Patterns Recognition for Shrimp Aquaculture

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Abstract. Mexico is one of the main exporters of shrimp at international level. The environmental quality in prawn ponds is essential for good production of species. If there exists any change in one of the environmental parameters, and this is not early controlled, it could generate instability into the pond, the organisms will be stressed and as a result they can get sick, in some cases, the sickness could be mortal. Nowadays, there is not software that attacks this point. In this work, we create environmental variables patterns, such as temperature, salinity, pH, dissolved oxygen and turbidity, and they are recognized by a feedforward neural network. This patterns recognition makes possible to diagnose and to present the trend of shrimp artificial habitat behavior and to take actions of control and prevention.

1 Introduction

In the coastal zones, the fishing contributes to generate important gains. The production can be affected by environmental factors, such as tropical storms, cyclones or diseases. Artificial sowing of the species tries to intensify the amount of the product and the quality in the same one.

Mexico is considered as the fourth producer at international level. Shrimp artificial sowing is not simple, this species is very sensible and any change in its habitat as much produces great negative effects in its growth as in its reproduction. The farms that are dedicated to the culture of the shrimp have exclusively dedicated laboratories to control the environment to generate a production greater.

The shrimp aquaculture in Mexico and the world has not advanced computational systems to supervise the artificial habitat of the farms and laboratories. A computational system of this type helps significantly to improve the environmental conditions and to elevate the production and its quality [1], [2].

The main idea of this work is the creation of a system, which can help the biologists to recognize patterns of problems and their evolution in shrimp aquaculture, and thus to respond with greater rapidity against the negative effects.

Bad control on the shrimp artificial habitat produces organisms with the high stress and as consequence losses in their defenses. It generate low nutrition, low reproduction or worse still, they prearrange to acquire lethal diseases. The proposed system helps to control this problem [3].

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Control, Virtual Instrumentation and Digital Systems.
Research in Computing Science 24, 2006, pp. 95-104

The established hypotheses are the following ones:

1. It is possible and necessary to establish patterns of environmental variables with nonlinear relationships to classify the artificial habitat state of shrimp.
2. A feedforward neural network, with a linear activation function for output neurons, allows to recognize and to quantify the shrimp artificial habitat state, which is given by environmental variables patterns.

2 Technical Support and Schemes of Operation

The main environmental variables are measured of automated way or introduced to a computer by the operator, and these are the following ones:

1. Temperature (°c)
2. Dissolved oxygen (mg/L)
3. Salinity (g/L or ppt)
4. pH
5. Alkalinity (mg/L $CaCO_3$)
6. Turbidity (cm)
7. Total ammonium (mg/L)

A distributed system [4], [5] is used in the automated measurement (pH, temperature, Dissolved oxygen, etc.). An operator makes laboratory measurement (Salinity, Alkalinity, Total ammonium, etc.). The Fig. 1 shows an installation for shrimp aquaculture and the Fig. 2 presents a simplified scheme of the distributed system.

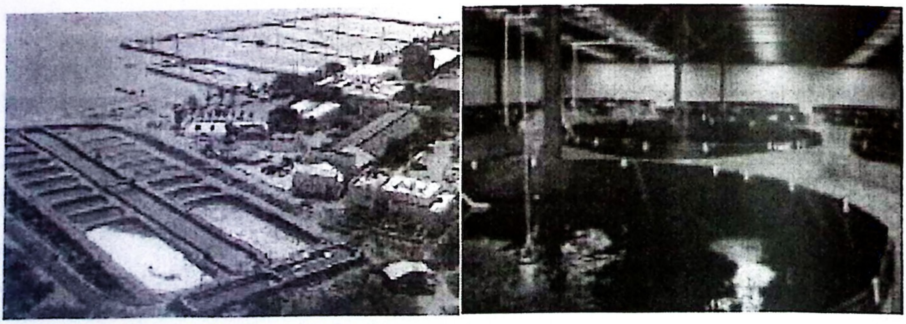

Fig. 1 Example of an installation for shrimp aquaculture

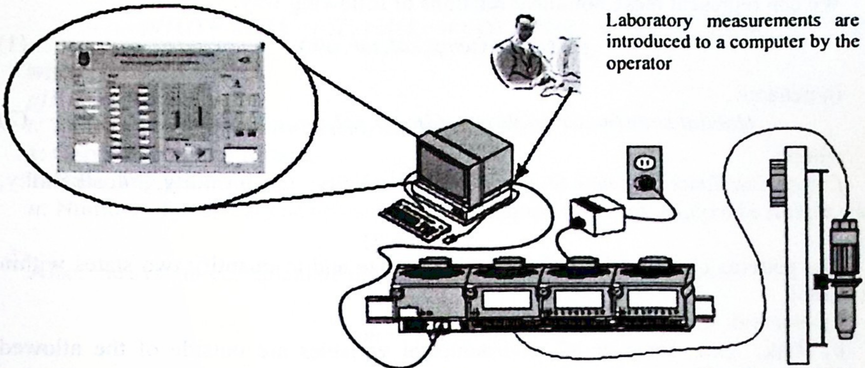

Fig. 2 Scheme of the distributed system

3 Patterns of environmental variables with nonlinear relationships

Environmental variables as pH, temperature, salinity, dissolved oxygen and turbidity have an important effect in the suitable growth of the shrimps and influence in their health. For example for Shrimp Maturation and Spawning [6], [7] almost all hatcheries require availability of oceanic-quality water on a 24-h basis. Salinity and temperature are the most important water parameters impacting production of shrimp in the hatchery, and must be maintained in a narrow range, between 27 and 36 ppt salinity and 28 C (82 F) plus or minus two degrees for most penaeids. These and other important factors in the maturation and spawning of penaeid shrimp are discussed in detail by Treece and Fox [8].

Parameters for tropical shrimp maturation and allowable ranges/24 hr [6]

Salinity:
27-36 ppt +/- 0.5
Temperature
28 C +/- 2 (80.5-84.2 F)
pH
7.8 +/- 0.2
Light
14 L, 10 D
D.O. (Dissolved oxygen)
5 ppm

These values allow to create normal patterns. In general, these variables have nonlinear relations, which have been observed and proven experimentally, although the equations that represent them have been formulated, which is very difficult [9].

We can represent these nonlinear relations of following way:

$$pH(t) = f(temp, sal, tur, alk) \tag{1}$$

In general:

$$Habitat\ state\ (water\ quality) = f(temp, sal, tur, alk, do, ta, ...) \tag{2}$$

where:

f: nonlinear function; *temp*: temperature; *sal*: salinity; *tur*: turbidity; *alk*: alkalinity; *do:* dissolved oxygen; *ta*: Total ammonium.

The patterns classification is made to recognize and to quantify two states within the pool:

a) **Normal**: Everything is well.

b) **Risk**: One, some or all environmental variables are outside of the allowed interval, which generates problems.

The neural network [10], [11] will have to recognize the state and to quantify it, in others words, how normal or risky it is, which allows to find trend of the water quality. The total ammonium only, can cause a danger state; therefore, this situation is found by means of conditions if-else.

In Table 1 are the environmental variables of greater importance, the values and the combinations of these, for which the pool is in a normal state, of risk or danger.

Table 1. States classification by means of the combination of environmental variables.

NORMAL	
Environmental variables	**Range**
Temperature	23 – 30 °C
Salinity	15 – 25 (mg/l)
pH	7.6 – 8.6
Dissolved oxygen	6 – 10 (mg/l)
Total ammonium	Less than 0.1 (mg/l)
Turbidity	35 – 45 (mg/l)
RISK	
Temperature	Greater than 30°
Salinity	Greater than 25 (mg/l)
pH	Less than 7.6 or greater than 8.6
Dissolved oxygen	Less than 6 or greater than 10 (mg/l)
Turbidity	Less than 35 or greater than 45 (mg/l)
DANGER	
Total ammonium	Greater or equal than 0.1 (mg/l)
Dissolved oxygen	Less than 3 (mg/l)

The method determines if a danger state exists, and in such case it gives to the present values of ammonium and oxygen. If a danger state does not exist, then the neural network recognizes and quantifies the normal state or the risk state. In the three situations, the user could consult the historical values of the environmental variables.

These historical values (for example for pH) are defined as:

$$pH(t) = pH(k-n)T, pH(k-n+1)T, pH(k-n+2)T, ..., pH(k) \quad (3)$$

where:
pH(t): Historical value.
t: Time interval for the historical, defined for user.
k: Current sampling instant.
T: Sampling period.
n: Number of necessary samples for the historical, so that:

$$(n+1)T = t \quad (4)$$

Also, the system can calculate the historical average and variance, as:

$$\overline{ph} = \sum_{i=k}^{k-n} ph(i)/(n+1) \quad (5)$$

and the variance, as:

$$Vph = \sum_{i=k}^{k-n} (ph(i) - \overline{ph})^2 /(n+1) \quad (6)$$

The user can solicit a trend analysis, linear or polynomial [12].

The classification of the real measurements in training patterns was made in farms of test in several periods of sowing, and 400 patterns were used, which represent different levels of normal state and different levels of risky state.

Total ammonium is considered more danger than others variables. A minimum concentration of ammonia is enough for creating a danger state. The system recognize a danger state with this variable only when the maximum level is reached, this is done using an if-else programming and not with a neural network.

4. Neural network

Fig 3 presents the topology of better results for this application. The neural network also is able to give a deviation of the centre of the state, in other words, the state what so normal or risky is. This deviation allows to have historical of the classifications, same that make possible to establish a trend of the evolution of the water quality or artificial habitat, and the technologists can control better at shrimp habitat.

The neuron that recognizes the normal state gives the value of 1 if the state within the pool is best, if this state is deteriorated, then neuron will give inferior values to 1, and will go in reduction. In the same way, the neuron that recognizes the risk state gives the value of -1 when the neuron of normal state is in 1, and will go in ascent if the deterioration state increases. If the state within the pool is very deteriorated, then the classification will be of risk and the neuron that recognizes the risk will give a value of 1 (see Fig. 4). The Fig. 5 presents the performance in neural network training.

The Table 2 has the test results of patterns recognition for values combinations of environmental variables. This test was successful.

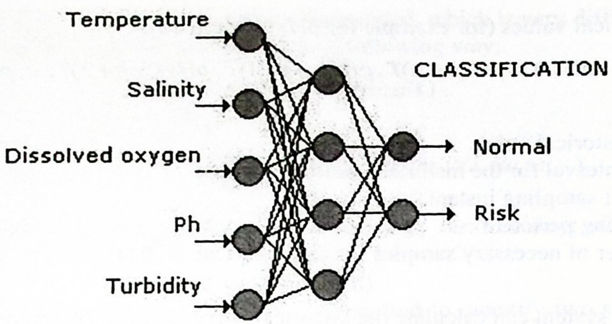

Fig. 3 Feedforward neural network

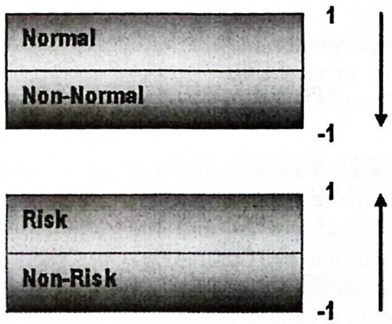

Fig. 4 Operation of output neurons with linear activation function

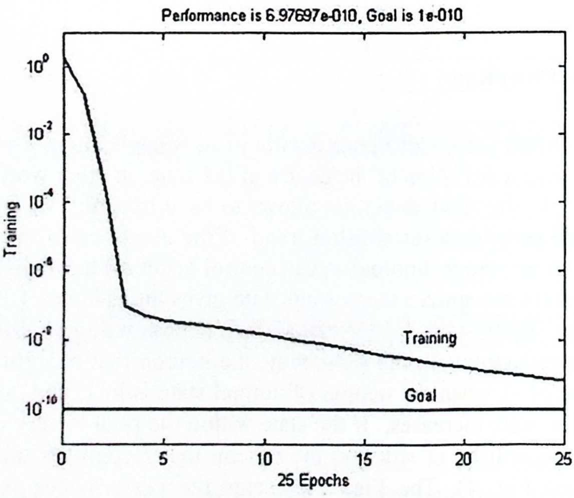

Fig. 5 Performance in neural network training

Table 2 Some tests of patterns recognition made by neural network.

Tempe-rature(^{0}C)	Salinity (mg/l)	Dissolved oxygen (mg/l)	pH	Turbidity (mg/l)	Normal	Risk
33	15	15	9	35	-1	1
23	25	6	8.2	40	-1	1
32	20	5.3	7.5	38	-1	1
40	32	5.5	9.2	39	-1	1
30	25	9	7.8	41	-1	1
27	20	8	8.5	40	-1	1
28	31	4	7.8	17	-1	1
28	28	3	7.9	12	-1	1
28	23	3	8.9	15	-1	1
27	26	2	8.1	15	-1	1
28	31	3.2	7	11	-1	1
28	34	2.3	6.5	17	-1	1
28	32	2.2	8.5	18	-1	1
23	35	3	8	11	-1	1
33	34	9	9	48	-0.60357	0.87094
37	32	15	8.3	48	1	-0.99741
34	33	7.3	8	37	-1	1
37	35	7.2	8.7	24	-1	1
35	35	11	5	24	-1	1
35	33	15	8.5	18	-1	0.81304
35	31	15	7.8	17	-1	0.87243
34	28	15	7.9	12	-1	1
34	23	15	8.9	15	-1	1
35	26	15	8.1	15	-1	1
32	31	15	7	11	-1	1
33	34	15	6.5	17	-1	0.83643
33	32	15	8.5	18	-1	0.80734
30	35	15	8	11	-1	1
33	15	8	9	35	-1	0.86891
23	25	6	8.2	40	-1	0.76977
32	20	5.3	7.5	38	0.68359	-1
40	32	5.5	9.2	39	-1	1
30	25	9	7.8	41	1	-0.99741
27	20	8	8.5	40	1	-0.99741

5. Analysis of results

The patterns classification given by the environmental variables confirms its nonlinear interrelation. The pool state cannot be determined only by a environmental variable, this is determined due to the variations of a set of them, therefore, a trained feedforward neural network represent suitably the nonlinear relations between the environmental variables.

Figures 6, 7, 8 and 9 were obtained using as reference the Table 2, and present four examples of the variations of environmental variable of individual way in axis X, versus axis Y that presents the recognized state, by the neural network, using the values of the set (pattern) of all environmental variables.

No any environmental variable by itself defines the state of the habitat, for example, in Fig. 6, for a normal salinity of 24.5 mg/l, the neural network recognizes a normal state; for a normal salinity of 23,5 mg/l the neural network recognizes a moderate risky state.

The presented examples allow to understand the nonlinear relations between the environmental variables. These nonlinear relations are represented suitably by feedforward neural network.

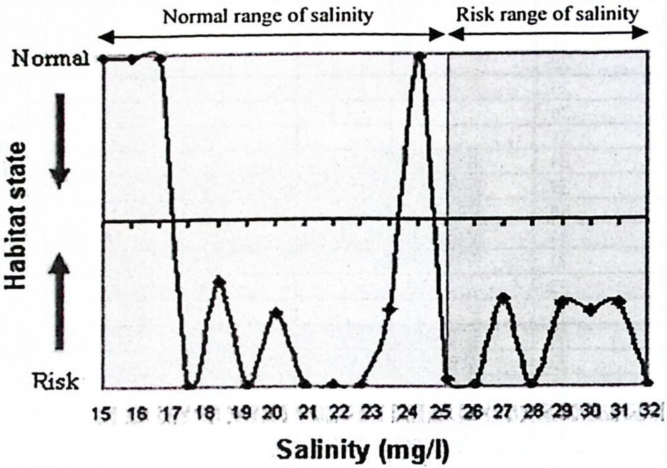

Fig. 6 Salinity variations and recognized habitat state

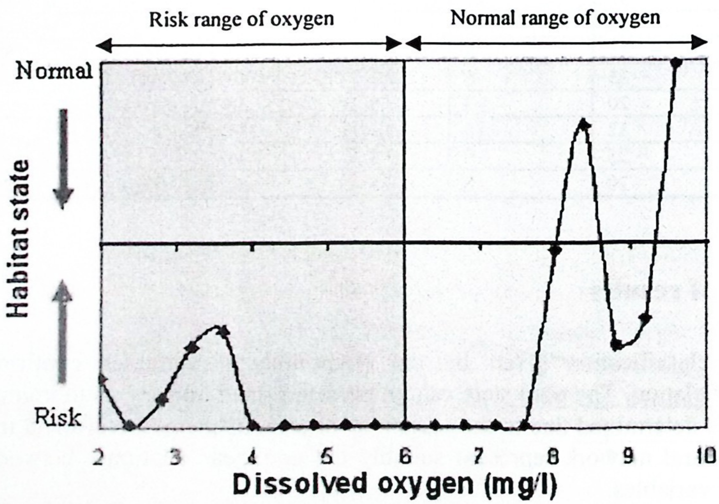

Fig. 7 Dissolved oxygen variations and recognized habitat state

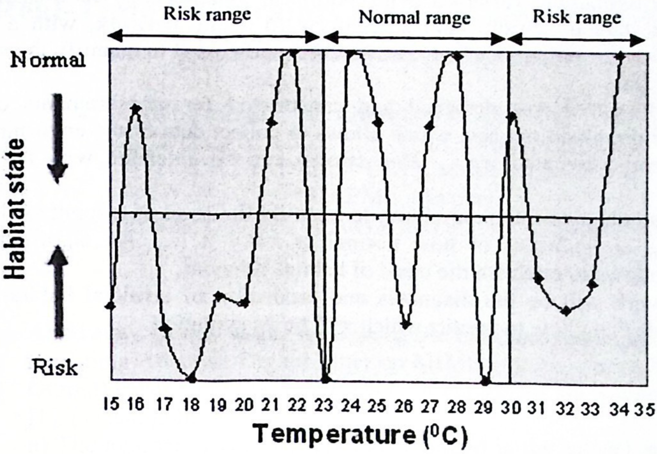

Fig. 8 Temperature variations and recognized habitat state

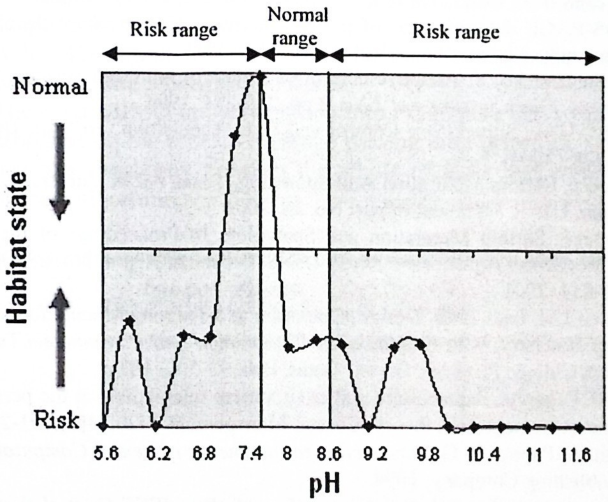

Fig. 9 pH variations and recognized habitat state (normal: 7.6-8.6)

Conclusions and Future Work

In the shrimp aquaculture, it is difficult to maintain a similar water quality to natural environmental conditions. This work allows to diagnose any problem early, being able to make an opportune treatment and to obtain harvests of better quality.

The hypotheses were demonstrated: It is possible and necessary to establish patterns of environmental variables with nonlinear relationships to classify the artificial habitat state of shrimp, and a feedforward neural network, with a linear activation function for output neurons, allows to recognize and to quantify the shrimp artificial habitat state.

A distributed system was designed and constructed for measurements of pH, temperature and dissolved oxygen, which allows to collect data of the environmental variables, of semi-automated way. This system can be extended with relatively simple changes.

The developed diagnosis method allows to quantify the level of recognized habitat state, presenting an indicator of how normal or risky it is. An algorithm was developed that allows to establish the trend of habitat behavior.

The future work will be the diagnosis and prediction of artificial habitat state, adapting methods that allow to predict which will be its evolution.

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