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Analysis of temporal behavior of climate variables using artificial neural networks: an application to mean monthly maximum temperatures on the Spanish Central Plateau

A. L. LABAJO
Departamento de Informática y Automática. Universidad de Salamanca. España

J. L. LABAJO
Departamento de Física General y de la Atmósfera. Universidad de Salamanca. España
Corresponding author; e-mail: jll45@usal.es

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RESUMEN

Se desarrolla un modelo de predicción de temperaturas máximas medias mensuales usando una Red Neuronal Artificial (RNA) del tipo perceptron multicapa. El modelo realiza predicciones del valor de temperatura media mensual del mes siguiente al último dato de la serie. El área de estudio considerada es la meseta central española (Castilla-León, Castilla La Mancha). Los datos de temperatura máxima media mensual se obtuvieron de las observaciones en las estaciones de la red sinóptica y climatológica de la Agencia Estatal de Meteorología (AEMET) de España. El conjunto de datos es dividido en dos subconjuntos, el de entrenamiento y el de prueba. El conjunto de entrenamiento se usa para el desarrollo del modelo y el de prueba para la evaluación del modelo establecido. Los parámetros de la RNA se ajustan experimentalmente. Se utilizó un algoritmo de retropropagación con tasa de entrenamiento variable para llevar a cabo un entrenamiento supervisado. Posteriormente se evaluaron las capacidades de predicción del modelo a partir del coeficiente de determinación (R^2), el error cuadrático medio (MSE) y las gráficas de dispersión y secuencia entre las series simuladas y las reales. Los resultados obtenidos con el modelo (que indican un buen ajuste entre las series reales y simuladas) se comparan con los obtenidos con modelos ARIMA. Los resultados son similares, si bien el modelo RNA es capaz de ajustar los valores extremos de las series de trabajo y algunas anomalías, lo que no sucede con modelos ARIMA.

ABSTRACT

A forecasting model for the mean monthly maximum temperatures (TMaxMean) using an artificial neuronal network (ANN) of the multilayer perceptron type (Multilayer Perceptron, MLP) has been developed. This model forecast the TMaxMean variable one month ahead after the last data point of the climate series. The study area considered is the central plateau of the Iberian Peninsula (Castilla y León and Castilla la Mancha). The data series of mean monthly maximum temperature (TMaxMean) were obtained of the observations at the stations of the synoptic and climatological network of the Agencia Estatal de Meteorología (AEMET). The data set is divided into two samples of training and testing. The training data set is used for the model development and the test set is used to evaluate the established model. The parameters of the ANN are fitted experimentally. A supervised training of the MLP ANN is performed. We used a backpropagation (BP) training algorithm with a variable learning rate. After that we evaluated the forecasting skills of the model from the coefficient of determination (R^2), the mean square root error (MSE) and the dispersion and sequence graphics of the real and simulated series. The results obtained with the model (indicates a good fit between the real and simulated series) are compared with those obtained with ARIMA models. The results are similar, while the model ANN is able to adjust the extreme values of the real series and certain anomalies, which is not the case with ARIMA models.

Keywords: Prognostic models, maximum temperature, neural networks, multilayer perceptron, backpropagation.

1. Introduction

The climate system is extremely complex as regards its various components and the interactions that occur among them (Cannon and McKendry, 2002). Climate is considered to be a dynamic system influenced by a large number of external factors, such as solar radiation and the topography of the earth's surface, and –apparently– also by insignificant phenomena such as the flapping of a butterfly's wings. In the paradigm of a chaotic climate model, and in particular one of the atmosphere, a small perturbation introduced into the system at some initial moment will lead the system to evolve to a different state from what would have occurred had this perturbation not been introduced (Von Storch and Zwiers, 1999).

Prediction of the behavior of the climate system has aroused considerable interest in the scientific community and has been subject to intense scrutiny, and studies on climate change have been in the limelight for some years now. In view of the perturbations to which the climate has been subjected much of the work carried out has addressed the influence of human activity on the environment and the possible future behaviour of the climate system. Current models aimed at the diagnosis of the behaviour of temperature (Schönwise *et al.,* 1994; Esteban-Parra *et al.*, 1995; De Gaetano, 1996; Oñate and Pou, 1996; Kadioglu, 1997; Labajo and Piorno, 1998, 1999; Galán *et al.,* 2001, among others) have more or less confirmed the existence of global warming, and the differentiation of climate behavior in different regions of the planet.

Prediction models of time series provide future values of such series based on present and past values. To accomplish this, the model must be able to describe the underlying relationships in the past observations in order for temporal data sets to be extrapolated (Wedding and Cios, 1996; Lendasse *et al.,* 1998; Zhang, 2003). The modelling is particularly useful when there is some information available in the data involved in the generating process or when there is no model able to satisfactorily explain the dynamics of the process (Zhang and Qi, 2005).

Among the statistical models available, of considerable interest are simple and multiple regression models, trend modelling, averages, probability distributions, analysis of canonical correlations, ARIMA methodology, and principal component analysis (PCA). The ARIMA methodology, which describes self-regressive integrated processes and those of mobile means, has been widely used. This methodology can be applied to the modelling and prediction of the behavior of temporal series of observations of a given variable (Navarro *et al.,* 1998). Its popularity is due to its statistical properties and to the Box-Jenkins methodology. Its greatest limitation is the assumed linear form of the model. Non-linear patterns can be captured by ARIMA models, although the approximation of linear models in complex problems of the real world is not always satisfactory, since predictions of future values must necessarily be functions of past observations. Owing to the relative simplicity involved in their understanding and implementation, linear models have occupied center stage in the research and tools applied over the past few decades (Zhang, 2003).

Recently, ANNs have found use in the development of time series prediction models, in particular climatic models (Ciocoiu, 1998; Tang *et. al.,* 2000; Qi, and Zhang, 2001; Cannon and McKendry, 2002). Often, ANNs provide results as good as if not better than those obtained with traditional methods of prediction, making them valuable tools apart from the arsenal of statistical methods already available (Nelson *et al.,* 1999). ANNs were originally conceived as an attempt to model, understand, and explain the biophysiology of the human brain and they comprise simple elements operating in parallel. Such elements are inspired in the biological nervous system. The network function is determined by the connections among the elements. It is possible to train an ANN to achieve a particular function by adjusting the values of the connections among the elements (Demuth and Beale, 2000).

Comrie (1997) used an ANN for ozone forecasting. Mihalakakou *et al.* (1998) for modeling ambient air temperature time series. Bertil and Mohsen (2007) and Lu and Viljanen (2009) for the prediction of indoor temperature and relative humidity. Juhos *et al.* (2009) for the prediction of NO and NO_2 concentrations.

The greatest advantage of ANNs is their highly flexible capacity to perform non-linear modelling, relying on the property of universal approximation (Curry and Morgan, 2006). It is not necessary to specify a particular form of the model; rather, the model is adapted to the traits present in the data (Zhang, 2003). Nevertheless, ANN models also have several drawbacks: the architecture of an ANN must be determined by the user or must be optimized heuristically. Most training algorithms require the initialization of some parameters, such as the learning rate and the momentum, which are defined by the user. Suitable values of these parameters cannot be deduced directly from the training data. Moreover, such training is strongly dependent on appropriate parameter selection.

Research carried out in several fields, in particular in the prediction of time series, has shown that one of the most widely used ANNs is the MLP (Wong, 1991; Tangang *et al.,* 1996; Cannon and McKendry, 2002; Zhang and Qi, 2005; Wu *et al.,* 2006).

Treatment of the working series prior their application to the model may improve the results provided by the ANN. According to Zhang and Qi (2005), ANNs are not able to capture seasonal variations and trends effectively unless data treatment aimed at achieving a stationary deseasonalized series has been implemented previously. Dorffner (1996) also proposed deseasonalization of a series in a phase prior to model application.

This work aims to establish a model that allows estimating climatic variables by fitting an ANN. We show an application to monthly average maximum temperature data series.

2. Artificial neural networks

Here, ANNs are considered as artificial data treatment models inspired in the biological nervous system. ANNs are implemented on a computer by means of informatics algorithms that artificially simulate simple elements called neurons. These neurons are interlinked via weighted connections. The information is presented to the ANN in numerical format and by means of a group of input neurons to the network. This information is transmitted to all the neurons of the network through connections, which provide numerical outputs as a result of the input data and the form of propagation of those data through the neurons of the network.

A neuron is a simple unit of data processing. Figure 1 shows the structure of an artificial neuron and the form of transmission of the input data through it. The following notation is used:

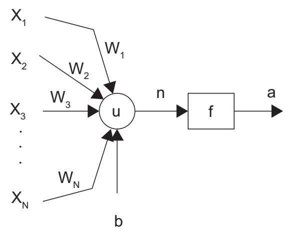

Fig. 1. Scheme of an artificial neuron.

$\vec{x} = (x_1, x_2, \ldots, x_N)$ Vector of input data to the neuron.

$\vec{w} = (w_1, w_2, \ldots, w_N)$ Vector of weights associated with the input connections to the neuron.

u: Network function.
f: Activation function.
b: Threshold of neuron activation.
n: Effective input to the neuron.
a: Output from the neuron.

The network function determines the effective input to the neuron, modelling the rule of the propagation of information through each of them. Below, the linear-base and radial-base network functions are shown.

$$n = u(\vec{w}, \vec{x}) = \sum_{i=1}^{N} w_i x_i \tag{1}$$

$$n = u(\vec{w}, \vec{x}) = \sqrt{\sum_{i=1}^{n} (x_i - w_i)^2} \tag{2}$$

The activation function of the neuron affords the response of the neurons to the stimulus provided according to the rule of propagation of the numerical information. This response characterizes the state of activation of the neuron. Assuming that the network function is of linear base, the output of an artificial neuron can be obtained thus:

$$n = \sum_{i=1}^{N} X_i W_i + b \tag{3}$$

$$a = f(n) = f\left(\sum_{i=1}^{N} X_i W_i + b\right) \tag{4}$$

An ANN comprises several neurons linked together by connections. The simplest form of grouping neurons is in layers. In turn, an ANN is made up of several layers. Generally, the neurons of the same layer are characterized by having the same activation function, while the neurons of different layers may have different activation functions.

Figure 2 shows a layer of *m* neurons, which receive a set of *s* data as input. The *m* neurons jointly receive the data input to the network. Figure 3 represents this in a more simplified way.

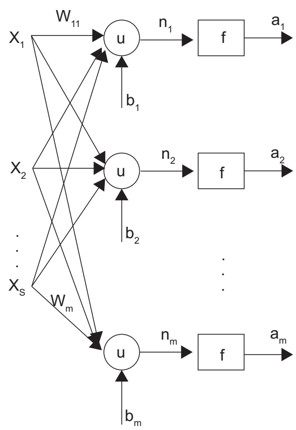

Fig. 2. Scheme of a layer of *m* neurons.

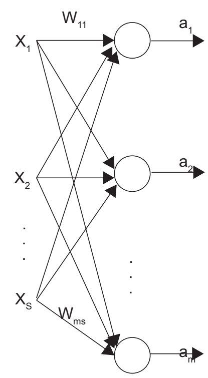

Fig. 3. Simplified scheme of a layer of *m* neurons

Several layers of neurons can be combined to obtain an ANN. Figure 4 shows a graphic model corresponding to an ANN with an input layer, an output layer and several intermediate layers. It may be seen that the data inputs to a layer are the outputs from the previous layer.

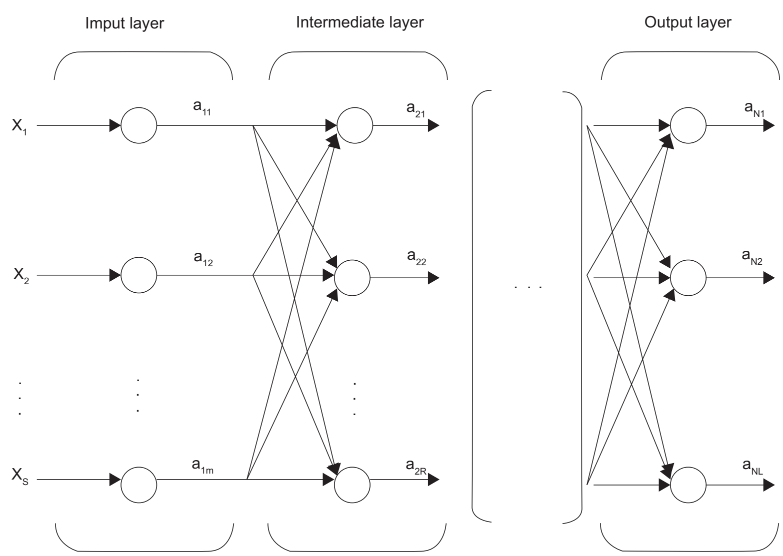

Fig. 4. Scheme of an ANN with input and output and several intermediate layers.

1.1 Training and testing of an ANN

The structure of ANNs, with weighted connections, makes it necessary to perform a previous calculation of the weights associated with each connection before its application to numerical data in the context of a given problem. The numerical data are grouped in patterns, such that some of those patterns are reserved for the fitting of the weights associated with the connections of the ANN, while the rest –in a second step– are used to check the capacity of the ANN to solve the problem. Within the context of the application of an ANN to the prediction of the future values of a time series, some of the observations of the time series are reserved to calculate the weights associated with the connections and the rest are used to validate the capabilities of the ANN. The first step is called the learning step of the ANN and the second one is called test step.

In the training step of the ANN, the weights are modified by means of a training algorithm implemented on the computer. This fitting of the weights values affords the ANN the ability to learn the solution to a problem. There are different types of training algorithms, and the one used will vary depending on the type of ANN to be trained. In the testing step, the ANN provides the outputs corresponding to the data reserved for such purposes with the weights calculated in the training step.

The different types of training of an ANN give rise to different types of learning, which are adapted to the needs of the problems to which they are to be applied. The way in which the data are presented to the ANN in the form of patterns, the learning rule used to modify the weights associated with the connections, and the way of modifying the weights are all important. All these aspects are combined, giving rise to different types of training. We use a variant of the backpropagation algorithm, with a variable learning rate than can be found in the bibliography (Corchado *et al*., 2000; Demuth and Beale, 2000).

3. Methodology

The prognostic model used is a one time ahead prediction model (Fig. 5), in which estimation of the later moment of time is obtained from the previous values of a data set, based on an ANN of the MLP type adapted to three layers (Fig. 6). The training and testing patterns are parts of the time

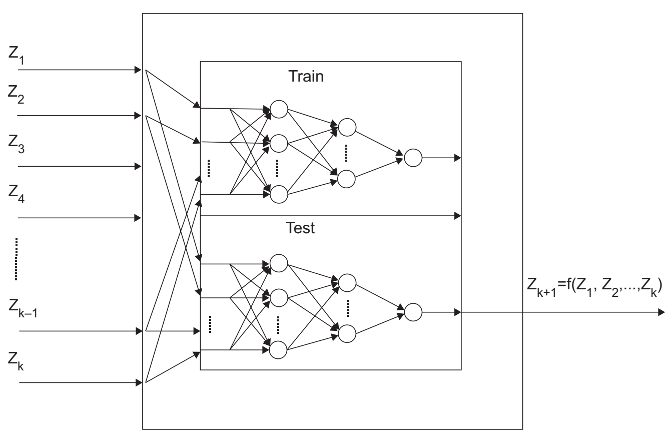

Fig. 5. Scheme of the ANN prediction model of time series.

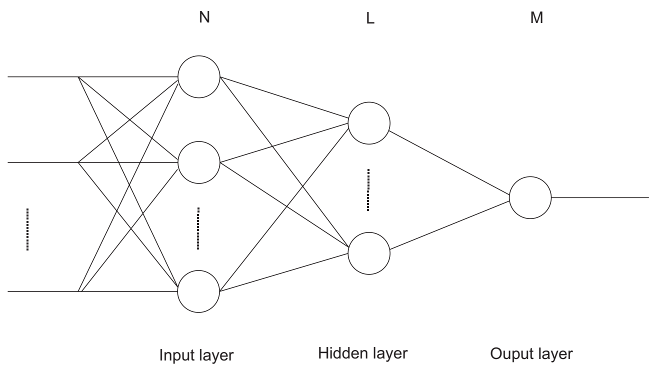

Fig. 6. The adapted ANN MLP with three layers of neurons.

series, of the same length and lagged at one moment in time. They are obtained according to the scheme shown in Table I. This configuration has been proposed by Isasi and Galván (2004), among others. In the table, N is the number of data per pattern; NTr is the number of training patterns, and NTe is the number of testing patterns.

Table I. Configuration of the training and testing patters according to the one time ahead prediction scheme.

Pattern	Input	Output
Training 1	t(1), t(2),…, t(N)	t(N+1)
Training 2	t(2), t(3),…, t(N+1)	t(N+2)
⋮	⋮	⋮
Training NTr	t(NTr), t(NTr+1),…, t(NTr+N–1)	t(NTr+N)
Test 1	t(NTr+1), t(NTr+2),…, t(NTr+N)	t(NTr+N+1)
Test 2	t(NTr+2), t(NTr+3),…, t(NTr+N+1)	t(NTr+N+2)
⋮	⋮	⋮
Test NTe	t(NTr+NTe), t(NTr+NTe+1),…, t(NTr+NTe+N–1)	t(NTr+NTe+N)

The MLP ANN used requires two phases: training and testing. In the former, the ANN is trained with the BP and some of its variants. In the testing step, the model is validated from the R^2 and MSE values between the real and simulated series, and the corresponding sequence and dispersion graphics, also of the real and simulated series. The process of model configuration was performed with the temperature series observed at the weather station in Ávila.

A spatio-temporal study was made of the data sets of the TMaxMean variables at the weather stations on the central Spanish plateau. Thus, study of the differences and similarities as regards the temporal evolution of the working variable according to geographic location was facilitated. We used the graphics of the temporal sequence of the observations of the TMaxMean variable corresponding to the different stations, the monthly sequences of observations of each series, the box diagrams of the monthly distributions and statistics such as the mean, standard deviation, asymmetry coefficient, and the kurtosis of the distributions of the data corresponding to each month of the year. Finally, the results corresponding to the Kolmogorov-Smirnoff test are offered to check the fitting of the monthly distributions of data to a normal distribution.

We also carried out an experimental determination of different parameters of the model. Among them, of importance are the following: the length and number of patterns, activation functions by layers, the learning rate and momentum when using the BP algorithm, variants of the BP algorithm, end of training conditioning, and the number of neurons of the hidden layer.

It should be noted that an almost perfect training does not guarantee a better yield by the model. Additionally, overtraining the ANN may give rise to problems when applying the prognostic model. Initially, the training ends after 20 000 iterations of the algorithm. This allows one to determine the training algorithm (between BP and its variants) that best performs this step. Model validation with this algorithm allows the problem of overtraining to be checked.

In order to avoid overtraining, an alternative condition is added as regards the MSE between the real and simulated series. This allows the process to be ended after 20 000 iterations or when a given match between the real and simulated series is obtained in that phase. The end of training MSE is fitted experimentally.

After this set of experiments had been completed, we performed new assays with a view to determining the prior processing of the data with which the model would give the best results. In these experiments, the model was fed with data patterns in which the series had previously been processed by means of differentiation, deseasonalization, anomalies, normalization, and standardization. This previous data treatment made it necessary to carry out a later step of inverse treatment of the data before the results could be validated, as shown in the scheme in Figure 7.

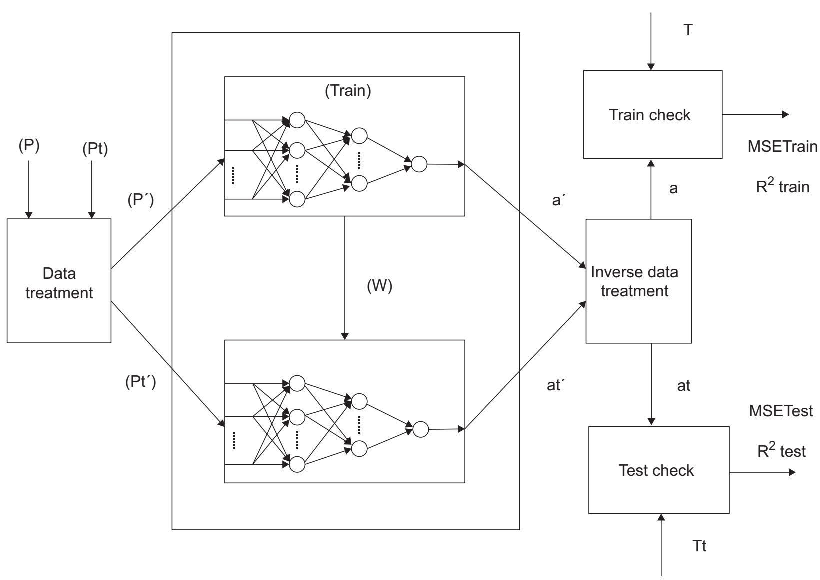

Fig. 7. Prognostic model with pre-processing of the data sets.

The model was applied to the TMaxMean series observed at the meteorological stations of the synoptic and meteorological network of the Instituto Nacional de Meteorología on the central Spanish plateau.

To check the goodness of the prognostic model based on the ANN, the results obtained with it were contrasted with those obtained using ARIMA methodology, using the same data sets and the same validation period. To accomplish this, we selected some weather stations in Castilla-León (Valladolid and Salamanca) and Castilla-La Mancha (Ciudad Real and Cuenca). The orders of the ARIMA model were determined from a study of the sequence plot, the simple eigencorrelation function (SEF) and the corresponding partial eigencorrelation function (PEF) in combination with an experimental methodology. The results obtained with both methodologies were compared, using the values of the coefficients of determination and of the MSE in the validation step between the real and simulated series with ARIMA methodology and with the ANN-based methodology. We also compared the corresponding sequence graphics.

4. Data

The data sets were obtained from daily measurements of the TMaxMean variable at a series of weather stations belonging to the synoptic and meteorological networks of the Instituto Nacional de Meteorología located in the regional communities of Castilla-León and Castilla-La Mancha (central Spanish plateau) in the period between 1961 and 2004. Initially, the stations considered were those in Ávila, Burgos, León, Palencia, Salamanca, Segovia, Soria, Valladolid, Villanubla (Valladolid) and Zamora, in Castilla-León, and Albacete, Los Llanos (Albacete), Ciudad Real, Cuenca, Guadalajara and Toledo, in Castilla-La Mancha.

The files of the daily TMaxMean data series, which initially had a matrix structure, were modified with a view to organizing them in the most suitable format for comparison with one another. To accomplish this, we developed the software necessary to transform the matrix structure into a single column of the temporal sequence of all the data. Once transformed, the data sets were debugged by applying a series of logic filters (to limit the highest and lowest values, etc.), removing those that were clearly mistaken.

For a more intense debugging, we compared all the series with each other to establish those cases in which one data point in them clearly differed from the rest, which would suggest that it was mistaken despite being within the limits set by the logic filters. We then filled them in using linear regression techniques. In nearly all cases, the values of the coefficients of determination obtained in these regressions surpassed a value of 0.9, confirming the goodness of the method. Additionally, we discarded series that had more than 20% of gaps. This meant that we did not consider the series of observations from Albacete and Palencia. From the filled series, we established the series of mean monthly values. Finally, we checked the homogeneity of variance using the Levene (1960) test.

As a result of the analysis and treatment of the initial data, the definitive working series were those corresponding to the observations made at the weather stations in Ávila, Burgos, León, Salamanca, Segovia, Soria, Valladolid, Villanubla (Valladolid) and Zamora, in Castilla-León, and Los Llanos (Albacete), Ciudad Real, Cuenca, Guadalajara and Toledo in Castilla-La Mancha. Figure 8 shows the geographic locations and coordinates of the stations considered.

5. Results

The prognostic model developed was applied to the TMaxMean series observed at the weather stations on the Spanish central plateau and was fitted as shown in Table II. The study period was from January 1961 to December 2004, owing to the availability of data at the time the study was carried out. Study of the spatio-temporal behaviour of the data sets allowed the similarities in behavior among the observations from the same region to be established.

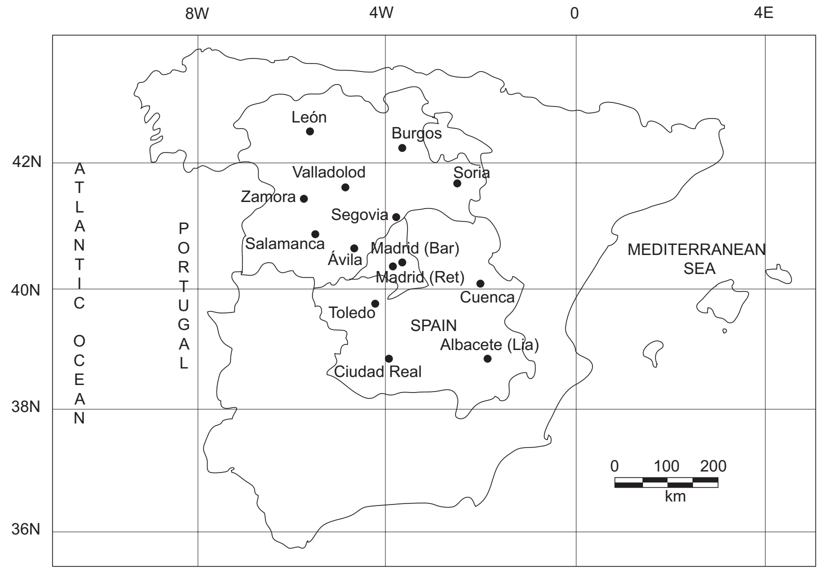

Fig. 8. Geographic location of the weather stations of the synoptic and climatological network of the Instituto Nacional de Meteorología on the Spanish central plateau.

Tables III and IV show the results obtained, and Figures 9 and 10 show the corresponding plots. The sequence graphics plot the temperature (ºC) on the ordinates and the date (month and year) is represented on the abscissa. The thick line corresponds to that simulated by the model and the other line represents the real one. In the case of Castilla-León, the results are shown in Table III and Figure 9. For Castilla-La Mancha, the same can be seen in Table IV and Figure 10.

In general, the values of R^2 and MSE in Tables III and IV reveal a better fit between the real and simulated series in the training step as compared with the model testing or validation phase. They also point to the good agreement between the real and simulated series in the testing step in nearly all cases; in some cases this agreement is very high, as is the case of all the weather stations, with the exception of Guadalajara, in Castilla-La Mancha. A more detailed study of the indices shown in Table III, corresponding to Castilla-León, reveals that the R^2 values in the ANN training step are above 0.960, with the exception of the weather station in Burgos. This situation is the same for the MSE, where –at all the stations– it lies between 1.98 and 2.00. In the case of the Burgos station, the MSE is similar to that of the rest of the stations. These values imply that the model established by the ANN is to a large extent able to fit the real series in the training step.

Regarding model validation, it is noteworthy that all the weather stations, with the exception of Salamanca, had an R^2 above 0.900 and MSE values between 4.64 and 5.46. For Salamanca the R^2 was 0.893 and the MSE was 6.39. The weather station showing a coefficient of determination closest to 1 was Valladolid, with a value of 0.924. However, the stations with the best MSE were Villanubla and Burgos with values of 4.64.

Scrutiny of the plots shown in Figure 9 (Castilla-León) reveals the following highlights:

- Both curves show good agreement, although the greatest differences are seen in some extreme values. This effect is more pronounced for the highest values of the series. In general the mean monthly temperature series predicted by the model maintain the same characteristics as regards evolution and trend as the real series.

Table II. ANN model: series used; input patterns in the model; ANN configuration, and data treatment.

Series used	Variables	Mean monthly maximum temperatures (TMaxMed)			
	Seasons	Castilla-León	Ávila, Burgos, León, Salamanca, Soria, Valladolid, Villanubla and Zamora.		
		Castilla -La Mancha	Los Llanos (Albacete), Ciudad Real, Cuenca, Guadalajara and Toledo.		
	Time interval	From January 1945 to December 2004			
Configuration of patterns	Training scheme	Prediction based on a unit of time (1 month).			
	Number of patterns and data	Training	539		
		Test	60		
		Data per pattern	120		
Artificial Neuronal Network	Architecture	Type	Adapted MLP		
		Nº of layers and neurons per layer	Nº of layers		3
			Nº of neurons per layer	Input	120
				Hidden	60
				Output	1
		Activation functions	Input		Tangent hyperbolic
			Hidden		Tangent hyperbolic
			Output		Ramp
	Learning algorithm	Type	Backpropagation algorithm with variable training rate.		
		End of training	Iterations		20.000
			MSE		2
Data treatment	Differentiation of the series				

- The series of real values corresponding to all the stations show the same general characteristics, as may be seen for example in the first months of 2000.
- The series simulated by the model show the same general characteristics.
- The model is not able to completely fit the anomalies appearing in the real series, as can be observed for the first months of 2000 and the central months of 2003. This may be due to the fact that the training patterns did not include anything even remotely similar to this anomaly.

Table III. Coefficients of determination and MSE, in the training and testing phases, obtained upon applying the local model to the TMaxMean series observed at the weather stations in Castilla-León.

Experiment	Stations	Training		Test	
		R^2	MSE	R^2	MSE
MLAv	Ávila	0.963	1.98	0.917	4.74
MLBu	Burgos	0.906	1.99	0.906	4.64
MLLe	León	0.962	2.00	0.909	4.82
MLSa	Salamanca	0.966	1.99	0.893	6.39
MLSo	Soria	0.965	1.98	0.912	5.09
MLVa	Valladolid	0.966	2.00	0.924	5.02
MLVn	Villanubla	0.965	1.99	0.922	4.64
MLZa	Zamora	0.965	1.99	0.912	5.46

Table IV. Coefficients of determination and MSE, in the training and testing phases, obtained upon applying the local model to the TMaxMean series observed at the weather stations in Castilla-La Mancha.

Ref.	Stations	Training		Test	
		R^2	MSE	R^2	MSE
MLLla	Los Llanos (Albac)	0.969	1.99	0.918	5.35
MLCR	Ciudad Real	0.972	1.99	0.931	4.86
MLCu	Cuenca	0.967	2.00	0.920	4.89
MLGu	Guadalajara	0.969	1.99	0.924	5.17
MLTo	Toledo	0.969	1.99	0.933	4.57

Application of the model to the data sets collected in Castilla-La Mancha, with the exception of Guadalajara, afforded slightly better results than those corresponding to Castilla-León. The values of the indices shown in Table IV reveal that the R^2 values are higher than those obtained for the weather stations in Castilla-León. The station with an R^2 closest to unity is Toledo (0.933) and the one with the lowest value is Los Llanos (Albacete), with 0.918. The same situation is seen in the study of the MSE, where the station with the lowest MSE is Toledo (4.57) and the one with the highest MSE is Los Llanos (5.35). Of interest is the strong agreement between the data sets provided by the model and the real series.

Scrutiny of the plots shown in Figure 10 indicates that the general characteristics are the same as those of the plots obtained on applying the model to the TMaxMean series of the weather stations in Castilla-León. It may be seen that the anomaly detected in the series of real TMaxMean values at the stations in Castilla-León during the first months of 2000 also appears in the series for Castilla-La Mancha, and in this case the model is not able to fit it perfectly either.

Table V and Figure 11 show the results obtained with ARIMA models and with the model based on the MLP ANN, when they were applied to the TMaxMean series obtained at the stations in Valladolid, Salamanca, Ciudad Real and Cuenca. The values of the indices shown in Table V indicate a high degree of fit between the real series and the simulated ones in all cases.

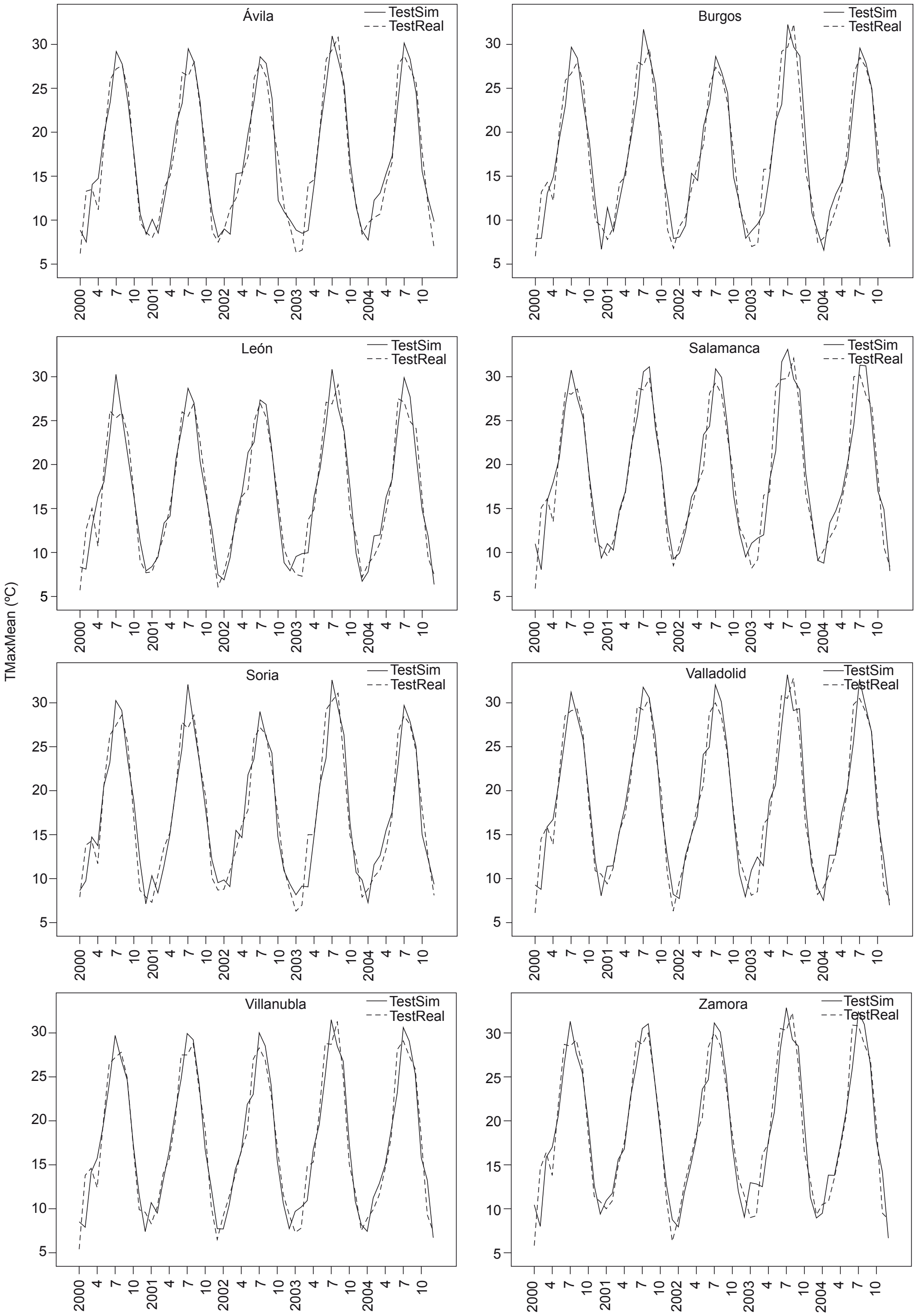

Fig. 9. Sequence plots of the real series (TestReal) and simulated series (TestSim) corresponding to application of the local model to the TMaxMean (ºC) series observed at the weather stations in Castilla-León.

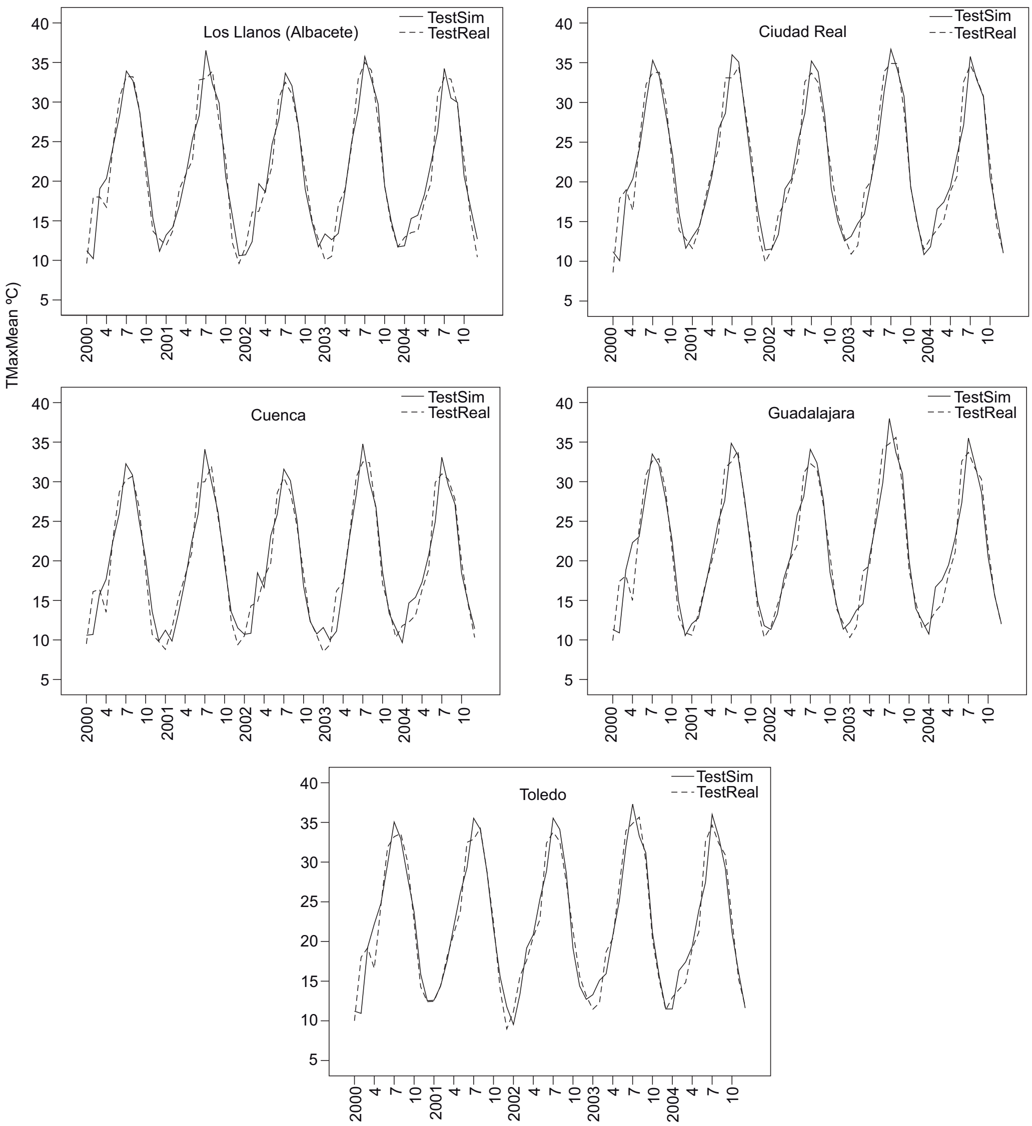

Fig. 10. Sequence plots of the real series (TestReal) and simulated series (TestSim) corresponding to application of the local model to the TMaxMean (ºC) series observed at the weather stations in Castilla-La Mancha.

Table V. Coefficients of determination and MSE corresponding to the real series and those simulated with the ARIMA and ANN models for the TMaxMean series observed at the weather stations selected in Castilla-León and Castilla-La Mancha.

Experiment	Stations	ARIMA model		ANN model	
		R^2	MSE	R^2	MSE
ArVA1	Valladolid	0.958	2.91	0.930	4.59
ArSA1	Salamanca	0.935	3.99	0.899	5.99
ArCR1	Ciudad Real	0.960	2.99	0.926	5.48
ArCU1	Cuenca	0.955	2.96	0.920	4.15

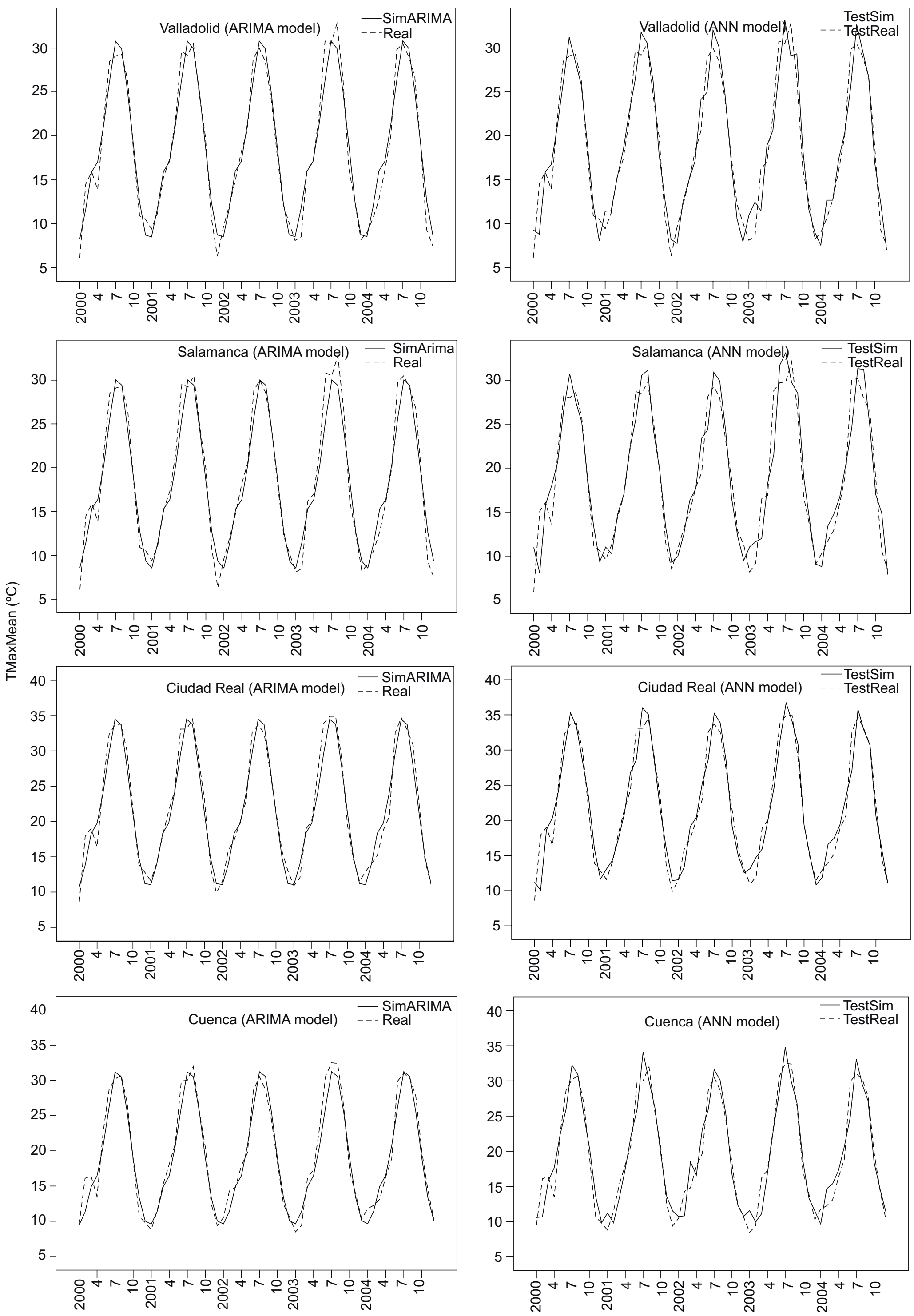

Fig. 11. Sequences between the real and simulated TMaxMean (ºC) series obtained with the ARIMA model and with the ANN model for the weather stations in Castilla-León and Castilla-La Mancha selected.

The ARIMA methodology provided slightly better values of the R^2. However, the sequence plots, simulated with ARIMA methodology, shown in Figure 11 hardly vary from one cycle to another, showing that the model does not fit the variation in the extreme values of the real series. In contrast, in many cases the ANN model does fit the evolution and trend characteristics of the real series and it is also able to capture some apparent anomalies that are not situated in the extreme values of the series. The Figure 12, which includes the dispersion plots between the real and simulated TMaxMean series obtained with the ARIMA model and with the ANN model for the weather stations selected, shows a clustering in the ARIMA case but not in the ANN case accordingly with the comparison of results discussed previously and showed in Figure 11.

6. Conclusions

The experimental methodology developed for the fitting of the MLP ANN has shown its efficiency in the design of the model, although this methodology is not necessarily the only one that can be used. The three-layer MLP ANN with the described activation functions, adapted for this study, is able to model in a non-linear fashion the future values of a TMaxMean time series simply from the past values of the same time series.

The simulated series (forecast) by the ANN show excellent agreement with the real ones, both in the training phase and in the testing step. The fitting between the simulated and real series in the training phase is better, as seems logical, than the fitting of the corresponding series of the validation step.

The predictive capacity of the ANN model is seen in the fact that the series simulated in the testing phase by the model maintain the same general characteristics as regards evolution and trend for the real series. In general, the ANN model is able to fit the variations in the extreme values shown by the data sets observed. Moreover, the model is able to fit some variations in the real series that seem to be anomalies in comparison with the temporal evolution of the series in previous periods.

Application of the ARIMA methodology to the mean monthly maximum temperature series, using a validation period identical to that employed with the ANN model and observed at some weather stations in Castilla-León and Castilla-La Mancha, provides values of the coefficient of determination and of the MSE that are slightly better than those obtained with the ANN model. Additionally, the sequence of the series simulated with ARIMA methodology is almost periodic. However, the ARIMA model is not able to fit the variations in the extreme values shown by the real series and neither is it able to fit the values that depart from the normal evolution of the real series.

However, it is interesting that the ANN model is able to fit the evolution and trend characteristics of the part of the real series corresponding to the validation period and –in many cases– it is also able to fit variation in the extreme and apparently anomalous values from previous values of the corresponding time series. This means that the MLPANN is more useful for the prognosis of TMaxMean values than the ARIMA methodology.

Accordingly, from the results obtained in the present work it may be accepted that prognostic models based on ANNs are more useful for obtaining future values of mean monthly maximum temperatures than currently used statistical methods.

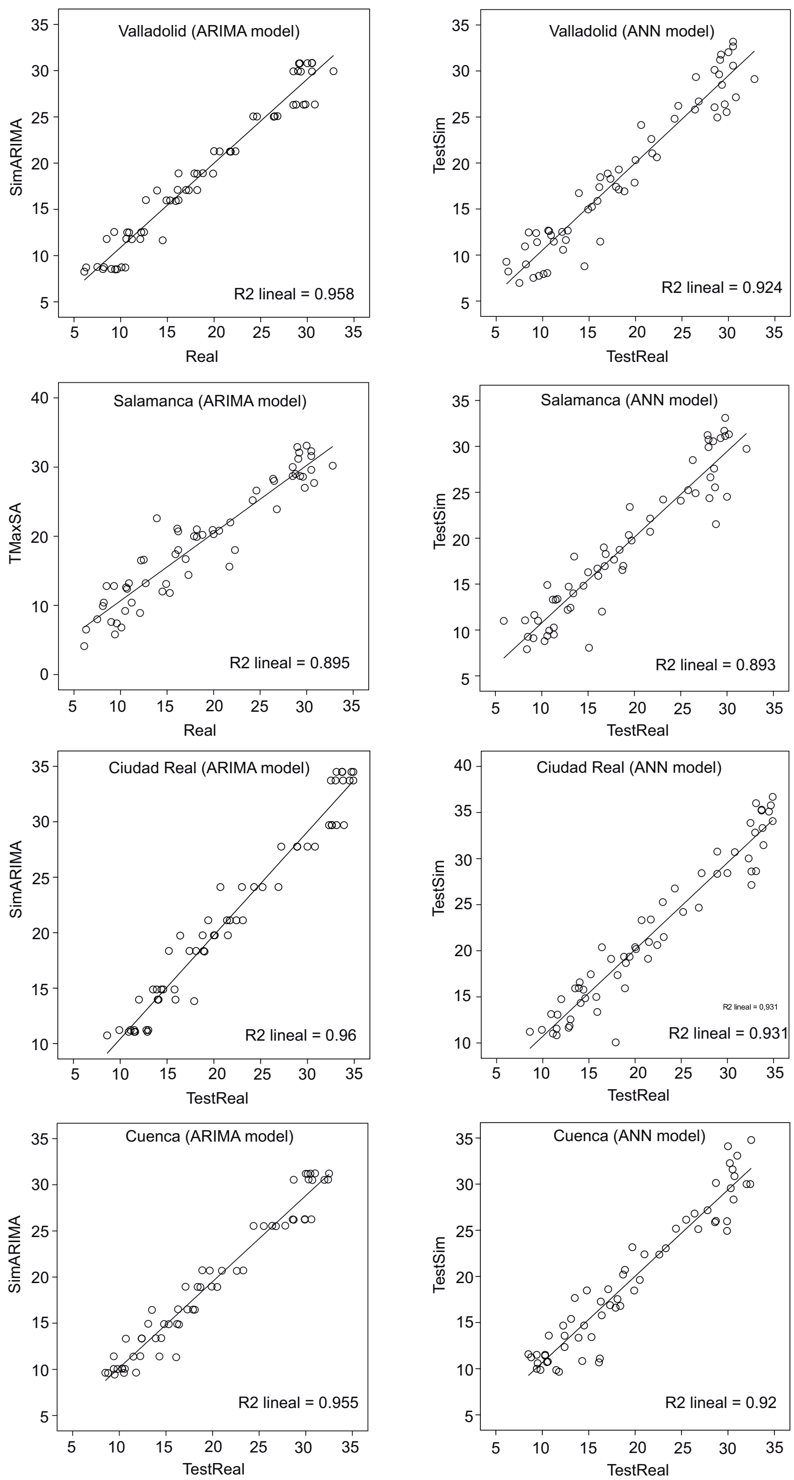

Fig. 12. Dispersion plots between the real and simulated TMaxMean (ºC) series obtained with the ARIMA model and with the ANN model for the weather stations in Castilla-León and Castilla-La Mancha selected.

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References

Bertil T. and S. Mohsen, 2007. Artificial neural network models for indoor temperature prediction: investigations in two buildings. *Neural Comput. Appl.* **16**, 81-89.

Cannon A. J. and I. G. McKendry, 2002. A graphical sensitivity analysis for statistical climate models: application to Indian monsoon rainfall prediction by artificial neural networks and multiple linear regression models. *Int. J. Climatol.* **22**, 1687-1708.

Ciocoiu I. B., 1998. Time analysis using RBF networks with FIR/IIR synapses. *Neurocomputing* **20**, 57-66.

Comrie A. C., 1997. Comparing neural networks and regression models for ozone forecasting. *J. Air Waste Manage.* **47**, 653-663.

Corchado J. M., F. Díaz, L. Borrajo and F. Fernández, 2000. Redes neuronales artificiales. Un enfoque práctico. Servicio de Publicacións da Universidade de Vigo, 209 pp.

Curry B. and P. H. Morgan, 2006 Model selection in neural netwoks: Some difficulties. *Eur. J. Oper. Res.* **170**, 567- 577.

De Gaetano A. T., 1996. Recent trends in maximum and minimum temperature threshold exceedences in the Northeastern United States. *J. Climate* **9**, 1646-1660.

Demuth H. and M. Beale, 2000. Neural network toolbox. User's Guide. (Version 4). http://www.mathworks.com/access/helpdesk/help/pdf_doc/nnet/nnet.pdf.

Dorffner G., 1996. Neural networks for time series processing. *Neural Netw World* **4**, 447-468.

Esteban-Parra M. J., F. S. Rodrigo and Y. Castro, 1995. Temperature trends and change points in the Northern Spanish Plateau during the last 100 years. *Int. J. Climatol.* **15**, 1031-1042.

Galán E., R. Cañada, F. Fernández and B. Cervera, 2001. Annual temperature evolution in the Southern Plateau of Spain from the construction of regional climatic time series. In: *Detecting and modelling regional climate change*. (M. Brunet and D. López, Eds.). Springer-Verlag NY, 119-131.

Juhos I., L. Makra and B. Tóth, 2009. The behaviour of the multi-layer perceptron and the support vector regression learning methods in the prediction of NO and NO_2 concentrations in Szeged, Hungary. *Neural Comp. Appl.* **18**, 193- 205.

Isasi P. and I. M. Galván, 2004. *Redes de neuronas artificiales. Un enfoque práctico*. Pearson Educación. España, 656 pp.

Kadioglu M., 1997. Trends in surface air temperature data over Turkey. *Int. J. Climatol.* **17**, 511-520.

Labajo J. L. and A. Piorno, 1998. Análisis del comportamiento temporal de la temperatura en Castilla y León: Primeros resultados. In: *El clima y medio ambiente urbano en ciudades ibéricas e iberoamericanas,* F. Fernández García, E. Galán Gallegos andR. Cañada Torrecilla (Coords.), Ed. Parteluz. Madrid, pp. 577-591.

Labajo J. L. and A. Piorno, 1999. Comportamiento de variables climáticas en Castilla y León: temperatura mínima media anual. In: *La Climatología española en los albores del siglo XXI*. (J. M. Raso and J. Martín-Vide, Eds.). Publicaciones de la AEC. Serie A, nº 1, pp. 259-266.

Lendasse A., M. Verleysen, E. De Bodt, M. Cottrell and P. Grégoire, 1998. Forecasting Time-Series by Kohonen Classification. European Symposium on Artificial Neural Networks, Bruges (Belgium), D-Facto Publications (Brussels) pp. 221-226.

Levene H., 1960. Robust test for equidity of variance. In: *Contributions to probability and statistics: Assays in Honour of Harold Hotelling*. (I. Olkin, S. G. Ghurie, W. Hoeffding, W.G. Madow and H. B. Mann, Eds.). Stanford University Press, Stanford, California, 278-292.

Lu T. and M. Viljanen, 2009. Prediction of indoor temperature and relative humidity using neural networks models: model comparison. *Neural Comput. Appl.* **18**, 345-357.

Mihalakakou G., M. Santamouris and D. Asimakopoulos, 1998. Modeling ambient air temperature time series using neural networks. *J. Geophys. Res.* **103**, 19 509-19 517.

Navarro J., D. Ginestar and A. Gallardo, 1998. Metodología general para la estimación del tamaño del proyecto. Aplicación a la gestión y disposición de los residuos sólidos urbanos. Actas del IV International Congress on Project Engineering. Cordoba (España) 7-9 October.

Nelson M., T. Hill, W. Remus and M. O'Connor, 1999. Time series forecasting using neural networks: Should the data be deseasonalized first? *J. Forecasting* **18**, 359-367.

Oñate J. J. and A. Pou, 1996. Temperature variations in Spain since 1901: A preliminary analysis. *Int. J. Climatol.* **16**, 805-815.

Qi M. and G. P. Zhang, 2001. An investigation model selection criteria for neural network time series forecasting. *Eur. J. Oper. Res.* **132**, 666-680.

Schönwise C. D., J. Rapp, T. Funchs and M. Denhard, 1994. Observed climate trends in Europe 1891-1990. *Meteorol. Zeitschirft* **3**, 22-28.

Tang B., W. W. Hsieh, A. H. Monahan and F. T. Tangang, 2000. Skill Comparisons between neural networks and canonical correlation analysis in predicting the equatorial Pacific sea surface temperatures. *J. Climate* **13**, 287-293

Tangang F. T., W.W. Hsieh and B. Tang, 1996. Forecasting the equatorial Pacific sea surface temperatures by neural networks models. *Clim. Dynam.* **13**, 135-147.

Von Storch H. and F. W. Zwiers, 1999. *Statistical analysis in climate research*. Cambridge University Press, UK, 484 pp.

Wedding D. K. and K. J. Cios, 1996. Time series forecasting by combining RBF networks, certainty factors, and the box-Jenkins model. *Neurocomputing* **10**, 149-168.

Wong F. S., 1991. Time series forecasting using backpropagation neural networks. *Neurocomputing* **2**, 147-159.

Wu A., W. W. Hsieh and B. Tang, 2006. Neural Network forecast of the tropical Pacific sea surface temperatures. *Neural Networks* **19**, 145-154.

Zhang G. P., 2003. Time series forecasting using a hybrid ARIMA and Neural Network Model. *Neurocomputing* **50**, 159-175.

Zhang G. P. and M. Qi, 2005. Neural network forecasting for seasonal and trend time series. *Eur. J. Oper. Res.* **160**, 501-514