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Electrical Load Forecasting using a Hybrid Model with Artificial Neural Networks

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Abstract—**Electrical load forecasting is a very important research field in the planning and operation of power systems. To provide electrical energy safely and reliably without interruptions, the forecasting must be as precise as possible. The use of hybrid techniques has been recently extended to time series predictions with good results. This work develops a hybrid prediction model for short term load forecasting using the ARIMA (autoregressive integrated moving average) of Box and Jenkins and artificial neural networks trained by the Levenberg-Marquardt algorithm. The results were tested with data from a Brazilian company over three periods and compared with other methods considering the same time series. The proposed model has a high performance for the three applications.**

Keywords—component;ARIMA models by Box and Jenkins, short term load forecasting, artificial neural network, Levenberg-Marquardt training formattin)

I. INTRODUCTION

Load forecasting is very important for ensuring that electrical companies can provide energy securely, reliably and economically without interruptions. Advanced knowledge of the load allows the planning of the electrical system expansion, the load flow, economical operation, security and the control analysis of the electrical systems. The following techniques for load forecasting are found in the literature [1]: simple or multiple linear regression, exponential smoothing, state estimation, Kalman filters, and the ARIMA (autoregressive integrated moving average) of Box and Jenkins [2]. These methods apply the previous modeling of the load. The meteorological conditions, such as the nebulosity, the wind speed, the temperature variations and several other factors, such as nonconventional days (holidays, strikes, etc.), are used to aid the load modeling; therefore, the prediction improves with more available information [2]. A necessary condition to realise the electrical load forecasting is to obtain information from the past codified in data and to assume that the behavior of the past will be repeated in the future [3].

Methods based on artificial intelligence have shown efficiency when applied to several real life problems. Currently, artificial neural networks (ANN) [4] have been used to realize electrical load forecasting due to their ability to learn and generalize. The generalization is the capacity to produce adequate outputs for inputs that are not presented during the training, and, therefore, solve complex problems and difficult to address. Several works usevarious neural network architectures to execute electrical load forecasting [3], [5-7].

A very interesting proposal found in the literature is to use the ARIMA models with ANN exploring the advantages of linear and nonlinear modeling, providing a robust high-quality prediction model [8]. The works using the hybrid methodology with ARIMA and ANN explores time series applied to several real problems [9-13]. For example, the work of Koutroumanidis [11] describes the contribution of renewable energy sources to produce electricity, where the ARIMA is responsible for generating the load parameters and ANN to predict the price of selling wood in Greece. The hybrid model provides good results allowing a rational use of wood production and the associated market. The works of Khashei and Bijari [14], [15], consider the following time series: the solar spots by year, the number of people that are arrested per year at the Mackenzie River and the dollar/pound exchange rate. The objective is to obtain a precise prediction using the hybrid model with the ARIMA and the ANN, where the ARIMA models are used in the first phase to generate the necessary data from historical time series and forward the data to a neural network to model the data generated from the ARIMA and to predict the time series future. Each of these works divides the time series into a linear part and a nonlinear part, where the ARIMA considers the linear part and the ANN the nonlinear part of the ARIMA errors. Certain works using ARIMA and ANN combine the use of fuzzy rules [14] and genetic algorithms to improve the results [15].

This work proposed the development of a hybrid model to short-term load forecasting using ARIMA models and ANN, specifically an MLP (multi layer perceptron) trained by the Levenberg-Marquardt algorithm. The hybrid model aims to overcome the use of ARIMA and ANN individually, once the ARIMA models address the linear part of the time series and the ANN the nonlinear. Although other works use hybrid models with ARIMA and ANN [8-13], the hybrid methodology developed in this work is different, once the ANN predicts a random error that will be used in the ARIMA model to predict the electrical load. This technique has never been applied to load demand forecasting. Therefore, this work innovates in this research area. The demand series is seasonal and, thus uses the seasonal ARIMA called SARIMA. In this work the SARIMA model provides the simulated series of the real load, i.e., the model works with the linear part of the time series. The residuals are obtained by the difference of the real load and the simulated load, which are treated by the neural network (that will predict the residuals), and afterwards are substituted on the SARIMA model to effectuate the electrical load prediction. The advantage of the neural network is that it works with the nonlinear part without using a mathematical model.

The proposed model is tested with 30, 60 and 90 days of the historical load, with the aim of predicting the load for the next day. The results were compared with other works that use the same data of the same electrical company, and the proposed model performs better.

II. HYBRID METHODOLOGY

A. ARIMA models of Box and Jenkins

The ARIMA models from Box and Jenkins were the most important models for time series prediction in several areas for at least 50 years. These methods only depend on the series data to specify the best model [1].

The ARIMA model is denoted by ARIMA (p,d,q). The future value of one variable is assumed to be a linear function of several past values and random errors. The process that generates the time series is in accordance with equation (1) [16]:

$$\emptyset(B)\Delta^d Z_t = \theta(B)a_t \tag{1}$$

Z_t : real values at period t;

a_t : random errors at period t;

$\emptyset(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$: order p auto-regressive operator;

$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q$: order q moving average operator;

$\Delta^d = (1 - B)^d$: series differentiation;

d : number of times that the series were differentiate to become stationary.

If the series is already stationary, the term d does not exist, and the model becomes an ARMA (p,q) model, which is represented by equation (2) [16].

$$\emptyset(B)Z_t = \theta(B)a_t \tag{2}$$

When a time series presents seasonality the seasonal ARIMA models are used which are known as seasonal autoregressive Integrated Moving Average (SARIMA) and represented by SARIMA $(p, d, q)(P, D, Q)_m$. The seasonality indicates the repetition of a pattern in a time period. The representation is according equation (3) [17].

$$\phi(B)\Phi(B^m)\Delta^d \Delta_m^D Z_t = \theta(B)\Theta(B^m)a_t \tag{3}$$

where:

$\Phi(B^m) = 1 - \Phi_1 B^m - 1 - \Phi_2 B^{2m} - \cdots - 1 - \Phi_P B^{Pm}$: order P seasonal auto regressive operator;

$\Theta(B^m) = 1 - \Theta_1 B^m - 1 - \Theta_2 B^{m2} - \cdots - 1 - \Theta_Q B^{mQ}$: order Q seasonal moving average operator;

$\Delta_m^D = (1 - B^m)^D$: differentiation of the seasonal series;

D : number of seasonal differences.

The time series prediction by Box and Jenkins [1] consists of adjusting the ARIMA(p,d,q) model to a data set. The building of this methodology is approached in the identification, estimation and verification cycle.

B. Artificial Neural Netwoks

Artificial neural networks are one of the most important models for prediction nonlinear time series. The advantages of using ANN has the advantage of being able to address nonlinear problems without using a mathematical model, and the capacity in generalizing can address non- stationary characteristics. The advantages of ANN encourage researchers to use it in time series prediction.

The MLP neural network is an important one because it is easy to implement. The MLP neural network is a feedforward architecture having at least one hidden layer between the input and output layers with supervised training [4].

One of the principal characteristics of the ANN is the capacity to learn. The ANN must be trained by an algorithm and the one chosen is the Levenberg-Marquardt which uses second order partial derivate to adjust the weights [5].

The learning rule is based on equation (4) [5].

$$W(k+1) = W(k) - [J^T(W)J(W) + \mu_k I]^{-1} J^T(W)e(W) \tag{4}$$

where:

W : synaptic weight vector;

J : Jacobian matrix;

I : identity matrix;

μ_k : Levenberg-Marquardt constant;

$$e(W) = \sum_{i=1}^{n} (y_i - y_{ei})$$

y_i : output given by the network;

y_{ei} : real output.

The Levenberg-Marquardt constant μ_k is used as a stabilisation factor, which adjusts the approach to the Newton method by avoiding steps that can lead to convergence error. This algorithm is considered the fastest one and requires only a few iterations when using a moderate number of parameters. If the quantity of these parameters is large, the method is not adequate due to the computational effort required for matrix inversion [18].

III. DEVELOPMENT OF THE PROPOSED METHODOLOGY

A time series is considered as nonlinear function of past observations and random errors. Thus, the first step is to use the autoregressive integrated moving average models to identify the characteristics of the electrical load time series and estimate the parameters and coefficients to ultimately find the best SARIMA model of the load series. Therefore the historical data (electrical load time series) are applied into the software R by the forecast library [19, 20] to obtain the best ARIMA model.

Figure describes the first step of the hybrid methodology.

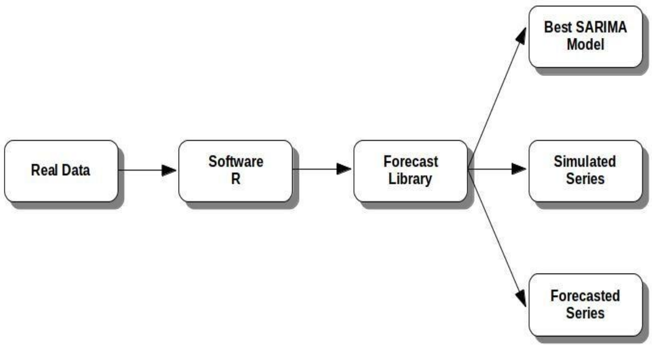

Figure 1. Flowchart of software R.

The software R provides the parameters and the coefficients of the load series and consequently the best model.

By the simulated series of the SARIMA model, the error E_h can be found by to equation (5).

$$E_h = R_h - S_h \tag{5}$$

where R_h are the real load values and S_h the simulated loads, both at hour h.

The next step of the hybrid methodology is to use the error E_h as the input of the neural network presented in Fig.2.

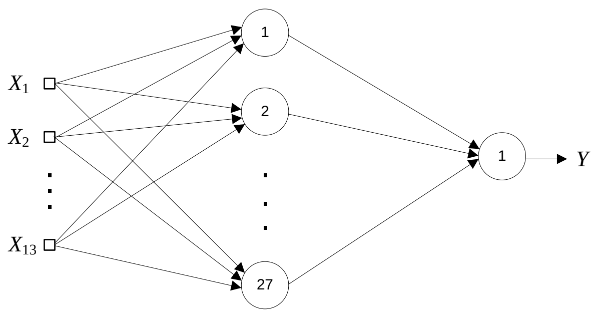

Fig. 2.- Neural network structure.

The set containing the input and output vectors of the neural network are defined as follows:

$$X_h = \left[te \;\; E_{(h-3)} E_{(h-2)} E_{(h-1)} E_{(h)} \right]^T, \;\; X \in R^b \tag{6}$$

$$Y = \left[E_{(h+1)} \right], \;\; Y \in R^1 \tag{7}$$

where:

b	:	dimension of vector X;
$E_{(h-v)}$	:	error v hours previous to the current time$h$;
$E_{(h+1)}$	:	error corresponding to the subsequent hour to the current h;
te	:	time vector corresponding to the historical data (holidays, day of the week, hours) in binary (-1,+1).

The neural network used in this work contains three layers, with 13 neurons at the input layer, 27 neurons at the hidden layer and one neuron at the output. It is worth mentioning that the numbers of neurons that make up each layer are chosen according to the system characteristics. According to our research group experiences, in the presented heuristic-based method, the quantity of the neurons in the hidden layer, (QNHL), is greater than or equal to the maximum of the quantity of neurons in the input layer (QNIL), and the quantity of neurons in the output layer (QNOL), equation (8). Therefore, this is the criterion that is used to determine the quantity of neurons in the hidden layer. For example the quantity of neurons in the input layer is QNIL = 13, and in order to obtain a solution with a higher quality $(2 \cdot \mathrm{QNIL} + 1)$ criterion has been used that results 27 neurons in the hidden layer."

$$QNHL \geq \max\{QNIL, QNOL\} \tag{8}$$

At the input layer, the vector te represents nine inputs composed of binary data corresponding to exogenous variables such as: holidays, days of the week and hour of the day respectively. The last four values correspond to the errors $E_{(h-3)}E_{(h-2)}E_{(h-1)}E_{(h)}$, obtained by the difference between the real data series and the simulated series, according to equation (5). The goal of the neural network is to predict the error 24h in advance.

Adding the predicted error E_{h+1} to error E_h the vector $\hat{E}_h$ is obtained represented by equation (9).

$$\hat{E}_h = \left[E_{(h-v)} \ldots E_{(h-1)} E_{(h)} E_{(h+1)} E_{(h+2)} \ldots E_{(h+23)} \right]^T \tag{9}$$

The error $\hat{\mathrm{E}}_\mathrm{h}$ is substituted in the residuals a_t of equation (3), providing equation (10), which predicts the electrical load. Thus, the load forecasting is realized by the SARIMA model adapted from the residuals from the ANN.

$$\phi(B)\Phi(B^m)\Delta^d \Delta_m^D Z_t = \theta(B)\Theta(B^m)\hat{E}_h \tag{10}$$

The training and test phases of the neural network were executed using the MATLAB software with the Neural Network toolbox [20]. MATLAB was also used to realize the load forecasting after the substitution of the error $\hat{\mathrm{E}}_\mathrm{h}$ into the SARIMA. Figure 3 presents a flowchart of the proposed methodology.

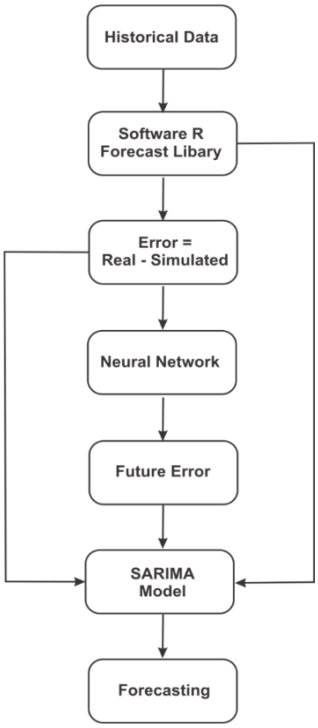

Fig. 3.- Flowchart of the proposed model.

IV. Application of the Proposed Model in Load Forecasting

This section presents the results obtained by the hybrid model for short-term load forecasting, i.e. 24 h in advance. To test the efficiency, three different applications are realized according to the quantity of historical data used for training, and compared with the paper by Nose Filho [22] that uses the same data with the same period of training for different neural network architectures and with the SARIMA itself for each application.

Application 1 considers 31 days composed by 744 vectors, with a vector corresponding to each hour. The 744 vectors are applied into the software R, yielding the model SARIMA $(2,0,0)(2,0,2)_{24}$. Equation (11) describes the coefficients of SARIMA model for application 1.

$$(1-1{,}3641.B+0{,}3879.B^2)(1-0{,}2462.B^{24}-0{,}7523.B^{48})Z_t = (1+0{,}0971.B^{24}-0{,}7523.B^{48})a_t \tag{11}$$

Application 2 considers 61 days, composed by 1464 vectors and the software R provides the SARIMA $(2,0,2)(2,0,2)_{24}$. Equation (12) shows the coefficients for this application.

$$(1-1{,}6914.B+0{,}7166.B^2)(1-0{,}5885.B^{24}-0{,}4105.B^{48})Z_t = (1-0.3069\cdot B-0{,}2185.B^{48})(1-0{,}4444.B^{24}-0{,}4060.B^{48})a_t \tag{12}$$

Application 3 considers 84 days and 2208 vectors and the model SARIMA $(3,0,1)(2,0,2)_{24}$ which are described in equation (13).

$$(1-0{,}3999.B-0{,}8949.B^2+0{,}3808.B^3)(1-0{,}7955.B^{24}-0{,}2037.B^{48})Z_t = (1-0{,}9779.B)(1-0{,}5533.B^{24}-0{,}2837.B^{48})a_t \tag{13}$$

The SARIMA models are generated, and the errors (equation (9)) which will be used on the training and diagnosis of the ANN, are obtained. Then, the models (ANN) will predict 24 errors in advance.

Table 1 shows the parameters and specifications for the neural network.Several tests were performed, until it appears the parameters that best fit the system.

TABLE I. Neural Network Parameters

Parameters	***Application 1***	***Application 2***	***Application 3***
Quantity of layers	3	3	3
Quantity of neurons per layer	13-27-1	13-27-1	13-27-1
Goal	0,001	0,001	0,001
Maximum number of iterations	39	45	67
Minimum gradient	10-10	10-10	10-10
Levenberg-Marquardt coefficients	0,12	0,15	0,20
Decreasing Levenberg-Marquardt coefficient	0,12	0,15	0,20
Increasing Levenberg-Marquardt coefficient	10	10	10
Maximum Levenberg-Marquardt coefficient	1010	1010	1010

Figures 4, 5, and 6, present the vector errors, $\widehat{E}_h$, obtained from the difference between the real load series, the simulated load series (SARIMA), which are depicted in blue lines, while the predicted error of the ANN are depicted in red line. The error vector $\widehat{E}_h$ is substituted on the residuals of the SARIMA model, a_t, which are represented by equations (11), (12), and (13) to obtain the short-term load forecasting, Z_t.

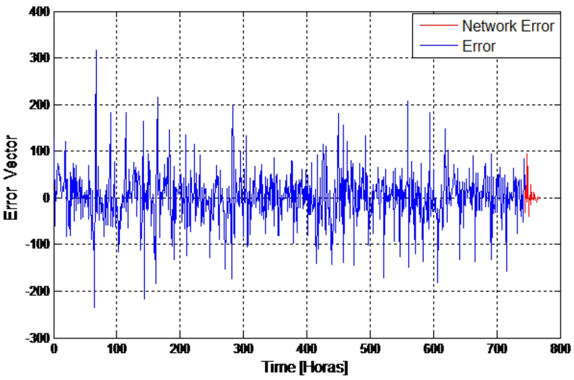

Fig. 4.- Error Vector (application 1).

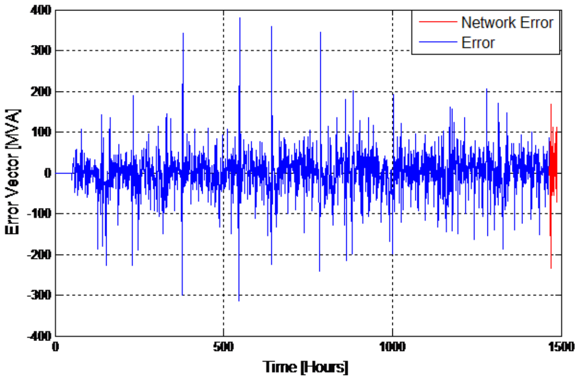

Fig. 5.- Error Vector (application 2).

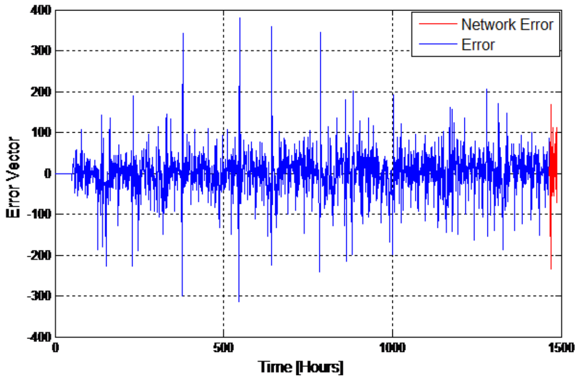

Fig. 6.- Error Vector (application 3).

The literature usually creates the analysis for the results of load forecasting using the mean absolute percentage error (MAPE) and the maximum percentage error [3], [6], which are calculated according to equations (14) and (15) [23]:

$$MAPE = \frac{1}{NT}\sum_{h=1}^{N}\left\{\frac{\left|L(h) - \underline{L}(h)\right|}{L(h)}\right\} \times 100\% \quad (14)$$

$$Max\ Error\ (\%) = máx\left\{\frac{\left|L(h) - \underline{L}(h)\right|}{L(h)}\right\} \times 100\% \quad (15)$$

where:

L(h): real load referred to by hour h;

$\underline{L}$(h): load estimated by the hybrid model referred to by hour h;

NT: total quantity of hours.

The obtained results are compared with the different architectures and trainings of ANN, such as MLP with descent gradient with momentum, MLP with Levenberg-Marquardt, the adaptive neural fuzzy inference system (ANFIS) and the general regression neural network (GRNN) from reference [22], well as with SARIMA itself considering the MAPE and maximum error for evaluation. The results are shown in Tables 2, 3, and 4 for applications 1, 2 and 3 respectively.

TABLE II. MAPE AND MAXIMUM ERROR FOR APPLICATION 1

Models	***MAPE***	***Max Error(%)***
Hybrid Model	0.908	1.016
SARIMA	9.096	18.623
ANN perceptron trained by descent gradient with moment [22]	1.998	4.845
ANN Perceptron with Levenberg-Marquardt training [22]	1.178	3.560
ANFIS [22]	1.090	2.861
GRNN [22]	1.003	2.410

TABLE III. MAPE AND MAXIMUM ERROR FOR APPLICATION 2

Models	***MAPE***	***Max Error(%)***
Hybrid Model	0.892	0.954
SARIMA	7.774	16.955
ANN perceptron trained by descent gradient with moment [22]	2.093	5.022
ANN Perceptron with Levenberg-Marquardt training [22]	1.490	4.267
ANFIS [22]	1.403	3.848
GRNN [22]	1.118	3.650

TABLE IV. MAPE AND MAXIMUM ERROR FOR APPLICATION 2

Models	***MAPE***	***Max Error(%)***
Hybrid Model	0.634	0.875
SARIMA	8.747	18.630
ANN perceptron trained by descent gradient with moment [22]	2.313	7.088
ANN Perceptron with Levenberg-Marquardt training [22]	1.698	4.687
ANFIS [22]	0.973	3.757
GRNN [22]	1.288	4.246

Analysis of Tables 2, 3 and 4 shows that the hybrid model is superior to the other neural networks and the SARIMA model for the three applications proposed. Considering the economical generation point of view, results with less than 5% precision present a significant reduction in the generation costs [24]. Thus, decreasing this precision is economical and the proposed model obtains results below 1%.

As the quantity of vectors increase, better results are obtained,which is a fundamental property of the ANN, which assures that, as more data are used for training better results are obtained at the diagnosis (test phase).

Figures 7, 8 and 9 present the loads 24 h in advance.

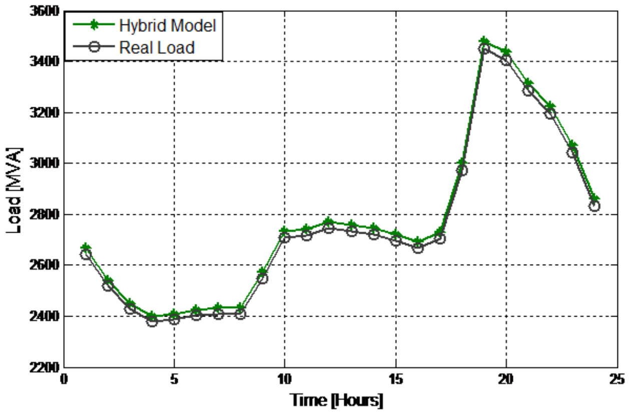

Fig. 7.- Load forecasted by the hybrid model: Application 1.

As shows in Figures 7-9, the curves obtained by the hybrid model can follow the prediction curves for the three applications proposed, demonstratingthe good precision of the proposed model.

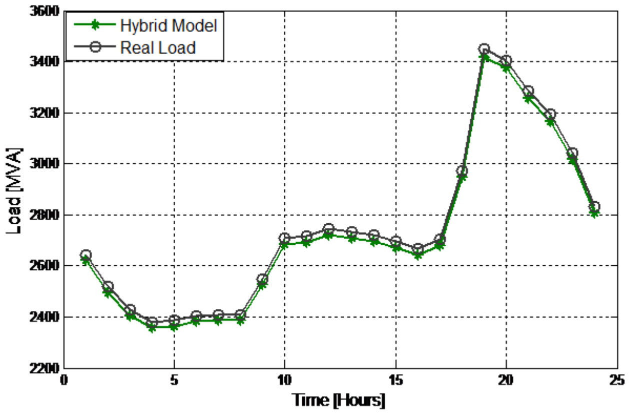

Fig. 8.- Load forecasted by the hybrid model: Application 2.

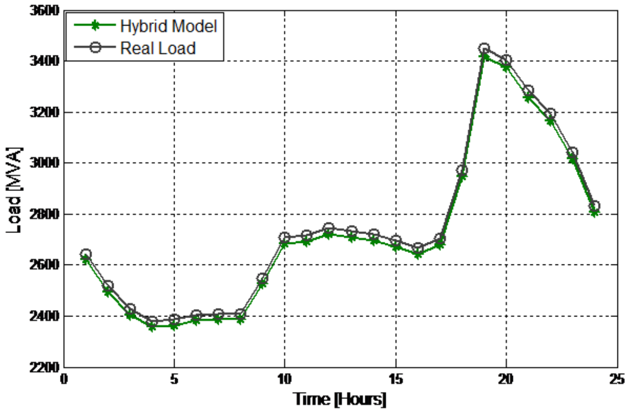

Fig. 9.- Load forecasted by the hybrid model: Application 3.

V. CONCLUSION

This study developed a hybrid methodology for short term electrical load forecasting using the ARIMA of Box and Jenkins and a neural network trained with the Levenberg-Marquardt algorithm. The ARIMA models generate the load parameters (the best model) and realize the desired prediction. This prediction is executed after the ANN realizes the error prediction, which is used with the error determined by the difference between the real data and the simulated data substituted into the ARIMA model to finally calculate the prediction. Three tests were performed for different periods by considering the historical data of a Brazilian electrical company. The short- term load forecasting considers 24 h in advance, where the proposed model performs well with a MAPE of less than 1 % and maximum errors of less than 1.1%. Thus, the proposed model can realize predictions, including non-conventional days such as weekends, reliably and with high performance. The prediction error decreased, and better results were found by increasing the data set.

The short-term load forecasting proposed in this work is efficient and the results are important considering other models found in the literature.

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