Iterative Parameter Selection Based Artificial Neural Network for Water Quality Prediction in Tank-Cultured Aquaculture System

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ABSTRACT
Water Quality plays an important role in attaining a sustainable aquaculture system, its cumulative effect can be detrimental to the aquatic organisms as well as the environment, which in turn leads to poor growth, increased diseases and production losses. The amount of dissolved oxygen alongside other parameters such as Temperature, pH, Alkalinity and Conductivity are used to estimate the water quality index in aquaculture. There exist different approaches for the estimation of the quality index of the water in the aquatic environment. One of such approaches is the use of the Artificial Neural Network (ANN) in the prediction of this Index, however, its efficacy lies in the ability to select and use optimal parameters for the network. Thus, this work proposes the development of an Iterative Parameter Selection (IPS) algorithm for the selection optimal network parameters for the ANN such as the number of neurons in the hidden neurons. The performance of the proposed algorithm on a typical BP-ANN was evaluated using the Mean Square Error (MSE), and the Nash-Sutcliffe Efficiency (NSE) metrics. Furthermore, a comparison of the proposed algorithm with two other known algorithm shows the proposed IPS has having a better performance. Thus, this demonstrates the capability of the IPS algorithm in obtaining optimal ANN parameters for effectively determining water quality index in Aquaculture system.
Keywords: *Aquaculture System; ANN; Dissolved Oxygen; Prediction; Water Quality Index.*

1 INTRODUCTION

Aquaculture deals with all activities aimed at rearing and cultivating of fishes and other aquatic animals and plants under controlled conditions and environment(Garcia, Sendra, Lloret, & Lloret, 2011; Oyakhilomen & Zibah, 2013). This production method is fast growing and forecasted to be on the increase for the nearest future to come (Kristofersson & Anderson, 2006). According to the Food and Agriculture Organization of the United Nation (FAO) report in 2011, there is a global substantial growth in the aquaculture production up to the tune of 52.5 Million tonnes in 2008 as compared to the 32.4 million tonnes in 2000 (FAO, 2011). This sector of agriculture continues to dominate other sectors as the fastest growing animal food producing sector which accounts for over 45.6% of the total world's food fish consumption in 2012 as compared to the 33.8% in 2000 (Atoum, Srivastava, & Liu, 2015; FAO, 2011).

The importance of water in aquaculture cannot be over emphasized as it forms the basis of any aquatic ecosystem and its quality index can make or mar wellbeing of the entire aquatic environment (Wei & Huang, 2010). The level of dissolved oxygen (DO) in the aquatic environment is the default factor used in estimating and characterizing of the water quality index. The concentration of the DO reflects a balance in the oxygen producing and oxygen consuming processes and activities in the system (Olyaie, Abyaneh, and Mehr, 2016).

Furthermore, other environmental parameters such as temperature, salinity, turbidity, pH as well as water level in the system also plays significant roles in the estimation of the DO and consequently the water quality in the system. The water quality is also influenced by the inefficiency of feeding systems which counts for considerable amount of waste from the unconsumed feeds dispensed (Garcia et al., 2011). Aside these factors, the excreta of the aquatic organisms also add to the effect on the water quality.

There exist different approaches for the estimation of the water quality index in the aquatic environment with respect to the DO level in it. One of such approaches is the application of the Artificial Neural Network (ANN) in developing reliable DO model for the prediction of this Index (Olyaie, et al., 2016).

The ANN mimics the information processing capability of the human nervous system in solve complex problems such as the prediction and modeling of DO with respect to other parameters. However, its efficacy lies in the ability to select and use optimal network parameters in developing the associated model (Schmid and Koskiaho, 2006; Antanasijevic et al. 2014; Olyaie, et al., 2016). Based on this, the paper proposes the development of an iterative algorithm for the selection of optimal network parameters for the ANN in the quest to develop an optimal DO prediction model.

The remaining section of this paper is divided as follows; Section II presents the review of the related past works. In Section III the description of the methodology as it relates to the dataset used and the proposed algorithm in relation to ANN. In Section IV the result obtained from the developed Model is presented and discussed. Finally, Section V concludes the work.

2 REVIEW OF RELATED PAST WORKS

Advancement in Artificial Intelligence and computational Intelligence have led to the various techniques adopted in the prediction and modeling of the water quality. These techniques involves the use of Artificial Neural Network (Gustilo & Dadios, 2011; Miao et al., 2010; Nan et al., 2006; Schtz, Lima, Eyng, & Bresolin, 2015; W. Wang, Changhui, & Xiangjun, 2014; Xuemei, Yingzhan, & Xingzhi, 2011), Particle Swarm Optimization (Deng, Wei, & Guo, 2006; Xu, Hu, & Liu, 2011). The use of Genetic Algorithm, Fuzzy Logic Control (Chang & Xinrong, 2013; Fu, Qiao, Han, & Meng, 2015; Hidayah, Tahir, Rusop, & Rizam, 2011; Wang et al., 2006), Gray wolf Optimization (Sweidan, El-Bendary, Hassanien, & El-karim, 2013).

Furthermore, one remarkable merit made in the past in quest to proffer reliable solution to the water quality problem is in development of various ANN based prediction system for the quantification of the water quality index with respect to the DO parameter in the aquaculture system. A review of the some works with respect ANN approaches and techniques developed are as follows;

Antanasijevic et al. (2014) presented a review of various approaches of ANN used for the prediction of dissolved oxygen with respect to water quality. The review indicates backpropagation feedforward ANN has high performance in the prediction of the dissolved oxygen. Thereafter a comparison of a General Regression Neural Network and the Monte Carlo Simulation was made. The obtained results depict the GRNN outweighing the Monte Carlo simulation hence the ANN is effective in the prediction of dissolved oxygen.

In another related work, Olyaie, et al.,(2016) presented a comparative analysis of the different computational intelligence namely the Multi-Layer Perceptron (MLP) ANN, Radian Basis Function (RBF) ANN, Linear Genetic Programming (LGP) and Support Vector Machine (SVM) based algorithms for the prediction of dissolved oxygen level as a function of water quality in Delaware River. The results indicate the SVM has the best result next to the LGP, the MLP and the RBF with minimal difference, which depicts the MLP and RBF have the capability of producing better prediction results for the dissolved oxygen.

Malek, Salleh and Ahmed (2010) carried out an investigative analysis on feedforward ANN and the fuzzy logic for model estimation with both algorithms giving similar results, an indication that both algorithms are applicable in the estimation of water quality. Schtz et al. (2015) investigated the effects change or altering the Network parameters to the performance of backpropagation ANN on the simulation of the dissolved oxygen in river waters. The number of hidden layers, learning rate and momentum term were varied in quest to obtain a suitable ANN model for the prediction of the Dissolved Oxygen.

Furthermore, Luo, Liu, and Huang (2010) carried out a similar research to investigate the effect on variation in the number of layers and the neuron in each layer of the ANN structure on the value of prediction output obtained. The obtained results supports the findings similar research findings of Schmid and Koskiaho, 2006 that investigated the performance of variation of the number of layers, neurons in each layer and the learning rate on a MLP ANN model for prediction dissolved oxygen as a function of water quality.

Based on the foregoing, it is evident that the parameters of the ANN such as the type of system architecture, the activation functions, number of neurons in each layers as well as the learning rate are paramount to attaining a reliable model (Olyaie et al., 2016; Schtz et al., 2015) . Thus, optimal network parameters plays significant roles on the ANN model performance (Antanasijevic et al., 2014). Thus, this paper proposes an Iterative Parameter Selection (IPS) approach for the selection of the ANN parameters to be used in estimating the water quality index in a Tank Cultured Re-Circulatory Aquaculture System.

3 METHODOLOGY

The methodology is divided into three sections. In the first section, a detailed description of the dataset used is presented, while the second section presents an overview of the proposed iterative parameters selection algorithm as it relates to the ANN and the evaluation metrics.

3.1 DATA SET DESCRIPTION

The data set for this study was obtained from the Water Resources, Aquaculture and Fisheries Technology (WAFT) Laboratory through a continuous monitoring of the water quality parameters of the Tank-Cultured Re-Circulatory Aquaculture System. The dataset consists of measured parameters of the Temperature, Dissolved Oxygen, Alkalinity, Conductivity and pH. The typical ranges of values of parameters in the dataset are as presented in Table 1.

TABLE 1: TYPICAL RANGE OF THE DATASET PARAMETERS.

Parameter	Range of Values
$Temperature$ (T)	(20.6- 34.1) OC
$Conductivity$ (C)	(108-271) $\mu S/cm$
$Alkalinity$ (A)	(7.0-112) mg/L
pH (p)	6.4-8.7
$Dissolved\ Oxygen\ (DO)$	(2.9-6) mg/L

The temperature is a measure of degree of hotness or coldness of the water environment of the aquatic species. The temperature also has an inverse relationship with the dissolved oxygen, as the temperature increases a resultant decrease in the value of the dissolved oxygen. Aside the effect on dissolved oxygen, it also affects the feeding rate of the fishes (Anyachebelu, et al., 2014).

The pH is an indication of the how acidic or basic the water environment is. It is the measure of the hydrogen ion concentration in water. Often at night there is an increase in the values and a decrease during the day times. Typical recommended range for pH is 6.5 to 9.0. Characteristically, as the pH increases, the toxic ammonia and other nitrates becomes hazardous to the health of the fishes (Anyachebelu, et al., 2014).

The Alkalinity refers to the ability to resist sudden changes in the values of the pH in the aquatic environment. It is also the true measure of acid neutralizing capacity of the water. The total Alkalinity increases pH and available bases which in turn leads to less toxic actions (Anyachebelu, et al., 2014).

Conductivity is a measure of the available dissolved salts and Minerals present in the water. It also refers to the ability to allow electrons through water. The presence of dissolved minerals and salts like iron, calcium has significant effect on the growth and well been of the fishes. Furthermore, there is a relationship between the temperature and the conductivity. The warmer the water, the higher the conductivity (Anyachebelu, et al., 2014).

Dissolved Oxygen remains the most important water quality parameter. It is the measure of the available oxygen in water for the healthy survival of the fishes. The Dissolved Oxygen is influenced to a large extent by the temperature and has an inverse relationship with it. The Dissolved oxygen also has effects on the feeding rate of the fishes as well as growth and disease tolerance of the species (Anyachebelu, et al., 2104).

3.2 ARTIFICIAL NEURAL NETWORK.

The ANNs are an attempt at modeling the information processing capability of the human nervous system has coordinated by the Brain. The ANN remains a very useful and powerful tool for modeling complex linear as well as nonlinear problems. Although there exist numerous types of ANNs which are often characterized by the nature of problems they are required to handle. This study adopts the typical Multi Layered Perceptron with the Back-Propagation Algorithm (MLP-BP). The MLP-BP are known to have good performance for many complex linear and nonlinear problems involving modeling and prediction of many water quality and ecological related problems. The structure adopted MLP-BP is as depicted in Figure 1, the ANN consists of one input node and two layers namely the Hidden and Output layers.

The Temperature, pH, Conductivity and Alkalinity are fed through the Input nodes as input to the Neural Network and Output layer presents the desired target which is the DO. The hidden layer is an intermediate layer between the input nodes and the output layer.

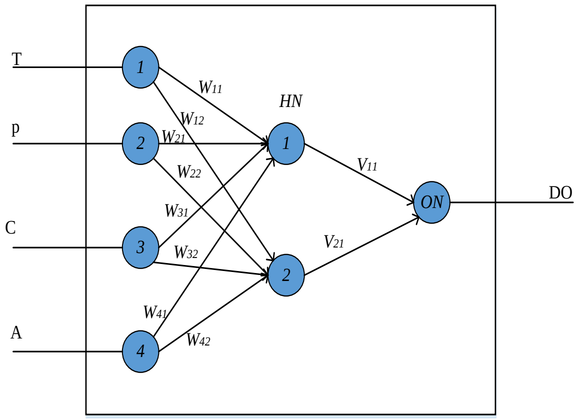

Figure 1: The Structure of the ANN Model

The layers consist of neurons whose output is a function of weights and activation functions in the neurons, and is defined by:

$$y = \varphi\left(\sum_{i=1}^{n} w_{ji}x_i + b_j\right) \qquad (1)$$

$where;$ w is the $interconnecting$ $weight;$
x is the $input$ to the $neuron$
b is the $connecting$ $bias$
i is the $number$ of $inputs$
j is the $number$ of $neurons$ in the $layer$
φ is the $activation$ $function$ of the $layer$

Thus, in this paper, the DO is used as a basis of the water quality index. The DO model presented herein this work is a function of Temperature (T); pH (p); Conductivity (C); and Alkalinity (A). The relating model is depicted as;

$$DO = f(T, p, C, A) \qquad (2)$$

The algorithm for the proposed Iterative Parameters Selection (IPS) is as depicted in Table 2. The goal of the algorithm is to obtain the most optimal values of the number of neurons in the hidden layer and its associated activation function. The iterative-ness of the algorithm arises for the multiple iterations that happens within before a possible solution is being obtained through the evaluation metrics. The values of the input parameters are preprocessed to ensure the dataset are of same range using the Min-Max normalization technique defined as;

$$Minmax = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (3)$$

$where;$
$x\ is\ the\ values\ of\ the\ T, C, p, A\ and\ DO\ in\ the\ dataset$
$x_{min}\ the\ minimum\ values\ of\ the\ T, C, p, A\ and\ DO$
$x_{max}\ the\ maximum\ values\ of\ the\ T, C, p, A\ and\ DO$

TABLE 2: THE IPS ALGORITHM

Start
for i=1 to 2^{2n-1} %i=No of Neurons in hidden layer; n is %range $(\mathbf{1} < \boldsymbol{n} \le \mathbf{4})$
for j=1 to 3 %j is the type of activation function in %hidden layer;1=tansig;2=logsig;3=purelin.
Set the Number of hidden layer to 1.
Initialize ANN
Evaluate performance of ANN for Result %Based on %choosen %Metrics(mse).
Save and Increment j
End j
Save and Increment i
End i
[Optimalvalue OptimalIndex]=best(Evaluation Result)
Return value of i, j for Optimal Index
End

The process starts from the initialization of the number of neurons in the hidden layer defined by a maximum search range of $\boldsymbol{2^{2n-1}}$ where n is the range value that varies between 1 to 4. The value of n=3 has been set for this paper. Thereafter, the activation function is initialized and the counter also set. After this process, appropriate values of the neurons number and activation function of the hidden layer are inputted to the ANN network. The evaluation results are then processed for the best values obtained with corresponding values of the parameter presented.

In this research, emphasis has been laid on the capability of the proposed IPS algorithm in selecting an optimal number of neurons in the hidden layer. Furthermore, the algorithm has features of also determining the best activation function in the hidden layer. Furthermore, the performance evaluation metric adopted in this work helps in providing varying details on the predictive capability of the developed Network and it is based on the Mean Squared Error (MSE) and the Nash-Sutcliffe Efficiency Coefficient (NSE) and they are defined as follows;

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(DO_p(i) - DO_A(i)\right)^2 \quad (4)$$

$$NSE = 1 - \frac{\sum_{i=1}^{n}\left(DO_p(i) - DO_A(i)\right)^2}{\sum_{i=1}^{n}(DO_A(i) - \overline{DO_A})^2} \quad (5)$$

$where;$
$DO_p(i)\ is\ the\ predicted\ value\ of\ the\ DO.$
$DO_A(i) is\ the\ actual\ value\ of\ the\ DO_A$
$\overline{DO_A}\ is\ the\ mean\ value\ of\ the\ DO.$
$n\ is\ the\ size\ of\ sample.$

4 Result and Discussion

In quest to evaluate the performance of the developed IPS algorithm a Three-layered network ANN was developed using the Matrix Laboratory (MATLAB) software 2015a version. Furthermore, as a measure of evaluating the effectiveness of the developed algorithm, results obtained was compared with that of standard approaches for determining the most optimal number of Hidden layer neurons as identified in Basheer and Hajmeer (2000). The Jadid (J approach) and Upadhayaya (U approach) approaches defined by (6) and (7) respectively were adopted for comparison in this research.

$$HN = \frac{Row_N}{Range\ (Output_{PE} + Input_{PE})} \quad (6)$$

$where;$
$HN\ is\ the\ number\ of\ neurons\ in\ Hidden\ Layer$
$Row_N\ is\ the\ number\ of\ rows\ in\ Training\ data\ set;$
$Range\ \ is\ a\ constant\ which\ ranges\ from\ 5 - 10;$
$Input_{PE}\ Number\ of\ processing\ element\ in\ the\ input\ layer\ ;$
$Output_{PE}\ Number\ of\ processing\ element\ in\ the\ output\ layer\ ;$

$$HN = I + log_2^N \quad (7)$$

$where;$
$HN\ is\ the\ number\ of\ neurons\ in\ Hidden\ Layer$
$N\ is\ the\ number\ of\ Training\ patterns;$
$I\ is\ the\ size\ of\ input\ vector.$

The approaches had the capacity of the determining the optimal number of neurons in the hidden layer of the 3 layered ANN, when the parameters in Table 3 are substituted into the respective equations.

TABLE 3: PARAMETERS OF VALUES.

Parameters	Row_N	*Range*	$Input_{PE}$	$Output_{PE}$	*N*	*I*
Values	100	5	4	1	100	4

To ensure uniformity in the Neural Network created for evaluation, the Levenberg-Marquardt (LM) training function and the Gradient Descent Method (GDM) learning function adopted and remained unchanged during the process for the three methods. The IPS approach was used to determine the most suitable activation function of three different types namely Tansig, Purelin and Losig functions to be used in the hidden layer. The Logsig function was selected as the most optimal for the layer. The number of neurons for hidden as obtained from the three approaches and the corresponding performance evaluation results based on the earlier defined metrics are as depicted in Table 4.

TABLE 4: COMPARISON OF THE APPROACHES

	MSE	NSE	NHN
J Approach	0.0350	0.5633	4
U Approach	0.0386	0.5185	27
IPS Approach	0.0234	0.6100	40

The result of the performance of the 3 approaches with respect to the earlier defined metrics of evaluation and the number of neurons in the hidden layer are as depicted in the Table 4. This indicated the IPS approach as having a larger number of neurons in the hidden layer as compared to the J approach as well as the U approach with lower and constant defined number. The reason for the higher numbers associated with the IPS approach is owing to the wider space and the iterative nature of the approach. Furthermore, researchers have argued that the number of neurons in the hidden layer has effect on the performance of ANN to which it can make or mar the performance. This is evident in the result obtained.

Furthermore, the results also depict the IPS approach as having the least MSE values of 0.0234. The implication of this is that the approach has a reduced error margin between the predicted and the actual values of the DO. The main essence of the MSE is to create a measure of the error margin as well as measures of the deviation of the model output from the actual output represented by the dataset used. The smaller the values of the performance evaluation index the better the model performance. With this result, the IPS approach has the better performance as compared to other two approaches and the J approach outweighs the U approach. In addition, with the Sutcliffe Efficiency (NSE), which is a measure of the goodness of fit of a predicted model as compared to the actual model shows the IPS approach having a better performance as compared to others. The value of the NSE ranges from $-\infty$ to 1 wherein if the value is 1 there is a perfect match of the predicted model to the actual model, thus the closer the efficiency value is to 1 the better the model. Thus, the J approach has a better NSE value of 0.56 as compared to the U approach, however the IPS approaches produces a better result as compared with that of the J approach. Thereby placing the IPS approach with NSE of 0.610 as better solution as compared to the other 2 approaches. A plot of the output of the three approaches as compared with Normalized actual DO values is as presented in Figure 2.

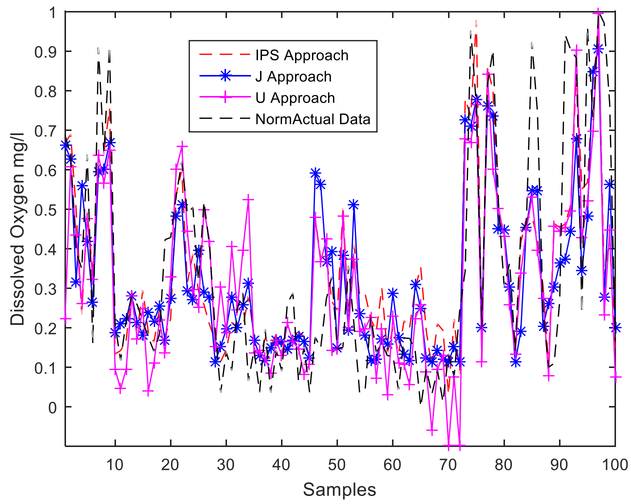

Figure 2: The Normalized Actual DO Vs the three approaches Model Output

5 CONCLUSION

In this paper, we have presented comparative comparison of different approach in determining the number of neurons in the hidden layer of a typical ANN. This is with the view of predicting the water quality index as a function of the Dissolved Oxygen in a Tank Cultured Recirculatory Aquaculture System. The results obtained shows the effect of the number of neurons in the hidden layer on the performance of a typical Back propagation ANN model. In this paper, we developed an Iterative Parameter Selection Algorithm for the determination of the hidden neuron number and the performance compared with two other known approaches namely the Jadid and Upadhyaya approaches. Furthermore, the performance of the approach was investigated with a BP ANN using the MSE and NSE metrics. The results show the IPS approach has having a better performance than the other approaches and consequently a better prediction result. Conclusively, the result obtained showed the capability of the algorithm as well as the ANN in offering reliable solution for determining the level of dissolved oxygen and robust artificial intelligence technique means of determining water quality index in aquaculture systems.

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