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RESEARCH ARTICLE

MULTIPLE REGRESSI ON FOR THE FORECAST OF SPARE PARTS FOR MEDICAL EQUIPMENT

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ABSTRACT

The constant search for efficiency in the provision of hospital services confronts the health sector with greater challenges in terms of managing the maintenance of medical equipment. Forecasting the demand for spare parts is a complex process due to their intermittent behaviour. As part of this process, the PREDSTOCK algorithm is proposed in this manuscript to predict the stock of spare parts for medical equipment using Multiple Regression as a quantitative estimation technique.

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INTRODUCTION

Medical devices are goods with a direct effect on human life. They require considerable investment and often have high maintenance costs. It is therefore important to have a properly planned and managed maintenance programme, as the resources required for maintenance are difficult to project. This requires a maintenance background and knowledge of when equipment can fail (OMS, 2012). In the planning of a maintenance program it is possible to foresee by consulting the manufacturer's recommendations, which parts will need to be replaced and how often. Although the demand for spare parts for medical equipment may vary, depending on the geographical conditions in each region, the location of the health facility, or for other social or political reasons (Rosas, 2013). In the last decade, the development of mathematical models to forecast the demand for spare parts has given rise to a series of applications in various areas of society: the petrochemical industry, aviation, telecommunications, automobile sales and distribution companies, the copper mining industry, among others (Rosas, 2013; Regattieri, 2005; Hua, 2006; Godoy, 2008; Huang, 2010; Jianfeng, 2011; Zhou, 2012; Chackelson, 2013; Frazzon, 2014; Vasumathi, 2015; Yang, 2018; Van der Auweraer, 2018; Costantino, 2018; Kian, 2019).

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However, there has been a lack of practical applications for forecasting medical equipment spare parts stocks, in relation to the relevant theoretical proposals developed for the process of forecasting spare parts demand. In addition to the complex characteristics of the medical equipment and the great heterogeneity of brands and models that make difficult the use of quantitative methods in the forecast of the spare parts stock. This paper presents the PREDSTOCK algorithm based on data analysis to predict the stock of spare parts in medical equipment using Multiple Regression as a quantitative estimation technique. The manuscript is divided into four sections. In the first section: Materials and methods, the fundamental concepts used in the development of the algorithm are discussed, explaining how it works step by step. On the other hand, in the section: Results and discussion, the "Prediction and Stock Management Module" of the System for the Management of Clinical Engineering and Electromedicine (SIGICEM) is presented as a practical contribution to the solution. In addition, this section presents a detailed analysis of the operation of the algorithm, which allows its contribution to the improvement of the accuracy of the predictions of the stock of spare parts for medical equipment in Cuba. Finally, section four presents the conclusions and future projections made by the authors in relation to the prediction of the stock of spare parts in medical equipment.

MATERIALS AND METHODS

The forecast of demand for spare parts stock plays a key role in the strategy of numerous manufacturing or service organizations (De La Fuente, 2016). The terms stock or stock, are used to refer to items that remain stored in the company pending a later use, in some cases for the proper and continued operation of production equipment or services. The reasons for keeping stocks are related to improvements in customer service (Carreño, 2011). The process of forecasting demand for spare parts stock is characterized by being a complex process, due to the intermittent behavior of demand. Because demand for parts appears sporadically, with some periods of time showing no demand at all. When demand occurs, it may not be a single unit or a constant size, making it difficult to predict and errors can be costly in terms of obsolete stock or unsatisfied demand (Syntetos, 2005). In the process of maintenance management to establish the demand for spare parts it is necessary the exhaustive analysis of indicators defined in the literature worldwide, such as: mean time between failures, mean time of repair, technical availability, frequency of maintenance, operational reliability, frequency of failures, historical stock of parts planned in previous years, among others. For this reason, the PREDSTOCK algorithm includes functions that allow the prediction of the technical availability of medical equipment from a Markov model, the calculation of the operational reliability of equipment and the frequency of failure of the parts or components of these devices through intelligent data analysis. In order to do this, PREDSTOCK takes into account that medical equipment has a dynamic working behavior, which passes through a finite number of absorbent states: Running (F), Faulty (D), Broken (R).

Sampling Techniques in Data Management: The application of sampling techniques in data management during the process of forecasting the demand for spare parts stock expands the possibilities and flexibility with regard to the information that can be obtained. In this way the selection of a sample can produce more accurate results than the complete enumeration. There are several sampling techniques: simple random, for proportions and percentages, stratified random, systematic, by cluster or cluster, among others (Hernández, 1998). The sampling technique used by the authors for this paper was stratified random sampling. The population of N units was first divided into subpopulations of $N_1, N_2 \dots N_L$ respectively. These subpopulations do not overlap and as a whole comprise the entire population, therefore, $N_1 + N_2 + \cdots + N_L = N$.

Subpopulations are called strata. To obtain the full benefit of stratification, the values of the N_L must be known. Once the strata had been determined, a sample was drawn from each stratum. The extractions were made independent in the different strata. The sample sizes within the strata are denoted with $n_1, n_2, \cdots n_L$, respectively. A simple random sample was then taken from each stratum.

Data Management in PREDSTOCK: The data used to predict the stock of spare parts for medical equipment comes from two different sources: the Clinical and Electro medical Engineering Management System (SIGICEM) database, which includes current data, and the Reportech software database, which includes historical data. Both databases are available from the National Electro medical Center of Cuba. For this reason, the data were not standardized, so the need arose to extract the necessary data to locate them in a single source of information. To this end, the extraction, transformation and loading (ETL) processes were carried out from SQL sentences, which were executed through a script in the MySQL Database Management System, without the need to use tools designed to carry out ETL processes, since a high degree of transformations, calculations and processing was not required (Morales, 2016).

Selecting Indicators for the PREDSTOCK Algorithm: The selection of indicators in the prediction of spare parts stock was made from a bivariate correlation analysis using Pearson's linear correlation coefficient ($\boldsymbol{\rho}$). The results obtained showed that the indicators: failure frequency, technical availability, operational reliability show a statistically significant relationship with the stock history of parts planned in previous years, with a $\boldsymbol{p\_valor \leq 0.05}$. Therefore, these indicators were considered as explicative variables in the process of predicting the stock of spare parts for medical equipment.

Selecting the Forecast Method: The Weka 3.7.10 tool was used to evaluate experimental data (historical data from pieces of medical equipment) with causal methods such as Multiple Linear Regression (MRL) and other soft-computing methods: multilayer Perceptron network (MLP) and decision trees ($REPTree$). The comparison was made from the accuracy indicators: correlation coefficient ($\bar{R}^2$), MAD, $RMSE$ and $MAPE$. The best results were achieved with the LRM method because it yielded the highest values of the determination coefficient ($\bar{R}^2 = 0.9403$) and lowest error indicators ($MAD = 4.7949 RMSE = 6.2038; MAPE = 32.0629$).

PRESTOCK Algorithm Functions: The PREDSTOCK algorithm groups four functions (FFP, CONFEM and DISTEM), which will be described below.

FFP function: Allows the calculation of the failure frequency coefficient of parts ($\bar{X}$) in medical equipment in correspondence with the reports in the service orders registered in the health units (equation 1). To do this, the following indicators are used: number of breakages or affectations per year (x_i) and the number of years (n) in which the equipment has passed through the states: Faulty (D) or broken (R) according to the specified piece.

$$\bar{X} = \frac{x_i}{n} \tag{1}$$

CONFEM function: allows the calculation of the operational reliability coefficient (C_o) from the intelligent analysis of failure patterns in medical equipment. This function is based on the theoretical foundations described by Espinosa (2011) (Espinosa, 2011). CONFEM constructs the sequence of absorbent states that a medical team has passed through. Subsequently, C_o (equation 2) is calculated based on the maintenance times: Mean Time Between Failures ($MTBF$) and Mean Time to Repair ($MTTR$) (Morales, 2018).

$$C_o = \frac{MTBF}{MTBF + MTTR} \tag{2}$$

DISTEM function: Allows the calculation of the technical availability coefficient, based on the Markov chain in discrete time. It is based on the Markovian property (equation 3), in which it assumes that the transition from one current state to another in the future, depends only on the current state, where

Algorithm PREDSTOCK

Input:

listEquipment: List of equipment reported in service orders
eReportlist: List of medical equipment reports
listENMCO: List of normal equations by the method of Ordinary Least Squares
listVector: List with the elements of the observation vector
listCoef: List storing the coefficients of the stock prediction equation
varLongEq: Length of the equipment list
varSpec: Electromedical specialty belonging to a medical equipment
varNameE: Name of medical equipment
varDescripP: Description of a piece of medical equipment
varNA: Number of years of medical equipment reports
varX$_{1i}$: Frequency of failure of a piece of medical equipment
varX$_{2i}$: Operational reliability of medical equipment
varX$_{3i}$: Technical availability of a medical equipment
varY$_i$: Sum of elements of the observation vector

Output:

varStock: Prediction of the stock of a spare part for medical equipment

for i=1 to i< varLongEq do
    for j=1 to j<varNA do
        eReportlist [j] = FillList (listEquipment [i],varSpec,varNameE, varDescripP)
    End for
    if varNA < > 0 do
        varX$_{1i}$ = FFP (eReportlist)
        varX$_{2i}$ = CONFEM (eReportlist)
        varX$_{3i}$ = DISTEM (eReportlist)
    End if
End for
listENMCO = BuildNormalEquations (varNA, varX$_{1i}$, varX$_{2i}$, varX$_{3i}$)
listVector = BuildVectorObservations (varY$_i$, varX$_{1i}$, varX$_{2i}$, varX$_{3i}$)
listCoef = EstimateCoefficients (listENMCO, listVector)
varAux$_1$= MeanValue (listReporteE)
varAux$_2$= MeanValue (listReporteE)
varAux$_3$= MeanValue (listReporteE)
varStock = listCoef [0]+ listCoef [1] varAux$_1$+ listCoef [2] varAux$_2$+ listCoef [3] varAux$_3$
Return varStock

Figure 1. PREDSTOCK Algorithm

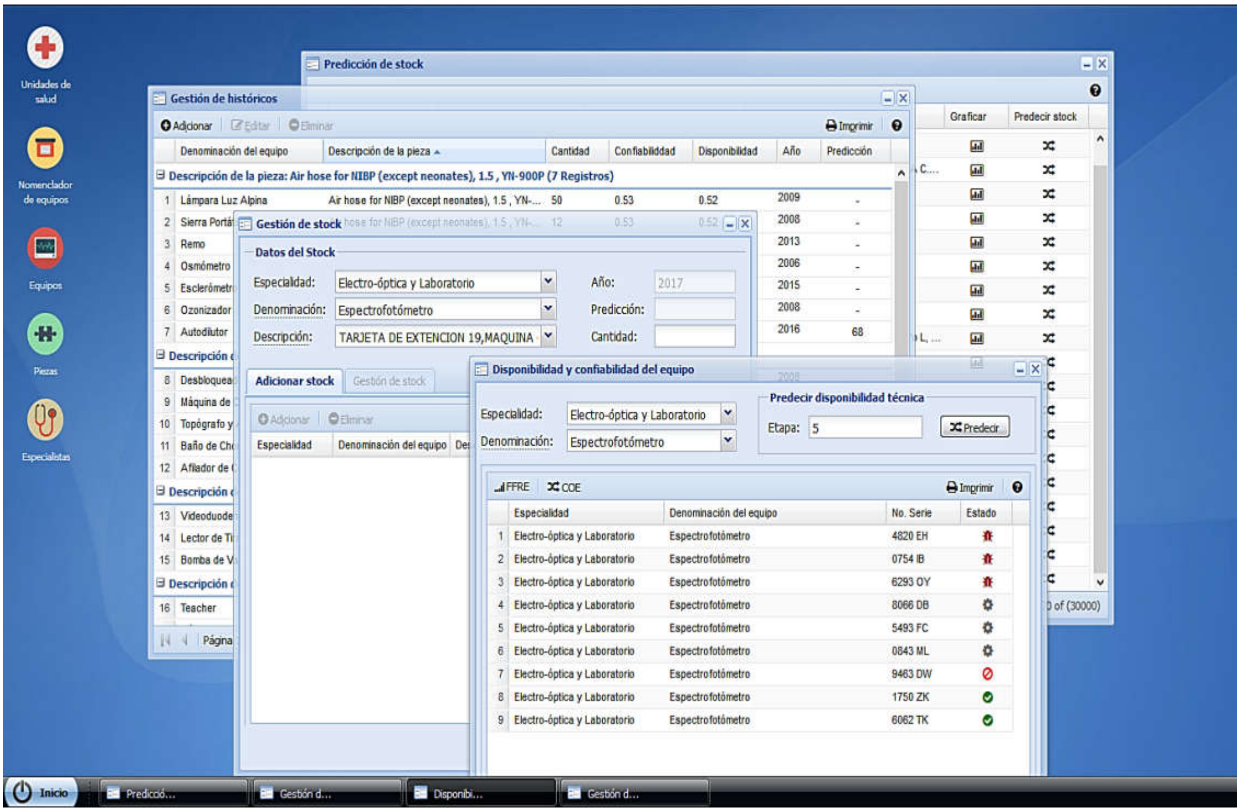

Figure 2. Interfaces of the SIGICEM "Prediction and Stock Management Module

Table 1. Statistics of related samples

	$Middle$	N	Z	$Sig.(p\_valor)$
Observed stock	91,173	36	1,288	0,198
Forecast stock with PREDSTOCK	93,500			

Table 2. Statistics of related samples from experiment two

		$Middle$	Z	$Sig.(p\_valor)$	N
SEE	Without the Predstock	7,1936		0,000	
	With Predstock	3,2907			
MAD	Without the Predstock	5,0236		0,000	
	With Predstock	2,1799			
$RMSE$	Without the Predstock	6,1009		0,000	
	With Predstock	2,6318	5,2238		36
$MAPE$	Without the Predstock	42,5637		0,000	
	With Predstock	16,0671			
$\bar{R}^2$	Without the Predstock	0,7855		0,000	
	With Predstock	0,9695			

t is given in months and takes values between 1 and 12. Its result is given by a row vector (π), invariant of 1×3, where the first value is associated to the probability that the equipment is working, the second to the probability that the equipment is affected and the third value to the probability that the equipment is in a broken state (equation 4) (Morales, 2015).

$$P_r\left(X(t_{n+1}) = P_r\big(X(t_{n+1}) = i_{n+1} | X(t_n = i_n)\big)\right) \qquad (3)$$

$$\boldsymbol{\pi A} = \boldsymbol{\pi} \qquad (4)$$

Finally, the PREDSTOCK algorithm is executed according to the output obtained from functions FFP (X_{i1}), CONFEM (X_{i2}) and DISTEM (X_{i3}). This algorithm starts from $k+1$ quantitative variable, being y, the response variable (annual stock) and X_{1i}, X_{2i}, $\dots X_{ki}$ the explanatory variable and implements the method of ordinary least squares (MCO) to estimate the population parameters in the LRM ($\beta_0, \beta_1, \beta_2, \beta_3$).

PREDSTOCK Algorithm: The prediction of the annual stock of spare parts for medical equipment was made in n stages. The PREDSTOCK algorithm is described below (Figure 1). The Multiple Linear Regression was used as an estimation technique to predict the stock of parts. PREDSTOCK has as input parameters the list of equipment reported in the service orders in the health units. The temporal complexity of the algorithmis $O(n^3)$.

RESULTS AND DISCUSSION

The PREDSTOCK algorithm was incorporated into the business component of MPREDSTOCK: Multivariate prediction model of spare parts stock for medical equipment (20). For this reason, PREDSTOCK receives as input for its execution the same parameters of MPREDSTOCK. To validate the effectiveness of the PREDSTOCK algorithm, the experimental method was used based on having each piece independently. As a practical contribution to this work, the Prediction and Stock Management Module of the Management System of Clinical Engineering and Electromedicine (SIGICEM) was implemented (Figure 2). The non-parametric Wilcoxon sign ranges test was applied to demonstrate that the observed spare parts stock from previous years does not differ statistically ($p\_value > 0.05$) from the spare parts stock calculated from the PREDSTOCK algorithm. For this purpose, 30.843 reports of the technical status of medical equipment carried out in service orders of health centers in the national territory in the years from 2003 to 2014 available in the Reportech System (Cabrera, 2007) were taken as the unit of analysis. Based on the reports, a case database was created with 385 instances, which represents 1.25% of the total data selected as the SIGICEM unit of analysis. These instances were divided into $k = 10$ training sets, so 356 instances were used for training and 39 for testing.

Application of the non-parametric test of Wilcoxon sign ranges

Experiment 1: Compare the stock observed and the stock predicted by PREDSTOCK with respect to its medians with the selected experimental group.

Measuring

- Observed stock.
- Forecast stock with the PREDSTOCK algorithm.

Wilcoxon test hypothesis

H_0: There are no differences between the averages of the stock observed and predicted by PREDSTOCK.

H_1: There are differences between the averages of the stock observed and predicted by PREDSTOCK.
Decision rule: if$p \geq 0.05$does not rejectH_0.

The experimental results show a $p\_value > 0.05$ therefore, the null hypothesis is not rejected, which indicates that there are no statistically significant differences between the values of the stock observed and predicted with the PREDSTOCK for $z = 1.288$, $p\_value = 0.198$.

Experiment 2: Demonstrate that there are statistically significant differences ($p\_valor \leq 0.05$) in predicting spare part stock before and after PREDSTOCK application.

H_0: There are no differences between the medians of the accuracy indicators measured before and after the application of PREDSTOCK.

H_1: There are differences between the medians of the accuracy indicators measured before and after the application of PREDSTOCK.

Decision rule: if $p\_valor \leq 0.05$ rejects H_0.

The experimental results in table 2 show a $p\_value < 0.05$, therefore, the null hypothesis is rejected, which indicates that there are statistically significant differences between the median accuracy indicators obtained before and after PREDSTOCK was applied. The SEE, $MAD, RMSE$ and $MAPE$ indicators showed lower values with the application of PREDSTOCK, indicating a trend of data concentration close to the mean, with a value of $\bar{R}^2$, which is desired. For this reason, 96.95% of the variability of the stock to its average is explained by the adjusted regression model.

For this reason, the PREDSTOCK using the multiple regression method is a suitable model to describe the relationship between the variables used in the forecast, which favors an improvement in the accuracy of the predictions.

Conclusions and future projection

The PREDSTOCK algorithm is based on the analysis of reports on the technical status of medical equipment carried out in service orders of health units. This allows to extend the number of reports without altering the temporal complexity of their execution. The results and discussion show that it is satisfactory that the algorithm is based on the distillation of the information collected, classified, organized and integrated in the SIGICEM database, with which the data are adequately represented for use by the developed computer system. As future projections, the group of authors recommends developing a decision tree for the classification of medical equipment maintenance according to the failure rate and the technical availability coefficient obtained with the application of Markov Models, which facilitates decision-making regarding the management of maintenance of these technologies.

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