2B.1 MULTI-FREQUENCY RADAR ESTIMATION OF CLOUD AND PRECIPITATION PROPERTIES USING AN ARTIFICIAL NEURAL NETWORK[1]

Andrew L. Pazmany[2], James B. Mead Steve M. Sekelsky and David J. McLaughlin
University of Massachusetts, Amherst, Massachusetts
Howard B. Bluestein
University of Oklahoma, Norman, Oklahoma

1. INTRODUCTION

The University of Massachusetts (UMass) and the University of Oklahoma (OU) have been collaborating to study severe storms with a pair of mobile radar systems operating at 10 and 95 *GHz*. The radars will be deployed in the US Central Planes in the spring of 2001 to collect co-located radar reflectivity profiles in tornadoes and their parent storms. The data will be processed with an artificial neural network algorithm to estimate liquid water content (*LWC*) and drop size of precipitation. This paper describes this algorithm, which was originally conceived for detecting in-flight aircraft icing conditions [1].

The problem of extracting cloud parameters from measured range profiles of backscattered power is a good example of a problem without well-defined rules for estimation. The forward problem is straightforward: for a given drop-size distribution, the radar observed reflectivity, accounting for attenuation, can easily be calculated using Mie scattering formulas. Also, cloud and precipitation properties, such as *LWC*, rain rate or mean drop size can be directly calculated from the drop-size distribution. Solving the inverse problem, that is, calculating cloud parameters from measured reflectivity profiles, is difficult, in part due to the non-linearity of the forward problem. Artificial neural networks are ideal for solving problems where the forward problem is well characterized but the inverse problem is complex.

2. THE NEURAL NETWORK ALGORITHM

The multi-frequency radar measurement concept is illustrated in Figure 1. Neural networks were trained to estimate *LWC*, mean volume diameter (*MeVD*) and mean Z diameter (*MeZD*) from profiles of multi-frequency radar observed (i.e. including attenuation) reflectivity factors (*Z)* at various frequency combinations (10-95, 10-35-95, 10-35 *GHz*).

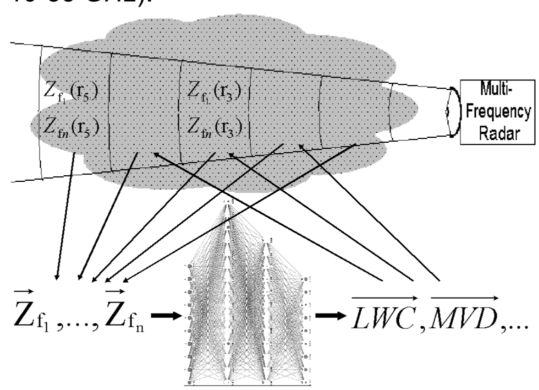

Figure 1. Multi frequency measurement concept. Radar observed (attenuated) reflectivity, from five consecutive range cells, is input to a neural network to estimate liquid water content (*LWC)* drop size parameter in the middle three cells.

The drop size parameters *MeVD* and *MeZD* are defined as the diameter corresponding to the mean volume (*MeVD*) and the diameter corresponding to the mean radar reflectivity factor (*MeZD*):

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[2] Corresponding Author Address: Andrew L. Pazmany, University of Massachusetts, Amherst MA, 01002;

$$MeVD = \frac{\int_0^{\infty} D^4 f(D) dD}{\int_0^{\infty} D^3 f(D) dD} \mu m \qquad (1)$$

$$MeZD = \frac{\int_0^{\infty} D^7 f(D) dD}{\int_0^{\infty} D^6 f(D) dD} \mu m, \qquad (2)$$

where f(D) is the number of drops per cubic meter per micrometer drop-diameter. Mean Z diameter is a size parameter biased towards larger drop diameters. When the size distribution is narrow, *MeVD* and *MeZD* are almost equal. *MeZD* is considerably larger than *MeVD* for drop-size distributions with widely distributed particle sizes.

Control over the neural network algorithm is exerted in two ways: 1) the topography of the network and 2) the variety, quantity and quality of the training data set. The network must contain a sufficient number of hidden layer nodes so the quality of the algorithm is not limited by the size of the network. On the other hand, excessively large networks require a large training data set, which slows training and data processing. It was found that for the two frequency networks, (10-95 and 10-35 *GHz*), 15 and 12 nodes in the two hidden layers were sufficient along with the 10-node input and 9-node output. The three-frequency, 10-35-95 *GHz* network was configured slightly larger, consisting of 15 input (reflectivity from 5 range gates from three radars) nodes, 20 and 12 node hidden layers, and a 9-node output layer. For each network, the nine outputs are *LWC*, *MeVD* and *MeZD*, corresponding to the middle three range gates.

The input nodes of the multi-frequency networks accept measured profiles of reflectivity at X-band, Z_X, as well as differential reflectivity gradient vectors for the attenuating wavelengths. The differential reflectivity gradient vectors, ΔZ_{X-Ka} and ΔZ_{X-W}, normalized to the first element are expressed as follows:

$$\Delta Z_{X-W}(i) = Z_X(i) - Z_W(i) - \left[Z_X(1) - Z_W(1)\right] \qquad (3)$$

$$\Delta Z_{X-Ka}(i) = Z_X(i) - Z_{Ka}(i) - \left[Z_X(1) - Z_{Ka}(1)\right] \qquad (4)$$

where $Z_X(1)$, $Z_{Ka}(1)$ and $Z_W(1)$ represent radar observed reflectivities in the first range gate of the X, Ka, and W-band radars in dBZe. The use of (3) and (4) allows uncalibrated radar data to be used for the attenuating radar frequencies. As long as the X-band data is calibrated, the removal of the absolute reflectivities Z_{Ka} and Z_W has little effect. The advantage of removing the absolute reflectivities at millimeter wave frequencies is that 1) it is no longer necessary to calibrate the associated radars, a process which is often difficult, and 2) that the attenuation at millimeter wavelength between the radar and the first range gate does not affect the algorithm.

The neural networks were trained with the simulated liquid cloud and precipitation model based on modified gamma drop size distribution [3]. The modified gamma distribution relates liquid drop diameters to the number of drops per drop size interval in a unit volume according to:

$$f(D) = a\left(\frac{D}{2}\right)^{\alpha} e^{-b\left(\frac{D}{2}\right)^{\gamma}}, \qquad (5)$$

where

$f(D)$ is the drop size distribution in units of number of drops per micrometer per m3,

$$a = \frac{3LWC\gamma b^{b_2}}{4e^6 \pi \Gamma(b_2)}, \qquad (6)$$

$$b = \frac{\alpha}{\gamma R_c^{\gamma}}, \qquad (7)$$

$$b_2 = \frac{\alpha + 4}{\gamma}, \qquad (8)$$

and α and γ are shape parameters, D drop diameter and Rc is the mode radius of the distribution.

The following modified gamma distribution parameters were used to generate 10,000 five range cell profiles of cloud and precipitation conditions for training:
Rc varied from .5 to 200 micrometers, according to

$$R_c(r) = \exp\{2.3[cX_R(1) + (1-c)X_R(r)] - 6\}, \quad (9)$$

where c is the range cell to range cell correlation (0.3 or 30 %) and $X(r)$ is a uniform random variable for the r-th range gate. LWC was varied from .001 to 2 g/m^3, as a function of Rc as

$$LWC(r) = \exp\{\ [0.366 - 3.366\sqrt{5\times10^3 R_c}\ ]\times [cX_{LWC}(1) + (1-c)X_{LWC}(r)]\ \}, \quad (10)$$

γ from .3 to 1.8, as

$$\gamma(r) = 1.5[cX_\gamma(1) + (1-c)X_\gamma(r)] + 0.3, \quad (11)$$

and α from .1 to 4.1 according to

$$\alpha(r) = 4[cX_\alpha(1) + (1-c)X_\alpha(r)] + 0.1. \quad (12)$$

Also, temperature was assumed to uniformly vary from –15 to +5 deg. C in the Mie scattering and extinction equations used for calculating the radar observed reflectivity profiles. The network topology, training and data processing were implemented with the Stuttgart Neural Network Simulator (SNNS) software (ftp.informatik.uni-stuttgart.de) running under Linux 6.0.

3. EXPERIMENT RESULTS

The neural network algorithm was first tested with multi-frequency radar reflectivity data collected during the Mount Washington (New Hampshire) Sensors Project (MWISP) in March and April of 1999 [1]. MWISP was a multi-investigator experiment with participants from Quadrant Engineering, NOAA Environmental Technology Laboratory (NOAA/ETL), the Microwave Remote Sensing Laboratory (MIRSL) of the University of Massachusetts and others. Radar systems from UMass and NOAA/ETL were used to measure X-, Ka- and W-band backscatter data from the base of Mt. Washington, while simultaneous in-situ particle measurements were made from aircraft and from the observatory at the summit. Figure 2 shows altitude profiles of the neural net estimated (*) and an in-situ ATEK probe derived (solid line) LWC measured on April 14 at 19:07 UTC, agreeing in altitude to within a few hundred meters and in magnitude to an error of less than 20%.

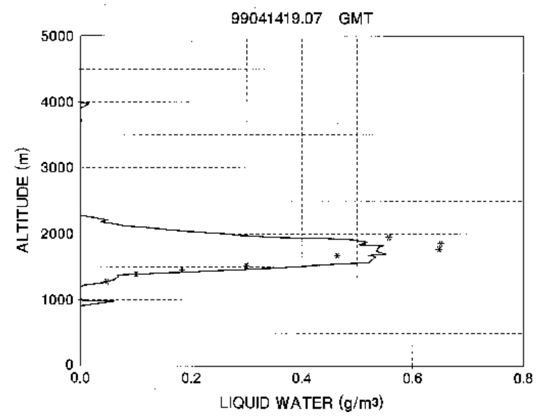

Figure 2. LWC derived from ATEK soundings (solid line) with overlay of radar-derived LWC (*'s).

4. CONCLUSIONS

Extracting quantitative information from radar measurements, other than range and Doppler velocity, is difficult. Artificial neural networks offer a possible solution to a class of problems when the forward problem is well characterized. Here, an artificial neural network was applied to estimate liquid water content and drop size in clouds and precipitation from 10, 35 and 95 GHz radar reflectivity profiles. The retrieved liquid water content agreed with in situ radiosonde measurements to within 20% in magnitude.

5. REFERENCES

[1] Quadrant Engineering Inc., 2001 "Millimeter-wave Radar Field Measurements and Inversion of Cloud Parameters from the 1999 Mt. Washington Icing Sensors Project" *Final Report*, Contract: C-75630-J.