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SOLAR RADIATION FORECAST USING ARTIFICAL NEURAL NETWORKS IN SOUTH BRAZIL

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ABSTRACT

Forecasts from Eta/CPTEC model, expressing the future atmospheric conditions, are used as inputs in Artificial Neural Networks (ANNs), in order to achieve more reliable short-term forecasts for the incident solar radiation. Global solar radiation measurements performed by two stations of the SONDA project located in south Brazil (Florianópolis and São Martinho da Serra) are used as the targets during ANNs training and for forecasts evaluation. Solar radiation forecasts from ANNs present higher correlation coefficients and lower errors than the Eta model output for shortwave radiation on ground. The well-know bias observed in solar radiation forecasts by the Eta model was removed by the use of ANNs. The improvement in RMSE obtained with ANNs over the Eta model was higher than 30%, estimated with a skill-score. This improvement is a response to a constant demand from the energy sector for more accurate ways of forecasting the solar energy power, so as to support the management of the national generation and distribution systems of electricity.

1. INTRODUCTION

The study of the incident solar radiation has several implications for agriculture, illumination and heating of buildings and residences, and, of course, for meteorological research. In addition, owing to the fast increase in importance of the solar energy resource as viable and promising source of renewable energy, its demand for solar radiation studies has expanded accordingly.

Economical and environmental reasons have motivated the increasing use of alternative and renewable sources of energy in Brazil and in the rest of the world: environmental damages caused by fossil fuels consumption; concerns about the elevation of atmospheric carbon levels and consequent temperature increasing and climate changes; the commitment for reduction of carbon dioxides (and other greenhouse gases) emissions by the countries that ratified Kyoto Protocol; the perspectives of oil depletion in next decades (Bentley, 2002; Geller, 2003); the increasing demand for energy to support the new expanding economies such as China, India and Brazil (Goldenberg and Villanueva, 2003); the demand from energy matrixes for complementary resources to overcome instabilities such as that observed in hydroelectric generation during dry seasons; and causes such as the international crises that impact the oil price.

Solar energy is one of the most promising options of renewable energy resources in Brazil. Since most of the Brazilian territory is located in the inter-tropical region, a high potential of solar energy is accessible along whole year (Colle e Pereira, 1998). The current disadvantages of this energy resource are the high costs, the inconstant and unknown availability, and the dependence on the weather and climate conditions. Solar energy costs are expected to fall in next decades, due to technologic advances and market demands. On the other hand, while technologic advances are foreseen, studies are required for a more reliable assessment of the regional availability, the temporal variability and the predictability.

There is a worldwide demand from the electricity energy sector for accurate forecasts of solar energy resources so as to manage co-generation systems. In addition, accurate short-term forecasts of solar radiation is an important information for the management of energy dispatch in transmission lines, since the solar radiation influences the heat dissipation by the cables.

Forecasting solar irradiation, even one day in advance, is a complicated task. Part of the difficulties arises from the solar radiation dependence on clouds and meteorological conditions, which intrinsically involves non-linear physical processes. Other difficulties are linked with the inaccuracy of weather forecasts by numerical models, due to the complexity of the non-linear processes involved, and also due to the difficulties of forecasting the optical properties for the future state of the atmosphere.

Mesoscale weather forecast models usually have radiation parameterization codes, since solar radiation is the main energy source for atmospheric processes. The Eta model that runs operationally in the Brazilian Center of Weather Forecast and Climate Studies (CPTEC/INPE) has outputs for many meteorological variables, including solar radiation incidence on ground. However, these radiation forecasts are greatly overestimated.

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As an attempt to get better predictability for the solar energy resources using Eta model, Artificial Neural Networks (ANNs) were used as a statistical post-processing model. This study aims to developing an operational process to forecast the incident solar radiation to be supplied to corporate stakeholders in energy generation and distribution. Therefore, it constitutes an application of meteorology to the production sector of the society.

2. DATA AND METHODOLOGY

The solar radiation incident on a perpendicular plane on the Earth's top of atmosphere (*top of atmosphere* will be referred as *TOA* hereafter) is almost constant in time. Despite variations of ± 0.6 W·m^{-2} along the 11-year solar-activity cycle and ± 3.4% along the year, due to the eccentricity of the Earth's orbit around the Sun, the so-called *solar constant* is about 1368 W·m^{-2}. Considering the incidence on a horizontal plane on TOA, some geometrical factors should be considered to compute the solar irradiance, since the solar zenith angles depends on latitude, declination (variable along the year) and time of day.

The atmosphere modifies the solar flux up to its incidence on ground. Absorption and scattering are the main processes that affect the solar radiation transmittance through the atmosphere. Clouds are the main factor that controls the solar radiation incidence. (For more details about solar radiation and atmospheric influences see Kidder e Vonder Haar, 1995; Liou, 1980; or Robinson, 1966; Iqbal, 1983).

To model solar radiation, the atmospheric optical properties should be known. These properties depend on clouds, aerosols, humidity and other factors. Forecasting solar irradiation depends on the anticipate knowledge of the future atmospheric conditions. Despite the intrinsic uncertainties, the numerical weather prediction (NWP) models provide information about many meteorological variables.

The statistical refining used in this work consists on feeding the outputs of a mesoscale model in ANNs. These outputs represent the future atmospheric conditions. Further, the calculated solar radiation on the *top of Atmosphere* (TOA) was also supplied to ANNs, as the quantity that is modeled by the Atmosphere. The goal is to obtain a solar radiation forecast with error levels lower than the forecasts provided directly by the mesoscale model through its radiative code, for a given site of investigation.

In this work the Eta/CPTEC model was used as the mesoscale model to have its solar radiation forecasts refined by statistical post-processing. The actual data used as reference for training ANNs and for evaluation of forecasts were the solar radiation measurements taken from two SONDA-project stations, located in south Brazil.

2.1. Eta/CPTEC model

The Eta model is an international mesoscale weather forecast model and runs operationally at Brazilian Center of Weather Forecast and Climate Studies (CPTEC/INPE) since 1996. The model area covers the most of South America continent and neighboring oceans: latitudes between 50.2ºS and 12.2ºN, and longitudes between 83ºW and 25.8ºW. The version that is running since 1996 has 40 km of horizontal resolution and 38 vertical levels.

Detailed descriptions about Eta model can be found in literature: Mesinger *et al*. (1988), Janjić (1994), Black (1994) and Ničhović *et al*. (1998). Finite difference schemes are applied to the model system of equations in space and time. The discretization of the model domain is done with the semi-staggered Arakawa E-grid in the horizontal and the Lorenz grid in the vertical. One of the features of this model is the vertical coordinate, η (Mesinger, 1984), defined as

$$\eta = \frac{p - p_t}{p_{sfc} - p_t} \frac{p_{ref}(z_{sfc}) - p_t}{p_{ref}(0) - p_t} \qquad (1)$$

where p_t is the pressure at the top of the model atmosphere, p_{sfc} and z_{sfc} are the pressure and height of the model bottom boundary (surface), and p_{ref} is a reference pressure vertical profile. The bottom surface heights can take only discrete values since the orography is represented by step-like functions and the tops of model mountains coincide with the η-coordinate surfaces (Ničhović *et al*., 1998). The constant η-surfaces are relatively horizontal, so that the errors associated with the determination of the pressure gradient force along a steeply sloped coordinate surface are minimized.

The radiation parameterization uses the schemes of Lacis and Hansen (1974) for shortwave radiation, and Fels and Schwarztkopf (1975) for longwave radiation. Chou *et al*. (2002) showed that Eta/CPTEC model systematically overestimates the solar radiation incidence and the surface fluxes of sensible and latent heat. This bias in solar radiation was also observed by Hinkelman *et al*. (1999) using the Eta/NCEP model.

The Eta/CPTEC model runs twice a day, with initial conditions at 00UT and 12UT. The initial conditions are the NCEP analyses. The lateral boundary conditions are taken from the

CPTEC/COLA Atmospheric Global Circulation Model (AGCM) and updated every 6 hours.

Every day, Eta/CPTEC model provides two sets of data (00UT and 12UT) comprising forecasts for future instants, 6-hourly spaced, coinciding with the synoptic times (6, 12, 18 and 24UT). Currently, the 40-km Eta/CPTEC model is integrated from the initial condition time to 7 days (or 168 hours) forward, providing forecasts for 29 future synoptic times (reference times).

Some of the predicted variables are instantaneous for their reference times. Other variables are averages, integrals or cumulative quantities related to the 6-hour period before the reference time. In each future synoptic time, and each predicted variable, there are available data for all model area, in grid-points spatially spaced by 0.4° of latitude and longitude. In this work, Eta-data for just two grid-points, located near two radiometric stations (described in next sub-section), were extracted and used.

Among the whole set of predicted variables disposed by Eta/CPTEC model, there are variables provided with values for several vertical atmospheric levels (*profile variables*) and variables with a single value representing the whole vertical atmospheric column or surface conditions (*single variables*). For the current study, just single variables were used. Altogether, a set of 31 variables were taken, comprising data for: surface temperature, humidity, pressure and wind; precipitation; clouds; surface fluxes of sensible and latent heat; shortwave and longwave radiation fluxes; besides other quantities.

The variable representing the Eta model forecast of solar radiation incidence, called *ocis*, represents the forecast that the refining models (ANNs) aim to improve. In this work, this Eta-forecast is evaluated using radiation measurements, and its performance is compared with the ANNs forecasts.

2.2. SONDA radiometric stations

SONDA (*Sistema de Organização Nacional de Dados Ambientais para o Setor de Energia* – National Organization System of Environmental Data for the Energy Sector) is an INPE project coordinated by CPTEC that aims to install and maintain a network of radiometric and aeolic stations so as to improve the database of environmental data. These data are required for the survey and the exploration-planning of solar and aeolic energy resources in Brazil.

In this work, measurements of global solar radiation performed by SONDA stations using *Kipp & Zonen CM-21* pyranometers (Kipp & Zonen, 2006) were used. The data were taken from two stations located in south Brazil:

– Florianópolis (SC): *FLN station* (*Lat.: 27.60°S; Long.: 48.52°W*)
– São Martinho da Serra (RS): *SMS station* (*Lat.: 29.44°S; Long.: 53.82°W*)

The locations of these stations are showed in Figure 1. Their radiation data are available as mean irradiances for each 1 minute, along 24 hours of each day. The data used comprise periods from January/2001 to October/2005 for FLN, and from July/2004 to October/2005 for SMS. The Eta model data for each location were taken for these same periods.

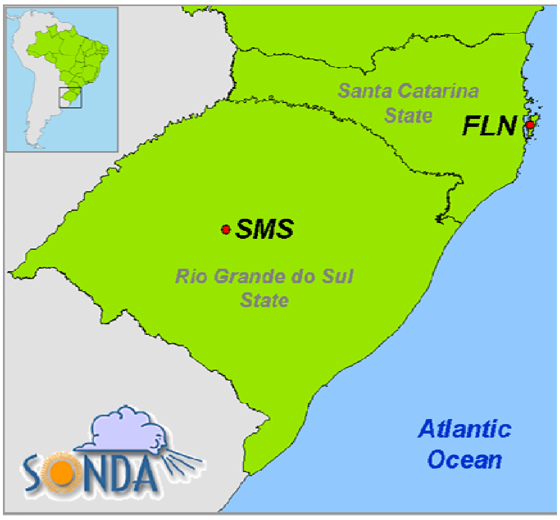

Figure 1: SONDA radiometric stations in south Brazil: FLN and SMS stations.

2.3. Data samples

The solar radiation forecasts provided by Eta model (*ocis* variable) are values representing whole 6-hour intervals: the forecasts available for each reference time are the averages of solar irradiances along the 6-hour periods preceding the reference times. In order to achieve the same time-scale, the solar radiation measurements (with 1-minute resolution) were averaged in 6-hour intervals and represented by its final times. Both data, measured and forecasted, were converted to energy integrals, expressed in $MJ \cdot m^{-2}$ (mega joules per squared meter).

Those Eta model forecasts disposed as instantaneous values in each reference time were averaged with the value for the preceding reference time in order to obtain a value that better represent the variable along the 6-hour intervals. Thus, all forecasted and measured values have now the same temporal resolution and represent the same time-intervals.

Solar radiation incident on TOA was calculated according Iqbal (1983), with 1-minute resolution, for the locations of both SONDA stations and for the whole data periods. These values were averaged and disposed in units of $MJ \cdot m^{-2}$ similarly the process performed with radiation measurements, described before. During these calculations the mean solar zenith angle and the mean air mass were also determined, so as to be used as additional inputs in ANNs.

From Eta variables, two more quantities were calculated: relative humidity and wind speed. Altogether, 36 variables can be used as predictors in ANNs, among Eta forecasts and additional calculated quantities.

Since the 36 predictors and the variable to be simulated (measured solar radiation) are disposed in 6-hour variables, each variable has values for 4 times in each day: 6:00, 12:00, 18:00 and 24:00UT; each of them representing the intervals 0:00-6:00UT, 6:00-12:00UT, 12:00-18:00, and 18:00-24:00UT, respectively.

Among these intervals, the highest fraction of daily solar energy occurs between 12:00 and 18:00UT, in both studied stations and along whole year (63 – 80% of daily total amount). Because of this, we just evaluate solar radiation forecasts for this daily time-interval in this work. Hereafter, this interval will be just referred as *Rad18UT*.

To forecast solar radiation for the period Rad18UT of a day, we can use the outputs of several Eta model-runnings: the 00UT-running of the same day; the 00UT- or 12UT-runnings of the preceding day; or the runnings of more days in advance. In this work we analyze just the forecasts with minimal antecedence, obtained from the Eta-model's 00UT-runnings generated in the same days to be forecasted. These forecasts are referred as *P00UT*.

So, from Eta model variables calculated in the beginning of each day, we have the atmospheric and surface average conditions predicted for the period Rad18UT of the day. The refining models (ANNs) take these variables as the predictors that control the solar energy transmission from the TOA to the ground.

Several tests were performed applying different sets of predictors in ANNs, in order to find a reduced set of variables that can led to a performance similar that obtained with the use of 36 predictors. It was found a set of 8 predictors, including: solar radiation on TOA, relative humidity, surface temperature, precipitable water amount, zonal wind speed at 10-m height, and predictors for cloud fractions. The ANNs using 36 and 8 predictors will be called *ANN-36p.* and *ANN-8p.*, respectively.

After a data-quality verification applied to the data periods of each site, 1150 valid days for FLN and 472 valid days for SMS were taken for the analyses. These data were subdivided in three sets: training set (575 days for FLN and 236 days for SMS), validation set (288 days for FLN and 118 days for SMS) and test set (287 days for FLN and 118 days for SMS). Training set is used for ANNs' learning and validation set is used for real-time evaluation of learning process and to determine the end of training. The test set is used for simulations and to evaluate de performance of solar radiation forecasts supplied by ANNs and Eta model.

2.4. Artificial Neural Networks (ANNs)

Artificial Neural Networks (ANNs) are computing systems which attempt to simulate the structure and function of biological neurons. The networks generally consist of a number of interconnected processing elements, called *neurons*. In *feedforward networks*, the neurons are disposed in layers. Signals flow from the input layer through to the output layer via unidirectional connections, called *synapses*. Synapses connect each neuron with the neurons of neighboring layers (Haykin, 1994).

Figure 2 presents an artificial neuron. The input values (x_i) are weighted by values associated with each synapse (w_{ij}), called *synaptic weights*. All weighted values are adding together and with another value called bias (b_j). This sum is the *activity level* of the neuron (υ_j). The output of a neuron is finally computed by an *activation function* ($\varphi(\upsilon_j)$), generally a linear or hyperbolic-tangent function. The use of non-linear function as hyperbolic-tangent function allows ANNs to learn non-linearity behaviors and complex patterns.

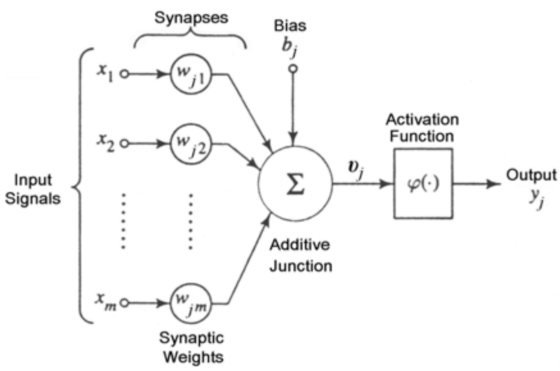

Figure 2: Artificial Neuron models and its parts. Source: Adapted from Haykin (1994).

There are several structures of ANNs, but feedforward is the most used. Feedforward ANNs with multiple layers of neurons are commonly called *multilayer perceptrons*. In this work we have trained multilayer perceptrons using as inputs the meteorological data generated by the Eta/CPTEC model, and other theoretically calculated values as the solar radiation on the TOA. These ANN models are illustrated by Figure 3.

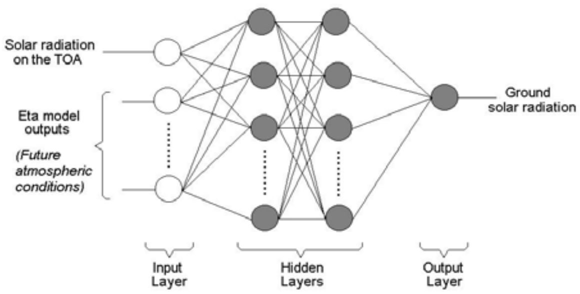

Figure 3: Artificial Neural Network model used.

Preliminary tests revealed that, for the purposes of this study and with the specific sets of available inputs, better ANNs' performances are acquired using 2 hidden layers of neurons. Table 1 shows the best neurons distributions verified for each ANN-model. The number of neurons of input and output layers is equivalent to the number of inputs and the expected output.

Table 1: Layers' neurons in of each ANN model.

	ANN-36p.	ANN-8p.
Input layer	36	8
First hidden layer	36	16
Second hidden layer	18	8
Output layer	1	1

During the training-phase the training algorithm uses the training set of data to adjust the network parameters (weights and bias), in order to reduce the errors in output. For each iteration, the output produced with a set of inputs is compared with the *target* (or the expected value, in this case, solar radiation measurements), and incremental corrections are calculated for each network parameter, aiming to reduce the error in output.

The validation set is used to verify the performance of the ANN with an independent data sample, not directly used in learning. This verification allows to check the generalization capacity along the training and to determine automatically the appropriate moment to stop the training, avoiding *overlearning*. The most widespread training algorithm used for multilayer perceptrons are the *Backpropagation* algorithm (Rumellhart *et al*., 1986). In this work, we use a modified version of Backpropagation, called *Resilient Backpropagation* or *Rprop* (Riedmiller and Braun, 1993).

After training, the weights and bias are fixed, and the ANN is ready to be used in simulations, using the test set of data. The performances of the ANNs are calculated using just the test set.

2.5. Forecasts evaluation

The test set of data was used for evaluation of both, ANN ant Eta model forecasts. The forecasted values (*forecasts* – *F*) were compared with measured values (*observations* – *O*), and deviations between them (*F* - *O*) are calculated. The performance of the models was checked with two statistical indices: mean error (ME) or bias, and root mean squared error (RMSE). ME provides information about the systematic errors of the models, indicating the amount of overestimation or underestimation in the forecasted values. RMSE provides an estimative of the mean absolute deviations between forecasts and observations.

To ease the comparison, both indices are normalized and expressed as percentages of the mean measured global solar radiation value. The resulting non-dimensional scores (or, relative errors) are:

$$ME\% = 100 \cdot \frac{\sum_{i=1}^{N}(F_i - O_i)}{\sum_{i=1}^{N}(O_i)}\% \tag{2}$$

$$RMSE\% = 100 \cdot \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(F_i - O_i)^2}}{\frac{1}{N}\sum_{i=1}^{N}(O_i)}\% \tag{3}$$

where N is the number of pairs (forecast and observation) used in the evaluation (in this work, it is equivalent to the number of days in the evaluated data set). It was also calculated the Person's correlation coefficient (R):

$$R = \frac{\sum_{i=1}^{N}(F_i - \overline{F})(O_i - \overline{O})}{\sqrt{\sum_{i=1}^{N}(F_i - \overline{F})^2} \cdot \sqrt{\sum_{i=1}^{N}(O_i - \overline{O})^2}} \tag{4}$$

The determination coefficient (R^2) was calculated taking the square of correlation coefficient.

To calculate the improvement of a forecast over some reference forecast, we used the *skill-score*, calculated as follows:

$$Skill\ \ (Score, ref) = \frac{Score - Score_{ref}}{Score_{perf} - Score_{ref}} \tag{5}$$

where $Score$ can be the ME% or the RMSE% calculated for the new forecast, $Score_{ref}$ is the score calculated for a reference forecast (the old forecast or the forecast over which we want to calculate the improvement) and $Score_{perf}$ is the score value expected for perfect-forecast (zero, for ME% and RMSE%).

3. RESULTS

In a preliminary analysis using all data for both stations, Eta model forecasts and measurements of solar radiation were compared. As previously observed by other authors (Chou *et al.*, 2002; Hinkelman *et al.*, 1999), it was observed a significant positive bias (overestimation) in solar radiation forecasts by Eta model.

Table 2 show the performance scores calculated for the solar radiation forecasts by Eta model (P00UT-Rad18UT), using all data (1150 days for FLN and 472 days for SMS). It is important to underline that all analyses presented in this section are accomplished with P00UT-Rad18UT forecasts.

Since the data in training and validation sets were used for ANNs adjustment, ANN models can be evaluated just using the test sets of data. Because of this, Eta model forecasts were evaluated again, using just the data pertaining to the same test sets used for ANN evaluations (N = 287 for FLN; N = 118 for SMS).

All analyses presented hereafter were performed using just the test sets of data. The evaluation results of solar radiation forecasts (P00UT-Rad18UT) by Eta model and by ANNs are presented together for comparison.

Table 2: Performance scores for solar radiation forecasts by Eta model (P00UT-Rad18UT), using all data.

Scores	**FLN** N =1150	**SMS** N =472
R	0.747	0.790
R^2	0.558	0.624
ME%	24.7%	27.8%
RMSE%	39.7%	41.9%

Figure 4 and 5 present scatter-plots, where the forecasts are compared with observations, for FLN and SMS stations, respectively. Besides the scatter-plots for Eta model, ANN-36p. and ANN-8p., it is also showed a plot for *persistence forecast* evaluation.

Persistence forecast consists in to take the value observed in a previous day, as the forecast for the current day. It is the simplest forecast available in the absence of another method. A forecast is useful if it can lead to results better than the persistence forecast.

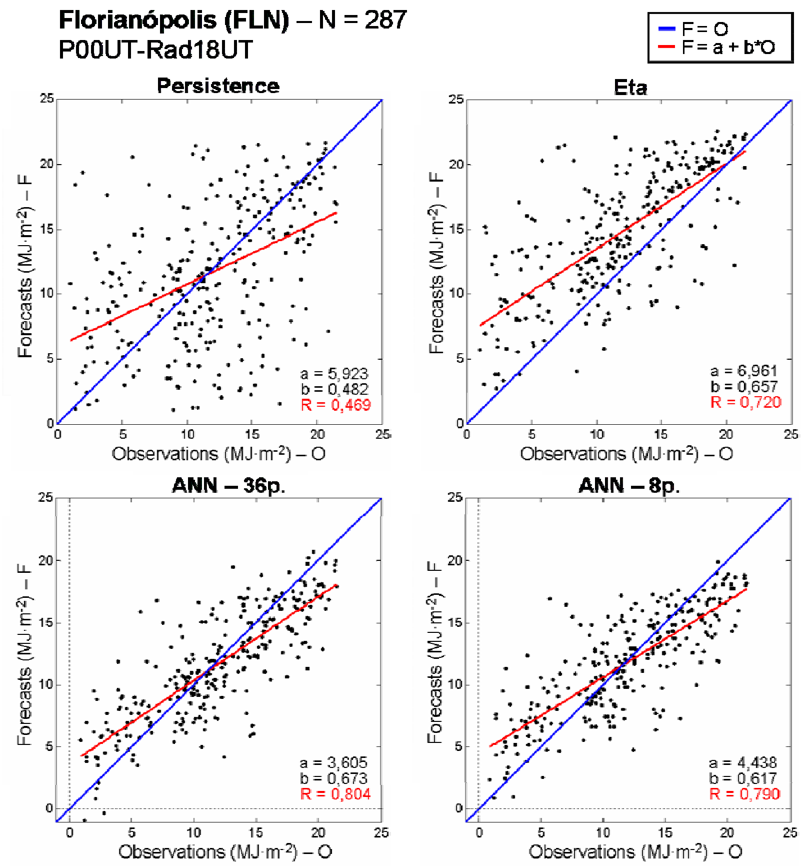

Figure 4: Scatter-plots of forecasts against observations for persistence, Eta model, ANN-36p. and ANN-8p., for FLN station.

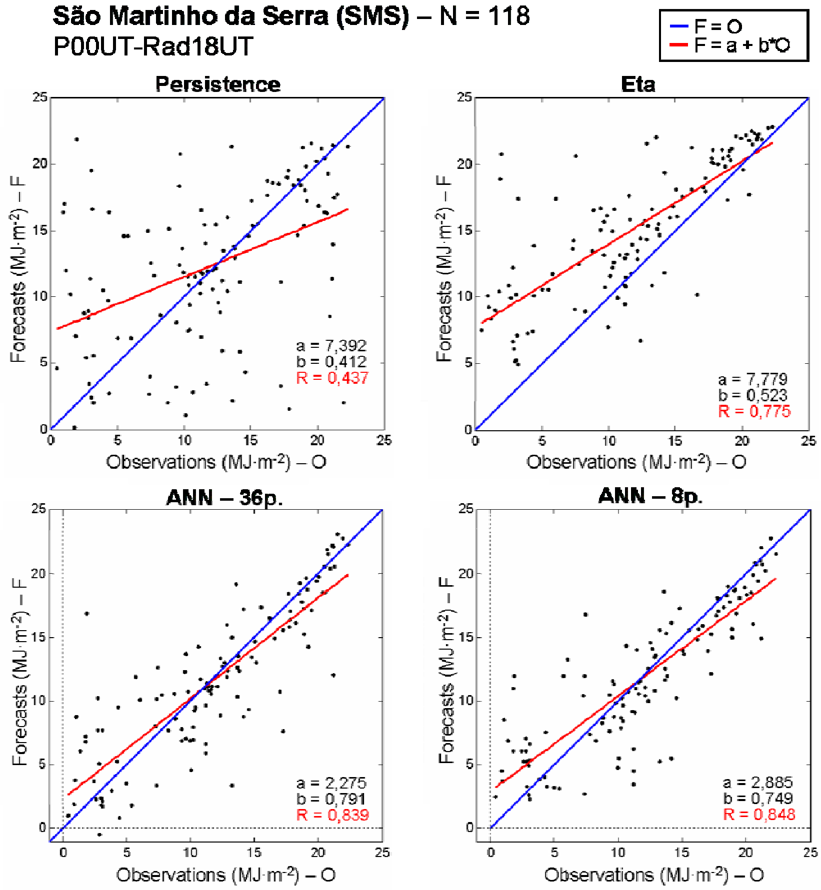

Figure 5: Scatter-plots of forecasts against observations for persistence, Eta model, ANN-36p. and ANN-8p., for SMS station.

According to Figures 4 and 5, Eta model presents forecasts better than persistence, in general. However, we can observe the positive bias mentioned before. Eta forecasts are overestimated, especially the forecasts for days with low incidence of solar radiation. The scatter-plots for ANNs show a higher proximity between forecasts and observations, and most part of the points are located near the perfect-forecast line (blue line). No clear differences are observed between ANN-36p. and ANN-8p., indicating that most of the 36 predictors are not necessary for the solar radiation forecasts.

Tables 3 and 4 summarize evaluation scores values calculated for each forecast, for FLN and SMS, respectively. We can observe the increase in correlation coefficients for ANNs over Eta model, and the reduction in ME% and RMSE%. ANN did not show systematic overestimation as observed in Eta forecasts.

Table 3: Evaluation scores for the forecasts of each model analyzed, for FLN station.

Model	**R**	**R^2**	**ME%**	**RMSE%**
Persistence	0,469*	0,220	1,6%	45,9%
Eta	0,720*	0,519	24,6%	40,0%
RNA-36p.	0,804*	0,646	-2,1%	26,2%
RNA-8p.	0,790*	0,625	-0,8%	26,9%

Table 4: Evaluation scores for the forecasts of each model analyzed, for SMS station.

Model	**R**	**R^2**	**ME%**	**RMSE%**
Persistence	0,437*	0,191	3,7%	53,8%
Eta	0,775*	0,600	28,0%	43,2%
RNA-36p.	0,839*	0,704	-1,7%	28,8%
RNA-8p.	0,848*	0,720	-0,7%	27,6%

The values of R, R^2, ME% and RMSE% presented for Eta forecasts in tables 3 and 4 are similar to that in table 2. This indicates that the test sets chosen are representative of the whole set of data, at least for Eta forecasts.

Figure 6 shows fragments of temporal series taken from the test sets of FLN and SMS stations. Forecasts from Eta model and ANNs are compared with observations for the days in Winter/2005 and Summer/2004-2005. We can observe that the ANNs forecasts are closer to observations than the overestimated forecasts from Eta model. The deviations between forecasts and observations were calculated in each day of these periods and are presented in Figure 7.

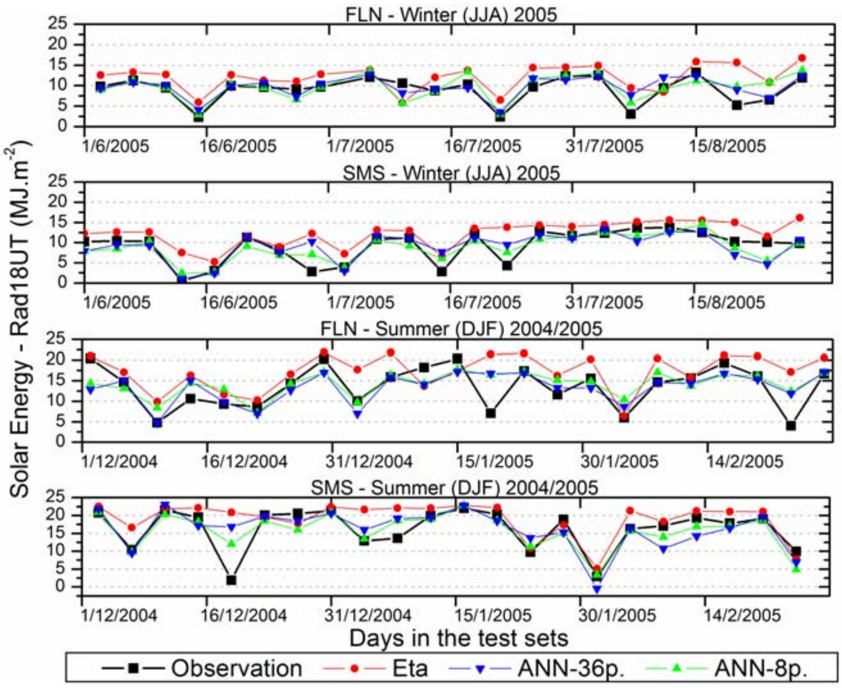

Figure 6: Temporal series for forecasts and observations of both stations analyzed. The series corresponds to days in the test sets for FLN and SMS.

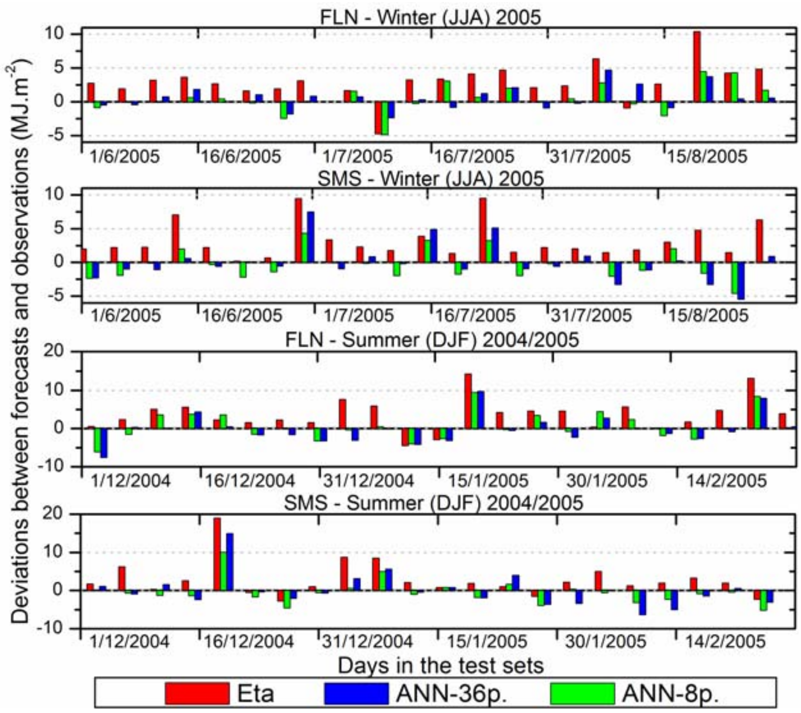

Figure 7: Deviations between forecasts and observations calculated from the same days showed in Figure 6.

From the above results we can observe that an important improvement over Eta-model's solar radiation forecast was achieved with the use of ANNs supplied with the future atmospheric-state data from Eta-forecasts. However, no significant differences were observed between ANN-36p. and ANN-8p., and the use of just 8 predictors are enough for a good performance. To quantify the improvement acquired by the use of ANNs over the Eta model forecasts of solar radiation, the *skill* values were calculated using RMSE% score, and the results are presented in Table 5. We can conclude that, in general, ANNs lead to improvements higher than 30% in RMSE%.

Table 5: Skill-score calculated with RMSE% score for ANNs over Eta model.

Skill(RMSE%,Eta)	**FLN**	**SMS**
ANN-36p.	0.344	0.333
ANN-8p.	0.328	0.361

4. CONCLUSIONS

It was observed an increasing in performance by the use of ANNs (using a set of Eta model forecasts as inputs) over the forecasts of solar radiation directly provided by Eta model. The comparison of forecasts with observations, accomplished in the SONDA project stations of Florianópolis (FLN) and São Martinho da Serra (SMS), showed a similar performance between the ANNs using 36 and 8 predictors, and both these models provide forecasts better than the Eta model, in general. The bias normally observed in the Eta forecasts of solar radiation, was not observed in ANNs forecasts, and improvements higher than 30% were acquired in terms of RMSE%-reduction. The improvements in predictability from Eta model to ANN models were observed in correlation coefficients as well: from 0.72 to 0.80 at FLN, and from 0.78 to 0.85 at SMS.

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