DOI: 10.24850/j-tyca-2019-01-10
Notes

Artificial Neural Network and Fourier series to forecasting temperatures of Irrigation District 075, Sinaloa México

Red Neuronal Artificial y series de Fourier para pronóstico de temperaturas en el Distrito de Riego 075, Sinaloa México

Rocío Cervantes-Osornio[1]
Ramón Arteaga-Ramírez[2]
Mario Alberto Vázquez-Peña[3]
Waldo Ojeda-Bustamante[4]
Abel Quevedo-Nolasco[5]

[1]INIFAP, Campo Experimental Valle de México, Km. 13.5, Carretera Los Reyes-Texcoco, Coatlinchán, C.P. 56230, A.P. 307 y 10, Texcoco, Edo. de México, México, Tel. 01 800 088 2222, Ext. 85565, rcervanteso@hotmail.com

[2]Universidad Autónoma Chapingo, Departamento de Irrigación, Sección Meteorología agrícola, Km. 38.5, Carretera México-Texcoco, C.P. 56230, Estado de México, México, Tel. 01 (595) 95 21500, Ext. 5157, arteagarr@gmail.com

[3]Universidad Autónoma Chapingo, Departamento de Irrigación, Sección Meteorología agrícola, Km. 38.5, Carretera México-Texcoco, C.P. 56230, Estado de México, México, Tel. 01 (595) 95 21500, Ext. 5157, mvap52@hotmail.com

[4]Instituto Mexicano de Tecnología del Agua, Paseo Cuauhnáhuac 8532, Colonia Progreso C.P. 62550, Jiutepec, Morelos, México, wojeda@tlaloc.imta.mx

[5]Programa de Hidrociencias, Colegio de Posgraduados, Texcoco, Montecillos, Estado de México, 01 (595) 95 20200 Ext. 1383, anolasco@colpos.mx

Correspondence author: Ramón Arteaga-Ramírez arteagarr@gmail.com

Abstract

Temperature is a transcendental variable in aspects such as evapotranspiration calculation, growth, development and yield of plants, in the study of the transmission pests and diseases, in the weather forecast, in determination of heat fluxes, in the calculation of the real vapor pressure, all these processes affected by global warming. The objective of this work was to compare the best results of two models: one of artificial neural network (RNA) backpropagation, and another of Fourier series. Daily data of maximum temperatures (T_{max}) and minimum (T_{min}) of the Santa Rosa 1, Ruiz Cortínes, Batequis and Santa Rosa 2 stations, of the Irrigation District 075 Valle del Fuerte, Los Mochis, Sinaloa, Mexico were used. In RNA, 1484 data vectors were used for training, validation and testing and 229 to forecasting. For training, the input variables of the RNA were: Julian day, longitude, latitude and altitude. Were obtained 96 scenarios with one, two and three hidden layers, with different numbers of neurons in each hidden layer. With the 1484 data, the best adjustments were obtained for the Fourier series models for maximum and minimum temperatures, and 229 data were predicted for the four stations. The best RNA backpropagation models for the prediction of maximum and minimum daily temperatures obtained similar performances in comparison with those made by the best models of Fourier series, for the study stations.

Keywords: Forecasting, artificial neural network, maximum temperature, minimum temperature

Resumen

La temperatura es una variable trascendental en aspectos como el cálculo de la evapotranspiración, el crecimiento, desarrollo y rendimiento de las plantas, en el estudio de la transmisión de plagas y enfermedades, en el pronóstico del clima, en la determinación del flujo de calor, en el cálculo de la presión real de vapor, todos estos procesos afectados por el calentamiento global. El objetivo de este trabajo fue comparar los mejores resultados de dos modelos: uno de red neuronal artificial (RNA) backpropagation, y otro de series de Fourier. Se utilizaron datos diarios de temperaturas máximas (T_{max}) y mínimas (T_{min}) de las estaciones Santa Rosa 1, Ruiz Cortines, Batequis y Santa Rosa 2, del Distrito de Riego 075 Valle del Fuerte, Los Mochis, Sinaloa, México. En la RNA, 1484 vectores de datos fueron utilizados para entrenamiento, validación y prueba y 229 para pronóstico. Para el entrenamiento las variables de entrada de la RNA fueron: día juliano, longitud, latitud y altitud. Se obtuvieron 96 escenarios con una, dos y tres capas ocultas, con diversos números de neuronas en cada capa oculta. Con los 1484 datos, se obtuvieron los mejores ajustes para los modelos de series de Fourier para temperaturas máximas y mínimas, y se pronosticaron 229 datos para las cuatro estaciones. Los mejores modelos de RNA backpropagation para el pronóstico de temperaturas máximas y mínimas diarias obtuvieron desempeños similares en comparación con los realizados por los mejores modelos de series de Fourier, para las estaciones de estudio.

Palabras clave: pronóstico, redes neuronales artificiales, temperatura máxima, temperatura mínima

Recibed: 11/08/2017

Accepted: 02/07/2018

Introduction

The maximum and minimum temperatures are important in the estimation of the reference evapotranspiration (Hargreaves & Samani, 1985; Segura-Castruita & Ortiz-Solorio, 2017), for the calculation of the irrigation requirement in the Irrigation Districts. They are also used for local detection of temperature change (Lobato-Sánchez & Altamirano-Del-Carmen, 2017) that affects the evapotranspiration of crops.

Likewise, it has a marked influence on all the physiological processes of the growth and development of plants (photosynthesis or respiration), and are important for the harmful effects on crops (Elías & Castellvi, 2001).

Artificial neural networks are a useful forecast model, given the high non-linearity they handle. In Turkey Cobaner, Citakoglu, Kisi and Haktanir (2014) to estimate monthly temperatures: minimum, maximum and average air, used an artificial neural network, a neuro-fuzzy inference system and a multiple linear regression model or the approach of Alexandridis & Zapranis (2013) of a Wavelet neural network to model the daily average temperature. Other models have also been used to estimate the temperature, hourly, daily or monthly, by means of multiple linear regressions with predictive variables such as: latitude, longitude, altitude and continentality, these are classic approaches for the modeling of temperature (Monestiez, Courault, Allard, & Ruget, 2001 y Cristóbal, Ninyerola, & Pons, 2008). On the other hand Thornley & France (2007) indicate that the air temperature has a sinusoidal behavior, therefore, it is feasible to use a Fourier series model for its estimation. The objective was to make the forecast of maximum and minimum daily air temperature with artificial neural networks for different scenarios and transfer functions (purelin and tansig) and compare the best results with those obtained by the Fourier series model, for use in different applications.

Materials and methods

The daily information of maximum and minimum temperatures (April 1997 to December 2001) was obtained from four automatic meteorological stations (EMAS, for its acronym in spanish), from the Irrigation District 075 Valle del Fuerte, in Los Mochis, Sinaloa, whose names (keys), latitudes, lengths and altitudes are: Ruiz Cortines (3843 II-2), 25° 39′ 15″, 108° 45′ 20″, 31 masl; Batequis (3546 II-3), 25° 45′

49”, 108° 48’ 41”, 32 masl; AC Santa Rosa 1 (3765 III-1), 25° 45’ 03”, 108° 57’ 21”, 40 masl; AC Santa Rosa 2 (9610 III-1) 25° 51’ 16”, 108° 52’ 03”, 61 masl.

To obtain the Fourier series model, the Matlab Curve Fitting Tool was used (MathWorks, 2001). The software for training, validation, testing and forecasting of the artificial neural network was the Toolbox of Matlab®, nnet (Demuth & Beale, 2001).

Fourier series model

With the data from April 1997 to May 2001, the Fourier series models were generated and from June to December 2001 they were used for the validation of these. The input variable was Julian day, and the output, maximum or minimum temperature.

The equation for the Fourier series presented by Dubbel (1977) is:

$$f(x) = a_0 + \sum_{i=1}^{n} a_i cos(nwx) + b_i sin(nwx) \quad (1)$$

where: a_0, a_i and b_i are the constants of the Fourier series, for *i* = 1 oscillation or fundamental wave, and for *i* = 2, 3, ...n, higher waves or higher harmonics, *w* is the fundamental frequency of the signal, *n* is the number of terms (harmonics) in the series, and in this case: $1 \leq n \leq 8$; *x*, is the dependent variable.

Artificial neural networks

In the artificial neural network, the backpropagation algorithm was applied (Haykin, 1994).

For training, evaluation and validation were used the daily data of maximum or minimum temperatures from April 1997 to May 2001 and for the forecast from June to December 2001. The input variables are: Julian day, longitude, latitude and altitude, and output: maximum or minimum temperatures.

The structures of the 96 different scenarios for training the neural network backpropagation are shown in Table 1, combined number of layers and number of neurons in these, we used two different training algorithms.

Statistical evaluation of the results of the models

The average standard error (*RMSE*) was used, its equation is: $RMSE = \left(\frac{\sum_{i=1}^{N}(a_i - t_i)^2}{N}\right)^{1/2}$, where a_i is the data estimated by the model, ti is the observed data and *N* is the total number of observations, (Cai, Liu, Lei, & Pereira, 2007).

Table 1. Scenarios 1, 2, 3 and 4, structure of construction for these, with changes in: transfer function (tansig, purelin), training algorithms (trainbr, trainlm), number of hidden layers, and number of neurons in these.

Four entries for the RNA (Julian day, latitude, longitude and altitude)			
Scenarios 1 {e1}	Scenarios 2 {e2}	Scenarios 3 {e3}	Scenarios 4 {e4}
Output T_{max} (function): f(tansig) for {e1}	Output T_{max} (function): f(tansig)	Output T_{max} (function): f(purelin) for {e3}	Output T_{max} (function): f(purelin)

Output T_{min} (function): f(tansig) for {e1}	Output T_{min} (function): f(tansig)	Output T_{min} (function): f(purelin) for {e3}	Output T_{min} (function): f(purelin)
Training algorithm trainlm	Training algorithm trainlm	Training algorithm trainlm	Training algorithm trainbr
{ neurons }	{ neurons }	{ neurons }	{ neurons }
1 hidden layer f{tansig}	-	1 hidden layer f{tansig}	1 hidden layer f{tansig}
{4}	-	{4}	{4}
{8}	-	{8}	{8}
{12}	-	{12}	{12}
{16}	-	{16}	{16}
{20}	-	{20}	{20}
{24}	-	{24}	{24}
{28}	-	{28}	{28}
{32}	-	{32}	{32}
{36}	-	{36}	{36}
{40}	-	{40}	{40}
2 hidden layers, f{tansig}xf{tansig}	2 hidden layers, f{tansig}xf{tansig}	2 hidden layers, f{tansig}xf{tansig}	2 hidden layers, f{tansig}xf{tansig}
{4x4}	{8x4}	{4x4}	{8x4}
{8x8}	{12x4}	{8x8}	{12x4}
{12x12}	{16x8}	{12x12}	{16x8}
{16x16}	{20x8}	{16x16}	{20x8}
{20x20}	{24x16}	{20x20}	{24x16}
{24x24}	{28x16}	{24x24}	{28x16}
{28x28}	{32x16}	{28x28}	{32x16}
{32x32}	{36x20}	{32x32}	{36x20}
{36x36}	{40x20}	{36x36}	{40x20}
{40x40}	-	{40x40}	-
3 hidden layers, f{tansig}xf{tansig}xf{ tansig}	-	2 hidden layers, f{tansig}xf{tansig}	3 hidden layers, f{tansig}xf{tansig}xf{ tansig}

{4x4x4}	-	8x4	{8x8x4}
{8x8x8}	-	12x4	{8x12x4}
{12x12x12}	-	16x8	{8x16x4}
{16x16x16}	-	20x8	{8x20x4}
{20x20x20}	-	24x16	{8x24x8}
{24x24x24}	-	28x16	{8x28x8}
{28x28x28}	-	32x16	{16x32x16}
{32x32x32}	-	36x20	{16x36x16}
{36x36x36}	-	40x20	{16x40x16}
{40x40x40}	-	-	-

T_{max}: maximum temperatures; T_{min}: minimum temperatures; trainlm: Levenberg-Marquardt training algorithm; trainbr: Bayesian regularization training algorithm; tansig: Tangent-sigmoid transfer function; purelin: Rigid limit transfer function.

Results and discussion

Training, evaluation and validation (1484 data), for the 96 scenarios of the artificial neural network

All the scenarios were determined (Table 1), the ranges of variation of the RMSE of these, for the variable maximum temperature were: 1.2540 {e4} {20} to 2.4858 {e4} {40x20}; 2.1790 {e3} {40x40} to 2.2765 {e4} {8x12x4}; 2.3280 {e1} {40x40x40} to 2.4277 {e4} {16x40x16} and 2.5093 {e3} {40} to 2.6276 {e4} {16x32x16}, for stations Santa Rosa I, Ruiz Cortinez, Batequis and Santa Rosa 2, respectively.

For the minimum temperature they were: 2.2372 {e1} {36x36} to 2.2554 {e4} {32x16}; 2.0152 {e3} {40x40} to 2.17 {e4} {16x40x16}; 2.1523 {e3} {36x36} to 2.2934 {e4} {8x8x4} and 2.01

{e3} {40x20} to 2.0809 {e4} {32x16}, for stations Santa Rosa 1, Ruiz Cortinez, Batequis and Santa Rosa 2 in that disposition.

Forecast (229 data) with RNA

The ranges of the *RMSE* of all the scenarios (Table 1), first for the maximum temperature, then for the minimum temperature, and for the seasons: Santa Rosa 1, Ruiz Cortinez, Batequis and Santa Rosa 2, in that order were: 2.4448 {e4} {12x4} to 2.5522 {e1} {4x4x4}; 2.4697 {e3} {4x4} to 2.5420 {e2} {8x4}; 2.4915 {e1} {4} to 2.5246 {e1} {4x4x4}; 2.8649 {e1} {12} to 2.9574 {e1} {4x4}, and 2.0223 {e4} {16x32x16} to 2.1713 {e2} {36x20}; 1.9922 {e4} {16x32x16} to 2.09 {e4} {24x16}; 2.0346 {e4} {8} to 2.1776 {e2} {12x4}; 2.3035 {e1} {8} to 2.3865 {e3} {32x16}.

Of all the scenarios presented for the training and the forecast of daily maximum and minimum temperatures, the best estimators are the scenarios {e3} for the first, {e4} and {e1} for the second, for these it is applied in the output layer the function of rigid limit (purelin), except for {e1}, and in the intermediate layers the tansig function. Şahin (2012) made monthly mean air temperature estimates with remote sensing and artificial neural networks and obtained *RMSE's* of 1.254 and 1.263 K in their best settings and used the same transfer functions, in the output and in the hidden layer. Most of the *RMSE's* in the present study are not less than 2 °C, since daily temperature values were used.

The differences of the *RMSE* of all the ranges of the scenarios presented for both the training and the forecast are not greater than 0.16 °C for both temperatures (maximum and minimum) and in the four seasons (Table 2), so that use any scenario The exception is the maximum temperature of the Santa Rosa 1 station (1.2 °C).

Table 2. Differences in the ranges of variation of the RMSE obtained for the variables T_{max} and T_{min}.

Station	Training (1484 data)		Forecast (229 data)	
	T_{max}	T_{min}	T_{max}	T_{min}
Santa Rosa 1	1.2318	0.0582	0.1074	0.149
Ruiz Cortínez	0.0975	0.1548	0.0723	0.0978
Batequis	0.0997	0.1411	0.0331	0.143
Santa Rosa 2	0.1183	0.0709	0.0925	0.083

T_{max}: maximum temperatures; T_{min}: minimum temperatures.

The best scenarios of the trainings do not coincide with the best scenarios of the forecasts (Table 3). Also in most of the best workouts, for both temperatures, the largest number of neurons in the hidden layers have an *RMSE* close to zero, but not necessarily the trainings with the highest number of hidden layers will always be those that get the best adjustments, only one of the scenarios with three hidden layers presented one of the best settings (Batequis station). It is also observed that unlike training, in the forecasts most of the best adjustments occur when the number of neurons in the hidden layers are the lowest, this corroborates what comment Demuth and Beale (2001) and Tymvios, Michaelides, & Skouteli. (2008), that one of the problems that occurs when an RNA is being trained is that the training set is over-adjusted and does not generalize well for a new data set (forecast), as in the present work.

In addition, (Table 3) there is no specific scenario that has been the best, both in training and in the forecast.

What matters are the best forecast scenarios, since these guarantee that the estimated data are closer to the observed ones (*RMSE's* close to zero). As the best forecast scenarios do not correspond with the best ones of the training, the decision was made to work with the forecast ones presented in the last two columns (Table 3).

Table 3. Best scenarios with their respective neurons in the hidden layer(s) and RMSE's, for training and forecasting.

Station	Better scenarios with your error

	Training		Forecast	
	Maximum temperature	Minimum temperature	Maximum temperature	Minimum temperature
Santa Rosa 1	{e4}, {20}, 1.25	{e1} {36x36}, 2.24	{e4} {12x4}, 2.44	{e4} {16x32x16}, 2.02
Ruiz Cortinez	{e3} {4x40}, 2.18	{e3} {40x40}, 2.02	{e3} {4x4}, 2.47	{e4} {16x32x16}, 1.99
Batequis	{e1} {40x40x40}, 2.33	{e3} {36x36}, 2.15	{e1} {4}, 2.49	{e4} {8}, 2.05
Santa Rosa 2	{e3} {40}, 2.51	{e3} 40x20}, 2.01	{e1} {12}, 2.87	{e1} {8}, 2.30

Comparison of the best scenarios of the RNA forecast with the best fit Fourier Series models

The best forecast scenarios of the RNA were compared with the best Fourier Series models obtained for each of the stations, in Figure 1 (Santa Rosa I) shows the behavior of the differences of the observed values of maximum temperature with the predicted values with each of these two models. These differences present the same trends and are far from the line of zero value in the same proportion. In addition, it is observed that the range of the differences is between 10 °C and -6 °C. This comment is also presented in the other three stations and for the minimum temperature (Figure 2).

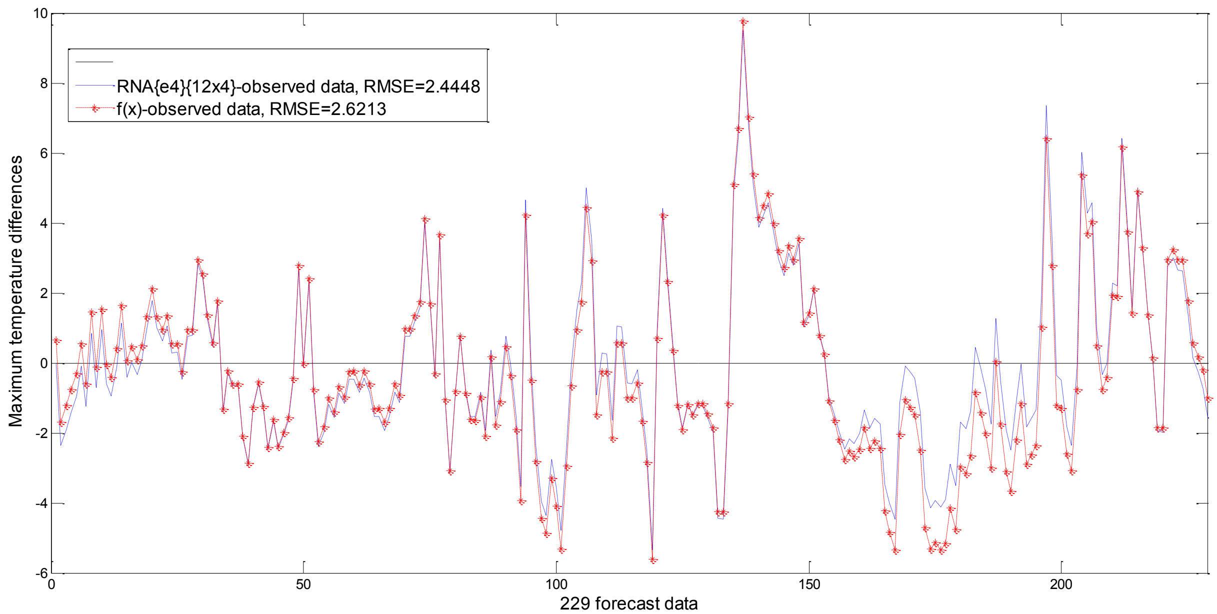

Figure 1. Differences between the RNA and Fourier series models with the observed maximum temperature data for Santa Rosa I AC; Fourier model with n = 5: $f(x) = 31.86 - 0.6201 \cos(0.01727x) + 5.871 \sin(0.01727x) + 0.8935 \cos(2*0.01727x) - 0.0709 \sin(2*0.01727x) - 0.745 \cos(3*0.01727x) + 0.6926 \sin(3*0.01727x) + 0.3822 \cos(4*0.01727x) + 0.1923 \sin(4*0.01727x) - 0.227 \cos(5*0.01727x) + 0.1547 \sin(5*0.01727x)$.

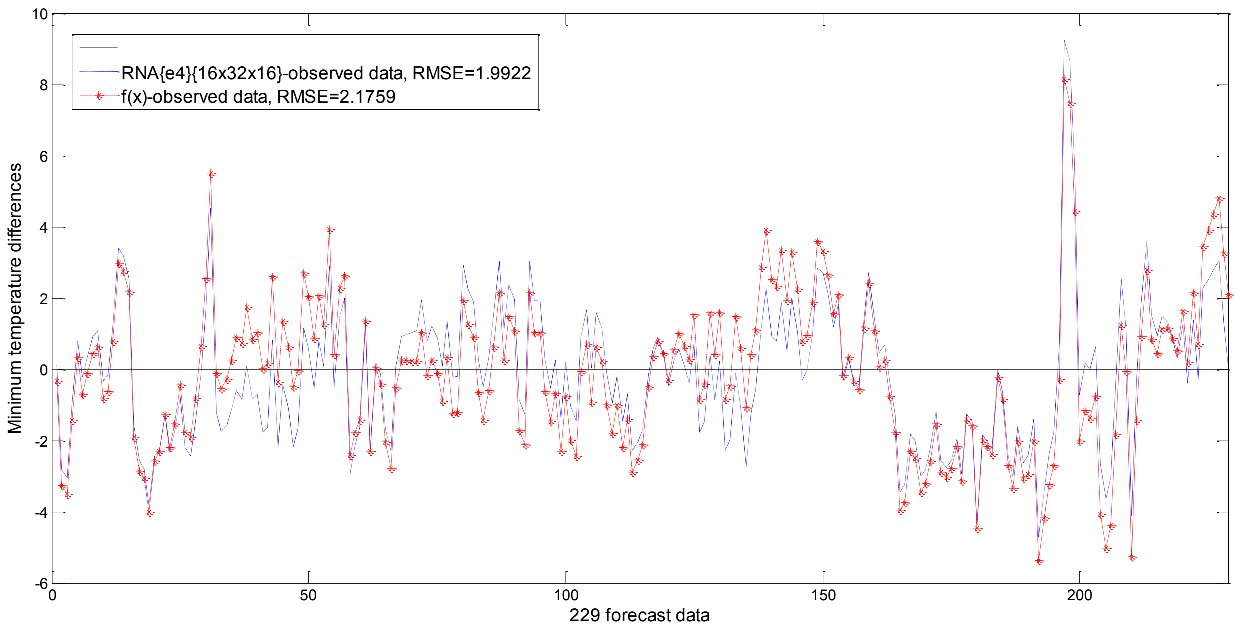

Figure 2. Differences of the observed data of minimum temperatures with the RNA and Fourier series models, for Ruiz Cortínez; Fourier model with n = 8: $f(x)$ = 15.98 – 2.83 *cos*(0.0172x) + 8.476 *sin* (0.0172x) - 0.5298 *cos*(2*0.0172x) – 1.121 *sin*(2*0.0172x) – 1.142 *cos*(3*0.0172x) + 0.3966 *sin*(3*0.0172x) + 0.1746 *cos*(4*0.0172x) - 0.6291 *sin*(4*0.0172x) + 0.1938 *cos*(5*0.0172x) - 0.1892 *sin* (5*0.0172x) - 0.04237 *cos*(6*0.0172x) + 0.09564 *sin*(6*0.0172x) + 0.2258 *cos*(7*0.0172x) + 0.05545 *sin*(7*0.0172x) – 0.4136 *cos*(8*0.0172x) – 0.02458 *sin*(8*0.0172x).

In the estimation of the maximum and minimum temperature variables, the best Fourier series models for only two stations are described under Figures 1 and 2. The *RMSE's* obtained, for the adjustment (1484) and the validation (forecast) of the model (229), for the maximum temperature were: Santa Rosa 1, with *n* =5, 2.553, 2.6213; Ruiz Cortinez, with *n* =7, 2.266, 2.5321; Batequis, with *n* =7, 2.417, 2.6847 and Santa Rosa 2, with *n* =7, 2.555, 3.0855. And for the minimum temperature: Santa Rosa 1, *n* =7, 2.379, 2.1415; Ruiz Cortinez, *n* =8, 2.163, 2.1759; Batequis, *n* =8, 2.289, 2.1822 and Santa Rosa 2, *n* =7, 2.135, 2.5005.

When comparing the *RMSE's* (Table 3) of the RNA with those of the Fourier series model for maximum temperature in the four seasons for the forecast, the first ones are better, by hundredths, the same happens when comparing the *RMSE's* for the minimum temperature. By considering the temperatures are recorded to tenths of a degree, the RNA present better performance (lower *RMSE's*) in maximum three tenths, than the Fourier model for all seasons. However, to train this type of neural network (backpropagation) you need to know four input variables (Julian day, latitude, longitude and altitude) and for the Fourier series model only the series of time in days.

The obtained in this work corroborates the findings of Şahin (2012), which proposes the artificial neural network as an alternative method to estimate the air temperature with sufficient accuracy. The importance of the models of Fourier series obtained is as commented by Coronas and Baldasano (1984), that the equations are representative of annual form for where they were generated and their advantage is that they represent a large amount of data in a single equation and new data is easily incorporated. Finally, Almonacid, Perez-Higueras, Rodrigo & Hontoria (2013) also made a comparison of three methods to estimate hourly temperatures for Spanish localities: that of artificial neural networks provided the best results, the transfer function they used was purelin in the layer of output and sigmoid tangent in the hidden layer, obtaining *RMSE's* in a range of 0.53 - 1.20 °C, these functions were those that performed better in the present work both in the adjustments, as in the forecasts.

Conclusions

In the forecast of the maximum or minimum temperatures in irrigation district 075 for any of its applications, such as the calculation of the reference evapotranspiration, any of the RNA scenarios can be used. The transfer functions that offer better performance in the adjustment for the training and/or forecast of the maximum or minimum daily temperature with the RNA backpropagation were: sigmoid tangent in the hidden layer and purelin in the output layer. The best RNA backpropagation models for the prediction of maximum and minimum daily temperatures obtained similar performances in comparison with those made by the best models of Fourier series, for the study stations.

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