Forecasting Electricity Demand for Small Colombian Populations.

Pronóstico de la demanda de electricidad para pequeñas poblaciones colombianas.

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Abstract
The socioeconomic and cultural behavior of a population may be reflected in the consumption of electrical energy. Due to the foregoing, researchers and academics have developed models to predict electricity demand in the short, medium and long term. This paper presents an Artificial Neural Network (ANN) for the prediction of daily electricity demand (GWh) in small Colombian populations. The methodology proposed by Kaastra and Boyd is used for the construction, training and validation of the network and the development of the model in the statistical software SPSS. This paper conclude that the predicted values with models constructed with Artificial Neural Networks (ANN) present a greater degree of approach with the real values of electricity demand (GWh). Also it indicates that the values obtained using models developed with other forecasting techniques (game theory, time series, simulation models, and others) allow to include variables and external factors that are difficult to quantify with simple equations.

Keywords: Electricity demand, forecasting models, multi-layer perceptron, artificial neural networks, seasonal time series.

Resumen
El comportamiento socio económico y cultural de una población puede verse reflejado en el consumo de energía eléctrica. Debido a lo anterior, investigadores y académicos han desarrollado modelos que permitan pronosticar la demanda de la misma en el corto, mediano y largo plazo. Este trabajo presenta una red neuronal artificial (RNA) para el pronóstico de la demanda diaria de electricidad (GWh) en pequeñas poblaciones colombianas. Para la construcción, entrenamiento y validación de la red se empleó la metodología propuesta por Kaastra y Boyd en el software estadístico SPSS. Con el desarrollo de este trabajo se concluye que los valores pronosticados con modelos construidos con redes neuronales artificiales (RNA), presentan un mayor grado de acercamiento a los valores reales de la demanda de electricidad (GWh), que los valores obtenidos con modelos desarrollados con otras técnicas de pronóstico (teoría de juegos, series de tiempo, modelos de simulación, entre otros), ya que permiten incluir variables y factores externos que son difíciles de cuantificar por medio de simples ecuaciones.

Palabras clave: Demanda de electricidad, modelo de pronóstico, perceptron multicapa, redes neuronales artificiales, series de tiempo estacionales.

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Introduction

The different methods used in Artificial Neural Networks (ANN) allow the consideration of variables and external factors difficult to quantify with other methodologies, and the behavior of data series. Predicting energy consumption in small populations is a task of great importance for generators and distributors allow them to set optimization strategies for their generation portfolio.

Due to the above, power demand has motivated researchers and academics to design models that make it possible to predict the demand for power in the short, medium and long term. This work presents an artificial neural network for the daily prediction of electric power demand (GWh) in small Colombian populations. The methodology used for the construction, training and validation of the network was proposed by Kaastra & Boyd, (1996), and was implemented in the statistical software SPSS.

This paper is organized as follows: after this introduction, it presents a contextualization of the artificial neural network, the methodology used for the construction of the model, the results obtained, and the validation of the network. Finally, we present the conclusions. This work conclude that the ANN facilitate the forecasting process of electric power demand because it allows the inclusion of variables that are difficult to quantify through simple equations.

Artificial Neural Networks

Artificial Neural Networks (ANN) are a branch of artificial intelligence (AI) which arose from the need to obtain an information processing system that mimics the human brain (Lázaro et al.,2013). Which has a parallel operation and non-linear, by what cannot be represented by linear models (Lázaro et al., 2013). ANN are an excellent tool in non-linear systems modeling (Pan et al., 2015). In addition, thanks to the possibility of parallel deployment, and its relatively quick response an incentive is provide for research on problems involving non-linear dynamic systems (Valverde & Gachet, 2007).

The Multi-Layer Perceptron (MLP) is one of the most widely used kinds of neural networks. It consists of a network based on multiple layers of perceptron-type neurons , trained by the back propagation technique (Sáenz & Ballesteros, 2002). The MLP generates a predictive model for one or more dependent variables (destination) based on the values of the predictors (SPSS, 2007). This is characterized by non-linearity in the output, layers of hidden neurons and a high degree of connectivity. It is supervised training and uses the algorithm of retro-error propagation. This algorithm is based on the rule of learning by error correction, considered as a generalization of the least squares algorithm (LMS), used in adaptive filtering through simple linear networks (Barbosa et al., 2001) and (Caparrini, 2015).

In the architecture of the autoregressive neural network, the dependent variable Y_t is obtained as a non-linear function of its P past values Y_(t-p) , for p =1,…, P (Velásquez et al., 2011) :

$$y_t^* = \eta + \sum_{p=1}^{P}\varphi_p y_{t-p} + \sum_{h=1}^{H}\beta_h G(\omega_h + \sum_{p=1}^{P}\alpha_{p,h} y_{t-p}) \tag{1}$$

Where G(,) is the adaptive sigmoid function (Velásquez et al., 2011), (Chandra & Singh, 2004) defined as:

$$G(u) = \left[\frac{1}{1+\exp(-u)}\right]^M \tag{2}$$

Figure 1 presents the overall network architecture:

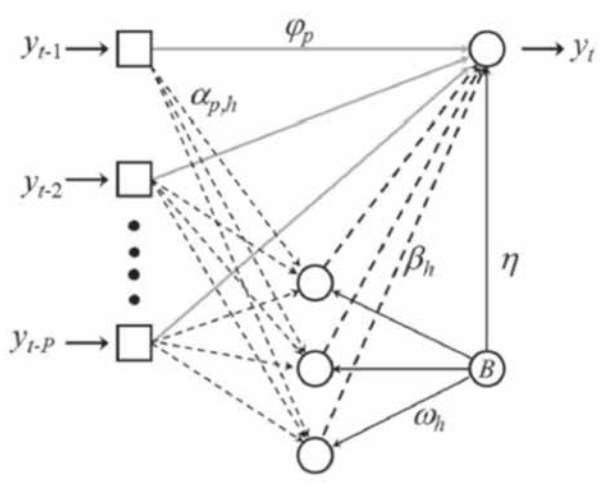


Figure 1. Multi-Layer Perceptron (MLP)
Source: Velásquez et al. (2011)

The parameters of the model η ,φ_(p),β_h ,ω_h ,α_(p ,h) y M for p =1,…, P y h =1,…, H are estimated by minimizing the error of regularization (Velásquez et al., 2011):

λE (3)

In the equation (3), λ it is an external parameter defined by the user; e_t are the errors between the prognosis y_t^* and the desired value y_t , T is the length of the time series y_t. The latter amount is a function only of the parameters of the model (Velásquez et al., 2011):

$$E_* = |\eta| + \sum_{h=1}^{H}\left(|\beta_h| + |\omega_h|\right) + \sum_{p=1}^{P}|\varphi| + \sum_{p=1}^{P}\sum_{h=1}^{H}|\alpha_{p,h}| \quad (4)$$

The model exhibited in Equation (1) is reduced to a multi-layer perceptron by imposing the restriction:φ_1= φ_2=…=φ_p, Similarly, the neural network is reduced to an autoregressive model by imposing H = 0 (Velásquez et al., 2011).

Demand Forecasting Methodology

This proposal uses a simulation model with demand forecasting methodology. Numerous methods have been developed for electricity demand forecasting, and most of these algorithms are used for demand forecasting, especially short-term (STLF) (Aggarwal et al., 2009). Time horizon varies from hour-ahead to a week-ahead forecasting. The demand-forecasting models have been classified in three sets, and these three sets have been further divided into subsets as shown (Aggarwal et al., 2009).

Game Theory Models

The first kind of demand forecasting techniques are Game Theory Models (GTM). This technique is based on game theory. It is of great interest to model the strategies of market participants, and identify the solutions of those games. These models involve the mathematical solution of these games, and demand evolution can be considered as the outcome of a power transaction game (Aggarwal et al., 2009). In this group of models, equilibrium models take the analysis of strategic market equilibrium as a key point. There are several equilibrium models available, like Nash equilibrium, Cournot model, Bertrand model, and supply function equilibrium model (Aggarwal et al., 2009).

Time Series Models

The second kind of demand forecasting techniques are Time Series Models (TSM). Time series analysis is a method of forecasting which focuses on the past behavior of the dependent variable (Box et al., 2008). Sometimes exogenous variables can also be included within a time series framework.

Weron and Misiorek (2014) have investigated the short-term forecasting power of 12 time series models for electricity spot prices in two markets and under various market conditions. The point forecasting results allow us to conclude that models with the system load as the exogenous variable generally perform better than pure price models, at least for the California market (Weron & Misiorek, 2014). Crespo et al. (2004) used data from the LPX market, and indicate that an hour-by-hour modelling strategy for electricity spot-prices significantly improves the forecasting abilities of linear univariate time-series models, and assessing the process of arrival of price spikes, even if it is in a simple manner, can also lead to better forecasts. Based on time series, there are other three types of models:

Parsimonious Stochastic Models: Many stochastic models are inspired by the financial literature, and a desire to adapt some well-known and widely applied models. These are discrete time counterparts corresponding to the continuous-time stochastic models. finance-inspired stochastic models have certain characteristics of electricity demands (Aggarwal et al., 2009).

Regression or Causal Models: Regression-type forecasting models are based on the theorized relationship between a dependent variable (electricity demand) and a number of independent variables that are known or can be estimated (Moghram & Rahman, 1989). The demand is modeled as a function of some exogenous variables. The explanatory variables of this model are identified on the basis of a correlation analysis of each of these independent variables with regard to the demand (dependent) variable.

Artificial Intelligence (AI) models: These may be considered as non-parametric models that map the input–output relationship without exploring the underlying process. It is considered that (AI) models have the ability to learn complex and non-linear relationships that are difficult to model with conventional models. These models can be further divided into two categories:

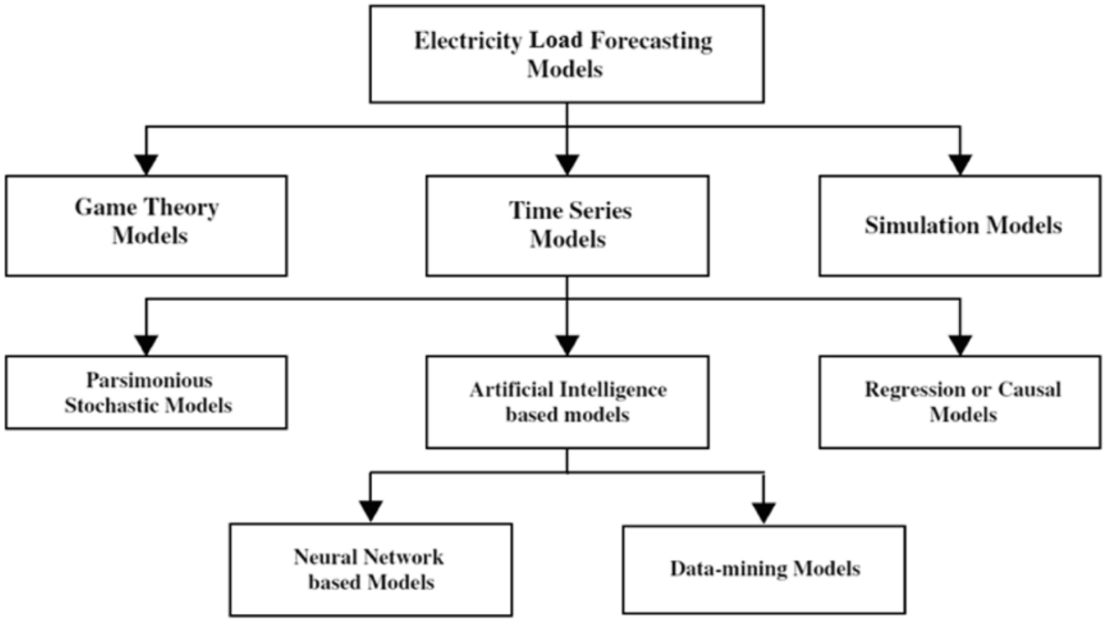
Artificial Neural Networks (ANN) Models: As a branch of artificial intelligence, Artificial Neural Networks (ANNs) have attracted considerable attention as candidates for novel computational systems (Guo et al., 2015). ANNs are found to be the most suitable tool, as they can map the complex interdependencies among electricity demand, historical demands and other factors (Wang et al., 2015). (Wang et al., 2015). The neural network approach predict market behaviors based on the historical demands, and future demands. The basic idea is to use history and other estimated factors in the future to "fit" and "extrapolate" the demands (Singhal & Swarup, 2011). The most valuable quality of neural networks is their ability to learn. .(Szymczyk, 2015).

Data-Mining Models: Data mining techniques, like the Bayesian categorization method, closest k-neighborhood categorization, reasoning-based categorization, genetic algorithm-based categorization have gained popularity for data interpretation and inferencing. All these models using data mining techniques have been covered in the category of data-mining models (Aggarwal et al., 2009).

Simulation Models

The last kind of demand forecasting techniques are Simulation Models (SM), where an exact model of the system is built, and the solution is found using algorithms that consider the physical phenomenon that governs the process (Aggarwal et al., 2009). Then, based on the model and the procedure, the simulation method establishes mathematical models, and solves them for demand forecasting (Aggarwal et al., 2009). Simulation methods are intended to provide detailed insights into system demands. However, these methods suffer from two drawbacks. First, they require detailed system operation data. Second, simulation methods are complicated to implement, and their computational cost is very high (Box et al., 2008). Figure 2 presents the electricity demand forecasting models classification:

Figure 2. Models Classification



Source: Aggarwal et al. (2009)

Solution

Table 1 presents the 8 steps proposed by Kaastra and Boyd (1996) for the construction of forecasting models with artificial neural networks:

Table 1. Steps for the Design of a Predictive Model Based on ANN.

Step	Description
1	Variable selection
2	Data collection
3	Data processing
4	Definition of set of training, validation and test
5	Selection topology of the neural network
6	Evaluation criteria
7	Training of the network
8	Implementation of the model

Source: Kaastra & Boyd (1996)

For the construction of a neural network, we used the data series for the energy consumption in (Gwh) for 31 consecutive days in a Colombian population in December, 2014. The data were obtained from X&M Company. Figure 3 presents the daily trend of electricity consumption in this period:

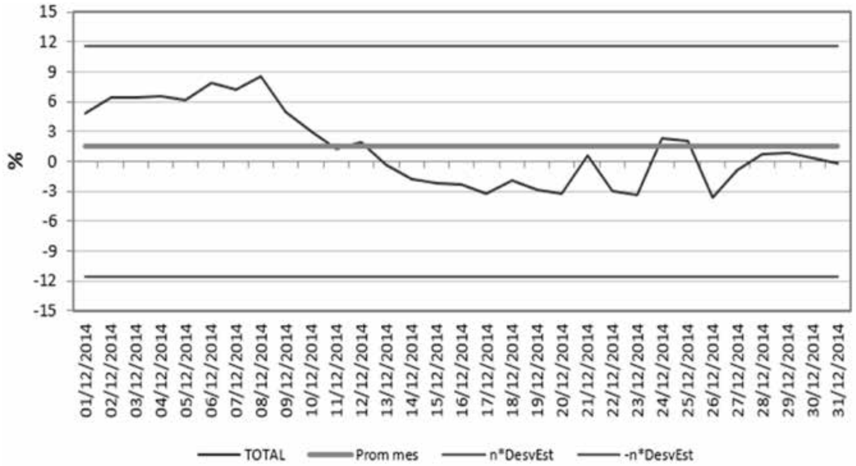


Figure 3. Daily Trend of Consumption (Gwh)
Source: X&M company (2014)

For the training of the neural network, and to facilitate the identification of trends and patterns, is noise was eliminated by analyzing the relevant processing of the input and output variables. Table 2 presents the real values of the electricity demand in (Gwh):

Table 2. Daily Electricity Demand, (December 2014)

Real Value (Gwh)	Date (dd/mm/aaa)	Real Value (Gwh)	Date (dd/mm/aaa)
25.538	01-12-2015	24.988	17-12-2015
26.425	02-12-2015	25.213	18-12-2015
26.534	03-12-2015	25.053	19-12-2015
26.574	04-12-2015	22.890	20-12-2015
26.443	05-12-2015	20.441	21-12-2015
24.774	06-12-2015	23.772	22-12-2015
21.035	07-12-2015	23.923	23-12-2015
20.877	08-12-2015	21.339	24-12-2015
25.567	09-12-2015	17.487	25-12-2015
26.003	10-12-2015	22.346	26-12-2015
25.666	11-12-2015	22.111	27-12-2015
25.774	12-12-2015	20.167	28-12-2015
23.288	13-12-2015	23.078	29-12-2015
19.892	14-12-2015	23.078	30-12-2015
24.526	15-12-2015	20.349	31-12-2015
25.175	16-12-2015	25.538	01-12-2015

Source: X&M company (2014)

Table 3 presents the descriptive statistical summary of energy consumption (Gwh) in the period considered:

Table 3. Descriptive Statistical Summary

Statistical	Value
Average	23.62
Typical Error	0.42
Median	24.22
Mode	25.53
Standard Deviation	2.40
Variance	5.76
Kurtosis	-0.35
Asymmetry Coefficient	-0.70
Range	9.09
Minimun	17.49
Maximun	26.58

Source: Author’s own elaboration (2015)

The data set used for training the neural network corresponds to 70% of the total data, i.e., the demands we have registered during the first 22 days. The data set used for the validation of the system corresponds to 30% of the total data, i.e., the 9 remaining consecutive days of the month in question, In the developed model a component of delay is considered, which inhibits the overfitting effect.

The number of input neurons is 31, corresponding to the number of days of the month in question, for which electricity demand was measured. One hidden layer has been used in the model to ensure the generalization of the network, due to the small number of data used. The number of hidden neurons corresponds to 80% of the total number of entries, i.e., 25 neurons. The number of output neurons used in the model is 1 because this is only going to predict the value of the selected variable for a day, and not to a set of days. Finally, we used a bipolar sigmoidal-type transfer function with output ranges between [-1, 1] to prevent the output of large values that can affect the neural network (Equation 1).

$$f = \frac{2}{1+\exp(-x)} - 1 \qquad (1)$$

Figure 4 presents the graph of the bipolar sigmoidal function:

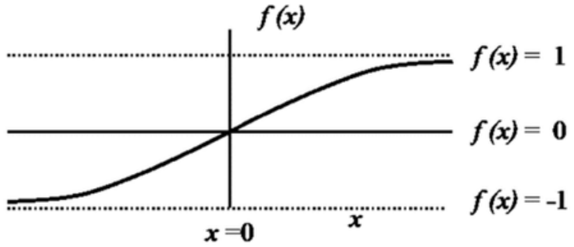


Figure 4. Bipolar Sigmoidal Function
Source: Author's own elaboration (2015)

Figure 5 presents the structure of the neural network developed:

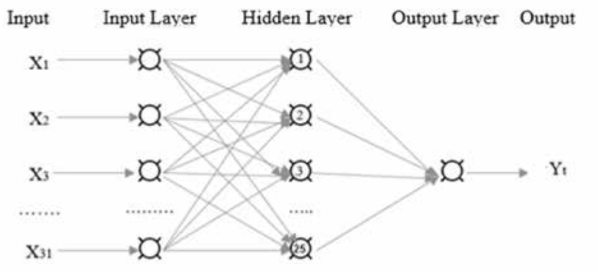


Figure 5. Neural Network Structure.
Source: Author's own elaboration (2015)

The programming of the network have among 12 to 22 values of training. We check the network, it should be very similar to data from the demand. Table 4 presents the results of this simulation.

Table 4. Simulation Training

Simulation Training (Gwh)			
25.379	25.543	23.924	24.394
25.428	25.386	23.377	24.733
25.526	24.685	23.822	24.434

Source: Author's own elaboration (2015)

The Root Mean Squared Error (RMSE, was the method employed for the measurement of the efficiency of the neural network, which was calculated as the difference between the real values and the predicted ones. In this phase, a fixed parameter was established 20 times, and the factor of (RMSE) is determined with threshold value of 0.02 (see Table 5).

Table 5. Real values vs. Predictec.

Real Value (Gwh)	Predictec Value (Gwh)	Error Residual
21.339	21.736	-397
17.487	19.058	-1.57
22.346	20.848	1.49
22.111	21.944	167
20.167	21.762	-1.59
23.078	22.435	643
23.078	23.166	-88
20.349	20.159	190
25.538	24.156	1.38

Source: Author's own elaboration (2015)

The coefficient of correlation of the model is $R^2 = 0.816$. It meets the condition of acceptance ($R^2 >= 0.8$), and presents a very good adjustment (see Table 6).

Table 6. Regression Statistics (RLS)

Regression Statistics	
Multiple Correlation Coefficient	0.903
Coefficient of Determination *R*	0.816
R Adjusted	0.786
Typical Error	1119.553

Source: Author's own elaboration (2015)

The training of the network is carried out with the top-down method immersed, with the algorithm of spread forward (Backpropagation), which will end if the number of iterations exceeds the number of times established. The evaluation function (EMC) takes a value below the target, if the error of the evaluation function is increased for a specified number of iterations. Table 7 presents the summary of the main components of the neural network:

Table 7. Regresión Statistics (RLS)

Variable	Description
Type	Multi-Layer Perceptron
No. of Training Data	22 (70%)
No. of Validation Data	9 (30%)
Activation Function	Sigmoidal
Estimation of the Error	Root Mean Squared Error (RMSE)

Source: Author's own elaboration (2015)

Conclusions

The daily forecasting electricity demand process shows a global vision of the socioeconomic and cultural behavior of a population. Among the different methods used to predict electricity demand, Artificial Neural Networks (ANN) allow the consideration of variables and external factors difficult to quantify with other methodologies, and suit the behavior of a data series better. Predicting energy consumption in small populations is a task of great importance for generators and distributors because it allows them to establish strategies for optimizing their generation portfolio. As a suggestion for future research, the development of forecasting models for predicting electricity demand with time series is proposed.

The (ANN) developed in this study for the prediction of daily electricity demand (GWh) was trained with the Backpropagation technique . The Root Mean Squared Error (RMSE) was the method employed for the measurement of neural network efficiency, which was calculated as the difference between the real values and the predicted ones. The model presents an R^2 = 0.816 >= 0.8, and an (RMSE) average of 113.96 (GWh). It may be concluded that the model presents a good adjustment.

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