

International Interdisciplinary Congress on Renewable Energies, Industrial Maintenance, Mechatronics and Informatics Booklets



RENIECYT - LATINDEX - Research Gate - DULCINEA - CLASE - Sudoc - HISPANA - SHERPA UNIVERSIA - Google Scholar DOI - REDIB - Mendeley - DIALNET - ROAD - ORCID

Title: Reference evapotranspiration prediction using neural network method

Authors: AGUSTÍN-RAMÍREZ Marco A., EL-HAMZAOUI, Youness and RUZ-Hernández, José A.

Editorial label ECORFAN: 607-8695 BCIERMMI Control Number: 2021-01 BCIERMMI Classification (2021): 271021-0001		Pages: 12 RNA: 03-2010-032610115700-14			
ECORFAN-México, S.C.			Holdings		
143 – 50 Itzopan Street La Florida, Ecatepec Municipality		Mexico	Colombia	Guatemala	
Mexico State, 55120 Zipcode		Bolivia	Cameroon	Democratic	
Phone: +52 55 6 59 2296	www.ecorfan.org	Spain	El Salvador	Republic	
Skype: ecorfan-mexico.s.c.		Spain		Republic	
E-mail: contacto@ecorfan.org		Ecuador	Taiwan	of Congo	
Facebook: ECORFAN-México S. C.		Domu			
Twitter: @EcorfanC		Peru	Paraguay	Nicaragua	

Introduction

- Methodology
- Results
- Annexes
- Conclusions

References

Introduction

Agriculture is a sector with great importance in our country, however at present there are three problems that are strongly linked to each other, First the excessive growth of the population, according to census conducted by INEGI there is an estimated population for the current year of 127 billion inhabitants only in Mexico, the second as it is due to greater demand in the production of food of agricultural origin, of basic basket such as (white corn, tomato, rice, beans) due to that increase in population and third climate change; according to statistical data worldwide there is a trend in the rise of temperatures around the world and a decrease in the amount of annual precipitation, as a consequence, there has been a decrease in water resources in figure 1 se shows a graph the use of water by sector, in it can be seen that in the agricultural sector the use of this resource exceeds 70%, 4.72% is used to generate electricity, 4.86% is used for industry and 14.38% is used for public supply, the scarcity of water worldwide makes it necessary to develop alternatives to make water use more efficient and implement irrigation systems that regulate its consumption.



Figure 1. Consumption by sector. Source (CONAGUA 2., 2020)

Methodology

Hargreaves method

The Hargreaves method is an empirical method considered in many studies because it is a method applicable to various geographical areas. This method is largely used for its great accuracy in daily irrigation plans.

Empirical equation

$$ETo = 0,0023 \cdot R_s(T_m + 17,8) \cdot (T_{m\acute{a}x} - T_{m\acute{n}})$$

Where:

 $ET_o =$ reference evapotranspiration, expressed in mm/day.

 $R_s = extraterrestrial solar radiation, expressed in mm/day. (Allen, 1998)$

 T_{med} = average daily temperature, understood as the average of the maximum temperature and the minimum temperature of the period, expressed in °C.

 T_{max} = maximum daily temperature, expressed in °C.

 T_{min} = minimum daily temperature, expressed in °C. (FAO, 1977)

Methodology

1. Data collection

4. Neural network training

2. Standardization and adequacy of data

3. Neural network architecture design

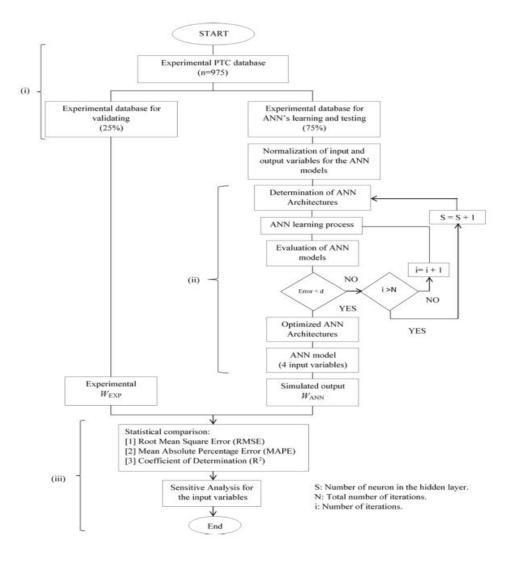
5. Analysis of the RESULTS

Get equation function of the neural network model

Artificial Neural Networks

Artificial neural networks are a model inspired by the functioning of the human brain.

It is formed by a set of nodes known as artificial neurons that are connected and transmit signals to each other. These signals are transmitted from the input layer, the hidden layer, to generate an output.



Artificial Neural Networks

The input variables of the network are the season of the year (spring, summer, autumn, winter), the date measurement, the maximum of minimum temperature, the temperature, average temperature and the incident solar radiation and experimental the response is evapotranspiration, the characteristics of the variables are found in table 1.

Season 0.1-0.4 Date no rank T _{max} 28-35 T _{min} 24-27 T _{prom} 24-35 R _s 10.9-16 ET_ 0-200		Variable input	Variable range	
Tmax 28-35 Tmin 24-27 Tprom 24-35 Rs 10.9-16 ET_ 0-200				
Tmin 24-27 Tprom 24-35 Rs 10.9-16 ET_ 0-200		Date	no rank	
Tprom 24-35 R_s 10.9-16 ET_c 0-200		T _{max}	28-35	
R _s 10.9-16 ET_o 0-200		T _{min}	24-27	
ET. 0-200		T _{prom}	24-35	
ET. 0-200		R _s	10.9-16	
		ETo	0-200	_
ble 1 Input variables for the neural netwo	le 1	I Input varia	bles for the n	eural networ

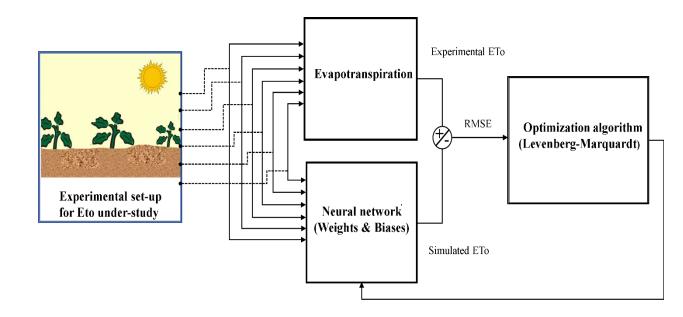


Figure 2 Neural network architecture recurrent to ETo values.

Table 1 Input variables for the neural network Source (*Own source*)

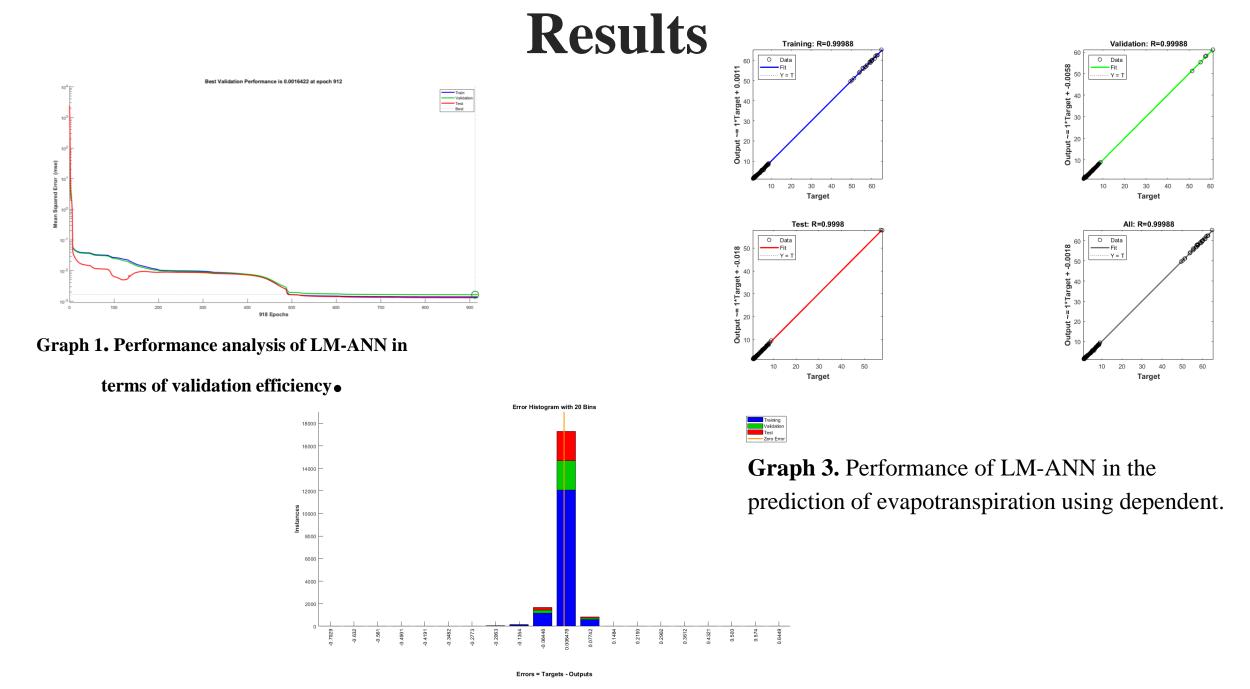
Artificial Neural Networks Method

10 neural network training algorithms were compared to know which algorithm had better performance.

Tests performed determine that the Levenberg-Marquatd algorithm is the best for making predictions of baseline evapotranspiration

FORWARD-BACKPROPAGATION ALGORITHM	FUNCTION	RMSE	ЕРОСН	CORRELATION COEFFICIENT	BEST LINEAR EQUATION	CPU TIME
LEVENBERG-MARQUARDT BACKPROPAGATION	TRAINLM	0.00215	1000	0.9999	Y= 0.999T+0.0077	104
BATCH GRADIENT DESCENT	TRAINGD	0.01657	2000	0.9888	Y=0.986T+0.927	135
BATCH GRADIENT DESCENT WITH MOMENTUM	TRAINGDM	0.01982	2000	0.987	Y= 0.988T+0.837	175
POLAK-RIBIERE CONJUGATE GRADIENT BACKPROPAGATION	TRAINCGP	0.03267	2000	0.979	Y=0.957T+2.53	227
SCALED CONJUGATE GRADIENT BACKPROPAGATION	TRAINSCG	0.44944	2000	0.974	Y= 1.020T+0.783	295
BFGS QUASI-NEWTON BACKPROPAGATION	TRAINBFG	0.48621	2000	0.971	Y=0.982T+1.23	383
POWELL-BEALE CONJUGATE GRADIENT BACKPROPAGATION	TRAINCGB	0.50821	2000	0.965	Y= 0.960T+2.03	497
ONE STEP SECANT BACKPROPAGATION	TRAINOSS	0.02754	2000	0.872	Y=0.617T+45.3	646
FLETCHER-REEVES CONJUGATE GRADIENT BACKPROPAGATION	TRAINCGF	0.01757	2000	0.782	Y=0.425T+34.8	839
VARIABLE LEARNING RATE BACKPROPAGATION	TRAINGDX	0.020397	2000	0.718	Y=0.386T+38	1090

Table 1. Comparison of 10 backpropagation algorithms with 3 neurons algorithms for neurons in hidden layer. Source (El Hamzaoui, y otros, 2011)



Graph 2. Performance analysis of LM-ANN in terms of error histogram.

Results

$$ET_{0} = \sum_{s=1}^{S} \left[W_{o(1,s)} \left(\frac{2}{1 + exp\left(-2\left(\sum_{k=1}^{K} \left(W_{i(s,k)} In_{(k)} \right) + b\mathbf{1}_{(s)} \right) \right)} - 1 \right) \right] + b2_{(l)}$$
(13)

$$ET_{o} = 2\left[\frac{w_{o(1,1)}}{1+e^{x_{1}}} + \frac{w_{o(1,2)}}{1+e^{e^{x_{2}}}} + \frac{w_{o(1,3)}}{1+e^{x_{3}}} + \frac{w_{o(1,4)}}{1+e^{x_{4}}} + \frac{w_{o(1,5)}}{1+e^{x_{5}}} + \frac{w_{o(1,6)}}{1+e^{x_{6}}}\right] - \left(w_{o(1,1)} + w_{o(1,2)} + w_{o(1,3)}\right) + b2_{(l)}$$
(14)

Where:

$$x_1 = -2(w_{i(1,1)}v_1 + w_{i(1,1)}v_2 + w_{i(1,1)}v_3 + w_{i(1,1)}v_4 +$$

Weights and bias of neural network model. Source (Ownsource

W _i (s,k)					
0.0087252519892508824395 (1,1)	- 0.0010689693911364740 297 (1,2)	0.5078621888451 6198813 (1,3)	-0.34034455094710758249(1,4)	0.074224938476511195806 (1,5)	0.42287743562763169258(1,6)
0.0081223395748641364494 (2,1)	- 0.0011517597181407821 134 (2,2)	0.3845770498976 3064063 (2,3)	-0.5439702414679934428 (2,4)	0.33513113636399294304 (2,5)	-0.44825995399759621662 (2,6)
0.00021658101627036578391 (3,1)	- 4.938244768256752817e -06 (3,2)	- 0.4255629353277 8288746 (3,2)	37401103609823516116 (3,2)	0.71793543628936073997 (3,2)	0.25896726816461623777 (3,6)
Wo			b1	b2	
-2.017154500(1,1)	-2.64094400(1,2)	- 1.802718000(1,3)	1.4512509324867599592 (1,1)	0.87266337252631542842	
			0.83307840581738845653 (1,2)		
			-0.17241637336249560075 (1,3)		

 Table 2. Weights and bias of neural network model.

Annexes

Date	Season	Tmax	Tmin	Tmed	Rs	ETor
9832	0.3	28	22	25	0.02507	2.63
9833	0.3	28.2	21.5	24.85	0.02507	2.77
9834	0.3	26.5	21.5	24	0.02507	2.34
9835	0.3	26.1	20.4	23.25	0.02507	2.46
9836	0.3	26.2	21.9	24.05	0.02507	2.17
9837	0.3	28.3	21.4	24.85	0.02507	2.81
9838	0.3	26	22.4	24.2	0.02507	2.00

Table **1**. Data sample with input variables for training, validation of Red Neuronal. Source: (*CONAGUA S*, 2020)

https://smn.conagua.gob.mx/es/observando-el-tiempo/estaciones-meteorologicas-automaticas-ema-s

Conclusions

This work presents a strategy that considers the modeling of evapotranspiration and estimates the operating conditions during the process of plant transpiration and soil evaporation by means of artificial neural networks. The results obtained were satisfactory since the neural algorithm adequately models the evapotranspiration behavior. Likewise, it has been observed that the Levenberg Marquardt method makes the network parameters converge faster to their weights and bias values. Therefore, this tool is powerful and flexible, since it allows evaluating what would happen in the system if one or the other alternative were taken, without affecting the real system.

Possible future work, perform a simulator implemented in MATLAB using inverse neural networks to validate the predictions by the algorithm, make a comparison between real data and those predicted by the algorithm, it is considered to make a physical prototype to be applied to an irrigation system and check the effectiveness of the algorithm proposed in this research work.



© ECORFAN-Mexico, S.C.

No part of this document covered by the Federal Copyright Law may be reproduced, transmitted or used in any form or medium, whether graphic, electronic or mechanical, including but not limited to the following: Citations in articles and comments Bibliographical, compilation of radio or electronic journalistic data. For the effects of articles 13, 162,163 fraction I, 164 fraction I, 168, 169,209 fraction III and other relative of the Federal Law of Copyright. Violations: Be forced to prosecute under Mexican copyright law. The use of general descriptive names, registered names, trademarks, in this publication do not imply, uniformly in the absence of a specific statement, that such names are exempt from the relevant protector in laws and regulations of Mexico and therefore free for General use of the international scientific community. BCIERMMI is part of the media of ECORFAN-Mexico, S.C., E: 94-443.F: 008- (www.ecorfan.org/booklets)