Forecasting erratic demand of medicines in a public hospital: A comparison of artificial neural networks and ARIMA models

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Abstract- *Demand planning is the process that helps in making decisions about inventory, in order to anticipate future demands from historical data. In an inventory with hundreds of items, a significant amount of these is subject to erratic demand. For these products, accurate forecasts are essential. This research work aims to show a comparison of ARIMA models and artificial neural networks for forecasting the demand medicines with an erratic nature.*

Keywords: ARIMA, Artificial Neural Networks, forecasting, erratic demand.

1. Introduction

The right to have timely and good quality health services is a prerequisite for maintaining proper health conditions of humanity requirement. One aspect of great importance in the health care is the access to medicines, because they are a basic input to healthcare process.

The *Results of the global partnership to achieve the Millennium Development Goals* report, from the World Health Organization (WHO), highlights the existence of great inequalities in regard to the availability of medicines in both public and private sector [6]. For this reason, the research focused on enhancing the hospital supply chain has been of great importance.

The hospital supply chain is more complex than industrial supply chains; since there are some hospital supplies, such as medicines, that can be considered critical for healthcare. Hence, its replenishment should have a high level of response. In addition to the requirement of quick replenishment, it has to take care of efficient management, since many of them are exposed to obsolescence [7].

Regarding hospital logistics cost, a major cost is the pharmaceutical one. There are 4 types of costs associated with the pharmaceutical inventory; namely, the acquisition costs, the ordering costs, the carrying costs and the stock-out costs [1].

In order to improve inventory management, demand forecasting plays a key role. This fact is highlighted in those medicines with an erratic pattern (i.e. those which exhibit large and unpredictable fluctuations over time), which tend to have a high acquisition cost. In this sense, an optimal control of these medicines will result in significant savings in the aforementioned costs.

Consequently, an adequate demand forecasting mechanism is indispensable. It contributes to the improvement of the inventory management; therefore, many research papers analyze the behavior of time series by means of quantitative forecasting models [4].

This paper aims to compare the utilization of statistical and AI-based mechanisms to forecast the erratic demand of medicines. To illustrate the former, we employ the widely used ARIMA models; while artificial neural networks have been developed to analyze the suitability of AI techniques.

The organization of this paper is as follows: Firstly, we introduce the ARIMA models. Secondly, we show the application of artificial neural networks for demand forecasting. Next, we analyze a specific case study. Finally, we conclude by revisiting our goals.

2. ARIMA Models

The autoregressive integrated moving average models (ARIMA) are the most important and used for time series analysis, these were introduced by Box & Jenkins in 1970. The ARIMA models are considered autoregressives because the variable to predict will be explained as a linear function of its observations in the past and random errors [8].

This type of modeling is useful when there is not a model which satisfactorily explains the relation between the forecast variable and other explicative variables. The ARIMA models are characterized for being flexible, this is, they represent different types of series, such as autoregressive (AR), moving averages (MA) and autoregressive moving averages (ARMA).

A non-seasonal ARIMA model can be classified as an "ARIMA (*p,d,q*)" model, where:

p *is the number of autoregressive terms;*
d *is the number of nonseasonal differences; and*
q *is the number of moving-average terms.*

The methodology Box-Jenkins includes three steps 1) model identification, 2) parameter estimation and 3) model checking.

Assuming for the moment that there is no seasonal variation, the objective of the model identification step is to select values of *d, p* and *q* in the *ARIMA (p,d,q)* model. The parameters estimated in the second step are a_i and b_i, finally in the model checking, it verified if the estimated model conforms satisfactorily to the observed series. If the estimation is inadequate, we have to return to step one and attempt to build a better model.

3. Artificial Neural Networks

The artificial neural networks (RNA) are techniques of computational modeling for complex problems. This discipline of artificial intelligence has emerged recently and has big acceptance in different areas [2].

One of the big areas of application of artificial neural networks is time series forecasting. In contrast to the quantitative forecasting models, the RNA have the learning ability by examples and it can identify the relations between the data, even though these are difficult to describe [9].

There are six important aspects to consider in the ANNs creation:

1. Network architecture

There are different network architecture, among them, should be highlighted the multilayer perceptron, because it has proven to be an effective alternative to quantitative techniques [3].

The multilayer perceptron, also named backpropagation network consist of inputs and outputs system with processing units knows as neurons or nodes (Fig.1). The neurons in each phase are interconnecting by forces called synaptic weights and output signals that are a function of the sum of the inputs to the neuron. Additionally to the processing neuron there is an slant neuron connecting to each processing unit of the hidden layer and output layer [5].

Other structure of ANN is the basis radial function (RBF), an RBF network is designed with neurons in the hidden layer activated by radial non-linear functions with its own gravitational centers, while the output layer is activated by linear functions.

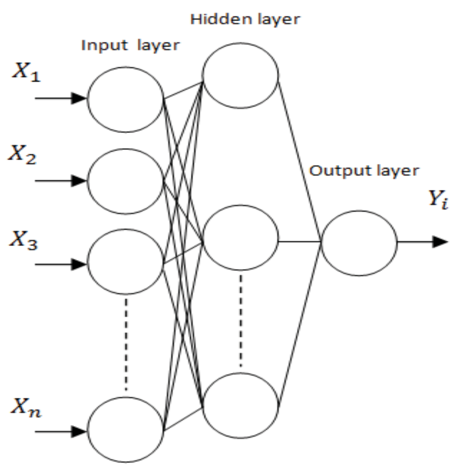

Figure 1. Multilayer perceptron neural network structure.

For a forecasting problem, the inputs to an ANN are usually the independent variables. The functional relationship estimated by the ANN can be written as:

$$y_i = f(x_1, x_2, x_3, \dots x_n)$$

Where $x_1, x_2, x_3, \dots x_n$ are independent variables and y_i is the dependent variable.

2. Network configuration

The network configuration is determined by:

- The number of input nodes.
- The number of hidden nodes and hidden layers.
- The number of output nodes.

3. Activation function

The activation function determines the relationship between input and outputs of a node. The commons activation functions are: the sigmoid function, the hyperbolic tangent function, the sine or cosine function and the linear function.

4. Training algorithm

The neural artificial training is an unconstrained non linear minimization problem in which are weights of a network are iteratively modified to minimize the overall mean or total squared error between the desired and actual output values for all output nodes over all input patterns. The training algorithm most used for the multilayer perceptron is the backpropagation.

5. Data normalization

The data normalization can be realized by four methods:

- Along channel normalization
- Across channel normalization
- Mixed channel normalization
- External normalization

The choice of the normalization methods generally depends on the composition of the input layer.

6. Training sample and test sample

Training and test sample are required for the execution of artificial neural network. The training sample is used for ANN model development and the test sample is adopted for evaluating the forecasting ability of the model.

7. Performance metrics

The most important measure of the results of a neural network is the accuracy in forecasting. There are different measures of accuracy in the forecasting; in this work we measure the Mean Absolute Deviation (MAD), the Mean Squared Error (MSE) and the Root Mean Squared Error (RMSE).

4. Medicine demand forecast

In this study, the demand of two drugs in a public hospital will be analyzed. Demand data of these medicines corresponds the period 2012 - 2015 and were obtained monthly, resulting in series of 48 data.

The selected medicines have the property of an erratic demand. That is, they show variations over time for example a zero demand and then large quantities of demand.

ARIMA models are considered for the forecast demand, they are executed in Statgraphics software and the application of neural networks is executed in SPSS software.

This section shows the time series graphics, residual autocorrelations functions and residual partial autocorrelations for the 2 medicines, which are identified by codes 5250 and 4250.

As a first stage of analysis the forecasts models were executed in Statgraphics and the best model was selected according to the Akaike criterion. The models selected were ARIMA (2, 0, 4) for 5250 medicine and ARIMA (0, 1, 3) for 4250 medicine. The figures 8 and 9 show the real demand and the forecast demand.

After the forecasts with ARIMA models, the forecasts with neural networks were realized. For that it was used the multilayer perceptron and the radial basis function. The structure of the neural network is similar to that showed previously in Figure 1, the inputs of the hidden layer are the demand in different periods and the output is the forecast demand.

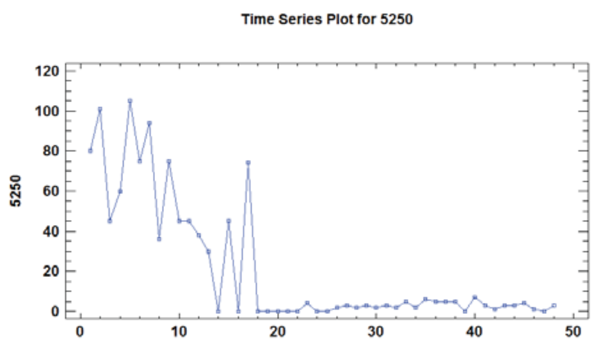

Figure 2. Time series 5250.

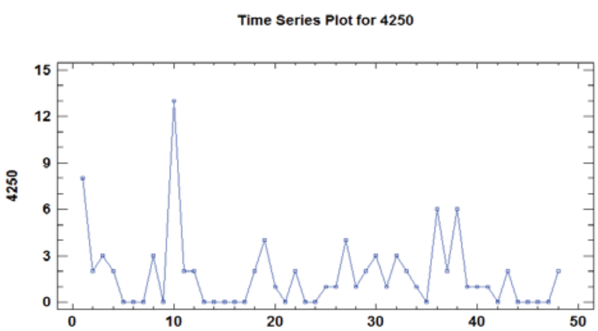

Figure 3. Time series 4250.

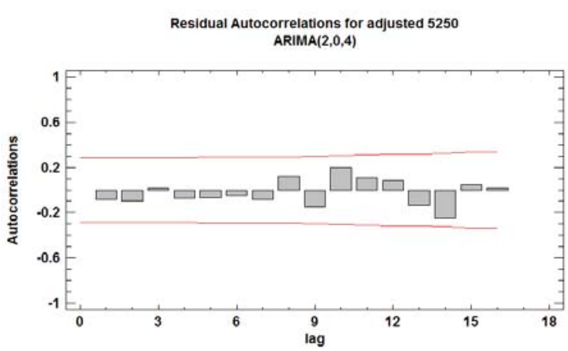

Figure 4. Residual autocorrelations function 5250.

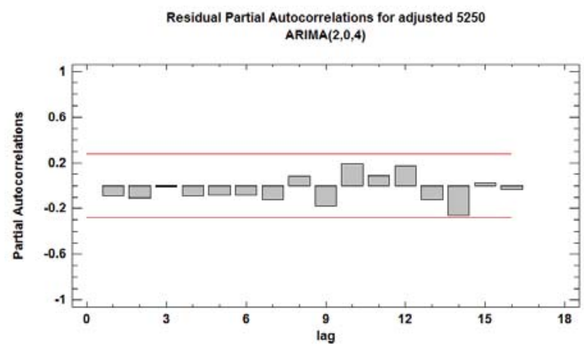

Figure 5. Residual partial autocorrelations 5250.

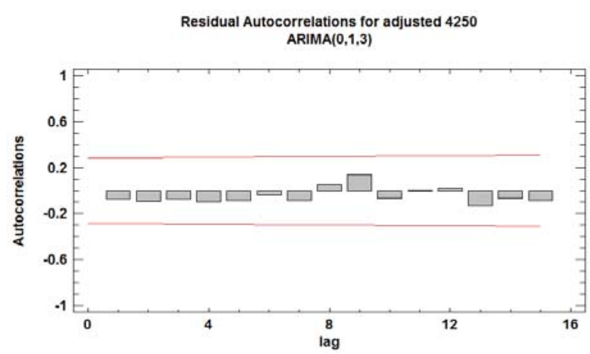

Figure 6. Residual autocorrelations function 4250.

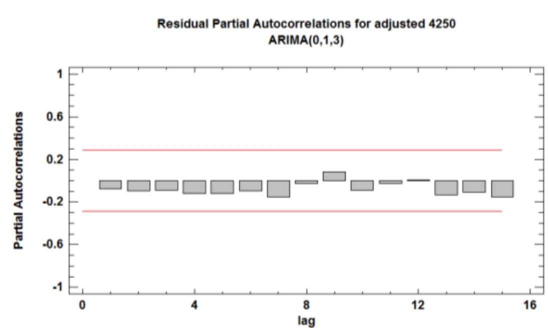

Figure 7. Residual partial autocorrelations 4250.

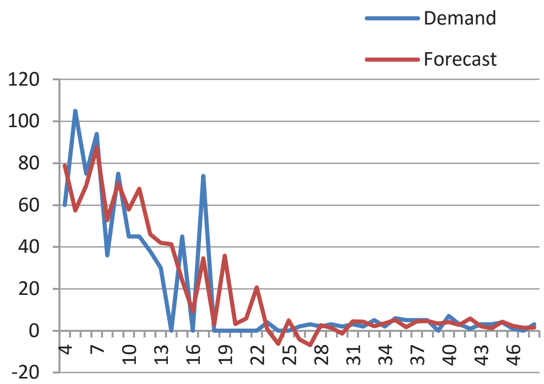

Figure 8. Demand and Forecasts graphic 5250.

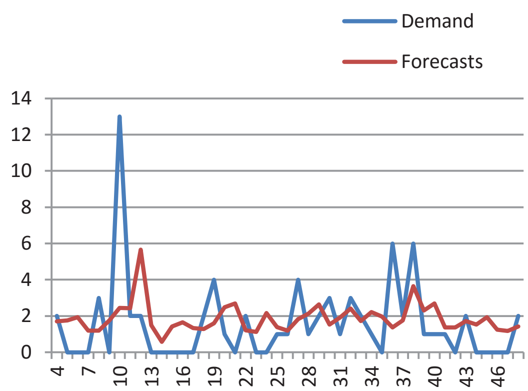

Figure 9. Demand and Forecasts graphic 4250.

Figures 10 and 11 show the real demand and the forecast demand.

In order to evaluate the forecast demand with ARIMA models and artificial neural networks we calculate the Mean Absolute Deviation (MAD), the Mean Squared Error (MSE) and the Root Mean Squared Error (RMSE). The results are in tables 1 and 2.

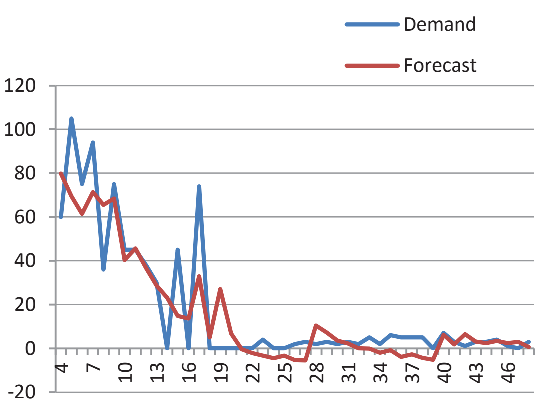

Figure 10. Demand and Forecasts graphic 5250 with ANN.

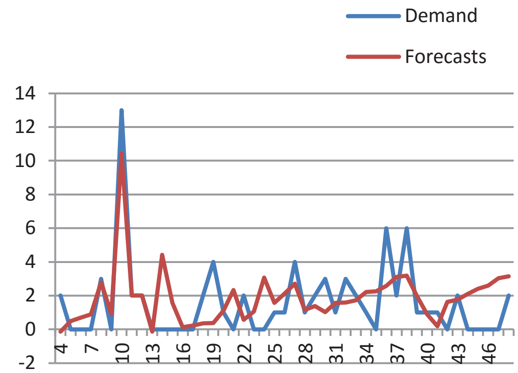

Figure 11. Demand and Forecasts graphic 4250

TABLE 1. Results of ARIMA model and ANN for 5250.

Model	MAD	MSE	RMSE
ARIMA (2,0,4)	8.952	216.770	14.723
ANN	8.783	180.443	13.432

TABLE 2. Results of ARIMA model and ANN for 4250.

Model	MAD	MSE	RMSE
ARIMA (0,1,3)	1.574	5.097	2.257
ANN	1.367	3.082	1.755

In both cases, the artificial neural networks mechanism showed better results in terms of the performance measure.

5. Conclusion

This paper presents an analysis of forecasting demand of medicines with erratic demand. These medicines are characterized by a high acquisition cost and a sporadic demand over time. These special chatacteristics cause a high precision requirement in the demand forecast.

In this regard, we analyze two different techniques, ARIMA models and AI techniques, such as MLP and RBFs ANNs. Our results show that for this type of medicines, the ANNs offer a better performance than the ARIMA models.

6. References

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