Remote Monitoring of Water Quality for Intensive Fish Culture

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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 is combined with web-server-embedded and 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.

Keywords: water quality monitoring, intensive fish culture, wireless sensor network, LSSVR.

1 Introduction

Aquaculture is the fastest growing food-producing sector in the world, with an average annual growth rate of 8.9% since 1970 [1]. 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 [2]. 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 1.6million tons in 1990 to 13.5million tons in 2005 [2,3].

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 water quality to keep the concentration of the water environment parameters in the optimal range can

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enhance the fish growth rate, impact dietary utilization and reduce the occurrence of large-scale fish diseases [4,5]. Without gathering information regarding 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 and in the right place.

However, there are a 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 and influenced by the personal experience. On the other hand, the process of forecasting is time-consuming and some contamination episodes might be missed [5]. 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 equipment has been developed to monitor remote areas in real-time [6-9]. At present, continuous monitoring of drinking water and wastewater quality at most treatment plants is applied in Europe, North America and Japan [10,11]. 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 [12]. However, the financial burden for building the fundamental hardware of these high-tech facilities may only be affordable to governments. Realizing 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 generation telecommunication technologies will become increasingly important in sensing networks.

In recent years, some researchers investigated integrated water quality remote monitoring systems [13,14] and management systems based on culture knowledge models and forecasting models [15-18], 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 fully viable alternative for high-density, open, and dynamic fish breed circumstances.

In this work, water quality remote monitoring systems using a GPRS service combined with IPsec-based virtual private networking (VPN) functionality were developed for constructing a wireless sensing network on a 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 dynamic trend of the water quality at different monitoring sites. The 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 Aquaculture and Water Quality Requirements

Aquaculture is defined as the high-density production of fish and plant forms in a controlled environment. Water quality for aquaculturists refers to the quality of water that enables successful reproduction of the desired organisms. The required water quality is determined by the specific organisms to be cultured and has many components that are interwoven. Aquaculture obeys a set of physical, chemical and biological principles. Since these principles compose the subject of water quality, in Section 2.1 we describe common water quality parameters related to these principles which have been used as indicators of water quality on fish culture, as well as the respective classification of these parameters by monitoring importance. In Section 2.2, we present a classification of the parameters based on their impact level in an ecosystem.

2.1 Physical, Chemical and Biological Analysis

The monitoring of environmental parameters in fish aquaculture allows the control and good management of water quality in fish ponds, avoiding the occurrence of unfavorable conditions that can be harmful for organisms [19,20] .

Water quality is based on the results of toxicity tests. These tests measure the responses of aquatic organisms to defined quantities of specific pollutants [21]. The aquatic species have different tolerances for a specific toxic compound; in this paper the characteristics of the fish are analyzed to evaluate the performance of the model.

Table 1. Water quality parameters classified by monitoring frequency

Monitored daily	*Monitored Weekly*	*Monitored by request*
Temperature (Temp)	Total ammonia (NH)	Alkalinity (Ak)
Dissolved oxygen (DO)	Nitrate (NO3)	Phosphorus (P)
Salinity (Sal)	Nitrite (NO2)	Hydrogen sulfide (H2S)
pH	Non ionized ammonia (NH3)	Non ionized hydrogen sulphide (HS-)
	Turbidity (Tb)	Dioxide of carbon (CO2)
		Suspended solids (Ss)
		Potential redox (Px)
		Silicate (Si)
		Chlorophyll A (ChA)
		Total inorganic nitrogen (N)
		Total marine bacteria (Tmb)
		Vibrio (Vb)
		Fecal coliforms (Fc)

In extensive aquaculture systems on china, the water quality parameters are monitored in different frequencies. Dissolved oxygen, temperature, pH and salinity are monitored daily while ammonia, nitrates, turbidity and algae counts are analyzed weekly. Chemical analyses are not taken into consideration for water quality management on a routine bases, they are only monitored by request [22]. Table 1 lists common water quality parameters used as indicators of water quality on fish marine culture and their respective classification by monitoring frequency.

In order to understand the effects of these water quality parameters, Table 2 and Table 3 show the optimal and harmful ranges (reported in the literature) for daily, weekly and by request parameters which will be considered for the assessment of water quality in our work.

Table 2. Daily and weekly measured water quality parameters and their importance to fish farming

Parameters	*Importance on marine fish culture*
Temperature	The temperature of water plays an important role in both environmental and intensive aquaculture processes. First, it affects the ability of living organisms to resist certain pollutants. Some organisms cannot survive when the water temperature takes a value beyond a specific range. Changes in temperature rates can stress fish and consequently high mortality rates can be present in the population [23]. Second, it controls solubility of gases, chemical reactions and toxicity of the ammonia. The demand of dissolved oxygen increases when temperature is high [24]. Temperature can be considered as normal from 28 to 32 °C [22].
Dissolved oxygen	The dissolved oxygen is breathed by fish and zooplankton and is necessary for their survival. Fluctuation of dissolved oxygen, hypoxia and anoxia crisis are events that can be normally presented in aquaculture systems. Dissolved oxygen is considered the most critical quality parameter, since fish in low dissolved oxygen concentrations are more susceptible to disease. The minimum levels recommended by authors oscillate between 4 and 5 ppm. It is recommended that
Salinity	Salinity is the saltiness or dissolved salt content of a body of water. The salt content of most natural lakes, rivers, and streams is so small that these waters are termed fresh or even sweet water. The actual amount of salt in fresh water is, by definition, less than 0.05%. The water is regarded as brackish, or defined as saline if it contains 3 to 5% salt. The ocean is naturally saline and contains approximately 3.5% salt. High salinity concentrations reduce dissolved oxygen in water ponds, and it can be dangerous for fish cultivation [21]. The optimal concentrations of salinity are from 15 to 23 ppt [21].

Table 2. (*continued*)

pH	pH is a measure of the relative amount of free hydrogen and hydroxyl ions in the water. Water that has more free hydrogen ions is acidic, whereas water that has more free hydroxyl ions is basic. The values of pH range from 0 to 14 (this is a logarithmic scale), with 7 indicating neutral. Values less than 7 indicate acidity, whereas values greater than 7 indicate a base. Extremely low or high pH stresses fish and causes soft shell and poor survival [25]. Water bodies with 6.5 to 9.0 pH concentrations are appropriate for aquaculture production. Reproduction decreases outside of this range. Acid death appears with values below than 4.0 and an alkaline death in values above 11 [22,24]. The presence of chemicals in the water affects its pH, which in turn can harm the animals and plants that live there. For example, even a mildly acidulous seawater environment can harm shell cultivation. This renders pH an important water quality indicator.
Ammonia	Ammonia is the main end product of protein catabolism in crustaceans. Ammonia increases tissue oxygen consumption, damages gills and reduces the ability of blood to transport oxygen. Ammonia exists in water in both ionized (NH_4^+) and unionized (NH_3) forms. Unionized ammonia is the most toxic form of ammonia due to its ability to diffuse readily across a cell membrane [26]. The safe level for unionized ammonia, recommended by Chien (1992) and Wickins (1976) [27], is less than 0.1 mg/l and for total ammonia is under 1.0 mg/l.
Water nitrogen	Inorganic nitrogen in water is chiefly present as ammonia, nitrate and nitrite. In fish, the respiratory pigment is hemocynanin, which can still bind oxygen in the presence of oxidizing agents such as nitrite [28]. The safe concentration of NO_2 is from 0.4 to 0.8 mg/l. Nitrates are nitrogenous compounds which can be toxic when their levels rise. According to Clifford (1994) [29], the optimal level for nitrates is from 400 to 800 μg/l. The expected total inorganic nitrogen recommended for crops is from 2.0 to 4.0 mg/l. [21,25].
Turbidity	A high concentration of suspended solids can cause high turbidity in water, preventing the penetration of light and affecting photosynthesis. The amount of suspended solids can be determined indirectly by measuring the turbidity. The accepted range for suspended solids is from 50 to 150 mg/l; or turbidity from 35 to 45 cm depth [24].

2.2 Environmental Classification

Water quality parameters can be classified in different impact levels, depending on the toxicity and harmful situations the parameters introduce to the ecosystem. In order to classify the behavior of a water quality parameter, it is necessary to define levels and allowed deviations for optimal or harmful concentrations. These deviations are useful to determine the ranges where values are considered closer to or farther from

Table 3. Water quality parameters measured by request and their importance to fish farming

Parameters	*Importance on marine fish culture*
Alkalinity	Related to important factors in fish culture such as buffer effect on daily variation of pH in the pond, setting the soluble iron precipitated, and in ecdysis (molting) and growth [19,20].
Phosphorus	Nutritive element, mainly appearing as orthophosphate, essential to aquatic life. From Esteves [30], phosphorus acts particularly in metabolic processes of living beings, such as energy storage and in the structure of the cell membrane [20].
Hydrogen sulfide	In water, hydrogen sulfide exists in unionized (H_2S) and ionized forms (HS− and S_2). Only the unionized form is considered toxic to aquatic organisms. Unionized H_2S concentration is dependent on pH, temperature and salinity, and it is mainly affected by pH [25].
Dioxide of carbon	When dissolved oxygen concentrations are low, carbon dioxide prevents oxygen penetration. According to Boyd (2001) [31], the normal range of carbon dioxide is from 1 to 10 mg/l
Potential redox	This is an indicator of substance oxidation or reduction levels. Low values are indicators of strong reduction of sediment, which is associated with toxic metabolite formation, hypoxic or anoxic conditions and low pH values. In a pond, optimal ranges of potential redox are from 500 to 700 mV for water and from 400 to 500 mV for sediment [29].
Silicate	In water, silicate is a composite of high importance particularly for diatoms. Optimal levels for silicate are established from 0.1 to 0.3 mg/l. [20,30].
Chlorophyll A	Phytoplankton biomass represents the primary consumer feed, and indirectly determines the feed availability of the next trophic system level. The ideal concentrations for fish ponds are from 50 to 70 µg/l [29].
Total marine bacteria	Microorganisms, particularly bacteria, play a vital role in pond ecosystems. Both beneficial (nutrients recycling, organic matter degrading etc.) and harmful (such as parasites) issues are caused by bacteria in the pond ecosystem. The optimal range for total bacteria counts should be below 10,000 UFC/ml [20,31].
Vibrio	Vibriosis is a bacterial disease responsible for mortality of cultured fish worldwide [32]. Vibrio related infections frequently occur in hatcheries, but epizootics are also commonly in pond reared fish species. Optimal ranges are defined as being below 1000 UFC/ml
Fecal Coliforms	Fecal Coliforms in water come from the feces of warm-blooded animals and they are an indicator of water pollution. The optimal range of fecal coliforms is below 1000 MPN/ml and for crop it should not exceed 1400 MPN/ml [33].

specified levels. In this study, tolerance thresholds were chosen using minimal changes in water parameters [33]. The levels for classification of the water quality parameters were defined by taking into account the levels and limits reported in the literature (see Table 2 and 3). In Table 4, 5 and 6 we show the classification, in different impact levels, for the water quality parameters from Table 1. The deviation column in these tables represents the tolerance for each level.

Table 4. Classification levels for daily monitored parameters

Water quality parameters	*Deviation*	*Levels*				
		Hypoxia acid	*Low*	*Normal*	*High*	*Alkaline*
Temperature (°C)	1.0		0–20	20–30	< 30	
Dissolved Oxygen (mg/l)	0.5	0–2	2–5	< 5		
Salinity (ppt)	1.0		0–15	15–23	< 23	
pH	0.5	0–4	4–6.5	6.5–9.5	9.5–11	11–14

Table 5. Classification levels for weekly monitored parameters

Water quality parameters	*Deviation*	*Levels*		
		Low	*Normal*	*High*
Total ammonia (mg/l)	0.10	0–0.1	0.1–1.0	< 1.0
Nitrites (μg/l)	100	0–400	400–800	<800
Nitrates (mg/l)	0.10		0–0.5	< 0.5
Non ionized ammonia (mg/l)	0.01		0–0.1	< 0.1
Turbidity (cm)	1.00	4–35	35–45	< 45

The importance of water quality management, the correct interpretation of water parameters and the appropriate techniques for integrating these parameters are problems studied in the aquaculture field. This research deals with one of the most important objective of the aquaculture management: it proposes a new way to join dissimilar parameters for getting an accurate assessment of water quality, increasing the effectiveness of the proposed system over traditional methodologies. In this sense, we hypothesize that different effects and levels of parameter concentrations degenerate in different water quality, thus, an appropriate join of these parameters

Table 6. Classification levels for monitored by request parameters

Water quality parameters	*Deviation*	*Levels*		
		Low	*Medium*	*High*
Alkalinity (mg/l)	10	0–100	100–140	< 140
Phosphorus (mg/l)	0.01	0–0.1	0.1–0.3	< 0.3
Hydrogen sulfide (mg/l)	0.01	0–0.05	0.05–0.1	< 0.1
Non ionized hydrogen sulfide (mg/l)	0.001	0–0.002	0.002–0.005	< 0.005
Carbon dioxide (mg/l)	2	0–10	10–20	< 20
Suspension solids (mg/l)	5	0–50	50–150	< 150
Potential redox (mV)	10	0–400	400–500	< 500
Silicate (mg/l)	0.2	0–2.0	2.0–4.0	< 4.0
Chlorophyll A (μg/l)	5	0–50	50–75	< 75
Total inorganic nitrogen (mg/l)	0.2	0–2	2–4	< 4
Total marine bacteria (UFC/ ml)	1000	0–5000	5000–10,000	< 10,000
Vibrio (UFC/ ml)	100	0–500	500–1000	< 1000
Fecal coliforms (MPN/ml)	100	0–500	500–1000	< 1000

could determine a better assessment of water quality. This assessment could be achieved using a fuzzy inference system, which involves different situations generated by water quality parameters.

3 System Design

3.1 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, an intelligent "plug and play" sensor technology has been used.

As shown in Fig. 1, the basic structure of the system can be divided into three major parts: the data layer, the transport layer and the application layer for data acquisition, reliable transmission, intelligent information processing and logical operation, respectively. These three parts communicate with each other through the telecommunication system.

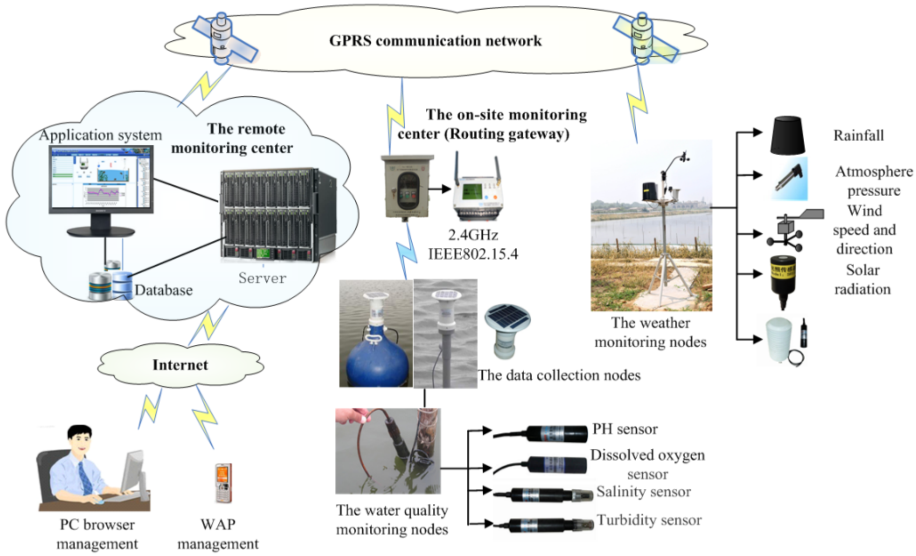


Fig. 1. The structure diagram of the digital remote wireless monitoring system

3.2 Remote Monitoring Platform

The remote monitoring platform (RMP) 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.

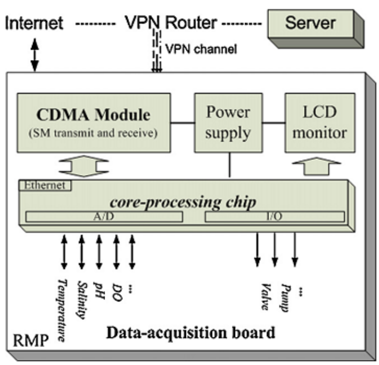


Fig. 2. System architecture of the remote monitoring platform

The function of the data-acquisition component is to obtain signals of the most important environmental factors by using various sensors. The main variables that can be monitored are reported in Table 7. With the current measurement methods, pH value is measured by the glass electrode method, dissolved oxygen by the 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.

Table 7. The water quality variables of data acquisition

Name	Variable	Units	Name
Water temperature	T_w	(℃)	Water temperature
Indoor temperature	T_a	(℃)	Indoor temperature
Solar radiation	S	(W/m^2)	Solar radiation
Percentage of oxygen saturation	DO_S	(%)	Percentage of oxygen saturation
Oxygen concentration	DO	(mg/l)	Oxygen concentration
Pouvoir Hydrogène	pH		Pouvoir Hydrogène
Electrical conductivity	EC		Electrical conductivity

The data transformation and transmission component is composed of the signal conditioning circuits, data-acquisition board, core-processing chip and GPRS module. The sensors and the signal conditioning circuits convert the various environmental factors to electrical voltage standard signals in the range of 0–5V. The signal is transmitted to the Web-based monitoring chip, and then is converted into the digital signal through A/D conversion. Onsite data-acquisition nodes compose a wireless LAN, and the GPRS module enables the RMP to receive the data and transmit them to a PC for further analysis.

3.3 Central Monitoring Platform

The central monitoring platform receives, pre-processes and analyzes the data from the RMP, predicates the trend of the parameters according to historical 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 a 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 an alarm in a specific tank. Real-time data is downloaded via web-based servers at scheduled intervals.

3.4 Forecasting Model of Dissolved Oxygen

One purpose of the current monitoring system is to detect a trend of water quality fluctuation using historical 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 is analyzed for temporal trends focusing on the dissolved oxygen half an hour after measurement. Due to their ease of development, decreased reliance on expert knowledge of the system under investigation and non-linear modeling capabilities, Least Squares Support Vector Regression (LSSVR) was selected as the modeling tool. In spite of this, the LSSVR performance heavily depends on the choice of several hyper parameters, which are necessary to define the optimization problem and the final LSSVR model. To design a LSSVR, one must choose a kernel function, set hyper parameters such as the kernel parameters and determine a regularization parameter γ. The hyper parameters that should be optimized include the regularization parameter γ and the kernel function parameters such as the gamma (σ) for the radial basis function (RBF) kernel. Thus, selecting appropriate model parameters has a crucial impact on the prediction accuracy [34]. Unfortunately, there no exact method to obtain the optimal set of LSSVR hyper-parameters, so a search algorithm must be applied to obtain the parameters.

In general, the search algorithms used to obtain LSSVR hyper-parameters can be summarized in two categories. One is based on analytical techniques, and the other is based on heuristic searches. The first kind of techniques determines the hyper parameters with gradients of some generalized error measures [35-39]. This procedure is time-consuming and can't converge at the global optimum. The second kind of techniques determines the hyper parameters with modern heuristic algorithms including simulated annealing algorithms, differential evolution, genetic algorithms, particle swarm optimization algorithm and other evolutionary strategies [40-44], which are applied to implement a robust research on the hyper parameters search space. Compared with other heuristic algorithms, for example, genetic algorithm, particle swarm optimization (PSO) does not need evolutionary operators such as crossover and mutation. Furthermore, the advantages of PSO are that PSO possesses the capability to escape from local optima, is easy to be implemented, and has fewer parameters to be set [45-47]. Thus in this study, the novel prediction method based on the combination of least squares support vector regression (LSSVR) and improved particle swarm optimization (IPSO) is proposed to the water quality prediction in the intensive aquaculture of river crab, which IPSO is applied to optimize the hyper-parameters. Traditional LSSVR model and BP neural network are used as comparison basis. The experiments results show that the predictive accuracy and capability of generalization is greatly improved by our proposed approach.

For the nonlinear LSSVR, its generalization performance depends on a good setting of parameters γ and the kernel parameters σ. Inappropriate hyper-parameters combination in LSSVR lead to over-fitting or under-fitting, so IPSO is used to optimize the parameters of SVR: γ and kernel parameter σ of RBF-kernel function, which are two attributes of each particle. In solving the hyper-parameter selection, each particle represents a potential solution, comprised of a vector $d = (\gamma, \sigma)$. The performance of each particle is measured according to the fitness function. In the training and testing process of LS-SVR, the objective is to minimize the errors between the actual values and prediction values of the testing samples. Therefore, the fitness function of IPSO is defined as:

$$Fitness() = \sqrt{\frac{1}{z}\sum_{j=1}^{z}(\hat{y}_{ij} - y_{ij})^2} \quad (1)$$

where z is the number of each subset as validation, y_{ij} represents the actual values, and $\hat{y}_{ij}$ represents the prediction values. The goal is to minimize the fitness, so the particle with the minimal fitness value will outperform others and should be reserved during the optimization process. Accordingly, also the optimal combinational parameters values of γ and σ are obtained.

The implementation process of water quality prediction based on IPSO-LSSVR is described in steps as follows:

(1) Input data of water quality, construct training sample set and test sample set. Initialize the original water quality data by normalization and then form training patterns.
(2) Set algorithm parameters, select the kernel function, the regularization parameter γ and the kernel function parameter σ.
(3) Train LSSVR on the training set, solve the optimization problem and obtain the parameters of LSSVR by IPSO, get IPSO-LSSVR prediction model. Test the performance of the prediction model with test sample.
(4) For a new application of the prediction task, extract water quality index and form a set of input variables x.

4 System Implementation

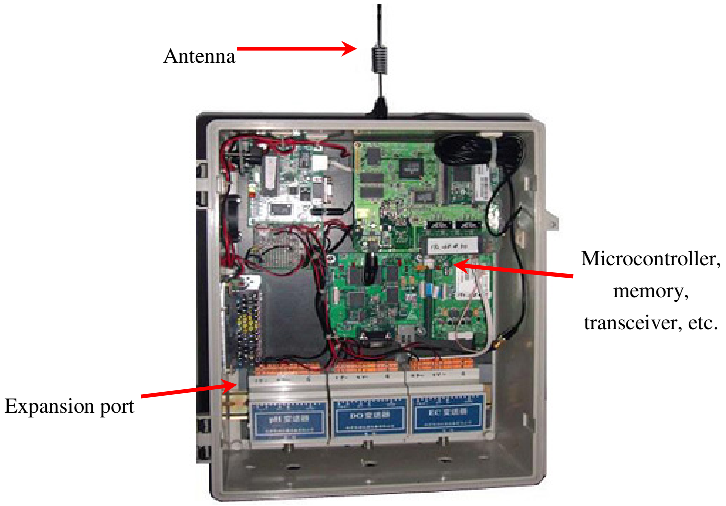
4.1 Testing Environment

In the testing environment set up for the purposes of this work, one central monitoring platform with an IPsec based VPN (Virtual Private Network) 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 [48]. Each fish tank is approximately 6.77m × 6.55m × 0.55m. The average fish stock density is 30–40 kg/m^3.

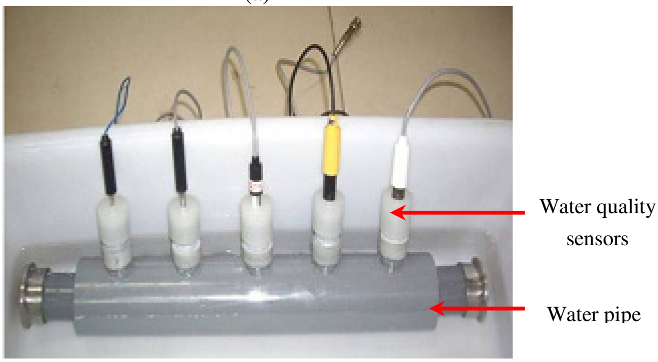
4.2 Remote Monitoring Platform

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

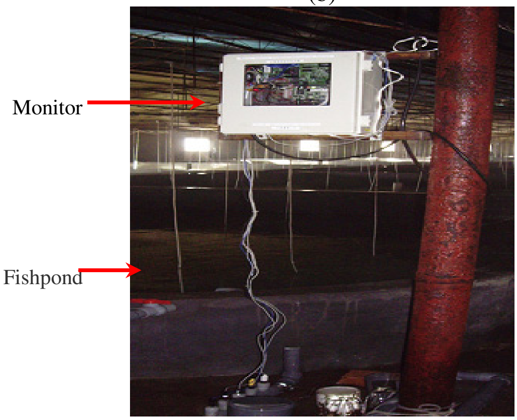
The probes of the sensor in the present study for temperature, DO, pH, salinity are made by the Nantu Company (China) with accuracies of 0.1 °C, 0.1mg/L, 0.1, 0.1 ppt, respectively. The HQ 40d18 (HACH, USA) is chosen as a contrast providing long-term stability and high accuracies of ±1.0% for relative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



(a)



(b)



(c)

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 experimental workshop in Shangdong Fengze fish farm

The RMP uses PICNIC2.0 (TriState, Japan) as the core-processing chip and a GPRS module (FASTRACK M1203 Q2358, InRouter210C, China) for data transformation and transmission. The data recorded by the sensors is transmitted to the remote information server through the China Unicom's GPRS services. Once the virtual local area network based on GPRS and IPsec VPN 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 the 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.

4.3 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 environment 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 of the system (Fig. 4).

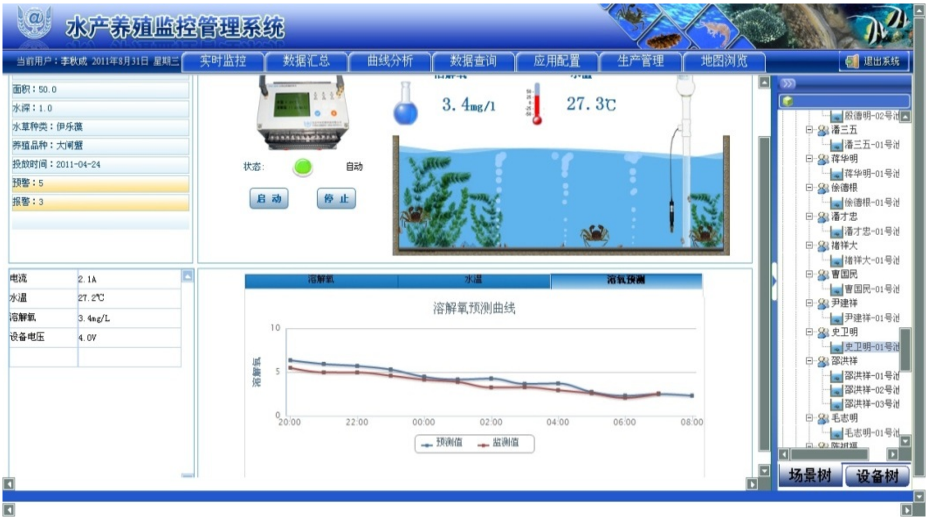


Fig. 4. The monitor interface window of no. 5 workshop

5 Results and Discussion

5.1 Network Communication and Data Acquisition

The entire system have been tested and verified for about 30 months from November 2010 to August 2012. 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 April 2009. Each RMP has an isolated local area network which is connected to the Internet via GPRS (China Mobile). That means that a sensing network node can be a building block to construct a large-scale wireless sensing network in GPRS signal covered areas. The monitoring system is also easy expandable with more sensor channels as well as GPRS bandwidth.

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 matches the curve collected manually very well, with the maximum difference being less than 0.4mg/L for dissolved oxygen content. 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.

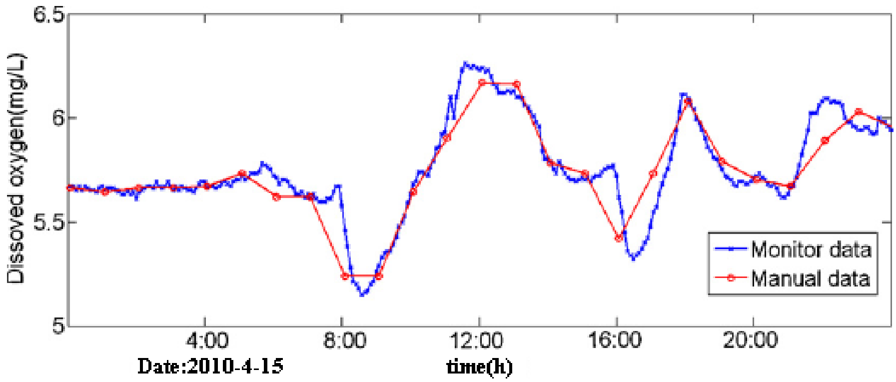


Fig. 5. The monitoring data of dissolved oxygen for a single day collected by RMP#1 on April 15th, 2010

As we can see from Fig. 5, there is a rapid decrease 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.

Table 8. Summary statistic on various water parameters in 4 months

Name	April 2010			May 2010			June 2010			July 2010		
	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
Tw (°C)	17.2	16.4	21.3	20.8	18.5	25.0	25.4	21.0	29.1	25.2	20.3	27.7
pH	7.95	7.56	8.18	6.00	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	7.4
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
Mortality	0.7%			1.5%			1.6%			0.5%		

After the system has been deployed, the pH was relatively constant, with an average pH of 7.943 (Table 8). 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 8). 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.

5.2 Pre-treatment Data

In many real applications, the observed input data cannot be measured precisely since distinct numerical variable have different dimensions, and should be normalized in the first instance. In order to improve the accuracy of prediction, all data samples are standardized and normalized to the interval of [0,1] according to the following linear mapping function:

$$\bar{x}_k^d = \frac{x_k^d - \min(x_k^d \mid_{k=1}^l)}{\max(x_k^d \mid_{k=1}^l) - \min(x_k^l \mid_{k=1}^l)} \quad ,d=1,2,\ldots,m \tag{2}$$

Where d is the number of dimensions and l is the number of samples, $\bar{x}_k^d$ and x_k^d are the original data and the normalized data, respectively.

5.3 Experimental Environment and Algorithm Parameter Settings

The proposed IPSO-LSSVR algorithm has been implemented in the JAVA programming language. The experiment is performed on a 2.50GHz Core(TM)2 CPU personal computer with 2.0G memory under Microsoft Windows Server 2003 R2 editions. From Fig. 6, it is clear that the proposed model of IPSO-LSSVR has strong learning capability for small samples and simultaneously achieves excellent generalization performance since the LSSVR is a good compromise for guaranteeing both stability and accuracy improvement, and it is a suitable and effective method for predicting the DO content of the water quality in the intensive aquaculture.

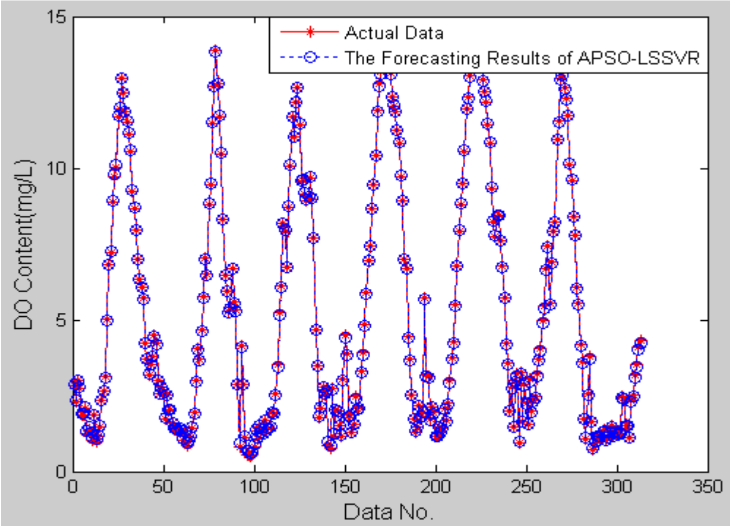


Fig. 6. The water quality prediction result based on IPSO-LSSVR model

5.4 Model Performance Evaluation

In order to analyze and evaluate the prediction performance of IPSO-LSSVR, the models (standard LSSVR and BP neural network) are selected to deal with the aforementioned water quality samples data. The standard LSSVR parameters are found by 5fold cross-validation method, and the selected optimal values of γ and σ are 120.1530 and 1.6839, respectively. The initial architecture of the BP neural network consisted of six input variable, one output variable, the hidden layer with six initial neurons, and the learning rate is 0.08 and stimulating function is sigmoid, three thousand training epochs are also adopted as the termination criterion. The root mean square error (RMSE), the mean absolute error (MAE), the mean absolute percentage error (MAPE) and mean squared error (MSE) are employed as performance indicators to evaluate prediction capability of three models. These performance indexes are respectively computed from the following equations:

$$RMSE = \sqrt{\frac{1}{M}\sum_{t=1}^{M}(y_t - \hat{y}_t)^2} \tag{3}$$

$$MAE = \frac{1}{M}\sum_{t=1}^{M}\left|y_t - \hat{y}_t\right| \tag{4}$$

$$MAPE = \frac{1}{M}\sum_{t=1}^{M}\frac{\left|y_t - \hat{y}_t\right|}{y_t} \tag{5}$$

$$MSE = \frac{1}{M}\sum_{t=1}^{M}(y_t - \hat{y}_t)^2 \qquad (6)$$

Where M is the total number of actual samples in the data set, y_t and $\hat{y}_t$ are actual and prediction values, respectively. The performance evaluate the prediction capacity of the three models are illustrated in Table 9.

Table 9. Error statistic of three prediction models

Model	RMSE	MAE	MAPE	MSE
BPNN	0.5523	0.4077	0.2668	0.1241
Standard LSSVR	0.2388	0.1561	0.0534	0.0570
IPSO-LSSVR	0.1687	0.0508	0.0159	0.0147

The obtained results indicate that our hybrid model has significantly yielded more reliable performance, generalization ability, and high prediction precision than LSSVR and BPNN model. For the same LSSVR, the relative RMSE, MAE, MAPE and MSE differences between the IPSO-LSSVR and standard LSSVR models are 29.36%, 67.46%, 70.22% and 74.21% in the test period, respectively. It is clear that the parameters optimized by IPSO are of better choice to construct LSSVR model for the design of water quality prediction than the ones by 5fold cross-validation method. The relative RMSE, MAE, MAPE and MSE differences between the IPSO-LSSVR and BPNN models are 69.46%, 87.54%, 94.04% and 88.15% in the test period, respectively. It is obvious that IPSO-LSSVR has more accurate result than BPNN.

This study presents an IPSO based approach, capable of searching for the optimal hyper-parameters values of LSSVR and RBF kernel function. The results of application in water quality prediction demonstrates that the prediction method based on IPSO-LSSVR is effective and feasible, and simultaneously this prediction information is important for decision making regarding the water quality management in modern intensive aquaculture, so the testing costs and production schedule can be optimized.

6 Conclusion

In this study, a remote wireless monitoring system using wireless communication technology and IPSO-LSSVR prediction model for the intensive aquaculture in China is introduced. Two prototypes of RMP deployed in an intensive aquafarm in Shandong have been tested over 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 DO, pH, salinity and temperature in 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 correctly predicts the further trend of dissolved oxygen half an hour after physical measurement.

(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 life span poles and the layout of sensor collection stations should be studied.

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