Time Series Analysis of Telecommunications Data Using Neural Networks

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Abstract

This paper shows a model of artificial neural networks (ANN) for the access to the advanced mobile service (AMS) of the mobile telephony of Ecuador to predict the demand of active lines by technology of mobile telephony of the data obtained by the Agency of Regulation and Control of Telecommunications (ARCOTEL) in the period December 2008 to August 2020, model that allows technically a better management of the social media that use the frequencies of the radioelectric spectrum as are the carriers CONECEL S.A., OTECEL S.A. and CNT EP. The methodology used is based on the analysis of the time series by means of processes of multilayer neural networks of the statistical package SPSS. For this purpose, 70% of the data was used for training of the neural network and the remaining 30% as test data of the network already trained and later to make the predictions of the application of the ANN model. This allows carriers to know the demand and make the best decisions for the management of new technology in the field of telecommunications.

Keywords: Neural networks, time series, mobile telephony, forecasting

Resumen

Este artículo muestra un modelo de redes neuronales artificiales (RNA) del acceso al servicio móvil avanzado (SMA) de la telefonía móvil del Ecuador para predecir la demanda de líneas activas por tecnología de la telefonía móvil de los datos obtenidos por la Agencia de Regulación y Control de las Telecomunicaciones (ARCOTEL) en el período diciembre del 2008 a agosto del 2020, modelo que permite técnicamente una mejor gestión de los medios de comunicación social que usan las frecuencias del espectro radioeléctrico como son las operadoras CONECEL S.A., OTECEL S.A. y CNT EP. La metodología utilizada se basa en el análisis de las series temporales mediante procesos de redes neuronales multicapa del paquete estadístico SPSS, para ello se ha utilizado un 70% de los datos como entrenamiento de la red neuronal y el 30% restante como datos de prueba de la red ya entrenada y posteriormente hacer las predicciones de la aplicación del modelo RNA. Lo que permite a los operadores conocer la demanda y tomar las mejores decisiones para el manejo de nueva tecnología en este campo de las telecomunicaciones.

Palabras clave: Redes neuronales, series temporales, telefonía móvil, pronósticos

Introduction

In [1], demand forecasting is one of the most important functions in decision making in organizations, on the other hand, in [2], the author states that ANN technique is an algorithm with several adjustable parameters, set after the training stage given by the connection weights in the artificial neuron.

In the last decade, Artificial Neural Networks (ANN) have received particular interest as a data mining technology, since it offers the means to efficiently model large and complex problems. ANN models are able to find relationships (patterns) inductively by means of learning algorithms based on existing data with the help of a modeler to specify the functional form and its interactions.

An artificial neural network (ANN) is a parallel distributed information processing system consisting of simple and adaptive processing elements interconnected with each other. In [3], it is stated that ANN works as a statistical model that performs an input/output transformation by adjusting a set of parameters called weights.

In [4], the establishes that the most widely used type of neural network is the multilayer perceptron. This kind of network models the conditional distributions of an output vector Y. For the present investigation, this value corresponds to the number of users of the installed active lines of some of the different service carrier, given the different possible values of an input vector X, which for the present case will correspond to the months of the data register controlled by ARCOTEL. The distribution of X is not modeled, so these networks are only suitable for regression and/or classification problems. For [5], among the most common applications of ANN are: nonlinear regressions, signal processing, function approximation, time series prediction, as in the present research, where one of the most relevant advantages of ANN over traditional statistical models lies in the type of less rigorous restrictions imposed by neural networks.

Methodology

In this research, ANN models were developed for the prediction of time series of data obtained in the Telecommunications Regulatory Agency of Ecuador ARCOTEL using pre-established algorithms of the SPSS statistical package as a predictive tool to apply to the data mining of the active lines of the Carrier CONECEL, OTECEL and CNT, as shown in Fig. 1.

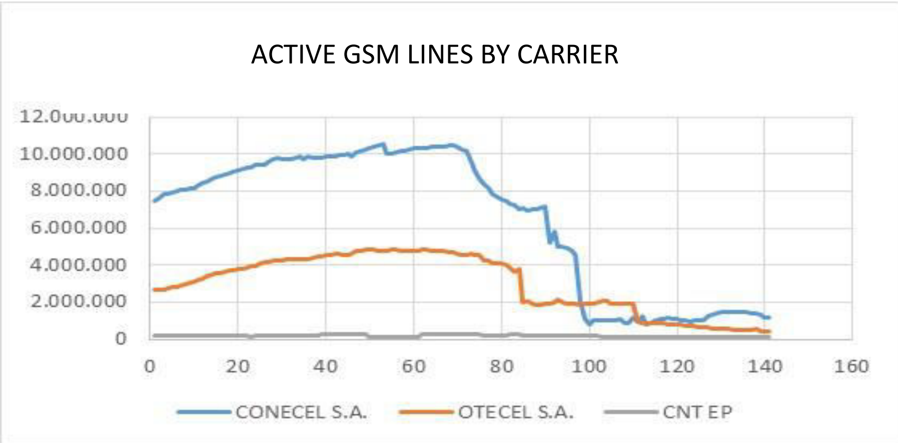


Fig. 1. Number of subscribers in the different technological developments.
Source: Authors

The following is the number of users of active lines with GSM technology from month 1 in December 2008 to month 140, August 2020 of CONECEL, as shown in Table 1.

Table 1. Active lines in CONECEL with GSM technology

Months	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
January		7,603,388	8,653,128	9,450,397	9,797,595	10,332,675	10,310,310	9,146,755	6,935,665	2,050,265	1,142,730	1,000,866	1,459,613
February		7,815,731	8,770,619	9,535,293	9,813,983	10,417,477	10,341,475	8,685,881	6,979,874	1,066,466	932,847	921,276	1,462,078
March		7,802,923	8,796,369	9,711,813	9,828,446	10,451,340	10,369,827	8,347,296	7,037,382	779,614	1,216,860	1,004,751	1,463,245
April		7,947,261	8,909,214	9,776,606	9,855,491	10,513,587	10,397,234	8,137,359	7,122,276	991,865	790,043	1,023,990	1,410,378
May		8,009,207	8,986,610	9,735,671	9,889,363	9,996,082	10,410,517	7,867,450	7,183,309	1,014,576	900,213	1,036,947	1,360,597
June		8,092,652	9,075,650	9,725,717	9,917,796	10,036,386	10,423,067	7,721,787	5,196,081	1,042,895	1,044,167	1,273,105	1,343,983
July		8,084,564	9,132,968	9,737,593	9,958,735	10,083,309	10,434,854	7,507,427	5,780,893	1,031,011	1,089,208	1,288,839	1,131,825
August		8,135,589	9,219,596	9,770,734	9,994,234	10,134,493	10,444,455	7,439,699	5,012,052	1,028,079	1,119,296	1,378,766	1,137,328
September		8,170,036	9,299,957	9,847,550	9,877,885	10,183,985	10,370,114	7,324,458	4,973,761	1,029,752	1,197,432	1,442,084	
October		8,320,558	9,238,584	9,746,336	10,075,412	10,245,644	10,218,872	7,225,301	4,914,141	1,091,698	1,077,847	1,463,023	
November		8,402,701	9,411,356	9,859,674	10,156,415	10,278,555	10,134,243	7,048,699	4,800,686	902,517	1,072,153	1,453,004	
December	7,499,370	8,532,691	9,419,193	9,774,865	10,252,457	10,287,259	9,581,956	7,065,313	4,571,999	873,346	1,039,373	1,452,334	

Source: ARCOTEL. http://www.arcotel.gob.ec/servicio-movil-avanzado-sma_3/

Model Development

It should be noted that with the emergence of artificial intelligence and techniques for modeling and forecasting, using artificial neural networks allow this model to be applied in this research to the data obtained monthly by ARCOTEL in order to learn from the relationships of the time series of the data recorded in the period of time investigated. For [11], the ANN model gives good results from the experience that are presented in other types of investigations that are presented even with a set of chaotic data that sometimes are presented with inaccurate information, with noise. For [12], in the referred model it is necessary that the data are ordered and recorded sequentially as a time series and, according to [13], in practice, this model of artificial neural networks has solved and represented the adjusted data in the various fields of engineering. The design criteria used in the present research is synthesized in the four stages of Artificial Neural Networks contained in the SPSS package as follows.

Data preprocessing. According to[6], the success of any neural model, is the training of the data for this, the data sets used must first be properly preprocessed, in order to increase the learning capacity of the network, so also to obtain good results a change of scale was made to the independent variable as follows.

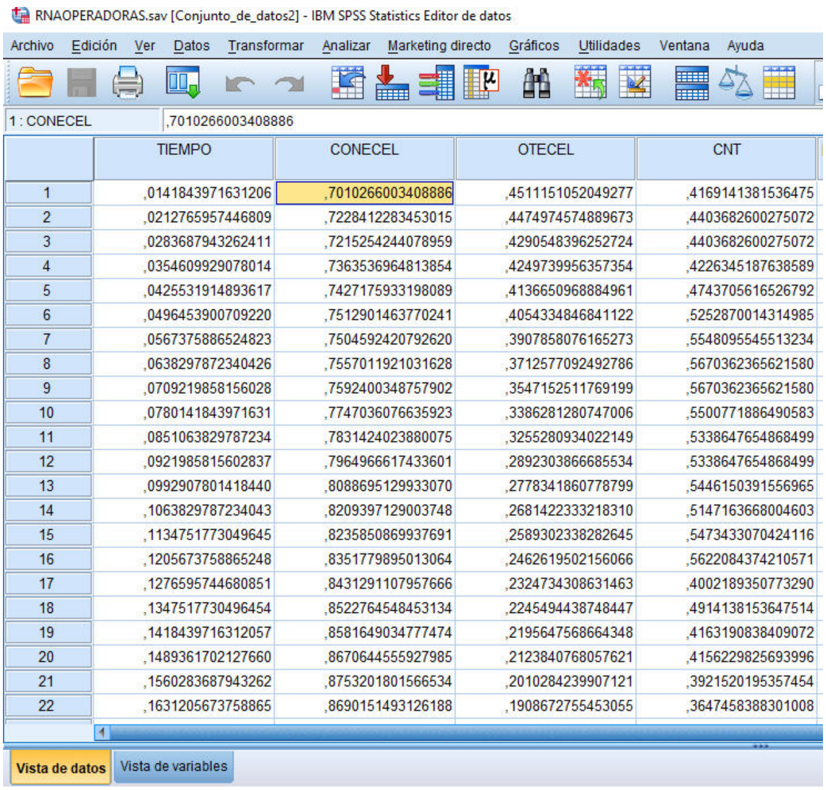
The time X in months was placed in the range from 0 to 1 with the relation:
Time=Xi =Number of month/ Total number of months
The dependent variable number of users of each carrier was rescaled with the following equation (I).

$$Y_i = \frac{y_t - Min}{Max - Min} \quad (1)$$

Where: $y_i = data\ with\ change\ of\ variable$

$$y_t = data\ with\ original\ scale$$
$$Min = data\ lower\ than\ the\ number\ of\ users\ in\ each\ carrier$$
$$Max = data\ higher\ than\ the\ number\ of\ users\ in\ each\ carrier$$

By performing the operations, the preprocessing data shown in Fig. 2 were obtained.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	TIEMPO	CONECEL	OTECEL	CNT
1	,0141843971631206	,7010266003408886	,4511151052049277	,4169141381536475
2	,0212765957446809	,7228412283453015	,4474974574889673	,4403682600275072
3	,0283687943262411	,7215254244078959	,4290548396252724	,4403682600275072
4	,0354609929078014	,7363536964813854	,4249739956357354	,4226345187638589
5	,0425531914893617	,7427175933198089	,4136650968884961	,4743705616526792
6	,0496453900709220	,7512901463770241	,4054334846841122	,5252870014314985
7	,0567375886524823	,7504592420792620	,3907858076165273	,5548095545513234
8	,0638297872340426	,7557011921031628	,3712577092492786	,5670362365621580
9	,0709219858156028	,7592400348757902	,3547152511769199	,5670362365621580
10	,0780141843971631	,7747036076635923	,3386281280747006	,5500771886490583
11	,0851063829787234	,7831424023880075	,3255280934022149	,5338647654868499
12	,0921985815602837	,7964966617433601	,2892303866685534	,5338647654868499
13	,0992907801418440	,8088695129933070	,2778341860778799	,5446150391556965
14	,1063829787234043	,8209397129003748	,2681422333218310	,5147163668004603
15	,1134751773049645	,8235850869937691	,2589302338282645	,5473433070424116
16	,1205673758865248	,8351779895013064	,2462619502156066	,5622084374210571
17	,1276595744680851	,8431291107957666	,2324734308631463	,4002189350773290
18	,1347517730496454	,8522764548453134	,2245494438748447	,4914138153647514
19	,1418439716312057	,8581649034777474	,2195647568664348	,4163190838409072
20	,1489361702127660	,8670644555927985	,2123840768057621	,4156229825693996
21	,1560283687943262	,8753201801566534	,2010284239907121	,3921520195357454
22	,1631205673758865	,8690151493126188	,1908672755453055	,3647458388301008

Vista de datos Vista de variables

Fig. 2. Data results of the preprocessing in the different technological developments.
Source: Authors

Neural network design. In order to apply the ANN method and to predict future values of the series of active lines of the carrier CONECEL in the country, it is necessary to build, train and test a neural network, considering that the fundamental parameters of the network are the number of layers, the number of neurons and the connections between them.

The information of the chosen neural network uses the multilayer perceptron network (MLP Multilayer Perceptron), [7] and [8] have shown that the multilayer perceptron is one of the most used architectures in problem solving due to its applicability and ease of use whose architecture is composed of three layers as described in Table 2.

Table 2. Information about the network.

Components and quantities

Layers		Variables and covariables	Action
Entry layer	Number of units=1 Number of hidden layers	Covariables=1 Typified	Change of scale for covariables
Hidden layer	Hidden layer 1a=7 Number of units=1	Dependent Variables 1 CONECEL	Sin incluir la unidad de sesgo Function of hyperbolic tangent activation
Output layer	Scale change method		Activation Function= identity Error function=sum of squares

Source: Own elaboration

In [9], it is indicated that the most used types of ANN are those of multilayer perceptron with nonlinear transfer function type Tangent hyperbolic or Sigmoid. In the present investigation, the procedure used allows to automatically select the best architecture as it is observed in Table 2, where a network with a hidden layer with an activation function is generated, whose purpose is that to the input values, by means of the hidden layer in which a nonlinear function is incorporated, values are generated and with a method of optimization of trial and error with the fixation of weights called backpropagation values are generated in the output layer, one of the activation function used is the Hyperbolic Tangent, which is indicated below.

$$\sigma(x) = \tanh(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \qquad (2)$$

Where it takes arguments of real value and are transformed at range $(-1,1)$ which relates the weighted sum of units in a layer to the values of units in the correct layer.

Another relationship considered in the analysis is the **Sigmoid** defined in equation (3) of the form.

$$\sigma(x) = \frac{1}{1 + e^{-x}} \qquad (3)$$

The Sigmoid function, represented in Fig. 3 has some characteristics that make it very interesting and it also takes real value arguments and transforms them to the range (0,1), which makes the propagation of the activations always stay in that range with the derivative according to equation (4).

$$\sigma'(x) = \sigma(x)\big(1 - \sigma(x)\big) \qquad (4)$$

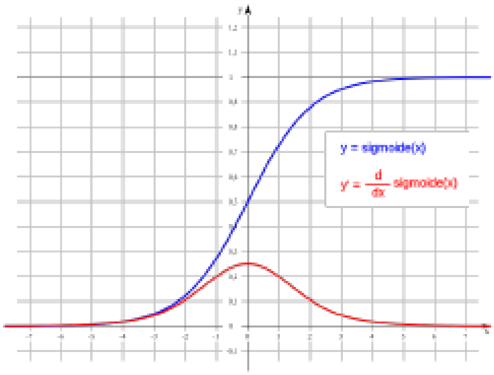

Fig. 3. Graph of the Sigmoid and its derivative

Implementation of the artificial neural network. In this stage, the most appropriate implementation is completed through training and validation of the performance of the network.

For this, as shown in Fig. 4., 70% of the series data was estimated as training set of the neural network and 30% of the data as control set to validate the network.

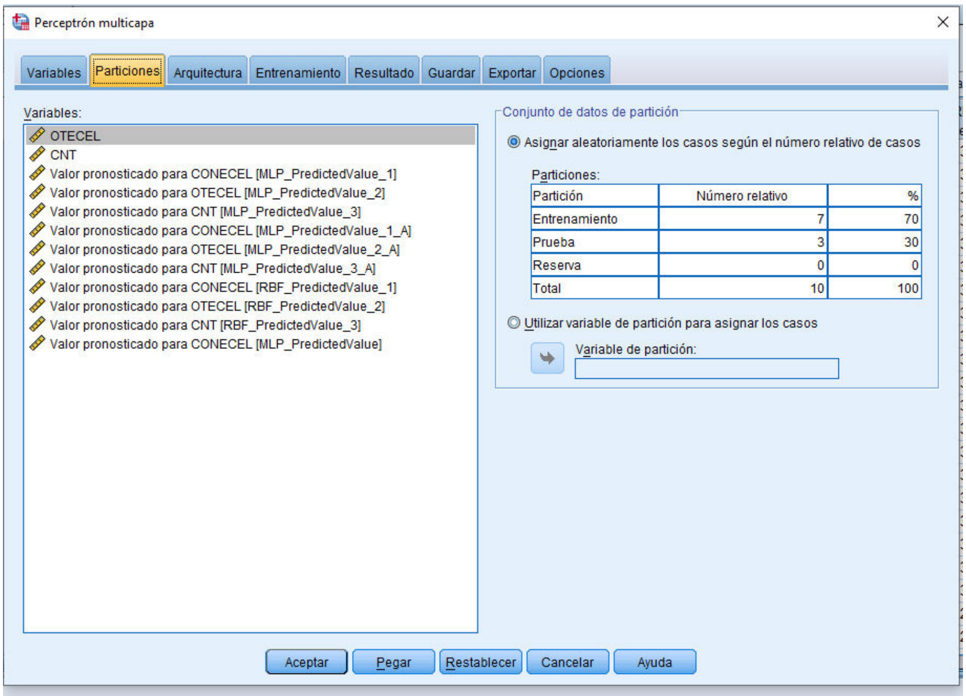

Fig. 4. Partition data set.
Source: Authors.

Validation. For the validation of neural networks, two criteria are used: the quadratic error and the relative error, to determine through the magnitudes the predictive performance of the network is within the appropriate parameters.

Equations (5) and (6) have been used.

One of the most frequently used criteria in curve fitting especially when using machine learning is the *mean squared error*, it is a statistical estimator that measures the average of the squared errors of the recorded value and the arithmetic mean or average of the approximate or adjusted value using neural networks and is defined by the function

$$mse = \frac{1}{n}\sum(y_n - \bar{y})^2 \qquad (5)$$

Relative error = It is defined as the quotient between the absolute error and the true value.

That is to say

$$\epsilon_r = \frac{\text{true value} - \text{approximate value}}{\text{true value}} \qquad (6)$$

Results and Discussion

The technique of artificial neural network used in this research consisted of a simple process of the treatment of active lines working with an algorithm with several adjustable parameters, which are set after the training stage shown in Table 2, that to start the process was selected 70% of the data and after the process were taken into account 66.4 % of these data, as observed in Table 3. The degree of iteration between the neural networks is given by the connection weights between them determined by learning, for this from Table 2 and 3 showing that 30 % of the data were selected for testing and, after the process, 33.6 % of these test data were taken into account.

Table 3. Summary of the processing of cases.

Group	No. of Data	Percentage
Sample	140	100%
Training	93	66.4%
Test	47	34%
Excluded	0	
Total	140	

Source: Authors.

From the structure of the resulting model for the data set of the number of users of GSM technology of CONECEL, it is observed that a MLP neural network poses minimum requirements on the assumptions applied to identify the number of users in the time series as a function of measurements that minimizes the error in forecasting this number, as indicated in Fig. 5, which is very useful to identify how to model this function.

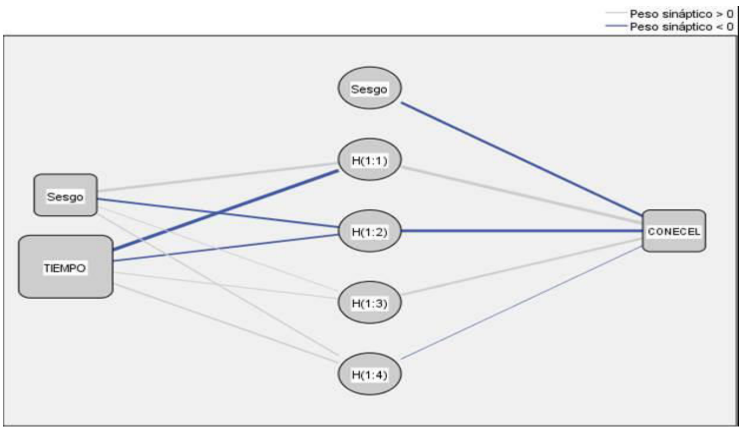

Fig. 5. Activation function of the hidden layer: Hyperbolic tangent.

Next, a summary of the results of the neural network is shown in which it is observed that the results of the training improve in the test that is carried out later, and it is so this statistic when measuring the average of the errors to the square of the difference between the measured value and what it estimates, improve the values from 0.974 to 0.466 managing to reduce from the phase of training to the phase of test the deviations to the square of the predictions of the real values with the application of the function of activation of the hyperbolic tangent function to the output layer.

Another statistic used to determine the accuracy of the estimation of the values in the time series is the relative error, noting that the measurement of the number of users of GSM technology in the training phase is 0.021 and in the verification phase of the neural network is 0.018 which means that the degree of accuracy of the model has a percentage error of 1.8% which is quite acceptable as indicated in Table 4**.**

Table 4. Summary of the model

Phase	Training time		
	Statistic	Value	Observation
Training	Sum of squared errors	0.974	The rule used without error reduction
	Relative Error	0.021	
Test	Sum of squared errors	0.466	Training time: 0:00:00,01
	Relative Error	0.018	

Source: Authors

The estimation of the parameters of synaptic weights or approximation in the neural process is given in Table 5, for which the coefficient estimates are shown, which is the ratio between the units of a given layer to the units of the next layer, based on the training process of the active data divided as shown in Fig. 3, based on the training and testing data.

Table 5. Estimation of parameters

Predictor		Forecast				
		Hidden layer				Output layer
		H(1:1)	H(1:2)	H(1:3)	H(1:4)	CONECEL
Input layer	(Sesgo)	1.253	-0.391	0.210	0.246	
	TIEMPO	-2.339	-0.295	0.213	0.261	
Hidden layer 1	(Sesgo)					-1.131
	H(1:1)					1.671
	H(1:2)					-1.323
	H(1:3)					0.667
	H(1:4)					-0.17

Source: Own elaboration

As a result of the application of the neural network method, the normalized values were obtained in the interval [0,1] which indicates some of the measured and adjusted values in the analyzed time period as indicated in Table 6.

Table 6. Standardized Values.

Month	Standardized Time	Standardized Measured Value	Standardized Adjusted Value
1	0.007092199	0.690340522	0.78531627
2	0.014184397	0.7010266	0.78531627
3	0.021276596	0.722841228	0.78531627
4	0.028368794	0.721525424	0.785316271
5	0.035460993	0.736353696	0.785316274
6	0.042553191	0.742717593	0.785316285
7	0.04964539	0.751290146	0.785316321
8	0.056737589	0.750459242	0.785316431
9	0.063829787	0.755701192	0.785316764
10	0.070921986	0.759240035	0.78531773
11	0.078014184	0.774703608	0.785320446
12	0.085106383	0.783142402	0.785327823
13	0.092198582	0.796496662	0.785347188
14	0.09929078	0.808869513	0.785396303
15	0.106382979	0.820939713	0.785516607
⋮	⋮	⋮	⋮
138	0.978723404	0.059686112	0.04212803
139	0.985815603	0.057979306	0.04212803
140	0.992907801	0.036183684	0.04212803

Source: Own elaboration.

With the data in Table 6, it can be observed that if plotting the normalized data, and after using artificial neural networks with the methodology indicated above, the adjustment shown in Fig. 6 is obtained.

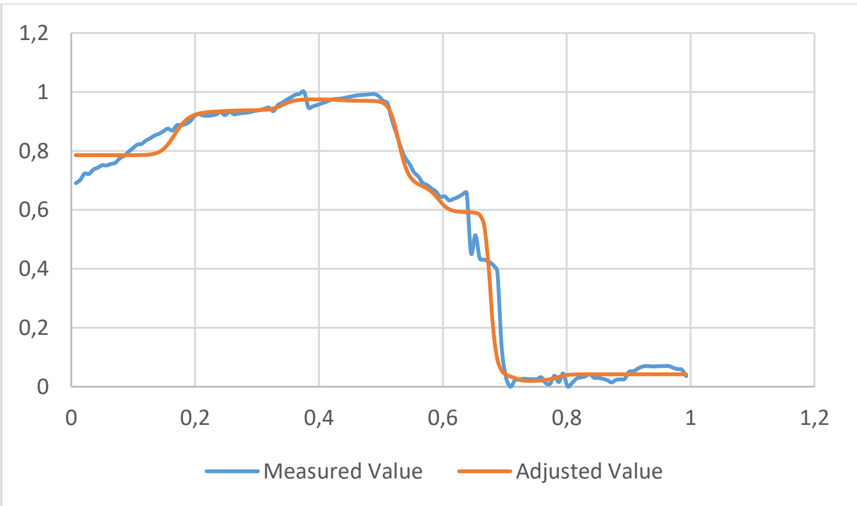

Fig. 6. Normalized Curves Chart of Carrier CONECEL.

For the verification of the model, the residual analysis is carried out, observing in Fig. 7 that the graphical representation of the residual series is quite acceptable for the predicted values of the time series of the CONECEL data, since they revolve around a mean (μ=0) that fluctuates with values ± 0.2

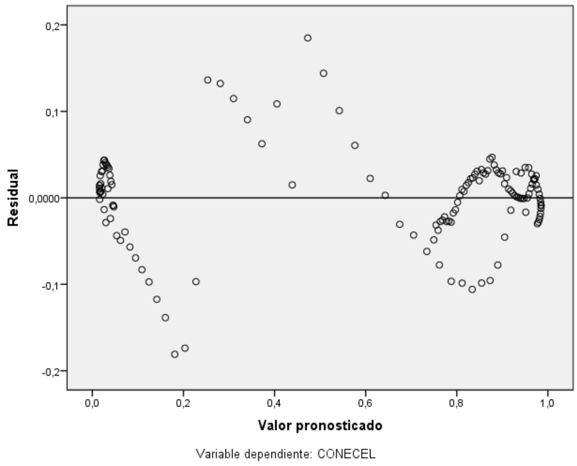

Fig. 7. Residual value of the predicted value of the carrier CONECEL

The following is the graphical representation of the results obtained with the adjusted and projected values as of June 2021. The graph shows that the adjusted curve has a high probability of adjustment control, since the adjusted values are under statistical control due to the small range of variation that represents the lower and upper control limits, as shown in Fig. 8.

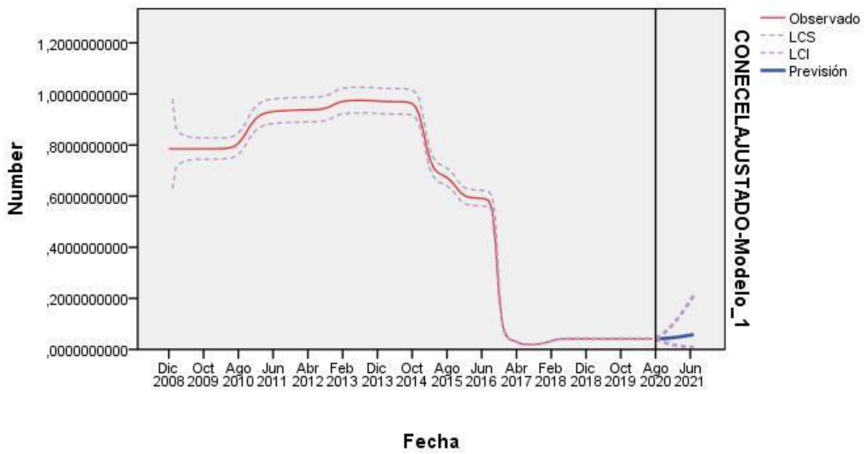

Fig. 8. Projection curve of the adjusted values of Carrier CONECEL

Based on the values in Table 6 and performing an inverse process to that described in the pre-processing of the data described above, the values shown in Table 7 have been obtained, in which values adjusted to August 2020 and predicted up to July 2021 are observed.

Table 7. *Forecast of CONECEL's Active lines users as of July 2021*

Months	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
January		8,423,861	8,424,640	9,570,109	9,899,185	10,195,708	10,235,664	9,212,980	6,643,402	1,307,373	1,061,271	1,189,687	1,189,687	1,230,565
February		8,423,861	8,425,811	9,678,999	9,903,152	10,229,940	10,228,417	8,586,997	6,589,402	1,175,655	1,103,036	1,189,687	1,189,687	1,246,852
March		8,423,861	8,428,579	9,750,223	9,906,091	10,248,974	10,223,887	8,067,216	6,564,008	1,117,718	1,141,416	1,189,687	1,189,687	1,265,079
April		8,423,861	8,434,876	9,795,618	9,908,478	10,258,717	10,221,436	7,743,563	6,551,790	1,065,378	1,167,587	1,189,687	1,189,687	1,285,022
May		8,423,862	8,448,612	9,824,552	9,911,063	10,263,448	10,220,130	7,567,348	6,543,854	1,010,267	1,181,160	1,189,687	1,189,687	1,306,524
June		8,423,862	8,477,106	9,843,412	9,915,052	10,265,565	10,219,134	7,468,260	6,534,872	982,194	1,186,831	1,189,687	1,189,687	1,329,483
July		8,423,863	8,532,469	9,856,315	9,922,586	10,266,206	10,217,317	7,397,375	6,517,607	973,764	1,188,840	1,189,687	1,189,687	1,353,839
August		8,423,866	8,630,733	9,865,889	9,937,463	10,265,725	10,211,968	7,322,102	6,454,592	973,288	1,189,463	1,189,687	1,190,008	
September		8,423,876	8,784,479	9,873,804	9,965,467	10,263,920	10,195,425	7,217,490	6,109,391	977,407	1,189,634	1,189,687	1,191,756	
October		8,423,902	8,988,364	9,881,014	10,012,122	10,260,146	10,147,027	7,070,515	4,766,295	986,290	1,189,676	1,189,687	1,196,732	
November		8,423,974	9,211,501	9,887,824	10,075,723	10,253,707	10,018,365	6,897,948	2,775,625	1,001,713	1,189,685	1,189,687	1,205,098	
December	8,423,861	8,424,162	9,413,571	9,894,013	10,142,397	10,244,877	9,726,018	6,744,979	1,687,384	1,026,243	1,189,687	1,189,687	1,216,519	

Conclusions

In the present investigation, it can be concluded that the models of multilayer neural networks used in the analysis of the time series of the active lines by technology of the carrier CONECEL of the data monitored in the country by the Agency of Regulation and Control of Telecommunications allow to know the level of demand of the technology with advanced mobile system (AMS) and to obtain forecasts of its auto adaptive capacities due to the self-learning of the nonlinear functions in time series.

In the modeling it could be observed that, for a correct specification of the topology, the input layer, the hidden layer, the lags and the type of transfer function must be taken into account. In the process, it was possible to obtain the adjustment of the data to ANN models of the number of users that use GSM technology, for which the methodology of selection of parameters used by the SPSS software of a neural network model that uses established and reliable techniques with satisfactory results as a reliable technique of forecasts and its feasibility of use and establishment in the analysis of serial data constituting a tool for decision making of the operative levels of mobile telephony.

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