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FUTURE PROSPECTS IN THE IMPLEMENTATION OF A REAL-TIME SMART WATER SUPPLY MANAGEMENT AND WATER QUALITY MONITORING SYSTEM

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ABSTRACT

The optimum use of water requires an effective water supply management system that is smart enough to measure the flow rate, estimate consumption, estimate stored water, detect defects in the pipeline, automate actuators, measure water quality and produce details for the end user. Real-time implementation of such a water supply system requires a range of sensors with low power consumption and longer life with accuracy. Recent emerging sensors for water quality and flow rate have been discussed in detail. The real-time adaptability of these sensors in water supply management systems has been discussed. Based on these sensor technologies, possible advancements have been proposed for the future. The emerging capability to improve sensor performance by image processing and computer vision-based methods has been discussed. Integration of computer vision with sensors can improve sensor capability. The IoT is an emerging technology capable of connecting end users to the access quality of water resources, monitoring flow and daily consumption. A futuristic model has been proposed based on computer vision technology integrated with IoT.

Keywords: WQ, IoT, Water Supply Management, Sensor, Computer Vision

INTRODUCTION

The drinking water quality that is being supplied to us through the water supply system has a direct impact on public health (WHO, 2022). Traditionally, WQ is monitored at a particular time interval, but real-time data analysis is needed, especially for drinking water (Acharya et al., 2020). The UN has predicted that the population of the world may rise up to 9 billion by 2050 and that drinking water resources will slowly decrease. Water is distributed unevenly for different locations and depends on time within a year. Most drinking water is wasted because it is not managed properly. The motive behind developing a smart water management model is to achieve water safety at all levels (source, supply, distribution, storage and uses). Some of the primary features of the water management system model include water flow management, smart leakage location detection techniques for water networks, maintenance of the water cycle, smart water meter technology and smart water quality monitoring. This water supply system needs to supply water of better quality. To ensure a better quality of water, we will need sensors of various types (Pandey et al., 2021).

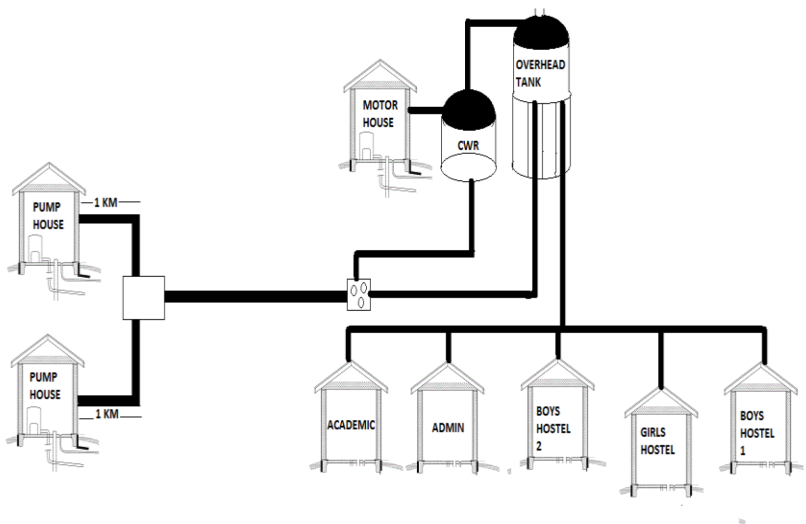

Figure 1: Smart Water Supply Management System of REC Sonbhadra

In the study of Kulkarni and Farnham (2016), many smart water supply systems and studies have been investigated, and wireless connectivity model solutions for the total cost of ownership framework have been explained in detail. In Serra et al. (2019), a novel, efficient, low-cost conductivity sensor for water was explored, and its use in important parameter analysis was thoroughly explained. In Nasser et al. (2020), data obtained from the Hall Effect sensor are stored, sent to the cloud, and processed using machine learning tools, and the need for water is estimated for each household. In Vinothini and Suganya (2014), accurate prediction methods for water leakage and consumption for a very complex water supply network were proposed. Piasecki et al. (2017) discussed a system that can issue alerts to warn consumers about excess consumption of water, providing better monitoring and control capability to the water supply system. Various water supply network-related key parameters can be detected using variation in pressure; temperature and conductivity of water have been discussed (Tharanyaa et al., 2013). An IoT technology with wireless fidelity (Wi-Fi) and web page accessibility is used in applications to monitor the equally distributed water level, and water in real time has been explained (Piasecki et al., 2017). A portable, low-cost, easy-to-configure and flexible system can solve the problem of water wastage (Tharanyaa et al., 2013). A laser sensor with HC12 transceiver is used for detecting the leakage in the tanks, and the cloud platform Adafruit is used. A model for a water supply system has been implemented based on a survey of the water supply system at REC located in Sonbhadra district of Uttar Pradesh, India, which is at 24.7°N 83.07°E (Pandey et al., 2021). It has an average elevation of 1080 feet from sea level. It is located in the southeastern range of the Vindhyanchal Mountains. Using different sensors and actuators, an IoT model for smart water supply management has been made for monitoring and controlling water resources.

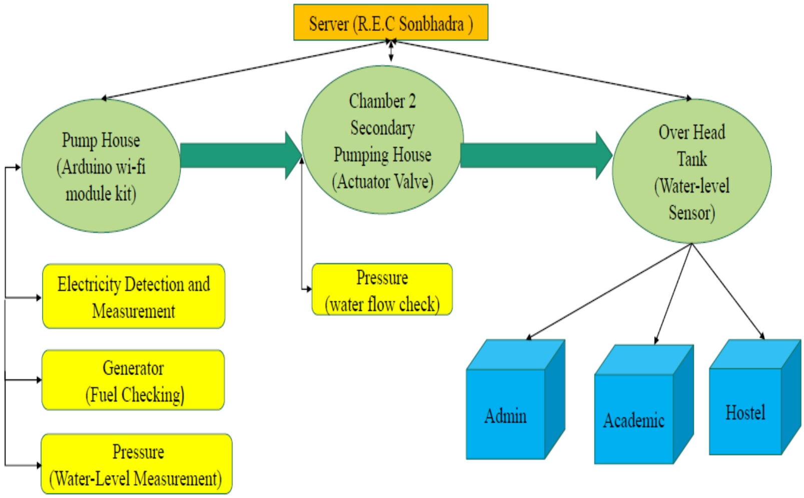

Figure 2: Variety of sensors deployed at various locations

Fig. 1 shows the distribution line of the water supply management system of REC Sonbhadra. Here, water is supplied from the water resource (Pump House) to the end-user. Water pipelines of different diameters are used for supply. The model of this supply system has already been implemented and studied. While implementing this model, the flow rate at various locations must be measured. Conventional sensors are not effective due to changing the diameter of the pipeline. To overcome various limitations in traditional sensors, a new range of capabilities must be developed in sensors. Flow meters are important for the overall estimation and optimization of water use. The flow meter is also useful in finding out defects in pipelines by detecting variations at distinct locations. If there is an abrupt change in flow rate, then we can detect that the water pipeline has been damaged.

If the sensor is low cost, then we can deploy it more frequently at a nearer location to identify the approximately exact location of the defect in the pipeline. For such use, we can deploy sensors having less accuracy but are capable of detecting change. Each of these sensors will be connected through an IoT network to the server. At the server, data will be analyzed, and based on it, commands will be sent to actuators. Fig. 2 shows the different sensors required at various locations in the water supply system shown in Fig. 1. This paper has been divided into 6 sections. Section 2 addresses different important water parameters. Section 3 addresses the need for real-time WQM. Section 4 addresses different recent sensors to measure different water quality parameters and other parameters. Section 5 discusses challenges and observations. In section 6, a computer vision-based model is proposed based on observation to overcome challenges.

WATER QUALITY PARAMETERS

The water quality of drinking water coming through the water supply becomes important because it will have a direct effect on the health of humans. There are various indicators of water quality: (1) physical indicators: temperature, color, turbidity, and conductivity; (2) chemical indicators: pH and alkalinity; and (3) biological indicators. The presence of different water quality parameters, their acceptable limits, and causes and effects are discussed in detail in Table 1.

Table 1: Water quality parameters, sources, effect and allowed limit

Water Quality Parameter	Allowed limit in drinking water	Effect	Reference	Source
Nitrate (NO3)	10 mg/L	Excessive presence can kill aquatic plant and animal and cause serious illness in infants	EPA	Fertilizer, Industrial Waste
Phosphate (PO4)	4 mg/L	Excessive presence can kill aquatic plant and animal	EPA	Soil Rock
Ammonium (NH4)	20 microg/L	Direct Toxic Effect	EPA	Decomposition of organic compound
Heavy Metal (Cr)	100 microgram/L	Allergic dermatitis	Public Water Systems	Pulb and Steel mill discharge
Heavy Metal (Hg)	2 microgram/L	Kidney damage	Public Water Systems	Refineries and natural source
Heavy Metal (Pb)	15 microgram/L	Delay in physical and mental development	EPA	Natural source and Plumbing system
pH Low pH: acidic and High pH: alkaline	6.8-8.2	Damage plant and animal	EPA	Ground water carbonate, bicarbonate and hydroxide

Dissolved Oxygen (DO)	< 7 mg/L	Low DO is harm	- EPA - Bayram et al. (2015)	Dissolved Oxygen
Conductivity	< 200 mg/L	Lung irritation, rashes and other allergic reaction	Wu et al. (2019)	Dissolved Solid
Turbidity		Presence of large contamination	Wu et al. (2019)	Dissolvable materials

NEED OF REAL-TIME WQM

The traditional method for WQM is shown in Fig. 3. It will consume a long time. When health is related to consumables such as drinking water, it becomes important that real-time data are present for water being consumed. In the traditional method, accuracy is high, but longer time consumption will make it less useful. Therefore, we need sensors that are capable of providing real-time data (Olatinwo and Joubert, 2019).

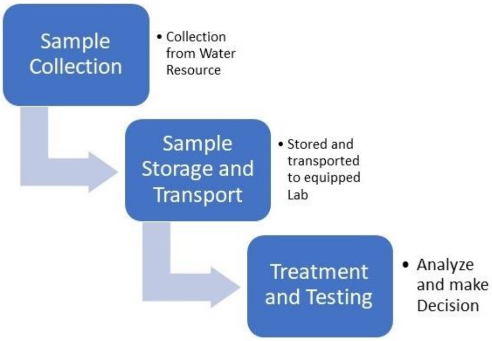

Figure 3: Traditional method for WQM

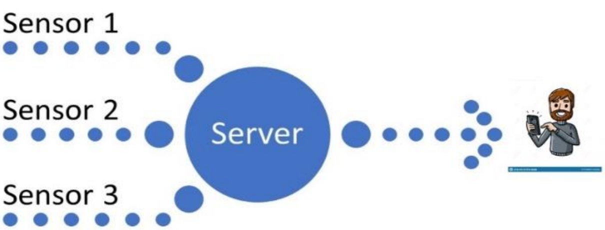

Figure 4: Real-time WQM by using IoWT

Advanced sensor networks must be connected to communication mechanisms so that data in real time can be transmitted to the server. Data obtained from the sensor will be mathematically processed through well-defined, established and calibrated equations. From the server, the end user can obtain the information required or alert in real time.

RECENT SENSOR DESIGN AND WORKING

Sensors for different water quality parameter measurements and water supply management need to be advanced so that they can meet the requirements. The sensor design currently plays an important factor because data must be analyzed in real time. Recent advancements in the sensor are due to the out box thinking of researchers. The integration of conventional methods with recent technology has created major breakthroughs. Any new proposed sensor must be calibrated with data obtained from conventional methods. After proper calibration, the relationship between the WQS parameters and sensor parameters is established if a possible mathematical formulation is also achieved. These results will be tested from time to time to determine whether the sensor is working properly. Few sensors for various parameters are discussed below.

Flow rate measurement is important in water supply management because overall control and automation are largely dependent on it. Flow rate measurement will result in overall water consumption, estimation of the need for water, peak hour analysis and other water parameters so that optimization methods can be applied. We can also detect the possible defect in the water pipeline by the use of a flow meter. The varying diameter of the pipeline causes a measured challenge in its deployment. A few recent flow sensors are listed in Table 2.

Table 2: Recent flow rate sensor

Reference	Basic Principle	Advantage	Limitation	Future Scope
Wrasse et al. (2019)	Two phase meter containing Venturi meter and Twin Cap. Sensor	No need of calibration, Works for various diameter pipe.	Valid for Low flow rate measured. If water bobbles may cause error.	Can be divided into more sub division using more twin cap. Sensor to get more accuracy. High Flow rate can be calibrated.
Ponce et al. (2021)	PDW meter integrated with magnetic field meter and chip	Totality water meter can be upgraded to water flow meter	Data are dependent on PDW meter accurate working	Other devices using such magnetic metering devices can be upgraded.
Hitomi et al. (2017)	Ultrasound monitoring using doppler shift frequency	High accuracy	High voltage needed, Error depend on flow nature	Multiple ultrasound lines to 3 D monitoring and phase flow.

Wrasse et al. (2019) discussed a flow sensor using a venturi meter and Twin capacitor, as shown in Fig. 5a. The phase fraction is measured by a Twin capacitor sensor. The twin capacitor pair will have an Emitter and receiver pair, the input is multiplexed, and the output at the receiver will help to obtain the permittivity in different regions. A differential pressure device using a venturi meter will use the change in pressure to calculate the mass of the liquid. Area and mass will result in flow rate. Athematic mathematical approaches have been used. Ponce et al. (2021) used the conventional PDW meter shown in Fig. 5c with integrated signal processing methods. Many estimation methods used to process data are the direct angle estimator, KT IF estimator, DQPLL estimator, and STFT. In PDW, the turbine housing is axially aligned and magnetically coupled with the meter housing changes the magnetic property with the flow of water. A three-axis HE sensor IC with a built-in ADC and digital filter are used to capture magnetic information. Hitomi et al. (2017) used the ultrasound velocity profiler shown in Fig. 5b at a sampling rate of 60 Hz. A high-frequency pulse with an input voltage of 150 V is emitted, and an echo signal with an intensity of a few millivolts is emitted. Based on different reflection ratios and acoustic pressures at the interface, three-phase flow can be measured and validated by a high-speed camera.

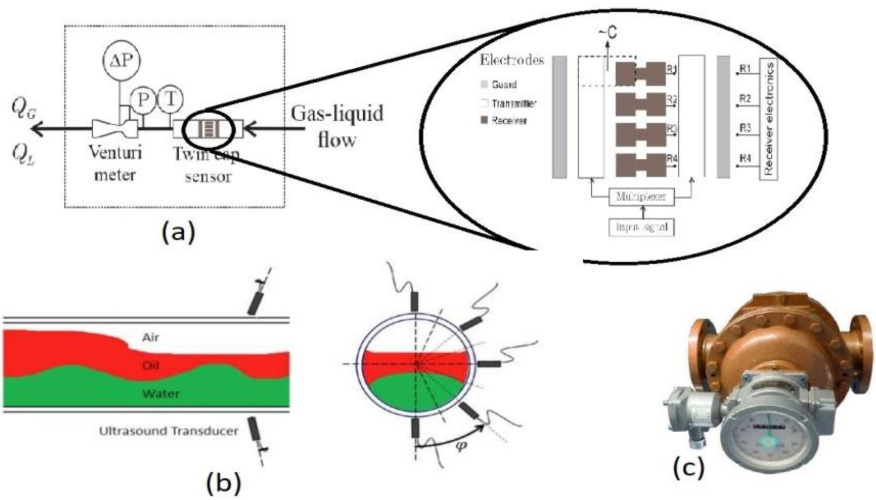

Figure 5: Flow Rate Sensor. (a): Venturi Meter with Twin-Plan Capacitive Sensor (Wrasse et al., 2019). (b): Ultrasound velocity profiler (Ponce et al., 2021). (c): Conventional PDW with a magnetic coupling chip (Hitomi et al., 2017)

A turbidity sensor is used to measure the clarity of the water. In conventional turbidity sensors, the light scattering method is used. The conventional sensor is expensive and cannot be used for real-time data analysis. A few recent turbidity sensors are listed in Table 3.

The black cylindrical structure of 20 mm diameter shown in Fig. 6a has a hole for the near-infrared LED, a hole for the photodiode in the LOS, and a hole for the phototransistor at one orthogonal position (Wang et al., 2018). The design is calibrated for different resistance values so that the power consumption is low. An optical backscatter transducer with a modulated light source is shown in Fig. 6c according to Kirkey et al. (2018). Low-frequency square wave modulation is added to achieve high sensitivity. It is also known as STAR: submersible turbidity meter with the rejection of ambient light. The RGB LED, reference photodiode, signal photodiode with ADC, and high pass filter are shown in the circuit. SPD output that is high pass filtered will have OBS information, and it is fed to the multiplexer LED modulation at low frequency. By variation in frequency, the impact of electromagnetic interference is minimized.

Table 3: Recent Turbidity Sensor

Reference	Basic Principle	Advantage	Limitation	Future Scope
Wang et al. (2018)	Light intensity due to scattering is measured by photo transistor and photo diode	Low cost, Low power Easy Fabrication, easy to integrate with IoT network	90% accuracy Low accuracy for lower NTU values	Another photo transistor can be added at orthogonal position for better results. Additional amplifier circuit can be added to improve resolution.
Kirkey et al. (2018)	Optical backscatter transducer with light source modulated with low frequency.	In situ water quality monitoring for long term, Real time data, High accuracy 5.4% error at 1 NTU.	Loss of sensitivity due to biological growth and deposition of sediments. Many pins of microcontrollers are still unused. Routine cleaning and calibration is needed.	Few more sensors can be integrated using same design, Dynamic behavior can be controlled by adding Automatic gain controller, mechanical vipers can be added.

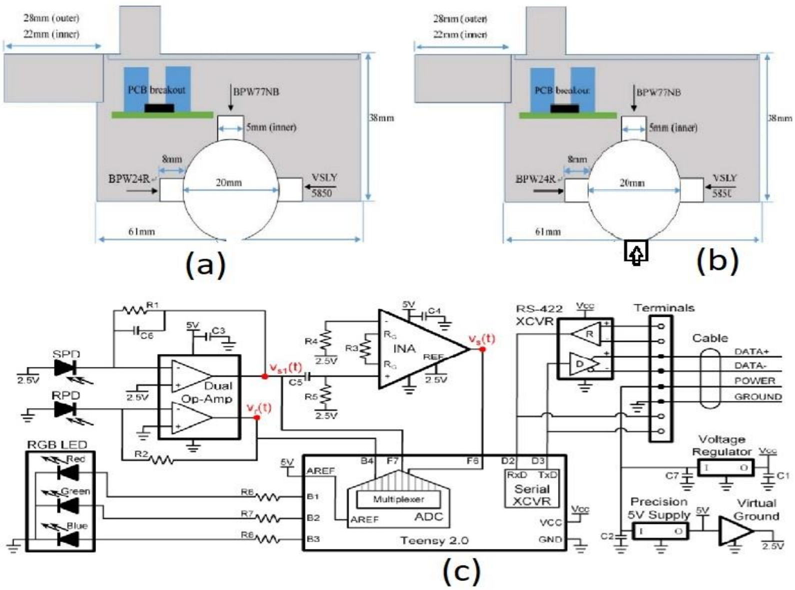

Figure 6: (a) Low cost using IR LED, photo diode and photo transistor (Wang et al., 2018). (b) Modified and proposed design of (a). (c) Optical backscattering transducer with light modulation (Kirkey et al., 2018).

DO, pH and heavy metal sensors are used to measure the level of these parameters; if these parameters are not within the limit shown in Table 1, then they can cause a health problem. Sensors related to these parameters are discussed in Table 4.

Table 4: Recent sensors of water quality parameters

Ref	Water quality parameter measured	Woking Principle	Advantage	Limitation	Future Scope
Zhang et al. (2019)	Nitrate, Phosphate and Ammonium contamination Heavy Metal, pH Dissolved oxygen, Conductivity	Resonant frequency and S parameters of Microwave RF Circuit integrated on PCB	Low cost, Easy Fabrication	Need spectrum analyzer, Formulation for variation, Long range of frequency	These designs can be investigated in detail and proper formulation can be achieved through machine learning. These resonators can be integrated with antenna and data can be directly transmitted to server
Mehaney et al. (2021)	pH and presence of heavy metals	Biological Sensor Based System with	High Accuracy and reliability of system	Huge training data is needed,	Fish can be replaced with any combination of different

		computer Vision		Fish is being used as indicator	combination of material having color sensitivity with various impurity
Yuan et al. (2018)	Heavy metal pollutants (CuSO4, MgSO4 and MnSO4)	Photonic Eco-Sensor With demultiplexer 2 Dimensional solid fluid photonic crystal having 3 demultiplexer	Good selectivity and sensitivity, Crystal size of 1 mm and range of frequency is in range of KHz.	Detection is limited to certain selected metals	Demultiplexer work as spectrum analyzer for a range of frequency rather this design can be investigated with more diameters of crystal and more branches of demultiplexer.
Manjakkal et al. (2021)	pH, Resistance, Capacitance, Conductance	ISFET for pH, eight electrodes for impedance and VCO for frequency and voltage converter	Real time data, low size, very low power consumption. Mathematical model is presented	180 nm Mos technology for water characterization is small	ISFET can be modified to get better output. Few more sensors can be added to Arduino board
Manjakkal et al. (2020)	pH and DO	Potentiometric pH sensor	Low cost, easy to fabricate, low size	Temperature sensitive, slow response time	More strip can be added for better sensitivity and design of electrode can be changed.

According to Zhang et al. (2019), Fig. 7a shows five different sizes of complementary split ring resonators (CSRRs) resonating at different frequency ranges: 1 GHz to 10 GHz. Contamination changes the dielectric properties and conductivity. Change in real values of permittivity: ammonium, nitrate, and phosphate change in imaginary values of permittivity is used to characterize different pH values. Zebra fish have been used as an indicator and integrated with computer-based image processing techniques (Menhaney et al., 2021). The system assembly is shown in Fig. 7b. Zebrafish color and behavior change in real time according to pollutants added to water. RNN and LSTM neural network-based classification models are implemented. The velocity vector, rotational angle, position parameter, and color component are analyzed with different levels of toxicity added to water. A photonic Eco-Sensor, as shown in Fig. 7c, has been used (Yuan et al, 2018). The crystal cell size was chosen so that the frequency range was 105 kHz-210 kHz. PnC has stainless steel and water as the substrate. A T-shaped waveguide structure is obtained by removing the row and column, which will work as input radiation. Three rows attached with T removed so that they work as output. Output lines (demultiplexer lines) with a hollow cylinder of different radii are used, which will result in frequency domain performance depending on different metals. ISFET for pH with eight electrodes for impedance is used, as shown in Fig. 7d (Manjakkal et al., 2021). CMOS integrated system having ISFET with 8 electrodes having SR latch, XOR gate, amplifier, VCO, and current comparator. pH to frequency and impedance to frequency converters are used using an Arduino Uno board. Variations in capacitance and voltage applied at different frequencies are provided to the ADC. According to Manjakkal et al. (2020), the potentiometric pH sensor shown in Fig. 7e was used. The sensitive electrode in which one will work as a reference electrode and the other will change according to pH and DO. The RuO2 used will give better sensitivity. The RE electrode will have a thick film of Ag/AgCl/KCl.

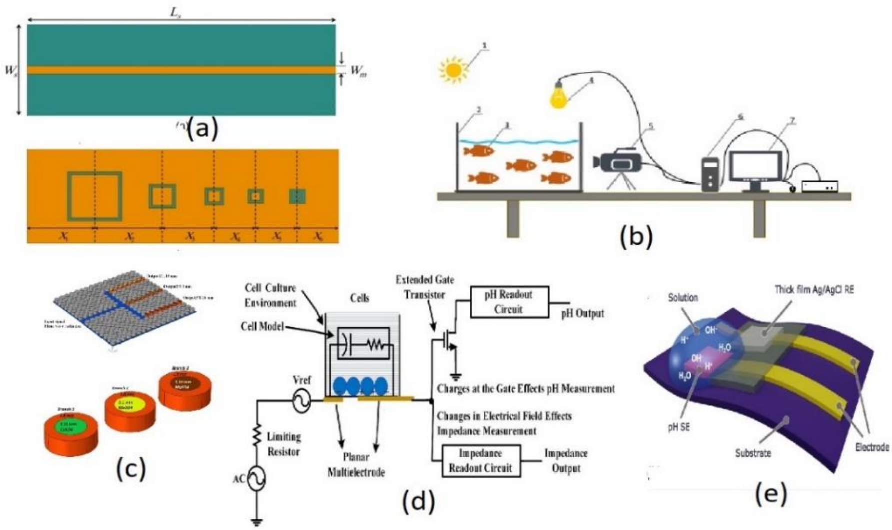

Figure 7: (a) CSRR-based microstrip design (Zhang et al., 2019). (b) Biological Computer vision Sensor using Zebra fish (Menhaney et al., 2021). (c) Photonic Eco-Sensor with 3 demultiplexers (Yuan et al., 2018). (d) ISFET with multielectrode (Manjakkal et al., 2021). (e) Potentiometer pH sensor using different materials (Manjakkal et al., 2020).

OBSERVATION AND CHALLENGES

From the discussion in the previous section, we observe that advancements in sensor technology have used research outcomes of RF technology advancement, photonic advancement, material advancement, ISFET technology, etc. As recent advancements in different technological domains have progressed, researchers have begun to use it as a sensor. 3D printers have provided good freedom for the novel design of sensors. In RF technology, variation in resonant frequency and the S parameter are used to measure different water quality parameters. However, this causes a major challenge because mathematical equations obtained from calibration are not mature enough to be applicable universally. A very wide range of data is required so that data from these RF sensors can be converted into established equations. In real-time operation, data must be collected from sensors and simultaneously processed to make a prediction. With the increase in the number of sensors with a relative error of 5%, the overall system performance will degrade. A large number of sensors with even a small error may result in an incorrect prediction. Therefore, high sensitivity and minimum error are major requirements of a real-time system.

In a water supply management system, various sensors with different ranges of operation are needed; for example, a flow meter should be capable of measuring flow accurately for different pipe diameters. Based on the requirement of the real-time system, we can use two types of flow sensors. At various node points of the pipeline, i.e., at the source of the pipeline, at joints of the pipeline, at distribution points, and at the end-user flow rate, it is an important parameter and should be accurately measured. At these particular nodes, a flow sensor with less error should be used. In a very long pipeline, if we are able to develop a very low-cost flow meter, then it can be deployed at various locations in a pipeline just to measure defects in the line.

Turbidity is an important parameter and a major indication of contamination. Turbidity sensors must be deployed at the water source and water storage tank. The turbidity sensor proposed uses only one phototransistor at the orthogonal location. These two transistors can be added at two different orthogonal positions. This will certainly improve the sensitivity of the sensor. Different turbidity sensors are effective only within a certain specified limit and result in large errors out of that range. Few sensors work accurately for low turbidity ranges, whereas few sensors work accurately for higher turbidity ranges.

Water quality sensors measuring pH, presence of heavy metals, and DO are those parameters in which end-users will be most interested. These parameters have major health relations. These parameters need to be monitored at the water source and end-user end. The sensors used in the measurement of these parameters may also be of two types. One is used at the source end, and the other is used near the end user.

Many of these sensors use a distinct microcontroller for data processing, and many pins of these controllers are unused. These pins can be used with another sensor present at the same location. All these sensors must be connected to the cloud through a wireless connection. At the cloud, data will be processed and analyzed, and the results will be predicted. This prediction will lead to generating alert messages or performing actuation operations.

FUTURE PROSPECTIVE-BASED PROPOSED MODEL

Different types of sensors are required at the same and different locations. Major concerned sensors are flow rate sensors, turbidity sensors and pH sensors. Computer vision is now making the camera capable of identifying color, identifying objects and calculating velocity. Based on these capabilities, a camera can work as an effective sensor that can measure different parameters by processing images.

Computer vision-based turbidity can be measured by exposing turbid water to white light and a black background. Different black color shapes of variable thickness can be visualized. The computer vision-based flow rate can be measured by comparing different frames of very short duration. Changes in the frame will result in a flow rate. A new proposed model is shown in Fig. 8. pH can also be measured using a few chemical strips. There are a few chemicals that change color with variations in pH. Phenolphthalein changes color in different shades of yellow, red and blue depending on different ranges of pH. A strip can be dipped into the water through an automated mechanical process, and color change can be detected by the camera at a remote location.

Image processing-based models can help to improve the accuracy of sensors because different mathematical models may be required for different ranges of the sensor. Image processing can help in identifying the appropriate range so that a suitable model can be adopted and accurate calibration can be performed.

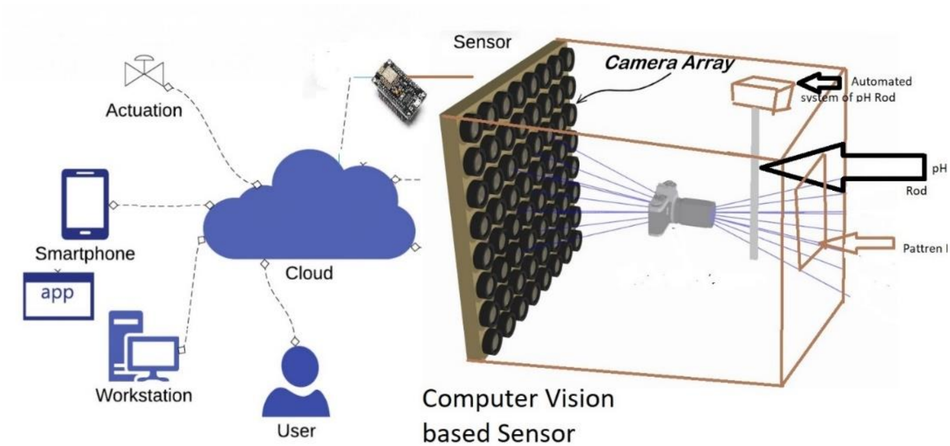

Figure 8: New proposed model for WQS in smart water supply management system

The above discussion clearly indicates that computer-based vision can replace multiple sensors and help to improve the accuracy of different sensors being used in smart water supply management systems.

In the water supply management system, many sensors have been deployed at remote locations. It becomes important that these sensors have a longer lifetime. There are many alternatives for a longer life, such as using a low-power processor and image sensors and using energy harvesting techniques. Low-power processors integrated with machine vision are emerging for IoT applications (Maheepala et al., 2020). Based on pixel data, the camera can be reconfigured. Camera reconfiguration will allow the same camera to be used for various applications. Energy harvesting will include the generation of power through flowing water, solar energy, etc.

CONCLUSION

The rapidly increasing application of IoT can be implemented to optimize water supply management systems. Water quality parameters have become important due to people becoming health-conscious. Real-time data can be reported to end-users by integrating the IoT with a range of sensors. Few recently proposed sensors have been studied in detail, and their applicability in water quality monitoring in water supply management systems has been investigated. Many limitations of these sensors have been observed, and methods to overcome that limitation have also been suggested. After a detailed investigation, a model was proposed that uses computer vision capability to find various parameters related to smart water supply management systems. In the future, with the increasing capability of computer vision-based processors, conventional sensors may be replaced by these. Water is a life liquid for living organs on earth, and the proposed model will judge requirements and regulate them accordingly.

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