Very Short-Term Load Forecasting Based on ARIMA Model and Intelligent Systems

Luciano Carli Moreira de Andrade, and Ivan Nunes da Silva

***Abstract*-- The main purpose of this paper is to achieve a comparative analysis among Autoregressive Integrated Moving Average model, Artificial Neural Networks and Adaptive Neuro-Fuzzy System techniques for load demand forecasting in distribution substations. The system inputs are three load demand time series, which are composed by data measured at intervals of five minutes each, during seven days, from substations located at Andradina, Ubatuba and Votuporanga. Autoregressive Integrated Moving Average models with suitable results have been analyzed, whereas several input configurations and different architectures have been investigated for Artificial Neural Networks and Adaptive Neuro-Fuzzy System techniques aiming the forecasting of twelve further steps. The results showed the Artificial Neural Network based technique superiority for such forecasting, followed by Autoregressive Integrated Moving Average model and Adaptive Neuro-Fuzzy approach. The load demand forecasting can minimize costs of energy generation as well as improve the electric power system safety.**

***Index Terms*-- Autoregressive integrated moving average processes, feedforward neural networks, fuzzy systems, intelligent systems, load forecasting, time series.**

I. Introduction

LOAD demand forecasting has had important role regarding investments in energy distribution, planning and management strategies. Furthermore, inaccurate forecasting can increase the operational costs.

Some papers [1]-[2] mention that, there is estimation that 1% of increasing in the forecasting error could imply in 10 million pounds of increasing in the operational costs regarding the predominantly thermal British power system in 1985.

Short-term demand forecasting tries to estimate load demand for the next hours and days. This class of forecasting is used in operational planning of load requirements and their generation units, and energy market transactions.

There are several researches and publications regarding short-term forecasting [3]-[9], but it is particularly more essential to estimate the load demand of the next minutes, to avoid undesirable disturbances, and to perform an accurate load frequency control of energy management systems.

The forecasting of the next few to several minutes is classified as very short-term forecasting. Although load forecasting has received increasing attention, there are only a few researches about very short-term load demand forecasting [10]-[13]. Such load forecasting procedures, associated with information about transmission availability, generation costs, price of energy commodity in the market and requirements of energy reserve, are employed to determine the best strategy of resources use. Thus, load demand forecasting became very important in the deregulated industrial market [14].

Very short-term load demand forecasting requires a distinct approach, where the relationship among load, time, weather conditions and any other factor that affects load demand are not considered. The main concern is related to the behavior of previous measures in order to forecast the next ones. Very short-term load demand forecasting methods are not so numerous [14]. The techniques applied in this work employ the Autoregressive Integrated Moving Average Model (ARIMA), the Artificial Neural Networks (ANNs) and the Adaptive Neuro-Fuzzy Inference System (ANFIS).

The article is organized as follows. Section II presents information about the analyzed time series. Section III presents the forecasting methodologies. In Section IV the results are presented and Section V concludes the work.

II. Time Series

The load demand time series are composed by data measured at intervals of five minutes each, during seven days from substations located at Andradina, Ubatuba and Votuporanga, cities located in São Paulo state. Fig. 1 shows the load time series graphics in MW per time.

Time series have seasonal behavior, meaning that the energy demand is low in the first hours of the dawn, increasing during the morning and slightly decreasing in the beginning of the afternoon. It starts increasing again and reaches maximum peak in the beginning of the evening. After this peak, during the night, the load demand decreases until it reaches its minimum value.

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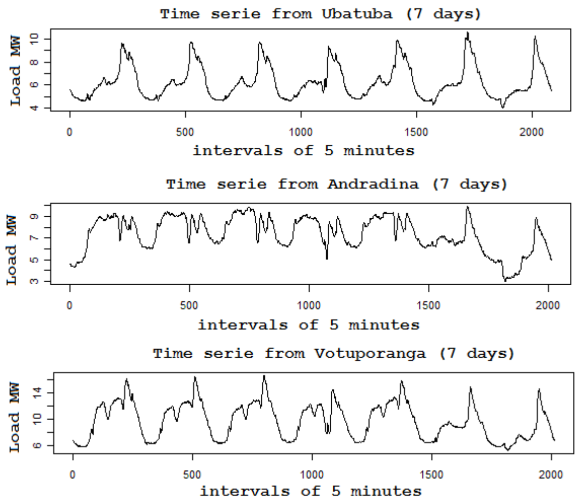

Fig. 1. Load demand time series from Ubatuba, Andradina e Votuporanga, respectively.

III. Forecasting Methodologies

A. Autoregressive Integrated Moving Average Model

It is important to mention that the seasonal patterns are diverse and of complex analysis. Furthermore, there is the possibility of seasonal models combination. Therefore, the time series analysis of this work is complex, due to the potential combination of seasonal patterns that sets hurdles to the identification of the correct parameters to be employed by the ARIMA model. In this case, cleverness and knowledge are required to define, with accuracy, the model parameters that are necessary [15].

The purpose of ARIMA analysis is to find a model that accurately represents the past and future patterns of the time series, which means, the methodology applied for the ARIMA model estimation aims to find the proper parameters that describe the following structure:

$$SARIMA(p,d,q)(P,D,Q)$$

where p is the order of the auto-regressive model; d is the number of differentiations, to accomplish stationarity; q is the order of moving average model; P is the order of seasonal auto-regressive model; D is the seasonal differentiations, to accomplish stationarity too; and Q is the order of seasonal moving average model.

In [15], the mentioned parameters and the methodology to find them are described in detail and, in this work, it was performed the following way:

In the preparation step, the data were depicted as illustrated in Fig. 1.

The graphics demonstrate that the data have non stationary and seasonal behavior, because as described in Section two, the data daily repeat their behavior.

Hence, seasonal and non seasonal differentiations are necessary to accomplish stationary time series [15].

In case of the time series of this paper, two non seasonal differentiations and one seasonal differentiation were necessary to accomplish stationarity.

In the model selection step, the resulting time series of the differentiations are evaluated through their Auto-Correlation Function (ACF) and Partial Auto-correlation Function (PACF).

Fig. 2 depicts the ACF and PACF graphics to the differentiated time series of Andradina.

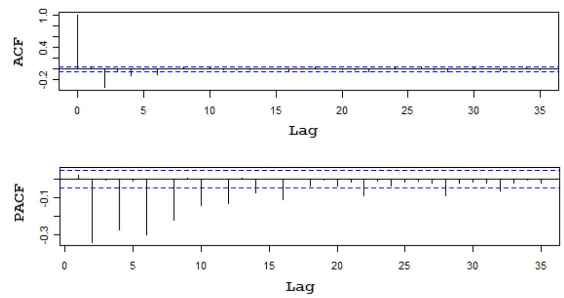

Fig. 2. ACF and PACF graphics of the differentiated time series of Andradina.

The analysis of the Auto-correlation Function and Partial Auto-correlation Function, depicted in Fig. 2, demonstrates that a candidate model to be evaluated is the following:

$$SARIMA\ (1,2,2)(0,1,1)$$

because the ACF graphic exhibits a peak much different than zero and the PACF graphic exhibits a exponential fall of negative values [15].

Fig. 3 depicts the ACF and PACF graphics of the differentiated time series of Ubatuba.

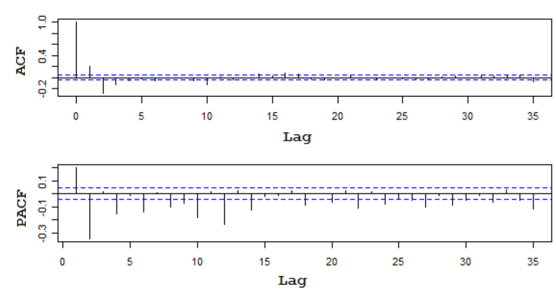

Fig. 3. ACF and PACF graphics of the differentiated time series of Ubatuba.

The analysis of the Auto-correlation Function and Partial Auto-correlation Function, depicted in Fig. 3, demonstrates that the candidate model to be evaluated is the following:

$$SARIMA\ (3,2,2)(0,1,1)$$

because the ACF graphic exhibits three peaks much different than zero and the PACF a exponential fall of negative values [15].

Fig. 4 depicts the ACF and PACF graphics of the differentiated time series of a substation located in

Votuporanga.

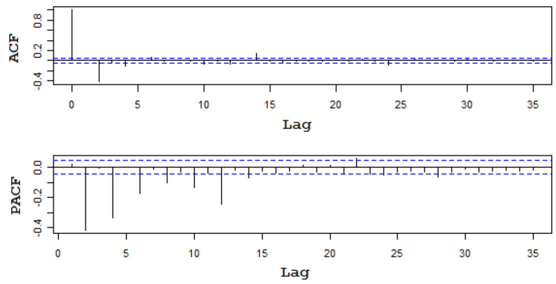

Fig. 4. ACF and PACF graphics of the differentiated time series of Votuporanga.

The analysis of the Auto-correlation Function and Partial Auto-correlation Function graphics, depicted in Fig. 4, demonstrates that the candidate model to be evaluated is the following:

$$SARIMA\ (1,2,2)(0,1,1)$$

because the ACF graphic exhibits a peak much different than zero and the PACF graphic exhibits exponential fall of negative values [15].

A joint analysis of the examined time series reveals that the candidate models are similar, although their ACF numbers of peaks are different.

The next step is to perform the analysis of residuals of the candidate models to verify their adequacy (residual not correlated or normally distributed), and afterwards, in a final step, to use them for forecasting.

The analysis of residuals (ACF, Ljung-Box test and Box-Pierce test) indicated that the candidate model of Andradina (*SARIMA(1,2,2)(0,1,1)*) had still correlated residual; then, through the use of the R software, other models were evaluated resulting that the best model in the case of the Andradina time series is the following:

$$SARIMA\ (3,2,2)(0,1,1)$$

Fig. 5 depicts the ACF and Ljung-Box test of the residual of the Andradina final forecasting model.

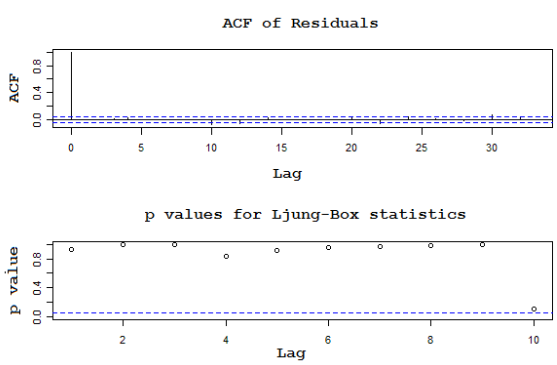

Fig. 5. The ACF and Ljung-Box test of the residual of the Andradina final forecasting model.

The ACF graphic of residual doesn't depict detached peaks, which means that the chosen model is well fitted, as well as, the Ljung-Box statistics *p*-values are nearby one, which indicates that the chosen model is also adequate.

The same procedure was employed in the case of the candidate model of Ubatuba. The analysis of residual reveals that the model (*SARIMA (3,2,2)(0,1,1)*) had correlated residual. Therefore, with the R software, other models were evaluated, resulting in the following model:

$$SARIMA\ (4,2,2)(0,1,1)$$

Fig. 6 depicts the ACF and the Ljung-Box test of the residual of the Ubatuba chosen model.

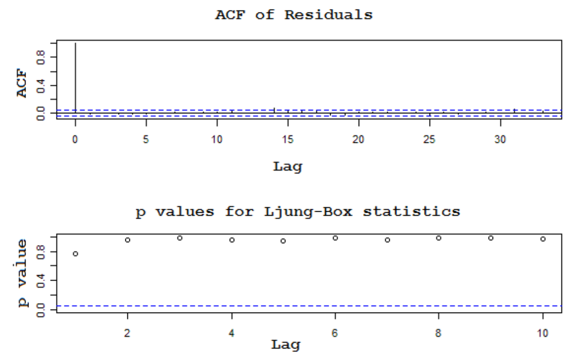

Fig. 6. The ACF and Ljung-Box test of the residual of the Ubatuba final forecasting model.

It can be observed that the ACF of the Ubatuba final model doesn't have detached peaks, and its *p*-values are nearby one, that is, which means that its residuals are not correlated.

The same procedure was applied in the case of Votuporanga time series. The residual analysis of the candidate (*SARIMA (1,2,2)(0,1,1)*) model indicates that the residual were correlated. Therefore, with the R software, other models were evaluated, resulting in the best model in case of Votuporanga, which is the following:

$$SARIMA\ (3,2,2)(0,1,1)$$

Fig. 7 depicts the ACF and the Ljung-Box test of the residual of the Votuporanga chosen model.

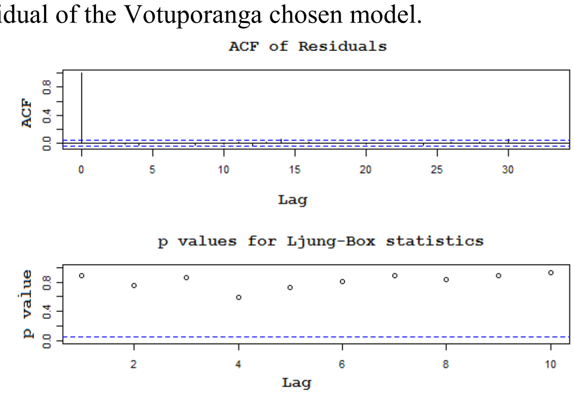

Fig. 7. The ACF and Ljung-Box test of the residual of the Votuporanga final forecasting model.

In case of Votuporanga, the ACF and Ljung-Box test indicates also that the residuals are not correlated regarding the final chosen model.

Another analysis that has to be performed about the residual is to verify whether they have normal distribution, which indicates that they are not correlated. Although it was not presented in this paper, the histogram and the qq-norm plot of the residual of Andradina, Ubatuba e Votuporanga were evaluated, which demonstrates that the residual has normal distribution, which means that they are not correlated.

In [15] the steps performed in this paper are described in detail.

The last step is the forecasting, where the chosen models (the residual not correlated) were exploited to twelve forecasting steps. Section IV describes the results.

B. Artificial Neural Networks

The ANN employed in this paper was a MLP (Mulitlayer Perceptron) with one hidden layer and Levenberg-Marquardt learning algorithm, which offers better weights adjustment and faster convergence, in comparison to conventional backpropagation algorithms [16].

The cross-validation methodology was employed for the ANN selection. Several input patterns were evaluated (two, three and four past measures and past days measures were applied as inputs) and the best performance achieved has four past measures and one measure of the same time in the previous day.

The data were normalized between minus one and one and they were split in training set, with one thousand and seven hundred measures, and testing set, with twelve measures.

It's important to mention that a hidden layer number of neurons between two to fifteen were explored and three neurons presented the smallest MAPE (Mean Absolut Percentage Error).

Therefore, the best architecture in the case of ANNs is formed by five input signals, three hidden neurons and one output neuron.

C. Adaptive Neuro-Fuzzy System

The cross-validation methodology was also employed here. As in the case of ANNs, the best input pattern had four past measures and one previous day measure.

After the input pattern formation, determined the number of membership functions was. Two and three numbers of membership functions were explored and the number of three membership functions presents the best result, as well as, distinct membership function were explored, as Gaussian curve built-in membership function, Gaussian combination membership function and Trapezoidal-shaped built-in membership function. But, the Generalized bell-shaped built-in membership function presents the best results [17]-[18].

Then, the optimization methods, backpropagation and hybrid were explored, with the best results to the second one.

Therefore, the best architecture formation found has five inputs and three membership functions.

D. ARIMA, ANNs and ANFIS Evaluation

The chosen way to evaluate the ARIMA, ANNs and ANFIS models was through the MAPE determination (Mean Average Percentage Error) for the next twelve steps.

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{d_i - o_i}{d_i}\right| \times 100\% \qquad (1)$$

where d is the desired output, o is the chosen approach output e N is amount of testing patterns.

IV. RESULTS

After the analysis through the ARIMA model and the ANNs and ANFIS best architectures establishment, the results were tabulated and depicted in graphics for the three explored locations (Andradina, Ubatuba e Votuporanga).

Fig. 8 depicts the graphic of the results of Andradina.

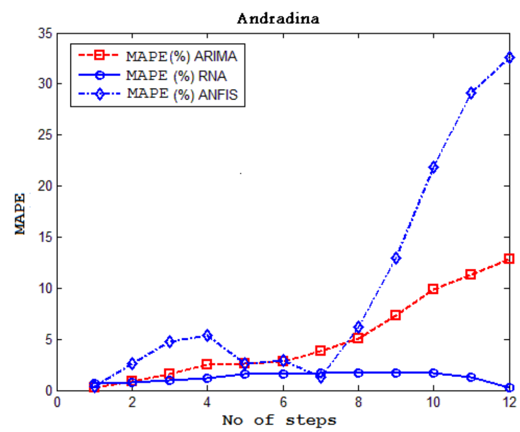

Fig. 8. Graphic of the MAPE of the next twelve forecasting steps of the Andradina location

Fig. 8 demonstrates that the best performance was obtained from ANNs, because they presented the smallest MAPE for all twelve future steps. The ARIMA model presented good performance for the first six steps, but, in the six last steps, the MAPE increased sharply. In case of ANFIS, the performance was good for the first six steps, but from the seventh step the MAPE increased sharply as well.

The MAPE of Andradina were tabulated and can be seen in Table 1.

The MAPE determined in case of Ubatuba location were tabulated and plotted also, which are presented in Fig. 9 and Table 1.

As in case of Andradina, the ANNs achieved the best performance. It can be seen in Fig. 9 that the ANNs achieved a very low MAPE for all twelve future steps. The ARIMA model achieved the second best result, where it's forecasting, although worst, doesn't deteriorate throughout the twelve forecasting steps. The ANFIS achieved good results to the first two steps, but, from the third step, its MAPE starts to increase sharply.

Table 1. MAPE(%) and Variance of the next twelve forecasting steps of Andradina, Ubatuba and Votuporanga.

	MAPE(%) of Andradina			MAPE(%) of Ubatuba			MAPE(%) of Votuporanga		
	ARIMA	RNA	ANFIS	ARIMA	RNA	ANFIS	ARIMA	RNA	ANFIS
Step 1	0.3	0.62	0.31	4.71	0,00	1.25	0.38	0.06	1.88
Step 2	0.89	0.8	2.63	4.15	0.05	4.78	0.99	0.06	5.32
Step 3	1.61	0.99	4.75	3.65	0.15	8.66	2.27	0.02	9.17
Step 4	2.46	1.19	5.38	3.07	0.32	12.34	3.75	0.05	14.04
Step 5	2.58	1.57	2.62	2.78	0.29	14.75	4.85	0.18	18.22
Step 6	2.78	1.61	2.9	2.52	0.3	16.94	6.06	0.19	20.98
Step 7	3.86	1.65	1.23	2.07	0.5	19.57	6.24	0.09	23.32
Step 8	5.02	1.71	6.16	1.54	0.59	22.19	6.42	0.2	23.96
Step 9	7.33	1.7	12.95	0.57	0.73	25.72	7.1	0.01	24.5
Step 10	9.84	1.65	21.84	0.64	0.86	29.45	7.85	0.07	25.62
Step 11	11.31	1.31	29.08	2.06	0.68	33.17	8.4	0.17	26.76
Step 12	12.8	0.24	32.62	3.64	0.16	35.81	8.98	0.04	27.64
Average	5.07	1.25	10.21	2.62	0.39	18.72	5.27	0.1	18.45
Variance	1.80E-03	2.42E-05	1.29E-02	1.72E-04	7.93E-06	1.22E-02	8.20E-04	4.78E-07	7.77E-03

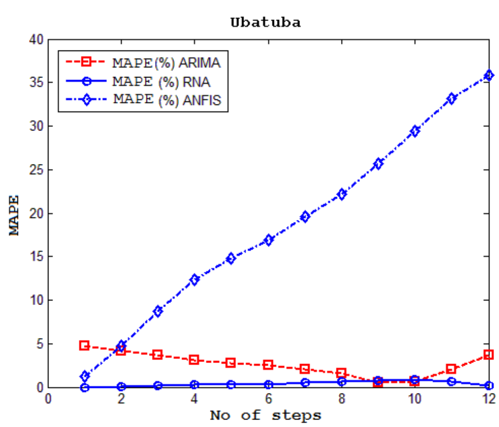

Fig. 9. Graphic of the MAPE of the next twelve forecasting steps of the Ubatuba location.

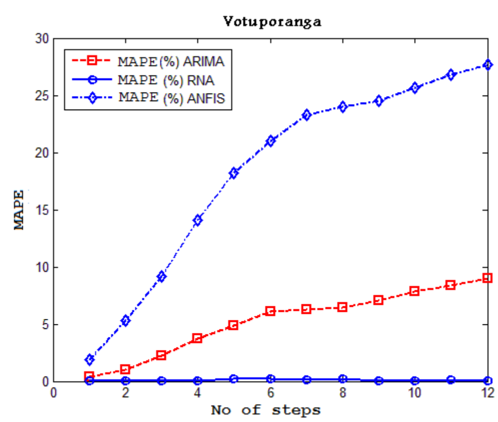

Fig. 10. Graphic of the MAPE of the next twelve forecasting steps of the Votuporanga location.

Regarding Votuporanga location, the ANNs achieved the best performance. Fig. 10 graphics illustrates that the MAPE doesn’t increase throughout the twelve forecasting steps. In case of ARIMA model and ANFIS, according to the increasing steps, the MAPE increases too, more sharply in the case of ANFIS

The MAPE for each forecasting steps depicted in Fig. 10 were also tabulated and it can be seen in Table 1.

The variance of the MAPE was calculated for each explored location, as seen in Table 1. The variance values were very low; denoting that any step doesn’t have a much higher MAPE in comparison to the other steps.

V. Conclusion

The results achieved demonstrate that the ANNs have the best ability of adjustment and learning in case of load demand forecasting

The ARIMA model, despite of the fact that it requires more knowledge of the expert and presents inferior performance in comparison to the ANNs, also demonstrated a good performance. In case of ANFIS, the results demonstrate a good performance for the first forecasting steps, but it presents an expressive growth of the MAPE from the second or third next steps.

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VII. Biographies

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