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PREDICTION OF STORM SURGE LEVEL USING ARTIFICIAL NEURAL NETWORK: A CASE STUDY FOR TYPHOON HAIYAN

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ABSTRACT: Storm surge is considered as one of the greatest threats to life and property during a tropical cyclone, especially to a community living near the coastal area. The Philippines is particularly susceptible to the effects of coastal calamities like storm surges and tsunamis since it is an archipelago nation. One way to reduce the risk is to improve the ability of the community to monitor and forecast the hazard through technological research. As such, it is imperative to develop a numerical model that can predict and perform necessary calculations before a storm surge strikes in a coastal area. This paper utilized the Artificial Neural Network (ANN) to predict the storm surge level with 2013 Typhoon Haiyan (Yolanda) as a case study. The proposed model is tested, trained, and validated using the available 101 test data collected from the Guiuan station of PAGASA and NAMRIA. The collected data is composed of six (6) input variables and one (1) output variable. The input variables are the following: astronomical tide, central atmospheric pressure, rainfall intensity, wind radius, wind speed, and depth, while the output parameter is the storm surge level. The optimum mathematical model, as determined by the back-propagation technique in the artificial neural network (ANN) model, is Bayesian Regularization with twelve (12) hidden neurons, with a regression coefficient (R) of 0.99386 and a mean squared error (MSE) of 0.0051569, respectively. The results obtained are quite promising and demonstrate the potential application of the ANN model for disaster risk reduction during tropical storm activity.

Keywords: Storm surge, Disaster risk reduction, Artificial neural network, Typhoon Haiyan, Numerical modeling.

1. INTRODUCTION

In recent times, there has been an increased focus on coastal catastrophic occurrences on a worldwide scale. When it comes to potential fatalities and property damage, storm surges are among the most dangerous natural calamities [1]. The Philippines is an archipelago, which makes it highly vulnerable to coastal disasters such as flooding, storm surges, and tsunamis. Storm-related fluctuations in surface air pressure and wind drag on the sea surface cause storm surges, which are variations in water levels caused by atmospheric forcing [2]. It is considered as the rise in the sea level that occurs during hurricanes, storms, tropical cyclones, or typhoons. Generally, the strong winds from the storm will push the seawater into the shore, resulting in flooding in the land area. Tropical storm intensity contributes to storm surge height, but it is also related to the angle of approach (relative to the coast), central pressure, and forward speed of the storm; the local topography and bathymetry are also the factors considered [3]. Of all the geophysical risks to coastal regions, storm surges are the most severe [4]. The largest loss of life associated with tropical cyclones is caused by storm surges [5].

Because the Philippines is an archipelago, there is a greater chance that the tropical cyclone winds and storm surges may act together to amplify the damage [6]. These natural disasters can cause economic and human losses, which in turn may directly affect the economic growth and sustainability of the country. Over the last twenty years, the yearly disaster loss in the Philippines has held at ₱19.7 billion [7, 8]. The cornerstone of the social and economic programs of the government that guarantee the growth and sustainability of the nation is the creation and implementation of disaster risk reduction. One way to reduce the risk is to improve the ability of the community to forecast and monitor the hazard through technological research. As such, it is imperative to develop a numerical model that can perform and predict necessary calculations before a storm surge strikes in a coastal area.

Previous studies have shown that there are two (2) kinds of general approaches in storm surge analysis. The first approach is the deterministic one, which focuses on the impacts of presumed sources and is based on the notion that storm surges are completely foreseeable via effect sequences [9,10]. Second, is the probabilistic approach which is based on statistical analysis that requires historical data to build a model. One of the components of storm surge analysis is determining the storm surge level in the coastline area. There are numerous methods that can be used to predict the storm surge level in a coastal area, and these are the following: (1) empirical, (2) neural network, (3) numerical, and (4) statistical. In this study, the author used the Artificial Neural Network (ANN) using Matlab software to generate a model for storm surge level using Typhoon Haiyan as a case study.

2. RESEARCH SIGNIFICANCE

Tropical cyclones, which have the potential to cause storm surges, require accurate prediction of storm surge levels to ensure the safety of those living near the shore. The present work is focused on the development of an ANN-based storm surge prediction model, which could significantly increase the preparedness of the coastal community. The findings are of paramount importance and provide a significant contribution to coastal planners and decision-makers in the preparation of mitigation measures, forecasting adaptation strategies, and thus building resilience in at-risk regions.

3. LITERATURE REVIEW

3.1 Typhoon Haiyan (Yolanda)

One of the strongest typhoons to ever make landfall in Philippine history is Typhoon Haiyan, also known as Yolanda for the local name. Just prior to landfall, it reaches its highest sustained wind speed of 315 kilometers per hour, with gustiness reaching 379 kilometers per hour. It is also considered a Category 5 typhoon on the Saffir–Simpson hurricane scale. Typhoons classified as Category 5 have the ability to inflict severe harm, including a significant portion of framed homes being destroyed, isolating residential areas from electricity poles and fallen trees, prolonged power outages lasting weeks or months, and complete collapse of walls and roofs [11].

The Joint Typhoon Warning Center (JTWC) at 1800 UTC on November 7, 2013, reported that the one-minute sustained wind speed is approximately 315 kph, making it one of the strongest typhoons to make landfall in the Philippines [12]. As a result of its strong intensity, the typhoon caused a massive storm surge in many islands in the Philippines [13]. Typhoon Haiyan made landfall in Guiuan, Eastern Samar, on 8th November 2013 at 04:40 AM local time.

3.2 Disaster Risk Reduction (DRR)

The UN Office for Disaster Risk Reduction (UNISDR) defines disaster risk reduction (DRR) as the concept and practice of reducing disaster risks through systematic efforts to analyze and manage the causal factors of disasters, such as reduced exposure to hazards, reduced vulnerability of people and property, appropriate land and environmental management, and improved preparedness for adverse events. In order for the reduction of risk in a disaster to be possible, it requires an improvement to the abilities of the community to monitor and forecast, continuous awareness and reducing the vulnerability to natural hazards. The framework adapted by the UN Office for Disaster Risk Reduction (UNDRR) for disaster risk reduction. Proper response through early warning and preparedness is needed in order to minimize the impact of a disaster. Moreover, there is a need to consider the complete awareness about the risk factors of the community such as vulnerability affecting the economic, environmental, physical and social factors; and hazards to the environmental, biological, geological, hydro-meteorological, and technological aspects that can contribute to the impact of a disaster. Thus, disaster risk reduction is a cycle process in which the best practices and strategies can only be attained by continuous monitoring, evaluation and improvement of plan and policies towards a sustainable and resilient community.

There have been significant advancements in the national disaster risk reduction efforts of the government, particularly following the aftermath of Typhoon Haiyan (Yolanda) in the Philippines. Indeed, government investments in structural mitigation for big buildings and infrastructure, as well as the construction of early warning systems, evacuation routes, and shelters, are beneficial in reducing fatalities [14]. Nonetheless, disaster risk mitigation and response efforts at the national level are insufficient to protect communities from the catastrophic effects of a disaster. This is because it takes the government longer to act and mobilize resources to the affected area. With that, it is important to empower the people in the community with a proper tools and knowledge to ensure resiliency in response to the natural hazards.

One way to mitigate the effect of natural hazards in a community is by using technological research. Using this process, one can develop a knowledge-based system such as an early warning device which can be used for disaster preparation and response. An early warning device or system can be in a form of a numerical modeling that could predict the magnitude of the incoming natural hazard.

Many methods exist for the prediction of storm surge. For instance, Flather [15] used the modified depth-averaged equations with a numerical scheme to generate a model for narrow channels and open sea. The comparison of forecast and hindcast simulations of the April 1991 event has indicated the significance of accurate predictions of cyclone track, cyclone development and particularly in an area with large tidal range as here of landfall time. The barotropic tide-surge model was employed by Woth et al. [16] to determine storm surge climate and extremes based on meteorological conditions. They found out that storm surge extremes may increase along the North Sea coast towards the end of this century. Rajasekaran et al. [17] used the support vector regression (SVR) model in forecasting the storm surges and surge deviations. They found out from their simulation that the SVR method has the potential to predict storm surges with higher accuracy in a shorter computation time relative to neural networks. Mori et al. [18] revealed that a non-linear shallow water equation can be used in the Surge-wave coupling model (SuWAT). Based on their analysis, they found out that the storm surge level was 5-6 m, and local amplification of water surface elevation due to seiche was found to be significant inside Leyte Gulf. Westerink et al. [19] applied the finite element (FE) method to study the behavior of tides and hurricane storm surges. They integrated finite elements into a Generalized Wave-Continuity Equation (GWCE) to generate a model that leads to very accurate and efficient flow solutions. Mattocks and Forbes [20] adopted the North Carolina Forecast System (NCFS) to predict the storm surge with a high-resolution, two-dimensional, depth-integrated version of the ADCIRC (Advanced Circulation) coastal ocean model with winds from a synthetic asymmetric gradient wind vortex. They found out that the new system produces remarkably realistic predictions of winds and storm surges. A real-time storm surge forecast system designed for the North Indian Ocean regions vulnerable to cyclonic storms was implemented by Dube et al. [21]. Jia and Taflanidis [22] used kriging metamodeling for real-time assessment of risk during an incoming event. They demonstrated that their proposed model can be used for real-time risk assessment of the Hawaiian Islands. Lee [23] utilized the neural network in order to forecast the storm surge using the four input factors such as wind velocity, wind direction, pressure, and harmonic analysis tidal level. He found that the proposed artificial neural network can be used to predict the storm surge tidal level since the correlation coefficient is 0.9864. Rego and Li [24] applied the Finite Volume Coastal Ocean Model (FVCOM) to the storm surge induced by Hurricane Rita along the Louisiana - Texas coast, and they found that landfalls at low tide had the largest nonlinear effect. It can be observed from these journals that different methods can be applied in order to model and predict the storm surge level in a certain area. The majority of authors utilized software for model generation. Neural networks were subsequently employed to establish the non-linear relationships between system parameters.

3.3 Artificial Neural Network (ANN)

ANN is an artificial intelligence technique that is patterned to mimic the behavior, operations, and structure of biological neurons [25]. It can establish a non-linear relationship between input and output variables through a learning process. The output of the learning process can be used for modeling, prediction, and pattern recognition for science and engineering applications. The input, hidden, and output layers make up an artificial neural network. Numerous neurons comprise each layer, and sets of matching weights connect the layers together. Neural network topology is composed of the connections made by individual neurons [26].

Using its robust learning, training, and validation capabilities, the ANN can create a model expressed as an equation from numerical data. It may, therefore, be applied as a useful tool in engineering. The Neural Network Toolbox in MATLAB R2019a can be utilized to develop artificial neural network models. In this study, three ANN models were generated by applying the following algorithms: (1) Levenberg–Marquardt, (2) Bayesian regularization, and (3) Scaled-Gradient descent.

Recently, the storm surge level in a coastal location has been predicted using artificial neural network (ANN) models. Based on field data, Tsai and Lee [27] and Lee and Jeng [28] employed ANNs for tide forecasting. The use of back-propagation artificial neural networks (ANNs) for forecasting short-term storm surges and long-term tidal levels was suggested by Lee [29, 30]. Furthermore, by integrating it into an operational storm surge prediction, Lee [23], Sztobryn [31], and Tissot et al. [32] showed how ANNs may be used directly for storm surge forecasting. Sahoo and Bhaskaran [33] established the potential of ANN model to produce a high predictive skill level in predicting storm surge and coastal inundation in comparison with the conventional model and in situ data.

4. METHODOLOGY

In this study, three different models have been developed using the Artificial Neural Network (ANN) Method. A total of 101 data sets were collected from Guiuan station of PAGASA and NAMRIA to examine whether the ANN can predict the storm surge level during the period of Typhoon Haiyan(Yolanda) from November 4 to 8, 2013. Scaled Conjugate Gradient, Levenberg-Marquardt, and Bayesian Regularization are the three ANN training techniques that were employed. In the ANN modeling, the following assumptions were made: Training Data=70% of Whole Data, Validating Data=15% of Whole Data, Testing Data=15%. For 101 experimental data sets, a feed-forward back-propagation neural network model is created to forecast the storm surge level. Thirty samples were shared evenly between the ANN validation and testing procedures (15 of which were selected as testing data sets, and the remaining 15 for network validation). Of these, 71 randomly selected data were utilized for training the network.

In the ANN structure, several iterations with a single hidden layer were attempted. To find the most ideal topology (highest R value) for the storm surge level, the Regression (R) values were tested against different neurons (6, 8, 10, 12, and 14) in the hidden layer.

The six (6) input variables used in this study are the following: (a) wind speed (kph) (b)wind radius (km) (c) central atmospheric pressure (hPa) (d) astronomical tide (m), (e) rainfall intensity (mm) and (f) depth (m). The output parameter is storm surge level (m). The researcher obtained from PAGASA the windspeed, wind radius and rainfall data during Typhoon Yolanda while the central atmospheric pressure, astronomical tide and storm surge level from Guiuan Station were obtained from NAMRIA office in Manila. The depth of the ocean floor was obtained from Digital Elevation Models (DEM) Global Mosaic by considering track and position (latitude and longitude) of the typhoon Haiyan. And, there were 101 data rows collected from the PAGASA and NAMRIA and these data served as the parameters for neural network modeling.

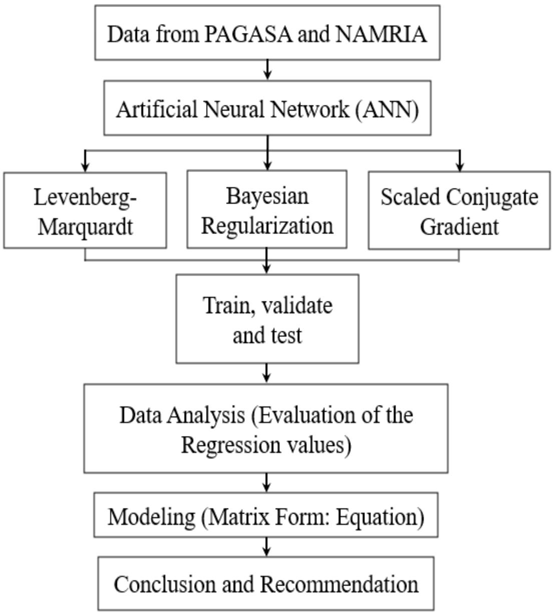

Fig. 1 Theoretical Framework

The theoretical framework of the study can be seen in Fig. 1. All the data came from the Philippine Atmospheric, Geophysical and Astronomical Services Administration (PAGASA) and National Mapping and Resource Information Authority (NAMRIA). ANN was carried out utilizing three algorithm methods: Bayesian Regularization, Scaled Conjugate Gradient and Levenberg Marquardt, all of which were simulated in Matlab software. For each algorithm, the data was trained, validated, and tested. All ANN-generated models were assessed by comparing regression and mean squared error values. The greater the regression (R) value, the more accurate the model is among the created models.

5. RESULTS AND DISCUSSION

Table 1 displays the statistical information for the input and output variables. The following parameters are included in statistical data: mean, standard deviation, minimum, and maximum.

Table 1. Characteristics of the data set

Parameters	Max	Min	Mean	Standard Dev.
windspeed (kph)	231.50	64.82	154.84	58.04
wind radius (km)	148.16	0.00	89.67	54.43
air pressure (hPa)	1002.00	895.00	946.36	39.14
astronomical tide (m)	0.70	0.10	0.32	0.13
rainfall intensity (mm)	145.20	3.00	41.99	58.02
depth (m)	6987.00	2.00	3811.46	1425.14
storm surge level (m)	2.38	1.65	1.87	0.25

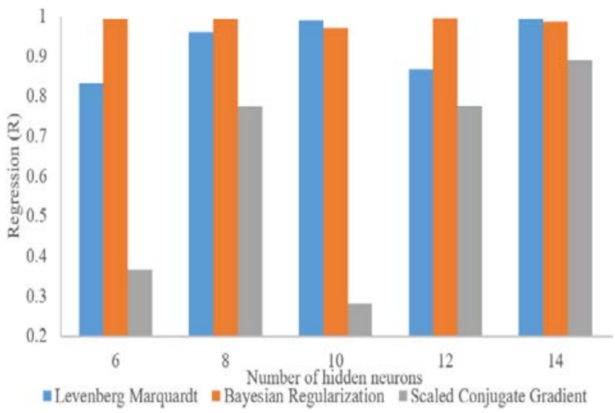

Fig. 2 ANN result for the regression

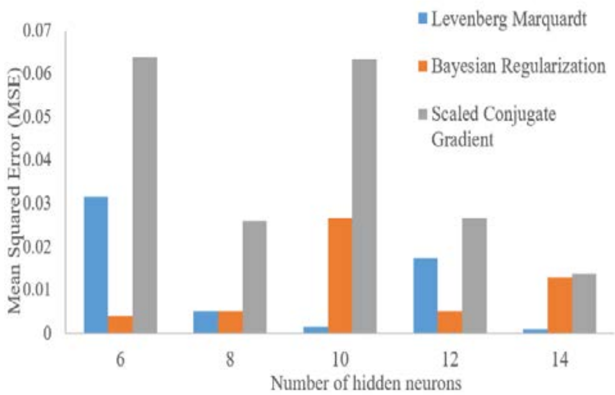

Fig. 3 ANN result for the Mean Squared Error (MSE)

Figures 2 and 3 compare the regression and mean squared error for each of the three ANN algorithms.

It can be observed that the BR_12 model, which has 12 neurons, had the lowest MSE value of 0.0051569 and the greatest regression value of 0.99386. The ANN with 12 neurons in the hidden layer seemed to be the ideal topology for storm surge level using the Bayesian Regularization procedure.

Table 2. Regression Value of ANN models

Model	R	Model	R	Model	R
LM_6	0.83152	BR_6	0.99236	SG_6	0.36672
LM_8	0.96049	BR_8	0.99154	SG_8	0.77222
LM_10	0.98829	BR_10	0.97042	SG_10	0.28246
LM_12	0.86609	BR_12	0.99386	SG_12	0.77472
LM_14	0.99222	BR_14	0.98476	SG_14	0.88818

Table 2 displays a comparison of the regression values from the three artificial neural network-developed models. Higher R values suggest that there is good agreement between the obtained and experimental data. After comparing each model, it can be said that the best model is the BR_12 model, which stands for Bayesian Regularization with 12 neurons. This is similar to the result of Bass [34] wherein Bayesian Regularization obtained the best performing ANN for predicting the storm surge.

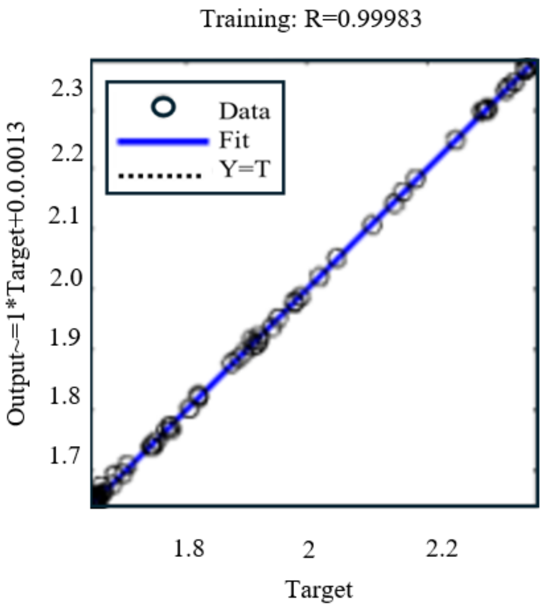

Fig. 4 Training Regression Plot for Bayesian Regularization Model with 12 Hidden Neurons

The three plots represent the performance of the optimized model (Bayesian regularization algorithm with 12 hidden neurons) in regression by comparing its prediction against the target values. Figure 4 shows that the training data aligns closely with the predicted values, with an R-squared value of 0.99983.

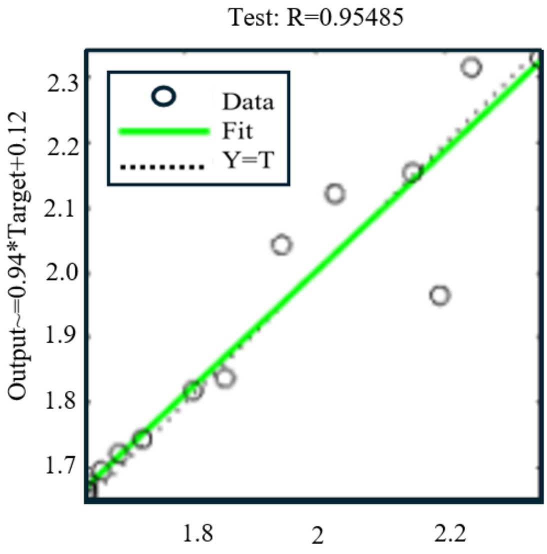

Fig. 5 Testing Regression Plot for Bayesian Regularization Model with 12 Hidden Neurons

For the test data as seen in Fig. 5, the green data points are slightly more dispersed around the solid green line, indicating some deviation in the prediction model with an R-squared value of 0.95485.

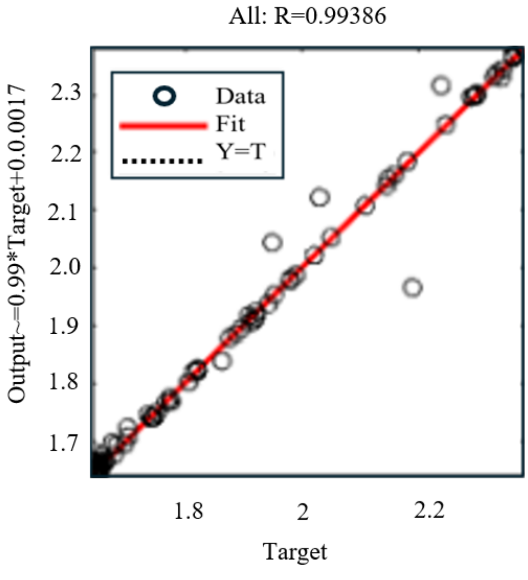

Fig. 6 Overall regression plot for Bayesian Regularization algorithm with 12 hidden neurons

The overall regression value is 0.99386 as seen in Fig. 6. It means that there is a good agreement between the predicted data (using matrix equation) and the actual data. This is similar to the findings of Elbisy [35], in which they found out that a neural network model (GRNN) can be used in forecasting tidal levels with an R value of 0.996.

The generated equation from the best model using Matlab can be seen below as Equation 1 which is a function of the following variables: (1) LW(Layer Weight), (2) IW(Input Weight) (3) B1(Bias Value for Layer1) and (4) B2(Bias Value for Layer 2) and (5) Xi(Input Variables). A tansig activation function was used to convert the input signals to output signals by considering the values inside the function, which consist of input weights (IW), bias values for layer 1 (B1), and input variables (Xi). In order to use the equation for the prediction of the storm surge level, five input variables with numerical values are needed. The five input variables are as follows: windspeed (kph), wind radius (km), air pressure (hPa), astronomical tide (m), rainfall intensity (mm), and depth (m).

$$Storm\ Surge\ Level = LW * tansig(IW * Xi + B1) + B2 \quad (1)$$

where:
LW(Layer Weight), IW(Input Weight), B1(Bias Value for Layer1), B2 (Bias Value for Layer 2) and Xi (Input Variables).

$$LW = \begin{bmatrix} 2.1999 \\ 2.5274 \\ 3.1362 \\ -2.5537 \\ -2.2303 \\ 1.8033 \\ -3.3121 \\ 1.2142 \\ 1.2944 \\ -1.9842 \\ -1.7115 \\ -2.3791 \end{bmatrix} \quad B1 = \begin{bmatrix} 0.3884 \\ -0.7678 \\ -2.3109 \\ -1.3876 \\ -2.4830 \\ 1.0984 \\ 0.7617 \\ -1.7064 \\ -0.5129 \\ 1.0080 \\ 0.4956 \\ 0.4904 \end{bmatrix} \quad B2 = [0.5934] \quad X_i = \begin{bmatrix} X_1 \\ X_2 \\ X_3 \\ X_4 \\ X_5 \end{bmatrix}$$

Fig. 7 Layer weight (LW) and Bias values (B1 and B2) and Input variables (Xi) in matrix form of the equation.

$$IW = \begin{bmatrix} -1.3965 & 1.0263 & 2.6139 & 2.2293 & -1.2259 & -0.0102 \\ 0.0320 & 1.4987 & -0.3250 & -2.3729 & -0.7676 & 0.3289 \\ 0.5907 & 1.7985 & -0.6588 & -1.5918 & 0.3925 & -0.8329 \\ 2.0909 & 1.8017 & -1.1593 & -2.3000 & -3.2567 & -1.3892 \\ -0.3010 & 1.7918 & 1.7645 & -3.2186 & 0.0211 & 3.1078 \\ -0.4044 & -0.5456 & 0.0107 & -0.6427 & 0.9753 & -0.9706 \\ 0.3035 & -0.5241 & 0.2829 & 0.8527 & 1.2346 & -2.2803 \\ 1.6089 & 1.2339 & -1.3468 & 2.7822 & -1.0089 & 0.6693 \\ -0.5809 & -3.0604 & 0.5280 & -6.2270 & 1.3799 & 0.7095 \\ -1.5475 & 0.9671 & 1.0061 & -4.1458 & 0.5867 & -0.7200 \\ 0.0349 & -1.8919 & 0.2996 & 1.3814 & 0.1321 & 4.3106 \\ 1.6670 & -2.1949 & -1.7940 & -2.4453 & -0.8626 & 0.4996 \end{bmatrix}$$

Fig. 8 Input weight (IW) factor in matrix form of the equation.

Recent years have seen a shift from conventional techniques of forecasting storm surges to the adoption of Artificial neural networks (ANNs) which are new global optimization-based forecasting tools. Lee [29, 30] demonstrated the effectiveness of ANNs for predicting both short-term storm surge (one to six hours ahead) and long-term tidal levels. The neural network model for long-term tidal level prediction agreed well with observations derived from harmonic analysis.

Conventional techniques frequently depend on intricate computational fluid dynamics models such as the finite volume method (FVM), which consume a lot of computer power and demand information on tides, winds, friction, shear stress, and topographical boundary conditions. Lee [30] found that FVM numerical method was outperformed by ANNs in forecasting storm surges for short lead times (for 1-6 hours) as the correlated values were higher. This indicates that – for operational purposes – ANNs are helpful for predictions and early warning systems.

6. CONCLUSION

The results of this study demonstrated that Artificial Neural Network (ANN) models can be used to predict the storm surge level in the Philippines. ANN models have regression values ranging from 0.28246 to 0.99386 and MSE values ranging from 0.001 to 0.06383. This study shows that storm surge level may be predicted with accuracy using ANN. The Bayesian Regularization with twelve (12) neurons, or BR_12 model, produced the optimal results for mathematical models, with mean squared error (MSE) and regression (R) values of 0.0051569 and 0.99386, respectively. The BR_12 model, which combines Bayesian Regularization with 12 neurons, is the best ANN for training data with an R squared value of 0.99983. Results obtained are quite promising which demonstrate the potential application of ANN model for disaster risk reduction during a tropical storm.

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