Contemporary Engineering Sciences, Vol. 10, 2017, no. 24, 1153 - 1161
HIKARI Ltd, www.m-hikari.com
https://doi.org/10.12988/ces.2017.710132

Probabilistic Load Flow with Load Estimation Using Time Series Techniques and Neural Networks

Fernando Mesa

Department of Mathematics and GEDNOL
Universidad Tecnológica de Pereira
Pereira, Colombia

Pedro Pablo Cárdenas Alzate

Department of Mathematics and GEDNOL
Universidad Tecnológica de Pereira
Pereira, Colombia

Carlos Alberto Rodríguez Varela

Department of Mathematics
Universidad Tecnológica de Pereira
Pereira, Colombia

Abstract

This paper contains the realization of a probabilistic load flow estimating the load previously using time series techniques with a set of previously classified data, the demand for 2007 is predicted based on data from previous years (2000-2006), thus forming two time series that include known data and forecasts of ARIMA models and neural networks, then the series are adapted to a normal probability distribution, the Monte Carlo method is implemented to enter samples Randomly distributed from the estimates made of the load to a node of a test network and using the algorithm Newton Raphson obtains a power value generated by the slack node for each sample of random load, the output values are classified to graph A histogram product of the iterations of the algorithm. This procedure is performed for different nodes of the network in order to know the behavior of this and the effectiveness of the method used.

Keywords: Load flow, probability, uncertainty, Monte Carlo, deterministic flow, time series, ARIMA models, neural networks, forecast

1 Introduction

The load flow is a common tool in the evaluation of power systems under steady state conditions and under the prescription of a set of parameters of the network, generation, load and lines. The classic form of resolution is the deterministic methodology that contributes information of the network only during an instant. However, due to the presence of uncertainty, it is necessary to evaluate the network giving anticipation to the randomness of the generation and the load through a probabilistic load flow (FCP), in the latter the objective is to obtain a probability distribution for the desired output variables (such as voltage, load, or in the present case, values of power generated at a node) when inputs such as generation or load are expressed as random variables with associated distribution functions [1]. A popular method of probabilistic load flow resolution is the Monte Carlo method in which random samples are generated from a probability distribution of a random variable, for this case the load, and the deterministic manner is solved for each sample , thus obtaining a set of output values, product of the random samples, which in turn create a probability distribution by the number of iterations made in the flow. For this application the creation of the probability distribution to work is generated from a time series containing data of energy generation previously classified and adapted to a normal distribution, in addition is made the comparison of results of the flow of load for two distributions , generated with additional predicted data from the time series, ARIMA models and artificial neural networks (RNA) [2].

2 Development of the method: ARIMA models

The ARIMA (AutoRegresive Integrated Moving Average) models were developed by Box and Jenkins, which consider the link between the data, which means that each observation at a given moment is modeled based on the previous values, it also allows to describe a value as a linear function of previous data and errors due to chance, where some cyclical or seasonal component can be included, so the elements necessary to describe the phenomenon must be present [3]. The autoregressive models (AR), moving average models (MA), autoregressive and moving average models (ARMA), form the autoregressive and integrated moving average models (ARIMA): To explain the correlation structure between the observations of a series stationary are basically considered two models, the model autoregressive in Eq.(1) and the moving average model in Eq.(2)

$$X_t = \sum_{p=1}^{\infty} \phi_p X_{t-p} + a_t \tag{1}$$

$$X_t = \mu + \sum_{q=0}^{\infty} \theta_q a_{t-q} \tag{2}$$

where white noise a_t is a random variable with zero mean, constant variance, uncorrelated with each other and with the past values of the series. These two basic models for stationary series combine to produce ARMA models (p, q). In general the time series are not stationary but by means of transformations of variance and differences can be transformed into stationary. The ARIMA models result from integrating the estimated ARMA stationary series with respect to the differences and transformations that were necessary to turn it into a stationary series. In summary the ARIMA models study the correlation structure between the observations of a series and based on the estimated structure calculates the forecasts and respective prediction intervals.

3 Artificial neural networks

Artificial neural networks (RNA) have their behavior based on neural networks which can be implemented in both hardware and software and are able to deal with abstract and poorly defined problems. They are designed to learn and generate decision and solution strategies based on typical pattern behaviors, this is done from the formation of arbitrary relationships between input and output data, relationships are constructed from the training of the network which in brief is a mathematical method that adjusts the network system by means of pattern learning, allowing a task to be executed later without having to program it [4].

$$u_k = \sum_{j=1}^{m} w_{kj} x_j \tag{3}$$

$$y_k = f(u_k + b_k) \tag{4}$$

Eq.(3) represents a linear combination of the inputs x_j and their respective input synaptic weights w_{kj}. On the other hand, Eq.(4) defines a firing function $f(u_k + b_k)$ that can be of the sigmoid or hyperbolic tangent type.

4 The direct application of the method

The direct application of the method in this paper focuses first on the prediction of the power values and then on the observation of the generation in the slack node of a given power system from the simulation of the estimated load as a distributed random variable usually [5]. Therefore, the load estimation is given by:

1. Forecast the time series using ARIMA models.

2. Forecast of the time series using Artificial Neural Networks.

3. Comparison of forecasts with real values.

4. Proof of normal probability of forecasts.

Now, the load flow using the Monte Carlo method is given by:

1. Generate a random sample of the input variable, which in this case is the active power demand, previously estimated with time series techniques, for a system node.

2. Solve the load flow for the system, (Newton Raphson algorithm).

3. Store the output variable of the iteration; in this case, the power generated by the slack node.

4. Repeat the previous steps until fulfilling the criterion of convergence; here the criterion is achieved by reaching a specific number of iterations.

5. After the simulation is finished, the descriptive statistics (average value and standard deviation) are calculated and the histogram of the data sample is obtained.

6. Finally the method is applied to different nodes to obtain different results and to determine the sensitivity of the slack node to the uncertainty of the demand.

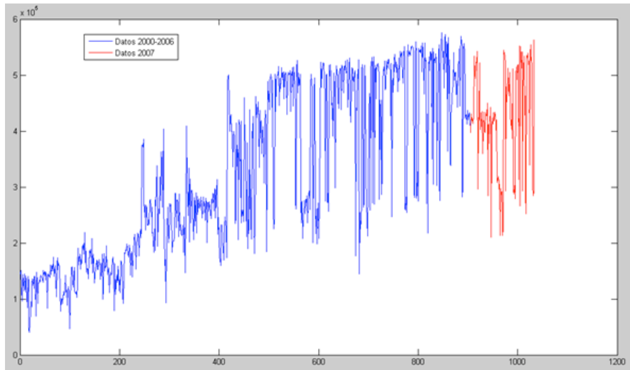

Figure 1: Time series

5 Application and results

With generation data classified for 1 am from 2000 to 2006 (blue, 905 data), for business days, Monday through Thursday, without holidays and for the dry season months of January, February, March, June, July, August, September and December, separating them from the data of year 2007 (red, 128 data), (Figure 2), on which it is proposed to perform the forecast and implement the load flow that compares the predictions and later check the normality in the data [6].

5.1 Prediction with ARIMA models

Using the IBM SPSS Statistics software you enter the data to work and it is checked the autocorrelation (FAC) and partial autocorrelation (FAP) graphs, with their corresponding values, are observed in the series from the graphs of the correlograms [7].

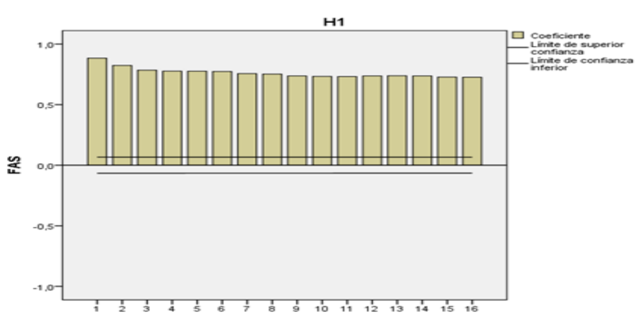

Figure 2: Correlogram FAC

In the previous figures it is observed that the series graphically is not stationary, therefore it is proceeded to apply differences to achieve the stationarity and thus to be able to realize the forecasts.

After graphically verifying that the series is stationary after applying a difference, Figures 4 and 5, it is possible to make predictions.

5.2 Prediction with RNA

Two predictions were made to compare which yielded the best results, graphically, mathematically and statistically, with the Matlab toolbox for NARX neural networks, which shows all the prediction results on the time series.

The structure of the neural network for the two predictions is the same, for other arrangements other than those specified the errors were larger. The network has two layers, a hidden layer with 10 neurons that have direct contact with the inputs and that are activated with the tansig function (sigmoid hyperbolic tangent). There is also the output layer, which has only one neuron and has a linear activation function.

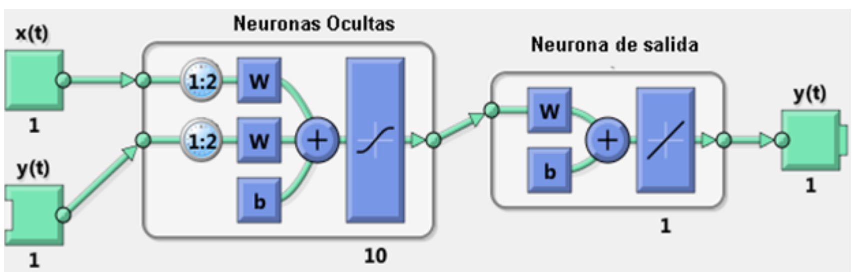

Figure 3: NARX neural network

The 905 generation data from the year 2000 to 2006 were used in the design of the network, of which 70% were for training, 15% for validation and 15% for testing, which for the usefulness of the study are obtained; the time series plotted predictions of Figure 6, the prediction error, and the descriptive statistics; of the initial data (2000-2006) and of the forecasts (2007).

6 Conclusion

Under the observation of the results obtained from the FCP and in comparison with those of the CDF, we conclude in the proposition of a new alternative to the FCP, in which the load adapted to a normal distribution carried out by the SMC and provides information on the network response to the uncertainty of demand. Taking into account the power value generated by the slack node

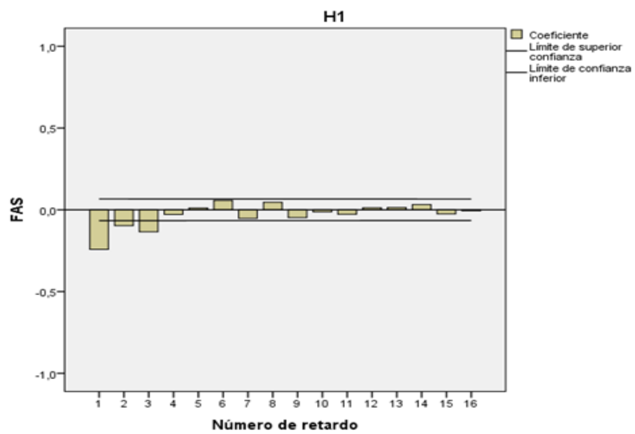

Figure 4: Correlogram FAC

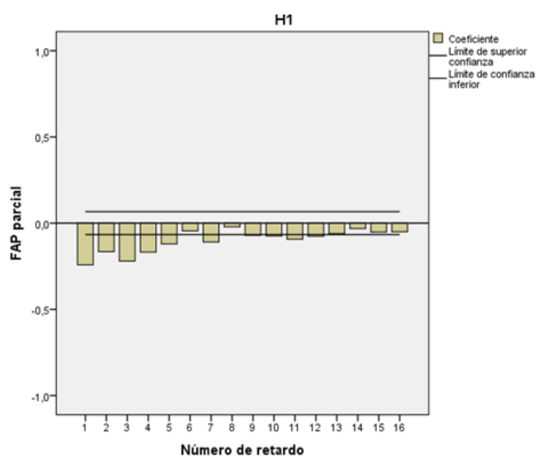

Figure 5: Correlogram FAP

under FCD conditions, it is observed the change that it has under FCP, the generation varies according to the node on which the SMC is applied, reason why it is had that the nodes with greater load, make that the slack gives less power to the system, this can also be explained by the power balance that the network must have to compensate for a lower value of load.

As for the topology of the nodes it can be seen that the difference of generation of the slack when applying SMC; between the node 12, which is closest to the slack, and the node 17, which is further away, the generation gap is not very important, whereas between node 12 and node 16, adjacent to the node 17, this difference is more noticeable, an interesting result that may be due to the position of the node 16 between two meshes.

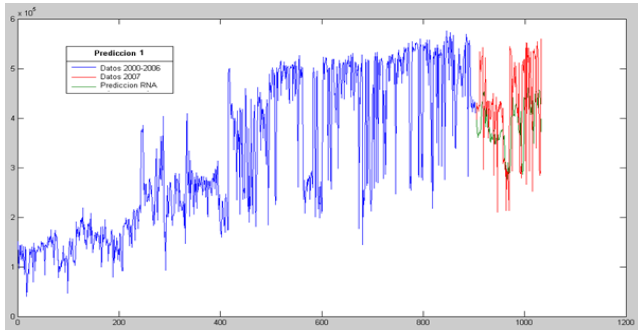

Figure 6: Forecast series 1, RNA

Acknowledgements. We would like to thank the referee for his valuable suggestions that improved the presentation of this paper and our gratitude to the Department of Mathematics of the Universidad Tecnológica de Pereira (Colombia) and the group GEDNOL.

References

[1] W. El-Khattam, Y. Hegazy and M. Salama, Investigating distributed generation systems performance using Monte Carlo simulation, *IEEE Transactions on Power Systems,* **21** (2006), 524-532.
https://doi.org/10.1109/tpwrs.2006.873131

[2] B. Marah, A.O. Ekwue, Probabilistic load flows, *2015 50th International Universities Power Engineering Conference,* (2015), 1-6.
https://doi.org/10.1109/upec.2015.7339770

[3] Victor Manuel, Guerrero Guzman, *Análisis Estadístico de Series de Tiempo Económicas*, Thomson Editores, Mexico, 2003.

[4] F. Cardona, J. Henao, Predicción de los precios de contratos de electricidad usando una red neuronal con arquitectura dinámica, *Revista Innovar,* **20** (2010), 7-14.

[5] J. Hamilton, *Time Series Analysis*, Vol. 2, Princeton University Press, 1994.

[6] A. Hernández, R. Isaza, R. Rendón, Comparación de flujos de carga probabilšticos empleados en sistemas de distribución levemente enmallados, *Scientiae et Technica,* **19** (2014), 153-162.

[7] A. Doucet, N. Gordon, An introduction to sequential Monte Carlo methods, Chapter in *Sequential Monte Carlo Methods in Practice,* Springer, 2001, 3-14. https://doi.org/10.1007/978-1-4757-3437-9_1

Received: October 21, 2017; Published: November 20, 2017