Tropical Cyclone Intensity Prediction Using Regression Method and Neural Network

By Jong-Jin Baik[1] and Hong-Sub Hwang

Department of Environmental Science and Engineering
Kwangju Institute of Science and Technology, Kwangju, Korea

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Abstract

Using the multiple linear regression method and the standard back-propagation neural network, tropical cyclone intensity prediction over the western North Pacific at 12, 24, 36, 48, 60, and 72 h intervals is attempted. The data contain a 31-year sample of western North Pacific tropical cyclones from 1960 to 1990 and eight climatology and persistence predictors are considered. The percent of variance explained by the neural network model is consistently larger than that explained by the regression model at all time intervals with an average difference of 12 %. The average intensity prediction errors from the neural network model are 10–16 % smaller, except at 12 h where the errors are nearly equal, than those from the regression model. This study clearly shows potential of the neural network in the prediction of tropical cyclone intensity.

1. Introduction

Although the skill of tropical cyclone track prediction has been steadily improved (Elsberry, 1995), the skill of tropical cyclone intensity prediction has not been so promising. There are many possible reasons why current operational models fail to predict intensity accurately. These include coarse horizontal model resolution, which cannot adequately resolve convective rainband activity (nonhydrostatic in nature) through which subsequent intensity change tends to occur, sparse observational data near the storm center, *etc.* Although accurate numerical-model prediction of intensity appears to have potential with the emergence of sophisticated numerical models, new observing platforms, and very high-performance computing facilities, it might still be useful to design and use a statistical model for predicting tropical cyclone intensity — at least until such a reliable numerical prediction system becomes available and practical.

There are some statistical studies which relate tropical cyclone intensity change to climatology and persistence or synoptic factors over the North Atlantic (Pike, 1985; Merrill, 1987; DeMaria and Kaplan, 1994, hereafter denoted by DK), over the western North Pacific (Nyoumura and Yamashita, 1984; Elsberry *et al.*, 1988), and over the Australian region (Leslie and Holland, 1991). Using multiple regression methods, DK showed that the SHIPS (Statistical Hurricane Intensity Prediction Scheme) model, which includes synoptic factors such as the difference between the current storm intensity and an estimated maximum possible intensity, the vertical shear of horizontal wind, the flux convergence of eddy angular momentum at 200 hPa, *etc.*, improves upon the climatology and persistence model. However, they showed that the SHIPS model explains only 36–54 % of the variability of the observed intensity changes.

Artificial neural networks can be regarded as analytical systems that address problems whose solutions are not explicitly formulated (Chester, 1993). Neural networks have their origin in the mathematical model of a nerve cell (McCulloch and Pitts, 1943). Neural networks for data analysis have been rapidly developed and improved since Rumelhart *et al.* (1986) introduced the back-propagating algorithm. Because of their excellent ability in tackling problems which are difficult to treat using traditional analytical techniques, neural networks have provided a wide range of applications in science and engineering problems (Hinton, 1992; Chester, 1993).

1 Corresponding author: Prof. Jong-Jin Baik, Dept. of Environmental Science and Engineering, Kwangju Institute of Science and Technology, 572 Sangam-dong, Kwangsan-ku, Kwangju 506-712, Korea. E-mail: jjbaik @aromi.kjist.ac.kr

In this paper, an attempt to apply a neural network to tropical cyclone intensity prediction is undertaken. The objectives of this study are twofold. The first objective is to construct a multiple linear regression model for predicting tropical cyclone intensity over the western North Pacific and to compare these results with those obtained for Atlantic storms in DK. The second objective is to construct a neural network model for predicting tropical cyclone intensity and to compare these results with those computed using the regression model. For these objectives, a 31-year (1960–1990) sample of tropical cyclones over the western North Pacific is used and climatology and persistence factors are considered. In Section 2, data used in this study are described. In Section 3, regression analysis and neural network are described. In Section 4, results from regression and neural network models are presented and compared. Finally, conclusions follow in Section 5.

2. Data

The data used in this study were obtained from a 31-year sample of tropical cyclones from 1960 to 1990 over the western North Pacific. The 6-h positions and intensities for each of these storms were determined by the RSMC (Regional/Specialized Meteorological Centers) Tokyo-Typhoon Center. In this study, storm intensity is represented by the minimum surface pressure and storms over land or islands are excluded. Using the same data and the monthly mean sea surface temperature data for each year, Baik and Paek (1998) examined a climatology of sea surface temperature and the maximum intensity of western North Pacific tropical cyclones. The numbers of observations used to construct prediction models for tropical cyclone intensity at 12, 24, 36, 48, 60, and 72 h intervals are 11204, 9764, 8586, 7576, 6629, and 5768, respectively.

3. Regression analysis and neural network

In the development of a statistical prediction model, it is important to include independent variables (predictors) which significantly affect the dependent variable (in this study, intensity change expressed as the change in the minimum surface pressure). Although many environmental factors have been shown to influence tropical cyclone intensity (*e.g.*, DeMaria *et al.*, 1993), this study considers only climatology and persistence factors. These are: 1) initial storm intensity (PMIN), 2) intensity change during previous 12 h (DPMIN), 3) absolute value of Julian date −244 (JDATE), 4) initial storm latitude (°N) (LAT), 5) initial storm longitude (°E) (LONG), 6) magnitude of storm motion vector (SMT), 7) eastward component of storm motion vector (SMU), and 8) northward component of storm motion vector (SMV). The climatological peak frequency of Pacific storms in this data sample occurs around early September and this is included in JDATE.

The above eight predictors were used to develop the multiple linear regression model for Atlantic storms (climatology and persistence model) by DK. With these eight predictors, multiple linear regression equations for predicting storm intensity changes at 12, 24, 36, 48, 60, and 72 h intervals are obtained following the method described by Walpole and Myers (1989). In order to allow for the comparison of regression coefficients for different variables and different prediction intervals, each of the dependent and independent variables is normalized by subtracting the mean and dividing by the standard deviation before constructing each regression equation (DK).

In this study, an attempt is made to train a neural network to perform tropical cyclone intensity prediction. For this, the back-propagation neural network — the most commonly used network — is employed. The neural network consists of a layer of input units, a layer (or layers) of hidden units, and a layer of output units. The back-propagation neural network repeatedly adjusts the connection weights between hidden units and output units and the connection weights between input units and hidden units so as to minimize the error between the desired output and the actual output (Rumelhart *et al.*, 1986). The back-propagation neural network is most useful in situations where the relationship between input and output is nonlinear and training data are abundant (Hinton, 1992). The standard back-propagation algorithm in its essence reads as follows (Zell *et al.*, 1995):

$$\Delta w_{ij} = \eta \delta_j o_i, \tag{1}$$

$$\delta_j = \begin{cases} f_j'(x_j)(d_j - o_j) & \text{if unit } j \text{ is an output unit,} \\ f_j'(x_j)\sum_k \delta_k w_{jk} & \text{if unit } j \text{ is a hidden unit.} \end{cases}$$

Here, i is the index of a predecessor to the current unit j with link w_{ij} from i to j, j the index of the current unit, k the index of a successor to the current unit j with link w_{jk} from j to k, Δw_{ij} the changes in the connection weights, δ_j the error of unit j, d_j the desired output of unit j, and o_i the output of the preceding unit i. The factor η in (1) is the learning rate which is related to the speed of the error convergence. In (2), the x_j is a sum of the connection weights multiplied by the outputs and the function f is the activation function (or input-output function). The f' in (2) means the derivative of the function f. The activation function is necessary to introduce nonlinearity into the neural network and is usually given in the sigmoid function. To make a neural network generalize best, data are split into the training data set, validation data set, and test

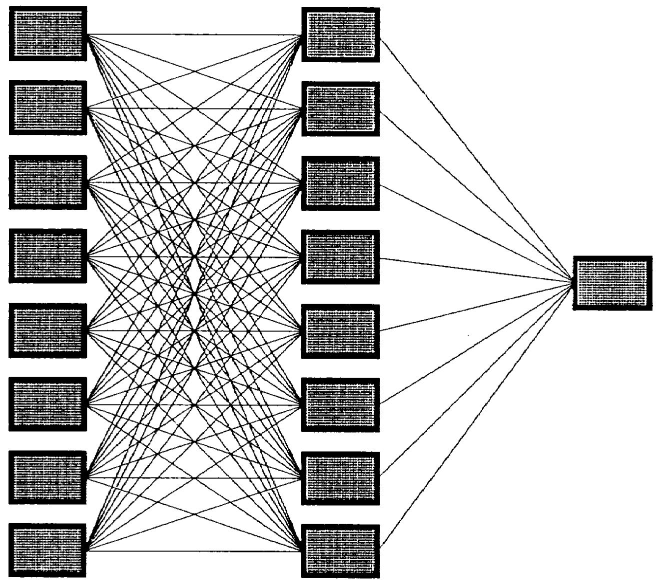

Fig. 1. The three-layer neural network used in this study. The input layer has eight units, the hidden layer has eight units, and the output layer has one unit.

data set and the learning is repeated until the error for the validation data set becomes minimal (Zell *et al.*, 1995). Here, the training data set is used to train a neural network, the validation data set is used to determine the performance of a neural network on patterns which are not trained during the learning, and the test data set is used to finally check the overall performance of a neural network (Zell *et al.*, 1995).

Figure 1 shows the three-layer neural network used in this study. The input layer has eight units (that is, eight predictors described above), the hidden layer has eight units, and the output layer has one unit (that is, tropical cyclone intensity change). This study employs the standard back-propagation neural network in the SNNS (Stuttgart Neural Network Simulator) (Zell *et al.*, 1995). The learning rate η is specified as 0.05. Since the sigmoid function takes values between 0 and 1, it is convenient to have values of the dependent variable lie in that range by a proper transformation. For this, the dependent variable normalized by subtracting the mean and dividing by the standard deviation is divided by twice the maximum absolute value and then 0.5 is added. Each of the independent variables is divided by its maximum absolute value, hence taking values between -1 and 1. If these transformations were applied to the construction of multiple linear regression equations, the result would be the same as that from the above-mentioned regression analysis. This is because the transformations are linear. Based upon the error evolution for the validation data set, the number of learning for each prediction interval is shown to lie between 2000 and 3000.

4. Results and discussion

Table 1 shows the normalized regression coefficients in the multiple linear regression equations for the eight climatology and persistence predictors and different time intervals. The intercepts in the regression equations are zero because of the normalization. All the regression coefficients except for those of SMT at 12 h and SMV at 72 h are statistically significant at the 95 % confidence level. For each predictor, the regression coefficient has the same sign at all prediction intervals.

The initial storm intensity (PMIN) is negatively correlated with the storm intensification. As pointed out by DK, this is because strong storms have an intensity that is closer to their maximum possible intensity and thus have less potential for further intensification. For all prediction intervals except at 12 h, the magnitude of the regression coefficient for PMIN is largest among the eight predictors and becomes larger for the longer time intervals. The intensity change during the previous 12 h (DPMIN) is positively correlated with intensification. That is, storms are likely to intensify further if they have intensified during the previous 12 h. The regression coefficient for DPMIN is largest at 12 h among

Table 1. Normalized regression coefficients for the eight climatology and persistence predictors and different time intervals. All the regression coefficients are statistically significant at the 95 % confidence level except for the values with symbol * and r^2 is the percent of variance explained by the regression model.

variable	12 h	24 h	36 h	48 h	60 h	72 h
1) PMIN	−0.26	−0.38	−0.47	−0.55	−0.61	−0.65
2) DPMIN	+0.45	+0.33	+0.24	+0.17	+0.12	+0.10
3) JDATE	+0.14	+0.20	+0.23	+0.25	+0.26	+0.26
4) LAT	+0.21	+0.29	+0.34	+0.35	+0.35	+0.34
5) LONG	−0.08	−0.11	−0.13	−0.14	−0.15	−0.15
6) SMT	+0.02*	+0.04	+0.06	+0.08	+0.08	+0.07
7) SMU	+0.11	+0.12	+0.11	+0.11	+0.08	+0.08
8) SMV	−0.05	−0.05	−0.05	−0.05	−0.04	−0.02*
r^2 (%)	35.5	38.3	43.4	49.1	53.9	58.3

the predictors and decreases with increasing prediction time interval. The regression coefficient for the Julian date predictor (JDATE) shows that as the number of days from peak frequency for western North Pacific storms becomes small, storms tend to intensify. Latitude (LAT) is positively correlated with intensification because the sea surface temperature generally decreases toward the north. Longitude (LONG) is negatively correlated with intensification. That is, storms tend to weaken toward the west. This might be partly related to the land or islands effect of reducing storm intensity as storms approach land or islands, although the sea surface temperature generally increases toward the west over the western North Pacific. This result is different from that for North Atlantic storms. Over the North Atlantic, storms tend to intensify toward the west and this was attributed to a tendency of increasing sea surface temperature toward the west (DK).

The regression coefficients associated with storm motion (SMT, SMU, and SMV) indicate that storms that move more rapidly and more eastward are likely to weaken, while storms that move more northward are likely to intensify further. It seems physically reasonable for both rapidly moving and eastward moving storms to weaken. This is because this motion indicates that such storms are embedded in the westerlies. The westerlies are typically associated with stronger vertical wind shear and many previous studies (*e.g.*, DeMaria *et al.*, 1993) have shown that high values of vertical wind shear are detrimental to storm intensification. Note that the regression coefficients associated with storm motion are relatively small compared with those for other predictors.

Table 1 indicates that among the climatology and persistence predictors considered in this study, PMIN, DPMIN, JDATE, and LAT generally have the largest magnitudes at each prediction interval. This table also shows that DPMIN is the most important predictor for the 12 h intensity prediction, while PMIN becomes dominant for the longer time intervals.

Table 1 shows that the percent of variance explained by the regression model (r^2) increases with increasing time interval ranging from 35 % at 12 h to 58 % at 72 h. Table 1 also shows that the climatology and persistence predictors only explain a small proportion of the variance. This suggests that synoptic predictors should be included to increase the percent of variance explained further (DK). It will be shown in this study that the neural network model with the same climatology and persistence predictors can also improve upon the regression model.

To compare the performance of the multiple linear regression model for Pacific storms with that for Atlantic storms, the percent of variance versus prediction time interval for both the ocean basins is shown in Fig. 2. Note that the same eight predictors are used for both the ocean basins. However, the intensity of Atlantic storms in DK was expressed in terms of the maximum wind speed, while we defined intensity in terms of the minimum surface pressure for Pacific storms. This figure indicates that the percent of variance explained by the regression model is consistently larger for Pacific storms than for Atlantic storms. The difference in the percent of variance explained becomes larger for the longer prediction intervals, ranging from 6 % at 12 h to 17 % at 72 h with an average difference of 13 %. This implies that the intensity of western North Pacific storms is more likely to be predictable than that of North Atlantic storms when the multiple linear regression model with the climatology and persistence predictors is used. However, the method of expressing storm intensity (maximum wind speed versus minimum surface pressure), analysis period, data size, *etc.* might also result in some difference in the percent of variance explained for the Atlantic and Pacific basins. This needs to be investigated further.

Figure 3 shows the percent of variance explained

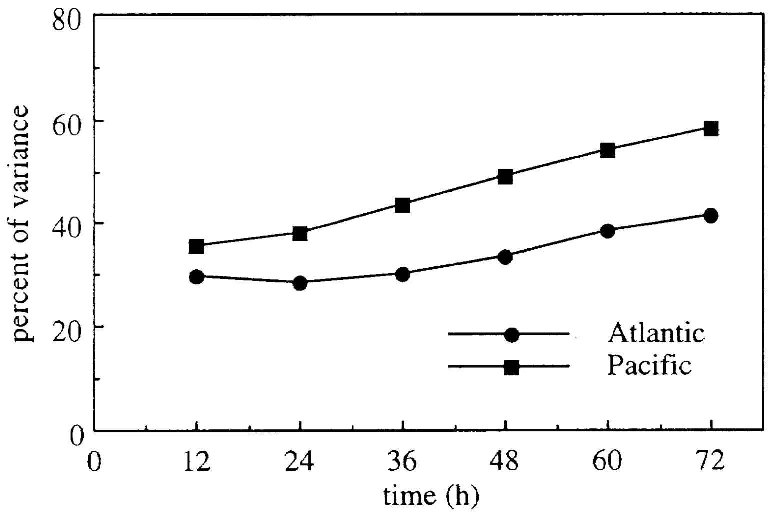

Fig. 2. The percent of variance explained by the multiple linear regression models versus prediction time interval for North Atlantic storms (DeMaria and Kaplan, 1994) and western North Pacific storms (this study).

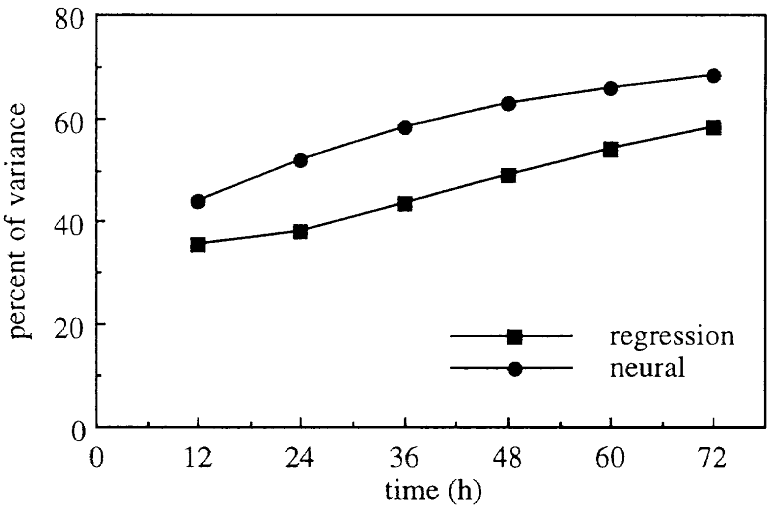

Fig. 3. The percent of variance explained by the multiple linear regression model and the neural network model versus prediction time interval.

by the multiple linear regression model and the neural network model. Although the criterion of representing the proportion of variance for linear models is not the same for nonlinear models, it can be applied directly to nonlinear models if the sample size is large (Zell *et al.*, 1995); then a fair comparison can be made between the two models. The variance explained by the neural network model is consistently larger than that explained by the regression model at all time intervals. The difference in the percent of variance between the two models lies between 8 % at 12 h and 15 % at 36 h and its average value is 12 %. Note that all the data are used to compute the variance in Fig. 3.

Next, the intensity prediction of western North Pacific storms is performed using the regression and neural network models. For the neural network, 80 %, 10 %, and 10 % of the total data are selected to make the training, validation, and test (prediction) data sets, respectively. The test data set is considered to be an independent data set. The same 80 % of data are used to construct a multiple linear regression model for the comparison of results. For the same reason, the test data set is used to perform prediction experiment with the regression model. Figure 4 shows the average intensity prediction errors from the multiple linear regression model and the neural network model. The intensity prediction errors from the neural network model are 10–16 % smaller, except at 12 h where the errors are

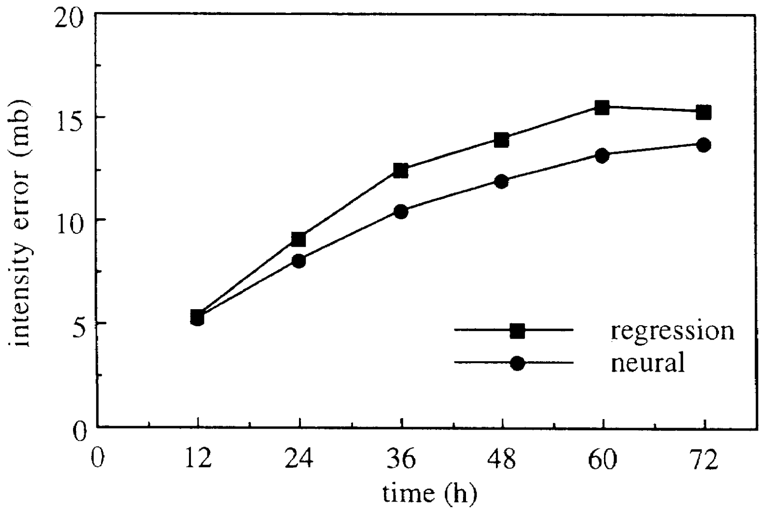

Fig. 4. Average intensity prediction errors (in mb) from the multiple linear regression model and the neural network model versus prediction time interval for the test data set.

nearly equal, than those from the regression model. DK showed that the average intensity prediction errors are reduced by 10–15 % when the regression model includes synoptic predictors. Figure 4 indicates that with the climatology and persistence predictors improvement of a similar degree can be also achieved by replacing the regression model with the neural network model. The results of this study and DK suggest that the performance of the neural network model for tropical cyclone intensity prediction would be improved further if synoptic predictors are included.

Figures 3 and 4 show that the neural network model improves upon the multiple linear regression model in the prediction of tropical cyclone intensity. This is because the neural network takes into account the nonlinear interactions among units by including the nonlinear activation function. For the given data, it might be possible to construct a multiple nonlinear regression model. DK showed that the inclusion of a quadratic nonlinear predictor increases the percent of variance by 1–2 % relative to the linear regression. Sarle (1994) translated neural network jargon into statistical jargon and showed the relationships between neural networks and statistical models. For example, the neural network used in this study (a multilayer perceptron) in principle corresponds to the multiple nonlinear regression model. Therefore, it appears that judicious inclusion of certain nonlinear combinations of predictors might further improve the performance of the regression model. However, an assumed best nonlinear functional relationship is very hard to find and providing physical interpretations to nonlinear terms is not always possible. In a viewpoint that neural networks and statistics are not competing methodologies for data analysis, better communication between the two fields would benefit both (Sarle, 1994). This will also make meteorological applications broaden in a unified viewpoint.

5. Conclusions

The intensity prediction of western North Pacific tropical cyclones was attempted using the multiple linear regression method and the standard back-propagation neural network. The results clearly showed that the neural network model improves upon the regression model, suggesting potential of the neural network in the prediction of tropical cyclone intensity.

In this study, only climatology and persistence predictors were considered. Many environmental factors affect tropical cyclone intensity. These are the vertical shear of horizontal wind, the sea surface temperature, the flux convergence of upper-level eddy angular momentum, the tropospheric water vapor flux, the land effect, and so on (Nyoumura and Yamashita, 1984; Merrill, 1987; DeMaria *et al.*, 1993; Rodgers *et al.*, 1994; DK). With these factors included in the neural network, it is likely that the model performance would be improved further. In this study, the standard neural network was used without detailed sensitivity tests. To construct a better neural network model for predicting tropical cyclone intensity, it is necessary to test other neural networks and examine sensitivity to the network such as the number of hidden layers, the number of units in the hidden layer, *etc.* These areas will be examined in more detail in the near future.

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重回帰法とニューラルネットワークによる熱帯低気圧の強度予報

Jong-Jin Baik・Hong-Sub Hwang

(Kwangju Institute of Science and Technology, Korea)

線形重回帰法と標準的なバックプロパゲーション・ニューラルネットワークによって、北西太平洋の熱帯的圧の 12, 24, 36, 48, 60, 72 時間先の強度予報を試みる。データは 1960 ～ 1990 の 31 年間の北西太平洋の熱帯低気圧で、気候学的及び持続的予報的な 8 個の説明変数を用いる。ニューラルネットワーク・モデルによって説明される分散の割合は、すべての予報時間で重回帰モデルによる分散の割合より一貫して大きく、平均して 12 %の違いがある。ニューラルネットワーク・モデルによる強度予報の平均的な誤差の大きさは、誤差がほとんど等しい 12 時間先以外は、重回帰モデルによるものより 10 ～ 16 %小さい。この研究は、熱帯低気圧の強度予報におけるニューラルネットワークの可能性を明瞭に示している。