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A method for predicting dissolved oxygen in aquaculture water in an aquaponics system

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ABSTRACT

Aquaponics systems combine vegetable cultivation with fish culture (Rao et al., 2017). Several environmental factors influence water quality, among which dissolved oxygen is the most critical. The dissolved oxygen-related processes are nonlinear and unstable and are characterized by considerable time delays and time variances. In an aquaponics system, the dissolved oxygen content is affected by changes in the aquaculture water and in the greenhouse climate. Understanding the changes in dissolved oxygen and ensuring its stability requires effective prediction approaches and corrective measures. Traditional prediction methods are characterized by low stability, low accuracy and poor timeliness. A dissolved oxygen prediction model based on fuzzy neural networks is proposed in this paper. With a large number of inputs, the fuzzy network has high dimensonality, a complex model structure, and low precision, among other limitations. A genetic algorithm can be used to optimize the centre and width of the fuzzy neural network's middle layer and determine the optimal parameter combination, thus improving the efficiency and predictive accuracy of the model (Liu et al., 2014). The results show that a fuzzy neural network optimized using a genetic algorithm is more stable, more accurate, and more suitable for predicting dissolved oxygen than a fuzzy neural network and backpropagation neural network in an aquaponics system. Predicting dissolved oxygen is critical to the stability of an aquaponics system.

1. Introduction

Aquaponics is an integrated system that links hydroponic plant production with recirculating aquaculture (Rao et al., 2017). Aquaponics systems use resources and energy more efficiently than single production systems, thus facilitating sustainable and environmentally-friendly food production (Datta et al., 2018). Recirculating aquaculture systems (RASs) are systems that treat and reuse the wastewater from fish farming. In an aquaponics system, fish wastewater from a recirculating aquaculture system is delivered to hydroponics systems. In a recirculating aquaculture system, ammonia and nitrite produced from the residual bait and faeces of fish are the major metabolic wastes that harm the growth of fish. Nitrification through biological filters converts NH_4 into NO_3 via NO_2, and NO_3 is an excellent fertilizer for plants. This process can purify fish wastewater, and then the water is recycled back to the aquaculture system. Recycling of the aquaculture water for plants saves water and nutrients.

Many water quality parameters exist in an aquaponics system. The important control parameters are electrical conductivity, temperature, pH, BOD, the amount of recycled microorganisms and dissolved oxygen; dissolved oxygen is the most important parameter (Carbajal-Hernández et al., 2013). Dissolved oxygen supports the entire metabolic process of the aquatic products. In low-oxygen conditions, a fish's excrement and remnants play an important role in the deterioration of water quality, which not only affects the healthy growth of fish but also seriously affects the yield and quality of the aquatic products, in some cases for a long period of time. A diminished oxygen state results in a large number of toxic substances in the water, causing fish illness or even death. Therefore, to increase aquaculture production, understanding the dynamics of dissolved oxygen in the water is important, including the causes of hypoxia, to improve the monitoring and management of dissolved oxygen in aquaculture water (Xu et al., 2017). However, a time lag exists between initiation of an oxygenation device for aeration and detection of an increased dissolved oxygen concentration in the water. Therefore, this paper uses intelligent prediction technology to accurately predict the dissolved oxygen concentration and trends in water and to identify the factors governing variations in dissolved oxygen over time to facilitate effective management of

Abbreviations: FNN, fuzzy neural network; GA, genetic algorithm; BP-NN, backpropagation neural network; DO, dissolved oxygen; RAS, recirculating aquaculture system; RMSE, root-mean-square error; MAE, mean absolute error; MAPE, mean absolute percentage error

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dissolved oxygen in fish-vegetable symbiotic aquaponics systems.

Due to the complex, nonlinear relationship between dissolved oxygen and environmental factors, measurements of dissolved oxygen lag behind the real-time conditions. Existing methods, such as the traditional Bayesian model, the fuzzy inference model, the grey model and the least squares support vector regression model, have disadvantages in the prediction of dissolved oxygen, such as poor model generalization, partial optimization, under-learning, over-learning and poor stability, among other issues. Providing sufficient information to ensure effective, real-time control of dissolved oxygen in a fish and vegetable symbiotic system is also difficult. To address the problem of dissolved oxygen prediction in aquaponics systems, this paper proposes a dissolved oxygen prediction method based on a fuzzy neural network (FNN) and optimizes the FNN using a genetic algorithm (GA) to overcome the poor stability and low precision of traditional algorithms.

2. Materials and methods

2.1. BP neural network

A BP neural network is a multilayer feed-forward neural network (Rumelhart et al., 1988). The standard BP neural network includes three layers: the input layer, the hidden layer, and the output layer. Each neuron on the input layer and the hidden layer is fully connected, each neuron on the hidden layer and the output layer is fully connected, and the neurons between the layers are not connected.

The learning process of a BP neural network is completed by forward propagation of information and back propagation of errors. When information is transmitted in forward propagation, the information is passed from the outside to the input layer, and then the result is transferred to the outside world through the transformation process of the hidden layer and the output layer. In this process, the weight of the network does not change. The back propagation process is performed only when the error between the output information and the expected output is large to modify the weight in the network to reduce the error. The error back propagation process applies to the error generated in the forward propagation process and starts from the output layer, passes through the hidden layer to the input layer, and modifies the weight and threshold of the network layer by layer to reduce the error. The working process of the BP neural network working signal and error signal is shown in Fig. 2.1.

Because the BP neural network is a network model based on a negative gradient descent algorithm, it has the disadvantages of slow convergence speed, easily falling into the local minimum, poor learning stability, poor generalization ability of the algorithm, etc. (Ta and Wei, 2018). Therefore, this method is only used as a control method.

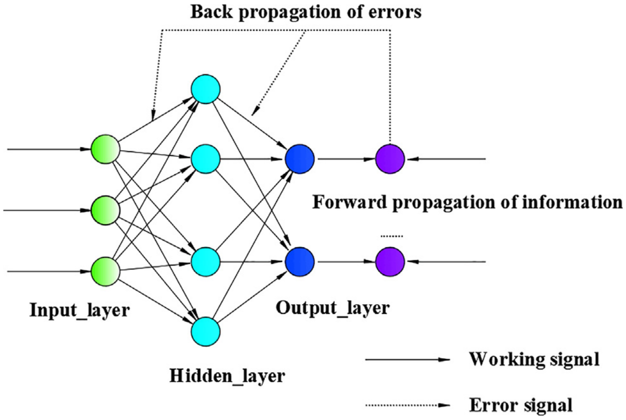

Fig. 2.1. The working process of the BP neural network working signal and error signal.

2.2. Fuzzy neural network

FNNs are a combination of fuzzy theory and neural networks, integrating learning, association, recognition and information processing to combine the advantages of neural networks and fuzzy technology. In this paper, a fuzzy neural network based on Takagi-Sugeno model is used, which is composed of a front piece network and a back piece network. An antecedent network is used to match the antecedent of the fuzzy rule, which is equivalent to the applicability of each rule. The back piece network is used to implement the back piece of the fuzzy rule. The total output is the weighted sum of the back pieces of each fuzzy rule, and the weighting coefficient is the applicability of each rule (Sun and Xu, 1997; Hu et al., 2015). The T-S fuzzy neural network is a system model with strong adaptive ability. This network also has an automatic updating system, a fuzzy membership function and a clear physical meaning. Every layer, or every neuron, has a physical meaning corresponding to the fuzzy logic system and is a new network expression of neural network connectionism to a fuzzy logic system (Zhu et al, 2016). The network training in this paper modifies the number of fuzzy rules and membership function parameter values (C_{ji}, b_i) (Jalota et al., 2017).

In the current system, the input parameters x_i (i = 1, 2, …, n) are the dissolved oxygen, temperature, humidity, carbon dioxide, atmospheric pressure and pH value at time t. The output parameter is y, the dissolved oxygen at time t + 1. The T-S fuzzy neural network adopts an "if-then" rule to describe the form of the fuzzy rules. The system of fuzzy inference rules is in the form

If x_1 *is* A_{j1}; x_2 *is* A_{j2};⋯;x_n *is* A_{jn}

Then

$$y_1 = w_{j0} + w_{j1} \times x_1 + w_{j2} \times x_2 + \cdots + w_{jn} \times x_n \tag{1-4}$$

where x_i is the input parameter, A_{ji} is the system of the fuzzy set, w_{ji} (i = 1, 2, …, m) represents the system parameters, and y_1 is the fuzzy rules output parameter. The fuzzy inference rule output is a linear combination of inputs; that is, the output of dissolved oxygen prediction at time t + 1 is a linear combination of dissolved oxygen, temperature, humidity and other input parameters at time t.

For the input parameter x = (x_1, x_2,…, x_k), the fuzzy membership value of the input variable x_i is first calculated according to the following fuzzy rule (Saatlo and Ozoguz, 2015):

$$\mu_j^i = \exp\left[-\left(\frac{x_i - c_{ji}}{b_i}\right)^2\right] \quad i = 1, 2, \cdots, m; \quad j = 1, 2, \cdots, n \tag{1-5}$$

where μ_j^i is the membership function of the Gaussian function, c_{ji} is the central value of the membership function, b_i is the width of the membership function, m is the number of input parameters, and n is the number of the fuzzy subset.

The predicted dissolved oxygen output for the fuzzy model is determined according to the following algorithm:

$$y = \frac{\sum_{j-1}^{l} \lambda_j y_j}{\sum_{j-1}^{l} \lambda_j} \tag{1-6}$$

where$\lambda_j = \mu_j^1(x_1) \bigwedge \mu_j^2(x_2) \bigwedge \cdots \mu_j^i(x_i)$ and $\bigwedge$ represents the fuzzy logic multiplication that requires the smallest value.

According to the demand, the structure of the network can be designed with five layers: the input layer, the fuzzification layer, the fuzzy condition layer, the fuzzy decision layer and the defuzzification layer (Liang et al., 2010). The fuzzy neural network topology structure is shown in Fig. 2.2.

The first layer is the fuzzy input layer. Each node represents an input variable:

$$I_i^1 = x_i; \ O_i^1 = I_i^1 \tag{1-7}$$

where I_i^k represents the *ith* neuron input value from the *kth* layer, O_i^k