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A MLP NEURAL NETWORK TO PREDICT THE WIND SPEED AND DIRECTION AT ZARAGOZA

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Abstract. In this work a Multi- Layer Perceptron (MLP) Neural Network to predict the wind direction and speed at Zaragoza is introduced. The model predicts there two variables, wind speed and wind direction, in an instant t from the TEMP and SYNOP data obtained in instants $t-6$, $t-12$, $t-18$ and $t-24$ hours before. One physical-mathematical wind prediction model was showed in [2] where two Neural Networks were presented, the "time expert" and the "spatial expert". Here, the TEMP data classification given in [5] and [6] is added to the "time expert". The Neural Network presented in this work, has only one hidden layer with four nodes. The outputs of model are compared with the real data obtained at Zaragoza.

Keywords: Neural networks, multi-layer perceptron, TEMP data, SYNOP data

AMS classification: 62-07,68T10,91C20,92B20

§1. Introduction

This article is included as a part of a general model for the study and the prediction of the wind and their properties in wind farms of Ebro Valley. For the implementation of a Physical-Mathematical Model to prediction the wind an initial model was built ([2]). Using meteorological data at mesoscale level, the model predicts the wind speed and direction in different wind farms.

In this first model, two neural networks were implemented, the "time" and the "spatial" experts. The "time expert" predicts the wind in some weather stations with a few variables as input. These has been collected in the same weather stations instants before. The "spatial expert" collects the output of the previous neural networks and then the wind in the wind farms is predicted. In this paper the "time expert" is rebuilt adding new variables predictors.

The meteorological data used in this work are variables of mesoscale level and they have been collected by the Instituto Nacional Meteorología, INM. They are basically two data types: the SYNOP and the TEMP data.

The first one contains measures taken at floor level in the weather stations each six hours, beginning at zero hours each day. These records have measurements of wind speed, wind direction, temperature and other variables.

In the same weather stations weather balloons are used to measure the TEMP data. These weather balloons perform measurements of wind speed, wind direction, temperature, pressure, point dew and geopotential, to different heights. The main problem of TEMP data is its complexity, too many measurements in too many different levels for each record.

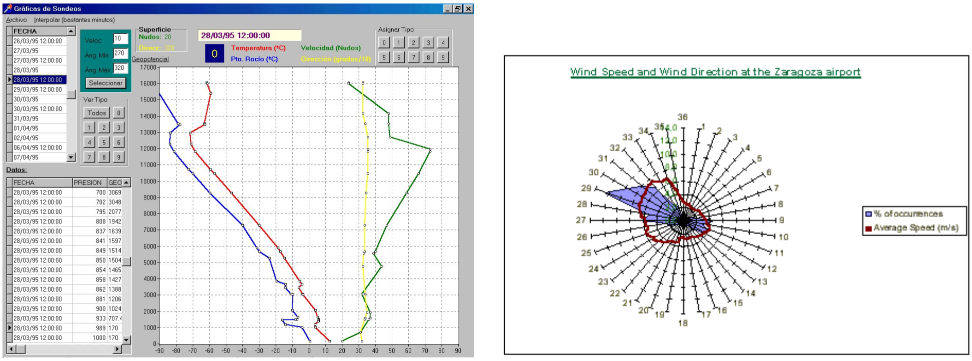


Figure 1: Plot TEMP data of the 28-03-1995 at 12:00 hours (left). Compass Rose in the Zaragoza Airport according to SYNOP data (right).

With the two database as input a MLP Neural Networks is implemented to predict the wind speed and the wind direction in an instant t. The TEMP data has been filtered and classified with a SOM Neural Network([6, 5]) before its use.

In the next section a brief description of the TEMP and SYNOP data is showed. The third section presents the MultiLayer Perceptron and its principal ideas. In the following section a MLP Neural Networks is created to predict the wind at Zaragoza. The inputs of the network are the TEMP and SYNOP data analysed in the previous section. The last part shows the conclusions of the article and the possible lines of study to continue the work.

§2. The database

2.1. The TEMP data

The TEMP data are measurements performed for the INM from different weather stations. Each twelve hours (0 and 12 o'clock) a weather balloon is sent for the obtention of meteorological measurements. The weather balloon accomplishes measurements of pressure, geopotential, temperature, point dew and wind speed and direction. The measurements are obtained in prefixed heights and in heights where a change is produced. In Figure 1-left, it can be seen the plot of one TEMP data, that shows the measurement of temperature (°C), point dew (°C), wind speed (knots) and the wind direction (grades) for the different geopotential. The pressure is not represented.

The principal problem of TEMP data is that each record has got different number of measures to different heights. For a first classification five pressures haves been used: 300, 500, 700, 850 and 1000 mb. In each one of this pressures the other variables haves been measured: geopotential height, temperature, wind speed and wind direction. Each record have got twenty variables, four measures in five pressures levels .

We work with measurements with begin on the 14-10-1990 and that finish on the 31-12-1999. Only the data with all measurements have been extracted (twenty variables). In total the studied series is composed of 33698 TEMP data. Logically it has not missing data.

2.2. The SYNOP data

The SYNOP data take in information about diverse meteorological variables. Those of greater interest for this study are the wind speed and wind direction. The measurements are made by the National Institute of Meteorology in a certain place every six hours, beginning at zero hours. The series contain data from the year 1972 to the present time. The database used in this article is collected in the Airport of Zaragoza.

Graphical analyses were made with the objective of discovering as much the predominant wind directions as the wind speeds in those directions. The results were those expected in Zaragoza: two predominant directions that correspond to winds known as “cierzo” (between 270° and 320°) and “bochorno” (between 90° and 120°). Take a look at Figure 1-right.

§3. The MLP to predict wind speed and direction

3.1. The Multi-Layer Perceptron Neural Network

A Multilayer Perceptron (MLP), also called Feedforward Neural Networks, is defined as “a network in which the directed graph establishing the interconnections has no closed paths or loops” ([3]). A neural network MLP associates, by means of functions and weights, some variables (called inputs) with others (called outputs). Usually, the Neural Networks (NN) are used for prediction or classification. In this paper a NN MLP is implemented to predict the wind in an instant t.

The MLP neural networks with only one hidden layer are universal approximators to continuous or to pth-power integrable functions so long as the node function satisfies the necessary condition of not being polynomial ([3, 7]). The principal problem is the number of hidden nodes, there is not theorem to calculate this.

More information, descriptions and algorithms for the MultiLayer Perceptrons can be found in [3], [7], [1] and [9].

3.2. The Multilayer Perceptron previous

The idea is to look for a method that allows us to predict the wind speed and the direction in certain zones of the Ebro Valley from SYNOP data of Zaragoza with the minimum possible error. The methods used were neural networks which adapt better to the behaviour of the data and provide better results than the previous ones, the linear and curvilinear regresion ([2]).

In order to make the prediction, two combined networks are used. The first one acts as a “time expert”, predicting the wind speed and the wind direction in the airport of Zaragoza for a moment t from the measurements of wind speed and direction in the same place at moments $t-6$, $t-12$, $t-18$ and $t-24$ hours. This network connects with another one, that acts as a “spatial expert”, which considers the wind speed and the direction at moment t in a wind farm from the prediction made by the “time expert” for the same moment t in the Zaragoza Airport. The two MLP network can be see in Figure 2, the “time expert”, and in Figure 3, the “spatial expert”.

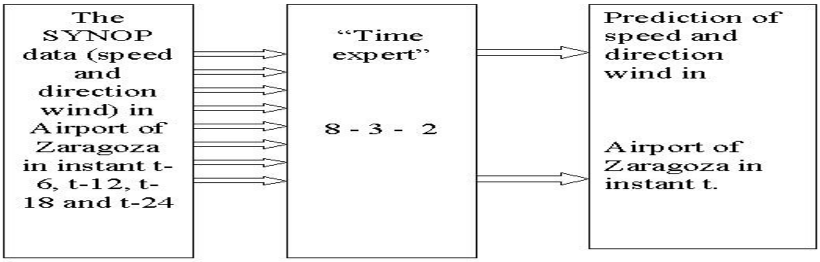


Figure 2: The previous MLP "time expert".

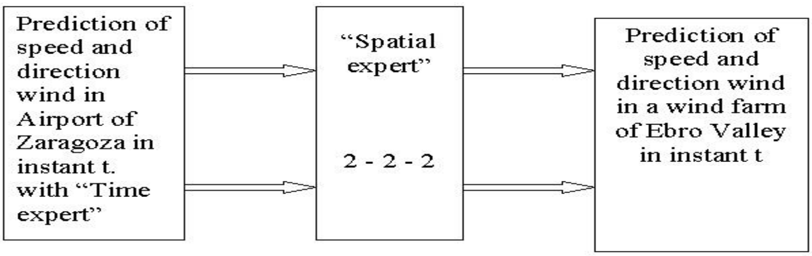


Figure 3: The previous MLP "spatial expert".

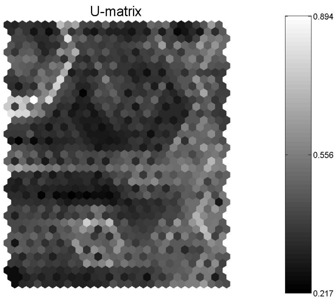
3.3. The TEMP data classes

Self-organizing Maps (SOM) ([4]) are neural networks with one of the most fascinating topics. The SOM neural networks can learn to detect regularities and correlations in their input and adapt their future responses to that input accordingly. The neurons of competitive networks, where the SOM are included, learn to recognise groups of similar input vectors. Of the same way the neurons physically near each other in the neuron layer respond to similar input vectors. The SOM was introduced for Tehuvo Kohonen in 1987 and it has been used for classifications and pattern recognition ([8]).

The SOM methods reproduce the data space in a reference space. If this reference space is, for example, two-dimensional, the graphics tools for the calculus of number of clusters can be used. Before the application of SOM is necessary to fix some parameters of method. In this work the SOM method has been applied to a reference space two-dimensional of 20×15 nodes and grid hexagonal, as it can see in [6].

The U-matrix is a SOM graphic tool that calculates the distance of each node with their neighbouring. The left of Figure 4 show the U-matrix with a gray scale for SOM obtained with TEMP data.

The coefficients and the graphic tools in the reference space indicate that the studied data could be divided in seven clusters([6, 5]). For the calculus of clusters , it is used the space reference with the same structure what the studied data and less number of data. The seven clusters are obtained with the method propose by Vesanto- Alhonimei ([10]), and the results



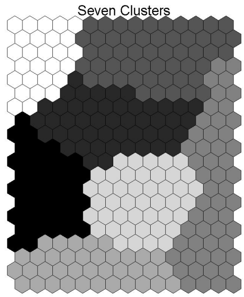


Figure 4: U-matrix of SOM with the TEMP data(left). Distribution of SOM in seven clusters(right).

of the partition in the reference space is showed in the right plot of Figure 4. The difference between the seven clusters can be seen in Figure 5, where the U-matrix in each one of twenty variables is showed. It can be seen the discriminant variables for each cluster.

3.4. The new Multi-Layer Perceptron

A new Multi-Layer Perceptron is presented in this section. This neural network improves the "time expert" presented in Subsection 3.2. With the same properties but different architecture. The new network has the input variables of the "time expert" (the SYNOP data) plus the classification showed in 3.3 (the TEMP data). A comparison between the results of new neural network and the old neural network will see in future jobs.

The architecture of the MLP is 10-4-2 (Figure 6). The ten variables input are the wind speed and direction in instant $t-24$, $t-18$, $t-12$ and $t-6$ (the four previous SYNOP data) and the cluster of two preceding TEMP data(instant $t-24$ and $t-12$, or $t-18$, $t-6$). The hidden layer has four nodes. The two output variables are the wind speed and direction in instant t. To sum up, the MLP network predicts the wind speed and the wind direction in a instant t by means of the four previous SYNOP data and the two previous TEMP data (Figure 6).

§4. Conclusions and future works

In this article a Multi-Layer Perceptron for the prediction of wind speed and direction is presented. The neural network predicts the wind in a instant t by means of the measures of wind in instant $t-24$, $t-18$, $t-12$ and $t-6$ (SYNOP data) and the TEMP data classification in two previous instants. The used variables are obtained in the Airport of Zaragoza for the INM (Figure 6).

The network output are compared with the wind speed and direction in instant t and the errors are calculated. The 80% of the data is used for the training of the network, training set, and the remaining, the 20%, is used for the validation of the network, validation set. The

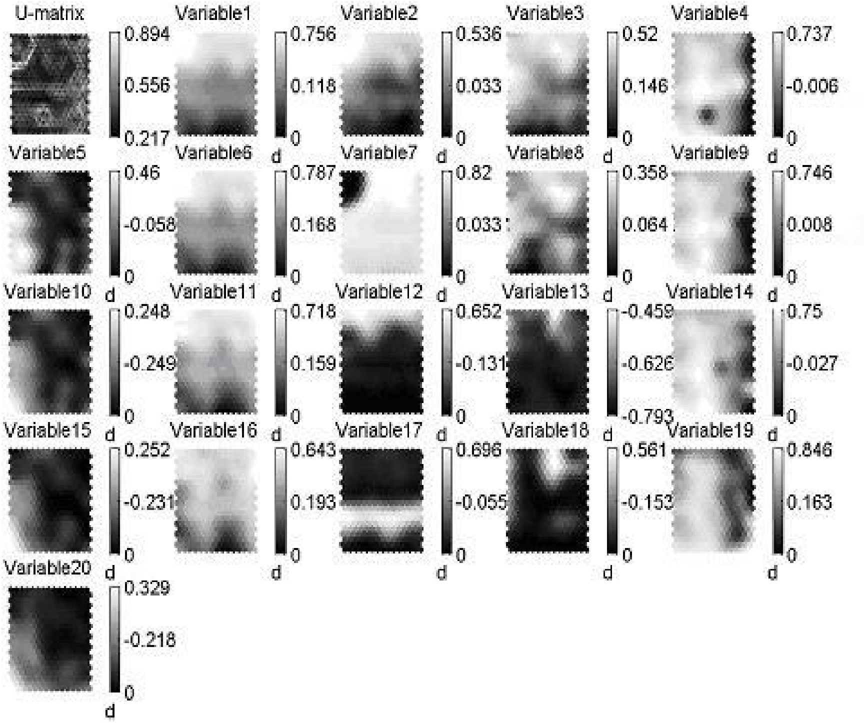


Figure 5: U-matrix complete where it can see the distance of each node of SOM with its neighbours in the twenty variables.

learning of the MLP network is accomplished for ten different training and validation sets, with different initial weights. The errors obtained in each learning can be seen in Figure 7. These plots shows the small differences between the errors for the validation and the training sets and between the ten runs. That is, the model has not problem with the generalisation or the overtraining of the network.

The obtained results for the model show a MSE over 50° ($\times 10°$ in the Figure 7) for the wind direction and over 2.5 m/s for the wind speed (Figure 7). This error is the same for the two set, the training and the validation set.

For future works we will add more predictors variables: TEMP and SYNOP data of another stations and more measures in the cluster of TEMP data, for example.

For the use of the model in the farm winds is proper to add the locals effects in its locations.

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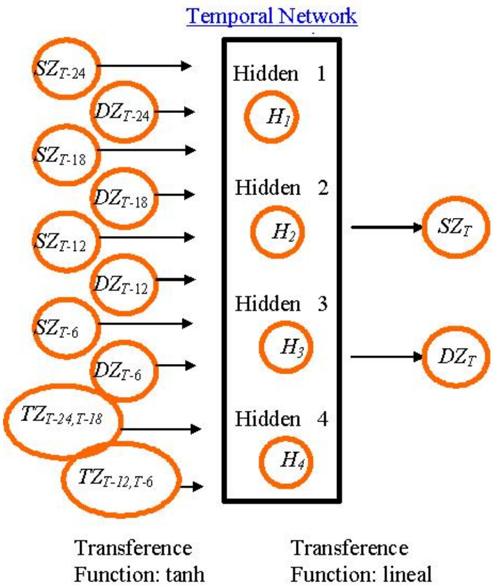

Figure 6: Architecture and variables, input and output, for the MLP proposed. SZ_s, DZ_s and TZ_s represented the wind speed and direction and the TEMP data in Zaragoza Airport in instant s, respectively.

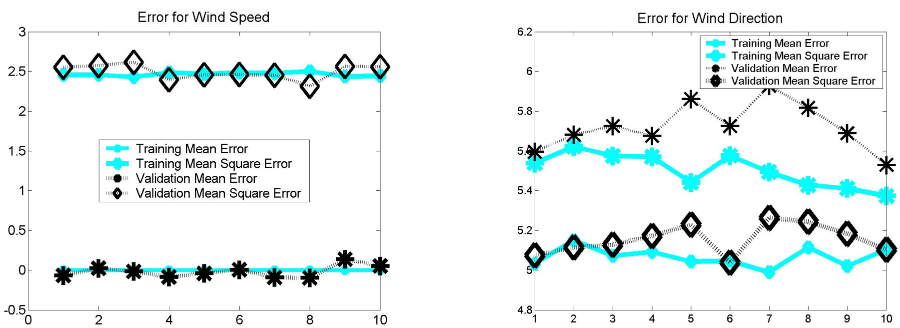

Figure 7: Errors obtained in the prediction of wind speed (left) and wind direction(right).

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