Computers and Electronics in Agriculture 71S (2010) S3–S9

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

A remote wireless system for water quality online monitoring in intensive fish culture

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ARTICLE INFO

Article history:
Received 20 September 2008
Received in revised form
29 September 2009
Accepted 7 October 2009

Keywords:
Water quality monitoring
Wireless communication technology
Intensive fish culture
ANN

ABSTRACT

Water quality monitoring and forecasting plays an important role in modern intensive fish farming management. This paper describes an online water quality monitoring system for intensive fish culture in China, which combined web-server-embedded technology with mobile telecommunication technology. Based on historical data, this system is designed to forecast water quality with artificial neural networks (ANNs) and control the water quality in time to reduce catastrophic losses. The forecasting model for dissolved oxygen half an hour ahead has been validated with experimental data. The results demonstrate that multi-parametric, long-distance and online monitoring for water quality information can be accurately acquired and predicted by using this established monitoring system.

1. Introduction

Aquaculture is the fastest growing food-producing sector in the world, with an average annual growth rate of 8.9% since 1970 (Subasinghe, 2005). China is one of the most important contributors to world aquaculture production. 41.3 million tons or 69.6% of the world production was produced in China (FAO, 2006). As a result of a significant shift from wild fishing to aquaculture in the 1980s, aquaculture development has accelerated throughout the country. The production of intensive fish culture has been increased rapidly in China from 1.84 million tons in 1970, to 1.6 million tons in 1990, and to 13.5 million tons in 2005 (Zhong and Power, 1997; FAO, 2006).

Automatic remote monitoring and computer-controlled intensive culture is the future trend in aquaculture. In modern aquaculture management, water quality monitoring plays an important role. Appropriate control of the water quality to keep the concentration of the water environment parameters in the optimal range can enhance the fish growth rate, affect dietary utilization and reduce the occurrence of large-scale fish diseases (Stigebrandt et al., 2004; Sim et al., 2008). Without gathering information of physical and chemical parameters of water quality together with the related ecological factors it is almost impossible to perform the appropriate water quality control at the right time in the right place.

However, there are few applications of systems which could carry out real-time water quality monitoring continuously in China. According to the conventional methods of water quality monitoring, samples of water are taken and transported to a chemical laboratory to analyze the hazardous substances. On the one hand, the maintenance of the measurements and control process is manual influenced by the personal experience. On the other hand, the process of forecast is time-consuming and some contamination episodes might be missed (Sim et al., 2008). For example, fish mortality occurred overnight in one incident and was only detected the next morning, after huge losses had already been caused.

With the advent of new sensor technologies, data telemetry and wireless communication technology, various equipments were developed to monitor remote areas in real time (Tor et al., 2001; Tseng et al., 2006; Liu et al., 2009; Vellidis et al., 2008). At present, continuous monitoring of drinking water and wastewater quality at most treatment plants is applied in Europe, North America and Japan (Tschmelak et al., 2005; Udy et al., 2005). In China, online monitoring installations have been constructed for several large rivers, such as the Huanghe River and the Huaihe River, to provide real-time information to support environmental protection decision-makers (Wei et al., 2008). However, the financial burden for building the fundamental hardware of these high-tech facilities may only be affordable to governments. How to realize real-time data collection in a secure, robust, manageable and low-cost manner, without long-distance cable connections, will likely become a bottleneck in the development of information monitoring in fish culture. Therefore, using web-server-embedded and next gener-

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0168-1699/$ – see front matter
doi:10.1016/j.compag.2009.10.004

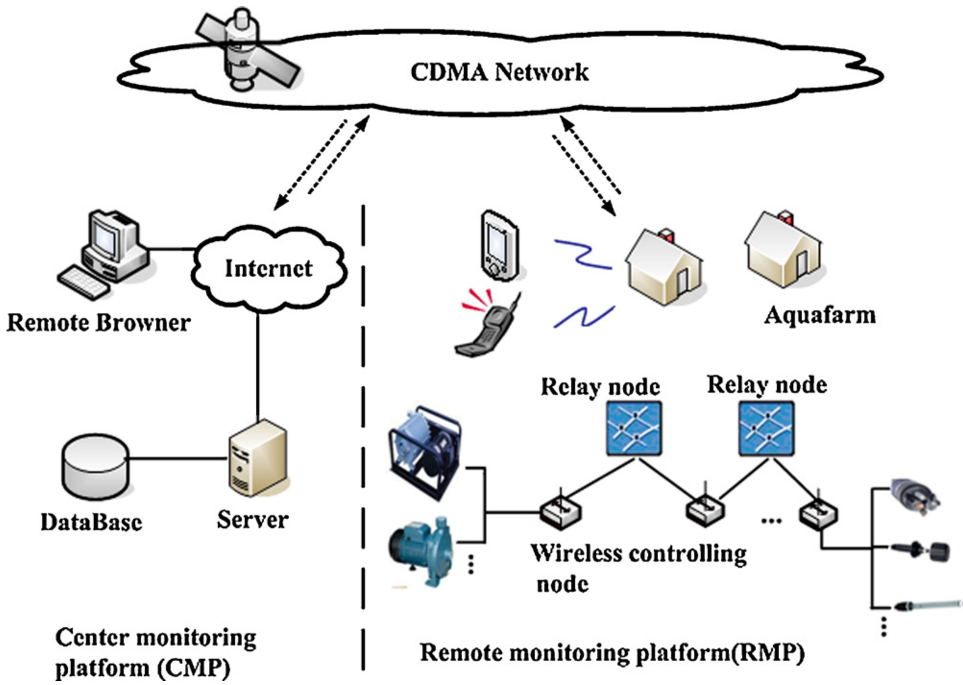

Fig. 1. Structural diagram of our proposed remote wireless water quality monitoring system.

ation telecommunication technologies will become increasingly important in sensing networks.

In recent years, some researchers investigated integrated water quality remote monitoring systems (Glasgow et al., 2004; Baltacı et al., 2008) and management systems based on culture knowledge models and forecasting models (Lee, 2000; Mariolakos et al., 2007; Lee et al., 2008; Hongbin et al., 2007), but these systems are not aimed at the present needs to develop aquaculture and not connected with any online monitoring system. Moreover, these installations cannot achieve real-time communication between data collection and control terminals, which is not yet a full viable alternative for high-density, open, and dynamic fish breed circumstances.

In this article, water quality remote monitoring systems using CDMA service combined with IPsec-based virtual private network (VPN) function were developed for constructing a wireless sensing network in countrywide scale. Integrated with a forecasting model on the basis of artificial neural networks (ANN), the system is able to provide real-time information and the dynamical trend of the water quality at different monitoring sites. These detected data can be collected and analyzed at any time via the Internet so as to know the status and changes of the system.

2. System design

2.1. System architecture

Accuracy, reliability, real-time and expandability are essential in the remote monitoring system. Therefore, the sensors of high sensitivity should be chosen and rationally distributed for data accuracy. Since some locations have no access to any cable network (telephone line) and harsh production environment could damage cable connections, wireless devices would be necessary. Accordingly, each station is designed to communicate with the server via wireless communication technology. In order to offer a better expandability, the intelligent sensor technology with the character of plug and play has been used.

As shown in Fig. 1, the basic structure of the system can be divided into two major parts: the remote monitoring platform (RMP) and the central monitoring platform (CMP) for data acquisition and data analysis, respectively. These two parts communicate with each other through the telecommunication system.

2.2. Remote monitoring platform

The remote monitoring platform contains three parts: data acquisition, data transformation and transmission, and water quality control components. The system architecture of the remote monitoring platform is shown in Fig. 2.

The function of the data-acquisition component is to get non-electricity signals of the most important environmental factors by using various sensors. The main variables that can be monitored are

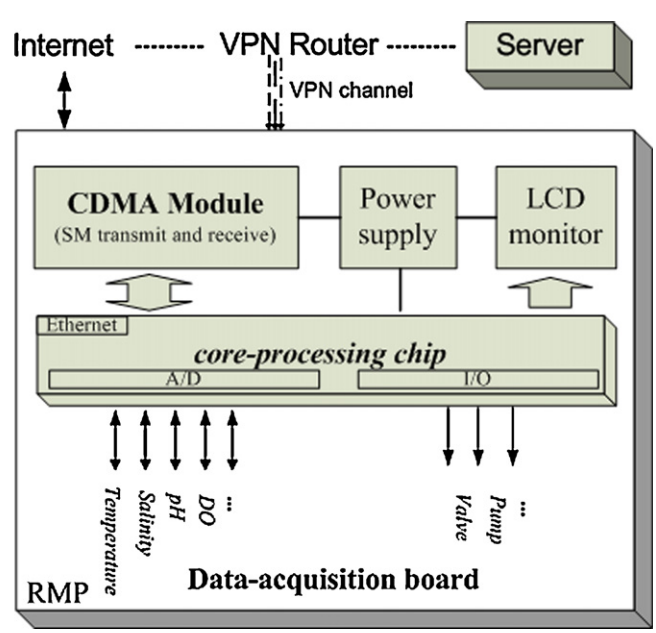

Fig. 2. System architecture of the remote monitoring platform.

Table 1
The water quality variables of data acquisition.

Name	Variable	Units	Measurement method
Water temperature	Tw	°C	Thermistor thermometer
Room temperature	Tr	°C	Mercury filled thermometer
Percentage of dissolved oxygen saturation	DOs	%	–
Dissolved oxygen concentration	DO	mg/L	Membrane electrode technique
pH value	pH		Glass electrode method
Electrical conductivity	EC		Four-electrode method
Salinity	S	ppt	–

reported in Table 1. With the current measurement methods, pH value is measured by glass electrode method, dissolved oxygen by membrane electrode technique, and temperature by thermometer sensing technology. A method of measuring the conductivity and transforming it to salinity has been adopted to replace the common method for measuring the salinity.

The data transformation and transmission component is composed of the signal conditioning circuits, data-acquisition board, core-processing chip and CDMA module. The sensors and the signal conditioning circuits convert the various environmental factors to electrical voltage standard signals in the range of 0–5 V. The signal is transmitted to the Web-based monitoring chip, and then is

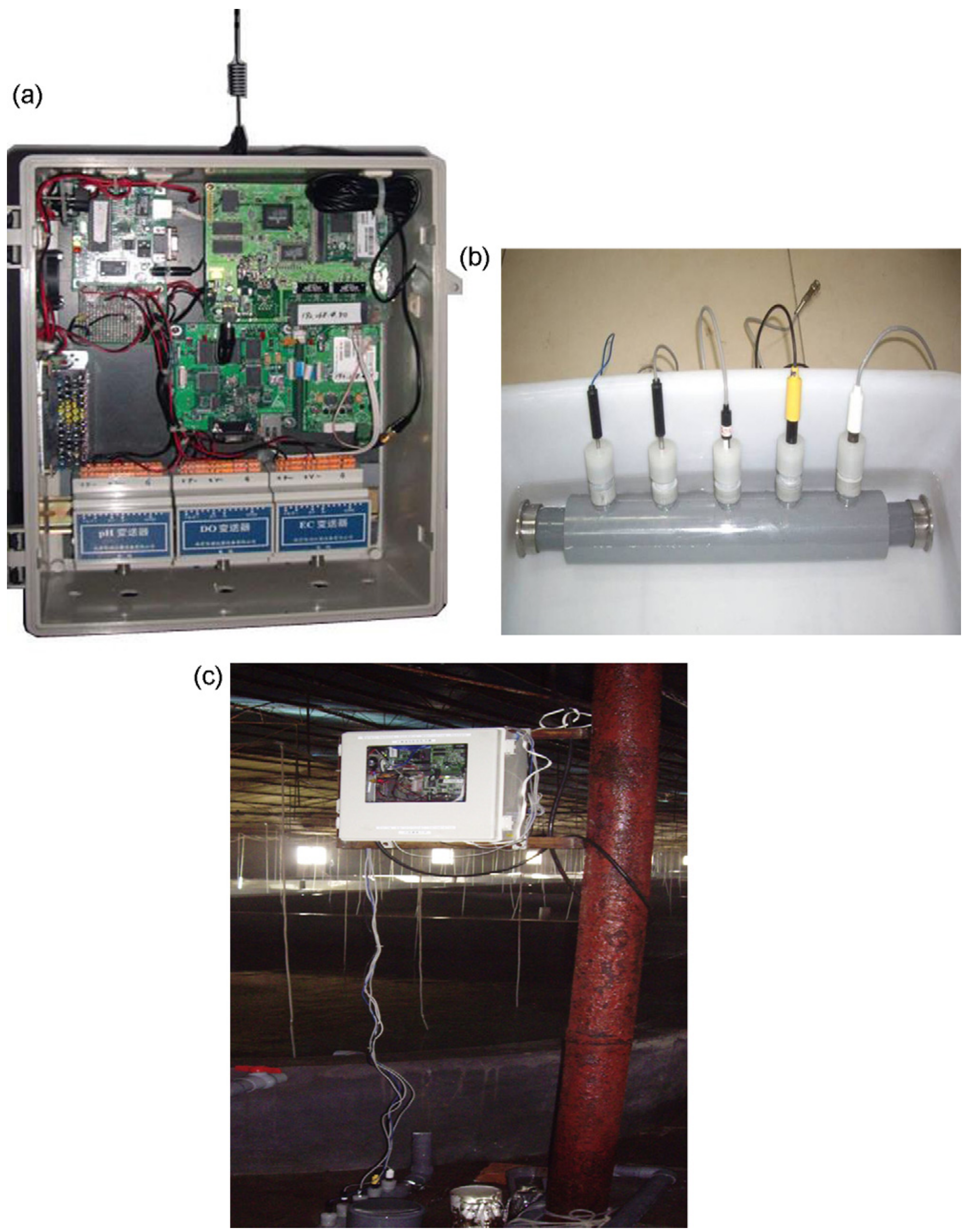

Fig. 3. Finished prototypes of remote monitoring platform (a) installation of each module in, RMP case, (b) sensors, and (c) a remote monitoring platform deployed in an experimented workshop, in Shangdong Fengze fish farm.

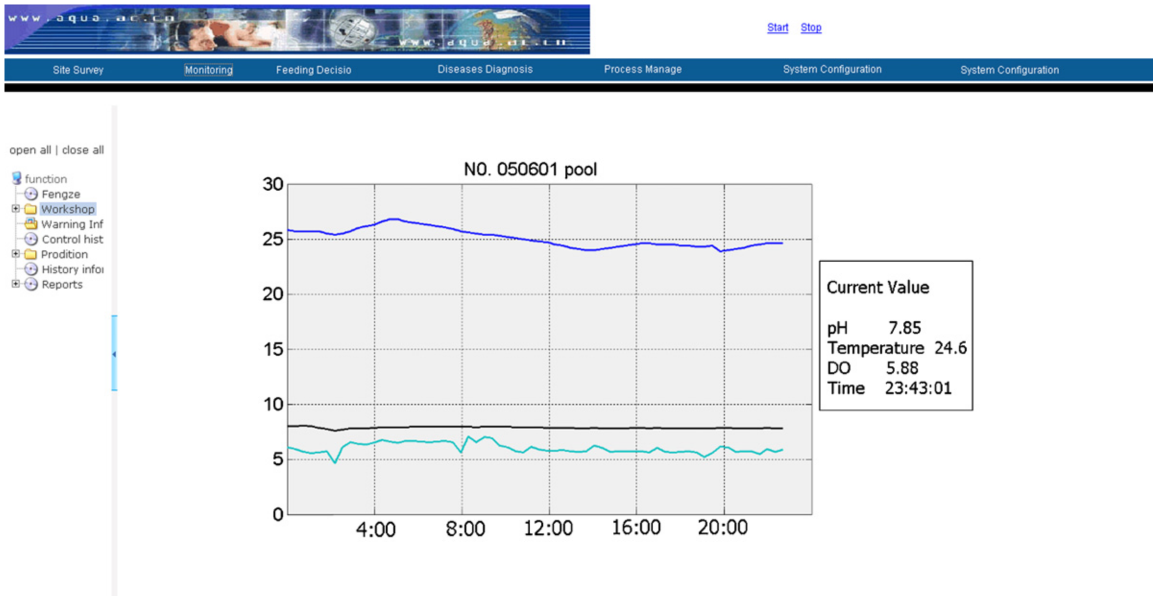

Fig. 4. The monitor interface window of no. 5 workshop.

converted into the digital signal through the A/D conversion. On-site data-acquisition nodes compose a wireless LAN, and the CDMA module enables the RMP to receive the data and transmit them to a PC for further analysis.

2.3. Central monitoring platform

The central monitoring platform receives, preprocesses and analyzes the data from RMP, predicates the trend of the parameters according to the history information, and then warns stakeholders through early audio warning or early short message warning, as shown in Fig. 1. The central monitoring platform stores the data to database daily, weekly, monthly and yearly. At the same time it compares measurements to the predefined acceptable limits calculated by the expert empirical knowledge. Furthermore, it records all measurements or functional errors in different log files, so that the personnel are aware that there has been alarm in the specific tank. Real-time data are downloaded via web-based servers at scheduled intervals.

2.4. Forecasting model of dissolved oxygen

One purpose of the current monitoring system is to detect a trend of water quality fluctuation using the history data. Most current models for prediction that focus on pollutants in a river or lake are not applicable for intensive aquaculture. In this study, the stored water quality data are analyzed for temporal trends focusing on the dissolved oxygen half an hour later. Due to their ease of development, decreased reliance on expert knowledge of the system under investigation and non-linear modeling capabilities, artificial neural networks were selected as modeling tool.

In order to model the relationship between the environment factors and the concentration of dissolved oxygen, three-layer BP neural network (Kwang-Seuk et al., 2001) with a sigmoid activation function (Hongbin et al., 2007) was programmed using neural network toolbox in Matlab 7.5. In the neural network, air temperature, pH, salinity, DO and water temperature of the entrance, and DO and water temperature in the exit are used as candidate inputs for the input layer, with the concentration of DO half an hour later in the tank as the output. Each neuron is connected to all neurons of adjacent layer. Neurons receive and send signals through these connections. Signals are transmitted only in one direction. Connections are given a weight that modulated the intensity of the signal they transmit.

In the process of training, an iteration of the algorithm can be expressed as

$$x_{k+1} = x_k - \alpha_k g_k, \tag{1}$$

where g_k is the current gradient, a_k is the learning rate and k is iteration, x_k is a vector array of current weights and biases, x_{k+1} is the value used as the input in the next iteration.

A momentum factor is recommended to accelerate the convergence speed.

$$\Delta\omega_{k+1} = \gamma \cdot \Delta\omega_k - (1-\gamma) \cdot \alpha_k \cdot g_k \tag{2}$$

where $\Delta\omega_k$ is the adjusting weight in kth learning, γ is the momentum factor and $0 \le \gamma < 1$.

3. System implementation

3.1. Testing environment

In this testing, one central monitoring platform with an IPsec-based VPN router (BV-601, NESCO Co., China) is deployed in China Agricultural University located in Beijing. The remote monitoring system is deployed in an intensive fish farm culture site, Fengze Corporation, located in Shandong province, which is a typical recycling aquaculture system (Colt, 2006). Each fish tank is approximately 6.77 m × 6.55 m × 0.55 m. The average fish stock density is 30–40 kg/m^3.

3.2. Remote monitoring platform

Two prototypes of remote monitoring platform have been installed in practical fish farm in Shandong to verify the performance of the system, as shown in Fig. 3.

The probe of sensor in the present study for temperature, DO, pH, salinity are made by the Nantu Company (China) with accuracies of 0.1 °C, 0.1 mg/L, 0.1, 0.1 ppt, respectively. The HQ 40d18 (HACH, USA) is chosen as a contrast providing long-term stability and high accuracies of ±1.0% for relative DO and ±0.1 °C for temperature.

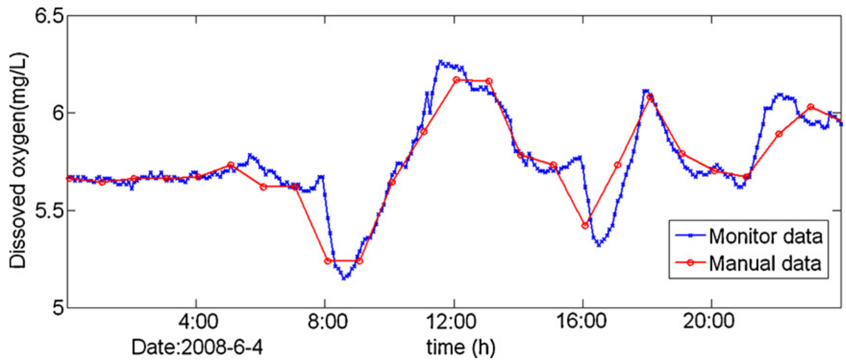

Fig. 5. The monitoring data of dissolved oxygen for a single day collected by RMP#1 on June 4th, 2008.

The RMP uses PICNIC2.0 (TriState, Japan) as the core-processing chip and the CDMA module (InRouter210C, China) for data transformation and transmission, and the CDMA module chip (module no.: FASTRACK M1203 Q2358) is used. The data recorded by sensors is transmitted to the remote information server through the China Unicom's CDMA services. Once the virtual local area network based on CDMA and IPsec VPN (Virtual Private Network) router for wireless secure transmission has been established, the programs in the server can have real-time access to the data. The set of data-acquisition nodes transmits the data by WiFi wireless LAN, while the computer running a communication program can transmit information to the remote server by TCP/IP protocol. Automated collection and web-based dissemination of data provides a centralized database for use and a detailed data analysis for all water quality stakeholders. Therefore, the users will be able to monitor the water parameter values via the Internet.

3.3. Central monitoring software

The central monitoring software is programmed with JSP, Servlet and short message technology using Model-View-Controller (MVC) architecture. It can operate on all operating systems that support this version of JAVA, so that the users can access the system through any commonly used browser such as Internet Explorer, Netscape, etc. Matlab 7.0 is used to implement and validate the algorithm. An Intel Core 2 Duo CPU personal computer with 1GB SDRAM is chosen as the test environment. The software of the monitoring system is developed under the software enrironment of Windows 2003, Eclipse, MyEclipse 3.2, MySQL 5.1, Apache Tomcat 5.5. A client software program is created to communicate with the server and provides a user interface so as to know the real-time status and its change (Fig. 4).

4. Results and discussion

4.1. Network communication and data acquisition

The entire system have been tested and verified for about 22 months from November 2007 to August 2009. Statistics of the data of all nodes show that the monitoring system is rather reliable; more than 95.2% of the data have been correctly collected since February 2008. Each RMP as an isolated local area network is connected to the Internet via CDMA (Unicom China) service. That means that a sensing network node can be a building block to construct a large-scale wireless sensing network in CDMA signal covered areas. The monitoring system is also easy expandable with more sensor channels as well as CDMA bandwidth.

Table 2
Summary statistic on various water parameters in 4 months.

	2008.5			2008.6			2008.7			2008.8		
	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
Tw (°C)	17.2	16.4	21.3	20.8	18.6	25.0	25.4	21.0	29.1	25.2	20.3	27.7
pH	7.95	7.56	8.18	7.86	6.00	8.77	8.11	5.87	8.96	7.85	5.77	8.61
Tr (°C)	17.7	16.1	23.7	19.4	16.9	24.8	25.6	22.0	32.4	25.4	22.0	31.3
DO (mg/L)	6.21	3.90	8.02	6.18	3.14	7.57	5.94	3.49	7.90	6.22	3.50	7.40
Salinity (ppt)	31.1	29.8	32.6	31.3	28.8	32.7	31.6	29.0	32.6	31.4	28.3	32.2
Fish mortality	0.7%			1.5%			1.6%			0.5%		

Table 3
The RMSE, RR, MRE for BP neural network model with different input combinations.

Room temperature (°C)	$DO_{entrance}$ (mg/L)	DO_{exit} (mg/L)	Water $temperature_{exit}$ (°C)	Water $temperature_{entrance}$ (°C)	EC	pH	RMSE	RR (%)	MRE (%)
×	×	×	×	×	×	×	0.12	93.16	7.02
×	×	×	×	×	×		0.15	92.89	7.26
×	×	×	×	×		×	0.13	92.33	7.29
×	×	×	×		×	×	0.15	91.07	9.34
×	×	×		×	×	×	0.59	59.39	15.12
×	×		×	×	×	×	0.63	77.96	14.97
×		×	×	×	×	×	0.30	56.73	14.8
	×	×	×	×	×	×	0.15	92.65	8.95
×	×	×	×	×			0.15	91.89	8.92
×	×	×	×				0.17	88.73	12.76

To validate the accuracy of the system, two sets of data sampled though different strategies (manually and automatically) have been compared. As shown in Fig. 5, the curve monitored by the system match the curve collected manually very well, with the maximum difference being less than 0.4 mg/L. So we can conclude that the proposed system can monitor the DO accurately and continuously. Obviously, the frequency of measurements (every 1 min) could not be achieved by manually sampling.

As we can see, there is a rapid descending of DO at about 8:20 and 16:20. This is because the feeding time is set at that time in this experiment. It is possible to monitor daily variations of dissolved oxygen to control aerators in time, typically after feeding. This form of time series permits monitoring of the daily amplitude of dissolved oxygen fluctuation, which is an accessory indicator of the water quality status. This frequency permits dissolved oxygen to be utilized as a warning parameter. The system can provide an early warning especially helpful for large scale, high-density and high risk aqua farms.

The detailed changes of temperature, pH and salinity are measured using the proposed monitoring system in the same way with satisfactory results.

After the system has been deployed, the pH was relatively constant, with an average pH of 7.943 (Table 2). Salinity was also high and relatively constant, with an average of 31.35 ppt and range of less than 1 salinity units (0.6 ppt) (Table 2). These two parameters are both around the optimal growth range with little fluctuation. Fish mortality has begun to drop to below 2% since the system was deployed.

4.2. Forecasting module

In order to achieve the best effect, the learning process is intentionally executed at different learning rates and with momentum factors. Before the BP learning process is performed, the order of training examples is randomized so that the changing of learning parameters is not affected seriously by some groups of training examples. Also, initial learning parameters are randomized and fixed for all learning cases.

The learning condition with $\gamma = 0.3$, $\alpha = 0.9$ has been chosen to illustrate the usefulness of applying the improved BP network in the modeling and forecasting of the dissolved oxygen. The initial data set is consisted of 2016 samples (288 samples per day), from which 4 days of data (1440 samples) were used for model calibration and 3 days of data (576 samples) for model validation. The calibration data set is further divided into 1152 training samples and 288 testing samples. It is found that the learning error is less than 6% after 4000 iterations. Then the error, converging slowly but continuously, comes to less than 3% after 10,000 iterations.

To evaluate the performance of the model, root mean square error (RMSE), maximum relative error (MRE), and recognition rate (RR) were taken as criterions.

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum (X_{\mathrm{O}} - X_{\mathrm{P}})^2} \tag{3}$$

where X_{O} denotes the observed variable and X_{P} denotes the predicted variable.

$$\mathrm{RR} = \frac{M}{N} \times 100\% \tag{4}$$

where M denotes the number of samples which satisfy the formula (5), N is the total number of samples.

$$\left|\frac{X_{\mathrm{O}} - X_{\mathrm{P}}}{X_{\mathrm{O}}}\right| \times 100\% < 4\% \tag{5}$$

$$\mathrm{MRE} = \mathrm{Max}\left|\frac{X_{\mathrm{O}} - X_{\mathrm{P}}}{X_{\mathrm{O}}}\right| \times 100\% \tag{6}$$

In order to obtain the most suitable model, a set of ANNs is created, with different input combinations according to Table 3.

It can be seen that model with 7 factors as input has a high practicability and accurate ability for DO concentration prediction. The different factor has different impact to the result of predict, in which pH, salinity had lowest impact. The neural network with air temperature, DO and water temperature of the entrance, and DO and water temperature in the exit as inputs, is selected to be the most relevant model.

5. Conclusion

In this study, a remote wireless monitoring system using wireless communication technology and artificial neural networks prediction model for the intensive aquaculture in China is introduced. Two prototypes of RMP deployed in an intensive aquafarm in Shandong have been tested nearly a 2-year period. It realizes the remote wireless monitoring of the water environmental parameters and alarm notification when monitored variables take anomalous values.

On the basis of the present study, the following conclusions can be made:

(1) The system can monitor the data of DO, pH, salinity and temperature real-time and continuously, considering that more than 95.2% of the data have been correctly collected. There are no significant effects on the monitored pH value since it is comparatively stable. The results indicate a periodic variation of water temperature, which has the similar regularity with air temperature. Salinity has sharply changed after a heavy rain event, so it could be an indirect indicator for early warning. Some other parameters of serious concern in aquaculture include ammonia nitrogen and hydrogen sulfide. The measurement and control of these and other key parameters will be performed in future work.

(2) The system can provide an early warning, especially helpful for high-density aquafarms. The forecasting model predicts the further trend of dissolved oxygen in half an hour correctly. Values of the coefficient of correlation and root mean square percent deviation are 0.91 and 1.56%, respectively. The accuracy of early warning is 81.4% and false alarm is zero.

(3) On the daily time scale, dissolved oxygen is found to repeat with a sort of regularity, mostly depending on the time of feeding. On the large seasonal scale, it shows an almost periodical trend, depending on the climatic situation. Therefore, it might be possible to improve the forecast model on this basis.

(4) The forecasting results of the dissolved oxygen are good after training, so changes in their coefficients will not be a priority for model improvement. Data sets of experiments that include all the necessary measurements along a growing cycle are not available. In addition, data sets from other pond environments with fish of different species are needed to make the model applicable to a wider range of culture environments. Special attention should be given to training data set as well.

(5) Application of the proposed system is still limited by its rather complicated operational requirements and high maintenance cost. The effects of water quality variations can be investigated in a good temporal and spatial resolution if more RMPs are installed. Moreover, the sensors need frequent cleaning and recalibration to prolong the useful span, because they need to have constant contact with the water, resulting in instrument fouling and loss in sensitivity and reproducibility. The long lifespan poles and the layout of sensor collection stations should be studied.

Conflict of interest

No conflict of interest.

Acknowledgements

This work has been financially supported by the National High Technology Research and Development Program of China (2007AA10Z238), National Key Technology R&D Program (2006BAD10A02-05) and Beijing Municipal Natural Science Foundation (4092024). The authors would like to thank the members of Fengze Company for their hospitality and for the assistance on the collection of the water quality data.

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