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Technical note

Generation of ambient temperature hourly time series for some Spanish locations by artificial neural networks

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ABSTRACT

In this paper, an artificial neural network (ANN) is used for the generation of ambient temperature hourly time series for some Spanish locations. The model was trained and tested with ten locations and different years of data. Results show that the proposed artificial neural network provides a better approach than other methods. The aim of this paper is to provide a complete description of this ANN so that, it can be used by anyone avoiding all the design, training and testing process again.

1. Introduction

For most solar energy applications, it is necessary to know some meteorological parameters such as solar radiation and temperature of places where implementing and promoting the use of this renewable energy is required. There are a lot of meteorological services that are recording those parameters. Nevertheless, daily and hourly time series of ambient temperature are many times very difficult to obtain. Furthermore, in different geographical areas where these data are not available, they must be estimated through different methods and models.

The aim of this paper is the generation of ambient temperature (T_a) hourly time series of some Spanish locations by using artificial neural networks (ANNs). In this case, a complete description of this ANN will be provided (weight of layers and biases) in order to facilitate any researcher the application of this methodology for obtaining ambient temperature series.

The paper is organized as follows: The first section is this introduction. The review of different methods for obtaining ambient temperature time series, particularly ANN-based methods, is described in the second. The proposed methodology based on artificial neural network is explained in section three. In order to test the model proposed, this model was compared with data measured and with data generated with some classical method. Results are shown in the fourth section. Finally, in the last section, conclusions are presented.

2. Background. Methods for generating ambient temperature series

2.1. Conventional methods

Among the most important methods for the generation of ambient temperature time series from available temperature data are:

- Cuomo et al. [1] studied and analyzed air temperature on a daily basis in the Italian climate.
- Amato et al. [2] discussed stochastic–dynamic models for both air temperature and solar irradiance daily time series in the Italian climate.
- Hernandez et al. [3] developed stochastic models for the prediction of daily minimum air temperatures.
- Macchiato et al. [4] analyzed cold and hot air temperatures measured at 50 stations in southern Italy.
- Aguiar [5] proposed a deterministic model to calculate the daily mean air temperature, the double cosine model, and used three sinusoidal segments to connect the times of occurrence of the daily maximum and minimum air temperatures.
- Erbs et al. [6] provided a method which only needs the monthly average ambient temperature to obtain estimates of daily bin data and monthly heating or cooling degree-days for any base temperature.
- Knight et al. [7] proposed a model to generate hourly ambient temperature series, including the random component, without introducing discontinuities between the last hour of one day and the first hour of the next day.

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- Heinemann et al. [8] developed an algorithm for the synthesis of hourly ambient temperature time series that takes into account a monthly average daily temperature pattern and other models have been developed for everywhere in Europe.
- Huld et al. [9] have presented a methodology for estimating the average profiles of daytime and daily ambient temperature from a spatially-continuous database for any location within Europe.

All of these methods will be considered in this paper as deterministic and "conventional" methods. Previous studies show that for Spain, and in general for the Mediterranean area, the best results from the generation of ambient temperature hourly time series over a year are provided by two conventional methods [10]: the method proposed by Aguiar [5] and the one proposed by Erbs [6]. These two methods are more detailed described in Appendix I.

2.2. Artificial neural networks methods

Also for predicting ambient temperature ANNs methodologies have been applied. Some examples of these cases are:

- Khotanzad et al. [11] developed an ANN that provides hourly temperature forecast for up to seven days in advance for U.S. locations. The forecasts are based on the most recent actual hourly temperatures and the predicted daily high and low temperatures for the seven days.
- Tasadduq et al. [12] utilized ANNs for the prediction of ambient temperature hourly mean values 24 h in advance for the coastal location of Jeddah, Saudi Arabia.
- Hipper and Pedreira [13] proposed a neural network-based methodology for temperature profile short-term forecasting that is directed to applications in load forecasting and they also proposed [14] an hybrid short-term forecasting system that combines linear models and multilayer neural networks in order to forecast hourly temperatures.
- Ceravolo et al. [15] used neural models to estimate the monthly average temperature in different Italian locations.
- Altan and Çivril [16] trained ANNs for the estimation of hourly ambient temperature in Denizli, Turkey.
- Adelar et al. [17] used the technique of neural networks for the generation of weather data sequences taking into account interactions between the different climatic variables.
- Morabito et al. in [18] and Marra et al. in [19] used fuzzy neural identification and forecasting techniques to process experimental urban air pollution data.

Although there are also some applications of ANN for predicting temperature, these ANNs are briefly described and have only been studied in very specific geographical areas. Neither of these ANNs provides a complete description that allows its use directly for any researcher.

The main aim of this paper is to develop an ANN for generation ambient temperature hourly time series. A complete description of this ANN will be provided (weight of layers and biases), so that, this ANN could be used by anyone without having to redesign it again.

3. Proposed method

3.1. The Multilayer Perceptron (MLP)

Among the different kinds of neural networks, supervised models have consolidated as the most robust an easy to employ [20]. Usually, these models are implemented via feed-forward architectures such as, for instance, the *Multi-Layer Perceptron* (MLP).

The MLP is the most widely used types of supervised neural network for approximation tasks [21–24], its topology defines several layers of neurons. The MLP, in static contexts, is usually trained via a simple gradient-descent-based supervised procedure. The specific topology of the MLP makes the application of the gradient-descent method a very efficient process called the back-propagation algorithm [25,26] in which the network weights are moved along the negative of the performance function gradient.

This study uses the advantages of neural networks (an MLP in this case) such as no required knowledge of internal system processes, less computational effort and a compact solution for multivariable problems.

3.2. MLP proposed for ambient temperature series

3.2.1. Structure

The MLP that we have designed, studied and proposed for future applications consists of three layers: *entrance layer*, *hidden layer* and *output layer*. The number of nodes in the input and the output layers are based on the input and output dimensions of the problem in the study, respectively. The number of hidden layer nodes has been determined empirically. The structure of MLP is mainly determined by experience, and there has not been found a valid formula that is suitable for the different situations [27–30].

In this case, several ANNs with different structure have been trained in order to find the best architecture, the one that better fitted the network output to the target. Finally, the developed ANN has five nodes as input: daily maximum, minimum and the daily mean air temperatures (T_{dmax}, T_{dmin} and $\overline{T}_d$), latitude (La) and altitude (Al). The altitude has been used as input because, although in most cases all classic models perform well at stations near sea level, some previous studies show that altitude can be a dominant parameter [31].

The artificial neural network has nine nodes in its hidden layer and twenty four nodes in the output layers: hourly temperature values over one day (Fig. 1).

3.2.2. Source data

The data, used is this work, were provided by the Spanish AEMET (Agencia Estatal de METeorología) [32]. Fig. 2 shows the different locations used in this study: locations used to evaluate the accuracy of the models and locations used for the MLP. Table 1 also shows the number of years and the number of data used in each case.

3.2.3. Training and validation process for the MLP

In the training process, the MLP receives information of the measured temperature. This *process* requires a set of samples of proper network behavior – network inputs and target outputs. The relationships between the inputs and outputs are given as follows: the input vector (T_{dmax}, T_{dmin}, $\overline{T_d}$, La and Al) is applied to the network input layer (see Fig. 1). During training, the network weights and bias are iteratively adjusted, using the scaled conjugate

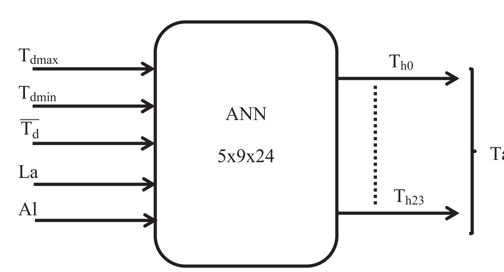

Fig. 1. Proposed structure for the artificial neural network.