COMPARATIVE EVALUATION OF ARTIFICIAL NEURAL NETWORK AND MIKE 21 IN ESTIMATING STORM SURGE LEVEL

ĐÁNH GIÁ MÔ HÌNH MẠNG NƠRON NHÂN TẠO VÀ MIKE 21 TRONG TÍNH TOÁN MỰC NƯỚC DÂNG DO BÃO

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Abstract*: Tropical cyclone or storm near the coast generates a local rise in sea level, called storm surge. There are two general approaches that have been used to estimate sea level in storm conditions; statistical modeling and numerical modeling. The aim of this paper is to find an effective model between MIKE 21 - numerical model and an Artificial Neural Network (ANN) model in predicting sea level height in Qui Nhon, Vietnam during four storm events: Ketsana-2009, SonTinh-2012, Nari-2013 and Wutip – 2013. The results from the two models were compared with observed sea level data in order to evaluate their respective performances. The results further indicate that the predictions from ANN and MIKE 21 model match well with the observed data. The verification shows that the neural network models have the potential for successful application in local water level forecasting systems.*

Keywords*: Estimating, Numerical Model, Artificial Neural Network, Storm surge, Tropical cyclone.*

Classification number: *2.4*

Tóm tắt: Nước dâng *trong* bão nhiệt đới *là hiện tượng mực* nước *tĩnh* dâng *cao hơn mực* nước *thủy triều thiên văn thông thường* do *gió* bão *dồn* nước *vào ven bờ. Hiện nay có hai phương pháp được sử dụng rộng rãi để xác định mực nước trong điều kiện gió bão: Thống kê và mô hình toán. Bài báo nghiên cứu xây dựng mô hình mạng nơron nhân tạo (ANN) dự báo mực nước trong điều kiện bão tại Qui Nhơn, Việt Nam. Mực nước tại trạm Qui Nhơn trong bốn cơn bão Ketsana-2009, SonTinh-2012, Nari - 2013 và Wutip-2013 được tính toán bởi mô hình mạng nơron nhân tạo và MIKE 21. Kết quả của hai mô hình được so sánh với số liệu đo thực tế để đánh giá hiệu quả mô phỏng. Việc so sánh đánh giá cho thấy mạng nơron nhân tạo có thể ứng dụng để dự báo nước dâng trong bão.*

Từ khoá*: Dự báo, mô hình toán, mạng nơron nhân tạo, nước dâng, bão nhiệt đới.*

Chỉ số phân loại: *2.4*

1. Introduction

The synoptic variation of atmospheric pressure and wind along the storm track causes a local rise in sea level. Storm surge begins to build up for periods of several hours while the storm is still far out at sea over deep waters. Extreme sea level can lead to large loss of human life, destruction of civil infrastructure and disruption of fisheries business. Hurricane Katrina, which occurred in 2005, is a prime example of the damage and devastation that can be caused by surges. Sea level in storm has long been used operationally for flood forecasting and warning in several countries. Accuracy is an essential element when predicting sea level in storm conditions. A suite of different models that aid in estimation of sea levels are widely available. There are two general approaches used to estimate sea levels - statistical modeling and numerical modeling.

When observed storm winds and pressures are used, numerical models can produce successful estimations of the sea level[1]. Numerical modeling of storm induced sea level has become a global activity. Several hydrodynamic models have been developed around the world such as SLOSH, ADCIRC, Delft3D, MIKE21, etc. Numerical approach has been a popular tool in studying storm tide. Scientists have made several efforts in simulating; however, the problem is still far from solved. Numerical models require accurate cyclone track parameters, a good set of topography and bathymetry in high resolution over a large domain. Thus, numerical simulation is a complex task and involves multiple interacting fields.

Recently, the use of artificial neural network (ANN) in the field of coastal and ocean engineering is increasing. Neural network can translate and learn the relation between the meteorological parameters and the sea-level variables. During the learning process, the neural network has the ability to recognize the hidden pattern in the data, and after learning, the neural network can predict the target values. The capability of neural networks to predict ocean wave has been evaluated in many works, as can be found in the study of Deo M.C[2], W.-B. Chen[3]. The increasing trend in using ANN model in ocean engineering demonstrates the effectiveness and practicality of the technique.

The primary aim of this paper is to find an effective model between numerical model and ANNs model in estimating sea level in the storm time in Qui Nhon city. According to national statistics, 2-3 storms strike the central coast of Vietnam annually.

In this study, MIKE 21 (a numerical model developed by Danish Hydraulic Institute), in which the hydrodynamics is simulated by solving the system of equations which describe the flow and water level variations-mass and momentum conservation equation[4], and ANN models were used to forecast the sea level in the presence of four storm samples: Ketsana (23–30 Sept, 2009), SonTinh (21–29 Oct, 2012), Nari (8–16 Oct, 2013) and Wutip (25–30 Sept, 2013). The tracks of these four storms are shown in figure 1.

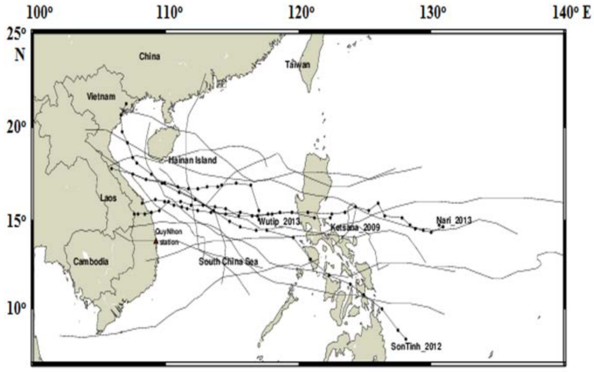

Figure 1. *Best track of twenty historic typhoons. The dotted lines are four samples - Ketsana (2009), SonTinh (2012), Nari (2010), and Wutip (2013).*

The neural network model’s estimations are based on twenty historic storms. These twenty historic storm tracks were obtained from the Joint Typhoon Warning Center–apparently Best Track data. The information in each track consists of time, geographical location and maximum sustained wind speed in knots as well as the minimum sea level pressure at typhoon center every six hours. Tidal level was extracted from the global tide model of Mike 21. The hourly water level data in meters, collected at Qui Nhon station (13.9^{o}N, 109.8^{o}E) (Figure 1), were used to test the accuracy of the proposed models. The results from the above mentioned prediction models were compared to observed data to evaluate the performance of each model.

2. MIKE 21 Hydrodynamic model

The historical wind and pressure fields are inputs into the coastal hydrodynamic model along with the tidal constituents as key driving factors to simulate the initial current and wind-induced wave at coastal scale. Then, considering river discharge and coastal protection works, storm surge is simulated using the regional hydrodynamic model with a fine spatial resolution structured mesh. A hydrodynamic model for the coastal area will be set up and calibrated against tide observed data.

2.1. Computation domain

The numerical storm surge with MIKE 21 was setup for the area between 12.5^{o}N to 17.5^{o}N and 106.5^{o}E to 111^{o}E, see figure 2. ETOPO1 Global Relief Model downloaded from NOAA with a grid resolution of 1 arc-minute, and local measured data were employed to develop a topographical profile of the entire study domain. The resolution of the structured mesh applied in the coastal hydrodynamic model is recommended to be set in a range of 1 km at the coastal zone to 10 km at the open ocean boundary. For the regional hydrodynamic model, the resolution can be more precise with an average of 300 m.

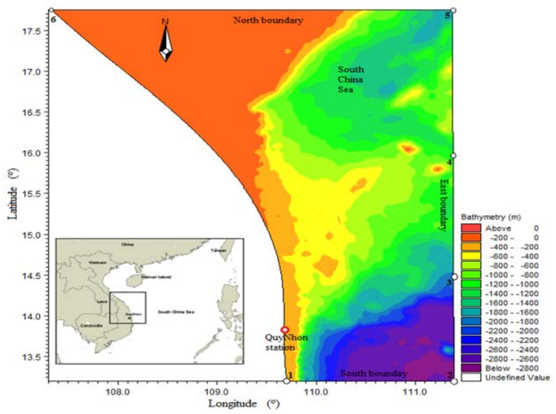

Figure 2. *Studied domain and bathymetry map.*

2.2. Input data

2.2.1. Open boundary

The surface elevation varies both in time and along the open boundary (East boundary, see Figure 2). The water level variations along the boundaries are created on the basis of the sea levels from the global tide model

2.2.2. Storm wind field

Storm wind and pressure field are calculated in this framework by applying the parametric model built in MIKE 21 Cyclone Wind Generation tool. Storm data required in the simulation are the storm track, the central and neutral air pressure, and the maximum wind speed.

2.2.3. Model Calibration

Simulation parameters are defined after calibration process. The storm surge level at Quinhon station during the storm Muifa (2004) has been simulated to validate MIKE 21 storm surge model with observed data, see Figure 3. Storm surge developed in MIKE 21 proved it was capable of closely agreeing with what was observed. Most of the computation errors of the high water level are less then 3cm.

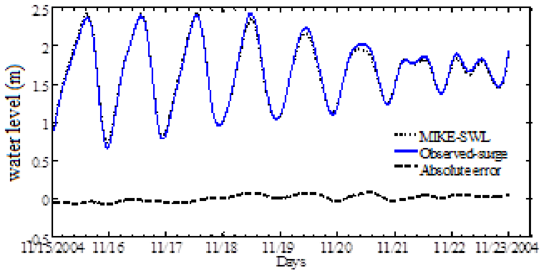

Figure 3*. Water level at Qui Nhon station during storm Muifa 2004.*

3. An Artificial Neural Network model for estimating storm surge

3.1. Artificial Neural Network

Artificial Neural network (ANN) is a system purposely constructed to make use of some organizational principles similar to those of the human brain. It therefore has the ability to learn, recall, and generalize[5]. Since that, there have been developed hundreds of different models considered as ANNs. The differences are in the activation functions, topology and learning algorithms. In principle, each artificial neuron (AN) receives signals from the environment, or other ANs, gathers these signals, and when fired, transmits a signal to all connected ANs. figure 4 is a model of an ANN model.

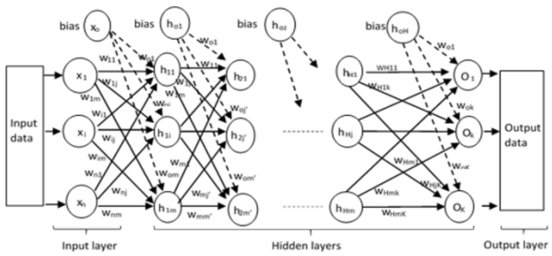

Figure 4. *An artificial neural network model*

The inputs that come from system causal variables form an input vector **x**= (x1, ..., xi, ..., xn) to such an artificial neuron. The sequences of weights $\mathbf{w}_{ij}$= (w1j, ..., w2j, ..., wnj) connect the **i**-th neuron in a preceding layer to neuron **j** in the hidden layer h_{km}. The output of **j** or **y**j is obtained by computing the value of the active function *f:*

$$y_j = f(x_i.w_j - b_j) \qquad (1)$$

Where **b**j is the threshold value or called bias associated with an artificial neuron. Several commonly used activation functions are identity function: f$(xi, wi) = xi$; Bias(Threshold) function: f$(xi, wi) = xi + wi$; Linear function: f$(xi, wi) = \beta xi + wi$, *where* β is steepness parameter; Sigmoid function: f$(xi, wi) = 1/[1+exp(-\beta xi)]$; Hyperbolic tangent: f$(xi, wi) = tan(-\beta xi)$.

An artificial neural network (ANN) is a layered network of ANs. An ANN may consist of an input layer, hidden layers and an output layer. An neural networks learn using an algorithm called backpropagation which is essentially a gradient descent technique that minimizes the network error function. The ANN learns through the overall change in weights accumulated over many epochs. For further information of ANN model references [6].

3.2. Setup an ANN storm surge model

The variation of storm surge is affected by many factors such as the central pressure, wind speed, speed of forward motion of the storm, storm location and coastal topography. The prediction of storm surge can be enhanced if many relative factors are applied. It is not easy to get all these factors. In this study, the estimation of storm surge is carried out by using three storm parameters: the maximum wind speed, central pressure and the distance from the storm center to the studied point, as in figure 5 - an ANN's storm surge predicting model with one hidden layer. These parameters are used as input nodes to feed the ANN model. The output is combined with tidal level to get the sea level height in storm condition.

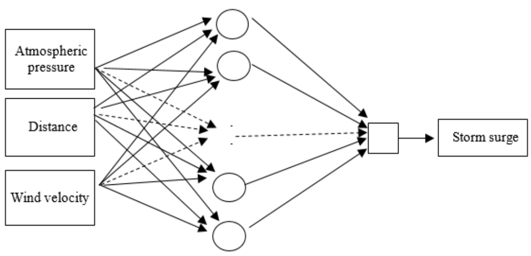

***Figure 5**. ANN storm surge prediction model*

The storm tracks and storm surge during the time of 20 storms (Figure 1) relative to Qui Nhon station, from 1994 to 2013 were collected. These values were organized as inputs and target output for the ANN storm surge model. The four storm samples: Ketsana - 2009, SonTinh - 2012, Nari - 2013 and Wutip - 2013 were used to validate the accuracy of the proposed ANN model. The remaining sixteen typhoons were used for the training phase.

In order to investigate the accuracy of the forecasting models, we changed the number of hidden units, learning rate, momentum rate, and the number of training iteration in the ANN to get the optimized structure of ANN. After a series of tests, the optimized ANN's model in this study was defined with 10 hidden nodes; $\gamma = 0.02$, $\alpha = 0.3$ and 5x103 epochs. To evaluate the performance of the ANN model, two criteria were adopted to compare the predicted results and the observational data: correlation coefficient (CC), and root mean square error (RMSE),. These criteria are defined by the following equations:

$$CC = \frac{\sum_{i=1}^{N}(Y_m)_i\,(Y_o)_i}{N} - \overline{Y_m}\,\overline{Y_o} \tag{2}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}[(Y_m)_i - (Y_o)_i]^2} \tag{3}$$

Where, N is the total number of data; Y_m is the predicted data; Y_o is the observational data.

Figure 6 shows the relation between the water level from ANN storm surge model and observed data. It showed that ANN surge model can estimate time series of storm surge levels with the CC of 0.77, and the RMSE of 0.132.

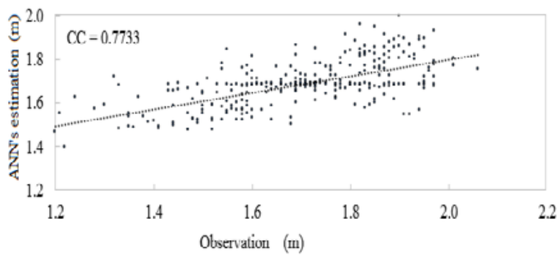

***Figure 6**: Comparison between water level estimated by ANN model and observed data.*

4. Comparative Evaluation of ANN storm surge model and MIKE 21 surge model

Figure 7 and Table 1 show the predicted sea level during the time of the four storms - Ketsana, SonTinh, Nari and Wutip. The simulation results indicate that the predictions from both models are generally in good agreement with the observation. Figure 7-b1,d1 show the sea level during the Ketsana and Nari. From these plots, it can be seen that the prediction is much different from the observation in the final 36 hour. However, there is only 3.12% for MIKE 21 model and 0.3% for ANN model, difference on average. Based on these simulation results, it is said that the prediction of the MIKE 21 model has worse accuracy in comparison with the ANN model. MIKE 21's prediction of sea level during Nari and Ketsana has higher RMSE of 0.1988 and 0.1378, respectively. In ANN model, however, the RMSE recorded is just 0.1374, and 0.1067 for Nari and Ketsana, respectively; but the two models obtained high correlations. Nonetheless, in all cases, the prediction from the two models have high accuracy (with CC larger than 0.90).

Table 1. *Performance of MIKE 21 model and ANN model in storm surge simulation.*

Case	MIKE 21		ANN surge model	
	RMSE	CC	RMSE	CC
Wutip 2013	0.0985	0.9571	0.0632	0.9765
Nari 2013	0.1988	0.9867	0.1374	0.9787
SonTinh 2012	0.1089	0.9473	0.1037	0.9376
Ketsana 2009	0.1378	0.9210	0.1067	0.9360

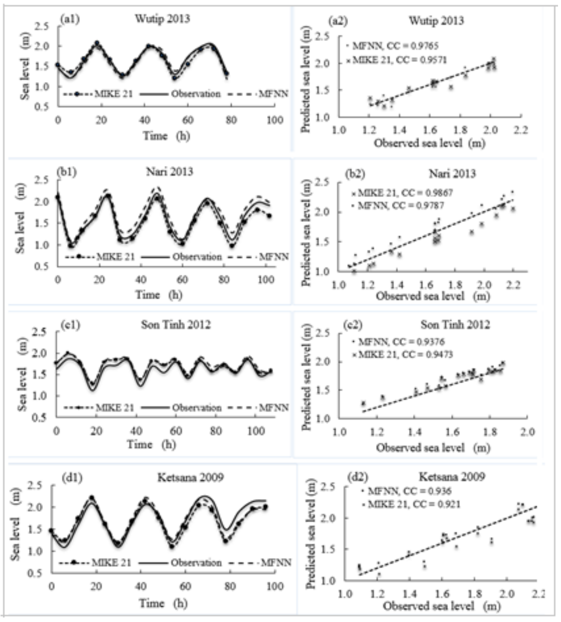

Figure 7*. Comparison of sea level during the four storms at Qui Nhon estimated by ANN, MIKE 21 and observed data.*

5. Conclusion

Accuracy in the storm surge prediction is very important for coastal areas. This paper highlighted the conventional numerical model - MIKE 21 and the alternative neural network - ANN model in estimating storm surge in QuiNhon station (Vietnam) during the time of four storms- Ketsana 2009, SonTinh 2012, Nari 2013, and Wutip 2013. Both MIKE 21 and ANN have highly efficient implementations with adequate accuracy. There is not much difference in terms of accuracy between MIKE 2D-hydrodynamic model and ANN when predicting storm surge. However, the existing numerical models are computationally intensive, expensive to run and require significant amounts of model input. Thus, ANN models can replace existing numerical models in real-time predictive mode, as storm surge estimation with relative confidence and sufficient accuracy for most emergency management purposes❑

References

[1] Gabriele G. (2012), A New Method of Approaching Extreme Storm Events For Design Level or Risk Analysis. Coastal Engineering, 13.

[2] Deo M.C., J.A., Chaphekar A.S., and K. Ravikant, (2001), Neural networks for wave forecasting. Ocean Engineering 28, 10.

[3] W.-B. Chen, W.-C. Liu, and M.-H. Hsu (2012), Predicting typhoon-induced storm surge tide with a two-dimensional hydrodynamic model and artificial neural network model. Natural Hazards Earth System Science 12.

[4] DHI-Water (2007), MIKE 21 FLOW Model - Scientifc Document. DHI Water and Environment.

[5] Madsen H.J. (2004), Cyclone induced storm surge and flood forecasting in the Northern Bay of Bengal. Coastal Engineering 51, 20.

[6] Rumelhart, D.E., Hintont, G.E., &Williams, R. J.(1986), Learning representations by back-propagating errors. Nature, 323(6088)

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