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Water Quality Index Estimation Model for Aquaculture System Using Artificial Neural Network[1]

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Abstract: *Water Quality plays an important role in attaining a sustainable aquaculture system, its cumulative effect can make or mar the entire system. The amount of dissolved oxygen (DO) alongside other parameters such as temperature, pH, alkalinity and conductivity are often used to estimate the water quality index (WQI) 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), however, its efficacy lies in the ability to select and use optimal parameters for the network. In this work, different WQI estimation models have been developed using the ANN. These models have been developed by varying the activation function in the hidden layer of the ANN. The performance of the ANN based estimation models was compared with that of the multilinear regression (MLR) based model. The performance comparison depicts the ANN model case 3 with a tangent activation function as the most accurate and optimal model as compared with MLR model and other ANN models based on the mean square error (MSE), root mean square error (RMSE) and regression (R) metrics. The optimal model has a goodness of fit of 0.998, thereby outweighing other developed models in its capability to estimate the WQI in the aquaculture system.*

Keywords: *Artificial Neural Network (ANN), Water Quality Index (WQI), WQI Estimation, Dissolved Oxygen (DO), Aquaculture.*

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I. INTRODUCTION

The activities involved in the cultivation of aquatic animals under controlled conditions and environment are referred to as Aquaculture [1, 2]. The quality of water available for use in this system of farming practice remains a challenge, as it has effects on the system performance [3]. The water quality is a measure of the suitability of the environment to the aquatic organisms [4]. A good water quality encourages improved productivity and vice-versa for a bad quality. The chemical, biological and physical properties as well as the activities of organisms are known to have effect on the state of the water quality [5]. The known parameters that influences the water quality in any aquaculture system includes the

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dissolved oxygen (DO), temperature; turbidity; pH; salinity; conductivity; alkalinity; ammonia and other nitrate content [6, 7].

The DO is the most influential parameter of the aforementioned parameters that influences water quality conditions [6]. It is also an essential quality for survival and a measure of the available oxygen in water. DO is influenced to a large extent by the temperature and has an inverse relationship with it [7, 8]. The feeding rate of aquatic organisms as well as their growth rate and tolerance to diseases is also influenced by the extent of the DO in the water environment [3, 9]. Hence, water quality models are often built around the DO, with respect to other parameters. Water Quality Index (WQI) models are used to estimate and predict the trends in the quality of water conditions based on the aforementioned parameters.

There exists different approaches for the estimation of WQI in the aquatic environment such as statistical and deterministic models [10, 11], Artificial Neural Network [10, 12-16], Particle Swarm Optimization [8, 17]. The use of Genetic Algorithm, Fuzzy Logic Control [18-21], Gray wolf Optimization [22].

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 systems for the quantification of the water quality index with respect to the DO parameter in the aquaculture system. Antanasijevic, et al. [5] presented a review of various approaches of ANN used for the prediction of DO as basis for 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 (GRNN) and the Monte Carlo Simulation was made. The obtained results depict the GRNN outweighing the Monte Carlo simulation hence, ANN is effective in the prediction of DO.

In another related work, Olyaie, et al. [7] 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 DO level as a function of water quality in Delaware River. The results indicate that 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.

Malek, Salleh and Ahmed [23] 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. [16] investigated the effects of changing the Network parameters to the performance of backpropagation ANN on the simulation of the DO 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 DO. Furthermore, Luo, et al. [24] 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 support the findings of similar research [25] that investigated the performance of varying the number of layers, neurons in each layer and the learning rate on a MLP ANN model for prediction DO 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 [7, 16]. Thus, optimal network parameters plays significant roles on the ANN model performance [5]. Thus, the concept of varying ANN parameters has been used to develop artificial intelligence based mathematical model for the estimation of WQI in aquaculture system, thereby providing a new approach for the estimating and predicting WQI values for aquaculture system.

The remaining section of this paper is divided as follows; Section II describes the methodology as it relates to the acquisition of the dataset used and the model formation procedures. In Section III, the result obtained from the developed models are presented and discussed. Finally, Section IV concludes this work.

II. METHODOLOGY

1. Data Set Acquisition and Description

The dataset for the research has been acquired and process using the scheme depicted in Figure 1. The process starts with acquisition of the required dataset from a tank-cultured recirculatory aquaculture system through a continuous process of monitoring. The dataset consists of measured parameters of the Temperature, DO, Alkalinity, Conductivity and pH. The description of the dataset is as depicted in Table 1[3, 9].

Figure 1: Dataset Acquisition Process

Table 1: DescriPtion of the Dataset.

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

To remove associated noise while acquiring the dataset from the system, a moving average finite impulse response filter was applied. The representation of the filter is defined by,

$$h(n) = \sum_{m}^{p} b_m \, x(n-m) \tag{1}$$

where $h(n)$ is the output of the filter, $x(n)$ is the input signal, p is the order of the filter and b is the gain of the filter.

Furthermore, the filtered dataset was preprocessed using the minmax technique. This is to ensure all the dataset are normally distributed [9].

$$Minmax = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{2}$$

where x is the corresponding values of parameters of the dataset, x_{min} and x_{max} are the maximum and minimum values of x.

2. Artificial Neural Network (ANN)

The ANN is an attempt at modeling the information processing capability of the human nervous system as coordinated by the Brain [26]. 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 [26]. 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 [26]. The structure adopted MLP-BP ANN is as depicted in Figure 2 [3]. The ANN consists of three layers namely, the input, the Hidden and Output layers.

The numbers of nodes in the input layer and output layer corresponds to the numbers of input variables and output variable respectively. The relationship between the input parameters (temperature, pH, alkalinity and conductivity) and output (DO), is created such that the water quality index (WQI) as defined by:

$$WQI = f(T, p, C, A) \tag{3}$$

The *WQI* model is formed as a function of the interaction between input variables (x_i), weights (w_i ; w_j) and bias (b_i ; b_j) through the network layers of the BP ANN to the output variables (y). The input nodes act as a buffer for distributing the input signals (temperature, pH, Conductivity, alkalinity) to the neurons in the hidden layer (4). The hidden layer neurons thereafter sum up its inputs signals after weighting them with the strengths of the respective connections (w_{ij}) from the input layer and computes it output based on the activation function threshold (5). The output of the hidden layer is thereafter passed as the input to the output layer, which in turn produces the network output (6) after the interaction with the respective weights (w_{ji}) and bias b_2.

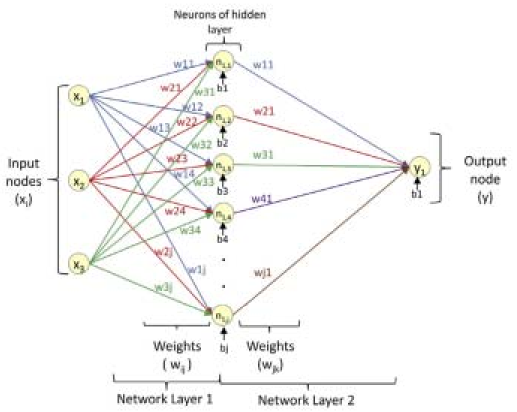


Figure 2: The ANN Structure Representation.

$$input = w_{ij}x_i + b_j \quad (4)$$

The output of the network layer 1 is;

$$y_h = \varphi\left(\sum_{i=1}^{m}(w_{ij}x_i + b_j)\right) \quad (5)$$

The output of the network layer 2 and the MLP is given by;

$$y_{output} = \alpha\left(\sum_{i=1}^{n}(w_{ji}y_h + b_2)\right) \quad (6)$$

Substituting (5) into (6)

$$y_{output} = \alpha\left(\sum_{j=1}^{n}\left(w_{ji}\varphi\left(\sum_{i=1}^{m}(w_{ij}x_i + b_j)\right) + b_2\right)\right) \quad (7)$$

where φ is the activation function of the hidden layer; α is the activation function of the output layer, w_{ij} and w_{ji} are the weights connection between the input and the hidden layer and that of the hidden layer to the output respectively, bj, and b_2 are the bias of the hidden and output layer respectively, j is the number of neurons in hidden layer, m is the number inputs.

In relation to the problem

$$\Gamma = \mathrm{WQI} = y_{output} \quad (8)$$

$$[T, p, A, C]^T = x_i \quad (9)$$

where T, p, A, C corresponds to the values of the Temperature, pH, Alkalinity and Conductivity respectively.

The weights connections w_{ij} and w_{ji} are adaptively selected and updated using the backpropagation algorithm such that a new weight at an instant (t) is dependent on the previous values at an instant (t-1) such that:

$$w_{ij}{}^{n}(t) = w_{ij}{}^{n}(t-1) + \Delta w_{ij}{}^{n}(t) \quad (10)$$

$$\Delta w_{ij}{}^{n}(t) = \eta\delta_j{}^{n}x_i{}^{n-1} + \mu\Delta w_{ij}{}^{n\,(previous)} \quad (11)$$

where Δw_{ij} is the increment of the change in the values of the weights in a layer (n), x_i^{n-1} is the input from the preceding $(n\text{-}1)^{th}$ layer of the ANN, η is the learning rate that controls the update step size, μ is the momentum coefficient and δ_j is the error term associated with weight in the layer (j). However, if the layer j is an output layer the error term is defined as;

$$\delta_j{}^{n} = (x_j{}^{n} - y_j)x_j{}^{n}(1 - x_j{}^{n}) \quad (12)$$

While for a hidden layer the error is defined as;

$$\delta_j^{\;n} = x_j^{\;n}\left(1 - x_j^{\;n}\right)\left(\sum_{L=1}^{k} \delta_L^{\;n+1}\, w_{Lj}^{\;n+1}\right) \quad (13)$$

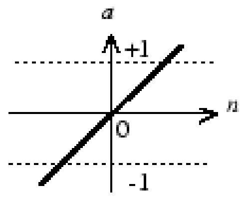
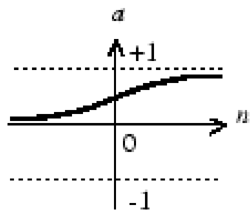
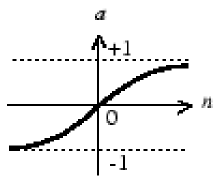
where $\delta_L^{(n+1)}$ is determined for the non-output layer (n) beginning with a layer one level (n+1) and moving down layer by layer. $\delta_j^{\,n}$ is determined via $\delta_L^{(n+1)}$ of the output layer calculated via (8).

Hence, the WQI model representing the system based on the ANN structure is therefore obtained by substituting (7), (8) and (9) to obtain,

$$\Gamma = \alpha\left(\sum_{i=1}^{n}\left(w_{ji}\varphi\left(\sum_{i=1}^{4}\left(w_{ij}[T,p,A,C]^{T} + b_j\right)\right) + b_2\right)\right) \quad (14)$$

Based on (14), it can be seen that the WQI model is dependent on the activation functions (φ, α), the number of neurons in the hidden layer on which the connecting weights w_{ji} and w_{ij} depend and the type of input data (T,p, A, C). For the purpose of this work, the number of neurons in the hidden layer was determined using the iterative parameter selection algorithm [3], while the activation function α is assumed to be a linear function such that the output WQI is linear. However, the activation function φ is varied thus producing the different estimation models. The properties of the 3 types of activation functions used in developing the different models are as depicted in Table 2.

TABLE 2: PROPERTIES OF THE ACTIVATION FUNCTIONS

Descriptive Name	Equation	Derivative	Range	Plot
Linear (Purelin)	$f(x) = x$	$f'(x) = 1$	$(-\infty, \infty)$	
Logistic (Sigmoid)	$f(x) = \dfrac{1}{1+e^{-x}}$	$f'(x) = f(x)(1 - f(x))$	(0,1)	
TanH (Tangent Sigmoid)	$f(x) = \dfrac{2}{1+e^{-2x}} - 1$	$f'(x) = (1 - f(x)^2)$	$(-1,1)$	

Case 1: When φ is a linear such that $f(x)=x$ and ranges from (-∞,∞), the WQI model is presented as:

$$\Gamma = \left(\sum_{j=1}^{n}\left(w_{ji}\left(\sum_{i=1}^{4}\left(w_{ij}[T,p,A,C]^{T} + b_j\right)\right) + b_2\right)\right) \quad (15)$$

Simplifying (14) to become

$$\Gamma = \psi(\rho[T,p,A,C]^{T} + b_i) + b_2 \quad (16)$$

where, ψ is the weights interconnection between in the hidden layer and the output node (w_{ji}), ρ is the weight interconnection between the inner layer and the hidden layer (w_{ij}).

$$\Gamma = (\psi * \rho) * [T,p,A,C]^{T} + (\psi * b_i) + b_2 \quad (17)$$

Case 2: When φ is a Logistic such that $f(x) = \frac{1}{1+e^{-x}}$ and ranges from (0,1), the WQI model is presented as:

$$\Gamma = \left(\sum_{i=1}^{n}\left(w_{ji}\varphi\left(\sum_{i=1}^{4}\left(w_{ij}[T,p,A,C]^{T} + b_j\right)\right) + b_2\right)\right) \quad (18)$$

$$\Gamma = \psi\left(\left(\frac{1}{1+e^{-\left(\rho[T_i,p_i,A_i,C_i]^{T} + b_j\right)}}\right) + b_2\right) \quad (19)$$

where, ψ is the weights interconnection between in the hidden layer and the output node (w_{ji}), ρ is the weight interconnection between the inner layer and the hidden layer (w_{ij}).

Case 3: When φ is a Tangent such that $f(x) = \frac{2}{1+e^{-2x}} - 1$ and ranges from (-1,1), the WQI model is presented as:

$$\Gamma = \left(\sum_{i=1}^{n}\left(w_{ji}\varphi\left(\sum_{i=1}^{4}\left(w_{ij}[T,p,A,C]^{T} + b_j\right)\right) + b_2\right)\right) \quad (20)$$

This implies that,

$$\varphi = \frac{2}{1+e^{-2x}} - 1$$

And

$$\Gamma = \psi\left(\left(\frac{2}{1+e^{-2\left(\rho[T,p,A,C]^{T} + b_j\right)}} - 1\right) + b_2\right) \quad (21)$$

where, ψ is the weights interconnection between in the hidden layer and the output node (w_{ji}), ρ is the weight interconnection between the inner layer and the hidden layer (w_{ij}).

The performance of the models developed in Case 1, Case 2 and Case 3 have been evaluated using the Mean Squared Error (MSE) (22), Root Mean Square Error (RMSE) (23) and Regression (R) (24). The MSE, and RMSE are a measure of the error between the actual and predicted values of the WQI, while the R is a measure of the good of fit of the developed model.

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\widehat{\Gamma_{(\iota)}} - \overline{\Gamma_{(\iota)}})^2 \quad (22)$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\widehat{\Gamma_{(\iota)}} - \overline{\Gamma_{(\iota)}})^2} \quad (23)$$

$$R = \frac{\sum_{i=1}^{n}(\widehat{\Gamma_{(\iota)}} - \widehat{\Gamma_{(\iota)}}^{M})(\overline{\Gamma_{(\iota)}} - \overline{\Gamma_{(\iota)}}^{M})}{\sum_{i=1}^{n}\left(\widehat{\Gamma_{(\iota)}} - \widehat{\Gamma_{(\iota)}}^{M}\right)^2 \sum_{i=1}^{n}\left(\overline{\Gamma_{(\iota)}} - \overline{\Gamma_{(\iota)}}^{M}\right)^2} \quad (24)$$

where, $\widehat{\Gamma_{(\iota)}}, \overline{\Gamma_{(\iota)}}$ are the actual and predicted values of Γ and $\widehat{\Gamma_{(\iota)}}^{M}$, , $\overline{\Gamma_{(\iota)}}^{M}$ are the corresponding mean values of actual and predicted values of Γ, and *n* is the number of samples in the dataset.

III. RESULTS AND DISCUSSION

The models have been developed using an acquired dataset of 129 samples after the filtering and preprocessing processes have been applied. In the training of the models, 70 samples of the dataset were used, while 30 samples were used for validation process and remaining 29 samples was used for testing the model.

The performance of Case 1, Case 2 and Case 3 models during the training and testing phases based on the earlier defined inputs and output parameters are as summarized in Table 3. It can be observed that the performance of individual models during the training and testing are similar and does not vary significantly, however, there exist substantial difference when compared with others. This establishes the consistency in the model performance during the training and testing phases. Furthermore, the statistical values of the metrics for the best fitted model also does not vary as well. This further establishes the consistency of the developed model. In addition, it is observed that Case 3 model has the least values of MSE as compared with other models during the training and testing phases. The lower the MSE, the smaller the error existing between the actual and predicted model and the better the model. Thus, making the Case 3 model with a tangent sigmoid activation function as the best model as compared to other in terms of the MSE. In addition to the MSE, Case 3 model also has the least value of RMSE as compared with other models. This justifies the existence of a reduced error between the actual and predicted values. The performance of the Case 3 model is as result of the dynamic range of the activation function of (-1,1) as compared to the ranges of (-∞,∞) and the (0,1) of the Case 1 and Case 2 respectively. The performance of the Case 2 model in terms of the MSE and RMSE outweighs the performance of the Case 1 model, having produced a model with a reduced value of the metrics. These results show that the type of activation function used has effect on the performance of the model output.

To further ascertain the suitability of the developed models, the R metrics was also used for their evaluation. In an opposite pattern to MSE and RMSE, the higher the R value, the better the goodness of fit of the model to the actual model and the better the model, however, the values of R cannot exceed 1. From Table 3, it can be observed that Case 3 model has the highest R value as compared to other models. These high R values predicts the WQI values of the model to be higher than those of Case 2 and Case 1 models. Thus, depicting Case 3 model as the model with best predictive capability in comparison with the Case 1 and Case 2. Conclusively, Case 3 model is presented as the best model for predicting the WQI as compared to other models in this study with respect to the MSE, RMSE and R metrics. This is as a result of the performance of the Case 3 during the training and testing phases. The performances of the developed models are as presented in Figure 3-4. A good observation of the closeness of Case 3 model during the training and testing, reveals how it supports its goodness of fit and predictive capability as compared to the Case 1 and Case 2 models. The final mathematical representation of the Case 3 model is as depicted in (25)

$$\Gamma = \psi\left(\left(\frac{2}{1+e^{-2\left(\rho[T,p,A,C]^T+b_j\right)}}-1\right)+0.3390\right) \quad (25)$$

where ψ is a [77x1] matrix, ρ is a [77x4] matrix and b_j is a [77x1] matrix

In addition, to the developed model cases a multiple linear regression (MLR) model was also developed for the purpose of comparing its performance with the best model produced using the ANN approach. The MLR was developed such that the input variables to the ANN serves as the independent variables (Predictors), while the output is used as the dependent variable. The obtained MLR is presented as;

$$\Gamma=-3.8222-\ 0.12078T + 1.1252p + -0.00149C + 0.02048A \quad (26)$$

The MLR model is depicted in (26), where the coefficients of the independent variables

Table 3 Performance Comparison of the models during training and testing Phases

	Training			Testing		
	MSE	RMSE	R	MSE	RMSE	R
Case 1 Model	0.4400	0.663	0.4380	0.4410	0.6633	0.5579
Case 2 Model	0.01325	0.1151	0.9874	0.01357	0.1154	0.986
Case 3 Model	0.00245	0.0495	0.9978	0.00245	0.0495	0.9981

(temperature (T), pH (p), conductivity (C) and alkalinity (A)) represents the WQI model. A comparison of this MLR and Case 3 model is presented in Figure 5. The performance of these models has been used to produce the summarized result in Table 4. The results depict the performance of the Case 3 outweighing the MLR model in terms of the MSE, RMSE and R metrics. The lower values of the MSE and RMSE and the higher values of R produced by the Case 3 model indicates its superiority over the MLR model. Conclusively, based on the results presented in Table 3 and Table 4, it is obvious that the performance of Case 3 model using the ANN approach for the estimation of water quality index is superior to other model developed in this research.

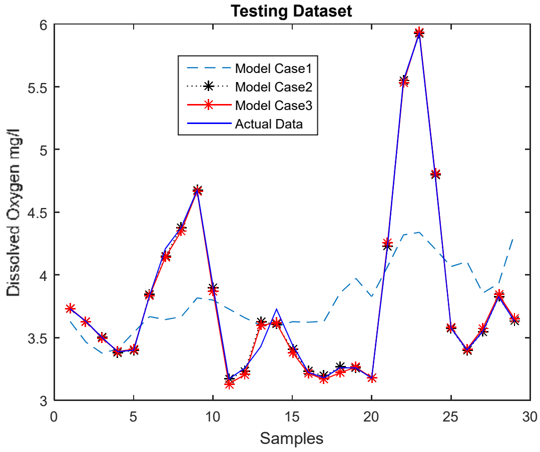


Figure 4. Testing Phase Model Performance.

Table 4 Performance Comparison of the MLR AND cASE 3 mODEL

	MSE	RMSE	R
MLR Model	0.4302	0.6550	0.5098
Case 3 Model	0.00245	0.0495	0.9981

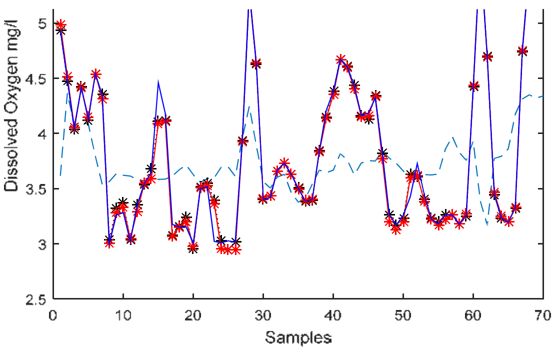


Figure 3: Training Phase Model Performance

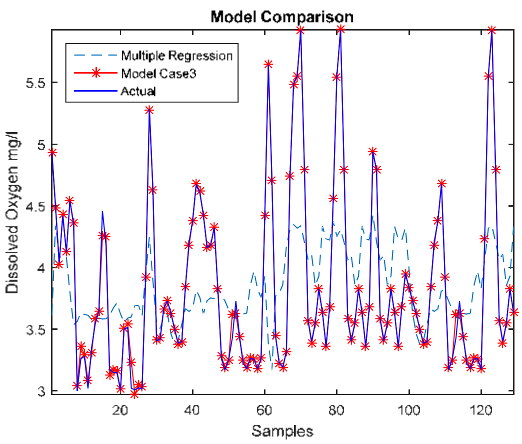


Figure 5. Testing Phase Model Performance.

IV. CONCLUSION

In this study, different models based on varying the network properties of the MLP ANN has been developed for estimating the water quality index in a typical recirculatory aquaculture system. The study utilized the DO as the basis for the estimation of water quality index, with temperature, pH, alkalinity and conductivity as the input to the ANN. The ANN models developed were based on the premise that the type of activation function has effect on the performance of the model. Thus, 3 different model were developed using the linear, sigmoid and tangent sigmoid activation function respectively at the hidden layer of the MLP-ANN while, the function at the output layer was made linear. The results of the comparison, shows that the Case 3 model with a tangent sigmoid activation function has the best capability in estimating the water quality index for the system. Additionally, the Case 2 model with a sigmoid function performance was found to outweigh that of Case 1 with a linear function. The performance of the Case 3 model was thereafter compared with the MLR model, which depicts the Case 3 model as a better model. Conclusively, based on the results presented herein this research shows that Case 3 model of the ANN has the overall best performance in estimating the water quality index as compared with the other developed models. Thus, showing the capability of the ANN in producing reliable and efficient solution for estimating water quality index in aquaculture systems.

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