USE OF THE MESOSCALE ETA MODEL FOR SHORT TERM WIND POWER FORECASTS IN BRAZIL

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Summary

The increase in the installed power of wind-generators in Brazil demands the development of forecast tools in order for this form of electrical energy generation to be integrated into the mainstream market of conventional energies. The objective of this work is to analyze the use of the results of the meteorological Eta model for this purpose. The application of the results of this mesoscale model to give forecasts is carried out together with an artificial neural network (ANN) procedure to adjust the model output. The ANN is adjusted and tested by means of a comparison with measured wind speed data obtained by CELESC, the electricity distribution company of the Brazilian federal state of Santa Catarina in southern Brazil.

Keywords: Wind forecast, Neural networks, Mesoscale model

1. Introduction

Within the next few years a considerable increase in the number of wind energy installations is expected in Brazil. PROINFA – Program of Incentives for Alternative Sources for Electrical Energy run by ELETROBRÁS – Brazilian Electrical Company has allowed the signing of contracts for the provision of installations for 1.1 GW wind generation capacity by December 2006 (see www.eletrobras.com.br [1]). For the state of Santa Catarina, located in the south of Brazil, than PROINFA plans the installation of more 220 MW, to be added to the current 5.4 MW, of today, at two sites: 130 MW in Bom Jardim da Serra and 90 MW in Agua Doce.

An increase in energy production from wind energy will require a forecast of the electrical energy generated in order to integrate this source into the mainstream market of conventional energies, [2].

For the generation of local forecasts either physical models – such as the German Previento [3] procedure - or data driven procedures (see e.g. Xiberta and Flórez [2])- such as the WPPT system (DTU Denmark) [4] using a classical statistical approach or the ISET(Germany) [5] model based on artificial neural networks (ANN) - may be applied.

The objective of this study is to present and discuss preliminary results of the use of an Artificial Neural Network to adjust the output of the mesoscale forecast model Eta to field data recorded by CELESC- the Electricity Distribution Company of Santa Catarina. The Eta model is in operational use by CPTEC – Center for climate forecast, of INPE, the Brazilian Space Research Institute.

2. Procedure

Experimental data from meteorological masts operated by CELESC allow a direct comparison with the data obtained by the mesoscale meteorological forecast model Eta – which will be presented in the next section - and the training of an artificial neural network to map the Eta output for these measurements.

The CELESC data were obtained from a network of stations in the Brazilian federal state of Santa Catarina [5]. Each station comprises a meteorological mast with anemometers installed at altitudes of 30 and 48 m. The latter were used for comparison with the Eta data. For the purposes of the training and testing of the ANN, the data set for each month or year of a specific site were divided into two halves. The first one was used to train the ANN and the second one for a test of the application of the trained ANN.

2.1 The Eta model configuration

The mesoscale model Eta applies the model equations expressed as the Eta coordinate, η, Mesinger [6], which is defined as.

$$\eta = \left[\frac{(p - p_t)}{(p_{sfc} - p_t)} \right] * \left[\frac{(p_{ref}(Z_{sfc}) - p_t)}{(p_{ref}(0) - p_t)} \right] \qquad (1)$$

where p is the air pressure and Z is the height. The indices t and sfc indicate model top and model surface, respectively. The index refers to values from a reference atmosphere, where, $p_{ref}(0)$ is the air pressure at height 0, and pref(Zsfc) is the air pressure at the surface, both being taken from a reference atmosphere. Since it is pressure based, the surfaces of the coordinate are approximately horizontal. This feature is particularly suitable for regions with steep orography such as South America because of the presence of the Andes Cordillera.

The time scheme is the forward-backward scheme modified by Janjic [7] for the adjustment terms and a modified Euler-Backward scheme for the advection terms. The space difference scheme prevents the two-grid internal gravity wave separation. The prognostic variables are temperature, specific humidity, horizontal wind speed, surface pressure, the turbulent kinetic energy and cloud liquid water. These variables are distributed on the Arakawa type E-grid.

The model uses the Betts-Miller scheme (see Janjic [8]), to produce convective precipitation. Stable precipitation is produced explicitly through the Zhao cloud scheme (Zhao and Carr [9]). The surface hydrology is solved by the Chen scheme (Chen et al, [10]). This scheme distinguishes 12 types of vegetation and 7 types of soil texture. The radiation scheme package was developed by the Geophysical Fluid Dynamics Laboratory. The scheme includes short wave (Lacis and Hansen, [11]) and long-wave radiation (Fels and Schwartzkopf [12]). The radiation tendencies are updated every 1 hour.

Initial soil moisture is derived from the monthly climatology, while the albedo is obtained from the seasonal climatology. The initial atmospheric conditions are taken from NCEP analyses. The lateral boundary conditions are inputed from the CPTEC global model forecasts (Bonatti [13]). The latter conditions are updated every 6 hours at the boundaries. The tendencies at these boundaries are distributed linearly within the 6-hour interval along the single outermost line of the model domain.

The resolution of the Eta model in this study was 40 km in horizontal and 38 layers in the vertical. The domain covers most of South America and part of adjacent oceans.

2.2 Use of ANN

Different ANN architectures, [14], were trained taking as input variables the output data from the Eta model and the measured data as a goal function. As Tlearn [15] tool was applied. Figure 1 shows the basic architecture of a multilayer perceptron with a hidden layer, [14]. Specifically the basic input data are the values for the latitudinal and meridional components u_1 and v_1 of the Eta velocity vector and the ΔT (=temperature difference between the layers at heights of 100 and 10 m) for a grid point of the Eta model.

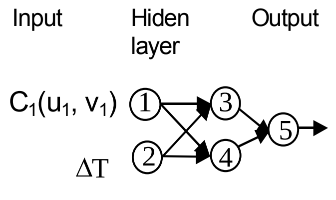


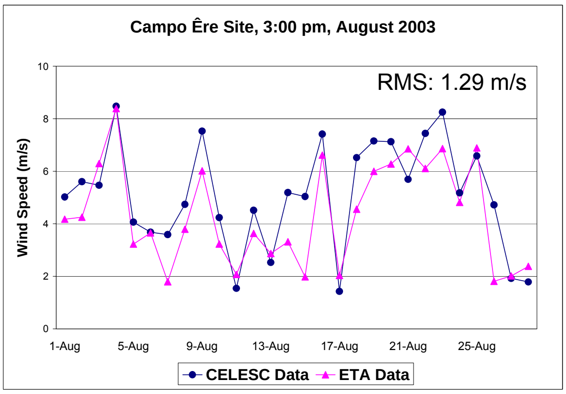
Fig. 1: Architecture of a multilayer perceptron

The ANNs were trained for a specific site and for 50% of the data obtained within a year (training set) and their tests were carried out by comparison of the output data with the other 50% of the data (test set).

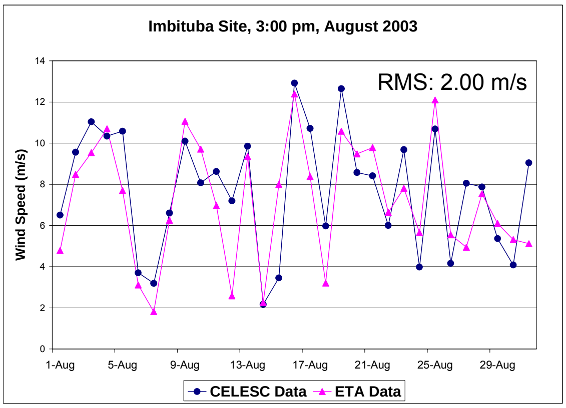
3. Results and discussion

3.1 Eta versus CELESC data

Figure 2 shows a comparison between the six hour forecasting Eta data and those measured by CELESC for August 2003, for two sites: Campo-Erê and Imbituba, located in the interior of Santa Catarina and at the coast, respectively. The Eta results considered were the second, and last, daily computed results which consider corrections based on the output from the first simulation computed 12 h previously. Eta data were obtained for a 10 m altitude and compared with those of CELESC for 48 m. The RMS for these samples were 1.29 and 2.00. As is to be expected, in all cases the Eta results underestimated the measured data. The best results were obtained for the second Eta forecast for 3 pm.



(a)

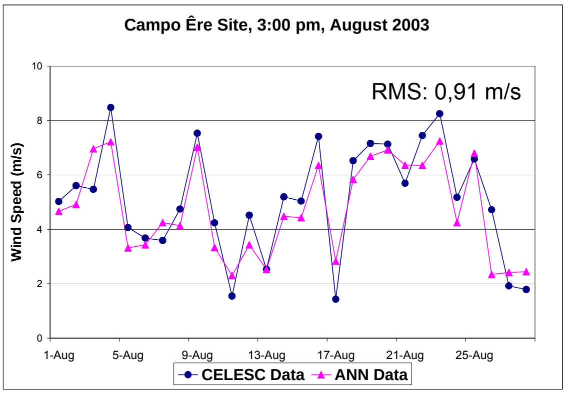


(b)

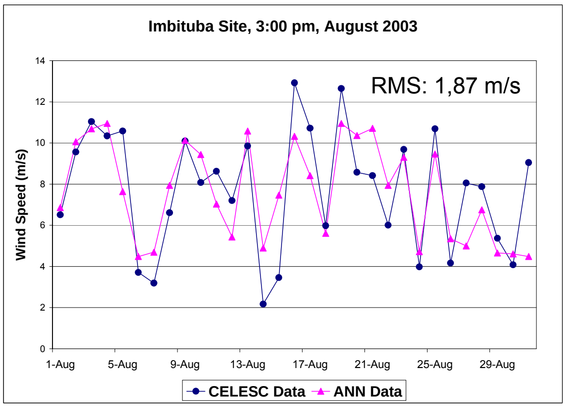
Fig. 2: Six-hour Eta forecast data for Campo-Erê and Imbituba sites compared with experimental CELESC data (without ANN).

3.2 Using artificial neural networks

Figure 3 shows a comparison of the Eta output after application of a trained ANN (multilayer perceptron, see Fig. 1) and the CELESC data. The best reduction of the RMS is obtained for the Campo Erê site (Fig. 3a). Campo Erê may be characterised by a simple terrain structure (gently rolling terrain, as compared to the complex situation of the coastal site at Imbituba).



(a)

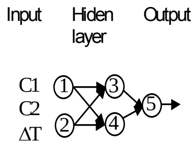
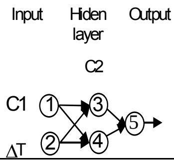
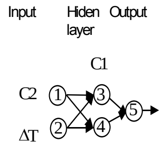
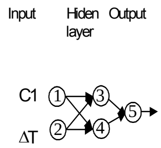
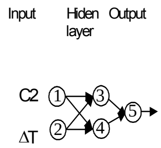


(b)

Fig. 3: Six-hour Eta forecast data for Campo Erê and Imbituba sites compared with CELESC data, with trained ANN (ANN Applied: Num X , Table 1)

Table 1 shows five architectures and input configurations for the multilayer perceptrons applied in this test. The basic configuration consists of five neurons. The types of activation function of the neurons applied can be seen in Table 2. For neuron 5 both a monomodal and a bimodal function are tested. For each configuration the RMS deviation of the network output and the CELESC data for the test set of 2003 are given in the right column of Table 1. The values not in brackets refer to the monomodal activation function for neuron 5, and those in brackets to a bimodal function. Due to some data failures the number of examples are reduced to 80 for Campo Erê, 170 for Agua Doce and 76 for Imbituba.

Table 1: Architecture of the trained ANNs

Nu	ANN Architecture	RMS (m/s)
1		CE – 1.697 (1.612) AD – 1.853 (1.722) Imb – 2.595 (2.610)
2		CE – 1.728 (1.842) AD – 1.460 (1.626) Imb – 2.841 (2.597)
3		CE – 1.740 (1.666) AD – 1.550 (1.507) Imb – 2.724 (2.766)
4		CE – 1.588 (1.623) AD – 1.558 (1.916) Imb – 2.700 (2.700)
5		CE – 1.538 (1.543) AD – 1.713 (1.896) Imb – 2.796 (2.791)

CE= Campo Erê, AD= Água Doce, Imb=Imbituba
( ) RMS using a bimodal function in neuron 5
C1= Eta components u_1 and v_1 for layer 1, at 10m;
C2= Eta components u_2 and v_2 for layer 2, at 100m;
ΔT = temperature difference between layers 1 and 2.

Table 2: Architecture of the trained ANNs

Neuron	Activation functions
1	Linear (-∞ to +∞)
2	Sigmoidal bimodal (-1 to 1)
3	Linear (-∞ to +∞)
4	Sigmoidal binary (0 to 1)
5	Sigmoidal monomodal (0 to 1) or Bimodal (-1 to 1)

Figures 4 shows a comparison of the measurements with the corresponding forecast points (forecast horizon 6 h) both for the original Eta output and after the application of the ANN. The data refer to the site 'Agua Doce' (also - as Campo Erê – a site with simple terrain in the interior of the state), from October to December 2003. For this example the first half of the data was used as a training set, the second half served as a test set. Figures 5a) and b) give the respective scatter diagrams for 6h forecast.

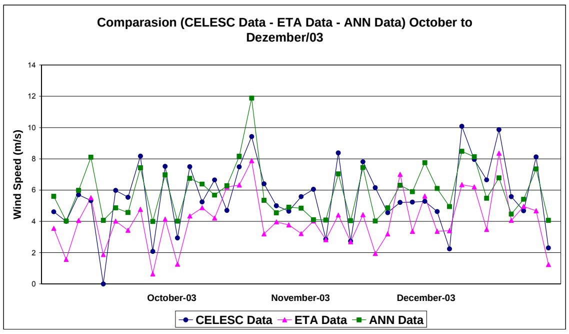
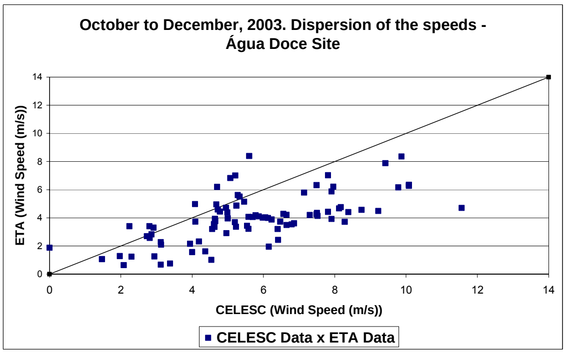
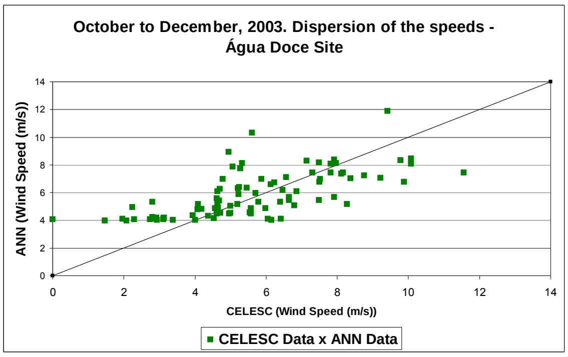


Fig. 4: Comparison of Eta data and ANN with CELESC data, for the Água Doce site.



(a)



(b)

Fig. 5: Dispersion of the speeds for Eta and CELESC data (a). Dispersion of the speeds for ANN and CELESC data (b).

4. Conclusions

The application of the output of the Eta meteorological model in combination with ANNs was tested using a set of measured data from a region in southern Brazil. Even though the RMS errors of the final forecasts are not as good as those obtained by forecast models in Europe (best case for the 6h forecast for Brazil: approx 1.5 m/s as compared to approx. 1 m/s for Europe) the results appear promising, taking into account the limited data set and the coarse resolution of the model grid (40 km). The latter may be the reason for the poor performance of the procedure for the station located on the coast. These problems may be solved through a reduction in the mesh size of the Eta model, which may be applied to confined regions, and an increase in the empirical data set.

Acknowledgments

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