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THE ACCURACY OF DEMAND FORECAST MODELS AS A CRITICAL FACTOR IN THE FINANCIAL PERFORMANCE OF THE FOOD INDUSTRY

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ABSTRACT

Every organization needs to balance their production capacities with demand. The role of demand forecasting is to assist in the organization's strategic planning; this process allows administrators to anticipate the future and plot an appropriate course of action. On its own, however, a system of demand forecasting is not enough. It is the quality of information obtained by this system which enables the organization to achieve better operational planning. In this context, this paper presents case study research to: (a) define the quantitative model to forecast demand with greater accuracy; and (b) to verify the influence of accuracy in demand forecasting on financial performance. This is an *ex-post facto* descriptive inquiry with a time series in which we made use of historical data from five groups of products over the period 2004–2008. The results suggest that if a company employs the ARIMA model for groups A, B, and E; the Holt model for group D; and the Winter model for group C, revenues will increase by approximately $1,600,000 annually.

Key-words: Accuracy. Demand forecasting. Financial performance.

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A ACURACIDADE DOS MODELOS DE PREVISÃO DE DEMANDA COMO FATOR CRÍTICO PARA O DESEMPENHO FINANCEIRO NA INDÚSTRIA DE ALIMENTOS

RESUMO

Toda organização precisa saber dimensionar suas capacidades produtivas de modo que estas se encaixem perfeitamente com as demandas. O papel da previsão de demanda é fornecer subsídios para o planejamento estratégico da organização. Este processo permite que os administradores antecipem o futuro e planejem de forma mais conveniente as suas ações. Não basta, entretanto, ter um sistema de previsão de demanda. É a qualidade da informação obtida por este sistema que capacita a organização a obter melhor planejamento das operações. Dentro deste contexto, este trabalho apresenta um estudo de caso com os objetivos de: (a) definir o modelo quantitativo de previsão de demanda de maior grau de acurácia e (b) verificar a influência da acuracidade da previsão de demanda no desempenho financeiro da organização. Trata-se de uma pesquisa descritiva *ex-post fact* em que foram utilizados dados históricos de demanda de cinco grupos de produto, no período de 2004 a 2008. Os resultados demonstram que se a empresa empregasse o modelo ARIMA para os grupos A, B e E, o modelo de Holt para o grupo D e o modelo de Winter para o grupo C, o faturamento poderia ser aumentado em, aproximadamente, dois milhões e oitocentos mil reais anuais.

Palavras-chave: Acurácia. Previsão de demanda. Desempenho.

1 INTRODUCTION

Changes occurring in Brazil's political and economic context in recent decades obliged companies to explore income-generating solutions to maintain their business. To achieve competitive advantage in an environment subject to constant fluctuations, organizations have to make correct and timely decisions based on quality information. In this respect, demand forecasting represents an important managerial tool in decision-making.

According to DeLurgio (1998), there are basically two forecasting methods: qualitative, and quantitative, the latter divided into temporal series and multivariate models (causal). Quantitative techniques use specified and systematic procedures, whereas qualitative techniques involve aspects such as intuition, personal judgment, and experiences. In practice, demand prediction is commonly used in organizations that operate in consumer markets. When demand patterns vary little, demand prediction can be made based on historic demand allied with the administrator's personal intuition. In more volatile settings, this method does not adequately predict future needs, so applying quantitative demand forecasting models takes on a pivotal role.

Queiroz and Cavalheiro (2003) argue that the food industry constitutes a representative sector in the national economy, and like other sectors it needs to plan its production, which is sensitive to the seasonality of supply and demand, perishable, and very diverse. Every organization needs to somehow know how to efficiently allocate its productive capacity so that it perfectly fits demand. Whether for a food company or a company in a different sector, the role of forecasts is to provide support to the organization's strategic planning. Within this context, the forecast allows administrators to anticipate the future and plan their actions appropriately.

Nevertheless, having a demand forecasting system in the organization is not enough. It is the quality of the information obtained through such a system that enables it to better plan its operations. According to Kuo and Xue (1999), obtaining a precise demand forecast is the critical point in the quality of the decision process. The forecast attempts to calculate and predict future circumstances, providing the best possible evaluation of the available commercial information.

The accuracy of the forecast has a direct impact on the level of service offered to consumers, the level of safety stock, and the total cost of the supply chain. A more accurate forecast means that production can better anticipate customer demand (Meijden, Nunen, and Ramondt, 1994). On the other hand, an inadequate forecast can jeopardize the results of the supply chain and generate three situations: stock-outs (not meeting demand), backlogs (delay in meeting demand), and/or inventory surplus. Besides increasing product costs, these situations compromise cash flow and business rentability.

In today's highly competitive world, the line between failure and success is so thin that survival depends to a large extent on the quality of the information that shapes managerial decisions. Finne (2000) describes the managerial process required for an organization's data to produce actions: an individual processes data to produce information, and processes information to produce knowledge.

Knowledge, in turn, is used for the decision-making that generates the final actions. Thus, information obtained through the use of specific quantitative models provides support for managerial decisions and assists the activities of operational areas or departments. Martinsons, Davidson, and Tse (1999) state that in the "information era," companies need technology to ensure efficiency in the production and delivery of their products and services.

Not only is it difficult to measure the costs generated by forecast errors, but it is also rare to find a model in the marketplace that adequately assimilates the particulars of each company's operation. Therefore, given that there are different possible forecast methods, it becomes necessary to identify, through performance indices, the best methodology in each case. The two central concerns of this study emerge: (a) what is the most accurate quantitative model of demand forecast for five groups of products in the portfolio of a food company? And (b) what is the influence of the accuracy of the demand forecast on the organization's financial performance?

To define the objective of this work, we resorted to a cut-out of the organization's strategic map, shown in Figure 1. A strategic map is an illustration of the company's strategy: in other words, it is a visual representation of the cause-and-effect relationships among the key components of an organization's strategy. A strategic map allows the visualization of how the different parts of an organization directly or indirectly contribute to its overall performance (Buytendijk, Hatch, and Micheli, 2010).

Figure 1 shows the cause-and-effect relationship between forecast accuracy, demand responsiveness, and company turnover. This illustration emphasizes that the accuracy of the demand forecasting method used is a critical factor which significantly affects the company's financial performance. In measuring the accuracy of the forecast, an administrator can analyze whether the organization is implementing the strategies planned. It is also an opportunity to gather information, promote cost reductions in the supply chain, and improve responsiveness to customers.

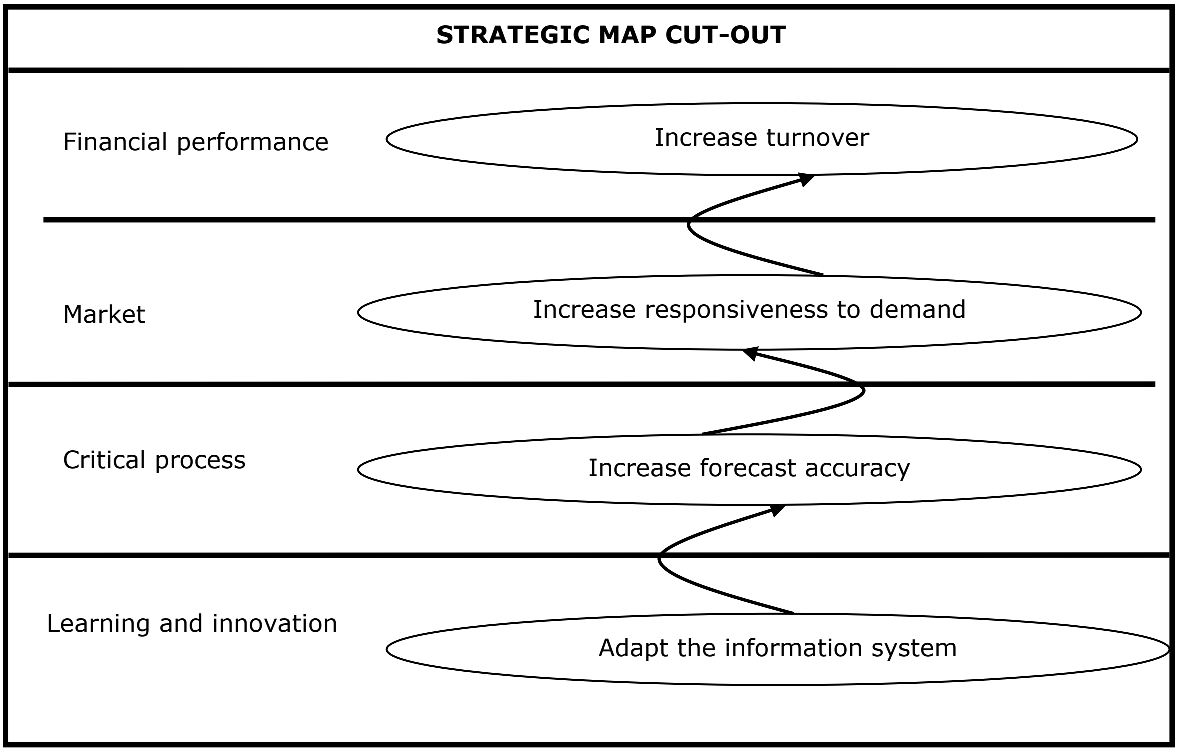

Figure 1: Strategic map cut-out for the organization under study

Source: Adapted from Duclós and Santana (2009)

Within this context, this work aims to determine which demand forecast model presents the highest degree of accuracy compared with the method currently in use by the company. The results of this analysis will help in assessing the influence of demand forecast errors in the company's financial performance, using the fill rate to indicate the level of service offered to consumers, as well as the opportunity cost in responding to demand. The study will be conducted in five groups of products from the portfolio of a company that produces perishable goods, with historic demand data from the period 2004–2008.

2 THEORETICAL FRAMEWORK

Forecasts are a probabilistic estimate or description of a value or future condition. Forecasts include an average, a variation within certain limits, and a probabilistic estimate of the variation. A number of different methods can be used in forecasting, but most share the same basic concept: past behavioral patterns will continue in the future, i.e., it is assumed that sales of a product in a given past period will be equivalent to sales in a corresponding period in the future. By and large, almost all forecast models are built on the central idea that the past will repeat itself (Morettin and Toloi, 1987; DeLurgio, 1998; Makridakis, Wheelwright, and Hyndman, 1998; Chopra and Meindl, 2003).

All companies—whether small, medium, or large, and whether state-owned enterprises, privately-owned domestic operations, or multinationals—need to take into account uncertain future conditions when planning the resources allocated to production, distribution, and purchase of inputs or services. Moreover, the need for demand forecasting is common in a company, at both the macro level and within the various functional departments (marketing, production, sales, logistics and finance). Demand forecasting is a fundamental element in the decision-making process; there are at least seventy different techniques to quantitatively forecast demand (Kerkanen, Korpela, and Huiskonen, 2009).

Picture 1 describes the two quantitative models used in this study that do not consider trend and/or seasonality contained in the temporal series.

MODELS	FORMULA	APPLICATION
Simple Moving Averages (SMAs)	$M_t = \frac{Z_t + Z_{t-1} + \cdots + Z_{t-r+1}}{r}$ M_t = level estimate Z_t = data of each period r = average of the periods (Makridakis et al., 1998; Faria et al., 2008; DeLúrgio, 1998; Camargo and Amarante, 1999)	For demands without trend or seasonality. Simple method, easily implemented.
Simple Exponential Smoothing	$\bar{Z}_t = \alpha \bar{Z}_t + \alpha(1-\alpha)\bar{Z}_{t-1} + \alpha(1-\alpha)^2\bar{Z}_{t-2} + \ldots$ $\bar{Z}_t$ = exponential smoothed value α = smoothing constant (Souto et al., 2006; Martinez and Zamprogno 2003; Taylor, 2007; Baldeon and Russo, 2006)	For demands without trend or seasonality. Uses adjustment of the error of the previous forecast.

Picture 1: Characteristics of quantitative models that do not consider trend and/or seasonality contained in the temporal series

Source: Faria et al., 2008; Delúrgio, 1998; Camargo and Amarante, 1999; Souto et al., 2006; Martinez and Zamprogno, 2003; Taylor, 2007; Baldeon and Russo, 2006

Picture 2 demonstrates the three quantitative models used in this study which encompass trend and/or seasonality contained in the temporal series.

MODELS	FORMULA	APPLICATION
Holt's Model	$\mathbf{L_{t+1} = \alpha\, D_{t+1} + (1- \alpha)\,(L_t + T_t)}$ $\mathbf{T_{t+1} = \beta(L_{t+1} - L_t) + (1 - \beta)T_t}$ L_t = estimate of level of period t L_{t+1} = estimate of level of period t+1 T_t estimate of trend of period t T_{t+1} = estimate of trend of period t+1 D_{t+1} = real demand observed in period t+1 α = smoothing constant for level Β = smoothing constant for trend (Delurgio, 1998; Holt, 2004; Martinez & Zamprogno, 2003)	For demand that shows trend. Requires use of computation packages.
Winter's Model	$\mathbf{L_{t+1} = \alpha\,(D_{t+1}/S_{t+1}) + (1- \alpha)\,(L_t + T_t)}$ $\mathbf{T_{t+1} = \beta(L_{t+1} - L_t) + (1 - \beta)T_t}$ $\mathbf{S_{t+p+1} = \gamma\,(D_{t+1}/L_{t+1}) + (1 - \gamma)S_{t+1}}$ L_t = estimate of level of period t L_{t+1} = estimate of level of period t+1 T_t = estimate of trend of period t T_{t+1} = estimate of trend of period t+1 S_{t+1} = estimate of seasonality factor t+1 S_{t+p+1} = estimate of seasonality factor t+p+1 D_{t+1} = real demand observed in period t+1 α = smoothing constant for level β = smoothing constant for trend γ = smoothing constant for seasonality (Delurgio, 1998; Baldeon and Russo, 2006; Segura and Vercher, 2001).	For demand that shows trend and/or seasonality. Ease of interpretation of the indices of seasonality and managerial understanding. Can adapt to efficient algorithms.
ARIMA Model	$\boldsymbol{\phi\,(B)[(1-B)^d y_t-\mu] = \theta(B)u_t}$ ϕ= auto-regressive parameters θ =Moving averages parameter $\phi\,(B)$ = polynomial of AR $\theta(B)$ = polynomials MA (Box, Jenkins, and Reinesl, 1994; (Zang, 2003)	For temporal series that show auto-correlation. Hard to operationalize. Requires computational programs.

Picture 2: Characteristics of quantitative modes that consider trend and/or seasonality contained in the temporal series

Source: Delúrgio, 1998; Martinez ande Zamprogno, 2003; Baldeon e Russo, 2006; Holt, 2004; Segura and Vercher, 2001; Box, Jenkins and Reinesl, 1994; Zang, 2003

These quantitative methods usually employ temporal series. A temporal series is a selection of numeric data obtained from regular periods of time, i.e., a set of observations ordered in time. The main objective in analyzing temporal series is to investigate the mechanism that generates data and describe its behavior by building graphs to verify the existence of trend, cycles, and seasonal variations (Martinez and Zamprogno, 2003).

In temporal models, every demand observed can be separated into a systematic and a random component. The systematic component gives the expected value of the demand; the random component is part of the forecast deviated from the systematic part, i.e., it encompasses the measure of error in a forecast. The objective of the forecast is to eliminate the random component and estimate the systematic component. Therefore, a forecast error measures the difference between the demand forecast and the real demand (Chopra and Meindl, 2003).

A forecast demand would be perfect if the forecast error were zero. If the error increases from zero to a positive value, the total cost, the instability of the production programming, and the level of service increase (Xie, Lee and Zhao, 2004). A positive bias usually improves the level of service of the system because it generates a better use of capacity and produces a larger quantity of products than necessary. In this situation, the cost of a missing unit is reduced, but the costs associated with the level of inventory, as well as total cost, increase significantly.

When a negative bias occurs, the total cost increases, whereas the level of service decreases. This occurs because the system produces a smaller quantity of products than is really necessary. In this situation, the level of service is reduced and the cost of a missing unit significantly increases (Xie et al., 2004). These observations reveal that accuracy in demand forecast can significantly improve the performance of the production system by reducing total costs and adapting service levels.

Forecast errors may have different causes. To make the situation even more complex, these causes can coexist and change according to conditions inherent to the organization, the methodology used, and market and product variations. The literature describes various measures of forecast error; one of the most popular is mean absolute percentage error (MAPE). Analyzing the accuracy of a forecast first requires defining the flow of planning between predicted and real value. Next, the role of demand information in the planning process is analyzed. Moreover, one should understand how forecasts are produced, the most substantial sources of error, and how these sources can be affected (Kerkanen, et al., 2009).

The National Forecast Institute was established some thirty years ago with the primary goal of assessing the progress of forecasts made in temporal series. Within this period, various quantitative forecast methods have been applied and compared in diverse situations in specific products and markets. Though a number of studies have been described in the literature, conclusions do not suggest which conditions make a given method better than another. For this reason, situations involving complexity, seasonality, and perishability, such as those occurring in the food market, still require investigative studies about the most adequate forecast method for each condition of study.

Published works about forecast demand have analyzed various products, such as beer (Calôba, Calôba, and Saliby, 2002); fresh milk (Doganis, Alexandridis, Patrinos, and Sarimveis, 2006); other perishable products (Higuchi, 2006); food retail (Zotteri; Kalchschmidt, and Caniato, 2005); wireless subscribers (Venkatesan and Kumar, 2002); supermarket sales (Taylor, 2007), number of births (Souto, Baldeon, and Russo, 2006); plastic products (Pellegrini and Fogliatto, 2000); price forecast (Medeiros, Montevechi, Rezende, and Reis, 2006); and analysis of stock market indicators (Faria, Albuquerque, Alfonso, Albuquerque, and Cavalcante, 2008), among others.

For the food industry in particular, few studies have been published to this date. Most of these analyze the food market in other countries, such as Australia (Calôba et al., 2002); Holland (Dekker, van Donselaar, and Ouwehand, 2004); China (Kuo, 2001); the UK (Taylor, 2007); the US (Zeng, 2000), Greece (Doganis et al., 2006); and Italy (Zotteri et al., 2005). The Brazilian market for food products has been a subject of research only in recent years (Queiroz and Cavalheiro, 2006; Higuchi, 2006; Medeiros et al., 2006). These scientific works, however, have not succeeded in fully exploring the complexity this segment presents.

A number of works emphasize the application of a forecast model, but do not research the use of the information obtained in the decision-making process or its impact on the supply chain as a whole. Some studies assess the accuracy of the forecast model employed, but do not analyze the influence of forecast errors on the management of the supply chain. More recent studies have revisited the impact of forecast errors on some portions of the supply chain, such as the instability of production programming (MRP, Master Production Schedule) and the level of service offered (Xie, Lee, and Zhao, 2004).

Other studies have explored the relationship between forecast errors and organizational performance measures. However, results are contradictory. Some studies demonstrate that forecast errors have a significant impact on total costs, on production programming, and on the level of service rendered (Xie et al., 2004), whereas others demonstrate opposite results (Price and Sharp, 1985; Ho and Ireland, 1998). Kerkanen, Korpela, and Huiskonen (2009) state that the real impact of demand forecast errors is only possible when the evaluation includes specific systematic characteristics of each company.

In this sense, we propose a study case (Yin, 1994) in order to provide a thorough and in-depth analysis of the demand forecast in a food company. The objective is to achieve deep and detailed knowledge about the cause-and-effect relationship between the accuracy of the demand forecast model, demand responsiveness, and the organization's financial performance. Section 3 describes the methodology used to establish the relationship among these three variables.

3 METHODOLOGY

This work proposes an investigation into the causal relationship between three variables: the accuracy of demand forecast (independent variable), demand responsiveness (dependent variable I), and financial performance (dependent variable II). These three variables present a cause-and-effect relationship, but these are not the only conditions necessary for the phenomenon to occur. This fact characterizes the current work as a descriptive study.

Demand forecast accuracy is measured by the difference between the forecast and the real demand for the period t (Chopra and Meindl, 2003). This variable will always be operationally calculated based on the mean absolute error (MAPE), mathematically expressed by equation 1:

$$MAPE_n = \frac{\sum_{t=1}^{n}\left|\frac{E_t}{D_t}\right|100}{n}, \qquad (1)$$

where:

$|E_t|$ = absolute value of the error in period t;

$|D_t|$ = absolute value of real demand in period t;

n = all of the periods.

Responsiveness in satisfying the demand can be defined as the percentage of demand met directly at the sales point during the supply cycle (Zeng, 2000). The demand responsiveness index is also known as fill rate (FR) and can be calculated as demonstrated in equation 2:

$$FR = 1 - \frac{Number\ of\ stock-outs\ expected\ per\ cycle}{Number\ of\ units\ required\ per\ cycle} \qquad (2)$$

The financial performance depends on the difference between possible income and costs (Lima, 2003). Thus, the financial performance will be measured in this work as the cost of opportunity through the fill rate, thus expressed:

$$\text{FR} = 1 - \frac{\alpha G_{\mu}(K)}{Q}, \qquad (3)$$

where:

μ = average,

α = standard deviation,

K = safety factor,

αG_{μ} (*K*) = function of lost standard unit (stock-out),

Q = order quantity.

Based on the technical procedures used, data collection is the most important element in identifying the outline of a survey (Gil, 2002). The current study used historical data of the demand for five groups of products encompassing the period 2004–2008. It is a cross-sectional, temporal *ex post facto* case study, conducted based on the current configuration of the phenomenon about which data were collected. The research problem was addressed in a quantitative manner, justified by the nature of the object of study and the procedure used to amass data. The analysis period was selected due to the need to obtain at least sixty time series to enable the identification of patterns such as level, trend, and seasonality.

The industry under study is a company that has strong representation in the Brazilian food market, one of the five leaders in the segment. It comprises industrial and business units concentrated in the main regions of the country, and its portfolio comprises a mix of great diversity within each division.

Despite the diverse portfolio, the individual analysis of all company products is not relevant to managerial objectives. Many groups of similar products can be aggregated through predetermined criteria in a temporal series and jointly analyzed. The choice of the appropriate level of aggregation depends on the decision-making process that the forecast expects to support (Zotteri et al., 2005).

In the present study, this grouping was based on the inherent characteristics of the products, joined according to similarity with one another. Data aggregation allowed the formation of five groups of products: Group A, products representing 70 percent of the company's overall sales volume—this line consists of a total of 59 Stock Keeping Units (SKUs); Group B, products accounting for 10.5 percent of the company's overall sales volume—this line consists of 9 SKUs; Group C, products representing 8.5 percent of the company's overall sales volume—this line consists of 13 SKUs; Group D, products accounting for 10 percent of the company's overall sales volume—this line consists of a total of 8 SKUs; and Group E, products representing 1 percent of the company's entire sales volume—this line consists of 2 SKUs.

Four quantitative models of forecast demand were applied to the historic temporal series of each group of products: simple exponential smoothing (SES), Holt's model (HM), Winter's model (WM), and Auto-Regressive Integrated Moving Average (ARIMA). Results were compared to the actual values of the demand so as to choose the most accurate model for each product group. Next, we measured the for the most accurate index of responsiveness to meeting demand (fill rate) of the various quantitative demand forecast methods, based on the smallest value of the MAPE, for each of the five product groups. These results were finally compared to the fill rate of the company being studied to determine the difference between satisfied demand and actual demand. The financial performance was assessed as an opportunity cost through the function of the fill rate.

The limitation of this study is due to the quality of the data supplied by the company analyzed, as well as the numerous variables that compose the business. The analysis did not take into consideration market information about the history of the data collected. Thus, certain conditions such as promotions, campaigns, and competitive actions may have interfered in some monthly results of demand variation. Likewise, this study has not considered possible restrictions in the production capacity of the organization being analyzed, nor the minimum size of lots being sold. The next section will present the results obtained from the application of the methodology described above.

4 RESULTS

To facilitate the analysis of the results, this section will be divided into three parts: (a) previous data analysis, (b) comparison between demand forecast methods, and (c) demand responsiveness and financial performance.

4.1 PREVIOUS ANALYSIS

Before applying forecast methods it is essential to analyze the data under study in order to identify the patterns or component factors of the curve, such as trend, seasonality, irregular variations, and random variations. These patterns are not taken into consideration in some demand forecast models and in these cases reduce the accuracy of the forecast. Figure 2 graphically represents the series of the aggregate demand for the products from Group A. As mentioned by Tubino (2000), random and irregular variations are observed mainly in the year 2006. It is also possible to observe trend and a slight seasonality.

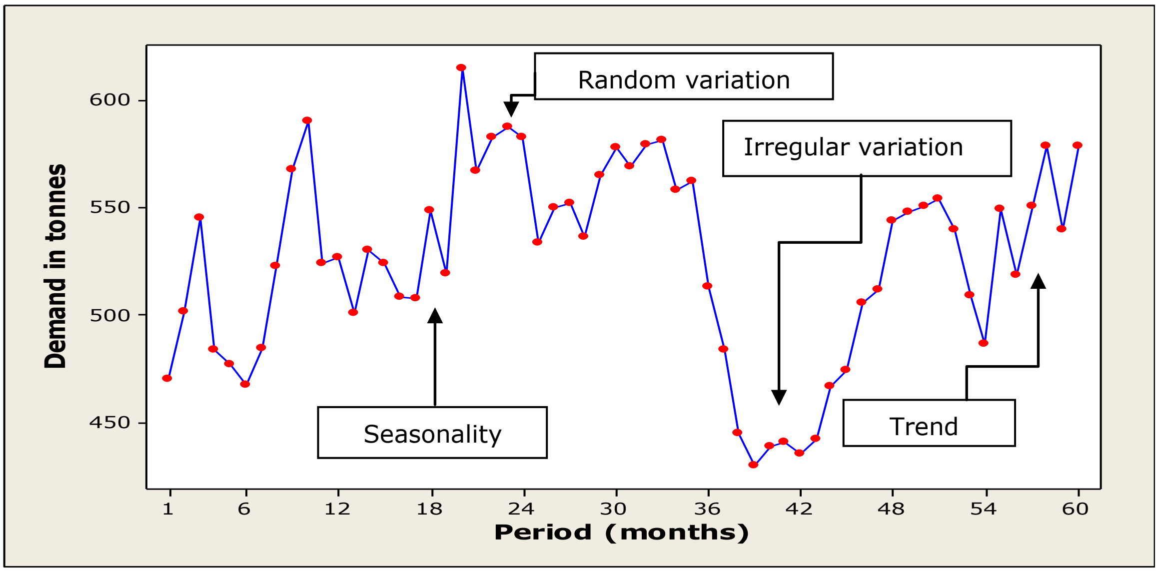

Figure 2: Analysis of the historic data on demand for Group A products between 2004 and 2008

Source: Research results

The same patterns observed in Figure 2 can be seen in the analysis of historic data on demand for products Groups B, C, D, and E (Figure 3). Due to the variation in the horizontal scale (demand in tonnes), the products from Group A were analyzed separately, as they represent 70 percent of the company's overall sales volume.

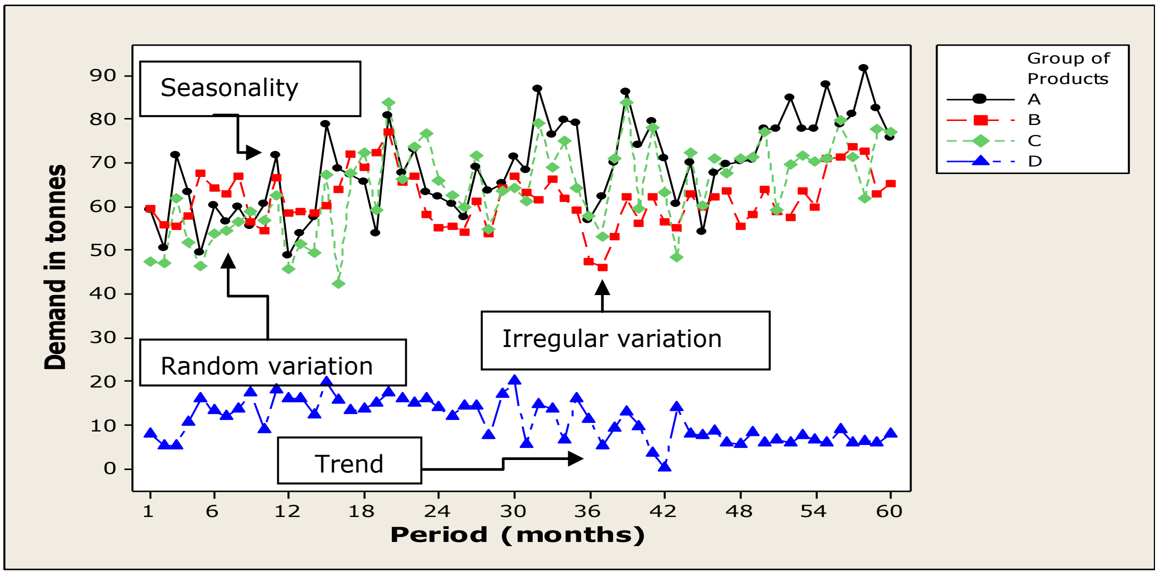

Figure 3: Analysis of the historic data on demand for products from Groups B, C, D, and E between 2004 and 2008

Source: Research results

4.2 COMPARISON BETWEEN DEMAND FORECAST METHODS

The marketing department of the company under study is currently in charge of forecasting demand. It uses the simple moving averages method allied with a qualitative valorization, which can oscillate according to market actions. The forecast is based on Microsoft Excel® software. No other specific or mathematical software is used. Demand forecast is made through electronic spreadsheets. According to DeLurgio (1998), this method yields good results only when demand does not present a pattern, i.e., there is no trend or seasonality. The moving averages method has several limitations and for this reason its application in practice is restricted. However, this method is simple, easily implemented, and can be manually processed.

The smoothing constants adjusted for the SES, Holt's, and Winter's models are described on Table 1. For these models, the adjustment data were generated by the statistical program NNQ-STAT® for 12 periods (seasonal). For the ARIMA model, forecast adjustments were made by the statistical program NCSS® (2007). For this model, the following adjustment parameters were considered (p, d, q) in function of the smallest value of the MAPE: products from Group A (1,0,1), products from Group B (1,0,1), products from Group C (1,1,2), products from Group D (1,0,1), and products from Group E (2,0,2).

Table 1: Values of the smoothing constants and weights used in the demand forecast models

Models	SES	Holt's		Winter's		
Groups of products	α	α	β	α	β	γ
A	0.57	0.86	0.01	0.75	0.10	0.10
B	0.14	0.01	0.03	0.01	0.01	0.01
C	0.63	0.64	0.01	0.46	0.01	0.01
D	0.18	0.94	0.01	0.22	0.01	0.01
E	0.25	0.05	0.99	0.03	0.99	0.01

Source: Research results

Forecast adjustments for all groups of products were made from 2004 to 2007 in order to project the demand forecast to the year 2008; i.e., the calculations of forecast, error, and comparisons to the actual demand spanned a period of 12 months (01/Jan/2008 to 31/Dec/2008).

Figure 4 graphically demonstrates the results obtained from the application of the forecast models studied to Group A products. For this group, the ARIMA presented the highest degree of accuracy, with a MAPE value of 3.71. The forecast model adopted by the company presented the smallest degree of accuracy of all the forecast models used in the analysis, with a MAPE value of 6.15.

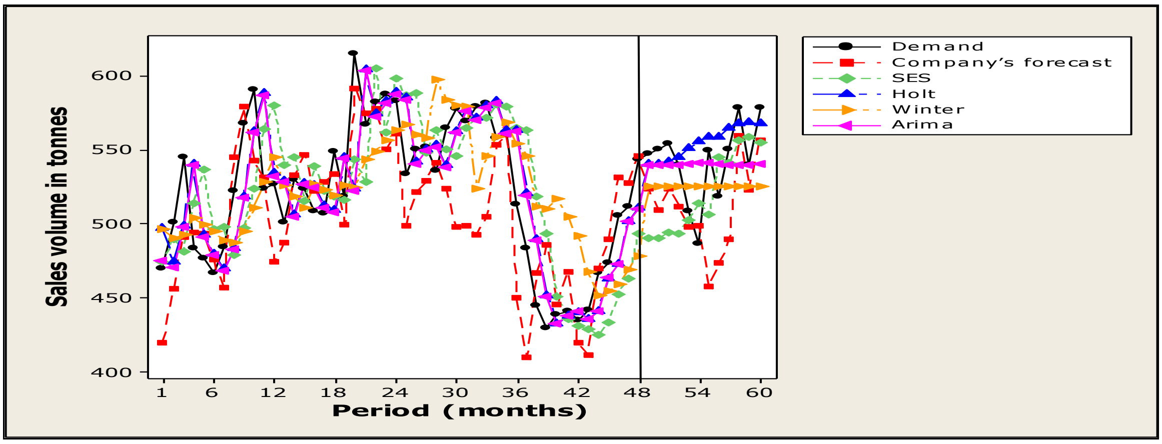

Figure 4: Forecast demand for Group A products between 2004 and 2008

Source: Research results

Figure 5 graphically demonstrates the results obtained from the application of the forecast models studied to Group B products. For this group, the ARIMA model presented the highest degree of accuracy, with a MAPE value of 7.52. The company's model showed an accuracy degree superior to that of the SES model and a result inferior to those of the other models.

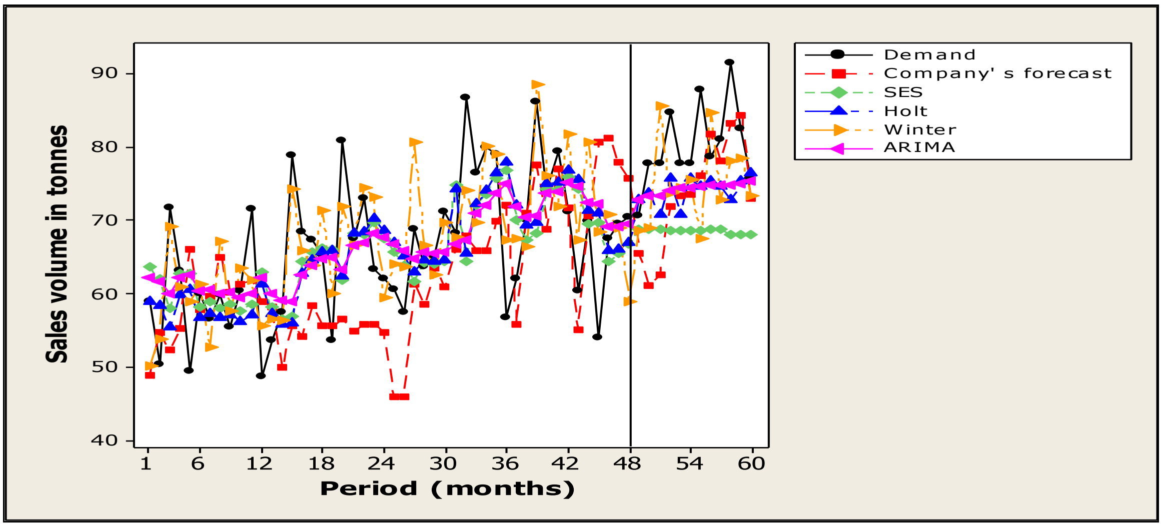

Figure 5: Forecast demand for Group B products between 2004 and 2008

Source: Research results

Figure 6 graphically demonstrates the results obtained from the application of the forecast models studied to Group C products. For this group, Winter's model presented the highest degree of accuracy, with a MAPE value of 7.43. The company's model presented a degree of accuracy superior to those of the SES, Holt's, and ARIMA models.

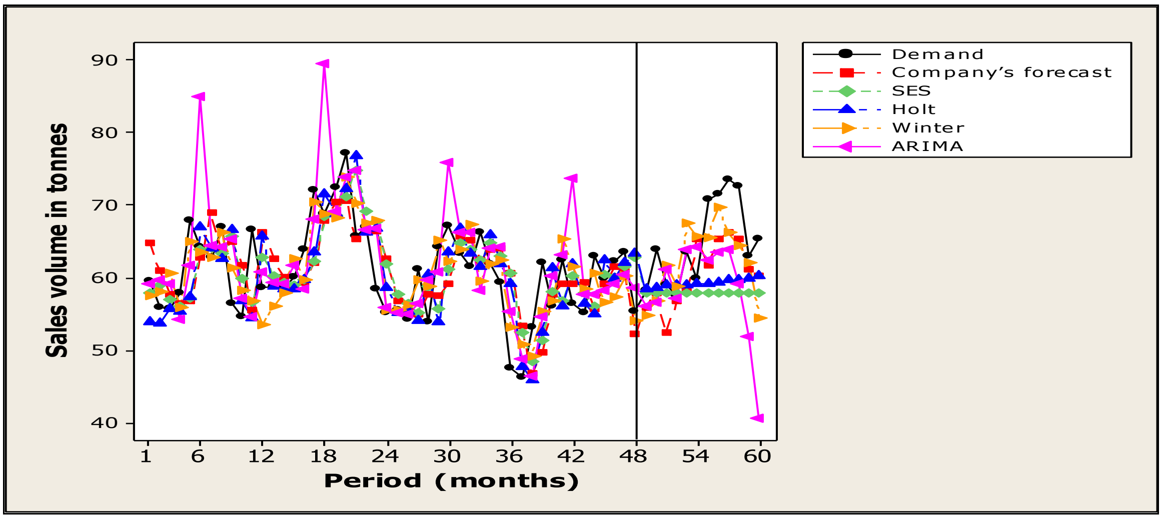

Figure 6: Forecast demand for Group C products between 2004 and 2008

Source: Research results

Figure 7 graphically demonstrates the results obtained from the application of the forecast models studied to Group D products. For this group, Holt's model presented the highest degree of accuracy, with a MAPE value of 6.44. The company's model presented a degree of accuracy superior to those of Winter's model and inferior to the others.

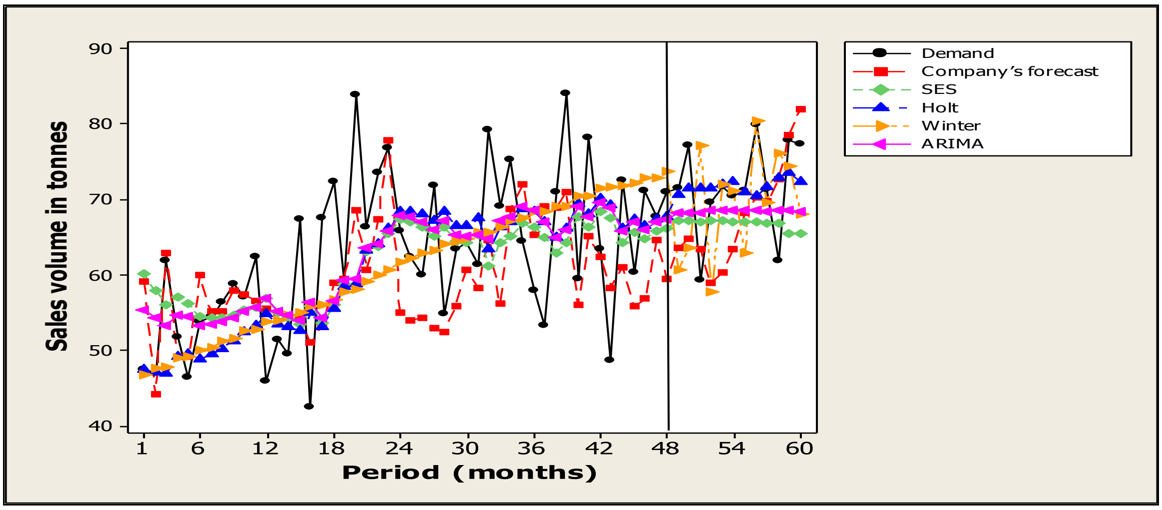

Figure 7: Forecast demand for Group D products between 2004 and 2008

Source: Research results

Figure 8 graphically demonstrates the results obtained from the application of the forecast models studied to Group E products. For this group, the ARIMA model presented the highest degree of accuracy, with a MAPE value of 11.49. The company's model presented a degree of accuracy superior to the SES, Holt's, and Winter's models.

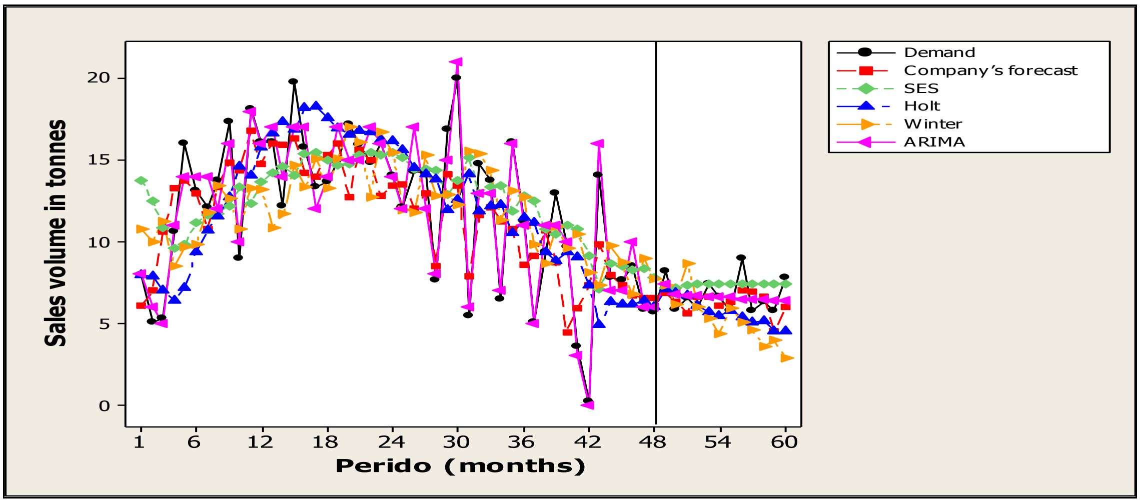

Figure 8: Forecast demand for Group E products between 2004 and 2008

Source: Research results

Table 2 sums up the MAPE results obtained from the application of the four demand forecast models to product Groups A, B, C, D, and E. In short, it can be said that for the product Groups A, B, and E, the ARIMA model presented the highest degree of accuracy; for Group C products, Winter's model, and for Group D products, Holt's model. As a function of this result, the ARIMA, Winter's, and Holt's models were adopted for calculating the fill rate, as demonstrated in Table 3

Table 2: Degree of accuracy of demand forecast models for groups of products A, B, C, D, and E according to MAPE

Forecast Model	MAPE Group A	MAPE Group B	MAPE Group C	MAPE Group D	MAPE Group E
Company	6.15	9.13	7.93	9.81	14.29
SES	4.88	14.2	10.34	9.50	17.18
Holt's	4.16	8.0	8.56	**6.44**	17.67
Winter's	6.14	8.91	**7.43**	11.26	26.42
ARIMA	**3.71**	**7.52**	11.44	7.97	**11.49**

Source: Research results

4.3 DEMAND RESPONSIVENESS AND FINANCIAL PERFORMANCE

Just as occurred in the previous subsection, calculations of demand responsiveness and financial performance spanned a period of 12 months (01/Jan/2008 to 31/Dec/2008). The total demand for Group A products in 2008 was 6,503.26 tonnes. The level of responsiveness in meeting the demand was 94.20 percent according to the company's forecast model, and 99.70 percent according to the ARIMA model.

For Group B products, total demand in 2008 was 963.28 tonnes; the level of responsiveness in meeting the demand was 91.90 percent according to the company's forecast model, and 92.65 percent according to the ARIMA model. For Group C products, total demand in 2008 was 778.54 tonnes; the level of responsiveness in meeting the demand was 93.31 percent according to the company's forecast model, and 96.02 percent according to the ARIMA model. For Group D products, total demand in 2008 was 858.28 tonnes; the level of responsiveness in meeting the demand was 95.01 percent according to the company's forecast model, and 97.09 percent according to Holt's model.

Finally, for Group E products, total demand in 2008 was 81.09 tonnes; the level of responsiveness in meeting the demand was 93.40 percent according to the company's forecast model, and 98.53 percent according to the ARIMA model.

Table 3 demonstrates fill rate results and the financial impact of demand forecast errors. The values presented on Table 3 were calculated under normal conditions of the retail market—in this case, the indices of indemnity, breakage, and product returns generated by negotiation errors and the reception capacity of the retailer. Likewise, the analysis considered neither possible limitations in the production capacity of the organization under study, nor minimum size of sale lots.

Table 3: Analysis of the company's financial performance during 2008

Real Demand in tonnes		Sales implemented through the Company Forecast model					Forecast implemented though the model of best performance based on MAPE					
Group of products	tonnes	tonnes	error (tonnes)	fill rate	R$ - value per kg	loss of turnover	tonnes	error (tonnes)	fill rate	R$ - value per kg	loss of revenue	Model
A	6,503.26	6,126.26	377.00	94.20	6.37	2,401,490.00	6,484.00	19.26	99.70	6.37	122,686.20	ARIMA
B	963.28	885.29	77.99	91.90	8.27	644,977.30	892.50	70.78	92.65	8.27	585,350.60	ARIMA
C	778.56	726.50	52.06	93.31	9.69	504,461.40	747.55	31.01	96.02	9.68	300,175.92	winter's
D	858.28	815.42	42.86	95.01	9.80	420,028.00	833.30	24.98	97.09	9.80	244,821.32	HOLT'S
E	81.09	75.74	5.35	93.40	15.00	80,250.00	79.90	1.19	98.53	15.00	17,850.00	ARIMA
					Total	**4,051,206.70**				**Total**	**1,270,884.04**	

Source: Research results

In short, the results demonstrate that the ARIMA model estimates demand satisfaction from between 92.65 and 99.70 percent for products from Groups A, B, and E. Winter's model estimates a demand satisfaction of 96.02 percent for Group C products, and Holt's model estimates a demand satisfaction of 97.09 percent for Group D products. By and large, it can be stated that all the models studied presented a potentially good forecast, keeping in mind the MAPE value of around 10 percent.

The results demonstrated for product Groups of A, B, C, D, and E confirm that forecast accuracy directly influences the level of service offered to consumers, and consequently the organization's overall financial performance. Using the current forecast method, the company fails to supply 377.00 tonnes of

Group A products to the market/demand, with an approximate loss of revenues of R$ 2,401,490.00. For Group B products, an approximate loss of revenues of R$ 644,977.30. For Group C products, this discrepancy reaches 52.06 tonnes, with an approximate loss of revenues of R$ 504,461.40. For group D products, the figure is 42.86 tonnes, with an approximate loss of revenues of R$ 420,028.00. For group E products, the shortfall is 5.35 tonnes, with an approximate loss of revenues of R$ 80,250.00. The financial impact of demand forecast errors on the company is approximately R$ 4,051,206.70 yearly. If the company used the ARIMA model for products from Groups A, B, and E, Holt's model for Group D products, and Winter's model for Group C products, revenues could increase by some R$ 2,780,322.66 annually.

5 FINAL CONSIDERATIONS

The uncertainties inherent in the food market, as well as the objectives and promotions of the company here studied, means the process is by nature somewhat inaccurate. The use of demand forecast models with higher accuracy means a smaller degree of uncertainty associated with managerial decisions. Companies can obtain important improvements such as reductions in inventories of finished products and raw materials, improvements in production planning, better allocation of personnel, and an overall reduction of financial losses.

By and large, the most convenient demand forecast models are the parsimonious ones. In other words, those containing few parameters tend to provide more precise forecasts. However, no forecast model can be universally considered the best in discerning the specific situations of the process, product, and market. For this reason, complex and specific situations, such as those occurring in the food market, require investigative studies about the most suitable forecast model for each condition of study.

This case study exposed the difficulties in modeling actual data, seen from the randomness found in a number of temporal series, contextualized with the market reality of the company. The results obtained were satisfactory compared to the actual demand, and serve to assess the performance of the forecast process of the company, and concomitantly to propose modifications. Performance improvements require great changes, and that includes changes in the measurement and management systems currently in use.

The accuracy of the forecast method employed demonstrated a causal relationship adapted to evaluate the company's financial performance, considering that demand forecast is a critical factor for organizations. Effective predictions are essential to reach the strategic and operational objectives of organizations and depend directly on the quality of data and the application of an appropriate forecast method. However, due to the company's varied portfolio, the study demonstrated the need to use distinct quantitative models, which increases costs and hinders the implementation of a process of change in management. For this reason, despite so many benefits, demand forecast may not be feasible for organizations. For a forecast model to be routinely followed, it should be easily applicable and have a low structural cost.

Given the limitations of this study, new investigative research studies are suggested with multiple criteria to select and evaluate the forecast techniques. Recent studies indicate that the use of multiple forecast models, and subsequently their combination into an actual forecast, is more efficacious than the choice of an individual model. It is also suggested that future research modify the levels of aggregation adopted in the data and apply models of artificial intelligence, neural networks, and fuzzy logic for comparison with the results obtained in this study.

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