availability of enough power for front-end signal processing and data transmission (to the nearest node).

The self-contained node is expected to contain active circuits that drive the transducer in contact with the environment. This drive circuitry is often called Analog Front-End (AFE) and is critical in determining the quality of the data collected. Traditionally, the analog signal is digitized and processed in a digital backend before communicating to an external reader. There are multiple design considerations and challenges to designing these electronic modules. As explained earlier, the electrochemical sensors can be either voltametric, potentiometric or conductometric. While both voltametric and potentiometric measurements can be 2 or 3 electrode based, conductometric measurement is either 2 or 4 electrode based. In all these options, there are some basic similarities in instrumentation techniques (e.g., the electrodes need to be excited with a voltage or a current) that results in the measurement of a current or a voltage, which is then amplified and filtered before being digitized. In the case of current measurement, the first stage is a trans-impedance amplifier that converts the current to a voltage, and then the same signal chain follows.

Signal to noise ratio (SNR) is a more obvious choice for describing the performance of an analog frontend (AFE) circuit. Whereas SNR describes what is actually achieved with a certain signal range in mind, dynamic range (DR) can be used to describe the performance that is possible to achieve with a system. The electrochemical sensors for WQM may have to detect harmful toxic concentrations as low as parts per billion (ppb) while some atmospheric gases of interest, such as  $O_2$ , are present in concentrations 10 million times larger. Hence, the sensors discussed in Section 2 could generate a wide range of DC current outputs that the electronic interface should be able to measure. This varies from currents at sub-pA level (to achieve high sensitivity for scarce target) to  $\mu A$  level (for large concentrations) and all ranges in between [161]. Hence, AFEs for sensor interface need to have a very wide dynamic range, along with sub-pA limit of detection.

Depending on how the WQM device is deployed and used, there could be a very stringent requirement for a power-management unit (PMU) that drives the AFE. In general, all wireless devices would require some sort of PMU to maintain a uniform power supply and create the necessary bias voltage/currents used in the analog domain. In WQM sensors, the need for a high-performance PMU is even more important since these devices, by definition, encounter a high degree of variation in their operating environment (temperature, pressure, humidity, vibration, radiation etc.), which could be often quite harsh. The sensitivity of the AFE depends on the quality of the available supply and biases. Since the future of WQM devices are remote stand-alone modules that continuously monitor the surrounding environment, it is expected that these will be either battery powered, or RF powered.

The classical calibration process consists of comparing a sensor in a controlled environment, for example, in a laboratory with high-cost instrumentation, where the sensor response is measured under different controlled conditions. Contrary to lab-based instruments, devices that are deployed in the field normally do not go through user-initiated calibration cycle. In

Analog Front End	Data Communication	Leakage
<ul style="list-style-type: none"> <li>Noise requirement</li> <li>Drift/offset/artefact reduction</li> <li>Resolution</li> <li>Biasing requirement</li> <li>Calibration necessity</li> </ul>	<ul style="list-style-type: none"> <li>Sampling frequency</li> <li>Resolution</li> <li>Communication distance</li> <li>Bi/Uni-directional data</li> <li>Packet size</li> </ul>	<ul style="list-style-type: none"> <li>Transducer supply voltage requirement</li> <li>Sleep/wake cycle time</li> <li>CMOS Process technology</li> <li>External temperature</li> </ul>

Fig. 8 Power consumption trade-offs for custom integrated wireless sensor nodes.

most cases, this is not practical and/or desirable. However, frequent (re-)calibration is an important requirement for any sensor to rule out the possibility of data errors, particularly when it is in direct contact with the environment. Ideally, the transducer and the interface electronics, both should be calibrated independently. Calibration of the electronics can be done by disconnecting it from the transducer and connecting it to a known signal which is locally generated. This is also possible by using a dummy signal chain which is expected to behave similarly to the main one. Though the quality of the known signal could be a matter of concern as well, the results can be extrapolated using some prior knowledge about the system. The complete AFE, ADCs, reference sources etc., can benefit from such calibrations. Similar to digital processors, analog BIST (Built-in-self-test) technique has been adopted in complex mixed-signal chipset for some time [162]. Calibration including the transducer in the loop is however a much-complicated procedure. This could be rarely done using a single sensor module alone. A network of sensors is necessary for such a procedure [163]. The sensor parameters can be self-calibrated and adjusted in reference to another sensor of the network, whether calibrated with a ground-truth reference node, calibrated with respect to already calibrated sensor nodes (e.g., distributed calibration, group calibration), or with respect to not-calibrated sensor nodes (e.g., blind calibration) [164]. Consequently, calibration procedures suitable for sensor placed in field conditions have been widely investigated in the past two decades and continues to be an important future topic.

An important specification while designing the electronic interface to the transducer is power consumption. The energy budget of the sensor node determines several aspects of the overall system. In the case of battery-operated devices, it is often the primary determinant of the system form-factor (given by the battery volume) and lifetime. For energy harvesting devices, the power consumption determines the feasibility of the implementation itself. However, determining a uniform set of specifications for power consumption in water quality sensors is a complex task. It depends on a wide variety of topics roughly dependent on what is being measured, how often and from how far [165]. One of the key problems in such sensor networks is the communication protocol being used. Table III shows a comparison between different communication standards commonly used for such a distributed wireless sensor network. While the trade-off between data rate and power consumption is obvious, it should be noted that variables being

TABLE III: COMPARISON OF WIRELESS COMMUNICATION STANDARDS

Communication standard	Frequency Band	Speed	Range	Relative power consumption
Wi-Fi	2.4 & 5GHz	150Mbps	~200m	High
Zigbee	2.4 GHz	250 Kbps	~100m	Low
Bluetooth/BLE	2.4GHz	3Mbps	~100m	Very low
LoRa	Sub GHz	250 kbps	10 km	Very Low
SigFox	Sub GHz	1kbps	>20km	Very low

monitored in a WQM sensor (e.g., pH, DO, conductivity) rarely change at a very fast rate. This factor has resulted in an interest in custom integrated wireless sensor nodes that could work on a smaller battery or use harvested energy for environmental monitoring. Though the design process of such integrated circuits is more complex, they can provide a customized solution that consumes much lower power and has a miniaturized form factor that can be integrated into a wider variety of devices [166, 167]. However, these monolithic solutions must deal with many design trade-offs depending on the application. Fig 8. shows the power consumption trade-offs in three major subsections that can be used to determine the necessary design specifications.

### C. Communication between sensor networks

Robust communication protocols are needed for live information extraction from the data generated by sensor networks. Unfortunately, standard communication based on electromagnetic (EM) waves are not an option in water, except at very short ranges and at a high energy cost. Optical communications are also limited in range to a few meters to a few 10s of meters depending on water visibility conditions. In practice, the most reliable and widely used communication systems is based on acoustics. In this case, the available transfer rate is often limited (a few bits/s to a few kbits/s), the acoustic bandwidth is narrow (10-20 kHz), and dispersion and multipath are prevalent. These limit the options for Code-division multiple access (CDMA) and Frequency-division multiple access (FDMA) protocols and promote the use of slower Time-division multiple access (TDMA) approach. However, acoustic systems offer the advantage of combining communication and ranging, enabling joint localisation of sensor nodes and communication network management [168, 169]. They enable in-situ monitoring of water parameters such as plankton density, water quality and pollutant detection, requiring the integration of multiple sensor modalities into a single package, including on-board processing to limit the requirements on transfer rate and energy. There is obviously a trade-off between energy consumed in local processing and spent in transmission. However, low power electronics have made significant progress and when integrated with modern batteries and energy harvesting, they can provide a solution to long term deployment. An example of such a system developed in the EPSRC funded USMART project is depicted in Fig. 7a.

## IV. SPATIO-TEMPORAL DATA ANALYSIS & PREDICTION

In depth analytical evaluation of quality assured, water quality data depends very much on the purposes of the

monitoring programme from which the data have been extracted. There are many purposes labelled under tasks of operation and surveillance, including monitoring to report on status (e. g. reporting on water quality to national regulations such as the Water Framework Directive), evaluation of the effect of an intervention (e. g. upgrade to a wastewater treatment works), detection of a change (e. g. as a result of flow status), population surveillance (e. g. appearance of illegal drugs or covid), or some form of real time or near real time decision making (e. g. water abstraction and reuse). Across these purposes, the data will have both temporal and spatial properties. Thus, the broadest definition of the current analytical tools which are widely used, would be spatiotemporal models incorporating temporal modelling to evaluate trends over time and detect changes, and spatial modelling to evaluate trends over space and pinpoint hotspots.

For the spatial aspects of any catchment or basin network, we must consider the spatial/network dependence in the sensor locations and hence in the data generated. WQM networks will often be designed to provide spatially representative coverage but they are also connected sharing the same catchment area and linked through directed river flow. Spatial correlation may be related to Euclidean distance and river discharge but are more commonly connected through river distances and stream order. To achieve an understanding of the spatial patterns, spatial models must be developed taking into account the network structure and in the past decade, there has been considerable work to build models that have non-Euclidean spatial correlation structures [170-173].

For the temporal aspect of the network data, the fundamental design question concerns the temporal frequency of measurement, with many historical networks being dependent on physical sampling (often monthly), while newer networks, have seen increased resolution to 15 mins and higher (determined by the temporal scale of the environmental processes). The classic analysis choice in time series modelling remains whether to model in the time or frequency domain. In the time domain, classical time series models of autoregressive or moving average (ARIMA models) have been used but as the temporal resolution of monitoring has increased there has been more and more research using the frequency domain, where wavelets and other transforms have been used [174, 175]. Further developments in the modelling of environmental time series has come from the application of functional data analysis (FDA) methods [176]. In this context, the “data point” becomes the time series curve [177, 178] this approach often is computationally efficient since it offers substantial data dimension reduction. Another important area of analytics frequently used in WQM concerns extreme value modelling (often using peak over threshold (POT) models). While used most commonly in flow modelling, this approach is also of use in quality modelling. Recent developments here have seen the extension of theory to spatio-temporal extremes [179, 180].

Increasingly, there has been much interest in the use of algorithmic learning and artificial intelligence (AI) tools applied to network data as developed intelligent wireless systems routinely generate large volumes of data. Such volumes

of data have required the adoption and development of new analytical methods including machine learning as artificial neural networks (with their many variations generally known as deep learning methods), as well as support vector machines, classification trees, adaptive neuro-fuzzy inference systems, etc.[181-183]. Many statistical models like decision trees, non-hierarchical classification methods, and Bayesian networks have become the backbone of machine learning tools. More broadly termed as AI methods, these techniques, after being properly trained with large data sets, can extract information and detect patterns without use of network equations. They are computationally fast and efficient, are able to identify structures

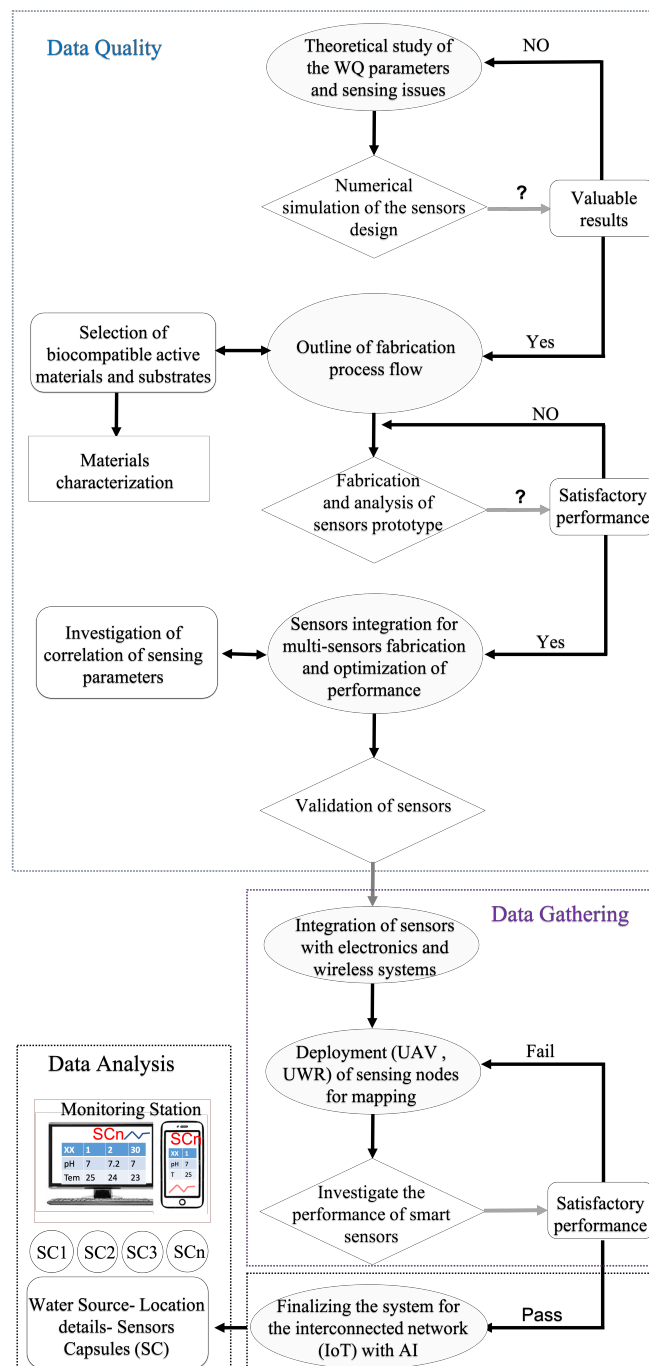


Fig. 9: Methodology for an advanced water quality monitoring system.

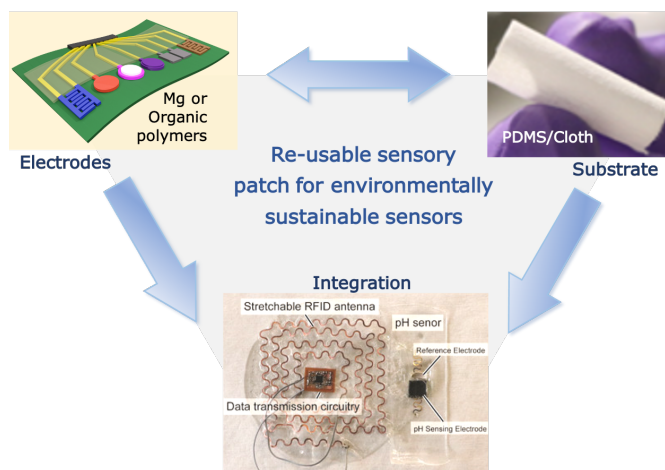


Fig. 10: Schematic representation of reusable multi-sensory patch for environment friendly sustainable sensing.

and dependencies automatically [184, 185] and can operate in near or real time. The fundamental principle of such methods is to learn from data with less human intervention (in the more classical analytical tools, the analyst must prescribe the structure and relationships parametrically). This is especially important since our knowledge about the ecological and environmental processes may be incomplete. Dealing with the data volume as well as the different data streams have also presented challenges [186]. In this space, there are new developments concerning methods to fuse and assimilate different data streams [187-189]. By harnessing the power of AI algorithms and big data analytics, water utilities can maximize information and data available to make better decisions while enhancing service delivery and reducing costs [190]. In addition, feeding the data generated by social media, mobile phones, and the Internet of Things (IoT) directly into AI could be new opportunity for WQM.

## V. DISCUSSION AND FUTURE DIRECTIONS

New connected sensors, at local, regional and global scales, offer tremendous environmental monitoring opportunities in delivering real time data which will allow our understanding of environmental processes to improve. The use of sensor networks and internet communications combined with GIS tools will be having an important role in the future and can be very beneficial to stakeholders in not only efficiently managing the water quality but also in water distribution management, agriculture and landscaping sectors where it can reduce water consumption and wastage.

### A. Sensor integration

While the opportunities and potentials are great, there remain challenges [191]. Design of networks remains an area of scientific interest, developing quality assurance procedures to detect anomalous observations [192], performance issues (both on sensor and in data communications). Integration (and fusion) of data streams from different sensors is also an area of research. Extensive use of sensing and ICT devices comes with new environmental challenges such as increased electronic waste. To overcome these challenges, several research steps are required as summarised by the flow chart in Fig. 9. This starts

from identifying the water quality parameters, materials for sensors, fabrication of sensors, their integration, deployment and finally the analysis. Currently, a fragmented approach is taken with many of these steps carried out without strong linkages with the others. An integrated or holistic approach will go a long way in the direction towards effective WQM and could also offer new opportunities for monitoring in other areas such as environment, agriculture and healthcare etc.

### B. Sustainable and reusable sensors

The large number of sensors and associated electronics is likely to add to the current issues such as electronic waste, which could be addressed by using biodegradable, natural and biocompatible materials for sensing electrodes, conducting path, substrates and protective layers etc. [75, 193]. The current substrates for sensors such as flexible PET, PVC etc. require long time to degrades and are potential source of new pollutants such as microplastics. The electrodes from costly, scarce and highly purified materials such as Pt, Ag, and Au. also need to be replaced. In this regard, conducting polymers or degradable metals, and carbon-based electrodes are attractive alternatives. Currently, metal oxides such as  $\text{RuO}_2$  are popular material for pH sensors as they lead to high performances. However, these materials are toxic, in addition being costly and hence alternative biocompatible metal oxides need to be explored. To reduce the environmental impact of electronic waste, the WQM system should promote both disposable and reusable devices. For example, for the sensors could be disposable and the electronics and communication modules would be designed for reusability [57, 194, 195]. In such a design, one of the options is to develop electrodes (for SE, RE and conducting path) using biocompatible or dissolvable materials (e. g. operational life  $\sim 24$  hr.) and reuse the substrate to develop new electrodes given in Fig. 10. Likewise, the interface electronics can be reused. The controlled degradability of these sensors can be achieved with suitable packaging. Such schemes could be easily implemented with mobile sensor nodes provided by the autonomous water and aerial vehicles, as discussed in Section III. For example, electronic skin like multisensory patches in flexible form factors could be attached to autonomous vehicle. Some of options for SE fabrication include biodegradable conducting polymers including PEDOT: PSS or sustainable carbon-based electrodes [57, 196, 197]. Printed carbon-based electrodes could also be used for RE and CE fabrications, as reported for wearable biosensors [198].

### C. Energy autonomous sensors

For remote quality monitoring the energy autonomy of sensor system or network and power management also need attention. The recent studies show that the energy autonomy in WQ sensors can be addressed by using self-powered system such as solar powered sensors [33, 108, 199-201] or triboelectric/piezoelectric based sensors. Further new renewable solutions such as harnessing wave energy using triboelectric nanogenerators (TEENG) could be used to power the sensors as well as the autonomous vehicles [202-204]. Such energy autonomous sensing networks can also be useful for monitoring of water quality in fish farms, pollution in river water and the drinking water in the pipelines (supply system in metropolitan areas) and open water bodies. For example, the

smart networks could be deployed in pipelines using snake-like robots, even though it will be more challenging than using UAV or UWR in large water bodies. On other hand, the water in metropolitan supply pipelines is likely to be treated already and hence much lower spatio-temporal variations is expected with respect to the open waters. Considering this, the use of sensor nodes at fixed location may be sufficient.

#### D. Selective sensing material

Implementation of sensors for WQM need to consider many parameters such as: (i) selectivity, (ii) lifetime (iii) low cost (iv) environmentally friendly materials and (v) easy integration with smart connected network. In potentiometry or an amperometric type of sensors the selectivity, stability and lifetime purely depend on the type of sensitive electrode. Moreover, in these two types of sensors the stability and lifetime also depend on the RE. The typical thick or thin film Ag/AgCl based REs show stability issues during long measurement time. One way to overcome the above issue is to use other type of sensor. For example, using the chemi-resistive sensor which do not use RE. But the selectivity and power requirement are the major challenges in chemi-resistive sensor. Hence, there is a trade-off between the type of sensor, the material, the measurement method, sensitivity and stability. The development of sensors with materials exhibiting excellent ionic and electronic conductivity could also offer attractive solution. For example, selectivity of Pb free ceramic based perovskite materials could be tuned by suitable doping. The thick film based multi-sensing electrodes can also help in terms of selective sensing. The major advantage of this type of sensor the easy integration. A comparative analysis of the thick film-based sensors with other methods is shown in Fig. 11.

Despite the promising performances of individual sensors reported in literature, the stability and reliability issues over a long time could occur due to material degradation. In this regard, frequent calibration along with proper data analysis could be helpful. To understand the influence of material degradation, the long-term studies, involving electrochemical sensors in real condition, are required. Avoiding antifouling resistance during sensors deployment is another challenge. To this end, suitable packaging or frequent replacement of sensors

or using sensors made from naturally degradable materials could help.

#### E. Data handling and Cost effectiveness

The increasing nutrients, chemical loads and other sediments require networked WQM solutions at regional and global scale [205-209]. At such scales, the number of sensor and the data generated by them could require significant computing resources. The modelling or discrete observation routes and the sensor network with satellite based monitoring technique with data handling in cloud or sending data packet with a suitable protocol can help overcome such challenges [210-215]. For commercial viability the cost of full sensor system also need attention. The cost of connected sensors systems depends on the materials, fabrication method, sensor/electronic devices, integration strategy and communication technology. If deployment using robotic vehicles is needed, then their addition costs related to robotic vehicles need to be considered too. The cost-benefits of such deployments against the traditional sampling and laboratory analysis are an important factor. As an example, currently the high cost of traditional sampling and laboratory analysis (e.g., in a low-income country such as India the marginal cost per test is ~\$7.25 [216]) is a major factor that is hampering the monitoring of large supplies (e.g., in urban settings). Transport and labour together constitute half of this cost and as a result a limited number of monitoring centres exist. Such costs can be easily reduced by real-time monitoring with suitable sensor network. Likewise, a commercially available buoy could cost \$5K-6K [155]. On other hand, lightweight low-cost airborne drones (<5kg take-off weight) costs <£3.5K. This means, for the same cost of a commercial buoy (which are fixed in water bodies), it is possible to gather much richer data by deploying sensors using robotic vehicles. The lower costs could also improve the compliance with monitoring requirements.

In relation with the sensors, the cost is influence by the materials, fabrication method and integration technology [217]. For example, the higher cost of RuO<sub>2</sub> based sensitive material in pH sensor is a major issue, which is being addressed through the use of binary oxides. The binary oxide-based pH sensors have been reported with excellent sensitivity. In terms of fabrication cost and easy integration, the methods such as low temperature co-fired ceramic (LTCC) based pH sensor or printed sensor are some of the attractive routes. The pH measured by LTCC based sensors is in good agreement with sensors using conventional glass pH electrode. In another work based on IDE based sensor, the authors observed that the total cost of the polymer-based sensors is low (\$1) as compared to commercial sensors (\$250-300) [54], but the pH measurement range is also low (6.5 to 9) [54]. The method of fabrication of such sensors has significant influence on their cost. In this regard, printed electronics technology is attractive as it makes it easy to process various materials at low temperatures and enables the development of sensors in flexible form factors [124]. Recently 3D printing technology for pH sensor has also found application for WQM [108-110]. 3D printing-based approaches have advantages in terms of low cost and packaging [218-221]. The multi-material 3D/4D printing is offering interesting opportunities for direct printing of conducting tracks and other functional devices on complex shapes [108-110].

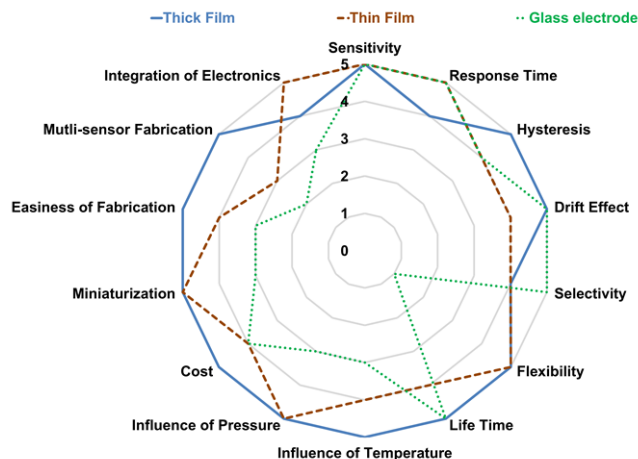


Fig. 11: Comparison of various type of electrodes for sensors fabrication [54].

## VI. CONCLUSION

The connected sensor technologies for water quality monitoring (WQM) could provide the bridging solution for current disconnect between data quality, data gathering and data analysis and enhance the global data intercomparability. With this in view, this article has reviewed key sensing technologies, sensor deployment strategies and the emerging methods for data analysis. The review evaluated various sensing materials, substrates and designs of sensors including multisensory patches. For data gathering various components of sensor interface electronics and communication system have been discussed along with innovative deployment strategies using sensorized buoys, drones and underwater robotic vehicles. Diverse techniques for data analysis of the sensors are briefly discussed along with the potential opportunities for real-time water quality monitoring with artificial intelligence. Finally, the challenges related to discussed approaches, their solutions and potential opportunities enabled by the holistic discussion about WQM have been discussed.

It is noted that ICT provides a unique opportunity for water stakeholders to obtain information in near real time about a number of physical and environmental variables such as temperature, soil moisture levels, rainfall, and others through web enabled sensors and communication networks, and can thus have accurate information about the situation at hand (without physically being there) for their forecasts and decisions. The WQM sector will hugely benefit from the sensor networks and techniques that being developed for internet of things (IoT). Such methods have already advanced the monitoring activities in areas such as healthcare, agriculture and environment monitoring etc. Given many similarities there is no reason why they cannot be tried to WQM. The opportunity to obtain real-time WQ parameters in a cost-effective manner is a huge gain that these new technological advances offer.

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