



## Demand Energy Forecasting Using Genetic Algorithm to Guarantee Safety on Electrical Transportation System

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Demand estimation models are used for energy planning activities. Their primary function is focused on securing energy supply to final users using available resources in generation, transport and interconnection. Long-term planning models typically use non-linear optimization techniques considering an error not exceeding 5%. The reference model used by UPME in Colombia is limited to an average error of 1.6% considering non-linear modeling estimation techniques. However, they are limited in their ability to anticipate uncharacteristic variations in curves or externalities, which increases the probability of an erroneous prediction. Therefore, this research proposes a model to forecast electricity demand using neural networks in order to anticipate non-characteristic variations. The study first documents current methodologies for the prediction of maximum power demand, as well as the current deficiencies in the used forecasts, A new model is then formulated with the application of neural networks using the algorithm *Cascade-Forward Back propagation* using MATLAB R2017a. During the model comparison process, it was identified that the data obtained reflects the characteristics of demand behavior with an acceptable margin error equal to 0.5%.

**Keywords:** Cascade-Forward Back Propagation; neural networks; peak power demand forecast; long-term demand estimation model.

### 1. Introduction

Since the 1960s, the growth of the electric energy demand has generated a research focus trying to establish tools to estimate its factor for an accurate planning process. Electrical power systems began to include tools to monitor, forecast and control system operation in order to ensure control of the operating variables of interconnected systems (Gellings, 2009). In 1970, the ARIMA models were developed aimed on identify, estimate and diagnose dynamic time series models in which the time variable plays a fundamental role, and today they are only a small part of what is commonly known as "Time Series Econometrics" but, without a doubt, one of the most widely used (Maple, 2010). These techniques have been widely accepted to evaluate demand energy forecasts.

Otherwise, the demand energy forecasting techniques are a continue research area focused on develop techniques able to correlate variables and provide an accurate estimation of energy resources (Lim et al., 2018). This has created two important trends: Estimating non-conventional generation participation capacities such as wind and solar energy to support demand requirements and including externalities to estimate demand energy forecasting guarantying accurate values (Theo, et al., 2017). Also ANN is used to estimate efficiency indicator in final users energy consumptions (Ahmad, et al., 2017). These topics brought the use of artificial Neural Networks (ANN) as alternative to evaluate possible sceneries and not relate variables. **Errore. L'autoriferimento non è valido per un segnalibro.** summarizes research works that has been done by similar

case studies in a region to estimate forecast scenarios applying models for demand forecasting using ANN. The table lists authors, year of publication, contribution of the model.

*Table 1. Forecasting techniques applied in regions considering artificial neural networks during the process.*

Country	Reference	Forecast strategy	Contribution
Greece	(Economou, 2010)	multilayer perceptron model (MLP)	It is considered an appropriate solution of long-term energy estimation using non-stationary data.
Iran	(Azadeh, et al., 2010)	Integrated fuzzy regression algorithm with non-stationary data	Consider non-stationary scenarios using diffuse regression and compare with ARIMA models using non-linear optimization techniques.
Poland (Szczecin)	(Szoplik, 2015)	multilayer perceptron model (MLP)	Results showed that using MLP can be predicted the gas consumption at any time (day, month, season) for residential users and small industries.
United Kingdom	(Antenucci and Sansavini, 2017)	Stochastic Optimization Model considering security constraints	Evaluation of optimal location of thermal (gas) generation plants considering scenario of high wind penetration applying N-1 criteria.
Slovenia	(Potočnik, et al., 2007)	Mixed models: linear and non-linear optimization	Estimate the cash flow from the risk model considering day-ahead dispatch.
Turkey	(Antenucci and Sansavini, 2017)	Swarm Particles	A novel strategy to estimate the energy demand scenario for medium and long term.
Turkey	(Es, et al., 2014)	Feed-Forward back propagation.	Consider three scenarios for the Turkey energy demand. Compare results with the official forecast Turkey model MAED (Model for Analysis of Energy Demand).
Turkey	(Hotunoglu and Karakaya, 2011)	Colony Optimization	Estimate of Turkey's net energy demand considering artificial neural networks (ANN)
Turkey	(Birim and Tümtürk, 2016)	Multiple Linear Regression (MLR)	Estimation is compared with a real case provided by TEIAS (Turkey energy transmission system Utility)
Colombia	(Sarmiento and Villa, 2008)	Multi-Layer Perceptron (MLP) using training algorithm based on Backpropagation, and Radial Basic Function (RBF)	Results obtained were realized for demand energy estimations in the region of Antioquia and Chocó. The use of ANN shows an accurate estimation.

According with state of art reviewed, it can be assumed that the development of a demand energy forecasting model for a region or country should be preceded by works that evaluate the impact of several factors related to demand energy behavior in order to optimize to choose the adequate variables and its ranges according with the purpose of the objective function and the accepted prediction horizon (Szoplik, 2015).

It should be noted that artificial neural network (ANN) applications can be used in different scenarios and case studies involving demand estimation and their modeling process variate according with the needs detected in the case study, which implicates training. Also, to find a better solution can be used hybrid models that combine different artificial intelligence techniques. Previous works presented in Otherwise, the demand energy forecasting techniques are a continue research area focused on develop techniques able to correlate variables and provide an accurate estimation of energy resources (Lim et al., 2018). This has created two important trends: Estimating non-conventional generation participation capacities such as wind and solar energy to support demand requirements and including externalities to estimate demand energy forecasting guarantying accurate values (Theo, et al., 2017). Also ANN is used to estimate efficiency indicator in final users energy consumptions (Ahmad, et al., 2017). These topics brought the use of artificial Neural Networks (ANN) as alternative to evaluate possible sceneries and not relate variables. **Errore. L'autoriferimento non è valido per un segnalibro.** summarizes research works that has been done by similar case studies in a region to estimate forecast scenarios applying models for demand forecasting using ANN. The table lists authors, year of publication, contribution of the model.

Table 1 have been selected as reference of successful modeling integrating forecast scenarios and considering optimization techniques. Other works such as (Chen, 2017) presents a power load forecasting algorithm based on empirical mode decomposition however this method is still experimental and it has some imperfections.

In Colombia, the responsible the entity in charge to direct energy planning is UPME (Mining and energy planning unit). The forecast realized is econometric and a combination of forecasting to estimate long-term demand scenarios. Since 2013, an Endogenous and Exogenous VAR Model was implemented to simplify the econometric analysis, reducing the number of equations considered in the model. This Methodology has shown a high degree of precision according to the UPME bulletin "Projection of Electric Energy Demand and Maximum Power in Colombia (UPME, 2017).

Table 2 shows the follow-up to the Average Quadratic Error published by the UPME using the VAR model. Table 2. Average Quadratic Error between Demand Projection and Actual Demand (UPME, 2017).

Period	Nov 2013	Mar 2014	Jul 2014	Nov 2014	Mar 2015	Oct 2015	Jan 2016	Jun 2016	Oct 2016	Feb 2017
Mean Square Error Considering special big consumers (%)	0,48	0,25	0,39	0,43	0,28	0,64	0,57	0,54	0,42	0,19
Mean Square Error Without consider Special Big Consumers (%)	0,40	0,16	0,19	0,21	0,15	0,14	0,38	0,29	0,19	0,13

The UPME in the projection process of energy demand and maximum power estimation macroeconomic, social and climatological variables being the GDP, population and average temperature respectively forming a group of historical data and projected data with a defined seasonality and a correlation between them, Table 3 shows the variables described above. However, the model does not consider externalities such as the case of the oceanic Niño index, fuel price variations, which can be a constraint towards an accurate estimation.

Table 3. macroeconomic, social and climate variables used in the projections (UPME, 2017).

Year	GNP (Millions of USD)	Average temperature in location areas of the National Interconnected Electrical System	Population	Annual Growth (%)		
				GNP	Temperature	Population
2010	142	23,73	45.918	3,97%	-0,07%	1,10%
2011	151	23,86	46.406	6,59%	0,57%	1,06%
2012	157	23,99	46.881	4,04%	0,55%	1,02%
2013	165	23,98	47.342	4,87%	-0,03%	0,98%
2014	172	24,01	47.791	4,39%	0,12%	0,95%
2015	177	23,94	48.229	3,08%	-0,29%	0,92%
2016	181	24,08	48.654	2,33%	0,55%	0,88%
2017	187	24,09	49.068	3,13%	0,06%	0,85%
2018	194	24,00	49.469	3,66%	-0,35%	0,82%
2019	201	24,01	49.856	3,92%	0,01%	0,78%
2020	209	24,10	50.229	3,93%	0,40%	0,75%
2021	218	24,22	50.587	3,99%	0,47%	0,71%
2022	227	24,26	50.931	4,13%	0,17%	0,68%
2023	236	24,19	51.261	4,07%	-0,29%	0,65%
2024	246	24,22	51.576	4,09%	0,14%	0,62%
2025	256	24,26	51.878	4,08%	0,16%	0,58%
2026	266	24,27	52.165	4,10%	0,02%	0,55%
2027	277	24,33	52.439	4,05%	0,26%	0,52%
2028	288	24,36	52.698	3,94%	0,13%	0,49%
2029	299	24,32	52.944	4,03%	-0,14%	0,47%
2030	311	24,30	53.175	4,01%	-0,09%	0,44%

In Colombia has been registered research projects using ANN to estimate the energy demand growth. In (Sarmiento and Villa, 2008) showed an energy optimization to estimate energy resources using *Multi-Layer Perceptron (MLP) with Backpropagation and Radial Basic Function (RBF)* algorithm as is showed in Otherwise, the demand energy forecasting techniques are a continue research area focused on develop techniques able to correlate variables and provide an accurate estimation of energy resources (Lim et al., 2018). This has created two important trends: Estimating non-conventional generation participation capacities such as wind and solar energy to support demand requirements and including externalities to estimate demand energy forecasting guarantying accurate values (Theo, et al., 2017). Also ANN is used to estimate efficiency indicator in final users energy consumptions (Ahmad, et al., 2017). These topics brought the use of artificial Neural Networks (ANN) as alternative to evaluate possible sceneries and not relate variables. **Errore. L'autoriferimento non è valido**

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Table 1. Other works such as (Daza-Guzman et al., 2016) and (Ojeda-Camargo, et al., 2017) model energy demand based in UPME scenarios.

## 2. Methodology

In order to develop the demand forecasting algorithm were considered three phases. The selection of variable that will be used as input data, the algorithm model selected and finally the comparison process used during the research. The modeling process considered the Caribbean Coast Region of Colombia.

### 2.1 Input data

The information used on the demand forecasting model proposed considered economic, social and climatological variables which represent the region. The Gross National Product (GNP) which is related in Table 3. The social variables selected are number of habitants (THabCar), total number of dwellings (TVivCarb) and total number of homes (THogCarb). Table 4 shows social variables.

Table 4. Social variables considered in the model (UPME, 2017).

Year	THabCar	TVivCarb	THogCarb	Year	THabCar	TVivCarb	THogCarb
2000	8418747	1705400	1749043	2009	9540456	2107381	2167331
2001	8533075	1747113	1792605	2010	9674611	2160051	2221464
2002	8647236	1788749	1836341	2011	9811070	2212277	2275222
2003	8769952	1830571	1880561	2012	9948531	2265588	2330140
2004	8894440	1872981	1925710	2013	10086980	2319642	2385848
2005	9020469	1916447	1972266	2014	10226181	2374161	2442046
2006	9147630	1959593	2016092	2015	10365692	2429013	2498593
2007	9276497	2006443	2063893	2016	10506651	2486913	2558269
2008	9407859	2056074	2114689	2017	10647346	2544345	2617462

In addition to the economic and social variables presented above, the climatological variable selected has an equal importance and they are directly related to the consumption energy in the region, however, two climatological variables will be used in this research, The first is the monthly historical average temperature of the Colombian Caribbean region with a monthly seasonality showed in Table 3 and the second is the oscillation of the Oceanic Niño Index (ONI) which generally has a five-year seasonality, with a 3 month running mean temperature value variation (NOAA, 2018).

### 2.2 ANN model

For the execution of the energy demand forecasting was used MATLAB. The Feed forward and Cascade forward consider the back back Propagation algorithm. It consists on the learning of a predefined set of a pair of input and output given as example: first, an input pattern is applied as a stimulus for the first layer of the neurons in the network, it is propagated through all the upper layers until an output is generated, the result in the output neurons is compared with the desired output and an error value is calculated for each output neuron. These errors are then transmitted backwards from the output layer to all the neurons in the middle layer that contribute directly to the output. This process is repeated, layer by layer, until all the neurons in the network have received an error describing their relative contribution to the total error. Based on the value of the received error, the connection weights of each neuron are readjusted so that the next time the same pattern is presented, the output is closer to the desired one (Valencia Reyes, et al., 2006).

The importance of the backpropagation network algorithm is the ability to self-adapt the weights of the neurons in the middle layers to learn the relationship between a set of input patterns and their corresponding outputs. A variation of the Feed-forward scheme is the Cascade-Forward, which contains an additional input of the input

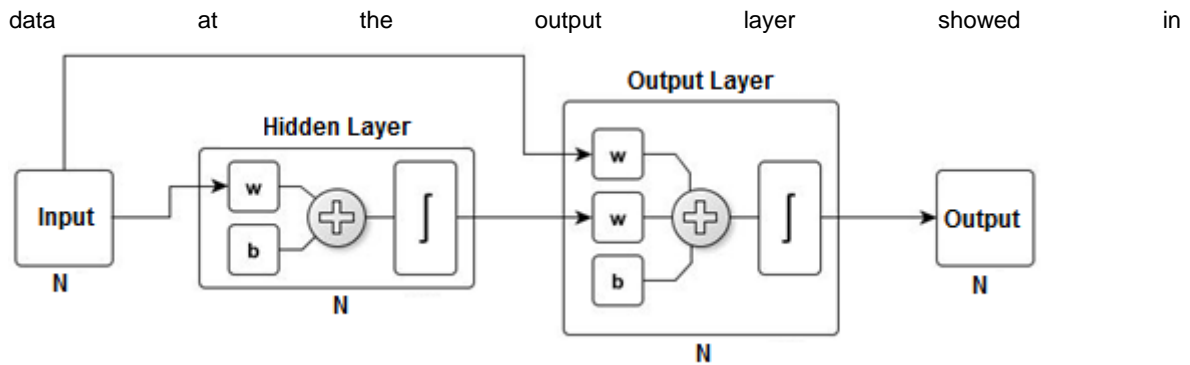


Figure 1 (MATLAB, 2018).

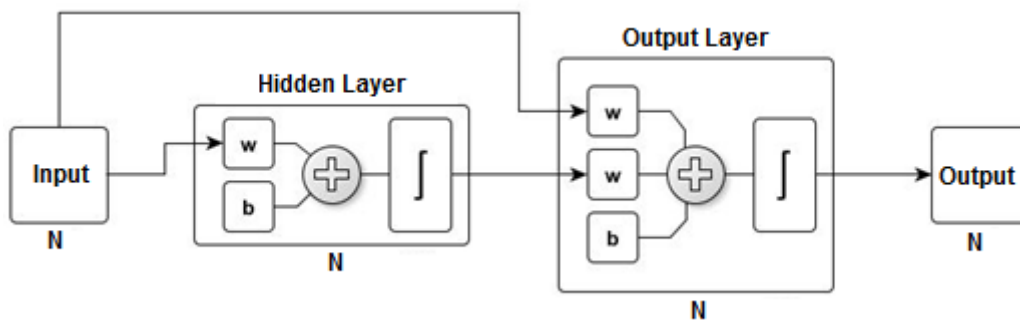


Figure 1. Cascade forward back Propagation

### 2.3 Training and Evaluation

The Neural Network selection process was divided into three phases: training, simulation and evaluation. For the purpose of finding the optimal performance. First, 96 neural networks were created, only 30 networks successfully converged, showing a better performance of the networks trained with the TRAINLM function with 97% of the total success. The networks trained with the TRAINLM function were evaluated against another group trained with the TRAINGDM function, obtaining similar results. From 96 neural networks only 28 converged, all trained with the TRAINLM training function. In addition, The networks with better simulations results had TANSIG and LOGSIG as Transfer function, in addition to the PURELIN function as output function (MatLab, 2016). The neuronal network models obtained will be compared with the current models of maximum power demand projection implemented by the UPME (UPME, 2017).

### 3. Results

Using the ANN Cascade-Forward backpropagation, 115 successful networks (90%) were identified, defining the effective network type for the projection, the number of layers and the number of neurons per layer, as well as the training functions. Finally, the five neural networks that obtained the best simulation performance were selected, demonstrating a correlation close to 1 and a low mean square error in comparison with the other networks. The mean quadratic error is shown in Table 5.

Table 5. Regression and Mean Quadratic Error in Neural Networks results.

Scenario Tittle	Annual Growth (%)			Correlation (R)	MSE
	Training	Validation	Test		
network124	0.995050	0.977450	0.979920	0.990480	1.16357E+14
network113	0.991100	0.988540	0.987860	0.989950	1.22374E+14
network98	0.990570	0.986820	0.979820	0.988960	1.3418E+14
network90	0.990370	0.980100	0.986990	0.988570	1.38648E+14
network99	0.990030	0.984750	0.987210	0.988530	1.454E+14

Figure 2 represents the simulations made of the neural networks, projecting the growth of the maximum demand of electrical power for the Caribbean area from 2017 to 2032, on average the 5 networks reported an annual

growth of 3.53% and by 2032 the total demand of power would have increased by 43.2% with respect to December 2017, going from 2100 MW to 3700 MW.

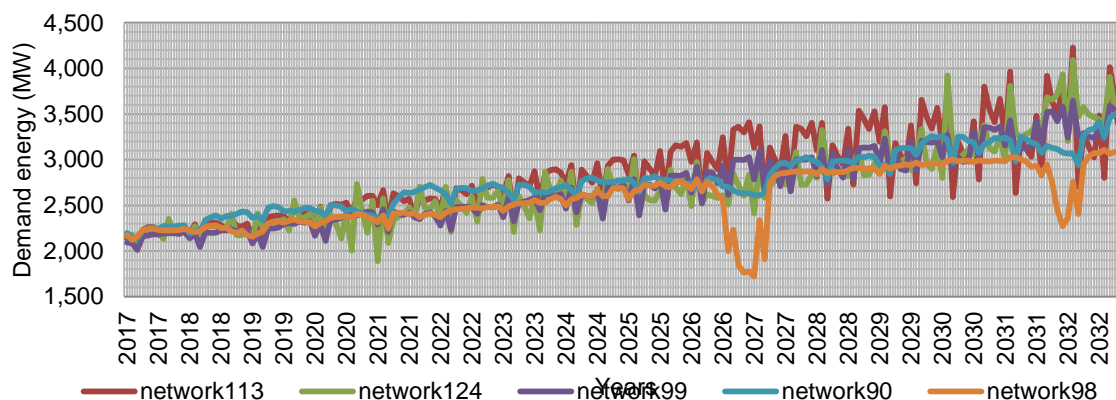


Figure 2. Projection of Maximum Power Demand using Neural Networks from 2017 to 2032 in the Caribbean Coast Region of Colombia.

It was selected the “network 124” because it had the smallest quadratic error and it is compared with three scenarios (high, mid and low energy demand scenarios) proposed by UPME in (UPME, 2017), considering the Colombian Caribbean Coast Region energy demand. Comparing energy demand forecasting with real demand there was identified that the estimation error in Network 124 (0.4%) was not higher than UPME estimation (1.5%). Table 6 describe compared result of UPME forecasting with the Network 124 considering low, medium and high energy demand scenario.

Table 6. UPME Percentage error result of energy demand forecasting vs. Neuronal Networks considering low, medium and high scenario.

Forecasting 2017	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	mean
Low Scenario UPME	0.2%	4.8%	4.5%	9.3%	10.3%	8.6%	7.6%	8.5%	7.3%	10.6%	8.1%	5.8%	7.1%
Low Scenario Network 124	-0.3%	1.8%	6.8%	7.3%	9.1%	7.7%	7.6%	12.1%	1.5%	10.8%	6.8%	3.0%	6.2%
Medium Scenario UPME	-5.8%	-0.9%	-1.3%	3.9%	5.0%	3.1%	2.0%	3.0%	1.8%	5.2%	2.6%	0.1%	1.6%
Medium Scenario Network 124	-6.3%	-4.1%	1.2%	1.7%	3.6%	2.1%	2.1%	6.8%	-4.4%	5.4%	1.2%	-2.8%	0.5%
High Scenario UPME	-12.2%	-6.9%	-7.3%	-1.9%	-0.7%	-2.7%	-3.8%	-2.8%	-4.1%	-0.5%	-3.2%	-5.9%	-4.3%
High Scenario Network 124	-12.7%	-10.4%	-4.7%	-4.2%	-2.1%	-3.7%	-3.8%	1.2%	-0.6%	-0.3%	-4.7%	-8.9%	-5.4%

#### 4. Conclusions

The Caribbean Coast Region Energy Demand was considered as a case study to evaluate the proposed algorithm to forecast energy demand using ANN with a Cascade-Forward backpropagation algorithm. During the comparison process, it was identified that the data obtained reflects the characteristics of demand behavior with an acceptable margin error to 0.4%. In general, the best neural network modeled “Network 124” showed an error equal to 0.4%, from the total low, medium and high scenarios evaluated in 2017. The percentage error of the UPME maximum power demand regional projection was 1.5% clearly evidencing the behavior of the two projection methodologies and demonstrating the applicability of ANN to represent demand energy forecasting accurately. On the other hand, the neuronal network projection allows planners to anticipate typical and atypical events such as growth and seasonal changes as the case of the Oceanic Niño Index (ONI).

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