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Research article

An intelligent aerator algorithm inspired-by deep learning

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Abstract: Aerator is an indispensable tool in aquaculture, and China is one of the largest aquaculture countries in the world. So, the intelligent control of the aerator is of great significance to energy conservation and environmental protection and the prevention of the deterioration of dissolved oxygen. There is no intelligent aerator related work in practice and research. In this paper, we mainly study the intelligent aerator control based on deep learning, and propose a dissolved oxygen prediction algorithm with long and short term memory network, referred as DopLSTM. The prediction results are used to the intelligent control design of the aerator. As a result, it is proved that the intelligent control of the aerator can effectively reduce the power consumption and prevent the deterioration of dissolved oxygen.

Keywords: intelligent aerator, long term memory network, deep learning

1. Introduction

Aerator is a machine used in aquaculture industry. When the aerator is working, the water is stirred through the impeller to dissolve the oxygen in the air into the water and increase the oxygen in the water [1,2]. The aerator is usually driven by the power engine, which involves the problem of power consumption. It is of great significance to reduce unnecessary waste and achieve energy saving and emission reduction in the use of aerator [3,4]. The concentration of dissolved oxygen is the concentration of dissolved oxygen in the water. The concentration of dissolved oxygen in aquaculture is easily influenced by factors such as solar radiation, water temperature, pressure, salinity and water nutrition. The concentration of dissolved oxygen usually reaches the highest value around 4 p.m. and the lowest value at around 4 a.m. Therefore, according to the lethal concentration of critical dissolved oxygen in the animal, the critical concentration of shrimp is 4.0mg/L. If the lowest concentration of dissolved oxygen at 4 a.m. is lower than that of 4.0mg/L, the value of dissolved oxygen will have a tendency to deteriorate [5]. There is no any intelligent aerator in realities and research.

Artificial intelligence including artificial immune [6–8], artificial neural network [9,10] and etc., has received more and more attention in the field of computer science. It has been applied in robot, economic, political decision making, control system [11–13], simulation system, and etc. The concept of deep learning [14] is derived from the artificial neural network. At present, deep learning has been successfully applied in the fields of machine vision, fingerprint identification, face recognition, electric power prediction, medical rehabilitation, and so on. However, there is no research on the aerator control algorithm design in the breeding industry.

At present, the common prediction models includes curve fitting (CF) [15], auto-regression (AR) [16], neural network (NN) [17], grey models (GM) [18], support vector machine (SVM) [19] and so on. However, these methods need much training data, and the prediction accuracy can continue to be improved. Long and short term memory network has the advantages of less training data and high prediction accuracy. In order to explore a new method of dissolved oxygen prediction method and improve the prediction accuracy, the paper proposes the dissolved oxygen prediction method with long and short term memory network.

The intelligent technology control of the aquaculture aerator based on deep learning is to build a prediction control algorithm with the Long-Short Term Memory (LSTM) [20,21] in deep learning. The model is used to accurately predict the concentration of dissolved oxygen in aquaculture industry, and the predicted data can be used to intelligently control the work time of the aerator, to ensure that the energy consumption of the aerator is at the lowest level when the concentration of dissolved oxygen is suitable. In the breeding of pond shrimp, when the dissolved oxygen cannot be known in advance, the work time of the aerator is 12 hours a day so as to prevent the concentration from deterioration. If the concentration of dissolved oxygen is predicted precisely, and the minimum concentration of the predicted value of the second day is no less than 4.0mg/L, it can be reduced by 4 hours in the second day, that is to open 8 hours a day; and if the value is less than 4.0mg/L, the work time of aeration need to add two hours more, which is 14 hours a day, by doing so to improve the dissolved oxygen and avoid further deterioration of water quality.

This paper mainly studies the intelligent control of aerator based on deep learning, and proposes an algorithm combining the dissolved oxygen prediction with long and short term memory network (DopLSTM). In this way, the aerator could work intelligently. When the dissolved oxygen is sufficient, the aerator reduces the work time and thus reduces the power consumption. However, when dissolved oxygen is insufficient, the aerator would increase the work time, which will increase the dissolved oxygen. Finally, we compare the power consumption of the intelligent aerator with that of the existing aerators. We use 10 consecutive days' data of three ponds in the experiments, among which the first seven days data are regarded as training data, and the last three days as test data. The results of intelligent control of power consumption by aerator are compared. As a result, the intelligent control of the aerator based on the deep learning can effectively reduce the power consumption, prevent the deterioration of the dissolved oxygen and improve the economic efficiency.

2. Proposed dissolved oxygen prediction algorithm

Long-Short Term Memory (LSTM) is a kind of deep learning neural network based on Recurrent Neural Network (RNN) [22], which is proposed by Sepp Hochreiter and Jürgen Schmidhuber, and improved and promoted by Alex Graves [23]. The long and short term memory network which contains memory units can deal with the problem of RNN gradient disappearance, so it can predict more accurately. The proposed dissolved oxygen prediction algorithm with LSTM neural network is described as follows.

2.1. The structure of the algorithm

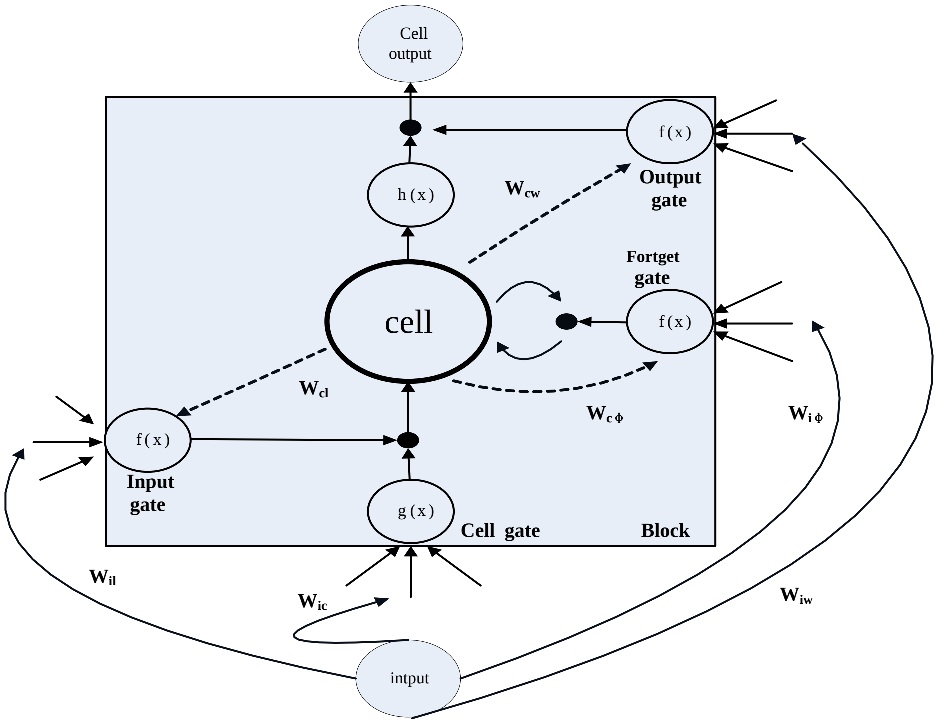

Figure 1. LSTM Cell Structure.

The cell unit structure of LSTM based on recurrent neural network RNN is improved as shown in Figure 1 [24,25].

The cell unit of long and short term memory network contains Cell Gate, Input Gate, Forget Gate and Output Gate. The Cell Gate is mainly used for receiving data, and the Forget Gate is mainly used for processing the data at the last time, that is, selective discarding. Input Gate, Output Gate, and Forget Gate all contain their own offset bias, as shown in Figure 1. There is a connection between various doors and cells. This connection is called weight. The real line represents the weight of the current time, and the dotted line represents the weight of the time at the last moment.

2.2. The calculation of the algorithm

The calculations of the cell unit structure of the long and short memory network are shown below [24,25]. Firstly, we define the current time Input as x^t, the last time as b_h^{t-1}, and the Cell value of the cell at the last time as s_c^{t-1}. Secondly, g(x), f(x) and h(x) represent different activation functions. W_{il}, W_{ic}, W_{iw} and $W_{i\varphi}$ are the weights from input to and Input gate, Cell gate, Output gate and Forget gate, respectively. Equation (1)–Equation (15) give the detailed algorithm calculation process.

The Input Gate value of the cell unit b_l^t is calculated as follows,

$$a_l^t = \sum_{i=1}^{I} w_{il} x^t + \sum_{c=1}^{C} w_{cl} s_c^{t-1} + \sum_{h=1}^{H} w_{hl} b_h^{t-1} \tag{1}$$

$$b_l^t = f(a_l^t) \tag{2}$$

The Forget Gate value b_ϕ^t of cell unit is calculated as follows:

$$a_\varphi^t = \sum_{i=1}^{I} w_{i\varphi} x_i^t + \sum_{c=1}^{C} w_{c\varphi} s_c^{t-1} + \sum_{h=1}^{H} w_{h\varphi} b_h^{t-1} \tag{3}$$

$$b_\varphi^t = f(a_\varphi^t) \tag{4}$$

The Cell value of cell unit s_c^t is calculated as follows:

$$a_c^t = \sum_{i=1}^{I} w_{ic} x_i^t + \sum_{h=1}^{H} w_{hc} b_h^{t-1} \tag{5}$$

$$s_c^t = b_\varphi^t s_c^{t-1} + b_l^t g(a_c^t) \tag{6}$$

The Output Gate value [24-25] of the cell unit b_w^t is calculated as follows:

$$a_w^t = \sum_{i=1}^{I} w_{iw} x_i^t + \sum_{c=1}^{C} w_{cw} s_c^t + \sum_{h=1}^{H} w_{h\varphi} b_h^{t-1} \tag{7}$$

$$b_w^t = f(a_w^t) \tag{8}$$

The Cell Output value [24,25] of cell unit b_c^t is calculated as follows:

$$b_c^t = b_w^t h(s_c^t) \tag{9}$$

According to the Equations (1)–(9), the correlation value of cell structure of the long and short memory network can be calculated. In the process of training the model, the weight needs to be updated. Therefore, the gradient of each weight needs to be solved, and then the global optimal solution is found by using the training samples for random gradient descent.

First, we define the related loss function, as follows.

$$L(x,d) = -Lnp(d|x) = -\sum_{k=1}^{K} d_k Lny_k \quad K=1,2,3,\ d_k \text{ is the true value.} \tag{10}$$

The gradient about Cell Output value of cell θ_c^t is calculated as follows:

$$\theta_c^t = \frac{\partial L(x,d)}{\partial b_c^t} = \sum_{k=1}^{K} \delta_k^t W_{ck} + \sum_{g=1}^{G} W_{cg} \delta_g^{t+1} \tag{11}$$

The gradient about Output Gate of cell unit δ_w^t [24-25] is calculated as follows:

$$\delta_w^t = \frac{\partial L(x,d)}{\partial a_w^t} = f'(a_w^t) \sum_{c=1}^{C} \theta_c^t h(s_c^t) \tag{12}$$

The gradient about Cell value of cell units θ_s^t is calculated as follows:

$$\theta_s^t = \frac{\partial \mathcal{L}(x,d)}{\partial s_c^t} = \delta_w^t w_{cw} + \theta_c^t b_w^t h'(s_c^t) + b_\varphi^{t+1} \theta_s^{t+1} + w_{cl} \delta_l^{t+1} + w_{c\varphi} \delta_\varphi^{t+1} \tag{13}$$

The gradient about Forget Gate of the cell Forget Gate δ_φ^t is calculated as follows:

$$\delta_\varphi^t = \frac{\partial \mathcal{L}(x,d)}{\partial a_\varphi^t} = \sum_{c}^{C} s_c^{t-1} \theta_s^t f'\left(a_\varphi^t\right) \tag{14}$$

The gradient about Input Gate of cell unit δ_I^t is calculated as follows:

$$\delta_I^t = \frac{\partial L(x,d)}{\partial a_I^t} = \sum_{C=1}^{C} g(a_C^t) \theta_s^t f'(a_I^t) \tag{15}$$

Combining Equation (11) -Equation (15), the algorithm then use $\Delta w^n = m\Delta w^{n-1} - \alpha \frac{\partial L}{\partial w^n}$ to update weights where $m \in [0,1]$, α is the learn rate and $\frac{\partial L}{\partial w^n}$ is the calculated gradient. In most cases, m is set as 1. This is also called as the Backward Pass. In the algorithm, the iteration includes Forward

Pass and Backward Pass.

The above long and short term memory network can be built to predict the dissolved oxygen in aquaculture industry, so as to realize the intelligent control of the aquaculture aerator. On the basis of accurate prediction of dissolved oxygen, the intelligent control of the aerator can prevent water deterioration, reduce the loss of aquaculture, save electrical energy, reduce energy waste and reduce the costs of aquaculture.

3. Experiments

The data of the experiments are three representative shrimp ponds taken from Beihai, Guangxi, China. The shrimp pond, with 3 blade aerators which power is 1.5 KW, covers an area of three mu. DopLstm includes 9 nodes in input layer, 16 nodes in middle layer, and 3 nodes in output layer. As for the parameters, the learning rate is set as 0.01 and the iterations are 3000.

In the experiments, the dissolved oxygen data at 4 a.m. of seven days was trained and studied. The dissolved oxygen was predicted by the LSTM for the eighth, the ninth, the tenth days, and the work time of the aerator was intelligently controlled according to the prediction concentration of dissolved oxygen.

3.1. Data processing of dissolved oxygen

(1) Data normalization

The data of dissolved oxygen in three shrimp ponds are normalized respectively. There are many normalization methods for the data pre-processing. We use the vector normalization method [26]. The value of the selected dissolved oxygen data is x_i, and the normalized formula is defined by Equation 16.

$$x_{norm} = x_i / \sqrt{\sum_{i=1}^{I} x_i^2} \tag{16}$$

(2) Division of training and test data

The data of 10 days are divided into four groups: 1~3, 2~4, 3~5, 4~6 days, which are used to input training, respectively, 4, 5, 6 and 7 days data are used to output training for each group.

(3) The prediction of dissolved oxygen

The data of 5~7 days are used to predict the eighth day value, and then the eighth day's real value would be put into the test to optimize the model, and the value of the ninth days would be predicted by the former eighth days' real value, and so on.

Figure 2 gives the relationship of iterations and training accuracy. From the Figure 2, we can see that from the first iteration to the 501st iteration, the training accuracy is increasing, the 501st iteration's accuracy is a litter decreasing. However, since then, the training accuracy has been increasing until the 2147th iteration. The training accuracy is smaller than 10^{-6} and iterations stop.

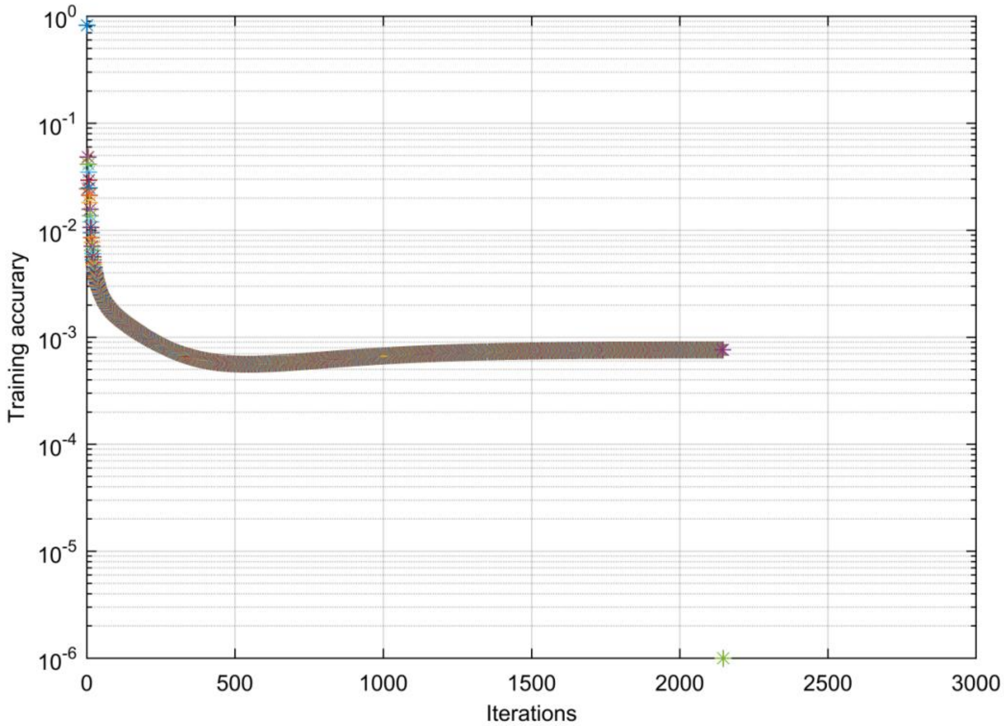

Figure 2. The iteration and training accuracy.

3.2. Experimental results

In this part, the results of dissolved oxygen prediction are given and analyzed. On this basis, the power consumption based on DopLSTM algorithm is compared and analyzed. Furthermore, the development cost of prototype system is discussed.

3.2.1. The dissolved oxygen prediction

The predicted results of the three ponds (Figure 3, Figure 4 and Figure 5) are in good agreement with the actual value. For Figure 3–5, the metric unit of y axis is mg/L. The next three days of the first ponds are less than 4.0mg/L, which is judged to be a worsening situation. Then the aerator should open more 2 hours than the normal in the next three days to improve the concentration of dissolved oxygen and the water environment. The value of the next three days in the second and third ponds are higher than that of the 4.0mg/L, so the aerator should work 8 hours every day. And it is 4 hours less than aerator without intelligent control every day.

For the first pond, the dissolved oxygen tends to be deteriorated. The actual values of dissolved oxygen in three days were 3.8, 3.7 and 3.5, respectively. The predicted values were 3.96, 3.8 and 3.75, respectively. The maximum prediction error is 0.25 and the maximum prediction error percentage is 6.67%. For the second pond, dissolved oxygen was the normal case. The actual values of dissolved oxygen in three days were 4.49, 4.2 and 4.2, respectively. The predicted values were 4.34, 4.24 and 4.24, respectively. The maximum prediction error is 0.15 and the maximum prediction error percentage is 3.4%. For the third pond, the dissolved oxygen also showed a normal case. The actual values of dissolved oxygen in three days were 4.09, 4.02 and 4.01, respectively. The predicted values were 4.09, 4.02 and 4.01. The maximum prediction error was 0.29 and the maximum prediction error percentage was 7.23%. All the three predicted experimental results meet the actual requirements.

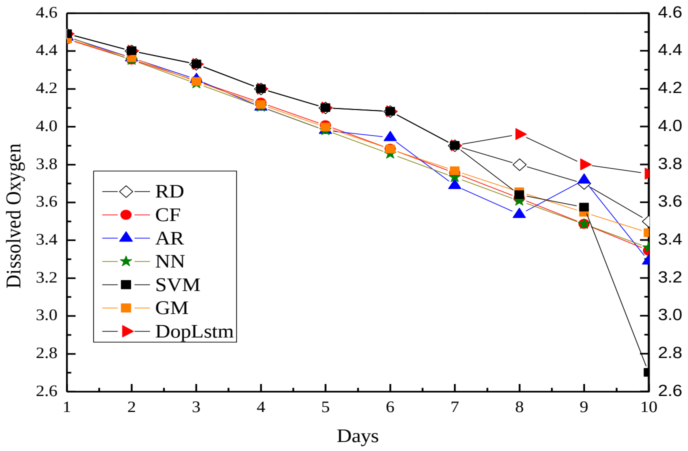

Figure 3. The predicted value of dissolved oxygen in first pond.

In Figure 3, for the predicted three days, DopLstm achieves the 4th, 2nd, 3rd accuracy, respectively. Although it does not achieve the highest accuracy, it meets the needs of practical application.

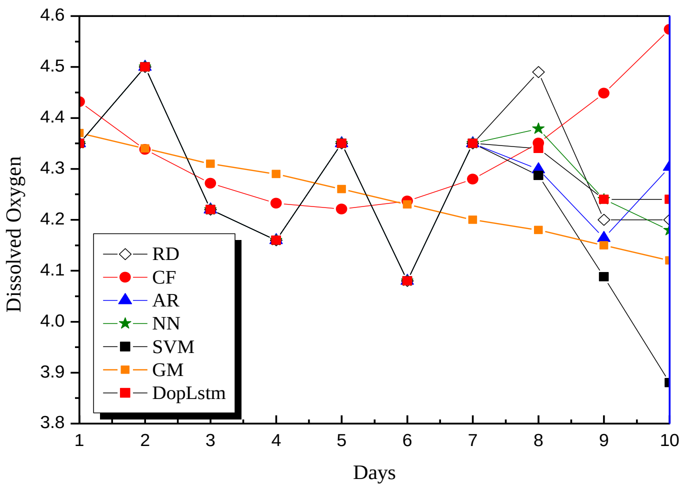

Figure 4. The predicted value of dissolved oxygen in second pond.

In Figure 4, for the predicted three days, DopLstm achieves the second highest accuracy, which follows the NN. However, DopLstm is the highest for the last two days.

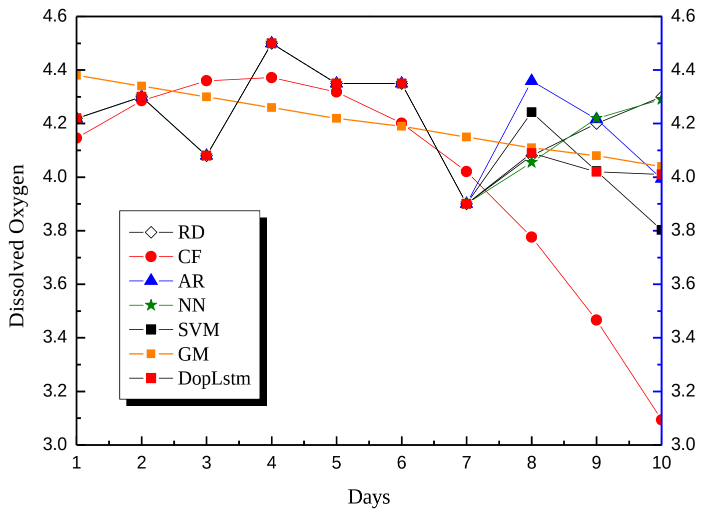

Figure 5. The predicted value of dissolved oxygen in third pond.

In Figure 5, for the predicted third day of the third pond, DopLstm achieves the highest accuracy including CF, AR, NN, SVM, and GM. However, the NN is better than the DopLstm for the last two days. However, both of them are effective.

In general, among the six prediction methods, DopLstm obtains satisfactory prediction accuracy for three experiments, which can meet the needs of practical application in aquaculture industry.

3.2.2. The contrast of power consumption of each pond

The power consumption of the three ponds (Figure 6, Figure 7 and Figure 8) is calculated according to the parameters of the three shrimp ponds selected by the experiments. For Figure 6–8, the metric unit of y axis is KWH. It is divided into the power consumption without intelligent control aerator and the power consumption adding intelligent control .As the above data shows, the last three days dissolved oxygen of the first pond is deteriorate, while the second and the third are apposite.

3.2.3. The power consumption comparison

Table 1. The comparison of power consumption.

Models	Deterioration	Normal circumstances
Power increment	16.67%	−33.33%

Table 1 shows the changes in power consumption of pond applied to intelligent control under normal and deteriorative conditions. As we can conclude from the result, the shrimp pond with the intelligent aerator could predict the deterioration trend of dissolved oxygen in advance, so it would increase 2 hours of using aerator to avoid further deterioration, improve the concentration of dissolved oxygen and avoid unnecessary loss. In the deteriorative conditions, the power consumption of pond with intelligent control will increase by 16.67% but it is necessary, while the power consumption will be reduced by 33.33% in normal situations. Because the deteriorative conditions of the shrimp ponds will only occur in a sudden deterioration of the environment or in a few cases, the intelligent control of the aerator can be used to reduce the energy consumption effectively. Therefore, the intelligent control of the aerator in the shrimp pond can effectively prevent the deterioration of dissolved oxygen and avoid the loss of the breeding industry; on the other hand, it can save the loss of electric energy and increase the economic benefit.

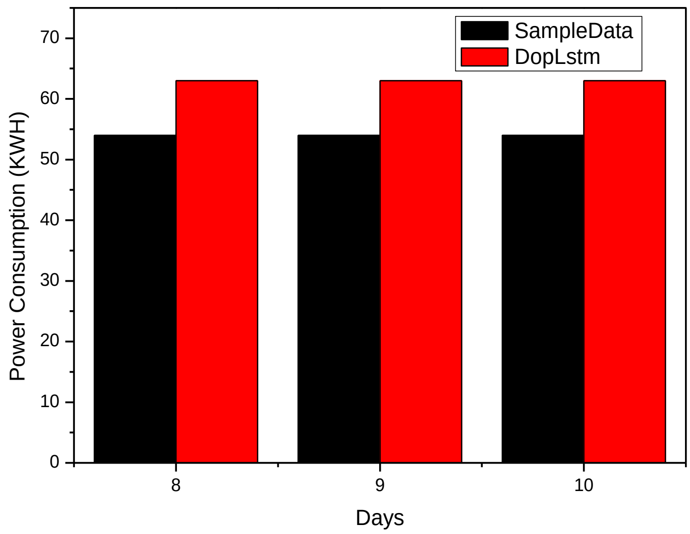

Figure 6. The contrast of power consumption with the first pond.

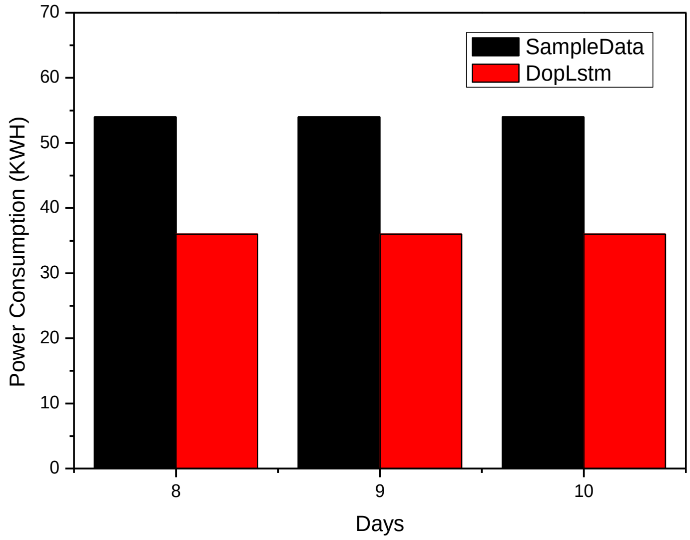

Figure 7. The contrast of power consumption with the second pond.

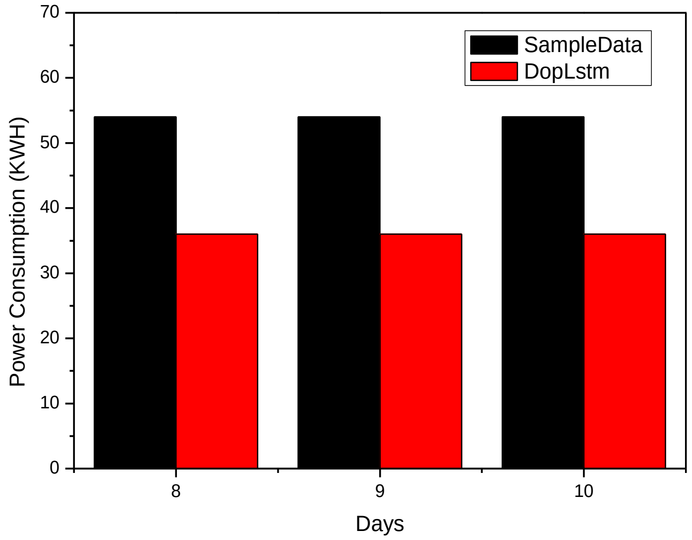

Figure 8. The contrast of power consumption with the third pond.

Followed by the energy comparison of the intelligent aerator, we further discuss the prototype building cost. After the dissolved oxygen sensors collect the data and send them to the computer, the algorithm only needs a small amount of data to achieve accurate prediction. So, the data can be even stored in Excel files and the algorithm does not need high-performance computers to achieve. Therefore, the prototype building cost is the implementation of the algorithm. At present, the algorithm is mature and stable, but an intelligent aerator need a single chip computer (SCM) to control. .As for the hardware cost, the common aerator takes about ￥2000. However, the intelligent aerator needs a SCM (such as ATmega 16) and a circuit board. Each of them takes about ￥10. As for the software development and time cost, a skilled programmer can implement in two working days including the circuit board soldering. So the software cost is about ￥1000 in China. The software cost could be shared for each intelligent aerator instead of the hardware cost. The more intelligent oxygen generators that we produce the, the lower that the software development cost is. Without purchasing additional high performance computers and software development is easy, so the building cost of an intelligent aerator is almost with the common one. The scale of the world's aquaculture industry is quite huge, so the intelligent aerator has broad application prospects.

4. Conclusions

China as a large aquaculture industry, the rational use of aerator can effectively prevent the deterioration of dissolved oxygen, increase the utilization rate of resources and reduce energy consumption. The intelligent control of aerator based on deep learning can make the aerator achieve this effect. The proposed algorithm, DopLstm, does not need large data for training, and can be continuously optimized in the process of prediction, making the prediction more accurate. The intelligent aerator, combing with the control of the deep study and the control of the traditional aerator, can control the opening time of the daily aerator intelligently, thus improving the utilization rate of the electric energy, reducing the power consumption of the aerator and improving the economic benefit of the aquaculture industry. Thus, it has good practical application significance in aquaculture.

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Conflict of interest

The authors declared that they have no conflicts of interest to this work. We declare that we do not have any commercial or associative interest that represents a conflict of interest in connection with the work submitted.

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