NEURAL NETWORK TECHNIQUE APPLIED TO ESTIMATE HOURLY DIFFUSE SOLAR RADIATION IN THE CITY OF SÃO PAULO

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Abstract: A neural network technique is applied to estimate hourly values of diffuse solar radiation at the surface in São Paulo City, Brazil, using as input global solar radiation and other meteorological parameters measured from 1998 to 2001. The neural network verification was performed using the hourly measurements of diffuse solar radiation obtained during the year of 2002. It was found that the inclusion of the atmospheric long wave radiation as input improves the neural network performance because it acts as surrogate for cloud cover information on the regional scale. An objective evaluation has shown that the diffuse solar radiation is better reproduced by neural network synthetic series than by correlation model.

Keywords: Hourly diffuse solar radiation, Perceptron neural network, São Paulo City.

Resumo: Técnica de rede neural é aplicada para estimar valores horários da radiação solar difusa na superfície da cidade de São Paulo, Brasil, usando como dados de entrada radiação solar global e outros parâmetros meteorológicos medidos de 1998 a 2001. A verificação da rede neural foi feita utilizando medidas horárias de radiação solar difusa obtidas durante o ano de 2002. Foi encontrado que a inclusão da radiação atmosférica de onda longa como entrada de dados melhora o desempenho da rede neural por atuar como informação da cobertura de nuvem em escala regional. Uma avaliação objetiva mostrou que a radiação solar difusa é reproduzida melhor por séries sintéticas geradas por rede neural do que por modelos de correlação.

Palavras-chave: Radiação solar difusa horária. Rede neural, Cidade de São Paulo.

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INTRODUCTION

The importance of knowing the temporal and spatial variations of diffuse solar radiation at surface has been explored in several papers (Collares-Pereira and Rabl, 1979; González and Calbó, 1999; Oliveira *et al*., 2002a). However, solar radiation data are frequently available from only a few stations and over short periods of time. An alternative procedure to obtain solar radiation data is using numerical modeling but the main problem is the need of appropriate representation of cloud effects (Iqbal, 1983). As pointed out by Oliveira *et al*. (2002a) these problems are particularly severe in tropical regions, like Brazil, where cloud activity is a dominant feature of local climate and the solarimetric network is sparse with most of the stations located in urban areas.

A common alternative is to estimate the diffuse component of solar radiation from empirical relationships derived from statistical analysis of direct and global solar radiation temporal series observed at surface (Liu and Jordan, 1960; Collares-Pereira and Rabl, 1979; Erbs *et al*., 1982; Satyamurti and Lahiri, 1992; Jacovides *et al*., 1996). These empirical models are based on the correlation between hourly, daily and monthly values of clearness index (energy flux received from the sun at surface over the energy flux received at the top of atmosphere) and diffuse fraction (diffuse/total solar radiation). The empirical relationships used to estimate hourly diffuse component of solar radiation are, in general, expressed in terms of n^{th}-degree polynomials dependent on latitude, precipitable water content, atmospheric turbidity, surface albedo, altitude, solar elevation angle (LeBaron and Dirmhirn, 1983; Soler, 1990).

Oliveira *et al*. (2002a) used measurements of global and diffuse solar radiation at surface in the City of São Paulo (Brazil) to derive empirical models to estimate hourly, daily and monthly diffuse solar radiation from values of global solar radiation at surface, based on the correlation between the diffuse fraction and clearness index (K_T). The correlation models performed well for daily and monthly values. However, in the case of the hourly values, the expressions derived for São Paulo performed poorly. According to Erbs *et al*. (1982) the empirical models obtained from hourly value correlation do not produce good results because the hourly values of global solar radiation are very sensitive to the cloud type. In the case of São Paulo, cloud information (sky fraction, type and altitude) with hourly resolution is not available.

Here, to avoid this shortcut inherent in correlation models, the hourly diffuse solar radiation was assumed to be a nonlinear function of other relatively easily measured meteorological parameters and estimated using multilayer perceptron (MLP) neural network with non-linear transfer function (Rumelhart *et al*., 1986; Lawrence, 1091). The meteorological data, used in this work, were carried out between 1998 and 2002 at the City of São Paulo (Brazil).

The neural network technique has been previously applied to several studies of radiation with hourly resolution, as for example to estimate hourly global solar radiation (Sfetsos and Coonick, 2000) and global photosynthetically active radiation (López *et al*., 2001), however to the knowledge of the authors, the neural network technique has never been applied to estimate hourly values of diffuse solar radiation.

The performance of the MLP neural network was objectively tested using mean-bias-error (MBE), root-mean-square-error (RMSE) and t-statistic (t_S) (Stone, 1993).

METEOROLOGICAL DATA SET

Several surface meteorological parameters have been regularly measured in São Paulo City, Brazil, since May 1994. The measurements were taken on a platform located at the building top of "Instituto de Astronomia, Geofísica e Ciências Atmosféricas da Universidade de São Paulo" at the University Campus, in São Paulo western side, at 744 m amsl ($23^0$33'35"S, $46^0$43'55"W), with a sampling frequency of 0.2 Hz (12 min^{-1}) and stored at 5 minutes intervals. All data was checked, questionable data was removed, and the shadow-band blocking effects on the diffuse solar radiation values were taken into consideration (Oliveira *et al*, 2002b). All solar radiation quantities used in this work are expressed in units of megajoules per unit of area (MJ m^{-2}) and correspond to the flux of energy per one hour.

The measured parameters were: (1) global solar radiation, (2) diffuse solar radiation, (3) longwave atmospheric emission, (4) air temperature, (5) relative humidity and (6) atmospheric pressure. They were all measured at the surface level.

Global solar irradiance and its diffuse component were measured by a pyranometer model 8-48 and model 2, respectively; both built by Eppley Lab. Inc. These sensors were calibrated periodically (Oliveira *et al*, 2002b) using as secondary standard another spectral precision pyranometer model 2 – (Eppley).

The diffuse component of the solar radiation was measured using a shadow-band device developed by the Laboratory Solar Radiation of UNESP, named "movable detector device"

(Oliveira *et al*, 2002c). Comparatively to other devices commercially available, this new device has a low cost and is much easier to operate and performs well for low latitude locations.

The longwave atmospheric emission was measured by a Precision Infrared Radiometer (Model PIR Pyrgeometer) from Eppley, which is an instrument used for performing hemispherical, broadband, infrared radiative flux measurements, using thermopile temperature difference. Its composite transmission window is about 4-50 μm. The model PIR pyrgeometer comes with a battery-powered resistance network that provides a voltage that expresses the radiative flux contribution of the temperature reservoir. The longwave data used here was obtained considering the manufacturer's optional battery –compensated output.

The air temperature and relative humidity were estimated using a pair of thermistor from Vaisalla. A pressure transducer from Setra measured the atmospheric pressure.

Some results obtained here will be compared to the results obtained by Oliveira *et al*. (2002a). The solar radiation data set used by Oliveira *et al*. (2002a) was taken on the same platform of the data used in this work and comprised the period of 62 months, from May 1, 1994 to June 30, 1999.

NEURAL NETWORK

There are several types of artificial neural networks and the selection of the proper one is a crucial point for the investigated problem. Here it is used the three-layer perceptron artificial neural network with nonlinear transfer function which has been shown to be effective alternative to more traditional statistical techniques (Schalkoff, 1992). The topology of three-layer perceptron neural network consists of several neurons in the input layers (each one representing one input feature), several neurons in the hidden layer and one neuron in the output layer representing the modeled parameter. Neurons have nonlinear sigmoid transfer function $f(x)=1/(1+e^{-x})$. The standard back propagation algorithm (Rumelhart *et al*., 1986) was used for training the MLP.

In short, the method of construction of MLP based model consists of (Božnar and Mlakar, 1998): (i) Feature and pattern selection, (ii) Determination of proper MLP topology, (iii) Training and (iv) Verification.

The purpose of feature determination and pattern selection techniques is to condense the most relevant information from the database making training process more efficient and the results significantly better.

In all the experiments performed here, the *training set* (learning and optimization dataset) consists of the period from 1998 to 2001. The *testing set*, taken from the year 2002, was employed for testing the validity of the generated series and also for comparison with the correlation method (Oliveira *et al*., 2002a).

The optimization data set consisted of randomly selected 10% of patterns from the original training set and was used during the training process to periodically test the MLP performance using the “unknown” data set to determine the MLP’s generalization capabilities. The final network was the one that gave the smallest error on the optimization data set and not on the training set.

Experiments

Here 3 different experiments were performed and all networks were trained with patterns from almost 4 years long (January 1998 to September 2001) and verified using 1 year long dataset (year of 2002). Each measured or calculated parameter of this database represents a potential MLP input feature. The diffuse solar radiation (E_{DF}) or its fraction over global solar radiation (K_{DF}) is the MLP output feature. Every hourly interval vector of all selected parameters represents a pattern (Mlakar and Božnar, 1997).

Firstly the database was analyzed using feature determination techniques (Mlakar, 1997) to decide which parameters are the most relevant for the MLP construction. It was used two techniques - contribution factors and saliency metric – both based on the analysis of weight of MLP trained with all the available and random parameters and all available patterns.

Contribution factor of a particular parameter is the sum of the absolute weights guiding from the correspondent input neuron to the neurons in the hidden layer. The highest scores indicate the most relevant parameters to be input features for the final network.

The saliency metric, by the other hand, is based on weights of the whole neural network, not only the input layers (Mlakar, 1997).

Firstly the analysis was performed using all available parameters: the six measured parameters plus the year, local time, true day, true hour, local time sunset, local time sunrise, true time sunset, true time sunrise, day duration, solar zenith angle, solar elevation angle, solar hour angle, solar azimuth angle, correction factor of diffuse solar radiation (Oliveira *et al*, 2002c), partial pressure of the water vapor in the atmosphere, mixing ratio, theoretical solar radiation at the atmosphere top, fraction of diffuse over global solar radiations and a random parameter. After that, the process was repeated using the 9 best ones: diffuse solar radiation (E_{DF}), theoretical solar radiation at the atmosphere top (E_T), global solar radiation (E_G), longwave atmospheric emission (LW), relative humidity (RH), partial pressure of the water vapor in the atmosphere (VP), theoretical solar elevation angle (SEA), theoretical solar zenith angle (SZA) and theoretical solar azimuth angle (SAA), from 1998 to 2002 plus random parameter.

In both methods the long wave radiation is an important input parameter, as important as the global solar radiation.

Physically the long wave radiation short scale variations, associated with the presence of clouds and theirs effects over solar diffuse radiation, were captured by the neural network. Therefore, the long wave radiation measured at the surface seems to be a good surrogate for the cloud cover information over the region. On the other hand traditional meteorological parameters, like air temperature and atmospheric pressure, are not important as neural network input.

The pattern selection technique was also used in one of the network construction. There are two main reasons for its use: (i) when the available training database is really huge the training process may be too slow and (ii) if some types of patterns are too frequent, but do not contain relevant information, they may “hide” the less frequent but very relevant patterns and consequently the final model may have a poor performance. Here, the hourly diffuse solar radiation values are more or less equally distributed over the whole range and therefore a good network should perform equally well in the entire spectrum of output values, as a contrast to pollution networks where a good model must predict well peaks of concentrations.

Table 1 summarizes the experiments performed and the most successful combination of input features, obtained after several trials. The output features were the hourly diffuse over global solar radiation fraction.

	EXP I	**EXP II**	**EXP III**
Input features			
E_T	Yes	Yes	Yes
E_G	Yes	Yes	Yes
K_T	Yes	Yes	Yes
LW	Yes	**No**	Yes
RH	Yes	Yes	Yes
SEA	Yes	Yes	Yes
SZA	Yes	Yes	Yes
SAA	Yes	Yes	Yes
VP	Yes	Yes	Yes
Selected patterns	No	No	**Yes**

Table 1: Experiment descriptions.

RESULTS

In all the experiments performed here, the standard back propagation algorithm was used with learning rate 0.5 and momentum 0.9. The networks were trained using almost 4 years data (January 1998 to September 2001) and verified using 1-year data (2002) that was not presented during the network training period.

The first network (Experiment I) was trained with all available input features. To verify the importance of the long wave radiation as an input feature, Experiment II was performed using as input all the input features used in Experiment I except for long wave radiation.

Trying to improve the network performance, the final experiment (Experiment III) was built similar to Experiment I but including pattern selection technique. The idea is to develop the reconstruction of the patterns with high values of diffuse solar radiation. Therefore, the neural network was trained with higher percentage of patterns having diffuse solar radiation greater than 1. For that reason, it was used only 40% randomly of the patterns with diffuse solar radiation less than 1 and all patterns with higher values of solar radiation.

Performance Evaluation

To evaluate the performance of the MLP neural networks, for the City of São Paulo, a statistical comparison is performed using the indicator proposed by Stone (1993), a *t-statistic* (t_S). This indicator is used along with two other well-known parameters: MBE and RMSE. Both MBE and RMSE have been specially employed as adjustment of solar radiation models (Oliveira *et al*., 2002a; Soler, 1990; Halouani *et al*., 1993; Ma CCY and Iqbal, 1984; Targino and Soares, 2002).

To determine whether a model's estimates are statistically significant, one has simply to determine a critical t_c value obtainable from standard statistical tables, e.g., t_c ($\alpha/2$) at the α level of significance, and N-1 degrees of freedom (Targino and Soares, 2002).

A summary of the statistical parameters is shown in Table 2 for the values of E_{DF} obtained in Experiments I, I, III and using the correlation model obtained by from Oliveira *et al*. (2002a). The critical values are relative to a level of confidence of 95 %.

	Sample size (h)	MBE (MJ m^{-2})	RMSE (MJ m^{-2})	t_S	t_c
Correlation model obtained by Oliveira *et al*. (2002a)	15258	-0.0169	0.193	11.16	1.96
MLP neural network – Exp. I	2928	0.0116	0.121	5.19	1.96
MLP neural network – Exp. II	2928	0.0291	0.152	10.63	1.96
MLP neural network – Exp. III	2928	0.0110	0.155	3.86	1.96

Table 2: Model statistics. t_c is given at a level of confidence of 95 %.

The worst statistical result is given by the diffuse radiation hourly values derived for São Paulo using correlation model. The best result was obtained by Experiment III whereas it still not inside the acceptance region. Once that the hourly values of solar radiation are very sensitive to the cloud cover, the improvement obtained in Experiment I when compared with Experiment II (without longwave radiation) seems to confirm that the longwave radiation can be used as a surrogate to the cloud cover over the region.

Comparison between MLP and correlation model

Hereafter, due to the best statistic performance of Exp. III, the discussion will be focused only in this experiment.

The dispersion diagrams between the hourly values of diffuse solar radiation observed and obtained using MLP network are displayed in Fig.1. The coefficient correlation obtained using MLP (Fig. 1a; r = 0.94) is larger than that using correlation model (Fig. 1b; r = 0.91), indicating the better performance of the MLP network.

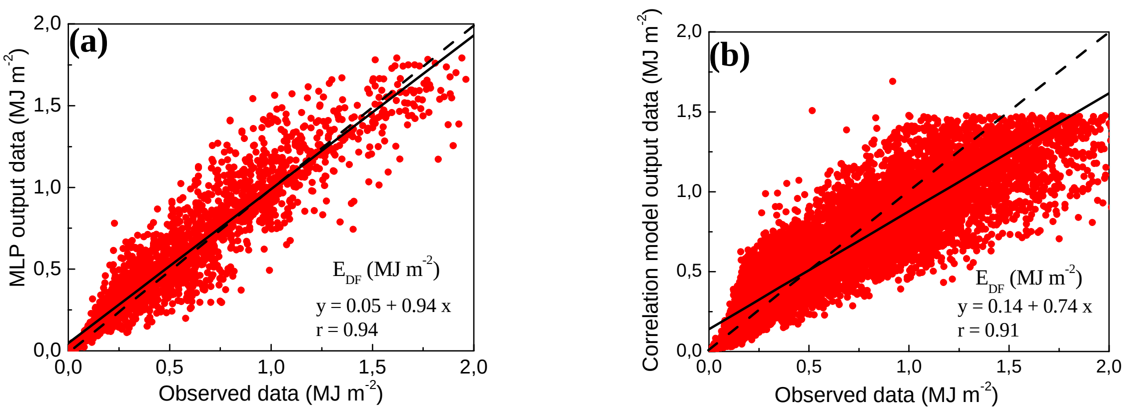

Figure 1: Dispersion diagram between the hourly values of diffuse radiation observed and (a) using MLP based on 2928 pairs of points and (b) using correlation model based on 15,258 pairs of points (from Oliveira *et al*., 2002a). Dashed line corresponds to diagonal and continuous line corresponds to curve fitted by least squares method. The correspondent linear equations are indicated in the bottom of each diagram and r is the correlation coefficient.

Histograms of the difference between solar diffuse radiation synthetic and observed are shown in Fig. 2. The standard deviation and the mean error value are also presented in the figure. In the case of MLP and of the correlation model the standard deviations are, respectively, 0.132 and 0.182. In both cases, the mean values are in the vicinity of zero demonstrating a good performance of the MLP network.

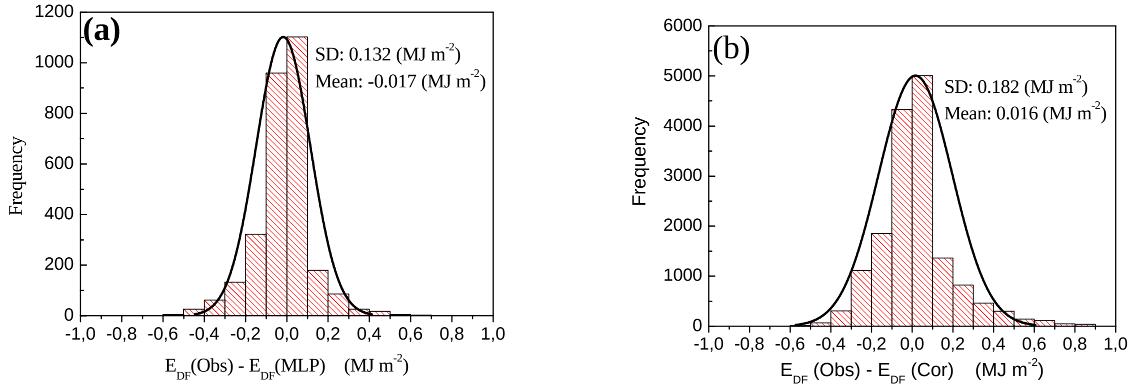

Figure 2: Histogram of diffuse solar radiation difference between observed and modelled values. (a) MPL based on 2928 points and (b) Correlation model based on 15,258 points (from Oliveira *et al*., 2002a). "SD" denotes the standard deviation and "Mean" the average error.

The correlation between diffuse fraction and clearness index can be displayed in terms of K_T - K_{DF} scatter diagrams. Fig. 3a shows K_T observed in São Paulo versus K_{DF} obtained using MLP network, based on 2928 pairs of points. Fig. 3b displays K_T and K_{DF} observed values, based on 15,258 pairs of points, obtained by Oliveira *et al*. (2002a).

To characterize objectively the climatic behavior of the diffuse solar radiation at São Paulo, a 4^{th}-degree polynomial was fitted through the data points in K_T versus K_{DF} diagrams (Fig. 3). This choice was based on fact that most of the expressions, available in the literature for hourly values, are 4^{th} -degree polynomials (Oliveira *et al*., 2002a; Erbs *et al*., 1982; Jacovides *et al*., 1996; Newland, 1989) allowing a straightforward comparison with previous works. The polynomial obtained using the data of Experiment III (Fig. 3a, continuous line) is:

$$K_{DF} = 0.90 + 1.10\,(K_T) - 4.50\,(K_T)^2 + 0.01\,(K_T)^3 + 3.14\,(K_T)^4$$

Oliveira *et al*. (2002a) obtained the polynomial expression (Fig. 3b, dashed line):

$$K_{DF} = 0.97 + 0.80\,(K_T) - 3.00\,(K_T)^2 + 3.10\,(K_T)^3 + 5.20\,(K_T)^4$$

The resemblance between the observed and synthetic polynomial curves (dashed and continuous lines in Fig. 3) indicates that the neural network generated data preserve the regional climate feature of São Paulo.

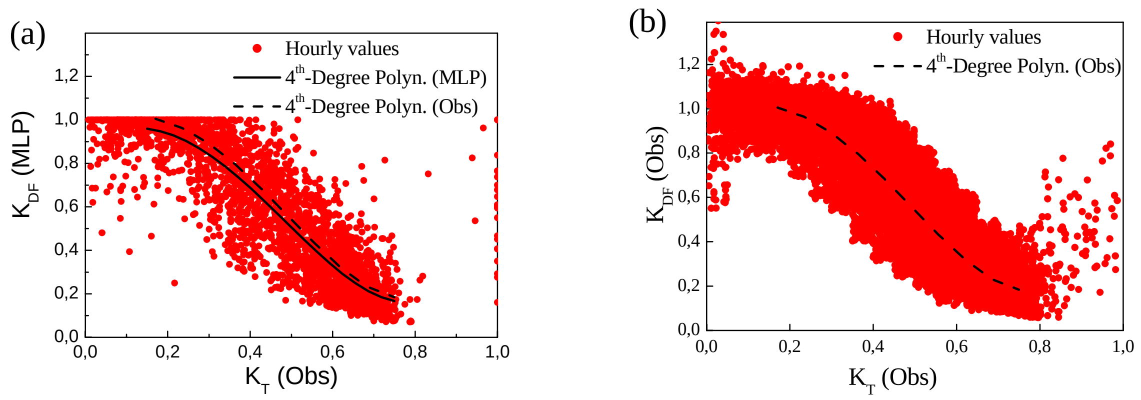

Figure 3: K_T - K_{DF} scatter diagram for hourly values of solar radiation. (a) K_{DF} obtained using MLP, based on 2928 pairs of points and (b) K_{DF} observed in São Paulo City, based on 15,258 pairs of points (from Oliveira *et al*. 2002a). The continuous and dashed lines display the 4th-degree polynomial curves obtained, respectively, from MLP and Oliveira *et al*. (2002a).

DISCUSSION AND CONCLUSION

In this work, a time series of almost 4 years of data was used to train MLP neural networks and 1 year of data was generated and used in the statistical analysis. The MLP methodology is based on the possibility of implicitly employing information associated with the problem without knowing the existing relationships between different variables and sources of information.

The best result was obtained by Experiment III (which includes the long wave radiation and uses pattern selection technique) whereas it is still not inside the acceptance region of the t-statistic test. A polynomial expression was obtained fitting a 4th-degree polynomial through the data points of K_T observed in São Paulo versus K_{DF} obtained using MLP network. The resemblance between the observed and synthetic curves indicates that the neural network generated data preserve the feature of the regional climate of São Paulo.

A significant result is the importance of atmospheric long wave radiation as a surrogate to the cloud cover information on the regional scale, a very difficult parameter to measure and express in diffuse solar radiation models. In contrast, traditional meteorological parameters, like air temperature and atmospheric pressure, are not as important as long wave radiation.

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