PREDICTIVE MODELLING OF PH LEVELS FOR OPTIMIZING WATER QUALITY IN SHRIMP FARMING
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การสร้างแบบจำลองการพยากรณ์ค่าความเป็นกรด-ด่างเพื่อเพิ่มประสิทธิภาพการจัดการคุณภาพน้ำในการเลี้ยงกุ้ง

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ABSTRACT

Water quality is a critical factor in shrimp farming, directly influencing the growth, reproduction, and survival of shrimp. pH is one of the key parameters that affect water quality, with deviations from the optimal range (5.5–8.5) leading to stress, weakened immune responses, and potential infections in shrimp. This research presents the development of an automated pH monitoring and forecasting system aimed at improving water quality management in shrimp farms. The system uses a moving average algorithm to predict future pH levels based on real-time data collected by a pH sensor. The predicted and real-time values are transmitted to a cloud database, and farmers receive alerts via the Line application if pH levels deviate from the acceptable range. The system's performance was evaluated through six experiments, using different data collection intervals and durations. The most accurate forecasting results were achieved with 10-minute data collection intervals over a 2-hour period, yielding a mean squared error (MSE) of 0.003050 and a root mean square error (RMSE) of 0.038628. The system also demonstrated its ability to send real-time alerts to the farmer, ensuring prompt corrective action in the event of critical pH values.

บทคัดย่อ

คุณภาพน้ำเป็นปัจจัยสำคัญในอุตสาหกรรมการเลี้ยงกุ้ง ซึ่งส่งผลโดยตรงต่อการเจริญเติบโต การสืบพันธุ์ และอัตราการรอดชีวิตของกุ้ง โดยค่า pH เป็นหนึ่งในตัวแปรสำคัญที่มีผลต่อคุณภาพน้ำ หากค่า pH เบี่ยงเบนจากช่วงที่เหมาะสม (5.5–8.5) จะทำให้กุ้งเกิดความเครียด ภูมิคุ้มกันอ่อนแอลง และเสี่ยงต่อการติดเชื้อ งานวิจัยนี้นำเสนอการพัฒนาระบบตรวจสอบและพยากรณ์ค่าความเป็นกรด-ด่าง (pH) แบบอัตโนมัติที่มีวัตถุประสงค์เพื่อปรับปรุงการจัดการคุณภาพน้ำในฟาร์มกุ้ง ระบบนี้ใช้เทคนิคการพยากรณ์แบบค่าเฉลี่ยเคลื่อนที่ (Moving Average Algorithm) เพื่อทำนายค่าความเป็นกรด-ด่างในอนาคต โดยอิงจากข้อมูลแบบเรียลไทม์ที่เก็บรวบรวมจากเซ็นเซอร์ตรวจวัดค่า pH ข้อมูลค่าที่ทำนายและค่าที่วัดได้ในปัจจุบันจะถูกส่งไปยังฐานข้อมูลบนคลาวด์ และเกษตรกรจะได้รับการแจ้งเตือนผ่านแอปพลิเคชัน Line หากค่าความเป็นกรด-ด่างเบี่ยงเบนออกจากช่วงที่เหมาะสม ประสิทธิภาพของระบบได้รับการประเมินผ่านการทดลอง 6 ครั้ง โดยใช้ช่วงเวลาและระยะเวลาการเก็บข้อมูลที่แตกต่างกัน ผลการพยากรณ์ที่แม่นยำที่สุดได้รับจากการเก็บข้อมูลทุก ๆ 10 นาทีเป็นระยะเวลา 2 ชั่วโมง ซึ่งให้ค่า MSE (Mean Squared Error) เท่ากับ 0.003050 และค่า RMSE (Root Mean Square Error) เท่ากับ 0.038628 นอกจากนี้ ระบบยังแสดงความสามารถในการส่งการแจ้งเตือนแบบเรียลไทม์ไปยังเกษตรกร ทำให้สามารถดำเนินการแก้ไขได้อย่างทันท่วงทีเมื่อเกิดค่าความเป็นกรด-ด่างที่ผิดปกติ

INTRODUCTION

Shrimp farming is an important sector of Thailand's economy, providing significant income to cultivators. However, the success of shrimp farming is highly dependent on various environmental factors that affect shrimp growth, reproduction, and survival rates. Among these factors, water quality plays a critical role. Factors such as pH levels, oxygen concentration, and salinity directly influence the health and productivity of shrimp (*Komarudin et al., 2021; Hsieh et al., 2021; Kim et al., 2024*). Maintaining optimal water quality is essential to ensure the long-term sustainability of shrimp farming operations (*Ariadi et al., 2020; de los Santos et al., 2020; Tarunamulia et al., 2024*).

One of the most important indicators of water quality is the potential of hydrogen ions (pH), which measures the acidity or alkalinity of the water. The pH scale ranges from 0 to 14, with a value of 7 considered neutral. Water with pH levels below 7 is acidic, while levels above 7 indicate alkalinity (*Gambin et al., 2021*). In shrimp farming, maintaining pH levels between 5.5 and 8.5 is essential to minimize stress, promote healthy growth, and prevent infections in shrimp (*Yu et al., 2020; Ariadi et al., 2023*). Extreme fluctuations in pH can lead to stress, poor growth, and susceptibility to diseases, impacting the overall productivity of shrimp farms (*Supriatna et al., 2023*).

Fluctuations in water pH are primarily caused by natural processes such as photosynthesis and respiration in aquatic environments. During the day, photosynthesis by phytoplankton reduces carbon dioxide (CO2) levels in the water, causing a decrease in acidity and a rise in pH. At night, the respiration of aquatic organisms increases CO2 levels, resulting in higher acidity and a drop in pH (*Qiao et al., 2020*). Such fluctuations can disrupt the balance of microorganisms and chemical parameters in the water, making pH monitoring essential for effective water management in shrimp farming (*Durai et al., 2021; Shirly-Lim et al., 2024*).

Given the importance of pH stability, predictive systems that can forecast pH levels in advance are valuable tools for shrimp farmers. By anticipating changes in pH, cultivators can implement timely interventions to maintain water quality and optimize shrimp production. Previous studies have successfully applied predictive models to monitor and forecast water quality parameters in aquaculture. For example, *Mirsanjari and Mohammadyari (2018)* used time series models to predict groundwater quality, while *Monteiro* and *Costa (2018)* evaluated statistical models to forecast dissolved oxygen concentrations in river water. Similarly, *Thai-Nghe et al. (2020)* developed an IoT-based system for real-time water quality monitoring and prediction using deep learning techniques.

Building upon this body of knowledge, the present study introduces a predictive model aimed at forecasting pH levels in shrimp farming systems. By utilizing historical pH data, this model seeks to anticipate fluctuations and alert shrimp farmers to potential deviations from optimal water quality conditions. The development of such a model is expected to contribute significantly to improving water management strategies in shrimp farming, ultimately enhancing shrimp health, growth rates, and overall farm productivity.

MATERIALS AND METHODS

This research was conducted in shrimp farm of Mr. Prasopchoke Somsua, a shrimp cultivator from Donka district, Bangpae province, Rachaburi city, Thailand. The experiments were performed during January to March 2024. The experimented farm consisted of 4,000 square meters with 120 population of shrimps per square meter. The method used in this research were as followed.

System Infrastructure Design

The system developed for this study consists of four key components that are an automatic water quality measurement system, a processing and reporting system, a cloud-based database, and an automatic notification system. Figure 1 illustrates the overall infrastructure of the pH forecasting system.

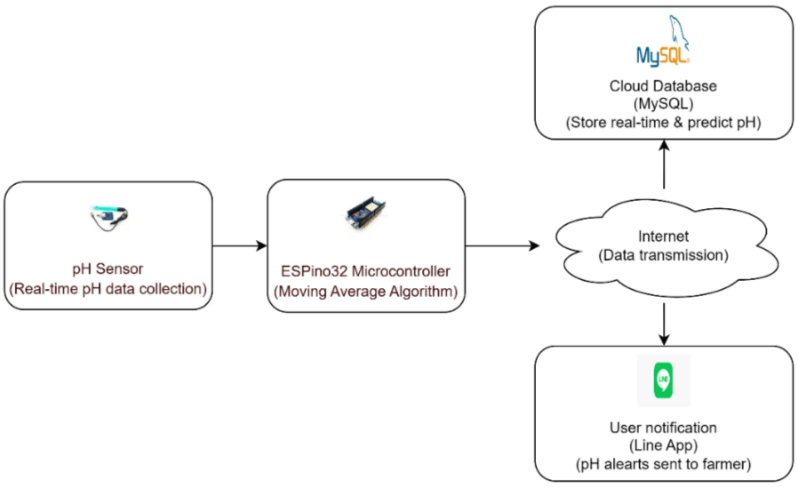

Fig. 1 - Infrastructure of the pH forecasting system for shrimp farms

- Automatic Water Quality Measurement System, a pH sensor was used to continuously monitor the water's pH level. This sensor was connected to an ESPino32 microcontroller, which collected real-time pH data.

- Processing and Reporting System, the collected pH values were processed using a moving average model to predict future pH levels. The predictions were then reported to the cloud database and the user's mobile device via the Line application.

- Cloud-Based Database, all collected and predicted pH data were stored in a MySQL cloud database for easy access and management. This cloud-based system allowed the data to be accessed remotely by the shrimp farmer at any time.

- Automatic Notification System, the system was configured to automatically notify the user via the Line application if the pH level deviated from the acceptable range (5.5–8.5). Both real-time pH values and predicted future pH values were sent to the farmer's device, allowing for immediate corrective actions if necessary.

pH Monitoring and Forecasting System

The pH monitoring and forecasting system operates in a sequential manner to ensure real-time data collection, analysis, and predictive capabilities. The process begins with the collection of pH values from the shrimp pond and continues through data processing, forecasting, and notification to the farmer. The system's workflow is outlined as follows.

1. Data Collection

The system initiates by collecting real-time pH values from the shrimp pond using a pH sensor. This data serves as the basis for both immediate evaluation and predictive modelling.

2. Data Processing

Once the pH value is collected, the system processes the data to assess its validity and determine whether further action is required. The collected pH data is first evaluated against a predefined range of acceptable values (5.5–8.5), which represents the optimal water conditions for shrimp growth and health.

3. Critical Value Detection, the system then checks if the collected pH value exceeds the acceptable thresholds.

3.1 If the pH value is either higher than 8.5 or lower than 5.5, the system identifies this as a critical value. In this case, an alert is triggered to notify the shrimp farmer via a mobile application (Line notification). This notification prompts immediate corrective action to prevent potential harm to the shrimp population.

3.2 If the pH value is within the acceptable range, the system proceeds to the next step, bypassing the alert stage.

4. pH Forecasting

For pH values that fall within the acceptable range, the system uses a moving average algorithm to predict future pH values. This forecasting process is essential for identifying potential trends that could lead to unfavorable water conditions if left unaddressed. The forecasting model uses historical pH data collected over time to generate accurate predictions of future pH fluctuations.

5. Current and Future pH Reporting: The system outputs both the current pH value and the forecasted future pH value. These values are then stored in a cloud-based database (MySQL) for further analysis and record-keeping. The availability of historical and predicted data allows for long-term monitoring and provides insights into water quality trends.

6. Database Integration

The pH data, both real-time and forecasted, is stored in the system's cloud database. This storage provides a centralized platform for accessing and analyzing pH data, enabling the farmer to review historical water quality data and respond proactively to changes in water conditions.

7. System Termination

The system completes the workflow after storing the pH data and either alerting the farmer or completing the forecasting process. The system continuously loops, allowing for ongoing real-time monitoring of water quality.

Experimental Setup

During the first quarter of 2024, the experiments were conducted in the shrimp farm at Donka district, Bangpae province, Rachaburi city, Thailand. The experiment was conducted under six different data collection configurations to evaluate the performance of the pH prediction model. The configurations were as follows:

1. pH data collection every 10 minutes for 2 hours
2. pH data collection every 10 minutes for 4 hours
3. pH data collection every 10 minutes for 6 hours
4. pH data collection every 30 minutes for 2 hours
5. pH data collection every 30 minutes for 4 hours
6. pH data collection every 30 minutes for 6 hours

For each configuration, the collected pH data was used to generate predictions using the moving average model. The accuracy of the predictions was evaluated using the mean squared error (MSE) and root mean square error (RMSE) metrics. These metrics provided an objective measure of the model's predictive performance, with lower MSE and RMSE values indicating higher accuracy.

Accuracy Evaluation

Time series forecasting is a technique which solely depends on past collected data to predict future value of the collected data. It is based on the assumption that the future data can be predicted through the existing data. This research is conducted relied on moving average (MA) which is one of the three average value forecasting techniques, including, Naïve approach, constant model, and moving average. The MA equation is as shown in equation (1) (*Ivanovski et al., 2018; Amali et al., 2022; Huriati et al., 2022*).

$$MA = \frac{\sum(actual)}{n} \tag{1}$$

In this research, the accuracy of the predicted result is measured through mean squared error (MSE) and root mean square error (RMSE). The best result is selected from the predicted value with the lowest MSE and RMSE out of six calculation schemes. The selected result is considered the most accurate prediction since it has the least different value from the real data. The equations of MSE and RMSE are as shown in equations (2) and (3), respectively (*Hu et al., 2019; Eze et al., 2021; Ardiansah et al., 2021*; *Ensafi et al., 2022*).

$$MSE = \frac{\sum(actual - forecast)^2}{n} \tag{2}$$

$$RMSE = \sqrt{\frac{\sum(actual - forecast)^2}{n}} \tag{3}$$

RESULTS

The developed pH monitoring and forecasting system was tested in a shrimp farm to evaluate its performance in predicting water quality and ensuring real-time alerts in cases of critical pH values. The system collected pH data at regular intervals, processed the data, and generated both real-time and forecasted pH values, which were subsequently compared to the observed values.

Hardware Design

The hardware component, as shown in Figure 2, including the pH sensor (number 2) combined with a probe head (number 3) and the ESPino32 microcontroller (number 1), functioned reliably throughout the experimental period. Data collection was performed at 10-minute intervals over a 2-hour period, and the sensor demonstrated consistent accuracy in capturing real-time pH levels. The data was transmitted to the cloud database without notable communication delays or data loss, ensuring smooth operation across all components.

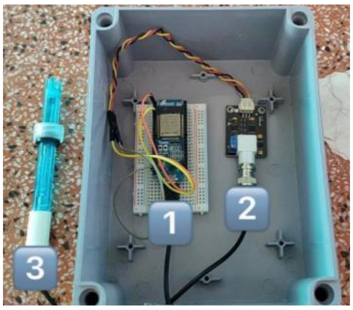

Fig. 2 - Hardware design of the pH forecasting

Prediction Accuracy

To assess the accuracy of the pH forecasting model, six experiments were conducted with varying data collection intervals and durations, ranging from 10-minute to 30-minute intervals, and covering periods of 2, 4, and 6 hours. For each experiment, the system generated both current and forecasted pH values. The accuracy of the forecasts was evaluated based on the mean squared error (MSE) and root mean square error (RMSE) metrics.

The experiment that collected pH data every 10 minutes over a 2-hour period produced the most accurate predictions, with an MSE of 0.003050 and an RMSE of 0.038628 (Figure 3a). In contrast, the experiment with 30-minute intervals over a 6-hour period yielded higher error values, with an MSE of 0.003307 and an RMSE of 0.042485 (Figure 3f). Table 1 presents the results of the forecasting accuracy for each experimental setup.

Fig. 3 - The results of six experiments for the pH forecasting

Real-Time pH Monitoring

During the experiment, the system continuously monitored the real-time pH values in the shrimp pond. Whenever the pH value deviated from the acceptable range (5.5–8.5), the system immediately triggered an alert. As shown in Figure 4, the system successfully notified the farmer via the Line application whenever the pH level fell below or exceeded the threshold, allowing the farmer to take prompt corrective actions. This immediate response helped maintain optimal water quality and minimized potential stress on the shrimp.

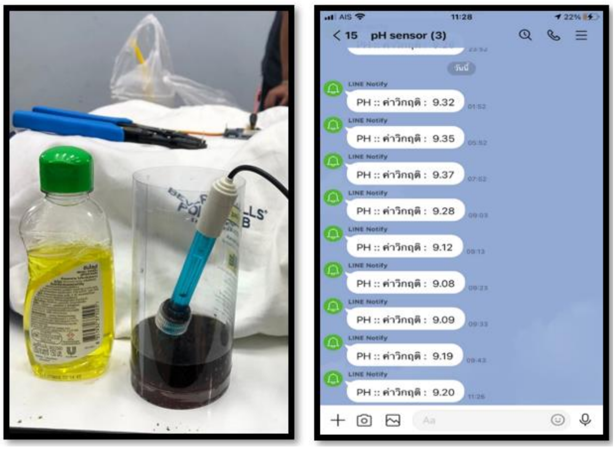

Fig. 4 - The result of system notification whenever the pH level fell below or exceeded the threshold

Predictive pH Analysis

The predictive analysis component of the system proved effective in forecasting pH values during the first quarter of 2024. The experiment as shown in Figure 5 was conducted, the shrimp pond was 4,000 square meters with 120 density of shrimps per square meter. The pH values were collected every 10 minutes within 2 hours for further prediction calculation. The monthly average collected pH, predicted pH, MSE and RMSE are as shown in Table 1.

The average deviation between the forecasted and actual pH values remained low across all months, with the lowest MSE (0.000225) observed in March 2024, demonstrating the robustness of the moving average algorithm in predicting pH fluctuations.

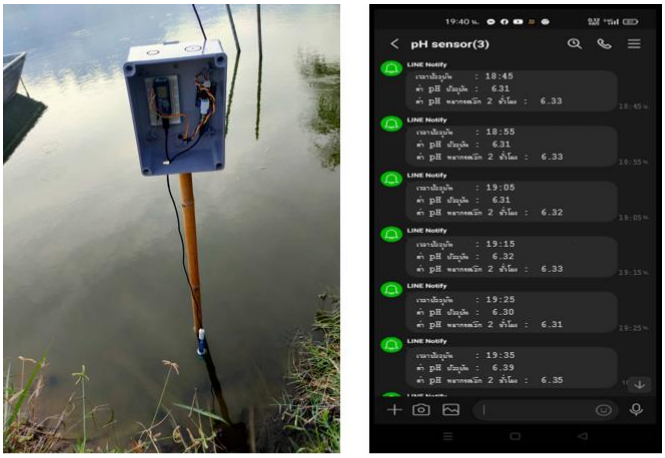

Fig. 5 - The experiment and the notification of current pH and predicted pH

Table 1

Results in actual pH, forecast pH, MSE and RMSE during the first quarter of 2024

Month	Actual average pH value	Forecast average pH value	MSE	RMSE
January 2024	7.85	7.83	0.000434	0.020833
February 2024	7.83	7.83	0.000711	0.026667
March 2024	7.83	7.83	0.000225	0.015000

Notifications and Data Storage

The system's notification functionality performed as expected, sending timely alerts to the farmer when critical pH levels were detected. Both real-time and forecasted pH values were successfully stored in the cloud-based MySQL database, ensuring that the data could be accessed at any time for further analysis or reporting purposes. The database provided a comprehensive record of water quality data, including historical trends and predictive insights, facilitating long-term water quality management.

Overall, the pH monitoring and forecasting system demonstrated a high level of accuracy and reliability in both real-time monitoring and predictive analysis. The system effectively maintained water quality within the acceptable range, reduced the risk of pH-related stress on the shrimp population, and provided the farmer with timely notifications of potential issues. These results suggest that the system is a valuable tool for improving the management of water quality in shrimp farming environments.

CONCLUSIONS

This research presents the development and evaluation of an automated pH monitoring and forecasting system for shrimp farming, designed to enhance water quality management. The system integrates real-time pH data collection, predictive analysis using a moving average algorithm, and automated notifications to alert shrimp farmers when critical pH values are detected.

The experimental results demonstrate that the system performs reliably in both monitoring and forecasting pH levels. The hardware components, including the pH sensor and ESPino32 microcontroller, consistently captured and transmitted pH data, ensuring stable system operation. Moreover, the cloud-based storage of real-time and forecasted data facilitates easy access to historical and predictive water quality data for future reference. The pH forecasting model, evaluated through multiple experiments, exhibited high accuracy in predicting future pH values. The experiment utilizing 10-minute intervals over a 2-hour period produced the lowest MSE and RMSE, indicating the effectiveness of the model in short-term pH forecasting. These predictions provided shrimp farmers with valuable insights into potential future fluctuations in water quality, allowing for timely interventions to prevent adverse conditions.

In addition, the system's automated notification feature performed as expected, sending immediate alerts to the farmer via the Line application whenever the pH values fell outside the acceptable range (5.5–8.5). This real-time feedback ensured that the farmer could promptly respond to changes in water quality, reducing the risk of pH-related stress on the shrimp population and improving overall farm productivity.

While the system has demonstrated effectiveness in monitoring and predicting pH levels, future enhancements could include the integration of additional water quality parameters, such as dissolved oxygen (DO) and salinity. This would provide a more comprehensive tool for managing water conditions in shrimp farming. Moreover, the use of advanced predictive algorithms, including machine learning techniques, may further improve the accuracy of the forecasts, particularly over longer time periods.

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