

Heterogeneous embedded monitoring of common carp pond water quality

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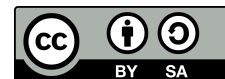
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ABSTRACT

Low-cost internet of things (IoT) systems are increasingly used in aquaculture, but many reports provide limited information on node architecture, signal processing, and validation scope. This paper presents a short-duration proof-of-concept evaluation of a heterogeneous two-node embedded system for a common carp pond. Node 1 used a LattePanda as a sensing node, coordinator, sink, edge gateway, and cloud interface; Node 2 used an Arduino UNO and an XBee router. Dissolved oxygen was measured at Node 1, while pH and temperature were measured at both nodes. The deployment produced 396 complete cloud records over 2 h 5 min 43 s, with a median positive interval of 16 s. Dissolved oxygen averaged 5.363 ± 0.105 mg/L. Against four field-reference readings, pH mean absolute errors (MAEs) were 0.1325 and 0.0775, and temperature MAEs were 0.1750 and 0.5250 °C for Nodes 1 and 2. The software calculated the U.S. Environmental Protection Agency (EPA) chronic ammonia criterion from pH and temperature; it did not measure total ammonia nitrogen (TAN). The results demonstrate end-to-end acquisition, wireless aggregation, cloud storage, and mobile visualization while defining the limitations of short-duration and non-time-matched reference data.

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1. INTRODUCTION

Aquaculture monitoring has evolved from isolated instruments toward connected sensing, cloud storage, and mobile decision support, although recent reviews still identify recurring limitations in calibration reporting, deployment duration, communication and data-quality assessment, and validation claims [1], [2]. Representative systems integrate temperature, pH, dissolved oxygen (DO), turbidity, salinity, or ammonia-related measurements with wireless communication and cloud platforms [3]–[13]. Multi-sensor integration improves spatial and temporal awareness, while edge devices can reduce dependence on continuous remote processing [12], [13]. However, high-frequency acquisition alone does not ensure scientific validity; sampling cadence, synchronization, sensor response, missing records, and the distinction between measured and model-derived variables must be reported explicitly [14].

Water temperature, pH, and DO influence fish metabolism, stress, behavior, and toxicity pathways [15]–[18]. These parameters are therefore important for common carp (*Cyprinus carpio*) ponds, which remain relevant to Indonesian freshwater aquaculture [19], [20], while broader pond water quality relationships and

management principles are discussed in [21], [22]. Temperature affects oxygen solubility and fish physiological load, whereas pH influences the relative fractions of ionized and unionized ammonia. Consequently, measurement uncertainty or incorrect interpretation of ammonia-related equations can produce misleading management conclusions [15]–[18].

The prototype integrates a LattePanda, Arduino UNO, XBee PRO S2B modules, ThingSpeak, and a React Native application, while a previous study by the authors separately evaluated the SEN0161 pH sensor [23]. Rather than claiming novelty as another generic internet of things (IoT) pond monitor, this work emphasizes a heterogeneous embedded architecture in which one platform simultaneously performs sensing, coordination, sink, edge-gateway, and cloud-interface functions, while a lower-complexity remote node performs distributed acquisition. This arrangement eliminates the need for a separate gateway computer and differentiates the functional roles of the two embedded nodes. The architecture follows the edge-computing principle of locating aggregation and communication functions closer to the sensing environment [24], [25].

A complete reanalysis of the archived field records and source code was conducted without a new experiment. The study contributes by: i) reproducibly describing the two-node coordinator-router architecture and end-to-end data path; ii) documenting sensor preparation, filtering, and calibration limitations; iii) analyzing all 396 archived cloud records rather than four reporting checkpoints; and iv) correcting the pH- and temperature-dependent U.S. Environmental Protection Agency (EPA) equation as a chronic ammonia criterion rather than a measurement of total ammonia nitrogen (TAN). Accordingly, the study evaluates a short-duration proof-of-concept embedded monitoring system while restricting its claims to the available evidence. Table 1 compares the proposed system with representative aquaculture-monitoring studies and highlights heterogeneous node roles and complete archived-data auditing as the principal contributions rather than a new sensing principle.

Table 1. Comparison with representative IoT aquaculture monitoring studies

Study	Main parameters	Architecture or method	Reported strength	Gap relevant to this work
Lin <i>et al.</i> [3]	pH, DO, temperature, and conductivity	Wireless multi-sensor platform	Integrated sensing	Different node roles were not emphasized.
Rashid <i>et al.</i> [4]	Water quality variables	IoT-based monitoring and prediction	Predictive component	Calibration and field-evaluation scope varied.
Blancaflor and Baccay [5]	Biofloc variables	Automated management system	Decision support	The control system was designed for a specific application.
Suriasni <i>et al.</i> [6]	TAN and reactor variables	Monitoring and control system	Direct TAN-focused system	The system used a more complex water-treatment configuration.
Hemal <i>et al.</i> [7]	Pond variables	Integrated Aquabot system	Monitoring and recommendations	The study employed a different deployment architecture.
Abid <i>et al.</i> [8]	Biofloc variables	IoT and machine learning system	Data-driven assessment	The system required a higher computational scope.
Shete <i>et al.</i> [9]	Water quality variables	Real-time IoT monitoring method	Implementation procedure	Node heterogeneity was not the central contribution.
Mamun <i>et al.</i> [10]	Biofloc variables	Real-time monitoring and control	End-to-end control	The system was evaluated in a different culture environment.
Malandrakis [11]	RAS variables	Monitoring and alerting system	Cost-effective deployment	The system was designed for recirculating aquaculture rather than a pond.
This work	DO, pH, temperature, and a derived ammonia criterion	LattePanda coordinator and edge gateway with an Arduino–XBee router	Heterogeneous node roles and a complete audit of archived data	Short-duration, single-site proof-of-concept evaluation.

2. PROPOSED EMBEDDED ARCHITECTURE

2.1. Heterogeneous node roles

Figure 1 summarizes the system. Node 1 used a LattePanda mini-computer with an integrated Arduino-compatible coprocessor. It acquired DO, pH, and water temperature; received the remote-node packet; separated the fields; and served as XBee coordinator, sink, edge gateway, and internet interface. Node 2 used an

Arduino UNO to acquire pH and temperature and was configured as an XBee router. The wireless link followed the coordinator-router model supported by IEEE 802.15.4-based XBee modules [26], [27].

The architecture intentionally assigned more functions to Node 1. This avoided adding a separate gateway computer: the same device that sampled data from local sensors also aggregated the remote payload and executed the cloud client. Node 2 remained a lower-resource sensing unit. The design therefore illustrates a practical heterogeneous edge topology rather than two identical sensor boards.

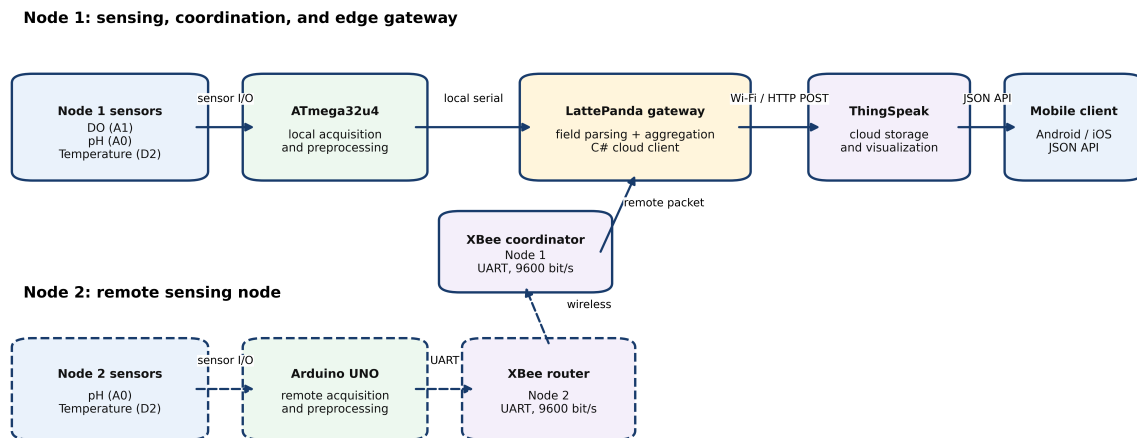


Figure 1. Heterogeneous two-node embedded edge-to-cloud architecture and end-to-end data path

2.2. End-to-end data path

The serial communication rate documented in the source material was 9600 bit/s. Node 2 transmitted a packet containing its node identifier and ordered data fields. The coordinator received and parsed the packet, combined it with Node 1 values, and forwarded seven fields to ThingSpeak through an HTTP POST request. The mobile application retrieved the stored feeds using the ThingSpeak application programming interface [28]. The system was designed to display separate Nodes 1 and 2 views on Android and iOS.

This study did not archive packet-level transmission attempts, received-signal-strength data, energy measurements, or end-to-end latency timestamps. Accordingly, the evaluation is limited to successful end-to-end operation and the timing of cloud records; it does not report packet delivery ratio, radio range, power efficiency, or network latency. Table 2 summarizes the hardware, interfaces, and functions assigned to each node and platform.

Table 2. Hardware, interfaces, and assigned functions

Element	Node/location	Interface	Function in the prototype
LattePanda with Arduino-compatible coprocessor	Node 1	Local analog-to-digital converter (ADC)/digital I/O, USB, and Wi-Fi	Local data acquisition, XBee coordinator, sink node, edge gateway, and cloud client.
Arduino UNO	Node 2	ADC, 1-wire, and software serial	Remote data acquisition and XBee router.
Analog DO kit	Node 1	Analog input A1	DO acquisition after saturation-point calibration [29].
SEN0161 pH interface	Nodes 1 and 2	Analog input A0	pH acquisition using single-point adjustment and filtering [23], [30].
DS18B20	Nodes 1 and 2	1-Wire digital input D2	Water temperature acquisition [31].
XBee PRO S2B	Both nodes	UART at 9600 bit/s	Coordinator-router wireless data transmission [26], [27].
ThingSpeak	Cloud	HTTP POST and REST feed	Storage and visualization of the seven transmitted data fields [28].
React native application	User device	ThingSpeak feed retrieval	Cross-platform mobile data visualization.

3. METHOD

3.1. Signal acquisition and preprocessing

The DO interface was connected to analog input A1. The code buffered 30 ADC values, sorted the temporary buffer and used a median statistic to reduce impulsive noise. The median voltage was divided by the stored saturation voltage and multiplied by the temperature-indexed saturation concentration table. The documented calibration routine immersed the probe in oxygen-saturated water, waited for stabilization, and stored the saturation voltage and calibration temperature in electrically erasable programmable read-only memory. This procedure is consistent with the operating principle of the low-cost galvanic kit [29].

A critical limitation was identified in the archived code: the dynamic update of the DO compensation temperature was disabled, so the computation used the stored calibration temperature or the default 25 °C value. The revised analysis therefore treats DO as a prototype output obtained after a single saturation-point procedure, not as a fully traceable, dynamically temperature-compensated measurement.

Each pH channel was connected to analog input A0. The source code collected 40 ADC values, discarded the extreme minimum and maximum contributions during averaging, converted the result to voltage, and applied the implemented linear relation $\text{pH} = 3.5V + \text{offset}$. The thesis documented a single-point adjustment using a pH 7 solution. No multi-point calibration curve, slope uncertainty, post-deployment drift test, or traceable calibration certificate was available. The method is consequently described as a single-point adjustment and field reference comparison rather than complete metrological calibration.

Water temperature was measured using waterproof DS18B20 probes [31]. The archived material did not contain a separate multi-point temperature calibration. Agreement was assessed against a mercury thermometer at four reporting checkpoints. The pH and temperature procedures must therefore be interpreted within the resolution and synchronization limitations of the available reference instruments. Figure 2 summarizes the implemented sequence from local sampling and filtering to field aggregation and cloud upload. The diagram is a functional summary; Node 2 performed its local acquisition and transmitted the resulting fields to Node 1 before the seven-field record was posted to ThingSpeak.

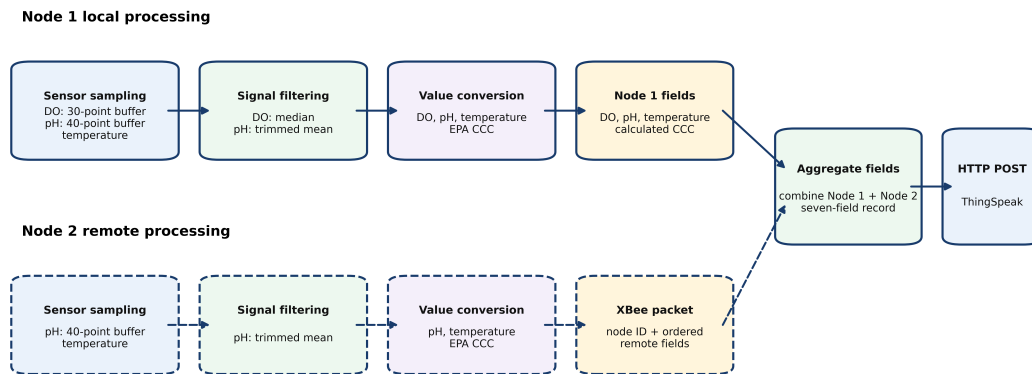


Figure 2. Two-node embedded data-processing and cloud-upload workflow

3.2. Calculated chronic ammonia criterion

The prototype did not contain an ammonia or TAN sensor. The fourth and seventh cloud fields were calculated from pH and temperature. Review of the source equation showed that it corresponds to the U.S. EPA freshwater chronic ammonia criterion or criterion continuous concentration (CCC), not to an equation that derives the actual TAN concentration from pH and temperature [32]. The original term “ammonia measurement” has therefore been removed throughout the revised manuscript. The implemented regulatory calculation is given in (1).

$$\text{CCC} = 0.8876 \left[\frac{0.0278}{1 + 10^{7.688 - \text{pH}}} + \frac{1.1994}{1 + 10^{\text{pH} - 7.688}} \right] \left[2.126 \times 10^{0.028(20 - \max(T, 7))} \right] \quad (1)$$

where CCC is the chronic ammonia criterion in mg N/L and T is water temperature in °C. The calculated quantity is a pH- and temperature-dependent regulatory criterion. It is not interchangeable with a laboratory TAN concentration and cannot be validated by computing sensor accuracy against a TAN laboratory result. The archived laboratory TAN value is therefore reported only as contextual information.

3.3. Field setup and acquisition protocol

The field test was conducted at an outdoor common carp pond on Jl. Bunga Cempaka, Tanjung Sari, Medan Selayang, Indonesia. The documented pond dimensions were 40 m × 11 m. The pond contained approximately 100 common carp with an indicated mass range of 200–400 g. Both nodes were placed at the pond edge because access to the center and the Node 1 power supply were limited. The exact node separation, immersion depth, pond depth, aerator position, feeding events, and meteorological conditions were not preserved in the archived records and are listed as limitations. Figure 3 presents only the documented pond dimensions and edge placement; it must not be interpreted as an exact map of node separation or probe depth.

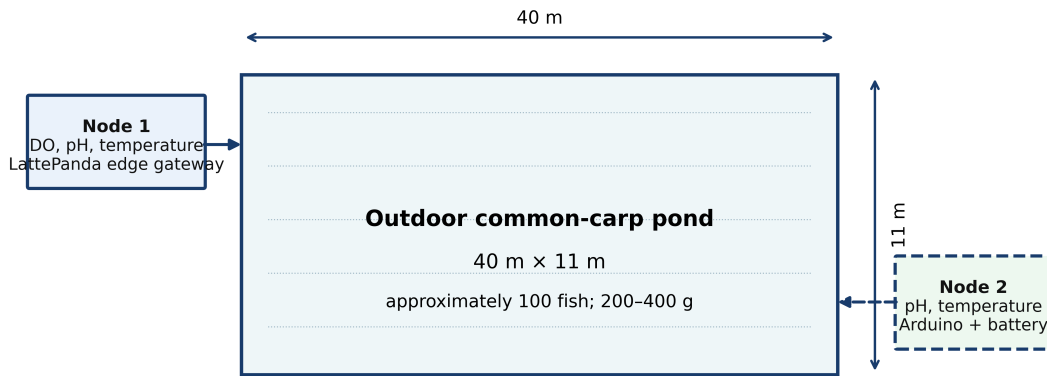


Figure 3. Conceptual placement of the two sensor nodes at the pond edge

Figure 4 shows the physical implementation of the two embedded nodes. Figure 4(a) presents the Node 1 assembly, which integrates the LattePanda-based sensing unit, XBee coordinator, and edge-gateway functions. Figure 4(b) shows the Node 2 assembly, consisting of the Arduino-based remote sensing unit and XBee communication module. These photographs document the implemented hardware assemblies but do not indicate the exact probe placement during the field measurement session.

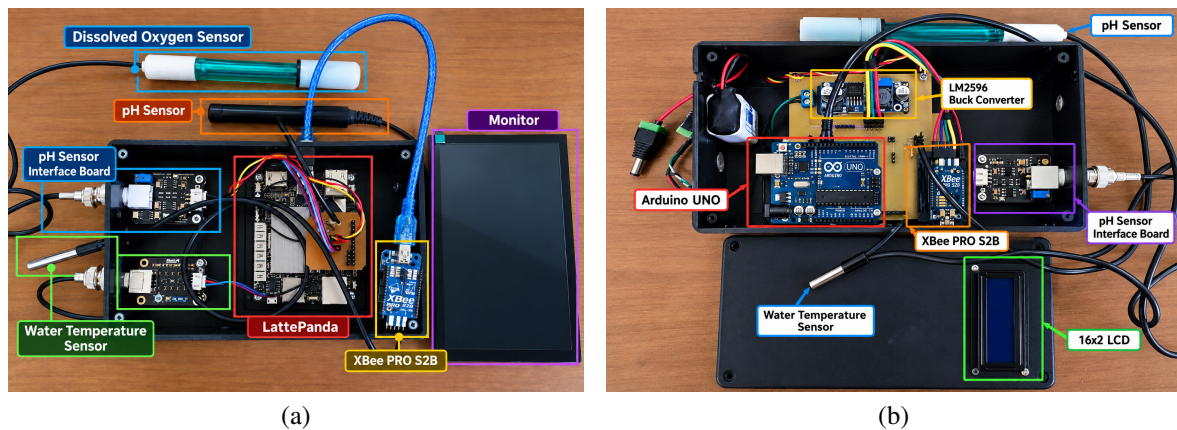


Figure 4. Implemented hardware assemblies; (a) Node 1 LattePanda-based sensing and edge-gateway unit and (b) Node 2 Arduino–XBee remote sensing unit

The complete cloud export contained 396 rows and seven numeric fields. The first timestamp was 2019-01-29 07:14:37 UTC, and the last was 09:20:20 UTC, corresponding to 14:14:37–16:20:20 Western In-

donesian Time (WIB). The observed duration was 2 h 5 min 43 s. The program targeted an update near 15 s; the median positive interval between archived timestamps was 16 s. The four rows previously reported at approximately 30 min intervals were only summary checkpoints and not the complete dataset. Table 3 consolidates the documented field protocol, reference devices, synchronization limits, and archived-record timing.

Table 3. Field-test and archived-data protocol

Item	Documented value
Pond and stock	Outdoor pond measuring 40 m × 11 m, containing approximately 100 common carp with an indicated mass of 200–400 g.
Node placement	Both sensor nodes were positioned at the pond edge. The exact distance between the nodes and the probe-immersion depths were not documented.
Deployment period	January 29, 2019, from 07:14:37 to 09:20:20 UTC, corresponding to 14:14:37–16:20:20 WIB.
Duration and records	The deployment lasted 2 h 5 min 43 s and produced 396 complete cloud records, with seven data fields in each record.
Update timing	The target update interval was approximately 15 s, while the median positive interval between archived records was 16 s.
Reference devices	A portable pH meter, a mercury thermometer, and one laboratory report containing DO and TAN measurements were used as reference sources.
Reference synchronization	The pH and temperature comparisons were limited to four checkpoints ($n = 4$). The laboratory sampling time was not matched to the complete cloud-recording period.

3.4. Reference comparison and statistical analysis

The revised analysis avoids percentage accuracy for pH and temperature. Percentage accuracy can appear artificially high when the denominator is a large absolute temperature or a pH number whose scale is logarithmic. For each set of four field-reference pairs, bias, mean absolute error (MAE), root mean squared error (RMSE), and maximum absolute error were calculated. In (2)–(4) define the three summary metrics used in the analysis.

$$\text{Bias} = \frac{1}{n} \sum_{i=1}^n (y_i - r_i), \quad (2)$$

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |y_i - r_i|, \quad (3)$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - r_i)^2}. \quad (4)$$

Here, y_i is a node value and r_i is the corresponding field reference. Because only one laboratory DO value and one laboratory TAN value were available and their sampling was not time-matched to the cloud sequence, neither was used to estimate accuracy, MAE, or RMSE. The complete 396-row series was summarized by the mean, standard deviation (SD), median, minimum, and maximum.

Timestamp quality control identified two non-monotonic records and 11 positive intervals longer than 30 s. These rows were retained because all seven fields were complete, but the timing anomalies were disclosed. The cloud export confirms successful stored records; it does not identify the number of attempted radio packets or failed HTTP requests. For chronological visualization, the time-series records were ordered by their actual WIB timestamps.

4. RESULTS AND DISCUSSION

4.1. End-to-end embedded and cloud operation

The remote Arduino node transmitted its pH, temperature, and derived-criterion fields to the LattePanda coordinator. Node 1 combined these values with local DO, pH, temperature, and derived criterion, and the C# cloud client mapped the seven values to ThingSpeak fields. The react native client retrieved the feed

and separated the two node views. The 396 complete cloud rows demonstrate that the implemented sensing-to-cloud-to-mobile chain operated during the archived field session.

The result is evidence of functional integration, not a radio reliability benchmark. No packet sequence counter, transmission-attempt log, received-signal-strength trace, or synchronized client-server latency record was available. Claims concerning packet delivery ratio, range, network delay, battery life, and long-term uptime were therefore removed.

4.2. Temporal water quality observations

Table 4 summarizes all 396 archived records and provides the statistical context for the time-series plots that follow.

Table 4. Descriptive statistics from all 396 archived cloud records

Variable	Mean	SD	Median	Minimum	Maximum
DO Node 1 (mg/L)	5.3626	0.1052	5.3300	5.1300	6.4300
pH Node 1	8.2352	0.1415	8.2300	7.8800	8.5600
Temperature Node 1 (°C)	30.8015	0.7334	31.3000	29.2000	32.2000
Calculated CCC Node 1 (mg N/L)	0.2747	0.0598	0.2720	0.1510	0.4400
pH Node 2	8.2319	0.1670	8.2200	7.8400	8.8600
Temperature Node 2 (°C)	32.0354	0.2807	32.2000	31.3000	32.6000
Calculated CCC Node 2 (mg N/L)	0.2570	0.0652	0.2540	0.0870	0.4400

Figure 5 shows an early transient in the DO output followed by a narrower band. Across the complete session, DO averaged 5.3626 mg/L with an SD of 0.1052 mg/L. The single laboratory value was 5.18 mg/L; however, the laboratory sample was not synchronized with the full sensor series. It is therefore shown only as contextual information. The previously reported mean of 5.97 mg/L was inconsistent with both the four checkpoint readings and the complete cloud export and has been corrected.

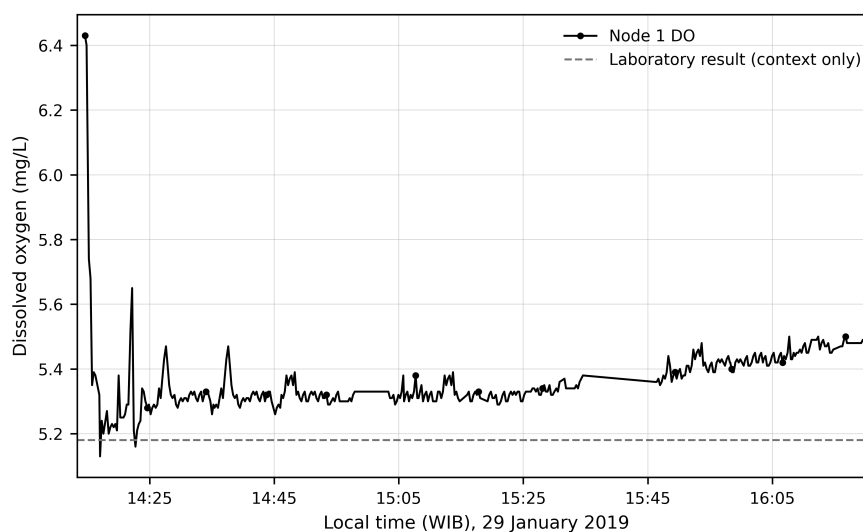


Figure 5. Dissolved-oxygen output at Node 1 plotted against the actual archived local timestamps

The mean pH values were nearly identical between nodes, although Node 2 had a larger SD and wider range. The time-series comparison in Figure 6 shows short-term fluctuations around a slightly alkaline central level. These fluctuations may combine real local variation, electrode response, ADC noise, and single-point-adjustment uncertainty. The archived experiment cannot separate those components.

Node 1 temperature decreased over the observation period, whereas Node 2 remained more stable and generally higher. The difference may reflect spatial placement, shading, probe contact, or sensor/reference timing, but the archived documentation is insufficient to assign a single cause. Figure 7 therefore presents the observation without treating the inter-node difference as proven pond-scale spatial heterogeneity.

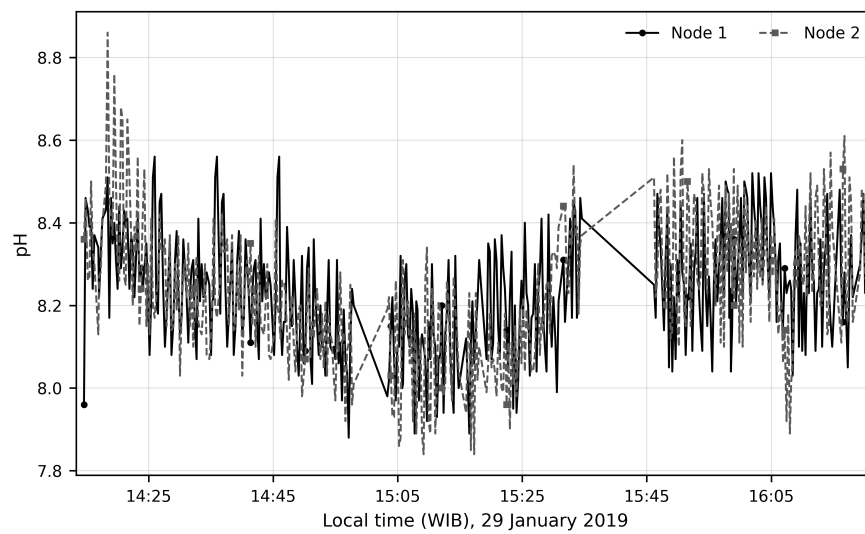


Figure 6. pH time series for Nodes 1 and 2

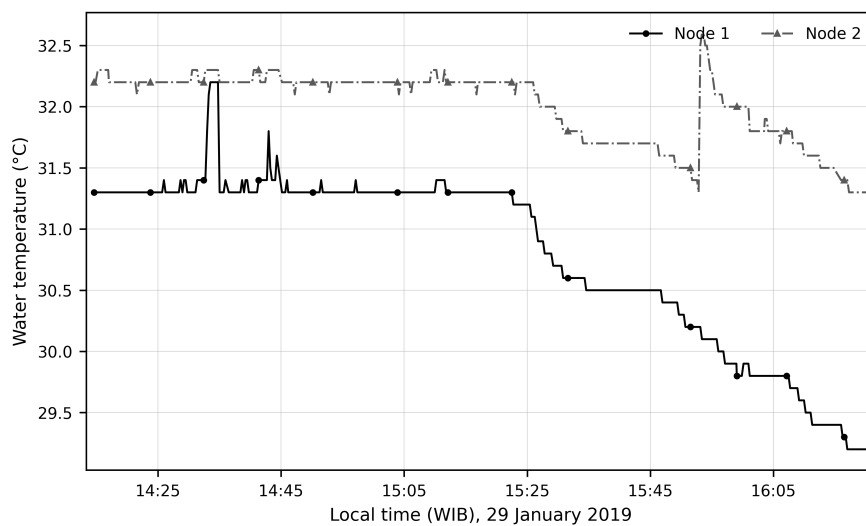


Figure 7. Water temperature time series for Nodes 1 and 2

4.3. Agreement with field references

Table 5 reports the checkpoint-level agreement metrics for pH and temperature at both nodes. The pH comparison was closer at Node 2 than at Node 1 according to MAE and RMSE. Temperature agreement was closer at Node 1, whereas Node 2 included a maximum absolute difference of 1.0 °C. These metrics are more interpretable than the previous values of approximately 98–99% “accuracy.” Nevertheless, $n = 4$ is insufficient for a general sensor-accuracy claim, confidence-interval estimation, or full agreement analysis. The results should be read as checkpoint-level field agreement.

Table 5. Agreement metrics based on four reference-matched observations per variable

Variable	n	Bias	MAE	RMSE	Maximum absolute error
pH Node 1	4	+0.0075	0.1325	0.1712	0.2600
pH Node 2	4	-0.0325	0.0775	0.0847	0.1100
Temperature Node 1 (°C)	4	-0.0750	0.1750	0.1803	0.2000
Temperature Node 2 (°C)	4	+0.0750	0.5250	0.6500	1.0000

4.4. Interpretation of the calculated ammonia criterion

Figure 8 plots the values produced by the U.S. EPA CCC equation. The Node 1 mean was 0.2747 mg N/L, and the Node 2 mean was 0.2570 mg N/L. Lower criterion values occurred when the pH-temperature combination made ammonia more restrictive. These series are useful as derived contextual indicators, but they are not TAN measurements. The laboratory TAN result of 0.266 mg/L cannot be used as a target for sensor-error computation because the calculated CCC and measured TAN represent different quantities [32]. Accordingly, Figure 8 displays only the two calculated CCC series; the laboratory TAN value is retained solely in the accompanying discussion.

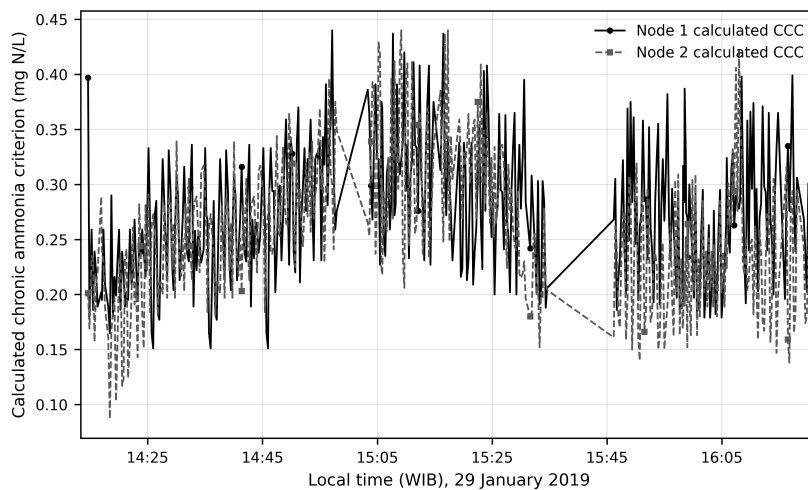


Figure 8. Calculated U.S. EPA chronic ammonia criterion for Nodes 1 and 2

This correction changes the scientific interpretation of the system. The prototype directly monitored DO, pH, and temperature. It additionally computed a criterion from pH and temperature. Any future claim of continuous TAN monitoring would require a direct ammonia measurement method, appropriate standards, and time-matched laboratory validation.

4.5. Cloud-record timing and data completeness

All 396 exported rows contained the seven expected numeric fields. The median positive interval was 16 s, close to the intended update rate. Two timestamps were non-monotonic, and 11 positive intervals exceeded 30 s. Figure 9 exposes these timing irregularities rather than smoothing them away. Possible causes include local buffering, timestamp ordering, cloud-update delays, or temporary communication interruption; the available logs cannot distinguish among them. Figure 9 visualizes the positive timestamp intervals, while Table 6 summarizes the corresponding completeness and timing indicators.

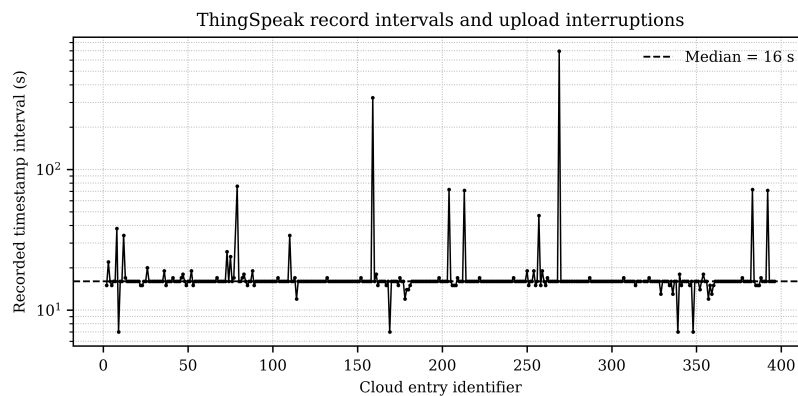


Figure 9. Intervals between consecutive cloud timestamps

Table 6. Archived cloud-record quality indicators

Indicator	Result	Interpretation
Complete rows	396 of 396	All seven expected fields were present in the exported cloud records.
Observed duration	2 h 5 min 43 s	The archived data represent only a short-duration proof-of-concept deployment.
Median positive interval	16 s	The observed median interval was close to the intended update interval of approximately 15 s.
Non-monotonic timestamps	2 records	Two timestamp-ordering anomalies were identified and disclosed, while the corresponding measurement values were retained.
Positive intervals greater than 30 s	11 intervals	These longer intervals may indicate temporary buffering or delays in wireless communication, internet transmission, or cloud storage.
Packet delivery ratio	Not available	The number of transmission attempts and packet-sequence counters were not recorded; therefore, the packet delivery ratio could not be calculated.

4.6. Relation to previous work and practical meaning

Compared with the systems summarized in Table 1, the main contribution is not a new sensing principle. It is the explicit heterogeneous assignment of embedded roles and the audit of an end-to-end implementation using the complete archived dataset. Recent systems increasingly include automated control, machine learning, alerts, or larger sensor sets [5]–[13]. The present prototype is simpler and older in hardware generation, but it demonstrates how a resource-rich edge gateway can aggregate a lower-resource remote node without a separate gateway computer.

The reanalysis also illustrates a broader reporting lesson for low-cost aquaculture IoT research. Complete time-series records, clear distinction between measured and derived quantities, calibration scope, synchronization, and communication-log limitations are essential for reproducibility [1], [2], [14]. Correcting these issues produces a more defensible proof-of-concept even though it reduces the breadth of the original claims.

4.7. Limitations

The study has seven principal limitations. First, the deployment lasted only about two hours at one pond and cannot characterize day-night cycles, seasonal changes, weather effects, feeding events, or long-term sensor drift. Second, pH adjustment was single-point and DO calibration was single-point saturation calibration; multi-point traceable calibration records were unavailable. Third, dynamic temperature compensation of DO was not active in the archived code. Fourth, only four pH and temperature reference pairs and one non-time-matched laboratory report were available. Fifth, node distance, immersion depth, pond depth, aeration, and meteorological conditions were not documented. Sixth, packet attempts, signal strength, latency, and power consumption were not logged. Seventh, the calculated ammonia criterion is not a TAN measurement.

These limitations prevent claims of commercial readiness, long-term reliability, complete spatial characterization, or validated ammonia monitoring. They also define the next experimental priorities: multi-point calibration, synchronized laboratory sampling, direct TAN sensing where required, longer deployment, packet-sequence and signal-strength logging, power profiling, and environmental-event annotation.

5. CONCLUSION

A heterogeneous two-node embedded monitoring system for a common carp pond was reconstructed and re-evaluated from the complete archived thesis records without a new experiment. The LattePanda combined local sensing, XBee coordination, edge aggregation, cloud communication, and gateway functions, while the Arduino UNO operated as a remote sensing router. The end-to-end chain stored 396 complete seven-field records over 2 h 5 min 43 s, with a median positive cloud interval of 16 s.

Across the archived session, DO at Node 1 averaged 5.3626 ± 0.1052 mg/L. For four checkpoint comparisons, pH MAE values were 0.1325 and 0.0775 for Nodes 1 and 2, and temperature MAE values were 0.1750 and 0.5250 °C. The previous DO average and percentage-accuracy claims were corrected. The values previously labeled as TAN were also corrected: they are U.S. EPA chronic ammonia criteria derived from pH and temperature, not measured TAN. The revised evidence supports a short-duration proof-of-concept for embedded acquisition, wireless aggregation, cloud storage, and mobile visualization. Longer synchronized validation, multi-point calibration, direct ammonia measurement, communication-performance logging, and power analysis remain necessary before operational deployment can be claimed.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : Conceptualization

M : Methodology

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Va : Validation

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I : Investigation

R : Resources

D : Data Curation

O : Writing - Original Draft

E : Writing - Review & Editing

Vi : Visualization

Su : Supervision

P : Project Administration

Fu : Funding Acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The authors also declare that they have no non-financial competing interests, including political, personal, religious, ideological, academic, or intellectual interests, that could be perceived as influencing this work.

DATA AVAILABILITY

The archived sensor dataset and the processed statistical summaries that support the findings of this study are available from the corresponding author upon reasonable request. The dataset contains environmental sensor records and does not include human-participant information.

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