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Decision making in inventory control by using artificial neural networks

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Abstract
The purpose of this work is to increase the sales of a store devoted to the purchase and sale of soft drinks, even though the store's inventory is overstocked. This occurs as a result of the business's lack of an effective management system that controls product ordering. Additionally, there is no analysis of future sales owing to the variations that may occur because of unforeseen occurrences. The main criterion was that the proprietors of the business submit monthly records from 2017 to July 2019. To accomplish this objective completely, we used the Monte Carlo simulation method to obtain data from August to December 2019; and neural networks to obtain data for all monthly periods in the years 2020, 2021, and 2022, which enabled us to generate records of demand and stock for each of the products. Finally, it was shown that the application of neural networks enables the solution of vehicle control issues, resulting in a maximization of more than 22% of sales, thus achieving the goal and giving an optimum solution to the company.

Keywords: Monte Carlo; Population; Inventories; Neural Networks; Sales

1. Introduction

Forecasting demand and supply for products in the sales shop are the main factors to consider while optimizing inventory management. That is, it must determine the timing and quantity of stock to produce. Similarly, it should demonstrate which items generate the greatest revenue and which generate losses for the company. This data is critical for making business choices that optimize sales via effective inventory management, thus increasing the store's market competitiveness. This is due to inventory management issues affecting shops and pantries. Regardless of whether a company has an excess or lack of goods in stock, it will lose money. Inadequate inventory management results in several issues, including higher expenses, product loss, diminished market competitiveness, and customer loss.

According to [1] a prediction model for weekly sales in the company's Americas was created for the ETB campaign to get a better understanding of the necessary expenditures. To create this model, the research variable's series are analyzed and the HoltWinters, ARMAX, and ARMA models are used. Among the data collected, it can be stated that the HoltWinters model is the greatest predictor of sales in the Americas BPS business during the ETB campaign. However, they utilized different statistical methods to predict sales. A comparison of neural network prediction against statistical techniques in sales forecasting was created, using data on a business's total sales in dollars. According to the study's results, neural networks provided a more accurate approximation to actual values than the other statistical techniques mentioned in the article (ARIMA and exponential smoothing). However, as the research explains, inaccuracies in data collection may result in additional costs for the business [2].

According to Veloz et al. [3], who provided an organization's inventory using two methods: the ABC technique for selective inventory control and the Mini-Max inventory policy. The outcomes of the study include a 19.778 percent decrease in inventory levels for some raw materials utilizing the two techniques described above, as well as an increase in inventory levels for raw materials that produced scarcity prices. However, as the authors describe, they do not have an application that incorporates these methods. Carreño et al. [4] proposed a plan to enhance the inventory management system for SMEs. Due to the fact that the company's study revealed a known and consistent demand rate, they used the EOQ model. Additionally, they developed QR code-reading software. The use of this approach resulted in a decrease in inventory maintenance expenses. Additionally, it established a reordering point that would keep the variables under study in check. However, in this project, the results of the computations are obtained using the Excel program. As a result, even if a device lacks a QR code reader, access to the program would be seamless, as was the case with the aforementioned project.

Asencio et al. [5] conducted a study of a pharmaceutical company's inventory management system. The issue developed because of inadequate inventory management, namely the absence of control systems for rotation time. The data was gathered using an accounting diagnostic in conjunction with scientific methodologies and techniques (observation, interviews, and surveys). The findings indicated a lack of emphasis placed on inventories in financial decision-making, and 60 percent of respondents indicated a lack of agility and efficiency in managing inventory requisitions. However, no remedy was offered for the issue. On the other hands, an inventory model was designed and deployed to account for demand fluctuation and lead time variability. Microsoft Excel was utilized to make this model accessible to SMEs engaged in fish marketing. The paper that resulted from the usage of this computational tool simplified the inventory management process for SMEs. Although Excel has been a valuable tool for SMBs, it falls short when it comes to automating operations, since each parameter must be manually entered, resulting in a huge number of files. In contrast to the current study, which used Visual Basic for Excel to provide an efficient solution for repetitive process programming [6].

2. Methods

Diverse methods were used in this research. First, we started by gathering real data on beverage sales and purchases from a store in Guayaquil. Then, monthly sales and acquisitions of inventory-related goods in the years 2017, 2018, and 2019 were analyzed. Additionally, inventories were discussed, which were utilized to manage the stock of big and small businesses alike. This is due to inventory is a systematic list of a warehouse's merchandise, detailed in units and economically valued according to a company-defined criterion; it is also inventory control, which entails the exercise of stock control, both physical and in the manufacturing process, and its comparison to current and future needs to establish stock levels [7] [8]. Further, a frequency table was used to see in detail the proportion of sales that have included a number of items over a certain time period. The data was organized in columns that reflect the various values gathered in the sample and their associated frequencies [9].

2.1. Data simulation

First, we used a random number for data simulation; as Coterio points out, random numbers between 0 and 1 are required for probabilities; a random number is that digit obtained at random, i.e., every number has the same probability of being chosen and the choice of one does not depend on the choice of the other [10]. If a number is pseudorandom, it means it has a uniform probability distribution, as shown in [11]. A random variable's probability distribution, which is a function that assigns a probability to each occurrence based on the variable, is also important [12]. Then, the Monte Carlo simulation was performed to simulate the data for monthly periods from August through December 2019. Its procedure entails reproducing or simulating the features and behaviors of an actual system. Thus, the primary goal of Monte Carlo simulation is to attempt to replicate the behavior of actual variables to evaluate or forecast their evolution to the greatest extent feasible [13]. Additionally, [14] shows that its usage is justified by two fundamental probability and statistics theorems: the weak law of large numbers and the central limit theorem.

Monte Carlo simulation algorithm

```
Begin
Initialize mean=0, deviation=0;
Read media;
```

```
Read deviation;
For i=1 up to 550
Prodem= Prodem + <element>;
End for;
Prodem = Prodem/30;
If inventario_inicial < 40 then
Inventario_inicial =  Inventario_inicial  +100;
End If
End
```

By using a tool, the method was utilized to produce the distribution that corresponds to the history of demand and supply. In [15], it is used to evaluate and identify the kind of probability distribution a collection of data has, in such a manner that the findings can be compared to those of many distributions assessed using a rating. Additionally, [16] demonstrate that it allows realistic modeling of real-world processes, including their inherent unpredictability and interdependence, to do predictive analysis of subsidies and adjustments in response to the environment and key performance metrics. Moreover, the Normal Distribution formula is used to determine the demand value for each simulated value in the last five months of the year. The Monte Carlo technique is used to determine the kind of distribution to employ.

Distribution algorithm in Stat::Fit

```
Begin
Enter the data of the monthly sales of the product.
Select "AutoFit" option.
Select continuous distribution.
Select the distribution with the highest value.
Deselect the remaining distributions.
Perform data simulation with the distribution obtained.
End
```

2.2. Normal distribution

The Normal Distribution is distinguished by the fact that as the number of repeats of the experiment increases, the graph of the random variable measuring the incidence of a particular event begins to resemble a Gauss bell. Its primary feature is its "normal" behavior [17].

$$x = \mu + \sigma \left[\frac{\sum_{i=1}^{n} R_i - \frac{n}{2}}{\sqrt{\frac{n}{12}}} \right]$$

Where μ denotes the mean, σ the standard deviation, R_i the random value, and n the total number of random.

Normal distribution algorithm

Begin
Generates u_1, u_2 (two random numbers in (0,1))

$$V_1 \leftarrow 2u_1 - 1$$
$$V_2 \leftarrow 2u_2 - 1$$
$$S \leftarrow V_1 + V_2$$

If $S \leq 1$ Then
$x_1 \leftarrow V_1\sqrt{-2(Ln\,S)/S}$
$x_2 \leftarrow V_2\sqrt{-2(Ln\,S)/S}$
End

2.3. Artificial neural network

The usage of neural networks, which are mathematical models that attempt to create a tiny replica of the working of the human brain, is the primary technique used in this research. While the neural network reacts to the inputs that are given to it in a simultaneous fashion, it does not carry out instructions. Although the outcome is not kept in a memory location, it does comprise the state of the network at the time equilibrium is reached. Learning and memory are not stored as instructions in a neural network; rather, they are stored as topology and the values of connections (weights) between neurons, which give the network its strength. In contrast to computer programs, neural networks respond to events, learn from their experiences, and self-organize themselves [18].

An artificial neural network's design is composed of three basic levels: the input layer, the hidden layer (which may include n layers), and the output layer. At the input layer, input nodes specify all input attribute values, whereas hidden nodes accept inputs from input nodes and output them to output nodes. The hidden layer is where the weights for the various probabilities of the inputs are allocated. A weight indicates the significance or value of an entry in a hidden node. The more weight given to an item; the more significant the element's worth. Weights may be negative, implying that an input might act as a preventative measure rather than a trigger for a specific outcome [19].

The network learns by analyzing individual records, producing predictions for each, and adjusting weights when a forecast is wrong. This procedure is repeated many times, and the network's predictions continue to improve until it reaches one or more stop conditions. At the start, all weights are random, and the network's replies may be meaningless. The network acquires knowledge via training [20]. If the topological structure of a neural network is n-h-s, it means that there are *n* input nodes, *h* hidden neurons and *s* output neurons. The input nodes receive the values to be processed, with x_j, with $j = 1, \dots, n$, the hidden neurons receive the inputs j x weighted by the weights and bias to generate the outputs y (outputs of each neuron of the second layer) that are calculated as: $w_{ij}\ b_i i$.

$$\mathrm{y_i} = \varphi_\mathrm{i}\left(\sum_{\mathrm{j=1}}^{\mathrm{n}} \mathrm{W_{ij} x_j} + \mathrm{b_i}\right) \text{ con } = 1,2, \dots, \mathrm{h}$$

Where $\varphi_i(.)$ is the transfer function of the neuron i. Finally, the output nodes make the weighted sum of the outputs of the hidden neurons and subsequently the activation function is applied to obtain the outputs of the neural network, that is,

$$\mathrm{y_s} = \varphi_\mathrm{i}\left(\sum_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{W_{si} x_i} + \mathrm{b_s}\right) \text{ con i} = 1,2, \dots, \mathrm{g}$$

For this study, the output neuron delivers the value of estimated sales for a given month. If this value is in decimal notation, $g = 1$ is sufficient. If $V(t)$ is the level of sales of the month t and k the number of previous periods, in this case months, to be used in the prediction, it can be said that the dataset $V(t-k), V(t-k+1), \dots, V(t-1)$ is the sales data of the previous months. Therefore, the goal that the neural network must fulfill is that its output $\hat{V}(t)$, given by the equation

$$\hat{V}(t) = \mathrm{F}[V(t-k), V(t-k+1), \dots, V(t-1), t]$$

be as close as possible to $V(t)$. Therefore, it can be said that $\hat{V}(t)$ is the estimation of sales for the period t. $F(i)$ is a nonlinear vector function of mapping between inputs and outputs of the network.

Training algorithm
For 1 to $N - k$
Forward propagation
Calculate the vector outputs of the first layer y_i^l
For up to $i = 1h$

$$y_i^l = \varphi_i\left(\sum_{j=1}^{k} W_{ij}V_{j+l-1} + \sum_{t=1}^{Nbits} W_{ti}x_i^l + b_i\right)$$

Calculate network output $\widehat{V}$

$$\widehat{\boldsymbol{V}} = \varphi\left(\sum_{i=1}^{h} W_{si}y_i^l + b_s\right)$$

Backward propagation

Calculate the error

$$\boldsymbol{e_l} = \boldsymbol{V_{l+k}} - \widehat{\boldsymbol{V}}$$

Calculate the local gradient of the output neuron

$$\boldsymbol{\delta_s} = \varphi'\left(\sum_{i=1}^{h} W_{si}y_i^l + b_s\right)e_l$$

Calculate the local gradient of the output neuron

For up to $i = 1h$

$$\delta_i = \varphi_i'\left(\sum_{j=1}^{k} W_{ij}V_{j+l} + \sum_{t=1}^{Nbits} W_{ti}x_t + b_i\right)W_{si}\delta_s$$

End of epoch

The entries x_t^l correspond to the bits that make up the month l, therefore x_t^l can be 0 or 1. Since the months are listed from 1 to 12, 4 bits are required to make a correct binary encoding, $N_{bits} = 4$. For example, for the month 9 (September), $x_1^9 = 1$, $x_2^9 = 0$, $x_3^9 = 0$, $x_4^9 = 1$. In addition, the value of the month is periodic (it is repeated every 12), that is, if during the execution of the algorithm $l = 20$, this value corresponds to the month 8 (August) of the third year.

Moreover, we used the solver excel add-in, this tool is extremely helpful for professionals who need to handle issues of resource scarcity and utilize them as efficiently as possible; usually, earnings are maximized, and expenses are minimized. Mathematical optimization determines goals by considering all decision variables' restrictions [21].

3. A case study

The goal of this project is to find a solution to the issues associated with the management of the store "Leonela" in Guayaquil city. A representation of the solution can be found in the prediction of sales that can be derived from the store, which is focused on three items that fall into the category of soft drinks. The effort is divided into two categories to accomplish this prediction. Simulations using Monte Carlo methods and simulations using artificial neural networks are also possible. These two solutions have entry values that correspond to the sales of the three goods in 2017, 2018, and the first few months of 2019 (up to and including July 2019), respectively. For simulating missing data for the year 2019, a Monte Carlo simulation based on the normal probability distribution was performed. As can be seen in Tables 5 and 6, this simulation was effective in retrieving the needed information.

Finally, the simulation was run for a period of three years into the future. The simulations for the years 2020, 2021, and 2022 may be found in the sections below. This simulation was accomplished via the use of a computer model of artificial neural networks, with the goal of increasing the number of store sales as much as possible. Because of the simulation, it was discovered that by using this model, sales may be increased by 22%, resulting in acceptable inventory management.

The purpose of this project is to address the store "Leonela" issues. The answer is represented in the prediction of sales derived from the store, with an emphasis on three items belonging to the soft drinks category. The study is built on two pillars to arrive at this prediction. Monte Carlo simulation and neural network simulation. These two solutions have entry values that correspond to the three items' combined sales in 2017, 2018, and the first months of 2019. Monte Carlo simulations based on the normal probability distribution were performed to simulate missing data for the year 2019. As shown in Tables 5 and 6, this simulation successfully recovered the lost data.

Finally, a three-year simulation was run. The 2020, 2021, and 2022 simulations are shown here. This simulation was carried out utilizing an artificial neural network computer model with the objective of optimizing the store's sales. The simulation revealed that by using this approach, sales might be increased by 22%, while maintaining acceptable inventory management.

4. Results and discussion

4.1. Data collection

The data collecting method was focused on determining the monthly supply of the "Leonela" store in the years 2017, 2018, and 2019, particularly the stock of three different brands of soft drinks in the store. Product 1 is a representation of the Coca-Cola brand, Product 2 is a representation of the Pepsi Cola brand, and Product 3 is a representation of the Inca brand. Similarly, we continued to collect sales data for each of these brands over a period of three years, but at monthly intervals, from which we were able to obtain the information that would serve as a foundation for the remainder of the research. It should be mentioned that the months from August to December 2019 were produced via the use of Monte Carlo simulation techniques.

4.2. Monte Carlo simulation

The Monte Carlo simulation method was used to simulate the values of both sales and purchases for the months of August through December of this year. To do so, various variables were collected that were required in order to accomplish a proper simulation of the data, among which were the frequency of each of the products, which allowed us to identify the range of random numbers that should be used in the simulation. In the same way, it is essential to compute the mean and standard deviation of both the sales made by the store and the purchases made by the customer.

4.3. Normal probability distribution

The sales and purchase history data were input into the Stat: Fit software to generate the probability distribution that would be used to replicate the data. As a result, the algorithm identified the normal probability distribution as the best fit. Figure 1 depicts one of the accepted instances to Stat: Fit, as may be seen below. A random integer, a mean, and a standard deviation are required in the equation for the normal probability distribution. Using these results, we were able to calculate a mean and a standard deviation. The random number was finally generated in Excel using the Random function ().

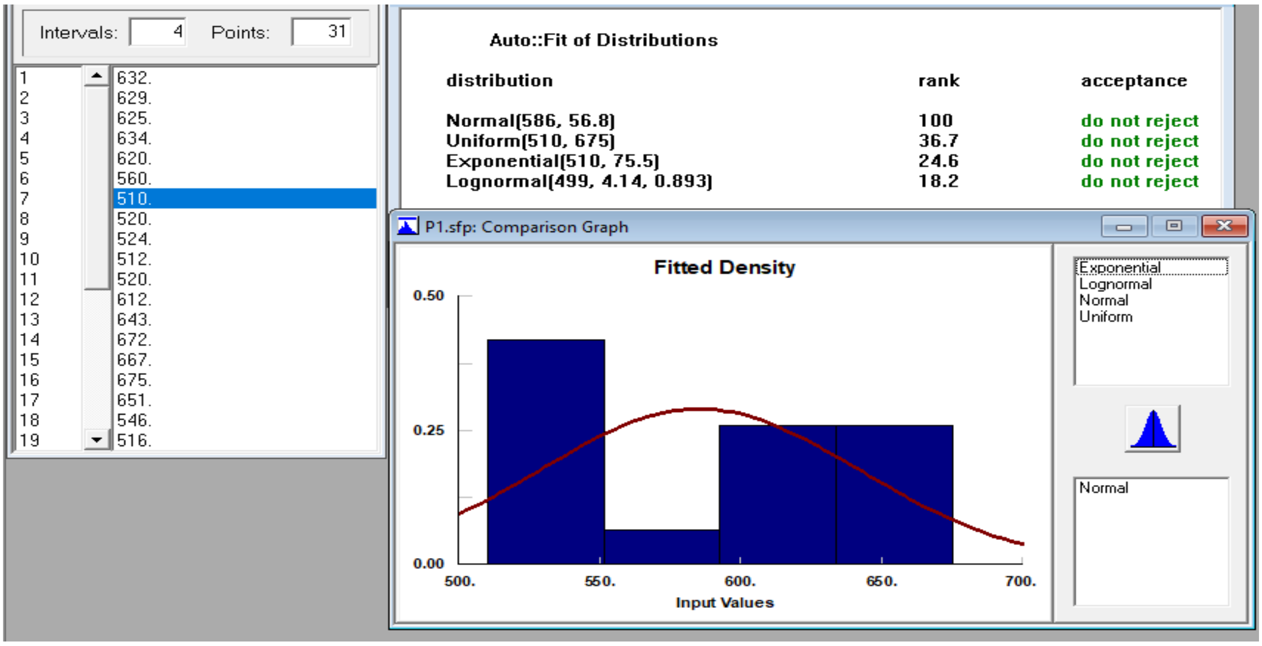

Figure 1. Stat Data::Fit

Table 1. Distribution of ProductSales 1

		2017		2018		2019	
Months	**Time**	**Unit sales**	**Sales in dollars**	**Unit sales**	**Sales in dollars**	**Unit sales**	**Sales in dollars**
January	1	632	632	643	643	653	653
February	2	629	629	672	672	648	648
March	3	625	625	667	667	612	612
April	4	634	634	675	675	598	598
May	5	620	620	651	651	586	586
June	6	560	560	546	546	534	534
July	7	510	510	516	516	540	540
August	8	520	520	521	521	618	618
September	9	524	524	515	515	594	594
October	10	512	512	525	525	611	611
November	11	520	520	536	536	610	610
December	12	612	612	621	621	605	605

Table 1 shows the value of sales of product 1 and its relationship to the general stock. Based on the data, it is concluded that products 1 and 2 have had a growth in the number of units sold over the years, while product 3 has had a small decrease in the last year. Therefore, it should be considered that product 3 can continue to lower its performance in the market over time.

Table 2. Distribution of ProductPurchases 1

		2017		2018		2019	
Months	**Time**	**Unit Purchases**	**Purchases in dollars**	**Unit Purchases**	**Purchases in dollars**	**Unit Purchases**	**Purchases in dollars**
January	1	636	572.4	660	594	660	594
February	2	636	572.4	672	604.8	660	594
March	3	636	572.4	684	615.6	660	594
April	4	636	572.4	684	615.6	600	540
May	5	636	572.4	684	615.6	600	540
June	6	564	507.6	600	540	552	496.8
July	7	528	475.2	528	475.2	552	496.8
August	8	528	475.2	528	475.2	635	571.5
September	9	528	475.2	528	475.2	605	544.5
October	10	528	475.2	528	475.2	636	572.4
November	11	528	475.2	540	486	633	569.7
December	12	636	572.4	660	594	616	554.4

Table 2 depicts the distribution of purchases (stock) of the store's product 1 throughout the three years covered by this research. After analyzing the data, it is concluded that although purchases of product 2 and 3 have decreased over time, they have nevertheless satisfied market demand. Similarly, product 1 had significant increase in year 2 relative to year 1, but also experienced a significant decline in year 3.

To conduct the simulation, each unit sold was treated as a neuron and assigned a random weight. Additionally, after the goal function of increasing sales by 22% was met, a random threshold was created for their training. The Visual Basic for Excel application produced the findings shown in Table 3, which match to product 1.

Table 3. Simulation by neural networks of Product 1

		2020		2021		2022	
Months	**Time**	**Unit sales**	**Sales in dollars**	**Unit sales**	**Sales in dollars**	**Unit sales**	**Sales in dollars**
January	1	928	$ 835,00	730	$ 656,64	1032	$ 928,93
February	2	947	$ 852,19	487	$ 438,03	503	$ 452,38
March	3	501	$ 450,48	761	$ 684,58	428	$ 385,04
April	4	395	$ 355,07	428	$ 384,92	427	$ 384,32
May	5	818	$ 735,79	924	$ 831,66	739	$ 665,09
June	6	729	$ 656,19	446	$ 401,83	352	$ 316,78
July	7	649	$ 584,36	590	$ 531,17	722	$ 650,24
August	8	794	$ 714,19	796	$ 716,06	770	$ 692,57
September	9	444	$ 399,66	683	$ 614,72	417	$ 375,19
October	10	687	$ 618,17	627	$ 564,39	737	$ 662,85
November	11	335	$ 301,75	730	$ 656,83	410	$ 368,69
December	12	899	$ 809,36	547	$ 492,73	572	$ 514,65

Optimization model using Solver

The store's sales were optimized using the Excel Solver tool. This was accomplished by entering average sales data for the years 2017, 2018, and 2019. Similarly, the goal value was specified.

Cost – benefit

Sales will grow by 22% during the projected three years at a cost of $15,670.62, resulting in a profit of $17,708.87.

Objective function

$$f(x, y, z) = 1.22(x + y + z)$$

Restrictions

$\boldsymbol{x > 0}$; $\boldsymbol{y > 0}$; $\boldsymbol{z > 0}$

$\boldsymbol{x + y + z <}$ 18.168 $(capacidad\ de\ almacenamiento)$

5. Conclusions

According to the results of this research, a monthly simulation using the Monte Carlo technique is shown, in which the demand and supply of each chosen product can be confirmed regarding the months of August to December of calendar year 2019 can be verified. This investigation was carried out at the "Leonela" Store with the goal of giving a solution to the inventory management issues that were encountered with these items.

The use of neural networks enabled us to make sales projections for the years 2020, 2021, and 2022 based on historical data. By analyzing the data, it was possible to identify the investments that needed to be made throughout these time periods, resulting in the maximum of sales for the optimum solution that was anticipated.

Neural networks have the capacity to learn specific features that occur in certain temporal occurrences and then use that knowledge. When dealing with prediction issues in which the variable to be estimated exhibits variable behavior, but with a consistent pattern of behavior over a certain length of time, it is feasible to use them.

Declaration of competing interest

The authors declare that they have no any known financial or non-financial competing interests in any material discussed in this paper.

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