An Explainable Machine Learning Model to Optimize Demand Forecasting in Company DEOS

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Abstract

Nowadays, having an accurate demand forecast is extremely important as it allows the company to manage resources in an optimal way and thus achieve greater productivity. There is a large demand for accurate forecasting, and utilizing artificial intelligence can help companies gain a better understanding of their market. In this research presentation, Machine Learning (ML) is used to optimize demand forecasting. The data collected was trained and due to the available data rate, the Cross-Validation technique was used to avoid overfitting. Using time-series, it will be possible to predict future sales for the first trimester of 2021. Finally, the impact of the ML tool on the deviation of the company's demand forecast was evaluated using indicators of accuracy (forecast accuracy) and bias (forecast bias).

Keywords
Demand Forecast; Machine Learning; Forecast Accuracy; Forecast Bias and Consumers Good Company.

1. Introduction
Due to the importance of an accurate demand forecast, the former Head of Demand Planning at the company was consulted. His explanation was given and will be utilized for the case study. The real name of the company will be omitted for the study due to confidentiality issues. Instead, the name Company DEOS will be used to refer to the company, and Demand Chief will be used to refer to the former Head of the Demand Planning team. Demand Chief (2021), indicates that: "demand forecasting is the mind of the business. It is the analytical portion of the solution. The forecast shows is believed to be what can be done and sold, for justified reasons, taking into account what has happened or what is known to occur, the forecast is made". In the case of a consumer goods company (CGC), these are affected by having an excessive number of products that do not rotate or a shortage of products due to high rotation. As Aktepe et al. (2021) mention: "Although inventories appear to be owned by the company, they have no return unless they are sold. Oversupplied raw materials for a production company occupy machinery and workers, creating additional labor costs as well as purchase costs." Excess inventory translates into a loss. Either due to excess or lack of inventories, it results in expired products and reduced sales. The main causes for an inaccurate demand forecast are the lack of data, unreliable data, peaks in demand, and the failure of taking into account life cycles. In addition, there is a great dependence on distributors because the vast majority of CGC sells their products to them so they can then sell it to the final consumer.

1.1 Objectives
The objective of this research is to improve the accuracy of the forecast of the monthly demand for deodorants in a CGC through the implementation of an alternative forecasting model and ML.

2. Literature Review

The present research work was carried out with the need to find agile and precise methods to execute a demand forecast, for this case, in the category of deodorants. Currently, there are 5 types of demand forecasts most deployed in companies: (i) Trend projection, (ii) Market research, (iii) Sales force composite, (iv) Delphi method, and (v) Econometric (Rheude 2020).

According to Lomelli (2021), it is also necessary to mention that within the quantitative methods most used by companies there are moving averages, weighted averages, or exponential smoothing. These methods are within the statistical methods for demand estimation. In addition to the methods mentioned, variations of the traditional models known as 'alternative models' can be found. These are based on the principle of time series; through a simulation, the forecast model is used to estimate beyond the interval of the data found based on the relationship with the variable in question. ML employs various algorithms and "shows that [...] when different models are based on different algorithms and data, a significant gain in accuracy can be made." (Bohdan 2019). The ML tool uses certain algorithms that may require a greater computing effort, as mentioned by Ulrich et al. (2021) but, a smaller deviation in the real versus the estimated forecast is obtained as a benefit and a better performance is achieved compared to others. The company takes into account the amount of data it will handle, since, using conventional methods, handling a large amount of data can no longer be beneficial. In this aspect, the ML tool is once again a highly attractive option because it increases the competitiveness of the company; by using a very large amount of data, while reducing the time it takes to analyze it and offering an accurate result. This also makes better use of your information. (Schreiber and Moroff 2017).

From 1960, Company DEOS decided to venture into the Peruvian market through a company already established in the country; however, according to EMIS (n.d.) the company controlled 51% of the shares and decisions. By 2003, the company used its name within the Peruvian market, already having categories of personal care, home care and food. This research work will focus on the category of deodorants, which is the second most important category of the company with an annual turnover of $5,000,000 by 2020. In Peru, Company DEOS according to EMIS (n.d.): "is dedicated to the elaboration, commercialization and distribution of food, and products of popular consumption for personal care".

The category of interest, deodorants, in the same way as the other five mentioned, makes a demand forecast using statistical methods. In the first trimester of 2021, it was observed that there is a problem based on the accuracy of future demand, as well as the deviation in the estimated versus the real. It was found that: the forecast accuracy ratio of the current month, compared to the previous month, does not exceed a percentage of 66% in the entire first trimester. The forecast bias ranges from -2% to -14% for the same evaluation and comparison periods. According to Demand Chief (2021), the company has a large amount of information, however, it is not easy to use or understand so it is not possible to take advantage of that resource and acquire all the insights. Also, the number of sources from which the information comes is very numerous. The fact that a user, and not a machine, is the one that processes, cleans and manages the data to be used implies a greater probability of error.

3. Methods

As a hypothesis of the research, the implementation of a forecast model using ML is aligned with the integration carried out by the study company to obtain benefits. It also seeks to increase the accuracy of the estimated monthly demand in the deodorant category and reduce the bias between the actual and estimated demand.

3.1 Focus

The approach is a mix of quantitative and qualitative information, which allows superior research to be achieved. (Guelmes et al. 2015). For the quantitative approach, it is necessary to know the impact that the application of the machine learning (ML) tool has on the accuracy of the demand forecast in the category of deodorants. With the qualitative approach, the main causes that prevent achieving an accurate forecast and their consequences have been identified.

3.2 Phases

The next three phases have been determined according to Eisenhardt, who establishes a series of steps to be able to comply with the investigation of the Case Study type (Dominguez, 2009).

3.2.1 Initial Phase
In this phase, the objective is to identify the problem in the demand forecast during the first trimester of 2021 in the deodorant category along with the general problems when making a forecast, and find the internal or external causes that influence the deviation from the fulfillment of the demand forecast. In this step, a collection of all the useful data for the case study is carried out. (Dominguez, 2009).

3.2.1.1 Techniques
As techniques used during this exploratory phase, a documentary review will be used that will allow knowing about the problem that the different consumer goods companies (CGC) are going through. According to Eisenhardt, it is necessary to carry out data collection with multiple researchers (Dominguez, 2009). At the same time, it has been considered to implement as a technique the use of interviews with demand coordinators and forecast execution specialists. There will also be a review of primary sources provided by the study company, in order to know the main problem and influential factors in the deviation from the forecast. According to Cuadrado (2013), it is suggested to collect all the data of the case by observation, noting events relevant to the investigation. In the case of indirect research, historical data on demand and sales are used. Among the useful instruments is the comparative matrix for relevant documents and for the first trimester of 2021 with the estimated forecast vs real forecast in the category of deodorants. Another necessary instrument for this phase will be the elaboration of a semi-structured interview guide. According to Hernández-Sampieri and Mendoza (2018), an interview of this type should be carried out in a Case Study, since pre-established questions will be taken, but in case more arise, these can be carried out. The information collected will be used in instruments such as the Pareto Diagram shown in Figure 1, which includes the root causes found when making a Cause-Effect Tree Diagram. As part of this phase, the support of the Head of Demand Planning and Demand Coordinator in the Deodorant Category (Demand Coordinator) was given to obtain the required information and meet the objective (Figure 1).

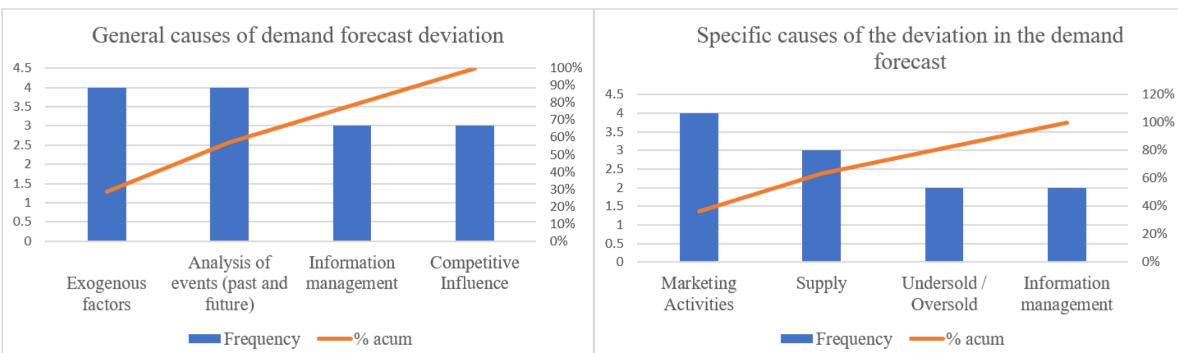


Figure 1. Pareto diagram

3.2.2 Field Immersion
In the second phase, the objective is to implement a simulation using Python, then evaluate and determine the most accurate model. The scope is correlational, where information will be collected based on the results obtained in the simulation and thus choose the most convenient model.

3.2.2.1 Techniques
It has been seen as desirable to align the activities to be carried out as the incorporation of the data set and analysis, as well as the observations (Dominguez, 2009). For the first objective, the simulation will be executed in python to evaluate the performance of the proposal. The simulation will be carried out using the modular code method which uses packages already created. It will be extracted from the Pycaret library that contains all the alternative models and ML using an open source software. PyCaret is an open-source platform that uses a few lines in the ML library in Python (Gonen, 2021). Regarding the collection of the data used for the execution of the model in Python, structured data from Excel was used. This contains the historical sales in tons from 2016 to 2021 of each sku that was then grouped into the category brands and separated by channels since they have different purchasing behaviors. In the case of the model, it will be evaluated with the MAPE, MAE, and RMSE of training and testing, as well as the trend graph for the forecast made. A previous step is an evaluation by means of statistical tests of the data to be used:

i. Ljung-Box: This test has as H0: The residuals are distributed independently. H1: The residuals are not distributed independently and have a correlation. (Zach 2020) .

ii. Shapiro test: According to Zach (2020): In this test you have H0: The data comes from a normal distribution. H1: The data does not come from a normal distribution.

iii. KPSS: The following hypothesis is proposed, H0: The time series has a stationary tendency. H1: The time series does not have a stationary tendency. (Zach 2022)

iv. ADF: The following hypothesis is raised, H0: The time series is not stationary, H1: The time series is stationary. (Zach 2021)

For the sales forecast, the evaluation of the forecast accuracy (FA) and forecast bias (FB) will be carried out, which, according to the DemandCoordinator (2021) are clearly from the supply area. To do this, it has been coded in Python under the following formulas:

- FA: "how accurate the forecast is." (Institute of Business Forecasting & Planning 2021)

$$\text{FA} = 1 - \frac{|SALES - FORECAST|}{SALES}$$

- FB: "tendency to either over-forecast, or under-forecast, leading to a forecasting error." (Singh 2021).

$$\text{FB} = \frac{SALES}{FORECAST} - 1$$

In this research as well as in the paper: Machine Learning and Statistics: A Study for assessing innovative Demand Forecasting Models, Ulrich et al. (2020) only time will be considered for the model while other possible factors that affect monthly demand will not be considered. The support of the Specialist in ML tool was given to dig into the subject.

3.2.3 Validation phase

In this phase, the indicators evaluated are: FA and FB, carrying out an analysis of the data (Dominguez, 2009) in order to complete the objective of the phase: validate whether there is an improvement in demand forecasting for the deodorant category when using ML.

3.2.3.1 Techniques

For this final phase, the technique to be used will be a semi-structured interview with the experts. This will allow to validate the findings obtained. Once this validation has been carried out, a justification table of the selected model will be prepared. Head of Demand Planning and Specialist in ML tool were the analysis units used to validate the results.

4. Results and Discussion

Based on the performance of the models executed in Python, the following were selected, shown in Table 1:

Table 1. Selected Models

MODEL	DESCRIPTION
Theta Forecaster (AM)	Based on the concept of modifying the local curvatures of a time series model. New lines are constructed, which extrapolate separately, and the forecasts are combined (Nikolopoulus et al. 2011)
Exponential Smoothing (ML)	It is used to forecast the demand for a product in a certain period of time, by using the average historical consumption for a given period. Greater weight is given to the most recent values. (Bermúdez et al. 2010)
LGBM Regressor (ML)	Light GBM is a gradient enhancement framework that uses a tree-based learning algorithm. (Mandot, 2017, para. 4). Used for both classification and regression problems. Trees are added one at a time to the assembly and adjusted to correct prediction errors made by previous models. (Browniee 2020)

Random Forest Regressor (ML)	It is a combination of unrelated decision trees and states that "For a classification, each node of the structure can make a decision and the class with the most votes decides the final classification (majority principle)." (Ulrich et al. 2021)

4.1 Forecast performance

The statistical parameters of each brand of the modern channel are shown in Table 2 where it is shown that DEOS1 presents greater variance and standard deviation compared to the rest.

Table 2. Statistics – Modern channel

BRAND/ STATISTICS	LENGTH	MEAN	MEDIAN	STANDARD DEVIATION	VARIANCE
DEOS1	68	10.42	6.39	7.45	55.50
DEOS3.1	68	11.22	12.09	5.11	26.13
DEOS3.2	68	2.77	2.59	1.26	1.59
DEOS4.1	68	8.86	8.48	2.61	6.82
DEOS4.2	68	7.86	6.81	3.71	13.73

The analysis of the data for all the brands was carried out with the statistical tests where the p-value for each test is presented and whether or not the hypothesis is met. The results for the modern channel are presented in Table 3 and for the traditional channel, in Table 3-5.

Table 3. Statistical test results – Modern channel

BRAND/ TEST	LJUNG-BOX	ADF	KPSS	SHAPIRO
DEOS1	p-value: 4.53x10-57	p-value: 0.58	p-value: 0.09	p-value: 1.05x10-6
	Correlation period 24 months	Non-stationary	Stationary trend	No normal distribution
DEOS3.1	p-value: 1.62x10-21	p-value: 0.16	p-value: 0.02	p-value: 0.009
	Correlation period 24 months	Non-stationary	No stationary trend	No normal distribution
DEOS3.2	p-value: 6.15x10-5	p-value: 6.79x10-6	p-value: 0.1	p-value: 0.0003
	Correlation period 24 months	It is stationary	Stationary trend	No normal distribution
DEOS4.1	p-value: 2.98x10-20	p-value: 0.65	p-value: 0.06	p-value: 0.002
	Correlation period 24 months	Non-stationary	Stationary trend	No normal distribution
DEOS4.2	p-value: 1.51x10-42	p-value: 0.98	p-value: 0.1	p-value: 0.003
	Correlation period 24 months	Non-stationary	Stationary trend	No normal distribution

The statistical parameters of each brand of the traditional channel are shown in Table 4-5 where it is shown that DEOS4.2 has variance and standard deviation greater than the rest.

Table 4. Statistics – Traditional channel

BRAND/ STATISTICS	LENGTH	MEAN	MEDIAN	STANDARD DEVIATION	VARIANCE

DEOS1	68	7.29	06.05	3.2	10.24
DEOS3.1	68	5.15	4.91	2.70	7.31
DEOS3.2	68	0.72	0.67	0.38	0.14
DEOS4.1	68	13.50	13.95	7.35	54.01
DEOS4.2	68	12.23	15.03	9.35	87.43

Table 5. Statistical test results – Traditional channel

BRAND/ TEST	LJUNG-BOX	ADF	KPSS	SHAPIRO
DEOS1	p-value: 0.0	p-value: 0.73	p-value: 0.04	p-value: 0.002
	Correlation period 24 months	Non-stationary	No stationary trend	No normal distribution
DEOS3.1	p-value: 8.26x10-22	p-value: 0.85	p-value: 0.1	p-value: 0.007
	Correlation period 24 months	Non-stationary	Stationary trend	No normal distribution
DEOS3.2	p-value: 1.71x10-6	p-value: 0.0003	p-value: 0.1	p-value: 9.26x10-6
	Correlation period 24 months	It is stationary	Stationary trend	No normal distribution
DEOS4.1	p-value: 2.20x10-58	p-value: 0.63	p-value: 0.02	p-value: 1.35x10-5
	Correlation period 24 months	Non-stationary	No stationary trend	No normal distribution
DEOS4.2	p-value: 2.91x10-81	p-value: 0.69	p-value: 0.1	p-value: 7.95x10-6
	Correlation period 24 months	Non-stationary	Stationary trend	No normal distribution

Table 6 shows the performance of the models selected for both channels when using the test data and then the prediction made with these models can be observed in the graphs in Figures 2 and 3.

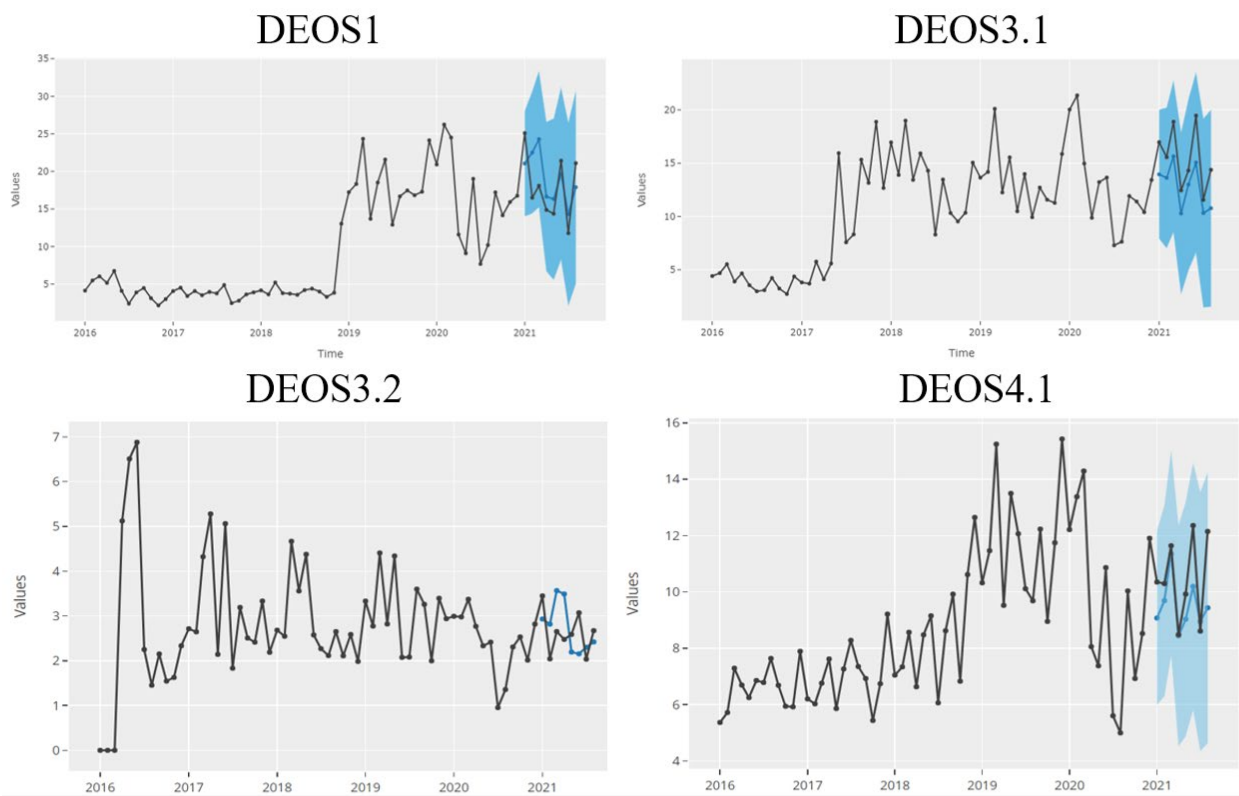
Table 6. Selection of models – Modern and Traditional Channel

	MODERN CHANNEL	TEST			
	WINNING MODEL	MAE	RMSE	MAPE	SMPAE
DEOS1	Theta Forecaster	3.4296	3.8317	0.1962	0.1822
DEOS3.1	Theta Forecaster	2.6188	2.8253	0.1656	0.1824
DEOS3.2	Random Forest Regressor	0.6308	0.6944	0.2448	0.2314
DEOS4.1	Theta Forecaster	1.0375	1.3688	0.0922	0.0995
DEOS4.2	Theta Forecaster	2.046	3.2493	0.1293	0.1523
	TRADITIONAL CHANNEL	TEST			
	WINNING MODEL	MAE	RMSE	MAPE	SMPAE
DEOS1	Random Forest Regressor	1.9479	2.4733	0.1599	0.1799
DEOS3.1	Theta forecaster	1.8323	2.2696	0.2273	0.2049

DEOS3.2	LGBM Regressor	0.1992	0.2221	0.1986	0.2214
DEOS4.1	Exponential smoothing	0.2861	3.4778	0.1448	0.1448
DEOS4.2	Theta forecaster	4.4802	5.7653	0.2062	0.2229

For the selection of these models, it is considered relevant to have a graph of the forecast with a trend equal to that of historical sales. It should be noted that MAPE according to one of the demand experts interviewed, is considered good for a consumer good company with a percentage of 0 - 30%.

In Figures 2 and 3, the blue line shows the sales prediction made with the selected model, while the black line shows the actual sales of each brand. The y-axis shows the number of tons sold and the x-axis shows the period of time in years from 2016 to 2021.



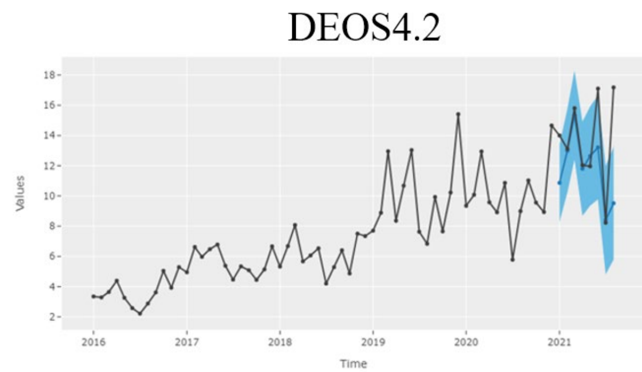


Figure 2. Modern channel – Current graph vs forecast

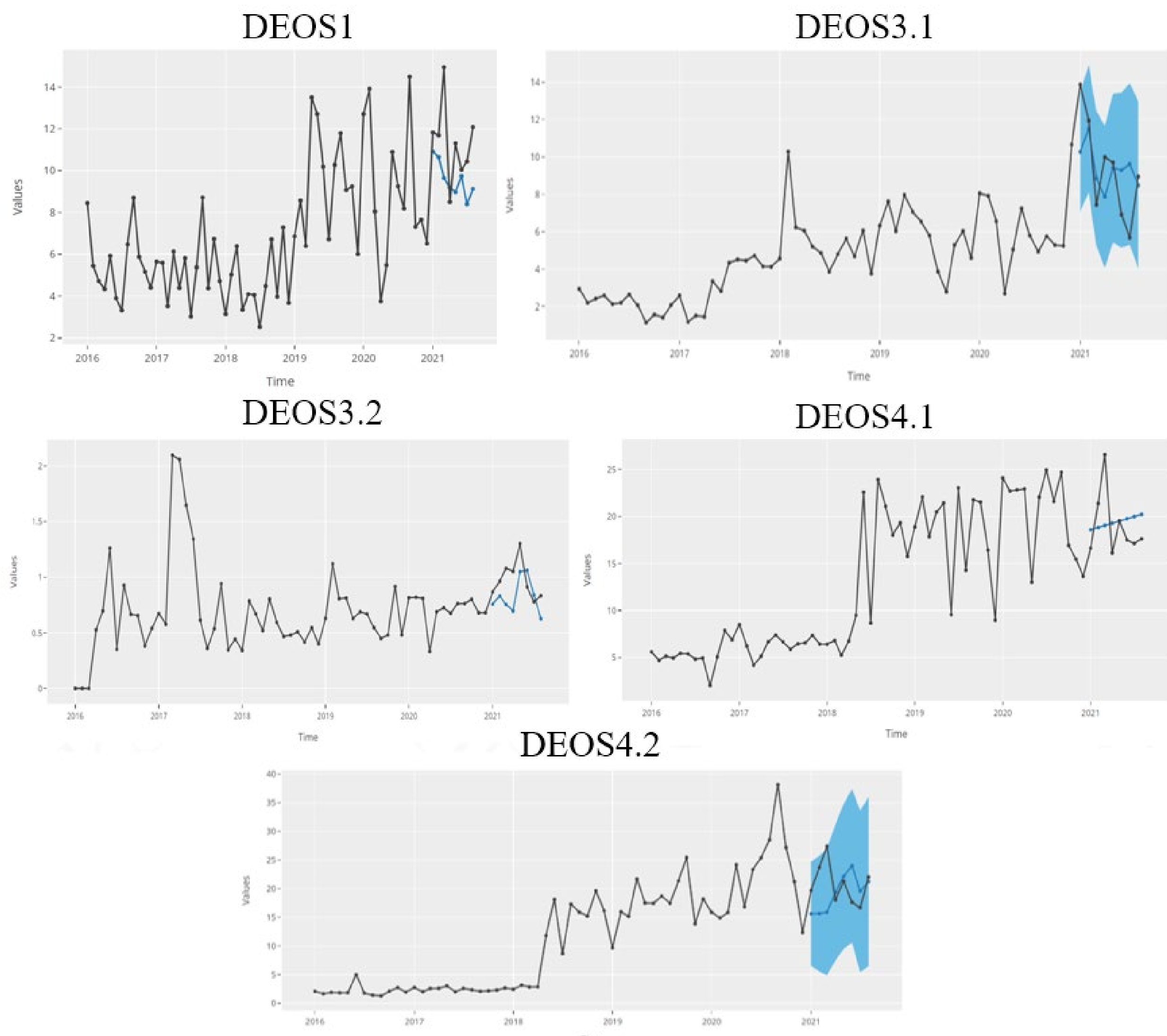


Figure 3. Traditional Channel – Current graph vs forecast

Table 7. Comparison of relevant company indicators - Modern channel

MARCH	MODEL	FORECAST BIAS Current vs Model	FORECAST ACCURACY Current vs Model
DEOS1	Theta Forecaster	Ene: -14% vs 19% Feb: -18% vs -27% Mar: -33% vs -25%	Ene: 35% vs 84% Feb: 45% vs 64% Mar: 35% vs 66%
DEOS3.1	Theta Forecaster	Ene: 13% vs 22% Feb: -22% vs 14% Mar: -1% vs 21%	Ene: 81% vs 82% Feb: 70% vs 88% Mar: 71% vs 83%
DEOS3.2	Random Forest	Ene: 101% vs 18% Feb: -45% vs -28% Mar: -20% vs -26%	Ene: 50% vs 85% Feb: 19% vs 62% Mar: 67% vs 66%
DEOS4.1	Theta Forecaster	Ene: -25% vs 14% Feb: -45% vs 6% Mar: -39% vs 2%	Ene: 41% vs 88% Feb: 17% vs 94% Mar: 30% vs 98%
DEOS4.2	Theta Forecaster	Ene: -6% vs 29% Feb: -26% vs 1% Mar: -1% vs 3%	Ene: 65% vs 78% Feb: 50% vs 99% Mar: 75% vs 97%

Table 7 shows that the modern channel in forecast bias (FB) compared to the current method is improved for the DEOS4.1 brand throughout the trimester. On the other hand, good results were obtained compared to the current method for all brands of the modern channel in the forecast accuracy (FA) indicator. It can be evidenced that the data of the brands in the modern channel are more in line with the alternative models than with those of ML. The Theta Forecaster model, has better performance in the indicators evaluated in four of the five brands. For the modern channel, it has been convenient to contrast the results obtained with those of the research: *Machine Learning and Statistics: A Study for assessing innovative Demand Forecasting Models.* To do this, the statistical measure has been used: RMSE, which according to Statologos (2021): "tells us how far our predicted values are from our observed values, on average."

Table 8. Comparing RMSE values to selected models

	Research Work					Machine Learning and Statistics: A Study for assessing innovative Demand Forecasting Models				
Models /Products	DEOS 1	DEOS3.1	DEOS3.2	DEOS4.1	DEOS4.2	A	B	C	D	And
Theta Forecaster	3.8317	2.8253	0.446	1.3688	3.2493	-	-	-	-	-
Random Forest	4.3064	6.002	0.6944	1.8296	3.6139	10.817	8.777	25.477	3.902	1.439
XGBoost	-	-	-	-	-	9.706	8.712	25.978	3.983	0.729

In Table 8, both the Theta Forecaster and XGBoost models do not present results for all the products evaluated because, in the case of the research carried out by Ulrich et al., the alternative Theta Forecaster model was not considered and for the case of XGBoost in the present work, the model was not available in the library used. The first highlight is that, for the work done by Ulrich et al., RMSE values are not mostly small values. While, for the research work, except for the deodorant brand DEOS3.1 the values obtained were less than 5 which indicates that there is no average distant value between the predicted versus the real. It must be taken into consideration that it cannot be said that the products to be compared are of the same category. In addition, the data of the present work was monthly of five years while that used by the research of Ulrich et al. was monthly of six years.

Table 9. Comparison of relevant indicators of the company – Traditional channel

MARCH	MODEL	FORECAST BIAS Current vs Models	FORECAST ACCURACY Current vs Models
DEOS1	Random Forest	Ene: -30% vs 8% Feb: -10% vs 10% Mar: 52% vs 55%	Ene: 57% vs 92% Feb: 74% vs 91% Mar: 65% vs 65%
DEOS3.1	Theta Forecaster	Ene: 30% vs 35% Feb: -6% vs 4% Mar: -33% vs -16%	Ene: 52% vs 64% Feb: 57% vs 96% Mar: 18% vs 81%
DEOS3.2	LGBM Regressor	Ene: 75% vs 15% Feb: 38% vs 16% Mar: 43% vs 43%	Ene: 50% vs 87% Feb: 64% vs 86% Mar: 61% vs 70%
DEOS4.1	Exponential Smoothing	Ene: -2% vs -10% Feb: 5% vs 14% Mar: 19% vs 39%	Ene: 76% vs 88% Feb: 85% vs 88% Mar: 69% vs 72%
DEOS4.2	Theta Forecaster	Ene: 18% vs 26% Feb: 2% vs 51% Mar: 12% vs 72%	Ene: 66% vs 79% Feb: 72% vs 66% Mar: 87% vs 58%

Table 9 shows that for traditional channel models the FB tends to oversell. For FA, the models mostly performed better compared to the current method. The data is better suited to the ML models than to the alternative ones, since the selected models were the winners for the MAPE indicators of training and testing, FA and FB in three of the five brands. It has been considered appropriate to compare the results obtained with those of the research: *Machine Learning Models for Sales Time Series Forecasting.* To do this, the validation error measure has been used, which according to Microsoft (2021): "it is an error that represents a failure in the validation with the method used."

Table 10. Comparison of validation error values with selected models

Forecast error of different models							
	Research work					Machine Learning Models for Sales Time Series Forecasting	
Models/Brands	DEOS1	DEOS3.1	DEOS3.2	DEOS4.1	DEOS4.2	A	B
Extra Tree	23.45%	28.56%	25.41%	19%	25%	14.60%	13.90%
ARIMA	31.86%	27.10%	45%	26.54%	28%	13.80%	11.40%
Random Forest	18.90%	29.08%	63%	21%	23%	13.60%	11.90%
Lasso	21%	26.90%	24%	26.39%	24.94%	13.40%	11.50%
Neural Network	-	-	-	-	-	13.60%	11.30%

As can be seen in Table 10, the values obtained in this research are of lower performance compared to the results of the *paper*. However, the same data is not used when testing the models. In the case of the research, the data comes from a consumer good company for the category of deodorants while the paper does not specify what data is used. Another difference that can be noticed is the study period: the research uses data from 2016 to 2021 while in the paper they use data from 2013 to 2015.

4.1 Validation

Table 11. Results at category level

	JANUARY	FEBRUARY	MARCH

	FB	FA	FB	FA	FB	FA
CURRENT	3%	63%	-14%	64%	-2%	66%
MODELS	17%	83%	7%	83%	16%	82%

It can be seen in Table 11 that using the alternative and ML models the FB is above the result with the current method in January and March. This means that the proposed models tend to underestimate sales. Underlined are the values where the current result was not exceeded. On the other hand, there is a notable improvement in the FA for the entire trimester, the results obtained are aligned with the company's policy of having this ratio by 80% or more. The short-term objective is the implementation of the ML tool in the company. This opportunity for improvement came due to the need to use the stored information. As the data analyst in charge of the implementation of the tool for Company Deos (Data Scientist Demand) comments, according to Data Scientist Demand (2021):

> "previously there was no way to read the data [..] we wanted to see how we could obtain the information more efficiently, how to centralize it in a single repository to generate data. We generate information within a *dataset.* Once we had the information, the next step was to go through a process to find out if it was correct. With this, the data quality process was carried out."

It is worth mentioning that, before making a sales prediction with a forecast model, it is sought to carry out a clustering process. According to Data Scientist Demand (2021):

> "With Machine Learning I can make a classification of the wineries to see what type of product is the most purchased and launch a specific promotion. Currently we do not have that reading, if we launch a promotion, we launch it for everyone; we are not being efficient with the resources we have."

This point is highly related to one of the causes identified as the most important in generating deviations in the demand forecast: Marketing Activities (Figure 1). It is due to non-focused point-of-sale activations without optimization of resources that less bias and greater accuracy are not achieved.

5. Conclusion

It was possible to identify the main causes that affect the monthly forecast and generate a deviation. In general, the most relevant causes were Exogenous Factors and Event Analysis (past and future). Specifically for the category of deodorants, the main cause identified is Marketing Activities. In addition, a forecast accuracy percentage greater than 80% was achieved in the first trimester of 2021 (January: 82%, February: 83%, March: 84%). This is aligned with the company's goal of having a high value to ensure more accurate forecasts. No expected results were achieved for the bias forecast because the models achieved values are outside the desired range of -5% to 5% (January: 16%, February: 7%, March: 14%). It should be noted that February was the only month that obtained a better result than the current method used by the company (7% vs -14%). Finally, the impact that Machine Learning can bring to the company if implemented was evaluated; the most outstanding benefit is that existing resources can be channeled to create a good marketing and sales strategy at the point of sale, which reduces the main problem of deviation.

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