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Correlation Analysis of PWM Duty Cycle, Dispersal Distance, and Tilapia Growth Performance in an Automated Feeding System

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***Abstract*—Aquaculture is an aquatic biota cultivation activity whose success is largely determined by water quality and feeding patterns. Water temperature outside the optimal range can disturb fish appetite, metabolism, and growth, while manual feeding on large multi-pond farms tends to be irregular, prone to feed excess, cannibalism, and increased production costs due to uneven feed distribution. This study designs and develops a fish feeder machine with an Internet of Things (IoT)-based multiparameter smart control system, analyzes its working mechanism, and evaluates its performance characteristics. An experimental method was used, consisting of sensor testing, feed-dispersal mechanism testing at PWM variations of 65–100%, and overall device testing on a biofloc-system tilapia pond in Gowa Regency for 10 days during the morning (07:00 WITA) and evening (17:00 WITA) sessions. The VL53L5CX sensor estimated feed availability with an average accuracy of 98.88% (testing error 0.33–1.25%). The feed-dispersal mechanism showed a direct linear relationship between PWM and dispersal distance (1.24 m at 65% PWM up to 1.95 m at 100% PWM) and an inverse relationship with dispersal time. The system automatically adjusted the feeding dose based on water temperature, with a timestamp-based scheduling deviation of less than 30 seconds per day. The 10-day field trial showed stable tilapia biomass growth, with an average daily growth rate of 3.6 grams/day under optimal temperature conditions. The prototype functions adaptively and responsively to changes in water temperature, with accuracy and reliability adequate to support efficient feed management in aquaculture.**

***Index Terms*—fish feeder, Internet of Things, VL53L5CX sensor, DS18B20, tilapia (nila) aquaculture, multiparameter smart control system**

I. Introduction

Aquaculture is a cultivation activity carried out to produce aquatic biota under controlled conditions for economic benefit. Water quality is one of the key supporting factors of aquaculture, since the life of aquatic organisms is closely tied to fluid balance, respiration, living space, and physiological processes; poor water quality can disturb growth, metabolism, and survival of the cultured organisms.

Fish are ectothermic vertebrates whose body temperature depends on the surrounding environment. Fish generally live normally within a water temperature range of 20–30°C; temperatures below or above this range trigger behavioral changes, reduce appetite, and disturb metabolism (Kelabora, 2010). In large-scale pond farming with many ponds, manual feeding tends to be laborious and irregular. Overfeeding or irregular feeding can lead to cannibalism, while high feed cost demands efficient feed utilization; broadcasting feed evenly across the entire pond surface is widely regarded as the best practice for addressing this problem.

Various automatic fish-feeding devices with temperature-abnormality detection have been proposed previously. Building on this direction, this study proposes a fish feeder machine equipped with an IoT-based multiparameter smart control system that continuously monitors water quality parameters such as temperature, pH, turbidity, and water level, and is accessible online through the Blynk application, so that the dispensed feed dose can be adjusted automatically and in real time to the pond's environmental condition.

Based on this background, the objectives of this study are: (1) to design and build a fish feeder machine technology with an IoT-based multiparameter smart control system; (2) to analyze the working mechanism of the device; and (3) to analyze its performance characteristics. The study focuses on the mechanical construction of the feeder and its multiparameter control system, compares the control system's accuracy against standardized measuring instruments, and evaluates feeding effectiveness on a biofloc-system tilapia (nila) pond.

II. Methods

A. Time and Place of Research

The research was conducted at the Control and Robotics Laboratory, Department of Mechanical Engineering, Faculty of Engineering, Universitas Hasanuddin, starting in February 2025. The stages consisted of literature review, tool design, preparation of tools and materials, device fabrication, integration, field testing on a biofloc tilapia pond in Gowa Regency, data collection, and reporting.

B. Tools and Materials

The prototype was built around an ESP32 microcontroller and an Arduino Uno for control and communication, connected to the Blynk IoT platform for remote monitoring. A VL53L5CX time-of-flight multizone distance sensor was used to estimate feed availability inside the hopper, while a DS18B20 one-wire digital sensor monitored pond water temperature. Feed dispersal was actuated by a 12 V DC motor driven through a BTS7960 H-bridge driver, together with a servo motor that opens the metering valve between the upper and lower feed tubes. Supporting fabrication tools included a drill, angle grinder, calipers, a 3D printer for custom housing parts, a welding

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machine, and standard hand tools; a 16x2 I2C LCD was used for local status display.

C. System Design and Research Method

The feeder was modeled in three dimensions at a 1:1 scale using Fusion 360 before fabrication, covering the feed hopper, dual-valve metering system, dispersal funnel, electronics enclosure, and sensor mounts, as shown in Fig. 1. The realized prototype (Fig. 2) integrates three subsystems: (1) a mechanical subsystem consisting of the feed tubes, dual valve, DC drive motor, servo motor, and dispersal funnel; (2) a sensing subsystem comprising the DS18B20 temperature sensor and the VL53L5CX distance sensor; and (3) a control and communication subsystem based on the ESP32 and Arduino Uno connected to the Blynk IoT platform.

Fig. 1. Isometric view of the feeder design: (A) feed-level sensor, (B) upper hopper, (C) lower hopper, (D) dispersal box with stepper and servo, (E) metering valve servo, (F) DC drive motor, (G) dispersal funnel with impeller, (H) LCD display, (I) electrical enclosure, (J) DS18B20 temperature sensor, (K) power supply.

Fig. 2. Realized prototype of the IoT-based automatic fish feeder.

D. System Flow

The control logic (Fig. 3) initializes the input/output peripherals, then continuously reads the VL53L5CX sensor to estimate feed availability. If the measured distance indicates fewer than 0.3 m of headspace (i.e., feed is available), the controller checks the current time against three scheduled feeding sessions (07:00, 13:30, and 17:00 WITA); when the schedule matches, the DS18B20 sensor reads the current water temperature. The feed dose is then set according to the temperature band: 30 g for 4–24°C, 40 g for 24–32°C, or 50 g for 32–37°C. Once the dose is determined, the DC motor and stepper/servo mechanism are activated to open the metering valve and disperse the corresponding amount of feed through the impeller-equipped funnel, after which the system returns to the monitoring loop.

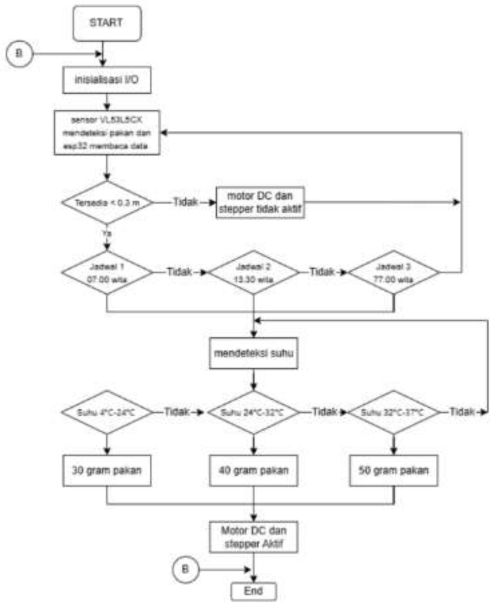

Fig. 3. Flowchart of the automatic fish feeder control system.

III. Results and Discussion

A. Device Specifications

The realized prototype has an overall height of 582 mm, a base length of 335 mm, a frame volume of 1,688,400 mm3, and a total weight of 5.715 kg. The BTS7960 motor driver operates at a 5 V logic level with a 6–27 V DC load range and a maximum current rating of 43 A. The metering servo operates at 4.8–6.6 V with a stall torque of about 1.08 N·m, while the 12 V DC dispersal motor runs at up to 12,000 rpm under no load. A summary of the key specifications is presented in Table 1.

TABLE I. Key Technical Specifications of the Feeder Prototype

Component	Parameter	Value
Overall unit	Height / length	582 mm / 335 mm
Overall unit	Weight	5.715 kg
BTS7960 driver	Logic / load voltage	5 V / 6–27 V DC
BTS7960 driver	Max. current	43 A
Metering servo	Operating voltage	4.8–6.6 V
Metering servo	Stall torque	1.08 N·m
DC drive motor	Operating voltage	12 V DC
DC drive motor	No-load speed	12,000 rpm

B. VL53L5CX Sensor Testing for Feed-Availability Estimation

The VL53L5CX sensor was tested by varying the feed mass inside the hopper from 0 g to 800 g in 200 g steps and comparing the sensor-based distance and weight estimate with a

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standardized scale and ruler measurement, as summarized in Table 2.

TABLE II. VL53L5CX SENSOR TEST RESULTS

Feed (g)	Ref. dist. (m)	Est. weight (g)	Sensor dist. (m)	Error (%)
0	0.400	0	0.403	0.75
200	0.270	198	0.256	1.00
400	0.250	395	0.225	1.25
600	0.220	598	0.194	0.33
800	0.190	791	0.164	1.13

A consistent inverse relationship was observed between feed mass and the measured distance: as more feed was added, the feed surface moved closer to the sensor, so the measured distance decreased proportionally, from 0.403 m at 0 g down to 0.164 m at 800 g. Across the tested range, the estimation error stayed between 0.33% and 1.25%, giving an average accuracy of about 98.88%. The largest error (1.25%) occurred at 400 g and the smallest (0.33%) at 600 g; this non-linear fluctuation is likely related to uneven feed-surface distribution and the infrared reflectance characteristics of the feed pellets rather than a systematic sensor bias. Overall, the VL53L5CX sensor is sufficiently reliable for use as an automatic feed-availability detector.

C. Feed Dispersal Mechanism Testing

The dispersal mechanism was characterized by varying the DC motor PWM duty cycle from 65% to 100% in 5% steps and measuring, for 30 g, 40 g, and 50 g feed batches, the time required to disperse the feed and the resulting throw distance. The average values across the three batch sizes are summarized in Table 3.

TABLE III. AVERAGE FEED DISPERSAL TIME AND DISTANCE VS. PWM

PWM (%)	Avg. dispersal time (s)	Avg. dispersal distance (m)
65	19.33	1.24
70	18.53	1.37
75	17.47	1.41
80	16.40	1.66
85	15.60	1.74
90	14.53	1.79
95	13.60	1.85
100	12.80	1.95

As the PWM duty cycle increased from 65% to 100%, the average dispersal time decreased monotonically from 19.33 s to 12.80 s, while the average throw distance increased from 1.24 m to 1.95 m. This confirms a direct linear relationship between PWM and dispersal distance and an inverse relationship between PWM and dispersal time, consistent across all three tested feed masses (30 g, 40 g, and 50 g), which indicates that motor speed rather than feed mass is the dominant factor governing throw distance within the tested range.

D. Temperature-Based Feeding Test

The response of the dispersal system to water temperature was evaluated by mapping discrete temperature bands (in 2°C steps from 20°C to 40°C) to the corresponding PWM level, dispersal rate, and dispersal time selected by the controller, as shown in Table 4.

TABLE IV. FEED DISPERSAL RESPONSE TO WATER TEMPERATURE

Temp. (°C)	PWM (%)	Rate (g/s)	Time (s)
20	65	2.07	14.5
24	75	2.29	13.1
28	80	2.44	16.4
30	85	2.56	15.6
32	90	2.75	14.5
36	95	2.94	17.0
40	100	3.12	16.0

The results show that the controller raises the PWM duty cycle as water temperature increases, from 65% at 20°C up to 100% at 38–40°C, which in turn raises the feed dispersal rate from 2.07 g/s to 3.12 g/s. This behavior is consistent with the intended control logic: higher water temperature is associated with more active fish metabolism and appetite, so the system dispenses feed faster while the dose band (30/40/50 g) still bounds the total quantity delivered, preventing overfeeding at high temperatures.

E. Field Testing on a Tilapia Biofloc Pond

The complete system was field-tested for 10 days on a biofloc-system tilapia pond in Gowa Regency, with feeding sessions at 07:00 WITA (morning) and 17:00 WITA (evening). The controller compared its dispensed dose against the temperature-based target dose at each session; a summary of the results is given in Table 5.

TABLE V. SUMMARY OF THE 10-DAY FIELD TEST RESULTS

Session	Temp. range (°C)	Dose range (g) / Mean |error| (%)
Morning (07:00)	27.6 – 29.1	39 – 41 g / 1.42%
Evening (17:00)	28.3 – 32.1	40 – 51 g / 1.28%

Morning water temperatures remained within a comparatively narrow range (27.6–29.1°C), so the dispensed dose stayed close to 39–40 g throughout the 10-day trial, with a mean absolute dosing error of about 1.42%. Evening temperatures were more dynamic (28.3–32.1°C) due to heat accumulation during the day, causing the system to alternate the dose between 40 g and 50–51 g in line with the temperature band, with a comparable mean absolute error of about 1.28%. Over the 10-day trial, tilapia biomass grew steadily, with an average daily growth rate of 3.6 grams/day under optimal temperature conditions, indicating that the temperature-responsive dosing strategy adequately supported fish growth on both sessions.

F. System Performance Analysis

Overall system performance was evaluated in terms of sensing accuracy, control responsiveness, and IoT monitoring effectiveness. The VL53L5CX sensor achieved an average feed-estimation accuracy of 98.88%, while the DS18B20 temperature sensor showed an average deviation of less than 0.3°C against a reference thermometer. The control system responded to a temperature reading and activated the dispersal motor within an average of less than 2 seconds, and switched smoothly among

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the 30 g/s, 40 g/s, and 50 g/s dosing modes without manual intervention; the timestamp-based scheduling mechanism maintained an accuracy of about ±30 seconds per day. Through the Blynk platform, sensor data (temperature and feed level) could be monitored remotely in real time, and the system issued an automatic notification when the feed level fell below a minimum threshold, allowing the operator to refill the hopper without needing to be physically present at the pond, which is expected to meaningfully improve feed-management efficiency for larger-scale aquaculture operations.

IV. Conclusion

An IoT-based multiparameter smart-control automatic fish feeder was successfully designed, built, and field-tested. The prototype integrates a mechanical subsystem (feed tubes, dual valve, DC motor, servo motor, dispersal funnel), a sensing subsystem (VL53L5CX and DS18B20), and a control and communication subsystem (ESP32 and Arduino Uno) connected to the Blynk IoT platform. The working mechanism proved adaptive and responsive to multiparameter conditions: the system automatically adjusts the feed dose based on water temperature (30 g at 4–24°C, 40 g at 24–32°C, and 50 g at 32–37°C), runs the timestamp-based feeding schedule with a deviation of less than 30 seconds per day, and provides remote real-time monitoring and low-feed notifications through Blynk. In terms of performance, the VL53L5CX sensor estimated feed availability with an average accuracy of 98.88%, the dispersal mechanism reached throw distances of 1.24–1.95 m across a PWM range of 65–100%, and the 10-day field trial on a biofloc tilapia pond showed stable biomass growth averaging 3.6 grams/day under optimal temperature conditions. Future work should add pH and dissolved-oxygen sensing for a more comprehensive multiparameter decision, explore machine-learning or fuzzy-logic control to further optimize dosing based on growth history, validate the system over a full 60-day production cycle at larger pond scale to quantify feed conversion ratio and economic return, and adopt an IP65-rated weatherproof enclosure for open-field deployment.

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