An adaptive method for fish growth prediction with empirical knowledge extraction

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Abstract

Fish growth prediction provides important information for optimising production in aquaculture. Fish usually exhibit different growth characteristics due to the variations in the environment, the equipment used in different fish workshops and inconsistent application by operators of empirical rules varying from one pond to another. To address this challenge, the aim of this study is to develop an adaptive fish growth prediction method in response to feeding decision. Firstly, the practical operational experience in historical feeding decisions for different fish weights is extracted to establish the feeding decision model. Then, a fish weight prediction model is established by regression analysis methods based on historical fish production data analysis. The feeding decision model is integrated as the input information of the fish weight prediction model to obtain fish weight prediction. Furthermore, an adaptive fish growth prediction strategy is proposed by continuously updating model parameters using new measurements to adapt to specific characteristics. The proposed adaptive fish growth prediction method with empirical knowledge extraction is evaluated by the collected production data of spotted knifejaw (*Oplegnathus punctatus*). The results show that established models can achieve a good balance between goodness-of-fit and model complexity, and the adaptive prediction method can adapt to specific fish pond's characteristics and provide a more effective way to increase fish weight prediction accuracy. The proposed method provides an important contribution to achieving adaptive fish growth prediction in a real time from the view of aquaculture practice for spotted knifejaw.

Keywords: fish growth prediction; feeding decision making; adaptive update; model adaptation; empirical knowledge extraction; spotted knifejaw

Abbreviation	
DEB	Dynamic energy budget
EP	Energy and protein fluxes
DO	Dissolved oxygen
RMSE	Root mean square error
Nomenclature	
BW	Individual fish weight
FR	Feeding ratio
N	Fish number
FA	Total feeding amount
f	Function relationship
p ($e.g.$ a,b,c,d,e)	Function parameter
IFA	Average feeding amount for individual fish

1. Introduction

Fish weight is regarded as an important indicator for commercial decision, such as time to market and profit forecast. Fish growth prediction model could provide real-time fish weight information to optimise feeding decision and reduce production cost. For fish growth modelling and fish weight prediction, many research results have been reported. Main modelling approaches include nutrient based models (Belal, 2005; Dumas, France, Bureau, 2010; L. Li & Yakupitiyage, 2003), dynamic energy budget (DEB) models (Dambrine et al., 2020; Stavrakidis-Zachou, Papandroulakis, Lika, 2019), and energy and protein fluxes (EP) models (Nobre, Valente, Conceição, Severino, Lupatsch, 2019). However, nutrient based models and DEB models always have complex forms and involve a large number of parameters. It may be difficult to determine the parameters of these mechanistic models accurately in practical production, which limits the practical usage of these models. Although the EP model can extend the traditional bioenergetic model to make the input parameters of model easy to access in fish farms, this model can only be applied to the widely cultured fish species, such as gilthead seabream, European sea bass and white grouper (Lupatsch & Kissil, 2003; Lupatsch & Kissil, 2005; Lupatsch, Kissil, Sklan, 2003) due to the available research results on the relationships analysis for the energy and protein in fish. For many other fish species, their growth characteristics, body composition and growth environment may have great differences. Therefore, for new and small-scale cultured fish species, mechanistic modelling approaches may be not suitable in practice. The data-driven modelling method can be a good alternative approach because there is a wide range of application scenarios in aquaculture, such as water quality monitoring (Yang et al., 2019; Yang, Hassan, Wang, Li, 2017), vaccination effect (Lu, Chen, Yang, Liao, 2020), fish counting (Zhang, Li, Liu, Zhou, Duan, 2020), fish mass estimation (Zhang, Wang, Duan, 2020), etc. Therefore, this paper pays more attention to the exploration of fish growth prediction method based on the analysis of historical production data from the view of aquaculture practice.

In different fish ponds and workshops, there may be deviations in production environment, equipment and feeding decisions from different operators. Therefore, these factors may cause fish in different ponds and workshops to exhibit different growth characteristics. The deviations mainly reflect on fish composition including protein, lipid, ash, moisture and so on, which is shown by the deviation of fish weight finally. After establishing a general fish growth model based on the analysis of historical production dataset, it is necessary to update this model in an adaptive way to decrease the influence of fish weight deviation. The adaptive models can provide an effective approach to adjust model output by using the updated data from specific production environment. Model adaptation methods have been extensively investigated in different fields, such as pharmaceutical manufacturing (Bano, Facco, Ierapetritou, Bezzo, Barolo, 2019), video object segmentation (Sun, Xiao, Lim, Xie, Feng, 2020), unmanned aerial vehicle (Kapteyn, Knezevic, Huynh, Tran, Willcox, 2020), tumour analysis (Tariq, Chen, Kirkby, Jena, 2016) and so on.

To predict fish weight, feeding decisions need to be known since they provide very important input information to the prediction of fish weight. Fish feeding is an important operation in aquaculture production. However, making effective fish feeding decisions is a complex task because many factors can affect the decisions that will significantly impact on fish growth. To ensure effective feeding decisions, many studies have explored different methods but they are mainly based on the appetite of fish and their behaviour. Papandroulakis, Markakis, Divanach, and Kentouri (2000) designed a fuzzy logic controller to determine the daily feeding amount of sea bream larvae. There were 316 rules in the fuzzy logic controller, where five linguistic variables were defined to describe population state. Wu, Huang, and Chen (2015) developed an adaptive neural-based fuzzy inference system to make feeding decision by dissolved oxygen (DO) to reflect the appetite of fish. Zhao, Ding, Zhao, and Gu (2019) proposed an adaptive neural fuzzy inference system to make feeding decision based on water quality parameters including DO and temperature. Zhou et al. (2018) proposed a neuro-fuzzy model-based fish feeding decision system by near infrared computer vision and image processing technology. An index to describe fish appetite and quantify feeding behaviour was extracted using image analysis. The review of An, Hao, Wei, Wang, and Yu (2020) summarised the intelligent feeding systems based computer vision technology. Computer vision methods were applied to obtain the changes of fish behaviour (e.g. fishtail swing frequency and movement speed) and the remaining amount of feed. In fish production practice, the common method is to determine feeding amount by fish weight measurement based on operational experience. Because fish biomass is directly related to feeding amount, it has been used to determine daily fish feed demand successfully (Papandroulakis et al., 2000). In practice, fish farming operators divide fish weight into different ranges, and different feeding ratios are determined based on practical experience when fish weight is in different ranges. For fish weight measurement, weighing fish manually every day is both very time consuming and impractical and it often causes damage to fish. As a result, the common practice is to manually measure fish weight only once a month. The feeding decision is adjusted monthly based on new fish weight measurement and its corresponding fish weight range. Although this is a simple and easy way to implement, the adjustment of feeding decision is rough due to the way of fish weight range segmenting and the long gap between two feeding decisions. The adjustment period of feeding decision is restricted by the measurement period of fish weight. This method cannot make feeding decisions based on variable fish weight in real time because of the monthly gaps between two measurement periods. To improve this process, one method is to monitor fish weight and length in real time through installing a video camera based on image analysis technology (Konovalov, Saleh, Efremova, Domingos, Jerry, 2019; Muñoz-Benavent et al., 2018; Shi, Wang, He, Zhang, Li, 2020), but this method will increase equipment and maintenance costs. In addition, the limitations of production environment (e.g. insufficient and uneven illumination condition, high humidity and temperature) can affect the accuracy of image analysis results. Another method is to establish a feeding decision model by analysing historical production data to extract feeding decision operational experience. The latter approach is not fully explored yet, and this paper pays more attention to establishing a feeding decision model based on empirical knowledge extraction by historical production data.

In summary, our literature review shows that few studies pay attention to the adaptive fish weight prediction from a view of practical application for the small-scale cultured fish species, spotted knifejaw. It also reveals that a very limited research focuses on the feeding decision modelling based on empirical knowledge extraction to improve feeding decisions and resource efficiency. Therefore, this study aims to address these gaps by proposing an adaptive fish weight prediction method with a feeding decision model based on empirical knowledge extraction in aquaculture.

To achieve the research aims, firstly, a feeding decision model was developed by extracting practical operational experience from historical feeding decisions for different fish weights. Three data fitting options were shown to fit this model. A fish weight prediction model was then established by regression analysis methods for historical fish growth production dataset. Three types of modelling methods were considered as options. In modelling process, expert knowledge was introduced to determine input and output variables of model and simplify its form. Subsequently, the real-time fish growth prediction was achieved by integrating feeding decision as the input information of the fish weight prediction model. Finally, an adaptive fish growth prediction strategy was proposed by continuously updating model parameters to adapt to the characteristics change of specific fish pond. The established models and proposed method were parameterised and demonstrated on the collected production dataset of spotted knifejaw (*Oplegnathus punctatus*) from an aquatic company in China to show feasibility. The results show that the established models achieve a good balance between goodness-of-fit and complexity, and the proposed adaptive prediction method can provide an effective way to increase fish weight prediction accuracy and adapt to specific fish pond's characteristics.

The novelty of this study is demonstrated from the following aspects: (1) The feeding decision model was established by extracting past practical experience on the premise of not increasing production cost to provide real-time feeding decision. This approach represents a novel attempt in model development as it strengthens the practical applicability and performance of the feeding decision model. (2) The fish weight prediction model was established by regression analysis methods to obtain real-time prediction. This method can ensure to improve its prediction performance by taking consideration of the real time data input obtained in a dynamic fish production environment. (3) To adapt to the specific characteristics of fish pond, the adaptive updating strategy was proposed to enhance its applicability and adaptability in practice. The real-time fish weight prediction can be obtained by responding to feeding decision as input information based on empirical knowledge extraction.

In section 2, the practical production dataset of spotted knifejaw is introduced. The feeding decision model and the fish weight prediction model are established by data analysis methods, respectively. Furthermore, the adaptive fish weight prediction method is developed. Section 3 presents model calibration and selection results and the validation of adaptive fish weight prediction method. Section 4 provides the conclusions of this study.

2. Data acquisition and model development

In this section, the proposed adaptive fish growth prediction method with empirical knowledge extraction is presented in detail, which mainly includes the following three components: (1) a fish feeding decision model, which is used to make feeding decision; (2) a fish weight prediction model, which is applied to predict fish weight at next step in response to feeding decision; (3) an adaptive model updating strategy of fish weight prediction model to adapt to the specific characteristics of fish pond. The framework of adaptive fish growth prediction method with empirical knowledge extraction is shown in Fig. 1.

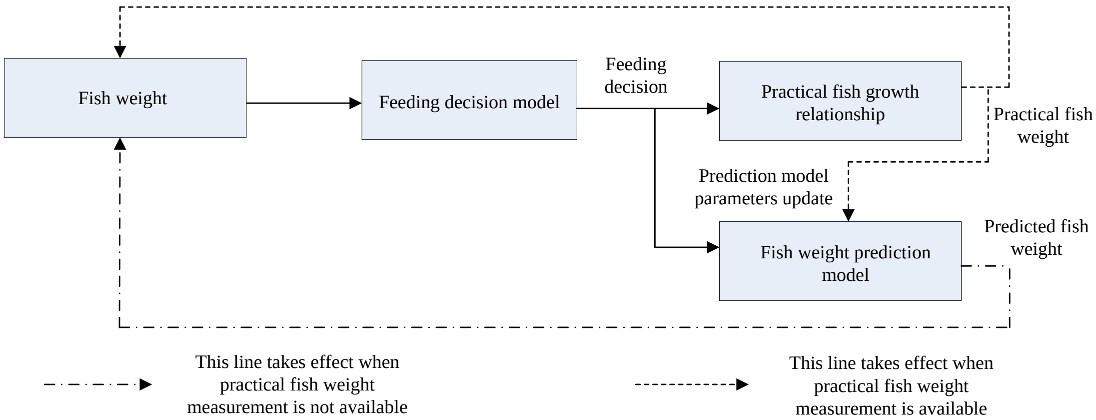


Fig. 1. Framework of adaptive fish growth prediction method with empirical knowledge extraction

The proposed adaptive fish growth prediction method is presented as follows. First, feeding decision is made by the fish feeding decision model based on initial measured fish weight. Then, the fish weight prediction model is used to predict fish weight at next step in response to feeding decision. Finally, fish weight is updated by the obtained fish weight prediction which is used as the new input of fish feeding decision model. Above process is repeated and forms a loop to achieve feeding decision making and fish weight prediction in real time. In this process, when the new fish weight measurement of specific fish pond is available, it is used to update the fish weight prediction model by adjusting model parameters to achieve model adaptation. At the same time, practical measurement is used to update fish weight at next step. Above process is expressed by different lines in Fig. 1. The role of lines in Fig. 1 is distinguished by using different forms based on the availability of fish weight measurements. In the following subsections, fish production datasets, the modelling process of feeding decision model and fish weight prediction model, and the adaptive model updating strategy will be analysed in detail.

2.1 Fish production dataset

In recent years, spotted knifejaw (*Oplegnathus punctatus*) has been introduced and cultured in China, becoming one of the important maricultured fish species because its high nutrition and economic values and taste. However, spotted knifejaw is a newly emerging aquaculture fish species and has not been widely cultured (Kawato, Yamashita, Yuasa, Miwa, Nakajima, 2017). Only a limited number of aquatic companies have carried out artificial breeding and rearing of the species. Studies on spotted knifejaw are still under development. Latest research includes results on immune system analysis (Liu et al., 2019; Zhang et al., 2020), genetic sex identification (Li et al., 2020), fish length estimation (Shi et al., 2020), environment effects (Yang, Song, Peng, Hallerman, Huang, 2019). This study focuses on the growth characteristics of spotted knifejaw. The production dataset of spotted knifejaw from an aquatic company is applied to fit and verify proposed method. The aquatic company was a land-based factory using a closed recirculating marine aquaculture system located in the Laizhou Bay of China. In this factory, every workshop was occupied about 20 fish ponds. The workers in this factory collected the production data from seven workshops for one year and carried out a statistical analysis for mass production data. The obtained datasets were characterised by the statistical average method when fish were at the same growth stage. Finally, 33 the production datasets of spotted knifejaw from seven workshops provided by factory were supplied for modelling and verification as shown in Table 1. The collected variables in the production datasets of spotted knifejaw include individual fish weight, fish number, total feeding amount and cultured time.

Table 1 The production datasets of spotted knifejaw

Data number	Initial individual fish weight (g)	Individual fish weight at the end of cultured time	Fish number	Total feeding amount (g)	Cultured time (day)

		(g)			
1	145	205	1450	4500	31
2	205	270	1450	4500	30
3	270	330	1450	5500	31
4	330	405	1309	5500	30
5	40	53	2778	2800	30
6	53	75	2778	3200	31
7	50	90	2479	4500	30
8	90	145	2479	5000	31
9	145	200	2479	6000	31
10	200	265	1500	4500	30
11	265	330	1500	6000	31
12	330	400	1375	5500	30
13	660	725	902	2145	31
14	725	735	873	2195	30
15	170	220	1723	5515	30
16	575	645	1237	5325	31
17	645	680	1237	5155	30
18	225	260	1072	3025	31
19	660	790	1171	6655	31
20	750	785	1098	5485	30
21	785	825	1088	5485	31

22	225	260	1294	3950	31
23	260	330	1287	5350	28
24	310	385	1183	5500	31
25	520	560	934	3875	31
26	175	195	2690	6285	30
27	195	235	2690	6530	31
28	235	285	1343	3585	30
29	585	690	1380	6910	31
30	690	755	1363	5770	30
31	755	780	1363	5770	31
32	35	43.5	5015	2000	30
33	43.5	55	4934	3435	31

2.2 Fish feeding decision model

In traditional fish production practice, the adjustment period of feeding decision is the same as the period of manual fish weight measurement, which is once a month. The specific process of fish feeding decision is described as follow: once a month some cultured fish are sampled in a random way and weighed to estimate the average fish weight in the same fish pond. The operators determine the feeding ratio for the range of measured fish weight based on past operational experience. The feeding amount is based on fish weight, feeding ratio and fish number, which is calculated by Eq. (1).

$$FA = BW \times FR \times N \tag{1}$$

where BW (g) is individual fish weight in a fish pond. FR (%) represents the feeding ratio and FA

(g) is total feeding amount in a fish pond. N represents cultured fish number in a fish pond. In general, the initial total cultured fish number in a fish pond is known. As production proceeds the change of fish number can be recorded by subtracting death number from the initial total number of fish. The determination principle of feeding ratio FR is that larger fish weight requires a smaller feeding ratio. The specific value of feeding ratio is set based on the growth characteristics of cultured fish, which is from operational experience. Although this is a simple and easy way to implement for operators in practical production, the simple division of fish weight range results in rough feeding decisions. Also, the measurement period of fish weight restricts the adjustment frequency of feeding decision. The real-time feeding decisions cannot be made for variable fish weight in a timely manner because of the long gaps between two fish weight measurements. Therefore, this study considers extracting operational experience by the analysis of historical fish feeding decisions. The fish feeding decision model was established to obtain feeding decision in real time from a practical application point of view. The feeding ratio FR was obtained by Eq. (2).

$$FR = f(BW, p) \tag{2}$$

where f is the function relationship between BW and FR. p is function parameter. The relationship f is obtained by the analysis of historical fish feeding decisions, which is fitted by different functions as options to choose more suitable one. The following three models were adopted to fit the relationship f and mimic reality, which are shown in Eqs. (3)-(5).

$$f_1(x) = a_1 \times e^{-b_1 \times x} + c_1 \tag{3}$$

$$f_2(x) = a_2 \times x^{-b_2} \tag{4}$$

$$f_3(x) = \frac{a_3}{x + b_3} \tag{5}$$

where x represents BW. $f_i(x)\,(i=1,2,3)$ represents FR. $a_i\,(i=1,2,3)$, $b_i\,(i=1,2,3)$ and c_1

represent p. Above three functions all meet the determination principle of feeding ratio, that is to say, a larger fish weight needs a smaller feeding ratio.

2.3 Fish weight prediction model

The fundamental task in fish growth control research is to understand and predict fish weight in response to feeding decision. For fish weight monitoring, the widely used method is to catch some fish by fishing net once a month and weigh them to calculate average fish weight in a fish pond. It is time consuming and impractical to weigh fish manually every day and manual weighing can cause damage to fish. The low measurement frequency of fish weight makes real-time fish growth monitoring difficult. Therefore, it is necessary to develop the fish weight prediction model to achieve real-time fish weight monitoring. The availability of feeding amount, fish weight, fish number and cultured time in historical production dataset makes the establishment of fish weight prediction model become possible. In this section, based on the analysis of historical production dataset from many ponds and workshops, a fish weight prediction model is established to predict fish weight in response to feeding decision in real time, which can provide timely indication of fish growth. The fish weight prediction model is expressed by Eq. (6)

$$BW_t = f_g(BW_0, FA, t, N, p_g) \tag{6}$$

where BW_0 represents initial individual fish weight. t (day) is cultured time. p_g is the parameter of function f_g. BW_t is individual fish weight at any given point in time (t).

The following three methods are used to determine relationship f_g:

Method 1: This method is performed using a multiple linear regression approach. The input variables include BW_0, FA, t and N, and the output variable is BW_t. It is expressed as shown in Eq. (7).

$$BW_t = a_{g1} \times BW_0 + b_{g1} \times FA + c_{g1} \times t + d_{g1} \times N + e_{g1} \tag{7}$$

In this method there are many parameters in the model described in Eq. (7). To simplify the form of model and decrease the number of parameters, expert knowledge and operational experience are introduced to determine input and output variables, which are shown in the following two methods.

Method 2: The second method uses the same multiple linear regression approach as the first method, but it has different input and output variables. The input variables include BW_0 and average feeding amount for individual fish IFA which is shown as Eq. (8), and the output variable is the increment of fish weight per day BW_z , which is calculated by Eq. (9).

$$IFA=\frac{FA}{N} \tag{8}$$

$$BW_z=\frac{BW_t-BW_0}{t} \tag{9}$$

Therefore, the relationship between input variables (BW_0 and IFA) and output variable BW_z is fitted by Eq. (10). The relationship f_g can be determined indirectly by Eqs. (8)-(10).

$$BW_z=a_{g2}\times BW_0+b_{g2}\times IFA \tag{10}$$

Method 3: This method uses linear regression approach which is shown as Eq. (11). Because BW_z includes the information of BW_0 , the number of input variables for Eq. (10) is reduced to one, and the output variable is the same as Method 2.

$$BW_z=a_{g3}\times IFA+b_{g3} \tag{11}$$

Table 2 summarises the modelling options for fish weight prediction model.

Table 2. Modelling options for fish weight prediction model

Modelling methods	Eqs.	Parameters
Method one (multiple linear regression)	(7)	$a_{g1}, b_{g1}, c_{g1}, d_{g1}, e_{g1}$
Method two (multiple linear regression)	(8), (9), (10)	a_{g2}, b_{g2}

Method three (linear regression)	(8), (9), (11)	a_{g3}, b_{g3}

Above fish feeding decision model and fish weight prediction model were integrated to make feeding decision and predict fish weight in real time. The models were parameterised using the historical production dataset of spotted knifejaw. The feeding decision model and fish weight prediction model options in sections 2.2 and 2.3 were calibrated to the production datasets of spotted knifejaw by estimating model parameters. Root mean square error (RMSE) between measurement and model fitting was used to assess model goodness-of-fit. The final model form was selected by balancing goodness-of-fit and model complexity. The fitting parameters and performance comparison of different model options and final chosen model will be shown in section 3.

For the representation of dynamic model, the most common approach is autoregressive modelling. Taking the simplest first order linear autoregressive format as the example, in this study, the input variable is average feeding amount for individual fish and the state variable is individual fish weight. The fish weight at a specific time was expressed as Eq. (12).

$$BW_t = a \times BW_{t-1} + b \times IFA \tag{12}$$

where a and b are the model parameters which need to be estimated. In this study, the objective was to obtain fish weight prediction every day. Using autoregressive model Eq. (12), the historical fish weight measurement every day needed to be available. However, in the historical production dataset of spotted knifejaw, only fish weight measurement once a month was available. Therefore, based on the characteristics of historical production dataset, above "Method 1" to "Method 3" in this study were used to fit fish weight prediction model. For Method 3, the model was transformed into the following form in Eq. (13) based on Eqs. (8), (9) and (11).

$$BW_t = (BW_0 + b_{g3} \times t) + a_{g3} \times t \times IFA \tag{13}$$

The fish weight at $t-1$ time point is expressed as Eq. (14).

$$BW_{t-1} = (BW_0 + b_{g3} \times (t-1)) + (a_{g3} \times t \times IFA - a_{g3} \times IFA) \tag{14}$$

Based on Eqs. (13) and (14), fish weight at t time point was described as in Eq. (15).

$$BW_t = BW_{t-1} + a_{g3} \times IFA + b_{g3} \tag{15}$$

By comparing Eq. (12) with Eq. (15), Method 3 in this study had a similar form to the typical dynamic model.

2.4 Adaptive prediction strategy

Because of the variability of specific fish pond characteristics, the developed fish weight prediction model using historical production datasets may not adapt to the production of a new specific fish pond. The concept of adaptive updating provides a way to solve above problem. Model adaptation is used to ensure the prediction performance of fish weight for specific fish pond. This section presents an adaptive model updating method for fish weight prediction model. The main idea of adaptive prediction of fish growth is to improve the prediction of fish weight in response to feeding decision by using the collected measurements of the specific fish pond. When a new specific fish pond is used as research target, the adaptive prediction process is described as below.

At the initial stage, the established fish weight prediction model by historical production dataset is applied to predict fish weight. When the specific fish pond production data was available, the parameters of established fish weight prediction model were updated by fitting new measurements of specific fish pond to achieve a smooth transition from a general model to a specific model in an adaptive manner.

Bayesian theory could be used to interpret our proposed adaptive model updating method. For the determination of model parameters, our proposed method included two aspects of information. The model parameters were obtained by historical production dataset analysis, which were regarded as prior parameters. On the other hand, the actual fish weight measurement of specific fish pond provided new information to update the parameters of established fish weight prediction model, which was regarded as posterior parameters. During an ongoing fish production process, more actual fish weight measurements of the specific fish pond will be used to update model parameters in an adaptive manner, which makes the model more adaptive to the specific characteristics and increases the accuracy of fish weight prediction.

For the relationship between general model and specific model, there are three situations: (1) all the specific model characteristics are included in the general model, or (2) there is a certain amount of overlap for the characteristics of two models, or (3) there is significant difference for the characteristics of two models. Therefore, in the results and discussion section, the following three scenarios are simulated to show the performance of proposed adaptive prediction method for different conditions.

Scenario 1: all the characteristics of specific fish pond are considered in the general model.

Scenario 2: part characteristics of specific fish pond are considered in the general model.

Scenario 3: no information of specific fish pond is covered in the general model.

To demonstrate our proposed method, the proposed adaptive prediction method was compared with the following two methods to demonstrate effectiveness including (1) only using the prediction model with no adaption for specific fish pond (This method is denoted as “no adaptation”) and (2) only using limited measurements from specific fish pond to establish model for fish weight prediction (This method is denoted as “no prediction”). All three situations were simulated to show the performance of proposed adaptive prediction method under different conditions. The model prediction method with no adaptation provided the baseline results against the performance of proposed adaptive prediction model.

2.5 The implementation of adaptive fish growth prediction method

The implementation process of adaptive fish growth prediction method is shown in Fig. 2. To achieve the real-time fish weight prediction in aquaculture, the implementation steps were presented as follows.

Step 1: Fish weight is used as input of feeding decision model to obtain feeding decision.

Step 2: Feeding decision is used to predict fish weight based on the fish weight prediction model.

Step 3: Judge whether the practical measurement of fish weight is available or not. If the answer is "Yes", shift to Step 4. If the answer is "No", shift to Step 6.

Step 4: The parameters of fish weight prediction model is updated.

Step 5: Update fish weight using the practical measurement. Shift to Step 1.

Step 6: Update fish weight using the prediction result. Shift to Step 1.

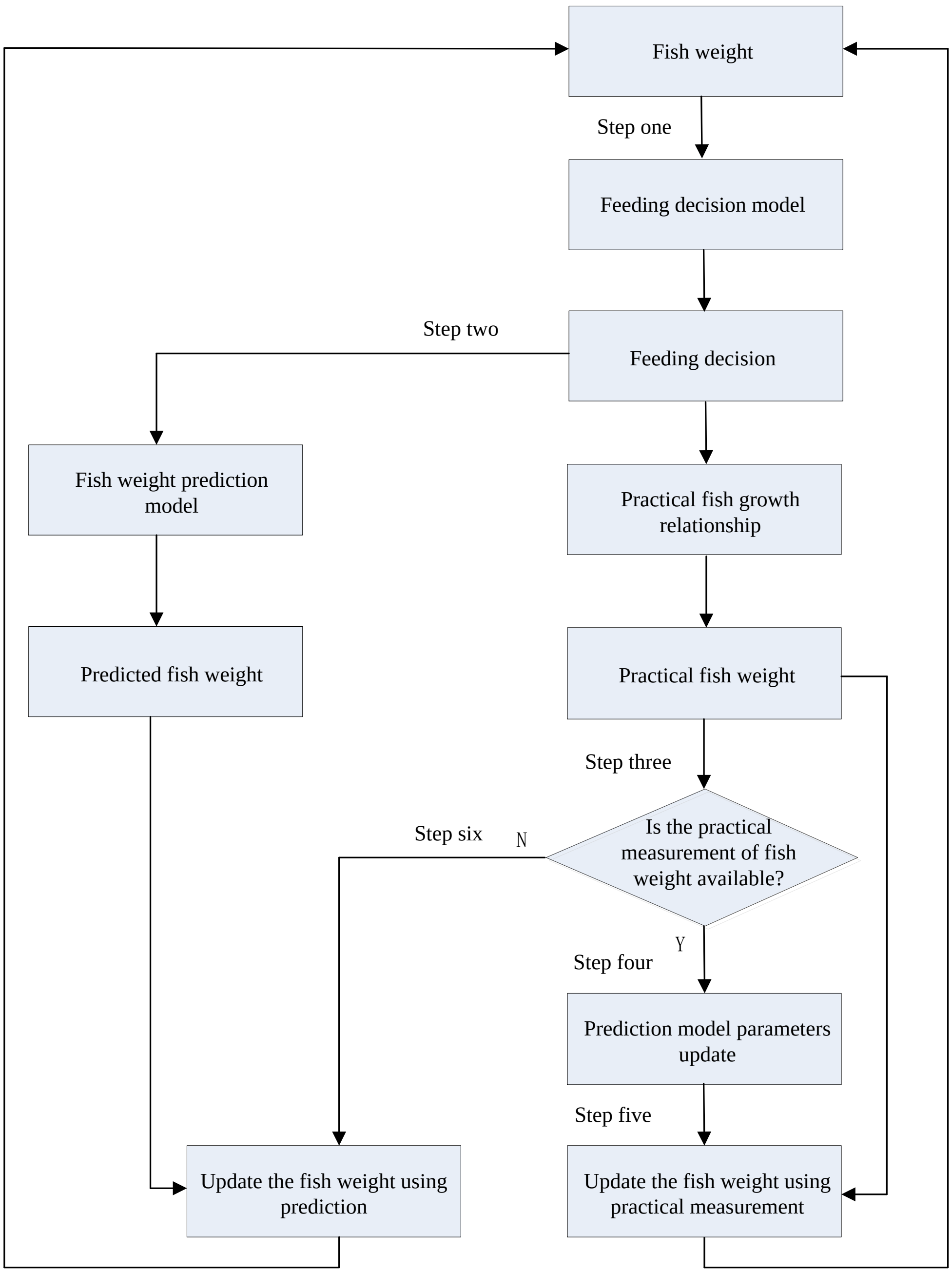


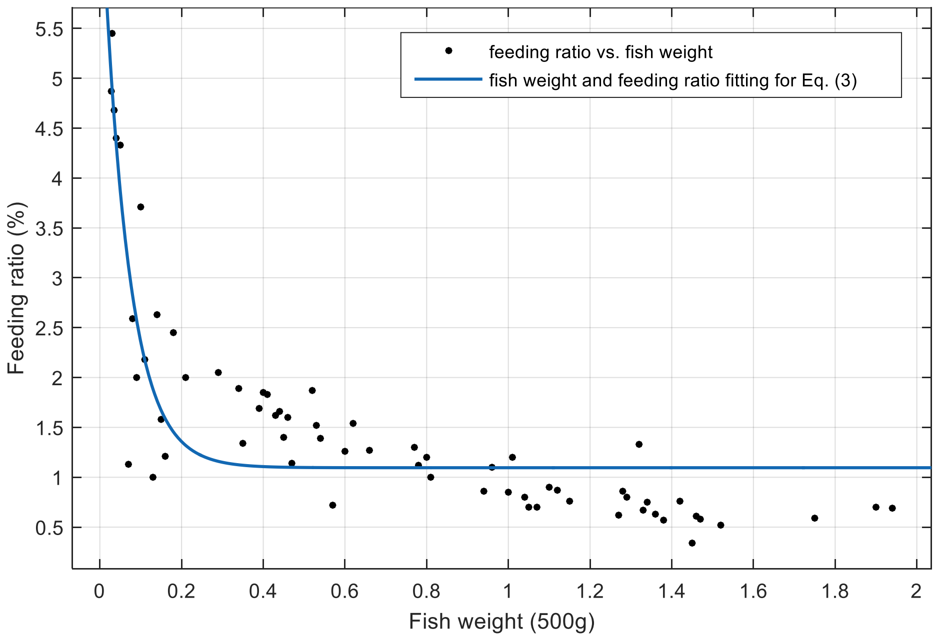
Fig. 2. Implementation process of adaptive fish growth prediction method

3. Results and discussion

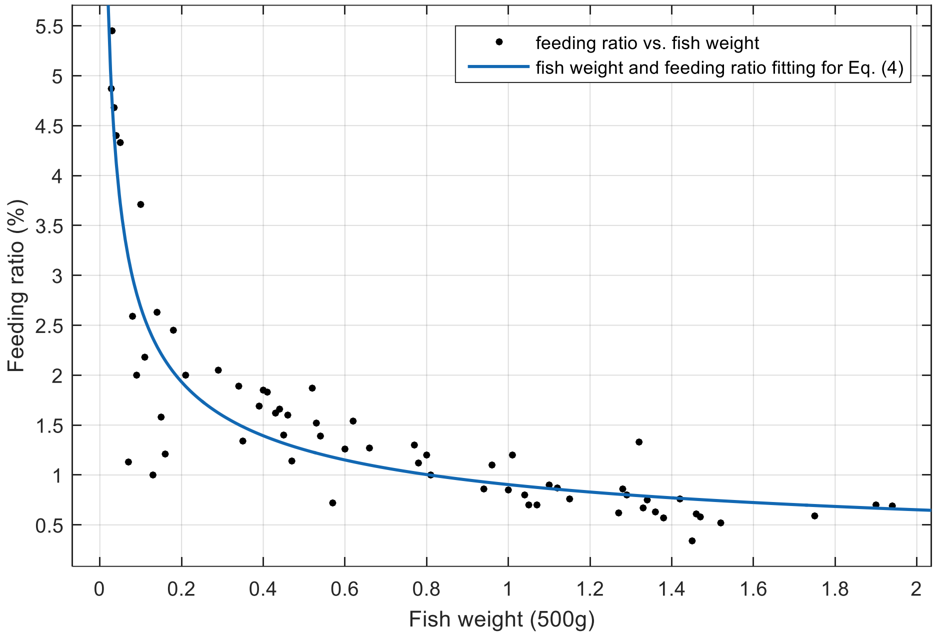
Two sets of results are shown in this section. One set of results is for model calibration and selection, and another set of results is for the adaptive fish weight prediction.

3.1 Model calibration and selection results

Model fitting plots for the fish feeding decision model options are shown in Fig. 3. The horizontal axis represents individual fish weight. The vertical axis represents feeding ratio which is a percentage (%). The calibration results of three options (Eqs. (3), (4) and (5)) for fish feeding decision model are shown in Table 3, including estimated parameters and RMSE. According to RMSE, the second model (Eq. (4)) has the minimum RMSE and a better goodness-of-fit performance. However, it does not include more parameters compared with other two models (Eqs. (3) and (5)). Therefore, the model 2 (Eq. (4)) appears to be a good representation for fish feeding decision making.



(a)



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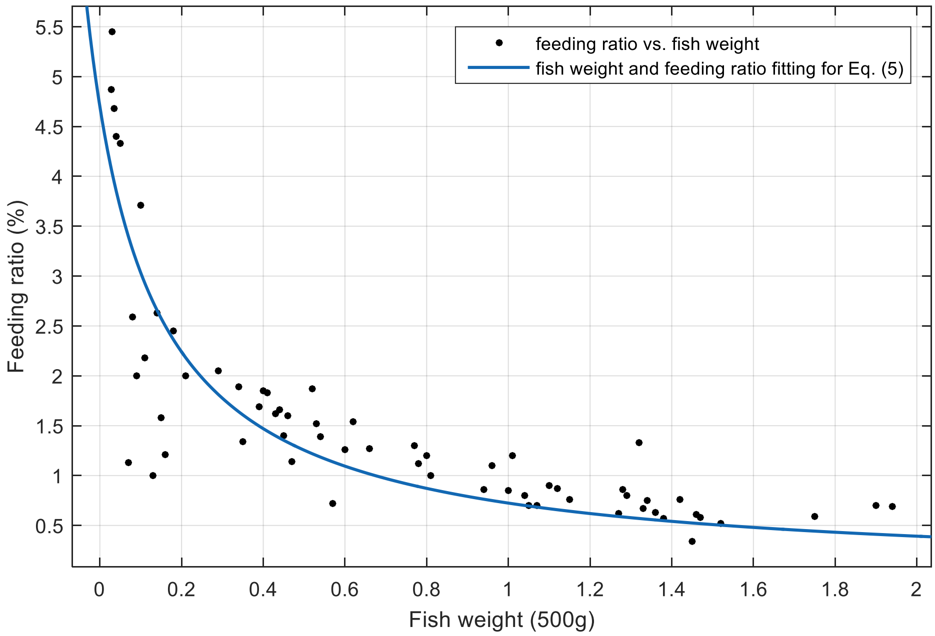


(c)

Fig. 3. Fitted feeding ratio against practical value for the feeding decision model options (a) model 1 (Eq. (3)), (b) model 2 (Eq. (4)) and (c) model 3 (Eq. (5))

Table 3. The calibration results for fish feeding decision model

Models	Parameters	RMSE
Eq. (3)	a_1=6.084 [4.481, 7.686] b_1 = 15.72 [10.4, 21.03] c_1 = 1.096 [0.9339, 1.257]	0.5577
Eq. (4)	a_2=0.9037 [0.7796, 1.028] b_2 = 0.4722 [0.4193, 0.5252]	0.4721
Eq. (5)	a_3=0.8559 [0.6523, 1.06] b_3 = 0.1821 [0.1162, 0.248]	0.5854

The calibration results of three options for fish weight prediction model are shown in Table 4, including the estimated parameters and RMSE. The first model (Method 1) with more parameters achieves better goodness-of-fit than other two models with simple form (Methods 2 and 3). The second model (Method 2) and the third model (Method 3) had similar fitting accuracy, which are from the simplification by expert knowledge and operational experience. For input variables, the introduction of initial individual fish weight provided very little benefit (RMSE was reduced from 0.1698 (Method 3) to 0.1694 (Method 2)), and improvement was not substantial. Therefore, the analysis for the input variables of the third model (Method 3) was reasonable. The initial individual fish weight can be removed from input variables, and the model form simplified. By trading off goodness-of-fit and model complexity, the third model (Method 3) appeared to be a more reasonable choice because of its straightforward implementation.

Table 4. The calibration results for fish weight prediction model

Modelling methods	Parameters	RMSE
Method 1	a_{g1}=0.5724, b_{g1}=0.1242, c_{g1}=0.0867, d_{g1}=−0.2021, e_{g1}=0.1202	0.1048
Method 2	a_{g2}=0.031646, b_{g2}=0.587013	0.1694
Method 3	a_{g3}=0.5908, b_{g3}=0.03239	0.1698

Fish weight was predicted by integrating the fish feeding decision model and the fish weight prediction model, and the prediction results were compared with fish weight measurements, which are illustrated in Fig. 4. The RMSE between prediction and measurement is 0.0543. Note that the established models can make feeding decision and predict fish weight effectively. The selected modelling option provided satisfactory results.

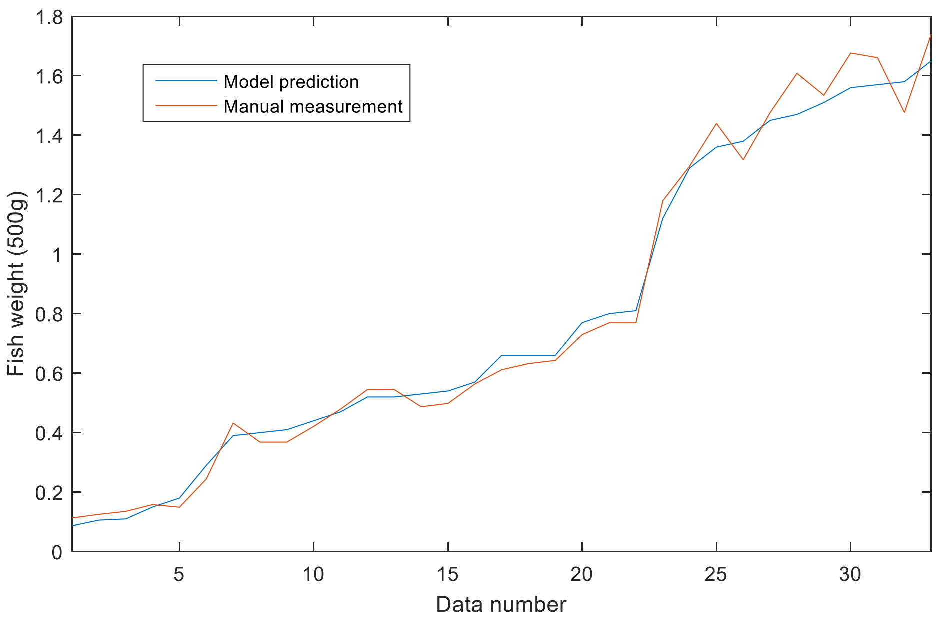


Fig. 4. Comparison between model prediction and manual measurements

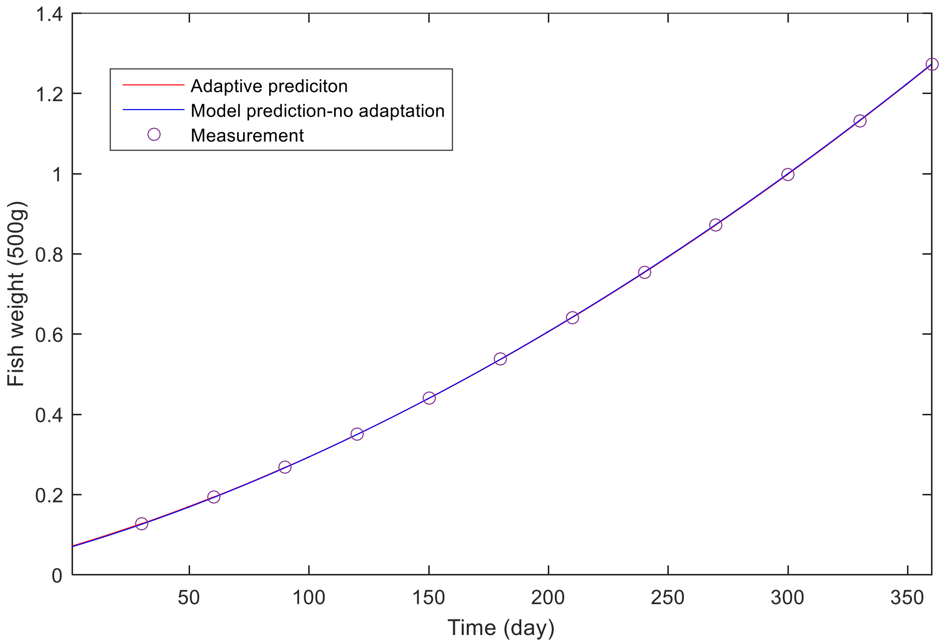
3.2 Adaptive prediction results

If the specific fish pond has unique characteristics that are not adequately covered in the general model, the general model has limited ability to predict fish weight. The general model thus needs to be updated by the measurement of specific fish pond to adapt to its variations. In this study, 25 datasets from six workshops were used as the historical datasets for modelling, and 8 datasets from one workshop were used as the measurements from a specific fish pond and workshop to verify the proposed fish weight predication method. Table 5 shows the RMSE of different fish weight prediction methods compared with fish weight measurements including proposed adaptive prediction method, general model prediction (i.e. no adaptation), and model fitting using limited new measurements (i.e. no prediction). The results of adaptive prediction are presented by using the selected fish feeding decision model (Eq. (4)) and fish weight prediction model (Method 3). It can be seen that proposed adaptive prediction method can update the parameters of general model and provide better fish weight prediction performance compared with other two methods. The general model had certain deviations compared with the specific fish pond. If no adaptive measures are implemented, then the prediction performance of general model will decline. When the new measurements of specific fish pond are very limited, it is difficult to represent the characteristics of specific fish pond accurately. Therefore, the prediction performance of "no prediction" is worse than other two methods.

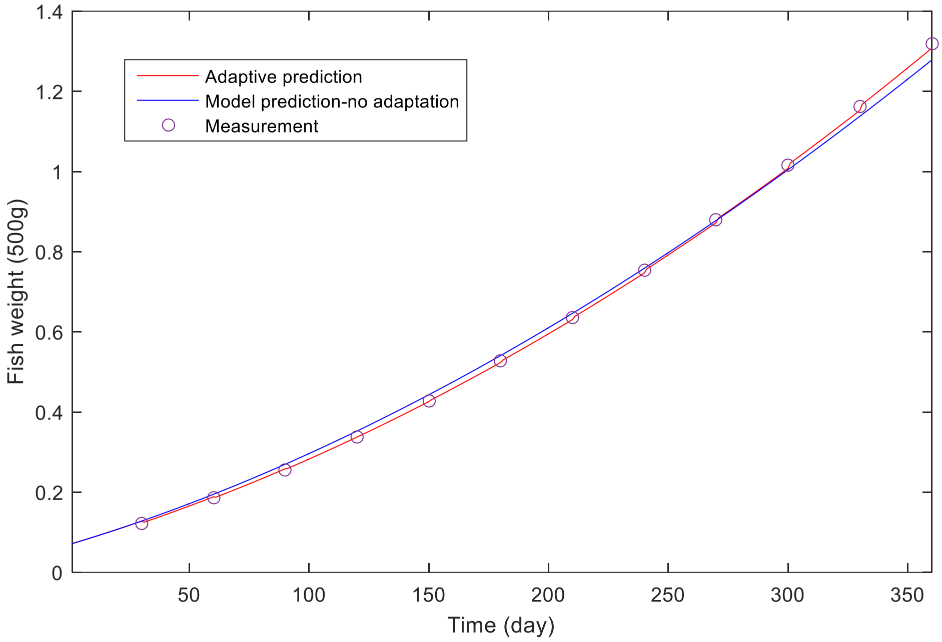
Table 5 The RMSE of different fish weight prediction methods compared with fish weight measurements

Modelling methods	RMSE
Proposed adaptive prediction method	0.0617
No adaptation	0.0622
No prediction	0.3459

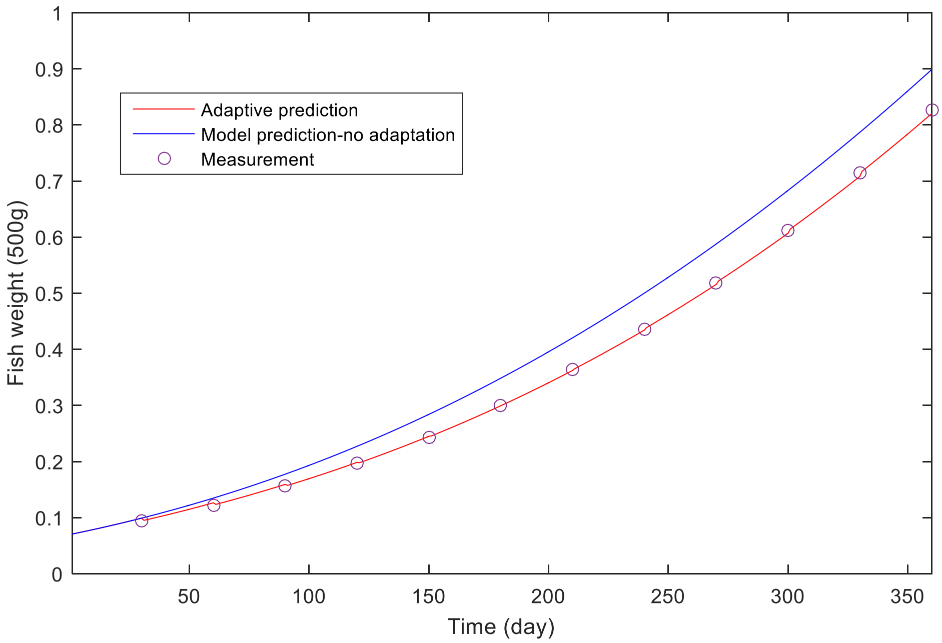
For the relationship between general model and specific model, the three situations in section 2.4 were simulated to show the performance of proposed adaptive prediction method in different conditions. The comparison results of proposed adaptive prediction method and model prediction with no adaptation for different situations are illustrated in Fig. 5. Because the growth period of spotted knifejaw occurs over about one year, the simulated cultured time was set as 360 d.



(a)



(b)



(c)

Fig. 5. Comparison results of fish weight prediction for different situations (a) scenario 1, (b) scenario 2 and (c) scenario 3

The fish weight measurement period is set as once a month, so for proposed adaptive predication method, the parameter updating period is once a month. In practical production process, the measured fish weight curve is unknown, and only the measurements once a month are available. To compare performances, Fig. 5 shows the simulation results of different situations. The RMSEs of adaptive prediction model and model prediction with no adaptation for different situations are shown in Table 6. It is noted that the adaptive prediction method improves the prediction performance to various extents for different situations. When all the characteristics of specific fish pond are covered in the general model (scenario 1), the model prediction with no adaptation performs well for a specific fish pond. The RMSEs of two methods are all very small. When the specific fish pond owns great differences compared with the general model (scenario 3), the improvement in prediction accuracy becomes more apparent. Scenario 2 is the middle degree. The performances of model prediction with no adaptation rely on the similarity between general model and specific fish pond. When the general model has a bigger similarity compared with specific fish pond, it will achieve better prediction performance for the specific fish pond with no adaptation. Inversely, when the similarity is low, the improvement role of proposed adaptive prediction method will be greater.

Table 6 The RMSEs of adaptive prediction model and model prediction with no adaptation for different situations

Condition	RMSE of adaptive prediction model	RMSE of model prediction with no adaptation
scenario 1	0.0004	0.0042
scenario 2	0.0062	0.0166
scenario 3	0.0038	0.0498

3.3 Discussion

By trading off goodness-of-fit and model complexity, the feeding decision model and the fish weight prediction model can be determined from available options. It should be noted that a complex model with a large number of free parameters would fit historical dataset better than a simpler one. However, complex models tend to over fit data and generalisation is not good enough. In addition, to adapt to the small amount of specific fish pond data quickly, the complex model form with too many parameters is not suitable. The proposed adaptive fish weight prediction method achieves a better performance compared with the methods including “no adaptation” and “no prediction”, which not only maintains the general characteristics from historical dataset, but also adapts to the specific characteristics from new fish pond. When adaptive prediction method is compared with “no prediction” method, the RMSE decreases 82.16%. The improvement degree of adaptive prediction method depends on the deviations between general characteristics and specific characteristics. More obvious deviations will show greater improvement role. When adaptive prediction method is compared with model prediction with no adaptation, the RMSE for different situations decreases 81.82% averagely.

In summary, the proposed adaptive fish growth prediction method with empirical knowledge extraction can reduce the impact of knowledge differences among different operators and provide real-time fish growth prediction for the dynamic production environment in an adaptive way.

4. Conclusions

In this study, an adaptive fish growth prediction method with empirical knowledge extraction was developed. The feeding decision model was established by extracting practical operational experience from historical production data. The fish weight prediction method was proposed using regression analysis. The feeding decision was used as the input information of the fish weight prediction method to obtain real-time prediction and adapted to the specific characteristics of new fish ponds. An adaptive updating strategy was proposed by continuously updating model parameters with new measurements. The proposed method was evaluated by the collected production dataset of spotted knifejaw. The results show that the fish growth prediction method can obtain real-time fish weight predication in response to feeding decision based on empirical knowledge extraction. The adaptive prediction method provides an effective way to increase fish weight prediction accuracy and adapt to the specific fish pond's characteristics.

This study can significantly contribute to the real-time fish growth prediction in aquaculture practice. However, this research has a few limitations that provide opportunities for future research. For example, in the process of feeding decision modelling, only fish weight is considered as the main factor for feeding decision. Future work may focus on exploring more other factors related with feeding decision to improve feeding decision, e.g. water quality parameters. In addition, the proposed adaptive strategy is a simple updating way by adjusting model parameters using new measurements. It is an important direction to increase the accuracy of adaptive fish weight prediction by improving model updating strategy further.

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Figure captions

Fig. 1. Framework of adaptive fish growth prediction method with empirical knowledge extraction

Fig. 2. Implementation process of adaptive fish growth prediction method

Fig. 3. Fitted feeding ratio against practical value for the feeding decision model options (a) model 1 (Eq. (3)), (b) model 2 (Eq. (4)) and (c) model 3 (Eq. (5))

Fig. 4. Comparison between model prediction and manual measurements

Fig. 5. Comparison results of fish weight prediction for different situations (a) scenario 1, (b) scenario 2 and (c) scenario 3