Model-based versus model-free feeding control and water quality monitoring for fish growth tracking in aquaculture systems*

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ABSTRACT

Aquaculture systems can benefit from the recent development of advanced control strategies to reduce operating costs and fish losses and increase growth production efficiency, resulting in fish welfare and health. Monitoring the water quality and controlling the feeding are fundamental elements to balancing fish productivity and shaping fish's life history in the fish growth process. Currently, most fish feeding processes are conducted manually in different phases and rely on time-consuming and challenging artificial discrimination. The ability of the feeding control approach influences the fish growth and breeding through the feed conversion rate; hence, controlling these feeding parameters is crucial for enhancing fish welfare and minimizing the general fishery costs. On the other hand, the high concentration level of the environmental factors, such as a high ammonia concentration and pH level, affect the water quality, affecting fish's survival and mass death. Therefore, there is a critical need to develop control strategies to determine optimal, efficient, and reliable feeding and water quality monitoring processes. In this paper, we revisit the representative fish growth model describing the total biomass change by incorporating the fish population density and mortality. Since the measurement data of the total biomass and population from the aquaculture systems are limited and difficult to obtain, we validate the new dynamic population model with the individual fish growth data for tracking control purposes. We specifically focus on relative feeding as a manipulated variable to design traditional and optimal control to track the desired weight reference within the sub-optimal temperature and dissolved oxygen profiles under different levels of unionized ammonia exposure. Then, we propose a Q-learning approach that learns an optimal feeding control policy from the simulated data of the fish growth weight trajectories while managing the ammonia effects. The proposed Q-learning feeding control prevents fish mortality and achieves good tracking errors of the fish weight under the different levels of unionized ammonia. However, it maintains a relative food consumption that potentially underfeeds the fish. Finally, we propose an optimal algorithm that optimizes the feeding and water quality of the dynamic fish population growth process. We also show that the model predictive control decreases fish mortality and reduces food consumption in all different cases of unionized ammonia exposure.

1. Introduction

Aquaculture is one of the largest and fastest-growing food production sectors in the world and is likely to become the primary source of seafood in the future [1], as illustrated in Fig.1. As commercial fish production continues to increase, its impact and reliance on protein sources provided by ocean fisheries are likely to expand. To mitigate these impacts, adequate growth models are relevant for efficient aquaculture management, as they provide an optimized protocol for feeding and monitoring fish welfare throughout the grow-out cycle from stocking through harvesting [2].

Growth is a biological process comprising many crucial processes and fish's life history [3]. For aquaculture systems to achieve better control, tracking and predicting fish growth trajectory is vital. However, the tracking of growth trajectory poses challenges where environmental factors influence fish

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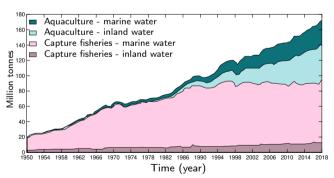


Figure 1: Marine and aquaculture worldwide production

feed, such as unionized ammonia dissolved oxygen, salinity, water temperature, and light [4].

The feeding process and water quality monitoring are usually done manually, on-site, or analyzed in laboratories after the data is collected [5]. This monitoring process delays the detection of abnormalities and the relevant control actions and is arduous to manage the costs and complexity of the cleaning, and the stabilization of the water quality [6]. Depending on water quality measurements, an electric on-off

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actuator was implemented, and the objective was to design a bang-bang controller that switches the valves and pumps on-off [7]. However, this type of controller requires a set of desired points so the controller can meet them. As a result, undesirable responses like chattering phenomena are induced. Proportional-integral-derivative (PID) controllers have been examined experimentally in aquaculture for water quality and feeding. For automatic feeding, the feeding rate and time have been implemented using PID controller to enhance the fish growth [8]. Whereas in [9], the nitrate concentration in water was controlled by PID controller to track the desired reference. The design of closed-loop systems guarantees the best performance against requirements. However, PID may not be efficient for various fish growth tracking systems due to different management factors that account for the overfeeding specifications. Therefore, optimal control law that ensures a trade-off between optimal growth rate performance guarantees, minimization of the costs, and system complexity is relevant to increasing the overall performance. Optimal control approaches using optimization techniques were developed to enhance aquaculture process economics. Many of these optimal control techniques enhance the plants aquaculture management and economics, considering the best harvesting time and the market variation [10], [11]. Another line of work is based on the fish price and mortality effects to provide the best schedule of feeding [12], [13]. However, these works focus on designing a generic framework and do not examine all the growth model's biological variables. To this end, they might lack to maintain fish growth tracking performance in the presence of model uncertainty, such as ammonia effects. The learning-based method for fish growth, such as reinforcement learning (RL), can alleviate the ammonia exposure effects. The Q-learning algorithm for fish trajectory tracking is a model-free RL algorithm, which has been developed in [14]. Specifically, the O-learning algorithm controller aims to track the fish growth trajectory while managing model uncertainties and environmental factors.

This paper proposes a fish population growth model that relies on the fish stocking density and mortality rate. The representative bioenergetic fish population growth model accounts for the biodiversity by expressing the total biomass change through the fish population density and mortality. This proposed model is a step beyond the results in [15] limited to a single bio-energetic fish growth model and does not consider the effect of UIA on mortality. Since the measurement data of the total biomass and population from the aquaculture systems is limited and difficult to obtain, we validate the new dynamic population model with the individual fish growth data [16]. We particularly zoom on the relative feeding as a manipulated variable to design traditional and optimal control to track the desired weight reference within the controlled temperature and dissolved oxygen (DO) profiles through different unionized ammonia (UIA) exposures. To reduce the mortality related to UIA exposure under varying levels of fish stocking density at which the fish growth rate tracks the desired growth reference, we propose an optimal model-based feeding and water quality controller that includes temperature, DO, and UIA and a Q-learning approach developed in [14] that only learns an optimal feeding control policy while managing the ammonia exposure.

The paper's outline is organized as follows: Section 2 describes the individual and the new population dynamic fish growth models. Section 3 provides the main results of the traditional and optimal feeding control problem and water quality monitoring. Section 4 highlights the performance assessments of the proposed controllers for controlling fish feeding along with numerical simulation tests. Thanks to the flexibility of the model-predictive framework, we provide the optimal feeding and water quality monitoring in which the temperature, dissolved oxygen, and unionized ammonia are controlled in Section 5. Finally, the paper summarizes the main contributions and some future works in Section 6.

2. Bioenergetic fish growth models

This section describes fish growth's individual and population dynamics. First, we validate the new dynamic population model with the individual fish growth data for control and monitoring purposes. Then, we highlight the correlation between ammonia exposure and mortality which underly fish growth performance.

The dynamic energy budget (DEB) model has recently provided the most complete and well-connected environmental variables effects for growth predictions by covering the entire life cycle of the fish organism [17, 18, 19]. The DEB model describes the metabolic processes of organisms in terms of energy. The description incorporates tools in the early organisms' life cycle which enables; to maintain beneficial knowledge before establishing new farms [20, 21], approximate the fish production and amount of food [22], and enhance the production by farming aquatic species in integrated fashion [23]. In line with this, the (DEB) growth model has become central in the modeling and analysis of many fish species. It can be formulated as in the metabolic process, which is the difference between anabolism and catabolism, according to Ursin's work [24].

• Individual fish growth models: The dynamics of the individual bioenergetic growth model is described in terms of fish biomass and fish population density as follows [15, 16]

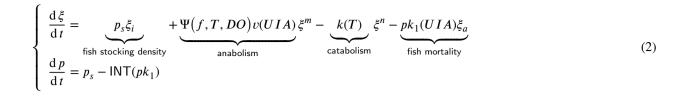
$$\frac{\mathrm{d}\,w}{\mathrm{d}\,t} = \underbrace{\Psi(f,T,DO)v(UIA)}_{\text{anabolism}} w^m - \underbrace{k(T)}_{\text{catabolism}} w^n \,(1)$$

where *w* is the individual fish weight, $\Psi(f, T, DO)$ (kcal^{1-m}day⁻¹) and *v*(*UIA*) are the coefficients of anabolism and *k*(*T*) (kcal¹⁻ⁿday⁻¹) is the fasting catabolism coefficient formulated as

 $\Psi(f,T,DO) = h\rho f b(1-a)\tau(T)\sigma(DO),$

and

$$k(T) = k_{\min} \exp\left(j(T - T_{\min})\right).$$



The model constitutes the effects of water quality parameters as temperature (*T*), dissolved oxygen (*DO*), and un-ionized ammonia (*UIA*) and feeding parameters as food availability [16]. Nomenclature and the fish growth model parameters are summarized in Table 4 [16]. The effects of temperature $\tau(T)$, unionized ammonia v(UIA), and dissolved oxygen $\sigma(DO)$ on food consumption and their formulations are found in Appendix [16, 15, 25].

• Population dynamic fish growth models: Population models are crucial to describe potential pathways for fish population dynamic recovery and the patterns in biodiversity to understand and predict the future of marine resources. The fish growth population models based on the DEB integrate the management variable, such as feeding, and environmental variables, like the temperature, dissolved oxygen, and ammonia, as effects for fish growth predictions and performance by covering the life cycle of the fish organism. Besides, these models capture essential information on environmental and biological changes in fishes, including mortality and fish stocking density [26, 27]. The dynamic of the population dynamic bioenergetic growth models is described in terms of fish biomass and population density as follows by (2). The states ξ and p are total fish biomass and fish number, respectively. p_s and ξ_i are stocking fish number and individual fish biomass during fish stocking, $k_1(UIA)$ is fish mortality coefficient, and ξ_a is mean fish biomass which equals to ξ divided by p. The fish growth model (2) can be written in a compact form as follows

$$\begin{cases} \frac{\mathrm{d}\xi}{\mathrm{d}t} = g\left(\xi, p, \underbrace{f, T, DO, UIA}_{u}, k_{1}\right) \\ \frac{\mathrm{d}p}{\mathrm{d}t} = p_{s} - \mathrm{INT}(pk_{1}) \end{cases}$$
(3)

where $\xi \in \mathbb{W} \subset \mathbb{R}$ denotes the state and $u = [u_1, u_2, u_3, u_4]^T$ is the input vector. $u \in \mathbb{U} \subset \mathbb{R}^4$ describes the manipulated control input vector corresponds to the feeding rate, temperature, and dissolved oxygen, and unionized ammonia respectively. The set of admissible input values \mathbb{U} is compact. The relative feeding rate $f = \frac{r}{R}$ is expressed in terms of the maximal daily ration *R* and the daily ration *r*.

2.1. Model simulation and validation

This subsection aims to validate the proposed population growth model to the individual bioenergetic growth model proposed in [16]. This step is essential to investigate the effectiveness of the proposed model and how it can reflect reality. Thus, one of the validation limitations is the lack of real data on total fish weight and population. This remains a challenge even for the individual fish since the normal procedure to measure the fish's weight is done manually. Due to these limitations, the validation process relies on the individual fish model (DEB) [16] because it has been tested and validated experimentally.

The objective of the validation is to have a similar response of individual fish model when the population is selected to be 1 in the proposed model given similar input profiles. The inputs, f, T, DO, and UIA, are generated within the range of their minimum and maximum as in Table 4 in Appendix. The initial weight for the proposed model and the individual fish (DEB) is selected to be 6.24 [g/fish]. And, the initials for the fish population are picked 1, 5, 10, 50, and 100 [fish]. Fig. 2 illustrates the validation results of the proposed model where Fig. 2(a) shows the total fish weight. The solid black line represents the result of [16] according to given the input profiles and the dashed red line is the result of the proposed model when the population is 1. It is clear that the responses of both models have similar fish growth trajectories in the case of the individual population. While as expected, increasing the fish population increase the total fish in the proposed model. Fig. 2(b) shows population dynamic of the proposed model. The results of the population are not changing due to non-toxic feeding and water quality input factors. This leads us to investigate the effects of feeding and water quality factors in the proposed model.

2.2. Feeding and water quality effects

This subsection studies the effects of the feeding and water quality factors. The water quality effects are a function of the temperature, dissolved oxygen, and unionized in (3). These functions appear in the system (2) as function of $\tau(T)$, $\sigma(DO)$, and v(UIA). Figs. 3 illustrates the effect of the water quality factors on fish food consumption where Fig. 3(a) corresponds to the effect of temperature on $\tau(T)$, Fig. 3(b) represents to the effect of dissolved oxygen on $\sigma(DO)$, and Fig. 3(c) corresponds to the effect of unionized ammonia on v(UIA).

We note that the optimal temperature, dissolved oxygen, and unionized ammonia result in maximum $\tau(T)$, $\sigma(DO)$, and v(UIA), which are equal to 1. In this case, the anabolism

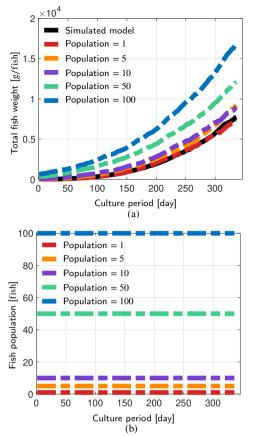


Figure 2: Validation results of the proposed model given similar input profiles. Figure (a) shows the total fish weight (dashed) compared to individual fish weight in [16] (solid black). Figure (b) illustrates the population dynamic of the proposed model.

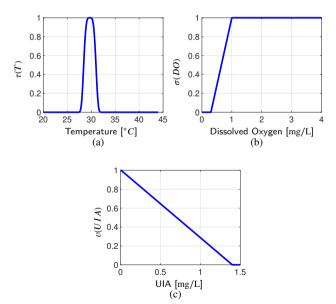


Figure 3: The effects of the water quality factors on fish food consumption. (a) $\tau(T)$ is the temperature factor ($0 \le \tau(T) \le 1$, dimensionless), (b) $\sigma(DO)$ is the dissolved oxygen factor ($0 \le \sigma(DO) \le 1$, dimensionless), and (c) v(UIA) is the unionized ammonia factor ($0 \le v(UIA) \le 1$, dimensionless).

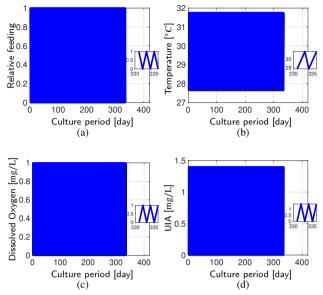


Figure 4: The generated input time-varying profiles for the sensitivity analysis. Figure (a) presents the relative feeding profile, (b) the temperature profile, (c) the dissolved oxygen profile, and (d) the unionized ammonia profile.

in (2) will be maximum, assuming the relative feeding f = 1. With that being mentioned, it is worth investigating the effects of feeding and water quality factors on fish growth and population. In particular, five cases are considered as follows

- Baseline case: The feeding and water quality are optimal, namely f = 1, $\tau(T) = 1$, $\sigma(DO) = 1$, and v(UIA) = 1
- Time-varying relative feeding (*f*)
- Time-varying temperature (T)
- Time-varying dissolved oxygen (DO)
- Time-varying unionized ammonia (UIA)

Figure 4 illustrates the generated input time-varying profiles for each case. They are designed to fluctuate the functions f, $\tau(T)$, $\sigma(DO)$, and v(UIA) between 0 and 1. Table 1 summarizes the performance results of the water quality and feeding factors. Feeding and water quality factors indeed affect the total fish weight compared to the baseline case. Particularly, unionized ammonia (UIA) directly affects the fish population, resulting in the death of 9 fish. From these observations, UIA is a dominant factor, and it is worth investigating the responses of various control methods to different UIA exposure.

3. Fish population growth tracking under ammonia exposure

This section studies the model-based feeding controllers for monitoring fish population growth under different UIA pro-

Table 1								
Sensitivity	analysis	of the	effect	on	feeding	and	water	quality
factor								

Cases	Fish weight [g]	Population [fish]
Maximum case	7922.9	10/10
Time-varying f	4549.2	10/10
Time-varying T	1220.15	10/10
Time-varying DO	4759.2	10/10
Time-varying UIA	0.066	1/10

files. Indeed, ammonia exposure remains a significant concern in the fish population growth model and the possible effects on fish health and survival in aquaculture systems. Besides, the high ammonia accumulation directly results in fish mortality and increases potential signs of stress resulting in behavioral responses and disease resistance. Therefore, it is crucial to analyze the fish growth responses under the different traditional and optimal controllers through the UIA exposure to monitor the value of UIA to enhance fish farming productivity. We start with the classical controllers, as the bang-bang and proportional-integral-derivative (PID) controllers; then, we move to the optimal control, namely model predictive control and Q-learning.

3.1. Bang-bang control

The Bang-bang controller is an on-off controller. It is considered one of the simplest controllers yet widely utilized in various market devices. It has been used to regulate water quality and automate feeding in aquaculture systems. For instance, the bang-bang controller was implemented to track the desired set-point of dissolved oxygen by switching the aerator on or off in [28]. The mathematical representation for tracking the desired set-point can be given as follows

$$u^{j}(t) = \begin{cases} \text{on} & \text{if } e^{j}(t) > 0, \\ \text{off} & \text{if } e^{j}(t) \leq 0, \end{cases}$$
(4)

where $u^j(t)$ is the input action to the system, *j* is the number of control variables and $e^j(t) = \mathcal{X}_d^j(t) - \mathcal{X}^j(t)$ is the error between desired references $\mathcal{X}_d^j(t) = [T_d(t), DO_d(t), f_d(t),$ $UIA_d(t)]$ and output measurements $\mathcal{X}^j(t) = [T(t), DO(t),$ f(t), UIA(t)]. For instance, consider the temperature to be the controllable parameter *T*, then the heater will turn on if $T_{\text{desired}} - T > 0 \implies T < T_{\text{desired}}$ or turn off if $T_{\text{desired}} - T \le 0 \implies T \ge T_{\text{desired}}$. The given conditions in the bang-bang controller are not restricted to tracking desired references but can also be set according to duty cycles. This enables the design of an automated feeding system. In the sequel, we monitor the feeding using the bang-bang controller to track the desired fish growth as follows

$$f = \begin{cases} 1 & \text{if } w_d - w > 0, \\ 0.1 & \text{if } w_d - w \le 0, \end{cases}$$
(5)

where $w = \frac{FB}{FP}$ is the mean weight of fish under the assumption that it is measurable, and w_d is the desired fish weight. In the case that f = 1, the provided food quantity is 10% of the fish's mean body weight. On the other hand, when f = 0.1, the provided food quantity is 1% of the fish's mean body weight. Using this structure of relative feeding allows the fish to be fed daily.

3.2. Proportional-Integral-Derivative (PID) controller

Proportional-Integral-Derivative (PID) controllers have been examined experimentally in aquaculture for water quality and feeding. For automatic feeding, the feeding rate and time have been implemented using a PID controller to enhance the fish growth [8]. Whereas in [9], the nitrate concentration in water was controlled by a PID controller to track the desired reference. Assuming that the objective is to drive temperature, dissolved oxygen, and feeding rate to desired references are $\mathcal{X}_d^j(t)$. PID controller is calculated from the error feedback as follows

$$u^{j}(t) = K_{p}^{j}e^{j}(t) + K_{i}^{j}\int e^{j}(t) dt + K_{d}^{j}\frac{de^{j}(t)}{dt}, \qquad (6)$$

where $u^{j}(t)$ is the input action to the system, $e^{j}(t) = \mathcal{X}_{d}^{j}(t) - \mathcal{X}^{j}(t)$ is the feedback or tracking error, K_{p}^{j} , K_{i}^{j} , and K_{d}^{j} are the gains of proportional, integral, derivative, respectively. These gains are tunable parameters tuned with trial and error. Similar to the bang-bang controller, the manipulated variable is the relative feeding, and the PID formulation is given as follows

$$f = K_p e + K_i \int e \, dt + K_d \frac{de}{dt},\tag{7}$$

where $e = w_d - w$ is the tracking error.

3.3. Optimal feeding under different UIA profiles (MPC¹)

Optimal control strategies are relevant to maximize efficiency growth rate while incurring the cost of wasted food due to overfeeding that adversely impacts water quality. Subsequently, these advanced control methods can handle disturbance attenuation of external factors such as time-varying environmental factors. In the case of the fish growth application, the closed-loop PID-type controllers and the bang-bang controller do not satisfy the desirable features such as optimizing the feed conversion ratio, which minimizes the feed while maximizing the predicted growth state.

The fish population growth reference tracking problem is formulated similarly to [15] as a minimization with a finite-time prediction horizon as follows

$$\min_{u \in \mathcal{U}(\epsilon)} J = \int_{t_k}^{t_{k+N}} \left(\left\| \frac{\tilde{w}(\tau) - w_d(\tau)}{w_d(\tau)} \right\|^2 + \lambda \left\| f(\tau) \right\|^2 \right) d\tau \quad (8a)$$

s.t.
$$\dot{\tilde{w}}(t) = g\left(\tilde{w}(t), f(t)\right)$$
 (8b)

$$f_{\min} \leq f(t) \leq f_{\max}, \quad \forall t \in [t_k, t_{k+N}]$$
 (8c)

$$\Delta f(t_k) = f(t_k) - f(t_{k-1}) \tag{8d}$$

$$w_0 \leq \tilde{w}(t) \leq w_{\text{end}}, \quad \forall t \in [t_k, t_{k+N}]$$
 (8e)

$$\tilde{w}(t_k) = w(t_k), \quad \tilde{w}(0) = w(t_0) \tag{8f}$$

where N is the prediction horizon, and λ is the weight parameter. Equation (8a) defines the objective function that minimizes the normalized difference error of tracking while minimizing the relative feeding over the prediction horizon. The constraint in (8b) is the growth model (3) used to predict the evolve $\tilde{w}(t)$ by bounded f(t) in (8c) and initial condition in (8e). w_0 and w_{end} are the desired initial and maximal fish weight constraints, respectively.

3.4. Q-learning based optimal feeding control under ammonia exposure

Reinforcement learning (RL) technology has demonstrated the ability to learn the optimal feeding control policy for the fish growth rate for aquaculture in our recent work [14]. Additionally, it has been applied to recognize the wave size to determine whether to continue or stop through an automatic fish-feeding system [29] and facilitate the feeding control process in [30]. RL is applied to fish robotic research and schooling navigation areas [31, 32, 33]. However, few studies have assessed fish-feeding control based on the RL methodology in monitoring and optimizing fish growth rate production for aquaculture systems. In line with this, we implement the Q-learning algorithm to solve the fish growth tracking problem under different levels of ammonia exposure. Q-learning algorithm optimizes a lookup table iteratively. This Q-table is usually built from a record of feeding actions related to fish weight, and population states [14]. Then, Q-learning algorithm maps the set of fish weight and population system states, S, to the set of feeding actions, A, such that the following reward, r_t [14]

$$r_t\left(s_t, a_t\right) = -\left[\left(\frac{w(s_t) - w^d(t)}{w^d(t)}\right)^2 + \lambda \left(f\right)^2\right],$$

minimizes the fish growth tracking error deviation and penalizes the feed ration under the sub-optimal temperature and dissolved oxygen profiles for the required action

$$\mathbf{a} = \max_{a'} Q(s, a'), \quad a \in \mathbf{A}, s \in \mathbf{S}$$

where f is the feeding rate, λ is a positive regularization term to assess the feeding input preference, $w(s_t)$ is the fish weight at the state s_t and $w^d(t)$ is the desired reference live-weight growth trajectory. At each time t, the temporal difference of the Q-learning algorithm uses sampling experiences to update the action-value function from the aquaculture environment's response according to the following equation [14]

$$Q\left(s_t, a_t\right) \leftarrow Q\left(s_t, a_t\right)$$

+
$$\alpha \left[r_t \left(s_t, a_t \right) + \gamma \max_a Q \left(s_{t+1}, a_{t+1} \right) - Q \left(s_t, a_t \right) \right],$$

where $Q(s_t, a_t)$ is the value function of the state-action pair (s_t, a_t) at each time *t*, $r_t(s_t, a_t)$ is the corresponding reward, γ is the discount factor and α is the learning rate.

4. Performance assessments of the different approaches for controlling fish feeding

This section aims to design and implement classical controllers such as bang-bang and PID, and optimal controllers such as model predictive control and Q-learning to monitor the fish population growth model under different unionized ammonia (UIA) profiles. In this numerical simulation, the individual fish weight is extracted from experimental data in [34] for Nile Tilapia (Oreochromis niloticus). We specifically zoom on the relative feeding as a manipulated variable to design traditional and optimal control to track the desired weight reference within the controlled temperature and DO profiles under different levels of unionized ammonia (UIA) exposure.

4.1. Case 1: UIA is maintained constant under its critical value

This case compares bang-bang, PID, MPC¹, and Q-learning controllers when UIA profile is maintained constant under its critical value. The temperature and dissolved oxygen (DO) profiles are controlled around the optimal temperature $T_{opt} = 29.7 \ ^{\circ}C$ and above the critical value $DO_{min} = 1$, respectively.

4.2. Case 2: UIA varies under its critical value

This case aims to test the controllers by controlling the relative feeding using a time-varying UIA profile under its critical value. The temperature and dissolved oxygen (DO) profiles are maintained similar to case 1.

4.3. Case 3: UIA varies under its critical value with a spike

The last case considers identical profiles of case 2. Thus, one spike is added to the UIA profile to investigate the responses of the three controllers in the presence of a disturbance. Indeed, this case shows how the UIA directly affects fish mortality and is sensitive to the fish population growth mortality while reducing the food quantity.

In what follows, we tuned the PID gains to achieve a good compromise between fish growth tracking error and food consumption rate performances. Then, after several trial and error tests, we selected the gains to be $K_p = 0.1$, $K_i = 12$, and $K_d = 0.01$. We also apply a saturation block when $f > 1 \implies f = 1$ and $f < 0.1 \implies f = 0.1$ which means 10% or less than 1% to prevent exceeding the boundary of the relative feeding. In the MPC¹ framework, the prediction horizon and regularization parameter are selected as N = 6, and $\lambda = 0.002$.

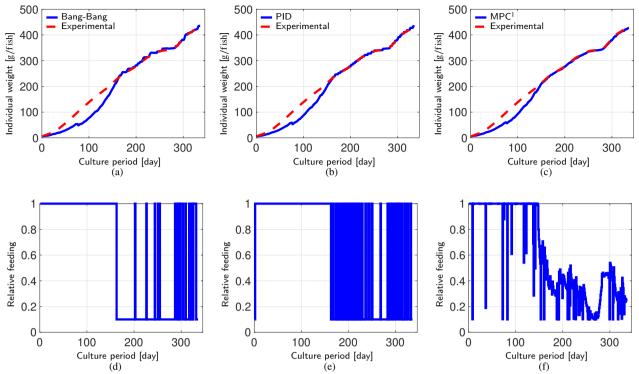


Figure 5: The result of case 3 when the fish population size is equal to 10 and UIA is varied under $UIA_{critical}$ within a spike. Figures (a), (b), and (c) illustrate fish individual growth weight tracking for Bang-Bang, PID, and MPC¹ controllers, respectively. Figures (d), (e), and (f) show the result of the manipulated variable (relative feeding) for Bang-Bang, PID, and MPC¹ controllers, respectively.

4.4. Results and discussion

Case 1: The three controllers bang-bang, PID and MPC¹ perform well in tracking and reach the final fish weight. Table 2 summarizes the performance assessment of all the controllers, including all cases, food consumption, RMSE, and fish mortality. The RMSE of the bang-bang controller is 14.109%, PID is 15.627%, and MPC¹ is 14.878%. Besides, the relative feeding of bang-bang and PID controllers are f = 1 till the day \approx 135. In contrast, MPC¹ seeks to track the desired fish weight while minimizing the relative feeding. To summarize this case, the tracking performance of the three controllers is quite similar (see Table 2). However, MPC¹ reduces the total food consumption by 17.47% and 18.73% compared to bang-bang and PID, respectively, even though the bang-bang RMSE is less than MPC¹.

<u>Case 2:</u> From Table 2, a similar conclusion can be extracted as in case 1. The bang-bang and PID maximize the relative feeding for the first ≈ 135 days while MPC¹ solves for optimal relative feeding in those days. Besides, MPC¹ reduces the total food consumption by 25.65% and 7.26% compared to bang-bang and PID, respectively.

Case 3: This case considers a spike in the UIA profile above its critical value. The resulting spike leads to one fish's mortality, indicating the need for further investigation of the three controllers' performances in Fig. 5. The tracking weight performances of the bang-bang, PID, and MPC¹ are illustrated in Figs. 5(a), (b), and (c), respectively. Moreover, the effect of the spike can be recognized on the day at 75 when the trajectories decreased. The RMSE of the bang-bang controller is 27.72%, PID controller 22.817%, and MPC¹ controller is 19.914%. Figs. 5(d), (e), and (f) show the result of the relative feeding of bang-bang, PID, and MPC¹ controllers, respectively. The relative feeding response of the MPC¹ controller is sufficient because it focuses on minimizing the relative feeding and decreases the RMSE under the presence of a spike.

On the other hand, Figure 6 illustrates the fish growth tracking performance results using Q-Learning when the fish population is 10 under different levels of unionized ammonia (UIA) exposure. Figs. 6 (a), (b), and (c) show the fish individual growth weight tracking for cases 1, 2, and 3, respectively. Figs. (d), (e) and (f) show the result of the relative feeding variable for case 1, case 2, and case 3, respectively. Figs. 6 (g), (h), and (i) present the policy improvement during the training episodes. We note that the proposed Q-learning feeding control prevents fish mortality to some degree compared to the model-based approaches and achieves better tracking errors of the fish weight for all the different levels of unionized ammonia exposures. However, Q-learning provides a feeding policy and maintains a relative food consumption that potentially underfeeds the fish.

Remark 1. The discretization of system (3) for *Q*-learning is sensitive to convert continuous dynamics to finite sets. Using a variable resolution grid scheme, introduced in [35], improves the performance of *Q*-learning.

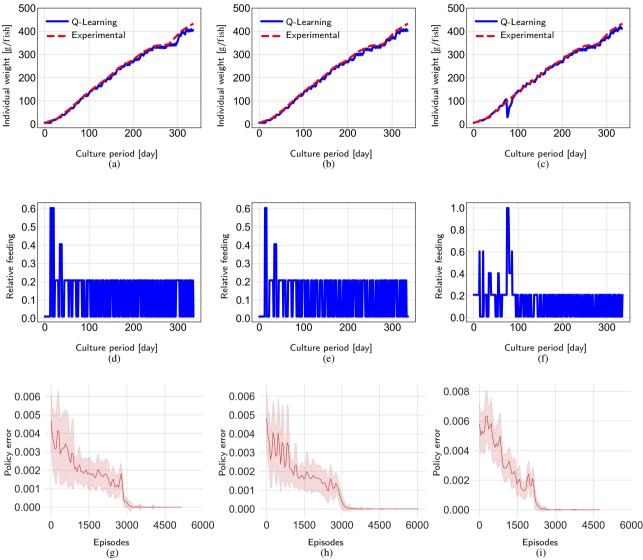


Figure 6: Performance results of Q-Learning under the three cases when the fish population is 10. Figures (a), (b), and (c) illustrates fish individual growth weight tracking for case 1, 2, and 3, respectively. Figures (d), (e), and (f) show the result of the manipulated variable (relative feeding) for case 1, case 2, and case 3, respectively. Figures (g), (h), and (i) present the policy improvement during the training episodes.

5. Optimal feeding and water quality monitoring (MPC²)

и

As presented above, a high concentration of exposure to UIA that is reflected by a spike in case 3 results in fish mortality by only controlling the feeding along with the density. To fill this gap in fish mortality related to UIA exposure under conditions of fish stocking density at which the fish growth rate tracks the desired growth reference, we design an optimal feeding and water quality monitoring that includes the temperature, dissolved oxygen (DO), and UIA in the objective function of MPC¹. We formulate this second model predictive control (called MPC²) as follows.

$$\min_{\boldsymbol{\in}\mathcal{U}(\boldsymbol{\varepsilon})} J = \int_{t_k}^{t_{k+N}} \left(\left\| \frac{\tilde{w}(\tau) - w_d(\tau)}{w_d(\tau)} \right\|^2 + \lambda_1 \left\| f(\tau) \right\|^2 \right)$$

$$+ \lambda_{2} \left\| T(\tau) - T_{d} \right\|^{2} + \lambda_{3} \left\| DO(\tau) - DO_{d} \right\|^{2} \\ + \lambda_{4} \left\| \frac{UIA(\tau) - UIA_{d}}{UIA_{d}} \right\|^{2} \right) d\tau$$
(9a)

s.t.
$$\dot{\tilde{w}}(t) = g(\tilde{w}(t), u(t))$$
 (9b)

$$u_{\min} \leq u(t) \leq u_{\max}, \quad \forall t \in [t_k, t_{k+N}]$$
 (9c)

$$\Delta u(t_k) = u(t_k) - u(t_{k-1}) \tag{9d}$$

$$w_0 \leq \tilde{w}(t) \leq w_{\text{end}}, \quad \forall t \in [t_k, t_{k+N}]$$
 (9e)

$$\tilde{w}(t_k) = w(t_k), \quad \tilde{w}(0) = w(t_0)$$
(9f)

where the prediction horizon is selected as N = 5, and the regularization parameters $\lambda_1 = 0.001$, $\lambda_2 = 0.2$, $\lambda_3 = 0.5$, and $\lambda_4 = 0.5$ are appropriately chosen to balance the objective function (9a). T_d , DO_d and UIA_d are the desired references. Model-based versus model-free feeding control and water quality monitoring for fish growth tracking

Table 2

Performance assessment of different controllers for the three cases (UIA constant, varying, and varying with a spike)

Cases	Controller	Fish mortality	RMSE	Food consumption [g]
Case 1	Bang-Bang	0/10	14.109%	3479.7
	PID	0/10	15.627%	3245.5
	MPC ¹	0/10	14.878%	2871.9
	Q-learning	0/10	11.71%	718.28
Case 2	Bang-Bang	0/10	15.645%	4054
	PID	0/10	18.385%	3249.8
	MPC ¹	0/10	17.69%	3013.8
	Q-learning	0/10	10.98%	668.06
Case 3	Bang-Bang	1/10	27.72%	2835.4
	PID	1/10	22.817%	3291
	MPC ¹	1/10	19.914%	2928.5
	Q-learning	0/10	12.09%	706.99
Case 3	Bang-Bang	4/25	56.428%	4607.5
	PID	4/25	57.799%	4106
	MPC ¹	4/25	57.0144%	3728.6
	Q-learning	0/25	14.74%	979.85

Table 3

Performance assessment of MPC^2 with different fish population density

Fish mortality	RMSE	Food consumption [g]
0/10	2.723%	2487.9
0/25	21.335%	3311.4

Performance results of MPC^2

Fig. 7 illustrates the performance results of MPC² when the fish population growth dynamics are 10 and 25. Figs. 7 (a)-(f), Figs. 7 (b)-(g), and Figs. 7 (c)-(d)-(e) and Figs. 7 (h)-(i)-(j) show the evolution of the fish growth trajectories, the feeding and the environmental factors for both stocking densities. Thanks to the flexibility of the model-predictive framework, MPC² achieves less food quantity and good tracking error performance for both stocking densities. Further, we notice from Table 3 that the feeding and environmental control inputs (*i.e.* temperature, dissolved oxygen, and UIA) are well maintained around their desired references for both stocking densities, and the fish mortality remains zero.

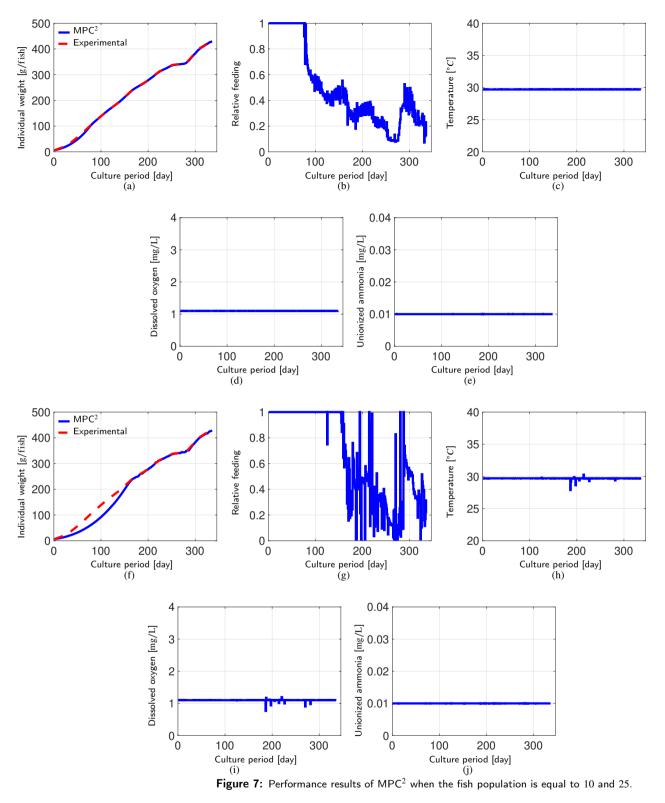
6. Conclusion

In this paper, we validated the new population dynamic fish growth model to achieve a sufficient overlap between the individual population fish growth data and the new dynamic model in which we consider the population state equal to one. Then, we designed classical and optimal control strategies, namely bang-bang, proportional-integral-derivative (PID),

and model predictive control (MPCs) schemes, to track a desired fish growth trajectory and monitor the feeding and water quality. First, we focused on determining the best feeding regimen to design these controllers within the sub-optimal temperature and DO profiles under different levels of unionized ammonia (UIA) exposures. Then, we proposed an optimal algorithm that optimizes the feeding and water quality of the dynamic fish population growth process. This optimal control relies on MPC, thanks to its flexibility to incorporate constraints and inputs in the objective function. We also showed that the model predictive control simultaneously decreases fish mortality and reduces food consumption in all different cases by an average of 26.9% compared to the bang-bang controller, 22.6% compared to the PID controller, and 14.3% compared to MPC1 controller. Our findings revealed that the proposed MPC² optimizes the food consumption and enhances fish survival and growth while optimizing food consumption while Q-learning policy provides a feeding policy and maintains a relative food consumption that potentially might underfeed the fish. For future works, we will investigate how model predictive control approach can support Q-learning framework to efficiently handle feeding constraint satisfaction and find better trajectories and policies from value-based reinforcement learning.

7. Appendix

The effects of temperature $\tau(T)$, unionized ammonia v(UIA)and dissolved oxygen $\sigma(DO)$ on food consumption are de-



scribed, respectively [16].

where $\kappa = 4.6$.

$$\tau(T) = \begin{cases} \exp\left\{-\kappa \left(\frac{T-T_{opt}}{T_{max}-T_{opt}}\right)^{4}\right\} & \text{if } T > T_{opt}, \\ \exp\left\{-\kappa \left(\frac{T_{opt}-T}{T_{opt}-T_{min}}\right)^{4}\right\} & \text{if } T < T_{opt}, \end{cases} \quad \nu(UIA) = \begin{cases} 1 & \text{if } UIA < UIA_{crit}, \\ \frac{UIA_{max}-UIA}{UIA_{max}-UIA_{crit}} & \text{if } UIA < UIA_{max}, \\ 0 & \text{elsewhere.} \end{cases}$$

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$$\sigma(DO) = \begin{cases} 1 & \text{if } DO > DO_{\text{crit}}, \\ \frac{DO - DO_{\min}}{DO_{\text{crit}} - DO_{\min}} & \text{if } DO_{\min} < DO < DO_{\text{crit}}, \\ 0 & \text{elsewhere.} \end{cases}$$

The fish mortality coefficient k_1 depends on unionized ammonia (*UIA*) factor. It has a form of logistic regression as follows,

$$k_1(UIA) = \frac{\mathcal{Z}}{1 + \exp\{-\beta(UIA - \eta)\}},$$

where \mathcal{Z} , β , and η are the three tuning parameters in the logistic fitting. The fish mortality points are extracted from real-experiment in [25] and the three tuning parameters turned out to be $\mathcal{Z} = 99.41$, $\beta = 10.36$, and $\eta = 0.80$. Fig. 8 illustrates the extracted points and the logistic fitting.

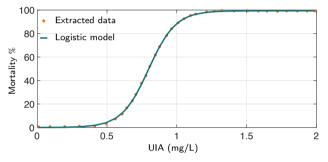


Figure 8: Relation between fish mortality coefficient and UIA

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Table 4

Nomenclature and main parameters of the growth model

Symbol	Description	Unit
ξ	Total fish biomass	kcal/pond
р	Total fish number	fish/pond
p _s	Stocking fish number	fish/day/pond
ξ_i	Individual fish biomass during fish stocking	kcal/fish
ξ_a	Mean fish biomass	kcal/pond
k ₁	Fish mortality profile	-
m	Exponent of body weight for net anabolism	0.67
t	Time	day
n	Exponent of body weight for fasting catabolism	0.81
f	Relative feeding rate	0 <f<1< th=""></f<1<>
T	Temperature	⁰ C
DO	Dissolved oxygen	mg/l
UIA	Unionized ammonia	mg/l
b	Efficiency of food assimilation	0.62
a	Fraction of the food assimilated	0.53
h	Coefficient of food consumption	0.8 kcal ^{1→m} day
k _{min}	Coefficient of fasting catabolism	0.00133N
j	Coefficient of fasting catabolism	0.0132N
T _{opt}	Optimal average level of water temperature	33 ⁰ C
T _{min}	Minimum level of temperature	24 ⁰ C
T _{max}	Maximum level of temperature	40°C
UIA _{crit}	Critical limit of UIA	0.06mg/1
UIA _{max}	Maximum level of UIA	1.4mg/l
DO _{crit}	Critical limit of DO	0.3mg/1
DOmin	Minimum level of DO	1mg/l
r	Daily ration	kcal/day
R	Maximal daily ration	10% BWD
BWD	Average body-weight per day	kcal/day
τ	Temperature factor	0<τ<1
σ	Dissolved oxygen factor	0<σ<1
v	un-ionized ammonia factor	0 <v<1< th=""></v<1<>
ρ	Photoperiod factor	$0 < \rho < 2$

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