A Neural Network Approach for Wind Retrieval from the ERS-1 Scatterometer Data

Part 1 - Determination of the Geophysical model function of ERS-1 Scatterometer

for OCEANS 94 OSATES

C. Mejia, S. Thiria, M. Crépon
Laboratoire d'Océanographie Dynamique et de Climatologie,
Lodyc, UPMC-CNRS, Paris

F. Badran
Conservatoire Nationale des Arts et Metiers
Cedric, CNAM, Paris

Abstract — The objective of the present work is to compute a new Geophysical Model Function (GMF hereinafter) for the ERS-1 scatterometer by the use of neural networks (NN hereinafter). This NN-GMF is calibrated with ERS-1 scatterometer sigma0 collocated with ECMWF analysed wind vectors. In order to check the validity of the NN-GMF systematic comparisons with the ESA's CMOD4-GMF (version 2 of 3-25-93) and the IFREMER's CMOD2-I3-GMF are done. The GMF is used in many algorithms to retrieve the scatterometer wind.

Résumé — Nous proposons dans ce papier une méthode pour calculer la fonction du modèle geophysique (GMF) du diffusiometre du satellite ERS-1. Cette méthode est fondée sur des techniques de réseaux de neurones (NN). La fonction anisi obtenue, NN-GMF, est étalonnée grâce à la collocation des sigma0 mesurés par ERS-1 avec les vecteurs de vent donnés par le modèle ECMWF. La validité de la méthode NN-GMF est verifiée en la comparant avec la méthode CMOD4-GMF (version 2 du 25-3-93) de l'ESA et avec la méthode CMOD2-I3-GMF de l'IFREMER.

1. INTRODUCTION

The transfer function allowing to compute the wind from the scatterometer signal is very difficult to be determined. It is a non linear function which may have ambiguities on the direction. Several algorithms have been proposed to model the wind retrieval transfer function. Most of them are based on the inversion of the Geophysical Model Function (GMF) which gives the sigma0 with respect to the wind vector. The study of the GMF is then of a fundamental interest. Furthermore the GMF can give useful information on the behaviour of the scatterometer. The present study is devoted on the modelling of the GMF by the use of Neural Networks.

Neural Networks have been used with success by the present team to retrieve the wind vector from the ERS-1 scatterometer data. The methodology is described in [2]. In the present study we propose to determine a new GMF the Neural Networks is calibrated onto ECMWF analysed wind vectors collocated with scatterometer sigma0.

2. THE NEURAL NETWORKS GEOPHYSICAL MODEL FUNCTION (NN-GMF) ALGORITHM

A. *The geophysical Problem*

Scatterometers are active microwave radar which accurately measure the power of transmitted and back scatter signal radiation in order to calculate the normalised radar cross section (σ_0) of the ocean surface. The σ_0 depends on the wind speed, the incidence angle (which is the angle θ between the radar beam and the vertical at the illuminated cell, Fig. 1) and the azimuth angle (which is the horizontal angle χ between the wind and the antenna of the radar). Empirically based relationship between σ_0 and the local wind vector can be established which leads to the determination of a geophysical model function.

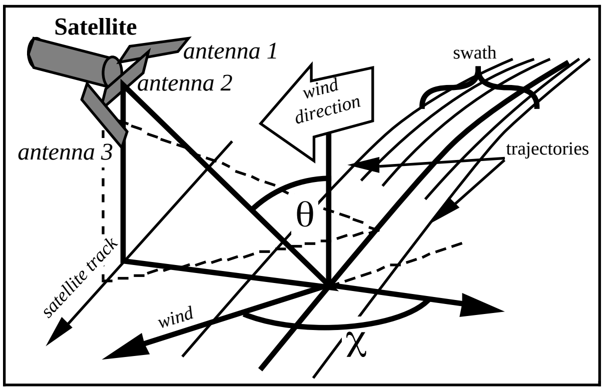

Fig. 1. Definition of the different geophysical parameters.

Recently different GMF have been proposed for the ERS-1 scatterometer. One can mention the IFREMER CMOD2-I3-GMF which is similar to (1) and is denoted now:

$$\sigma_0 = a + b \cos(\chi) + c \cos(2\chi) \tag{1}$$

and the ESA CMOD4-GMF which is of the form:

$$\sigma_0 = \left(d + e\cos(\chi) + f\cos(2\chi)\right)^{1.6} \qquad (2)$$

where χ is the wind direction.

The coefficients a, b, c, d, e, f depend on both the wind speed V and the angle of incidence θ.

B. Determination of the NN-GMF

The ERS-1 geophysical model function is modelled by using a small Neural Network (5-5-1) defined in Fig. 2.

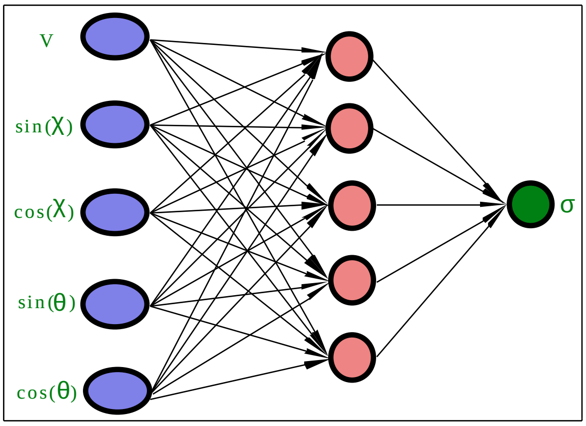

Fig. 2. Schematic Architecture of the NN -GMF.

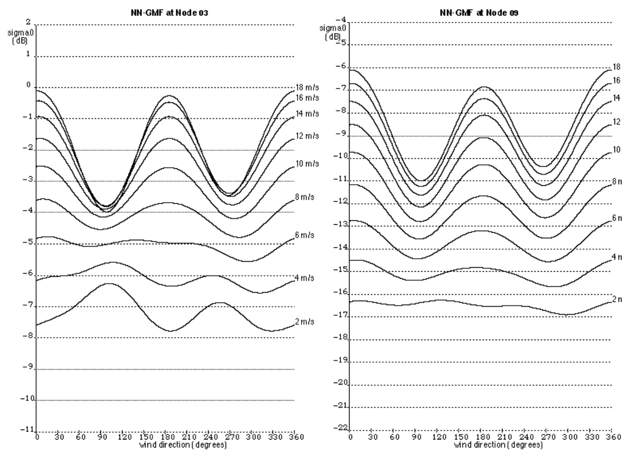

Fig. 3. NN-GMF at node 3 and 9 as a function wind direction at different wind speeds.

The input data are the wind speed V, the wind direction χ with respect to the antenna given by $\cos\chi$ and $\sin\chi$ and the incidence angle given by $\cos\theta$ and $\sin\theta$. The 5 neurones located on the input layer are connected to the 5 neurones of the hidden layer which are connected to the output neurone (Fig. 2).

The learning set (or calibration set) consists in 30000 collocated sigma0-analysed ECMWF wind vectors pairs for each incidence angle and the test set in 5000 independent collocated pairs. The data sets were taken on the North Atlantic ocean in 1993. The North Atlantic ocean wind is suspected to be of good quality owing to the relatively high number of observations which are assimilated in the forecasting numerical model.

C. Analyse of the NN-GMF

In order to investigate the pertinence of the NN-GMF we systematically compared it against the ESA's CMOD4-GMF (version 2 of 3-25-1993) and the IFREMER's CMOD2-I3-GMF. For these comparisons we used the above test set (5000 collocated sigma0-ECMWF wind vectors pairs taken on the North Atlantic ocean in 1993).

Figure 3 display the NN-GMF at different nodes as a function wind direction at different wind speeds.

First it is found that the NN-GMF exhibits the periodic structure with respect to the wind direction as found on the CMOD2-I3-GMF and CMOD4-GMF. A realistic small upwind downwind modulation with an upwind component larger than the downwind one is observed as found on the CMOD2-I3-GMF and CMOD4-GMF. At node 3 (Fig. 3) the NN-GMF still presents an upwind component larger than the downwind one while the CMOD4-GMF and the CMOD2-I3-GMF present a downwind component larger than the upwind one. Furthermore the minimum at constant wind speed of the NN-GMF does not correspond exactly to the cross-wind direction.

The dynamic range of the NN-GMF is smaller than CMOD4-GMF and CMOD2-I3-GMF. The NN-GMF gives smaller sigma0 values at high wind speed than the CMOD4-GMF and the CMOD2-I3-GMF (Fig. 4) and larger values at small wind speed. This is in agreement of the observations of Etcheto *et al* (1994 in preparation) who finds that high winds are under-estimated by ERS-1.

Statistical estimators have been computed. The bias and the RMS values of the three GMF are presented in Table I and II at different wind speeds and for three different incidence angles. In every case the NN-GMF RMS performs better than the CMOD4-GMF and the CMOD2-I3-GMF.

The bias is defined as

$$\overline{BIAS} = \frac{\sum\left(\sigma_{comp} - \sigma_{real}\right)}{N} \qquad (3)$$

where:

- σ_{comp} is the sigma0 computed by the GMF.
- σ_{real} is the sigma0 observed by ERS-1.
- N is the number of observations.

The RMS is defined as:

$$RMS = \sqrt{\frac{\sum(\sigma_{comp} - \sigma_{real})}{N}} \tag{4}$$

TABLE I
RMS OF NN-GMF, CMOD4-GMF AND CMOD2-I3-GMF

Node 03 - (Inner node)-	N	RMS *NN*- GMF (dB)	RMS *CMOD4*-GMF (dB)	RMS *CMOD2-I3*-GMF (dB)
Learning set	25919	1.44	1.65	1.64
Test set	4514	1.45	1.65	1.69
Sub-set test 2-6 m/s	781	1.87	1.99	2.09
Sub-set test 6-10 m/s	2219	0.94	1.23	1.19
Sub-set test 10-18 m/s	436	0.74	1.07	1.19

Node 09 - (Central node) -	N	RMS *NN*- GMF (dB)	RMS *CMOD4*-GMF (dB)	RMS *CMOD2-I3*-GMF (dB)
Learning set	25919	1.65	1.95	1.78
Test set	4514	1.65	1.97	1.79
Sub-set test 2-6 m/s	781	1.89	2.19	2.00
Sub-set test 6-10 m/s	2219	1.48	1.81	1.63
Sub-set test 10-18 m/s	436	1.41	1.83	1.65

Node 17 - (External node) -	N	RMS *NN*- GMF (dB)	RMS *CMOD4*-GMF (dB)	RMS *CMOD2-I3*-GMF (dB)
Learning set	25919	2.07	2.62	2.17
Test set	4514	2.02	2.55	2.12
Sub-set test 2-6 m/s	781	2.37	2.70	2.39
Sub-set test 6-10 m/s	2219	1.69	2.03	1.82
Sub-set test 10-18 m/s	436	1.70	2.19	1.94

CONCLUSION

The NN-GMF is a good candidate to model the ERS-1 scatterometer transfer function. The NN-GMF RMS is better than the CMOD4 and CMOD2-I3 RMS. The dynamic range of the NN-GMF is smaller than the CMOD4-GMF and the CMOD2-I3-GMF. The NN-GMF gives smaller sigma0 values at high wind speed than CMOD4 and CMOD2-I3 and larger values at small wind speed.

ACKNOWLEDGEMENTS

This work has been supported by the PNTS (Programme National de Télédétection Satellitaire), the CNES (Centre National d'Etudes Spatiales) and the CNRS (Centre National de la Recherche Scientifique).

TABLE II
BIAS FOR THE DIFFERENT GMF

Node 03 - (Inner node)-	N	BIAS *NN*- GMF (dB)	BIAS *CMOD4*-GMF (dB)	BIAS *CMOD2-I3*-GMF (dB)
Learning set	25919	-0.04	0.53	0.75
Test set	4514	-0.01	0.55	0.76
Sub-set test 2-6 m/s	781	-0.02	0.35	0.75
Sub-set test 6-10 m/s	2219	-0.04	0.74	0.71
Sub-set test 10-18 m/s	436	-0.10	0.71	0.90

Node 09 - (Central node) -	N	BIAS *NN*- GMF (dB)	BIAS *CMOD4*-GMF (dB)	BIAS *CMOD2-I3*-GMF (dB)
Learning set	25919	0.31	0.66	0.61
Test set	4514	0.31	0.66	0.61
Sub-set test 2-6 m/s	781	0.29	0.00	0.40
Sub-set test 6-10 m/s	2219	0.34	1.08	0.73
Sub-set test 10-18 m/s	436	0.26	1.12	0.82

Node 17 - (External node) -	N	BIAS *NN*- GMF (dB)	BIAS *CMOD4*-GMF (dB)	BIAS *CMOD2-I3*-GMF (dB)
Learning set	25919	0.21	0.64	0.52
Test set	4514	0.17	0.56	0.46
Sub-set test 2-6 m/s	781	0.31	-0.05	0.21
Sub-set test 6-10 m/s	2219	0.09	1.15	0.68
Sub-set test 10-18 m/s	436	0.04	1.25	0.73

REFERENCES

[1] F. Badran, S. Thiria, and M. Crepon, “Wind ambiguity removal by the use of neural network techniques,” *J. Geophys. Res., 96, 20521-20529*, 1991.

[2] S. Thiria, F. Badran, C. Mejia and M. Crepon, “A Neural Network Approach for modelling Non Linear Transfer functions: Application for Wind Retrieval from Spaceborne Scatterometer Data,” *J. Geophys. Res. 98, 22827-22841*, 1993.