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Tilapia feeding decision system based on adaptive neuro-fuzzy inference

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Abstract

In industrial recirculating aquaculture, the feed required by fish accounts for a major part of the total expenditure. In this paper, a multi-factor decision making system based on aggregation FIFFB of fish feeding behavior, water temperature T of environmental factors and biomass weight W was proposed to solve the problem of feed waste under the traditional mode. To verify the performance of this model, a fuzzy inference FIS model is constructed for comparison. The experimental results show that the root mean square error (RMSE) and mean absolute error (MAE) between the predicted and actual feeding amount of ANFIS triplet are 0.78 and 0.19, respectively, which are much lower than the FIS model, and this model is more suitable for predicting the feeding amount decision. At the same time, growth parameters such as WGR, FMAE, K and FCR were compared. The fish growth specifications were fatter and the economic benefits were higher, and the feed conversion rate was increased by 12.35%. Therefore, the triplet ANFIS feeding prediction and decision-making system based on fish aggregation degree, water temperature and body weight is effective and has guiding significance for the precise feeding design of unmanned aquaculture.

Keyword: Tilapia; Machine vision; Feeding behavior; Precise feeding; Control method

1. Introduction

Aquaculture has become an important part of food production in the world. In recent years, the industrialized circulating water industry has developed rapidly(An et al., 2021; Barbedo et al., 2022). The biggest factor affecting the economic benefits of farmers is the cost of feed(Chen et al., 2020). At present, the feeding method is based on the experience of the producer and the manual operation of the judgment, resulting in the instability of feed feeding. In the process of feeding, when the feeding amount is too small, the fish will compete fiercely, resulting in injuries to the fish during the competition and uneven feeding. When feeding too much, it will cause feed waste, increase the cost of aquaculture, and affect the PH, turbidity and ammonia nitrogen of aquaculture water quality (Ardianto, 2022). Therefore, it is an important way to reduce the cost of aquaculture in order to establish accurate fish feeding decisions. How to feed fish on demand has become a hot research topic in precision feeding.

In recent years, scholars have studied the feeding desire of fish based on changes in physiological and behavioral characteristics during feeding (Ubina et al., 2021; Feng et al., 2022). However, the main factors that affect fish appetite are aquaculture water quality, light duration, biomass, and feeding management levels. Dissolved oxygen (DO) and temperature (T) are important water quality parameters, which directly affect the growth and food intake of fish(Wang et al., 2022) . Carbajal-Hernández developed a fish feeding system on demand by using dissolved oxygen (DO) and temperature (T) information parameters combined with fuzzy logic control (FLC) technology(Liu et al., 2023). This FLC based feeding system, which requires the producer's experience to create reasonable fuzzy rules and constantly tries to correct them during feeding, is inefficient and has low feeding accuracy. At the same time, feeding systems based on water quality parameters such as dissolved oxygen and water temperature do not reflect the true feeding desires of fish. More parameters (such as fish weight, growing environment and climate) need to be considered to make decisions, which will improve the accuracy and efficiency of FLC feeding system. With the development of neural networks, the adaptive neural fuzzy inference system (ANFIS) based on hybrid learning has been applied in the field of aquaculture. Zhao proposed an adaptive neural fuzzy inference feeding system (ANFIS) based on water quality parameters(Zhao et al., 2019) . Compared with the fuzzy control (FLC) feeding system proposed by Carbajal-Hernández, the feed conversion rate increased by 22.59%, indicating the advantages of ANFIS system in feeding decision-making. Zhou used machine vision technology to analyze the feeding behavior of fish, and proposed an ANFIS tilapia feeding decision method based on aggregation index and struggle intensity of fish feeding behavior(Zhou et al., 2018) . The study was based on the feeding behaviour of the fish, but did not consider the effect of changes in body weight on the amount of feeding at different growth stages. Chen proposed an ANFIS feeding decision system based on fish body weight and water temperature(Chen, 2020) . This method selects the two factors that have the greatest effect on the amount of fish fed. Compared with the ANFIS feeding system based on water quality parameters, the feed utilization rate is increased by 13.57%, but the fish growth rate (SGR) is not much different. In addition, Gutie rrez-Estrada also developed a water quality regulation system, which uses three input variables and ANFIS model to regulate the inflow rate, which is more accurate than the dual-input model.

In summary, studies have shown the feasibility of ANFIS in feeding aquaculture decisions. However, there are few three-input ANFIS feeding models which combine feeding behavior parameters, water quality parameters and fish biomass. Therefore, this paper develops an automatic feeding system for industrialized circulating aquaculture based on ANFIS by integrating the multi-factor parameters that affect fish's appetite, and uses machine vision technology to extract and quantify the aggregation degree of typical fish's feeding behavior, combining environmental factors such as water temperature (T) and fish biomass information weight (W) as multi-input variables of ANFIS model, and making decisions on fish's required feeding amount. Based on the FLC fuzzy logic control feeding model, we develop a novel adaptive feeding decision system by comparing feeding prediction results, which is suitable for feeding decision making in unsupervised breeding farms. Finally, compared to conventional FLC controls based on water temperature and dissolved oxygen, a feeding decision is more in line with the fish's real-time feeding desires. In this way, the growth and feeding desire of fish are met, and the feed utilization rate and the economic benefit of farmers are improved.

2. Materials and methods

2.1 Experimental conditions of tilapia culture

This experiment, a freshwater fish tilapia with strong adaptability, large food intake and fast growth rate was chosen. This experiment was carried out in the Facility Laboratory of Jiangsu University. Two culture ponds with the same specifications (d=1.2m, h=1m) were used in the experiment, and 30 experimental fish with the initial average weight of 180 ±15/g were fed by two different feeding methods. A fuzzy control system (FLC) was established according to the experience of farmers and experimental data, which was used to feed in pond 1, and a bait feeder with ANFIS controller was used to feed in pond 2. Before the experiment, in order to eliminate the stress behavior of the experimental culture environment on the fish, the fish were domesticated by artificial fixed-point feeding for 14 days. The diet was fed with a 5 mm floating diet containing about 35% of the main protein (Zheng Da diet). The diet was fed twice a day (8:00-9:00 am and 15:00-16:00 pm).

At the same time, a fish growth monitoring system composed of multi-sensor components and image acquisition systems was established. Daily water temperature (T) was measured by a temperature sensor for water. Subsequently, a CCD camera (Hikvision MV-CE 056-31 GC, video frame rate of 24 frames /s, resolution of 2592 × 1944) was used to shoot the changes of biomass and behavior of fish during feeding. Then, the computer (Intel Core TM I 5-12400 CPU@4.4 GHz) was used to process the information that affects the feeding of fish. Finally, a three-fold ANFIS feeding decision model suitable for fish feeding needs is developed.

2.2 image analysis and behavior extraction in the process of fish feeding

In this paper, the image processing of fish feeding is based on Pautsina and Zhou (Zhou et al., 2019) . The histogram equalization is performed on the fish image, and then the target is extracted from the complex background by using the morphological edge detection algorithm. The length and width of the fish were extracted using a minimum-circulation rectangular instrument, and the real-time average weight of the fish was then calculated. At the same time, the Delaunay Triangulation (DT) method was used to calculate the aggregation index FIFFB for extracting feeding behavior.

2.2.1 Data acquisition and processing

The water temperature was automatically collected by the WQMA-4210 water quality parameter monitor. It can realize online real-time collection and wireless transmission storage of water temperature in the range of 0 - 50 °C. The average weight of the fish was weighed using an electronic scale with a range of 1000, and samples were weighed every three days and the average was calculated. During the process of experimental feeding, the aggregation degree of fish is changing constantly. After feeding the fish, the fish swim around. Monitor the feeding intensity of the fish based on the degree of aggregation. Feeding was stopped when the number of fish aggregated was about 400 and a small amount of residual bait remained on the surface. The remainder of the bait was dried and weighed, and the total amount of feed required was recorded.

2.2.2 Aggregation index of fish feeding behavior

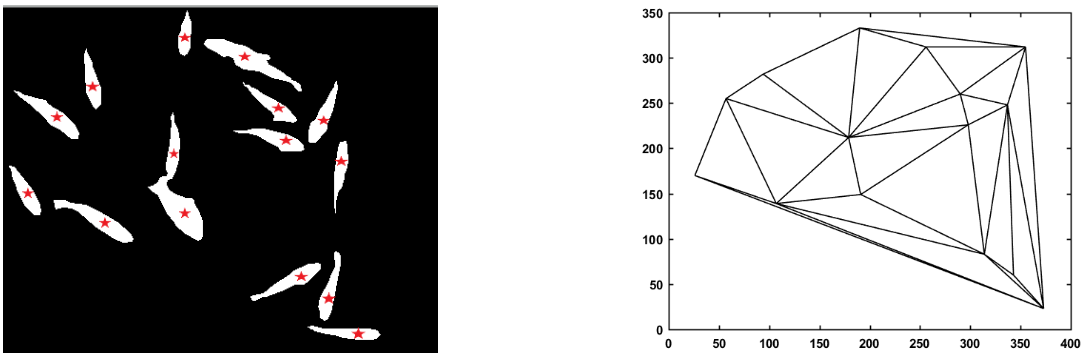
In this paper, we use histogram equalization to augment underwater object images and then segment and extract features from the augmented fish feeding images to obtain image targets. Since the pixels of the binarized image consist of 0s and 1s, the connected domain is determined by whether the pixels of the region are only 1s or not. The centroid of the fish is calculated by using the density f (x, y) of the labeled area of connected domain.

$$\overline{x} = \frac{\iint_D xFd\sigma}{\iint_D Fd\sigma}, = \frac{\iint_D xFd\sigma}{\iint_D Fd\sigma} \tag{1}$$

The centroid position is indicated by *, as shown in Fig 1, and then, Take the coordinates of the center of the fish to be the vertices of the Delaunay triangle. By the properties of Delaunay triangles, the total length of the three edges reflects the aggregation size of each vertex of the triangle(Zhou et al., 2018) . The *FIFFB* value is calculated by calculating the average perimeter of each triangle in the Delaunay triangulation, which is used to indicate the degree of fish aggregation and dispersal. Therefore, the *FIFFB* can be expressed as (1).

$$FIFFB = \frac{\sum_{i=1}^{n} C_i}{n} \tag{2}$$

In the formula, n is the number of Delaunay triangles, and C_i is the circumference of the ith triangle in Delaunay triangle. The lower the *FIFFB* value, the higher the aggregation level and vice versa.



(a) (b)

Fig.1. Fish aggregation calculation. (a) Fish centroid position (b) Triangulation triangle

2.3.Fuzzy inference system based on adaptive network

2.3.1 ANFIS model structure

The structure of the ANFIS model is based on fuzzy inference systems and adaptive neural networks. It has both the learning capability of adaptive networks, and the explanatory power of fuzzy reasoning systems. It can exploit the experience and language rules of experts and optimize the model by using input and output data. At the same time, the adaptive network can adjust the membership function and fuzzy rules, better fit the data, and make the output effect of the model more realistic.

The ANFIS model is based on the first-order Takagi-Sugeno fuzzy neural network model. The system is able to complete the control process from input variables to control decisions for fuzzy, ambiguous, and disambiguated reasoning(Wu et al., 2015; Zhao et al., 2018) . Firstly, the input variables (fish aggregation index, water temperature and average weight of fish) and an output language variable (feeding amount, expressed as fi in T-S fuzzy model) are defined to determine the decision-making results of the system. Then, according to the decision input variables, a fuzzy reasoning system with three inputs X, Y and Z is established, corresponding to an output F. For the T-S fuzzy network model, the i-th if-then rule is defined as Rule i:

$$Rule\ i: if\ x\ is\ A_j\ and\ y\ is\ B_k and\ z\ is\ C_m,\ then\ f_i = \ p_i x + q_i y + r_i z + s_i$$

Where x, y and z are the input variables of the feeding decision model, A_j, B_k and C_m are the input language labels; The parameters p_i, q_i, r_i and s_i in the output f_i are determined by training the sample data.

In the Sugeno fuzzy neural network model, the mapping process between input and output training samples is realized by fuzzy logic, which realizes feedforward decision control. Meanwhile, the parameters of the model output function f_i are unknown. In the process of realizing feedforward fuzzy reasoning (FIS), it is necessary to train the data samples with ANFIS to determine the output function parameters of the model. The model structure is shown in Fig 2. The model includes five layers: fuzzification layer, rule layer, standardization layer, conclusion reasoning layer and anti-fuzzification result output layer. The nodes in the same layer have the same function type, and the input of the next layer nodes in the network structure comes from the output signal of the previous layer.

The first layer: input layer

The input variables are fuzzified, and the input features x, y, z are fuzzified by using the membership function (generally bell function, bell function parameters are forward parameters). We get a membership function of [0,1], which is expressed by mu.

$$O_{1,i} = \mu_{Ai}(x_i), \quad (i = 1, 2)$$
$$O_{1,i} = \mu_{Bi}(y_i), \quad (i = 3, 4) \tag{3}$$
$$O_{1,i} = \mu_{Ci}(z_i), \quad (i = 5, 6)$$

In the formula, x_i, y_i and z_i are model input values; $O_{1,i}$ is the membership function, μ_{Ai}, μ_{Bi} and μ_{Ci} are the membership functions of linguistic variables A, B and C, respectively.

The second layer: fuzzy layer

Multiply the membership degree mu of each feature to get the trigger intensity of each rule, and get the weight of the fuzzy rule among variables.

$$O_{2,i} = w_i = \mu_{Ai}(x_i) \times \mu_{Bi}(y_i) \times \mu_{Ci}(z_i) \tag{4}$$

The third layer: rule layer

The triggering intensity of each rule obtained from the previous layer is normalized to characterize the triggering proportion of the rule in the entire rule base, that is, the degree to which the rule is used throughout the reasoning process.

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1+w_2+w_3} \tag{5}$$

The fourth layer: deblurring layer

The results of the calculation rules are generally given by a linear combination of input features indicating the contribution of the layer node calculation rules to the output results.

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i(p_i x + q_i y + r_i z + s_i) \tag{6}$$

The fifth layer: output layer

Clear calculation is realized and weighted average method is adopted.

$$O_{4,i} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{7}$$

In the feeding decision-making model, ANFIS mainly determines the optimal allocation of membership function through mixed learning algorithm. The mixed learning algorithm mainly uses the gradient descent method and the least square method to transmit signals back and forth. The input signal and the function signal are forwarded to the fourth layer, and the subsequent parameters are tuned by a least-squares method. In the backward propagation, the error signal is transmitted from the output node to the input layer and the preprocessing parameters are tuned by gradient descent.

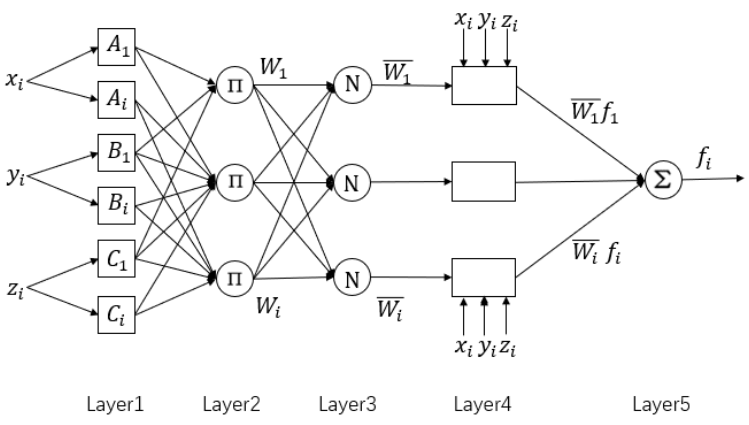


Fig.2 An ANFIS structure diagram

2.3.2 Fuzzy inference prediction model

In order to improve the accuracy of the fuzzy inference control system in feeding decision-making, ANFIS was built by MATLAB, and 100 groups of related data collected in feeding experiment were used as the training samples and test samples of the ANFIS feeding prediction model. Among them, 70 groups are used to predict the feed rate of the model, and the remaining 30 groups are used to test the prediction accuracy of the model. In this study, fish aggregation index FIFFB, water temperature T and average body weight of fish were selected as the feeding amount required for input and output. A corresponding neural fuzzy model was established to control the required feeding amount. The model system structure is shown in Fig 3.

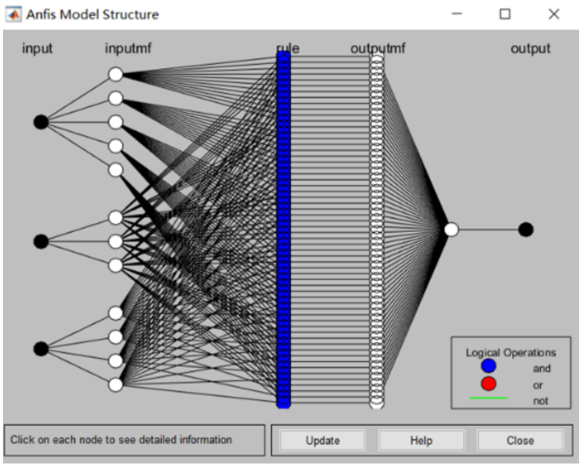


Fig 3. ANFIS model system structure

2.4 Method performance evaluation

In order to verify the accuracy of fish feeding amount prediction fuzzy model. Firstly, the test data samples are input into the trained FIS model to detect the difference between the predicted output value and the actual value of the model. The experimental data are predicted based on ANFIS model. The root mean square error (RMSE) and mean absolute error (MAE) were used to verify the performance of the model. Among them, f is the actual value of the test data output, f is the predicted value of the fish feeding amount prediction model, and n is the number of test samples. The smaller the RMSE and MAE indicators, the better the model performance(Chen, 2020).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (f-\hat{f})^2}{n}} \tag{8}$$

$$MAE = \frac{\sum_{i=1}^{n} \left|f-\hat{f}\right|}{n} \tag{9}$$

Meanwhile, the predictive performance of the ANFIS feeding model needs to be compared and defined in terms of fish biomass. The aim of this mode is to reduce feed waste and allow fish to grow healthier. The performance of this model was evaluated by growth performance biomass indicators, such as feed conversion rate (FCR), fish weight gain rate (WGR), average relative error of fish weight (FMAE) and fish condition factor (K).

$$FCR = \frac{w_F}{w_t - w_0} \tag{10}$$

$$WGR = \frac{w_t - w_0}{w_0} \times 100\% \tag{11}$$

$$FMAE = \frac{\sum_{i=1}^{n} \left|w_i - w_t\right|}{n} \tag{12}$$

$$K = \frac{w_t}{L^3} \times 100 \tag{13}$$

3. Results and discussion

3.1 Fish aggregation index FIFFB and temperature

Tilapia is a kind of warm-water fish. The growth temperature is 15-38 degrees Celsius, and the optimum growth temperature is 25-32 degrees Celsius. The video frame images of fish before and after feeding at different temperatures were extracted and analyzed, and the FIFFB value of each fish image was extracted and calculated. The changing curve of FIFFB at different temperatures is shown in Fig 4. When the optimum temperature of fish is 25 - 32℃, the change of fiffb is the smallest in 1 - 15 seconds, which indicates that the aggregation degree of fish has not changed much before feeding. Between 15-30 seconds, FIFFB decreased sharply, which indicates that fish are rapidly gathering and feeding, but the change amplitude of FIFFB is different at different temperatures. Among them, when the optimal growth temperature is 25 - 32℃, the aggregation index fiffb changes fastest. Between 100-200 seconds, the FIFFB value gradually increased and tended to be stable, indicating that fish tended to be saturated in food intake, decreased in appetite and gradually completed feeding. The range of FIFFB values at different temperatures is different, which indicates that the feeding desire of fish is different at different temperatures, but FIFFB tends to change in the same trend. This is almost the same as the actual feeding process of fish. Studies have shown that when feeding feed, fish always gather together and feed at a faster speed. As the decrease of appetite during eating, fish began to release the feeding area. From this, the aggregation index can be used to quantify changes in the feeding behavior of fish at different water temperatures. The FIFFB combined with the water temperature t is used as an input factor in the ANFIS feeding model decision.

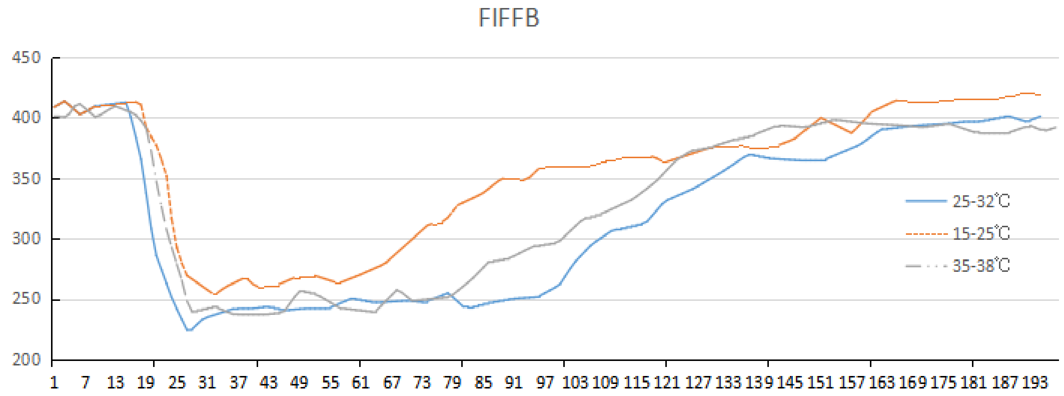


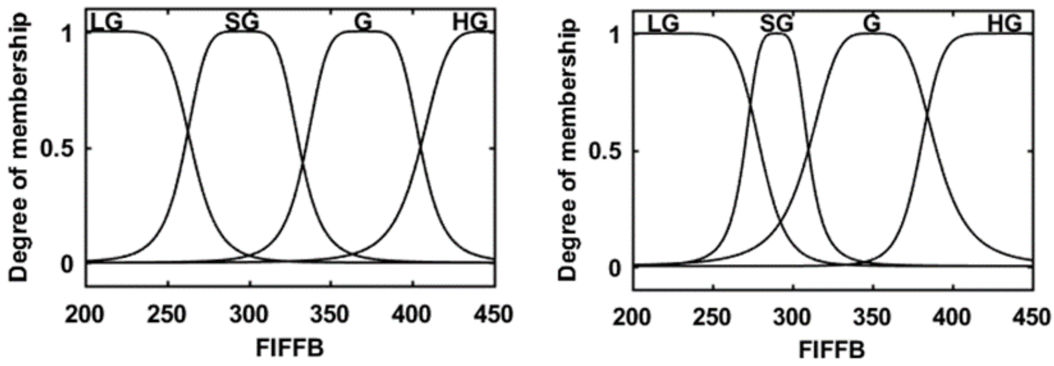
Fig.4 FIFFB change curve before and after fish feeding

3.2 Feeding prediction and performance evaluation of ANFIS model

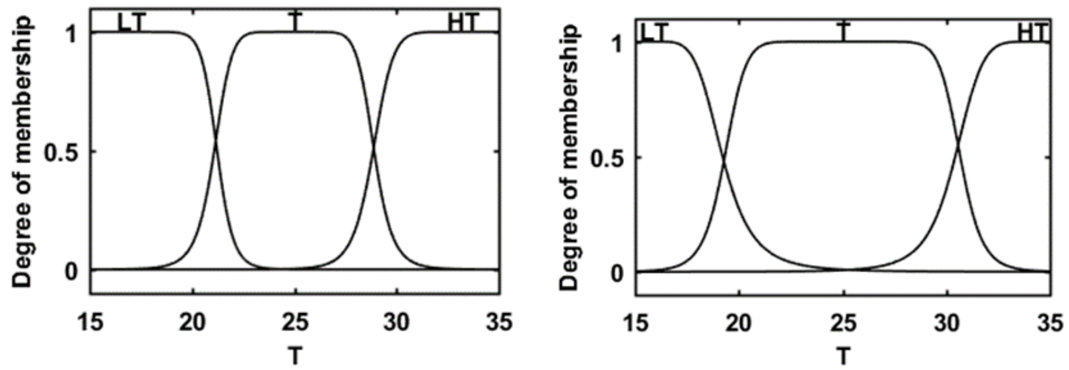
3.2.1 Modeling ANFIS

In this study, the ANFIS (Fig. 3) the Sugeno fuzzy model with three inputs contains 60 fuzzy if-then rules. The input variables of the model are chosen to be generalized bell membership function. Compared with other membership function types, the calibration error of the selected generalized bell-type membership function is smaller and the training iteration process has better accuracy and stability. For the fish aggregation index FIFFB, the scope of the domain is [200-450], and four mfs are designed. The language variables are expressed as {LG, SG, G, HG}, indicating that FIFFB has very small, small, medium and large. The range of water temperature T is [15-35], and it is divided into three mf. The linguistic variable is expressed as {LT, T, HT}, which means low temperature, moderate temperature and high temperature. The definition domain of fish weight is [100,550], and the unit is g. The average weight of fish is divided into five mf, and the language variables are expressed as {MVL, ML, M, MH, MPH}, which respectively represent very small, small, medium, large and very large. At the same time, the domain of the fuzzy reasoning decision-making output variable feed is [120,360], which is divided into 5 mf. The language variables are expressed as {MVF, MF, F, HF, HVF}, which means few, few, medium, many, and many.

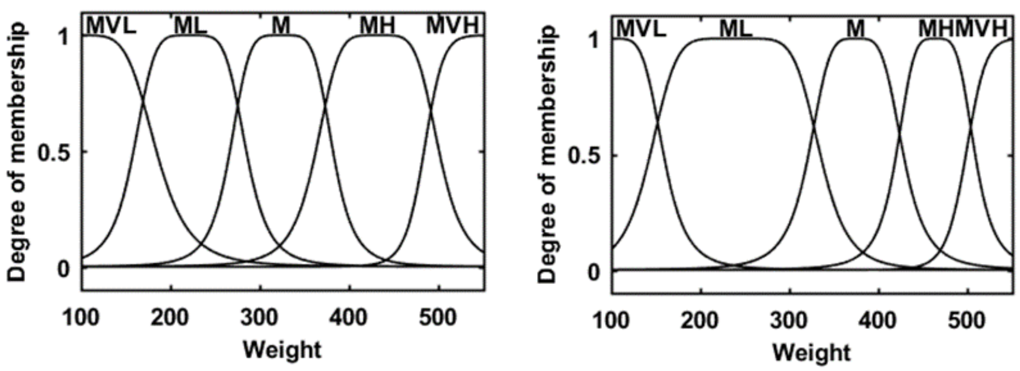
To improve the accuracy of fuzzy inference models, ANFIS models the mapping relationship between input and output data for training and modeling models through hybrid learning. Optimize the distribution of fuzzy subsets of membership function. Input the membership function and fuzzy subset distribution of the variables fish aggregation index FIFFB, water temperature and average weight of fish before training (as shown in Fig 5 .a, c, e), and the trained fuzzy subset distribution (as shown in Fig 5 .b, d, f) .By comparing the distribution of fuzzy subsets of membership functions before and after training, it can be seen that the membership function language label 'SG' of FIFFB becomes wider after training, which indicates that the change of FIFFB of language label 'SG' has a great influence on the decision output value. This is because the slow free feeding area of fish after feeding has a great influence on the feeding decision. After training, the language label 'HT' of the water temperature membership function is widened, which indicated that the influence of the water temperature change of the language label 'HT' on the decision output value was reduced. This is because tilapia is a warm-water fish, and the optimum temperature is (25-32℃); at the same time, the language label of the membership function of the average weight of the fish changed from narrow on both sides to wide in the middle, indicating that the fish grew slowly on both sides and fast in the middle. These results are due to the fact that ANFIS can enhance the inaccuracy of the fuzzy reasoning system during the training process of experimental data, making the input-output relationship more accurate, and meet the needs of fish feeding in actual production.



(a) (b)



(c) (d)



(e) (f)

Fig 5. Membership function changes before and after training

(a)and(b). Aggregation membership function graph before and after training

(c)and(d). Membership function of water temperature before and after training

(e)and(f). Figure of weight membership function before and after training

3.3 Analysis of model validation results

3.3.1 Feeding-decision prediction

To evaluate the feeding decision making ability of ANFIS in this study, a control treatment for FIS was constructed. Similarly, the FLC contains three inputs of aggregation degree FIFFB, water temperature T and average body weight W, as well as the output of feeding amount M. According to the experimental data and expert knowledge, the input variables include four, three and five bell mf (Fig 5 a, c, d), and the output variable is five bell mf (Fig 6).

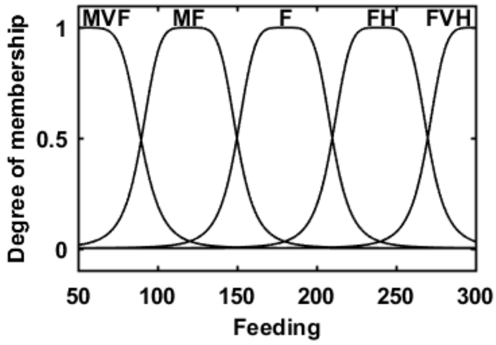


Fig 6.Changes in membership function of feeding amount

By comparing the relationship between the predicted feeding amount and the experimental feeding amount of the two models, as shown in Fig 7, it is found that the ANFIS model is closer to the experimental measured feeding amount than the FIS model, indicating the accuracy of the ANFIS feeding model. Some of the predicted and measured values are shown in Table 1. The minimum relative error is 0.22%, and the absolute error is between 0.23 g and 3.83 g.

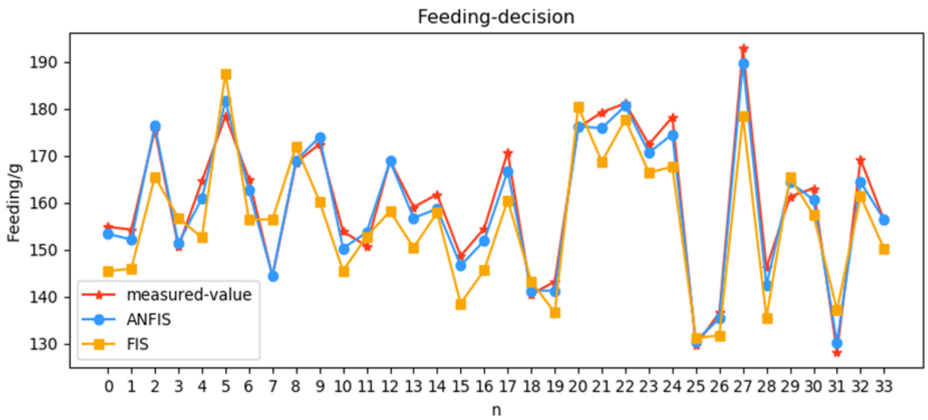


Fig 7.Relationship between feed prediction and actual measurement in two modes

Table 1 shows the comparison results of partial predicted values and actual values.

N	T	Average fish weight	FIFFB	Measured quantity	predicted quantity	Relative error	Absolute error
1	26.8	198.3	208.62	228.04	224.37	1.61%	3.67
2	24.2	169.6	336.77	167.25	163.42	2.28%	3.83
3	21.9	174	264.65	125.72	128.62	2.31%	2.9
4	30.2	277.1	207.68	241.05	240.52	0.22%	0.53
5	29.2	144.6	208.34	150.26	152.37	1.40%	2.11

The root mean square error (RMSE) and mean absolute error (MAE) between the predicted and actual values are calculated separately for the ANFIS model and the fuzzy inference prediction model, and the results of the prediction model are evaluated using these three metrics. As shown in Table 2, the RMSE and MAE of the ANFIS feeding prediction model are 0.78 and 0.19, respectively, and each index value is smaller than that of FIS prediction model, which shows that the fitting effect is better than that of FIS prediction model.

Table2 shows the comparison results of partial predicted values and actual values.

Parameter	ANFIS	FIS
RMSE	0.78	3.86
MAE	0.19	1.86

The reason for the large error of the feed prediction model of the fuzzy inference method is that the regular fuzzy logic method can fully exploit the fuzzy language information, but it cannot adjust the rules and membership functions online in real-time. In general, membership functions have no basis to follow, and most use empirical values. For this nonlinear and multivariable coupling complex system, the parameters in the model are adjusted according to the experimental data, and the parameters can finally converge to certain values, which has good adaptability and overcomes the limitations of the general linear model. Therefore, the prediction model of feeding quantity established in this paper can predict the feeding quantity well.

3.4 Evaluation of fish growth performance

An ANFIS-based model for fish feeding. The aim of this model is to reduce feed waste while providing benefits for fish growth. In this paper, the growth parameters of fish (initial average weight, final average weight, FCR, WGR, and FMAE) and fish conditioners were compared under different feeding models. The fish condition factor is an indicator of the fatness and growth rate of fish. This is an important measure of fish growth. It is also an important method to check the effect of feeding during the feeding stage. The results are shown in Table 3.

Table 3 is the growth performance evaluation index.

Method	Initial weight(g)	Final weight(g)	WGR%	FCR	FMAE	K
ANFIS	96.72	453.63	3.69	1.89	2.689	3.20
FIS	104.53	439.85	3.21	2.17	3.913	3.43
E-FIS	103.27	432.74	3.19	2.34	4.217	4.01

The FCR of FIS group was 1.89, and that of ANFIS group was 2.17, an increase of about 12.90%. At the same time, FAME has also increased by 31.28%, which shows that the fish specifications under this feeding method are more unified. Fatness K is between (2.8-3.4). It shows that the ternary ANFIS model studied in this paper can effectively improve feed utilization rate and reduce feed waste in the feeding process. The quality of fish growth is better.

Compared with the decision-making model Based on water quality (water temperature, dissolved oxygen) to adjust the feeding amount, the decision-making model based on fish aggregation, water temperature and weight adjustment feeding amount has advantages in FCR, FMAE, k and other fish growth performance evaluation indicators. This indicates that the model takes into account the real-time feeding desires of fish in different environments and the feeding needs of fish at different growth stages, making the feeding decisions more in line with the true needs of the fish. In the process of ensuring the improvement of the environment and quality welfare of fish growth, feed waste is reduced in the feeding process, water pollution is reduced, and the economic benefits to producers are improved.

4. Conclusion

In this paper, the changes of fish aggregation behavior during feeding under different water temperatures are compared. Combined with the weight of fish at different growth stages. The ANFIS model of multi-parameter fish feeding decision-making was established. The process of precise feeding can be carried out according to the real-time feeding desire of fish. Compared with the traditional FIS fuzzy reasoning model. ANFIS simulates, trains and models the mapping relationship between input and output data through mixed learning. The distribution of each fuzzy subset of the membership function is optimized to build an adaptive fuzzy rule base for feeding. And improve the prediction accuracy of the model. At the same time, the experiment shows that compared with other scholars' feeding decisions based on water quality factors such as water temperature and dissolved oxygen, the ANFIS model in this paper has more advantages in feed utilization rate, uniformity of fish specifications, and fat aesthetics. To sum up, the ANFIS model studied in this paper can realize feeding based on the real-time feeding demand of fish without supervision. can improve the growth and welfare of fish, and bring economic benefits to producers while avoiding feed waste. The development of the intelligent feeding decision-making system is of guiding significance to realize unmanned breeding.

Conflicts of Interest

For this study, The authors have no conflict of interest to declare.

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