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A Method for the Monthly Electricity Demand Forecasting in Colombia based on Wavelet Analysis and a Nonlinear Autoregressive Model

Método para la Predicción de Demanda Mensual de Electricidad en Colombia utilizando Análisis Wavelet y Modelos Auto-regresivos No Lineales

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Abstract

This paper proposes a monthly electricity forecast method for the National Interconnected System (SIN) of Colombia. The method preprocesses the time series using a Multiresolution Analysis (MRA) with Discrete Wavelet Transform (DWT); a study for the selection of the mother wavelet and her order, as well as the level decomposition was carried out. Given that original series follows a non-linear behaviour, a neural nonlinear autoregressive (NAR) model was used. The prediction was obtained by adding the forecast trend with the estimated obtained by the residual series combined with further components extracted from preprocessing.

A bibliographic review of studies conducted internationally and in Colombia is included, in addition to references to investigations made with wavelet transform applied to electric energy prediction and studies reporting the use of NAR in prediction.

Key words: electric load forecasting; nonlinear autoregressive neural model; time series forecasting; wavelet transform analysis.

Resumen

En este artículo se propone un método para la predicción mensual de la demanda en el Sistema Interconectado Nacional Eléctrico de Colombia. El método realiza preprocesamiento de la serie de tiempo utilizando un análisis multiresolución mediante tranformada *wavelet* discreta; se presenta un estudio para la selección de la *wavelet* madre y su orden, asi como del nivel de descomposición. Dado que originalmente la serie tiene comportamiento no lineal, se utilizó igualmente un modelo no lineal autoregresivo. La predicción se obtiene añadiendo a la tendencia, el estimado obtenido con el residual de la serie combinado con otros componentes extraídos durante el preproceamiento.

Se incluye una revisión bibliográfica de investigaciones realizadas internacionalmente y en Colombia en relación a la aplicación de la transformada *wavelet* y el modelo autoregresivo no lineal a la predicción de energía eléctrica.

Palabras clave: predicción de carga eléctrica; modelo neuronal no lineal autoregresivo; predicción en series de tiempo; análisis con transformada *wavelet*.

1. Introduction

Electricity is considered to be the basis for the progress of civilization, hence its great importance as a tool for the technological advance and economic development of society. Optimizing its distribution in terms of users and economic cost is currently a hot topic of research.

Different models for electric energy demand forecasting have been proposed in recent decades, which play an important role in economic planning and safe operation of modern power systems [2]. These models can be divided into two categories: the first includes the traditional algorithms of load forecasting, including time series analysis, regression and gray models. In the second category includes latest algorithms for load forecasting such as neural networks, and intelligent expert systems. These have been proposed as alternatives for improving prediction in electricity demand [3]. Various articles have shown better results for the nonlinear models such as neural networks when compared with traditional linear statistical models (gray [3], ARIMA [4, 5] and SARIMA [6]). As so, the focus of this paper is to apply neural network models for electricity time series forecasting.

On the other hand, several studies [7, 8] have concluded that a multi-resolution wavelet analysis (MRA) applied to a neural network for load forecasting has better performance rates than the same procedure on a statistical linear autoregressive model. However the computational costs are increased - especially when there is a large amount of data. The use of MRA as preprocessing has improved the performance of forecasting compared with those who do not use preprocessing [9, 10, 11].

One important feature of the prediction is the so-callled “horizon”. This refers to the period of time measured from a given instant in which the prediction is performed. This horizon determines the future time for which to perform the prediction [12]. Several authors have proposed different definitions: short-term going from several minutes up to one week [2, 5, 13, 14]; medium-term from one to five years [2, 5, 13, 14, 15]; and long-term from one to twenty years [2, 13, 15].

Likewise, the reported studies have used two different techniques to model the input data: the univariate technique, which considers as inputs only past consumption of electricity, and the multivariate, which include exogenous variables related to electricity demand. These include the climate, variables related to alternative fuels (natural gas, gasoline, oil, diesel, etc.), gross domestic product (GDP), population growth and technological advances aimed at the efficient use of energy [4, 11, 14, 16].

It is important to remark that those generating electricity make use of demand forecasting for production planning, deciding on their investments, defining their contracts and hedging their risks. Transporters and distributors use it to design their facilities. For marketers, demand forecasting is a basic and essential tool for buying and selling energy [14, 11]. Thus, a good prediction of demand brings both technical and financial benefits to all stakeholders involved in the electricity sector, including users [13].

The aim of this paper is to review studies on the international scope for forecasting monthly demand for electric energy using neural networks along with local studies in relation to the National Interconnected System (SIN) of Colombia. Additionally, it includes analysis of studies with wavelet transform in temporal series as well as studies in forecasting with nonlinear autoregressive (NAR) neural model. The features in each case are evaluated and different models and conclusions are reported in order to subsequently proposing a time-series forecasting model to be applied to monthly forecasting of power needs of the Colombian SIN.

2. State of the art

This review begins with those studies of energy demand forecasting with a monthly horizon [6, 4, 17]. Then the articles in energy consumption prediction are evaluated with wavelet analysis. Finally investigations with neural model NAR in time series forecasting are evaluated. In each work reviewed, the prediction horizon, the technique of data, pre and post-processing, the forecast model, the application and the recommendations are evaluated.

2.1. Electricity demand forecasting worldwide

Figure 1 shows the forecasting studies of monthly electric demand reported worldwide in scientific literature over the past several years.

To begin with, let us review some studies in neural networks that were designed to compare two or more models and evaluate them according to their performance. Guiassi et al. [5] in 2006 used an artificial neural network dynamics (DAN2) and the autoregressive model integrated moving average (ARIMA). They found that the proposed DAN2 network presented higher performance against the other architectures. Similarly in Abdel-Aal [2], an abductive network model and a neural network trained with back propagation (BP) using a univariate series were compared. This study concluded that the abductive model had greater predictive ability using less data. In 2010 Xia et al. [18], compared a neural network trained with back propagation BP, a network of generalize regression (GR) and a RBF network. They concluded that the model based on RBF has greater stability in the short, medium and long term forecasting.

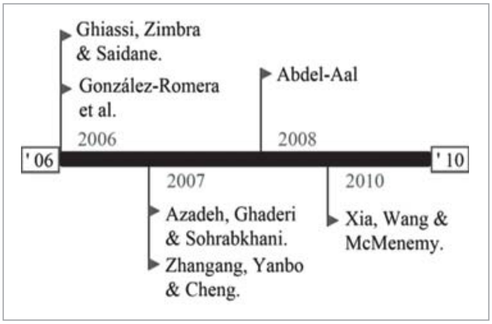

Figure 1. Baseline of studies reported in the worldwide in electricity demand forecasting.

Zhangang et al. [3] in 2007 implemented different hybrid models. They presented results of a load forecasting system based on neural networks radial basis function (RBF), in conjunction with a genetic algorithm (GA) to optimize the parameters of the radial basis functions, achieving better performance relative to the statistical gray model.

Some works used preprocessing of source data such as those presented by González-Romera et al [13] in 2006. They divided the original time series into two new series: the trend line and fluctuation about the trend line. Then, two neural networks were trained independently to forecast each separately. The final prediction is obtained from the sum of the predictions. In the case of the trend, they present a study of a moving average filter with spline smoothing. They concluded that the trend extraction process offers great improvement in accuracy of electricity demand forecasting using neural networks, and that it achieves the best performance with the RBF neural network, outperforming the MLP results and the statistical method ARIMA. Similarly, Azadeh et al. [19] in 2007 conducted a pre-processing of time series to extract the trend and seasonality using moving average. The prediction was performed using an MLP model and analysis of variance (ANOVA). They achieved better results when input data was conditioned to pre-processing.

2.2. Electricity demand forecasting in Colombia

In Colombia the official institute responsible for submitting the projection of electricity demand is *Unidad de Planeación Minero Energética* (UPME). Their approach takes into account recent trends in demand during the year as well as the econometric models that make use of exogenous variables. These variables include gross domestic product (GDP), electricity rates, population growth and more recently, new macroeconomic scenarios provided by the National Planning Department (DNP) and Ministry of Finance and Public Credit (MHCP). The final forecast is obtained by disaggregating the annual demands monthly in ARIMA statistical models and considering an average annual growth rate constant [1, 16]. As with the international studies, recent demand studies specific to Colombia are summarized in Figure 2.

A study with a monthly horizon was reported by Medina and Garcia in 2005 [20]. They compared an MLP with and without the use of a principal component analysis (PCA) to an adaptive neuro-fuzzy inference system (ANFIS). They concluded that the best performance was obtained with the MLP model without the use of PCA and they also showed that the training algorithm significantly influenced the error (precision) and the processing time.

Franco et al. [1] in 2008 presented the characterization of the monthly demand for electricity in Colombia. Their results indicated that the demand has a seasonal pattern with a deterministic annual period and a stochastic long term trend sustained growth since 2000. Subsequently, Velásquez et al. [4] in 2009 compared a statistical ARIMA model, an MLP network and an autoregressive (AR) neural network. This work corroborated that the series reflects seasonality and trend. These were removed using simple differentiation and seasonal differencing within a period of twelve months. They concluded that the AR neural network represents the best combination of performance and predictive capability, mainly given the nonlinearity of the series.

Figure 2. Baseline of studies reported in Colombia in electricity demand forecasting.

Similarly to [4], Rueda [6] in 2011 studied forecasting electricity demand of the Colombian SIN using a series that only considers the last entries of demand. First they applied simple differentiation to the series in order to remove the trend and after that seasonal differentiation with a period of twelve months to eliminate repetitive cyclic patterns. To make the forecast, they evaluated five nonlinear models. The statistical models evaluated included a seasonal model autoregressive integrated moving average (SARIMA), a multivariate adaptive regression model using splines (MARS) and a smooth transition regression (STR) model. The models based on artificial neural networks included a DAN2 network and a generalized single multiplicative neuron (GSMN) model.Lastly, they proposed a hybrid model combining SARIMA and a simple multiplicative neuron, called SARIMA-GSMN, which showed the best results compared to the performance achieved by [1, 4].

2.3. Wavelet analysis applied in the time series forecasting

After reviewing electric demand forecasting studies reported worldwide and in Colombia, we review the different studies performed with wavelet analysis applied to monthly electric energy demand forecasting, as summarized in Figure 3. We consider the method used in relation to the wavelet transform, the results and conclusions.

The wavelet analysis has been used mainly in two respects: the first focused on the pre-processing of time series, and the second focused on evaluating the parameters of a neural network.

With respect to the pre-processing of the time series, the wavelet transform is used to determine its trend and high frequency components. Some authors associate the high frequency components to noise signals, and removed them before processing. This is the case of Rocha Reis &Alves da Silva [21] and Pandey et al. [10]; both papers combine a multi-resolution analysis (MRA) with a wavelet transform to eliminate the components associated with high frequencies.

Other authors also used the wavelet transform to pre-process the signal, but differ from the previous ones by considering all components in the prediction, including high frequencies. Benaouda and Murtagh [7] in 2006 compared the performance of different models including an AR, an MLP and a generalized regression neural network (GRNN) models. They evaluated each of them with and without multilevel wavelet decomposition, in the same way Benaouda et al. [8] compared these models and added an Elman recurrent neural network (ERN). Experimental results have shown that nonlinear models based on wavelet ERNw and MLPw mostly outperform the multi-resolution wavelet analysis of the linear model (MAR). However, these two nonlinear methods are very slow, especially when training with relatively large data sets.

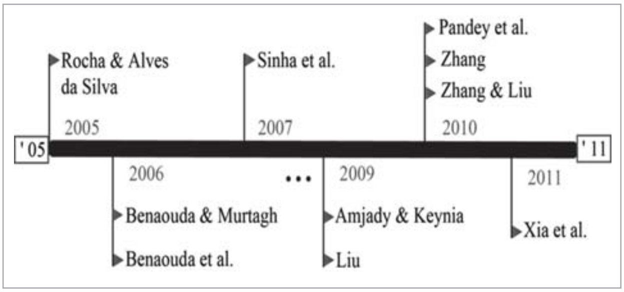

Figure 3. Baseline of studies reported using wavelet analysis applied to the time series forecasting.

Later in 2007, Sinha et al. [22] formulated a hybrid scheme that consists basically of three steps. The first step is the time series decomposition with wavelet analysis. In the second step, all the previously decomposed series are processed by the RBF model. In the third and final step, all the outputs from the previous step are combined and by using another RBF network, the final prediction is given. Meanwhile the number of inputs, centers, and spread factor of the RBF model were determined by using a genetic algorithm.

In 2009, Amjady and Keynia [23] decomposed the time series into three levels of detail. At each level exogenous variables were considered and forecasted separately by means of a hybrid between an MLP and an evolutionary algorithm. The final outcome was obtained by reconstructing the series with the wavelet inverse transform.

Some authors suggest that, the best way to make a forecast is through the combination of different models. The key is to know and determine the strength of each model for optimizing the results. Several studies are based on this premise. Xia et al. [11] in 2011 performed the wavelet decomposition of a time series into three levels with each level being predicted independently by a BP network. The final outcome was obtained by summing the three predictions.

Other studies have used the wavelet transform for activating the hidden layer neurons instead of using a nonlinear sigmoidal function. This model is called wavelet neural network, and is compared in different studies with one or several different models. An example of this is the work done by Liu [24]. In 2010, Zhang [25] and Zhang and Lu [26] proposed a new method of fuzzy rules with a wavelet neural network model for mid/long term load forecasting. First, they proposed the fuzzy rules and then used genetic algorithms to find the appropriate structure and parameters of the fuzzy logic systems. As a last step they used a wavelet neural network to perform the forecasting.

2.4. Nonlinear autoregressive model applied to time series forecast

We complete the review with studies on nonlinear autoregressive (NAR) neural models, applied to the prediction of time series. These methods are presented as baseline in Figure 4.

Here we find the use of NAR models and its extension, which considers exogenous variables (NARX) in predicting different types of time series for various applications. First, we will recall studies regarding NAR networks in electricity demand forecasting which, because of their relevance are the basis for further studies. Then we will discuss research reporting successful results in the use of NAR. After that we will consider studies that compare the NAR neural model with similar models, including neural and statistical

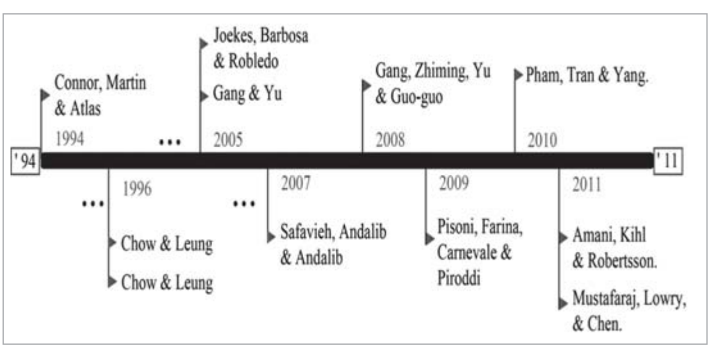

Figure 4. Baseline studies reported in NAR models applied to time series forecasting.

prediction and hybrid models. Finally, we will consider the latest works that reaffirms the improvements obtained with the NAR neural network over similar models.

Let us start by mentioning the work of Connor, Martin y Atlas [27] in 1994, that became one of the first to approximate a nonlinear autoregressive neural model (NAR), designed from a statistical model ARMA using a feed-forward network. Their study showed that NAR is a recurrent network, adequate to predict electrical demand. However the input configuration is critical for good performance.

Later, Chow and Leung [28, 29] presented a nonlinear autoregressive integrated (NARI) neural network model applied to load forecasting. This model included variable climate compensation coupled at the end of the neural network, which in this case reflects an improvement in the prediction model compared to the traditional NAR.

Both Gang and Yu [30] in 2005 and Amani et al. [31] in 2011 presented a NAR neural model. The model showed results very similar to the actual values. Its implementation was simple, although it had nonlinear characteristics.

Different studies have compared the NAR model performance, against other models or included a self-assessment. Joekes et al. [32] in 2005 presented two approaches using the NAR and ARMA models. The first one applied a statistical version, while the second approach applied a neural network. Although both showed very good results, the neural network model showed better performance. They concluded that analysis of time series using neural networks outperforms in this case statistical models.

Similarly, Pisoni et al. [33] in 2009 analyzed the potential benefits of using a NARX polynomial model (statistical nonlinear black box modeling) as opposed to the NARX neural network model. The results show that the NARX polynomial model performance is similar to, but not superior to that of models based on NARX neural networks.

Safavieh et al. [34] in 2007 emphasized the superiority of a NAR neural model over an AR neural model for various reasons. The AR uses a linear transformation on time series and estimates the model parameters using simple static methods. While the NAR is a nonlinear model that estimates the future values of the time series based on more recent data, the NAR also uses a nonlinear structure and neural network to estimate the model parameters.

The following year, Gang et al. [35] compared the neural network NAR model against two training techniques: a BP algorithm and a node-decoupled extended Kalman filter (NDEKF). They found the first one to be faster and more stable, and it performed better in the prediction.

A NARX-ARMA hybrid model presented by Pham et al. [36] in 2010, took advantage of the characteristics of the NARX neural model, which is more suitable for nonlinear sections, and an ARMA model, which was used to predict the error component in the linear prediction. They concluded that the NARX-ARMA model could be used as a potential tool for different forecast applications.

Finally Mustafaraj et al. [37] in 2011 presented a study that validated the claims made by Pisoni et al. [33] by comparing a linear autoregressive with external inputs (ARX) model and a NARX neural network. The results obtained with the NARX model were better than the ARX model because the series was governed by nonlinear equations.

3. Proposal for monthly electricity demand forecast

This section presents a method for the monthly electric demand forecast in the Colombian National Interconnected System (SIN). The method consists of several stages according to the recommendations presented in the literature review previously carried out.

3.1. General structure

The general configuration of the method consists of three stages, as seen in Figure 5,along with the modeling reported by [38] and the time series decomposition reported by [39, 40, 41].

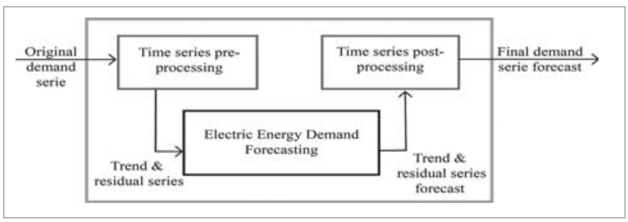

Figure 5. General structure of the proposed model in electricity demand forecast.

The input stage involves preprocessing the series of electric power demand; the second stage takes the pre-processed series and performs the prediction. The post-processing stage performs an inverse operation to obtain the final demand series forecast. A more detailed depiction of these stages is given in Figure 6. A discussion of each stage is explained next.

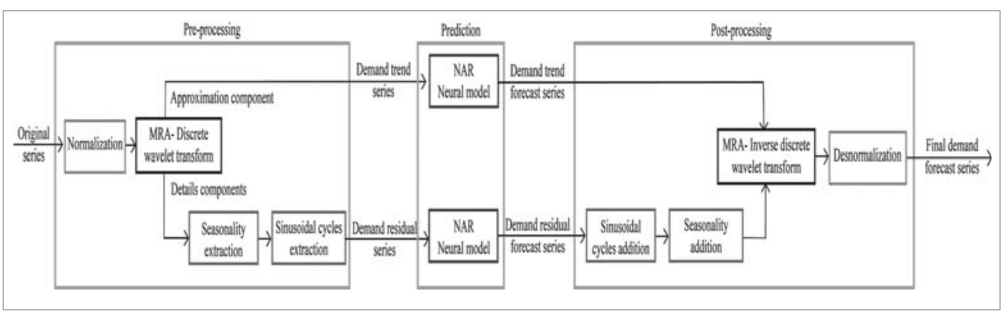

Figure 6. Complete structure of the proposed model in electricity demand forecast.

3.2. Pre-processing

The first stage performs pre-processing of the signal; it includes the multi-task manager to facilitate the training of the network and improve the final prediction results. Its representation is illustrated in Figure 7.

In the first step, the original series is normalized to the maximum value in the zero to one range (Equation (1)), since all entries must have the same weight; otherwise the inputs of two neurons in different ranges will give dominance to the input with highest scale due to distance-based rules in the training algorithms. Second, the transfer function of neurons is calculated using functions that are defined only in a limited range of values [19].

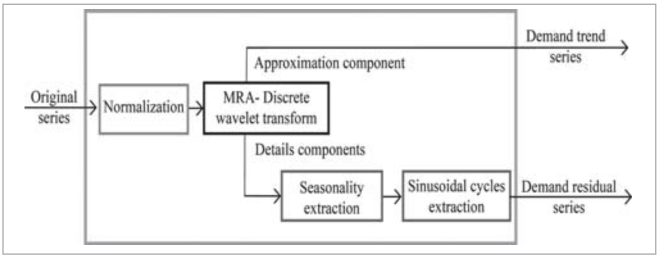

Figure 7. Pre-processing proposed structure.

$$\textit{Normalized demand time series} = \frac{\textit{Original demand time series}}{\textit{Original demand time series maximum value}} \tag{1}$$

According to the conclusions of [1, 6, 4] the Colombian SIN time series has two components: the first one is a rising trend in recent years and the second one corresponds to an annual seasonality.

On other hand literature confirms that wavelet analysis is a useful tool for this setting. The neural network training and performance results outperform models that do not use it, since it breaks down the number of entries in sub-series of different frequencies that reduce the effort of the network and simplify the calculation. Different approaches are proposed to work with all sub-signals generated after the wavelet decomposition analysis. We propose a pre-processing of the original time series to identify and separate the trend, this stage will use a multi-resolution analysis (MRA) based on discrete wavelet transform (DWT) in order to find the family wavelet that best fits the range of demand.

To this aim we must find the proper mother wavelet to decompose the series at different levels and thus obtain the trend and the fluctuations component approach that best represent the dynamics of the series with a more stable and less variance [21-23]. This has been applied to the (DWT) with various mother wavelet [39]: different types of bio-orthogonal and bio-orthogonal reverse, Coiflet, Haar, Daubechies and Symlet.

We proposed the use of Equation (2) corresponding to the Parseval theorem applied to DWT as an index of comparison for evaluating different types of mother wavelet on the normalized series [39]. As a result, different values in the indexes of the mother wavelet and their respective orders are obtained, and we select the configuration with the highest index value (stored energy in the signal).

$$\frac{1}{N}\sum |f[t]|^2 = \sum_{-\infty}^{j} \sum \left|d_j[n]\right|^2 + \sum_{n \epsilon Z} \left|a_j[n]\right|^2 \tag{2}$$

Once the trend is identified and extracted(approximation components), it is necessary to determine whether there is any seasonality or cycles in the series without sinusoidal trend (sum of the components of details). For this aim, we propose the use of an autocorrelogram and frequency analysis, often used to examine whether there is either a repetitive factor or peak value related to a sinusoidal seasonal cycle found in the time series.

If there is any seasonality in the series without trend removal, they are eliminated by computing the average of past values of the sum of the detail components; this, however, must meet the minimum number of periods given by Equation (3), thus obtaining a series without trend or seasonality [40].

$$Int\left(\frac{N}{d}\right) > 4 \tag{3}$$

If sinusoidal cycles exist, we proceed to extract by means of a moving average filter, as explained in [40]. Finally the residual series corresponding to the series without seasonal and without sinusoidal cycles, along with the trend series of electrical energy demand enter the prediction block. The inputs required to the prediction are determined from the autocorrelation analysis performed on the residual series.

3.3. Prediction

In the prediction stage, we propose a nonlinear autoregressive NAR neural model because of its success evidenced in the literature for different applications. Additionally, the NAR neural network can be adapted to the nonlinear characteristics of the Colombian SIN demand series, it is compatible with several predictions in advance, its structure is simple and results can be obtained without any change in the characteristics of the series. Figure 8 shows the prediction stage where there is an independent neural network for the demand trend series and for the demand residual series.

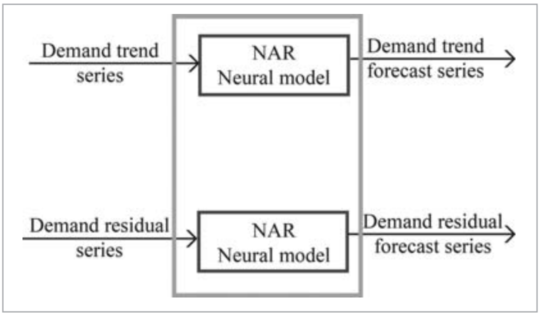

Figure 8. Post-processing proposed structure.

Table I. Neuronal NAR model standard values.

Parameter	Standard value
Number of layers	3 [27, 28,29,32]
Number neurons in the hidden layer	4 [29, 32, 37]
Number of neurons in the output	1 [27, 28, 29, 32]
Training algorithm	Levenberg–Marquardt [32, 34, 37]
Partition for training	Block[27, 28, 29, 32]
Number of training epochs	500 [36, 37]
Target	0 [41]
Validation checks	6 [41]
Gradient	1e-5 [41]
Rate of learning	0.01 [41]
Hidden layer activation function	Logistic sigmoid [32, 41]
Activation function of output layer	Linear[32, 41]

In order to make the actual prediction, we propose the division of the time series into two sets: in-sample for the estimation (training) and out-of-sample (test) to assess the predictive capability with data that are not known by the neural network during training. The in-sample series in turn is divided into two sets: one for estimation (training or fitting) parameters and the other to test the generalization (validation). The test set should have a length between 10% and 30% the size of the in-sample set. For series whose dynamic changes rapidly the test set tends to be smaller. If the series has a very stable behavior (e.g., a sine wave) the test set may be greater than 30%. The same logic follows for selecting the out-of-sample set [4].The standard configuration used in the scientific literature and proposal for the monthly electricity demand forecast is presented in Table 1.

3.4. Post-preprocessing

The post-processing stage reverses the functions used in preprocessing, performing the addition of sinusoidal cycles if is required and the corresponding seasonality. Then it performs an inverse wavelet transform which simply corresponds to a sum of the series plus the components above the forecast trend series. The ultimate outcome is achieved after the renormalization, as shown in Figure 9, with the maximum value used in preprocessing; this value is compared with the test set of the original series in such a way different levels of performance are obtained.

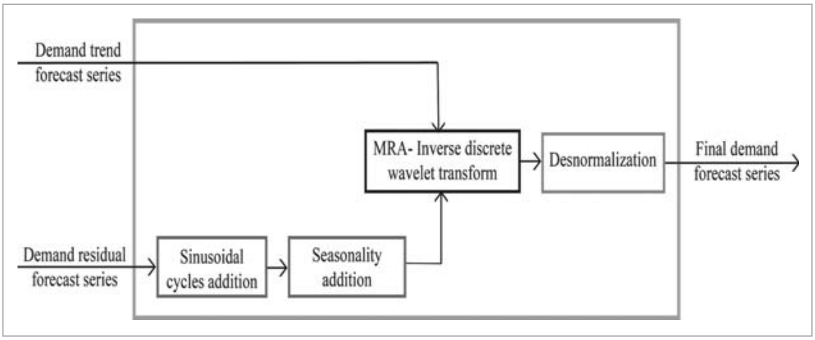

Figure 9. Post-processing proposed structure.

4. Discussion and conclusions

From the literature review we conclude that electric energy demand forecasting with nonlinear models such as neural networks obtain better results compared to traditional linear statistical models such as grey [3], ARIMA [4, 5]and SARIMA [6]. On the other hand, studies such as [7, 8] found that when a wavelet multi-resolution analysis (MRA) is applied to a neural network, it performs better than when applied to statistical linear autoregressive model, although an increase in computational costs is expected for large amounts of data.

The best results reported so far in the literature were obtained using a hybrid model, which involves a pre and post processing of the original time series using neural networks and wavelet analysis. In view of these results Therefore a method for the monthly electric energy demand forecasting for the Colombian SIN was proposed, which is based on a pre-and post-processing of the original series with multiresolution analysis (MRA) wavelet. The study of each of its parameters as well as guidelines regarding classical time series decomposition were given. The prediction is done with a NAR neural model with nonlinear characteristics allowing to obtain promising results in monthly forecast.

The MRA analysis allows obtaining the decomposition of the demand's series into the low frequency components related to the trend. As the level of decomposition increases, the curve is smoother however such an approach does not represent clearly the dynamics of the series because the trend has not been entirely removed. The determination of the mother wavelet and their respective order was carried out using Parseval's theorem which computes the amount of energy that these parameters bring about to the original series. We remark that this index had already been used in other applications but as far as we know not in the electric energy demand forecasting.

We conclude by noting that other approaches in electric energy demand forecasting for the Colombian SIN include identification and removal of trend and seasonality, but not other components specific to a time series such as sinusoidal cycles. The contribution of this paper is that those components were considered and their implications in forecasting electricity demand in Colombia were discussed.

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