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ORIGINAL CONTRIBUTION

Edge-First LoRa Water Quality Monitoring for Smart Aquaculture

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ABSTRACT

Aquaculture now supplies more than half of the aquatic-animal protein consumed worldwide, yet many small-scale farms still rely on manual water-quality measurements taken once or twice a day. These gaps can delay intervention until stock is already stressed. This paper presents a low-cost point-to-point LoRa telemetry system that continuously monitors water temperature and pH, evaluates readings on the receiving node using a deterministic and explainable assessment engine, and displays the results through a node-hosted dashboard. The dashboard provides live telemetry, trends, statistics, grading rationale and data export, operating entirely offline through the receiver's Wi-Fi access point without cloud or internet connectivity. A prototype using ESP32 and SX1278 modules was evaluated over 9 h 30 min, receiving 17,043 packets with 99.99% delivery at a mean RSSI of -52 dBm. Complete firmware for sensing, inference, logging and the web server occupies 68 kB of flash memory.

KEYWORDS: Aquaculture, LoRa, Internet of Things, edge inference, water quality monitoring.

1. INTRODUCTION

The Food and Agriculture Organization estimates that aquatic organisms currently supply about 52 % of the world's aquatic animal food, and projects that this share will exceed 60 % by 2030 as capture fisheries reach their sustainable limit [1]. Meeting that demand requires more intensive farming, which in turn requires closer control of water conditions than has so far been the norm. Temperature governs metabolism, feeding response and immunity, while pH regulates ionic balance and the toxicity of nitrogenous waste [8]. A deviation in either variable, whether gradual or sudden, disturbs the pond ecosystem and places the stock under stress.

The prevailing practice on small farms is a manual check once or twice per day, which creates three difficulties. First, the interval between readings is far longer than the timescale on which water quality actually changes. Second, manual sampling does not scale economically to

the number of ponds a single enterprise operates. Third, by the time an operator observes a deviation, the damage to the stock has usually already occurred. Low-Power Wide-Area Networks are well matched to this problem, and LoRa in particular has been shown to deliver kilometre-scale range at microamp-level node current [2], [3]. Most reported deployments, however, forward raw measurements to a remote server and leave both interpretation and presentation to that server, which is precisely the part of the chain least likely to be available on a rural farm.

The work presented here takes the opposite approach: acquisition, classification and visualisation are all performed on the receiving node, and no cloud service participates in the measurement path. An end-to-end LPWAN telemetry chain was implemented using commodity ESP32 and SX1278 modules, together with a lightweight explainable algorithm that converts temperature and pH readings into an

interpretable water-quality grade. The receiver also hosts a web application offering real-time monitoring, graphical trend analysis, data export, statistics and inspection of the grading rationale, all while disconnected from the internet. The prototype was then evaluated in terms of link reliability, memory footprint and runtime performance.

2. LITERATURE REVIEW

Adelantado *et al.* [1] examined the operating limits of LoRaWAN, showing how duty-cycle regulation, spreading-factor selection and collision behaviour bound the achievable throughput and node density in a deployment. Their analysis establishes why a low-duty-cycle telemetry application of the kind considered here fits comfortably within the technology's constraints, while high-rate or bidirectional applications do not.

Liando *et al.* [2] reported a large-scale measurement study of LoRa covering range, packet reception and the interaction between spreading factor and interference under field rather than laboratory conditions. Their results provide the empirical basis for treating kilometre-scale point-to-point links as reliable at moderate spreading factors, which motivates the SF9 setting adopted in this work.

Nguyen *et al.* [3] developed a LoRa-based sensor network for real-time monitoring of shrimp pond water quality in the Mekong Delta, demonstrating range of the order of several kilometres with node current drain in the microamp range. The work confirms the suitability of LPWAN telemetry for pond environments, but forwards raw measurements without any on-site interpretation.

Kodali and Mahesh [4] implemented a low-cost LoRa gateway bridged to an MQTT broker for smart aquaculture, publishing pond telemetry to cloud subscribers. The design illustrates the prevailing architecture in this domain, in which the gateway performs no analysis and the farmer's view of the pond depends entirely on the availability of the broker and the backhaul link.

Callebaut *et al.* [5] characterised LoRa point-to-point path loss through measurement campaigns over water, and found that surface reflections produce pronounced constructive and destructive lobes at separations no greater than the width of a

single pond. This is a significant practical consideration for in-pond deployments, since antenna placement rather than link budget may determine whether a node is reachable.

Horton [6] introduced the water-quality index, aggregating several measured parameters into a single rated value, and Boyd [8] documented the physiological tolerances of cultured species together with the interaction between temperature, pH and ammonia toxicity. Together these establish both the precedent for reducing multiple parameters to one interpretable score and the domain basis for the optimal windows and the temperature–pH interaction term used in Section V.

Two limitations recur across the reviewed systems. Most implementations are tied to a cloud backend, and none report what remains available to the farmer when the backhaul link fails. Where machine learning is applied, it operates on pooled data at the server, so neither the inference step nor any presentation layer exists at the pond itself. The system proposed in this paper addresses both gaps by performing classification and presentation entirely on the receiving node, retaining full functionality in isolation from the cloud while keeping the assessment logic transparent and reproducible by hand.

Automated aquaculture monitoring was first implemented in the early 2000s using wired instrumentation in land-based recirculating systems, where the cost of cabling was justified by the value of the stock held in a small volume. The move to IEEE 802.15.4 wireless links removed the cabling cost but introduced a range limitation, which was in turn compensated by the additional complexity of a mesh topology. Single-board controllers running Arduino- or Raspberry Pi-class firmware later offered cellular-connected alternatives, constrained by the power draw and recurring cost of the cellular modem.

The arrival of LoRa after 2016 renewed interest in long-range, low-power monitoring of aquaculture sites [2], [12]. A measurement study across a large deployment established the practical range and reliability limits of the technology under field conditions [3]. Nguyen *et al.* reported a sensor network over shrimp ponds in the Mekong Delta, with range estimates of the order of several kilometres and node current drain

in the microamp range [4]. Kodali and Mahesh implemented a LoRa gateway bridged to an MQTT broker, publishing pond telemetry to a cloud subscriber [5]. A propagation study conducted over open water found that reflections from the water surface create pronounced constructive and destructive lobes at separations no larger than a single pond, which is a significant consideration for any in-pond LoRa deployment [6].

Two limitations recur across this literature. Most implementations are tied to a cloud backend, and none report what the farmer is left with when the backhaul link fails. Where machine learning is applied, it operates on pooled data at the server, so neither the inference nor any presentation layer exists at the pond itself. The system described here sits between these gaps: it classifies and presents data entirely on-device and remains fully functional in isolation from the cloud.

3. SYSTEM ARCHITECTURE

The system is organised in four layers around the data path shown in Fig. 1. Each layer is self-contained, so that a malfunction in a higher layer does not disrupt the layers beneath it.

3.1. Perception Layer

The transmitting node uses a DS18B20 digital temperature sensor on the 1-Wire interface and a SEN0161 glass-electrode pH probe [10]. The 0–3.3 V analogue output of the probe is digitised by the ESP32's built-in SAR ADC. Both measurements are then packed as IEEE-754 single-precision floats into a fixed-size record for transmission.

3.2. Transport Layer

Physical transport uses an SX1278 433 MHz module [9]. Each record is sent point-to-point at spreading factor 9, 125 kHz bandwidth and 4/5 coding rate with CRC enabled, chosen to balance link budget against airtime. No network server, gateway or join procedure is used; the topology is deliberately reduced to a single transmitter and single receiver per farm.

3.3. Processing Layer

The receiving node unpacks each record, applies calibration corrections, runs the assessment algorithm described in Section V, and persists the

timestamped result to non-volatile storage without requiring any higher-level service.

3.4. Presentation Layer

The receiving node hosts its own access point and serves a complete web analytics application. This is the sole source of trend information, statistics and grading explanation in the system, which by design does not use the cloud for either storage or presentation.

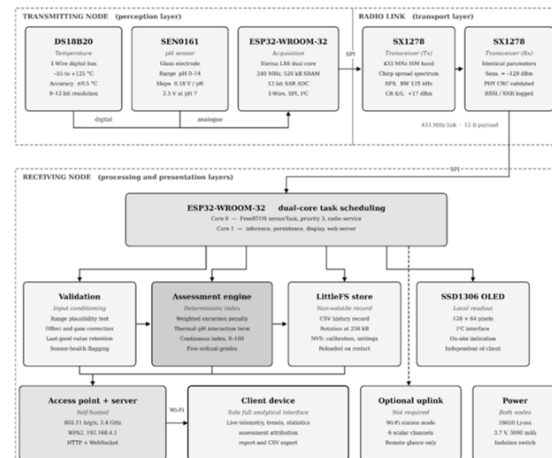


Figure 1: System block diagram, showing operating parameters for the sensing elements, the radio link and the processing and presentation stages. No part of the system depends on infrastructure beyond the two nodes.

4. HARDWARE REALISATION

Components were selected for low cost, availability, ease of use and reproducibility: an ESP32-WROOM-32 microcontroller [11], an SX1278 (Ra-02) LoRa module, a DS18B20 temperature sensor, a SEN0161 pH sensor, an SSD1306 OLED display for local indication, and a 3.7 V, 3000 mAh 18650 Li-ion cell. These are summarised in Table I.

The DS18B20 provides waterproof digital temperature measurement with $\pm 0.5^\circ\text{C}$ accuracy [10]. For the SEN0161, a millivolt transfer function was derived from the sensor characteristic and stored in non-volatile memory, from where it can be updated through the dashboard to account for electrode ageing and production tolerance. The analogue output of the pH sensor is connected to ADC1, since ADC2 is unavailable while the Wi-Fi radio is active.

Table II lists the SX1278 link settings. The same settings must be applied at both ends of the link: a mismatch in spreading factor, bandwidth or

coding rate leaves the receiving SX1278 unable to demodulate the incoming signal. Because point-to-point operation has no discovery phase, the result of such a configuration error is not an error message but simply silence, which makes the parameters in Table II the first thing to verify when a link fails to establish.

Table I. System Hardware Inventory

Element	Device	Interface / Principle
Processor	ESP32-WROOM-32	Dual-core Xtensa LX6, 240 MHz
Radio	SX1278 (Ra-02)	Chirp spread spectrum, 433 MHz
Temperature	DS18B20	Digital bandgap, 1-Wire
pH	SEN0161	Glass electrode, analogue
Display	SSD1306 OLED	128 × 64, I ² C
Supply	18650 Li-ion, 3.7 V	Rechargeable, 3000 mAh

Table II. LORA Link Parameters

Parameter	Value	Rationale
Carrier frequency	433 MHz (ISM)	Licence-exempt, good diffraction
Spreading factor	SF9	Range / airtime compromise
Bandwidth	125 kHz	Standard channel width
Coding rate	4/5	Lowest FEC overhead
TX power	+17 dBm	Within ISM limit
CRC / Payload	Enabled / 12 B	Rejects corrupt frames; fixed 3 × float32 record
Topology / Duplex	Point-to-point / half, uplink only	Single receiver per farm; no downlink needed

5. ON-NODE WATER QUALITY ASSESSMENT

The conventional approach of applying independent alarm thresholds to temperature and pH ignores the fact that the two variables interact. A given deviation from optimum pH is more or less dangerous depending on temperature, because temperature governs two critical processes: the conversion of ammonia to its toxic un-ionised form, and the quantity of dissolved oxygen the water can hold [8]. The assessment module therefore considers temperature and pH jointly.

5.1. Excursion Penalty and Quality Index

For a measured value v against an optimal window $[lo, hi]$, the excursion $e(v)$ is the distance by which the reading lies outside that window, and is zero whenever the value lies inside it, as defined in (1).

$$e(v) = \max(0, lo - v, v - hi) \quad (1)$$

Writing e_T and e_p for the temperature and pH excursions respectively, the penalty P is given by (2) and the quality index Q by (3).

$$P = w_T \cdot e_T^{\alpha_T} + w_p \cdot e_p^{\alpha_p} + k \cdot e_T \cdot e_p \quad (2)$$

$$Q = \max(0, 100 - P) \quad (3)$$

with Q clipped to the interval $[0, 100]$. The optimal windows are 26–30 °C for temperature and 6.8–8.2 for pH, drawn from established tolerances for warm-water finfish culture [8]. Because the exponents α_T and α_p exceed unity, a single large excursion is penalised more heavily than several small excursions of the same total magnitude, reflecting that one four-degree deviation is more harmful to the stock than four separate one-degree deviations. The cross term $k \cdot e_T \cdot e_p$ activates only when both variables are simultaneously out of range, capturing the compounded thermal and acid–base stress described above. The coefficient values used are listed in Table III.



Figure 2: Hardware prototype

5.2. Ordinal Grading, Confidence and Attribution

The continuous index Q is mapped onto five ordinal grades (Table IV) so that an operator is given a summary that is easy to remember, while the underlying value remains available on the dashboard for closer inspection or for export and later analysis. The thresholds and coefficients are

published for every grade, so that any individual assessment can be reproduced by hand.

Table III. Assessment Engine Coefficients

Symbol	Quantity	Value
$[lo, hi]_T$	Optimal temperature window	26.0 – 30.0 °C
$[lo, hi]_p$	Optimal pH window	6.8 – 8.2
w_T, w_p	Temperature / pH penalty weights	4.5 per °C / 18.0 per unit
α_T, α_p	Temperature / pH exponents	1.25 / 1.35
k	Interaction coefficient	0.9

Each grade carries a confidence value representing the normalised distance to the nearest threshold, reaching 1 at the centre of a band and 0.5 at its edges. This is not a probability; it indicates only how far the reading lies from a decision boundary. Since the instrument accuracy of 0.5 °C, together with a repeatability error of roughly 0.1 pH after two-point calibration, can easily place a reading on the wrong side of a threshold, a borderline result is deliberately reported in the worse grade, with the confidence value indicating the margin. This is the conservative bias appropriate to the application: the cost of a false alarm is far lower than the cost of undetected poor water quality.

In addition to the grade, the system compares the weighted penalty contribution of each parameter, rather than the raw excursions, to determine which factor dominates the result and in which direction, and therefore which countermeasure to recommend: reduced feeding and a partial water change for an alkaline drift, or additional pre-dawn aeration for temperature climbing too quickly. The computation is entirely deterministic and requires no training set or lookup table. It executes in a few microseconds from a program of under 200 bytes on a 240 MHz core.

6. LOCAL INTERFACE AND OPTIONAL UPLINK

6.1. Locally Hosted Analytical Server

Because rural sites frequently lack both broadband and reliable cellular coverage, the entire dashboard is hosted on the receiving node rather than in the cloud. Any smartphone able to join the access point published by the node reaches the dashboard directly at 192.168.4.1,

removing any dependence on external infrastructure. The dashboard uses WebSockets for live telemetry, charts and statistics, and a RESTful HTTP API to query and modify configuration values and to retrieve statistical summaries and grading rationale reports. Fig. 2 shows the live view.

Table IV. Index Thresholds and Grade Assignment

Grade	Index range	Operational interpretation
Excellent	$Q \geq 85$	Both parameters within window
Good	$70 \leq Q < 85$	Minor excursion, no action
Moderate	$55 \leq Q < 70$	Sustained excursion, monitor
Poor	$35 \leq Q < 55$	Significant stress, intervene
Critical	$Q < 35$	Severe stress, immediate action

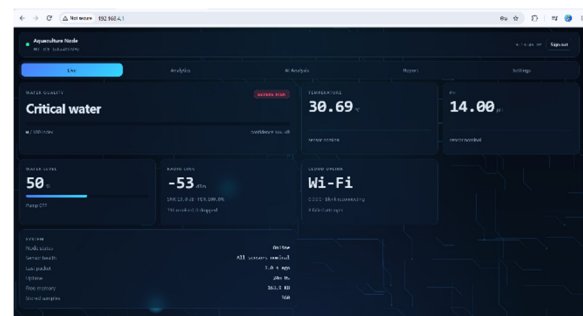


Figure 3: Live tab of the locally hosted dashboard, served from the receiving node at 192.168.4.1, showing the current water-quality grade and confidence, instantaneous temperature and pH, water level and pump state, LoRa link quality, cloud uplink status and node health counters.

6.2. Optional Blynk Cloud Uplink

When the receiving node is within range of an existing Wi-Fi network it can additionally operate in station mode and mirror a reduced set of telemetry channels to a Blynk cloud dashboard, allowing conditions to be inspected from outside the farm. Six virtual channels are published: temperature, pH, quality index, grade, water level and link quality. The uplink is strictly optional and additive; sensing, assessment, storage and visualisation all continue unchanged when it is unavailable, and the local dashboard remains the authoritative interface. Fig. 2 captures the uplink in a reconnecting state after eight failed attempts while the local dashboard continued to serve live data without interruption, which demonstrates the intended degradation behaviour. Fig. 3 shows the remote view when the uplink is available.

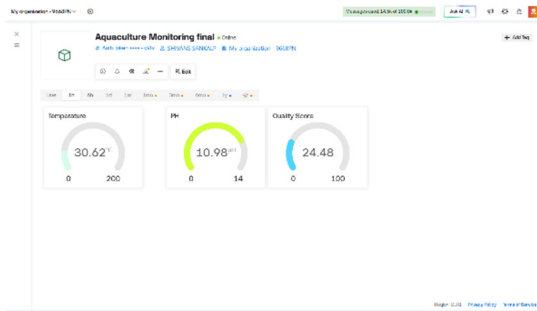


Figure 4: Optional Blynk cloud dashboard providing remote access to temperature, pH and quality score when an internet connection is available.

7. EXPERIMENTAL RESULTS

The prototype was operated continuously for 9 h 30 min at a sampling interval of 30 s. Over that period the receiver logged 17,043 packets with a delivery ratio of 99.99 %, a mean RSSI of -52 dBm and a mean SNR of 11.8 dB. The complete firmware, including sensing, inference, logging and the web server, occupied 68 kB of the 1408 kB flash region and left 161,000 bytes free of the 384,000-byte SRAM, which is ample headroom for the workload. These figures are collected in Table V.

Table V. SUMMARY OF MEASURED SYSTEM Performance

Metric	Value
Test duration	9 h 30 min
Sampling interval	30 s
Packets received	17,043
Packet delivery ratio	99.99 %
Mean RSSI	-52 dBm
Mean SNR	11.8 dB
Flash footprint	68 kB of 1408 kB
Free SRAM	161,000 B of 384,000 B

The dashboard delivered telemetry visualisation, statistics, trends, grading and report generation throughout, with no internet access at any point in the run. Fig. 4 shows the recent-samples panel, and Figs. 5 and 6 the temperature and pH history views with the summary statistics computed on the node itself.

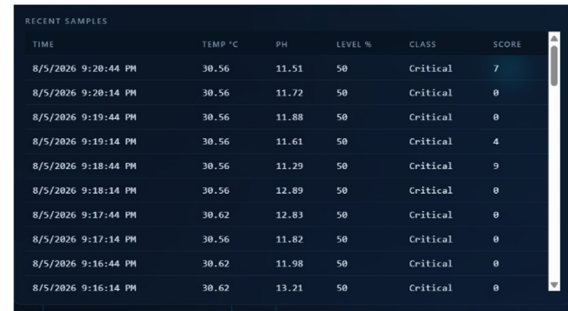


Figure 5: Recent samples panel of the dashboard, showing timestamped temperature, pH, water level, assigned grade and quality score recorded at 30 s sampling intervals.



Figure 6: Temperature history over a 360-sample observation window, with mean, minimum, maximum and hourly rate-of-change statistics computed on the node (mean 32.73 °C, range 29.62–33.69 °C, trend +0.90 °C/h).



Figure 7: pH history over the same 360-sample window (mean 9.60, range 7.48–14.00, trend -1.673 /h). The step near the end of the window corresponds to the electrode being lifted from the sample during handling, and illustrates the range-plausibility flagging described in Section III.

The one clear shortcoming observed was the absence of auto-calibration for the pH electrode. Readings drifted enough over the run that calibration is better performed at the bench before deployment than at the pond after installation.

8. DISCUSSION AND LIMITATIONS

Four limitations bound the present work. The system reasons over only two water-quality parameters, so anomalies in variables such as dissolved oxygen cannot be detected, even though dissolved oxygen is frequently the proximate cause of stock loss. The grading logic is heuristic, derived from published tolerance windows rather

than validated against a field-collected dataset, so the coefficients in Table III should be regarded as a starting point for calibration on a particular species and pond. The LoRa link carries no message authentication, which is acceptable for a single-farm point-to-point deployment but would not be so for shared infrastructure. Finally, the node depends on an external time source at start-up to timestamp its records.

Each of these is addressable within the existing architecture. Additional probes extend the perception layer without altering the transport or presentation layers; the assessment coefficients are already stored in non-volatile memory and updatable from the dashboard; and a per-record message authentication code would fit within the current 12-byte payload budget at modest airtime cost.

9. CONCLUSION

This paper has presented a LoRa-based, edge-first water-quality monitoring system for aquaculture that acquires, evaluates and visualises pond conditions on the device itself, with no dependence on cloud services or an internet connection. Testing demonstrated a packet delivery ratio of 99.99 % across 17,043 records over 9 h 30 min, with the complete firmware occupying 68 kB of flash. The results show that real-time, long-range, fully offline water-quality

monitoring and assessment can be achieved with simple and readily available hardware, and that the interpretation step usually delegated to a remote server can be performed at the pond without loss of transparency.

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