

AN APPLICATION OF NEURAL NETWORK TECHNIQUE TO IMPROVE QUALITY OF METEOROLOGICAL MEASUREMENTS

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ABSTRACT

This work describes an application of neural network technique to improve the quality of meteorological measurements. As an example it is shown one application of this methodology to correct dome effects on long wave radiation measured with pyrgeometer Eppley. Measurements of dome and case temperatures and meteorological variables available in regular surface stations (as global solar radiation, air temperature and air relative humidity) are enough to train the neural network algorithm and correct the observed long wave radiation for dome temperature effects in surface stations with similar climate of São Paulo city.

RESUMO

Este trabalho descreve a aplicação da técnica de rede neural para melhorar a qualidade das medidas meteorológicas. Como exemplo é mostrada uma aplicação deste método para corrigir os efeitos de emissão da cúpula nas medidas de radiação de onda longa efetuadas com pirgeômetro Eppley. Medidas de temperatura da cúpula e do corpo do pirgeômetro e de parâmetros meteorológicos disponíveis em qualquer estação meteorológica de superfície (como radiação global, temperatura e umidade relativa do ar) são suficientes para treinar o algoritmo de rede neural e corrigir as medidas de radiação de onda longa da atmosfera dos efeitos de temperatura da cúpula em estação de superfície com clima similar ao da cidade de São Paulo.

Key words: Neural network; meteorological measurements; pyrgeometer.

INTRODUCTION

The neural network (NN) technique has been previously applied to generate artificial data in several hydrology applications (Pereira Filho and Santos, 2006; Ramirez *et al.*, 2005), solar radiation modeling (Sfetsos and Coonick 2000; López *et al.*, 2001; Soares *et al.*, 2004) and meteorological applications in general (Gardner and Dorling, 1998; Hsieh and Tang, 1998).

The first time when NN was applied to improve quality of meteorological measurements was when NN was applied to correct pyrgeometer data by Oliveira *et al.* (2006).

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The objective of this work is to propose NN technique as a very powerful tool that can be applied to correct effects of sensor malfunctioning or time deterioration.

NEURAL NETWORK TECHNIQUE

The neural network consists of basic structures called neurons. The neurons only execute summation over weighted input values passing it to a nonlinear transfer function (tangents, hyperbolic, sigmoid, etc) to obtain a neuron output value (Oliveira *et al.*, 2006).

The three-layer perceptron artificial neural network with nonlinear transfer function is, in principle, a universal approximator and can be represented as a set of nonlinear equations used to calculate the output values from the input values. In the first layer each input parameter has its own neuron. The second layer is a hidden layer represented by several neurons. Each neuron in the second layer receives inputs from all the neuron outputs of the first layer. In the third layer this fully interconnected procedure is repeated again. There, the output layer has one neuron for each output parameter.

Each interconnected layer must have its own weighting factors. The weighting factors are the neural network parameters determined during the training. The structure, the weighting factors and the nonlinear transfer function give to the neural network the ability of a universal approximator (Božnar and Mlakar, 2002).

The three-layer perceptron artificial neural network with nonlinear transfer function is the most effective alternative to more traditional statistical techniques. Unlike other statistical techniques, the multilayer perceptron (MLP) makes no prior assumptions concerning the data distribution.

The neural network model consists of the determination of: (i) number of layers and number of neurons in each layer (topology); (ii) parameters to be used as input (input features) and (iii) data vectors of input and output pairs (pattern selection) used for training (learning and optimization) and testing.

The training process is basically the determination of the proper interconnection weights based on the learning set patterns so that the neural network output presents the best fit with the output given by the patterns in the optimization data set. In this way the neural network learns the information given in the learning set but still has the generalizing capabilities, not only memorizing capabilities. The generalizing capabilities ensure that the trained model is able to give reasonable results also for the unknown pattern (during the training period) that differs (but is still somehow similar) from all training patterns. The generalizing capabilities

make the multilayer perceptron neural network a good tool for atmospheric and related problems because the weather is always repeated but never exactly in the same way.

PYRGEOMETER CORRECTION

According to Fairall *et al.* (1998) the exclusive use of the manufacturer's instruction can lead to errors in the total flux up to 5% ($\sim 20 \text{ W m}^{-2}$). This error can be a serious problem when the longwave radiation flux is used, for instance, to perform energy balances or to recover surface temperatures.

In this work the NN technique is applied to correct the pyrgeometer data collected without correction of the dome emission effects. In the experiment performed here, the training set (learning and optimization dataset) employs data measured in the period from 15 October 2003 to 7 January 2004, corresponding to 73 days (1752 hours) at the City of São Paulo (Brazil).

Each measured or estimated parameter of the database represents a potential MLP input feature and the corrected downward longwave radiation is the MLP output feature. The database was analyzed and the most relevant parameters for the MLP construction to be used as neural network input were: (i) *observed longwave radiation*, (ii) *global solar radiation*, (iii) *air temperature*, (iv) *relative humidity* and (v) *local time*.

In the experiments performed here, the standard back propagation algorithm was used with learning rate 0.5 and momentum 0.9. Previous works show that this selection of parameters leads to a quick and effective learning (Božnar and Mlakar, 2002). The optimization data set was based on randomly selected 10% of patterns from the original training set and it was used during the training process to periodically test the MLP performance as 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.

The testing set used for check the validity of the generated series was taken from 8 January to 30 April 2004, comprising 89 days of continuous measurements of longwave radiation (2136 hours).

RESULTS

Figure 1 display, as an example, the hourly values of the air, dome and case temperatures. The dome temperature is considerably greater than the case temperature indicating an

important dome emission. During nighttime, very often, the dome is slightly warmer than the case and as consequence the dome emission effects are small but not zero.

The resemblance between the longwave value curves obtained from multilayer perceptron neural network output and using Fairall correction (Fig. 2) indicates that the data generated by the neural network is able to reproduce the corrected longwave measurements.

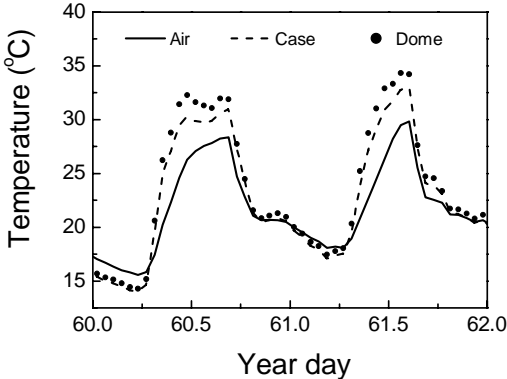


Figure 1. Diurnal evolution of hourly values of air (continuous line), case (dashed line) and dome (dot) temperatures.

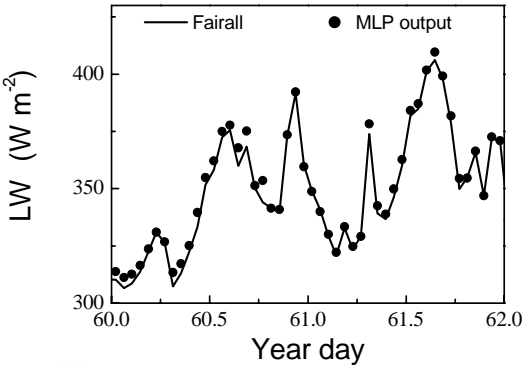


Figure 2. Hourly values of longwave radiations obtained as multilayer perceptron (MLP) neural network output (dot) and using Fairall *et al.* (1998) correction (continuous line).

The dispersion diagram between the hourly values of longwave radiations corrected using Fairall *et al.* (1998) and obtained using MLP network is displayed in Fig. 3. The coefficient correlation obtained is $r=0.99$, indicating the good performance of the MLP network. The histogram of the difference between longwave radiations corrected using Fairall *et al.* (1998) and obtained using MLP network is shown in Fig. 4. The standard deviation and the mean error value are also presented in the figure. The mean value is in the vicinity of zero demonstrating a good performance of the MLP network.

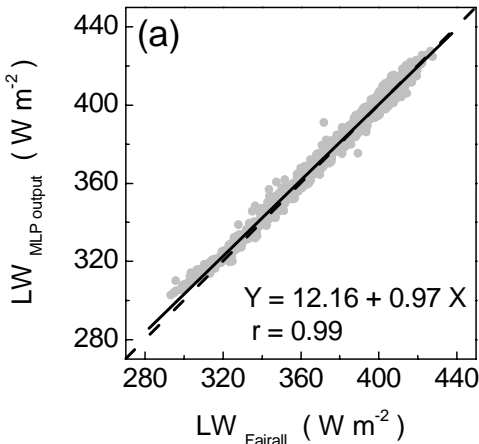


Figure 3. Dispersion diagram of hourly values of longwave radiation corrected by Fairall *et al.* (1998) and using MLP output. The dashed and continuous line in corresponds diagonal and to the fitted curve.

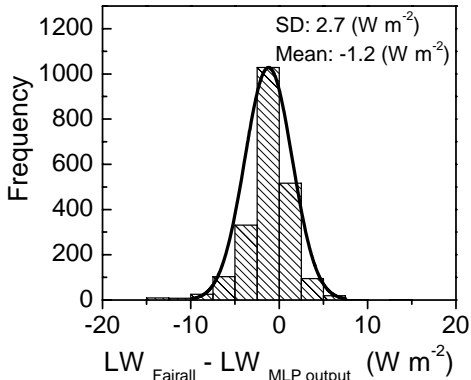


Figure 4. Histogram of longwave radiation difference between corrected by Fairall *et al.* (1998) and by MLP output. SD means the standard deviation.

CONCLUSION

This paper presents a methodology for generating synthetic series of longwave radiation, corrected for dome emission effects on pyrgeometer model PIR from Eppley, based on neural network called multilayer perceptron.

To apply the MLP parameters, developed in this work, is necessary having only accessible meteorological parameters (global solar radiation, air temperature and relative humidity) simultaneously to atmospheric longwave radiation measurements corrected only by manufacturer recommendations.

The methodology of MLP neural network described here can be used for other places and also for other sensors as a general approach to improve the quality of the existing meteorological data, including corrections based on the technological improvement of the sensors or even on removing systematic errors caused by sensor malfunctioning. Special care has to be taken concerning the procedure of pattern and feature selection.

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