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REFLECTIVITY IN C-BAND METEOROLOGICAL RADARSANALYZED WITH DATA MINING AND NEURAL NETWORKS, CASE STUDY: RADAR EL TABLAZO (SUBACHOQUE, CUNDINAMARCA, COLOMBIA)

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ABSTRACT

This paper shows the analysis of reflectivity data measured by a C-band weather radar located on El Tablazohill, Subachoque, Cundinamarca (Colombia), using data mining and fuzzy logic. A decoding of the data measured by the weather radar was done, and then an analysis of these data was made using neural networks that are trained with 10 and 20 neurons. In each case, the effectiveness of these networks is tested, hoping that the neural networks will allow the elimination of the erroneous information and then normalize it to the scale used according to the standard.

Keywords: weather radar, data mining, reflectividad, neural network, C-Band radar.

1. INTRODUCTION

Climatic phenomena have associated risks that can be mitigated if there is a timely reaction through an adequate early warning system that is capable of correctly identifying the amount and type of precipitation presented in a given area. In this way, events considered as possible threats will be informed the moment they occur, so that the necessary measures can be taken to avoid human losses and minimize the amount of material damage.

In recent years the Colombian state has made significant efforts in the acquisition of four C-band weather radars of similar technical characteristics located in Medellín (Santa Elena), Subachoque (El Tablazo), Corozal (Aeropuerto de brujas) and San Andrés Islas. However, the investment made and the benefits received are not the best, since at present there are no studies or research projects to develop our own algorithms to characterize the different rainfall patterns in the Colombian regions covered by radars.

The main difficulty in radar measurements is related to the diameter of the drops; due to this the use of polarimetric radars is required. These radars emit microwaves with double polarization, generating new measurement variables with respect to typical radar, called polarimetric variables: Z (reflectivity), the specific phase difference (KDP) and the differential reflectivity (ZDR). The first of these variables, KDP, gives an estimate of the specific phase difference between the received signals.

When the data measured by the radar is analyzed with the spatial and temporal information of the reflectivity field, a post-processing of the information is being carried out. With this treatment the spatial information is handled in the form of gradients in the reflectivity field, either horizontally or vertically [1]-[4]. In the literature related to weather radars there are different mathematical descriptions of the reflectivity field gradient, the most common being: texture, gyration [3] and statistical characteristics (mean, median, mode and standard deviation), all calculated in a specific radar scan. The parameters derived from the reflectivity gradient field have been used in different probabilistic classification algorithms including fuzzy logic [5]-[8], neural networks [9]-[12] and Bayesian [13], [14].

Computational developments are required in order to process radar data available in Colombia. This procedure uses the so-called polarimetric observables: differential reflectivity (ZDR), linear depolarization rate (LDR), phase specific differential (KDP), correlation coefficient (RHOV) [15].

The meteorological radars installed in Colombia have incorporated within their processing logic classification algorithms that have been developed and tested for meteorological conditions different from the equatorial zones; the Park and Marzano models define categories of hydrometeors such as: soft hail, graupel, snow, crystals, wet snow and others that do not correspond to the types of precipitation present in the Colombian region [16], [17].

1.1 General Description of the El Tablazoradar

Dual-polarization C-band radar, with operating frequency of 5.6246241GHz, PRF (Pulse Repetition Frequency) of 500Hz, 10 PPI (sweeps at different horizontal angles), each with 664 cells of size 450m, with a range of 298.8 Km. Located in the department of Cundinamarca (Colombia), municipality of Subachoque, specifically in the El Tablazohill, at an altitude of 3.544 m above sea level, with geographical coordinates: Latitude: 5.01180008053780, Longitude: -75.2036999762058 (Figure-1).

Figure-1. Real image of the C-Band Radar in the El Tablazohill [18].

1.2 Type of Data Measured by El Tablazo Radar

The data measured by the radar and then stored by its software is presented in a proprietary format from the radar manufacturer, in a file with the extension .NC, whose name includes the date and time when the data was taken. The file stores 103 variables of which only one was used for the neural network analysis (ID=94). The data from the 664 cells handled by the radar are included, the most important of these being the format shown in Table-1.

Table-1. Information measured by the El Tablazo radar.

ID	Variable	Units	Fill value	Scale Factor	Add offset
94	Z	dBZ	-128	0.5000	32
96	Z_{DR}	dB	-128	0.0625	0
97	Z_Corr	dBZ	-128	0.5000	32
98	KDP	Deg/Km	-128	1	128
99	PHIDP	deg	-128	0.7087	90
100	RHOHV	*	-128	0.0040	0.5059

Figure-2 shows the graphical representation of the reflectivity (Z) generated with the data taken by the El Tablazo radar (event dated 13/10/2012).

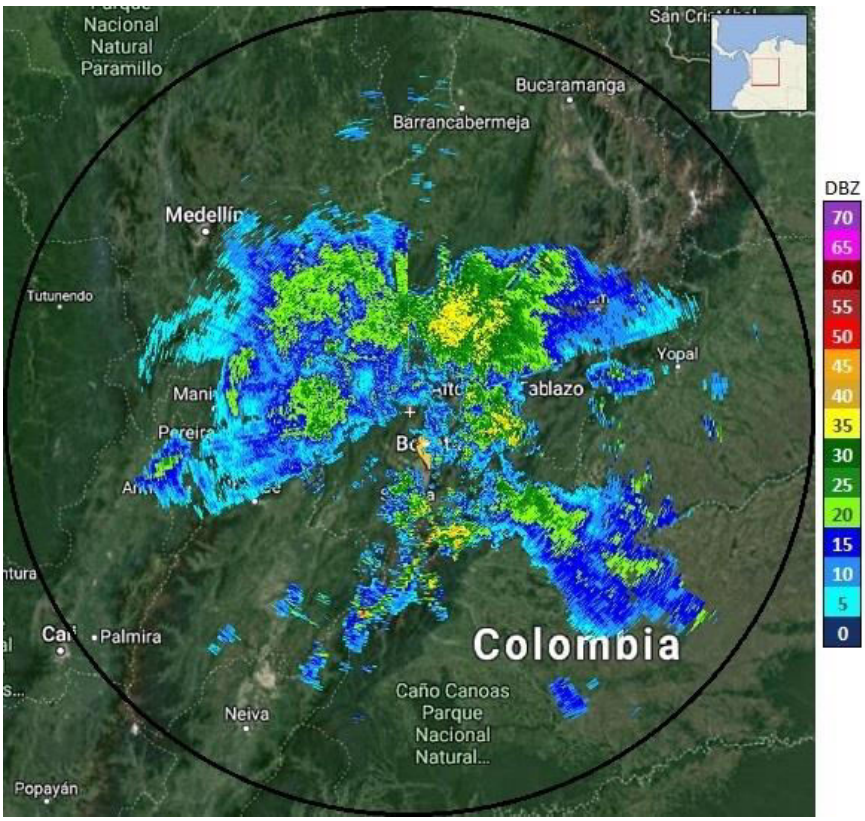

Figure-2. Graphic representation of the reflectivity of the El Tablazo radar.

When observing the radar image, one seeks among other things to see the distribution of precipitation and its intensity, also the type of hydrometeors present. The information on the intensity of precipitation called radar echoes is represented graphically by a series of colored pixels, each color has an associated intensity scale that represents what is called the reflectivity in dBZ (unit of reflectivity), and another scale that represents the corresponding rate of fall, which is an interpretation of the light or heavy form of precipitation [19].

2. CONVERSION OF THE REFLECTIVITY VARIABLE

The data generated by the radar have a format that is not suitable for the analysis of the information, so it was necessary to transform the reflectivity variable to standard units. Equation (1) shows the mathematical function used to convert the reflectivity variable (ID=94) presented in Table-1 to the appropriate format.

$$P\_Data = (O\_Data * Scale\_Factor) + Offset \quad (1)$$

Where *O_Data* corresponds to the value to be converted, *Scale_Factor* is the multiplication factor of the data, *Offset* is the value added to the product between *O_Data* and the *Scale_Factor* and *P_Data* corresponds to the result of the conversion. When a filler value is presented, it is not converted and remains at -128.

With the use of the MatLab computer tool, the data conversion process is initiated with the *netcdf.open()* function that opens the file with the .NC extension as a read-only file and stores the information read in a single variable (for the algorithm developed it is called x). With this data, information is obtained on the number of variables in the file, global attributes and the ID of each one of them with the function *netcdf.inq()*. Then the variable of interest is separated in order to be able to analyze it individually. For this, the function *netcdf.inqVar()* is used, which requires as input parameters the information stored in a variable (for this case the variable x) and the number of the variable to be separated (corresponds to the ID shown in Table-1).

The information of the variable read is stored in an array by means of the function *netcdf.getVar()*, to finish the process the adjustment of the data is made using what is shown in equation (1). In Figure-3 you can see the code of the conversion algorithm designed for the transformation of the Z (reflectivity) parameter.

```
x = netcdf.open('E:\data\tab20121013_032504.nc','nc_nowrite');

%File information, dimensions, variables
[numdims, numvars, numglobalatts, unlimdimID] = netcdf.inq(x);

%Reflectivity Correction
[varname, xtype, varDimIDs, varAtts] = netcdf.inqVar(x,94); %Variable #94
varid = netcdf.inqVarID(x,varname);
data = netcdf.getVar(x,varid);
Z=data; %Find the PPI
[F, C]=size(Z);


for ff=1:F
    if(Z(ff,1)==-128
        Z(ff,1)=Z(ff,1);
    else
        Z(ff,1)=(Z(ff,1)*0.5)+32; %Equation for conversion
    end
end
```

Figure-3. Code in MatLab for data conversion of the Z parameter.

With this treatment a data matrix of 360x664 (360°x664 cells) was obtained for the reflectivity variable (Z) [20].

3. TESTS AND RESULTS

For the analysis presented in this article, a neural network is defined with an input matrix of 360x664 (generated as explained in previous paragraphs) that corresponds to the size of the data generated by the weather radar for the variable Z. With an output set that validates with a value of 0 or 1 the possibility of rain in a specific area swept by the radar.

3.1 System Training with 10 Neurons

Figure-4 shows the representation of the neural network using Matlab's Neural Network tool (version 2018b), with the features mentioned above trained with 10 neurons, and also presents the time used for this process.

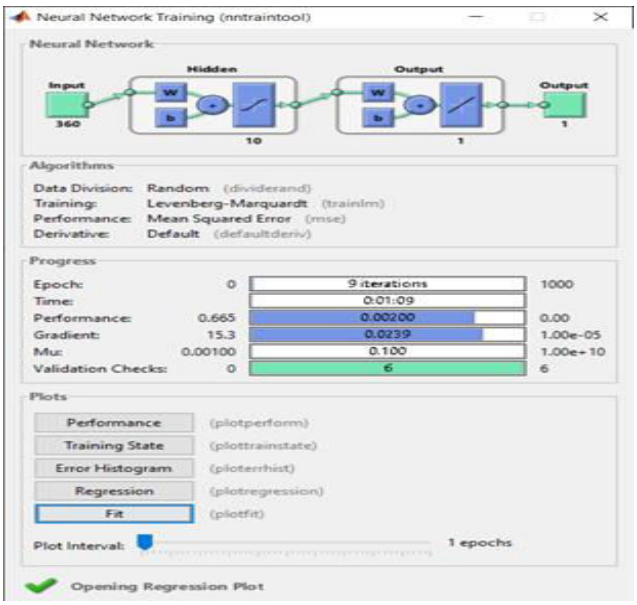

Figure-4. System training with 10 neurons.

The system training for this particular case presents good results giving a very high confidence margin, above 98%. Although the results with the simulation for the test reflect a slightly lower degree of confidence of around 74% (Figure-5).

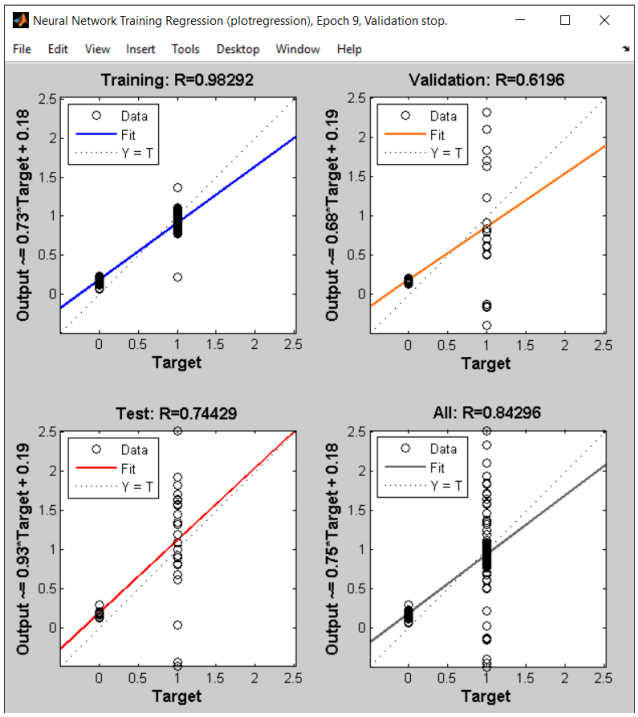

Figure-5. Result of the system training with 10 neurons.

With the above, it is necessary to improve the degree of confidence using a network with a greater number of neurons.

3.2 System Training with 20 Neurons

Since the results obtained were relatively low, the neural network is modified by training it with the same data and with 20 neurons. Figure-6 shows the modified network and the time taken for the training process.

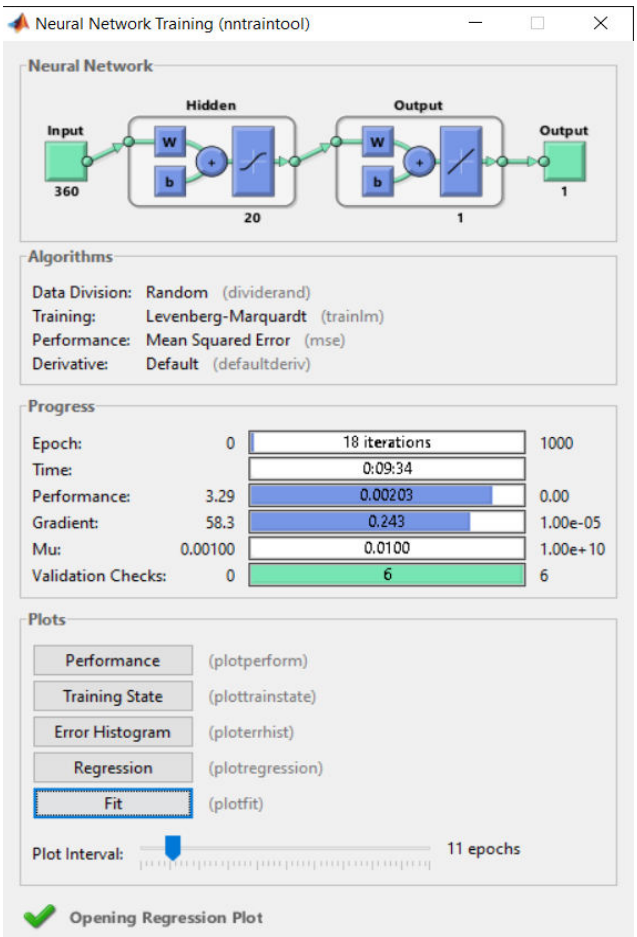

Figure-6. System training with 20 neurons.

The error generated decreases as the number of neurons increases as can be seen in Figure-7.

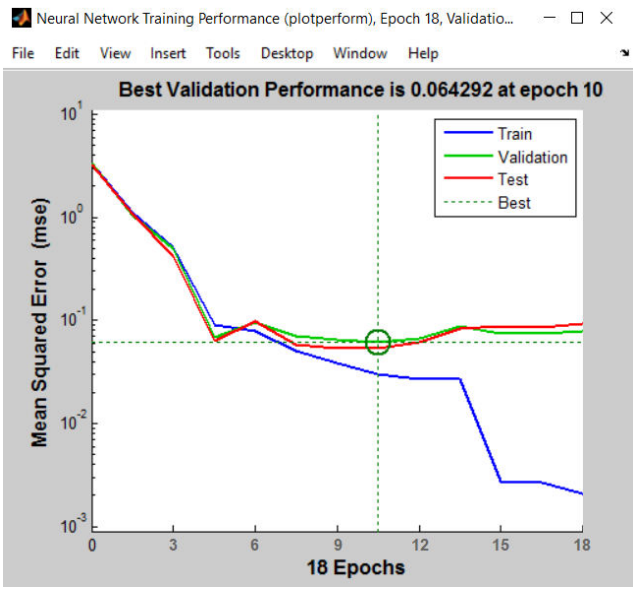

Figure-7. Error generated by training with 20 neurons.

Training with 20 neurons presents better results than the case with 10 giving a very high confidence

margin and showing simulation results with a confidence level of around 92%. For training and validation there were also improvements, especially in validation, which went from 61% for training with 10 neurons to 89% with 20 neurons (Figure-8).

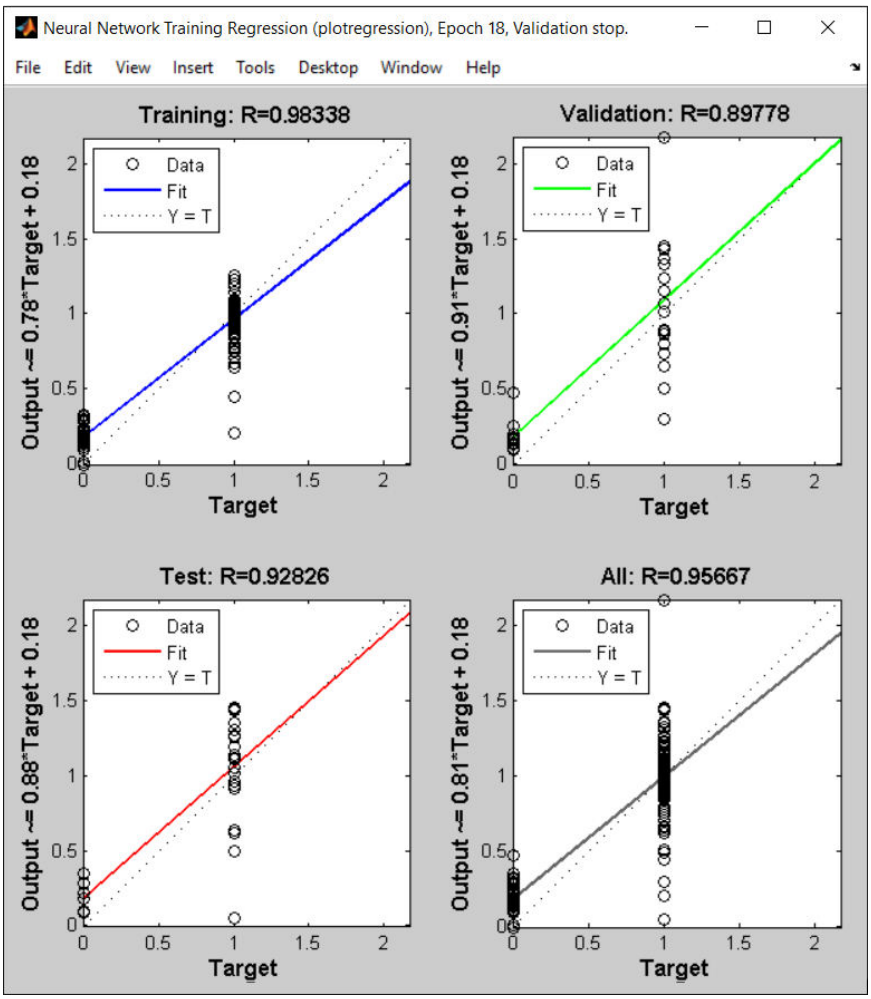

Figure-8. Result of the system training with 20 neurons.

4. CONCLUSIONS

When performing any kind of data analysis, the most important and usually the most time consuming process is the pre-processing and adjustment of the data, for this there are several tools and methods. In the case of the analysis carried out with the radar data, it was necessary to carry out an initial decoding process to decrypt the data, then transform it into a suitable format, clean it up by eliminating erroneous information and normalize it to the scale used according to the standard.

Neural networks are an efficient tool to perform data mining having low computational costs, in this case to perform any kind of analysis the most important and usually the most time consuming process is the pre-processing and adjustment of data, for this there are several tasks and methods.

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