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IoT-Enabled Advanced Water Quality Monitoring System

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Abstract— This work presents an IoT based water quality monitoring system with ESP32 for periodic sensing, evaluation, local indication and visualisation in cloud. The ESP32 connects to particular sensors to measure the pH, TDS, turbidity, and water temperature. The analogue channels are measured by the 12-bit ADC, averaged and converted from analogue to parameters and filtered and then evaluated. Estimation of TDS is done by taking temperature compensation. The threshold based score begins at 100 and there are points deducted for every programmed violation (pH between 6.5 to 8.5, TDS > 500 ppm, turbidity > 5 NTU or temperature > 35°C). The 16×2 I2C LCD shows the measured values, calculated score and status. Dangerous state indicated by buzzer. Wi-Fi will help to periodically transmit the temperature, pH, TDS, turbidity and score to ThingSpeak. The experimental outputs are prototype, LCD monitoring, ThingSpeak communication, parameter visualisation and score based evaluation. Implementation can be based on thresholds. Data collecting + validation yields machine-learning prediction.

"Keywords—ESP32, Internet of Things, water quality, pH, TDS, turbidity, DS18B20, ThingSpeak, threshold-based assessment."

I. INTRODUCTION

Water quality is an important requirement for domestic, One of the most important criteria for water use in homes, agriculture, industries and the environment is water quality. Several factors may affect the condition and suitability of a water sample such as acidity or alkalinity, dissolved compounds, suspended particles and temperature. Conventional monitoring methods involve regular sampling and lab testing, and if repeated monitoring needs to be done, it can be time-consuming. A small monitoring device that can be embedded can reduce manual effort by gathering numerous parameters and display these data with a single system.

Embedded and IoT based monitoring is a viable option to periodic field level monitoring. The controller is capable of interfacing with a number of water-quality sensors to collect raw measurements, process the sensor signals, assess the conditions and provide the resulting information locally. The same can be done for network connectivity (processed values can be sent to a cloud platform and the same measures can be viewed away from the actual sensing point).

A system is proposed that integrates the pH, TDS, turbidity, temperature sensors with an ESP32 controller. It performs repeated acquisition, 20 sample averaging, parameter conversion, filtering, threshold scoring, LCD display, buzzer alert, Wi-Fi management and uploading to ThingSpeak. The aim is to show a water-quality monitoring workflow that integrates sensing, embedded processing, local display and remote visualisation – and without unbacked claims of laboratory-certification or machine learning performance.

The novelty of the study lies in the combination of low-cost sensor data collection, embedded data conditioning, condition assessment based on scores, and IoT-based visualisation into a single process. A second computer is not needed to run the system normally since the ESP32 handles the interfaces with the sensors, output devices locally, wireless connection, and upload to cloud, in order. This makes the implementation appropriate for being used as a tiny academic prototype for the demonstration of connected environmental monitoring.

II. RELATED WORK

To overcome the limitations of laboratory-oriented and manually controlled water quality monitoring systems, the monitoring of water quality has increasingly been based on an IoT-based sensing platform in recent years. It has been demonstrated that the use of the embedded controllers, different sensors, wireless connectivity and cloud infrastructure for the monitoring of parameters such as pH, TDS, turbidity, temperature and others related to the environment. Periodic or near real-time data collection and remote visualisation of connected platforms [1]–[5] enhances the accessibility of IoT-enabled devices.

A few researchers have studied real-time water quality monitoring for drinking water, industrial effluent, treatment plants, and natural water sources and for off-grid populations. Typically, such systems include sensor nodes, microcontrollers, and communication networks that minimize manual observations and offer continuous access to observed data [6]–[10]. In parallel, recent studies also combine IoT technology and data-processing and machine-learning strategies for detecting anomalies and pollution, and making predictions [11]–[15]. However, the effectiveness of such systems relies on the calibration of the sensor(s), coverage of sensor parameters, the reliability of the communication links, as well as the correct interpretation of the measured values.

Current system consists of sensors like pH, TDS, turbidity and temperature which are connected to the controller (ESP32) and the local display, buzzer indication, Wi-Fi connectivity and cloud monitoring using ThingSpeak. A controller collects the data from the sensors sequentially, averages 20 samples, converts the data, filters the results, estimates the TDS for temperature compensation, compares to thresholds and produces a water-quality score. The assembled readings and assessment is presented locally, and uploaded to ThingSpeak for remote visualisation, providing a unified approach to embedded sensing, local monitoring and water-quality observation

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using the IoT. A trained predictive model is not used in the built prototype but deterministic threshold assessment is used, leaving machine learning as a potential future development.

III. MATERIALS AND METHODS

A) System Architecture

The proposed architecture consists of sensing, processing, output, communication and cloud-monitoring functions. The sensing layer is made of pH sensor, TDS sensor, turbidity sensor and DS18B20 temperature sensor. The ESP32 is the processing layer which takes data from the sensors, does analogue to digital conversion, averages, performs conversion equations, filters, calculates scores and determines the status. The LCD/buzzer (I2C 16×2) is used as the local output. Exploiting the communication layer with ESP32 Wi-Fi capability. Cloud visualisation interface will be used with ThingSpeak.



"Fig. 1. Block diagram of the proposed IoT-enabled water-quality monitoring system."

B) Hardware and Interface Configuration

"TABLE I. Hardware and interface configuration."

Component	Interface	Function
pH sensor	GPIO 34	Acidity/alkalinity measurement
TDS sensor	GPIO 35	Dissolved-solids estimation
Turbidity sensor	GPIO 32	Water-clarity indication
DS18B20	GPIO 4	Water temperature measurement
Buzzer	GPIO 27	Unsafe-condition alert
16×2 I2C LCD	I2C	Local value and status display
Wi-Fi/ThingSpeak	Built-in Wi-Fi	Cloud data transmission

We selected the ESP32 development board, as it has analogue inputs, digital interfaces, I2C communication capabilities, serial monitoring and built-in Wi-Fi communication. The analogue sensors output voltages which are processed by the ESP32 ADC. The DS18B20 is connected through a OneWire interface. The LCD screens a few displays and temperature, pH, TDS, turbidity, score and status can be seen directly on the prototype.

C) Signal Acquisition and Processing

There are 20 samples of analogue channels pH, TDS and turbidity for each acquisition cycle. Average and add readings and then convert to a voltage with the ESP32 12-bit ADC range and 3.3V reference. The average values iron out the short-term variations before the use of the conversion functions. The pH, TDS and turbidity measurement from the processed data are stored in circular buffers. Display, assessment, serially monitor and upload to cloud by using filtered results.

"ADC_avg = (1/n)ΣADC_i, V = (ADC_avg / 4095) × 3.3, n = 20."

The pH conversion is equipped with a settable offset and is restricted to the number of pH ranges (as implemented). The processed sensor voltage and measured water temperature are used to make the estimation of the TDS and temperature correction is done before applying the TDS conversion and calibration factor in the programd. The processed voltage is used to estimate turbidity using the polynomial relationship used, and below zero values of the processed voltage are clamped to zero. In case of an invalid value of the temperature sensor, the firmware resorts to 25°C as programd fallback temperature.

D) Water-Quality Score and Status

The water-quality score is 100 points to start. "Any programd threshold violation will be assessed 25 points. The parameters considered were pH outside range 6.5-8.5, TDS > 500 ppm, turbidity > 5 NTU and temperature > 35°C. The status is given from the final score. Excellent for Drinking: 75-100. Good for Domestic Usage: 50-74 Less than 50 means that purification is required.

"Score = 100 − 25(IpH + ITDS + ITurb + ITemp)."

"TABLE II. Programmed threshold conditions."

Parameter	Threshold condition	Penalty
pH	< 6.5 or > 8.5	−25
TDS	> 500 ppm	−25
Turbidity	> 5 NTU	−25
Temperature	> 35°C	−25

"TABLE III. Water-quality score classification."

Score range	Programmed status
75–100	Excellent for Drinking
50–74	Good for Domestic Usage
<50	Unsafe – Purification Required

E) Local and Cloud Monitoring Workflow

This processed information is shown in three display pages on LCD, TDS and turbidity, score and status. When the score is 50 or more, the buzzer will be off and on when the score is less than 50. The ESP32 fetches the state of Wi-Fi connection and uploads the filtered temperature, filtered pH, filtered TDS, filtered turbidity and water-quality score to ThingSpeak every programd upload interval. Local sensing and processing is carried out without connectivity, while the firmware attempts to reconnect.

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"TABLE IV. Firmware operation sequence."

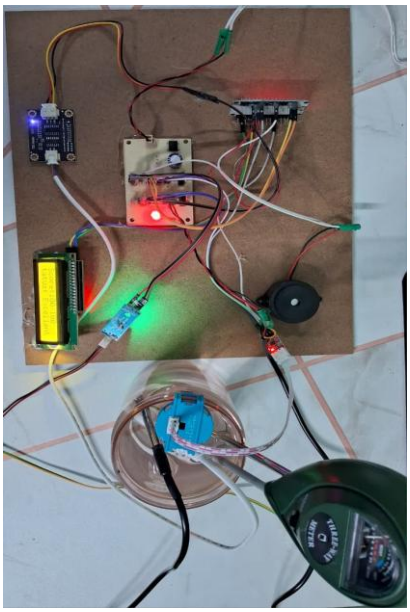
Step	Operation	Output
1	Initialize ESP32, LCD, sensor pins, Wi-Fi, and buffers	System ready state
2	Acquire temperature, pH, TDS, and turbidity readings	Raw/averaged measurements
3	Convert ADC values and apply filtering	Processed parameters
4	Apply threshold rules and score formula	Water-quality status
5	Update LCD and buzzer outputs	Local indication
6	Upload fields to ThingSpeak when Wi-Fi is available	Cloud visualization

This is repeated in normal mode of operation. The design is based on the principle that acquiring parameters should be different from interpreting the condition: the sensors provide values to be processed and the score logic turns the processed values into a small status message for the user. This way, it's possible to extend the architecture later on by connecting further sensors or machine-learning modules after the acquisition and filtering stage without changing the local and cloud interfaces' function.

IV. RESULTS AND DISCUSSION

A) Experimental Evaluation

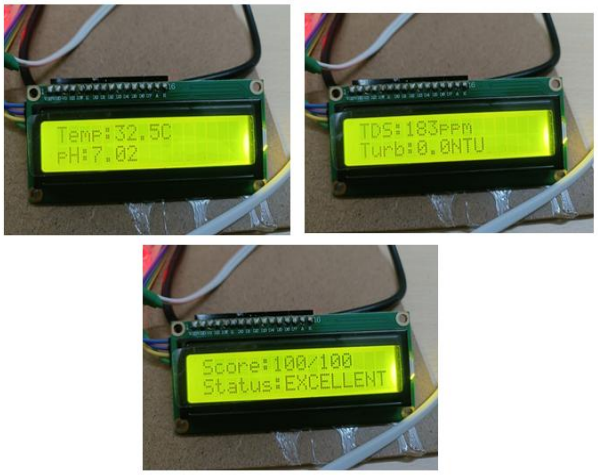
The prototype consists of sensing, processing, local indication and communication to the IoT, the combined performance of which was tested by using collected water samples of tap water, RO filtered water and bore water. The evaluation works. No controlled reference measurements were available to check accuracy percentages of sensors or error percentages, or precision, recall or F1-score. Hence, the study only presents data based on the created prototype and observed outputs.



"Fig. 2. Developed prototype used for water-quality monitoring."

B) LCD-Based Local Monitoring

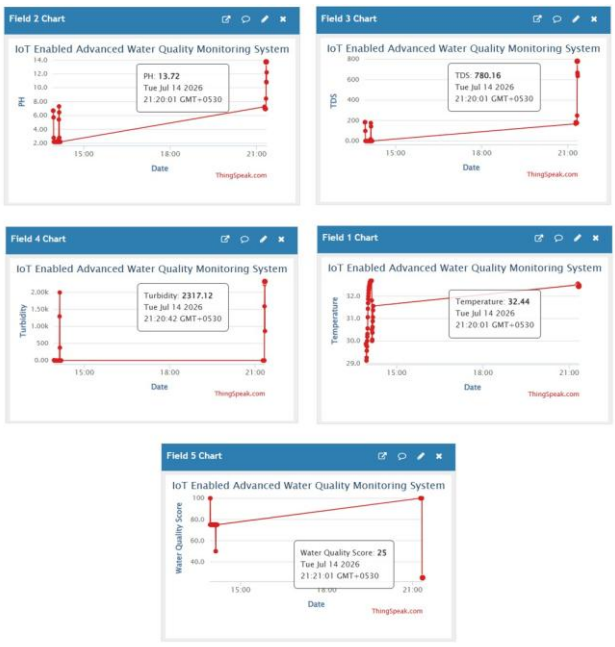
The processed values and the overall assessment are displayed directly in the monitoring station on site using the on-site LCD output. The observed display indicates a temperature of 32.5 °C, pH of 7.02, TDS of 183 ppm, turbidity of 0.0 NTU and a score of 100/100 and status of EXCELLENT. No penalty as all four parameters are within their programd limits and score is 100.



"Fig. 3. LCD-based local monitoring output for measured parameters and score."

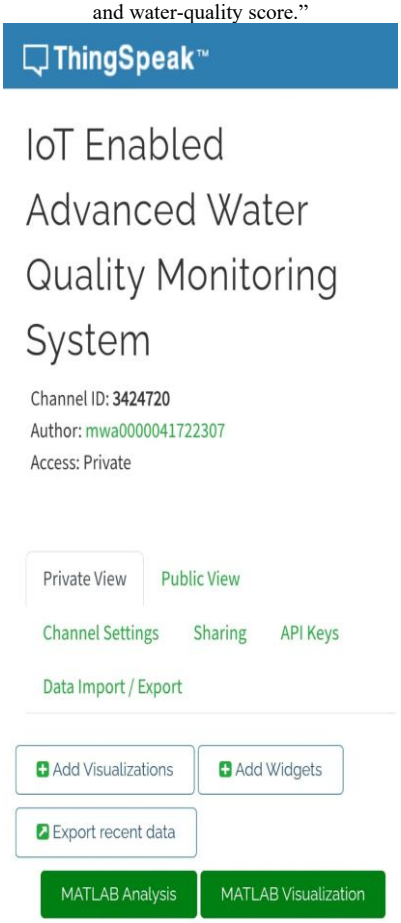
C) ThingSpeak Cloud Visualization

The five fields listed below are transmitted remotely and can be viewed on the ThingSpeak channel: The cloud graphs display values of pH, TDS, turbidity, temperature and score that have been uploaded to the cloud from the ESP32. The observed parameters were pH 13.72, TDS 780.16 ppm, turbidity 2317.12 NTU, temperature 32.44 °C and water-quality score 25. There are three threshold violations: pH, TDS and turbidity, which lowers the score from 100 to 25; the low temperature of 35°C does not affect the score.



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"Fig. 4. ThingSpeak visualization of pH, TDS, turbidity, temperature, and water-quality score."



"Fig. 5. ThingSpeak channel configured for remote monitoring."

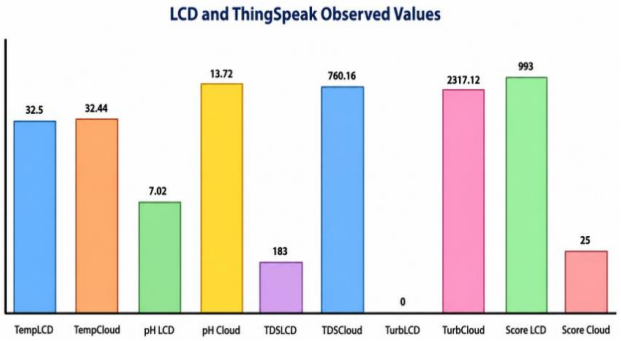
On a channel page we confirm that a special interface to a cloud is set up for the project, and that the fields we have entered are available for visualisation. This is in addition to the individual graphs, as it offers the monitoring environment in which the sensor values submitted can be retrieved.

D) Result Interpretation

"TABLE V. Representative observed outputs."

Parameter	LCD observation	Cloud observation
Temperature	32.5°C	32.44°C
pH	7.02	13.72
TDS	183 ppm	780.16 ppm
Turbidity	0.0 NTU	2317.12 NTU
Score	100	25

The LCD observation depicts a state in which all the monitored parameters are inside the applied limitations, which results in an Excellent status. The case of the cloud observation is when three parameters are above their thresholds. The consistent result with the formula and the equal 25 point deduction for each violation is 25. This makes sure that the embedded assessment layer adheres to the programd rule set that is running.



"Fig. 6. Combined chart of representative LCD and ThingSpeak observed values."

This comparison is also indicative of the potential reporting of normal and poor water-quality conditions. In normal observation, the pH, TDS, Turbidity and temperature are in the programd range and they also score high. The dangerous score occurs when there is high pH, high TDS and high turbidity in the degraded situation. The result shows the sensor functional consistency, threshold checking, the assignment of the status and local reporting and IoT visualisation.

E) Performance Scope and Limitations

The experimental results show that the sensors are acquired, averaged, converted, filtered, status calculated, displayed on LCD and monitored on ThingSpeak with Wi-Fi connectivity being functional. Processed values are displayed in the local display and in the cloud interface of the system. The score is an only operational signal of different threshold checks. Values that can change over time in the decision logic. This difference is minimized with repetitive sampling and circular buffer filtering.

The system, however, can only be used for four parameters measured and requires proper calibration of sensors. It is not used to measure dissolved oxygen, chlorine, nitrates, electrical conductivity or oxidation-reduction potential or microbiological contamination. The chosen calibration parameters can be changed with run-time commands, but, for the present project evidence, this is not possible for a full multi-point calibration study with certified reference devices.

By itself, this programd water-quality status does not constitute a regulatory or laboratory determination of the safety of the drinking water. The current assessment is rule based, and no learning will be done from the measurements taken previously. Only when a labelled dataset has been collected (sensor data and trusted reference results) and subsequently correctly trained, validated, tested and quantitatively assessed, machine learning will be possible.

A number of local and cloud observations are also summarized which further illustrate the value of the output. Each of the individual sensor numbers can be seen, but the total score provides an instant operating overview. For example, if LCD is observed, it is a good case for all thresholds; if ThingSpeak is observed, it is a low score that is a combination of three violations. This allows the user to

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not have to test all the parameters one by one before the programd situation is encountered.

The cloud layer is very useful for monitoring the evolution of parameters in time. The individual fields can be viewed separately through the data streams provided, and the water-quality figure is a composite of the overall impact of the fields measured. This will be convenient for later historical analysis as the same channel may be used for storing data for time-stamping for trend observation, anomaly assessment or future machine-learning data preparation.

The built-in monitoring workflow also has an advantage of separating local sensing and remote cloud connection. The basic monitoring function could work without Wi-Fi for some time, as the ESP32 would retrieve the sensor data, work out the average, filter the data, assess the threshold, compute the score and display it on the LCD. The user can still use the local measurements and condition evaluation despite the programd communication logic, as the controller is able to try to reconnect. Once connection is restored, the system can resume the periodic upload process for remote visualisation, which is scheduled in the ThingSpeak upload procedure.The system can then resume the periodic upload process (which is scheduled in ThingSpeak's upload procedure) for remote visualisation. This separation adds to the usefulness of the prototype, because if temporary communication failures render the entire prototype useless, the local observation of water quality indicators is not affected. This architecture can also enable future extension to additional sensors and monitoring locations, provided that the system is properly calibrated and validated using a reference system before being expanded into the field.

V. CONCLUSION

A prototype for water-quality monitoring has been developed using ESP32 to periodically sample the pH, TDS, turbidity and water temperature. 20 Sample analogue averaging, parameter converting, filtering, temperature compensated estimate of TDS, threshold based scoring, local LCD display, buzzer alerting, Wi-Fi management and data transfer to ThingSpeak. The results of the experiments verify the local and cloud-based observation of the monitored parameters, and demonstrate that the score obtained in the experiments fulfills the programd threshold criteria.

The prototype offers a small form factor to allow for integration of sensors and remote monitoring, but the results are functional and not laboratory certification results. Expansion of the sensor layer line is possible with the addition of dissolved oxygen, electrical conductivity, oxidation-reduction potential, chlorine, nitrate and microbiological indicators. Several points can be calibrated with laboratory reference measurements as a means for validation of results. Once a labelled dataset is developed and a suitable validation protocol is created, historical cloud data can then be used to perform anomaly detection, water-quality prediction and water-quality trend forecasting using machine learning. A dedicated mobile interface and automated treatment control could create the opportunity for the system to be extended to full water-quality management.

The present threshold based system can be the data acquisition layer for an IoT-and-ML expansion. Only a sufficient number of properly labelled water samples from various water sources are gathered and properly verified with reliable reference measurements to enable training of a supervised model. The ESP32-ThingSpeak process can offer an ongoing data collection and visualisation, and this addition can be utilized for class label estimation, anomalous change detection or future parameter trend prediction.

Future deployment may be able to further improve the workflow in a practical sense by splitting up the calibration/monitoring and alerting mode. The pH offset, TDS factor and turbidity factor can be calibrated using reference samples in the calibration mode. The system is able to regularly send consistent filtered readings to cloud during the monitoring mode. Crossing a threshold will trigger a local buzzer and remote notification, if the unit is set in the alert mode. This distinction would enable an easy use of the same prototype in longer-term field trials and preserve the simple embedded implementation of the current prototype.

Long-term IoT records can also be used to analyze seasonally or in certain sources. For example measurements of tap water, bore water, filtered water can be stored as distinct named groups which can be later compared for normal ranges and odd departures. Classification models, including decision tree models, random forest and support vector machines can be tested given a large enough data set. Regression models can also be used to predict trends. Such expansions of the scope of the model should only be presented after careful data collection and validation of the test sets, so that any claimed predictive performance is technically reasonable.

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