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An intelligent autonomous floating net cage system for water quality management based on adaptive repositioning in aquaculture environments

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ABSTRACT

The spatial variation in water quality might adversely affect fish productivity, mortality, and sustainability of floating net cage aquaculture. Traditional floating net cages are often fixed and rely on manual environmental monitoring, which restricts their responsiveness to varying water conditions. To solve this problem, this study developed and tested a self-propelled floating net cage that can automatically move in real time in response to water quality conditions. The suggested system includes water quality monitoring, waypoint selection using particle swarm optimization (PSO), fuzzy logic-based navigation, and cooperative formation control with autonomous sensor buoys. The system constantly checks environmental conditions to find proper relocation routes to locations of better water quality. Three fuzzy controller structures with 3, 5, and 7 membership functions were constructed and evaluated by field trials in aquaculture ponds. The results indicate that real-time water quality monitoring, PSO-based waypoint optimization, fuzzy navigation control, and cooperative formation maintenance may be successfully integrated into a single autonomous framework. The system identified the best spot out of four monitored regions and navigated to it based on the observed water quality. Among the investigated controllers, the configuration with seven membership functions showed the highest performance, lowering the average positioning error from 3.79 m to 1.25 m, while delivering smoother trajectories and more stable formation control. The results demonstrate that adaptive autonomous repositioning is technically feasible for floating net cage aquaculture under the field conditions evaluated. Still a proof-of-concept and needing long-term validation and broader performance comparisons, the study shows the potential of integrating real-time environmental monitoring, optimization-based navigation, fuzzy decision-making, and cooperative autonomous control to enable more adaptive and intelligent aquaculture management.

Keywords: autonomous floating net cage, adaptive repositioning, fuzzy logic control, particle swarm optimization, aquaculture environment, water quality.

INTRODUCTION

One of the fastest-expanding food areas in the world is aquaculture. Aquaculture is essential to meet the world's protein needs as the world's population increases and the harvest from fisheries in natural waterways is declining (Boyd et al., 2022). Floating net cages (KJA) are one of the most common fishery production methods in Indonesia because of their relatively inexpensive operational costs, installation flexibility, and adaptation to different water conditions (Astuti et al., 2023; Kumar and Karnatak, 2014). The approach is more efficient in the use of water bodies compared to conventional ways of farming. The growth of Indonesia's aquaculture sector is also predicted to continue to rise in the next decades to fulfill the needs of both domestic and international markets. However, environmental concerns are also becoming more and more problematic with the increasing development of fish farming (Arisanty et al., 2021). Activities for growing in floating net cages might lead to the accumulation of residual feed, fish excrement, and other organic debris that can degrade water quality near the cultivation site (Syandri et al., 2020; Harjoyudanto et al., 2020). These conditions can eventually lead to greater risks of eutrophication, lower dissolved oxygen (DO) levels, changes in pH, and higher concentrations of contaminants, all of which are detrimental to fish health and aquatic ecosystems.

In addition, the management of modern aquaculture systems is challenged by the dynamic changes in environmental circumstances, such as variation in temperature, water currents, wind speed, and the spatial distribution of water quality indices (de Lima et al., 2022). Previous research has shown that floating net cage cultivation activities can lead to deterioration of water quality around the cultivation area if the environmental capacity is exceeded. (Andayani et al., 2021; Araujo et al., 2022). This problem is exacerbated by the fact that most currently used marine cage systems are static. The position of the cages is generally determined during initial installation and rarely changes during operation. As a result, the cultivation system is unable to respond adaptively to deteriorating environmental quality at a particular location. Under these conditions, management processes remain heavily reliant on periodic human observation and intervention, often delaying responses to environmental changes. From the perspective of ecological engineering, there is a need for a growing system that can automatically adjust to changing environmental conditions. Such a system should not only be able to continually monitor the water quality but also be able to conduct corrective actions based on real-time environmental information.

The development in sensor technology, internet of things (IoT), wireless communications, and artificial intelligence has resulted in the development of many water quality monitoring systems for aquaculture applications (Wei et al., 2020; Aggrey Shitsukane et al., 2024; Ike Bayusari et al., 2021). These systems offer the ability to measure environmental factors in real time, allowing the operator to get information on the water conditions faster and more accurately than conventional approaches. Advances in intelligent monitoring technology have increased the capacity for environmental monitoring in aquaculture systems and even in the open sea. Additionally, the combination of IoT with water quality sensors has made continuous data collection possible to assist operational decision-making. Computer vision-based monitoring technology has also been utilized to detect the status of aquaculture infrastructure and activities taking place surrounding the aquaculture area (Akbar et al., 2018; Priyanto et al., 2020). Apart from the research linked to environmental monitoring, many other studies have been carried out to assess cage structural deformation, hydrodynamic behavior, and system robustness to harsh environmental conditions (Liao et al., 2022; Bai et al., 2021). These studies have made important contributions to improving the safety and reliability of aquaculture systems. However, most research still focuses on monitoring and analyzing environmental conditions, without considering the system's ability to directly respond to detected changes in conditions. In other words, most currently available technologies still function as environmental observation systems. Information obtained from sensors is used to support decision-making by human operators, while the ability to automatically take adaptive actions remains very limited.

In recent years, the concept of autonomous systems has begun to be widely applied to various environmental and marine applications. The use of autonomous surface vehicles (ASVs), unmanned surface vehicles (USVs), and multi-agent systems has shown great potential in supporting environmental monitoring, data collection, and adaptive navigation (Wang et al., 2024; Liu et al., 2022; Wang et al., 2024).

To support these navigation capabilities, various computational intelligence methods have been developed. Fuzzy logic is popular because of its ability to handle the uncertainty and nonlinearity of systems (Kamis et al., 2019; Wei et al., 2019). On the other hand, particle swarm optimization (PSO) is an effective technique to solve trajectory optimization, waypoint planning, and multi-agent coordination problems (Altun and Aydın, 2025; Dy et al., 2025; Hoang et al., 2018; Huan Liu et al., 2021). The combination of these two technologies provides the possibility to create navigation systems that are more adaptive to the changes of the environment.

The application of fuzzy logic and PSO in autonomous cars and robotic systems has been proven successful in different research. However, its implementation in autonomous floating net cage systems is less common. Most of the present research is centered on simulations, laboratory testing, or just ambient sensors as monitoring instruments without the ability to adaptively reposition according to water quality conditions.

Furthermore, there have been very limited research efforts to integrate water quality monitoring, waypoint optimization, autonomous navigation, and multi-agent formation control inside a single aquaculture platform and evaluate such work in the field. This incident underscores the need to design aquaculture systems that can autonomously monitor and respond to environmental changes. While there have been substantial advances in water quality monitoring, autonomous navigation, and intelligent control systems, current research usually studies these functions separately. Table 1 compares exemplary studies on aquaculture monitoring, autonomous navigation, optimization-based control, and floating agent coordination to better show the contributions of this research.

The previous studies were mostly focused on environmental monitoring, intelligent navigation, or formation control as independent research subjects, as shown in Table 1. Generally, studies on water quality monitoring lack autonomous environmental reaction capability, and navigation-oriented studies prioritize trajectory optimization without integrating real-time environmental information. Furthermore, multi-agent coordination has mostly been investigated in robotic or autonomous vehicle applications rather than in floating net cage systems. Experimental validation under practical aquaculture conditions is also limited.

Unlike earlier studies which considered water-quality monitoring, autonomous navigation, waypoint optimization, or multi-agent coordination individually, this study presents an integrated environmental-response framework that connects environmental sensing with autonomous corrective actions. The uniqueness resides in the combination of real-time water-quality assessment, PSO-based waypoint optimization, fuzzy-logic navigation control and cooperative formation maintenance in a closed-loop fashion in one intelligent aquaculture platform. The suggested framework is not just an environmental monitoring system, but also enables autonomous floating net cages to continuously assess environmental conditions and to autonomously move to advantageous environmental areas. This environmental-response mechanism upgrades the function of smart aquaculture systems from passive monitoring to adaptive environmental management.

Despite recent advances in autonomous aquaculture systems, most research considers environmental monitoring, autonomous navigation,

Table 1. State-of-the-art comparison

Reference	Research topic	Water quality monitoring	Autonomous navigation	Adaptive repositioning	Multi-agent formation	Field validation
(Wei et al., 2020)	Intelligent monitoring and control cage	Yes	No	No	No	No
(SHITSUKANE; et al., 2024)	Integrating fuzzy logic, solar power and IoT for real-time water quality monitoring in cage fish	Yes	No	No	No	Yes
(Liao et al., 2022)	Intelligent damage detection of far-sea cage	No	No	No	No	Yes
(R. Wang et al., 2020)	Formation of multiple biomimetic underwater vehicles	No	Yes	No	Yes	No
(Zhang et al., 2020)	Controlling GPS-intelligent buoy (GIB) systems	No	Yes	Yes	No	No
(Dy et al., 2025)	Water unmanned surface vehicle using PSO method for water quality monitoring	Yes	Yes	No	No	No
Proposed system	Autonomous floating net cage	Yes	Yes	Yes	Yes	Yes

or formation control as independent components. Limited emphasis has been dedicated to the creation of an integrated framework capable of integrating real-time water quality monitoring, adaptive decision-making, waypoint optimization, and coordinated autonomous repositioning under a single operational system. This gap inhibits the independent response of floating aquaculture platforms to dynamic environmental changes and sustainable aquaculture management. Hence, the present study aims at developing and experimentally evaluating a unified adaptive decision-making framework for an autonomous floating net-cage system that integrates real-time water quality assessment, PSO-based waypoint optimization, fuzzy logic navigation, and cooperative formation control. The purpose of this study is to fill the current gap in integrated autonomous aquaculture systems by studying whether the integration of these components into a single system may improve adaptive repositioning and environmental monitoring in dynamic water quality circumstances. It is expected that an integrated strategy such as this will provide improved navigation performance, stable construction of sensing buoys, and improved autonomous aquaculture management compared to current approaches that treat these functions independently. It is hypothesized that the proposed integrated system will improve the accuracy of autonomous repositioning while maintaining stable formation among the sensing buoys, thereby enabling more effective environmental monitoring and supporting adaptive aquaculture management under changing environmental conditions.

MATERIALS AND METHODS

Study area and experimental setup

This research was conducted in an aquaculture environment as seen on the map in Figure 1, namely at points -2.988545, 104.742687. This location was used as a testing ground for the autonomous floating net cage system. This area is a testing pond with fairly clear, clean water and no trash, and fish live in this pond. Water parameters are also good; pH and DO are standard, which can be seen with the naked eye, and the number of fish and plants living in this pond. The autonomous floating net cage system consists of one main floating net cage unit and four sensor buoys placed around the observation area. Each buoy is equipped with a water quality sensor to monitor environmental data in real time, including temperature, pH, and DO. The water quality data acquired from the sensor buoys serve as the foundation for decision-making in selecting the optimal site for the floating net cage. All the experiments were performed in real operational situations to verify the system's ability to change the location adaptively according to changes in the ambient conditions.

Autonomous floating net cage system architecture

The proposed system architecture seeks to integrate environmental monitoring, adaptive decision-making, and autonomous navigation into a single smart aquaculture platform. The system consists of a central floating net cage (KJA) unit that serves as a decision-making center and the primary unit for monitoring water quality, as these cages are used for fish farming. Around the floating net cages, four buoys are placed as sensors that act as environmental monitoring agents. If the water quality sensor on the cage is bad, the system compares sensors on each buoy and then travels to the buoy with good water quality.

From an environmental standpoint, the main role of the system is to get information on water quality at different sites concurrently, enabling a more representative mapping of water conditions than single-point measurements. This method permits detecting locations with superior water quality to support aquaculture activity. Each buoy is fitted with sensors to measure real-time water environment conditions such as temperature, pH,

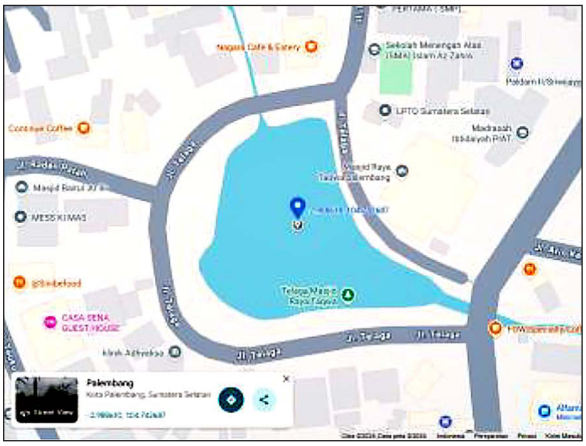


Figure 1. Location testing of autonomous floating net cage

and DO. The data generated is then communicated to the main floating net cage through a wireless communication system. This information is then utilized to calculate the best target location by comparing the measurements from each buoy to the cage. The suggested system differs from the usual static cage systems and can respond physically to changes in the environment through an automatic repositioning procedure. Thus, the system operates as a water quality monitoring system and also as an environmental management system that can adapt to dynamic water circumstances.

The autonomous floating net cage system was designed to be a floating platform that can move around based on the weather. The mechanical construction was made with SolidWorks. The frame of the cage was composed of light steel, while the sections that made it floated were made of high-density polyethylene (HDPE). In each corner of the cage, there was an HDPE float and a propulsion motor that worked as an actuator for planar motion. On one side of the cage, there was a sealed component box that held the embedded controller, power management system, and communication modules.

The net cage that floated was 4 × 4 m on the outside and 3 × 3 m on the inside. There were many autonomous buoys spaced out around the cage that checked the water quality. The cage was fitted with a GPS sensor and a digital compass so that it could tell you where it was and where it was going in real time. Figure 2 illustrates the overall system setup and the layout of the formation.

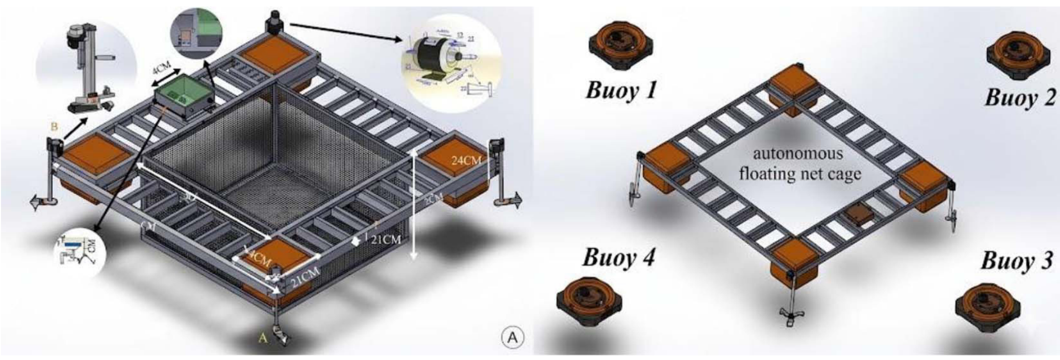
The autonomous floating net cage system is designed as a multi-agent structure consisting of one main floating cage and four autonomous buoys. The water quality sensor system, which includes pH, DO, and temperature sensors, a positioning system (GPS and compass), and a drive mechanism (motor and propeller), is placed on the floating net cages and on each float. Within this system, all elements communicate with one another and transmit sensor readings that are used to move in a specific formation. This autonomous floating net cage system has four main components:

- sensor units, including water quality sensors (pH, DO, and temperature), GPS, and compass.
- control unit, a microcontroller embedded with fuzzy logic and PSO control algorithms.
- drive unit, a motor equipped with a propeller.
- decision-making unit, consisting of a communication system (LoRa and TCP/IP) and an algorithm embedded in the microcontroller to select the ideal direction point based on water quality conditions.

Environmental monitoring and decision-making framework

This environmental monitoring and decision-making framework was created to enable the system to respond autonomously to water quality changes in the autonomous floating net cage system. The method starts with the measurement of water quality parameters using sensors installed on the cages and buoys placed around the cages at a distance of 20 meters from each other.

Water quality data from the cages and all buoys are gathered and evaluated to assess environmental conditions at each location. The result of the analysis is utilized for identifying areas with the most suitable water quality for the relocation of floating net cages. If the water quality of the cages is low, the environmental monitoring and decision-making framework will advise the cage system to migrate to an area with good water quality.



a) b)

Figure 2. System design and formation: a) design of an autonomous floating net cage, b) formation of the autonomous floating net cage system

This method enables the system to make adaptive judgments based on the actual environmental state and no requirement for the manual operator observation. This enables the system to adapt more quickly to changes in water quality during agriculture.

Figure 3 illustrates a flowchart related to the performance of the autonomous floating net cage system. The use of sensors based on real-world field data provides real-time input for the intelligent controller to control the movement of the cages and floats to positions with good water quality. The synergy between sensor readings in the autonomous floating net cage system, PSO, and logic control will improve the system's performance. Evidence of its performance can be seen from the position of the autonomous floating net cage system in a location where the water quality is good.

The sensor readings on water quality will be sent to a microcontroller containing a decision-making algorithm. If the water quality readings are poor, this algorithm will analyze and compare sensor data transmitted from surrounding autonomous buoys. This algorithm will identify buoys with optimal water quality, which will be used as the target position for the autonomous floating net cage system. The combined PSO-fuzzy system will regulate the movement of the autonomous floating net cage system based on GPS and compass data readings, so that the autonomous floating net cage system will be directed to the specified target position. This navigation process will repeat continuously in a closed loop until the distance error between the cage and the target location is less than 1 meter. Then, this system will re-evaluate the water quality parameters.

Figure 3(a) illustrates the flowchart where the combined PSO-fuzzy algorithm will begin system initialization, namely, activating sensors, actuators, and controller parameters. Real-time GPS and compass data will be read, indicating location and orientation. This data is used to determine deviations from the desired target waypoint. The PSO method will identify the optimal position of the specified target. The fuzzy logic controller will generate adaptive control signals based on differences in distance and orientation to the target. The signals from the sensor readings are then transmitted to the actuator. This process will be repeated until the target position is reached.

Meanwhile, Figure 3(b) illustrates the flowchart carried out by the decision-making algorithm based on water quality sensor readings. The main indicators of water quality read are water temperature and pH. If the water quality is in accordance with the predetermined setpoint specifications, the system will remain stationary. However, if it is not in accordance, then the water quality sensor data from the buoys scattered around the floating net cages is analyzed to identify the optimal location. After that, a new waypoint is obtained as a target to be reached, and the system will begin autonomous navigation towards the target while maintaining

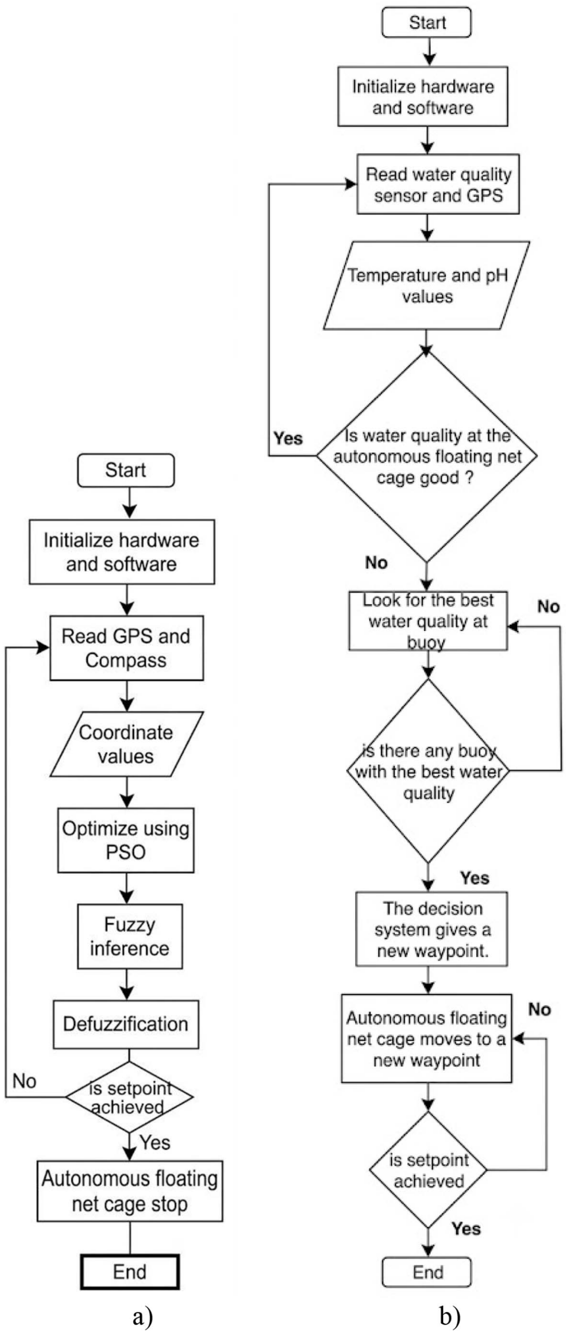


Figure 3. Autonomous floating net cage flowcharts: (a) PSO–fuzzy-based control flow; (b) water-quality-based decision flow

the position between the floating net cage and the buoy. Once the specified target waypoint has been reached, the system will stop and continue monitoring the water quality again. This workflow demonstrates the integration between environmental observations containing water quality, parameter, and position optimization, with intelligent control to create an autonomous floating net system.

Water quality parameters

In this study, three key water quality indices, including temperature, pH, and DO, were used. The choice of these three factors was due to the fact that they directly influence fish health, feed consumption efficiency, and the success of the cultivation process. DO is a measure of the amount of oxygen that is dissolved in water. Physiological stress in fish and reduction in aquaculture productivity can result from lowered DO levels. pH is also used to describe the acidity or alkalinity of water, and this influences the biological activity of aquatic creatures. Water temperature is also a major determinant of metabolic rates and growth rates of fish and the activity of microorganisms in aquatic ecosystems. So, these three factors are employed as the main parameters in the process of environmental quality evaluation and in the determination of the target location for the proposed autonomous floating net cage system.

Kinematic model of floating agents

The motion behaviour of the autonomous floating net cage and auxiliary floating buoys or floating agents is modelled using a planar kinematic representation. Since the system operates at low speed on the water surface and is primarily influenced by control inputs rather than high-frequency wave dynamics, a kinematic model is adopted to describe the position and heading evolution of each floating agent. This modelling method is widely used in floating autonomous systems and surface robotic platforms because it is simple and effective for control design and trajectory tracking

Table 2. Water quality parameters used in the decision-making process

Parameters	Optimal range
pH	6.5–8.5
Temperature	26–32
Dissolved oxygen (DO)	5 mg/L

analysis (Fu et al., 2023; Wang et al., 2024). It is assumed that each floating agent moves in a two-dimensional horizontal plane, which is defined by its Cartesian position and heading angle. The floating agent's state vector is shown as:

$$\mathbf{x}(t) = \begin{bmatrix} x(t) \\ y(t) \\ \psi(t) \end{bmatrix} \quad (1)$$

The planar position coordinates in the global reference frame represents the heading angle measured with respect to the north direction obtained from the compass sensor. The kinematic equations governing the motion of the floating agent are given by:

$$\dot{x}(t) = v(t)\cos\psi(t) \quad (2)$$

$$\dot{y}(t) = v(t)\sin\psi(t) \quad (3)$$

$$\dot{\psi}(t) = \omega(t) \quad (4)$$

The linear velocity of the buoy, namely the angular velocity, generated by the propulsion system. This control input is generated by the fuzzy logic controller based on distance and direction errors, which are relative errors to the desired waypoint and are interpreted as follows:

$$e_d(t) = \sqrt{(x_d - x(t))^2 + (y_d - y(t))^2} \quad (5)$$

$$e_\psi(t) = \mathrm{atan2}(y_d - y(t), x_d - x(t)) - \psi(t) \quad (6)$$

The error variable serves as input to the fuzzy inference system, enabling the generation of control commands that are adaptive to environmental conditions, in this case, varying water quality. The target coordinates of the desired waypoint can be obtained from the PSO process, where the optimal target position is selected based on water quality information and spatial constraints. For formation control between the floating net cage and multiple autonomous buoys, each buoy is modelled using the same kinematic structure, allowing coordinated motion within the formation. The relative position error between the cage and the -th buoy is expressed as:

$$e_{f,i}(t) = \sqrt{(x_i(t) - x_c(t))^2 + (y_i(t) - y_c(t))^2} \quad (7)$$

The navigation process is carried out by maintaining the relative distance between buoys and the floating cages within a predetermined distance limit, followed by formation stability until the target is reached. The kinematic model serves as the basis for controller design and performance evaluation. Separation of low-speed planar motion from complex hydrodynamic effects will enable the proposed model to implement effective intelligent control strategies. These modelling assumptions have been validated in autonomous surface vehicles and floating multi-agent systems operating under moderate environmental disturbances.

Waypoint optimization based on PSO

The PSO technique is employed to ascertain the ideal waypoint or goal position for the movement of the autonomous floating net cage. PSO was chosen because the system utilizes GPS coordinates, spatial information, and the environment. PSO is a stochastic optimization technique based on population dynamics, inspired by the social behaviour of swarms, wherein potential solutions develop through collaboration and information exchange among particles. Each particle signifies a target location delineated by latitude and longitude coordinates. The distance between the cage and the target is minimized, and the system also ensures smooth trajectory convergence. In the proposed framework, each particle represents a candidate waypoint defined by geographic coordinates obtained from the global positioning system (GPS). In navigation, the Haversine Theorem is an essential tool for determining the arc distance between two points on a sphere, such as the Earth's surface. The "Haversine Law" is a unique way of expressing spherical trigonometry. The Haversine Theorem allows us to calculate the distance between two locations on the Earth's surface using longitude and latitude as input variables. In this formula, the great circle distance between two points on a sphere is calculated using the Haversine Theorem. This formula assumes the Earth's radius is a constant, with an average value of approximately 6,367.45 km. The coordinates of the two points whose distance is to be measured are represented by their longitude and latitude values, namely lon1, lat1 for the first point, and lon2, lat2 for the second point. Using the Haversine Theorem, we can calculate the distance between two points on the Earth's surface with accuracy using the latitude and longitude data of both points. Finally, the Haversine Theorem can be written as the following equation (Alkodri et al., 2025):

$$\boldsymbol{a - sin^2\left(\frac{\Delta\varphi}{2}\right) + cos(\varphi_1).cos(\varphi_2).sin^2\left(\frac{\Delta\lambda}{2}\right)} \quad (8)$$

$$\boldsymbol{c - 2.atan2\left(\sqrt{a}, \sqrt{1-a}\right)} \quad (9)$$

$$\boldsymbol{d - R.c} \quad (10)$$

$$\boldsymbol{\Delta long = (long1 + long2)cos\left(\frac{lat1+lat2}{2}\right)} \quad (11)$$

$$\boldsymbol{\Delta lat = lat2 - lat1} \quad (12)$$

where: φ_1, φ_2 are the latitudes of the two points, λ_1, λ_2 are the longitudes of the two points, $\Delta\varphi = \varphi_2 - \varphi_1$ is the difference in latitudes between the two points, $\Delta\lambda = \lambda_2 - \lambda_1$ is the difference in longitudes between the two points, R is the radius of the Earth (6371 km), $\Delta long$ – change in longitude value, $long1$ – prototype longitude value, $long2$ – destination longitude value, Δlat – change in longitude value, $lat1$ – prototype latitude value, $lat2$ – destination latitude value.

The position of the *i*-th particle at iteration *k* is expressed as:

$$\mathbf{p}_i^k = \begin{bmatrix} x_i^k \\ y_i^k \end{bmatrix} \quad (13)$$

where: $\boldsymbol{x_i^k}$ and $\boldsymbol{y_i^k}$ denote the latitude and longitude components of the candidate waypoint, respectively.

The velocity of each particle is defined as:

$$\mathbf{v}_i^k = \begin{bmatrix} v_{x,i}^k \\ v_{y,i}^k \end{bmatrix} \quad (14)$$

The particle velocity and position are updated according to the standard PSO update equations:

$$\mathbf{v}_i^{k+1} = \omega \mathbf{v}_i^k + c_1 r_1 \left(\mathbf{p}_{i,\text{best}}^k - \mathbf{p}_i^k\right) + + c_2 r_2 \left(\mathbf{p}_{\text{global}}^k - \mathbf{p}_i^k\right) \quad (15)$$

$$\mathbf{p}_i^{k+1} = \mathbf{p}_i^k + \mathbf{v}_i^{k+1} \quad (16)$$

Where is the inertia weight controlling the balance between exploration and exploitation, and are the cognitive and social acceleration coefficients, and are uniformly distributed random numbers in the range. The terms and denote the personal best position of the particle and the global best position of the swarm, respectively.

$$J = \alpha\sqrt{(x_d - x_c)^2 + (y_d - y_c)^2} + \beta Q^{-1} \quad (17)$$

The objective of optimization is to minimize the distance between the autonomous floating net cage and the candidate waypoint while satisfying environmental suitability constraints. Where represent the candidate waypoint coordinates, denote the current position of the floating net cage, and is a normalized water quality index derived from sensor measurements. Weighing factors and regulating the trade-off between spatial proximity and environmental quality. The optimized waypoint coordinates obtained from the PSO algorithm serve as reference inputs to the fuzzy logic controller. Since waypoint optimization will be separated from motion control, the proposed method will increase the flexibility and robustness of the system, thus enabling adaptive repositioning of floating net cages in response to dynamic environmental conditions. Methods using PSO-based waypoint or target optimization have demonstrated their effectiveness in autonomous marine vehicles and multi-agent systems operating under uncertain conditions (Altun and Aydın, 2025; Sellers et al., 2022). The PSO calculates the ideal waypoints according to the given environmental quality values, which serve as navigation targets for the floating net cages (KJA).

Fuzzy-based navigation and formation control

The movement of a floating net cage during the repositioning procedure to a place with higher water quality is controlled with a fuzzy logic controller (FLC). Fuzzy logic is used to enable the system to navigate more flexibly in response to changes in the target position, external disturbances, and ambiguity in sensor measurements.

In this study, the membership functions employed are 3, 5, and 7, the inference mechanism of the fuzzy logic controller is the Sugeno type. Increasing the number of membership functions will improve the accuracy of the control actions but at the expense of the computations, which become more difficult and slower. The fuzzy rule base is developed based on basic IF-THEN rules that relate distance and course mistakes to the associated speed commands. The fuzzy controller output is a PWM to control the speed of the propulsion motor to drive the floating net cage to the waypoint obtained by the PSO algorithm. The fuzzy inputs are the distance to the destination point error and the course error. This strategy provides a smoother and more stable repositioning procedure compared to conventional control approaches. Besides helping in navigation to the target, the fuzzy controller also plays an important role in keeping the coordination of the main net cage and the buoy during the repositioning operation. The capacity to maintain this formation is vital to ensure the continued coverage of a representative observation area by the dispersion of sensors, so that information on water quality can be gathered more correctly and continuously.

Table 3. Water quality parameters used in the decision-making process

Heading direction (error θ°)	Variable
-90–(-46)	Turn left
-45–(-15)	Tilt left
-15–15	Straight
16–45	Tilt right
46–90	Turn right

In this study, triangular and trapezoidal membership functions are utilized due to their simplicity and computational efficiency, which are suitable for real-time embedded implementation. The input membership functions are presented in Tables 1 and 2, and Table 3 presents the output membership function. Distance data were obtained from the calculation of the latitude and longitude coordinates of the origin and destination points using the Haversine formula. The sensor readings for water quality, distance, and heading direction served as input values for the cage to maintain its position and formation, or to navigate to the buoy with the best water quality, utilizing fuzzy logic as the control system. The final phase in the fuzzy system is defuzzification, which aims to convert the output of the inference engine, presented as a fuzzy set, into a crisp numerical value. The defuzzification process in this study utilizes the weighted average method and Sugeno's zero-order fuzzy rules, starting with the average value based on membership functions.

In the present study, fuzzy logic is utilized as a method of navigation control; nevertheless, the main purpose of the application of fuzzy logic is not only to increase the precision of movement but also to support the system to respond to changes in environmental quality in an adaptive way. Hence, fuzzy logic is useful in designing a more intelligent and responsive. In this process,

Table 4. Input membership function (distance)

Distance (m) 7 members	Distance (m) 5 members	Distance (m) 3 members	Variable
0–2	0–1.5	-	Very close
1–3	1–3	0–2	Close
2–4	-	-	Slightly close
3–5	2.54	1.5–4	Medium
4–6	-	-	Slightly far
5–7	6	6	Far
6–8	-	-	Very far

Table 5. Output membership function (Pulse Width Modulation/PWM)

PWM 7 members	PWM 5 members	PWM 3 members	Variable
100	100	-	Very slow
150	150	150	Slow
170	-	-	Slightly slow
190	190	190	Medium
210	-	-	Slightly fast
230	230	230	Fast
255	255	-	Very fast

fuzzy rules are determined as a reference for obtaining the motor speed output. In this study, three conditions were used, each with 3 members, 5 members, and 7 members, so that the rules obtained and used in this test can be seen in Table 6. The final phase in a fuzzy system is called defuzzification, and its goal is to convert the inference engine‘s output, presented as a fuzzy set, into actual numbers. Using the weighted average method and the Sugeno zero-order fuzzy rule, the defuzzification process in this study takes the membership function-based average value as its starting point.

Performance evaluation metrics

System performance is evaluated using several parameters representing navigation capability, formation coordination, and response to environmental changes. These evaluation parameters are used to measure the system's effectiveness in carrying out monitoring and adaptive repositioning functions.

Positioning error

Positioning errors are used to measure the level of accuracy of KJA navigation to the specified waypoint.

$$PE = \sqrt{(x_t - x)^2 + (y_t - y)^2} \tag{18}$$

Formation error

The formation error is used to evaluate the ability of the system to maintain the correct distance between the main floating net cage and the sensor buoy during the repositioning procedure. This metric is calculated as a difference between the actual distance and a predefined reference distance. A small formation error number suggests that the system can maintain strong coordination between agents and the sensor distribution is appropriate to allow spatial water quality monitoring.

$$FE = [D_d - D_a] \tag{19}$$

where: D_d is the desired distance, and D_a is the actual distance; *FE* is formation error.

Convergence time

The convergence time measures the time the system needs to reach a destination after a waypoint has been selected. This metric characterizes the effectiveness of the navigation process and the ability of the system to adjust to changing environmental conditions. The less the convergence time, the more quickly the system can be transferred to a place with water quality better suitable for supporting aquaculture activities.

Table 6. Output membership function (pulse width modulation – PWM)

Rules	3 membership function			5 membership function			7 membership funtion		
	Direction	Distance	PWM	Direction	Distance	PWM	Direction	Distance	PWM
1	Turn__ left	Close	Slow	Turn__left	Very_ Close	Very_ Slow	Turn__ left	Very_ Close	Very Slow
2	Turn__ left	Medium	Medium	Turn__left	Close	Slow	Turn__ left	Close	Slow
3	Turn__ left	Far	Fast	Turn__left	Medium	Medium	Turn__ left	Slightly_ close	Slightly_ slow
4	Slanted_ left	Close	Slow	Turn__left	Far	Fast	Turn__ left	Medium	Medium
5	Slanted_ left	Medium	Medium	Turn__left	Very_ Far	Very_ Fast	Turn__ left	Slightly_ far	Slightly_ fast
6	Slanted_ left	Far	Fast	Slanted_ left	Very_ Close	Very_ Slow	Turn__ left	Far	Fast
7	Straight	Close	Slow	Slanted_ left	Close	Slow	Turn__ left	Very_ far	Very_ fast
8	Straight	Medium	Medium	Slanted_ left	Medium	Medium	Slanted_ left	Very_ close	Very Slow
9	Straight	Far	Fast	Slanted_ left	Far	Fast	Slanted_ left	Close	Slow
10	Slanted_ right	Close	Slow	Slanted_ left	Very_ Far	Very_ Fast	Slanted_ left	Slightly_ close	Slightly_ slow
11	Slanted_ right	Medium	Medium	Straight	Very_ Close	Very_ Slow	Slanted_ left	Medium	Medium
12	Slanted_ right	Far	Fast	Straight	Close	Slow	Slanted_ left	Slightly_ far	Slightly_ fast
13	Turn__ right	Close	Slow	Straight	Medium	Medium	Slanted_ left	Far	Fast
14	Turn__ right	Medium	Medium	Straight	Far	Fast	Slanted_ left	Very_ Far	Very_ fast
15	Turn__ right	Far	Fast	Straight	Very_ Far	Very_ Fast	Straight	Very_ Close	Very Slow
16	-	-	-	Slanted_ right	Very_ Close	Very_ Slow	Straight	Close	Slow
17	-	-	-	Slanted_ right	Close	Slow	Straight	Slightly_ close	Slightly_ slow
18	-	-	-	Slanted_ right	Medium	Medium	Straight	Medium	Medium
19	-	-	-	Slanted_ right	Far	Fast	Straight	Slightly_ far	Slightly_ fast
20	-	-	-	Slanted_ right	Very_ Far	Very_ Fast	Straight	Far	Fast
21	-	-	-	Turn__ right	Very_ Close	Very_ Slow	Straight	Very_ Far	Very_ fast
22	-	-	-	Turn__ right	Close	Slow	Slanted_ right	Very_ Close	Very Slow
23	-	-	-	Turn__ right	Medium	Medium	Slanted_ right	Close	Slow
24	-	-	-	Turn__ right	Far	Fast	Slanted_ right	Slightly_ close	Slightly_ slow
25	-	-	-	Turn__ right	Very_ Far	Very_ Fast	Slanted_ right	Medium	Medium
26	-	-	-	-	-	-	Slanted_ right	Slightly_ far	Slightly_ fast
27	-	-	-	-	-	-	Slanted_ right	Far	Fast
28	-	-	-	-	-	-	Slanted_ right	Very_ Far	Very_ fast
29	-	-	-	-	-	-	Turn__ right	Very_ Close	Very Slow
30	-	-	-	-	-	-	Turn__ right	Close	Slow
31	-	-	-	-	-	-	Turn__ right	Slightly_ close	Slightly_ slow
32	-	-	-	-	-	-	Turn__ right	Medium	Medium
33	-	-	-	-	-	-	Turn__ right	Slightly_ far	Slightly_ fast
34	-	-	-	-	-	-	Turn__ right	Far	Fast
35	-	-	-	-	-	-	Turn__ right	Very_ Far	Very_ fast

$$CT = [T_f - T_0] \quad (20)$$

where: T_f is target, time reached, T_0 is waypoint creation time, CT is convergence time.

Environmental response capability

The environmental response capability is adopted to assess the capacity of a system to adaptively respond to changes in environmental quality by decision-making and repositioning. This value reflects the integration of water quality monitoring, waypoint optimization, and autonomous navigation into a single integrated system. This capacity is important as it shows that the system is not simply a monitoring platform but is also able to automatically take corrective action when the environmental conditions in the crop area change.

Implementation details

To improve the transparency and repeatability of the proposed framework, the implementation parameters of the optimization and control algorithms are presented in this subsection. In the present work, the PSO algorithm has been implemented with a swarm size of 30 particles and a maximum of 100 iterations. The inertia weight was set to 0.7, while the cognitive and social coefficients were set at 1.5. These parameters were selected according to preliminary experiments and recommendations from earlier PSO-based navigation research. In this study, the data collected included distance and water quality sensor values (temperature and pH). The longitude and latitude values obtained from the GPS sensor were then converted into distance using the Haversine equation as PSO input. The PSO algorithm was used to obtain the best Pbest and Gbest values for use in the fuzzy logic controller (FLC). The working system or flowchart of the PSO algorithm can be seen in Figure 4.

The variables used by the PSO algorithm are selected during the initialization phase. Swarm initialization also uses longitude and latitude position data with random values determined during data collection. The first variable is position, representing the initial position of the buoy and floating net cage. The data collected consists of the longitude and latitude values for each buoy and floating net cage. The next variables are targetlatpso and targetlongpso, which represent the target position between the buoy and floating net cage, obtained from the particle swarm optimization algorithm. And also, the next variables are the targetlat and targetlong variables which represent the target position or destination position that the buoy and also the floating net cage will aim for. The final variable is velocity, which plays a crucial role in determining how particles in the population move within the search space. Furthermore, there are constant variables whose values are predetermined, such as inertia (w), cognitive learning (c1), and social learning (c2). The next step is to conduct a fitness evaluation to determine the ratio of the error between the particle's actual distance and its position coordinates. The fitness evaluation in this study involved converting the longitude and latitude values obtained from the GPS sensor into distance units using the haversine formula. Next, the optimal particle position is determined, which will be stored in the position variable and recalculated using the existing fitness function. This

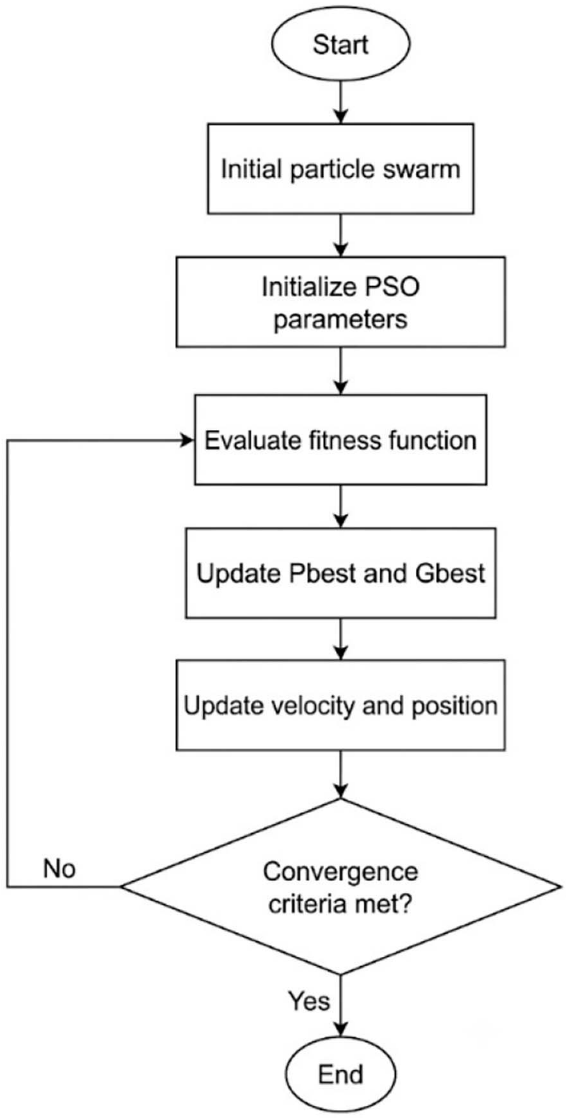


Figure 4. PSO algorithm flowchart

will then update the Pbest values for each particle. After obtaining the Pbest results for each particle, the PSO algorithm searches for the global optimal position (gbest) using the smallest fitness value of each particle in each iteration. The parameters used in the PSO algorithm can be seen in Table 7.

The fuzzy logic controller has two input variables, distance error and heading error, and one output variable, propulsion motor PWM command. Three controller configurations consisting of 3, 5, and 7 membership functions were evaluated. A Sugeno-type inference mechanism was utilized together with a weighted-average defuzzification method to generate smooth control actions suitable for real-time embedded implementation. The fuzzy rule base consisted of 15, 25, and 35 rules for the 3-, 5-, and 7-membership-function configurations, respectively.

RESULT AND DISCUSSION

Water-quality-based adaptive repositioning performance

This research designed a floating net cage system that can adaptively reposition using water quality information from the cage and four buoys, as illustrated in Figure 5. The decision-making procedure was based on the data of temperature, pH, and DO to find more ideal destination areas for aquaculture activities.

The test findings showed that the system can incorporate environmental monitoring, PSO-based waypoint optimization, and fuzzy logic-based navigation in one continuous operational cycle. This allows the cage to be repositioned automatically to better environmental conditions without operator interaction. In this study, the main hardware components include the HMC5883L compass, LoRa-02 module, DS18B20 temperature sensor, DFRobot pH sensor, ESP32 DevKit, and DC motor, as shown in Figure 6.

The DS18B20 temperature sensor operates over a supply voltage range of 3–5.5 VDC and is capable of measuring temperatures from −55 °C to 125 °C with a programmable resolution of 9 to 12 bits. Since the sensor is factory calibrated, it was used directly in this study without requiring additional calibration.

The DFRobot pH sensor operates with a 5 V power supply and requires approximately 1 minute to stabilize before providing reliable measurements. It has a measurement range of 0–14 pH and an operating temperature range of 0–60 °C, making it suitable for water quality monitoring applications.

Table 7. Implementation parameters of PSO

Parameters	Value	Description
Swarm size	30	Number of particles
Maximum iteration	100	Optimization stopping criterion
Inertia weight	0.5	Exploration-exploitation balance
Cognitive coefficient	0.5	Individual learning factor
Social coefficient	0.5	Global learning factor
Velocity limit	±2 m/s	Prevent excessive particle movement

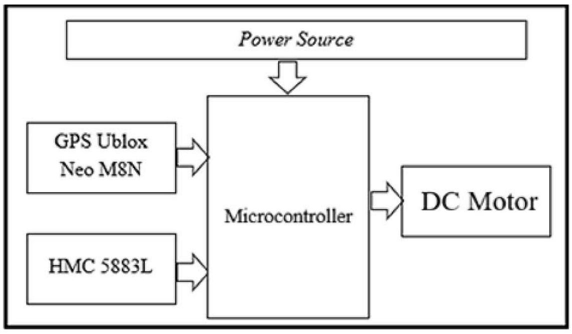


Figure 6. Hardware design

a) b) c)

Figure 5. Autonomous floating net cage system: (a) autonomous floating net cage; (b) buoy; (c) autonomous floating net cage moves to the target position

Prior to the experiments, the pH sensor was calibrated using three standard buffer solutions with pH values of 4.01, 6.86, and 9.18, representing acidic, neutral, and alkaline conditions, respectively. Each buffer solution was prepared by dissolving the corresponding buffer powder in 250 mL of water. This calibration procedure was performed to ensure accurate and reliable pH measurements throughout the experiments (Figure 7).

Based on the tests carried out, water quality data was obtained as shown in Table 8.

Navigation performance analysis

Direct testing of the autonomous floating net cage using fuzzy logic control is shown in Figure 8. It shows a graphical comparison of the target coordinates and route coordinates on an autonomous floating net cage using 3 membership functions in Figure 8a, 5 membership functions in Figure 8b, and 7 membership functions, as in Figure 8c. The target coordinates and those traversed by the autonomous floating net The target coordinates and those traversed by the autonomous floating net are shown in the graph, which features a red and blue line, with the former representing the target coordinate route to be followed by the autonomous floating net and the latter representing the route actually followed by the autonomous floating net using the fuzzy logic control method. The x-axis displays the longitudinal and latitudinal values, respectively. Figure 8 shows that the three images are similar to each other. However, the 7-membership function exhibits more similar points than the others. Furthermore, from the test, the longitude and latitude values are obtained, respectively, shown on the x-axis and y-axis. The latitude and longitude coordinate points are used to calculate the distance, where the calculation is based on the Haversine formula, namely, based on the coordinates of the autonomous floating net cage. The initial coordinate point is established before the autonomous floating net cage moves towards the target point. The experimental results showed that the three-membership fuzzy arrangement had the most placement errors, with an average of 3.79 m. This behaviour happened because the control actions had a limited resolution, which made speed changes less accurate and made course changes take longer. As a result, the system showed more deviation in its trajectory and less accuracy in its positioning, which is bad for real-world aquaculture uses. The five-member arrangement greatly improved positioning accuracy, bringing the average error down to 1.25 m. Adding more membership functions makes it easier to switch between control modes, which leads to better speed regulation and better trajectory alignment. Because of this, the system got to the target waypoint more quickly and with fewer oscillations. The seven-member setup had an average positional error of 1.25 m. The five-member design has slightly larger numerical errors, but the overall trajectory is much smoother compared to the three-member design. Because of this, the system showed more trajectory deviation and less accuracy in positioning, which is not good for real-world aquaculture uses. The five-member arrangement made positioning much more accurate, lowering the average error to 1.25 m than three-membership. Adding more membership functions makes it easier to switch between control states, which leads to better speed control and better course alignment. As a result, the system got closer to the goal waypoint more quickly and with fewer oscillations. The seven-member group had an average location error of 1.25 meters. With

Figure 7. Movement of the autonomous floating net cage based on water quality sensor readings

Table 8. Output membership function (pulse width modulation – PWM)

Sensor	DO (mg/L)	pH	Temp (°C)	Decision
Cage (KJA)	5.7	7.5	33.56	Bad
Buoy 1 / Point 1	5.5	7.5	33.25	Bad
Buoy 2 / Point 2	5.8	7.6	33.1	Slightly good
Buoy 3 / Point 3	5.65	7.6	32.6	Bad
Buoy 4 / Point 4	5.3	7.3	31.5	Good

its smaller numerical error compared to the five and three-member cases, the overall trajectory is much smoother. As illustrated in Figure 8, the cage follows a more continuous and stable path with minimal overshoot. From an engineering standpoint, a smoother trajectory is preferable because it reduces mechanical stress on the drive components and increases the system's durability during long-term operation.

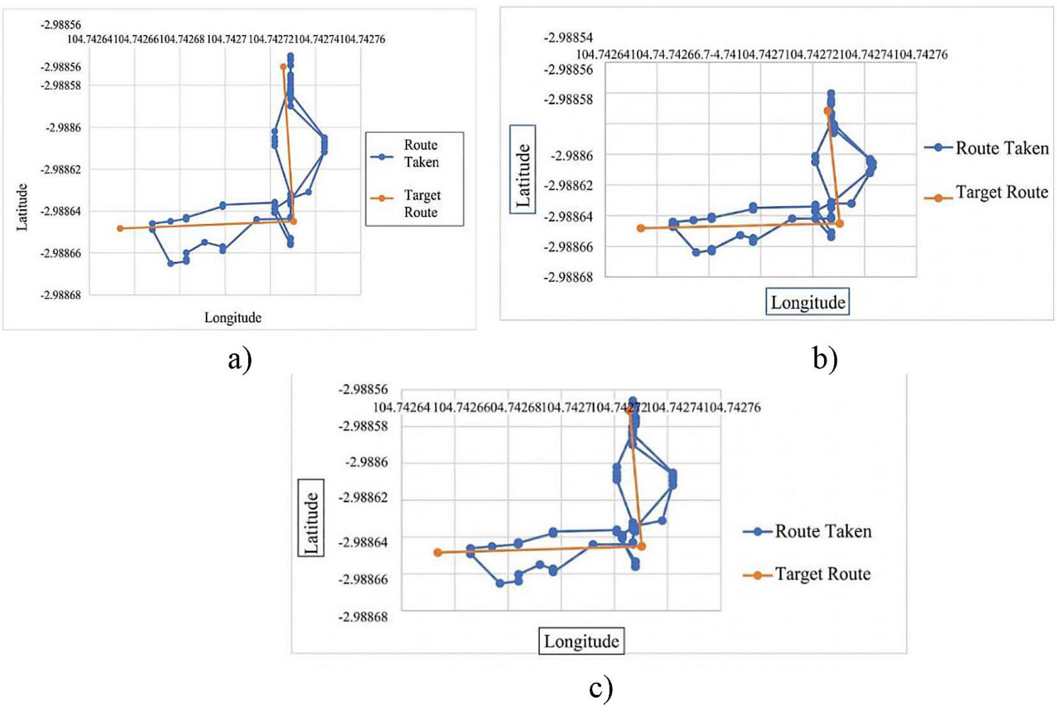
The relatively modest amount of the error reflects the ability of the system to reach the given waypoint with high accuracy, allowing to reposition effectively to sites with improved water quality. In addition, the smaller the inaccuracy, the more fluid and consistent the movement. The smoother trajectory generated by the proposed controller may reduce sudden mechanical disturbances during cage repositioning. However, fish behavioral responses were not quantitatively evaluated in the present study. Future studies should therefore specifically investigate the possible effect of adaptive repositioning on fish welfare.

Formation maintenance performance

The capacity to maintain formation is an important feature of the proposed system since the distribution of buoys defines the breadth of the water quality monitoring. The technology maintains the agents at a successful distance during the relocation process and allows the agents to continue to acquire information about the environment from several locations simultaneously.

From the environmental monitoring standpoint, the capability of maintaining formation provides geographically precise water quality monitoring and eliminates the danger of loss of information owing to sensor concentration at a particular place. Formation testing between floating net cages (KJA) and swarm buoys was performed using the PSO programming approach to search for the optimum position between the KJA and swarm buoys in this work. The PSO algorithm was employed to allow the KJA and swarm buoys to move collectively, like a flock of birds or swarm. Testing was performed to determine the formation produced by the KJA and swarm buoys by traveling between the KJA and swarm buoys.

Figure 9 shows the test route for the autonomous floating net cage formation control system's movement along the target route and the actual route based on the decision-making system. This decision-making system guides the autonomous floating net cage formation and buoys to move toward the target coordinate point and then return to the starting coordinate point based on the best water quality among the buoys.



a) b) c)

Figure 8. Comparison graph of the target coordinates and the coordinates routes taken by the autonomous floating net cage with (a) three members, (b) five members, and (c) seven members

Figure 9. Testing route coordinates for the formation of autonomous floating net cage

The blue graph in Figure 10 represents the coordinate route followed by the floating net cage using the seven-member fuzzy logic control method, which produces more accurate results for decision-making. The red graph depicts the intended target route followed by the floating net cage.

Based on the route coordinates in Figure 10, the fish cage will move to buoy 3 when the decision-making algorithm detects poor water quality and then shift to buoy 1. When the water quality at buoy 1 is better than at buoy 3, this research tested the movement of the buoy swarm or agents to assess the ability of the autonomous floating net cages and the buoy swarm to move in unison in a specific formation to reach a designated point and maintain this formation until the target is reached.

The performance of formation control is measured by how well the autonomous buoys can keep their relative positions to the main floating net cage while they are moving. The experimental results show that the proposed kinematic model and control strategy can keep the formation stable during the whole navigation process. The buoys follow the motion of the main cage but also maintain track of their desired relative positions. The fuzzy controller swiftly corrects slight errors in acceleration and turning, showing good cooperation between the agents. To accurately monitor the environment, it is necessary to be able to maintain formation such that water quality measurements are taken over the same area each time. From an applied engineering perspective, the shown formation stability verifies the suitability of the proposed system for multi-agent surface applications in aquaculture environments. Then, to strengthen the experimental validation, several test results are shown in Tables 9, 10, and 11.

The difference between the predetermined target and actual coordinates of the autonomous floating net cage upon reaching the destination is presented in Table 9. The distance was computed using the Haversine formula to determine the distance between the latitude and longitude points. As indicated in table, the average distance error of the KJA is 3.79 m. The distance was computed using the Haversine formula in a CPP program, based on latitude and longitude points. As indicated in Table 10, the average distance error of the KJA was 1.125 m, which was lower than that of the three-membership system.

The distance was computed using the Haversine formula in a CPP program, based on the latitude and longitude points. The average distance error of the autonomous floating net cage was 1.25 m, as indicated in Table 11. The evaluation

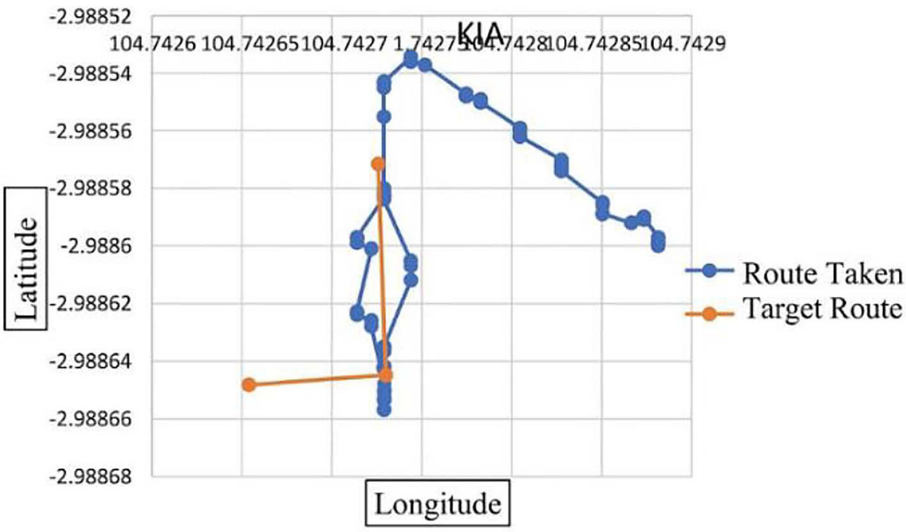


Figure 10. Comparison graph of routes taken by the formation of an autonomous floating net cage

Table 9. Distance error autonomous floating net cage- 3 members

Point	Autonomous floating net cage coordinates to target				Dist (m)
	Lat now	Long now	Lat now	Long target	
1	-2.988569	104.742729	- 2.988571	104.742725	0.50
2	-2.988641	104.742722	- 2.988645	104.742730	0.99
3	-2.988643	104.742683	- 2.988645	104.742730	5.22
4	-2.988644	104.742729	- 2.988648	104.742653	8.45

Table 10. Distance error autonomous floating net cage- 5 members

Point	Autonomous floating net cage coordinates to target				Dist (m)
	Lat now	Long now	Lat now	Long target	
1	-2.988564	104.742727	- 2.988571	104.742725	0.81
2	-2.988651	104.742727	- 2.988645	104.742730	0.75
3	-2.988643	104.742674	- 2.988645	104.742730	1.22
4	-2.988641	104.742727	- 2.988648	104.742653	1.72

Table 11. Distance error of the autonomous floating net cage utilizing the seven members

Point	Autonomous floating net cage coordinates to target				Dist (m)
	Lat now	Long now	Lat now	Long target	
1	-2.988566	104.742727	- 2.988571	104.742725	0.60
2	-2.988653	104.742728	- 2.988645	104.742730	0.92
3	-2.988645	104.742674	- 2.988645	104.742730	1.64
4	-2.988643	104.742727	- 2.988648	104.742653	0.94

aimed to assess the overall system performance by incorporating decision-making programming from prior assessments. The test utilized the fuzzy logic method with seven membership functions, demonstrating a superior average error rate when compared with the other two membership options. Furthermore, to show the performance of the net cage system, a comparison was made with the basic method or alternative method to show the superiority of the proposed PSO–fuzzy approach as shown in Figure 11. Figure 11 compares the trajectories generated by the proposed Fuzzy PSO controller and the conventional Fuzzy controller against the predefined target route. The Fuzzy

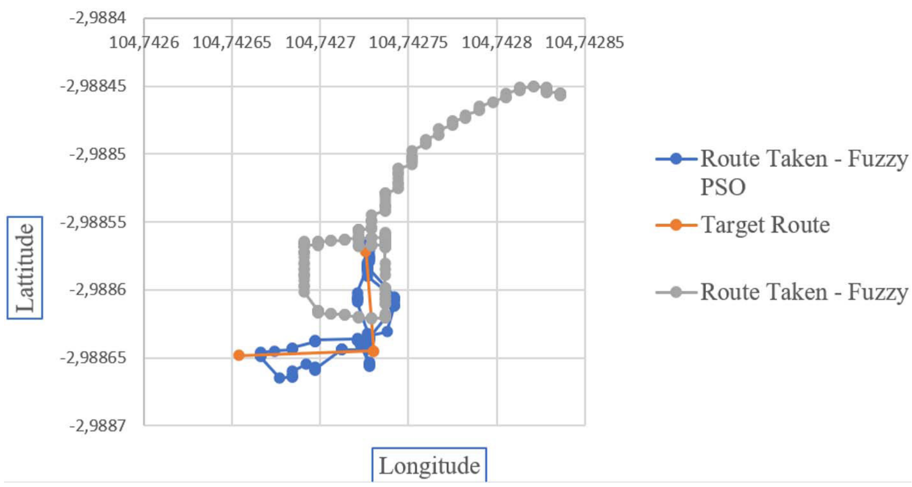


Figure 11. Comparison graph of routes taken by the formation of an autonomous floating net cage using Fuzzy-PSO, and only using Fuzzy Logic

PSO controller successfully follows the desired path with only minor oscillations around the turning waypoint, demonstrating accurate path-tracking performance and rapid convergence. In contrast, the conventional Fuzzy controller exhibits considerable deviation after approaching the waypoint, eventually diverging from the intended route. The accumulated positional error indicates insufficient corrective action and reduced trajectory stability. These results demonstrate that optimizing the fuzzy controller parameters using Particle Swarm Optimization significantly enhances navigation accuracy, minimizes tracking error, and improves overall path-following stability.

In this study, water current, wind, and sensor noise were assumed to be constant, as the primary objective was to develop an adaptive floating net cage capable of autonomously positioning itself based on water quality. Consequently, water quality was the only factor considered during the experimental evaluation. Future work will address this limitation by incorporating the effects of water current, wind noise, and sensor uncertainty to evaluate the robustness of the proposed system under more realistic environmental conditions.

Environmental implications of adaptive repositioning

The adaptive repositioning capability established in this research has crucial significance in aquaculture environment management. The proposed system is able to react to water quality variations automatically by migrating to a better place, unlike traditional stationary cage systems. This capacity could help reduce fish exposure to sub-optimal environmental circumstances, such as reduced dissolved oxygen levels, variations in pH, and temperature swings, which can affect fish health and growth. In addition, the adaptive repositioning capacity permits a more equitable distribution of aquaculture activities and hence leads to a reduction in the accumulation of organic waste at a given place. This technique has the potential, from an ecological engineering point of view, to allow for more sustainable water quality management, with integrated environmental monitoring and automatic remedial actions. The tests given demonstrate that the proposed approach is valid under the environmental conditions examined. The experiments were performed in South Sumatra which has a tropical climate and rather high temperature. However, more long-term trials with different wind, current, and weather conditions are needed to fully evaluate the robustness and generality of the suggested system.

CONCLUSIONS

The experimental results demonstrate that the objective of this study was achieved. The proposed integrated framework successfully combined real-time water quality monitoring, PSO-based waypoint optimization, fuzzy logic navigation, and cooperative formation control within a single autonomous aquaculture platform capable of adaptive repositioning under the investigated environmental conditions. The obtained results generally support the research hypothesis that integrating environmental sensing, adaptive decision-making, and autonomous navigation within a unified framework can improve repositioning performance while maintaining stable coordination among distributed sensing agents.

This work contributes to filling an important gap in autonomous aquaculture research, where environmental monitoring, navigation, and formation control have been traditionally studied as separate functions. The feasibility of adaptive environmental response based on continuous water-quality assessment and autonomous decision-making is demonstrated in this work by integrating these capabilities in a single operational framework and validating it under real aquaculture conditions.

The results provide a basis for the future development of intelligent aquaculture systems that can autonomously respond to dynamic environmental changes and reduce dependence on manual operator intervention. Yet, the current study is a validation of proof-of-concept under the operating conditions investigated. Future work should include long-term field validation and statistical evaluation of performance, robustness to different environmental disturbances and comparison with other navigation and optimization methods.

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