Emergency department forecasting in a hospital: a hybrid model between the Box-Jenkins methods and ANN

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Abstract

This article aims to compare the effectiveness of Box-Jenkins with Artificial Neural Networks method to obtain a more accurate forecast of patients admission in an emergency department of a cardiopulmonary public hospital. We used a database with 1,095 daily observations about patients admitted to emergency department among the years 2009-2011.

Keywords: Hospital Emergency Department; Time Series; Artificial Neural Networks.

INTRODUCTION

Brazilian public health systems daily confront a challenging to manage the resources required for the health care provision services due a substantial gap between supply and demand for such services, especially for urgent and emergency care, recognized by situations of uncertainty and periods of overcrowding (Hoot e Aronsky 2008; Yarak, 2013). This fact requires the development of effective strategies for managing financial, physical and human resources; so that studies covering hospital occupancy rate forecast provides a very relevant contribution to their managers. The understanding about this phenomenon, over the time, will be useful in decision-making processes regarding the appropriate management of these resources.

The models derived from the methodology Box-Jenkins such as ARIMA or even Artificial Neural Network (ANN) have become quite popular in the practice of the hospital demand forecasts, according Kadri et al. (2014), Schweiger et al. (2007) e Wang (2012) studies. However, the application of these methods to the Brazilian cases of the patient's admission forecasting at an emergency department opens the discussion for the development of research in this field.

Thus, this paper intends to compare the performance of these methods in order to obtain accurate forecasts for the admission of patients the emergency department of a Brazilian cardiopulmonary public hospital, based in a database with 1,095 daily data grouped into weekly observations about patients admitted through the emergency department between 2009 and 2011. In addition, for evaluation purposes, the accuracy of the results is done using the Mean Absolute Percentage Error (MAPE) as performance measurement technique. According to Sun et al. (2009), Souza (2013) and Jones et al. (2008) it is widely used for the evaluation and comparison of time series forecasting methods in the hospital sector.

Therefore, this study was divided into six sections: Theoretical Reasoning section discusses some theoretical aspects related to time series models of Box-Jenkins methodology and ANN. Methodology section presents the methodology used to develop the study, analysis and data collection. Results section indicates the results achieved with the ARIMA and ANN models. Final Considerations section makes comments on the results obtained from the research and bibliographic references used in this study, respectively.

Objective

The aim of this paper is to compare the performance of the models from the Box-Jenkins methodology and ANN, in order to obtain accurate forecasts for the patient´s admission in the emergency department of a Brazilian cardiopulmonary public hospital.

THEORETICAL REASONING

Time Series Forecasting in the Emergency Department Health Care

Earlier research such as Jones et al. (2007), Kadri et al. (2014) e Wang (2012) have some prospects of forecasting practices at hospital admission in the emergency department. These studies served as a subsidy for the proposed research.

Jones et al. (2008) in their research investigated the temporal relationship between the demands and the key features during hospitalization at the emergency department (ED) aiming to develop multivariate predictive models.

Kadri et al. (2014) developed ARIMA forecasting models for daily admittance to the emergency department of a hospital in Lille, France. As a result, these methods proved a useful and effective tool, because have been found satisfactory results in forecast performance, compared with real data. Now Wang (2012) uses the ANN as a satisfactory time series model to predict and anticipate the overcrowding peaks with four hours antecedence.

In summary, researches directed to the application of these models to forecasting demand in the emergency departments proved satisfactory results and the Brazilian case is a field of study still in development.

Box-Jenkins Models

Disseminated by the methodology proposed by Box and Jenkins (1976), models ARIMA (Auto-Regressive Integrated Moving-Average) generate forecasts from information contained in their own time series. These models are based on equations contained stochastic terms (linear stochastic difference equations) in a class of linear equations modeling to time series forecasts.

Also according Box and Jenkins (1976) and then emphasized by Ho et al. (2002), the use of the methodology is based on three parameters for the construction of ARIMA models. They are: autoregression (p) - number of the model terms describing the dependence between successive observations; differences (d) - evaluates the stationary point of the series and if not performs differentiation steps until reaching the stationarity of data; and moving average (q) - arithmetic mean which is based on the impact of the latest data of the series. In the model, these components are identify and describe mathematically as ARIMA (p, d, q).

In addition, based on the statement of the behavior stationarity of the serial data, it is also possible to find models characterized autoregressive terms (AR), moving average (MA) and these models called ARMA (p, q) or even can be identified series expressing behavior only in terms (AR) or (MA), individually. In another situation, the data series might have seasonal behavior; this aspect can be incorporated into the model, in this case receives the designation of SARIMA (p, d, q) x (P, D, Q) where the capitalized terms refer to seasonal parameters (Box e Jenkins, 1976; Ho et al. 2002).

In general, ARIMA models are adjusted to the original series and in case of identified aspects of non-stationarity are performed differentiation processes. Called ARMA models (p, q), it is considered that the series is stationary or has already passed the process of differentiation. Thus, since Y_t assuming a stationary series, the ARMA (p, q) can be generally described as:

$$Y_t = \theta_0 + \theta_1.Y_{t-1} + \theta_2.Y_{t-2} + ... + \theta_p.Y_{t-p} + \varepsilon_t - \varpi_1.\varepsilon_{t-1} - \varpi_2\varepsilon_{t-2} - ... - \varpi_q.\varepsilon_{t-q} \quad (1)$$

Where Y_t is a dependent variable at time; Y_{t-1}, Y_{t-2},...,Y_{t-p} are the dependents variables lagged in time; θ_0, θ_1, θ_2 ,..., θ_p refer to auto regression coefficients to be estimate; ϖ_1, ϖ_2,..., ϖ_p is the coefficients of moving averages and ε_t describe the error of times forecasting (Box e Jenkins, 1976).

Artificial Neural Network - ANN

The quantitative prediction traditional methods thus far have limited applications to their parametric data or assumed as a hypothesis to be a relationship between the numbers of values that can be explained by linear equations, such as the case of ARIMA models. However, there are behaviors in the time series that cannot be properly explained by parametric methods, then is necessary to apply non-parametric methods to meet the behavior of nonlinear functions, in this case are usually applied artificial neural networks (ANN) (Lee et al., 1992; Zhang et al., 1998; Zhang, 2003).

Many ANN models have been applied to predict, such as Singhal and Swarup (2011), the forecast demand for electricity.Chen and Du (2009) made use of ANN to provide financial data in period of crisis and Lee et al. (1992) for long-term financial forecasts.

Zhang et al. (1998) and Zhang (2003) exhibited a review of the main practices developed in this area for time series forecast demand. The main advantage of using ANN models for time series forecasting is to eliminate the need to specify a model for processing the data, because the ability to learn through examples and make inferences about what you have learned, gradually improving performance. For this, neural networks use a learning algorithm whose task is to adjust the weight of their connections.

In general, the artificial neural network architectures have similarities to the neurons of the human brain, hence the name of artificial neural networks. In this structure, data are interconnected layers formed by input layers, hidden layers, and output layers (Lee et al., 1992; Zhang et al., 1998; Zhang, 2003; Egrieglu et al., 2014). Badu and Reddy (2014) add that, in practice, is widely used an ANN of three layers with the models defined by weights on each connection for time series forecasting.

METHODOLOGY

This section presents the procedures and conditions for the construction of models. For this, we used a database of 1,095 observations of patients admitted daily by emergency department between the years 2009 and 2011. However, these data were grouped weekly to best fit the model. According to Wargon et al. (2010) the weekly separation is a fairly representative variable for admission forecast in the emergency department.

For modeling of ARIMA models, the Box-Jenkins methodology follows some steps to formulate the mathematical model and to determinate the parameters, in accordance with studies of Box and Jenkins (1976) and Konishi and Kitagawa (2008), as described below:

- Step 1: Identification of candidate models that best represents the behavior of the data;
- Step 2: definition of the parameters (p, d, q) model, based on the autocorrelation function (FAC) and partial autocorrelation function (PACF);
- Step 3: Verification and validation of the model - evaluate the model and the appearance of stability (unit root), thrift, waste in the form of white noise and homoscedasticity;
- Step 4: Insert data in the proposed model.

To emphasizing that for attending of these steps, the model was developed with the assistance of software GRETL 2015d, a specific program for forecasting and that is free availability on the Internet by its developers. For the prediction of the same data into ANN was used a demo version of the XLM Predictor Excel ® (2010) that even being a free version with limited use, met the needs of this research. The data was first fed into an Excel spreadsheet, initially being used to train the neural networks in the XLM Predictor program and then to generate the forecast period, from the estimation of connection weights in each of the layers automatically generated by the program. To this end, the training period was defined at 10,000 units of time and the activation function was defined as Sigmoid, according to Egrieglu et al. (2014), Kashei, and Bijari (2011).

To compare the individual performance of each model is measured the accuracy of forecasts. This measurement is to evaluate the extent of the forecast error, i.e., measure the distance from the values predicted by the model in relation to actual observed data (Makridakis et al., 1982; Makridakis and Hibon, 2000). Among the possible techniques, the calculation of the Average Error Absolute Percentage (MAPE) has a significant application in studies in the literature, especially in demand forecasting literature for the hospital sector (Sun et al., 2009; Souza, 2013; Jones et al., 2008).

$$\mathrm{MAPE} = \frac{\sum_{t=1}^{n} \frac{|R_t - P_t|}{R_t}}{n} \tag{2}$$

Where, R_t refers to the actual data, P_t represents the prediction data set, n is the number of expected data. Moreover, for validation of the results as satisfactory, it was empirically defined as an acceptable MAPE less than 15%. After all this theoretical background and detail of methodological procedures, results are presented in the following section.

RESULTS

Following the methodological procedures of Box-Jenkins (1976), in the first stage, different ARIMA models were tested to determine the best model that would fit the behavior of the analyzed data. For the selection of the model parameters were estimated from the analysis of correlogram FAC and FACP, based on the principle Akaike Information Criterion (AIC) which, according to Akaike (1974) is a technique used in the model of choice within a group of candidates. In this sense, the formulation of final model can be described as ARIMA (4, 2, 1).

The next step is to realize the significance test of the parameters. For this, it was examined if the residues had the aspect of white noise (without memory), i.e., if residues were normally distributed and if could be defined as homoscedastic (constant variance). According Hanke and Wichern (2008) to test for the existence of memory, two tests can be used: Correlogram Residual Test and Box-Ljung Statistic.

In application of these testing tools, also present in GRETL, it was found that the model ARIMA (4, 2, 1) did not present memory. At the normality residual test was confirmed characterization of normal distribution, so that model is capable of performing a good estimation for the data set. Furthermore, it was checked and confirmed the aspect of homoscedasticity in this data.

Thus, through this structural analysis, the model ARIMA (4, 2, 1) is a significant model to estimate the admission of patients in the emergency department. In summary, the data relating to the proposed model are shown in *table 1*, considering as acceptable a confidence interval for the statistical tests of at least 95%.

Table 1 - General data of model ARIMA (4, 2, 1)

	Coefficient	***P Value***
θ_1	-0,719	3,65E-19***
θ_2	-0,532	1,07E-07***
θ_3	-0,246	0,014**
θ_4	-0,18	0,027**
ϖ_1	-1,000	0,000***

*** Significant coefficients for the confidence interval of 99%.
** Significant coefficients for the confidence interval of 95%.

To develop an artificial neural network model, unlike the forecast by the ARIMA model, it is not necessary to perform statistical tests to validate the models; this method does not develop a specific model and the forecast is generated from the network, trained with data from before the forecast.

Both models were prepared with the 2009 and 2010 data set. In addition, the 2011 forecast data for both models are presented graphically for a preliminary assessment. Figure 1 shows the actual data for the corresponding weekly forecast period to 2011 and the forecast data calculated by both models.

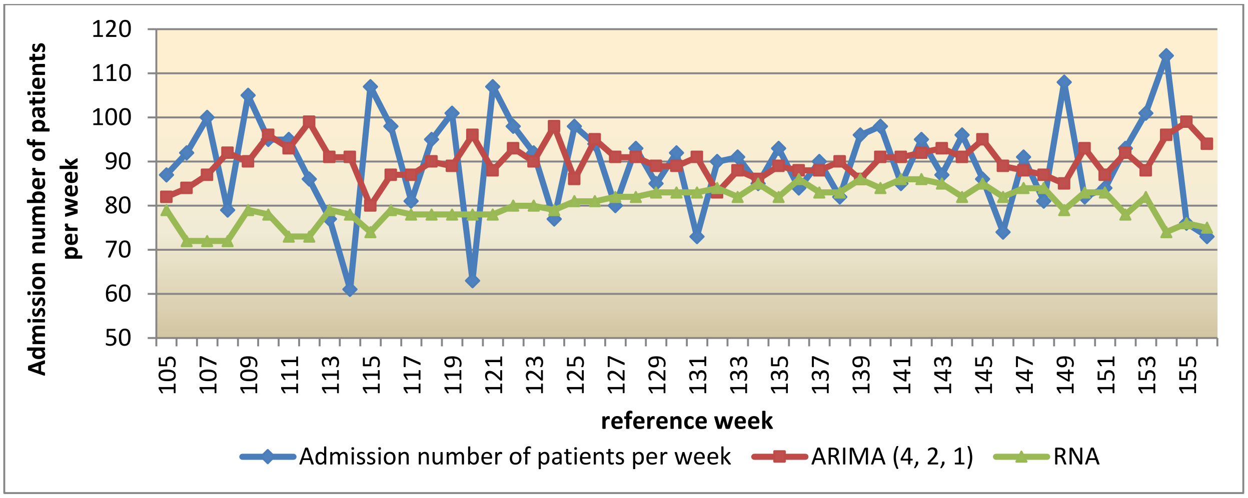

Figure 1 - Behavior analysis of forecast data versus actual data

Through the graphical analysis is promoted a comparison between the actual number of patients admitted to the forecast results by ARIMA and ANN models. This confrontation is also assessed by MAPE, which results are highlighted in table 2.

Table 2 - MAPE of each model

	MAPE
ARIMA (4, 2 ,1)	11,8%
ANN	12,5%

Generally speaking, it appears that the ARIMA (4, 2, 1) has superior performance compared to ANN. Moreover, the MAPE obtained for both models satisfies the requirement for the percentage error below 15%. Soon, the two models show themselves able to efficiently estimate the admission of patients at the emergency department of a Brazilian cardiopulmonary public hospital.

FINAL CONSIDERATIONS

Studies directed at high-performance forecasts can provide valuable contributions towards a better understanding and ease the daily crisis admissions in the hospital emergency department. Faced with the need to get good estimates to assist managers in the decision-making process, it turns out that the two models ARIMA (4, 2, 1) and ANN present satisfactory results for the prediction of patients admitted to the emergency department a Brazilian hospital. Furthermore, as identified in some literatures, the application of these methods in various fields of research results in satisfactory performance and in some cases superior, in relation to the application of traditional methods, such as moving average, decomposition and linear regression.

A possible continuation of this research could be the development and application of hybrid methods that integrate these two models, since it is possible to find satisfactory results in other research fields, as well as the works of Khashei and Bijari (2011); Zhang (2003); Badu and Reddy (2014). At the same data set is also suggested the application of other prediction methods using heuristic models.

ACKNOWLEDGMENTS

The authors would like to thank Centro Universitário da FEI and FAPESP (Process number 2014/50001-6).

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