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Source: Journal of Coastal Research, 85(sp1) : 781-785

Published By: Coastal Education and Research Foundation

URL: https://doi.org/10.2112/SI85-157.1

Journal of Coastal Research	SI	85	781–785	Coconut Creek, Florida	2018

The Study for Storm Surge Prediction Using Generalized Regression Neural Networks

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ABSTRACT

Lee. H.; Kim, S., and Jun, K., 2018. The study for storm surge prediction using generalized regression neural networks. *In:* Shim, J.-S.; Chun, I., and Lim, H.S. (eds.), *Proceedings from the International Coastal Symposium (ICS) 2018* (Busan, Republic of Korea). *Journal of Coastal Research*, Special Issue No. 85, pp. 781–785. Coconut Creek (Florida), ISSN 0749-0208.

Although the dangers of storm surge have recently garnered increasing awareness, studies on storm surge height predictions in accordance with regional characteristics are quite insufficient. However, accurate and prompt storm surge height prediction is necessary to promptly respond to disaster caused by storm surge. Currently, most storm surge height prediction figures are obtained from numerical modelling technique-based study, which has a number of analytical limitations. For example various meteorological data and complex physical factor analysis are lacking. Therefore, the Generalized Regression Neural Network(GRNN) is applied in this study in order to create a storm surge height prediction model through simplified data input and hidden layer and output layer. When the established GRNN was applied to the Tongyeong and Yeosu area, the obtained values were very similar to the actual surveyed data. When the model was applied to ungauged areas, the tendency of storm surge height was identified.

ADDITIONAL INDEX WORDS: *Storm surge, numerical modelling technique, generalized regression neural networks(GRNN), disaster.*

INTRODUCTION

Typhoon MAEMI in 2003 has caused enormous damage of 117 deaths and property damage worth 4.2 billion dollors (National Institute for Disaster Prevention, 2004). It is predicted that due to climate change, the scale of storm surge will increase as typhoon scale increases. Therefore, accurate and prompt prediction of storm surge height is necessary to minimize damage from a storm surge (Yoon, 2012).

Methods to predict the storm surge height include 1) using the empirical formula or empirical equation, and 2) using the numerical model. In order to simulate the storm surge using the numerical model, input data such as the following are needed: meteorological data and bathymetry. Additionally, the calculation process is complex and requires much time spent. On the other hand, the numerical model has the advantage of being able to predict storm surge by using meteorological data that can be acquired at a relatively short period of time. However, in order to obtain accurate storm surge height it is necessary to develop a mechanism that would consider complex actions such as tide, wave, temperature, bathymetry, depth, and wind.

The empirical formula has the advantage of being mainly composed of a simple formula that anyone can easily use. In the case of Japan, which has systematically accumulated meteorological data for a long time, the empirical formula is used at their coast to calculate storm surge height (National Institute for Disaster Prevention, 2002). In Korea the empirical formula is not being utilized because of the lack of such data accumulation. This research applied the GRNN (General Regression Neural Network) method, which is one of the ANN (Artificial Neural Network) method (Park, 2005), to predict storm surge height and to review the applicability of the method. The Artificial Neural Network method has advantages of not requiring the complex mechanism of the numerical model and also being able to overcome the lack of data limits of the empirical formula (Lee *et al.*, 2016). This study gathered meteorological data that contained water level difference of 30cm or more to compose a model for Artificial Neural Network method, and was conducted in South Korea's South Coast with Tongyeong, Yeosu, and Wando as the target places.

METHODS

A simple representation of the storm surge height would be what is formulated in (1) as the difference of the measured elevation of sea surface and the estimated level of astronomical tide (Son, 2009).

$$H_w = a\Delta p + b(U_{max})^2 \cos\theta + cH_{1/3} \quad (1)$$

In the formula, H_w is the storm surge height, Δp is the difference of mean pressure and minimum pressure in the sea surface (hPa), U_{max} is the maximum wind speed (m/s), θ is the effective wind direction (°), $H_{1/3}$ is the maximum significant wave height that is possible to occur, and a, b, c are defined

DOI: 10.2112/SI85-157.1 received 30 November 2017; accepted in revision 10 February 2018.
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parameter data obtained from previous sites. The third term on the right side of eqauation (1) is a constant that often gets completely ignored. Meteorological data from Table 1 were applied to the GRNN method to train and to select the optimum model. The selected optimum model was then used to conduct prediction and to review its applicability on ungaged areas.

Table 1. *Measured data of storm surge caused by typhoons (www.typhoon.or.kr).*

Location	Typhoon	Time	H_w (cm)	Δp (hPa)	U_{max} (m/s)	θ(°)
Tong-yeong	THELMA	1987-07-15 24:00	58.0	33.5	16.7	0.0
	ROBYN	1993-08-10 07:00	34.0	31.7	11.7	135.0
	FAYE	1995-07-23 17:00	55.0	27.1	21.8	45.0
	RUSA	2002-08-31 14:00	74.5	36.7	20.1	0.0
	MAEMI	2003-09-12 21:00	159.0	59.9	30.8	0.0
	NAMI	2005-09-06 16:00	30.5	26.4	13.9	157.5
Wando	THELMA	1987-07-15 19:00	79.0	46.0	20.0	67.5
	YANNI	1998-09-30 10:00	36.0	28.8	15.7	22.5
	OLGA	1999-08-03 13:00	47.0	28.8	27.3	22.5
	PRAPIROON	2000-08-31 11:00	44.0	23.0	21.8	0.0
	RUSA	2002-08-31 15:00	57.0	46.2	23.9	112.5
	MAEMI	2003-09-12 17:00	55.0	35.7	25.3	90.0
	EWINIAR	2006-07-10 09:00	72.0	31.6	26.0	0.0
	NARI	2007-09-16 19:00	40.0	25.5	22.5	202.5
Yeosu	THELMA	1987-07-15 24:00	55.0	38.2	22.0	45.0
	GLADYS	1991-08-23 14:00	38.6	31.4	20.0	90.0
	FAYE	1995-07-23 16:00	58.0	39.1	30.0	90.0
	YANNI	1998-09-30 16:00	46.0	25.0	23.5	45.0
	RUSA	2002-08-31 15:00	130.0	46.0	29.7	0.0
	MAEMI	2003-09-12 20:00	56.0	44.8	31.8	22.5
	NABI	2005-09-06 16:00	41.0	25.7	21.4	45.0
	EWINIAR	2006-07-10 10:00	38.0	24.1	14.9	0.0
	NARI	2007-09-16 17:00	60.0	25.2	24.4	22.5

Figure 1 shows the observation locations of data used in this study.The GRNN method used in this study is part of the ANN (Artificial Neural Network) method, categorized under the supervised learning method. The GRNN was a method that was first introduced by Specht (1991) which has its base on the probability density function of the measured data. The GRNN is comprised of 4 layers, as shown in Figure 2: input layer, pattern layer, summation layer, and output layer.

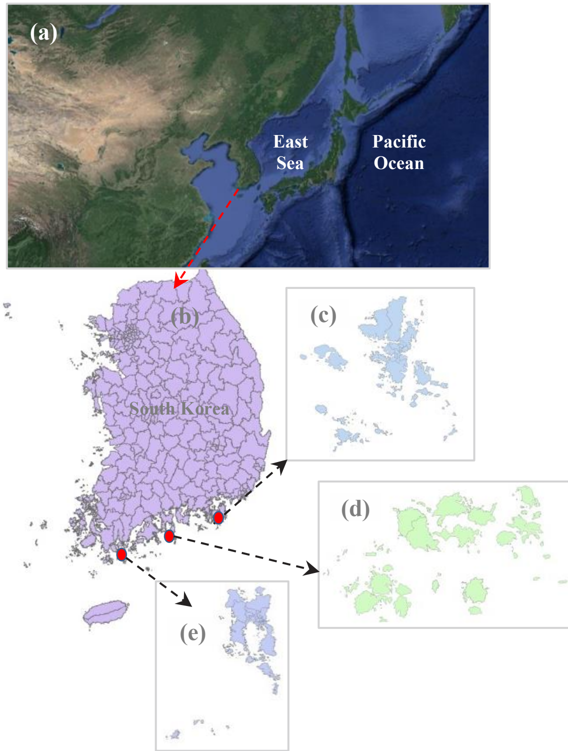

Figure 1. Observation locations used in this study ((a) East Asia, (b) South Korea, (c) Tongyeong, (d) Wando, and (e) Yeosu)

The first layer, which is the input layer, has the role of distributing the input patterns to neurons in each of the pattern layers, and it is connected to the second layer. The pattern layer has one neuron for each of the patterns in the training data, and at this point the weighing becomes the pattern elements in the training data. Each of the pattern layer neurons are represented by the training data as difference of the input pattern layer elements squared or as an absolute value. GRNN is used to calculate the response of each of the new inputs by inputting each of the training cases to the network. Then it positions the Gaussian kernel functions on the training position. The results from the input calculation is calculated again from the average weight of training case results, and the weighing is related to the distance from the point of calculation to the training point. The greatest advantage of the GRNN is that compared to the back propagation method, it requires relatively few number of data for training. Specht (1991) suggested that in order to obtain similar accuracy to the back propagation method only 1% of the training data is required.

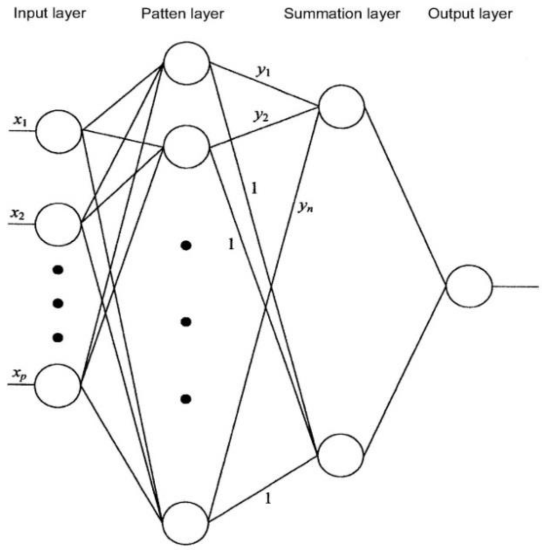

Figure 2. GRNN architecture

In order to apply the GRNN method, the correlationship between the difference of pressure (Δp), maximum wind speed (U_{max}), and effective wind direction was reviewed (θ) as found in Table 1. The results showed that the correlationship coefficient (CC) of the storm surge height and difference of pressure of the total data of Tongyeong, Yeosu, and Wando was 0.783, and the CC of the storm surge height and maximum wind speed was 0.586. With the exclusion of Wando, an island, and using only the measured data of 2 sites, Tongyeong and Yeosu, to review the correlationship, CC of the storm surge height and difference of pressure was 0.854, while the maximum wind speed was 0.685. Because using the data from 2 sites showed stronger correlationship than using all 3 sites, only the data from Tongyeong and Yeosu were used as training data. The effective wind direction (θ) had data value of '0', so the correlationship showed a negative (-) value; therefore, it was exempted from the input data construction. The combination of the input data were constructed by using input data used in training from Tongyeong and Yeosu's, and among the 16 data, 10 that were related to the typhoons (THELMA, FAYE, RUSA, MAEMI, NABI) that gave common impact were used for a total of 12 training data. Four data that were not used for the training were used for prediction.

The construction of training model for storm surge height calculation is shown in Table 2. The training model was conducted according to the input data and spread coefficient into 8 cases. Case 1 shows using only the difference in pressure (Δp) for the input data, while case 2 uses the difference in pressure (Δp) and maximum wind speed (U_{max}) for the input data.

During GRNN training it is repeatedly conducted by varying the spread coefficient between 0~1, and then the spread coefficient that shows excellent training output is determined as the optimum S output. In this work the determined optimum S output has been analyzed as 0.05.

RESTULTS

Table 3 suggests the statistical analysis results of the GRNN training. The CC was 0.908~0.999 per case, the coefficient of determination (R2) was 0.824~0998, RMSE (Root Mean Square Error) was 0.005~26.189, and the MAPE (Mean Absolute Percentage Error, %) showed a range of 0.04~031.97.

Table 2. *Construction of the General Regression Neural Network (GRNN).*

Model	Input	Spread Coefficient	Output
Case1-1	Δp	0.05(S005)	Storm Surge Level
Case1-2		0.08(S008)	
Case1-3		0.1(S01)	
Case 1-4		0.3(S03)	
Case 2-1	Δp, U_{max}	0.05(S005)	
Case 2-2		0.08(S008)	
Case 2-3		0.1(S01)	
Case 2-4		0.3(S03)	

In each training of model by case, it was found that rather than just using the difference of pressure (Δp) as the input variable, using both the difference of pressure (Δp) and maximum wind speed (U_{max}) as input variables for training resulted in superior performance. Through the analysis of CC, R2, RMSE, and MAPE the selected model for storm surge height prediction was CASE2-1.

Table 3. *Result of Training.*

Model	CC	R2	RMSE	MAPE(%)
Case1-1	0.993	0.986	4.361	4.65
Case1-2	0.984	0.969	6.940	7.34
Case1-3	0.967	0.935	10.250	11.61
Case 1-4	0.908	0.824	26.189	31.97
Case 2-1	0.999	0.998	0.050	0.04
Case 2-2	0.999	0.999	1.432	1.64
Case 2-3	0.995	0.991	4.122	6.26
Case 2-4	0.912	0.832	24.677	30.66

Figure 3 and Figure 4 shows training results using 12 measured data of Tongyeong and Yeosu. As shown in the graph, in both sites the best results came out at Spread Coefficient of 0.05. Moreover, using both the difference of pressure and maximum wind speed showed better results when compared to only using the difference of pressure.

The Case 2-1 model proved excellent performance in the GRNN training, and it was selected to be the final optimum prediction model. In order to verify the prediction performance of the model, 4 data from Yeosu location, which were not used in training, were used to make the prediction (Figure 5). The application results of the model were analyzed to show a relatively high prediction performance of CC of 0.961, R2 of 0839, and MAPE of 11.30%.

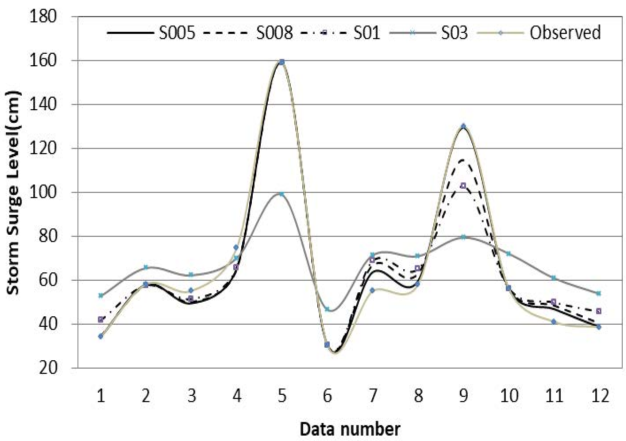

Figure 3. Training Results for Case1 Model Using GRNN.

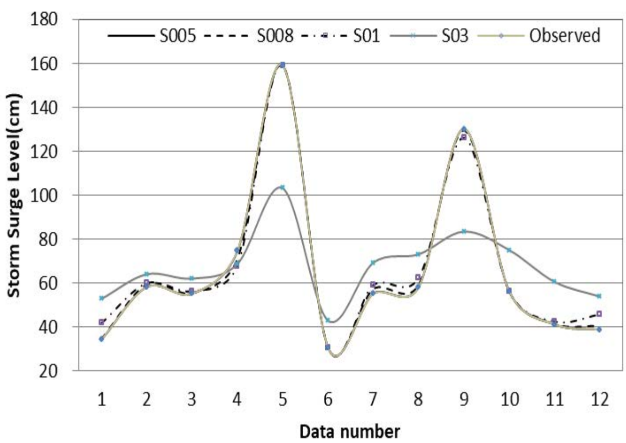

Figure 4. Training Results for Case2 Model Using GRNN.

Figure 5 shows the prediction results of Case 2-1 model which was chosen as the final prediction model. The graph shows a relatively good reproduction of measured data.The GRNN Case 2-1, which has been verified of training performance and prediction performance, was then applied to the nearby ungaged site of Wando. The application results were analyzed to CC of 0.872, R2 of 0.762, and MAPE (%) of 27.79. Figure 6 is a prediction on the ungaged site of Wando using the Case 2-1 model. The graph shows some differences in the storm surge height but the variation pattern for Wando's storm surge height is well-predicted.

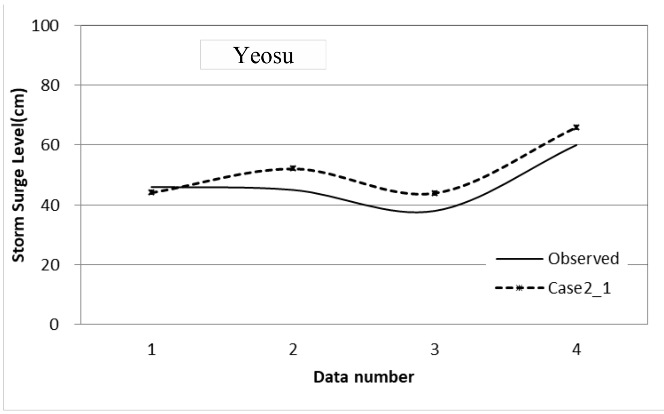

Figure 5. The predicted results of Storm Surge Level at Yeosu

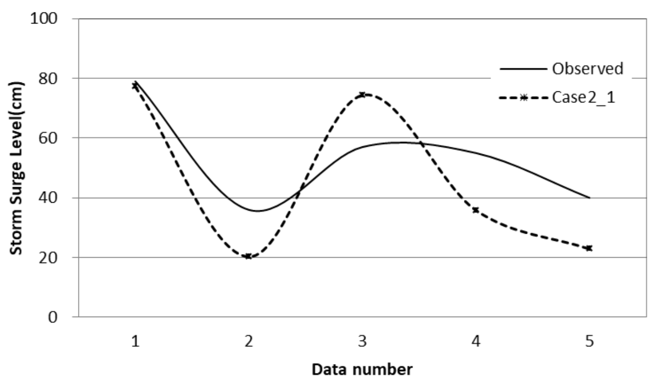

Figure 6. Predicted result of storm surge height at Wando.

DISCUSSION

Every year there are increases in climate change and disaster, and storm surge is one typical cause of disaster. South Korea is surrounded by the ocean in 3 sides and in the summer season heavy rainfall and typhoons occur intensively, therefore there is much damage from storm surge. To minimize damage from storm, accurate forecast of the storm surge height must precede.

Methods to predict the storm surge height include using the empirical formula and the numerical model. The numerical model makes it possible to come up with accurate predictions by using a large amount of input data, but the calculation process is complex and takes much time. The empirical formula is simpler in form and has the advantage of being able to predict in a short period of time and may be used by someone who is not an expert. However, the empirical formula has limitations to be used at current circumstances because it requires long-term accumulation of meteorological data.

This study sought to solve the above issues and applied a type of ANN method called the GRNN method to predict storm surge height. The GRNN method has the strength of being able to acquire good performance training with relatively little amount of data. Training were carried out in 2 types of cases, one with using only the difference of pressure, and the other using both the difference of pressure and maximum wind speed. In both cases when the spread of coefficient was 0.05 it produced the good training result. Moreover, when the measured data were both the difference of pressure and maximum wind speed, the training result was excellent. In accordance with these results the Case 2-1 model was selected as the optimum prediction model. The application results came out to a high prediction performance of CC of 0.916, R2 of 0.839, and MAPE of 11.30%. Moreover, when it was applied to the ungaged site, the results were analyzed as CC of 0.872, R2 of 0.762, and MAPE (%) of 27.29 which has determined that it is applicable to ungaged sites.

CONCLUSIONS

This study used measured data from 3 sites: Tongyeong, Yeosu, and Wando. When the data's correlationship was analyzed, the GRNN method was applied to consider two cases: one by using the difference of pressure alone, and second using both the difference of pressure and maximum speed of wind. The Case 2-1 showed the best training result and was selected to be the optimum prediction model.

After verifying the model's prediction results, it was confirmed that the model had excellent prediction performance. Using the GRNN method to predict the storm surge height has shown appropriate results, but continuous research through additional data accumulation is needed in order to improve accuracy.

ACKNOWLEDGMENTS

This work was supported by the New & Renewable Energy Core Technology Program of the Korea Institute of Energy Technology Evaluation and Planning(KETEP), granted financial resource from the Ministry of Trade, Industry & Energy, Republic of Korea . (No. 20151120100140).

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