UNIVERSIDADE CATÓLICA PORTUGUESA

Demand Forecasting in a Company

A Case Study from Footwear Industry

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Católica Porto Business School
2023

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A Case Study from Footwear Industry

Final Work in Academic Context presented to Universidade Católica Portuguesa to obtain the master's degree in Management with a specialization in Business Analytics

by

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Católica Porto Business School
April 2023

Acknowledgments

First, I would like to acknowledge and give my warmest thanks to my advisor, Professor Aydin Teymourifar, for guiding me throughout the process of executing this investigation, advising, and showing his availability and concern for the result. I would also like to thank the jury committee members for taking the time to read my dissertation and for their comments and suggestions, which will be helpful for my career.

I am also very grateful to the CEO of the company 8000Kicks, who provided me with the data to conduct this study. Without his help, this analysis would not be possible.

I would be remiss in not mentioning my family, especially my dad, sister, and boyfriend, for all the support and understanding.

Lastly, I would like to mention my friends. Their confidence in me has maintained my spirit and motivation during this time.

Resumo

O tema da previsão da procura tem vindo a ser investigado há décadas, por diversas áreas, como na produção, logística, e finanças, dada a sua importância no planeamento e tomada de decisão das empresas. Vários métodos foram testados em diferentes indústrias, não existindo ainda um consenso entre os autores de qual o melhor método a ser aplicado, uma vez que as características de mercado diferem de empresa para empresa.

O presente estudo pretende analisar métodos de previsão da procura numa empresa de calçado portuguesa, 8000Kicks, com o intuito de identificar o método com maior precisão para as características dessa mesma empresa, e as razões para esse método ter melhores resultados que os restantes testados.

Procedeu-se à realização de um estudo quantitativo, sob a forma de resolução de problema. O objetivo desta investigação é ajudar a resolver o problema da falta de eficiência, para a empresa em análise, na utilização dos seus recursos, no âmbito do planeamento e tomada de decisão.

Modelos de Séries Temporais, Regressão, e Inteligência Artificial foram selecionados e testados, analisando a sua exatidão através da medida de performance selecionada, Erro Quadrático Médio (EQM).

O modelo *Artificial Neural Network* demonstrou melhor precisão, com o valor mais baixo do EQM dos modelos testados, seguido da Regressão Não-linear. Conclui-se que, para o presente estudo, os modelos não-lineares apresentam melhores resultados comparativamente aos lineares, por efeito das suas características de adaptabilidade, melhor encaixe nos dados, e habilidade em capturar relações complexas e processos dinâmicos.
Palavras-chave: Previsão da procura, Calçado, Séries Temporais, Regressão, Inteligência Artificial.

Abstract

Demand forecasting has been investigated for decades, in several areas, such as manufacturing, logistics, and finance, due to its importance in corporate planning and decision-making.

Several methods have been tested in different industries, but there is still no consensus among authors, as to which method should be regularly applied since market characteristics differ from company to company.

The purpose of this study is to identify the demand forecasting method with the highest accuracy for the characteristics of the data provided by the Portuguese footwear company 8000Kicks, and the reasons for this method have better results than the others tested.

A quantitative study is carried out, in the form of problem-solving. The aim of this research is to help solve the company's problem of lack of efficiency in the use of company resources, impacting its planning and decision-making. Time Series, Regression, and Artificial Intelligence models were selected and tested, to analyse their accuracy, according to the chosen performance measure, Mean Square Error (MSE).

The Artificial Neural Network model revealed better accuracy, with the lowest MSE of the models tested, with a test value of 8,5865E-06, followed by Nonlinear Regression. It is concluded that, for this study, the nonlinear models appear to have better results when compared to the linear models, due to their characteristics of adaptability, better fit to the data, and ability to capture complex relationships and dynamic processes.

Keywords: Demand Forecasting, Footwear, Time Series, Regression, Artificial Intelligence.

Abbreviations

AI: Artificial Intelligence

AIC: Akaike Information Criterion

AICc: Corrected Akaike's Information Criterion

ANN: Artificial Neural Network

AR: Autoregressive

ARIMA: Autoregressive Integrated Moving Average

ARMA: Autoregressive Moving Average

BIC: Bayesian Information Criterion

CAIC: Consistent Akaike Information Criterion

CV: Coefficient of Variance

DES: Double Exponential Smoothing

ETS: Exponential smoothing

FNN: Feedforward Neural Network

HW: Holt-Winters

IQR: Inter Quartile Range

KPIs: Key Performance Indicators

LSTM: Long Short-Term Memory

MA: Moving Average

MAD: Mean Absolute Deviation

MAE: Mean Absolute Error

MAPE: Mean Absolute Percentage Error

MID: Multivariate Intelligent Decision-making

MPE: Mean Percentage Error

MSE: Mean Squared Error

OLS: Ordinary Least Squares

POS: Point of Sale

RMSE: Root Mean Squared Error

SC: Supply Chain

SE: Standard Error

SES: Simple Exponential Smoothing

SKU: Stock-keeping Unit

Std: Standard Deviation

SVM: Support Vector Machine

tStat: Student's T-Test

WMA: Weighted Moving Average

Notations

t	Time (represents the period)
p	Number of the previous periods considered
E_t	Estimation for period t
D_t	Demand for period t
W_t	Weight for period t
$i = t-p+1$	Last period considered
S_t	Smoothed value for period t
T_t	Trend for period t
L	Cycle
I_t	Seasonal Index of period t
ε_t	Error term for period t
β	Vector of parameters
χ	Vector of predictors
γ	Dependent variable
F	Regression Function
n	Number of observations

Table 1: Notations

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Number of words: 9996

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Table Index

1. Introduction

In the section, the general framework of the dissertation topic is covered, defining, and explaining its relevance. The research objectives are presented, as well as the methodology used for its development, and the macrostructure of this paper.

1.1 General Framework

Demand forecasting is the process of predicting demand for a product or service before it occurs. It represents a crucial role in planning and decision-make of the company activities, to predict the impact that certain events have on the company's production. Forecast helps companies to mitigate the risks and ramifications of production variables and constraints (Archer, 1980).

A more accurate demand forecast improves inventory management, intending to achieve optimal inventory levels and avoid stockouts or overages. The reduction of inventory decreases the amount of warehousing, eliminating costly losses. Demand forecasting also reduces costs related to other production tasks, such as job allocations and management, sourcing raw materials, and tasks related to the front office. It also allows to have effective logistics and to reduces transportation costs. Demand forecasting leads to more efficient and cost-effective production (Nenni et al., 2013).

Due to its importance, it has been a topic studied by different authors for several decades.

1.2 Objectives and research methodology

The purpose of this dissertation is to apply previously studied methods of demand forecasting to 8000Kicks, a Portuguese footwear company, to compare them and make conclusions based on the accuracy of the approaches in this company.

8000Kicks is a direct-to-consumer company, that started its business in 2019. They are the pioneers of industrial hemp-made waterproof footwear, and they sell other products besides shoes, such as backpacks. The analysis focuses on one model of shoe sold by them.

There are several qualitative and quantitative demand forecasting methods. However, due to their market characteristics, there is no suitable method for all companies.

Within the scope of this thesis, it is expected to understand which is the best-tested method to forecast demand for the 8000Kicks footwear company, to avoid inventory management problems and improve its performance. Another expected outcome is to recognize the reasons for the method's high accuracy. Time series, Regression, and Artificial Intelligence (AI) methods are applied in this study.

The objective is to identify the most accurate, straightforward procedure. Because of their simplicity, Time Series approaches are used in this context. The Artificial Neural Network (ANN) approach is tested due to the effectiveness and popularity of AI methods. Lastly, since they are frequently used to compare AI techniques, linear and nonlinear regression models are also used for this investigation.

Therefore, this dissertation will aim to answer the following research questions:

- Which method, out of the chosen Time Series, Regression, and AI, has the highest accuracy for the data from the footwear company 8000Kicks?
- What explains the method's high accuracy?

This research is focused on problem resolution. The first step is the literature review, where the methodologies and concepts already studied regarding this topic and the consequent results and conclusions are recognized. The second step is the application of the chosen methods for forecasting 8000Kicks’ demand, after data collection and processing. The third step consists of extracting those methods' experimental results and conclusions (Figure 1).

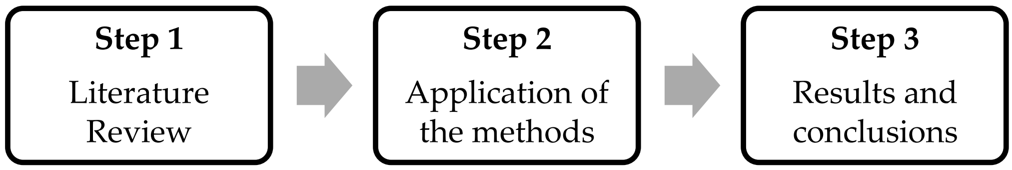

Figure 1: Research Methodology

1.3 Macrostructure

This dissertation is divided into six chapters. The first chapter contains the introduction of the dissertation topic, the objective, the research methodology used in its development, and its macrostructure. The second chapter concerns the literature review, intending to understand the progress made so far on this topic and the research gaps found. The third chapter defines the problem of the research and its questions. The fourth chapter describes the methods used for this study, its inputs and outputs, and the performance measure used to evaluate the accuracy of each technique. The fifth chapter concerns the experimental results. It starts with the dataset characterization, followed by its descriptive analysis, experimentation outcomes, and discussion of results. The sixth chapter contains the main conclusions of this study and areas for future work.

The last section is the bibliographical references used to support the arguments, concepts, and theoretical foundations throughout the thesis.

2. Literature Review

This section presents the theoretical concepts of demand forecasting and its application in the footwear industry. The methods used for demand forecasting are also introduced, as well as findings and conclusions from different studies.

2.1 Demand Forecasting

Forecasting can be described as the skill of foreseeing events before they happen. It is crucial to have reliable forecasts, made according to the objective of the study since all planning and related decision-making will be affected by it. The accuracy of the forecast depends on the approach chosen, the quantity and quality of the existing data, time, and other resource availability (Archer, 1980).

Sales forecasting is crucial for the purchasing, accounting, finance, marketing, and logistics departments, in addition to the sales department. On an organizational level, each of these departments is tied to the others and is impacted by forecasting accuracy, as they support their short and long-term decisions (Ramos et al., 2015).

Short selling seasons, a high level of uncertainty, and a lack of historical data, which is frequently brought on by innovation, are the key obstacles to forecasting demand (Nenni et al., 2013).

According to Thomassey (2010), forecasts should be divided according to their time horizon: a long-term horizon, to organize the manufacturing and sourcing, and a short-term horizon, to restock and adjust both the purchases and deliveries.

Demand forecasting should consider the different lifecycles of products: "basic items" that are sold the entire year, "best-selling items" that are sold each year, but with some modifications, and "fashion items", that are sold in a short period. However, since fashion items, called "one-shot", are sold on a one-off basis, and differ from year to year, the demand forecast does not take them into account (Thomassey, 2010).

Forecasts also include estimates of uncertain future demand, and it is common to be based on management judgment. Judgmental forecasts are subject to cognitive biases. Optimistic and pessimistic forecasting scenarios are judgmental forecasts and cause deviation from the optimal production decision levels, due to the overweighting of the last observation in the time series. It was proven by Goodwin et al. (2019) that forecasts with more information, as these scenarios, can detriment the accuracy of point forecasts and the quality of associated decisions. In the experimental study of these authors, it was found that even if participants had information on both scenarios, they would just focus on the scenario that is consistent with the last behaviour of the time series and ignore the alternative.

Demand forecasting on special days is another challenge, due to the variety of patterns and differences from the regular days. Public holidays, days surrounding them, and other calendar events are considered special days because it is when clients change their daily routines. Companies gain a competitive advantage by being able to forecast these events and avoid suffering costs from these days (Huber & Stuckenschmidt, 2020).

The impact of demand forecasting in the supply chain (SC) and the concept of inventory stock control are explored in Appendix A.1 and A.2, respectively.

2.1 Application in Footwear Industry

Demand forecasting represents a crucial role in the planning and decision-make activities of a company. There are demand attributes, especially in the fashion industry, which make it difficult to forecast demand, such as uncertainty, seasonal trends, and lack of historical data. The analysis of the trend and the cycle of demand for the product features is a crucial concern to have historical series with a larger population (Nenni et al., 2013).

Demand forecasting in the footwear industry, or fashion in general, is extraordinarily complex. The demand for this industry is characterised by volatility (overly sensitive to the effect), long replenishment lead times, strong seasonality of sales related to weather conditions trends, numerous stock-keeping units (SKU), and products with short life cycles (Thomassey, 2010).

Short-product lifecycles and the datedness of the retail calendar are the main factors that make variability of demand increases, and forecasting demand harder, consequently (Kharfan & Chan, 2018).

Nenni at al. (2013) believe that the fashion industry should be recognized as a "complex open system", due to its features which make demand nearly unpredictable, and imprecise forecasts. The demand for the footwear industry's products is very volatile and so extremely difficult to forecast, because of highly impulsive purchasing and variety. Companies are suffering a lot of pressure to give a quick response and have an agile supply chain, to keep up with consumer preferences.

2.2 Demand Forecasting Methods

Given that products have a short lifecycle, and a high number of different colours and sizes that are produced (huge number of SKUs), the historical data is usually aggregated to forecast sales. Classification methods based on quantitative and qualitative properties or hierarchical classification (family level), and then clustering, are usually implemented for this purpose and when there is a lack of historical data in the lowest level. A key success factor is to have relevant and reliable data in the information systems of the distributors (Thomassey, 2010).

The demand forecasting models include various explanatory variables to have a more accurate forecast and improve order decisions. However, it is very difficult to calculate their impact. Some variables are uncontrolled, and others are under control by the distributor. Even the variables under control, such as the weather and competition, can become unpredictable due to their fluctuations. Not all explanatory variables are known. It is, therefore, exceedingly challenging to have trustworthy and consistent variables in historical datasets (Thomassey, 2010).

Time series and regression methods, known as traditional techniques, are the most used. They are indicated when the number of predictors is limited, for instance, trend, seasonality, and cycle, and there is a large historical data. These methods include models such as Exponential smoothing (ETS), Holt-Winters model (HW), Box&Jenkins model, and regression models. The performance of each model differs depending on the final objective of the forecast (Thomassey, 2010).

Machine learning techniques allow to have an unlimited number of variables from different data sources and determine the ones that are relevant to the forecast goal. The author Thomassey (2010) concluded that fuzzy logic for long-term horizons and neural networks for short-term horizons are methods particularly suitable for the clothing industry, because of the fluctuating, incomplete, and nonlinear data. According to him, the most difficulty in this industry is to modelling relationships with such a limited amount of historical data. The use of these methods can be beneficial to evaluate distinct levels, such as reduction of the bullwhip effect, reduction of costs, and reduction of sales losses. After the implementation of these methods, the author made a simulation in order to quantify the impact of the forecast errors, in which he concluded that these errors on the initial forecast led to an increase in inventory, lost sales, and therefore decrease in retailer's gross margin – the beginning of a bullwhip effect.

Nenni et al. (2013) review different forecasting methods, to connect forecasting demand approaches to the market characteristics and to find an adequate framework for forecasting demand in the fashion industry. Identifying the demand pattern helps choose the forecasting method. Traditional methods for forecasting demand, such as ETS are adequate for steady and high-volume demand. They do not perform well when demand is intermittent (occurs when the demand has non-specific periods with zero demand), unpredictable (demand with high variability – erractiness), or lumpy (tendency to have low demand and then sporadic spikes).

Regarding traditional methods, statistic approaches perform poorly when there is a significant amount of lumpiness or erraticness in the demand pattern. In this review, it was also concluded that expert systems, such as ANN, are a more adequate option to capture a nonlinear pattern in that data, which is considered a limitation for traditional methods. Despite the benefits of ANN models producing more accurate forecasts, its implementation is severely hampered by the fact that the time needed to use it grows exponentially with the complexity or variety of the data. This impacts the fashion business in short-selling season, and quick response times (Nenni et al., 2013).

Huber and Stuckenschmidt (2020) analysed forecasting demand on special days. They concluded that machine learning methods are a good option to forecast demand with those patterns without leading to high forecast errors. The results that they got indicate that a more sophisticated and elaborate process of model-building and selection would be beneficial for a competitive and productive environment for long, large-scale, and different demand forecasting periods.

Processing and delivering the value of the categorical variables is a challenge for forecasting demand in the fashion industry, which can be done by using machine learning techniques, such as namely Regression and Classification

Trees, Random Forests, ANN, and k-Nearest Neighbor. These are more sophisticated approaches that aim to achieve better forecast accuracy when there are a significant number of predictor variables and data sources. However, lost sales were not considered, so real historical demand is not reflected. This happens when there are stockouts in the point of sales (POS), and demand is not satisfied (Kharfan & Chan, 2018).

There are two different types of forecasting approaches, numerical methods (quantitative) and qualitative methods. Numerical methods can be used to produce and analyse the data by building different models. Generally, these methods are based on two categories: time series, which includes the ETS model; or causal relationships, such as multivariable regression analyses, that analyses statistically potential explanatory variables. Qualitative approaches, such as a detailed survey, are founded on the expertise, practical experience, and intuition of the subject matter specialists The accuracy of qualitative approaches depends on wise judgment, but it is most likely to lack rigour. It is appropriated when there is a lack of updated and appropriated data (Archer, 1980).

The time series approach considers trends, linear or exponential, and cyclical changes. When these cycles are regular, it is easier to forecast, just by observing them. However, they hardly ever show a straightforward regularity, therefore, more complex techniques are satisfactory (Archer, 1980).

The moving average (MA) is the most straightforward method. Since it gives each observation the same weight regardless of how old it is, it is not a good solution when demand is rising. The ETS approach, unlike MA, takes into consideration the different weights of each observation, giving more importance to the most recent ones. In both approaches, extrapolation must exist to create a forecast (Archer, 1980).

The simple exponential smoothing (SES) approach is more suitable for the short-term, and ideal when demand is stationary, due to its simplicity in adding new products or modifying them, low computational cost, and it is usually robust. However, it is not appropriate when demand demonstrates growth characteristics, and that is the reason why it is not a good fit for the medium and long term (Lewis, 2000).

Archer (1980) defends that probably the most trustworthy forecasts are the ones that combine the two types of forecasting approaches - qualitative and quantitative. Even rigorous numerical methods include subjective judgement forecasts.

Autoregressive (AR), Autoregressive Moving Average (ARMA), and Autoregressive Integrated Moving Average (ARIMA) are time series methods widely used in forecasting. The authors Maia et al. (2008) present their main differences. The AR is a model that is used to determine a prediction of a variable based on its prior input values. ARMA is the combination of AR and MA models. Based on a limited, linear combination of historical values and error of the time series, ARMA estimates future values. ARIMA differs from ARMA in the differencing operator, which is employed to the time series until it becomes stationary. Since real-life time series are usually not stationary, ARIMA is more often applied.

There are three categories of time series methods: classical, AI, and hybrid methods. Classic techniques are based on statistical and mathematic models, including the ETS model and ARIMA. AI approaches are suitable and effective for modelling time series and non-time series, as they depict the sales data's dynamic nonlinear trend and seasonality. They incorporate ANN expert systems, fuzzy systems, and other intelligent techniques (Guo et al., 2013). Hybrid models combine time series and machine learning techniques, or regression. ARIMA-ANN and ARIMA-regression are examples of hybrid models (Punia & Shankar, 2022).

Punia and Shankar (2022) developed a hybrid model that combines Long-Short-Term Memory (LSTM) networks and random forests, that handles big data and forecast from short to long term. Its performance was better when compared with time series, machine learning, and other hybrid methods.

AI methods have been demonstrated to work successfully with lots of noisy data and enhance the precision of demand forecasting techniques, whether used alone or in conjunction with statistical techniques. AI methods include machine learning and deep learning techniques. Mediavilla et al. (2022) analysed the AI methods studied in the last five years, and it shows a trend for the use of deep learning approaches. Clustering and dimension reduction are strategies used to improve data quality to forecast demand.

Sales forecasting is essential to increase the competitiveness of the company concerned. Given how frequently data patterns change, is unrealistic to assume that the process of generating data is consistent, especially in a fast-response environment like the footwear industry. Therefore, univariate sales forecasting models, that use only past sales history, are not adequate for these circumstances, where there are constant changes of influencing factors associated with them. However, due to a lack of data, multivariate sales forecasting models cannot consider every element that affects sales, nor identify all these influencing factors (Guo et al., 2013).

ETS techniques, which are based on a description of trend and data seasonality, and ARIMA models, which explain the autocorrelations in the data, are the most frequently used approaches to time series forecasting. These approaches work better when the macroeconomic environment is largely steady. The ANN model and multi-step forecasts are preferred when they are volatile. In general, multi-step forecasts outperform one-step forecasts because they take more recent data into account (Ramos et al., 2015).

Villegas et al. (2018) proposed the Support Vector Machine (SVM) method for demand forecasting. Their study revealed that the model responds to volatile conditions successfully, with low biases and error values.

The accuracy of econometric models, in contrast to time series, depends on the accurate identification of predictable explanatory variables (Fildes et al., 2019).

When the sales pattern is affected by a variety of factors, which increases the model complexity, multivariate models typically produce better forecasting results than univariate models. The same is true for goods with low demand uncertainty and seasonal tendencies. However, many external factors are not available, and their impact is difficult to calculate. The authors Punia and Shankar found out that POS and external economic factors are the ones that most influence demand (Punia & Shankar, 2022).

After several years of study, there is still no consensus among authors as to which is the most accurate method to forecast demand. No single model excels in all circumstances and under all conditions. Further study is required to come up with a solution that raises the quality of the forecasts because each of them has flaws (Ramos et al., 2015).

Appendix A.2 covers less commonly used techniques. Table 2 summarises all discussed methods, and Table 12 the articles used in this section (Appendix A).

Time Series	ETS
	HW
	Box&Jenkins
	MA
	Autoregressive models: AR, ARMA, and ARIMA
AI	Fuzzy logic
	ANN
	Classification Trees
	Random Forests
	k-Nearest Neighbor
	LSTM
	SVM
Regression	Linear
	Nonlinear
Other techniques	Hybrid Methods (ANN-ARIMA; ANN-Regression)
	MID
	Qualitative approaches
	Other statistical methods: Binomial distribution, Croston’s model, bootstrap, and variants of Poisson model
	Econometric models

Table 2: Demand Forecasting Methods from Literature Review

3. Problem Definition and Research Questions

This section addresses the problem definition, as well as the research questions of this dissertation.

3.1 Problem Definition

The management of a company involves estimating the demand for its products, maximising the use of its resources, and reducing waste and consequently associated costs.

The biggest challenge for the 8000Kicks company is the lack of efficiency in the use of company resources, resulting in an inadequate inventory.

To solve this, an accurate forecast of demand is needed. Inefficient demand forecasting can lead to the existence of lost sales (demand that is not satisfied due to the lack of resources), or to an excess of inventory. These problems result in significant expenditures for the business, but they can be avoided by employing an accurate demand forecasting technique.

As concluded in the literature review section, there is no consensus between authors about the best accuracy method, as it depends on the market characteristics and other external factors. This research aims to cover this gap in the literature.

3.2 Research Questions

Given the problem defined in the previous subsection, this research intends to understand which method best suits the footwear company, 8000Kicks, given the characteristics of its market and the associated external factors. To contribute to the literature, this study also aims to explain the reasons why this method has better accuracy.

The research questions that are addressed in this dissertation are presented in Table 3.

Research Questions	Objectives
Between the chosen methods of Time Series, Regression, and AI, which one has the highest accuracy for the data of footwear company 8000Kicks?	Test the following methods to understand which one has the highest accuracy and fits better the 8000Kicks company data: Simple Average, Naïve method, MA, Weighted Moving Average (WMA), Simple Exponential Smoothing (SES), Double Exponential Smoothing (DES), and HW, Linear and Nonlinear Regression, and ANN.
What is the reason, compared to the others, that explains the higher accuracy for the respective model?	Analyse and explain the reasons for the differences in the methods' accuracy values, for the company data.

Table 3: Research Question and Objectives

4. Research Methods

This section presents and describes the methods used in the study, their inputs and outputs, and the performance measure used to evaluate them.

4.1 Methods Definition

Some Time Series, Regression, and AI methods are applied in this study. This section intends to define and discuss each chosen model.

4.1.1 Time Series

A time series is a collection of data that has been recorded and examined over a defined period (Profillidis & Botzoris, 2019).

The time series methods that are going to be implemented are the following: Simple Average, Naïve method, MA, WMA, SES, DES, and HW.

4.1.1.1 Simple Average

The simple average technique consists of adding up the demand values based on historical data, divided by the number of periods considered in that same sum. It is, therefore, an average of past values, as defined in Equation (1).

$$E_{t+1} = \frac{D_1 + D_2 + \cdots + D_t}{t}, \tag{1}$$

where E_t is an estimation for period t, and D_t is the demand for period t.

4.1.1.2 Naïve Method

Naïve Method involves estimating the demand for the following period based on the demand of the most recent one, defined as in Equation (2).

According to this method, the most crucial observation is the most recent one, and the past observations do not provide useful information to predict the future.

$$E_{t+1} = D_t \tag{2}$$

4.1.1.3 Moving Average

The MA approach smoothes time series by averaging a specified number of successive terms, named p. Each value of these terms is replaced with time (t), where the newest observations are sequentially included, while the oldest data is removed. The average is calculated based on p previous values. MA technique gives equal weight to all observations.

Generally, the series is smoother if this interval is longer. The difference between MA and the simple average is that MA only considers a limited most recent number of historical data (p), instead of every historical data.

MA is widely used to identify time series factors, such as trend and seasonality (OECD, 2005).

As described in Equation (3), the forecasted demand is equal to the last calculated average.

$$E_{t+1} = \frac{D_t + D_{t-1} + \cdots + D_{t-p+1}}{p} \tag{3}$$

4.1.1.4 Weighted Moving Average

WMA is a technique calculated in a similar way to the MA. However, WMA gives particular importance to the most recent observations and therefore, gives them more weight in the equation. The oldest observations are progressively given less weight in the calculation of the demand forecast, as in Equation (4).

$$E_{t+1} = \frac{W_t D_t + W_{t-1} D_{t-1} + \cdots + W_{t-p+1} D_{t-p+1}}{p}, \tag{4}$$

where

$$W_t > W_{t-1} > \cdots > W_{t-p+1},$$

and

$$\sum_{i=t-p+1}^{t} W_i = 1$$

4.1.1.5 Simple Exponential Smoothing

SES (Brown, 1959) is a method recommended for forecasting data that do not show clear patterns of trend or seasonality in its behaviour.

Forecasts utilizing the SES methodology are computed using weighted averages, where the weights of the oldest observations decline exponentially as new ones are added, hence the term “exponential smoothing”, as defined in Equation (5). The difference between WMA and SES models is that SES uses a smoothing parameter (α) to compute the weights. The value of this constant is between zero and one, where the sum of the weights is approximately one. The higher the value of α, the more weight is given to more recent observations (Hyndman & Athanasopoulos, 2018). The alpha (α) value should be low when observations do not undergo large oscillations over the periods, and high when they undergo high oscillations.

$$S_t = \alpha D_t + (1 - \alpha) S_{t-1} \tag{5}$$
$$E_{t+1} = S_t,$$

where S_t is the Smoothed value for period t.

4.1.1.6 Double Exponential Smoothing

DES, also known as Holt Model (Holt, 1957), is an exponential smoothing method with trend adjustments.

Defined in Equation (6), this approach is appropriate for data that shows the existence of a trend, and it has two smoothing equations – one for the level, as in SES, and another for the trend. The constant α is the smoothing parameter for the level, as for SES, and β is the smoothing parameter for the trend. This last constant, β, has the same constraint as α, its value is between zero (where the trend is constant: $T_t = T_{t-1}$) and one. β is small when the time series shows a relatively constant behaviour, therefore the weight of the last observed trend is higher. When there is a significant growth or decline in the data over time, β is bigger.

Forecasts based on the DES method are a weighted average of the past observations plus the weighted average of the estimated trend for period t.

$$\begin{aligned} S_t &= \alpha D_t + (1-\alpha)(S_{t-1} + T_{t-1}) \\ T_t &= \beta(S_t - S_{t-1}) + (1\text{-}\beta)\, T_{t-1} \\ E_{t+k} &= S_t + kT_t \end{aligned} \tag{6}$$

where T_t represents the trend for period *t*.

4.1.1.7 Holt-Winters

Holt (1957) and Winters (1960) created a triple exponential smoothing model, named the Holt-Winters model. This approach is an extension of DES since it not only includes trend adjustments but also seasonal effects.

HW technique is composed of three equations, in addition to the forecast equation – one for the level, one for the trend, and another for the seasonality. Each equation has an associated parameter, α and β already explained, and γ for the seasonal component.

After defining a cycle "L", which often is a year, the first step is to remove seasonality from the series, followed by smoothing the series and just add again the seasonal effect in the forecast.

The seasonal index (I_t) is interpreted as the proportion of the observed value that is above ($I_t > 1$) or below ($I_t < 1$) the average for that period.

This approach is divided into two methods: Holt-Winters additive, by Equation (7), and Holt-Winters multiplicative, by Equation (8). The HW additive method is preferable when seasonal variations of the series are roughly constant, while the HW multiplicative method is more adequate when the seasonal fluctuations change proportionally to the series level. The seasonal component is stated in absolute terms in the scale of the observed series using the additive approach, and in relative terms (percentage) using the multiplicative method. In the first method, the level equation adjusts the series for the season by deducting the seasonal component, and in the multiplicative approach, the series is adjusted by dividing it by the seasonal component (Hyndman & Athanasopoulos, 2018).

$$\begin{gathered} S_t = \alpha(D_t - I_{t-L}) + (1-\alpha)(S_{t-1} + T_{t-1}) \\ T_t = \beta(S_t - S_{t-1}) + (1\text{-}\beta)\, T_{t-1} \\ I_t = \gamma(D_t - S_t) + (1-\gamma)\, I_{t-L} \\ E_{t+k} = S_t + kT_t + I_{t-L}, \end{gathered} \tag{7}$$

where I_t is the Seasonal Index of period t.

$$\begin{gathered} S_t = \alpha(D_t / I_{t-L}) + (1-\alpha)(S_{t-1} + T_{t-1}) \\ T_t = \beta(S_t - S_{t-1}) + (1\text{-}\beta)\, T_{t-1} \\ I_t = \gamma(D_t / S_t) + (1-\gamma)\, I_{t-L} \\ E_{t+k} = (S_t + kT_t)\, I_{t-L} \end{gathered} \tag{8}$$

4.1.2 Regression

4.1.2.1 Linear Regression

Linear Regression (Papalexopoulos & Hesterberg, 1990), is a model based on the causal relationship between the forecast variable (E_{t+1}), and a single predictor variable (D_t), or more explanatory variables. When the dependent variable (demand) is correlated with other independent variables, it presents a cause-effect relationship. The forecast of a variable is based on the values of the predictor variables.

This method is highly helpful when there is a lack of historical data. It not only forecasts demand but also attempts to explain the business, through the correlations between variables.

Equation (9) shows the simplest regression model, with just one predictor variable (univariate data analysis). However, in multivariate data analysis, there can be more than one explanatory variable, as in Equation (10).

$$E_{t+1} = \beta_0 + \beta_1 * D_t \tag{9}$$

$$\gamma_t = \beta_0 + \beta_1\chi_{1t} + \beta_2\chi_{2t} + \cdots + \varepsilon_t \tag{10}$$

where ε_t is the error term for period t.

4.1.2.2 Nonlinear Regression

Nonlinear regression establishes a nonlinear curved relationship between two variables. Equation (11) presents the nonlinear regression function, which can include nonlinear and linear parameters, being more flexible and complex than linear regression.

Nonlinear Regression can include different types of functions and iterations, such as exponential and logarithmic, with unlimited relations.

The model's purpose is to use iterative numerical processes to minimize the sum of the squares as much as possible, i.e., for the model to fits better the dataset (Corporate Finance Institute, 2022).

The development of nonlinear models is more challenging, compared with linear models, since the function must be developed through many iterations, some of which may result from trial and error.

$$\gamma_t = f(\chi, \beta) + \varepsilon_t \tag{11}$$

where χ is the vector of predictors, β the vector of parameters, and F the regression function.

4.1.3 Artificial Intelligence

4.1.3.1 Artificial Neural Network

ANN is a computational learning system that uses calculations and mathematics to recreate the electrical activity of the human brain and nervous system (Patterson, 1996).

Neurons are organized into complex and nonlinear structures in ANN models. Weighted connections bind the neurons to one another. These models use learning and training techniques to compute every process (Malekian & Chitsaz, 2021). This approach processes multiple identified samples provided during training and uses this answer key to understand what input attributes are required to create the correct output.

4.1.4 Discussion of the methods

The nature of the data is the primary distinction between time series and regression analysis. Time series analysis examines data that changes over time, whereas regression analysis examines the relationships between variables.

The residuals in regression models are assumed to be independent and identically distributed, normally distributed, with a mean of zero and constant variance. The residuals in time series models are frequently correlated over time, which can be due to trends, cyclic, and seasonality features (Date, 2021).

Time series models capture linear relationships between the variables, as the linear combination of the errors from its past values in the MA model. The main difference from regression analysis is that it considers the temporal correlation in the data.

Nonlinear models, such as nonlinear regression and ANN, can cope with trends, cyclic, and seasonality attributes in time series data effectively. However, their performance depends on the complexity of the underlying patterns and the available data.

A more detailed discussion is elaborated in Appendix C.

4.2 Inputs and Outputs

In this subsection, the inputs and outputs of the regression and AI methods above discussed are presented.

For the linear and nonlinear regression approaches, six models were created with different inputs, to evaluate and improve their performance.

These models are based on a sample of the data. This sample contains only the "Explorer V2" model of shoe, for women and men, in all colours, for Portugal sales.

The first model has as its inputs the month number (1-12), the gender type of the shoe (1- women; 2- men), colour, size, price, and discounts.

The second model contains the month number, gender type, colour, and size as inputs.

The third model aggregates the equal sizes into month number, gender type, and colour of the shoe. These last three attributes are the inputs of this model.

The fourth model excludes shoe size and aggregates the data according to month number, gender, and colour, which correspond to its inputs.

The fifth model goes further and divides and classifies the months as being warmer or colder, as a binary variable. October, November, December, January, and February, which are the coldest months, are classified as the number 1, and the remaining months, from March to September, which are the warmest months, are classified as the number 2. The inputs of this model are the number of months attributed, the gender type, and the colour.

The sixth model has the same intent as the fifth but divides the months between those with more extreme temperatures (hot or cold) and those with milder temperatures. The inputs of this model are the month code (1 or 2), the gender type, and the colour.

The output of the six models is the quantity.

For ANN, model 1 is computed since it is the most complete one.

4.3 Performance Measure

This section covers the most used measures to evaluate the methods' performance.

Equation (12) defines the error, which is the forecast value minus actual demand.

$$\varepsilon_t = E_t - D_t \tag{12}$$

Mean Absolute Percentage Error (MAPE) is the sum of all absolute errors divided by the demand, through Equation (13). Although it is the most used approach to measure forecast accuracy, it is not recommended when there are high data oscillations. As it divides each absolute error by the demand, at periods with low demand, the error severely increases and impacts the MAPE, underestimating the demand forecast (Vandeput, 2019).

$$MAPE = \frac{1}{n}\sum_{t}\frac{|\varepsilon_t|}{D_t} \tag{13}$$

Mean Absolute Error (MAE), also known as Mean Absolute Deviation (MAD), represents the average of the absolute errors, defined by Equation (14). It spreads out the error over the entire series, which does not produce particularly precise results (Kumar, 2020).

$$MAE = \frac{1}{n}\sum_{t}|\varepsilon_t| \tag{14}$$

The Root Mean Squared Error (RMSE) is the residuals' standard deviation, defined in Equation (15). RMSE is frequently computed as a percentage to scale with demand, as Equation (16).

$$RMSE = \sqrt{\frac{1}{n}\sum_{t}{\varepsilon_t}^2} \tag{15}$$

$$RMSE\% = \frac{\sqrt{\frac{1}{n}\sum_t {\varepsilon_t}^2}}{\frac{\sum_t D_t}{n}} \tag{16}$$

Mean Squared Error (MSE) is another commonly used measure. Equation 17 defines it.

Compared to RMSE, MSE is quicker to compute and simpler to use. RMSE also assigns more weight to larger errors, which has a greater impact on its value (Vandeput, 2019). However, the MSE measure has a drawback. As the error is squared, it does not correspond to the original demand scale.

$$MSE = \frac{1}{n}\sum_{t} {\varepsilon_t}^2 \tag{17}$$

Mean Percentage Error (MPE) is the average of the errors scaled in percentage units, instead of variables' units, defined by Equation (18). MPE value is usually small because the negative and positive values cancel each other out. It is relevant in judging if forecasting is under or overestimated (Odeck & Kjerkreit, 2019).

$$MPE = \frac{\sum_t \frac{\varepsilon_t}{D_t}}{n} \tag{18}$$

There is not a single best error metric that applies to all forms of data.

Measures presented as a percentage have the advantage of being scaled with demand, which is mathematically better. However, they are not recommended when there are large swings in the data, and as there are months with zero demand for some shoe models, the errors for this study would be very high.

Measures that calculate the squared error are better than those using the absolute value error, as they are differentiable, easier to interpret, and represent better outliers. For that reason, MSE is used in MATLAB as the result of the ANN model.

That said, MSE is the chosen measure to evaluate the performance of each model. The model with the lower MSE is the closest to reality, as the estimated demand is close to the actual demand.

5. Experimental Results

This section aims to describe the 8000Kicks' company data, present a descriptive analysis, and discuss the results of the methods used.

5.1 Dataset characterization

From the sales data provided by the company 8000Kicks, a sample was selected to analyse the accuracy of the proposed methods. The dataset selected is related to the sales of the "Explorer V2" shoe model and contains the variables represented in Table 4. Billing country is the only categorical variable, the other variables are numerical. The dataset has 10267 observations. It includes detailed information from October 2020 to October 2022.

Product_name	Name of the product
Product_SKU	Stock Keeping Unit of the product (identification of the product)
Gender	Gender of the type of product (if it is sold for women or men)
Colour	Colour of the product
Size	Size of the product
Billing_Country	Country of the buyer
Month	Month in which the sale was made
Year	Year in which the sale was made
Price	The total amount paid by the buyer
Discount	Deduction of the total price that the buyer had with this sale
Quantity	Quantity sold in that purchase

Table 4: Dataset characterization

Monthly forecasts are more efficient than weekly forecasts because they smooth out fluctuations and detect seasonality more precisely. Monthly replenishment projections are more consistent and less susceptible to overreaction (Figures 2 and 3). Weekly forecasting is suitable when there are brief promotional periods, short lead times and restocking cycles, or products with a limited shelf life. Predicting weekly seasonality is significantly more complex and challenging, and the advantages achieved are often modest (Hiscox, 2019).

This analysis uses a monthly forecast since it guarantees superior stability and avoids the extra time consumed.

For reasons of confidentiality of the entity that holds these data, the magnitude of the data has been modified. The data has been multiplied by a factor, which will not be disclosed, to carry out this analysis. Therefore, the values that appear in the following graphs do not correspond to reality and may contain sales with values with decimal places (Appendix E).

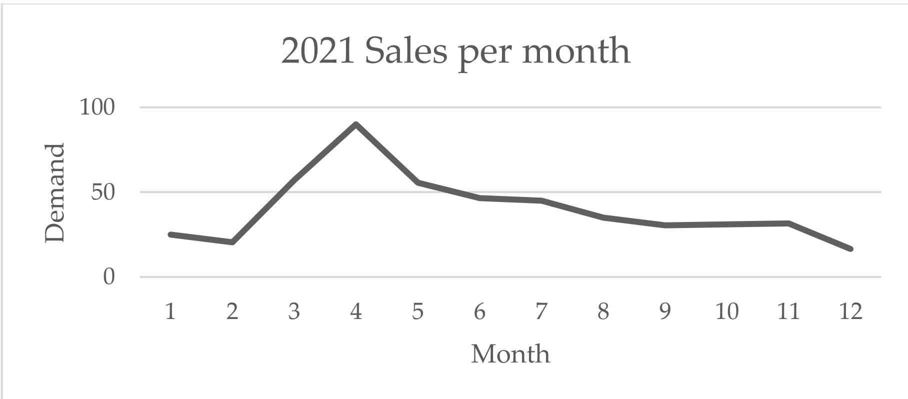

Figure 2: 2021 Sales per month

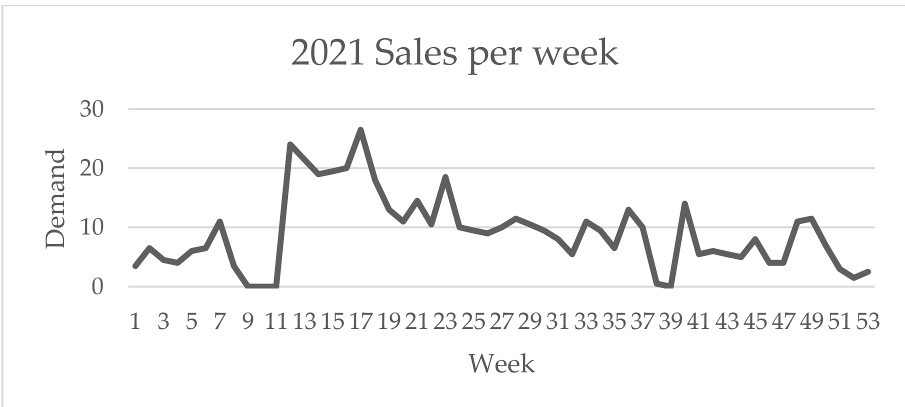

Figure 3: 2021 Sales per week

5.2 Descriptive analysis

This section offers data analysis, considering the relevant key performance indicators (KPIs) for the company. This analysis begins with an overview of the company's sales of the chosen product (Explorer V2). Following that, a more detailed analysis of Portugal sales of the same product is conducted.

Starting by analysing the evolution of sales, it can be seen they had ups and downs from October 2020 to October 2022, however, after this period, their values are almost the same (Figure 4).

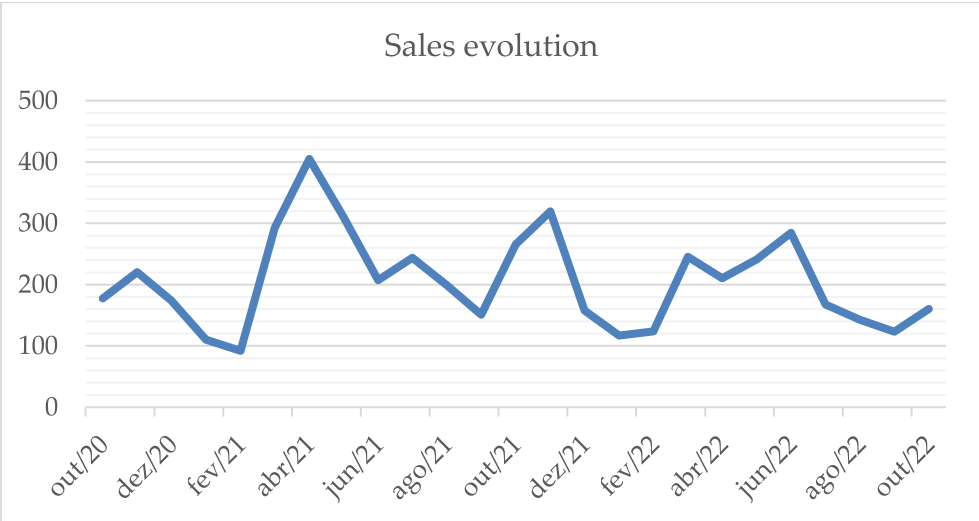

Figure 4: Sales evolution

The existence of seasonality is present in this data (Figure 5), although not very accentuated. November is the month with the highest sales, and January and February are the off-season months. In March, demand increases significantly. Since it refers to total sales of different countries, the seasonality and trend are not high, because the characteristics differ between countries.

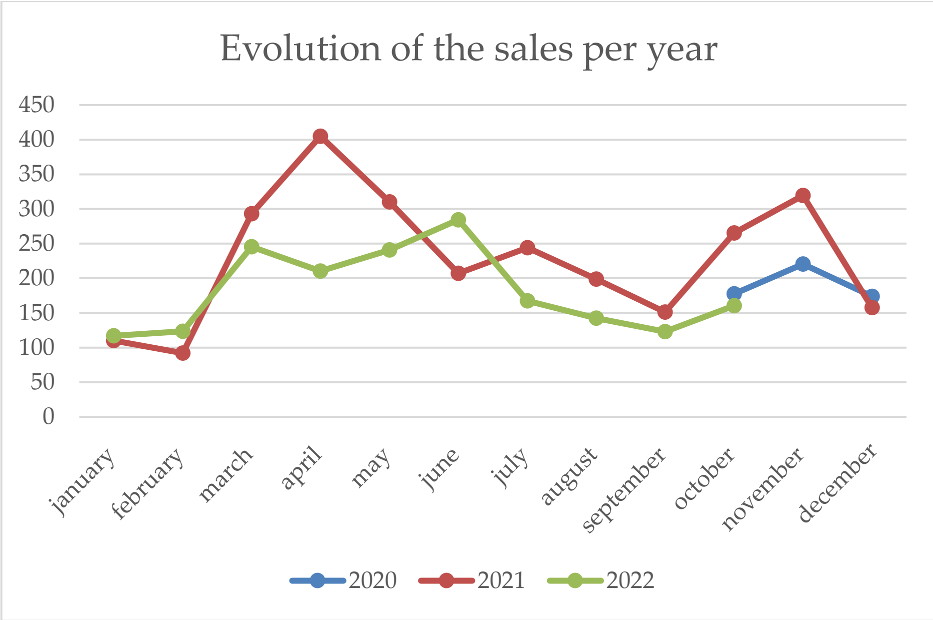

Figure 5: Evolution of the sales per year

Exports have a significant weight for this company (Figure 6). The countries with the highest demand for this product are the United States, Portugal, and Germany (Figure 7).

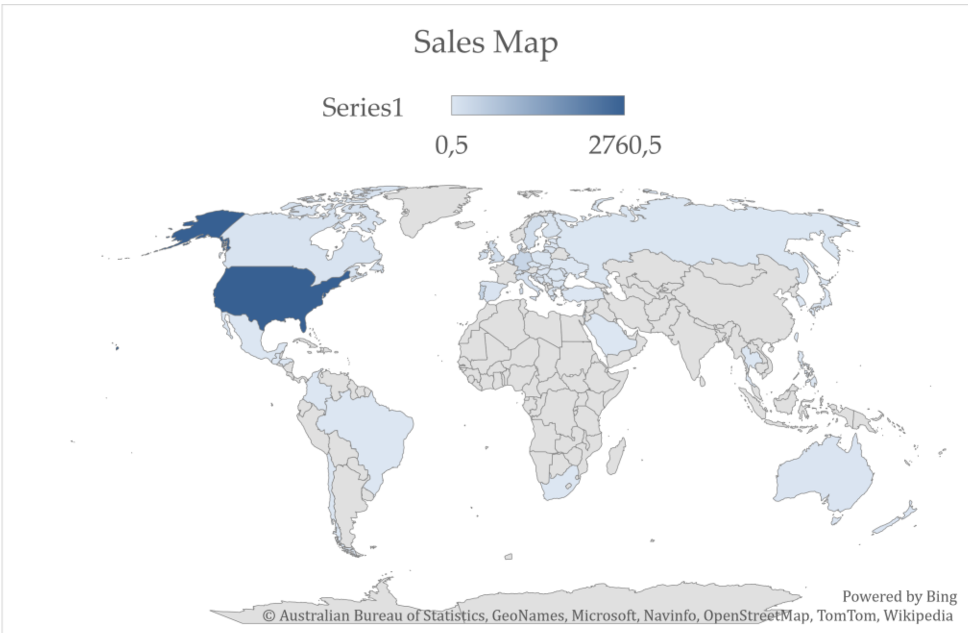

Figure 6: Sales Map

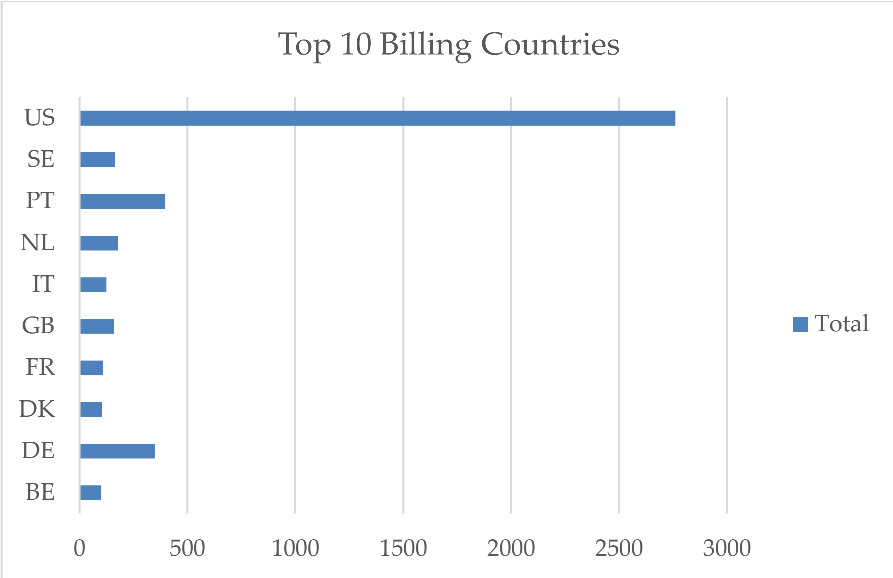

Figure 7: Top 10 Billing Countries

Shoe size is one of the biggest challenges of demand forecasting in this industry. The size that stands out in terms of sales volume is 43, which represents 20% of the total sales (Figures 8 and 9).

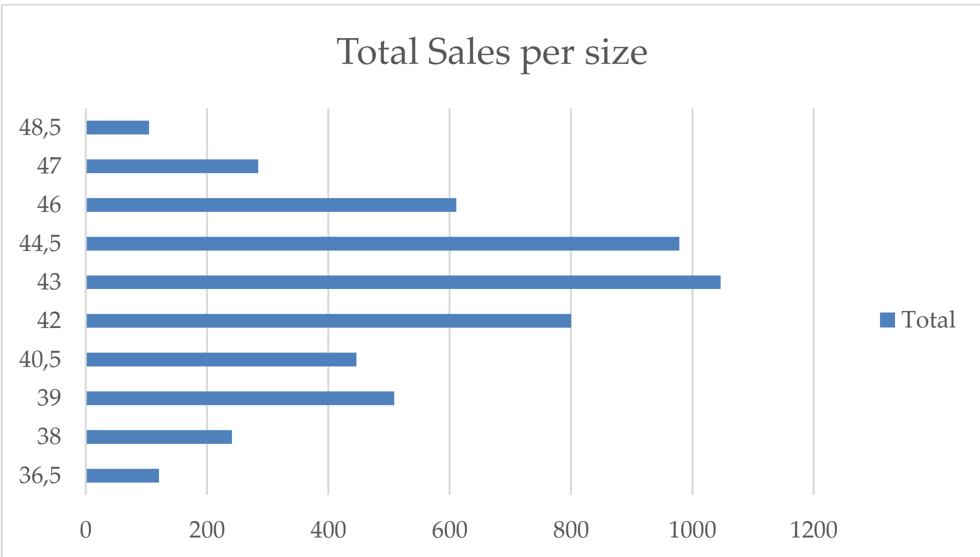

Figure 8: Total Sales per size

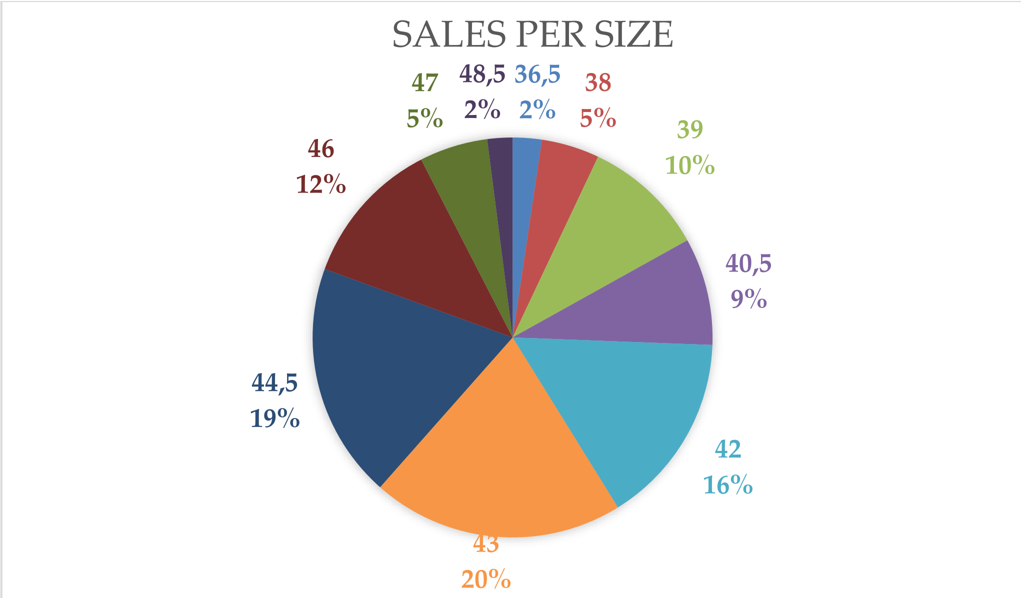

Figure 9: Sales per size (in percentage)

Colours are represented in codes: 1 – all beige; 2 – full black; 3 - navy blue; 4 – dark brown; 5 – dark green; 6 – beige and green; 7 – black and white; and 8 – light green. Shoes with colours "beige and green", "black and white", and "full black" are the best sellers, representing 23%, 21%, and 21% of the total sales, respectively (Figures 10 and 11).

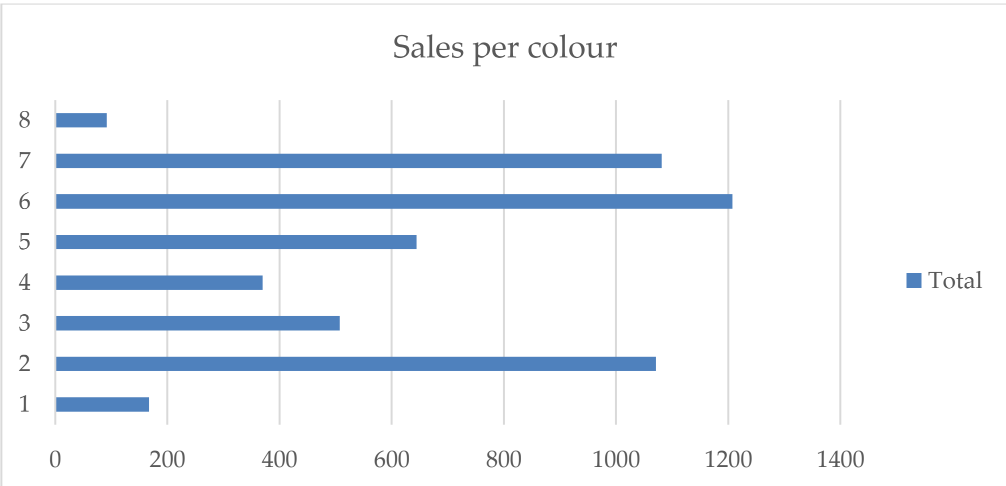

Figure 10: Sales per colour

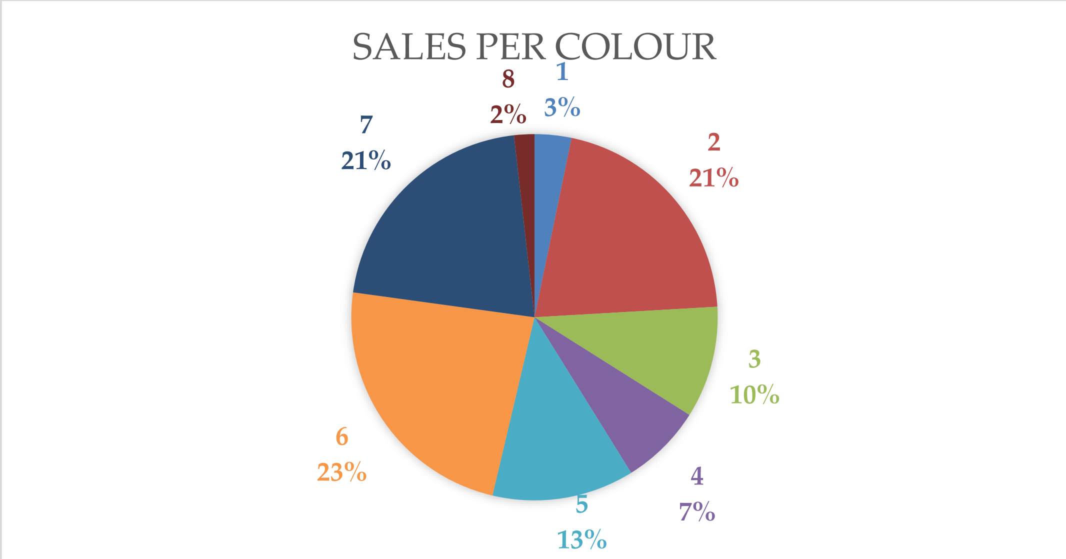

Figure 11: Sales per colour (in percentage)

Gender is represented by the following codes: 1 – women; 2 – men.

The total revenue for men's shoes is significantly higher than for women's shoes. The discount applied follows this pattern (Figure 12). The reason for this is that sales for women represent 20% of the total sales and for men the remaining 80% (Figure 13).

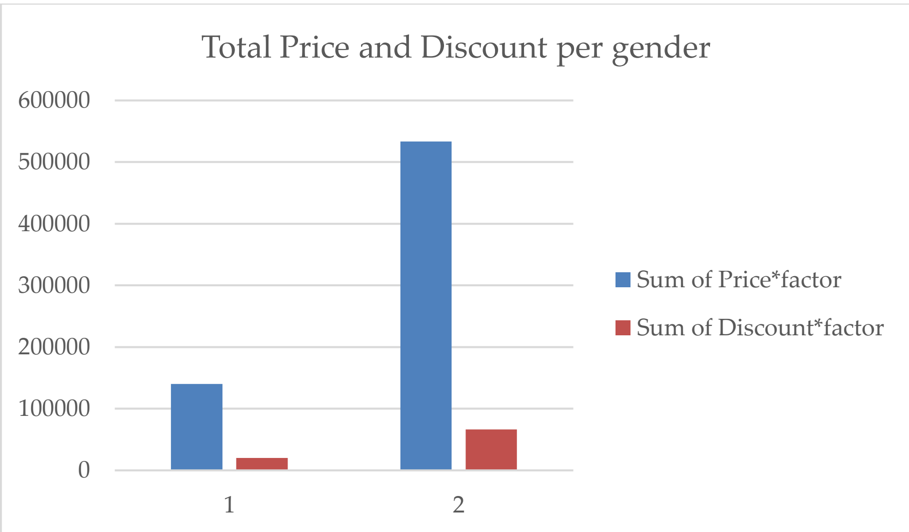

Figure 12: Total Price and Discount per gender

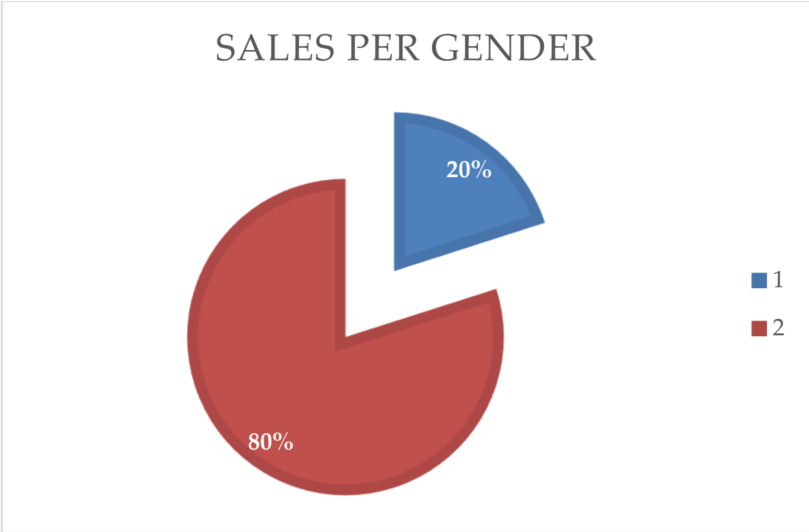

Figure 13: Sales per gender (in percentage)

5.2.1 Descriptive Analysis for Portugal data

As the characteristics differ from country to country, the following analysis is made only with data from Portugal.

The correlation between the variables “Quantity”, “Price”, “Month”, “Discount”, “Colour”, “Size”, and “Gender” was calculated, through the R-studio software. Size and gender are the variables with a high positive correlation, which is to be expected since men usually wear larger sizes than women. Although it is not considered a high correlation, Month and Price with Discount are the variables that present a significative positive correlation. This means that when the price or the number of the month increases, the discount also increases, in different proportions (Figures 14 and 15).

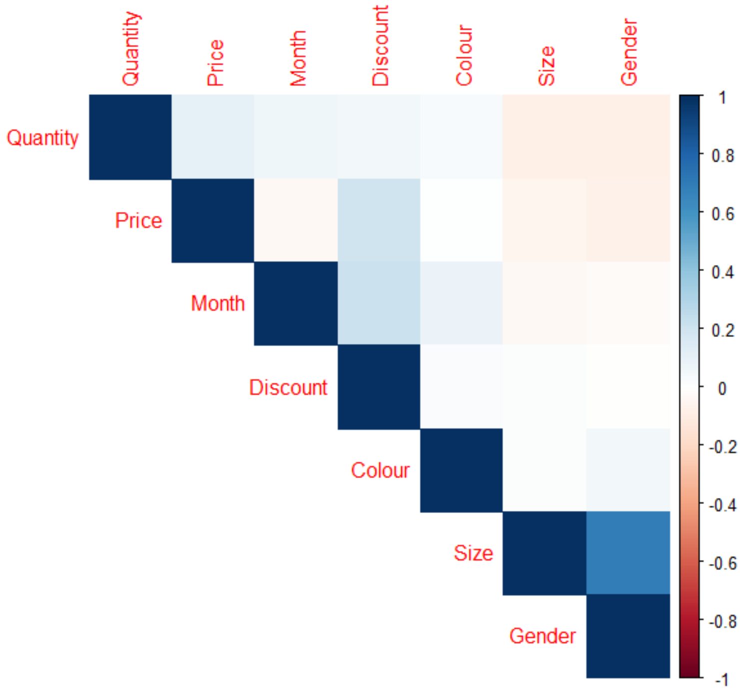

Figure 14: Correlation between variables

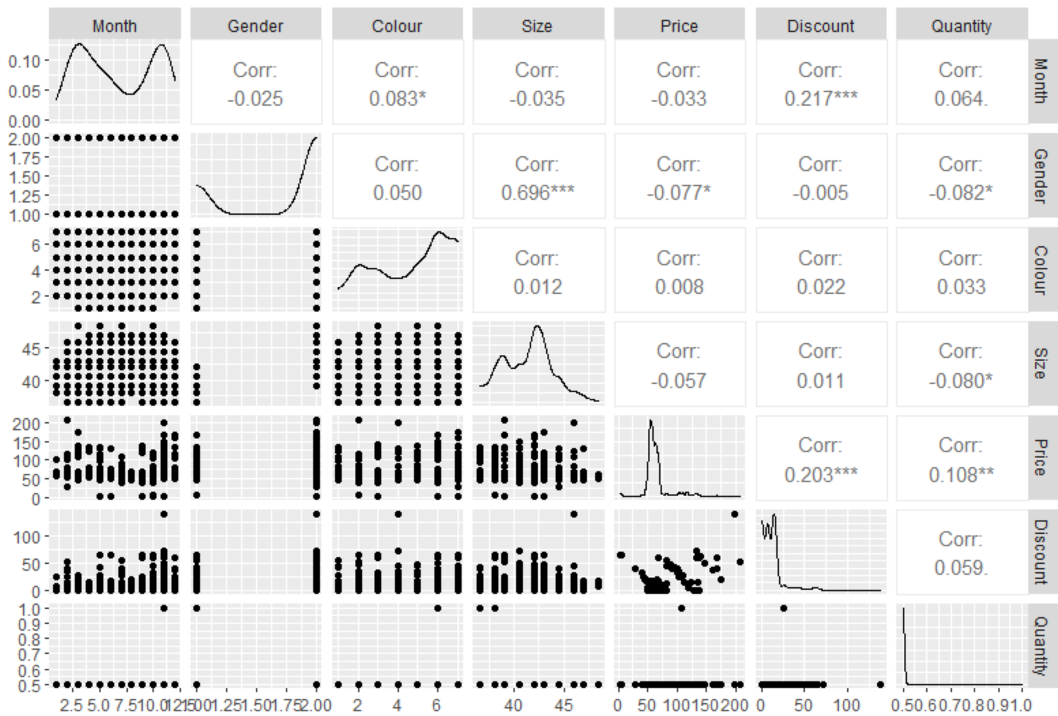

Figure 15: Scatter Plots and correlation between variables

Concerning the detail of the data description, the fourth model mentioned in section 4.2 is described in this section. It aggregates the data through its inputs (month, gender, and colour).

In Table 5, the descriptive statistics of this model are represented, where it can be observed the central position of the distribution (mean, median, 1st quartile and 3rd quartile) and the dispersion of the observations (Inter Quartile Range (IQR), Standard Deviation (Std) and Coefficient of Variance (CV)). The quantity sold has a mean of 2,796 and a median of 2, approximately. As the mean is higher than the median, the distribution is positively asymmetric. It means that most of the value of the quantity sold are clustered around the left side of distribution, which represent the lowest values (Figures 16 and 17).

	1st Quartile	Median	Mean	3rd Quartile	IQR	Std	CV
Month	4	6	6,43	9	5	3,301	0,513
Gender	1	2	1,563	2	1	0,498	0,318
Colour	2	4	4,148	6	4	2,017	0,486
Quantity	1	2	2,796	3,5	2,5	2,738	0,979

Table 5: Descriptive statistics of the numeric variables

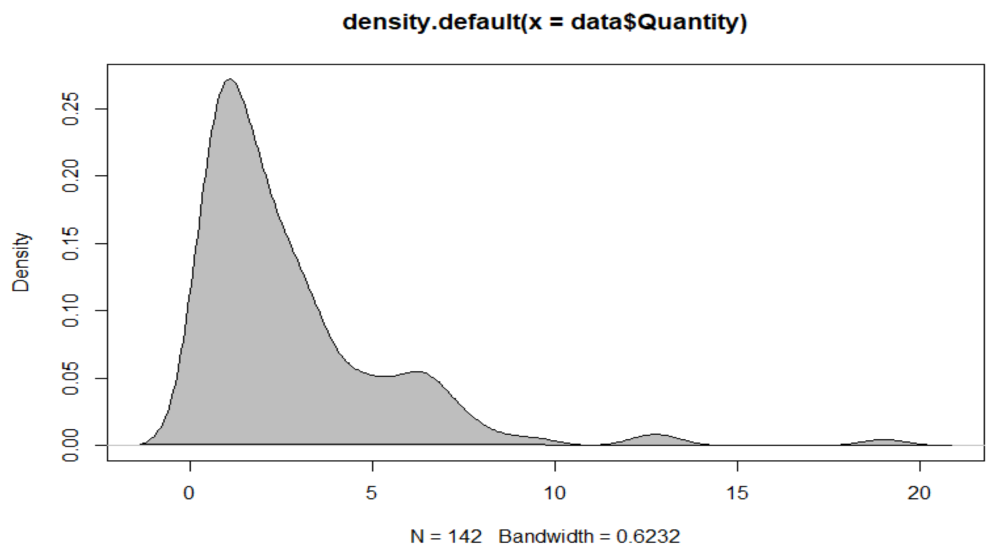

Figure 16: Density plot of Quantity

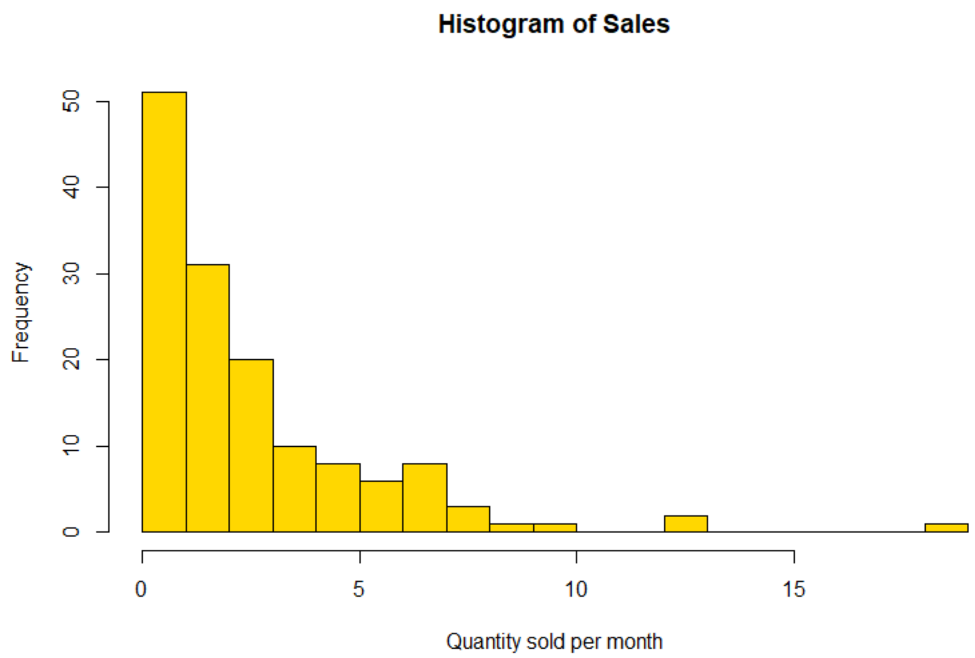

Figure 17: Histogram of Sales (Quantity sold)

It is critical to thoroughly investigate the dispersion of the observations. Figure 18 reveals an increase in the quantity sold in the months of spring and autumn, with a peak in November. February and March are the months with higher dispersion. The colours that stand out in the sales of this product are “beige and green”, and “black and white”, followed by “full black” colour. The colour “light green” is not represented in Figure 19 because there are no sales of this colour of shoes in Portugal. The demand is much higher for men than for women (Figure 20).

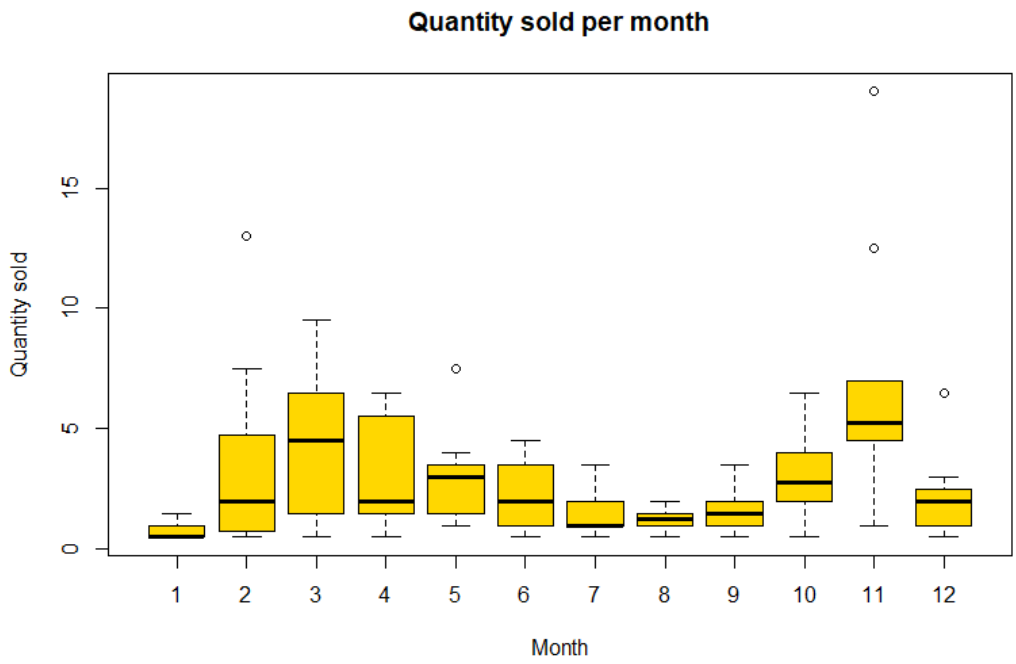

Figure 18: Boxplot of Quantity sold per month

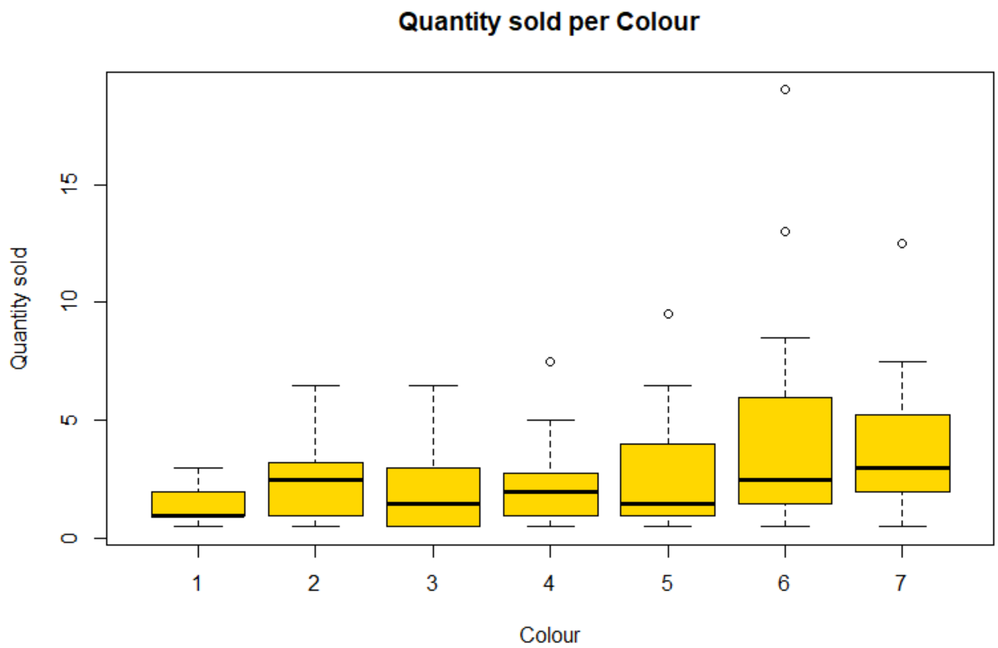

Figure 19: Boxplot of Quantity sold per Colour

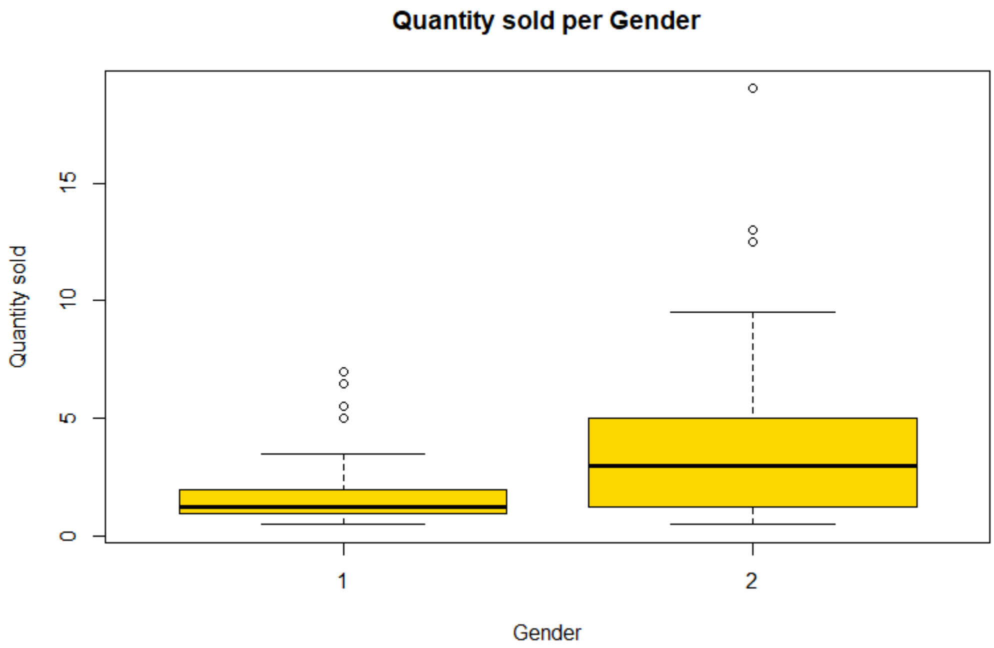

Figure 20: Boxplot of Quantity sold per Gender

The fifth model is used to describe the dispersion between the coldest months, represented by 1 (January, February, October, November, December), and hottest months, represented by 2 (March, April, May, June, July, August, September).

Although the colder months are fewer than the warmer months, sales in the colder months are higher and more dispersed (Figure 21).

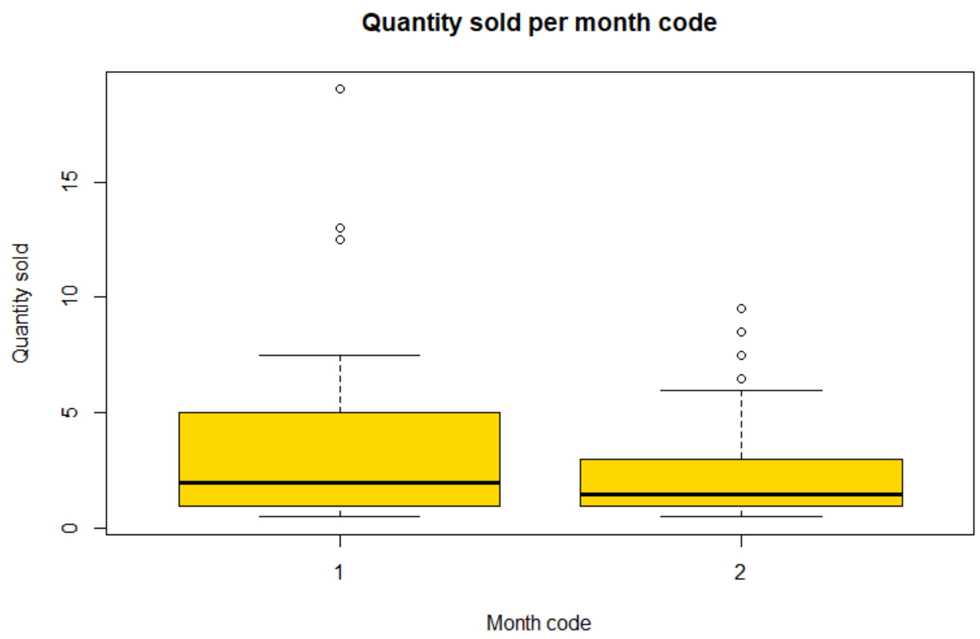

Figure 21: Quantity sold per month code (Model 5)

Lastly, the sixth model was added to understand whether there is seasonality in terms of months with extreme temperatures, either cold or hot, represented by number 1 (January, February, June, July, August, November, December) and months with mild temperatures, represented by number 2 (March, April, May, September, October).

The months with milder temperatures, although fewer, represent a higher quantity sold than the months with extreme temperatures (Figure 22).

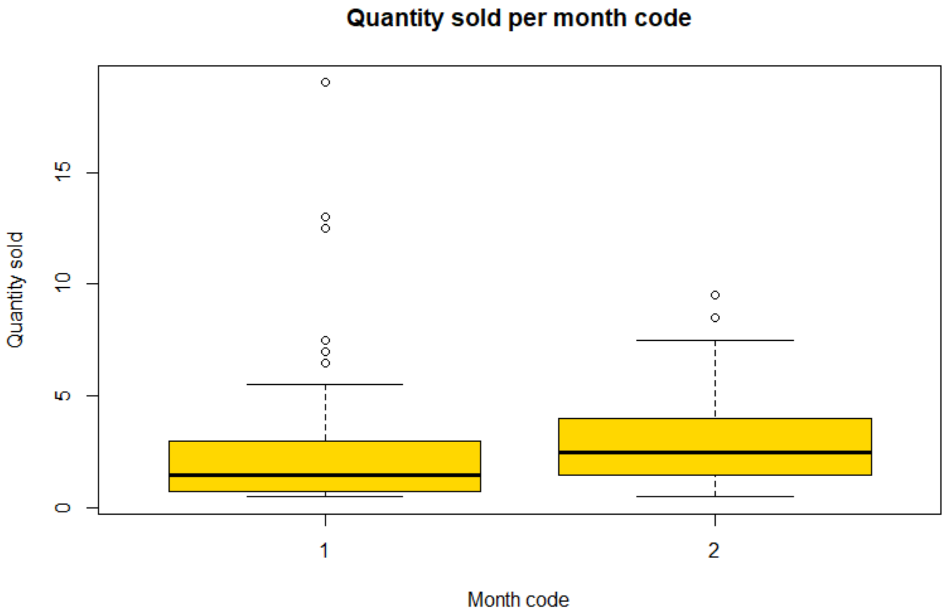

Figure 22: Quantity sold per month code (Model 6)

5.3 Results

This section aims to present the results obtained in the Time Series, Regression and AI models already described.

5.3.1 Time Series

Simple Average, Naïve method, MA, WMA, SES, DES, and HW (multiplicative and additive) are the time series models that were tested.

The first step, before implementing the methods, was to disaggregate the data, to be able to predict more accurately. First, the "Explorer V2" model was tested, only for one gender, one country, and one colour. However, since there are quite a few months with zero sales for all these combinations, the errors were substantially larger due to zero demand, which would not lead to reliable conclusions.

That said, the sizes were aggregated, and the chosen model consists of the sales data for Portugal, of the "Explorer V2" men's shoe model, in the best-selling colour "beige and green". In this data, January 2022 is the only month with zero sales. Figures 23 to 30 refer to this data.

It should be noted that the WMA model was tested with the last three observations (p=3). The parameters of the SES, DES, and HW models (alpha, beta, and gamma) were optimized through the excel solver function, to minimize the MSE. Table 6 shows the optimised values for these models.

	Alpha	Beta	Gamma
SES	0,261405	-	-
DES	1	0,421167	-
HW multiplicative	1	0	0
HW additive	0,871021812	0	0

Table 6: Optimised constraints values

In the SES model, the optimised alpha is small, implying that the most recent observations are given less weight. As the data do not exhibit significant oscillations, a small value for alpha is a preferable choice to increase the model's accuracy.

The optimised alpha for the DES model is 1, meaning that the weight is given to the most recent observation. The smoothed series is therefore very reactive to more recent changes. Therefore, the value of the smoothing equation for the level is equal to the demand for that same period (S_t=D_t). The beta has a value of 0,42, approximately, which means that the data do not show inconstant decline or growth. A beta value other than zero denotes a trend update based on the variations in the values from t-1 to t after smoothing. The larger this value, the larger the trend update.

The optimised value of alpha for the HW multiplicative model is 1, so the conclusion is equal to the DES model. The beta is zero, which means that the trend is not updated and is the same as the previous period (T_t=T_{t-1}). The value for gamma is zero, so the seasonal index is also the same as the previous period (I_t=I_{t-1}). The same conclusion can be drawn for the additive HW method, with the only difference that the alpha, despite giving more weight to the oldest observations, does not give full weight to the last observation as in the multiplicative HW model. As the seasonal variations are not roughly constant, HW is probably a better option, than HW additive.

The MSE values are shown in Table 7. It is possible to conclude that the method with more accuracy and the most fits in this data, given the chosen performance measure (MSE), is the HW multiplicative. Figures 23 to 30 show the results for each method.

Time Series Model	Performance Measure (MSE)
Simple Average	21,598
Naïve method	23,978
Moving Average	5,113
Weighted Moving Average	3,742
Simple Exponential Smoothing	14,732
Double Exponential Smoothing	46,088
Holt-Winters multiplicative	1,956
Holt-Winters additive	3,543

Table 7: Time Series models' accuracy

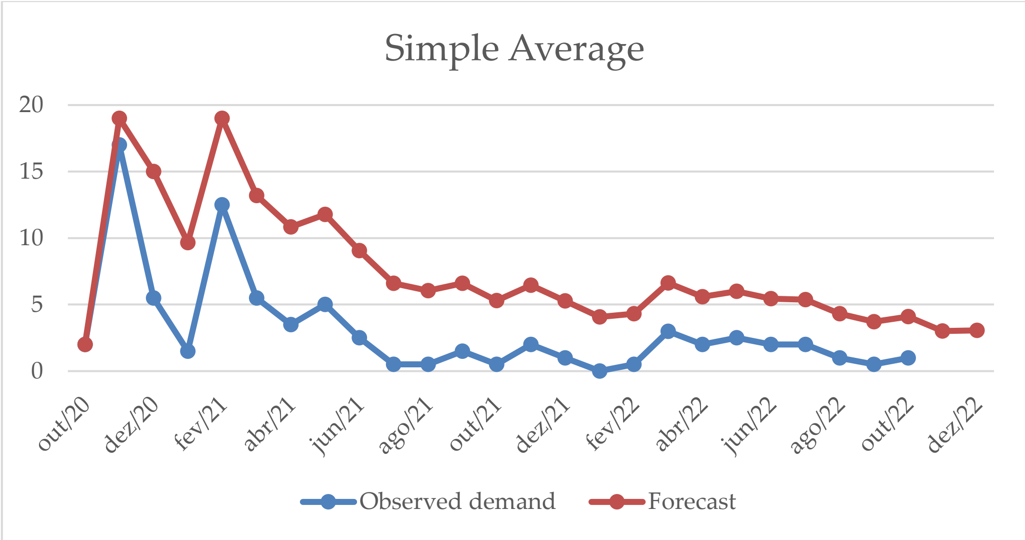

Figure 23: Simple Average

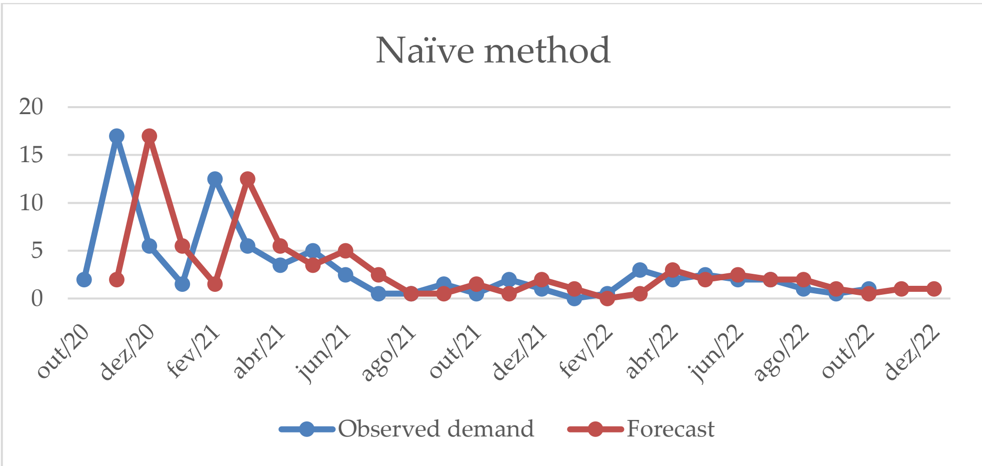

Figure 24: Naïve method

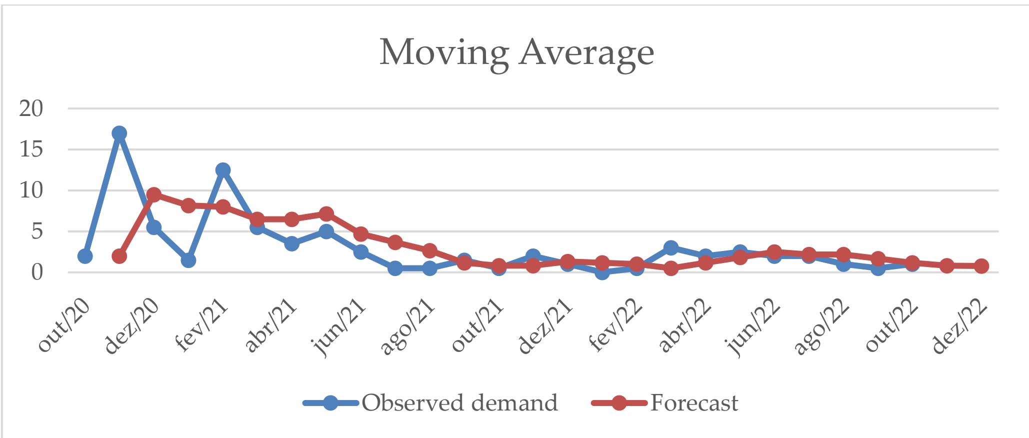

Figure 25: Moving Average

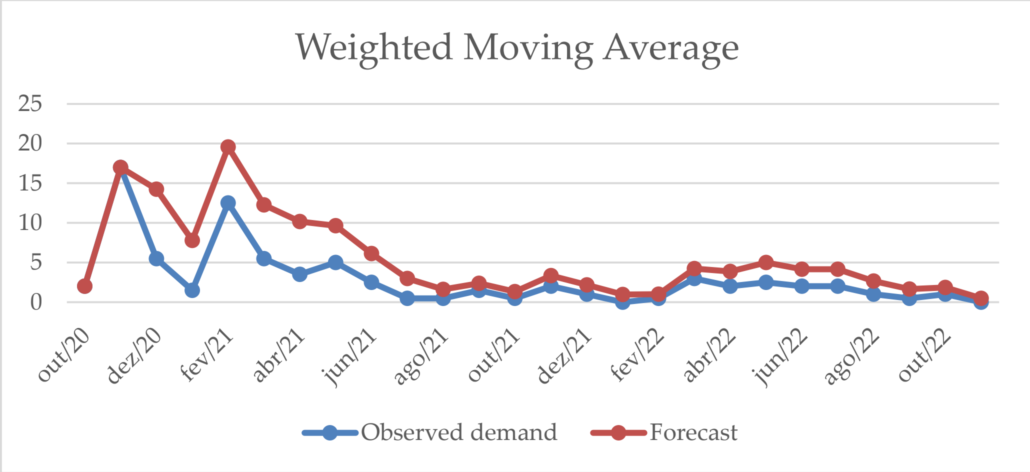

Figure 26: Weighted Moving Average

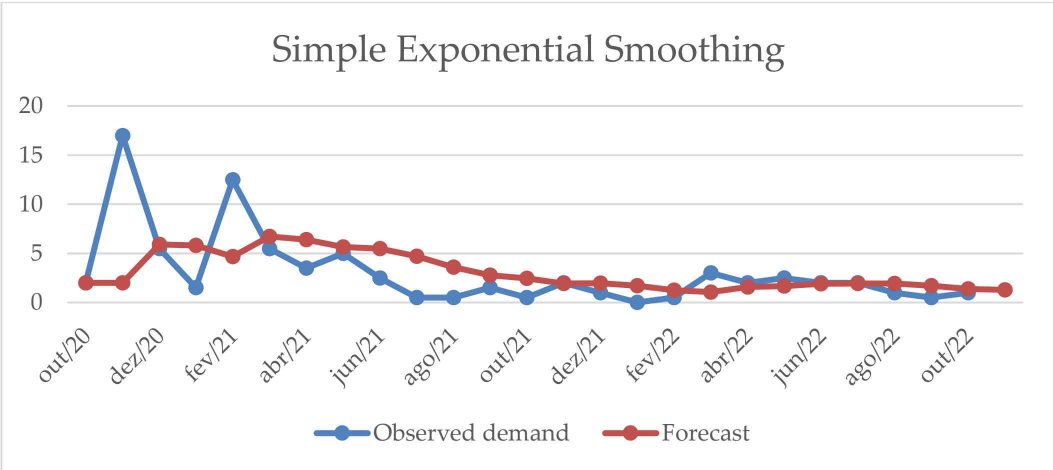

Figure 27: Simple Exponential Smoothing

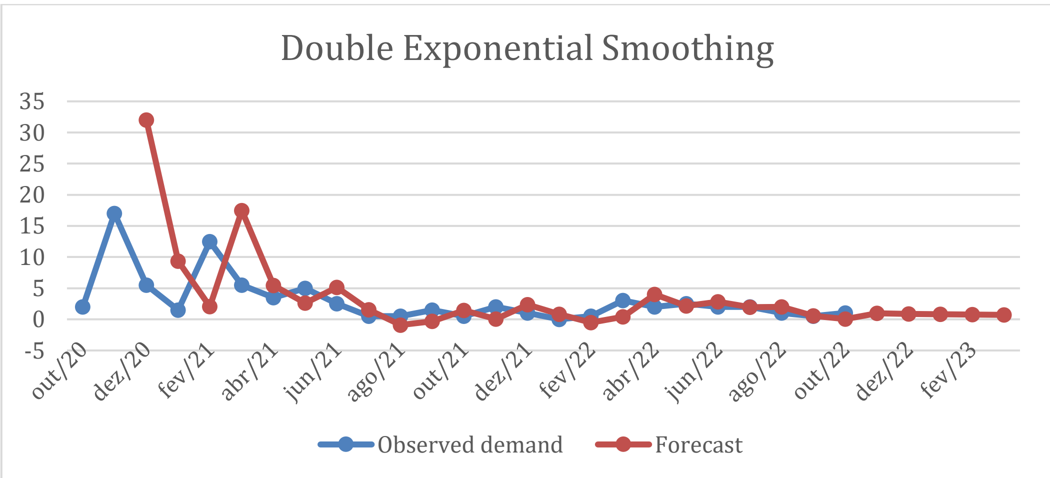

Figure 28: Double Exponential Smoothing

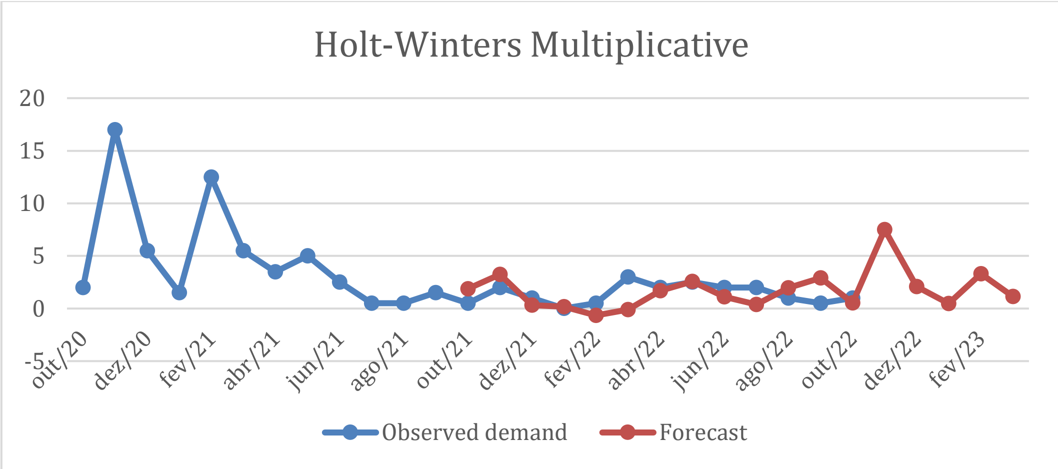

Figure 29: Holt-Winters Multiplicative

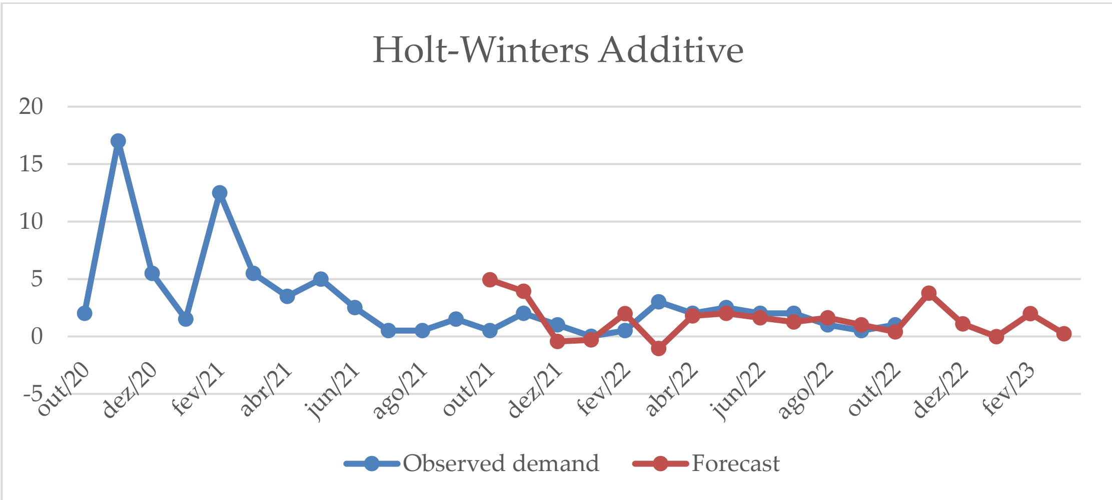

Figure 30: Holt-Winters Additive

5.3.2 Regression

The first regression model tested was the Simple Linear Regression (Figure 31). This model was computed in excel, with the same data as the previous time series models ("Explorer V2" for men model, beige and green, for Portugal sales). The MSE for the simple regression is 10,486. Equation (19) represents this model. The R squared is low, with a value of 0,2818, which means that this model does not fit very well in this data.

$$E_{t+1} = 414{,}56 - 0{,}0093 * D_t \tag{19}$$

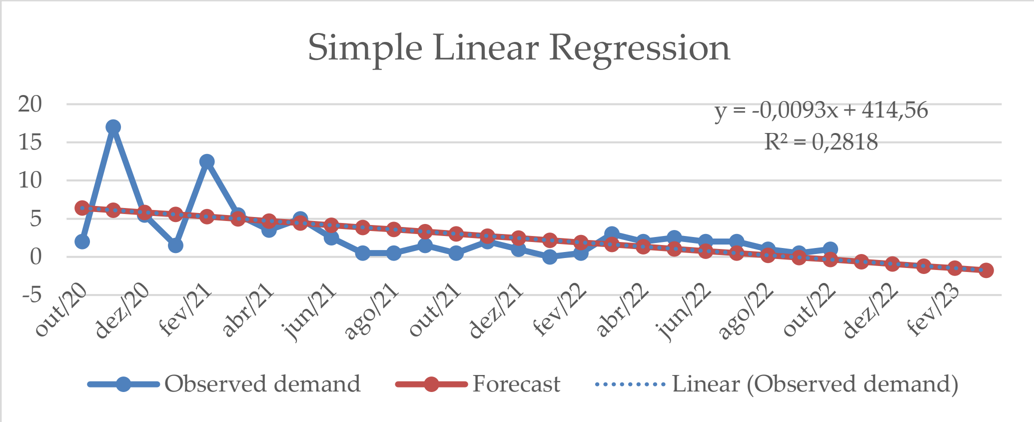

Figure 31: Simple Linear Regression

To test the significance of each variable and the accuracy of more aggregated models, the following six multivariate linear regression models, defined in Equation (20) and already described in section 4.2, were computed in MATLAB software.

$$
\begin{aligned}
&Model\ 1: Quantity_t \\
&\qquad = \beta_0 + \beta_1 Month + \beta_2 Gender_t + \beta_3 Colour_t + \beta_4 Size_t \\
&\qquad + \beta_5 Price_t + \beta_6 Discount_t + \varepsilon_t \\
&Model\ 2: Quantity_t \\
&\qquad = \beta_0 + \beta_1 Month + \beta_2 Gender_t + \beta_3 Colour_t + \beta_4 Size_t + \varepsilon_t \\
&Model\ 3: Quantity_t \\
&\qquad = \beta_0 + \beta_1 Month + \beta_2 Gender_t + \beta_3 Colour_t + \beta_4 Size_t + \varepsilon_t \\
&Model\ 4: Quantity_t = \beta_0 + \beta_1 Month + \beta_2 Gender_t + \beta_3 Colour_t + \varepsilon_t \\
&Model\ 5: Quantity_t = \beta_0 + \beta_1 Month\_code1 + \beta_2 Gender_t + \beta_3 Colour_t + \varepsilon_t \\
&Model\ 6: Quantity_t = \beta_0 + \beta_1 Month\_code2 + \beta_2 Gender_t + \beta_3 Colour_t + \varepsilon_t
\end{aligned} \tag{20}
$$

The results of the six models in linear and nonlinear regression are presented in Table 8.

Starting by analysing the linear regression models, the one with the lowest MSE was model 1, with a value of 6,20E-04.

The F-test is used to perform the global significance test. The six linear regression models have a p-value less than 0,05, which indicates that the null hypothesis is rejected, and globally, the variables of each model explain some of the variations of the dependent variable (Quantity).

The result for R^2 is low for the six models. Model 6 is the model with the highest R^2 value, at around 0,21, which indicates that about 21% of the variation in the quantity number is explained by this model. The adjusted R^2 has the same interpretation, however, is a more accurate measure than R^2 since it considers the impact of additional independent variables. R^2 value increases with the number of variables, even if these are not significant.

Log Likelihood value is another goodness of fit measure of the model. Model 1 has a higher value, which suggests a better fit for the data.

Akaike information criterion (AIC), Corrected AIC (AICc), Consistent AIC (CAIC), and Bayesian Information Criterion (BIC) are criteria for model selection. They assess the quality of statistical models, aiming for simplicity. Models with lower values are preferable, which in this case represent models 1 and 2.

Regarding the nonlinear regression models, a method with interactions between variables is tested. It includes an intercept and a linear term for each predictor, with the addition of all products of pairs of distinct predictors. Since it is a simple method with limited interactions, it is chosen to be tested first.

Model 1 has the lowest MSE. All nonlinear regression models are globally and statistically significant since the p-value of each model is lower than 0,05.

The largest R^2 and Adjusted R^2 is from model 5, with 25% and 21%, approximately. Model 1 has the highest log likelihood value, which indicates that it best fits the data.

The model with the lowest AIC and AICc value is the model 1, and with the lowest BIC and CAIC value is model 2 (Table 8).

Given these positive results, there is no need to test more complicated nonlinear models.

The individual significance test of linear and nonlinear models is explored in Appendix B.

	P-value	F-statistic	MSE	Log Likelihood	R^2	Adjusted R^2	AIC	AICc	BIC	CAIC
Model 1 Linear	0,00411	3,202200281	6,20E-04	1,80E+03	0,023890682	0,016429974	-3,59E+03	-3,59E+03	-3,56E+03	-3,56E+03
Model 1 Nonlinear	2,631E-06	3,16182547	5,96E-04	1,83E+03	0,07938602	0,054278366	-3,61E+03	-3,61E+03	-3,51E+03	-3,49E+03
Model 2 Linear	0,04186	2,491666762	6,26E-04	1,80E+03	0,012505751	0,007486721	-3,59E+03	-3,59E+03	-3,57E+03	-3,56E+03
Model 2 Nonlinear	0,00550	2,518974191	6,19E-04	1,81E+03	0,031245426	0,018841398	-3,59E+03	-3,59E+03	-3,54E+03	-3,53E+03
Model 3 Linear	4,87E-07	9,080175824	0,496853955	-4,47E+02	0,080476484	0,071613607	9,03E+02	9,03E+02	9,23E+02	9,28E+02
Model 3 Nonlinear	2,01E-05	4,113576564	0,498161873	-4,44E+02	0,091385241	0,069169722	9,10E+02	9,11E+02	9,55E+02	9,66E+02
Model 4 Linear	1,05E-06	11,3557085	6,143401662	-3,28E+02	0,197987416	0,18055236	6,65E+02	6,65E+02	6,77E+02	6,81E+02
Model 4 Nonlinear	2,55E-06	6,802095674	6,012524818	-3,25E+02	0,232136832	0,198009581	6,65E+02	6,65E+02	6,85E+02	6,92E+02
Model 5 Linear	5,87E-07	11,85813048	6,090054276	-3,28E+02	0,204951843	0,187668188	6,63E+02	6,64E+02	6,75E+02	6,79E+02
Model 5 Nonlinear	7,75E-07	7,375041188	5,89721622	-3,24E+02	0,246862963	0,213390206	6,62E+02	6,63E+02	6,82E+02	6,89E+02
Model 6 Linear	2,54E-07	12,58345492	6,014653035	-3,27E+02	0,214795371	0,197725705	6,62E+02	6,62E+02	6,74E+02	6,78E+02
Model 6 Nonlinear	1,04E-06	7,232495351	5,925489112	-3,24E+02	0,243252215	0,20961898	6,62E+02	6,63E+02	6,83E+02	6,90E+02

Table 8: Regression models' summary table

5.3.3 Artificial Intelligence

The ANN method was tested, with model 1 since it is the most complete and proved to be quite efficient. Using the MATLAB app "Neural Net Fitting", the ANN model was computed.

The ANN tested is a Multilayer Perceptron from Feedforward Neural Network (FNN), in which all the connections move forward, in one direction, and do not have cycles. The "w" represented in Figure 32 are the weights of the connections, and the "b" are the biases. The weights are automatically adapted during the process of training until the best performance of this model is found (Svozil et al., 1997).

The training algorithm used for this model was the Levenberg-Marquardt, which uses the optimisation function to increase performance, decreasing the MSE. It is supervised training, since the desired output is known, and the weight coefficients are adjusted to achieve it.

Each interconnected neuron is characterized by its weight, biases, and function, that in this case is the optimisation function.

This model has six inputs and one output, with a nonlinear relationship between them. The samples are sorted into training, validation, and test sets automatically, to prevent overfitting. Experimental tests were carried out, to understand what percentage of splitting the observations between train, validation, and test, and the number of hidden layers should be used to have better performance. The best result is to have five hidden layers in the input and one layer in the output, the training set represents 70% of the sample, and the validation and test set 15% each (Figure 32).

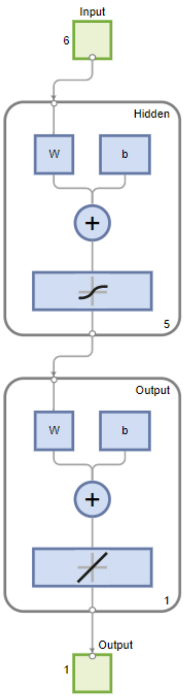

Figure 32: Function Fitting Neural Networks

The MSE for this method is low. For training, the value is 8,9799E-04, for validation 5,0037E-06, and test 8,5865E-06. R is the coefficient of correlation between χ (independent variables) and γ (dependent variable). As the R in the training section is positive, it means that they are positively correlated, even if only slightly, because the value is very low. The R in validation and test is zero, which means that there is no correlation (Table 9). From Figure 33, it is possible to observe that the set that best fits the data is the training since the validation and test have many outliers.

	Observations	MSE	R
Training	554	8,9799E-04	0,0827
Validation	119	5,0037E-06	0
Test	119	8,5865E-06	0

Table 9: ANN model summary

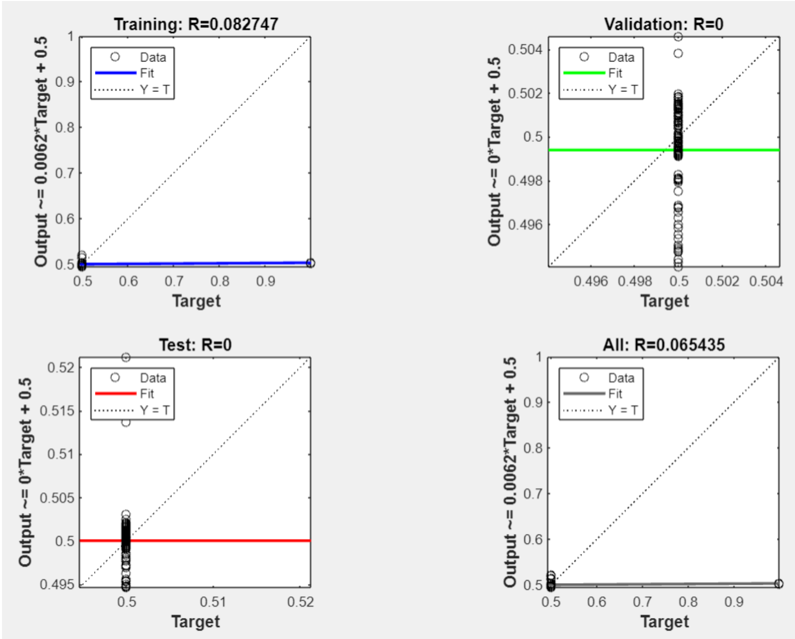

Figure 33: ANN Regression Plot

ANN continues to work to find a better solution. The target is to obtain an MSE value equal to zero, which indicates that there is no difference between the output and the real value. However, training stops as soon as the validation set cannot get better. The epoch represents the iteration of the complete training set, in which the ANN model stops because the results of the performance are getting stable, or worse. In this case, it stopped in the ninth epoch, and the best validation performance was in epoch 3 (Figure 34). The performance of the stopped value (nine) was 0,000451, which is a very good result. The elapsed time represents the time it took for the ANN to stop at the best solution for this model. (Table 10).

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	9	1000
Elapsed Time	-	00:00:01	-
Performance	0,0276	0,000451	0

Table 10: ANN Training Process

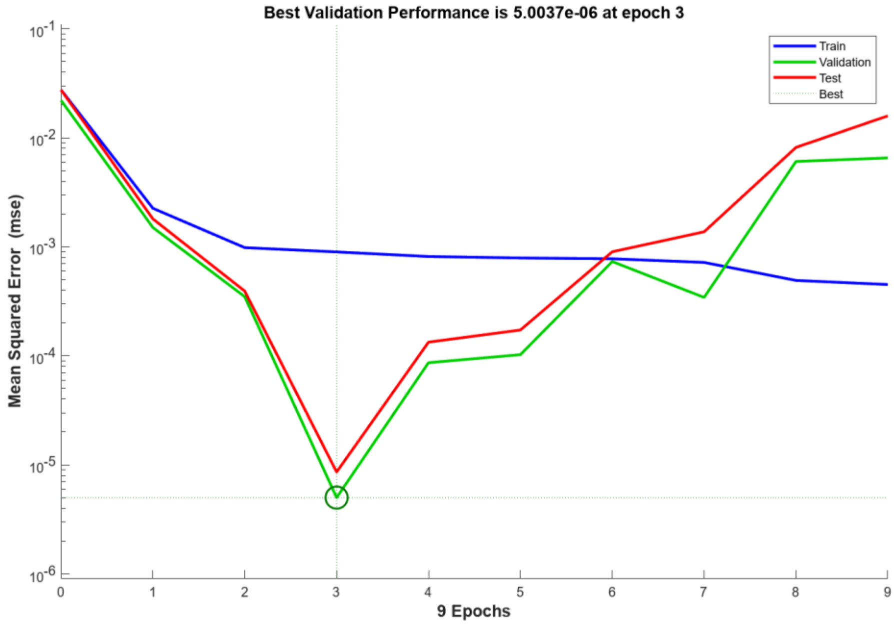

Figure 34: ANN model - Best Validation Performance

5.3.4 Discussion of results

The method that demonstrated to be most accurate through the used performance measure was the ANN. The nonlinear regression method also performed well, although slightly inferior, for model 1 and model 2 (more complete and less aggregated models). Table 11 presents the summary of the performance measure values for each model tested.

Hence, the nonlinear models performed better than the linear. They can capture complex relationships and patterns between variables, and dynamic processes, that linear models cannot. Nonlinear models allow fit the data more accurately and are adaptable to changing circumstances, leading to lower forecast errors. Although more accurate, nonlinear models require more computational effort, which represents a drawback for some companies. The ANN model represents nonlinearity better than nonlinear regression.

Some internal and external variables are neglected, as there is no information on them, which made this study more limited.

For 8000Kicks’ company, although there may be other methods that have similar accuracy to the ANN model, no further studies are required as this model represents well the future demand of the company.

At the end of this investigation, a report and a dashboard were developed. They include the results and major conclusions drawn from this study, to deliver to the company 8000Kicks and contribute to the improvement of the efficiency of the company processes (Appendix D.2).

Using the ANN model, it was possible to forecast demand for November and December 2022. The demand forecasting graph, presented on the dashboard, proved the high accuracy of this method since there are nearly no differences between the observed and forecast demand (Figure 38).

From a managerial point of view to the company, the suggestion for 8000Kicks is to record and measure the impact of variables on the data. Then, build the model based on those variables and forecast demand with the ANN model since it is the most accurate. Using the appropriate demand forecasting model for the company's data helps solve the initial problem of inefficient allocation of company resources.

Method	MSE
Simple Average	21,5981788
Naïve method	23,9779250
Moving Average	5,1129859
Weighted Moving Average	3,7421719
Simple Exponential Smoothing	14,7318144
Double Exponential Smoothing	46,0882047
Holt-Winters Multiplicative	1,9563456
Holt-Winters Additive	3,5432175
Simple Linear Regression	10,4861404
Linear Regression (model 1)	0,0006202
Linear Regression (model 2)	0,0006258
Linear Regression (model 3)	0,4968540
Linear Regression (model 4)	6,1434017
Linear Regression (model 5)	6,0900543
Linear Regression (model 6)	6,0146530
Nonlinear Regression (model 1)	0,0005963
Nonlinear Regression (model 2)	0,0006186
Nonlinear Regression (model 3)	0,4981619
Nonlinear Regression (model 4)	6,0125248
Nonlinear Regression (model 5)	5,8972162
Nonlinear Regression (model 6)	5,9254891
Artificial Neural Network (Training)	8,9799E-04
Artificial Neural Network (Validation)	5,0037E-06
Artificial Neural Network (Test)	8,5865E-06

Table 11: Models' Performance

6. Conclusion and Future Works

This dissertation focuses on finding a method of demand forecasting with high accuracy in a footwear company. It compares some methods of Time Series, Linear and Nonlinear Regressions, and the ANN method. The reason for the high accuracy of the best method is also described. The methods are tested and compared based on the MSE measure.

Through the literature review, it is concluded that there is no consensus among the authors as to which is the most accurate method to forecast demand, since product and market characteristics differ between industries, and even between companies in the same industry. This study explores this gap in the literature by testing some methods in a footwear company.

Before the chosen methods are applied, data characterisation and descriptive analysis are carried out to understand their characteristics and which explanatory variables to use in the models. Six different models are created for the implementation and comparison of the Regression and ANN models. The company has a high number of exports, however, the methods are applied using data from Portugal, since the external factors differ between countries. An analysis with disaggregated data is more accurate.

The nonlinear methods prove to be the most accurate, that best fit this data, with special emphasis on the ANN method. The MSE of the ANN method presents a very low value, which shows that this method is efficient for this company, and therefore, no future study is needed to find a more accurate method.

These findings lead to the conclusion that nonlinear models perform better on inconsistent and large oscillations data because they can fit the data more closely, capture complex interactions, develop dynamic procedures, and adapt to changing conditions. This dissertation is focused on a real problem in the

8000Kicks company, and therefore, the conclusions drawn are specific to this data.

A limitation found in this study was the lack of information on several variables that could have influenced and proven to be significant for the model.

Given the size limitation of this dissertation, not all methods relevant to demand forecasting in the literature were studied. For future studies, it would be interesting to study AR, ARMA, ARIMA, LSTM, SVM, and hybrid methods. It would also be interesting to complement this with a study of the company's inventory stock control if the respective data were available.

An evaluation of the work carried out can be found in Appendix F.

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Appendix

Appendix A: Literature Review

A.1 – Impact on the Supply Chain

Companies focus on improving their supply chain (SC) performance as it is a dominant factor in their success.

Effective production is based on the alignment of the available resources with customers' demands and market forces. Plannings based on poor forecasts can lead to an unwise decision of inventory (stock outs/high inventory), obsolescence, rush orders, inefficient resource utilization, and to the bullwhip effect in the SC (Nenni et al., 2013).

The bullwhip effect happens due to the lack of communication between the players in the SC. This phenomenon occurs when there are small fluctuations in demand at the retail stage, which leads to large fluctuations in demand in the upstream stages (wholesaler, distributor, manufacturer, and raw materials supplier) since the order decisions are based on the orders from the downstream participant. The main causes of the bullwhip effect are the lack of demand forecasting updates, order batching, price fluctuation, strategic rationing, and shortage gaming, which leads to misinformation about the real demand (Lee et al., 1997).

The goal of forecasting is to increase profitability by improving operational efficiency and reducing waste (Ramos et al., 2015). Recognizing the impact of the demand influencing factors provides the tools for effective SC planning and management, at strategic, tactical, and operational levels (Punia & Shankar, 2022).

The key participant in the SC is the distributor downstream of that process because it places orders with upstream businesses and supplies customers (Thomassey, 2010).

Companies in this industry usually adopt the agile supply chain strategy, which is based on flexibility, quickness, and responsiveness, through the ability to adapt to changes in demand (volatile and unpredictable demand), both in terms of volume and variability (Kharfan & Chan, 2018). Their efficiency is very reliant on the accuracy of sales forecasts, as a consequence of the growing competition in prices, which leads to a need of increasing the lead time and suppliers (Thomassey, 2010).

Demand forecasting is a crucial planning concern for companies' success in a competitive environment. As competition grows, companies are focused on meeting customer needs. Demand forecasting helps in the alignment of the product with customer needs, to increase their satisfaction and enhance companies' expansion and growth. With the development, diversification, and expansion of the companies, forecasting became one of the top priorities for any company (Ostdick, 2017).

A.2 – Impact on Inventory Stock Control

Inventory stock control is one of the main concerns for a company. It could implicate lost sales with shortage or losses with overstock. In order to face this challenge, demand forecasting is implemented. Each item has a life cycle, given its continuous evolution. It is particularly important to understand which items demand is decreasing, bearing in mind that from that stage onwards production will become more expensive as it is in smaller quantities. (Ritchie & Wilcox, 1977).

A.3 – Other Techniques

Concerning investment management, several methods, besides demand forecasting, can be used. It was proved by Conceição et al. (2021) that demand forecasting is the method closest to reality in terms of results. This study was carried out in a footwear company where it was revealed that the excess inventory was due to the demand not being correctly projected. Constant information update is one of the factors that makes demand more uncertain, which reinforces the idea that demand must be forecasted in order to anticipate the company's needs, maintain an adequate and balanced stock, and satisfy customer needs.

Due to the diversity in demand patterns, there is no single model for demand forecasting that achieve the highest forecasting accuracy for all products, it is necessary to match each demand pattern to an appropriate model. The authors Ulrich et al. (2022) proposed an automated model selection framework for retail demand forecasting, using a classification algorithm. It has been proved by this study that, although no one model is suitable for all industries and product categories, the Classification-based Model Selection can be a useful insight for demand forecasting methods.

In another study, Ritchie and Wilcox (1977) evaluated the forecasting spare demand method based on renewal theory. They conclude that despite its efficiency, the method's primary flaw is the computational effort required to establish the model parameters for each item as well as the expense of creating and maintaining the necessary data. Therefore, the ETS method with trend adjustment would probably be a better option for forecasting all-time future demand. However, once it calculates the mean and variance level of spare demand to produce forecasts, it does not quickly adapt to the demand drop phase.

Some products do not have available historical sales data. The authors Guo et al. developed an effective multivariate intelligent decision-making (MID) model. This model instead of forecasting sales based on the historical sales of a similar product, considers the early sales as an indicator of the overall sales, considering many influencing factors. MID model is effective and statistically significant to solve the multivariate sales forecasting problem and it can generate better forecasts than some machine learning methods (Guo et al., 2013).

The focus on managing the level of uncertainty was also defended by some authors, that developed a single algorithm to compare its accuracy with existing frameworks through a simulation approach. Two solutions were proposed: early sales and order over-planning, a procedure that focuses on forecasting each order from each customer instead of forecasting the overall demand (Nenni et al., 2013).

Statistical methods, such as binomial distribution, Croston's model, bootstrap, and variants of Poisson model are widely used and supported by several authors. Regarding these methods, the general agreement is that the accuracy of each technique varies depending on the level of attributes (Nenni et al., 2013).

There are three approaches to forecast sales for a new product: judgmental, based on experience; market approach, throughout surveys; and analogical approach, when it is assumed that the product behaviour is similar to another that already exists (Fildes et al., 2019).

To help forecast seasonal demand for new products in the footwear industry, the authors Kharfan and Chan (2018) created two models based on machine learning techniques – the general and the three-step model (clustering, classification, and prediction). Product, calendar, and price were the attributes used in those frameworks. The authors underline the importance of the data pre-processing phase. New variables are produced, as a result of the feature engineering process, adding the value of demand interpretation. The feature selection process enables an understanding of the significance of the various predictor factors and how they affect forecast accuracy. They concluded customised forecasts based on product attributes are more valuable, as they give better accuracy.

The sample size is also a determining factor for the analysis. Although there is no minimum or maximum sample size, it must be by the model selection. Shorter time series, although less complex, do not produce as stable an estimation as longer time series and thus do not support as many conclusions (Tran-The, 2022).

Source Information	Research Question/ Purpose	Methodology	Findings	Limitations	Future Research
Nenni et al., 2013	What are the most effective and efficient approaches for the fashion industry, with the actual context, to forecasting demand?	Review of different methodologies.	Identifying the demand pattern is helps choose the forecasting method.	Short selling seasons, a high level of uncertainty, and a lack of historical data are the key obstacle to forecast demand.	Use the features of the products that are repeated each season as forecasting units.
Conceição et al., 2021	Implementation of new inventory management in a footwear company.	ABC analysis methods, demand forecasting, safety stock, reorder point, and economic order quantity.	The demand was not being well projected, which generated a not balance inventory (excess of items and shortage of others).	Gaps for some materials could reduce the inventory, due to the not existence of enough indicators in this study.	Improving the indicators of the study; study of suppliers and the reduction of their delivery time; a study of obsolete items in inventory.
Goodwin et al., 2019	The availability of optimistic and pessimistic scenarios alongside time series information enhances or reduces the accuracy of demand forecasts and the quality of ensuing production decisions?	Experimental task with groups with different scenarios (statistical analysis).	Optimistic and pessimistic forecasting scenarios are judgmental forecasts and cause deviation from the optimal production decision levels, due to the overweighting of the last observation in the time series.	Scenarios detriment the accuracy of point forecasts and the quality of decisions that are associated with them.	Investigate how these biases might be controlled to extract value from these scenarios.
Ulrich et al., 2022	Does the CMS framework allow to address the ever more complex demand patterns encountered in retail practice?	Classification-based model selection (CMS).	CMS proved to be a useful addition to forecasting demand.	There is no "one-size-fits-all" method, it is necessary to adapt to every business setting.	-

Huber & Stuckenschmidt, 2020	Are machine learning methods a viable alternative to established approaches for the given forecasting scenario? Which method is most suitable for forecasting demand on special days? Which machine learning method provides the most accurate forecasts? Which modelling approach works best? How often do machine learning methods have to be re-trained so that their accuracy does not diminish?	Evaluation of different machine learning methods.	A more sophisticated and elaborate process of model-building and selection (machine learning methods) would be beneficial for a competitive and productive environment for long, large-scale, and different demand forecasting periods.	The data is noisier and new challenges arise due to the changing of stock, for example, new products.	Investigate whether an automated model-building process leads to better accuracy; if the classification approach is suitable for density forecasts; and how machine learning methods perform on the store-article level for daily forecasts.
Kharfan & Chan, 2018	Creation of a model that helps to forecast demand for new products.	General model and a three-step model (clustering, classification, prediction) using machine learning techniques.	This study's outcomes show how valuable customized forecasts based on product attributes are.	Lost data were not considered, due to the limitation of inventory data available.	Store inventory allocation, size curve analysis, and price optimization.
Thomassey, 2010	Describe the constraints and needs of the SC; Present forecasting methods, how to improve them, and highlight their benefits.	Fuzzy Inference Systems; Simulation.	Advanced forecast systems are an efficient solution to counteract the negative characteristics of the clothing industry.	If companies want to adopt these advanced forecasting systems to improve flexibility and robustness they should restructure their SC, to reduce lead times and minimum order quantities, which means high costs.	-

Ritchie & Wilcox, 1977	Find a method suitable for forecasting all-time future demand.	Renewal theory.	ETS method with trend adjustment is a better option for forecasting all-time future demand.	Renewal forecasting method requires high computational effort and has high maintenance costs.	-
Archer, 1980	Description of quantitative and intuitive techniques.	Numerical and qualitative methods.	The most trustworthy forecasts are the ones that combine the two types of forecasting approaches - qualitative and quantitative.	Even rigorous numerical methods include subjective judgement forecasts - "crystal ball gazing".	-
Lewis, 2000	Explanation of the theory and practice of demand forecasting methods, linking them with analysis of demand data.	Time series methods.	Conclusions about the link between methods and data and its characteristics.	-	-
Guo et al., 2013	Overcome a sales forecasting problem based on early sales.	Multivariate intelligent decision-making model (MID).	MID is an effective model and it can generate better forecasts for multivariate sales problems than machine learning methods.	The complexity of the model.	Use the MID model to address other multivariate forecasting problems; Compare how different variable selection techniques affect the MID model's predicting capabilities and make improvements.
Ramos et al., 2015	How to better forecast quality and how to model retail sales series effectively?	State space and ARIMA model.	The performance of ETS and ARIMA models is similar.	There is no consensus among authors as to which is the most effective method to forecast demand.	Find a way to balance the loss from stock-outs with the expense of safety stocks.

Punia & Shankar, 2022	Description of a big data predictive analytics model that can process a lot of data and produce short- to long-term forecasts.	Machine and deep learning techniques.	The developed method has better performance than time series, machine learning, and hybrid methods. POS and external economic factors are the most influencing indicators.	The method uses only food products, so its result cannot be generalized.	Judgment methods, different deep learning methods, and NN could be explored to extend the work.
Mediavilla et al., 2022	Analysis of AI methods.	AI methods.	The trend for the use of deep learning approaches. Clustering and dimension reduction are also very used strategies.	The gap of AI techniques that are effective with big data.	-
Fildes et al., 2019	Evaluate research literature on forecasting retail demand.	Review of different methodologies.	Retail sector is constantly changing and there is a need to adapt forecast methods. Online channel is a new competition challenge and there are few studies on it.	Increasing of new products with short lifecycles and their implications for the SC; Limitation of computational resources; need to adapt to online changes, etc.	Link technical forecasting issues with the market characteristics to find an explanation for different performances.
Maia et al., 2008	Test some models for forecasting interval-valued time series.	AR, ARMA, ARIMA, ANN, and hybrid approaches.	The hybrid models are more accurate than any individual method.	-	-
Villegas et al., 2018	Using AI techniques to improve the power of forecasting techniques	SVM method	SVM is an appropriated model for volatile data. It reveals a low error and biases.	Numerous stochastic processes might be necessary for a SKU to explain the observed data.	-

Table 12: Literature Review Table

Appendix B – Individual Significance Test

B.1 – Linear Regression

Individual significance tests are also performed to confirm the relevance of each variable in explaining the model.

Regarding linear regression models, from Table 13, it is possible to verify that only the variable "Price" is significant for model 1, since its p-value is lower than 0,05, so the null hypothesis ($\beta 5=0$) is rejected. Size is significant for model 3, and gender and colour are significant for models 3, 4, 5, and 6. Tables 13 to 18 present the coefficients of each model with the estimate, standard error (SE), t-statistic test (tStat), and p-value values.

	Estimate	SE	tStat	p-Value
(Intercept)	0,5096	0,0176	28,8798	1,59E-125
Month	4,07E-04	2,64E-04	1,5390	1,24E-01
Gender	-2,61E-03	2,78E-03	-9,38E-01	3,49E-01
Colour	3,90E-04	4,57E-04	8,55E-01	3,93E-01
Size	-4,05E-04	4,85E-04	-8,36E-01	4,03E-01
Price	1,21E-04	4,46E-05	2,7145	6,78E-03
Discount	5,44E-05	7,58E-05	7,18E-01	4,73E-01

Table 13: Linear Regression - Model 1

	Estimate	SE	tStat	p-Value
(Intercept)	5,18E-01	1,74E-02	2,98E+01	5,19E-131
Month	4,22E-04	2,58E-04	1,63534	1,02E-01
Gender	-3,05E-03	2,79E-03	-1,09427	2,74E-01
Colour	4,11E-04	4,59E-04	8,95E-01	3,71E-01
Size	-4,03E-04	4,87E-04	-8,28E-01	4,08E-01

Table 14: Linear Regression - Model 2

	Estimate	SE	tStat	p-Value
(Intercept)	1,80E+00	5,91E-01	3,05200	2,42E-03
Month	-6,51E-04	1,05E-02	-6,18E-02	9,51E-01
Gender	4,56E-01	1,00E-01	4,54499	7,22E-06
Colour	6,66E-02	1,72E-02	3,86850	1,27E-04
Size	-4,62E-02	1,66E-02	-2,78730	5,56E-03

Table 15: Linear Regression - Model 3

	Estimate	SE	tStat	p-Value
(Intercept)	-1,9793	8,97E-01	-2,20736	2,89E-02
Month	4,48E-02	6,33E-02	7,08E-01	4,80E-01
Gender	1,84717	4,20E-01	4,40321	2,12E-05
Colour	3,86E-01	1,03E-01	3,72664	2,82E-04

Table 16: Linear Regression - Model 4

	Estimate	SE	tStat	p-Value
(Intercept)	-6,74E-01	1,12888	-5,97E-01	5,51E-01
Month_code1	-5,67E-01	4,33E-01	-1,30912	1,93E-01
Gender	1,83596	4,18E-01	4,39443	2,20E-05
Colour	3,67E-01	1,04E-01	3,52323	5,79E-04

Table 17: Linear Regression - Model 5

	Estimate	SE	tStat	p-Value
(Intercept)	-2,99964	1,06046	-2,82863	5,37E-03
Month_code2	7,72E-01	4,15E-01	1,86153	6,48E-02
Gender	1,91502	4,16E-01	4,60076	9,44E-06
Colour	4,01E-01	1,03E-01	3,90981	1,44E-04

Table 18: Linear Regression - Model 6

B.2 – Nonlinear Regression

Concerning nonlinear regression models, as a result of having limited interactions in each model, the individual significance test can be performed using the hypothesis test indicated by the p-value. Considering a confidence interval of 95%, the variables are significant for the model if the p-value is lower than 5%. In model 1 the iteration between month and price, in model 5 and model 6 the iteration between gender and colour has a p-value of less than 5%, therefore, the null hypothesis is rejected, and it is concluded that these variables are statistically significant for the respective model. The remaining variables have a p-value of less than 5% and therefore the null hypothesis of not being significant for the model is not rejected (Tables 19 to 24).

	Estimate	*SE*	*tStat*	*p-Value*
(Intercept)	0,4736	0,1291	3,6678	2,61E-04
Month	4,33E-03	5,34E-03	8,12E-01	4,17E-01
Gender	-4,81E-02	5,27E-02	-9,12E-01	3,62E-01
Colour	2,63E-03	9,42E-03	2,79E-01	7,80E-01
Size	-3,92E-04	3,47E-03	-1,13E-01	9,10E-01
Price	1,57E-03	8,14E-04	1,93E+00	5,40E-02
Discount	1,74E-03	1,41E-03	1,23E+00	2,19E-01
Month:Gender	-8,06E-04	8,18E-04	-9,84E-01	3,25E-01
Month:Colour	5,40E-05	1,43E-04	3,79E-01	7,05E-01
Month:Size	-1,27E-04	1,46E-04	-8,70E-01	3,84E-01
Month:Price	3,53E-05	1,38E-05	2,55E+00	1,09E-02
Month:Discount	1,49E-05	2,62E-05	5,69E-01	5,69E-01
Gender:Colour	-5,35E-04	1,42E-03	-3,77E-01	7,06E-01
Gender:Size	1,81E-03	1,32E-03	1,38E+00	1,69E-01
Gender:Price	-2,44E-04	1,36E-04	-1,79E+00	7,31E-02
Gender:Discount	-1,48E-04	2,42E-04	-6,12E-01	5,41E-01
Colour:Size	-3,18E-05	2,62E-04	-1,21E-01	9,04E-01
Colour:Price	-5,79E-06	2,65E-05	-2,19E-01	8,27E-01
Colour:Discount	-3,16E-05	4,16E-05	-7,61E-01	4,47E-01
Size:Price	-3,02E-05	2,28E-05	-1,32E+00	1,86E-01
Size:Discount	-3,14E-05	4,05E-05	-7,76E-01	4,38E-01
Price:Discount	-1,12E-06	1,86E-06	-6,02E-01	5,48E-01

Table 19: Nonlinear Regression - Model 1

	Estimate	*SE*	*tStat*	*p-Value*
(Intercept)	0,613637	0,113458	5,408514	8,45E-08
Month	0,007018	0,005234	1,340866	0,180354
Gender	-0,08695	0,051675	-1,68256	0,09286
Colour	0,00645	0,009242	0,697873	0,485464
Size	-0,00329	0,003033	-1,08589	0,277862
Month:Gender	-0,00095	0,000804	-1,18267	0,2373
Month:Colour	0,000111	0,00014	0,794389	0,42721
Month:Size	-0,00013	0,000146	-0,91647	0,359701
Gender:Colour	-0,00073	0,001421	-0,51719	0,605169
Gender:Size	0,002398	0,00132	1,817475	0,069528
Colour:Size	-0,00013	0,000263	-0,50885	0,611002

Table 20: Nonlinear Regression - Model 2

	Estimate	*SE*	*tStat*	*p-Value*
(Intercept)	-0,25628	3,667285	-0,06988	0,944322
Month	-0,05086	0,186025	-0,2734	0,784681
Gender	0,744401	1,707156	0,436047	0,663032
Colour	0,301168	0,313619	0,960298	0,337472
Size	0,02101	0,098796	0,212657	0,831701
Month:Gender	-0,0185	0,030441	-0,60773	0,543706
Month:Colour	0,007597	0,005601	1,35628	0,175758
Month:Size	0,001094	0,005244	0,208675	0,834806
Gender:Colour	0,080829	0,05031	1,606601	0,108914
Gender:Size	-0,01393	0,043293	-0,32167	0,747864
Colour:Size	-0,01011	0,008897	-1,13659	0,256375

Table 21: Nonlinear Regression - Model 3

	Estimate	*SE*	*tStat*	*p-Value*
(Intercept)	1,38109	2,22963	0,61943	0,53668
Month	-0,06019	0,26620	-0,22610	0,82146
Gender	0,33302	1,23734	0,26914	0,78823
Colour	-0,51158	0,38480	-1,32946	0,18594
Month:Gender	-0,03970	0,12745	-0,31147	0,75592
Month:Colour	0,03814	0,03289	1,15965	0,24824
Gender:Colour	0,42898	0,20503	2,09227	0,03829

Table 22: Nonlinear Regression - Model 4

	Estimate	*SE*	*tStat*	*p-Value*
(Intercept)	-0,09953	3,49525	-0,02848	0,97732
Month_code	0,70854	1,75192	0,40444	0,68653
Gender	-0,20726	1,80969	-0,11453	0,90899
Colour	0,27956	0,49704	0,56245	0,57474
Month_code:Gender	0,14161	0,86535	0,16365	0,87025
Month_code:Colour	-0,35587	0,21865	-1,62756	0,10595
Gender:Colour	0,44694	0,20569	2,17295	0,03153

Table 23: Nonlinear Regression - Model 5

	Estimate	*SE*	*tStat*	*p-Value*
(Intercept)	0,31308	2,95232	0,10604	0,91570
Month_code	0,38989	1,60395	0,24308	0,80831
Gender	-0,63890	1,60044	-0,39921	0,69037
Colour	-0,11418	0,45367	-0,25168	0,80167
Month_code:Gender	0,50475	0,82946	0,60854	0,54385
Month_code:Colour	-0,09920	0,20402	-0,48623	0,62759
Gender:Colour	0,43596	0,20414	2,13558	0,03452

Table 24: Nonlinear Regression - Model 6

Appendix C - Discussion of the methods

Having presented the models applied in this study, this section aims to make a general comparison between them.

Simple Average and Naïve methods are the simplest models. They are based on historical data, without any other criterion. The latest period is the only significative observation to predict the future for Naïve method, and Simple Average considers all the data available to calculate the average.

The remaining time series models that do not consider the existence of trend or seasonality, MA, WMA, and SES, differ in the formula to calculate the average. They also differ in the sensitivity in handling the data, since WMA and SES give more weight to the most recent data, and MA is just concerned about calculating an average for a specific period, which can be beneficial because of its simplicity. The difference between WMA and SES is in the calculation of the weight since WMA is consistent, and SES is exponential. For that reason, SES can be considered a better indicator of a trend. (Banton, 2022).

DES is a better option when there is the presence of a trend, and HW is when there is the existence of seasonality in the data.

Regression and AI methods are better for including and evaluating the significance of the explanatory variables. The explanatory variables, being significant for the model, help explain the behaviour of the dependent variable. AI methods are much more complex, which can take to better conclusions, however with more computational effort.

Appendix D – Data Request and Presentation of Results to the 8000Kicks' company

This appendix section presents the letter sent with the request for collaboration of the 8000Kicks company in this study, as well as the letter, sent at the end of the study, with the presentation of results, containing a report describing them and a dashboard, to visualize the descriptive analysis done. In both documents, the Portuguese and English version was sent. The one presented here is only the English version.

D.1 – Data Request

"Dear 8000Kicks' Administration,

In the context of my master's final assignment (MFA) of the master's degree in Management with specialization in Business Analytics carried out at Católica Porto Business School, I hereby ask for your collaboration, with the approval of the supervisor responsible for this thesis Professor Aydin Teymourifar, to be able to apply the practical component in a real case study.

The MFA has as its theme "Demand Forecasting for a Company", which is a crucial planning concern for companies' success in a competitive environment. Within the scope of this thesis, we plan to provide tools to predict the impact of certain events on the production of a company. The tool will assist companies to mitigate the risks and ramifications of production variables and constraints. Consequently, a more accurate demand forecast will enhance inventory management, to achieve optimal inventory levels and avoid stockouts or overages.

We decided to focus this topic on manufacturing and service companies, with an emphasis on the footwear industry in Portugal, since this is one of the most relevant manufacturing sectors in our country. The purpose of this thesis is to apply studies on demand forecasting to a company, in order to compare them and make conclusions based on the accuracy of the approaches in this industry.

We intend to analyse the variation in demand by taking into consideration the following factors: seasonality/special days; promotions, markdowns, discounts; cannibalization effect (loss in sales caused by a company introducing a new product that displaces one of its own older products); and inventory.

Our demand forecasting tools will comprise both qualitative and quantitative methods. We will utilize most of the commonly applied tools in this area, which are typically based on statistical (regression, time series) and artificial intelligence methods.

With this study and in a way that makes sense for you as a company, we will present at the end as an output a dashboard containing both descriptive analysis and predictive analysis, to give your company tools to make your production more efficient.

To be able to carry out this work we would ask for your collaboration in providing the following data:

- Sales data (Date, quantity, price, discounts, and all the information related)
- Inventory (information about stocks, suppliers…)
- Products information
- Gross margin (prices information)
- Client data (country, city, age – to make a strategy analysis)

We would ask for a timeframe of at least two years. In case it is not possible to obtain any of the requested data or if the timeframe is too long, we can reduce it.

If you are interested in this collaboration, we are willing to provide more detailed information about our project.

Thankful in advance.

Looking forward to hearing from you.

Best regards,

Maria Francisca Pinto”

D.2 – Presentation of Results (Report and Dashboard)

“Dear 8000Kicks Administration,

I am sending this report as a presentation of the results of the study on the topic of "Demand Forecasting for a Company" based on the 8000Kicks’ company data.

The problem in question was first defined. It is based on the lack of efficiency in the use of the company's resources, with an inadequate inventory, which could lead to lost sales due to lack of resources, resulting in costs for the company.

Since the inventory information was too limited for further study of lost sales, this research focused on finding a method with high accuracy for the market characteristics of the 8000Kicks company, and the reasons for that.

To make this investigation more precise, we studied a specific model of shoes, the “Explorer V2”, in various existing colours. After choosing the methods to implement, a characterization of the data, and a descriptive analysis were carried out. This analysis was done monthly, instead of weekly, because the monthly forecast ensures greater stability, smoothing out fluctuations.

In terms of sales evolution, it is concluded that, despite the oscillations between the months, between October 2020 and October 2022, the sales values remain similar. March and November are the months with the highest number of sales. The United States is the country with the highest sales volume, followed by Portugal. The most sold sizes are the intermediate sizes, the most sold being number 43, representing 20% of total sales. Shoes in the colours “beige and green”, “black and white”, and “all black” are the best sellers, representing 24%, 22%, and 21% of total sales, respectively. Men's shoe sales represent 80%, and women are the remaining 20% of total sales.

To identify patterns that could explain the oscillations of sales between months, Portugal sales were analysed in detail. In terms of the correlation between the variables Quantity, Price, Month, Discount, Colour, Size, and Gender, it was concluded that only size and gender have a high positive correlation, as would be expected. There is a low positive correlation between month and price with discount.

Different models were created to assess seasonality. In the model where the months were divided between hot and cold, it is concluded that the hottest months, between March and September, have significantly higher sales quantities than the rest. In another model, using the same terms of comparison between months with more extreme temperatures and months with mild temperatures, it was found that the months with milder temperatures, despite being fewer (March, April, May, September, and October), show a significantly higher number of sales.

To answer the research questions the following methods were tested:

- Time Series: Simple Average, Naïve method, Moving Average, Weighted Moving Average, Simple Exponential Smoothing, Double Exponential Smoothing, and Holt-Winters.

- Regression: Linear and Nonlinear.

- Artificial Intelligence: Artificial Neural Network.

The method that showed more accuracy was the Artificial Neural Network (ANN), followed by Nonlinear Regression.

It is, therefore, concluded that the nonlinear models fit better than the others, and the ANN model represents nonlinearity better. Nonlinear models have better performance because they can fit the data more closely, capture complex interactions, develop dynamic procedures, and adapt to changing conditions.

Some variables are neglected since there is no information about them.

For the company 8000Kicks, although there may be other methods with similar accuracy to the ANN model, no further studies are needed as the ANN model represents well the future demand of the company.

A dashboard was made in order to better visualise the descriptive and strategic analysis, as well as the demand forecast (made only until the end of 2022). Please open the following link to visualize it:

https://app.powerbi.com/groups/me/reports/0ca79e3a-5da0-4c3c-b5d1-78e96ce2a0cb/ReportSectione8bf6450e181f465497f

From a managerial point of view to the company, the suggestion for 8000Kicks is to record and measure the impact of variables on the data. Then, build the model based on those variables and forecast demand with the ANN model since it is the most accurate. Using the appropriate demand forecasting model for the company's data helps solve the initial problem of inefficient allocation of company resources. This process should be done as less aggregated as possible to increase its accuracy, i.e., by shoe model and billing country.

I thank, once again, the collaboration of the company 8000Kicks for this study. I am available for further clarifications if you wish.

Best regards,

Maria Francisca Pinto”

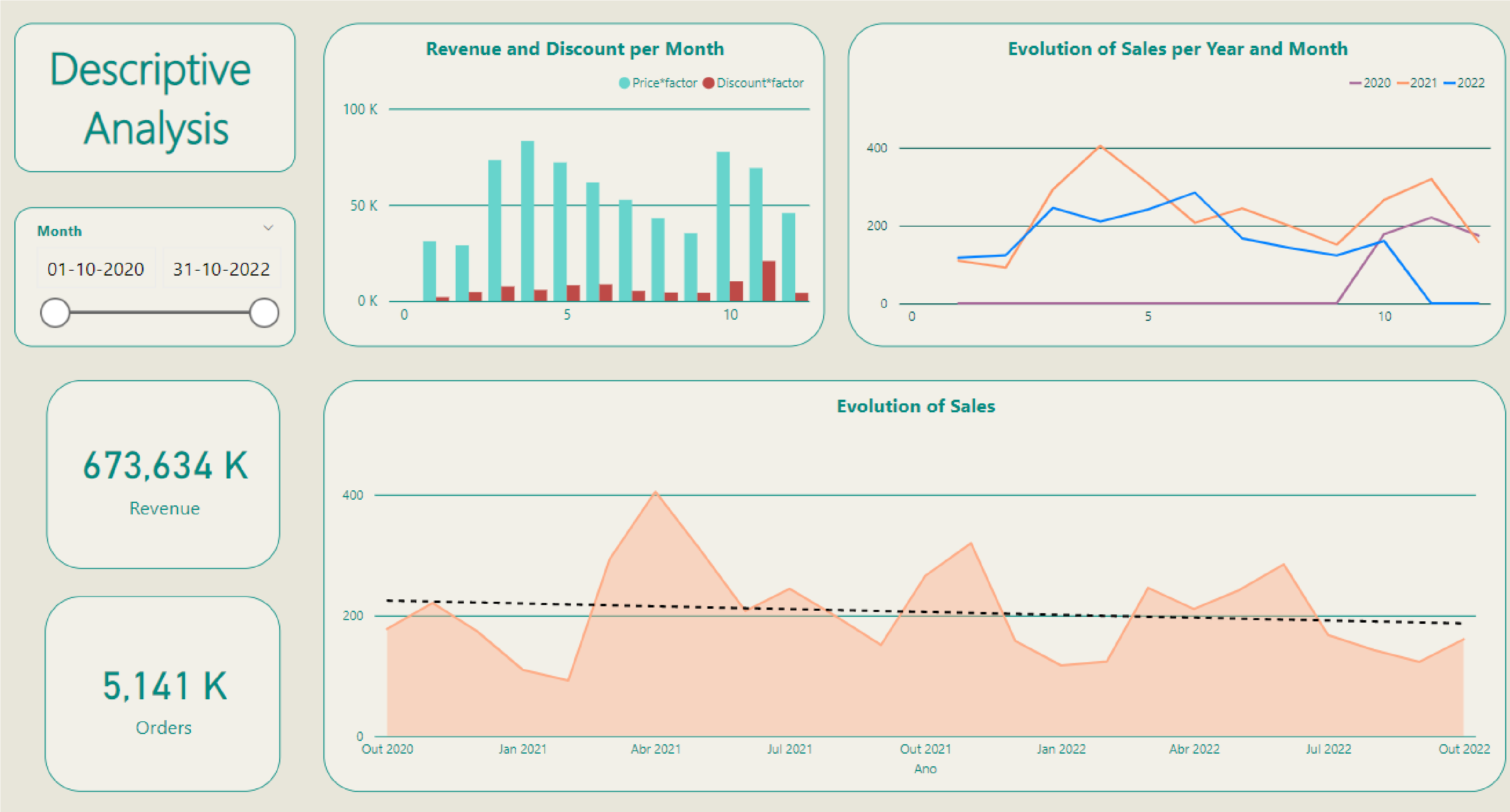


Figure 35: Descriptive Analysis Dashboard (1/2)

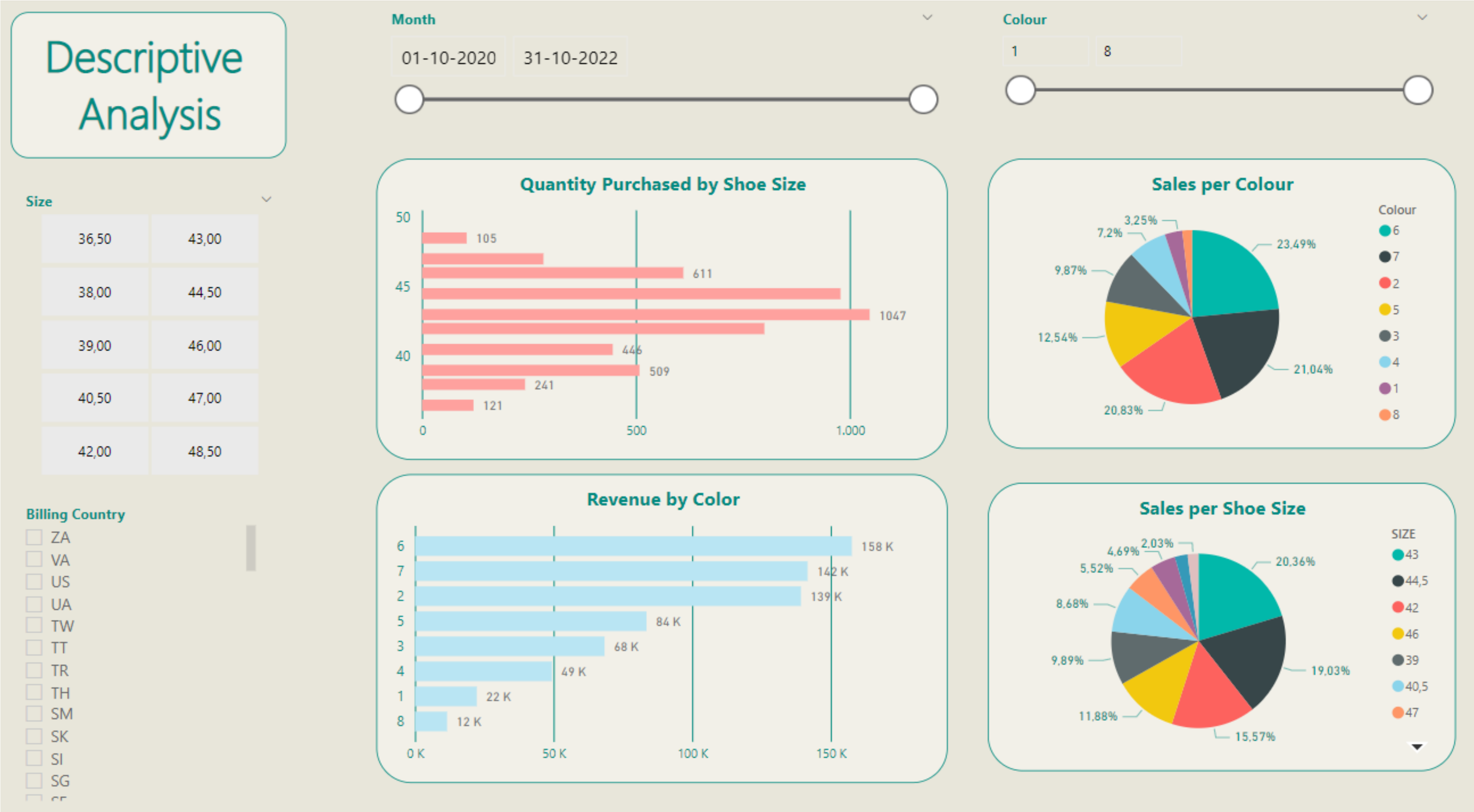


Figure 36: Descriptive Analysis Dashboard (2/2)

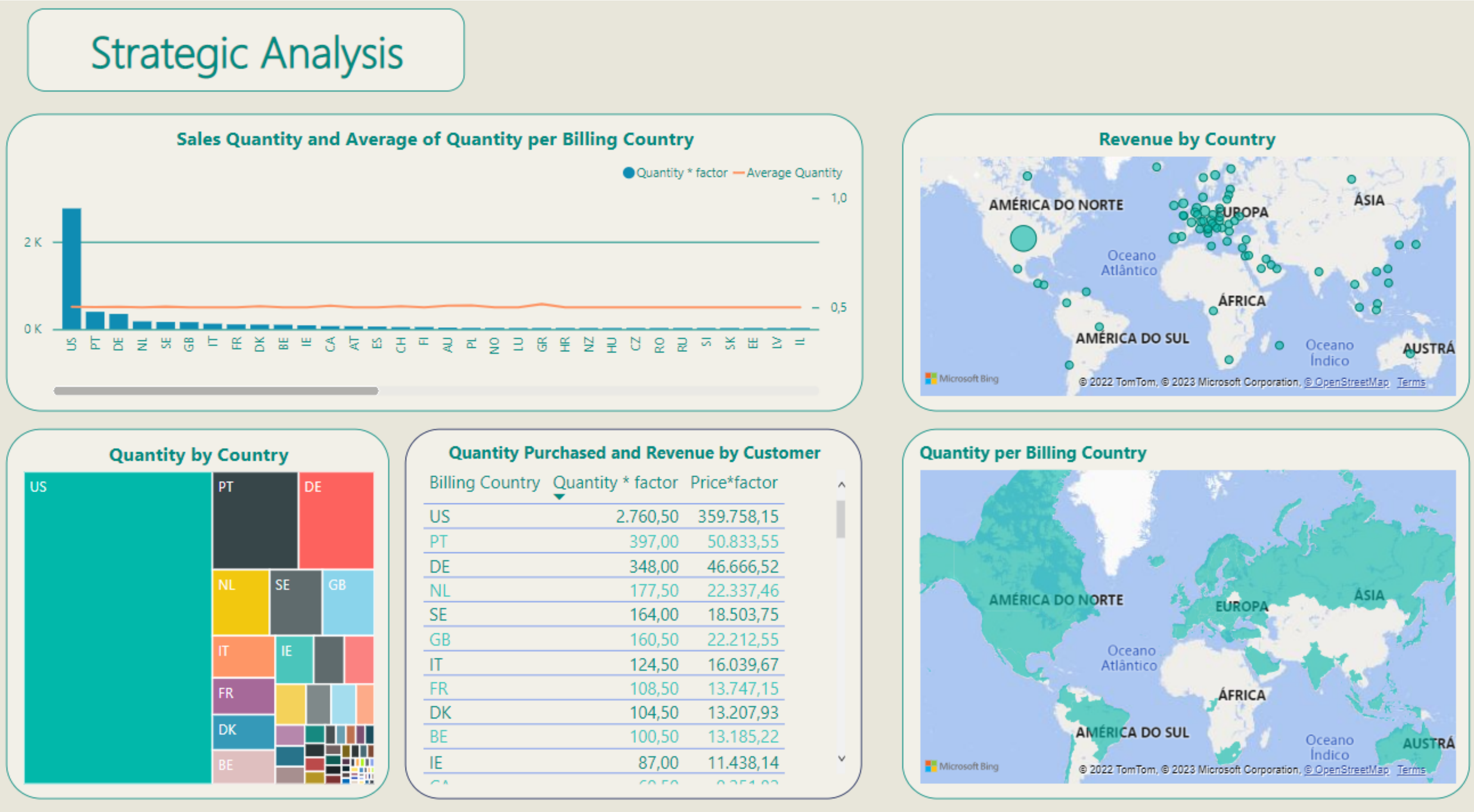
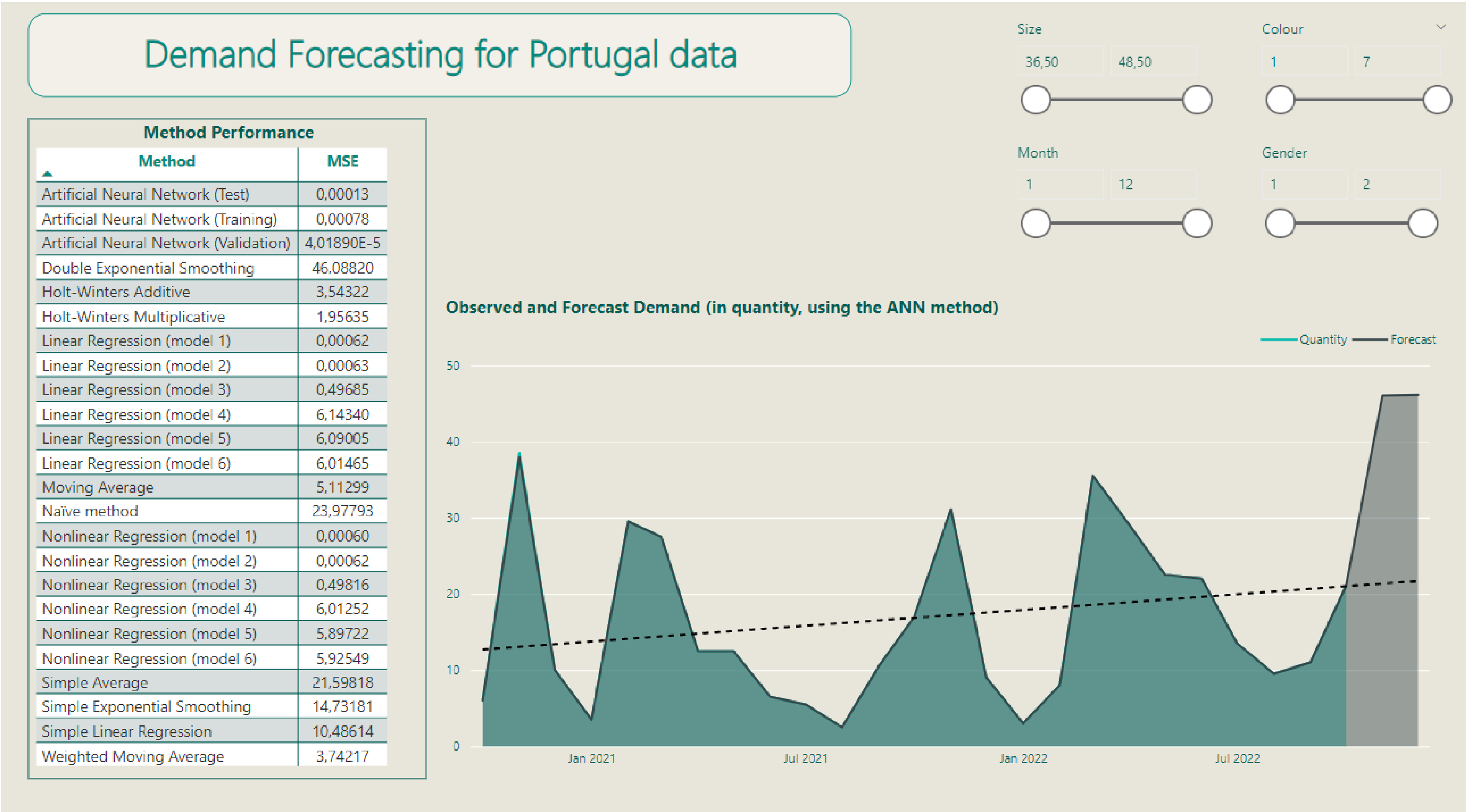


Figure 37: Strategic Analysis Dashboard



Method	MSE
Artificial Neural Network (Test)	0,00013
Artificial Neural Network (Training)	0,00078
Artificial Neural Network (Validation)	4,01890E-5
Double Exponential Smoothing	46,08820
Holt-Winters Additive	3,54322
Holt-Winters Multiplicative	1,95635
Linear Regression (model 1)	0,00062
Linear Regression (model 2)	0,00063
Linear Regression (model 3)	0,49685
Linear Regression (model 4)	6,14340
Linear Regression (model 5)	6,09005
Linear Regression (model 6)	6,01465
Moving Average	5,11299
Naïve method	23,97793
Nonlinear Regression (model 1)	0,00060
Nonlinear Regression (model 2)	0,00062
Nonlinear Regression (model 3)	0,49816
Nonlinear Regression (model 4)	6,01252
Nonlinear Regression (model 5)	5,89722
Nonlinear Regression (model 6)	5,92549
Simple Average	21,59818
Simple Exponential Smoothing	14,73181
Simple Linear Regression	10,48614
Weighted Moving Average	3,74217

Figure 38: Demand Forecasting for Portugal data Dashboard

Appendix E - Methodology: Ethics

This case study aimed to apply the chosen methods to an existing company in the footwear industry to draw more accurate conclusions.

The CEO of 8000Kicks was assured that the sales data he provided would be used exclusively for academic purposes. For confidentiality reasons, customer data was removed from the analysis, and the remaining data were multiplied by a factor not disclosed in this study.

Appendix F – Evaluation of the Work

This study allowed for the appreciation of several demand forecasting methods, through the observation of their performance and operation. It was possible to recognise traits already identified in the literature by other authors.

Through the chosen performance measure, it was possible to answer the first research question, identifying the ANN model as the one with the highest accuracy in forecasting demand for the 8000Kicks company. As for the second research question, the nonlinearity characteristics justify the difference between the accuracy of the nonlinear methods (ANN and Nonlinear Regression) of the remaining methods, being that the ANN method represents better the nonlinearity.

The low MSE value allows for the assumption that the ANN model demonstrates good performance for the company in question and therefore no future study would be necessary. However, since this study was only for a specific company in the footwear industry, it is not possible to conclude that ANN will have the same performance as the remaining companies in this industry. Future study is needed for the remaining companies.

That said, the research questions were answered, and the objectives of the study were fulfilled.

As limitations of this study, I highlight the lack of information on other variables that could influence demand. It was not possible to assess the volume of the company's inventory since they do not keep a constant record of it and, therefore, it is not possible to calculate the lost sales that they might have suffered.

Through this study, it was possible to understand the importance of demand forecasting in a company. It is a subject that has been studied for several decades, due to the lack of consensus among authors and the attempt to improve it. The identification of the explanatory variables, registration, and measurement is a very important stage in the forecasting process since historical information has a great impact on the accuracy of the demand forecasting model.