Performance Test of Back-Propagation Neural Network in Typhoon Track and Intensity Prediction

Jong-Jin Baik and Jong-Su Paek

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

(Manuscript received 27 March 2000, in final form 27 June 2000)

ABSTRACT

The performance of back-propagation neural network in predicting typhoon track and intensity at 12 h, 24 h, 36 h, 48 h, 60 h, and 72 h intervals is tested in comparison with multiple linear regression method. For this test, climatology and persistence predictors are used for tropical cyclones over the western North Pacific during the period of 1960-1996. The average track prediction errors for the neural network model are larger than those for the multiple regression model. On the other hand, the average intensity prediction errors for the neural network model is 3-9% smaller than those for the multiple regression model. Sensitivity experiments show that the average track and intensity prediction errors are almost independent of the number of hidden layers and the number of units in the hidden layer within the ranges of tested values.

1. Introduction

Artificial neural networks, or simply neural networks, can be regarded as analytical systems that address problems whose solutions are not explicitly formulated (Chester, 1993). Because of their excellent ability in handling unknown nonlinear behavior existing in variables, neural networks are effective alternatives to traditional statistical techniques in meteorology and oceanography (Gardner and Dorling, 1998; Hsieh and Tang, 1998). Numerical models are very useful tools for the purpose of prediction. However, there are cases in which current operational numerical models fail to accurately predict some important variables and even do not outperform, or even have less skills than, statistically-based models. Forecasting tropical cyclone intensity is such a case (DeMaria, 1997).

Recently, Baik and Hwang (1998) (henceforth BH) applied the multilayer perceptron, one kind of neural networks, that employs back-propagation algorithm (Rumelhart *et al.*, 1986) to tropical cyclone intensity prediction over the western North Pacific. They showed that the average intensity prediction errors for the neural network model are smaller than those for the multiple linear regression model. Will there be a similar improvement over the regression model when the neural network is used in the tropical cyclone track prediction? This question motivates present study.

The multilayer perceptron consists of a layer of input units, a layer (layers) of hidden units, and a layer of output units. Each unit is connected to every unit in the next and previous layer by weights and output signals. The hidden layer and hidden unit are free to be chosen in their number. This study also examines the sensitivity of the prediction errors of tropical cyclone track and intensity to hidden-layer structure.

2. Data and neural network

The data used in this study are positions and intensities of tropical cyclones over the western North Pacific during the period of 1960-1996. These data in 6-h intervals (00Z, 06Z, 12Z, 18Z) are archived at the RSMC (Regional/Specialized Meteorological Centers) Tokyo-Typhoon Center. In BH, 31-year data (1960-1990) were used for the typhoon intensity prediction. Storms over land or islands are excluded in the intensity prediction but included in the track prediction. Although many synoptic factors are known to influence tropical cyclone motion and intensity, this study only takes into account climatology and persistence factors to construct neural network and multiple regression models.

For the typhoon track prediction model, the dependent variable is changes in latitude and longitude of storm center (displacement of storm center) and eight inde-

Corresponding Author: Jong-Jin Baik, Department of Environmental Science and Engineering, Kwangju Institute of Science and Technology, Kwangju, Korea
Phone : 062) 970-2437
E_mail : jjbaik@aromi.kjist.ac.kr

pendent variables (predictors) considered are: 1) initial storm intensity, 2) absolute value of Julian date - 244, 3) initial storm latitude, 4) initial storm longitude, 5) eastward component of storm motion vector, 6) northward component of storm motion vector, 7) eastward component of storm motion vector at previous 12 h, and 8) northward component of storm motion vector at previous 12 h. For the typhoon intensity prediction model, the dependent variable is change in storm intensity and nine predictors considered are: 1) initial storm intensity, 2) intensity change during previous 12 hours, 3) absolute value of Julian date - 244, 4) initial storm latitude, 5) initial storm longitude, 6) magnitude of storm motion vector, 7) eastward component of storm motion vector, 8) northward component of storm motion vector, and 9) percent of land coverage in a 10° latitude by 10° longitude area centered on storm center. These intensity predictors are the same as those in BH except that the land coverage variable is included. Note that in this study storm intensity is represented in terms of the minimum surface pressure.

The back-propagation neural network repeatedly adjusts connection weights so as to minimize the error between the desired output and the actual output (Rumelhart *et al.*, 1986). In this study, the standard back-propagation neural network in the SNNS (Stuttgart Neural Network Simulator) (Zell *et al.*, 1995) is employed to construct neural network models that predict typhoon track and intensity at 12 h, 24 h, 36 h, 48 h, 60 h, and 72 h time intervals. The neural network designed for the track prediction has an input layer with eight units (eight predictors described above), a hidden layer with eight units, and an output layer with one unit. Note that changes in latitude and longitude of storm center are separately treated using the same eight predictors. The neural network designed for the intensity prediction (Fig. 1) has an input layer with nine units (nine predictors described above), a hidden layer with nine units, and an output layer with one unit. In order for a neural network to be generalized best, data are split into the training data set, the validation data set, and the test (prediction) data set and the learning is repeated until the error for

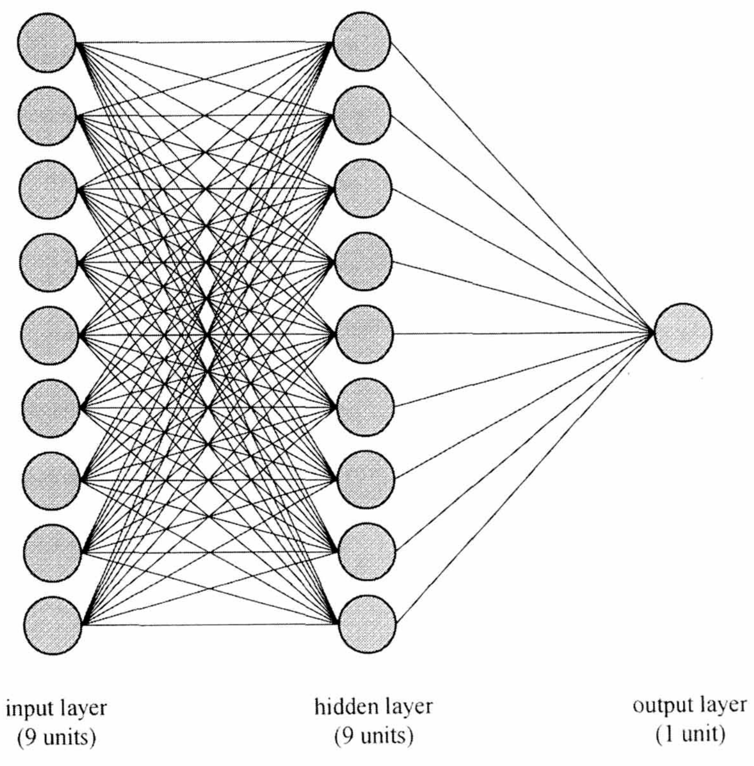

Fig. 1. A three-layer neural network used in the typhoon intensity prediction. The input layer, hidden layer, and output layer have nine units, nine units, and one unit, respectively.

the validation data set becomes minimal (Zell *et al.*, 1995). In this study, 34-year data set from 1960 to 1993 is split into the training data set (80% of total data), the validation data set (10% of total data), and the test data set (10% of total data) to have well constructed neural networks. The prediction performance is tested with 3-year data set during the period of 1994-1996. It is convenient for the dependent variable to have values in the range between 0 and 1 by a proper transformation because the sigmoid (or logistic) function takes values in that range. 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 having values between -1 and 1. For further details, see Zell *et al.* (1995) and BH.

To test the performance of neural network model against traditional statistical model in the tropical cyclone track and intensity prediction, multiple linear regression models at each time interval are constructed following the method described by Walpole and Myers (1989). Each of the dependent and independent variables is normalized by subtracting the mean and dividing by the standard deviation. The same 80% data set (1960-1993) as that (learning data set) in the neural network model is used to obtain multiple linear regression equations and the same three-year data set (1994-1996) is used for prediction experiments. Note that in this study, the predictors for the multiple linear regression model in the track or intensity prediction are also input units for the neural network model. However, a judicious selection of input units among possible variables can be important to develop a well-performed neural network. This requires a future study.

3. Results and discussion

Fig. 2 shows the average absolute errors of typhoon track prediction for the multiple linear regression model and the neural network model. The sample sizes for the three-year period (1994-1996) are 1534, 1365, 1208, 1068, 938, and 822 at 12 h, 24 h, 36 h, 48 h, 60 h, and 72 h, respectively. The average track prediction error for the neural network model tends to linearly increase with increasing time interval, ranging from 78 km at 12 h to 625 km at 72 h. The average track prediction errors for the multiple regression model are smaller than those for the neural network model. The maximum and minimum error differences between the two models are 35 km at 48 h and 8 km at 12 h, respectively.

Fig. 3 shows the average absolute intensity prediction errors for the multiple linear regression model and the neural network model. The sample sizes for the three-year period are 1260, 1083, 937, 812, 707, and 611 at 12 h, 24 h, 36 h, 48 h, 60 h, and 72 h, respectively. These sample sizes are smaller than those used in the track prediction because storms over lands or island and storms moved again into the ocean after landfall are excluded in the intensity prediction. The average intensity prediction error for the neural network model is smaller

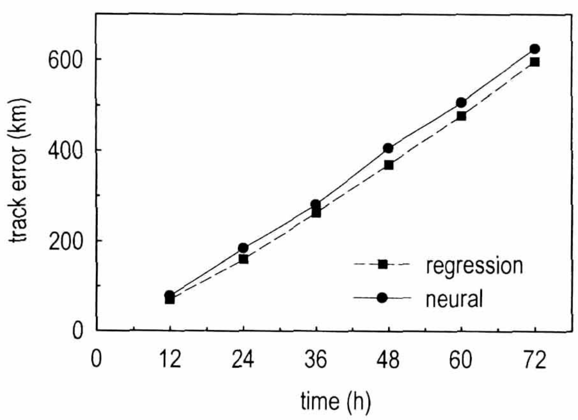

Fig. 2. The average track prediction errors for the multiple linear regression model and the neural network model versus the prediction time interval.

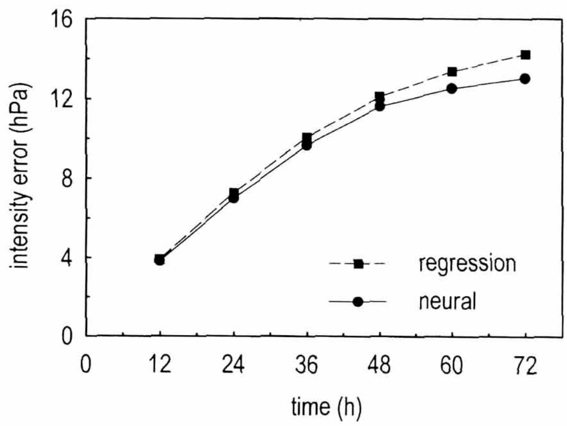

Fig. 3. The average intensity prediction errors for the multiple linear regression model and the neural network model versus the prediction time interval.

than that for the multiple regression model. The improvement of the neural network model upon the multiple regression model becomes large with increasing time interval. The average intensity prediction error for the neural network model at 72 h (12 h) is 9% (3%) smaller than that for the multiple regression model.

As in BH, Fig. 3 indicates that with climatology and persistence predictors the back-propagation neural network model improves upon the multiple linear regression model in forecasting typhoon intensity. However, the degree of the improvement in this study is less than that in BH. This might be related to the different partition of data, the year-to-year variabilities of intensity prediction errors by different models, etc. These or other points need to be further examined to construct more stable neural network in forecasting typhoon intensity.

Many environmental factors, such as the vertical shear of horizontal wind, the sea surface temperature, the upper-level eddy angular momentum flux convergence, the tropospheric water vapor flux, etc., influence tropical cyclone intensity (e.g., DeMaria *et al.*, 1993; Rodgers *et al.*, 1994). Using the multiple regression technique, DeMaria and Kaplan (1994) showed that the SHIPS (Statistical Hurricane Intensity Prediction Scheme) model, which includes climatology/persistence and synoptic predictors, improves upon the model with climatology and persistence predictors only. A similar improvement over the eastern North Pacific was reported by Petty (1997) in terms of the percent of variance explained by the multiple linear regression models. Therefore, based upon the results by DeMaria and Kaplan (1994) and Petty (1997) and the present result (Fig. 3), it is likely that the performance of neural network model in forecasting typhoon intensity would be further improved with synoptic predictors taken into account. This possibility is under investigation using the

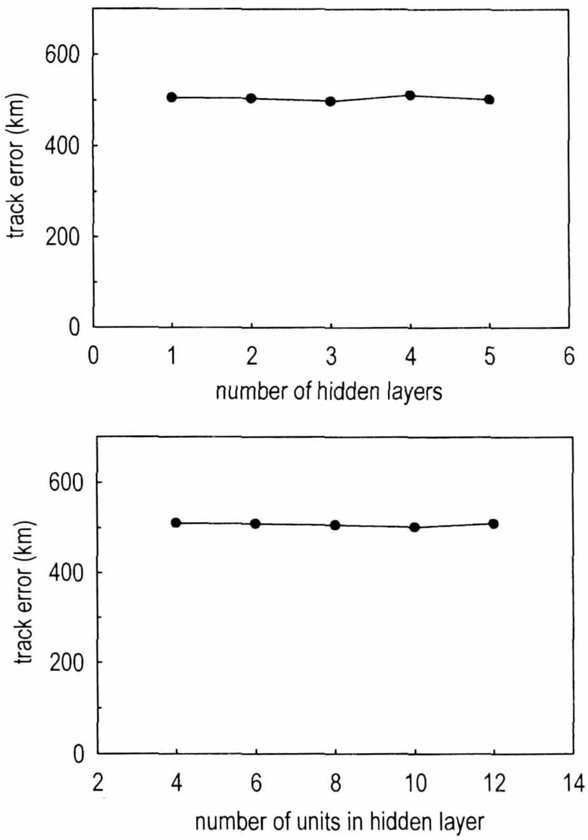

Fig. 4. The average track prediction errors at 60 h versus the number of hidden layers (upper panel) and the number of units in the hidden layer (lower panel) in the neural network.

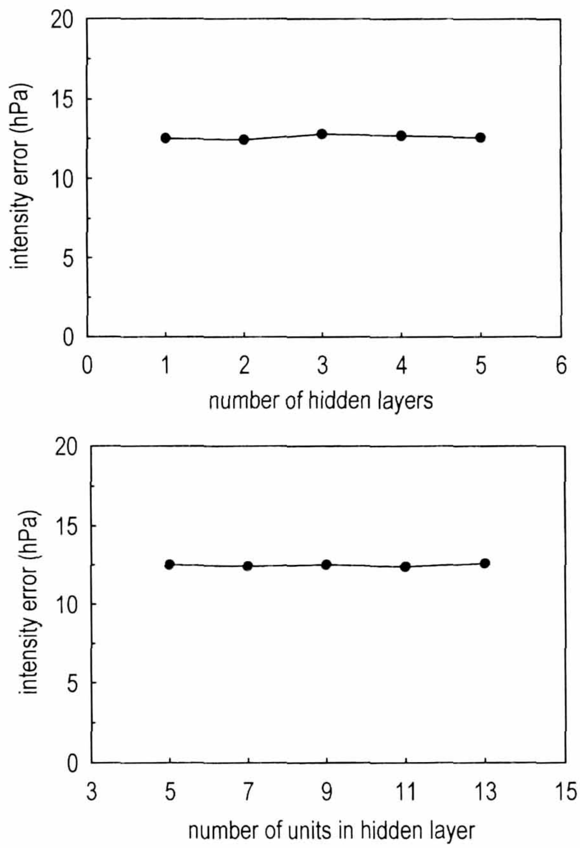

Fig. 5. The average intensity prediction errors at 60 h versus the number of hidden layers (upper panel) and the number of units in the hidden layer (lower panel) in the neural network.

NCEP/NCAR reanalysis data. A preliminary result indicates that the performance of neural network model is indeed further improved when synoptic predictors are included.

The hidden units in multilayer perceptrons are internal and not part of the input or output. However, their introduction plays an essential role in nonlinear learning representations. To examine the sensitivity of typhoon track and intensity prediction errors to hidden-layer structure, neural networks with different numbers of hidden layers and units are constructed.

Fig. 4 shows the average track prediction errors as a function of the number of hidden layers (upper panel) and the number of units in the hidden layer (lower panel). The time interval chosen for presentation is at 60 h. Each neural network structure is exactly the same as that described in section 2 except for a change in the number of hidden layers (2, 3, 4, 5) or in the number of units in the hidden layer (8 ± 2, 8 ± 4). The upper panel of Fig. 4 shows that the average track prediction errors are nearly equal in all the five cases in which the number of hidden layers varies but the number of units in each hidden layer is fixed at eight. The maximum error difference among the cases is 14 km. Similarly, all the five cases in the lower panel of Fig. 4, in which the number of units in the hidden layer changes but the number of hidden layer is fixed at one, exhibit nearly same track errors.

Fig. 5 shows that the average intensity prediction errors at 60 h versus the number of hidden layers and the number of units in the hidden layer. The average intensity prediction error remains almost unchanged as the number of hidden layers changes (upper panel of Fig. 5).. This is also true in the sensitivity tests in which the number of units in the hidden layer changes (9, 9 ± 2, 9 ± 4). The maximum error difference among the cases in the lower panel of Fig. 5 is 0.2 hPa. Results from Figs. 4 and 5 indicate that with climatology and persistence predictors typhoon track and intensity prediction errors for back-propagation neural network models are almost independent of the number of hidden layers and the number of units in the hidden layer within the ranges of tested values. Further study is needed to examine whether this finding holds true when synoptic predictors are included in neural networks.

In this study, the epoch number (number of learning) in the typhoon intensity prediction is determined based on the number at which the error for the validation data set is minimized. This epoch number lies between 1000 and 2000. However, in the typhoon track prediction, at all the prediction intervals except at 24 h, the error for the validation data set continues to decrease as the epoch number increases. Therefore, the minimum error for the track validation data set cannot be easily detected. This makes it difficult to determine when the learning process should be stopped to construct an optimal prediction network. In the present cases, the track prediction error abruptly increases beyond a certain epoch number (prediction error divergence point of about 100-200). Thus, the track prediction error appears to be very sensitive to the epoch number. The prediction networks in these cases are constructed based upon the point where the rate of decrease of validation error per epoch number is minimum around the divergence point. Although the present study shows that the multiple linear regression model improves upon the neural network model in the typhoon track prediction (Fig. 2), it is believed that the track prediction performance of neural network model would be similar to that of multiple linear regression model if well-designed neural network is used. This needs to be further investigated.

4. Summary and conclusion

In this study, it was shown that the average typhoon track prediction errors for the back-propagation neural network model are larger than those for the multiple linear regression model, while the average typhoon intensity prediction errors for the neural network model is 3-9% smaller than those for the multiple regression model. It was also shown that the average track and intensity prediction errors are insensitive to the number of hidden layers and the number of units in the hidden layer within the ranges of tested values.

Although neural network models have proven to be very useful in situations where the relationship between input and output is ñonlinear, so far no general theory has been proposed, which enables us to exactly determine the relationship by analyzing network weights. This black-box nature of neural networks limits its usefulness if the problem under investigation is to understand a physical process through variables. However, this black-box nature dose not matter if the problem is operational prediction or is not to find an exact input-output relationship. In this practical viewpoint, this study suggests potential of back-propagation neural network in forecasting tropical cyclone intensity.

Acknowledgments. The authors are very grateful to one of reviewers for providing valuable comments on this work. This research was supported by the Korea Ministry of Science and Technology.

REFERENCES

Baik, J.-J., and H.-S. Hwang, 1998: Tropical cyclone intensity prediction using regression method and neural network. *J. Meteor. Soc. Japan*, **76**, 711-717.

Chester, M., 1993: *Neural Networks - A Tutorial.* PTR Prentice Hall, 182pp.

DeMaria, M., 1997: Operational tropical cyclone guidance models at the National Hurricane Center. *Workshop on Typhoon Research in the Taiwan Area*, Boulder, CO, U.S.A., 50-56.

_______, and J. Kaplan, 1994: A statistical hurricane intensity prediction scheme (SHIPS) for the Atlantic basin. *Wea. Forecasting*, **9**, 209-220.

_______, J.-J. Baik, and J. Kaplan, 1993: Upper-level eddy angular momentum fluxes and tropical cyclone intensity change. *J. Atmos. Sci.*, **50**, 1133-1147.

Gardner, M.W., and S.R. Dorling, 1998: Artificial neural networks (The multilayer perceptron) - A review of applications in the atmospheric sciences. *Atmos. Environ.*, **32**, 2627-2636.

Hsieh, W.W., and B. Tang, 1998: Applying neural network models to prediction and data analysis in meteorology and oceanography. *Bull. Amer. Meteor. Soc.*, **79**, 1855-1870.

Petty, K.R., 1997: The effects of synoptic factors on the intensities of tropical cyclones over the eastern North Pacific ocean. *22nd Conf. Hurricanes and Tropical Meteorology*, Ft. Collins, CO, Amer. Meteor. Soc., 278-279.

Rodgers, E.B., J.-J. Baik, and H.F. Pierce, 1994: The environmental influence on tropical cyclone precipitation. *J. Appl. Meteor.*, **33**, 573-593.

Rumelhart, D.E., G.E. Hinton, and R.J. Williams, 1986: Learning representations by back-propagating errors. *Nature*, **323**, 533-536.

Walpole, R.E., and R.H. Myers, 1989: *Probability and Statistics for Engineers and Scientists*, 4th Ed., Macmillan Publ. Co., 765pp.

Zell, A., and collaborators, 1995: *SNNS*, User Manual, Version 4.1, University of Stuttgart, 312pp.