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Water Temperature Prediction Models in Northern Coastal Area, Vietnam

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Abstract

This paper presents the results of regression models (linear, nonlinear and stochastic regression) and artificial neural network models (ANN) using observed data of daily maximum air and water temperature at Bai Chay station in the coastal areas of Northern Delta, Vietnam. The accuracy of the models was evaluated and compared by R, RMSE, RMSE% and E indicators. The ANN model was highlight results with the RMSE = 1.24; R = 0.98; E = 0.9; RMSE% = 4. The results of the study also show that daily water temperature is affected by daily maximum and average air temperature of previous 1 and 2 days. The main contribution of this study is to identify the appropriate models and time lag factors for water temperature prediction from the air temperature applied to neighboring meteorological stations without water temperature monitoring data. The results of the study could be used as a basis for determining the spatial distribution of water temperature risk to aquaculture in the coastal areas of Northern Delta, Vietnam.

Keywords: Mathematical methods, Environmental issues, Climate, Water, Forecasting models, Model evaluation

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Ethical: This study follows all ethical practices during writing.

Contents

1. Introduction

Water temperature plays an important role in aquatic life, including aquaculture species [1, 2]. The water temperature affects other environmental parameters such as DO, BOD, algae growth, etc., and gets vulnerable to pathogenic bacteria. There are many factors affecting water temperature such as atmospheric conditions, topography and water flow [3]. Among atmospheric factors (solar radiation, air temperature, wind speed, humidity etc.), air temperature is the most factor affecting the variation in surface water temperature [4] that lead to series of water condition change.

In the northern coastal region of Vietnam, beside natural disasters which directly affect fisheries such as storms, floods .etc. every year, the air temperature in summer can reach 39-40^{0}C with hot temperature in long duration, which makes the water temperature too high for the tolerance of aquatic species. On the other hand, when the water temperature rises, aquatic species tend to be active in water of deeper level, leading to an increase in oxygen demand [4] increasing the risk for intensive aquaculture ponds, so temperature is a particularly important factor threatening the stable development of aquaculture sector. Therefore, when studying disaster risks for aquaculture, it is indispensible to consider the risks of maximum daily water temperature to determine the viability of aquatic species [5].

However, water temperature prediction is still a complexity [4] because water temperature depends on many factors. There are number of different application for water temperature predition model Loubna, et al. [6]. Caissie [3] divided into 3 main categories: regression, stochastic, and deterministic models. Otherwise, Caissie [3] and Zhu, et al. [2] gave two categories deterministic and statistical models that they have advantages and drawback.

The deterministic model applies simulations of water temperature using an approach that relates to the total amount of solar energy reaching the earth and the interrelated factors for determining water temperature (eg Sinokrot and Stefan [7]; Webb and Nobilis [8]). This approach is often impractical, complex and time-consuming in collecting and processing input data of many of the explanatory variables which are often difficult to collect such as solar radiation, wind, atmospheric energy [4, 6].

Statistical models could be classified in two categories including parametric and non-parametric models. Parametric models can also be decomposed into regression and stochatic models.

The regression model simulating water temperature based on air temperature is commonly used in many studies due to the simplicity of the collected data and applied for weekly, monthly and annual time steps of data. The regression models including: single and multi-variabe linear regression or nonlinear regression. Simple linear regression using air temperature (monthly or weekly data) is an explanatory variables to determine water temperature [9]. The nonlinear regression model proposed by Mohseni, et al. [10] provided the base to many successful studies [11, 12]. However, regression simulation (linear or nonlinear) is less suitable to apply for shorter time steps such as daily data (due to autocorrelation in time series of water temperature) [6].

The stochastic model [13, 14] was developed from the regression model, proposed by Kothandaraman [15] based on statistics of continuous time series of air temperature and water temperature to act as a basis for defining relationships through parameters. The stochastic model is generally applied to relatively short time data (hourly or daily data) and takes into account the time lag of the relevant factors.

None-parametric models (k-Nearest Neighbour, Artificial Neural Network model-ANN, etc.) use the structure of availble data [6]. Artificial Neural Network model (ANN) has recently been developed with 3 basic layers of multi-layer backpropagation network model [2, 4]: the input layer, one or more hidden layers, and the output layer. The model always uses input data divided into two categories, namely training and testing data set. Application of ANN method has been successfully proved by some studies for water temperature predition (ex: Anamarija [4]; Marijana, et al. [16]; Sahoo, et al. [17]; Zhu, et al. [2]; DeWeber and Wagner [18]). However, the comparison bettween models showed, in some cases ANN models provided better results, while in other case, some regression models provide higher accuracy of results [2]. Their resluts may depend on data quality and study areas, variables of time lags of the daily mean air temperature in multilayer perception ANN models. Therefore,the purpose of this study is to collect the appropriate model of water temperature prediction from air temperature data applying for the meteorological stations without observed water temperature and serving for determining the risk thresholds to aquaculture Northern coastal areas Vietnam.

2. Data and Methodology

2.1. Data

Data of Bai Chay station, Quang Ninh province was used to evaluate the accuracy of the models. 10-years data (2008-2017) of daily air temperature and water temperature including maximum air temperature(Ta_max); maximum water temperature(Tw-max); average air temperature(Ta_tb); average water temperature(Tw_tb) of Bai Chay station is collected.

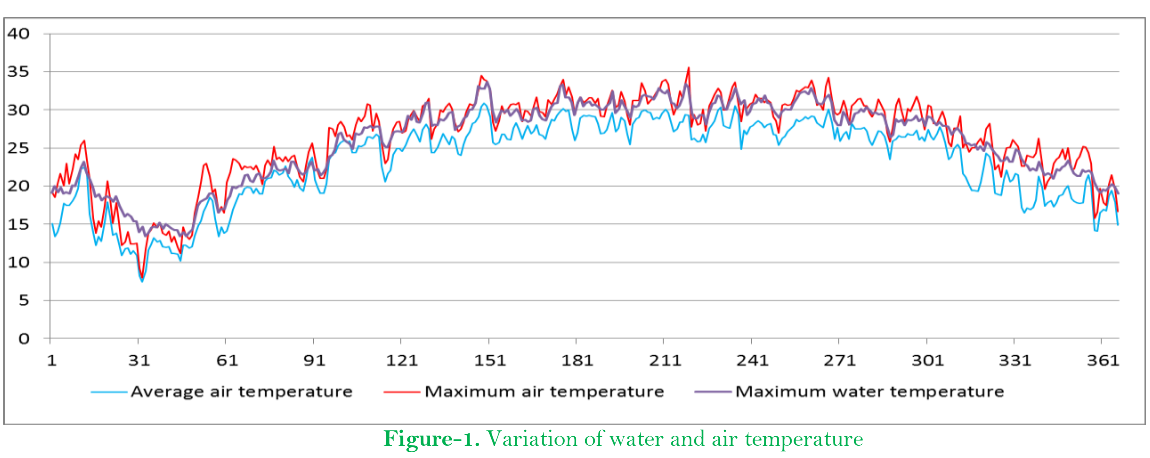

Figure-1. Variation of water and air temperature

Source: Data collected from Bai Chay station (e.g. of year 2008)

Figure 1 shows the correlation between the maximum water and the air temperature at Bai Chay station with the data 2008, points out that the water temperature always changes linearly depending on the maximum and average air temperature. During the year, the maximum water temperature is always lower than the maximum, but higher than the average air temperature. In some case, When fluctuation of day and night temperature suddenly change,the maximum water temperature may be higher than that ones of air temperature (in summer). Thus, the maximum water temperature in a period of time always changes slowly and is not synchronized with the maximum air temperature and it creates a delay time between T_{a_max} and T_{w-max}

2.2. Methodology

A. Simple Linear Regression Model

A simple linear regression model used a linear function with a single explanatory variable. The regression model simulates the variation of water temperature determined by the correlation with air temperature.

Simple linear regression equation:

$$T_{\mathrm{w}}(t) = a_0 + a_1 T_{\mathrm{a}}(t) + \varepsilon(t) \quad (1)$$

$T_w(t)$: water temperature in time t

$T_a(t)$: air temperature in time t; a_0, a_1 is the coefficient of the regression equation

ε(t): Error [6]

B. Nonlinear Regression Model

Most common nonlinear regression methods involve air and water temperatures [6] with 5 parameters..

$$T_w = \frac{\alpha}{1+e^{\gamma(\beta - T_a)}} \quad (2)$$

Where T_w: Daily maximum water temperature predition

T_a: Air temperature measured by day t

α, γ, β: The coefficient of the model, calculated by using the nonlinear regression model under the condition of minimum sum of squared difference (SSD).

C. Stochastic Model

Stochastic model proposed by Kothandaraman [15] and Cluis [19]. In the model, water temperature T_W is simulated by 2 basic components: (i) air temperature in long periods of time and water temperature in short time period.

$$T_W(t) = T_A(t) + R_W(t) \quad (3)$$

$$T_A(t) = a + b\sin[\frac{2\pi}{365}(t + t_o)] \quad (4)$$

sin () function in Equation (4) shows the trend of variation of water temperature by season or year cycle.

$T_A(t)$: Seasonal air temperature; a,b, t_0: The correlation coefficient of the model which can be identified by nonlinear regression model.

$R_w(t)$: Water temperature over short period of time

The stochastic model is used based on the development of a model proposed by Kothandaraman [15] that determines the time lag between water temperature and air temperature

$$R_W(t) = \beta_1 R_a(t) + \beta_2 R_a(t-1) + \beta_3 R_a(t-2) \quad (5)$$

Where: β1, β2 and β3 are the correlation coefficients of the model, calculated by using the nonlinear regression model under the condition of the minimum sum of squared differences.

$R_a(t)$, $R_a(t-1)$ and $R_a(t-2)$ is the air temperature at time t, (t − 1), (t − 2).

$$T_W(t) = a + b\sin[\frac{2\pi}{365}(t + t_o)] + \beta_1 R_a(t) + \beta_2 R_a(t-1) + \beta_3 R_a(t-2) \quad (6)$$

In model (6), the water temperature at time t is determined based on the dependence of daily air temperature by the sine function in Equation (4) and the lag over time (lag = 1 and lag = 2), corresponding to time t-1 (1 day before) and t-2 (2 days before) of air temperature Equation (5).

D. Artificial Neural Networks -ANN

In recent years, ANN has been applied quite widely in many areas related to estimation and forecasting due to high accuracy when complex nonlinear models are difficult to achieve by conventional mathematical equations [3, 17, 20]. In this study, ANN model are used to identify the daily maximum water temperature with the neurons as input data of the maximum and average air temperature in a time period to determine the time lag between air and water temperature.

Figure 2 show the basic structure of ANN consisting of three basic layers: (i) Input layer (data layer entered - Input layer) are neurons X_1, X_2, ... X_n; (ii) One or more hidden layers - (processing data layer -Hidden layer); and (iii) output data layer (output data layer created - Output layer). Each layer in ANN consists of nodes (neurons), each neuron connects to another neuron of the previous layer and moves from the data layer into the hidden layer to the output layer. In an ANN there might be multiple hidden layers, each neuron in the hidden layer consists of three components, including weights; bias and activation function. The activation function mainly used is sigmoid function (including logsig, tansig- Nonlinear function) or purelin - linear function.

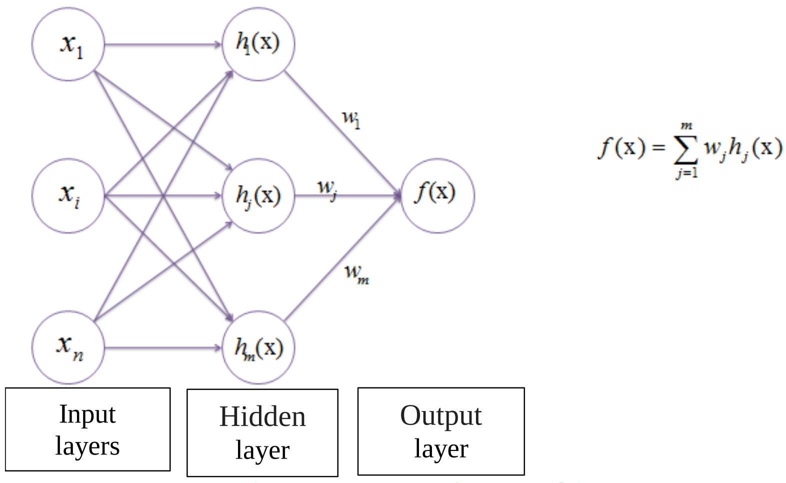

Figure-2. Structure of ANN model

Source: Modified from Srivastav, et al. [21]

According to Marijana, et al. [16] mathematically, neuron is calculated by the equation:

$$v = \sum_{i=1}^{n} w_i x_i - w_{n+1} = \mathbf{w} \cdot \mathbf{x}^{\mathrm{T}} - w_{n+1},$$

Y= ψ(v)

Where: **W**[w_1, w_2…w_n] Vector of the weight

X[x_1, x_2…x_n] Vector of input signal

W_{n+1} Bias

ψ(v) Activation function

ANN associated with machine learning methods, in which input data is divided into 2 parts: training (80%) and testing (20%) data. The training data was used to determine the parameters of the proposed models then the model adjust the weight of each neuron and the error. The quality of the resulting models was assessed using the test dataset. The entire process performed by dedicated software.

E. Model Evaluation

The accuracy of the output is the factor deciding the model's efficiency and is usually done by evaluating some parameters.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(T_{wi} - \hat{T}_{wi})^2} \quad (7)$$

$$RMSE\% = \frac{100}{\bar{T}_w}\sqrt{\frac{1}{n}\sum_{i=1}^{n}(T_{wi} - \hat{T}_{wi})^2} \quad (8)$$

$$E = 1 - \frac{\sum_{i=1}^{n}(T_{wi} - \hat{T}_{wi})^2}{\sum_{i=1}^{n}(T_{wi} - \bar{T}_w)^2} \quad (9)$$

$$R = \frac{\sum_{i=1}^{n}(T_{wi} - \bar{T}_w)(\hat{T}_{wi} - \bar{\hat{T}}_w)}{\sqrt{\sum_{i=1}^{n}(T_{wi} - \bar{T}_w)^2 \sum_{i=1}^{n}(\hat{T}_{wi} - \bar{\hat{T}}_w)^2}} \quad (10)$$

$\hat{T}_{wi}$: water temperature prediction in day i

T_{wi}: Observed water temperature in day i

$\bar{\hat{T}}_w$: Average value of $\hat{T}_{wi}$

$\bar{T}_w$: Average value of T_{wi}

n: Size of data set

Root mean square error – RMSE: The parameter describes the error between observed and calculated data It could be standardized by the percentage% (RMSE%) to describe relativity to the mean value.

Correlation coefficient R: provides information about the linear relationship between the calculated value and the observed value. R value ranges from 0-1. The closer the R=1 value is, the closer the correlation is.

Nash and Sutcliffe [22]: determine the effectiveness of the model. E assesses the relative difference between simulation value and observation value. E has a value of -∞ to 1. The minimum E value of 0.9 specifies an acceptable model.

3. Results and Discussion

In the study, the daily data including air and water observation at Bai Chay station of 10 years (2008-2017) are used and divided into 2 data sets: the data set from 2008-2014 is used as learning data (training data); The data set from 2015-2017 is used as testing data.

The training data (air and water temperature data) are used for coefficient identifiation of regression models including: Simple linear (Equation 1); nonlinear regression model (Equation 2); Stochastic model (Equation 5); artificial neural network model (Variables in Table 1). In the testing data, air temperature data and outputs of models identifying from training data were used to simulate water temperature. Then, the results of comparision between simulated and observed water temperature were implemented through parameters RMSE, R, E,

- *Simple Linear Regression Model*

The coefficients of a simple linear regression model are identified by training data set from 2008-2014 in Excel software. The results determine parameters as follows:

$T_w(t)=2.986+0.874*T_a(t)$

Figure 3 depicts the difference between the observed and the simulated data of the model. The evaluation of accuracy results are shown in Table 2. In which, the correlation coefficient between water temperature and air temperature at Bai Chay station are R = 0.89; RMSE = 1.68. However, NashSutcliffe coefficient E = 0.89 <0.9 shows, this model has a poor accuracy.

- *Nonlinear Regression Model*

Nonlinear regression model is applied similarly to linear regression model with logistic nonlinear regression in solver function in Excel software for training data 2008-2014 . The output of model enable to identify parameter of Equation (2) as follows:

$$T_w = \frac{170.12}{1+e^{0.04(67.93-Ta)}}$$

Figure 4 depicts the difference between observed and simulated data of nonlinear regression models. The results of the model implementation are shown in Table 2. In which, the correlation coefficient between water and air temperature at Bai Chay station is R = 0.9; Root Mean Square Error RMSE = 1.6 and NashSutcliffe coefficient E = 0,9 shows that this model could be applied for the calculation of water temperature from air temperature values.

- *Stochastic Model*

By using the 2-day time lag (t-1) and (t-2), parameters of the Stochastic model are calculated:

$$T_w(t) = 1.74 + 1.99sin\left[\frac{2\pi}{365}(t+1.83)\right] + 0.51T_a(t) + 0.09T_a(t-1) + 0.32T_a(t-2)$$

In the Table 2, the accracy indicators of model R = 0.94; RMSE = 1.4; NashSutcliffe coefficient E = 0.92, show the stochastic model is the outperform of these regression model. Figure 5 describes the correlation coefficient between water and air temperature at the Bai Chay station. It also show that the water temperature is not only influenced by the daily maximum air temperature but it is also greatly influenced by the temperature value of the previous 2 days. This means that when the air temperature rises or falls suddenly, the water temperature continues to fluctuate more slowly in about 2 days (48 hours).

- *Artificial Neural Network Model*

The calculation of network neurals is done by NNTOOL of MATLAB 2018a software, through 3 steps

Step 1 : Network Training

Network training is done through a training data set. Each MLP network configuration is performed with the maximum number of iterations 1000 times (1000 epoch). In the training set, input variables are neurons from MLP1 to MLP10 (Table 1). Through training data set, bias and weights through each loop are identified and adjusted. In this study, the algorithm used is Feed-forward back drop, LevenbergMarquardt (LMA) algorithm–TrainML in Matlap software.

Table-1. Variables in the Artificial neural network model

No	Neuron in the network	Interpretation
1	MLP1: T_{a_max}	Consider the effect of daily maximum air temperature
2	MLP2: T_{a_max}, T_{a_tb}	Consider the effect of maximum and average daily air temperature
3	MLP3: T_{a_max}, T_{a_tb} , T_{a_tb} -1	Consider the correlation of 1 day lag of water temperature with air temperature
4	MLP4: T_{a_max}, T_{a_tb}, T_{a_tb} -1, T_{a_tb} -2	Consider the correlation of the 2-day lag of the average air temperature with the water temperature Ta_tb -2: Daily average air temperature in 2 day before
5	MLP5: T_{a_max}, T_{a_tb}, T_{a_tb} -1, T_{a_tb} -2, T_{a_max} -1	Consider the relation of 1-2 day lag of average air temperature, Maximum air temperature with water temperature
6	MLP6: T_{a_max}, T_{a_tb}, T_{a_tb} -1, T_{a_tb}-2, T_{a_max} -1, T_{a_max} -2	
7	MLP7: T_{a_max}, T_{a_tb}, T_{a_max} (0,1,2), T_{a_tb} (0,1,2)	Consider the correlation of Ta_max variation in 3 days, 1-2 day lag of average air temperature, Maximum air temperature with water temperature
8	MLP8: T_{a_max}, T_{a_tb}, T_{a_max} (0,1,2), T_{a_tb} (0,1,2), T_{a_tb} -1, T_{a_tb} -2, T_{a_max} -1, T_{a_max} -2	Considering the correlation of the average progress in 3 days
9	MLP9: T_{a_max}, T_{a_tb}, T_{a_max} (0,1,2), T_{a_max} -1, T_{a_max} -2	Considering the correlation between variation of Ta_max in 3 days, 1-2 day lag of air temperature, Max air temperature with water temperature
10	MLP10: T_{a_max}, T_{a_max} (0,1,2), T_{a_max} -1, T_{a_max} -2	Consider the correlation of the progress and latency of Max air temperature with water temperature

Source: Defined by the author

Step 2: Testing

When the result of performing network training that satisfies the requirements of the number of iterations produces, the computer software will record the entire process with the weights, errors and adjustment coefficients of each iteration. This process then apply for target data to calculate water temperature prediction and to produce model results

Step 3: Output Evaluation

Evaluation of the accracy results is done by comparing the water temperature data measured and the water temperature generated from the model's testing data to identify the accuracy of the model.

Where:

T_{a_max}: Daily maximum air temperature

T_{a_tb}: Daily average air temperature

T_{a_max} (0,1,2): Average of daily maximum air temperature of 3 days (present and 2 previous days); (0:present day; 1: 1 day before; 2: 2 day before)

T_{a_tb} (0,1,2): Average of daily average air temperature of 3 days' average (present and 2 previous days); (0:present day; 1: 1 day before; 2: 2 days before)

T_{a_tb} -1: Daily average air temperature of 1 day before

T_{a_tb} -2: Daily average air temperature of 2 previous days

T_{a_max} -1: Daily maximum air temperature of 1 day before

T_{a_max} -2: Daily maximum air temperature of 2 previous days

The aim of the study is to find the best model for identifying the maximum water temperature through air temperature. Therefore, the daily maximium and average air temperature are included in all models. MLP4, MLP5, MLP6 models additionally consider the correlation between the water temperature and air temperature with t-1 values: 1 day lag; t-2: 2-day lag; MLP7 and MLP8 models added elements of the effect of air temperature variation in 3 consecutive days (current day and 2 days before).

The results of evaluation in each neuron network structure shown in the parameters in Table 2, Figure 6 show that MLP4 network model with MLP4 neurals: T_{a_max}, T_{a_tb}, T_{a_tb} -1, T_{a_tb} -2 give the outperform results with indicators RMSE = 1.24, RMSE% = 4.5%; correlation coefficient R=0.988 and E = 0.94.

The comparison of RMSE, R, E indicators show that the stochastic model and artificial neural network model with the same variables T_{a_max}, T_{a_tb}, T_{a_tb} -1 T_{a_tb} -2 give better results. From the output of the models, it can be seen that the daily maximum water temperature depends on: the daily average, maximum, and the average temperature of the 2 previous days. This also shows that the time lag of water temperature compared to air temperature is 2 days.

Table-2. Indicators of accuracy models

	Models	RMSE	RMSE%	R	E
1	simple linear regression	1,68	6,1	0,89	0,89
2	Nonlinear regression	1,6	5,8	0,90	0,90
3	Stochastic	1,4	5,1	0,94	0,92
4	ANN				
	MLP1	2	7,3	0,9	0,84
	MLP2	1,759	6,4	0,97	0,88
	MLP3	1,62	5,9	0,97	0,89
	MLP4	1,24	4,5	0,988	0,94
	MLP5	1,579	5,7	0,98	0,90
	MLP6	1,558	5,7	0,98	0,90
	MLP7	1,58	5,7	0,981	0,90
	MLP8	1,556	5,7	0,987	0,90
	MLP9	1,585	5,8	0,989	0,90
	MLP10	1,59	5,8	0,98	0,90

Source: Authors' calculation

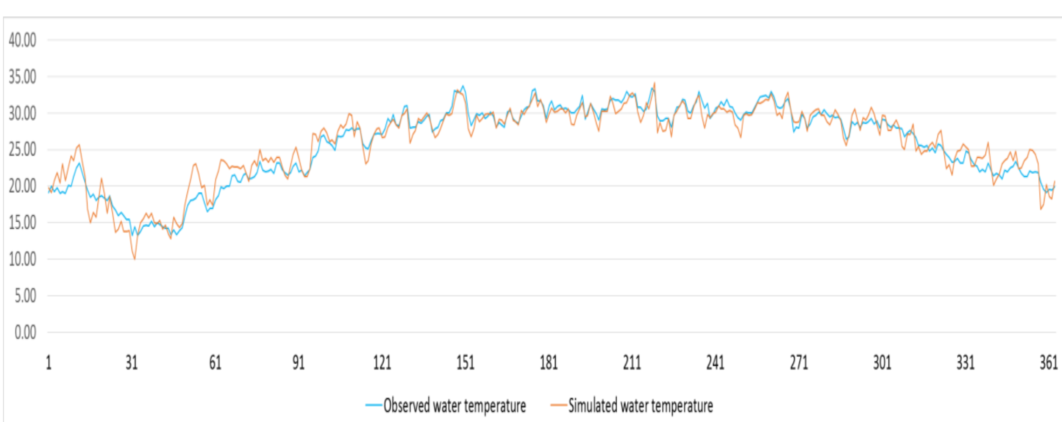

Figure-3. Simulated and observed water temperature in simple linear regression model

Source: Data collected from Bai Chay station (e.g. of year 2008)

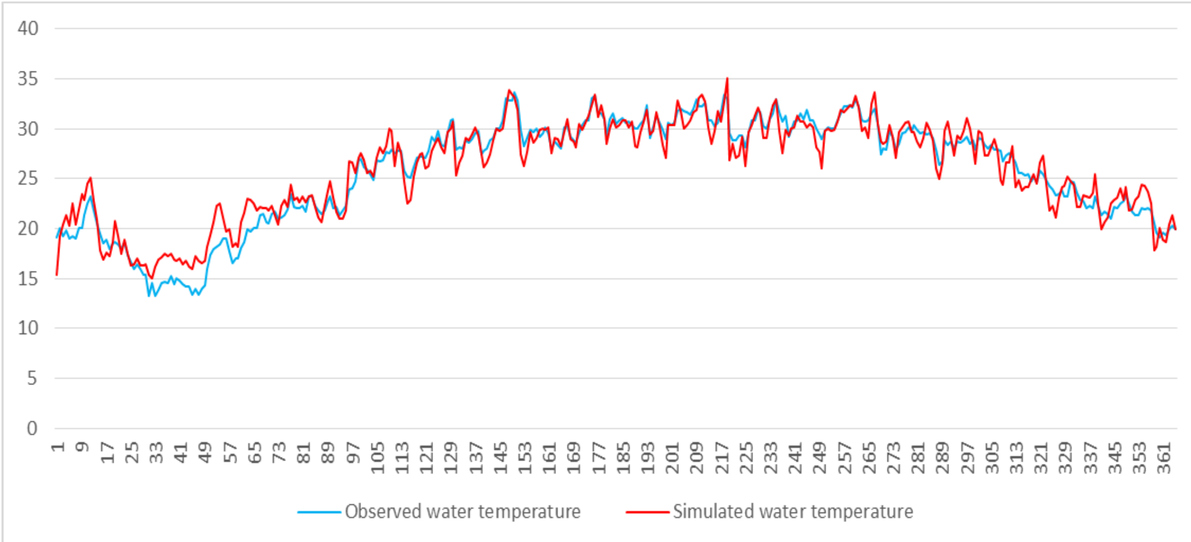

Figure-4. Simulated and observed water temperature in nonlinear regression model

Source: Data collected from Bai Chay station (e.g. of year 2008)

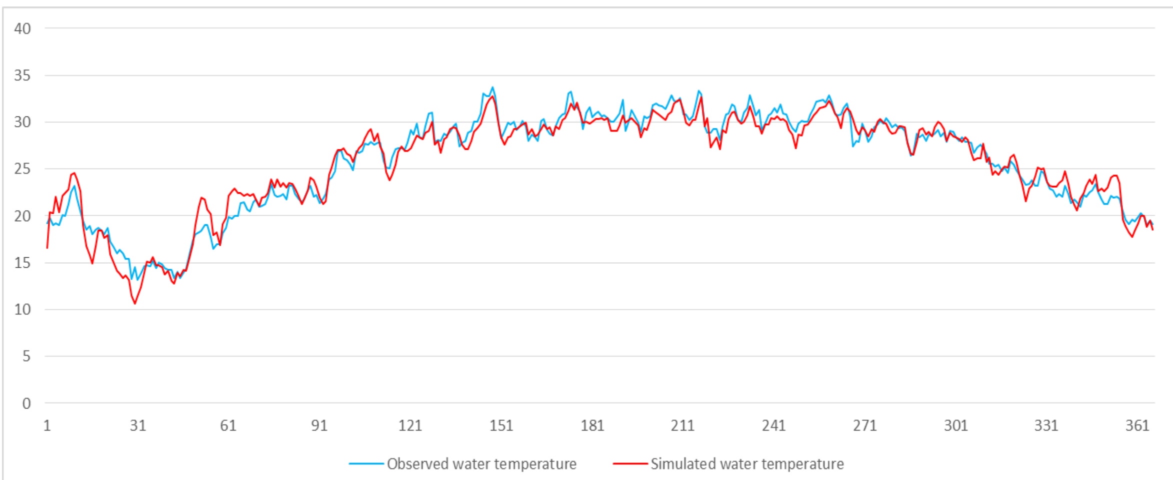

Figure-5. Simulated and observed water temperature in stochastic regression model

Source: Data collected from Bai Chay station (e.g. of year 2008)

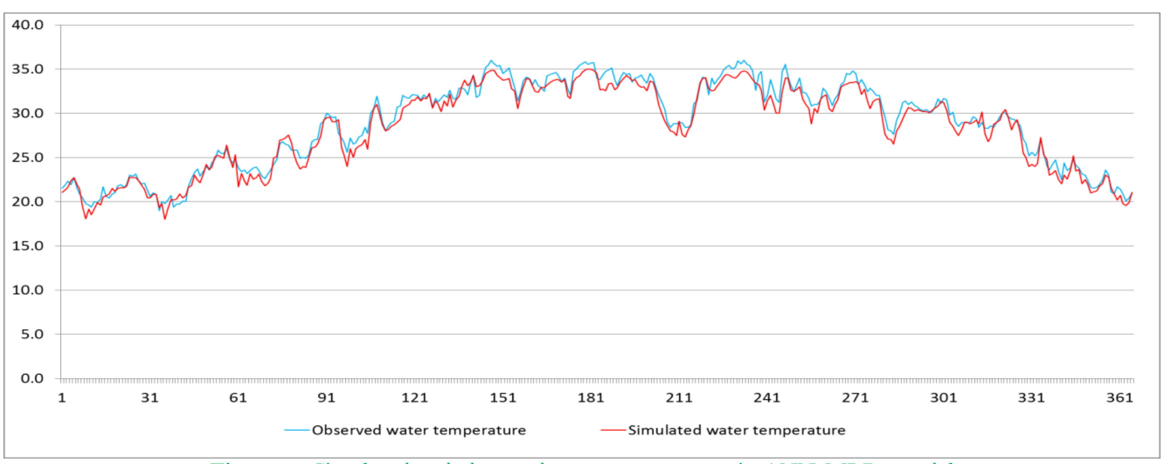

Figure-6. Simulated and observed water temperature in ANN-MLP4 model

Source: Data collected from Bai Chay station (e.g. of year 2008)

4. Conclusions

The study used the daily average, maximum air and water temperature data of Bai Chay station to assess output accuracy by implementing 03 regression models (linear regression, Nonlinear, stochastic regression) and artificial neural network models. In particular, artificial neural network model was built with 10 network structures (MLP1-MLP10) to determine some factors of air temperature affecting variation and time lag of water temperature. The results of 14 models identified that ANN-MLP4 model with 4 parameters T_{a_max}, T_{a_tb}, T_{a_tb} -1, T_{a_tb} -2 gave the best results with values of RMSE = 1.24; R = 0.98; E = 0.94. The study allows to identify that:The maximum temperature of water (T_{w_max}) depends greatly on the daily average and maximum air temperature .

The time lag between the daily maximum air and water temperature in this sutdy applying for the coastal area of the Northern Delta, Vietnam is 2 days. Daily average temperature is important factors because it It take values of daily minimum and day and night temperature fluctuations.

Stochastic model examines seasonal and short-term fluctuations between air and water temperature. This model gave the best results in the regression methods implemented. ANN model allows using complex input variables. This model should be considered for water temperature prediction as a base on disaster risk and climate change to aquaculture in coastal Northern areas, Vietnam.

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