

Development of a Wireless Sensor-Based Shrimp Pond Water Quality Monitoring System

Muhammad Ikbali¹

¹Universitas Hasanuddin, Indonesia

ARTICLE INFO

Received: 20 Jan 2025
Revised: 12 Feb 2025
Accepted: 23 Feb 2025
Available online: 01 March 2025

Keywords:

Shrimp Aquaculture
Wireless Sensor Network
Water Quality Monitoring
Dissolved Oxygen

Corresponding Author:
Muhammad Ikbali

Email:

Copyright © 2025, Journal of
Agrocomplex and
Engineering, Under the license
[CC BY- SA 4.0](#)



ABSTRACT

Purpose: The study aims to design, develop, and validate a wireless sensor-based monitoring system for shrimp ponds, addressing the limitations of conventional manual monitoring in capturing dynamic fluctuations of critical water quality parameters.

Subjects and Methods: The system was equipped with low-power sensors to measure dissolved oxygen (DO), pH, temperature, and salinity, integrated with solar-assisted power, wireless transmission, and a cloud-based dashboard. Calibration and validation were first conducted under laboratory conditions, followed by an eight-week field deployment across three shrimp ponds. Accuracy was evaluated against standard reference instruments, while network performance and energy autonomy were continuously monitored.

Results: Laboratory calibration achieved high accuracy with RMSE values of 0.08 for pH, 0.18 mg/L for DO, 0.15 °C for temperature, and 0.42 ppt for salinity. Field trials generated more than 190,000 valid measurements, revealing consistent diurnal water quality dynamics. Sensor data showed strong concordance with manual reference measurements (concordance correlation coefficient > 0.95). The wireless communication network achieved a packet delivery ratio of 96.7% with median latency of 2.3 seconds. Solar-assisted nodes maintained uninterrupted operation for more than 30 days, ensuring system robustness in outdoor aquaculture conditions.

Conclusions: The developed wireless sensor-based monitoring system proved reliable for real-time aquaculture applications, offering both technical accuracy and practical benefits for farm management. The system enabled proactive interventions, such as timely aeration during pre-dawn oxygen depletion, thereby reducing shrimp stress and mortality risk. Future improvements will focus on enhancing sensor resistance to biofouling and integrating predictive analytics for decision support. Overall, the study demonstrates the feasibility of Internet of Things (IoT)-enabled solutions to advance sustainable and precision shrimp aquaculture.

INTRODUCTION

Shrimp aquaculture has become one of the most rapidly expanding sectors in global food production, contributing significantly to food security and economic development in many coastal regions. Intensive cultivation systems, however, are highly sensitive to fluctuations in water quality parameters such as dissolved oxygen (DO), pH, temperature, and salinity (Mariu et al., 2023; Gorde & Jadhav, 2013; Nazneen et al., 2019). Even short-term imbalances in these

variables can induce stress, reduce growth rates, increase feed conversion ratios, and elevate the risk of disease outbreaks. Among these, low dissolved oxygen levels during pre-dawn hours remain a leading cause of mass mortality in shrimp ponds, often resulting in severe economic losses for farmers (Tenório et al., 2022; Mondal et al., 2025; Deans, 2022).

Traditionally, water quality in shrimp ponds has been monitored through manual spot-checks using portable devices. While such methods are inexpensive and widely adopted, they are inherently limited in frequency, labor-intensive, and incapable of capturing the dynamic, diurnal fluctuations characteristic of pond ecosystems. Consequently, critical events such as nocturnal oxygen depletion often go undetected until after significant damage has occurred. This monitoring gap underscores the urgent need for continuous, automated, and real-time observation systems that can support proactive pond management (Wang, 2024; Kanwal et al., 2024; Bose et al., 2024).

Recent advances in wireless sensor networks (WSNs) and Internet of Things (IoT) technologies have opened new opportunities for precision aquaculture (Rastegari et al., 2023; Liu et al., 2022; Prapti et al., 2022). Several studies have demonstrated the feasibility of using distributed sensor nodes to measure environmental parameters in real time, transmitting data to centralized platforms for visualization and analysis. However, many existing prototypes face challenges such as limited deployment duration due to energy constraints, reduced data reliability in field conditions, and inadequate integration with user-friendly interfaces for farmers (Fountas et al., 2015; Mössinger et al., 2022; Saiz & Rovira, 2020; Garg et al., 2016). Moreover, relatively few systems have been rigorously validated under long-term operational conditions in commercial shrimp ponds, leaving a gap between laboratory prototypes and field-ready solutions.

This study addresses these challenges by developing and deploying a wireless sensor-based water quality monitoring system specifically designed for shrimp ponds. The system integrates low-power, solar-assisted sensor nodes with robust wireless communication and a cloud-based data platform, enabling continuous monitoring of DO, pH, temperature, and salinity. The objectives of this research are threefold: (i) to evaluate the accuracy and reliability of the developed sensors under both laboratory and field conditions, (ii) to assess the stability of wireless data transmission and energy autonomy in a multi-week deployment, and (iii) to analyze the practical implications of real-time monitoring for aquaculture management. By bridging the gap between prototype development and field application, this work contributes to advancing sustainable and technology-enabled shrimp farming.

METHODOLOGY

This study adopts a research and development (R&D) approach combined with laboratory experiments and field case studies. The primary objective is to design, construct, and evaluate a wireless sensor-based water quality monitoring system for shrimp ponds, capable of operating in real time with low power consumption. The development process was structured in several stages: identifying system requirements and performance specifications, designing the system architecture, calibrating sensors under controlled laboratory conditions, and conducting extended field trials in representative aquaculture ponds. The prototype consisted of floating sensor nodes built on a low-power microcontroller platform with LoRa communication, equipped with sensors for pH, dissolved oxygen (DO), temperature, and salinity. These nodes transmitted data to an edge gateway, which relayed the information to a backend *time-series database* and visualization dashboard with integrated early-warning notifications.

The initial stage of the research focused on needs assessment and system specification, where accuracy targets were established (pH ± 0.1 ; DO ± 0.2 mg/L; temperature ± 0.2 °C; salinity ± 0.5 ppt). Communication performance was set at a minimum of 95% *packet delivery ratio* (PDR) with a median latency of less than five seconds. After hardware and firmware development, sensor calibration was performed in the laboratory using international standards: NIST buffer solutions (pH 4.01, 7.00, 10.01), two-point calibration for DO (sodium sulfite solution for 0% and air-saturated water for 100%), and KCl reference solutions for salinity. Stability tests were conducted through 72-hour immersion trials to evaluate repeatability and potential drift over time.

Following laboratory validation, the system was deployed in three intensive shrimp ponds (2,000–5,000 m² each) over an eight-week trial period corresponding to the grow-out phase (weeks 4–11 of the production cycle). Sensor nodes were anchored at 0.5 m depth within the mixing zone and configured to acquire measurements every five minutes, with adaptive sampling at one-minute intervals during rapid fluctuations. As ground-truth references, manual *spot-checks* were performed three times daily (06:00, 12:00, 18:00) using calibrated laboratory-grade instruments. With this setup, each pond generated approximately 16,000 data points per parameter, resulting in a dataset of more than 190,000 observations across the three ponds, ensuring sufficient statistical robustness.

The collected data were processed and analyzed to assess both technical performance and operational impact. Sensor accuracy was evaluated using *mean absolute error* (MAE), *root mean square error* (RMSE), and *mean absolute percentage error* (MAPE). Agreement with reference instruments was examined using *Bland–Altman plots* and *Lin’s concordance correlation coefficient* (CCC). Reliability was tested through intra-class correlation (ICC) and drift analysis over weekly intervals. Network performance was evaluated in terms of PDR, received signal strength indicator (RSSI), signal-to-noise ratio (SNR), and transmission latency. In addition, energy autonomy was estimated by monitoring average daily battery consumption and projecting operational lifetime under limited solar input. Operationally, system responsiveness was measured by recording the time between critical DO drops below 4 mg/L and the issuance of alarms, as well as the corrective actions taken by farmers.

Statistical analyses included normality testing (Shapiro–Wilk), paired *t-tests* or Wilcoxon signed-rank tests for sensor-reference comparisons, and linear mixed-effects models for examining pond-to-pond and temporal variability. Data quality assurance (QA/QC) protocols consisted of range checks, rate-of-change detection, and flatline detection, with flagged categories for “good,” “questionable,” or “bad” data. The overall success criteria were defined as meeting sensor accuracy thresholds, achieving PDR ≥95% with latency ≤5 seconds, and sustaining a minimum of 30 days of autonomous operation. Through this integrated methodology, the study not only delivers a technically robust prototype but also provides empirical evidence of the system’s effectiveness in supporting precision and sustainable shrimp aquaculture practices.

RESULTS AND DISCUSSION

Sensor Calibration and Laboratory Validation

The laboratory calibration results demonstrated that the sensors performed within the expected ranges of accuracy. Table 1 shows the summary of calibration results compared to the reference standards. The RMSE for pH and temperature sensors was below 0.1 and 0.2 °C, respectively, while the DO sensor achieved ±0.18 mg/L accuracy. The salinity sensor exhibited the highest variability, though still within the ±0.5 ppt target range.

Table 1. Sensor Calibration Results (n = 30 per parameter)

Parameter	Reference Range	RMSE (Sensor vs Reference)	Mean Bias	Target Accuracy	Achieved
pH	4.0 – 10.0	0.08	+0.02	±0.1	✓
DO (mg/L)	0 – 15	0.18	−0.05	±0.2	✓
Temp (°C)	20 – 35	0.15	+0.10	±0.2	✓
Salinity (ppt)	5 – 35	0.42	+0.20	±0.5	✓

These results indicate that the developed prototype is suitable for deployment in field conditions.

Field Deployment and Data Acquisition

The system was deployed in three shrimp ponds (P1–P3) for eight weeks, generating over 190,000 valid data points. Figure 1 illustrates a representative diurnal fluctuation of DO and pH recorded in Pond 1 during week 3 of observation. As expected, DO levels decreased at night, reaching critical thresholds (~4.5 mg/L before sunrise), while pH exhibited daily oscillations driven by photosynthetic activity.

Accuracy Evaluation in the Field

Comparisons between sensor data and manual spot-checks indicated high agreement. Table 2 summarizes the field validation statistics. DO and pH sensors achieved CCC > 0.95, indicating strong concordance, while salinity was slightly lower but still acceptable.

Table 2. Field Validation Statistics (Sensor vs Manual Reference, n = 504 pairs per parameter)

Parameter	MAE	RMSE	CCC	Evaluation
pH	0.07	0.09	0.98	Excellent
DO (mg/L)	0.16	0.20	0.96	Excellent
Temp (°C)	0.12	0.15	0.97	Excellent
Salinity (ppt)	0.38	0.45	0.93	Good

Network and Energy Performance

The wireless transmission system achieved an average PDR of **96.7%**, exceeding the 95% target, with a median latency of 2.3 seconds. Energy monitoring indicated that the solar-powered node maintained continuous operation with a projected autonomy of **33 days** under cloudy conditions, meeting the requirement for 30 days of independent operation.

Discussion

The results highlight the feasibility of using a low-power wireless sensor network for real-time monitoring of shrimp pond water quality. The system effectively captured diurnal dynamics of DO and pH, which are critical for pond management. High agreement with laboratory-grade instruments confirms the reliability of the developed prototype. From a practical perspective, early warning alarms triggered during pre-dawn DO drops allowed farmers to activate additional aerators in time, potentially reducing stress and mortality. The findings are consistent with previous studies on aquaculture IoT systems, yet this research extends prior work by demonstrating robust multi-week field deployment under real operational conditions. While salinity measurements showed slightly higher variability, this may be attributed to electrode fouling and warrants further refinement of sensor housings. Overall, the integration of wireless sensor nodes, cloud-based data management, and mobile dashboards demonstrates a viable pathway toward precision aquaculture.

CONCLUSION

This study successfully developed and validated a wireless sensor-based water quality monitoring system tailored for intensive shrimp aquaculture. Laboratory calibration confirmed that the pH, dissolved oxygen, temperature, and salinity sensors achieved the target accuracy, with RMSE values well within acceptable thresholds. Field deployment across three ponds over an eight-week period demonstrated the system’s robustness in capturing diurnal fluctuations of critical water quality parameters, particularly the pre-dawn decline in dissolved oxygen and the midday increase in pH.

The sensor readings exhibited strong agreement with manual reference measurements (CCC > 0.95), while the wireless transmission network achieved a high packet delivery ratio (96.7%) and stable latency, ensuring reliable real-time data flow. The integration of solar-powered nodes enabled continuous operation with more than 30 days of autonomy, confirming the system’s suitability for remote aquaculture environments. From a practical standpoint, the real-time alerts provided by the system allowed proactive interventions, such as timely activation of aerators, which can significantly reduce shrimp stress and mortality. Compared to conventional manual monitoring, this approach represents a step forward toward precision aquaculture, empowering farmers with continuous, accurate, and actionable information. Future improvements should focus on enhancing sensor stability under biofouling conditions and extending the system with predictive analytics and decision-support tools. Nonetheless, the findings confirm that wireless sensor networks represent a viable and effective solution for sustainable shrimp pond management.

REFERENCES

- Bose, R., Sutradhar, S., Mondal, H., Bhattacharyya, D., & Roy, S. (2024). Integrating environmental monitoring and bird attack prevention in fish farming: a combined solution for improved pond management. *Discover Applied Sciences*, 6(3), 81. <https://doi.org/10.1007/s42452-024-05621-x>
- Deans, F. S. C. (2022). *The influence of climate change on marine bacterioplankton communities and greenhouse gases in New Zealand waters* (Doctoral dissertation, University of Otago).
- Fountas, S., Carli, G., Sørensen, C. G., Tsiropoulos, Z., Cavalaris, C., Vatsanidou, A., ... & Tisserye, B. A. (2015). Farm management information systems: Current situation and future perspectives. *Computers and electronics in agriculture*, 115, 40-50. <https://doi.org/10.1016/j.compag.2015.05.011>
- Garg, K. K., Wani, S. P., & Patil, M. D. (2016). A simple and farmer-friendly decision support system for enhancing water use efficiency in agriculture: tool development, testing and validation. *Current Science*, 1716-1729.
- Gorde, S. P., & Jadhav, M. V. (2013). Assessment of water quality parameters: a review. *J Eng Res Appl*, 3(6), 2029-2035.
- Kanwal, S., Abdullah, M., Kumar, S., Arshad, S., Shahroz, M., Zhang, D., & Kumar, D. (2024). An optimal internet of things-driven intelligent decision-making system for real-time fishpond water quality monitoring and species survival. *Sensors*, 24(23), 7842. <https://doi.org/10.3390/s24237842>
- Liu, T., Liu, J., Wang, J., & Xu, J. (2022). Optimization of the intelligent sensing model for environmental information in aquaculture waters based on the 5G smart sensor network. *Journal of Sensors*, 2022(1), 6409046. <https://doi.org/10.1155/2022/6409046>
- Mariu, A., Chatha, A. M. M., Naz, S., Khan, M. F., Safdar, W., & Ashraf, I. (2023). Effect of temperature, pH, salinity and dissolved oxygen on fishes. *Journal of Zoology and Systematics*, 1(2), 1-12. <https://doi.org/10.56946/jzs.v1i2.198>
- Mondal, R., Azmi, S. A., Sinha, S., Bose, C., Ghosh, T., Bhattacharya, S., & Tyagi, B. K. (2025). Ecology and Behavior. In *Mosquitoes of India* (pp. 239-276). CRC Press.
- Mössinger, J., Troost, C., & Berger, T. (2022). Bridging the gap between models and users: A lightweight mobile interface for optimized farming decisions in interactive modeling sessions. *Agricultural Systems*, 195, 103315. <https://doi.org/10.1016/j.agsy.2021.103315>
- Nazneen, S., Raju, N. J., Madhav, S., & Ahamad, A. (2019). Spatial and temporal dynamics of dissolved nutrients and factors affecting water quality of Chilika lagoon. *Arabian Journal of Geosciences*, 12(7), 243.
- Prapti, D. R., Mohamed Shariff, A. R., Che Man, H., Ramli, N. M., Perumal, T., & Shariff, M. (2022). Internet of Things (IoT)-based aquaculture: An overview of IoT application on water quality monitoring. *Reviews in Aquaculture*, 14(2), 979-992. <https://doi.org/10.1111/raq.12637>
- Rastegari, H., Nadi, F., Lam, S. S., Ikhwanuddin, M., Kasan, N. A., Rahmat, R. F., & Mahari, W. A. W. (2023). Internet of Things in aquaculture: A review of the challenges and potential solutions based on current and future trends. *Smart Agricultural Technology*, 4, 100187.
- Saiz-Rubio, V., & Rovira-Más, F. (2020). From smart farming towards agriculture 5.0: A review on crop data management. *Agronomy*, 10(2), 207. <https://doi.org/10.3390/agronomy10020207>
- Tenório, G. S., Cintra, I. H. A., de Oliveira Alves, P. J., da Costa, R. M., Rodrigues, T. D. N. M., & Bentes, B. S. (2022). A pesca do camarão pelágico aviú Acetes paraguayensis na Amazônia oriental brasileira. *Boletim do Instituto de Pesca*, 48. <https://doi.org/10.20950/10.20950/1678-2305/bip.2022.48.e660>

Wang, L. (2024). Advances in monitoring and managing aquatic ecosystem health: integrating technology and policy. *International Journal of Aquaculture*, 14.