14A.6 HURRICANE INTENSITY FORECASTING WITH NEURAL NETWORKS

Michael G. McGauley *
University of Miami, Miami Florida

1. INTRODUCTION

Hurricane intensity forecasting has not made the same progress as hurricane track forecasting since the National Hurricane Center (NHC) began providing each to the public. For intensity predictions, one of two techniques available to the NHC is a Statistical Hurricane Intensity Prediction Scheme (SHIPS) that incorporates climatology, persistence and synoptic parameters in a multiple linear regression routine (DeMaria and Kaplan, 1999) to determine the hurricane's intensity. It is shown here that a new statistical technique incorporating Neural Networks (NN) improves upon SHIPS at 24 and 48 hour by ~5%. In addition, the NN can provide information about non-linear interactions that are difficult to do with regression-based schemes.

2. DATA AND METHODOLOGY

2.1 Neural Networks

NNs began as research in the biological fields to understand how the brain responds to stimuli and use it for pattern recognition. Although the typical architecture of a NN is somewhat straightforward (Fig. 1), its usefulness in providing predictions for training inputs was limited until the advent of a self-correcting routine that automatically alters the weights to minimize errors. Once this 'backpropagation of errors' algorithm (Hagan et al., 1996) was developed the NN was found to be highly useful in recognizing, not only linear behavior, but non-linear and non-continuous functions as well.

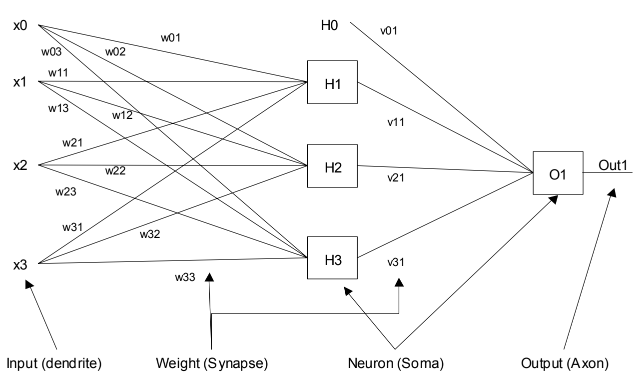

Figure 1: Common structure of a NN with biological analogies. Output signal(s): $\mathrm{Out}_i = f\,(\Sigma j v_{ij} \cdot f\,(\Sigma_k w_{jk} \cdot x_k))$, where the function, *f*, is constrained to be continuous and differentiable.

* *Corresponding author address*: Michael G. McGauley, RSMAS, MPO dept., 4600 Rickenbacker Cswy., Miami, Fl 33149. E-mail: mmcgauley@rsmas.miami.edu.

2.2 NN and SHIPS comparison

To compare the NN skill to SHIPS, climatological, persistence and synoptic indicators that are part of the SHIPS linear regression scheme are also included in the NN input (see Table 1: DeMaria and Kaplan, 1999), with the exception of the squared 'Maximum Potential Intensity – Initial Intensity' term (POT). Due to the fact this term was also included as a non-squared term; the ability of the NN to detect a quadratic relationship should be seen after NN training is complete. For skill comparison, each year from 1989 to 2002 was removed individually from both the SHIPS and NN routine. Once the SHIPS and NN were optimized, the weights from both were applied to the missing year and the difference in intensity forecasts for 24, 48 and 72 hours were calculated.

2.3 NN Design (Hagan et al., 1996)

A simple feedforward design with 12 inputs, 10 hidden neurons and one output (corresponding to predicted wind speed) is used. Although there are many other NN designs that are available and may provide higher skill, this initial construction was chosen for its simplicity. NN inputs were normalized by subtracting the mean and dividing by the standard deviation. Ten hidden neurons were chosen as a means to increase the degrees of freedom of the network without bringing in too many neurons that would increase training time. A tan-sigmoid transfer function (with an output range of -1 to 1) was used on the hidden layers while a linear function is used on the NN output (allowing predictions outside the range of the training set). Initial weights were randomly chosen and the NN training was performed using a Matlab *traingdx* routine. Ironically one of the biggest disadvantages of NNs is the ability to derive weights that can replicate the training set too accurately. With errors on the training set too low, future predictive skills tend to be poor. Using an 'msereg' algorithm, the network will have smaller weights and biases that tend to force the network response to be smaller and less likely to over fit.

3. RESULTS

Wind-speed predictions for SHIPS and the NN are shown in Fig. 2. The NN improved upon SHIPS during each year for the 24-hour predictions (a) and improved upon SHIPS for 13 out of 14 years for the 48-hour predictions (b). Mean skills for 24 hours are 6.22 m s^{-1} for SHIPS and 5.93 m s^{-1} for the NN, an improvement of 4.94%. This increase in skill is significant at the 95% level. Mean skills for 48 hour predictions were 9.47 m s^{-1} for SHIPS and 9.09 m s^{-1} for the NN, an improvement of 4.17%, also significant at the 95% level. Although the

NN predictions were better than SHIPS for 8 out of the 14 years, mean skills were 11.43 m s^{-1} and 11.45 m s^{-1} for SHIPS and the NN, respectively, a statistically equal skill for both.

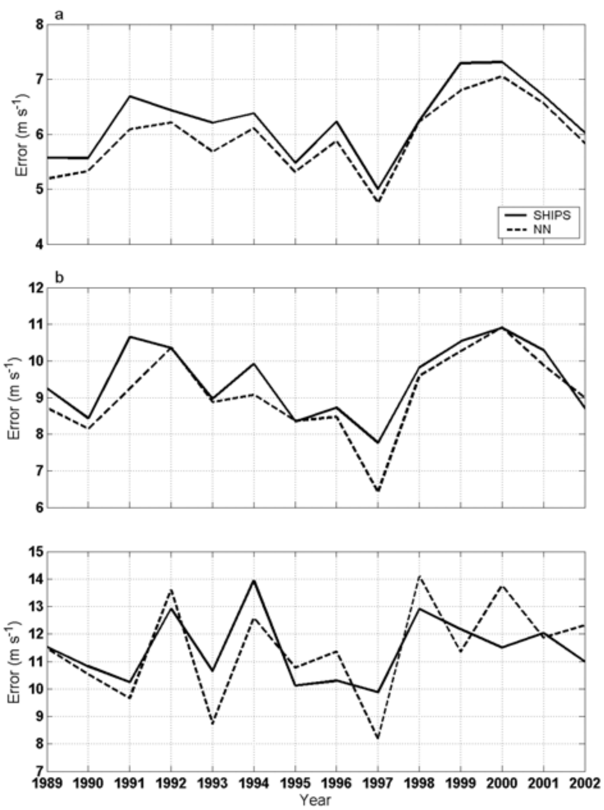

Figure 2: Predictions from SHIPS (solid line) and NN (dashed line) for 24 hours (a), 48 hours (b) and 72 hours (c). NN skill increases over SHIPS at a 95% significance level shown at 24 and 48 hours. No skill increase at 72 hours shown by either.

4. DISCUSSION

In a previous study comparing Pacific hurricane intensity predictions using a linear regression scheme to NNs, error decreases of 7 to 16% were observed (Baik and Paek, 2000). The 4 to 5% decrease in errors with this study using Atlantic hurricanes show similar results. These findings suggest that NNs can improve upon hurricane intensity forecasting and presumably as more data from future years are incorporated in the training routine, NN skill should also improve. Apart from the increased skill in intensity predictions, NNs can also provide information on what relationship each input has with other parameters. As discussed in Section 2.2, the only input that was removed from the NN training set but used in SHIPS was the squared function of POT. As expected, several of the independent variables showed quadratic characteristics and as shown in Fig. 3 the 24 hour forecast relating Maximum Potential Intensity (MPI) to wind speeds show a plateau of wind speed predictions at higher MPIs. This also agrees with results by DeMaria and Kaplan (1994, Fig. 2) suggesting the same phenomenon. Unfortunately, their theory (1999) that the negative regression coefficient found for POT^2 was attributed to the fact that smaller storms with large POT may not have the ability to intensify as much as bigger storms was not found by the NN.

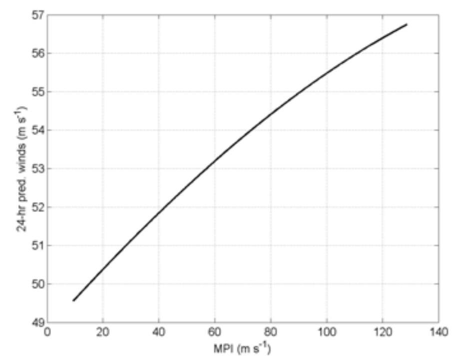

Figure 3: Plot of NN 24-hour predicted intensity (m s^{-1}). All inputs were equal to their mean except POT which was allowed to vary and initial wind speed which was set at 54 m s^{-1}.

5. REFERENCES

Baik, J-J. and J-S Paek, 2000: A neural network model for predicting typhoon intensity. *J. Meteor. Soc. Japan*, **78**, 857-869.

DeMaria, M., and J. Kaplan, 1999: An updated statistical hurricane intensity prediction scheme (SHIPS) for the Atlantic and Eastern North Pacific basins. *Wea. and Forecasting*, **14**, 326-337.

_________ and J. Kaplan, 1994: Sea surface temperature and the maximum intensity of Atlantic tropical cyclones. *J. Climate*: 7, 1324–1334.

Hagan, M.T., H.B. Demuth and M.H. Beale, 1996: *Neural Network Design*, Boston, MA: PWS Publishing.

6. ACKNOWLEDGMENTS

This author would like to thank Mark DeMaria and John Kaplan for the predictor data used in the SHIPS regression scheme, and to my advisor, Dr. Lynn Shay. Research support is provided by NSF.