Neural network approach to the determination of the geophysical model function of the ERS-1 C-band spaceborne radar scatterometer

Sami M. Alhumaidi
W. Linwood Jones

A neural network approach to the determination of the geophysical model function of the ERS-1 C-band space-borne radar scatterometer

Sami Alhumaidi[a], W. Linwood Jones[b]

[a]Remote Sensing Research Group
Electrical and Computer Engineering Program
Florida Institute of Technology
Melbourne, Florida 32901
[b]UCF Remote Sensing Laboratory
Dept. of Electrical and Computer Engineering
University of Central Florida
Orlando, Florida 32816-2450

ABSTRACT

Geophysical Model Functions (GMF) describing the relationship between the scatterometer normalized radar cross section (sigma-0) and useful geophysical parameters such as sea-surface wind vectors, wave heights, and sea-surface temperatures have been undergoing extensive research and development during the last decade. In this study, we investigate the use of two feed-forward neural networks, Multilayer Perceptron (MLP) and Radial Basis Functions (RBF), for developing a useful and accurate representation of the C-band GMF. Collocated radar sigma-0 cells with global wind vector models were used as the database of the study. The resulting well-known biharmonic relationship between the sigma-0 and the relative azimuth angle between the scatterometer antenna beam azimuth and wind direction shows the excellent agreement between the neural network and previous results. The applicability of the neural techniques in this application are clearly presented and the potential for possible enhancement over previous approaches are discussed.

1. INTRODUCTION

Spaceborne scatterometers are active microwave (radar) remote sensing instruments specifically designed to measure ocean surface wind speed and direction. The proof of concept was first demonstrated with the 1978 flight of the Ku-Band Seasat Scatterometer (SASS) [1]; and most recently, successful operational utility has been achieved with the flight of the C-band ERS-1 (1991) and -2 (1996) scatterometers [2,3]. For the scatterometer technique, the wind measurement is accomplished by first measuring the normalized backscatter cross section (sigma-0) of the ocean at different azimuth angles. Next, wind vectors are retrieved during ground data processing using an empirical geophysical model function (GMF) that relates the ocean backscatter (sigma-0) to wind speed and direction.

The formulation of scatterometer model functions has been the subject of considerable research [4-8]. This paper presents a novel approach to a GMF using Multilayer Perceptron (MLP) and Radial Basis Function (RBF) neural network techniques. Collocated radar sigma-0 measurements with numerical weather prediction model ocean surface wind vector provided the database for the study. The resulting well-known relationship between the sigma-0 and wind direction shows the excellent agreement between the neural network and previous results.

2. SASS MODEL FUNCTIONS

After the launch of Seasat-A, a GMF known as SASS-1 was used to retrieve ocean surface winds [4]. The formulation of this GMF assumed a logarithmic wind speed dependence of sigma-0 with wind speed and a two harmonic cosine series

SPIE Vol. 3077 • 0277-786X/97/$10.00

dependence of sigma-0 upon the wind direction. The empirical coefficients of the SSAS-1 model function were tuned using buoy anemometer measurements to cause SASS winds retrieved to fit the in situ data in a least-mean-squares sense. Later, Wentz et al. [5] developed another approach to derive the GMF. Using his technique, model function parameters were determined using the statistics of the global wind fields. This modified model function, known as SASS 2 will be briefly described below; further details are available in [5].

Assuming that the two orthogonal components of wind vectors, that are sampled by a given scatterometer polarization and incidence angle, are distributed according to a bivariate normal probability function, then the magnitude of the wind speed, U, is given by

$$P(U, \chi) = (U) \exp(-U^2/2\Delta U)/(2\pi\Delta U^2) \tag{1}$$

where ΔU is the standard deviation of the wind orthogonal components and χ is the radar azimuth relative to the upwind direction. With the exception of the term $2\pi^{-1}$, eq. (1) is a Raleigh distribution in wind speed. The term $2\pi^{-1}$ represents a uniform distribution in χ. Assuming a power law wind speed relation, the following four equations define the SASS 2 GMF:

$$\sigma^\circ = Ao + A_1 \cos\chi + A_2 \cos 2\chi \tag{2}$$

$$Ao = a_0\, U^{(\alpha_o)} \tag{3}$$

$$A_1 = (a_1 + \alpha_1 \log U)\, Ao \tag{4}$$

$$A_2 = (a_2 + \alpha_2 \log U)\, Ao \tag{5}$$

The exact values of the coefficients and the details of the method used to obtain these coefficients are discussed by Wentz [5].

3. CMOD MODEL FUNCTIONS

European Remote Sensing satellite (ERS-1), launched in 1991, carried a C-band radar scatterometer. The initial GMF known as CMOD1, assumed a power law relation similar to SASS-1 & -2. Later a refined version known as CMOD4 was accepted by the European Space Agency to be the operational GMF for the ERS-1 scatterometer. The following equations define this model function:

$$\sigma^\circ = b_0\, b_r\, [\, 1 + b_1 \cos(\chi) + b_3 \tanh(b_2) \cos(2\chi)\,]^{1.6} \tag{6}$$

$$bo = 10^{[\alpha+\gamma\, F1(U+\beta)]} \tag{7}$$

$$F1(x) = \begin{cases} 0 & ,\ \text{if } x \le 0 \\ 10 \log(x)\,, & \text{if } 0 < x \le 5 \\ \left(\sqrt{x}\ /\ 3.2 \right), & \text{if } x > 5 \end{cases} \tag{8}$$

α, β , and γ are expanded as Legendre polynomials of only the incidence angle, θ, whereas b_1, b_2, and b_3 are expanded as Legendre polynomials of both U and θ.

4. NEURAL NET MODEL FUNCTION APPROACH

Neural Nets have been used in a wide range of applications. Among these applications is the use of neural networks for function approximation. Almost exclusively, two types of feed-forward neural nets have been applied in this field. They are the Multilayer Perceptron (MLP) and the Radial Basis Functions (RBF) neural nets. Although recently a group of researchers at the Laboratoire d'Océanographie et de Climatologie (LODYC) at the University of Paris have been able to apply a MLP neural net technique to develop a C-band geophysical model function for the ERS-1 scatterometer [8], application of RBF nets was not investigated for this application.

In this study, we have two objectives:

- to show that both MLP and RBF neural techniques can be applied successfully in the generation and study of the physical relationship which governs scatterometer sigma-0 with surface wind, and
- to point out features and advantages that neural techniques can add to the study of scatterometer GMF's.

To achieve our objective, one year of globally distributed sigma-0 data from the ERS-1 scatterometer collocated with wind fields produced by weather prediction models at NOAA NMC was obtained. Since the ERS-1 scatterometer employs vertical polarization only, a single GMF was developed. Also, without loss of generality, data from only a single beam of scatterometer was used in this study.

One of the major problems faced by any scatterometer GMF developers is the fact that global wind speeds are not uniformly distributed over the range of wind speeds. In fact, the global wind speed distribution approaches a Raleigh distribution. In order for the neural net to give equal attention to features in the data at all wind speeds, the input data must be equalized with respect to each of the inputs, namely wind speed, relative azimuth, and incident angle. Once the input data is equalized properly, it is ready to be used for training the neural nets.

4.1 Multilayer perceptron network

The approach we followed in developing the MLP net is quite straightforward. A two-layer (single hidden layer) net with six neurons in the hidden layer was designed (Figure 1). The input layer consists of three input neuron which act as sensory cells. The input neurons receive wind speed (U), incidence angle (θ), and relative azimuth (χ), respectively. The hidden layer neurons are based on the bipolar sigmoidal activation function. The output layer, with a single neuron, contains a linear activation function

The MLP was trained using the preprocessed radar data with the backpropagation method. During training, the mean-squared error of the output of the net was carefully monitored. The net response, to a subset of the preprocessed data that was reserved for testing, was monitored to insure that the net was not overtrained, by memorizing the training data. After convergence, the net was applied inputs covering the range of wind speeds, incident angles, and relative azimuths to study its response to each variable. One common approach to assessing the results of a newly generated GMF is to plot the sigma-0's (output of the net) as a function of relative azimuth, from 0 to 360 degrees. As mentioned above, the shape of this curve should resemble a harmonic function with maxima at upwind and downwind, and minima at crosswind. Also, slight differences between sigma-0's at upwind versus downwind should be observed. Figure 3 depicts the output of the MLP neural net when plotted this way. We can see that all the features expected in the GMF are apparent in the figure.

4.2 Radial basis function network

The second neural model studied was a radial basis function network for generating the C-band GMF. This neural net was designed using the same number of hidden neurons in the input layer. The hidden layer consisted of thirty six Gaussian kernel functions. One linear output neuron existed in the output layer (Figure 2). Designing a radial basis function net can be thought of as performing the following tasks:

- determination of the number of kernel functions needed,
- suitably setting the centers of the kernel functions,
- suitably setting the width or spread of the kernel functions, and
- determination of the weights connecting the hidden and output layers.

The method used, to find an optimum number of radial functions to be placed in the hidden layer, was to start with a large number of functions that produce reasonable results. Next the number was decreased until the problem can no longer be solved. In this way, we can guarantee that our net is not responding to noise in the input data. Setting the centers of the Gaussian functions was more straightforward. Input vectors that cover the input data space, in approximately a uniformly manner, were chosen as centers for the radial functions. Although, this might sound trivial, extra care must be applied in setting up the center of the radial function as they could affect the output dramatically. The covariance matrix which governs the spread of each of the kernel functions was taken to be diagonal. One common standard deviation parameter was applied for all basis function. Its value was equal to number of basis function divided by the square root of twice the largest distance between the chosen center. Finally, the weights connecting the basis functions to the output neurons were solved algebraically using singular value decomposition [9].

The same approach in presenting the results of the MLP network was applied to RBF network. Figure 4 shows the expected relation between the scatterometer sigma-0 and relative azimuth. The plot also shows the response to several wind speeds.

5. RESULTS AND DISCUSSION

Although the results of the MLP and RBF algorithms were similar, some differences can be observed. The MLP seems to introduce a slight phase shift making the maxima and minima of the curve shifted with respect to upwind/downwind, and crosswind, respectively. Also, the MLP algorithm introduces slight differences in the two minima occurring at (or near to) 90 and 270 degrees. This effect has been suggested by some non neural network GMF developers [10]. The RBF results, however, agree more with the results obtained by the majority of non neural network methods. Two exceptions which can be observed from Figure 5 are an increase in the upwind / downwind modulation, slight asymmetry in the graph. These features seen in the neural network results may be unrealistic due to the fact that the training data used in this study failed to represent the physical system accurately or to physical properties that non neural techniques failed to account for. To address this response, further study needs to be performed with independent data sets, and possibly other beams. Also, other possible input parameters need to be examined.

Unlike previous model function derivation methods, in this general neural network setting, no a priori assumptions are made on the relationship between the radar sigma-0 and wind (e.g. power law, or azimuthal symmetry). Given that the training data represents the physical situation well, the neural net should learn this relation by adapting its weight connections in accordance with the features in the training data. This is a major strength of this technique.

Another advantage in applying neural techniques to this problem is the fact that the relationship between wind vectors and sigma-0 is a multivariate complex relationship to which no analitical solution exist. Therefore, other physical parameters (e.g. sea-surface temperature, atmospheric stability, wave height and wave age) might have an impact on its output. The neural techniques provide a straightforward approach to experimenting with a variety of input parameters where this might not be the case in some non neural development approaches that require analytical models to describe the relationship.

During the training phase, extreme attention must be given to the training data. The wind fields used to make up the training set must be of high quality. Accurate collocation must be performed to ensure that wind data coincide in time and space with sigma-0 cells. Moreover, an appropriate normalization should be performed to keep the dynamic range of the input/target values within the linear range of the bipolar sigmoidal functions contained in the hidden and output units. Finally, and most importantly, the statistics of the training wind fields should be adjusted by selective sampling of the data to have all wind speeds (in the range of interest) and all wind directions are equally represented in the data set.

6. CONCLUSIONS

Two feed-forward neural network algorithms were developed to provide a C-band geophysical model function for the ERS-1 scatterometer. In the first, a MLP neural net trained using the backpropagation method was designed. The second approach was based on the development of a radial basis network. Both neural nets were shown to produce outputs similar to traditional (non neural nets) empirically-derived model functions. Similarities and differences between the two neural network results were pointed out. Also, some of the new features that the neural techniques produced were explained. It was also explained that this work is preliminary and that one must be careful in reaching any conclusion on new features in neural GMF. Future studies to evaluate scatterometer wind retrieval accuracy's using our GMF's will be performed.

ACKNOWLEDGEMENT

The authors wish to acknowledge the support of Dr. Michael Freilich of Oregon State University for the collocated sigma-0/NWP surface winds data used in this study. This work was sponsored under contract to the NASA Scatterometer Project office of the Jet Propulsion Laboratory.

REFERENCES

1. L Jones, L. C., Schroeder, D. H. Boggs, E. M. Bracalente, R. A. Brown, G. Dome, W. J. , and F. J. Wentz, "The SeaSat-A Satellite Scatterometer: The Geophysical Evaluation of Remotely Sensed Wind Vectors Over the Ocean", J. Geophys Res, Vol. 87, No. C5, pp 3297 - 3317, April 30, 1982.
2. Attema, "The Active Microwave Instrument On-Board the ERS-1 Satellite," Proceedings of the IEEE, Vol. 79, No. 6, June 1991.
3. Anderson, D. L. T., A. Hollingsworth, S. Uppala and P. M. Woiceshyn, "A Study of the use of Scatterometer Data in ECMWF Operational Analysis - Forecast Model Part I, Quality Assurance and Validation," J Geophys Res, Vol. 96, 2619-2634, 1991
4. Britt, C. L., L. C. Schroeder, "SASS I Model Function Evaluation and Upgrade," IGARS '84, Strasbourg, France, Aug. 27-30, 1984.
5. Wentz, F. J., S. Peteherych, L. A. Thomas, "A Model Function for Ocean Radar Cross Section at 14.6 GHz," J. Geophys. Res., vol. 89, no. C3, May 20, 1984.
6. Woiceshyn, P. M., M. G. Wurtele, D. H. Boggs, L. F. McGoldrick, S. Peteherych, "The Necessity for a New Parameterization of an Empirical Model for Wind/Ocean Scatterometry," J. Geophys. Res., vol. 91, no. C2, Feb. 15, 1986.
7. M. Stoffelen, D. L. T. Anderson and C. Gaffard, "From Measurement to Model: ERS-1 Scatterometer Assimilation," IGARS 93 proceedings, 1993
8. C. Mejia, S. Thiria, F. Badran, and M. Crepon, "Determination of the geophysical model function of ERS-1 scatterometer by the use of neural networks," J. Geophysical Research, in press.
9. S. Haykin, *Neural networks a comprehensive foundation*, Macmillan Co., New York, 1994
10. Pierson, W. J., "A Note on the Modulation of Radar Backscatter as a Function of Wind Direction," Int. Report, CUNY Inst. Of Marine and Atm. Sc., The City University of New York, New York.

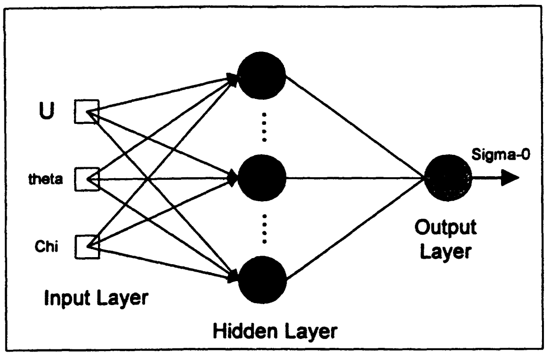

FIGURE 1 MLP neural net architecture

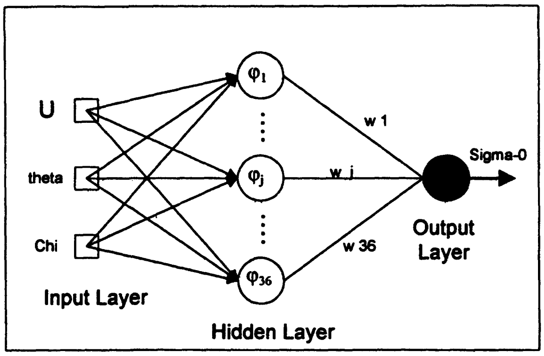

FIGURE 2 RBF neural net architecture

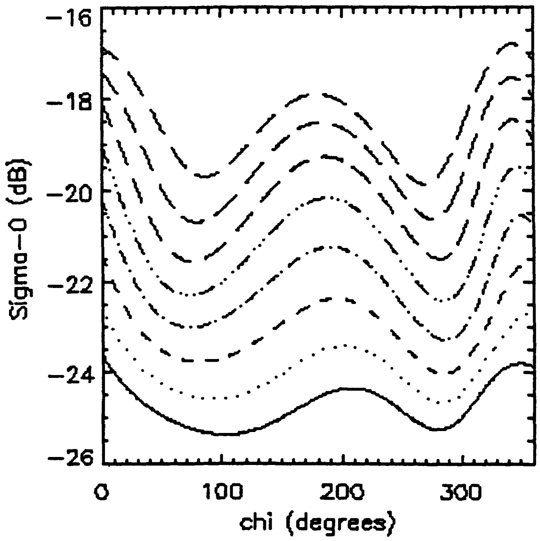

FIGURE 3 MLP GMF results for several wind speeds.

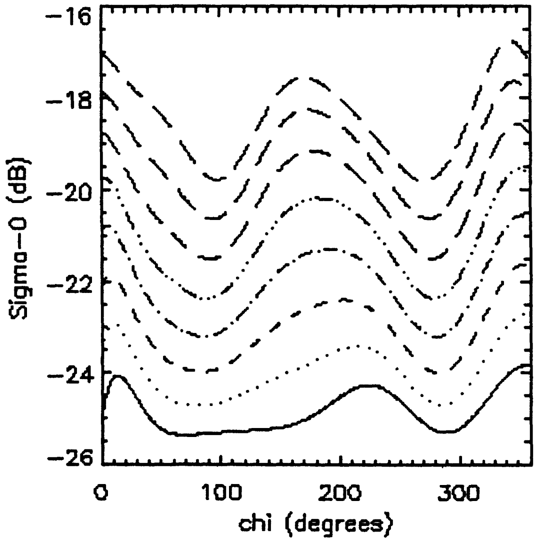

FIGURE 4 RBF GMF results for several wind speeds.

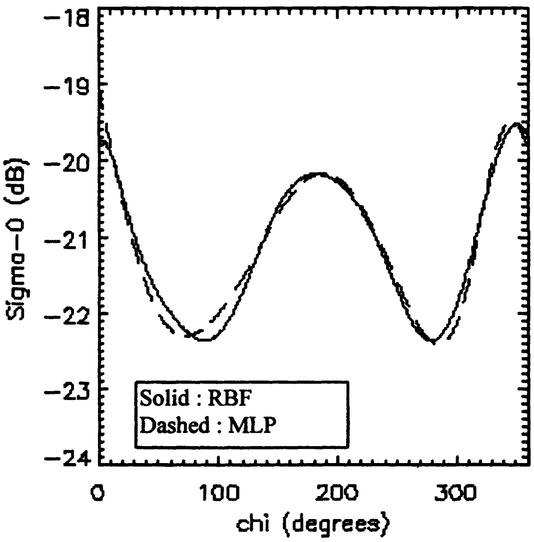

FIGURE 5 Comparisons between the GMF results of MLP and RBF for 7 m/s wind speed