PREDICTING CLOUD-TO-GROUND LIGHTNING WITH NEURAL NETWORKS

Arnold A. Barnes, Jr.
Atmospheric Sciences Division
Geophysics Directorate
Phillips Laboratory (AFSC)
Hanscom AFB, MA 01731

Donald Frankel and James Stark Draper
KTAADN, Inc.
Newton, MA 02159

ABSTRACT

Lightning is a hazard to ground operations, missile launch operations and recovery of the Space Shuttle at Cape Canaveral. The Air Force is responsible for providing the forecasts of lightning for these operations. In an effort to improve the forecasting of cloud-to-ground lightning, neural networks are being applied using the large data bases from the Cape Canaveral area which includes Cape Canaveral Air Force Station (CCAFS), Kennedy Space Center (KSC) and peripheral locations.

The initial study [1-3] employed the wind data from a number of different levels on 32 towers to predict lightning strikes in 16 blocks over Cape Canaveral for four time periods; 0-15 min., 15-30 min., 30-60 min. and 1-2 hours. The network was trained by backpropagation using the data from one day, 24 July 1988, and was verified on independent data from 25 July 1988. Comparisons were made with the convergence method of Watson et al [4] and were found to give similar results. The neural network results should improve with larger training sets and with the addition of more of the readily available meteorological data. Results of further training and the addition of ground based field mill data are discussed.

INTRODUCTION

ANS is a sub-discipline of artificial intelligence which deals with the relationships between sets of data. The excellent meteorological and field mill data sets from Cape Canaveral are being used as inputs and the lightning strike data from the Lightning Location and Prediction, Inc. (LLP) system are used as the output (predicted) data to train the networks. The objective is to predict lightning location and time from the meteorological and field mill data.

The purpose of this paper is to report on four additional extensions of the initial study. First, the training was expanded to include two days; second, the wind convergence values of Watson et al [4] were added as an input; third, five minute mean values from the ground-based electric field mills were added as input values; and forth, neural networks with two rather than one hidden layers were investigated.

ADDITIONAL TRAINING DAY

The initial study trained on just one day, 24 July 1988, and verified using independent data from 25 July 1988. Comparison with the Watson convergence was good as is shown in Table 1.

Table 1. Comparison of results

TYPE OF MEASURE	WATSON ET AL	INITIAL NETWORK
Probability of Detection	0.41	0.47
False Alarm Rate	0.57	0.56
Critical Skill Index	0.26	0.29

Two days, 21 and 23 July 1988, were added to the training base. This larger data base improved the results. (Limitations on the software and hardware of the MAC IIx restricted the training data files to just two days. We plan to overcome this restriction by connecting to large vax files through an ethernet.) Figure 1. shows the probability of detection (POD) on the independent data set, 24 July 1988. The hidden layer was run with 5, 6, 7 and 8 nodes, and the line WLHD shows the POD performance of the Watson convergence method. Note that there is substantial improvement at 1 hour for the networks with 6,7, or 8 nodes in the hidden layer.

DIVERGENCE AS AN INPUT

Watson et al [4] showed that convergence over the CCAFS/KSC area was a good predictor of lightning within 80-120 minutes, and this technique is presently available and being used by the Air Force forecaster. By adding these values as inputs to the neural networks, improvements were made in the POD as shown in Figure 2.

USE OF ELECTRIC FIELD MILL DATA

The success of the networks with the 1 hour predictions pointed out how poorly the predictions were for short lead times. We felt that data from the ground based electric field mills would help to improve the forecasts in the two shorter time period prediction epochs. Inspection showed that these field mill data were not very clean, so it was decided to take five minute averages which is the same time average used for the other data. Results of adding the electric field data are shown in Figure 3.

The results for the two shorter epochs were disappointing. This is attributed to the fact that the data are rather noisy and the impression that most of the information is in the rapid changes of the signals rather than in the five minute averages. This suggests that short term means and variances of the electric fields be used along with the LLP data to train a completely new ANS for short term forecasts of lightning employing just the ground based field mill data.

These electric field mill results are preliminary but it should be noted that one of the networks, the one shown with 10 nodes in the hidden layer in Figure 3, performed fairly well in the "NOW" time epoch.

USE OF TWO HIDDEN LAYERS

ANS with two hidden layers are more powerful than ANS with only one hidden layer. To quote from the DARPA Neural Network Study [5, pages 79-80] "The utility of the backpropagation algorithm stems from the surprising computational power of three-layer perceptrons with two hidden layers. These networks can form any desired decision region. ... They can thus emulate any traditional deterministic classifier by producing the decision region required by that classifier. Kolmogorov also proved a theorem described in Lorentz [6] which, in effect, demonstrates that a three-layer network can form any continuous nonlinear function of the inputs. This proof requires carefully specified nonlinearities with wide dynamic ranges. More recent theoretical work [7] has demonstrated that continuous nonlinear functions can be approximated to arbitrary precision using three-layer perceptron with sigmoidal non linearities. A three-layer perceptron can thus create any continuous likelihood function required in a classifier, given enough nodes."

Table 2. lists the steady state pass error for different training runs using wind data, convergence values, and field mill data from the 21st and 23rd of July 1988.

Table 2.

Nodes in 1st layer	Nodes in 2nd layer	Steady state pass average error
3	3	600
5	5	500
8	6	350
8	8	250
12	12	200

Since all these networks used the same data, the smaller value pass average errors show improvements with increasing numbers of nodes. Comparisons on independent data will be necessary to ascertain which of these networks is the best predictor. Those with the larger number of nodes are not necessarily the best predictors since they may be training specific and not have generalized.

Figures 4 and 5 are derived from exactly the same neural net program run on exactly the same data. The only differences are that they were run on two different MAC IIx at different times which meant that the initial weights, which were randomly chosen, were different. The training runs seem to be similar to about the 200th pass through the training data at which point the pass errors starts to fluctuate. These fluctuations in pass errors imply that both of these networks have wandered into rough-textured regions of the error surfaces near minima but not at minima. On the other hand, we do know that both are near minima because the pass errors dropped and flattened out before the fluctuations started. Since both runs exhibit the same characteristic, it would indicate that both are at the same minimum on the error surface which would suggest that they are near the global minimum. This could be further investigated by employing simulated annealing in the training.

CONCLUSIONS

Prediction of cloud-to-ground lightning using ANS improved with a second day's worth of data used in the training. The addition of the Watson convergence values improved predictions at 1 hour. Five minute averages of electric field data did not improve the short term predictions significantly, and perusal of the data suggests that short term electric field variations be used to improve the forecasting of lightning for periods up to one hour. Details are provided in [8] and [9]. In addition, ANS with two hidden layers were investigated and the results suggest that a global minimum is being approached on the error surface. Simulated annealing should be used in the training to test this.

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# Probability of Detection
Wind Data Only
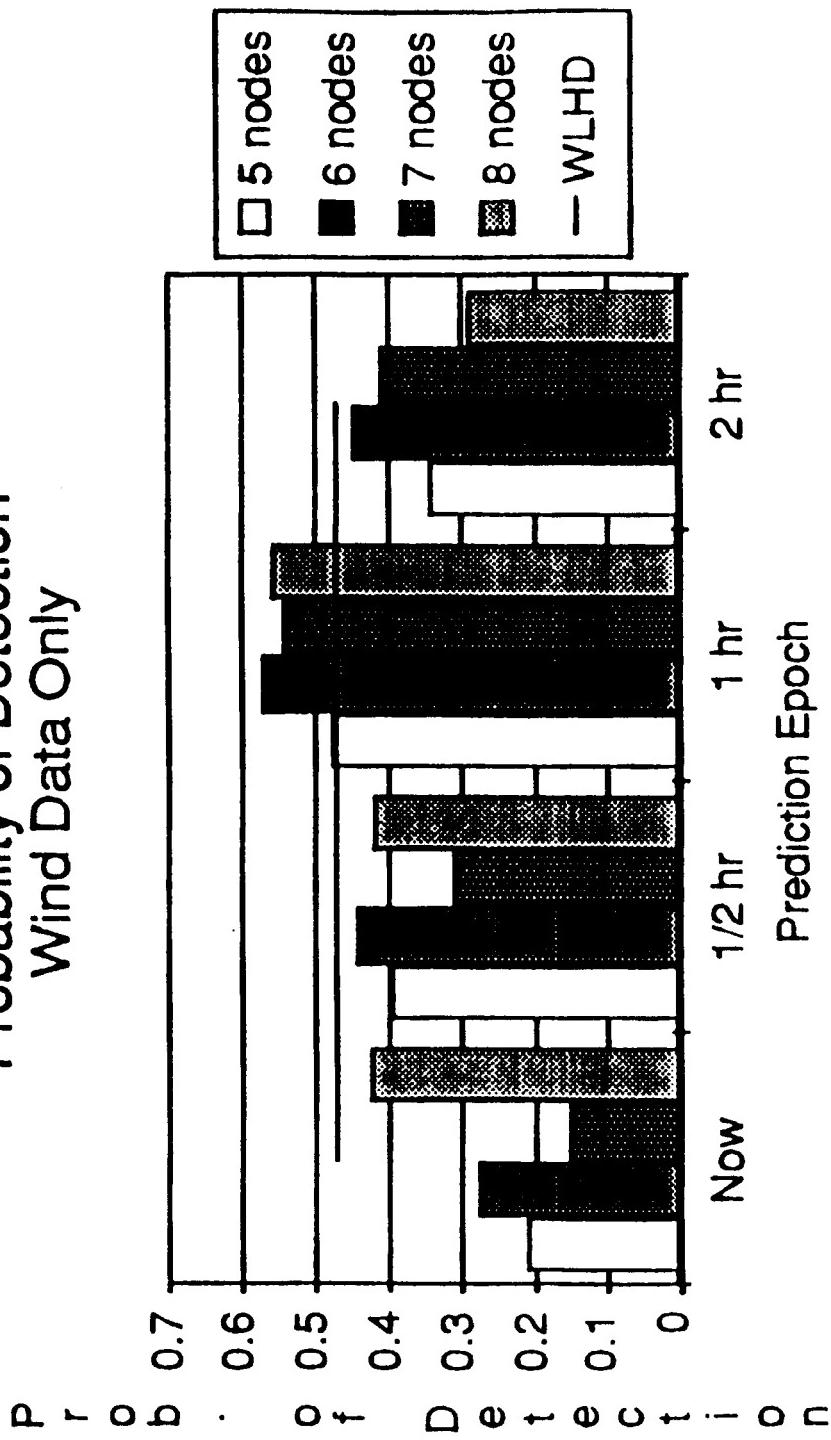
Figure 1 Probability of detection by time epoch of the ANS using two days of wind data as input. The horizontal line labeled WLHD is the level of performance of Watson et al. 1987 in predicting lightning for the entire KSC area at any time following a threshold crossing of the Total Area Divergence.
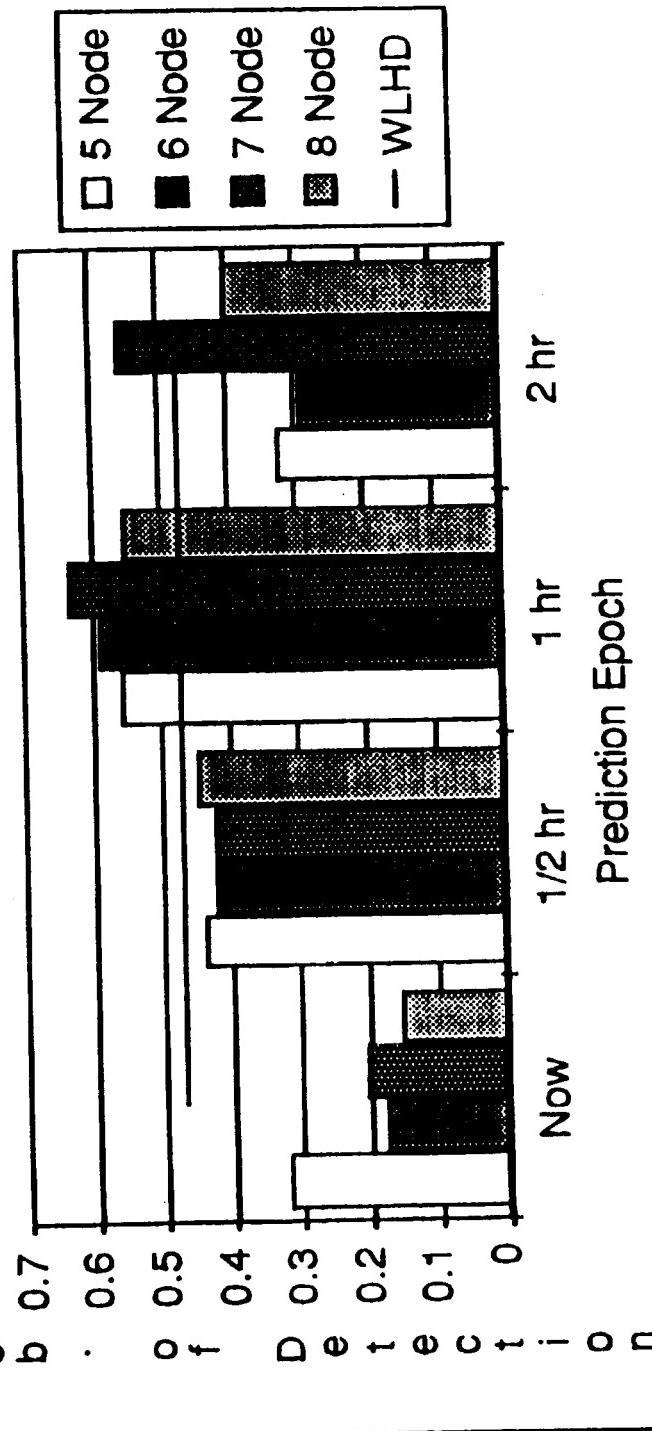
Figure 2. Probability of detection by time epoch of the ANS using two days of wind data and the Total Area Divergence as input. The horizontal line labeled WLHD is the level of performance of Watson et al. 1987 in predicting lightning for the entire KSC area at any time following a threshold crossing of the Total Area Divergence.
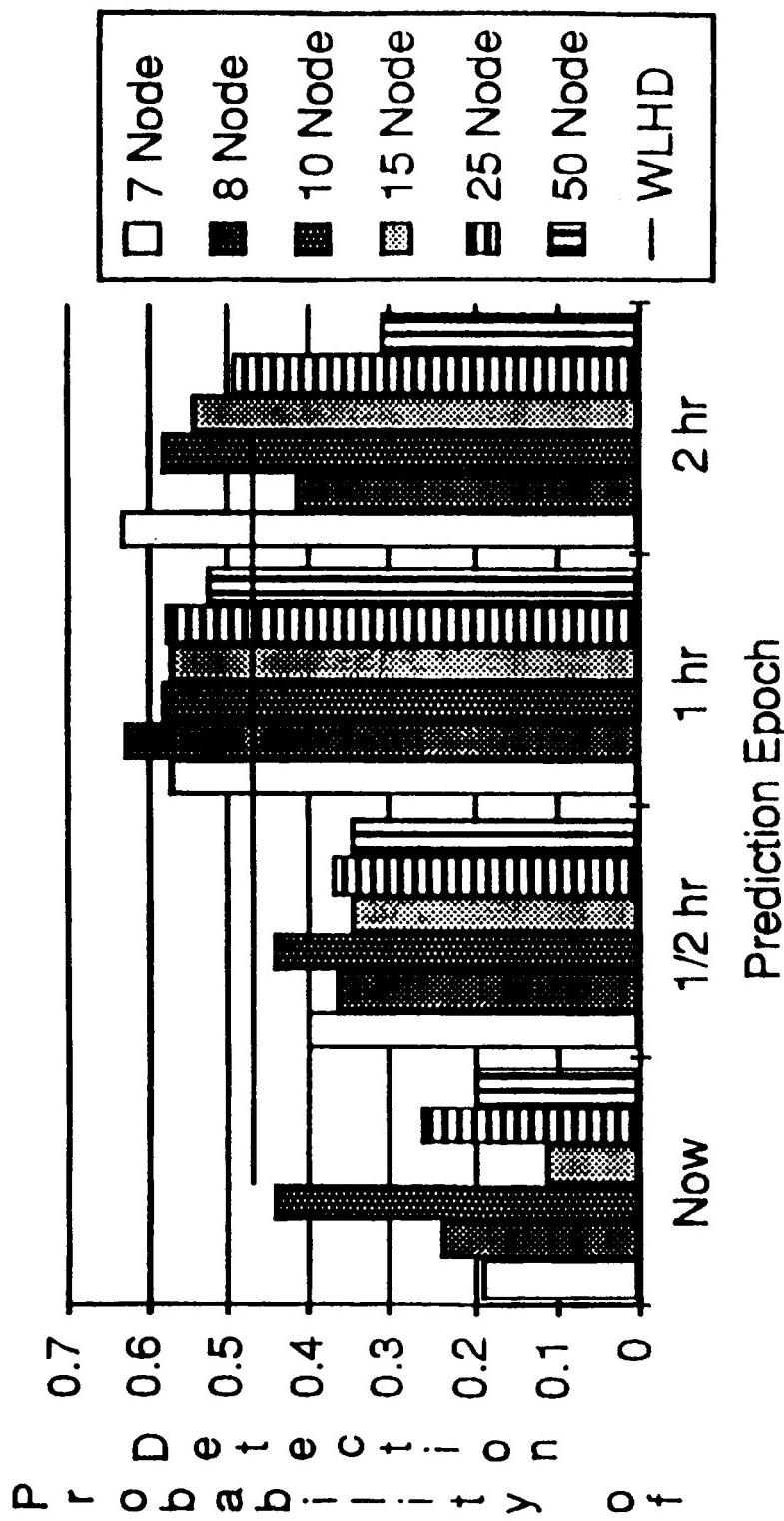
Figure 3 Probability of detection of the ANS using two days of wind data, the Total Area Divergence, and the electric field data as input. The horizontal line labeled WLHD is the level of performance of Watson et al. 1987.
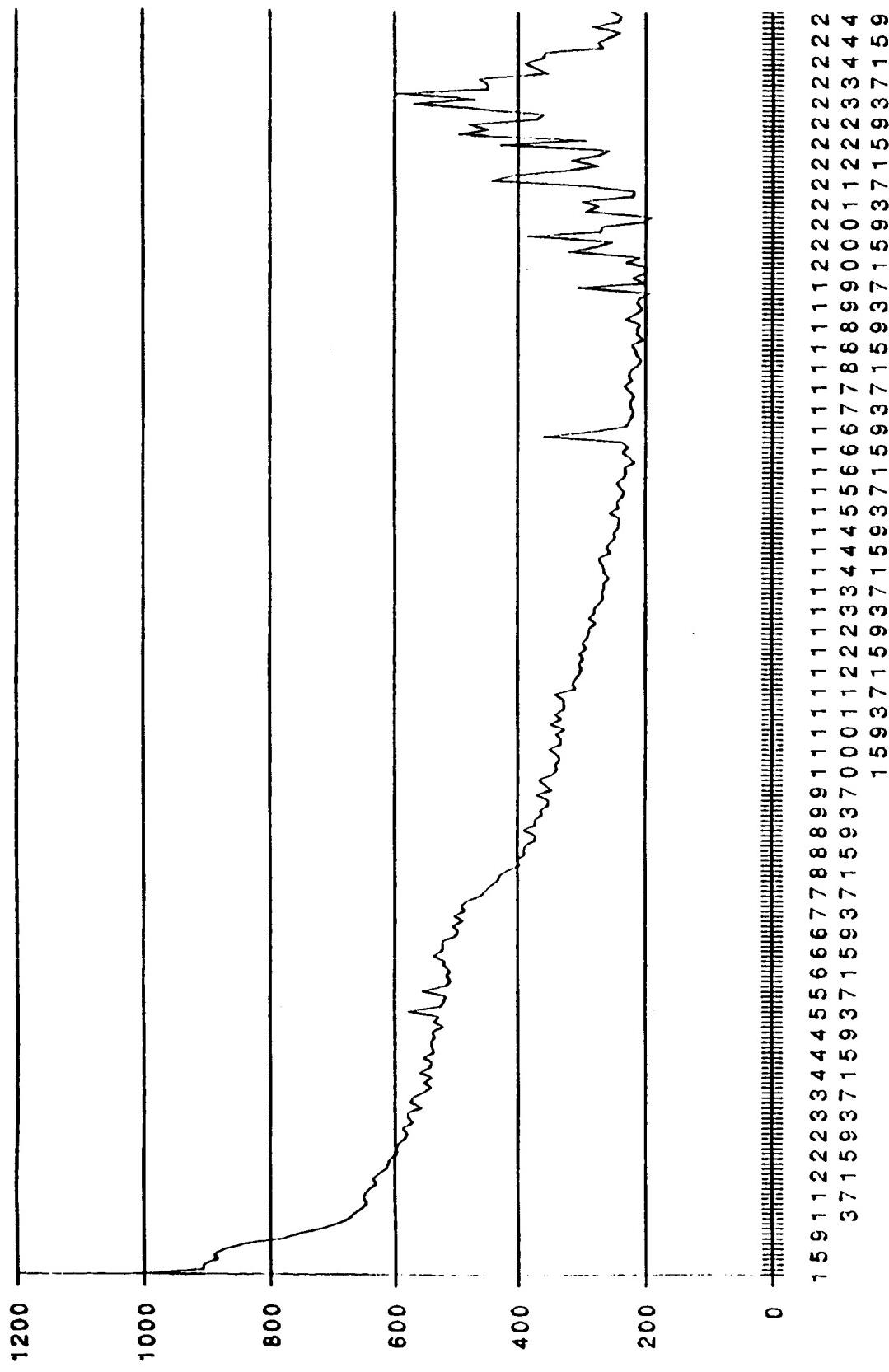
FIGURE 4. Pass errors for 249 training passes through the two hidden layer, 138x12x12x64 neural network using data from 21 and 23 July 1988 on the GP/CC MAC IIx.
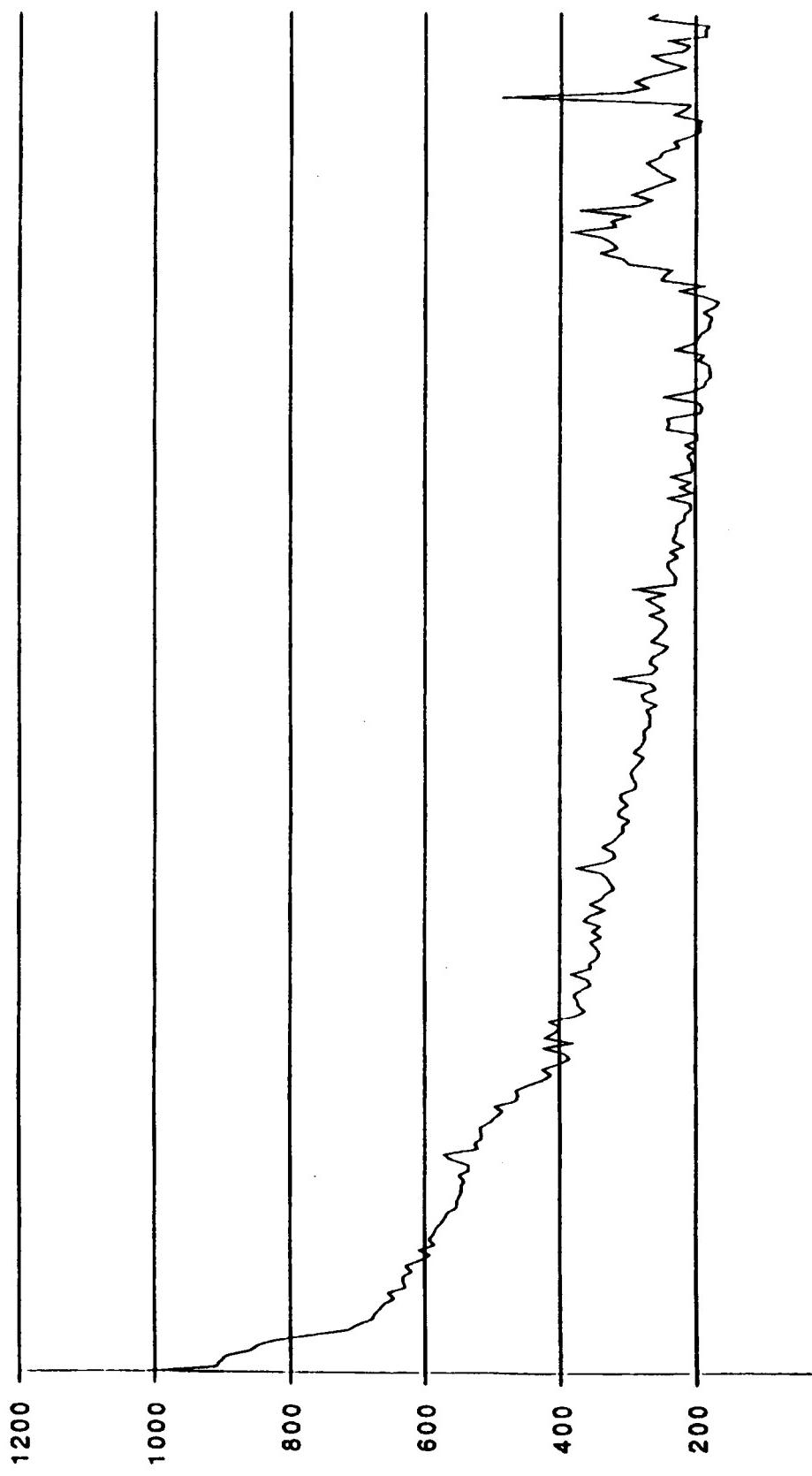
FIGURE 5. Pass errors for 257 training passes using the same
neural network and the same data as shown in Figure 4. The only
difference is that the MAC IIx from GP/PH was used therefore the
initial random weights were different.