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A NEURAL NETWORK TO RETRIEVE UPPER LEVEL WINDS FROM GROUND BASED PROFILERS

Young Yee*
Ed Creegan

US Army Research Laboratory
Atmospheric Effects Branch
Computational & Information Sciences Directorate
White Sands Missile Range, NM

1. INTRODUCTION

Accurate, real-time upper level wind measurements can provide essential input into operational mesoscale models for their initialization and verification. In artillery meteorology, measurements of upper level winds are important to the accuracy of calculated ballistic trajectories. Although there are a number of ground based wind profilers available (wind tracer lidar, Doppler radar, and acoustical sounders), measuring upper level winds can be problematic and is highly dependent on favorable atmospheric conditions. Other methods to obtain wind velocity profiles include satellite-based data, thermal wind approximations, cloud tracking (Nieman et al, 1997), and moisture field tracking (Velden et al, 1997). Each of these methods can provide useful information for some synoptic scale applications but each one has certain limitations.

Pioneer neural network research was conducted at the former Atmospheric Sciences Laboratory in the early 1990's (Measure & Yee, 1992). The research involved experimentation with neural network methods to retrieve temperature profiles from ground based microwave radiometers (Yee & Measure, 1992) as well as from satellite radiance measurements (Bustamante, etal, 1994). Neural networks were trained using simulated microwave radiometric measurements and archived radiosonde measurements to produce vertical profiles of temperature from the surface to approximately 10 kilometers The success of these earlier studies prompted wind vector retrievals using satellite radiances (Cogan, etal, 1997). Those experiments have yielded errors comparable to those achieved by other sounder based methods. Current studies involve the fusion of varied measurement sources to improve the upper level wind retrievals using neural network techniques. Neural networks are ideally suited for processing diverse data measurements and analyzing large data sets.

The ARL currently has three different wind profilers as part of the Atmospheric Boundary Layer Exploitation (ABLE) capabilities: Doppler Wind Tracer Lidar, 924MHz Radar Wind Profiler, and SODAR Profiler. All the wind profilers have certain limitations and atmospheric conditions play a very important role in the retrieval of reliable wind vectors. In many cases, it is difficult to obtain consistent winds at the maximum detectable heights of these remote sensors. A neural network has been developed to estimate upper level winds from these ground based wind profilers to extend their capabilities at a particular locale. To demonstrate the feasibility of this method, a large training and testing set was extracted from the NCDC archived radiosonde data of North America (1957-1994) for El Paso, Texas. The 700mb level winds were used as input into the neural network to derive the 400mb level winds in the simulated test runs. Preliminary results will be shown and future studies will be discussed.

* *Corresponding author address*: Young Yee, Computational & Information Sciences Directorate, Atmospheric Effects Branch, Army Research Lab, White Sands Missile Range, NM. 88002. yyee@arl.army.mil

2. ATMOSPHERIC WIND PROFILERS

The ARL has several different wind profilers with various characteristics as shown in figure 1. The three major systems are based on Doppler Lidar, radar, and acoustics. One of the salient features of wind profilers, in general, is that they can provide continuous measurements without the extra expenditure of resources that a radiosonde would require. Satellite measurements can collect wind information at higher atmospheric levels but the accuracy does not meet the requirements for precise artillery operations.

Wind Profiler	Description	Typical Max Range	Range Resolution
ARL CTI Doppler LIDAR	- Eye safe infrared laser source - 2.0µm wavelength - 2 mJ pulse energy - 500Hz rate - VAD scans	3-6 km	60 meters
ARL 924 MHz Wind Radar	- Phased array - Consensus processing - 10-30 minutes integration time	3-5 km	100 meters
ARL SODAR	- Acoustical source - 300 vertical layers - 2.85-4.75 Hz - 1-60 min/avg	.3-.5 km	5-100 meters

Figure1. Summary of some characteristics of several different types of wind profilers acquired by the ARL.

Figure 2 is a photograph of the 924MHz wind profiling radar antenna built onto a High Mobility Trailer (Creegan & Guiterrez, 2001). The processing hardware and software is installed into a covered shelter on a High Mobility Multi-Wheeled Vehicle (HMMWV). There are different radar signal processing methodologies to extract wind direction and speed. One technique is the Advanced Signal Processing (ASP) method and another one is the more traditional consensus method.

Figure 2. Photograph of the ARL 924 MHz wind profiling radar antenna towed by HMMWV. Processing hardware and software are housed inside the HMMWV's shelter.

The ARL CTI Doppler Lidar system consists of a scanning optics unit, laser source, receiver, data acquisition system, and signal processing software (Figure 3).

Figure 3. Photograph of the ARL Doppler Wind Tracer Lidar system (left) and the ARL Microwave Radiometer (Measure, etal, 1998) measuring moisture and temperature profiles (right) during the Joint Urban 2003 experiment in Oklahoma City, 2003.

Figures 4 and 5, wind speed and wind direction respectively, represent a sample derived wind profile from the wind radar using the consensus processing method. The data was taken at the White Sands Missile Range, New Mexico on August 10, 1999. The data was taken within several miles of a mountain range which may account for the variability in the vertical profile. When comparing wind profiling measurements with rawinsonde measured winds, past field data show reasonable agreement even though the wind profiler is a volumetric measurement versus a point by point displacement measurement used by the rawinsonde.

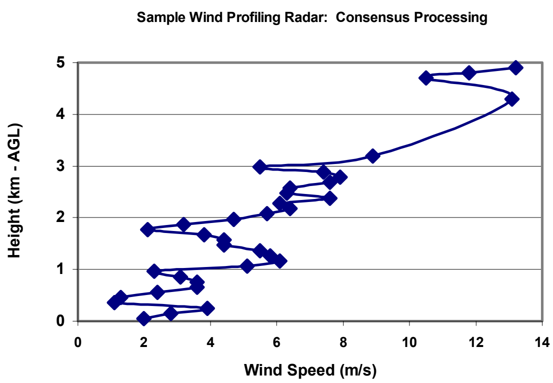

Figure 4. Wind profiling radar sample measurement showing wind speed from the near surface to 5 kilometers.

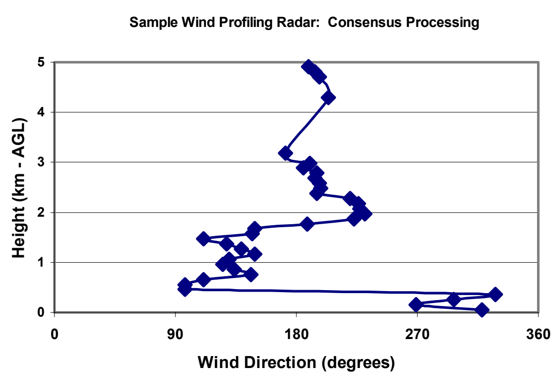

Figure 5. Wind profiling radar sample measurement showing the corresponding wind direction of the wind profile in Figure 4.

3. NEURAL NETWORK ARCHITECTURE

An overview of the neural network procedure is shown in figure 6. Training the neural network would involve the collection of coincident wind profiler data and rawinsonde data. These data would be filtered via algorithms that screen the data for missing fields and defective data records. If data is missing in any of the training set's data fields, that individual test case, ie wind profile, will be rejected for the purpose of training or testing. After extracting the wind direction and wind speed for selected height levels of interest, the wind parameters will be converted to U components (East-West) and corresponding V components (North-South) of the wind.

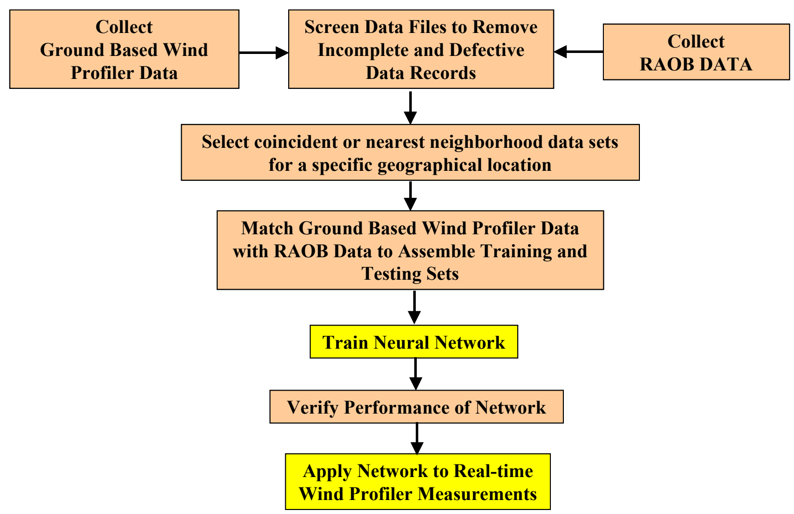

Figure 6. Flowchart of the neural network procedure to retrieve upper level winds.

To assemble the actual training and testing sets for the neural network, wind profiler data will be matched with the appropriate rawinsonde data. Although the wind profilers may have selectable integration periods, the rawinsonde wind data can take over an hour to complete its profile. Thus exact matching is not possible.

Previous work has shown that a back propagation, feed forward, neural network is appropriate for these types of physical measurements. Using a commercially available neural network development package, the following parameters were defined for the neural network (Table 1).

Table 1. Neural Network Parameters

Learning Rule	Delta-Rule
Transfer Function	Sigmoid
Summation	Sum
Noise	Uniform

4. DATA SETS FOR NN TRAINING

The first step in the neural network development was to obtain archived National Climatic Data Center (NCDC) meteorological data, "Rawinsonde Data of North America" (Vols 1-4, 1946-1994), with enough cases to adequately train the network. El Paso, Texas (latitude 31.84N, longitude 1.06.40W) was chosen as the test site and it is approximately 60 miles from the White Sands Missile Range, New Mexico. Data for both the 0000 UTC and the 1200 UTC cases were included in the assembled data sets. There currently is only a small data set of coincident wind profiler measurements along with the rawinsonde wind profiles to train the neural network; therefore, the rawinsonde measurements in the lower atmosphere were used in lieu of actual wind profiler data for these simulations. The number of cases, i.e. rawinsonde profiles, used for the training testing sets is shown in Table 2.

Table 2. Training and Testing Sets (Simulations)

Number of Training Cases	20,223
Number of Testing Cases	3,999

5. PRELIMINARY SIMULATIONS

In these simulations, the radiosonde winds that would correspond with winds taken by wind profilers were used as inputs to the neural network to retrieve upper winds.

5.1 Results

To show the feasibility of the methodology, preliminary neural network runs were made to derive 400mb upper level winds from the corresponding 700mb winds. In the locale of interest (El Paso), 700mb is approximately 3100 to 3200 meters in height and the 400mb level is approximately 7400-7500 meters in height above sea level. Figure 7 is a scatter diagram showing the results of the derived U component winds at 400mb versus the corresponding "true" profile, i.e. rawinsonde, U component wind at the same height level. Figure 8 is a scatter diagram showing the corresponding comparisons for the V component of the winds at 400mb level. The RMS error for the U component of the wind in the testing set was 9.1 m/s and the RMS error for the V component of the wind was 8.3 m/s. Comparing the ground-based derived winds at 400mb with previous derived winds from satellite radiances at the same height level, the RMS errors are comparable for the U component but there appears to be better correlation for the ground-based derived V component winds over the satellite derived V components (Cogan, etal, 1998).

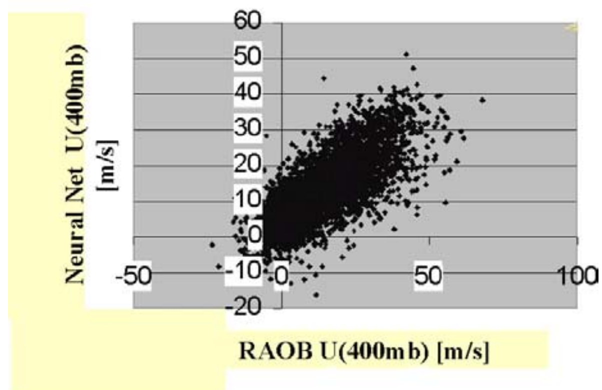

Figure 7. Scatter plot of the neural et retrieved U component of the winds at the 400mb height versus the radiosonde measured U component of the winds at 400mb.

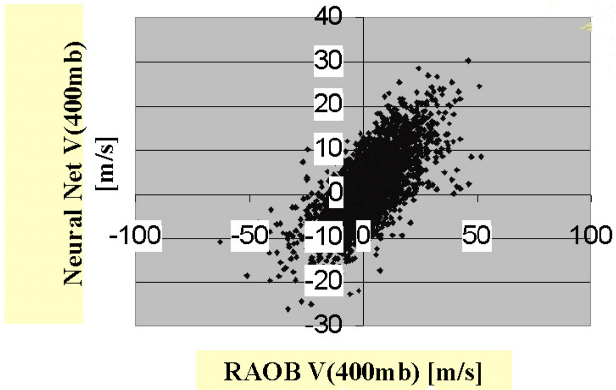

Figure 8. Scatter plot of the neural net retrieved V component of the winds at the 400mb height versus the radiosonde measured V component of the winds at 400mb.

5.2 Recommendations

From these preliminary studies, future work will center on the following directions:

- Collect more real measurements of coincident wind radar, sodar, lidar, and rawinsonde profiles to provide a large enough data set to train the neural network.
- Incorporate multiple lower level winds as input into the neural network for upper level wind inference.
- Combine multiple wind profiler measurements together in a training set to either decrease the RMS errors or increase the maximum retrieval height.
- Investigate other sites
- Train on data sets that covers a range of geographical locations to increase the robustness of the neural network

6. CONCLUSIONS

Earlier studies using near surface winds as input to a neural network to derive upper level winds at 400mb showed poor correlation with the "true" winds, i.e. rawinsonde, at the same height level. This suggests that one must measure winds above the lower boundary layer in order to retrieve reasonable upper level winds. The ARL wind profilers are capable of measuring winds above the boundary layer where there is practical correlation to upper level winds.

Simulations were developed to derive upper level winds at 400mb using winds at 700mb as input into the network. The results show U wind component RMS errors of 9.1 m/s and V wind component RMS errors of 8.3 m/s. The next step will be to use real wind profiler measurements as input into the trained neural network and compare the predicted upper level winds with the actual rawinsonde measured winds. Future work will be to develop neural networks that use information from both the satellite and ground-based wind profilers to produce optimal wind profiles. The results are encouraging but much work needs to be done to provide the optimal wind profile from the near surface up to 30 kilometers as required by future forecast models. As ground based profilers become more capable in terms of accuracy and range, neural networks can be expected to play a larger role in the retrieval of upper level atmospheric winds.

7. REFERENCES

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