# Electricity Demand Prediction using Artificial Backpropagation Resilient Neural Networks

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## SUMMARY

The research presented proposes a new model for predicting electricity demand based on artificial neural networks with the Backpropagation Resilient algorithm. The aim of the research is to evaluate the accuracy of this model compared to a previous model based on artificial neural networks with the traditional Backpropagation algorithm.

A field observation was made and 70128 observations of electricity demand were collected. Of these, 61344 were used to train the model and 8784 were used to assess its accuracy. After preprocessing data to correct for missing and atypical data, the results of both models were compared in terms of mean absolute error percentage (MAPE).

The Backpropagation Resilient neural network-based model was found to have an ASM of 2.47%, while the traditional Backpropagation-based model obtained an ASM of 2.63%. These results suggest that the Backpropagation Resilient neural network-based model is more accurate than the traditional Backpropagation-based model.

In conclusion, the results of this research suggest that the model based on the Backpropagation Resilient neural network is a more accurate option to predict the demand for electrical energy and it is recommended to perform an adequate preprocessing of the data before designing any neural model to obtain better results. Importantly, the research presented must be replicated and validated by other studies before it can be applied in the electric power industry.

***Keywords: Artificial neural networks; prediction model; Demand electricity.***

## ABSTRACT

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In conclusion, the results of this research suggest that the model based on the Backpropagation Resilient neural network is a more accurate option for predicting electrical energy demand and it is recommended to perform proper data preprocessing before designing any neural model to obtain better results. It is important to note that the research presented must be replicated and validated by other studies before it can be applied in the electrical energy industry.

**Keywords: Artificial Neural Networks; Prediction Model; Electric Power Demand**

## INTRODUCTION

Predicting electricity demand is a process that involves the future estimation of the amount of energy that will be needed to meet the needs of a region or country. This is done through the analysis of different factors, such as economic growth, demographics, technology, consumption patterns, among others. The accuracy of these predictions is important for the planning and construction of energy infrastructures, as well as for decision-making on power generation and distribution, (Ariza, 2013)andthere are numerous advantages for using neural networks for electricity demand prediction:

- Power generation planning: An accurate prediction of electric power demand would allow power generation to be planned more efficiently and ensure that enough energy is available to meet demand.
- Improving energy efficiency: Knowing the expected demand, measures can be taken to optimize energy use and improve overall energy efficiency.
- Cost reduction: An accurate prediction of energy demand can help reduce the costs associated with power generation and distribution, as steps can be taken to prevent excessive or insufficient energy production.
- Improving energy resilience: Predicting energy demand can also help improve energy resilience, i.e. the ability of the power grid to remain operational in the event of disruptions or disasters.

In summary, predicting electricity demand is essential for efficient energy management and for improving the security and resilience of the electricity grid.

There is several research published in scientific journals and conferences that use artificial neural networks based on Backpropagation to predict the demand for electrical energy. Here are some examples:

Recent research published in the Journal of Ambient Intelligence and Humanized Computing used an artificial neural network to predict real-time electrical power demand in a residential environment. The results showed high accuracy in predicting energy demand compared to other traditional methods.(Fong, and others, 1018)

Other research, published in Energy and Buildings, used (RNN) to predict electricity demand at the household level. The results also showed high accuracy in predicting energy demand and suggested that RNNs are an effective tool for managing energy demand in residential environments. (Skomski, et al., 2020)

"Forecasting electricity demand using Artificial Neural Networks: A comparative study with ARIMA" published in the journal Energy Conversion and Management. In this study, the authors compared the accuracy of predicting electrical energy demand using an artificial neural network with a conventional ARIMA model and found that the neural network was more accurate, (Hsiao-Tien, 2007).

"A neural network approach for electricity demand forecasting" published in the journal Expert Systems with Applications. In this study, the authors proposed an approach based on artificial neural networks to predict electricity demand and applied it to a real dataset from a power supply company. The results showed that the neural network was effective in predicting the demand for electrical energy, (Lee, 2009)

"Forecasting hourly electricity consumption using backpropagation neural network" published at the International Conference on Computer and Information Science (2011). In this study, the authors proposed an artificial neural network based on Backpropagation to predict the demand for electrical energy at the hourly level and demonstrated its effectiveness compared to an ARIMA model.

These studies demonstrate that neural networks can be an effective tool in predicting electricity demand and may have applications in optimizing energy generation and distribution

## METHODOLOGY

In this research work, a quantitative approach to research is adopted, experimental and descriptive research methods are applied in order to establish the potential effect of a manipulated variable, (Publishing, 2000)last but not least, statistical analysis was used allowed the interpretation of the results and the comparison of the accuracy of the predictions with the actual demand for electrical energy. In addition, indicators such as the percentage of prediction error were calculated, which allow evaluating the effectiveness of the machine learning models used in the research.

The following is an overview of the steps taken to implement an electric power demand prediction solution using artificial neural networks:

**Data collection and preprocessing:** The first stage was to collect historical data on electrical energy demand and preprocess it to ensure that it is in a format suitable for use in the neural network. This process included removing outliers and normalizing the data to be in a similar range.

In order to technically confirm the presence of outliers in the time series of electrical energy demand and temperature, three fundamental statistical techniques were applied: the box plot, the quartile method and the Grubbs test. The results of this application revealed the existence of 406 missing or unrecorded values and 320 outliers in the time series of electrical energy demand and temperature, as shown in Figure 2. (Ariza, 2013)

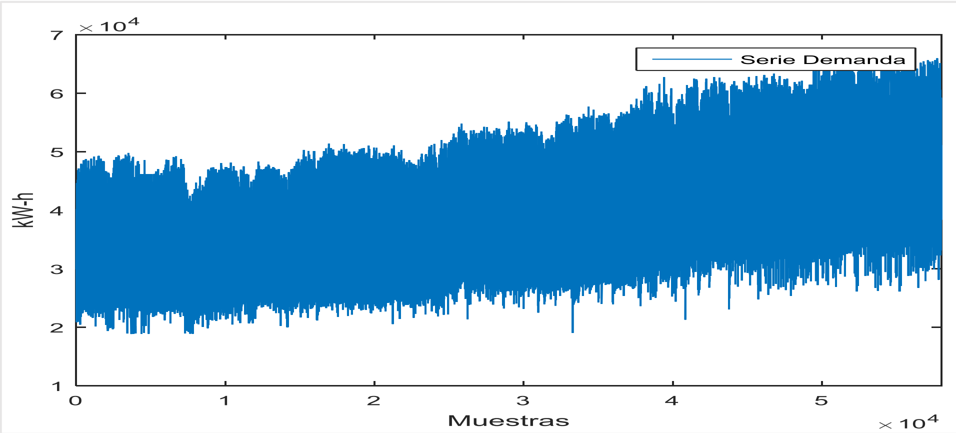


Figure 1: Time series of electricity demand without outliers.
Source: Made by: Iván Sinaluisa

In the context of this research, the decision was made to eliminate observations that presented missing and outliers, given that the percentage of such values was 0.58%. As a result, the database was composed of 60,618 observations.

In this research work, a database of 60,618 observations collected from the energy meters of three outputs belonging to the electric company of the center of the country, responsible for the transmission of electrical energy in the national interconnected system, was used(Centrosur, 2016).

The database was divided into two groups with a specific goal, the first group composed of 87% was used for neural network training, while the second group composed of 13% was used to test the operation of the model.

**Selection of input attributes: As a** next step, the input attributes to be used as input for the neural network were selected, in this research, the Pearson correlation method (r) was used to (Sampieri, 2010) identify the variables that have a direct or indirect impact on the demand for electrical energy. These variables include: temperature, humidity, date, time of day, day of the week and an indicator that indicates whether it is a holiday or weekend. Based on these variables, a matrix of predictor variables was constructed that were used as inputs in the neural network model.

**Neural network architecture design:** The third stage was the design of the neural network architecture, which would include selecting the number of hidden layers, the number of neurons in each layer, the activation function, etc.

The geometric pyramid rule for sizing the number of neurons in the hidden layer of a neural network is based on the idea that the number of neurons should decrease as you move into the deeper layers of the network. The proposal states that the minimum number of neurons in the hidden layer can be calculated from the following equation:(Masters, 1993)

$$n = \frac{n\ entrada + n\ salida}{2}$$

Where "n_entrada" represents the number of neurons in the input layer and "n_salida" represents the number of neurons in the output layer. The idea behind this formula is that the number of neurons in the hidden layer should be an intermediate number between the number of neurons in the input layer and the number of neurons in the output layer.

However, it is important to note that this formula is not a strict rule and that more or fewer neurons may be needed in the hidden layer depending on the complexity of the problem and the amount of data available to train the network. In addition, it is also possible to use more than one hidden layer with different numbers of neurons in each of them to achieve better performance.

The method of best local minima proposed by Branch and Valencia (2006) is a more sophisticated approach to sizing the number of neurons in the hidden layer of a neural network. This method is based on the technique proposed by Ash and Hirose, which consists of a dynamic and forced search for the best local minimums.

In this method, the network error is evaluated after each workout and if the error is below the expected value, a new neuron is added to the hidden layer. On the other hand, if the error is zero or very close to zero, a neuron is removed. In this way, it seeks to find the optimal number of neurons that allows obtaining an acceptable error without falling into overfitting.

The method of the best local minima is more sophisticated than the rule of the geometric pyramid proposed by Masters (1993), since it allows dynamically adjusting the number of neurons depending on the error obtained in the training, which can improve the accuracy and efficiency of the network. However, it is also important to note that this method can be more computationally expensive than the geometric pyramid rule, as it requires a dynamic search and error evaluation after each workout.

The FeedForward Backpropagation resilient neural network selected for this research paper has a specific architecture that has been optimized to predict electrical energy demand. This architecture is shown in Figure 3, and its main features are: it has 8 inputs that correspond to the predictor variables, 1 hidden layer with 27 neurons, 1 output layer that corresponds to the predicted electrical energy demand, specific activation functions for each layer, sigmoid (tagsig) for the hidden layer and the linear function (purelin) for the output layer, two error functions to evaluate performance: the mean square error

(MSE) and absolute percentage mean error (MAPE) and a specific learning function resilient backpropagation ('trainrp'). (Cortina Januchs, 2012)
This architecture has been optimized to predict electrical energy demand as accurately as possible as shown in Figure 2.

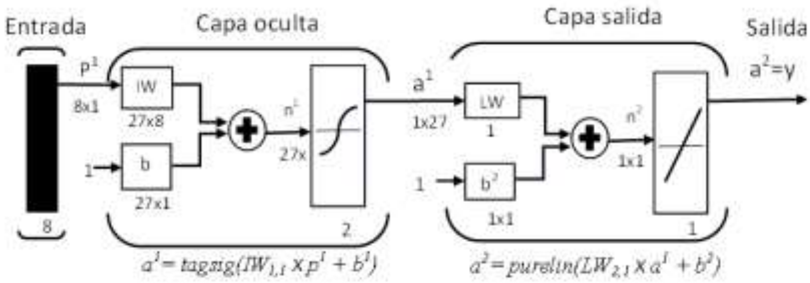


Figure 2: Neural Network Architecture
Source: Conducted by: Iván Sinaluisa from (Demuth, 2002).

**Neural network training:**
For the training of the neural network, the Resilient Backpropagation technique, a variant of the backpropagation algorithm, was used. The goal of this technique is to minimize the error function by finding the right weights and bias by adjusting neural network weights during training.
Figure 3 shows the evolution of the learning of the Neural Network, where it can be seen that optimal performance is achieved in 153 interactions out of a total of 159 performed. Therefore, it can be concluded that the training is effective and suitable for this case.

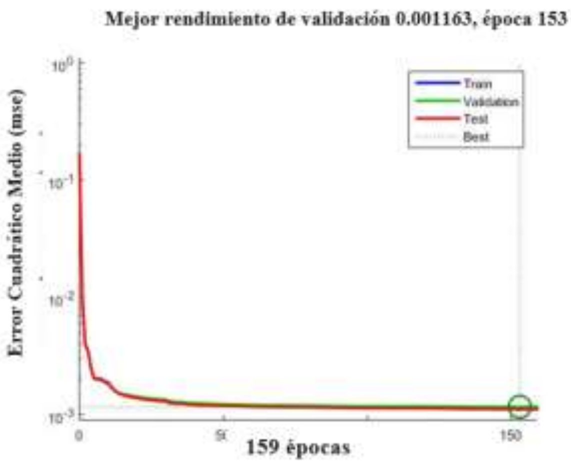


Figure 3: Training performance of the Neural Network.
Source: Made by Iván Sinaluisa

In addition, the correlation coefficient obtained in the training is 0.98473, which indicates a strong correlation between the actual observations and the values predicted by the neural network, since this value approaches 1.

**Neural network evaluation and testing:** The metrics used to evaluate the accuracy of the neural network model in the sample period were Absolute Mean Error Percentage (MAPE) and Pearson correlation coefficient (r). The application of ASM made it possible to assess the magnitude of the error in percentage terms, while Pearson's correlation coefficient indicated the linear correlation between actual and predicted values. A model with a low ASM and a high Pearson correlation coefficient would be considered accurate in predicting the results, (Technological University of Pereira, 2013).

The MAPE (Absolute Mean Error Percentage) is a metric widely used in the evaluation of forecasting models to measure the accuracy of predictions. It is calculated as the arithmetic mean of the absolute ratio between the error (difference between the actual value and the predicted value) and the actual value, multiplied by 100. This gives a measure of the difference between the predicted value and the actual value in relative terms and allows the magnitude of the error to be assessed in percentage terms.

$$MAPE = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{y'_t - y_t}{y_t}\right| \qquad (2)$$

Where

n is the number of observations considered

YT is the real demand

y't is the demand estimated by the model.

The Pearson correlation coefficient (r) is a statistical measure that measures the linear correlation between two variables. This coefficient ranges from -1 to 1, where a value of 1 indicates a perfectly positive correlation, a value of -1 indicates a perfectly negative correlation, and a value of 0 indicates that there is no linear correlation between the variables.

$$r = \frac{n\sum_{i=1}^{n}(y'y) - [\sum_{i=1}^{n} y'][\sum_{i=1}^{n} y]}{\sqrt{\left[n\sum_{i=1}^{n} y^2 - [\sum_{i=1}^{n} y^2]\right]\left[n\sum_{i=1}^{n} y'^2 - [\sum_{i=1}^{n} y'^2]\right]}}$$

## RESULTS AND DISCUSSION

The next section refers to the results of an experiment that compared the performance of a prediction model trained with preprocessed data versus prediction model with non-preprocessed data. It was observed that the model trained with preprocessed data presented a better performance, with an improvement of approximately 2%. In addition, the correlation coefficient (R) was closer to 1, indicating a higher linear correlation between actual values and predicted values as shown in Table No.1

Table 1: Comparison model with preprocessed data and model with unprocessed data

| DATA | MAE (kw-h) | MAP (%) | YIELD(%) | R |
|---|---|---|---|---|
| **Preprocessed smoothing MM5** | 1085,81 | 2,63 | 97,37 | 0,98555 |
| **MM3 preprocessor and smoothing** | 1308,05 | 3,17 | 96,83 | 0,98221 |
| **Unsmoothed pre-processed** | 1394,30 | 3,34 | 96,66 | 0,98185 |
| **No Preprocessing** | 2099,57 | 4,81 | 95,19 | 0,93737 |

Clearly it can be seen in table 2, the model based on Backpropagation Neural Networks (RNA) has better performance than the model based on Resileint Backpropagation (RNAR), trained, validated and tested with the same historical data. The RNAR model obtained an average of 97.53% performance compared to 97.37% of the RNA model.

Table 2: Comparison models with Backpropagation vs Resilient Backpropagation Neural Networks

| **METRICS** | **MAP (%)** | | **Performance (%)** | | **Pearson correlation** | |
|---|---|---|---|---|---|---|
| **MY** | RNA (learngdm) | RNAR (trainrp) | RNA (learngdm) | RNAR (trainrp) | RNA (learngdm) | RNAR (trainrp) |
| **January** | 3,27 | 3,06 | 96,73 | 96,94 | 0,97 | 0,98 |
| **February** | 2,85 | 2,74 | 97,15 | 97,26 | 0,97 | 0,97 |
| **March** | 2,89 | 2,58 | 97,11 | 97,42 | 0,97 | 0,98 |
| **April** | 2,34 | 2,26 | 97,66 | 97,74 | 0,98 | 0,97 |
| **May** | 2,42 | 2,22 | 97,58 | 97,78 | 0,98 | 0,98 |
| **June** | 2,40 | 2,36 | 97,60 | 97,64 | 0,98 | 0,98 |
| **July** | 2,43 | 2,36 | 97,57 | 97,64 | 0,98 | 0,98 |
| **August** | 2,59 | 2,40 | 97,41 | 97,60 | 0,98 | 0,98 |
| **September** | 2,38 | 2,32 | 97,62 | 97,68 | 0,98 | 0,98 |
| **October** | 2,59 | 2,45 | 97,41 | 97,55 | 0,98 | 0,99 |
| **November** | 2,50 | 2,42 | 97,50 | 97,58 | 0,98 | 0,98 |
| **December** | 2,88 | 2,50 | 97,12 | 97,50 | 0,97 | 0,98 |
| **MEDIA** | 2,63 | 2,47 | 97,37 | 97,53 | 0,98 | 0,98 |

## CONCLUSIONS

- The review of models for the prediction of electricity demand carried out in this research allowed to determine the limitations of traditional models and to select a prediction model based on more efficient neural networks, which was considered more accurate and suitable for the task of predicting electricity demand.
- The preprocessing allowed to obtain optimal results of the chosen prediction model, since the data used to train the model must be accurate, consistent and representative of the problem to be solved.
- The results of this research suggest that the Backpropagation Resilient neural network-based model is a more accurate option for predicting electrical energy demand compared to the traditional Backpropagation neural network-based model .

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