IoT based Smart Aquaculture System with Automatic Aerating and Water Quality Monitoring

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Abstract

Aquaculture is a vital economic and food source in numerous countries. However, because of environmental limitations and the impact of aquatic diseases, aquaculture requires considerable manpower, involves high material costs, and relies on the experience of aquaculturists to increase production capacity. Water quality is among the most crucial elements in aquaculture. Accordingly, in this paper, we propose an IoT-based smart aquaculture system (ISAS) for detecting the water quality of an aquafarm and providing automatic aeration to increase the survival rate of aquatics. In the ISAS, the parameters used for detecting water quality are temperature, pH value, dissolved oxygen, and water hardness, which are recorded using different sensors. Users can check the condition of an aquafarm from the sensed data. Moreover, the ISAS can automatically control the aerator and feeder of an aquarium on the basis of sensed data and predefined fuzzy rules. Our experiments revealed that under the same conditions, the shrimp survival rate in an ISAS-based aquarium increased by 33.3% compared with that in conventional aquariums.

Keywords: Aquaculture, Internet of Things, Automatic aeration, Water quality Control, Fuzzy rule

1 Introduction

With the increasing global population, the demand for food is also increasing. However, because of the intensification of the greenhouse effect and the reduction of global resources, the area available for agricultural and livestock farming has decreased continually. Aquatic products are easy to capture and rich in protein and can be farmed; therefore, humans are increasingly dependent on fishery resources [1]. According to the State of World Fisheries and Aquaculture (SOFIA) report [2] released by the Food and Agriculture Organization (FAO) of the United Nations, the global average fish consumption was 20.5 kg per person per year in 2018. Fish consumption is estimated to increase in the next 10 years.

However, in recent years, overfishing along with factors such as coastal area development, water pollution, and climate warming has engendered a sharp decrease in the quantity of fish and shrimp. Because of increasing demand, aquaculture has been developed rapidly in recent years. Owing to advancements in biotechnology and engineering technology [3], such as Internet of Things (IoT) [4], artificial intelligence (AI) [5], and big data, the aquaculture production capacity has increased considerably and can meet more than half of the world's demand for aquatic products. However, to improve the survival rate of aquatics, some businesses use chemicals to maintain the water quality in aquafarms and apply medications to protect fish and shrimp against diseases. This impacts the environment and harms the health of consumers. In recent years, the demand for organic aquatic products has gradually increased, and consumers are paying more attention to food safety, quality, and green earth. Therefore, managing water quality and increasing production capacity without using chemicals are the essentials of smart aquaculture.

Water quality is a major factor affecting the production of aquatic products in aquafarms. Poor water quality may pose a health risk for people and ecosystems. Traditional methods of evaluating water quality involve manually sampling water from an aquafarm and testing it using test papers or devices in a laboratory. However, such methods are time-consuming and require excessive manpower. This paper presents an IoT-based smart aquaculture system (ISAS) for monitoring various water quality parameters in an aquafarm. In the ISAS, four sensors—temperature sensor, pH sensor, dissolved oxygen sensor, and water hardness sensor—are connected to an Arduino development platform and Raspberry Pi computer, and the sensed data are transmitted to a cloud database so that users can monitor the data and receive warning messages when the quality of water in an aquafarm is poor. In addition, the ISAS can automatically activate air pumps or suspend feeders based on fuzzy processing results. The ISAS can detect the water quality of an aquafarm and thus improve the survival rate of fish and shrimp and reduce labor costs. The contributions of this paper are listed as follows.

1. The ISAS utilizes a fuzzy inference process for rapid and automatic operation of aerators and feeders in aquafarms.
2. Users can easily monitor water quality of an aquafarm by using mobile devices and remote computers.
3. The ISAS utilizes four sensors to monitor water quality in order to create a suitable aquaculture environment.
4. The ISAS can increase the survival rate of shrimp by 33.3% compared with that of the traditional approach.

The rest of this paper is organized as follows. The water quality parameters and relevant studies are described in Section 2. The ISAS is presented in Section 3. The experiments and results are demon-strated and discussed, respectively, in Section 4. Finally, the conclusions and future studies are presented in Section 5.

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2 Preliminary and Related Studies

2.1 Water Quality Parameters

Several parameters can be adopted to examine the water quality of an aquafarm, such as pH, dissolved oxygen, redox potential, conductivity, temperature, water hardness, and nitrite and nitrate concentrations. An overview of these parameters is provided as follows.

- pH: pH is a scale (0 – 14) of the activity of hydrogen ions and is a measure of the acidity or alkalinity of a solution. Maintaining the pH value of aquatic farms at a similar level to that in the native environment is beneficial for the growth and reproduction of aquatics. Effective control of pH is a crucial issue for aquaculturists. In general, the pH value in marine aquaculture is approxi-mately 7.9–9.0.
- Dissolved oxygen: Dissolved oxygen is a major indicator of water quality. Most aquatics require >5 mg/L of dissolved oxygen. Sufficient oxygen ensures the growth of aquatics and survival of aerobic bacteria. However, numerous factors, such as biological size, water temperature, and pressure, may affect the amount of dissolved oxygen. Therefore, continually monitoring and controlling the dissolved oxygen in an aquafarm would be vital.
- Redox potential: The redox potential (or oxidation – reduction potential, ORP) indicates the overall oxidation status of an environment and is an indicator of microbial activity. In addition, the ORP represents the activity of the nitrogen cycle. A high ORP value indicates the abundance of nitrifying bacteria in organic waste, signifying high water quality. By contrast, a low ORP value indicates incomplete nitrification and accumulation of toxic substances in the water. In general, an ORP value maintained at >200 mv indicates that the microorganisms in the water can effectively decompose organic matter. An ORP of <50 mv indicates accumulation of organic matter, insuffi-cient oxidation–reduction, and poor water quality. Therefore, the measurement of the ORP of the bottom water layer can help predict changes in the water quality environment.
- Conductivity: This represents the conductivity of ions in a certain volume of solution. The more the number of movable ions, the smaller the resistance and the stronger the conductivity. A high conductivity level means that the concentration of inorganic salts in the water is relatively high, and it is also an indicator of water quality. Conductivity is affected by temperature; thus, it must be compensated by using the temperature correction formula during measurement. The standard conductivity of aquatic water is approximately 3,000 μS/cm for freshwater aquatic products.
- Temperatur: Temperature is the most crucial environmental parameters for all aquatics. It affects the amount of dissolved oxygen and the reproduction and growth of all aquatics. Different aquatics have different temperature requirements. If the temperature of an aquafarm is higher than the upper-bound temperature or lower than the lower-bound temperature, it can inhibit the growth of aquatics. Moreover, sudden temperature fluctuations may reduce the disease resistance and increase susceptibility to infection.

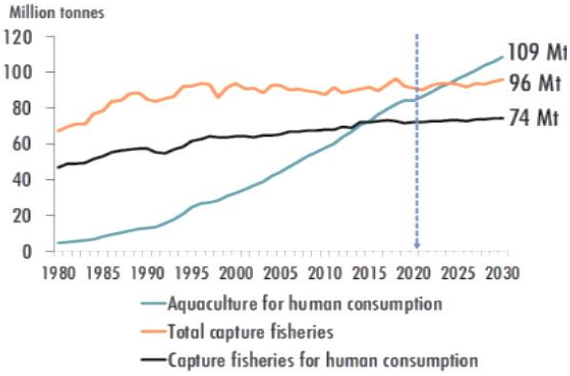


Figure 1. Statistic and prediction of aquaculture production and consumption [6]

- Water hardness: In general, water hardness refers to the total concentration of calcium and magnesium ions in water; it can be divided into carbonate hardness and noncarbonate hardness. Calcium is a vital element in water systems because it is the chief ingredient of fish bones and crustacean and mollusk shells. Some fish species do not hatch in calcium-free seawater. Furthermore, magnesium affects their development.
- Nitrite and Nitrate: Nitrite is an unstable anion. In the nitrogen cycle, it is an intermediate product of the oxidation–reduction process of nitrogen-containing substances. It is one of the nutrients for aquatic plants. Generally, the concentration of nitrite in unpolluted water is very low (approximately 0.01 mg/L). However, a very high nitrite concentration means that the water is polluted by organic matter and often indicates a deteriorating ecological environment. A high nitrite concentration in an aquafarm indicates incomplete nitrification and reduces the food availability for fish and shrimp, hindering their growth and even causing death from poisoning.

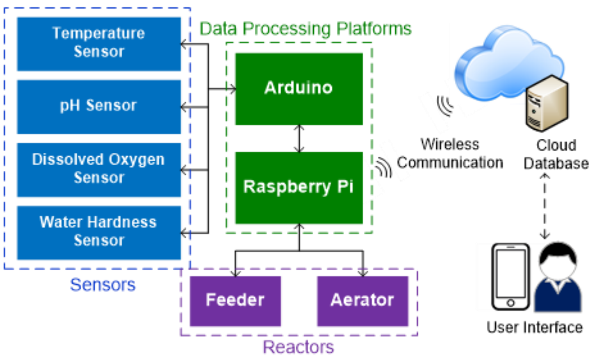


Figure 2. Architecture of the ISAS

Nitrate is the most stable nitrogen-containing compound in various forms; it is also the final oxidation product of nitrogen-containing organic matter after ammonization and nitrification. Its toxicity to organisms is low. However, when the water environment is poor, nitrate is transformed into toxic ammonia and nitrite, which not only directly harm aquatic creatures but also make algae flourish.

2.2 Related Studies

According to the 2020 FAO's SOFIA report (Figure 1) [2], the global fish production was 178 million tons in 2018. Approximately 88% of world fishery production is directly used for human consumption. Global fish production is expected to continue growing, reaching a projected production level of 196 million tons by 2025, with aquaculture accounting for the major growth. Increased fish production from aquaculture has boosted fish consumption. Technological progress is the major reason for this growth in production capacity.

In the past decade, IoT has been widely used in various applications, such as smart homes [7], Internet of vehicles (or vehicle-to-everything, V2X) [8], and smart factories [9]. IoT can also be applied to human, animal, and plant populations; for example, it can be used in heart rate monitors to prevent heart disease, can be incorporated into collars to check the location and health of pets, or used in sensors in agricultural equipment to solve agricultural problems.

Ma and Ding [10] designed a 24-h online monitoring system to monitor the dissolved oxygen in an aquaculture pond. This monitoring system utilizes an optical dissolved oxygen sensor and a polarographic dissolved oxygen sensor, in addition to the narrowband-IoT communication technology and a programmable logic controller. Their system can quickly respond and adjust the level of dissolved oxygen for precise control of dissolved oxygen and decreased energy consumption. Aziz *et al*. [11] developed a catchment monitoring system for continuously monitoring water quality by using five sensors: a temperature sensor, a light intensity sensor, a pH sensor, a GPS tracker, and an inertial movement unit. This system is not specifically designed for aquaculture but is mainly used to prevent water pollution.

Balakrishnan *et al*. [3] designed an aquaculture system for controlling water parameters, including temperature, conductivity, turbidity, and the nearness of oil layer over the water. Users can access the system through a cloud environment and resolve uncontrollable situations in aquaculture ponds. Acar *et al*. [12] presented an IoT cloud concept using integrated tools (e.g., RabbitMQ, Kafka, Orion, and ActiveMQ) and various communication technologies (e.g., Message Queuing Telemetry Transport (MQTT), Advanced Message Queuing Protocol, and Hypertext Transfer Protocol (HTTP)) to provide users with an easy IoT construction method. Lin and Tseng [13] developed a FishTalk system that utilizes several aquarium sensors to drive the aquarium actuators in real time. They investigated the relationship between the aquarium sensors and actuators and developed an analytic model to evaluate the effects of IoT message delay and loss on water quality control. Khan *et al*. [14] utilized AI to improve the interoperability of sensed data and accordingly developed new applications. Khan reported that integrating AI technologies into aquaculture through IoT-based solutions can improve the decision-making, production control, and management of aquaculture systems. Dupont *et al*. [15] presented several key considerations for the use of sensors in an aquafarm, including sensors' reliability, accuracy, cost, and maintenance. Moreover, they recommended that in addition to water quality monitoring, data analysis and prediction should be considered in aquafarm management.

3 Proposed ISAS

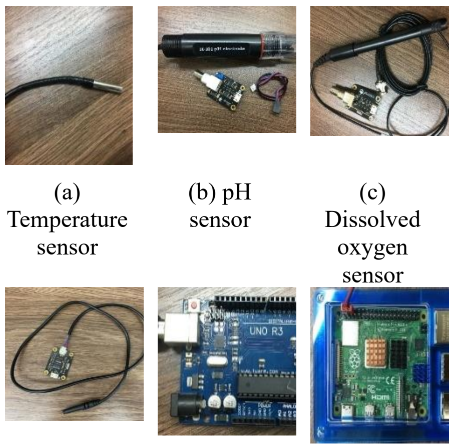
In this section, we introduce the architecture of the proposed ISAS and then describe the fuzzy-based control policy.

3.1 Architecture of ISAS

The architecture of the ISAS, as shown in Figure 2, comprises four sensors (i.e., a temperature sensor, pH sensor, dissolved oxygen sensor, and water hardness sensor), two data processing platforms (i.e., Arduino and Raspberry Pi), a feeder, an aerator, and a cloud database.

The temperature sensor (Figure 3(a)) is the DS18B20 digital thermometer [16], which measures temperatures from −55°C to +125°C and provides a programmable resolution of 9–12 bits. The proposed system applies the DFROBOT SEN0169 analog pH meter (Figure 3(b)) [17] to measure pH. The SEN0169 (Figure 3(c)), which has the features of fast response and good thermal stability, is highly suitable for long-term monitoring. A DFROBOT SEN0237 sensor (detection range: 0–20 mg/L; Figure 3(d)) [18] serves as the dissolved oxygen meter. A DFROBOT SEN0244 [19] (measurement range: 0–1000 mg/L) analog total dissolved solid sensor is employed to measure the hardness of aqueous solutions.

Figure 3(e) and Figure 3(f) depict the Arduino microcontroller and Raspberry Pi single-board computer, respectively, employed in the proposed system. The Raspberry Pi computer comprises an ARM Cortex A72 processor and 8 GB of RAM and provides multiple communication interfaces (e.g., WiFi, Bluetooth, USB, and Mini HDMI). The Arduino microcontroller integrates the data sensed by the sensors and then transmits the data to Raspberry Pi for processing. The last 7 days' sensed data are stored in the internal memory of Raspberry Pi. All sensed data are transmitted to the cloud database from Raspberry Pi via WiFi and the MQTT protocol. Through the graphical API, users can check the water quality of an aquafarm through the web and smartphones. When the water quality is poor, Raspberry Pi activates the aerator and suspends the feeder to maintain a certain level of oxygen.



(a) Temperature sensor

(b) pH sensor

(c) Dissolved oxygen sensor

(d) Water hardness sensor

(e) Arduino microcontroller

(f) Raspberry Pi single-board computer

Figure 3. Sensors and data collection platforms of the ISAS

The ISAS detects the four most crucial parameters for a shrimp pond. The other three parameters can also be detected, but these may not affect the shrimp survival rate considerably. Different types of aquatics require different types of living environments; therefore, for other aquatics such as perch and scallops, the ISAS can utilize different sets of sensors to monitor different water quality parameters. Thus, the ISAS can flexibly adapt to special environments for some aquatics.

3.2 Fuzzy-based Automatic Control Polity

To automatically activate an aquafarm's aerator and suspend its feeder when the water quality of the aquafarm is poor, the fuzzy inference process is invoked. Figure 4 illustrates the automatic control flow of the ISAS, wherein the fuzzy inference process is the key component of the activation decision process. When the concentration of dissolved oxygen is lower than a predefined threshold, the ISAS triggers its fuzzy inference process, which assesses the water temperature, pH, and hardness. The output of the fuzzy inference process enables the Raspberry Pi computer to control the aerator and feeder.

The fuzzy inference process comprises four parts, namely fuzzification, fuzzy rule base, fuzzy inference engine, and defuzzification. The four aforementioned input parameters serve as the input vector. Therefore, the fuzzy system is an extension of multivalued logic. The process produces two output parameters. Fuzzification is the process of transforming crisp values into grades of a membership function, and each of the grades can in turn be associated with a linguistic term. A fuzzy inference engine interprets the values of the input vector and, based on a set of rules, assigns fuzzy values to its outputs. In the ISAS, Mamdani's fuzzy inference method is applied. Defuzzification is the process of mapping an output fuzzy value to a crisp set. Here, four membership functions are used, namely Z-shaped, S-shaped, Gaussian, and triangular; Eqs. (1)–(4) present their mathematical expressions.

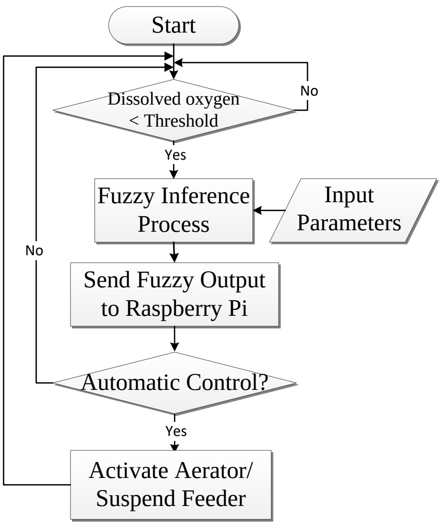


Figure 4. The automatic control flow of the ISAS

$$\mu_{\tilde{A}}(x) = \begin{cases} 1 \ , \ x \le \alpha \\ 1 - 2\left(\frac{x-\alpha}{\gamma-\alpha}\right)^2 , \ \alpha < x \le \beta \\ 2\left(\frac{x-\gamma}{\gamma-\alpha}\right)^2 , \ \beta < x \le \gamma \\ 0 \ , \ x > \gamma \end{cases} \quad \textbf{(1)}$$

$$\mu_{\tilde{A}}(x) = \begin{cases} 0 \ , \ x \le \alpha \\ 2\left(\frac{x-\alpha}{\gamma-\alpha}\right)^2 , \ \alpha < x \le \beta \\ 1 - 2\left(\frac{x-\gamma}{\gamma-\alpha}\right)^2 , \ \beta < x \le \gamma \\ 1 \ , \ x > \gamma \end{cases} \quad \textbf{(2)}$$

$$\mu_{\tilde{A}}(x) = e^{\left(-\frac{(x-m)^2}{2\sigma^2}\right)} \quad \textbf{(3)}$$

$$\mu_{\tilde{A}}(x) = \begin{cases} 0, \ x \le a \\ \frac{x-a}{b-c}, \ a < x < b \\ 1, \ x = b \\ \frac{c-x}{c-b}, \ b < x \le c \\ 0, \ x > c \end{cases} \quad \textbf{(4)}$$

In these equations, $\mu_{\tilde{A}}(x)$ is the output of a membership function. In Eqs. (1) and (2), β, defined as $(\gamma + \alpha) / 2$, is the crossover point of the S-function; it is a typical value of the fuzzy set. Moreover, α and γ are the lower and upper bounds of an input value, respectively. In Eq. (3), the modal value m represents the typical element of $\mu_{\tilde{A}}(x)$ and σ represents a spread of $\mu_{\tilde{A}}(x)$. Higher values of σ correspond to larger spreads of the fuzzy sets. In Eq. (4), b denotes a typical value of the fuzzy set, and a and c denote the lower and upper bounds of the input value, respectively.

The four membership functions are individually given the four aforementioned input parameters and two output decisions. The fuzzy sets are defined as follows.

(1) *Temperature*:$\{Low, Medium, High\}$
(2) *pH*: $\{Low, Medium, High\}$
(3) *Dissolved oxygen*: $\{Low, Medium, High\}$
(4) *Water hardness*: $\{Low, Medium, High\}$
(5) *Aerator activation*: $\{Suspend, Activate\}$
(6) *Feeder activation*: $\{Suspend, Activate\}$

Each set has three fuzzy terms (low, medium, and high), except for the aerator activation set and feeder activation set, the value of which can only be suspended or activated.

The parameter settings of the four inputs are listed in Table 1; the Z-shaped membership function is given a low fuzzy term, the Gaussian membership function is given a medium fuzzy term, and the S-shaped membership function is given a high fuzzy term. The triangular membership function is applied to aerator activation and feeder activation. The values assigned to the input parameters of a membership function in the following simulation are listed in the fourth column of Table 1; the values set in this table were based on a shrimp aquafarm.

The input parameters of a membership function in the ISAS are illustrated in Figure 5 to Figure 10. For temperature, pH, dissolved oxygen, and water hardness, three member functions are used to represent the parameters in each figure. For example, in Figure 5, low, medium, and high terms listed in Table 1 are represented by the Z-shaped, Gaussian, and S-shaped membership functions, respectively. The same applies to the other three figures. However, in Figure 9 and Figure 10, only the triangular membership function is adopted.

Table 1. Parameter settings of fuzzy inputs

Input Parameter	Fuzzy term	Membership Function	Value of input parameter
Temperature	Low	Z-shaped	$\boldsymbol{\alpha = 18,\ \beta = 21.5,\ \gamma = 25}$
	Medium	Gaussian	$\boldsymbol{m = 25,\ \sigma = 1}$
	High	S-shaped	$\boldsymbol{\alpha = 25,\ \beta = 27.5,\ \gamma = 30}$
pH	Low	Z-shaped	$\boldsymbol{\alpha = 6.5,\ \beta = 7.25,\ \gamma = 8}$
	Medium	Gaussian	$\boldsymbol{m = 8,\ \sigma = 1}$
	High	S-shaped	$\boldsymbol{\alpha = 8,\ \beta = 8.75,\ \gamma = 9.5}$
Dissolved Oxygen	Low	Z-shaped	$\boldsymbol{\alpha = 2,\ \beta = 3,\ \gamma = 4}$
	Medium	Gaussian	$\boldsymbol{m = 4,\ \sigma = 1}$
	High	S-shaped	$\boldsymbol{\alpha = 4,\ \beta = 5,\ \gamma = 6}$
Water Hardness	Low	Z-shaped	$\boldsymbol{\alpha = 50,\ \beta = 125,\ \gamma = 200}$
	Medium	Gaussian	$\boldsymbol{m = 200,\ \sigma = 1}$
	High	S-shaped	$\boldsymbol{\alpha = 200,\ \beta = 250,\ \gamma = 300}$
Feeder	Activate	Triangular	$\boldsymbol{a = -1,\ b = 0,\ c = 1}$
	Suspend	Triangular	$\boldsymbol{a = 0,\ b = 1,\ c = 2}$
Aerator	Suspend	Triangular	$\boldsymbol{a = -1,\ b = 0,\ c = 1}$
	Activate	Triangular	$\boldsymbol{a = 0,\ b = 1,\ c = 2}$

The employed fuzzy ruleset comprises all possible relationships among the four input parameters and two output parameters in the IF–THEN format. Each input parameter has three fuzzy terms; therefore, a total of 81 (= 3^4) rules are generated for the four input parameters. In the fuzzy inference engine, the Mamdani model converts the aggregated fuzzified data, expressed as

$$\mu_{\tilde{A}_{Aerator}} = \max_{k}[min[\mu_{\tilde{A}}(Temperature), \mu_{\tilde{A}}(pH), \mu_{\tilde{A}}(Dissolved\ Oxygen), \mu_{\tilde{A}}(Water\ Hardnes)]],\ \text{for } k = 81 \quad \textbf{(5)}$$

into normalized scores. In the proposed system, the centroid method [20], also known as the center-of-gravity method, is adapted as the defuzzification function, which can be expressed as follows:

$$\boldsymbol{Aerator^{*}} = \frac{\int x\mu_{\tilde{A}_{Aeraotr}}(x)dx}{\int \mu_{\tilde{A}_{Aerator}}(x)dx} \quad \textbf{(6)}$$

where Aerator* is the scores of the aerator activate decision. A similar fuzzy inference engine is designed for the feeder as well.

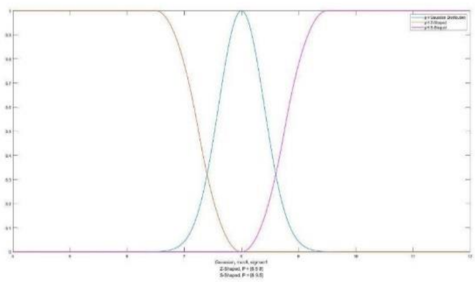


Figure 5. Input parameter temperature of three membership functions (Low: Z-shaped; Medium: Gaussian; High: S-shaped)

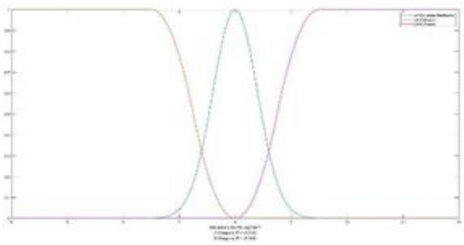


Figure 6. Input parameter pH of three membership functions Z-shaped; Medium: Gaussian; High: S-shaped

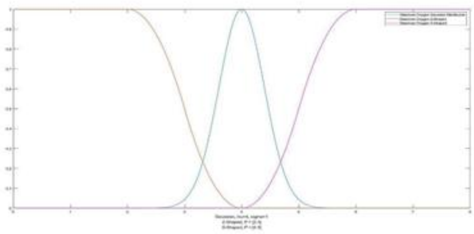


Figure 7. Input parameter dissolved oxygen of three membership functions (Low: Z-shaped; Medium: Gaussian; High: S-shaped)

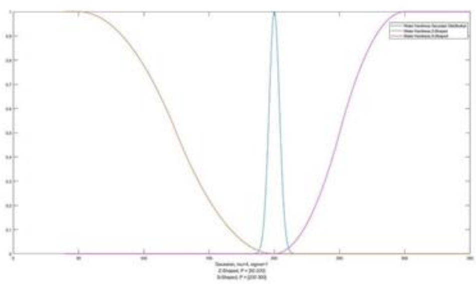


Figure 8. Input parameter water hardness of three membership functions (Low: Z-shaped; Medium: Gaussian; High: S-shaped)

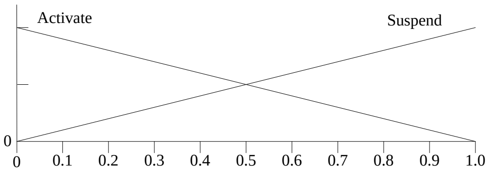


Figure 9. Output parameter Feeder of Triangular membership function

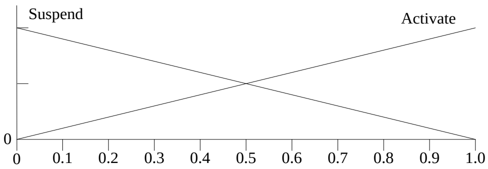


Figure 10. Output parameter Aerator of Triangular membership function

Although machine learning (ML)-based IoT systems can yield similar or superior results to those generated by the ISAS, fuzzy-based control is adopted in the proposed system owing to its fast response and ease of application. Compared with fuzzy-based systems, ML-based systems require long training time and must be redesigned for different aquatics. Moreover, the data processing platforms Raspberry Pi and Arduino are not suitable for ML due to the limitation of their computing power. Thus, the ISAS is based on the fuzzy inference process.

4 Experimental Results

Figure 11 illustrates our experimental environment. In these experiments, the sensors sensed data once every 3 min, and the sensed data could be stored in the Raspberry Pi computer and a cloud database implemented using a PC with an Intel i7 processor, 16-GB RAM, and 1-TB SSD. A user could check the past sensed data through web pages. Figure 12 and Figure 13 show two examples of temperature and dissolved oxygen data collected within 6 h, respectively. Data collected within 1 h, 1 day, 1 week, 1 month, and 3 months could also be visualized, either on the webpage or on users' mobile devices. Figure 14 shows the sensed data dashboard on a user's mobile device.

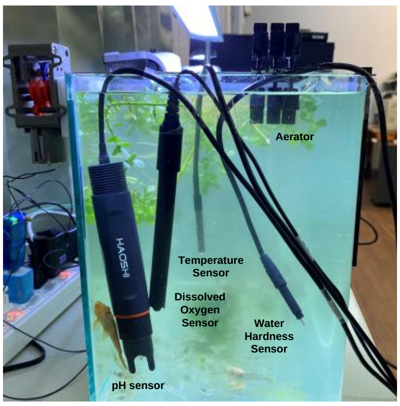


Figure 11. Experimental environment of the ISAS

Figure 12. The temperature sensed data example

Figure 13. The dissolved oxygen sensed data example

Figure 14. Sensed data dashboard from user's mobile device

To verify the feasibility of the ISAS, two aquariums were built: one for the experimental group and the other for the control group (Figure 15). The ISAS was implemented in the experimental group to monitor water quality of the aquarium. Initially, 60 shrimp and some aquatic plants were added to each of the aquariums. The shrimp in the control group were fed once daily, whereas those in the experimental group were fed depending on the fuzzy result.

Figure 15. Experimental group and control group of the ISAS

Figure 16 illustrates the survival rates of the shrimp during a period of 1.5 months. In the first week, many shrimp in both groups died because of unsuitability. The survival rates dropped rapidly. However, in the experimental group, baby shrimp were born on April 7 and 13, and in the control group, baby shrimp were born on April 19. Therefore, the total number of shrimp increased, and the survival rate increased accordingly. On May 5, the number of remaining shrimp in the experimental (control) group was 36 (16). The survival rate of the experimental (control) group was 60% (26.7%). Accordingly, when the ISAS was applied, the survival rate of the shrimp increased by 33.3% (= 60% − 26.7%).

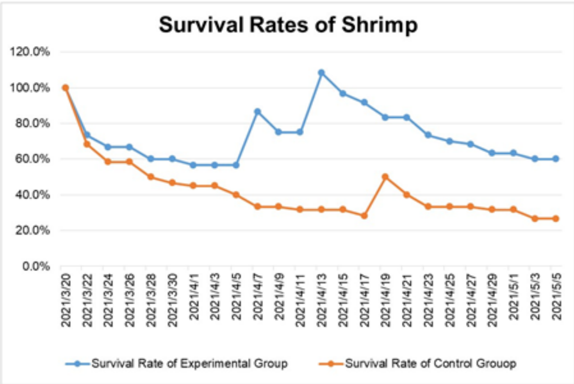


Figure 16. Survival rates of shrimps during the 1.5 months of our experiment

Because implementing a real aquafarm is difficult, in our experiment, two aquariums were developed to verify the feasibility of the proposed system. However, in general, more sensors are required to monitor different areas of an aquafarm. The water quality of an aquafarm can be monitored in two manners: (1) creating several independent ISAS systems in a large aquafarm and using each ISAS system to detect the water quality of a specific area; (2) integrating the sensed data in a medium-scale aquafarm and then inputting the data to a single ISAS system for decision-making.

5 Conclusion and Future Studies

In this paper, an IoT-based aquaculture system is proposed for detecting the water quality of an aquafarm in order to increase aquatic production capacity. Four sensors are utilized in the proposed system, and the sensed data are gathered and transmitted to a cloud database through an Arduino Uno microcontroller and a Raspberry Pi computer. Users can easily check the aquafarm's water quality through a smartphone or a remote computer. Moreover, when the water quality is not suitable for aquaculture, the ISAS automatically activates the aerator according to the fuzzy ruleset installed in Raspberry Pi. In our experiments, the survival rate of shrimp is increased by 33.3% when the ISAS was used compared with that obtained for the control group.

Although the ISAS can monitor four major parameters of water quality and automatically activate the actuator of an aquafarm, other water quality parameters such as water hardness, nitrite, and nitrate must be sensed to satisfy different requirements of different aquaculture systems. In addition, in the ISAS, only the actuator and feeder are controlled. In future studies, we will add devices such as automatic water replenishment and temperature regulators so that the water quality can be controlled effectively and the productivity of aquatic products can be highly increased.

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