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Article

A Methodology for Demand Forecasting Inventory Classification in Wholesale Supplier Companies

Metodología para pronosticar demanda y clasificar inventarios en empresas comercializadoras de productos mayoristas

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ABSTRACT

Objective: To recommend a methodology that allows for inventory classification and demand forecasting, by wholesale supplier companies, as critical factors to implement performance optimization.

Methods and techniques: The methodology relies on the use of a multilayer artificial neural network developed with Weka software, which adds a solution to inventory item classification problems, which is based on ABC and analytics of hierarchy processes (AHP). The methodology was developed in three phases, the first one was in charge of inventory classification, the second was related to forecasting, and the third, to integrated result analysis.

Main results: A hierarchical scale of variables was suggested for inventory item classification, as well as weigthing opinions and sub-opinions, and its selection extent. An effective way of forecasting individual demands was presented for every inventory item.

Conclusions: The application of this methodological tool by ACINOX sales company in Holguin province corroborated its effectiveness to solve inventory classification problems and demand forecasting. As a result, all the executives have access to a tool that contributes to decision-making, in order to favor better items classification and forecasting.

Key words: demand forecasting; aggregate planning; artificial neural networks; inventory classification; ABC classification.

RESUMEN

Objetivo: Proponer una metodología que permita la clasificación de inventarios y el pronóstico de la demanda, en empresas comercializadoras de productos mayoristas, los cuales son factores claves para optimizar su desempeño.

Métodos y técnicas: La metodología se sustenta en el uso de una red neuronal artificial tipo perceptrón multicapa creada con el *software* Weka; con el agregado de resolver problemas de clasificación de ítems del inventario, basados en ABC y el proceso de análisis jerárquico AHP. La metodología constó de tres fases, la primera encargada de la clasificación de los inventarios, la segunda del pronóstico, y la tercera del análisis integrado de los resultados.

Principales resultados: Se propuso una escala jerárquica de variables para la clasificación de ítems del inventario, así como de los pesos de los criterios y subcriterios que la conforman, y su rango de selección. Se mostró una manera efectiva para pronosticar la demanda de forma individualizada para cada ítem del inventario.

Conclusiones: La aplicación de la herramienta metodológica en la empresa ACINOX UEB Holguín comercializadora, de la provincia Holguín, Cuba, validó su efectividad para resolver problemas de clasificación de inventarios y pronóstico de demanda. Como derivado de su aplicación, se proporcionó a sus directivos, un instrumento que permite la toma de decisiones en aras de favorecer aquellos ítems mejor clasificados y sus pronósticos.

Palabras clave: pronóstico de la demanda; planeación agregada; redes neuronales artificiales; clasificación de inventarios; clasificación ABC.

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INTRODUCTION

The search for process improvements in sales companies is a priority reality for success nowadays. In this sense, it is important to conduct proper management of critical processes to estimate demands, inventory management, and aggregate planning.

The fact that sales companies can predict the demand of their products in the market ensures optimum strategy design of chains of tasks through the commercial process, which will certainly enhance sales levels, and lead to management success.

According to Jacobs and Chase (2014), there are two basic sources of demand: dependent and independent. The former is the demand of a good or service caused by the demand of other goods or services; it is an internal demand that needs no prediction. The latter is not directly derived from other goods, so it requires prediction studies; the object of this study is focused on the study of this type of demand, particularly.

Today, several prediction techniques have been developed; they are used to predict one or more than the four components of the demand: trend, cycle, seasonality, and randomization (Krajewski, Malhotra & Ritzman, 2018; Rivas, 2017; Stevenson, 2018).

- This trend considers gradual change in time series for a long period of time.
- The cycle analyzes any pattern of value sequences above or below the tendency line.

- Seasonality considers regular variability patterns within certain periods of time.
- Randomization is caused in a short time; it is impossible to anticipate, and it has no recurring factors.

In turn, a forecast is usually classified by the time horizon it comprises, and it is classified into three categories: short, mid, and long term. Mid and long term forecasts are distinguished from short time forecasts by the fact that it is more accurate, among other elements. Forecast accuracy is likely to decrease the longer the time horizon (Heizer, Render & Munson, 2017).

Short term forecasts are used to conduct aggregate planning. Meanwhile, the forecasting techniques used may be qualitative and quantitative. Qualitative techniques are characterized by having a subjective background, since they rely on estimates and opinions. In turn, quantitative techniques can be divided into time series, causal relations, and simulation:

- Time series are characterized by a historical analysis of events through time, in order to project future.
- Causal relations try to understand the underlying system surrounding the element to be predicted.
- Whereas simulations rely on dynamic models, usually computer-assisted models, which allows the person in charge to make suppositions of the internal variables and the external environment of the model.

Inventory classification is a necessary addition to predict the demand, and to plan operations in wholesale companies.

One of the most commonly used techniques in decision-making is Pareto analysis, which is used to determine a number of tasks that predict a significant effect. It is based on the principle of considering the analysis of all data from the highest to the lowest frequency, which helps identify the few vital factors to be considered, and the many trivial factors to be ignored.

ABC analysis uses the Pareto principle, though it generally considers one criterion for item selection. These few items, on which most sales contributions fall, are called class-A items; they are critical for the business, and their existence makes the largest share of investment of inventory resources. Other items known as B and C are numerous, but their contribution is less significant.

As part of aggregate planning, most resources should be earmarked to class-A resources (greater yields), whereas expenses in the other resources, with a lower effects on company profits, are kept at minimum values. Thus, the efforts and resources saved on low value items (items B and C) are used to enhance the sales of goods known as class-A. ABC analysis is the traditional method used to classify inventories. In that sense, multicriteria classification requires hierarchical analysis of the corresponding variables.

Depending on the variables defined, the annual value of certain good demands and the critical nature of the product were classified in the inventory items (Flores & Whybark, 1989). Meanwhile, Flores, Olson & Dorai (1992) showed the same procedure; however, they considered the addition of variable “better time” as valid. In the pharmaceutical industry, for instance, an artificial neural network was used to classify random items based on unit price, cost, demand, and delivery time (Partovi & Anandarajan, 2002). Other opinions, such as unit cost and time, were suggested by Hadi (2010), using a programmed non-linear model. Rezaei & Dowlatshahi (2010) suggested a system based on fuzzy rules relying on price, annual demand, time, and durability. In turn, Balaji & Senthil (2014) presented a solution for a car maker based on hierarchical arrangement of classification, a technique based on the procedure suggested in this paper. Zowid, Babai, Douissa, & Ducq (2019) used ABC with a Gaussian model but only applied to a set of theoretical data.

The analytics of hierarchy process (AHP) dates back from the 1980s. It was developed by Saaty, in order to solve complex problems of multicriteria classification; the author created a scale (Table 1).

Table 1 Main scale for analytics of hierarchy process

Ij value	Description
1	Criterion in which i and j are equally important
3	Criterion in which i is slightly more important than j
5	Criterion in which i is more important than j
7	Criterion in which i is much more important than j

9	Criterion in which i is absolutely more important than j
2,4,6,8	Mean values

Source: Based on Saaty (1980)

This process consists in the disintegration of complex problems into sub problems, and in turn, they become a hierarchic structure, which is evaluated according to the previous scale by criterion pairs on item impact. This procedure is, according to experts, a critical step in decision-making. AHP consists of four steps (Balaji & Senthil, 2014):

(1) The problem is disintegrated into a hierarchic structure based on objectives, criteria, sub criteria, and alternatives.

(2) Criteria and alternatives are compared in pairs, in relation to the importance of the objective.

(3) The results of comparison by criterion pairs may be aggregate in a comparison matrix (A) n * n, with formula 1.

A = (a_{ij}), where i, j = 1, 2, 3….n. (1)

Formula 2 is used to calculate the weight of priority of the comparison matrix.

$A_w = h_{max}W$ (2)

Where A is the n element in the comparison matrix, h_{max} is the maximum of every A value, and w is every vector corresponding to h_{max}.

(4) The consistence index (*CI)* can be calculated to evaluate the matrix consistency, using the equation 3.

$$CI = \frac{h_{max} - n}{n-1} \qquad (3)$$

To measure the level of consistence of *CI* of the consistence radius *CR* is calculated using equation 4.

$$CR = \frac{CI}{RI} \qquad (4)$$

Where *RI* is the random index.

The value of *CR* must be below 0.10; otherwise, the procedure should be repeated to improve consistence.

The integration of demand forecasting and inventory classification has been considered by several researchers due to the high impact on aggregate planning of organizations.

Recent research in this area evidenced that some authors integrated the two topics simultaneously, many times suggesting improvements or alternatives to classic algorithms. Snyder, Koehler & Ord (2002) developed an inventory model that stems from exponential smoothing forecasting. Little & Coughlan (2008) studied the optimization of safety stocks based on restrictions in hospitals. Ferbar (2010) suggested the integration of the inventory and forecasting models by optimizing the parameters and the initial values. Teunter, Syntetos, Babai & Stephenson (2011) studied the effect of forecasting models on the costs and service levels; they suggested considering these factors, along with error minimization, to evaluate the model for application. Meanwhile, the forecasting technique of Holt-Winters, with the addition of service level differentiation by ABC classification, was used by Arango, Giraldo, and Castrillón (2013) in sales and service companies.

DEVELOPMENT

Machine learning methods have demonstrated better yields than all the statistical techniques used for time series analysis (Fry & Brundage, 2020; Makridakis, Spiliotis & Assimakopoulos, 2018). The capacity of universal approximation of neural networks (NN) for continuous functions containing first and second derivatives throughout their domains, has been verified mathematically. Additionally, several research studies demonstrate that NN can approximate several types of complex functional relations accurately.

In that sense, quite a few studies deal with various forms of confirming NN to conduct demand forecasting. Medeiro, Tersvirta & Rech (2006) suggest a hybrid model between an auto-regressive model (AR), and a neural network with only one layer concealed. Its main advantage is the low computing cost of solution. Others, like Li, Luo, Zhu, Liu & Le (2008)**,** consider the combination of AR models and NN with generalized regression (GRNN). The result indicates that it is an effective model to get the best from the two in just one model.

Khashei, Reza & Bijari (2008) suggest a hybrid model based on the basic NN concept with a fuzzy regression model to achieve more accurate forecasts with incomplete data. Then, two of these authors (Khashei and Bijari, 2010), presented a new hybrid based on a NN model, using the ARIMA methodology (autoregressive model integrated mean mobile) to achieve a more accurate forecast. The combination of ARIMA and NN was the solution provided by Wang, Zou, Su, li & Chaudhry (2013), in which three datasets were used with similar results.

Wang, Fang & Niu (2016) proposed a hybrid model based on Elman recurrent neural networks (ERNN), with stochastic time series, in which they demonstrated that neural networks have greater yields than linear regression, complex invariant distance (CID), and multi-scale (MCID). Neural networks with multilayer perceptron were used by Rivas (2017) with better mean estimation error results for forecasting. The same NN typology was used by Xu & Chan (2019) to predict the demand of medical supplies. Moreover, machine learning of power demand was used with the K-Nearest Neighbor (KNN) classification algorithm, by Grimaldo & Novak (2020).

In that sense, this paper suggests the utilization of this technique as part of the methodology to perform forecasting (NN-PMC), after demonstrating its efficiency previously. The methodology proposed has three phases and ten steps. A graph explaining its logic is shown in Fig. 1

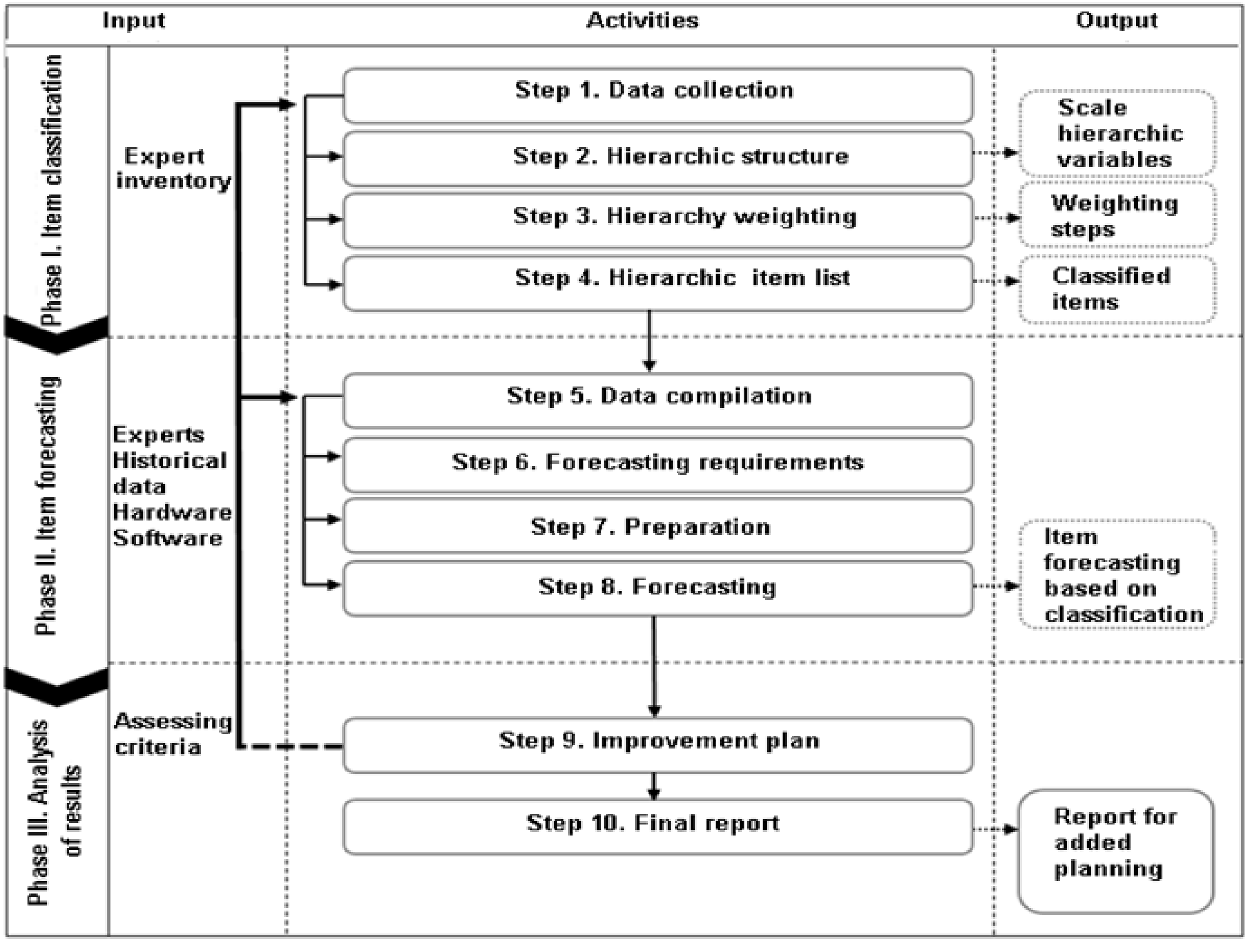

Fig.1. A methodology to forecast the demand based on ABC multicriteria and neuron networks

Source: Made by the authors.

Phase I. Item classification

Description: The data from the items to be classified were gathered, their hierarchical relations, and weighting were determined, with emphasis on the organization and the strategy to pursue.

Step 1. Data collection

The company data from a year, minimum, is collected; a list of the variables known by the entity was made for variable selection. Then, the experts are consulted to indicate the potentially correlated variables with forecast goods, which were not included in the previous list.

Step 2. Hierarchic structure

Considering the criteria for inventory control, variable demand (determined in this case by the number of item mobility values), unit price, weight, and volume in storage.

Step 3. Hierarchic weighting

Upon item compilation and analysis using Microsoft Excel, all the data are interpreted by a specialist appointed by the company. This person analyzes the criteria and sub criteria (according to the Saaty scale), and compares them to alternatives. Then, a final result of weights is given. This ensures the establishment of item rankings based on ABC classification.

Step 4. Hierarchic list of items

In this step, each item is ranked by ABC category, according to the type of corresponding order of weighting.

Phase II. Item forecasting

Description: The forecast is performed according to the priority order defined by ABC ranking from Phase 1, in keeping with the procedure of Lao, Rivas, Pérez, and Marrero (2017).

Step 5 Data collection

Information referring to each item will be gathered, which will be necessary to apply the instrument; in this case, the period to be forecast. A table with the chosen variables included on the columns, and the historical records (instances), on the rows, will be created. The information on the rows can be daily, monthly, quarterly, or annual. The dependent variable will always go at the end of the table, since software Weka (recommended for forecasting in this research) places the dependent variable (variable to be forecast) on the last column.

These variables are classified as follows:

- Nominal: the values represent categories that should obey intrinsic ordering;
- Ordinal: the values represent categories with some ordering; or
- Scale: the values represent categories arranged in a meaningful metrics.

Step 6. Forecast requirements

First, the minimum requirements for the test and operation will be defined, considering the hardware (2 GB ram, 3.7 GHz, and 100 GB hard drive capacity), Weka software on

Linux. The variables to be used in the forecast of good demand will be chosen; the correlated variables should be studied.

Step 7. Preparation

The information handled in the tables will be converted into the format of Weka data mining tool. Excel-ArffConverter can be used then; alternatively, the process can be done manually. The format extension is *.arff.

Step 8. Forecasting

The following steps will be taken to represent the outcome of forecast:

1. Open Weka explorer.
2. Choose the working dataset. *Open file.*
3. Go to *classify*, then click on *choose* to get the *Multilayer Perceptron* regression algorithm.
4. Click on *Start* to begin the construction of the model, and evaluate the model.

Phase III. Analysis of results

Description: The forecasting results of each item, and the improvement possibility of the methodology are presented.

Step 9. Improvement plan

A group of correction measures based on performance will be recommended for the implementation of the methodology, in order to reorient and readjust actions that demonstrate the capacity for improvements. To achieve that, an instrument is applied to the actors of the methodology to gather information that helps identify the problems to be addressed, and to define activities for improvements of the procedure. Each measure will have people in charge, resources, and control and accomplishing dates.

Step 10. Final report

A table shows the list of items from the sales organization arranged by their relevance determined in Phase 1, with the individual forecast corresponding to the resulting period analyzed in Phase 2.

Results

As a result of the implementation of this methodology in ACINOX company, UEB Holguin, the following hierarchic scale of variables was made for inventory item classification.

Level 1: Demand scale by item mobility

- Class 1: items with 25 or more mobility data.
- Class 2: items between 15 and 24 mobility data.
- Class 3: items between 5 and 14 mobility data.
- Class 4: items between 1 and 4 mobility data.
- Class 5: items with no mobility in the last year.

Level 1: Scale of prices

- High: items over 100 pesos.
- Mid: items between 10 and 100 pesos.
- Low: items below 10 pesos.

Level 1: Weight scale

- High: Items over 20 kg.
- Mid: Items between 1 and 20 kg.
- Low: Items below 1 kg.

Level 1: Storage scale

- High: Item covering 1 m^3.
- Mid: Item covering between 0.5 and 1 m^3.
- Low: Item below 0.5 m^3.

Then, as shown in Table 2, the weights of each variable were established.

Table 2. Hierarchic scale of criteria and sub criteria

Level 1	W	Level 2	W	I_{ij}
		Class 1	0.5616	0.04386
		Class 2	0.2521	0.01969
Demand scale by item mobility	0.0781	Class 3	0.1129	0.00881
		Class 4	0.0505	0.00394
		Class 5	0.0228	0.00178
Scale of prices	0.2413	High	0.7403	0.17863

		Mid	0.2037	0.04915
		Low	0.0560	0.01351
		High	0.0604	0.00186
Weight scale	0.0309	Mid	0.2099	0.00648
		Low	0.7297	0.02254
		High	0.0484	0.03144
Storage scale	0.6497	Mid	0.1599	0.10388
		Low	0.7917	0.51436

Source: Made by the authors.

CR: 0.007 157 28

I_{max} = 9.090 097 084 995 08 * 10^{-5}

I_{min} = 0.000 142 328 534 92 * 10^{-5}

Now, as shown in Table 3, the ANC classification is established, based on an interval scale.

Table 3 Scale for classification intervals

Item interval		AHP-based classification	ABC
Min	*Max*		
2.0 * 10^{-5}	9.0 * 10^{-5}	A	
0.1* 10^{-5}	2.0 * 10^{-5}	B	
0.000 14* 10^{-5}	0.1 * 10^{-5}	C	

Source: Made by the authors

Table 4 shows the list of arranged items as an output of Phase 1.

Table 4 Item classification

Item data		Classification data in the period					
Item name	Classifier	Quantity of mobility data	Price	Weight (kg)	Volume (m^3)	I_{ij}	ABC
12.7 mm corrugated steel bar	002BD0129G40M	78	498	4	0.2	2.61 *10^{-5}	A
3/8 corrugated bar	274ACCSA3/8A9FC0311	42	498	3	0.2	2.61 *10^{-5}	A
5/8 corrugated	004PLT901114049M	29	498	4	0.2	2.61 *10^{-5}	A

bar							
Construction scaffolds	400590	2	293	25	3	$0.00188*10^{-5}$	C
6 mm x 152 mm wood drills	C06-10040001	18	1	0.05	0,01	$0.0256*10^{-5}$	C
Standard 1/2.9 mm impact mortar buckets	C06-A4558F	10	2	0.1	0.02	$0.138*10^{-5}$	B
Phosphor bronze torch 80 mm	2215TOR0BRO-40	4	315	1	0.2	$0.37* 10^{-5}$	B
Table knife model 9400	TN0510-1-9400-007A	7	0.60	0.4	0.1	$0.0619* 10^{-5}$	C
LED tube 120/18ws	C98-189350421011191	88	5.50	0.03	0.1	$0.687* 10^{-5}$	B
30 cm steel float	C09-65950	3	5.34	0.5	0.2	$0.0619*10^{-5}$	C
1/2 x100 m hose	C48-20-0-8014	1	4.10[1]	40	0.3	$0.0023*10^{-5}$	C

[1]The price of the hose is by meter, whereas the other prices are by unit

Source: Made by the authors

As part of the 9th step of the methodology, the company's personnel in charge of the application was interviewed; they expressed their satisfaction with the design and application.

After the classification of the inventory, the second phase was implemented, with the collection of these data; a NN-PMC was built, and the results produced the forecasting shown in Table 5, with the hierarchic order determined in the previous phase.

Table 5 Forecast of classified items

Item data		Classification data in the period		Forecasting First quarter of 2020, by unit		
Item name	Classifier	I_{ij}	ABC	Jan	Feb	March
12.7 mm corrugated bar	002BD0129G40M	$2.61 * 10^{-5}$	A	75	60	74
3/8 corrugated bar	274ACCSA3/8A9FC0311	$2.61 * 10^{-5}$	A	54	62	15
5/8 corrugated bar	004PLT901114049M	$2.61 * 10^{-5}$	A	23	18	42
Standard 1/2 9 mm impact mortar bucket	C06-A4558F	$0.138 * 10^{-5}$	B	5	3	9
80 mm Phosphor bronze torch	2215TOR0BRO-40	$0.37 * 10^{-5}$	B	0	2	0

LED tube 120/18ws	C98-189350421011191	$0.687 * 10^{-5}$	B	24	13	26
Construction scaffold	400590	$0.00188 * 10^{-5}$	C	0	0	1
6 mm x 152 mm wood drills	C06-10040001	$0.0256 * 10^{-5}$	C	1	7	4
Table knife model 9400	TN0510-1-9400-007A	$0.0619 * 10^{-5}$	C	1	2	0
30 cm steel float	C09-65950	$0.0619 * 10^{-5}$	C	0	0	1
1/2 x100 m hose	C48-20-0-8014	$0.0023 * 10^{-5}$	C	0	0	0

Source: Made by the authors

CONCLUSIONS

This paper offers a methodological tool that offers a more effective way of forecasting demands based on classification of inventory items. Accordingly, it can be said that multi-criteria inventory item classification is not only a mechanism for the control of inventories, but also a tool capable of establishing an order of priorities to the company's characteristics, and its strategic process.

Demand forecasting is an indispensable process of aggregate planning; therefore, it is not only done with the purpose of forecasting future sales, but also its integration with inventory classification mechanisms is feasible and necessary when decision-making requires critical additions.

The validity and feasibility of the methodological tool was evaluated in practice through application in the sales company chosen for this study: ACINOX UEB Holguin. It demonstrated the effectiveness to solve inventory classification problems and demand forecasting.

Besides the methodology, the hierarchic scale of variables for inventory item classification, weighting of criteria and sub criteria, were also important contributions of this research. It also provided executives of the company with a tool that allows them to perform demand forecasting of classified items in a three-month period, with all the results of application.

Due to the complexity of the environment, further studies should consider fuzzy variables to determine weights in inventory classifications, which will support decision-making.

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Conflicts of interest and conflict of ethics statement

The authors declare that this manuscript is original, and it has not been submitted to another journal. The authors are responsible for the contents of this article, adding that it contains no plagiarism, conflicts of interest or conflicts of ethics.

Author contribution statement

Carlos Jesús Madariaga Fernández. Information management for paper updating. Preliminary conception (original idea), and article design. Theoretical rationale, project and development of the methodology, generation of formula and graphic indexes. Analysis of results Drafting of conclusions.

Yosvani Orlando Lao León. General theoretical review of the manuscript. Improvements to abstract and conclusions. Improvements in the results and logistic inferences. Review of bibliographic references.

Dagnier Antonio Curra Sosa. Review of formula and indexes, data processing, redaction of metainferences.

Rafael Lorenzo Martín. Technical review and utilization of terminology (specialized thesaurus) of the manuscript. Research coherence and logic, redaction and proofreading (structure and links) of the manuscript. Management of article stock for publication.