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Case Report

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Prediction of demand through artificial neural networks of a primary distribution circuit

Abstract

In this research, a case study about the behavior of active power in a Primary distribution circuit is presented. Some collective responses to the use of active circuit power demand, where residential loads predominate, are also described. Based on the information collected in a NU LEC measurement and protection device, a prediction model of demand behavior based on the use of artificial neural networks with a correlation coefficient of 0,94 was formalized.

Keywords: electric power, residential sector, model of demand, collective answers, artificial neural network

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Abbreviations: RNA, redes neuronales artificiales.

Introduction

The energy sector in Cuba since the revolutionary triumph in 1959, has been a constant concern for the country. In its beginnings to the present, it is a priority to ensure energy carriers for economic and social activity. These activities require constant advances in their service guarantee energy production and daily life of society. Energy base of the country, characterized by high dependence on imported fuel by about 53%, requires strategizing to ensure satisfaction of non-residential and residential customers by planning, determination and coordination of activities that promote improvement continuous energy matrix. Currently, one of the strategies that more you work is related to the development of power generation to more efficiently meet the demands of primary and tertiary activities, secondary country. In the case of the residential sector, service of the National Electric System (SEN) reaches almost 99% of the population, however, studies of the collective responses of the use of energy carrier electricity and knowledge of the charges present are required that allow strategize regarding energy policy and technical decisions for better use. By analyzing the characteristics of consumption in the residential sector, it is like the highest importance from a quantitative point of view. To exemplify those characteristics that distinguish a primary distribution circuit for the specific study of demand, which have a high incidence residential loads is selected. In this case, the behavior of the main electrical circuit variables, the characteristic curves of demand in the different days of the week and the difference between the behavior during periods of winter and summer is evident. Demand modeling is also presented by using artificial intelligence techniques,

Case presentation

One of the most difficult variables to define when carrying out any study on the distribution networks is the behavior of the loads. These charges are composed of elements of moderate or low consumption, such as electronic equipment, efficient lighting and equipment with high demands, such as those used in food processing; the latter have greater influence on the load chart. Replacement of domestic fuel for cooking electric energy, activity performed in a range of very limited time, introduced drastic changes in demand, consumption and power factor. In this paper the characteristics of the load curves, focused to a primary circuit distribution where most electrical loads belonging to the residential sector located in multi-family buildings exposed. There are several methods for estimating the electricity demand, which usually perform long-term studies. However, to determine the time required to analyze behavior is practically measurements in existing installations, also analyzing the composition of the associated receivers. Loading graphics residential sector is characterized by high demand in the early hours of the night, when most of the family returns home and using equipment intensifies. The presence of the UN-LEC (protection and measuring devices) has become more widespread at the country level. Measurement facilities offered by these devices allow research on distribution circuits, improving predictions of variables, allowing implement appropriate changes. Uniformity guzzling household equipment has a strong tendency to establish similar graphics in most sectors of the population. For analysis a distribution circuit 3 km was selected. The percentage that demand is distributed as follows: 64% related loads in the residential sector, 27% by the state sector and about 9% for losses. (Figure 1) shows data characterizing the behavior of the active power (kW) in the circuit under test is. a valley seen in the morning hours, and three peaks: minimum, mean and maximum, that are pronounced between 7:00 to 8:00 pm, 11:30 to 13:00 h and 19:20 to 20:00h respectively.

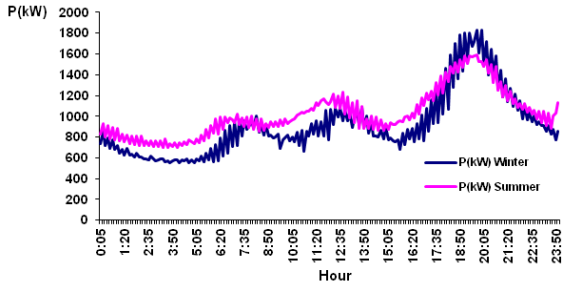

Figure 1 Chart demand curves average winter and summer.

In Cuba there are two normed schedules, winter and summer. The winter schedule extends from November to February, and summer time remaining months. DST is implemented for better use of sunlight, and this establishes a difference between the demand curves. In the summer time, the demand curve is substantially greater than the winter curve from 0: 00-17: 00h. From 17:00pm until the end of the day, demand in the summer is lower than the winter. In winter the minimum demand value is 550.67kW, and the maximum value 1833.00kW. In the case of the summer demand curve, the minimum value is 702.83 kW and the maximum value reaches 1587.50kW. In this circuit there is permanently a current unbalance between the phases. The C phase is the most loaded throughout the day, and phase B has less load with respect to phase A but with a small difference and at various times practically overlap. Day mean values are: IA=48.0A, IB=47.06A and 51.53A. IC=regarding these values average standards for distribution systems, which expresses met the unbalance It should not exceed 5%. The power factor of an electrical system indicates the degree of utilization of energy. In the case of residential circuits because of higher power loads are resistive character implies that the power factor rises and shop to 1. The graph in (Figure 2) the average power factor values are appreciated circuit analysis.

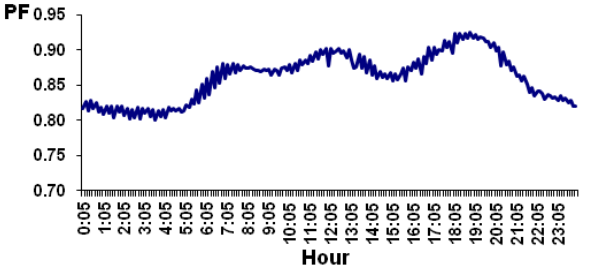

Figure 2 Curve of average power factor of the year.

The minimum value is reached in the morning hours, about 3:35 hours with a value of 0.8. This is because virtually no use of resistive loads at that time. The maximum value is reached at the time of the evening at approximately 18:50, with a value of 0.92, coincident with the peak power demand. In the case of the voltage in phase C is greater than in the remaining phases. The highest peak registered 8002.60 V is the hours of the morning at approximately 4:50 am. The voltage in phase B is less than the phase A and is the smallest of all, reaching up to 7655.79 falls V in the hours of about 21:55 hours. However, voltage variations do not exceed 2% in any of the three phases, which indicates that the established standard for this voltage level is met, which states that there must be no greater than 5% imbalances. Predicting demand through a system based on artificial neural networks model. The traditional method to solve complex engineering problems is by models represented by equations that seek to reproduce more or less accurately, the physical space in question. Unfortunately, not all systems can be addressed in this way because sometimes the performance of each variable is not clearly defined or because there are certain uncertainties that would require research to extend the time or resources to employ prohibitively expensive. This difficulty can be saved with artificial intelligence applications.[1] One of the tools of artificial intelligence are neural networks. These networks are composed of mathematical elements, called neurons, which have been inspired and to some extent, try to imitate the functional activity of the human central nervous system. Generally based on artificial neural networks (ANNs) model can be formalized by the following expression as the Matlab:[2]

Y = f 3 (f 2 LW3,2 (LW2,1 f 1 (IW1,1p+b1)+b2)+b3

Where: -output of RNA.

p - Input data.

f1, f 2, f 3 -transfer functions of the different layers of neurons.

IW1,2, LW2,1, LW 3.2-weights of the different layers of neurons.

b1, b2, b3 - polarizations of the different layers of neurons.

A neural network can interpret the universe as a black box which concur number of input variables X (p) and has as output variables Y, although the contribution researcher expertise. Applications of RNA have grown substantially even where the relationships between variables are known. In the case of predicting demand and consumption of electricity in the literature relevant papers addressing various specific examples and conceptual elements of their application in these types of energy systems.[1,3–14] However each individual case, such as the one presented in this research requires prior recognition system and an appropriate strategy for selecting data corresponding training and validation. Perhaps the most difficult to build a good model of neural network part is related to selection and collection of information fed to it in the training phase.[3,9] The details of selected factors as explanatory load curve variables are discussed: Calendar There are several related to the calendar that affect electricity demand curve effects:

Time of the day: Rt is evident that the electricity demand made at 3 lat dawn will not be equal to the one held at 6 pm. In (Figure 3) it can be seen as the bulk of the power demand accumulates in the period between 5 pm and 9 pm. For the model is able to reflect this effect should include a variable representing the time of day. This requires a numeric variable which range between 0 and 23. Oscillate [55 0:05, 1,2 ... 22,23] is used.

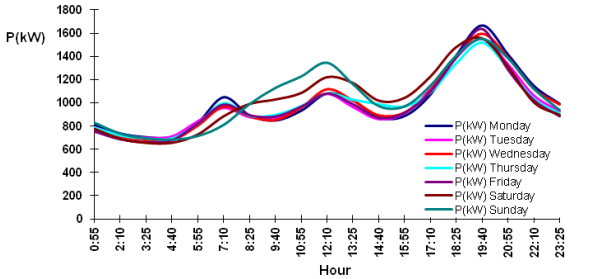

Figure 3 Graph average weekday demand.

Day of the week: The same analogy can be intuited that electricity demand made at the same time in different days, it will also be different. Thus the demand for a Wednesday at eleven o'clock probably will not match held Sunday at the same time. (Figure 3) also appears every working day have a profile very similar lawsuit, except Thursday between the hours of about 12:00 to 14:00 h energy consumption is a bit higher compared the other days. On weekends seen as the same time detected pattern it is not repeated consumption on weekdays, overall the average consumption is much higher. For the model to be able to identify the load profile associated with each day of the week should include a variable that collect this effect. This variable will be coded as:

Season: In this variable data are collected by separate winter and summer. It is true that there is the same power consumption in each of these stations energy. In the analysis of demand for summer and winter in the circuit, it was concluded that the greatest energy consumption

occurs in the summer; except for rush hour winter demand exceeds the summer. This variable is the binary number type. Winter=1; summer=0.

Month of the year: Depending on the month the average demand diarito vary significantly. This is mainly due to the effect of the seasons. In the winter months, regardless of climate impacts already considered (mainly temperature), it has fewer Daylights and people tend to spend more time at home. Regarding the summer power consumption can also experience a significant increase resulting from the use of air conditioning systems. It has been found that the demand curves winter and summer reach maximum values and different behaviors. Therefore it is included in the model a variable that collect this seasonal component of electricity demand. This requires a categorical variable; whose values represent the different months of the year will be used. This variable is encrypted by assigning values that go from January=0, until December=11. Initially, for an approach to the behavior of demand, parametric modeling was used, for which the identification tool Mat lab was used. The entire set of models of this tool was tested to obtain the best result of approximation by a self-regression to the following ARX structure: 25 [25 25 25 25]. It is a polynomial of high order with an adjustment of a 54.13% adjustment. Given this result, it was decided to choose another modeling tool, in this case the RNA. To predict demand by RNA, a network of feed-forward back propagation type was selected, with a training function trainlm type, formed by three layers of neurons. The first layer comprises four neurons logsig transfer function. The intermediate or hidden layer comprises 19 neurons logsig transfer function. The third layer or output is formed by one neuron or type PURELINE linear activation. Training for gradient descent method with back propagation back and with time was used. Schematically this model that provided the best results shown in (Figure 4).

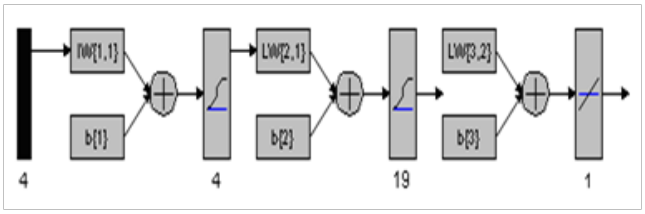

Figure 4 Schematic representation of the RNA used.

Determining the optimum number of neurons in the hidden layer it is made by a process of trial and error, ensuring the best correlation between the output data resulting model and measured values. In any case, the goal was to provide the network with an adequate number of neurons in the hidden to be able to learn the characteristics of possible relationships between sample data layer. Taking advantage of the properties attributed to the unidirectional RNA is necessary to approximate the load curve, given the available data set, later to make predictions about future values. The input variables used in modeling correspond to the time of day, day of the year, the month of the year and the season (summer or winter). Given the level of disaggregation required (h values), obtaining data series concerning the electric charge has been a particularly laborious task. This was obtained through readings NU-LEC (measuring device and protection) located in the substation under study. All series are in hourly averages, covering the period between 0:55:00 on Sunday October 7, 2007 and 23:55:00 on Sunday 30 September 2008. This makes available a total of 6893 observations, of which 1608 will be used in training the network, being reserved for other observations 1608 model validation. Observations for training and validation were selected properly so that cover data input variables extended by every month. This learning model was established approximately 75 iterations. Learning ability was estimated by comparing the training set and real-time data for different numbers of neurons in the hidden layer. An amount of 19 neurons in the hidden layer is selected finally, as was the value that gave a best combination of these data. After 1000 iterations, the network reached a mean square error of 0.0016. The neural network based model, has a correlation coefficient of 0.94 between the values predicted by the neural model (x) and the measured values (y) see (Figure 5). The values shown are normalized between 0 and 1 a recommendable for learning work element.

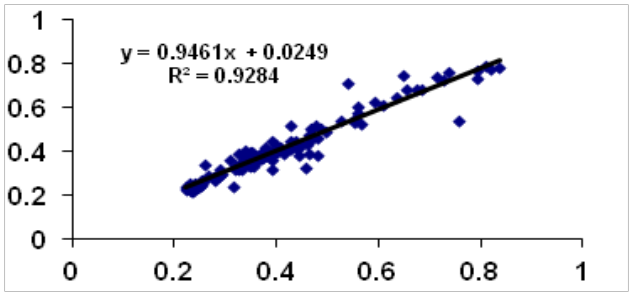

Figure 5 Scatter plot between the normalized values predicted by the RNA and measured in the circuit.

Discussion

Which can be summed up Monday through Friday there are three peaks in demand at different times of day with an average of 992.47 kW, 1068.11 kW, 1593.36 kW respectively. For Saturday and Sunday the first peak disappears, and there are only two peaks, with an average consumption of 1283.89 and 1553.11 kW kW. The observed current imbalance occurs between 3 and 9%, and affects the losses to the first processors in each phase, with a value of about 4 MWh/year. The difference between the maximum and minimum values with respect to the rated voltage (13.8 kV) is between 1 and 4%, in line with medium voltage standards. The power factor ranges in the day in 2 average values, from 12:55 to 4:40 am takes values between 0.80 and 0.81, and 7:40 pm, reaches a value of 0.92. In the summer time, the demand curve is substantially greater than the curve winter in almost 19% from 0:00 pm until about 17:00 h. Between the hours of 17:05 has 21:55 h, consumption in winter is 13% more than the summer, and the rest of the day summer demand is 10% higher than the winter. It was estimated more than 94% accuracy demand distribution circuit through an artificial neural network feed-forward back propagation type. Its basic architecture has three layers of neurons (4-19-1) with transfer functions logsig in the first two and PURELINE in the third. The general equation of the model based on RNA and their respective coefficients matrix are presented below.

LW {1,1}=[3.9404 4.8024 0.081 6596; -0.19055 0.08764 6.6866 1.1391; 7.1281 0.0045263 -1.5644 -6.1007; 0.8303 -0.17897 12.5538 -5.0629].

LW {2,1}=[30.3169 -26,701 -43.3956 -7.0362; -2.6762 19.0132 1.7125 8.2139; -3.8735 14.0715 -1.7092 1.1806; -0,948 -9.7624 5.3026 0.27102; -32.3095 19.7862 -8,579 1.1039; -22.1443 0.47253 -4.1227 25.6262; -1.5669 -7.4578 1,208 2.5975, -17.2247 4.1769 4.0662 16.6268; -1.0629 -1.6258 -0.27033 3,835; -3.0701 6.4527 0.78766 -2.2267; -2.9586 8.7452 0.11337 -3.7419; 13.0005 -9,943

2.6885 -4.1625; -11.4636 6.6628 -2.6479 2.6083; -8.2986 -39.7619 -8.6776 -11,927; -12.3059 -3.4093 -5.3094 -7.8135; 7.5757 -12.1849 -0.43645 0.83744; -15.0179 9.1683 4,126 9,041; 0.3734 -1.8889 -38.5848 -1.3717; 35.3704 -21.8356 9.8781 -6.0829].

LW {3,1=[4.7547 -1.4222 -13.3665 1.0423 -16.1462 -1.4122 -26.0567 0.63651 16.8746 40.3501 -33.0301 -5,997; - 7.1183 -0.26747 0.94152 9.9309 -2,029 14.1696 -11.6508].

b{1}=[-13.0431; -4.9257; -2.3262; -4.6645].

b{2 =[-2.1663; -21.81; 1626; -12.3137; 13.0809; -25.1373; -0.91973; -4.3974; -3.0172; -0.36378; 0.302; -1.5427; -2.7332; 43.3485; 10.3983; 2.1293; -15.3921; 42.03; -13.3321].

B {3}=[14.1734].

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Conflict of interest

There is no conflict of interest or financial interest.

References

1. Weapons Teyra Marcos A, Gómez Sarduy July, Carlos Perez Tello. Artificial intelligence applied to energy systems analysis with Matlab. *Comfenalco Technological University Foundation*. 2007;269.
2. MathWorks. Mat Lab Version for 7.7.0.471 (R2008b). 2008.
3. Ulises Garcia Cortes, Béja Javier Alonso, Antonio Moreno Ribas. Artificial Intelligence. (Ediciones UPC). Barcelona: Spain; *ISBN*. 1994;84(7653):286.
4. Damborg MJ, Park DC, MA El Sharkawi, et al. Electric load forecasting using an artificial neural network. *Transactions on Power Systems IEEE*. 2002;6(2):442–449.
5. Pedro A Gonzalez, Zamarren Jesus M. Prediction of hourly energy consumption in buildings based on a neural network artificial feedback. *Energy and Buildings*. 2005;37(6):595–601.
6. Hippert HS, Pedreira CE, Souza RC. Neural Networks for short-term load forecasting: a review and evaluation. *Transactions on Power Systems IEEE*. 2001;16(1):44–55.
7. Hsu Che Chiang, Chen Chia Yon. Regional load forecasting in Taiwan: applications of artificial neural networks. *Energy Conversion and Management*. 2003;44(12):1941–1949.
8. Kalogirou Soteris. Artificial Intelligence in Energy and Renewable Energy Systems. In: Sayigh AAM, editor. New York: Nova Science Publishers; 2007. p. 1–6.
9. Mallo Gonzalez C. Prediction of time electrical demand by artificial neural networks. 2004.
10. Reineris Montero Perez Calos, Gongora Ever, Secundino Marrero. Prediction of electricity and LPG at a hotel by artificial neural networks. *Energy*. 2009;(42):8.
11. Park DC, Sharkawi MA El, Marks RJ, et al. Electric load forecasting using an artificial neural network. *Transactions on Power Systems IEEE*. 1991;6(2):442–449.
12. Park KY, Lee YT, Cha JH. Short-term load forecasting using an artificial neural network. *IEEE Power & Energy Society*. 2002;7(1):124–132.
13. Souza HS, Hippert CE, Pedreira RC. Neural Networks for short-term load forecasting: a review and evaluation. *Transactions on power systems IEEE*. 2002;16(1):44–55.
14. Sunny Wan. Power Facility Usage with Artificial Neural Networks Prediction. San Luis Obispo: California; 2009.