Predicting Short-Term Electricity Demand Through Artificial Neural Network

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Abstract Forecasting the consumption of electric power on a daily basis allows considerable money savings for the supplying companies, by reducing the expenses in generation and operation. Therefore, the cost of forecasting errors can be of such magnitude that many studies have focused on minimizing the forecasting error, which makes this topic as an integral part of planning in many companies of various kinds and sizes, ranging from generation, transmission, and distribution to consumption, by requiring reliable forecasting systems.

Keywords Primary feeder · Demand short-term electricity prognosis · Neural networks · Forecast accuracy

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1 Introduction

Electricity demand forecasting is basically defined as the science or art of predicting the future load on a given electric system for a specific future time period. This prediction can range from a few minutes for operational purposes to years for planning purposes [1]. Due to the importance of predicting daily load, different forecasting methods have been developed, including methods based on artificial intelligence, particularly neural networks. This research is developed using the information of demand measured by the SCADA system [2, 3] of a feeder in the city of Medellin in Colombia, taking readings every 15 min in order to create the database for designing and building an artificial neural network (ANN) that will forecast the short-term energy demand through the MATLAB tools.

2 Development

2.1 The Training Set

The training set is the set of data used by the neural network to learn the patterns present in the data, defined as the weights of the network. In network development, this dataset will represent a total of 3,125 consumption measurements of 3,850 available data.

The selected data corresponds to 48 months of the analyzed set of 50 months, corresponding to a period of 5 years of measurements [4].

2.2 Validation Set

The validation set is used for the final checking of the network, where the data used are the most recent consequent to the last value of the sample.

2.3 Test Set

The test set is selected from the database. In this case, it corresponds to the data remaining after the training patterns are selected. This selected dataset, corresponding to the last 48 consumption records in the database under study (last three months), is used to assess the network accuracy [5].

2.4 Selection of the Neural Network Architecture

According to the literature review, there are several ways to determine the architecture to develop a predictive neural network, in most cases, using networks with back-propagation training algorithm [6, 7]. In order to create a neural network, the following elements must be selected.

2.4.1 Number of Input Neurons

The number of input neurons corresponds to the measurements recorded by the SCADA system at the exit of the circuit under analysis in a time interval of one year, which in the database is equivalent to 12 months, and the consumption of each selected month would be equivalent to 24 data. In this case, the number of input neurons is 24 data.

For the development of this research, a single hidden layer was considered, which is sufficient to ensure the ability to generalize the network, so the network would have a total of three layers: the input layer, the hidden layer, and the output layer.

The number of neurons making up the hidden layer will be 75% of the total inputs [8]. The number of network entries is 24, which is equivalent to the number of hours of the day with the highest consumption of a month, of the 49 months of the database, so that the number of neurons contained in the hidden layer will be 18 neurons.

In order to decide the number of neurons to be contained in the output of the neural network, it was established to use just one output neuron, because multiple output neural networks, especially if these outputs are widely spaced, will produce lower results compared to a single output network. It is recommended to have a specialized network for each of the desired outputs in each prediction.

In this study, the number of neurons in the network output layer will be one, because the research only intends to predict the value of the selected variable for the following month [9].

2.4.2 Transfer Function

This function is intended to prevent the exits from reaching very high values, which can paralyze the network and stop its training. The sigmoidal function (whose output range is between -1 and $+1$) was used as the transfer function, which is preferable for prediction tasks according to [7].

2.5 Evaluation Criteria

For the evaluation criteria to measure the network efficiency, the mean-squared error (MSE) was considered. The calculated mean-squared error is defined as the difference between the network output and the desired response, which is used as the completion factor of the training. For this phase, a parameter of 300 iterations was set, and the termination factor used from the MSE has a threshold value of 0.5 [10].

The network training uses the descending gradient technique immersed in the back-propagation algorithm. The neural network training will stop when any of the following variants occur:

1. The programmed number of iterations is reached.
2. If the evaluation function (MSE) falls below the stated goal.
3. If the error measured by the evaluation function is increased for a specific number of iterations (the latter case requires the existence of the validation set). In any case, the weights obtained are those found in the minimum error measured by the evaluation function [11].

2.6 Implementation of the Prediction Model with Neural Networks

In order to implement the proposed model, the procedure summarized in Table 1 [2] was carried out. In the table, the structure of the implementation and functioning of the neural network developed in MATLAB can be interpreted.

Figure 1 shows the training of the network once iteration 300 was reached, which

Table 1 Summary of data from the developed neural network

Pre-processed database	3125 measurements
Variable	kW
Data frequency	Monthly
Number of iterations	400
Number of data for neural network training	3.850
Number of data for neural network test	48
Number of input neurons	24
Number of hidden layers	1
Number of neurons hidden in each layer	18
Number of output neurons	1
Transfer function	Sigmoidal function
Error function	Quadratic mean error

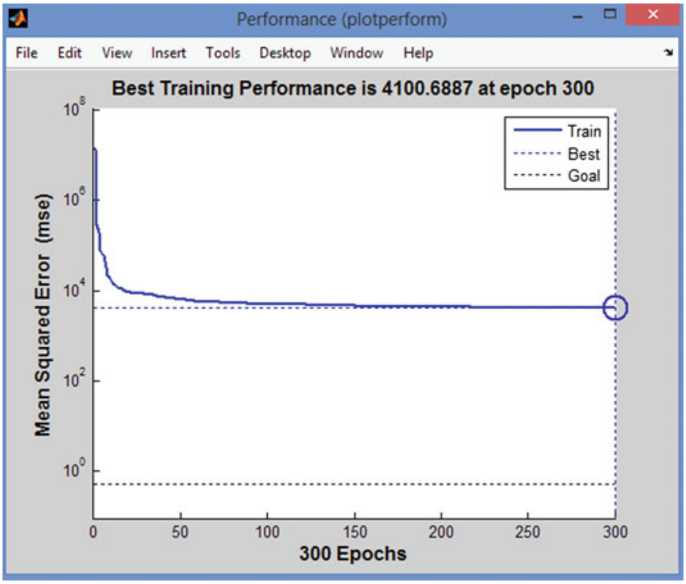

Fig. 1 Training performance

was the maximum number of iterations allowed, as the training stop condition. It is necessary to save the already-trained network to use it in the calculation of the error level. As the final data on the implementation of the neural network model, the following graphical results that measure the efficiency of the network are presented in Fig. 1.

Figure 2 shows that the correlation coefficient is quite high ($R = 0.99014$), which is very close to 1, so it can be said that there is a high correlation between real values (abscissa) and forecasts (oriented). The blue line indicates the points at which the real values coincide with or are equal to the predicted values [12].

2.7 Calculation of the Error of the Proposed Model

For the calculation of the neural network error, the remaining 48 records of electricity consumption from the database are used, which correspond to the last 2 months. These data will be used to determine the error level of the forecast of demand in the medium term (months). The prediction of the next 2 months (48 data) of demand, using the selected neural network, is compared with actual demand data to validate the developed neural network model. Tables 2 and 3 present the demand values for the last two months of the database and the values obtained with the prediction made by the implemented neural network [8].

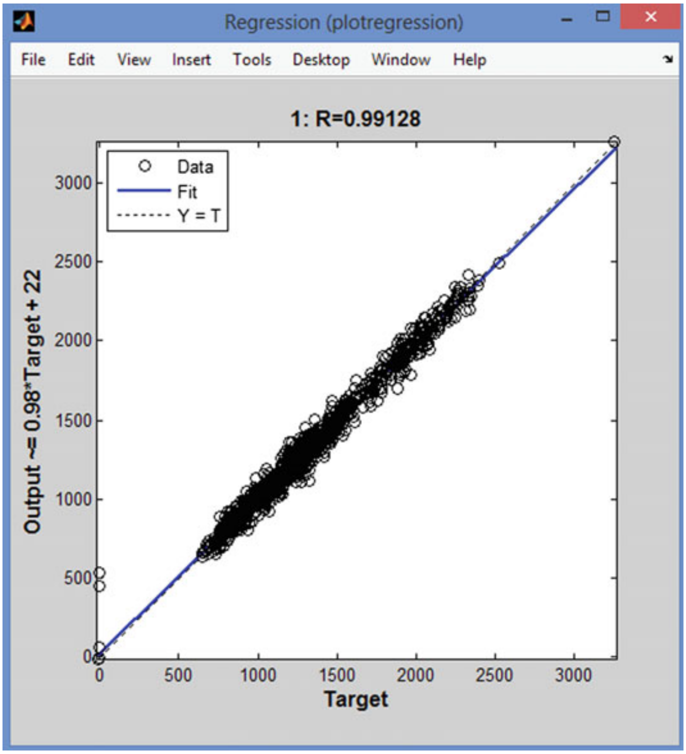

Fig. 2 Correlation between actual values and consumption forecasts

With the results obtained presented in Table 2, the behavior of the implemented neural network was evaluated and validated with a set of test data. The comparison is made between the predicted values and the actual consumption, the last two months of the database were taken as reference. Table 2 shows the accumulated forecast error for each case with a limit of 300 iterations in the network training.

3 Results

Through the validation of the neural network, it is possible to have an acceptable certainty margin to make the prediction of the possible electricity demand of the circuit under analysis for the following month by using the developed neural network. The procedure is described below.

In order to complete the forecasting, it is necessary to create a new database that includes the creation of an Excel sheet where the last month of consumption is located, in this case, the day of highest consumption of the month, which is equivalent to 24 data previous to those that will be predicted [13–16].

Table 2 Prediction of the last 48 electricity consumption data, applying the developed ANN

Month	Time	Actual consumption (kW)	Prediction (kW)	Relative error level (%)
August	1	2035	2014.41	−2.36
	2	1020	1002.23	−3.35
	3	952	958.30	+1.1
	4	952	968.11	+2.85
	5	987	1020.03	+4.36
	6	1254	1325.02	+3.58
	7	1520	1482.32	−2.8
	8	1352	1299.14	−2.5
	9	1254	1262.21	+0.68
	10	1140	1204.35	+3.5
	11	1547	1458.21	−4.3
	12	1685	1750.36	+3.85
	13	1585	1498.47	−3.54
	14	1895	1785.24	−2.4
	15	1547	1578.41	+0.9
	16	1547	1585.14	+1.1
	17	1458	1495.24	+1.3
	18	1487	1498.36	+0.5

Table 3 Next month's neural network forecast

Time	Feeder demand (kW)
1	2015.71
2	1012.33
3	959.40
4	978.71
5	1035.03
6	1347.12
7	1474.92
8	1289.14
9	1272.32
10	1214.41
11	1447.21
12	1796.33
13	1447.47
14	1736.24
15	1574.41
16	1569.15

When executing the developed code lines, the consumption forecast of the following month of the circuit under analysis is obtained. Table 3 shows the results obtained.

4 Conclusions

A forecast of daily-load consumption allows considerable money savings for the supplying companies, by generation and operation costs. In order to obtain a good result, it is necessary to reduce the forecast error to the minimum possible.

The results show the performance and accuracy of the neural networks for forecasting the demand in the short term, with minimal prediction errors.

Future research should evaluate the behavior of electricity demand considering data grouping techniques, in particular the cluster technique, to form a more compact and reliable database by eliminating atypical data and looking for a metrics of characteristic consumption curves to form the neural network database.

References

1. Hu, C., Du, S., Su, J., et al.: Discussion on the ways of purchasing and selling electricity and the mode of operation in China's electricity sales companies under the background of new electric power reform. Power Netw. Technol. **40**(11), 3293–3299 (2016)
2. Xue, Y., Lai, Y.: The integration of great energy thinking and big data thinking: Big data and electricity big data. Power Syst. Autom. **40**(1), 1–8 (2016)
3. Wang, Y., Chen, Q., Kang, C., et al.: Clustering of electricity consumption behavior dynamics toward big data applications. IEEE Trans. Smart Grid **7**(5), 2437–2447 (2017)
4. Rong, L., Guosheng, F., Weidai, D.: Statistical Analysis and Application of SAS (China Machine Press, 2011)
5. Sanchez, L., Vásquez, C., Viloria, A., Meza-Estrada, C.: Conglomerates of Latin American countries and public policies for the sustainable development of the electric power generation sector. In: Tan, Y., Shi, Y., Tang, Q. (eds.) Data Mining and Big Data. DMBD 2018. Lecture Notes in Computer Science, vol. 10943. Springer, Cham (2018)
6. Sánchez, L., Vásquez, C., Viloria, A., Rodríguez Potes, L.: Greenhouse gases emissions and electric power generation in Latin American countries in the period 2006–2013. In: Tan, Y., Shi, Y., Tang, Q. (eds.) Data Mining and Big Data. DMBD 2018. Lecture Notes in Computer Science, vol. 10943. Springer, Cham (2018)
7. Perez, R., et al.: Fault diagnosis on electrical distribution systems based on fuzzy logic. In: Tan, Y., Shi, Y., Tang, Q. (eds.) Advances in Swarm Intelligence. ICSI 2018. Lecture Notes in Computer Science, vol. 10942. Springer, Cham (2018)
8. Perez, R., Vásquez, C., Viloria, A.: An intelligent strategy for faults location in distribution networks with distributed generation. J. Intell. Fuzzy Syst. Preprint 1–11 (2019)
9. Ghia, A., Rosso, A.: Análisis de respuesta de la demanda para mejorar la eficiencia de sistemas eléctricos, 2nd edn. Camara Argetina de la Construccion, Buenos Aires (2009)
10. Pérez Arriaga, J.I., Sánchez de Tembleque, L.J., Pardo, M.: La gestión de la demanda de electricidad vol. I, no. I (2005)

11. Silva, V., Jesús, A.: Indicators systems for evaluating the efficiency of political awareness of rational use of electricity. In: Advanced Materials Research, vol. 601, pp. 618–625. Trans Tech Publications (2013)
12. Perez, R., Inga, E., Aguila, A., Vásquez, C., Lima, L., Viloria, A., Henry, M.A.: Fault diagnosis on electrical distribution systems based on fuzzy logic. In: International Conference on Sensing and Imaging, pp. 174–185). Springer, Cham (2018)
13. Ozger, M., Cetinkaya, O., Akan, O.B.: Energy harvesting cognitive radio networking for IoT-enabled smart grid. Mob. Netw. Appl. **23**(4), 956–966 (2017)
14. Bradley, P., Fayyad, U., Mangasarian, O.: Mathematical programming for data mining: formulations and challenges. Informs J. Comput. **11**, 217–238 (1999)
15. Rahmani, A.M., Liljeberg, P., Preden, J., Jantsch, A.: Fog Computing in the Internet of Things. Springer, New York (2018). ISBN 978-3-319-57638-1, ISBN 978-3-319-57639-8 (eBook)
16. Abualigah, L.M., Khader, A.T., Al-Beta, M.A., Alomari, O.A.: Text feature selection with a robust weight scheme and dynamic dimension reduction to text document clustering. Expert Syst. Appl. **84**, 24–36 (2017)