IJRAR.ORG E-ISSN: 2348-1269, P-ISSN: 2349-5138

INTERNATIONAL JOURNAL OF RESEARCH AND ANALYTICAL REVIEWS (IJRAR) | IJRAR.ORG

An International Open Access, Peer-reviewed, Refereed Journal

Review of Water Quality Monitoring using Internet of Things (IoT)

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Abstract- Water pollution is one of the biggest and serious threats to society. Water has a significant impact on human health. The quality of the water must be monitored in real-time to ensure its safety and supply. Monitoring water in traditional ways takes longer, which can take up to from 24 to 96 hours to identify contaminants in water supplies, which are more time taking. This project aims at developing a water quality monitoring system using sensors and IoT (Internet of Things). The water quality parameters like temperature, pH, and turbidity are measures using sensors and the water quality index is determined. The measured values from the sensors will be processed using a microcontroller, and alert message will be sent to the user via an android application developed using MIT app inventor in case of any abnormalities. The sensor data can be viewed on the ThingSpeak GUI platform for monitoring and correction of the critical water quality parameters. The sensed data will be stored in the cloud or local storage and a machine learning algorithm will be implemented using the sensed parameters to predict the short term and long-term water quality in phase two of the project.

Keywords – Temperature, pH, Turbidity, Arduino UNO, ESP8266 Wi-Fi Module, ThingSpeak GUI, MIT App Inventor.

I. Introduction

People in various regions are threatened by water scarcity, which has primarily been studied from a water quantity perspective. The global water scarcity is caused by both water quantity and water quality issues and quantifying the need to expand clean water technologies (Such as desalination and treated wastewater reuse) to reduce the number of people affected by water scarcity,' as the United Nations' Sustainable Development Goal 6 demands. When water quality (temperature, salinity, organic pollution, and nutrients) is taken into account, the percentage of the world's population suffering from severe water scarcity rises from 30 percent (22 percent – 35 percent monthly range; water quantity only) to 40 percent (31 percent – 46 percent; both water quantity and quality). Water quality has a particularly negative impact in areas with severe water scarcity, such as eastern China and India. Excessive sectoral water withdrawals in these areas not only contribute to water scarcity in terms of quantity, but polluted return flows also degrade water quality, exacerbating water scarcity. [1]

To address water-related environmental issues, precise information is required, as well as knowledge of what the problem is, where it occurs, how serious it is, and what is causing it. This data is essential for determining cost-effective and long-term solutions to water-related issues. The goal is to provide an accurate picture of current water-quality conditions and trends in water quality and water use, as well as to make it easier to identify new issues and future priorities.

II. DISCUSSION

2.1. Water Quality Measuring Methods

[2] In this paper the researchers mentioned that, wireless sensor networks (WSNs) have grown in popularity among researchers as a promising infrastructure for a variety of control and monitoring applications. These low-cost networks make it possible to monitor processes remotely, in real time, and with minimal human intervention. The two main components of a typical WSN network are the node and the base-station. A node is a device with sensing, processing, and communication capabilities that is responsible for monitoring the parameters associated with a specific application. And showed that, a base station is in charge of capturing and distributing all measurement data from the nodes, as well as providing gateway services that allow the data to be managed remotely. To relay measurement data to the base station, WSNs typically use the Wireless Personal Area Network (WPAN) or Low Power Wide Area Network (LPWAN) standards. ZigBee, and Bluetooth are examples of these standards. There is no single connectivity solution that is considered suitable for all WSNs, and the standard chosen is entirely dependent on the communication needs and resource constraints of a specific application.

[3] Water quality is monitored by physically visiting water bodies and collecting samples, which are then sent to laboratories for testing. This is an inefficient and time-consuming method. Water quality monitoring sensors, Arduino IDE, and RF modules are placed in water sources to automate this process. The sensors collect information such as pH, temperature, and turbidity, which are then sent to the Arduino IDE for binary to digital conversion. This information is sent to the lab via a radio frequency transmitter module, obviating the need to physically visit water bodies, ensuring real-time on-demand data on contamination levels, and serving as a warning system for dangerous levels of contaminants.

[4] As a method of water quality anomaly detection and warning provision, a combined approach integrating a wavelet artificial neural network (wavelet-ANN) model and high-frequency surrogate measurement is proposed in this study. A regression-based surrogate model was used to generate high-frequency time series of major water quality indexes. A low-frequency signal was imported into a back-propagation neural network for one-step prediction to identify the major features of water quality variations after wavelet decomposition and denoising. The time series of residual errors are produced by the precisely trained site-specific wavelet-ANN. When the actual residual error exceeds a certain threshold, a warning is issued. The results show that for high-frequency surface water quality prediction, the wavelet-ANN model is slightly more accurate than the ANN, and it meets the requirements for anomaly detection. The proposed method's stability was demonstrated through analyses of performance at different stations and over different time periods. The presented approach can support timely anomaly identification and be applied to urban aquatic environments for watershed management by combining monitoring instruments and surrogate measures.

[5] In this paper, they developed a smart data analysis method for analyzing and estimating water quality in a comprehensive environment, taking into account all of the water quality standard indicators. This method also includes models for estimating biological water quality indicators using Zero-Inflated Poisson Regression (ZIP) and Zero-Inflated Negative Binomial Regression (ZINB) based on real historical data. They compared different influence factors to arrive at their findings, which show that our models can accurately predict the biological indicators evolution process, particularly for the trend. They also provide future control decision support in the water supply system, as well as share interesting findings from the data analysis process.

[6] Using the Internet of Things, this paper proposes a low-cost system for real-time water quality monitoring and control. Temperature, turbidity, conductivity, pH, and flow are among the physical and chemical parameters of water that can be measured by the system's physiochemical sensors. Water contaminants are detected using these sensors. Raspberry Pi processes the sensor data and sends it to the cloud. Finally, using cloud computing, the sensed data is made visible on the cloud, and the water flow in the pipeline is controlled via IoT.

[7] Using naturally occurring flow conditions in the well, this study describes a lowcost method for sampling individual fractures in open wellbores in crystalline bedrock. To identify transmissive fractures and vertical flow direction, the method employs the Dissolved Oxygen Alteration Method (DOAM). By requiring a tracer-free zone prior to sampling, additional dissolved oxygen injected during the DOAM procedure serves as a tracer to ensure the water quality in the sampling zone is characteristic of the fracture of interest. The sampling procedures for nine bedrock wells with varying flow conditions and one, two, or three transmissive inflowing fractures are conceptually described. Two crystalline bedrock wells with one and two transmissive inflowing fractures were used to demonstrate the method. The DOAM, hydraulic isolation with a single control pump, and a simple sampling device was used to demonstrate the ability to measure the water quality in individual fractures in open crystalline bedrock wellbores. If contaminant concentrations are particularly high, the technique can identify fractures that are a good candidate for sealing or long-term monitoring.

[8] The first steps in the development of a drinking water quality monitoring system are described in this paper. This system uses a wireless sensor network to detect and locate any change in water quality in real-time, quantify its significance, assess its consequences, and determine the best actions to take to mitigate its effects. They began by determining the most optimal location for the drinking water quality control points. After that, an anomalies detection algorithm was created to detect contamination and malicious acts in the drinking water distribution system. Finally, they propose a data aggregation method that takes into account the system's environmental parameters in order to reduce network load while minimizing source node energy consumption.

[9] The purpose of this paper is to evaluate the water quality of the Ghataprabha river. Water samples are collected from the river using the WQM system at designated sampling points and subjected to linear regression analysis to determine the parameters' relationships and goodness of fit. Temperature, pH, dissolved oxygen, electrical conductivity, biochemical oxygen demand, nitrate, and total dissolved solids are all used by the WQM to control water quality. Once the parameter relationship is established, the water samples are subjected to a one-way ANOVA, and the water quality is assessed using the ANOVA hypothesis. The WQM system can also be trained using the river dataset.

[10] The main goal of this project is to create a system that uses the Internet of Things to continuously monitor water quality parameters. To measure the required parameters, the proposed model uses a variety of sensors. The measured parameter values from sensors are processed with the help of a core controller. The core controller for the entire model is Arduino. Measured data from sensors is viewed on the cloud platform via a Wi-Fi module.

[11] The value of a surface water quality improvement to a household varies as a function of the distance between the household and the affected streams and rivers, the degree to which the water quality has been improved, the number of stream and river miles improved, and the size of the affected streams and rivers, according to this study. The findings show that value decreases linearly with distance, there is no evidence that large rivers are worth more than small rivers, and there is no evidence that willingness-to-pay is nonlinear in terms of water quality improvement or stream miles improved. These findings suggest that in applied work, it may be reasonable to value small, spatially explicit water quality improvement projects separately and then add them together. This study's findings have significant implications for cost-benefit analyses of specific water quality interventions, as well as regulatory impact analyses of national regulations. According to the findings of this study, changes in water quality of this magnitude could result from the adoption of agricultural best management practices or from national regulations under the Clean Water Act.

2.2. Water Quality Monitoring Algorithm

[12] This study uses the satellite remote sensing technique to develop a methodology for real-time water quality measurement in a river at 30 m spatial and 1-day temporal scales to support daily water quality monitoring typically done at gauges. Because all current satellite products have limited Spatio-temporal resolutions, this study combines the corrected band-specific Landsat and Moderate-Resolution Imaging Spectroradiometer (MODIS) surface reflectance values with observed pollutant concentrations using a physically-based approach. Landsat versus MODIS surface reflectance and Landsat surface reflectance versus in-situ pollutant concentrations are used to estimate eight water quality parameters using a combination of regression analysis and Genetic Algorithm (GA) based multivariate nonlinear formulations. The methods have the potential to be used in ungauged river reaches, according to a Monte-Carlo simulation-based uncertainty and sensitivity analysis of the used algorithms. The coupled relations between the Landsat spectral reflectance and measured pollutant concentration, as well as Landsat and MODIS spectral reflectance, are used in this study to develop a methodology for river-scale real-time water quality measurement at finer temporal and spatial resolutions. These spectral algorithms include a physically-based identification of spectral band containing the pollutants' signatures, as well as multivariate nonlinear regressions using SPSS and the genetic algorithm (GA).

[13] The goal of this paper is to investigate a real-time system for analyzing and monitoring river water quality. The application of an adaptive Wireless Sensor Network (WSN) is investigated using river beaches along Portugal's Cávado River as a case study. Sensors that measure a variety of physical-chemical, microbiological, and other substances considered by the Ministry of Environment to be indicators of pollution will be installed in zones identified as being at risk in order to implement this network. Sinks will also send requests to the sensors on the surrounding river beaches in order to obtain their readings. The adaptive capability of the adopted control algorithms allows for an increase in the frequency of sensor readings whenever an anomaly in the read values is detected, in order to monitor the location where the anomaly was detected more closely. CupCarbon, which integrates the OSM (OpenStreetMaps) API, and Google Maps, which allows the development of a prototype based on real locations, were the platforms used for the implementation, reconfiguration, and monitoring of the communication algorithms adopted.

[14] Water quality assessment was analyzed using the grey correlation method of water quality evaluation factors sensitivity, with the sensitive parameters as the main parameter of water quality evaluation, according to Yangzhou 8 surface water monitoring station of 412 groups of measuring data. The water quality of eight surface water monitoring stations were assessed. Individual factor results are compared to the overall results. The results show that in the case of large amounts of data, the artificial neural network model can solve the complex nonlinear relationship between the evaluation factor and the water quality. The end result is a high level of dependability, accuracy, practicality, and objectivity. Yangzhou's water quality is partly reflected in this.

[15] Researchers used four standalone algorithms (Random Forest (RF), M5P, Random Tree (RT), and Reduced Error Pruning Tree (REPT)) as well as 12 hybrid datamining algorithms (combinations of standalone with bagging (BA), CV parameter selection (CVPS), and randomizable filtered classification (RFC) to create Iran WQI (IRWQIsc) predictions. Ten different input combinations were created using Pearson correlation coefficients. Several statistical and visual evaluation metrics were used to assess the models. Total solids (TS) and fecal coliform (FC) had the greatest and least effect on IRWQIsc prediction, respectively, according to the findings. The best input combinations differed between algorithms; in general, variables with very low correlations performed poorly. The prediction power of several standalone models was improved by hybrid algorithms, but not all of them. The goal was to create and propose new algorithms not only for WQI prediction but also for other aspects of water science in areas where water quality gauging stations are sparsely distributed.

[16] For evaluating and interpreting a large complex matrix of water quality data collected, non-supervised and supervised pattern recognition algorithms were used. The researchers looked at 21 physical, chemical, and microbiological parameters collected from 80 different WQ sampling stations. Using three internal validation indexes, the k-means algorithm was used to identify classes of sampling stations based on their associated WQ status. As a result, two WQ classes were established, representing low (C1) and high (C2) pollution levels, respectively. The k-NN/GA algorithm was used on the available data to create a classification model with the two WQ classes as dependent variables and the 21 physical, chemical, and microbiological

parameters as independent variables, as defined by the k-means algorithm. This algorithm reduced the multidimensional space of independent variables to only nine, which are likely to explain the majority of the structure of the two WQ classes identified.

[17] They proposed an alternative machine learning method for predicting missing values of total algal count during water quality monitoring at drinking water treatment plants that combines the benefits of the Random Vector Functional Link Network (RVFL) and the Moth Search Algorithm (MSA). At different sizes of training tests, the MSA-RVFL outperformed the Support Vector Machine (SVM) and the Adaptive Neural Fuzzy Inference System (ANFIS) models. When compared to the GA-RVFL and PSO-RVFL methods, using the MSA-RVFL reduced the number of input variables and processing time. The MSA-RVFL model has the potential to reduce the number of input variables from thirty-four to eighteen, and ultimately to four. pH, NO3, P, and Ca were the most important variables chosen by the MSA-RVFL to predict total algal count. As a result, the MSA-RVFL model is a cost-effective tool for monitoring water quality. Finally, the MSA-RVFL performed better than traditional ANN models when the number of inputs was large or small, indicating that our proposed method outperforms them.

[18] This paper presents a system for water quality monitoring that is cost-effective, time- and energy-efficient, and uses innovative technology such as the Internet of Things, wireless sensor networks, modern communication technology, and data analysis techniques to provide you with an alert and preventive action to take in the event of an emergency. Realtime water quality monitoring system with various sensors (carbon dioxide, pH, turbidity, temperature, and water level) to help gather water parameters, ARM-based microcontroller (STM32 Nucleo-board) to convert the analog signal to digital signal, Zig-Bee module to send the data to a personal computer, and data analysis operation to notify the user wirelessly. The system monitors water pollution and keeps track of it through data analysis using an optimization data fusion algorithm, and if necessary, alerts the user to take preventive action on a regular basis.

[19] The Dolphin Swarm Algorithm was used to optimize the Extreme Learning Machine algorithm in this paper. The best position of the Dolphin Swarm was found by creating a virtual team and searching for the optimal weight and threshold of the Extreme Learning Machine algorithm. To evaluate the level of the water, four parameters were chosen: Ph, dissolved oxygen (DO), potassium permanganate index (CODMn), and ammonianitrogen (NH3-N), and the Extreme Learning Machine algorithm optimized by Dolphin Swarm Algorithm (DSA-ELM) was used as the water quality evaluation model.

[20] The design of a rural drinking water monitoring system based on wireless sensor networks is proposed in this paper, with nodes using STM32 as the core chip, WLK01L39 as the wireless communication module, and Beidou S1216 as the GPS module to achieve node localization. The corresponding communication protocol and time synchronization algorithm are also proposed at the same time. This paper has automated the collection of water quality indicators and data upload via the GPRS network. Experiments show the system's power consumption and data transmission performance, with a packet loss rate of 6.2 percent when the system's data communication distance is 150 meters in an open area.

[21] This paper uses water quality data from small watersheds near Chongqing, China, to develop a new wavelet neural network model for forecasting the China Water Quality Index with a small amount of data (WQI). The goal of this research is to improve prediction results by reducing prediction errors in current machine learning algorithms by using the main environmental pollutant in small watersheds as an input. The results show that when the water quality characteristic attribute and WQI have strong interaction and correlation, the MAPE of the wavelet neural network model training results decreases. Furthermore, the Chongqing WQI forecast is found to be highly dependent on geographic location.

2.3. Water Quality Monitoring using Hardwares

[22] This paper describes a low-cost turbidity sensor that can be used for continuous online water quality monitoring. The proposed sensor is 2-3 orders of magnitude less expensive than existing commercial turbidity sensors because it uses both transmitted light and orthogonal scattered light detection principles. When compared to existing low-cost turbidity sensors, the proposed design can measure turbidity within the range of 0-1000 Nephelometric Turbidity Unit (NTU) with improved accuracy and robustness using an 850-nm infrared LED and dual orthogonal photodetectors. Both 0-200 NTU high resolution and accuracy sensing and 0-1000 NTU lower resolution and accuracy sensing are possible with the combination of orthogonal and transmitted light detection units. The results of a calibration experiment show that the proposed sensor design produced turbidity readings that were comparable to those of a commercial turbidity sensor.

[23] A sensor-based water quality monitoring system is proposed in this paper. A microcontroller for system processing, a communication system for inter and intra node communication, and several sensors are the main components of a Wireless Sensor Network (WSN). Remote monitoring and Internet of Things (IoT) technology can provide real-time data access. With the help of Spark streaming analysis through Spark MLlib, Deep learning neural network models, and the Belief Rule Based (BRB) system, data collected at the separate site can be displayed in a visual format on a server PC and compared to standard values. If the acquired value exceeds the threshold value, the agent will receive an automated warning SMS alert. The novelty of this proposed paper is that it aims to develop a water monitoring system that is high-frequency, mobile, and low-powered. The research is focused on real-time monitoring of river water quality. This project could be expanded into a local area's efficient water management system.

[24] The user of the water quality parameters in real-time. The system can measure flow, temperature, pH, conductivity, and oxidation-reduction potential, among other physiochemical parameters of water quality. Water contaminants are detected using these physicochemical parameters. The sensors are connected to a microcontroller-based measuring node that processes and analyses the data, which is designed from the ground up and implemented with signal conditioning circuits. For communication between the measuring and notification nodes, ZigBee receiver and transmitter modules are used in this design. When the water quality parameters reach unsafe levels, the notification node displays the sensor readings and generates an audio alert. The sensors are shown to work within the accuracy ranges that they were designed for. The measurement node can send data to the notification node via ZigBee for audio and visual display. The findings show that the system is capable of reading physiochemical parameters and processing, transmitting, and displaying the data.

[25] A water quality monitoring system based on low-power hardware is presented in this paper. In three regions of the Peruvian Amazon, six sensor nodes for water quality monitoring in pisciculture have been installed. The sensor node is a piece of modular hardware that includes control, communication, and sensor module for measuring pH, conductivity, and temperature. All data is managed by a software platform built with opensource tools, which allows for the control of water pollution and its impact on pisciculture.

[26] This paper presents a reconfigurable smart sensor interface device for a water quality monitoring system in an IoT environment. The smart WQM system is comprised of an FPGA design board, sensors, a Zigbee-based wireless communication module, and a personal computer (PC). The proposed system's core component is an FPGA board that is programmed using Quartus II software and the Qsys tool in very high-speed integrated circuit hardware description language (VHDL) and C programming language. Water pH, water level, turbidity, carbon dioxide (CO2) on the surface of the water, and water temperature are among the five parameters of water data collected in parallel and in real-time by the proposed WQM system from multiple sensor nodes.

[27] The Arduino hardware platform is used to create a smart water turbidity level measurement system with wireless data transmission. The developed system collects data from a turbidity level sensor and uses it as a tool for water monitoring. Furthermore, the collected data is sent to Mobile Apps via Bluetooth and Wi-Fi, which are two types of wireless connections. The sensor was used to determine the range of high and low-level parameters. This project has the potential to solve current water pollution problems and to be commercialized for use in environmental monitoring. The mobile apps monitor not only the sensor readings, such as turbidity, pH, and temperature but also the condition of each sensor, such as whether it is dangerous or safe to use. Furthermore, mobile apps provide notifications and warnings in three different ways: text message, voice alarm, and phone screen monitoring. Overall, it can be concluded that the implementation of the sensors was successful.

[28] Using wireless sensor networks and cellular communication technologies, they have proposed a reliable and efficient environmental monitoring system for ponds. They created a hardware and software ecosystem that can limit data loss while reducing node energy consumption. The data transmission between the nodes is acknowledged by a lightweight protocol. To save energy, data is transmitted to the cloud using a cellular protocol. The data in the cloud is being mined so that users can receive real-time warning notifications. If the values exceed the threshold, the server will send an alert to the pond owner's phone, allowing him to take corrective action as soon as possible. The client application system also includes a feature that allows the user to manage the trend of a physical environment, such as shrimp ponds, by viewing graphs of the collected data over time, such as hours, days, and months. They tested our system with temperature and pH level sensors and deployed it using IEEE 802.15.4 Standard, ZigBee, and Texas Instrument's KIT CC2530. Their findings showed that the proposed system has a low rate of data loss, along with energy life, and can provide real-time data for water quality monitoring at a low cost.

[29] Water samples were collected to test water pH in the lab, and a sub-sample of collected drinking water was tested for water pH with a portable pH meter in this paper. Drinking water samples were collected for laboratory testing of other chemical parameters such as iron, manganese, and salinity. According to this study, the majority of households used low-quality drinking water, as measured by WQI values. Iron, manganese, and arsenic levels in drinking water were elevated. To improve public health, it is necessary to raise awareness about the chemical content of drinking water at the household level.

[30] Water-monitoring systems have been transformed by wireless sensor networks (WSNs), which provide reliable inspection, practical communication, and high-performing applications. This research presents a comprehensive review of software and hardware solutions for water pipeline infrastructure monitoring that have been proposed in the literature. To achieve optimal and reliable results, an integrated energy-aware system-on-chip solution based on high-performance hardware is proposed.

[31] They present an SoC WSN node prototype based on the Leon 3 processor for water pipeline leak detection using the Kalman Filter in this paper (KF). To save energy, the hardware acceleration of the KF has been designed and implemented. In addition, the paper compared the algorithm's software implementation and hardware acceleration in terms of execution time, energy consumption, and area requirements. The results show a 97% reduction in energy consumption and execution time with no visible increase in area.

III. CONCLUSION

The various methods for network design available in the hydrologic literature were evaluated by taking into account the monitoring program's spatial scale, sampling objectives, data requirements, temporal effects, and applicability range. To track water quality, an efficient real-time algorithm should be developed. In an IoT environment, a hardware/software based smart sensor interface device for Water Quality Monitoring can intelligently collect sensor data. It's ideal for the real-time and cost-effective needs of a highspeed data acquisition system in an IoT environment.

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