CHEMICAL ENGINEERING TRANSACTIONS

VOL. 67, 2018

A publication of AIDIC

The Italian Association of Chemical Engineering
Online at www.aidic.it/cet

Guest Editors: Valerio Cozzani, Bruno Fabiano, Davide Manca

ISBN 978-88-95608-64-8; **ISSN** 2283-9216

DOI: 10.3303/CET1867132

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

Jorge I. Silva-Ortega[a,*], Brian Cervantes-Bolivar[b], Idi A. Isaac-Millan[c], Yulineth Cardenas-Escorcia[b], Guillermo Valencia-Ochoa[d]

[a]Ph.D. Student at Universidad Pontificia Bolivariana UPB, research member at energy optimization group GIOPEN, Universidad de la Costa.
[b]Grupo de investigación en Optimización Energética, Universidad de la Costa, Barranquilla. Calle 58 No. 55-66.
[c]Research member at Transport and Distribution Group, Universidad Pontificia Bolivariana, Medellín. Cq 1 No. 70-01
[d]Research member at KAI group, Universidad del Atlantico, Barranquilla. Km 9 Via Puerto Colombia.
jsilva6@cuc.edu.co

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 electric energy demand growth 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 power system operation to ensure its operating variables (Gellings, 2009). In 1970, the ARIMA model were developed aimed on identify, estimate and diagnose dynamic time series models. Today they are only a small part of what is commonly known as "Time Series Econometrics" but, without any doubt, they are one of the most widely used techniques in demand energy forecast (Maple, 2010).
The demand energy forecasting techniques are a continue research area focused on provide an accurate estimation of energy resources (Lim et al., 2018). This has created two important trends: (1) Estimating non-conventional generation participation capacities such as wind and solar energy to support demand requirements and (2) including externalities to estimate demand energy forecasting guarantying accurate values (Theo, et al., 2017). These topics brought the use of artificial Neural Networks (ANN) as alternative to evaluate possible sceneries and not relate variables. ANN is used to estimate efficiency indicator in final users energy consumptions (Ahmad, et al., 2017).
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. The works presented in Table 1 have been selected as reference of successful modeling integrating forecast scenarios and considering optimization techniques.

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

Country	Reference	Forecast strategy	Contribution
Greece	(Ekonomou, 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 previous works, it can be assumed that the development of a demand energy forecasting model for a region must be preceded by works that evaluate the impact of several factors related to demand energy behavior in order to optimize and choose the adequate variables and its ranges according with the objective function and the estimation horizon (Szoplik, 2015). Other works such as (Chen, 2017) describe a power load forecasting algorithm based on empirical mode decomposition, however this method is still experimental.

In Colombia, the demand electric energy forecast is econometric and it has a combination of techniques 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 precision degree according to the UPME bulletin "Projection of Electric Energy Demand and Maximum Power in Colombia (UPME, 2017). Table 1 presents the follow-up to the Average Quadratic Error published by the UPME using the VAR model. In Colombia, the projection process of energy demand and maximum power estimation consider macroeconomic, social and climatological variables being the Gross Domestic Product (GDP), population and average temperature respectively, forming a group of historical data considering a defined seasonality and a correlation between them, Table 2 presents the variables described above. However, the model does not consider externalities which can be a constraint towards an accurate estimation such as the oceanic Niño index, the fuel price variations.

Table 1. 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

In Colombia has been registered research projects using ANN to estimate the energy demand growth. In (Sarmiento and Villa, 2008) is showed an energy optimization to estimate energy resources using *Multi-Layer Perceptron* (MLP) with *Backpropagation and Radial Basic Function* (RBF) algorithm as is presented in Table 1. Other works such as (Daza-Guzman et al., 2016) and (Ojeda-Camargo, et al., 2017) use energy demand models based in UPME scenarios.

Table 2. macroeconomic, social and climate variables used in the projections (UPME, 2017).

Year	GDP (Millions of USD)	Average temperature in Interconnected Electrical System	Population	Annual Growth (%)		
				GDP	Temperature	Population
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%

2. Methodology

In order to develop the demand electric energy forecast algorithm were considered three phases. (2.1) The selection of variable used as input data, (2.2) the algorithm model selected and (2.3) the comparison process used during the research. Variables used in this paper represent the Caribbean Coast Region of Colombia.

2.1 Input data

The information used on the demand forecasting model considered economic, social and climatological variables which represent the region. The Gross Domestic Product (GDP) which is related in Table 2. The social variables selected are number of habitants (THabCar), total number of dwellings (TVivCarb) and total number of homes (THogCarb). Table 3 shows social variables.

Table 3. Social variables considered in the model (UPME, 2017).

Year	THabCar	TVivCarb	THogCarb	Year	THabCar	TVivCarb	THogCarb
2006	9147630	1959593	2016092	**2012**	9948531	2265588	2330140
2007	9276497	2006443	2063893	**2013**	10086980	2319642	2385848
2008	9407859	2056074	2114689	**2014**	10226181	2374161	2442046
2009	9540456	2107381	2167331	**2015**	10365692	2429013	2498593
2010	9674611	2160051	2221464	**2016**	10506651	2486913	2558269
2011	9811070	2212277	2275222	**2017**	10647346	2544345	2617462

In addition to the economic and social variables presented above, the climatological variable selected has equal importance and they are related to the consumption energy in the region. The two climatological variables used in this research, The first is the monthly historical average temperature of the Colombian Caribbean region with a monthly seasonality showed in Table 2 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 energy demand forecast was used MATLAB. The Feed forward and Cascade forward consider the 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. For that reason, 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 data at the output layer showed in Figure 1 (MATLAB, 2018).

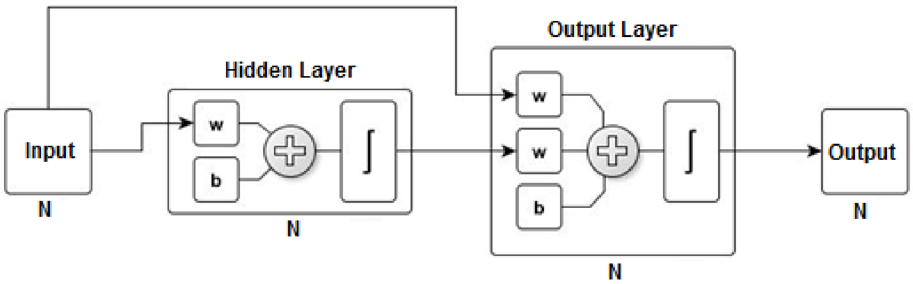

Figure 1. Cascade forward back Propagation

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 4.
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.

Table 4. Regression and Mean Quadratic Error in Neural Networks results.

Scenario Tittle	Annual Growth (%)				MSE
	Training	Validation	Test	Correlation (R)	
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

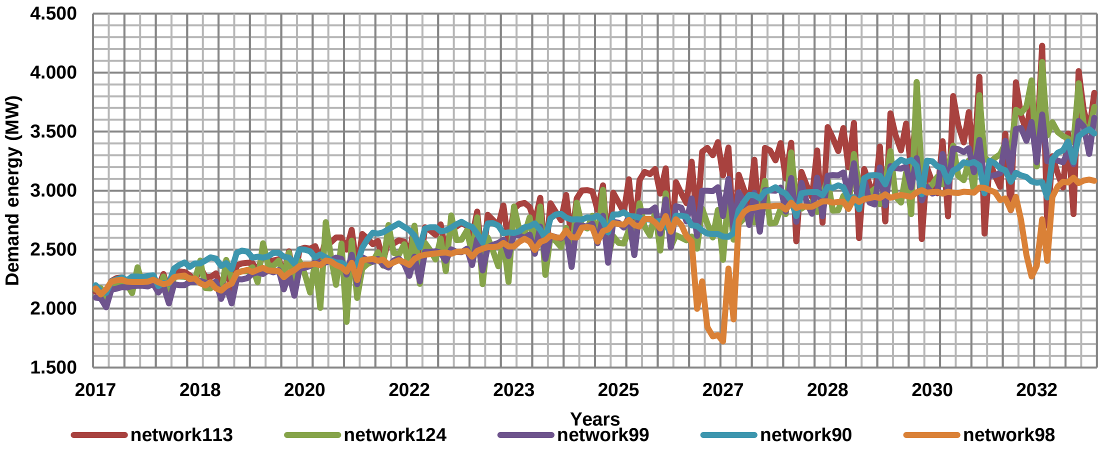

Figure 2. Projection of Maximum Power Demand using Neural Networks from 2017 to 2032 in the Caribbean Coast Region of Colombia.

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 5 describe compared result of UPME forecasting with the Network 124 considering low, medium and high energy demand scenario.

Table 5. 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).

References

Ahmad, Z., Bahadori, A., and Zhang, J. (2017). Prediction of Combustion Efficiency using Multiple Neural Networks. Chemical Engineering Transactions, 56, 85–90. http://doi.org/10.3303/CET1756015

Antenucci, A., and Sansavini, G. (2017). Gas-constrained Secure Reserve Allocation with Large Renewable Penetration. IEEE Transactions on Sustainable Energy, 9(2), 1–9. http://doi.org/10.1109/TSTE.2017.2756091

Azadeh, A., Saberi, M., and Seraj, O. (2010). An integrated fuzzy regression algorithm for energy consumption estimation with non-stationary data: A case study of Iran. Energy, 35(6), 2351–2366. http://doi.org/10.1016/j.energy.2009.12.023

Birim, Ş., and Tümtürk, A. (2016). Modeling and Forecasting Turkey ' s Electricity Consumption by using Artificial Neural Network. American Scientific Research Journal for Engineering, Technology, and Sciences, 25(1), 192–208.

Chen, Q. (2017). Research on Intelligent Power Load Forecasting Algorithm Based on Empirical Mode Decomposition. Chemical Engineering Transactions, 59, 841–846. http://doi.org/10.3303/CET1759141

Daza-Guzman, J. D., Rueda-Lopez, J. C., Silva-Ortega, J. I., Candelo-Becerra, J., Umaña-Ibañez, S., Mercado-Caruso, N., … Palacio-Bonill, A. (2016). A 75 bus bars model to evaluate the steady state operation of a sub-transmission electrical power grid. Revista Espacios, Vol. 38 (N(ISSN 0798 1015), Pág. 10.

Ekonomou, L. (2010). Greek long-term energy consumption prediction using artificial neural networks. Energy, 35(2), 512–517. http://doi.org/10.1016/j.energy.2009.10.018

Es, H. A., Kalender, F. Y., and Hamzacebi, C. (2014). Forecasting the net energy demand of turkey by artificial neural networks. Journal of the Faculty of Engineering and Architecture of Gazi University, 29(3), 495–404.

Gellings, C. (2009). The Smart Grid: Enabling Energy Efficiency and Demand Response. Retrieved from http://books.google.com/books?id=OzWDEILCyyYCandpgis=1

Hotunoglu, H., and Karakaya, E. (2011). Forecasting Turkey's Energy Demand Using Artificial Neural Networks: Three Scenario Applications. Ege Academic Review, 11(June 2016), 87–94.

Lim, J. S., Ho, W. S., Klemeš, J. J., Sununta, N., Sedpho, S., and Sampattagul, S. (2018). City Carbon Footprint Evaluation and Forecasting Case Study: Dan Sai Municipality. Chemical Engineering Transactions, 63(2011), 277–282. http://doi.org/10.3303/CET1863047

MATLAB. (2018). Neural Network Toolbox User´s Guide (2018a ed.). Natick: Mathworks. Retrieved from www.mathworks.com/help/pdf_doc/nnet/nnet_ug.pdf

NOAA. (2018). Cold and Warm Episodes by Season. Retrieved May 13, 2018, from origin.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ONI_v5.php

Ojeda-Camargo, E., Candelo-Becerra, J. E., and Silva-Ortega, J. I. (2017). Solar and Wind Energy Potential characterization to Integrate Sustainable Projects in Native Communities in La Guajira Colombia. Espacio, 38, 11–27.

Potočnik, P., Thaler, M., Govekar, E., Grabec, I., and Poredoš, A. (2007). Forecasting risks of natural gas consumption in Slovenia. Energy Policy, 35(8), 4271–4282. http://doi.org/10.1016/j.enpol.2007.03.001

Sarmiento, H., and Villa, M. (2008). Inteligencia artificial en pronostico de demanda de energia electrica: una aplicacion en optimizacion de recursos energetico. Revista Colombiana de Tecnologías de Avanzada, 2, 94–100.

Szoplik, J. (2015). Forecasting of natural gas consumption with arti fi cial neural networks. Energy, 85, 208–220. http://doi.org/10.1016/j.energy.2015.03.084

Theo, W. L., Lim, J. S., Ho, W. S., Hashim, H., and Lee, C. T. (2017). Review of distributed generation (DG) system planning and optimisation techniques: Comparison of numerical and mathematical modelling methods. Renewable and Sustainable Energy Reviews, 67, 531–573. http://doi.org/10.1016/j.rser.2016.09.063

UPME. (2017). Proyección de la Demanda de Energia Electrica y Potencia Máxima en Colombia. Bogotá.

Valencia Reyes, M. A., Yáñez Márquez, C., and Sánchez Fernández, L. P. (2006). Algoritmo Backpropagation para Redes Neuronales : conceptos y aplicaciones. Instituto Politécnico Nacional Centro De Investigación En Computación, (125), 1–12.