Improving the close-out supply forecast accuracy at Nike Inc.

graduation project performed at Nike European headquarters, to improve the performance of Nike in predicting the excess inventory after a selling season

Nederpel, L.

Award date:
2012

Eindhoven, February 2012

Improving the close-out supply forecast accuracy at Nike Inc.

Graduation project performed at Nike European Headquarters, to improve the performance of Nike in predicting the excess inventory after a selling season

by

L. Nederpel
BSc Industrial Engineering and Management Science – TU/e (2008)
Student identity number 0570819

In partial fulfillment of the requirements for the degree of
Master of Science
In Operations, Management and Logistics

1st Supervisor TU/e	Dr. ir. Broekmeulen, R.A.C.M.
2nd Supervisor TU/e	Dr. Tanrisever, F.
Supervisor Nike	Dijkers, M. (Inventory Management Director)

TU/e. Department of Industrial Engineering and Innovation Sciences
Series Master Theses Operations, Management and Logistics

Subject headings: Time Series Analysis, Forecasting, Leftover Inventory, Excessive Inventory, Sports and Fashion Industry, Attribute Forecasting, Binary Logistic Regression, Demand Planning

Abstract

This Master thesis describes the analysis directed at improving the medium-term forecast of close-out supply on lower material levels, which is defined as the leftover or excess inventory after a selling season. This close-out inventory is sold for reduced prices to wholesalers and Nike Factory Stores (NFS), and these NFS have to complete their assortment of close-out inventory with specially bought products. Therefore, the NFS need a forecast of close-out supply on lower material levels to be able to plan the remaining products efficiently. Current close-out supply forecast performance is measured and traditional forecast heuristics are applied on historical data. The process of materials ending up in close-out inventory is very complicated and it involves multiple unquantifiable flows. Therefore, traditional forecast heuristics (moving average, regression procedures and exponential smoothing) are not applicable to this situation to obtain a reliable forecast. Another method called distribution analysis, which involves the projection of the buy quantity on category and gender level on the aggregate close-out supply, is proposed. This study shows that distribution analysis is a realistic option, but that attribute forecasting is the most promising method to predict close-out supply on lower material levels. A prototype is created which shows the benefits of using attribute forecasting for predicting on medium term in the sports fashion industry.

Preface

This Master Thesis is the final result of my graduation project at Nike Inc. in Hilversum, where I have been working in the departments Demand Planning and Inventory Management. This research project was the last phase towards the Master of Science degree in Operations, Management and Logistics. After completing the Bachelor program Industrial Engineering and Management Sciences in 2008, I started this Master at the University of Eindhoven. This research project marks both the end of my time as a student at the TU/e and the start of my career in logistics.

The start of this research project was in February 2011, when I started as a fulltime intern Demand Planning at Nike in Hilversum. After finishing the Master Thesis Preparation on site the official start date of this project was in April. The first months were a totally new experience to me, since I never had the opportunity to work fulltime in a business environment related to my study. Furthermore, it seemed like a dream had come true that I had the opportunity to start my career at an amazing, inspiring and sport-related company as Nike. I had to absorb lot of information about Nike, the supply chain and processes, which was all enthusiastically shared by my new colleagues at Nike. Therefore, I would like to thank Monique Dijkers, Nike supervisor of this graduation project, for her support and active participation in this project and for the extensive knowledge about Nike she shared with me during the interesting discussions we had throughout the project. I would also like to thank my other colleagues at Nike, especially Daan and Marco, for their support during my internship and the nice moments we had during work, lunch and particularly the soccer and tennis matches at Nike European Headquarters. After leaving Nike in September, having completed the project successfully from Nike's point of view with a final presentation, I had to finish the project from University. Although I finally managed to do all the analyses and write this report, I have had some difficulties during this period in achieving the desired results.

Especially during this last period of the research project, I have had a lot of support from Rob Broekmeulen, my first supervisor at the TU/e. His critical notes and his continuous flow of new ideas and opportunities to fulfill the research objectives have helped me a lot during the project. Therefore, special thanks for Rob Broekmeulen. I would also like to thank second supervisor Fehmi Tanrisever, for his useful and refreshing ideas during the project.

Furthermore, I would like to thank my family and friends for their support during my whole study. Particularly, I would like to thank my parents who gave me the (financial) opportunity to start this study and my girlfriend Emmy who has been very patient and supportive during the last years of my study. Important is to thank my colleague student and friend Paul, for his refreshing ideas during this research project, which gave me new insight in possibilities to write the thesis. Also special thanks to my other colleague students and friends Harm, Zeno and Rens for completing all those courses together, but especially for the fun we had during the lectures and the many not-study related activities all those years.

Last but not least I would like to mention that I am very thankful for the opportunity to fulfill this research project at Nike, which I do consider as one of the most interesting companies and brands worldwide. I will always keep in mind the amazing time I have had there and hope to return sometime in Hilversum as a fulltime employee, since I am even more inspired by the brand Nike than I was before this project. Furthermore, I think this research project has contributed to a major extent that I am currently successfully employed as Logistics Analyst at Logitech.

Lennart Nederpel
Eindhoven, February 2012

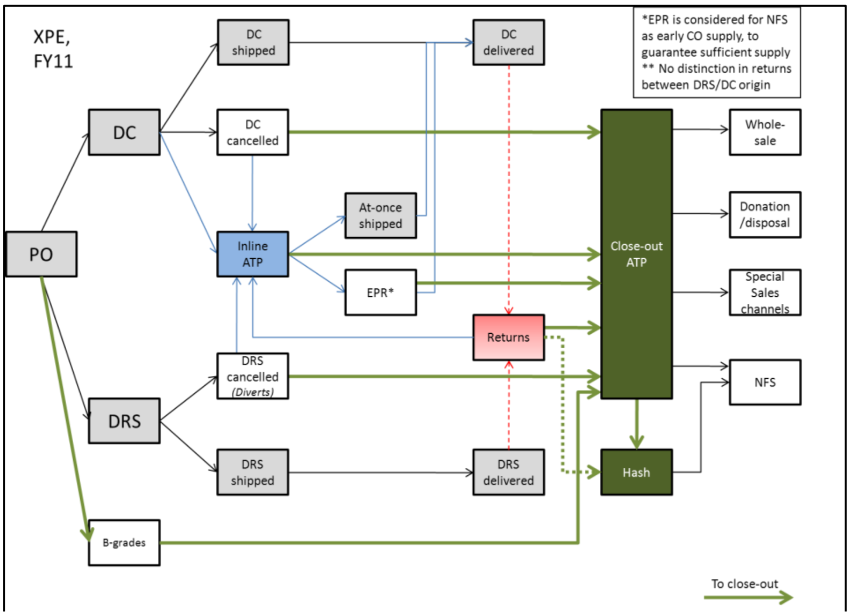
Management Summary

This thesis is the last part for the fulfillment of the Master Operations, Management and Logistics at the University of Technology Eindhoven. The research has been done at Nike Inc., a major manufacturer of footwear, apparel and equipment for a wide variety of sports from the United States. It is world leader for footwear and apparel products. Nike Inc. was founded in 1964 by Bill Bowerman and Phil Knight as distributor for imported shoes. In 1978, the name was changed to Nike and the product range was extended to footwear and apparel for a few different sports. Since then, Nike has grown into the leading manufacturer of sportswear it currently is. Nike differ their supply chain into three types of products (called product engines), which are called apparel (APP), footwear (FTW) and equipment (EQM). These products are introduced to the market via wholesalers or Nike's own retail channel.

The research topic is close-out inventory, which is defined as the leftover stock after a selling season when product lifecycle status is changed from active to inactive. Nike uses four selling seasons a year, in which new products are introduced to the market. Customers need to place their sales orders approximately six months before, if they require supply during a selling season. These are called future orders. These future orders can either be shipped directly (Direct Shipments, DRS) or via the ELC in Laakdal. The fourth month after a selling season they can order at-once orders, which are the remaining products which are on stock in the distribution center (ELC) in Laakdal. After this fourth month, products are dropped into close-out inventory. Not taking into account exceptions, products have an active lifecycle of four months before these become inactive and are dropped into close-out supply. This close-out inventory is sold to both wholesalers and Nike Factory Stores (NFS), which are stores designed to bring the close-out inventory with a certain discount to the market. The close-out inventory does not represent a complete assortment in both volume and products; therefore the assortment has to be completed with 'rebuy' products. These products are only sold via NFS and the planners for the NFS have to order these products also 6 months before introduction in the NFS. Since the planners for the NFS need to know the volumes of close-out supply they receive, a forecast should be given by the department Inventory Management, responsible for planning inline products (sold during the regular selling seasons). Currently, the close-out supply forecast performance is not as desired, and this forecast should be given 6 to 9 months out on lower material levels. Therefore, the research question for this research project is defined as:

How can the predictability on (both short-term and) medium-term of the close-out supply to NFS be improved by developing a procedure which takes into account historical data on close-out supply, information about drivers for the close-out supply and the current way of working at Nike?

The research project involves all three product engines, excluding the category Golf. The scope of the project is Europe, excluding small DC's in Russia and Turkey. In fact, the close-out supply process is complicated, involving multiple flows which all influence the close-out supply. All products flowing back to the ELC will eventually be included in the close-out supply, if these are not sold to customers before as at-once products. That means that all returns and cancellations from customers are eventually included in the close-out supply process. This close-out supply is logically dependent upon sales to customers, the quantity that is not sold will become close-out inventory. Furthermore, customers and NFS have the opportunity to buy close-out inventory as early price reduction (EPR) the last week of the selling season. This is considered as an early close-out supply. Focus of the project is on close-out supply, which consists of all materials which really become available for NFS. Part of the materials will have their status changed in the system, but these will not become available for multiple reasons. A process overview has been created of how products end up in close-out inventory from the moment the purchase order (PO) is created by the planning department. This process overview is shown in Summary Figure 1.



Summary Figure 1 Overview of products introduced in Spring and the order dates and close-out drop

An extensive explanation of this process overview can be found in the report. The purpose was to quantify all origins and all flows in the process overview. However, this was impossible and the conclusion was drawn that the process of close-out supply is extremely complex and unquantifiable. That will have a major influence on the possibility to improve forecasting using traditional forecast methods, which rely heavily on predictable, visible flows in a process.

The objective was to improve close-out supply forecast performance. To be able to improve forecast performance, current forecast performance should be measured to be able to compare improvements to a certain benchmark and to analyze the forecast problem. Current forecast performance measurement results are represented in Summary Table 1.

Summary Table 1 Current forecast performance at Nike

Comparison (incl. EPR)	FTW	APP	EQM	All PEs
MAD (000)	136	393	131	477
MAPE	12%	22%	34%	15%
MASE	0.75	0.71	0.64	0.56

Forecast performance has been measured using MAD (mean absolute deviation), MAPE (mean absolute percentage error) and MASE (mean absolute scaled error), which are considered the most appropriate forecast accuracy measurement tools. MAPE is considered as most appropriate of these three, since it shows the error compared to total close-out supply volume. MASE fails in comparing different product categories and MAD only shows the actual deviation, which does not give an indication of the impact of the error. The contradicting results for MAPE and MASE are immediately visible, which has its root cause in the fact that MASE compares to the naïve forecast which varies over the different product categories. Therefore, it will be concluded that MASE is not suitable for comparing between different product engines and going forward MAPE and MAD will be used as measurement tools. Current overall forecast performance for forecast horizons of 1, 3, 6 and 9 months out is 15% inaccurate. Product engine FTW performs best with 12% inaccuracy. A benchmark retailer predicting regular demand also obtains an inaccuracy of 12%. A distinction of performance per horizon shows that forecast performance increases when forecast horizons decreases, because more information is available closer to the close-out drop.

Traditional forecast heuristics were applied on product engine level historical data on close-out supply to see if forecast performance could be improved. These traditional forecast heuristics were not applied on lower material levels, since products are introduced each season and no historical data is therefore available for new introduced products. The results of the application of traditional forecast heuristics on aggregate level can be found in Summary Table 2. The applied heuristics are the (weighted) moving average procedure, regression models and exponential smoothing (which can be extended with trend and seasonality).

Summary Table 2 Forecast heuristics applied on product engine level

Heuristic9	Method	MAPE	MAD	MASE	CurrentMAPE
FTW	Winters	13%	185,706	0.93	
FTW_opt	Winters	11%	157,312	0.80	9%
APP	WintersDT	29%	674,935	1.32	
APP_opt	WintersDT	19%	425,227	0.82	38%
EQM	MA2	24%	89,343	0.30	
EQM_opt	WintersDT	20%	83,091	0.29	72%
XPE	WintersDT	23%	905,333	1.33	
XPE_opt	WintersDT	15%	573,529	0.82	27%

The results show that Winters' method, exponential smoothing with trend and seasonality, performs best for the majority of the product engines, also when smoothing parameters were optimized (which indicate the ratio between weight to historical values and average values). This shows that seasonality is an important component of the Nike close-out supply. Since these results do not deliver a procedure to apply at material level, two other regression methods were proposed and tested.

The first method is the influence of three other time series on the close-out supply, taking the distribution among these other time series on lower material levels and reflecting this on an aggregate close-out supply forecast. These three other time series are last year's close-out supply, the demand planning forecast (prediction of what will be sold during the regular selling season) and the buy quantity (what is bought for the regular selling season). The expectation is that the distribution among buy quantity is the best reflection on close-out supply, since close-out supplies are the residuals of the initial buy quantity. Results of this distribution method for FTW are shown in Summary Table 3. Buy quantity distribution is the best predictor and this method is an opportunity to forecast close-out supply on lower material levels. Although analysis on category and gender level show promising results, lower material levels do not yield useful predictions.

Summary Table 3 FTW category level reflection of distribution on aggregate close-out supply

Category level	Aggregate forecast: Winters			
Percentage based on	Average with horizon	Same period, horizon	MAPE	MAD
CO supply		12 months	28%	40,077
CO supply	9 months		37%	43,338
CO supply	6 months		37%	39,865
Buy Quantity		9 months	19%	21,019
Buy Quantity	9 months		33%	22,605
Buy Quantity	6 months		30%	22,203
DP Forecast		12 months	23%	22,836
DP Forecast	9 months		28%	23,867
DP Forecast	6 months		28%	22,958

The second method is predicting the close-out supply using the differences in attributes of products. The chosen attributes are size, price, silhouette and color. A one-way ANOVA was applied on each of these attributes and significant differences were found between the different levels of the attributes. The conclusion is that close-out supply contains significantly more products that have odd sizes (extreme large or small), high prices and more standard colors (black/grey and white). This difference in attributes in close-out supply has an important implication for the distribution analysis, because that becomes less useful since these differences are not found in the buy quantity. A reflection of the buy quantity will therefore never be optimal.

These significant differences from the ANOVA are an opportunity for further research, since Nike introduces new products each season and no historical sales data are available on these new products. Attributes of these materials might give a reliable prediction of what quantity will become close-out supply. A proof of concept has been created for APP involving the attributes color and size, with a selection of these attribute values. Binary logistic regression has been used to create a model which predicts the probabilities of close-out supply on material level based on attributes. Logistic regression has been chosen since it requires fewer assumptions and was able to create a model with significant variables. The probabilities are calculated using a logit function, which is defined below:

$$P_{ij} = \frac{1}{(1 + e^{\beta_0 + \beta_i Size_i + \beta_j Color_j + \varepsilon})}$$

For each unique combination of size attribute value i and color attribute value j, the probability is calculated using this equation. If particular combinations do not exist, the probabilities can be rewritten so that it sums up to 1, which is the advantage of using these probabilities. This model should be a starting point for further research, in which a more sophisticated model with all attributes and values should be developed to predict the close-out supply on lower material levels. This proof of concept has given the indication that attribute forecasting is a promising method to improve the close-out supply forecasts on lower material levels with a medium term horizon.

The overall conclusion of the research project is that it is currently almost impossible to predict close-out supply accurate on lower material levels due to limited historical data, low visibility and a complex process. Current forecast performance is not as desired, quantifying the process flow was impossible and the traditional forecast methods did not deliver required results on lower material levels. However, if more data will become available and the distribution or the attribute method are applied, eventually in combination with Winters' method on aggregate close-out supply, close-out supply forecast performance on lower material levels can be improved. A model should be created on attribute forecasting to check the performance if all variables are included, but for the short-term implementation of the distribution method is an opportunity.

Table of Contents

Introduction

Company

Nike Inc. is a major manufacturer of footwear, apparel and equipment for a wide variety of sports from the United States. It is world leader for footwear and apparel products. Nike Inc. was founded in 1964 by Bill Bowerman and Phil Knight as 'Blue Ribbon Sports' and started as distributor for the Tiger Shoes which were imported from Japan. In 1978, the name was changed to Nike and the product range was extended to footwear and apparel for a few different sports. Since then, Nike has grown into the leading manufacturer of sportswear it currently is. Nike Inc. is described here as manufacturer of products, but it also operates an own retail channel in addition to selling products to other retailers. An important and well known aspect of Nike Inc. is the swoosh logo, Nike's famous trademark.

At the end of the fiscal year 2010 (May 2010), Nike Inc. had total revenues of $19.0 billion. Nike Inc. is active worldwide in more than 160 countries and employs more than 36.000 employees globally. Some products of Nike are sold under the own brand, but there are also a few brands belonging to Nike, called affiliates:

- Cole Haan – luxury brand offering footwear accessories and outwear
- Converse – diverse portfolio of premium lifestyle footwear and apparel
- Hurley International – action sports apparel for surfing, skateboarding and youth lifestyle apparel and footwear
- Nike Golf – golf apparel equipment etc
- Umbro – athletic and casual footwear, apparel and equipment, primarily for the sport of football (soccer), under the Umbro trademarks

World headquarters (WHQ) is situated in Beaverton, Oregon in the USA, while Nike European Headquarters (EHQ) is situated in Hilversum, from where supply to the Europe region is operated. This projects' scope is limited to EHQ operations. The Europe Logistics Center (ELC), the distribution center to cover this region, is situated in Laakdal (Belgium) and will further be referred to as ELC or ELC in Laakdal. The European region is divided into different kind of regions. First, Europe is divided into West Europe (WE) and Central and East Europe (CEE). These are called geographies. These geographies are divided into territories, i.e. the UK, Russia and Greece. In the UK, a distinction is made between countries, like England and Scotland. The last distinction is made based on accounts, which are the customers (retailers) of Nike.

Problem context

The project concerns the close-out forecast accuracy. Close-out products are defined as "the leftover products from the supply chain process at the end of a selling season as the products life-cycle is changed from active to inactive". These close-out products are sold (after the season) for a reduced wholesale price to either the Nike Factory Stores (NFS) or to normal retail stores. The objective of the study is to develop a methodology/model/process around close-out volume predictability to increase close-out forecast accuracy.

The project focuses within Nike Inc. on the departments Demand Planning (DP), Inventory Management (IM) and Retail. The purpose of Demand Planning is to develop a forward looking view of product demand, by analyzing historical sales data of the same and/or similar products using market knowledge. The output of Demand Planning, a buy plan, is used as input for Inventory Management. Inventory Management uses the demand forecasts to generate detailed inventory requirements at product, location and time intersections by evaluating the demand plan against existing inventory and by evaluating factory minimums, lead-times, capacities, cancellations and close-out risks. Nike Retail is the own retail channel through which products are brought on the market. Special focus will be on the NFS, which sell the close-out inventory. NFS are stores which are specially founded to sell the excess inventory. NFS require a mix of close-out and 'rebuy' products to have right assortments in stores to attract the shoppers. The 'rebuy' products are products, specially purchased to complete the assortment, since close-out inventory on its own does not represent a right assortment (in products and/or volume). NFS refers in this report to the planning department for NFS, which differs from the actual factory stores which receive the products and sell them. The planning department has to cope with the close-out inventory supply. The forecast for this close-out inventory supply has to be given by the department Inventory Management.

Problem definition

The problem definition consists of a description of the current close-out process at Nike, concluded with a problem definition. It is necessary to create a better overview of the close-out process (how products end up as close-out inventory) and all drivers to understand this problem. Therefore, first we will give a detailed overview of important aspects closely related to the close-out process and important for the rest of the master thesis project. This will start with the description of the product engines, different order types, inventory qualifications, season milestones, cancellations and returns. Then a more detailed overview will be given of the close-out drop and supply process, before all origins for the resulting close-out inventory are identified.

Description of important aspects

Product Engines

Nike distinguishes between three Product Engines (PEs):

- Footwear (FTW) – including all shoes
- Apparel (APP) – including sportswear or clothing for sporting
- Equipment (EQM) – including socks, balls and other equipment used for sporting

The product category that does not fall into these three PEs is golf. Golf is operated by a separate department, which will be kept outside the scope of research. The three PEs are differently operated disciplines. Furthermore, within each PE the global categories are defined. These categories are Sportswear, Football Soccer, Running, Women's Training, Athletic Training, Young Athletes, Action Outdoor and Other. Nike is currently transforming the business from a PE differentiation towards a category differentiation.

Order types

Future orders

Future orders are placed approximately six months before delivery and can only be delivered during the predetermined selling seasons. The customers are given a guarantee that they get these products delivered on a predefined date. For the majority of the future orders, a purchase order (PO) is placed at the factories, which in turn manufacture the goods and ship them either directly to the customer (DRS) or to the ELC, from where it is delivered to the customers. The future orders which will arrive at the ELC in Laakdal, will be kept in stock as reserved quantity, which means the goods are assigned to customers and will be shipped in the future upon goods request from the customer.

At-once orders

At-once orders are the other type of orders. They are booked against free available products in ELC in Laakdal. This type of orders exist for customers (retailers) who need more products than initially ordered because sales are above expectations and the customer wants to sell more of this type of products. These orders are taken from the free available stock in the ELC, which is called the ATP (Available to Promise) stock. This type of stock is not (any more) assigned to future order of customers, and its specific purpose is to offer the opportunity for fast delivery of orders to customers during the selling season. At-once orders are shipped in the fourth month of a season since the ATP are the remaining materials not dedicated for immediate delivery and Nike offers an option for customers to react to increased sales. Thus, ATP also includes materials which were assigned on order to customers, but these orders are cancelled and the products become available for interested customers.

Qualifications in inventory
Despite the difference in ATP and reserved quantity, there are more distinctions/ qualifications in inventory which is stored in Laakdal. These will be mentioned next.

- There is a difference in A, B or C-grade products. This difference does depend on quality and/or appearance of the products. Lower quality products are labeled as B-grade products, and these B-grade products are only sold in NFS, not in normal retail stores. C-grade products have such low quality that they are destroyed.
- In the ELC in Laakdal they distinguish between close-out inventory and inline. Inline are the products with an active lifecycle, close-out inventory with an inactive lifecycle.

Milestones during selling season
The process of products ending up in close-out inventory will be described in this chapter. Nike divides the year into four selling seasons of three months each, which are called Spring (SP), Summer (SU), Fall (FA) and Holiday (HO). The products are introduced each selling season in each of the three months. The materials should be ordered by customers six months before the introductions in that month (these are future orders). However, the materials introduced in the selling seasons have a 120-day lifecycle, and the fourth month (prop period), the first month after the season is dedicated for at-once orders. These at-once orders are taken from available stock (ATP). At the end of the first three months, there is an evaluation for a possible EPR (Early Price Reduction) to accelerate sales during the last month of the selling season. EPR is thus only possible for at-once orders and will be considered an early close-out supply during the project. This because if EPR is not bought as EPR, it would be bought as close-out inventory after the close-out drop. There are three milestones for products during a selling season: Future Product Offer Date (FPOD), which indicates the start of the three-month selling season, the End Future Offer Date (EFOD), indicating the end of the selling season, and the End Product Offer Date (EPOD), which is the time at which the product is dropped in close-out (not taken into account exclusions).

Figure 1 Selling season overview

Figure 1 shows the selling season as defined with milestones. This process is applicable for all PEs, because Nike aligned the PEs during the start of this project. This description excludes Always Available (AA) products. Always Available products have a lifecycle of 12 months or more. These products are carried over multiple times before dropping into close-out.

Process of products ending up in close-out inventory
After the last date of the 120-day lifecycle, there are two possibilities for the products (decisions taken in last month, for EQM before lifecycle):

- The products are carried over (c/o) to the next period and sold to customers for the normal wholesale price (their lifecycle is extended)
- The products' status is changed from active to inactive and the product is dropped in close-out (once a month)

It is important to note that the majority of the products have their lifecycle changed from active to inactive at the end of the 120-day lifecycle. Thus, decisions to carry over products to next periods can be considered as exceptions, for reasons that have to do with late delivery, inventory issues or merchandising decisions. Before introduction of the products, it has already been determined when products will drop into close-out.

The close-out inventory which is dropped at the end of the selling season is sold in both normal retail stores and in NFS. Nike has defined the objective to sell 80% of the close-out inventory via the NFS, which means that 80% of all units that hit the market as close-out should be sold to NFS. The remainder will be sold to other retailers (wholesalers), eventually special sales channels and finally less preferred options as donation or disposal are possible. The NFS are given an advantage of five days to order products which have been dropped in close-out. After these five days, other retailers are given the possibility to buy the close-out products.

The retailers and Nike retail (where NFS belongs to) are sold the products from close-out inventory with a specific discount on the wholesale price. Retail prices are their own decision. NFS are specially founded to get rid of the close-out products in a controlled manner. They determine the retail price, which is probably lower than the normal retail price, thus resulting in less overall margin for Nike. However, the NFS are a very profitable business for Nike, which is indicated by the fact that Nike is currently expending effort to increase this business. Furthermore, other less preferred options (i.e. donating or disposal) would not generate any revenue or even incur costs, since the cost price has already been paid for the product.

However, the close-out inventory does not cover the total desired assortment in a NFS, so this has to be made complete with 'rebuy' (or 'built') products. These rebuy products are manufactured exclusively for NFS, not for other retail stores. However, because the NFS needs to know how much rebuy products to order, Inventory Management is supposed to give a forecast of the close-out supply 9 months before. The ratio between close-out products and rebuy products at NFS is approximately 65% close-out versus 35% rebuy, but this fluctuates per PE and category. It is important to note that the employees in the NFS as well as the customers are not aware of the difference between rebuy and close-out inventory. Rebuy products can be considered as non-outstanding products since these are specially bought for the NFS, which do not require expensive, fashionable products but standard products which are able to complete their assortment.

The buy is done 6 months before introduction of the products in the selling season. After that four-month selling season, the products are dropped in close-out (if the products are not sold). The forecast for what will drop into close-out inventory should therefore be given 6 months before close-out drop, since rebuy products are also bought 6 months before introduction in the NFS. This means that the forecast for the close-out drop has to be given during the buy for the same products which will eventually end up in close-out drop. This indicates the complexity of forecasting the close-out drop. For example, see Figure 2. Suppose it is currently spring and IM is buying for fall. The products of fall will drop during the holiday season (first month of holiday season still dedicated for at-once orders for fall products). Simultaneously, the close-out drop for holiday has to be predicted, which consists of the products with selling seasons during fall.

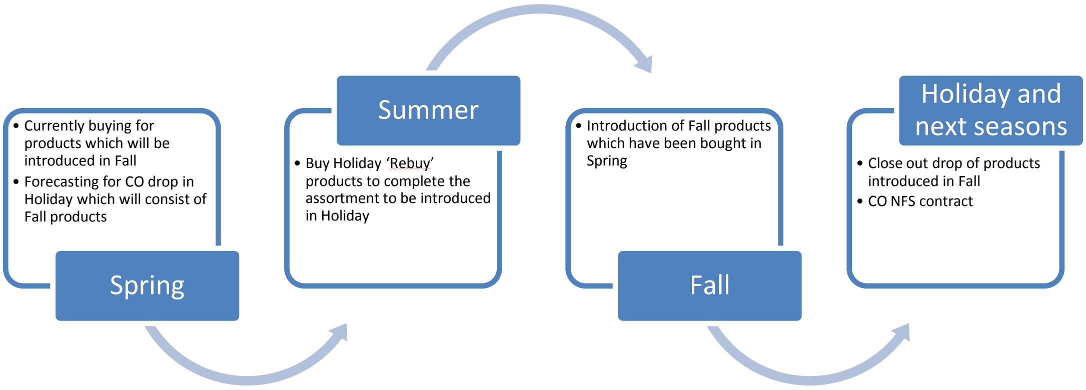


Figure 2 Example of CO drop for Fall products in Holiday

There is a difference in close-out drop and close-out supply, two terms which will be used during this research. Rebuys are not considered as part of the close-out drop and supply.

- Close-out drop – consists of all materials which will have their product lifecycle status changed at the end of their lifecycle (EPOD) from active to inactive and, therefore will become close-out inventory (in status in the systems)
- Close-out supply – consists of all products that become available as close-out ATP for Nike retail (NFS) but part of it not immediately after EPOD

The difference concerns the lifecycle change (drop) versus physical supply. Therefore, it is possible that there exist a difference between drop and supply in amount. Consider the following example:

If some stock in ELC is assigned to a future order, but the customer did not request the goods for whatever reason, the stock might reach EPOD in stock at ELC. Then the products are given a lifecycle change from active to inactive and are thus included in close-out drop. Then it might happen that the customer does request these products after lifecycle change and the products are shipped to the customer at full price. That means they are not included in close-out supply and not available to NFS.

One important note after the explanation on close-out and rebuy is that close-out is created with a purpose. The NFS are a profitable business and these should be supplied with materials. That means that it is the purpose of Nike to buy extra materials, which can be sold as close-out inventory after the selling season in the NFS. Nike does not buy according to the newsvendor model, since the forecast is (without exceptions) what is bought. Furthermore, quality of close-out materials is supposed good (excluding B-grades), the only difference is that selling season has passed.

Cancellations and returns

In the Nike Supply Chain there are a lot of processes which are important to understand before the close-out drop and supply process can be described in detail. The concepts cancellations and returns have a big influence on the close-out supply process.

Cancellations include (future) orders which are cancelled before delivery at the customer. There are cancellations by customer and cancellations by Nike Inc. In the subgroup cancellations by Nike there can be distinguished on product related cancellations, delivery related cancellations, end-of-season cancellations (open orders which are cancelled because products' lifecycle status is changed to inactive) and aged-orders cancellations. In the subgroup cancellations by the customer there exist credit related cancellations, non compliance related cancellations (customer did not follow Nike guidelines) and customer request cancellations (no reason).

Returns are goods which are returned from customers after delivery. Customers have ordered and received these products but sales or quality are below expectations. Nike takes these products back from the customer, will perform a quality check, put the products back in the ELC and then these will also become ATP. This does not imply that returns are only possible until the third month, since customers can delay delivery of their orders and delivery can even occur after supposed selling season. This delay is in their own interest, since they will be later on the market than their competitors. Thus, the main difference between cancellations and returns is that cancellations are owned by Nike, while returns have already been physically delivered to the customer.

Close-out supply process

An overview will be created of the close-out supply process, involving all possible flows of a purchase order. This process is quite complicated, taking into account the number of origins, but the actual physical flows of a product ending up in a NFS or at a customer (retailer) is less complicated. That is represented in Figure 3. Products manufactured in Asia are either shipped directly to the customer or via the ELC to the customer. It is possible that customers return products. Cancellations are not represented, since these stay physically in the ELC. From ELC, close-out inventory is shipped towards the NFS.

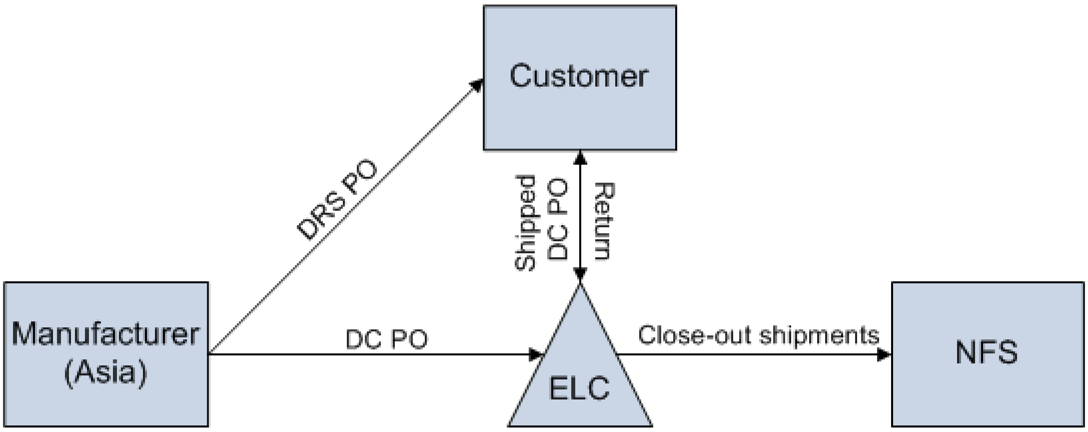


Figure 3 Physical flows in close-out supply process

Figure 3 shows a clear and simple overview of the physical flow of the products, but the flow of a purchase order through the system is more complicated, especially when timing is taken into account. This process is captured in Figure 4.

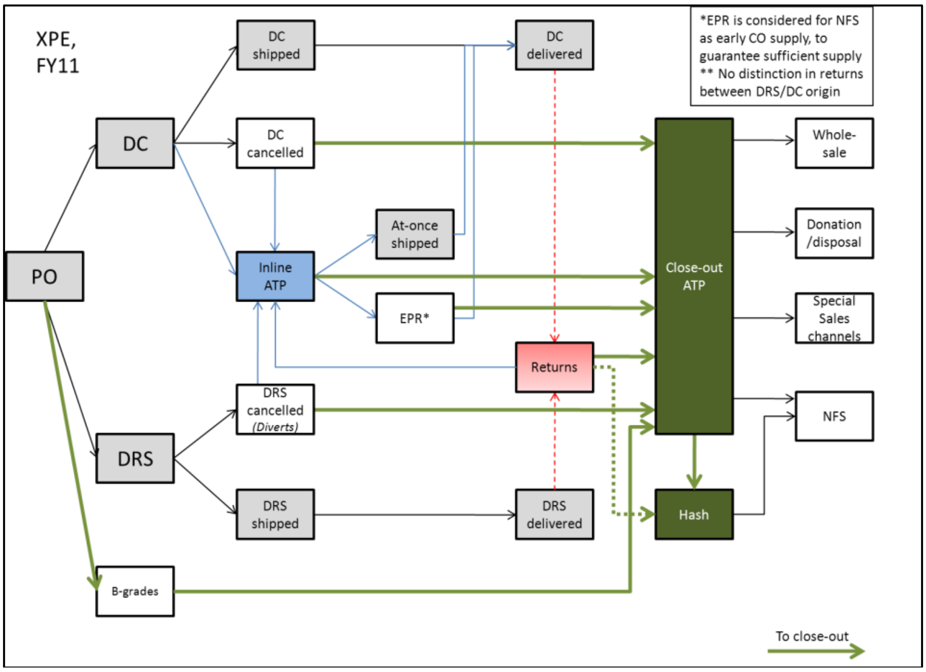


Figure 4 Process of products ending up as close out inventory

The described close-out supply origins have different moments in time at which they become available for NFS and wholesale and follow different routes until they end up in close-out inventory. These different moments complicate analysis of the close-out supply, since the possibility exists that products that already have the status inactive, did not become available yet. The start of this process in Figure 4 is a PO (Purchase Order) which is placed at the factories. This can either be a DC order, which will be shipped via the ELC, or a DRS order which will be shipped to a customer, in some cases via a deconsolidator. If the quality of the products is below expectations, it is called a B-grade. This is already checked at the factories, so B-grades are shipped to the ELC in Laakdal and will be labeled close-out inventory or hash immediately.

The DC PO can be divided in a majority of DC orders which are regularly shipped to the customers, some orders which will be cancelled by customers and a quantity which is not directly related to a sales order which will go into ATP (Available-to-Promise) in ELC to fulfill immediate (at-once) demand. The DC orders are delivered to the customer, and a small percentage will be returned by customers. These have been physically out of the ELC. DC cancellations have two destination options. If these orders are cancelled before the close-out drop they will be added to the ATP in ELC, else they will go immediately into close-out inventory. DC cancellations have not been physically shipped, but were reserved. The ATP has three destination options. The products can be shipped out as at-once orders to customers, and these are therefore regarded as DC delivered products. Part of this will be returned by customers, similar to the DC shipped orders. Another part will be bought as EPR by wholesale and NFS to ensure they have enough close-out supply (see EPR description). The remaining quantity will be involved in the drop and will go into close-out inventory.

The DRS PO can be divided in a DRS which is either cancelled (DRS Diverts) or delivered. DRS cancellations have two destination options. If these are cancelled before the close-out drop the materials will be dropped into Inline ATP, if these are cancelled and received after the drop, the materials will be added to close-out inventory immediately. Only a small percentage of the DRS which are delivered to the customers will be returned, like the DC returns. Returns have the same options as the DC cancellations and the DRS cancellations (Diverts). If these are received in ELC in Laakdal before the close-out drop they will be dropped into inline ATP, else they will move immediately into close-out ATP. Since returns have a significant lead time to be returned to ELC, it is plausible that the majority will drop in close-out immediately. Part of the returns will have diminished quality and will be hashed immediately.

The objective was to quantify all the percentages or values on the arrows to increase insight into the close-out process. However, it was impossible to gather all this data, due to limited availability of particular information and the different operation systems at Nike. Therefore, it was i.e. not possible to distinguish between cancelled orders which were shipped to either close-out ATP or inline ATP. It can be concluded that the process of close-out supply is too complicated to be quantified. Multiple departments are involved in the close-out supply, which makes visibility low since information is on later moments available than desired. This will complicate the forecasting improvement process, since visibility is low and therefore it is difficult to predict what will happen in the process.

Close-out supply chain facts

There are a few important close-out supply chain facts which are important to recognize when improving close-out forecast performance. These are the distribution in close-out inventory sold to NFS and wholesale and the distribution between rebuy products and close-out products bought by the NFS. Furthermore, the scope of the project excludes the Turkey and Russia DC, and an analysis will show why this is excluded from the research project. These figures are shown in Appendix A.

Research question

The problem definition has indicated what the difficulties are for Nike to forecast the close-out supply. Based on this problem definition, the research question for the graduation project will be defined. Therefore, a short recap of the problem will be given next. Nike Factory Stores (NFS) are supplied with both close-out inventory and rebuy products. Based on the forecast of the close-out supply they decide, on a medium term on which rebuy products to buy and on a shorter term, how to adjust policies (EPR) to delay or accelerate sales. Thus, close-out supply projection is important and currently Nike is not performing as desired. The objective of the project is thus twofold.

1. The medium term forecast they receive needs to be accurate so the rebuys they plan will complete the assortment in the right quantities. The NFS need to order rebuy products just like other future orders, approximately six months before. Therefore, a forecast of close-out supply needs to be given before that time, so NFS can adjust their rebuy orders based on information about close-out availability. Therefore, they need information on the amount of close-out supply nine months before close-out supply. This amount of close-out supply should be given on product engine, category and gender level, for NFS to optimize their rebuys. Since the rebuy is finalized six months before, the forecast of six months before close-out supply is also taken into account. If this forecast is not accurate, the rebuys will not represent the right addition to the close-out supply. Thus, this forecast has a horizon of 9 months. This is illustrated in Figure 5.

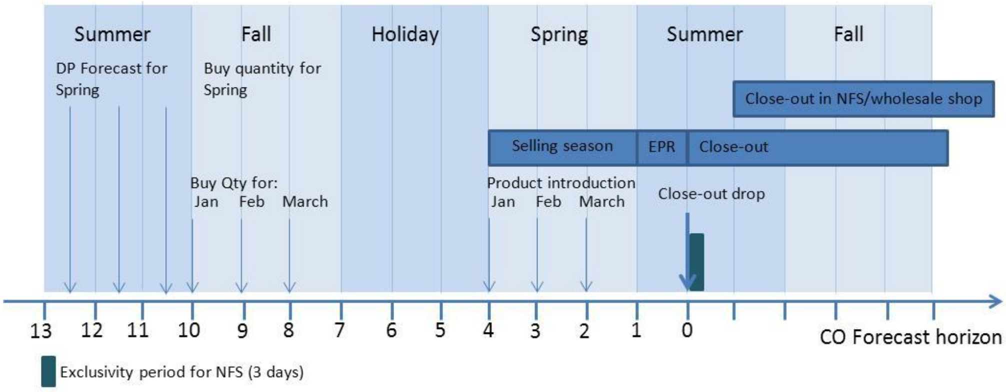


Figure 5 Timeline with horizons and decision moments

2. The short term forecast they receive needs to be accurate so the plan/policy for that season can be adjusted to the forecast. This forecast, with a horizon of 3 months (between 1 and 3 months before close-out drop), will indicate whether Nike was in the right direction with the earlier forecasts. NFS require that this forecast will be given on product engine, category and gender level, and if possible on silhouette. With this information they can adjust their short-term strategy to create a balanced assortment on product engine, category, gender and silhouette.
    - If there is much less supply compared to what was expected, NFS needs to collect extra supply of products (EPR) to complete the assortment in the factory stores. EPR is considered an early close-out supply, it offers the NFS the opportunity to be ensured they have sufficient supply, which they would have bought later if there was no shortage.
    - If there is too much supply of close-out inventory compared to what was expected, Nike holds too much inventory, causing extra costs. Furthermore, they need to get rid of these products, and there are three options to send the products to; NFS, regular retail channels (wholesale) and special sales channels. These options will also cause extra costs, since discounts will be given and margins will decrease. Other less preferred options are donation and disposal. In the case of too much close-out supply, NFS also needs to accelerate sales with special advertisement or discounts.

Concluding, in the case of too much supply, Nike incurs extra costs for holding excess inventory and for giving discounts to sell it to customers.

For both forecast moments it is not desirable for Nike that there exist big gaps between projected and actual quantities, and therefore it is really important that close-out inventory forecasts are accurate. Of course, it is impossible to constantly give a perfect forecast on close-out inventory for a future state, but Nike should strive to achieve a certain performance level of forecasting. The gap between projected and actual close-out inventory supply does not only exist on aggregate level, but also on category, gender and silhouette levels. The assortment of NFS should be balanced over all categories, as well as on gender level and on silhouette, thus the supply to NFS consisting of close-out and rebuys will have to be balanced over categories, gender and silhouette as well. It is the purpose of the NFS to have a complete assortment which is in balance.

The goal of the graduation project, as defined by Nike, is to develop a methodology/model/process around close-out volume predictability. Since the more accurate Nike can forecast, the better Nike can plan rebuys to create a stable supply to NFS.

Improving the predictability does not concern that the quantity close-out supply is on a certain level, this is out of scope of the project. It is important the forecast of this quantity close-out supply is accurate, so the total supply towards NFS can be adjusted with rebuys. The NFS receives the forecast of the close-out inventory as an input, and compares the close-out inventory forecast with the NFS expected demand to determine the rebuy quantity to complete the assortment. An important aspect of the predictability is the visibility of close-out inventory. A part of close-out inventory is not available for NFS because it is still in transit, but the NFS thinks they can buy it. However, another internal project is currently ongoing on the visibility and availability of close-out inventory, so that will be out of scope of this project. Furthermore, another internal project is ongoing on improving the short-term close-out supply (1 month horizon), so the focus of this graduation project will be on the medium-term close-out supply forecast.

The research question should therefore be defined as:
How can the predictability on (both short-term and) medium-term of the close-out supply to NFS be improved by developing a procedure which takes into account historical data on close-out supply, information about drivers for the close-out supply and the current way of working at Nike?

Related sub questions to be able to answer the research question will be mentioned in the chapter analysis.

Scope and assumptions

- The scope of this research is the European region, excluding Turkey and Russia DC processes.
- All three product engines will be analyzed, but Nike Golf is excluded.
- The long lead times will be taken as a given during this research.
- EPR is considered as early close-out supply
- Rebuys are not taken into close-out supply, since rebuys are adjusted based on the close-out supply forecast. The gaps between close-out supply and close-out demand are supposed to be filled with rebuy products.

Data sources

Multiple systems are used at Nike for daily operations of the Planning departments. These multiple systems are not totally aligned, since they make snapshots on different moments or have slightly different selection criteria. Therefore, an overview of used data sources for data collection is given in Appendix B.

Analysis

Literature review

The methods to assess forecast performance as well as forecast methods have been described in literature. These methods are applied on data which contains historical forecasts of close-out supply at different points in time (for different forecast horizons) which will be compared to the actual close-out supply. This chapter will first describe the forecast methods and forecast measurement methods for time series analysis.

Traditional forecasting methods

Silver et al. (1998) provide an overview of forecasting methods, starting from the simpler or basic methods to some more advanced approaches to forecasting. They consider the following standard model of short-term forecasting for individual products, with the dependent variable x_t, the demand in period t.

$$x_t = (a + bt)F_t + \varepsilon_t$$

The variable a represents the demand level, while b represents the linear demand trend. F is the seasonal coefficient model and ε is the independent random variable with mean 0 and σ^2 = constant. If there is no seasonal component or no trend model, then respectively F can be removed out of the equation and b will become zero.

Simple Moving Average (MA) and Weighted Moving Average (WMA)

Silver et al. (1998) start by describing the simple moving average, which is the model without seasonal component and trend. The simple N-period moving average for x_t, at the end of period t, is given by the mean of the last n observations.

$$\bar{x}_{t,N} = \frac{x_t + x_{t-1} + x_{t-2} + \cdots + x_{t-N+1}}{N}$$

Another possibility when predicting with moving average is the Weighted Moving Average, which assigns most weight to the most recent observations.

Regression procedures

Silver et al. (1998) explain the regression procedures for the simple case of an underlying model that assumes that demand is a linear function of time. Regression procedures focus on the relationship between the dependent variable (x_t) and the independent variables (a and b). The simple regression model can be described by;

$$x_t = a + bt + \varepsilon_t$$

The values a and b are calculated based on the last n historical observations. This approach gives each of the historical observations the same weight in the calculated forecast. The formulas for calculating a and b are given by Silver et al. (1998).

$$\hat{b} = \frac{\sum_{t=1}^{n} t x_t - \left(\frac{n+1}{2}\right) \sum_{t=1}^{n} x_t}{\frac{n(n^2-1)}{12}}$$

$$\hat{a} = \sum_{t=1}^{n} \frac{x_t}{n} - \frac{\hat{b}(n+1)}{2}$$

The forecast is now given by $\hat{x}_{t+h} = \hat{a} + \hat{b} * t$, with h the forecast horizon. It is also possible to extend this linear regression model to a seasonal regression model.

Attribute forecasting

One specific form of regression procedures is attribute forecasting. According to Fisher and Raman (2010), the best way to buy is to carry a set of SKUs that includes all possible values of these attributes and pick the attributes that customers favor. Therefore, Fisher and Raman (2010) propose to define each SKU as a collection of attributes, like price, color and raw materials used. Then prior sales data are used to forecast the market share in a store for each attribute and this forecast is used for each individual SKU. This way it is possible to forecast sales for products which are new in the market. Nike business is especially suitable for this, since Nike products are introduced each season and have short lifecycles, so probably no information is available on historical sales for that particular item. Therefore, these attributes might indicate the sales of new introduced products. Attribute forecasting is a regression procedure, since it predicts the behavior of a dependent variable with (multiple) other variables.

Aspects like color or size might give an indication of close-out supply at the end of the season. For example, if green shirts are bought for the inline season, but they never end up in close-out, this could imply that green shirts have high selling rates during the season and are always sold out before the end of the season. Therefore, an analysis will be done on the attributes to check if certain attributes are predictors of close-out supply. The attributes which will be analyzed are size, price, silhouette and color. It can be expected that extreme large or small materials will end up in close-out, since these are more unique. NFS have the objective to act as an outlet store; therefore they do not sell extreme expensive products. However, it can be expected that these end up more in close-out inventory, increasing the possibility of expensive leftover stock even after the close-out selling season(s). Furthermore, it could also be expected that buying behavior differs per price category, i.e. planners buy less careful for cheaper materials. Color can be chosen, since color is a fashion aspect and fashion might influence the remaining materials at the end of a season. If materials have a color that can be categorized as fashion color, it is expected that this material will be bought more during that particular season, resulting in less close-out. Each of these attributes will be separately analyzed on buy quantity and close-out, starting with color.

Exponential smoothing

This provides a forecast which is a smoothed average of last *N* observations, calculated using a discount or smoothing constant *d*. These models use a weighted average of past values, in which the weights decline geometrically over time to suppress short-term fluctuations in the data. The underlying assumption of this technique is that the data follows a certain historical pattern in which the more current the observation is, the more relevance it has in predicting the future (Alon et al., 2001).

Simple exponential smoothing

The smoothed average is calculated as $(1-\alpha)$ multiplied with actual sales and α multiplied with actual demands of the previous period. Since the discount *d* has a value between 0 and 1, the weighting of historical data is decreasing over time. The most recent observations are the most reliable for a forecast. First an exponential smoothing model will be described based on an underlying demand model without trend or seasonal components ($x_t = a + \varepsilon_t$), called simple exponential smoothing. Silver et al. (1998) give the formula to compute the estimate of l, leading to forecast $\hat{x}_t$:

$$l_t = \alpha x_t + (1-\alpha)\hat{a}_{t-1}$$

with α the smoothing constant and $l_2 = x_1$. This smoothing constant will be chosen according to the following formula (Silver et al., 1998), depending on the value *n*, the number months taken into account in the forecast.

$$\alpha = \frac{2}{n+1}$$

The forecast for the following period (depending on forecast horizon *h*) is given by $\hat{x}_{t+h} = l_t$. The simple moving average, earlier explained, can be considered as an exponential smoothing technique, but with unweighted variables.

Exponential smoothing with (damped) trend

Exponential smoothing can be extended with a trend model *($x_t = a + bt + \varepsilon_t$)*, suggested by Holt (1957, in Silver et al., 1998). A regular least squares regression on the historical data available needs to be executed to calculate *a* and *b* to derive the forecast x_t. It can also be extended with a damped trend if a linear trend is not accurate enough. According to Silver et al. (1998), the formulas for defining *a* and *b*, with α_{HW} and β_{HW} the smoothing constants, are:

$$\hat{a}_t = \alpha_{HW} x_t + (1 - \alpha_{HW})(\hat{a}_{t-1} + \hat{b}_{t-1})$$

$$\hat{b}_t = \beta_{HW}(\hat{a}_t - \hat{a}_{t-1)} + (1 - \beta_{HW})\hat{b}_{t-1}$$

Calculation of the smoothing constants should be done using *α* and *β*:

$$\alpha_{HW} = (1 - (1 - \alpha)^2)$$

$$\beta_{HW} = \frac{\alpha^2}{1 - (1 - \alpha)^2}$$

The forecast for the following period (depending on forecast horizon *h*) is given by $\hat{x}_{t+h} = \hat{a}_t + \hat{b}_t$.

In the situation when a linear trend is not very accurate and especially when forecasting several periods ahead, Silver et al. (1998) propose to use a damped trend. The damping parameter φ is multiplied with every on the value $\hat{b}_{t-1}$ in the formulas for $\hat{a}_t$ and $\hat{b}_t$, and if *$0<\varphi<1$* the trend will be damped. If φ is 1 the trend is linear, while if *$\varphi>1$* the trend is exponential. The forecast for the following period is then given by $\hat{x}_{t+h} = \hat{a}_t + \hat{b}_t \phi$.

Exponential smoothing with trend and seasonality (Winters)

When the demand pattern includes both trend and seasonality, Winters' exponential smoothing procedure can be used. Winters' model is a three parameter exponential smoothing model which incorporates a simple smoothing series, a trend effect and a seasonal effect (Alon et al., 2001). Winters (1960, in Alon et al., 2001), showed that this model is superior to the simple exponential model and the naïve model in predicting sales of three different products.

The model needs estimates for the variables *a*, *b* and *F*, for which formulas are developed based on three smoothing constants. These smoothing constants are between 0 and 1, to achieve the geometrically decreasing importance of historical data. The model becomes considerably more complicated, because of the presence of both trend and seasonal factors. Therefore, Silver et al. (1998) describe the process of defining the forecast estimate in three steps.

1. The initial estimation of level including trend for each historical period by creating moving averages over multiple periods for one period. This is the required initialization period, which requires that there is sufficient data in time length to estimate these parameters. Sufficient data means three 'seasons' or 'periods' of demand, the first for initialization, the second for creating the forecast and the third for measurement.

2. Estimation of the seasonal factors, by dividing the actual demand by the moving average over multiple periods. This estimate shows a seasonality pattern, which is called the *F*.
3. The estimation of the values for variables $\hat{a}_t$, $\hat{b}_t$ and $\hat{F}_t$ by using the formulas from the regression procedure. These formulas are given next, in which α_{HW}, β_{HW} and γ_{HW} are the smoothing constants and *P* represents the number of seasons.

$$\hat{a}_t = \alpha_{HW}\left(x_t/\hat{F}_{t-P}\right) + (1-\alpha_{HW})\left(\hat{a}_{t-1} + \hat{b}_{t-1}\right)$$
$$\hat{b}_t = \beta_{HW}(\hat{a}_t - \hat{a}_{t-1}) + (1-\beta_{HW})\hat{b}_{t-1}$$
$$\hat{F}_t = \gamma_{HW}(x_t/\hat{a}_t) + (1-y_{HW})\hat{F}_{t-P}$$

The forecast for period x_{t+h} can now be defined as $\hat{x}_{t+h} = (\hat{a}_t + \hat{b}_t h)\hat{F}_{t+h-P}$

The explained traditional forecast methods are not the only possibilities to improve close-out forecast accuracy at Nike. Another possibility is attribute forecasting, which investigates the influence of particular attributes of products on the result, in this case close-out supply.

Forecast accuracy measurement methods

It is important to measure the accuracy of forecasts, because it serves as feedback on current forecasting performance. The feedback can be used as input for future forecasts because it will provide insights on mistakes or on which methods are suitable and which not. This chapter will first describe measures of forecast variability, then measures of the forecast bias and conclude with corrective actions in forecasting.

Measures of forecast variability

Measurement of forecasting variability is done by comparing the forecasts made one period ahead with the actual observed quantities. Different measures are in use to determine the accuracy of forecasts. Silver et al. (1998) describe the different methods for measuring forecast errors. These are the mean square error (MSE), the mean absolute deviation (MAD) and the mean absolute percentage error (MAPE). To describe these forecasts measurements, they also take into account the σ_1 and the σ_L. These represent:

- σ_1 = the estimate of the standard deviation of forecast error over one basic period
- σ_L = the estimate of the standard deviation of forecast errors over a leadtime of duration L basic periods

<u>Mean Square Error (MSE) and Root Mean Square Error (RMSE)</u>

The mean square error (MSE), one of the most used methods, describes the average of all squared deviations, which can be compared to σ_1. The formula used to calculate the MSE is:

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(x_t - \hat{x}_{t-1,t})^2$$

The MSE can be extended to RMSE (Root Mean Square Error), giving the root of the MSE.

<u>Mean Absolute Deviation (MAD)</u>

The mean absolute deviation (MAD), which is computational simple, gives the average of all absolute deviations. According to Silver et al. (1998), the MAD is currently of less importance, since there are more advanced possibilities for performing complex computations. The MAD and MSE, which are scale- dependent measures, can be used to compare different forecast methods on the same data set, but these are not useful when comparing different data sets (Hyndman and Koehler, 2006).

$$MAD = \sum_{t=1}^{n}\left|x_t - \hat{x}_{t-1,t}\right|/n$$

Mean Absolute Percentage Error (MAPE)
The mean absolute percentage error (MAPE) presents another measure of forecasts errors, and it shows the average of all percentage errors from actual demand. The advantage of the MAPE is that this method is scale-independent, is simple to calculate, easily interpretable and can be used to compare different data sets (Hyndman and Koehler, 2006). However, the disadvantages of MAPE are that it is undefined if the Y_t(actual quantity) is zero, that it creates an extremely skewed distribution when any value of Y_t is close to zero, that they assume a meaningful zero and that they put a heavier penalty on positive errors than on negative errors (Hyndman and Koehler, 2006 and Silver et al., 1998).

$$MAPE = \left[\frac{1}{n}\sum_{t=1}^{n}\left|\frac{x_t - x_{t-1,t}}{x_t}\right|\right] \times 100$$

Mean Absolute Scaled Error (MASE)
Another measurement tool for forecasts is MASE. MASE (Mean Absolute Scaled Error) is proposed by Hyndman and Koehler (2006) as the standard measurement tool for comparing forecast accuracy across multiple time series after a comparison across various accuracy measures for univariate time series. MASE can be calculated using the scaled error defined by Hyndman and Koehler (2006):

$$q_t = \frac{e_t}{1/(n-1)\sum_{i=2}^{n}|Y_i - Y_{i-1}|}$$

The MASE can be calculated by taking the average of the absolute values of the scaled errors (Hyndman and Koehler, 2006):

$$MASE = mean(|q_t|)$$

The formula to calculate the MASE is based on the one-step naïve forecast model. This one-step naïve forecast model is supposed to have low forecast accuracy, since the forecast is based on the last observation and seasonality and trend are not included in that model. The scaled error is calculated by dividing the error between forecast and actual quantity by the average of all one-step naïve forecast model errors. If the scaled error is less than one it is a better forecast than the average one-step naïve forecast computed and conversely, if the scaled error is greater than one the forecast is worse than the average one-step naïve forecast (Hyndman and Koehler, 2006).

Hyndman and Koehler (2006) compare MASE to the other common measurement techniques and show that MASE performs better under certain circumstances. They explain that MAD and RMSE are useful when time series are on the same scale, while these methods are easy to explain. MAPE is considered as an appropriate, easy interpretable, measurement method across time series when data is positive and much greater than zero. However, Hyndman and Koehler (2006) show that when data exists on very different scales including data which are close to zero or negative, MASE is the best available measure of forecast accuracy.

Measures of forecast bias
Another important tool for measuring forecast accuracy is the forecast bias. If there is a forecast bias, this indicates that on the average, the forecasts are substantially above or below the actual demands (Silver et al., 1998). If there is a constant negative or a constant positive forecast, the forecast is biased. Silver et al. (1998) define two ways to measure the forecast bias, the cumulative sum of forecast errors and the smoothed tracking signal.

The cumulative sum of forecast errors results in a tracking signal which shows if the forecast is biased or not. This tracking signal is calculated by dividing the cumulative error by the average MAD.

In the ideal unbiased situation, the cumulative error will be zero, because the positive and negative errors will compensate each other. If there are only negative or only positive errors, the forecast is biased, and the cumulative error will become large compared to the average MAD. The disadvantage of this measurement method is that large errors influence the tracking signal significantly. The cumulative sum of errors tracking signal should be between -4 and 4 to be regarded unbiased (Silver et al., 1998). If the tracking signal is close to zero it means that there is no bias.

The smoothed tracking signal is also used together with the MAD. The smoothed error tracking signal shows the behavior of forecast errors over time and is defined by:

$$T_t = \frac{z_t}{MAD_t}$$

With

- T_t = value of the smoothed error tracking signal at the end of period t
- MAD_t = mean absolute deviation at the end of period t
- z_t = smoothed forecast error at the end of period t

The values z_t and MAD_t (same formula for MAD_t) will be updated with a smoothing constant α:

$$z_t = \alpha\left(x_t - \hat{x}_{t-1,t}\right) + (1-\alpha)z_{t-1}$$

This smoothed tracking signal will always be between -1 and 1. The same rule applies here, that if the smoothed tracking signal is close to zero, the forecasts are unbiased.

Quantitative analysis of the close-out goods flow process

The process scheme which was created showed the origins of close-out supply, but it was impossible to quantify all flows. It is important to quantify these origins, to be able to show which flows are most important for close-out supply. This chapter shows the percentage existence of all close-out origins in the close-out supply. However, some assumptions had to be made, since not all data was available over the investigated time period. This analysis of close-out supply covers the year 2010 (Jan-Dec), since that is the only period all data is available. The assumptions are:

- DC cancellations, ATP close-out drop and promo had to be considered as one close-out origin, since it was not possible to distinguish in the data between these materials
    - Because the major part of DC cancellations drops into close-out before the ATP close-out drop it was not possible to separate these values
- Hash might be included in some other close-out origins, but because it is impossible to track this, it is considered as a separate component of close-out supply.

These assumptions constrain the accuracy of the output of this analysis, although it still shows the percentage existence of all close-out supply origins. Table 1 shows the average values of close-out origins in 2010 compared to the total close-out supply. The error resulting of hash included in the other close-out origins is at most 5% (for all PEs), since the total hash shipments account for only 5% of total close-out supply.

Table 1 Existence of CO origins

CO origins (averages 2010)	%APP	%FTW	%EQM	%XPE
EPR	11%	12%	12%	12%
Returns	16%	22%	18%	18%
DRS Diverts	11%	23%	17%	16%
Hash	3%	9%	1%	5%
B-grades	3%	3%	15%	4%
DC clx (ATP, Open qty and promo)	56%	30%	37%	45%

Most obvious result is that the B-grade value and percentage for EQM is extreme high compared to FTW and APP. In first instance it was even higher percentage, but is has been adjusted by taking the average over last years to be sure this overview does give a right representation. The reasons why EQM has higher percentage B-grade shipments are the following:

- The EQM planning department compensated insufficient close-out supply with extra B-grade supply from ATP stock during the investigated period.
- The definition of B-grades is less restrictive for EQM, therefore more products are included as B-grade.

The DC cancellations represent the major part of the close-out supply, while returns and DRS diverts are also important close-out origins. The resulting 2% EPR of total close-out supply is a logical result, since EQM department stopped buying EPR. The other PEs have higher percentages of EPR (11-12%), showing that the option to guarantee supply to NFS is valuable. Hash is just a small part of the close-out supply for all PEs. The results from Table 1 are graphically represented in Figure 6.

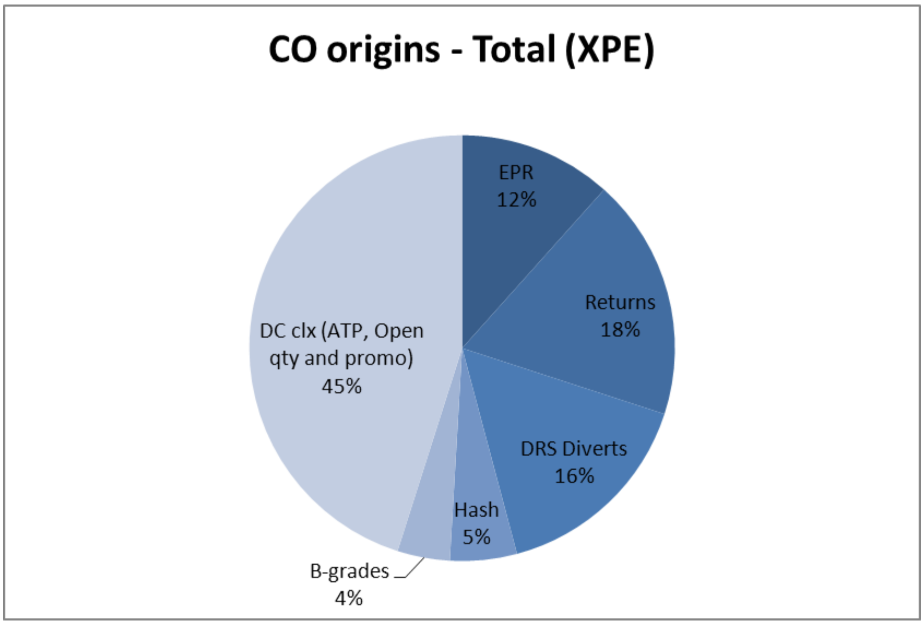


Figure 6 Close out origins in percentages measured over all PEs

Research question and design questions

The research question was defined as:

How can the predictability on (both short-term and) medium-term of the close-out supply to NFS be improved by developing a procedure which takes into account historical data on close-out supply, information about drivers for the close-out supply and the current way of working at Nike?

The research question can be translated into several design questions, which should be answered to be able to answer the final research question.

1. *Which forecast accuracy measurement tool is preferred for determining close-out supply forecast performance at Nike?*

The measurement tool for measuring forecast performance should be selected. The expectation is that MAPE (Mean Absolute Percentage Error) is the preferred method for measuring forecast accuracy at Nike. The advantage of the MAPE is that this method is scale-independent, is simple to calculate, easily interpretable and can be used to compare different data sets (Hyndman and Koehler, 2006). Since the product engines have different volumes, another opportunity to measure forecast accuracy, if MAPE does not return the required results, is MASE (Mean Absolute Scaled Error), which is also proposed by Hyndman and Koehler (2006).

2. *What is the current close-out supply forecast accuracy (measured for each PE)?*

Since Nike initiated the project on close-out supply forecast improvement, it is expected that forecast performance is less than desired. Benchmark for comparing forecast performance is given by Wong and Guo (2010), who have analyzed different forecast heuristics on real sales data of a retailer in China. The average MAPE in their study (same period and horizon) is 11.6%. It is expected that current forecast performance at Nike is worse than this value, since the benchmark considered regular demand forecast. Furthermore, the three product engines will be compared on forecast performance. Therefore, an analysis will be done on the differences between the product engines, to be able to indicate which product engine will probably have best close-out supply forecast results. In Appendix C this comparison between the product engines is given. Based on that comparison on aspects which differ between the product engines, it is expected that forecast performance will be best for product engine FTW. The reason is that FTW has the most standardized processes in the supply chain (see Appendix C). Furthermore, it is expected that forecast performance will increase by decreasing the forecast horizon.

3. *What models can be used to develop a better close-out forecasting system? Which forecast tool performs best predicting the close-out supply at Nike?*

Creating a new neural network is time consuming and it requires extensive process knowledge (Zhang et al., 2005), therefore this will not be possible for this research project. Traditional forecast methods described by Silver et al. (1998), including moving average, regression procedures and exponential smoothing can be tested on their performance at Nike. These methods will be included with trend and seasonal factors. Since Nike has defined four selling seasons, it is expected that seasonality will play a major role in the close-out supply and thus in defining the forecast. Therefore, it is expected that Winters' model (exponential smoothing with trend and seasonality) will deliver best results. Regression models will also be tested and it is expected that the buy quantity and the demand planning forecast are predictors of close-out supply, since the close-out supply is a leftover of these two facts.

4. *Is it possible to create a more predictable flow to NFS using the distribution of the buy quantity or demand planning forecast?*

Other opportunities will be investigated to improve close-out forecast accuracy. It is possible that exponential smoothing and moving average methods do not yield desired results, and therefore other methods will be implemented as well. It is possible to reflect the buy quantity or demand planning distribution among categories on the total expected close-out supply to obtain a forecast. It is expected that the buy quantity is a better predictor of close-out supply than demand planning forecast. The demand planning forecast is the first indicator of close-out supply. The buy quantity can be considered as an adjustment of the demand planning forecast, since the planning department (IM) drops materials or adjusts values of the demand planning forecast to their final buy quantity. The remaining products which are leftover after the selling season (close-out supply) are therefore residuals of the buy quantity. If something drops into close-out, it must have been included in buy quantity, and not necessarily in demand planning forecast.

5. *Are there differences among attributes in close-out supply and can attribute forecasting improve the close-out supply forecast?*

Another possible solution is to analyze the close-out supply on attributes. These attributes might also be predictors of close-out supply. Attributes which were possible to analyze (data availability) and were thought to have significant influence are size, price, silhouette and color. It is expected that strange sizes (extreme large and small) will end up more in close-out. The reason is that planners have to buy these products in higher values than expected to be able to fulfill possible demand. The possibility that these products will drop into close-out inventory will therefore increase. The second attribute, prices, depend on the strategy of the planning department. If planners would be more careful in planning expensive products, it would be expected that less expensive products would drop more in close-out. Currently, there is no distinction in buy quantity on price, therefore it is expected that expensive products will drop more in close-out than less expensive products since these are more sensitive. Fashionable colors are also more sensitive to demand, and therefore it is also expected that odd colors (not black/white/blue), will drop more in close-out. Attribute silhouette is also investigated to check whether there is a relationship between silhouette and close-out inventory.

Hypothesis 1: Extreme large and small sizes (odd sizes) drop significantly more in close-out than more regular sizes.

Hypothesis 2: Higher priced products drop significantly more in close-out than lower priced products.

Hypothesis 3: More fashionable colors will drop significantly more in close-out than more standard colors like black/white and blue.

One other obvious opportunity to create a more predictable flow to NFS is lead time reduction. Lead time reduction will reduce the need of the forecast 9 and 6 months before the selling season. If NFS can order their rebuys at a later moment (closer to the close-out drop), they also need the forecast from IM at a later moment. However, lead time reduction is very hard to accomplish, since transferring the materials from Asia to Europe takes approximately a month. One option is to transfer the units with airfreight, which will only gain approximately two weeks, but this is too expensive and not desirable. Production in countries closer to the European market is another option to reduce lead times, but the low manufacturing costs in Asia outweigh this option. Nike has implemented one solution to reduce lead times, by changing some EQM materials into always available. These materials have a shorter time to market, because these are not restricted to one selling season and will be continuously shipped to Europe.

The research question and related design questions have been defined, hypotheses are deducted from these questions, and the process of products ending up in close-out has been extensively analyzed. Conclusion is that the process is very complex and unpredictable, and traditional forecast methods are not considered as a realistic option to improve close-out supply forecast. However, to check whether forecasts need to be improved, current forecast performance will be measured first.

Current close-out forecast performance

Nike initiated the project on close-out forecast accuracy because current forecast performance is not as desired. This close-out performance will first be measured using historical data, which is generated on a product engine level. Since the product engines APP and EQM only had a seasonal close-out drop until now, it is not possible to measure this on a monthly basis. For FTW, measurement will be done on a monthly basis, but the forecast performance for seasonal drops will also be measured for comparison with the other product engines. The available data on historical forecasts goes back to season FA09 (June 2009) and can be measured until SP11, which is March 2011. This covers in total seven seasons. Measurement will be based on seasons (and not on quarters of the fiscal year), since NFS and the department Inventory Management view it as a seasonal drop. As indicated before, EPR is included in the close-out supply, while rebuys are left out of consideration.

Since the NFS have indicated they require forecasts at different moments in time, these will be compared. Therefore, the forecast horizons which will be measured are:

- 9 months before drop, because then indication is needed for rebuy
- 6 months before drop, because then rebuys are ordered based on that forecast
- 3 months before drop, because it will give an indication for the short-term strategy (accelerate sales, buy EPR etc.)
- 1 month before drop, because it will give an indication for the short-term strategy (accelerate sales, buy EPR etc.)

The first two forecasts (9 and 6 months before close-out drop) will be given most attention, since currently other employees are also developing tools to improve close-out forecast on the short term. Data is extracted from liquidation sheets, which show the behavior of close-out inventory on both demand and supply side, and which give a forecast for the following months. The forecasts given out for the following months were used (if available) to measure against the given actual close-out supply. The MAD, MAPE and MASE will be used as forecast measurement methods for variability. This measurement will also be used to indicate which method is best.

- The MAD shows the absolute deviance, which is useful because this value shows the difference in close-out supply which should be solved, by either accelerating sales or by creating extra supply.
- The MAPE shows the percentage deviance, which gives insight into the relative importance compared to the total close-out supply. MAPE also offers the opportunity to compare the percentage error between product engines. Since there is no data on lower materials, all data contains values which are not close to zero or zero, thus MAPE gives reliable results. However, when data will be analyzed on lower material levels, the values will approach zero and MAPE will give less reliable results.
- MASE will be used, since it, according to Hyndman and Koehler (2006), gives the best results when data exists on very different scales including data which is close to zero.
- Another measurement tool which will be used is the forecast bias. The forecast bias will show if the forecasts are on average substantially above or below the actual demands. This technique will show if there is a positive or a negative trend in forecasting.

Forecast Performance: all product engines (X-PE)

The difference between the forecasts given at different moments in time for the specific seasons and the actual close-out shipments during that season are shown in Appendix B. **Error! Reference ource not found.**The actual close-out supply for all product engines can be graphically represented as in Figure 7. There is a massive decline from HO09 to SU10 in close-outsupply, while afterwards close-out supply is back on a basic level. This decline has its major cause in APP, as is visible in Figure 7 where FTW and EQM are quite stable.

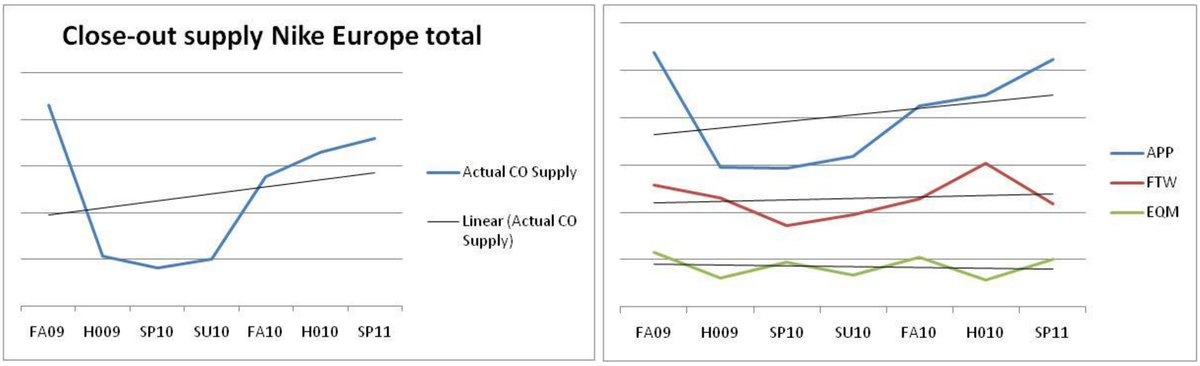


Figure 7 Actual close out supply for X-PE and for all PEs separately

The forecast performance measurement of Nike for all PEs is given in Table 2. Average close-out supply is also given, since that shows the differences between the volumes per product engine. On average, over all forecast horizons and for all PEs, Nike has a 15% forecast inaccuracy (MAPE). This means that on average the forecast deviates 15% of the actual supply. The absolute deviation is 477k units on average over all forecast moments. The MASE shows the scaled error, which is compared against the naïve forecast. As was earlier explained, MASE compares the forecast by the naive forecast and if the MASE is lower than one, the forecast is better than the naïve forecast. Since MASE is lower than one, forecasting at Nike is better than the naive forecast, which should be considered usual.

Table 2 Close out supply forecast performance of all product engines

Comparison (incl. EPR)	FTW	APP	EQM	All PEs
Average CO shipments	1147	2030	428	3605
MAD (000)	136	393	131	477
MAPE	12%	22%	34%	15%
MASE	0.75	0.71	0.64	0.56

MAPE and MAD

The MAPE, the most used forecast measurement tool, shows inaccuracies of 12%, 22% and 34%, with an average for all PEs of 15%. It should be compared to forecast performance in the same industry to be able to judge this performance. Wong and Guo (2010) have conducted an analysis to six different (medium-term) forecast techniques using real sales data from one of the largest fashion retail companies in Mainland China. This is considered a comparable situation to Nike, as sports fashion apparel and footwear manufacturer, since the analysis of Wong and Guo (2010) also involves medium-term forecasting techniques for quarterly sales data. Current forecast performance at Nike is measured for seasonal sales data for medium-term forecast horizons. Wong and Guo (2010) propose to use RMSE, MAPE and MASE as measurement tools, while for this analysis at Nike MAPE, MAD and MASE are considered most appropriate. The average MAPE in the study of Wong and Guo (2010) for all cities (city level is sales per quarter in one city) is 11.6%, while on category level it is 33.4%. This shows a slightly better performance than the PE FTW at Nike, but APP and EQM perform far worse than this example in the study of Wong and Guo (2010). Therefore, it can be concluded that forecast performance at Nike is for FTW equal to comparable companies in the same industry, while APP and EQM perform worse. However, it should be noted that Wong and Guo (2010) forecast demand, while this analysis is directed at forecasting close-out supply, which is a more complicated forecast. Therefore, the forecast on aggregate level at Nike can be considered good.

It is clear that most close-out supply consists of APP, which also has the highest absolute deviation between actual close-out shipments and forecast (MAD = 393k). However, FTW has far more close-out supply, but the deviation (MAD) is almost equal to the EQM MAD. Therefore, the MAPE gives a better indication of the performance, since it shows the deviation compared to the volume shipped.

The underlying reasons for the more accurate forecasts of FTW are the low percentage of carry-overs and Always Available products in this product engine. There is more certainty that products will drop into close-out after a regular selling season, since for APP and EQM they might be carried over to the next season. Therefore, it is easier to predict the amount of close-out supply for FTW. EQM has a high percentage deviation (34%), but because it is compared to FTW and APP a small absolute deviation the impact for Nike is not that huge. Figure 8 shows the MAPE, MAD and the average actual close-out supply per PE, so it is possible to compare the accuracy and the volumes of the product engines.

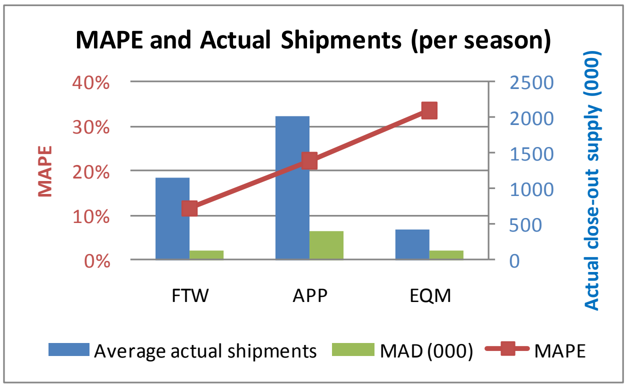


Figure 8 Graphical representation of forecast performance of PEs

MASE

However, MAD and MAPE have to be viewed together to get a good overview on forecast performance, since MAPE gives the percentage error compared to the total shipments. Therefore, MASE is another useful measurement tool, as discussed earlier. MASE shows contradicting results compared to the MAD and MASE, which both show that FTW performs better than the other product engines. The reason for this contradicting result can be the fact that the naïve forecast performs better for FTW than for the other PEs, resulting in a scaled error which is worse than the other PEs, since it is compared to the naïve forecast. Therefore, an analysis is done on the performance of the naïve forecast. This is measured for all PEs and the results are in Table 3.

Table 3 Forecast performance of the naive forecast

MAPE for naïve forecast	MAPE
FTW	18%
APP	33%
EQM	37%
Total	25%

Table 3 show that FTW performance for the naïve forecast is better than the other PEs. Therefore, the MASE for FTW is worse than the other PEs, because the forecast errors are compared to performance of this naïve forecast when calculating the MASE. This result explains that the MASE is also not optimal for comparing different time series. The reason that the MASE for all PEs is lower than the MASE for PEs separate can also be explained by the performance of the naïve forecast (see Table 3 and Table 2). It was expected that overall MASE would be approximately the average of all PE MASEs. This also highlights the disadvantage of using the MASE, since it is dependent upon the performance of the naive forecast.

The NFS require predictions with different forecast horizons, as earlier explained. The available data has been analyzed to measure the performance for the different forecast horizons. It was expected that the longer the forecast horizon, the less accurate the forecast is. The results, given in Table 4, confirm this statement. Table 3 shows that the forecast accuracy on the long term is worse than the forecast accuracy on the short term. The reason for this difference is that more information is available closer to the close-out drop. However, for FTW the results are not as was expected, since the 9 months forecast has better performance. This is caused by limited data for the 9 months forecast, for which only a few measurement points were available which all had only small forecast errors.

Table 4 Forecast inaccuracy for all PEs per forecast horizon

	FTW			APP			EQM			Average		
	MAD	MAPE	MASE	MAD	MAPE	MASE	MAD	MAPE	MASE	MAD	MAPE	MASE
9 months	109	9%	0.51	618	38%	1.20	272	72%	1.35	333	40%	1.07
6 months	172	14%	0.72	592	36%	1.00	174	47%	0.82	313	32%	0.65
3 months	175	16%	0.87	443	22%	0.91	120	28%	0.45	246	22%	0.65
1 month	80	7%	0.33	105	6%	0.12	26	6%	0.15	70	6%	0.07

Figure 9 shows the forecast accuracy per PE for all different forecast horizons. This figure shows that usually the forecast performance improves for decreasing horizons, except for FTW. Thus, at least the MASE and MAPE are aligned here, since both show that FTW performs better for longer forecast horizons. This will be discussed in next paragraphs.

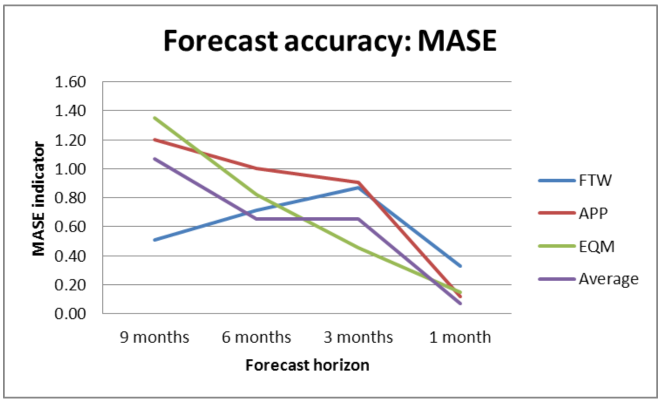


Figure 9 Forecast accuracy: MASE for all horizons per PE

Forecast bias

The forecast bias was also calculated, which will show if the average of all forecast errors is constantly too high or too low. Forecast bias was tested using two tracking signals, the cumulative sum of errors tracking signal and the smoothed tracking signal. Both results will give insight in the bias of the close-out forecasts at Nike. Table 5 shows the result of both forecast bias techniques.

Table 5 X-PE Forecast bias using cumulative tracking signal and smoothed tracking signal (for all PEs)

Tracking signal	Cumulative	Smoothed		
Forecast horizon		α=0.1	α=0.2	α=0.3
1 month	(4.40)	(0.82)	(0.61)	(0.35)
3 months	(2.87)	(0.67)	(0.32)	0.04
6 months	(4.08)	(0.94)	(0.85)	(0.71)
9 months	(2.66)	(0.96)	(0.93)	(0.91)

The cumulative sum of errors tracking signal indicates that forecasts have been given constantly too high, implicating that actual values turned out to be lower than expected. The values for the 1 and 6 month forecast indicate that there exists a forecast bias (tracking signal > 4). The relative high values for the 3 and 9 month forecast indicate, together with the negative results for the other horizons, that forecasts were too high during the investigated period. However, the cumulative sum of errors tracking signal can be influenced by one or more extreme high deviations. The smoothed tracking signal does not have this disadvantage, since the signal is smoothed (more weight given to more recent observations).

The smoothed tracking signal also indicates that the forecasts have been biased, and that they have indeed been too high. The smoothing constant α has a significant influence on the forecast bias, as can been seen in the difference between the values for α. For α=0.3 the forecasts are less biased than for α=0.1. The reason is that the smoothing constant α indicates the weight on the error of that month, while (1-α) indicates the weight on the previous smoothed forecast error. If the error of the investigated month will change from positive to negative (or vice versa) versus the previous month, the smoothed MAD and smoothed error will change approximately the same quantity in the direction of 0. Therefore, the percentage smoothed error compared to the smoothed MAD will increase, since the difference is approximately the same and the values are closer to 0.

Since the tracking signals show the result that all forecast are positively biased, it is important to take a look at all the forecast errors. The forecast errors are given in Table 6. This shows that in the beginning of the analyzed period, the forecast errors were large and negative. Since the tracking signal contains information about all past seasons, these large negative values have an important influence on the tracking signal a few season later. Therefore, it can be concluded that forecast is biased, but that this was mainly caused by the large negative values in the beginning of the investigated period. It is remarkable that during the first four seasons almost all forecasts were too high, while during the last three seasons all forecasts were too low. A possible reason is the economic crisis during 2010 which might have decreased purchasing power. This was also visible in total close-out supply (Figure 7), which decreased during the period forecasts turned out to be too high.

Table 6 X-PE Forecast errors per season per horizon

	FA09	H009	SP10	SU10	FA10	H010	SP11
Δ9 months			(1,220)	(968)		no app	133
Δ6 months		(1,487)	(1,243)	(280)	no app	(92)	312
Δ3 months	(737)	(944)	(634)	(406)	495	295	350
Δ1 month	(190)	(475)	(70)	108	11	27	22

Taking the results of both tracking signals and the information about the forecast errors, it should be concluded that the forecasts for the 1 month, 6 months and the 9 months horizon contained a forecast bias, and that forecasts were too high. The results for the 3 month forecast horizon shows that this forecast is not biased. However, it should be noted that the tracking signal is heavily influenced by large errors, because it contains information about all past seasons. Thus, the tracking signal can be used to investigate forecast bias, but it is useful to investigate the data to verify the results. Table 7 shows the average deviation over the measured period, and for all horizons only 1 positive average has occurred, indicating that forecasting has indeed been too positive.

Table 7 X-PE Over/undershooting of the forecast for all horizons

Average overshooting/undershooting				
Horizon	Total	FTW	APP	EQM
Δ9 months	(685)	(25)	(183)	(272)
Δ6 months	(558)	(110)	(164)	(174)
Δ3 months	(226)	(141)	(39)	(47)
Δ1 month	(81)	(5)	(81)	5

For each product engine a separate analysis has been carried out on forecast performance. This will be discussed in Appendix D, including the forecast performance for the FTW monthly close-out supply.

Conclusion; current forecast performance

Average close-out supply forecast inaccuracy is 15%, which is the percentage deviation of the forecast from the actual close-out supply. FTW performs best in percentage deviation compared to the volume close-out supplied per season with only 12% inaccuracy, but this can be explained by the comparison between the product engines. FTW has the most standardized procedures and processes, which make forecasting easier. EQM has the lowest accuracy, but the volumes in EQM are small compared to the other PEs. FTW is the only PE which does not have increasing accuracy for decreasing horizons, but that can be explained by extensive analysis of the data. Overall close-out supply had a significant decline between HO09 and SU10, which was mainly caused by the decline in APP close-out supply. The positive forecasts for that same period show that this decline was not expected. EQM close-out supply shows a typical seasonal pattern which should be further analyzed. Overall forecast performance is increasing, since MAPE is decreasing for all horizons over time, which is promising. The differences between the PEs in forecast performance will be explained using a comparison of other aspects between the PEs.

The unexpected result was that MASE for FTW was worse compared to the other PEs. However, after an analysis which showed that the naïve forecast showed highest accuracy for FTW compared to the other PEs, this could be explained. Therefore, this can be considered a drawback of using the MASE. If there are deviations between accuracy of the naïve forecast between different time series, this method does not yield useful results, since performance is measured against accuracy of the naïve forecast. MAPE can be regarded as the most appropriate measurement tool, eventually combined with MAD if implications for the business are necessary. However, it can also be concluded that comparing the product engines is impossible, since the product engines are different on a lot of supply chain characteristics, which is shown in Appendix C.

Forecasts were biased, and there was a tendency to forecast too high. The actual close-out supply turned out to be lower than predicted. This result was tested with the cumulative sum of errors tracking signal and the smoothed tracking signal and both showed approximately the same results. Smoothed tracking signal is preferred since it ignores large de. However, the results should be verified by investigating the forecast errors.

Diagnosis

The conclusion from introduction and analysis is that the close-out supply process is a very complex process, involving multiple origins which are not quantifiable. The proposed methods to improve close-out forecast are traditional forecast methods, involving moving average, exponential smoothing and regression procedures. This chapter will show the results of applying the traditional forecast methods on aggregate historical close-out supply data for all product engines. Design chapter will show sophisticated regression procedures.

Application of traditional forecast heuristics on aggregate data

The developed forecast heuristics can be applied to close-out supply data at Nike, to analyze which forecast heuristic will lead to the best forecast accuracy. Application of forecast heuristics is done on aggregate single time series of close-out supply using the described heuristics.

Single time series forecasting methods

The data in the liquidation sheets, which are communicated with the NFS, do contain sufficient historical data to analyze the effect of applying forecast heuristics. The liquidation sheets contain close-out supply data on aggregate level per product engine from July 2008 (FA08) until March 2011 (SP11), a period consisting of 11 seasons. The disadvantage of this approach is that NFS require close-out supply forecasts on lower material levels and not only on aggregate level. However, it is important to test whether these heuristics would improve close-out forecast accuracy at aggregate level. These forecasts can be used later, i.e. the reflection of the distribution in the buy quantity on the close-out supply aggregate forecast. Forecasts are tested on horizons of 6 and 9 months.

The applied heuristics (explained in the chapter 'forecast methods for time series') are the following:

1. Simple Moving Average (with 4-month MA, 2-month MA and all month MA)
2. Weighted Moving Average
3. Linear Regression
4. Exponential Smoothing
5. Exponential Smoothing with trend
6. Exponential Smoothing with damped trend
7. Exponential Smoothing with trend and seasonality (Winters)
8. Exponential Smoothing with damped trend and seasonality (Winters with damped trend, WIntersDT)

These heuristics were applied on the data from the liquidation sheets and the performance of all heuristics was tested. The results are given for both a 9-month and a 6-month horizon. However, to be able to have a benchmark for performance of the heuristics, current forecast performance will be summarized to compare it to performance achieved when applying heuristics. In this chapter, only the best performing heuristic will be presented. Overview of performance of all heuristics is presented in Appendix E, also for heuristics applied with optimized parameters. An initialization period of one year (4 seasons) was used to estimate the parameters for these heuristics, which is required.

9-month forecast horizon

Table 8 shows a summary of the 9-month forecast horizon as was measured in the chapter on forecast performance.

Table 8 Current forecast performance 9 month horizon for all PEs

Current9	MAPE	MAD
FTW	9%	109,018
APP	38%	618,079
EQM	72%	272,176
XPE	27%	773,821

Table 9 shows the optimal method for each product engine with the forecast measurement methods. Furthermore, all methods based on exponential smoothing use the smoothing parameter α, which determines with which extent the forecast takes the previous forecast and the actual results into account. A formula for α has been defined, which has been calculated to create the forecast. However, it is also possible to determine the optimal value for α using the Solver tool in Microsoft Excel. Therefore, Table 9 shows both the resulting forecast performance when using the formula as defined by Silver et al. (1998) and the optimized α for best forecast accuracy, measured using MAPE. The initial value for α based on the formula (Silver et al., 1998) is 0.286. The value for the smoothing parameter for seasonality is also calculated using Silver et al. (1998).

Table 9 Optimized forecast performance for the 9 month horizon for all PEs

Heuristic9	Method	MAPE	MAD	CurrentMAPE
FTW	Winters	13%	185,706	9%
FTW_opt	Winters	11%	157,312	
APP	WintersDT	29%	674,935	38%
APP_opt	WintersDT	19%	425,227	
EQM	MA2	24%	89,343	72%
EQM_opt	WintersDT	20%	83,091	
XPE	WintersDT	23%	905,333	27%
XPE_opt	WintersDT	15%	573,529	

The results from the heuristics shows that APP, EQM and XPE do improve when applying these heuristics, which is obvious since currently no scientific or plausible explainable method is used to create the close-out forecast on aggregate level at Nike. Only FTW forecast performance would decrease when applying the best performing heuristic. However, for FTW the current 9-month horizon forecast performance is based on only 3 measurement points, so the high current accuracy might be a coincidence. Since for FTW, APP, EQM_opt and XPE the optimal method is exponential smoothing with trend and seasonality (Winters), it can be concluded that seasonality is important when calculating forecasts for these product engines. Table 9 also shows that implying that damping the trend is important in Winters' models.

EQM would improve significantly if the moving average method would be used in which the average of last two periods was used. This would imply that seasonality does not have a significant influence on the close-out supply, but that optimized forecast performance would be achieved when assuming a moving average of last periods. However, using the 2-period moving average obtains the best results and one of these two periods is the same season of the previous year, in which the same pattern can be assumed due to seasonality. Furthermore, it has to be noted that there is no difference in EQM and EQM_opt, because the moving average heuristic does not require the smoothing constant α. Since the 6-month forecast gives approximately the same results as the 9-month horizon, this is presented in Appendix E. There all results for all forecast heuristics and both horizons are shown as well. The Winters' method even gives exact the same result, since all information is taken from the same period previous year, which is a forecast of 12 months instead of 6 or 9 months. However, that forecast can also be communicated 6 or 9 months before.

Concluding, it is clear that for both the 6 and 9 month horizon forecast, Winters method does perform best for FTW, while Winters method with damped trend does perform best for APP and XPE. The reason could be that trend is less present in the APP and XPE close-out supply. The results of applying all heuristics also showed that the method linear regression achieves worst forecast accuracy. This can be explained by the fact that seasonality is important and the linear regression method tries to plot a straight line onto the time series, ignoring seasonality.

Since the process is complex and unpredictable, it will be impossible to predict close-out supply on lower material levels using these exponential smoothing or moving average procedures. The quarterly introduction of new products and the short selling seasons made this type of forecasting, using historical data of that particular product, impossible. Exponential smoothing and moving average assume sufficient historical information is present. Regression procedures will therefore offer a more realistic opportunity.

Regression procedures

Regression procedures involve multiple time series analysis. The regression involves close-out supply as dependent variable and the buy quantity and the demand planning forecast as independent predicting variables. These two variables are defined as:

- The Buy Quantity (BuyQty is the quantity materials which is bought for the selling season by the Inventory Planners. The majority of these materials which will not be shipped out during the season, will drop into close-out after this selling season and will thus be included in the close-out drop of next season.
- The Demand Planning Forecast (DP Forecast), which is the forecast, based on sales orders and history, given 9 months out (of the selling season) by the Demand Planners to the Inventory Planners on the expected demand during the selling season. Based on this Demand Planning Forecast and all Sales Orders which are already entered, the Inventory Planners finally take the decision on the Buy Quantity.

The process of buy quantity and demand planning forecast is visualized in Figure 10. It is expected that buy quantity will, in particular, give a better forecast than the demand planning forecast, since the forecast is an input for the buy quantity. Furthermore, the close-out supply is in fact a residual of the initial buy quantity.

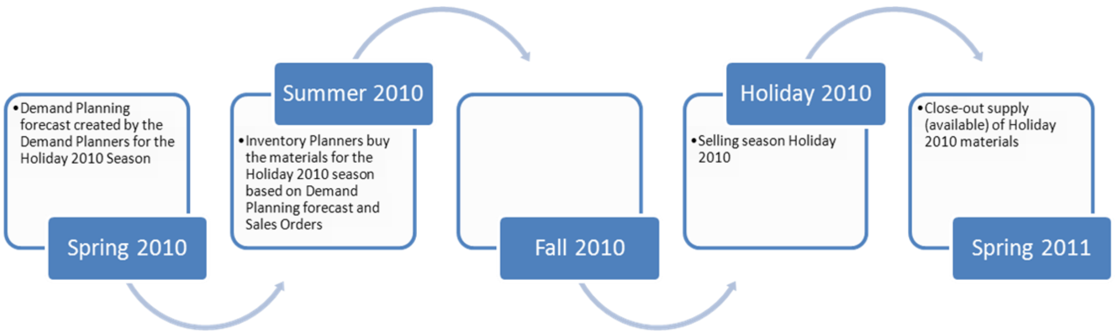


Figure 10 Graphical overview of timeline Buy Quantity, Demand Planning Forecast and the final close-out supply

The regression procedure, which is extensively described in Appendix F, shows that the buy quantity is indeed the best predictor of close-out supply. This is only on aggregate level, all tests on lower material levels showed disappointing results. However, data limitations and the complexity of the close-out supply process made this method less preferable to test, like the other traditional single time series forecasting methods. The conclusion is that this method is not suitable for improving the close-out supply forecast at lower material levels, but that on aggregate level it shows that buy quantity can be a predictor of close-out.

Design

The results in the chapter diagnosis show that traditional methods do not achieve the desired results on lower material level. Therefore, in this chapter the final design towards improvement of close-out forecast on lower material levels will be presented.

Close-out supply process scheme and traditional forecast heuristics

The process scheme has shown the problems with quantifying the origins of close-out supply. The process is complex and IT systems do not offer the opportunity to quantify these origins. This has implications for using traditional forecast heuristics on the time series. The complex and unpredictable process prevents the traditional heuristics to perform as desired. Traditional methods rely on predictable processes and data. Furthermore, the fact that there is actually no history on the lowest material levels, since products are introduced each season, makes it impossible to quantify on lower material levels. There should at least be some degree of aggregation to be able to create time series, since on material level the majority of the time series is only 1 season in length.

Therefore, the traditional forecast heuristics are considered not applicable to this situation. Two other methods will be proposed which have the opportunity to improve close-out forecast on lower material levels.

Close-out supply forecast based on distribution buy quantity

Results from the regression analysis showed that buy quantity has a significant influence on the close-out forecast. Furthermore, the results from the application of all single time series forecast heuristics on the liquidation sheets time series have given the optimal forecast calculation for each product engine. Therefore, it is possible to combine those two techniques. The buy quantity has a major influence on the close-out supply, since what is not bought will surely not end up in close-out inventory. Therefore, an analysis will be done on the distribution of the buy quantity among the category, gender and silhouette codes for horizons of 6, 9 and 12 months. It is expected that the distribution among categories in the buy quantity (or demand planning forecast) will be in the same extent present in the final close-out supply. The same distribution will be applied on the aggregate forecast determined by the heuristic and this will result in a forecast for each category and gender level. An example of this approach with random fictitious values is given in Table 10. The disadvantage of this approach is that the forecast accuracy on category level depends on the forecast accuracy of the aggregate level. However, results from the heuristics applied at aggregate level showed moderate results.

Table 10 Applying the distribution of buy quantity on the aggregate close-out forecast

CatCd	BuyQty	%BuyQty	Aggregate CO forecast	Forecast Category level
Cat1001	1250	28%		281
Cat1002	900	20%		202
Cat1003	500	11%		112
Cat1004	200	4%		45
Cat1005	1600	36%		360
Total	4450	100%	1000	1000

An extensive explanation of forecast horizon, including close-out drop/supply, buy quantity decision and demand planning forecast creation is given in Figure 11, where SP (spring) is assumed selling season and close-out drop happens in Summer. The close-out drop is considered time point zero, since it concerns close-out supply, which will become available from that time point.

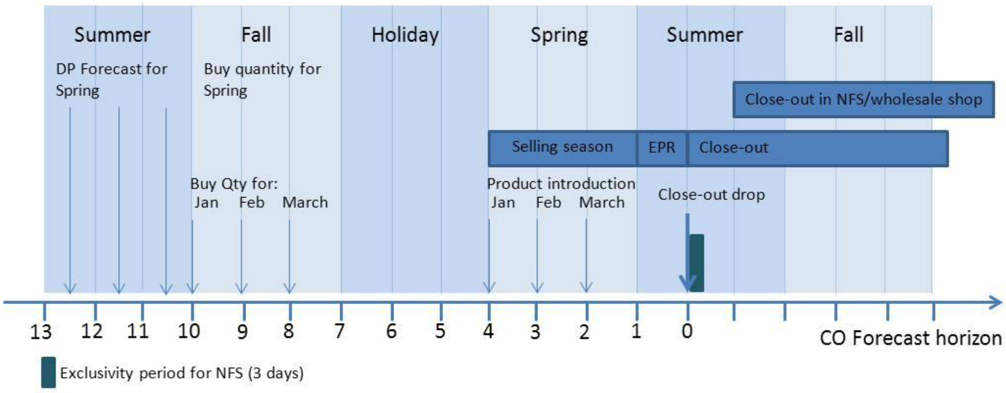


Figure 11 Timeline of close-out drop/supply, buy quantity and demand planning forecast

Because demand planning forecast is given between 13 and 11 months before close-out drop, the 12 month forecast horizon has to be used as well. However, information available 12 months before the close-out drop is also available 9 and 6 months out, so the 12 month forecast can be assumed a 9 or 6 month forecast. Furthermore, Figure 11 shows that products are dropped in close-out the 1st of May, but actually will be sold in the retail shops (either NFS or wholesale) from the 1st of June. That means that products from the Spring inline selling season, will be sold as close-out in the last month of Summer and majorly in Fall. Furthermore, some products are restricted to certain selling seasons (jackets, shorts, gloves etc.), these will be sold in NFS a year later than the regular selling season for these products.

Calculations for the distribution in close-out supply are done using the following inputs:

- The buy quantity snapshots on category and gender level
- The demand planning forecast on category and gender level
- The close-out supply on category and gender level of the previous year
- The aggregate close-out supply forecast

This forecast method will be tested for both FTW and APP, as will be described in next paragraphs.

Footwear

Category level

Results from this FTW category level analysis are given in Table 11. The first column describes which distribution has been chosen, which can be the close-out supply of the previous year, the buy quantity or the DP Forecast. Furthermore, two different approaches for determining this distribution have been chosen. Either it is the average of all previous seasons until the forecast horizon, or it is the same season distribution (same season for close-out supply means the same season in the previous year). Logically, the same season distribution should return the best results, since that particular distribution should also be present in close-out supply. Analysis has been done based on three seasons (HO10, SP11 and SU11), since Winters' exponential smoothing method did not deliver more aggregate forecasts until the moment of analysis.

Table 11 FTW category level close-out prediction using distribution analysis

Category level	Aggregate forecast: Winters			
Percentage based on	Average with horizon	Same period, horizon	MAPE	MAD
CO supply		12 months	28%	40,077
CO supply	9 months		37%	43,338
CO supply	6 months		37%	39,865
Buy Quantity		9 months	19%	21,019
Buy Quantity	9 months		33%	22,605
Buy Quantity	6 months		30%	22,203
DP Forecast		12 months	23%	22,836
DP Forecast	9 months		28%	23,867
DP Forecast	6 months		28%	22,958

On category level, it is clear that close-out prediction using the distribution of the buy quantity for the considered season delivers best forecast accuracy results. The same period distribution does return best results compared to the calculation of the distribution based on average of previous seasons. The low MAPE of 19% is promising, since it shows that it is possible to achieve high forecast accuracy on category level. The forecast heuristics applied on inventory snapshot data had optimal forecast performance on category level with a MAPE of 28%. However, it has to be noted that forecast accuracy using this distribution method is extreme dependent upon aggregate level forecast. The percentage deviation on aggregate level returns on the lower material levels.

Gender level

Results from the same analysis as carried out on category level have been summarized in Table 12 for gender level. Analysis has been done in the same period, using the same inputs.

Table 12 FTW gender level close-out prediction using distribution analysis

Gender level	Aggregate forecast: Winters			
Percentage based on	Average with horizon	Same period horizon	MAPE	MAD
CO supply		12 months	47%	22,717
CO supply	9 months		60%	24,851
CO supply	6 months		74%	22,255
Buy Quantity		9 months	59%	16,775
Buy Quantity	9 months		39%	15,659
Buy Quantity	6 months		42%	15,808
DP Forecast		12 months	51%	18,553
DP Forecast	9 months		46%	16,798
DP Forecast	6 months		43%	16,444

These results imply that on gender level the same period forecast does not yield optimal results. However, the buy quantity is the best predictor on category and gender level for the close-out supply distribution. The inaccuracy of 39% for the 9 month forecast and the inaccuracy of 42% for the 6 month forecast are no improvements compared to the 39% inaccuracy achieved when using heuristics applied at inventory snapshots. However, the difference between the types of data implies that it is not possible to compare the different methods applied.

Apparel results for the distribution analysis are shown in Appendix G, since these show approximately the same results as for FTW. The only difference is that APP performance is worse, but current forecast performance is also worse compared to FTW results. That can be explained by the percentage analysis between the product engines, which was given in Appendix C.

Conclusion on distribution analysis

Results of distribution analysis are promising, but do not yield the required results to improve the forecast on lower material levels. It is an improvement compared to previously tested methods. Distribution analysis has previously been used at Nike, and therefore implementing will not be time and resource consuming. However, disadvantage is that this distribution analysis relies on the aggregate forecasts, which have proven to be inaccurate as well, especially for APP and EQM.

Attribute forecasting: ANOVA

As earlier mentioned, Fisher and Vaidyanathan (2009) state that best retail buyers consider their products as packages of attributes. Therefore, an analysis can be carried out on the predicting behavior of these attributes. This attribute analysis is done on the product engine Apparel, because determination and classification of sizes is more straightforward in APP and other forecasting techniques and current performance indicate that forecasting of close-out supply for APP is more difficult compared to FTW. EQM is not considered as realistic option to analyze, since shipment volumes are low compared to FTW and APP. The attributes which are chosen are size, price, silhouette and color. Determination of sizes is easier in APP, since FTW has sizes for Men and Women ranging in value from 4 to 22 with steps between sizes of 0.5, while kids' sizes have different values. Therefore, this will lead to 23 different sizes excluding kids' sizes. The solution would be to group certain sizes together, to create a few size buckets, However, for APP, sizes can be determined from XXS to XXXXL for both kids and adults, which gives more insight into the distribution among sizes. Therefore, it is interesting to check if this analysis will add value to the APP close-out supply forecasting.

Description of attributes

The different attributes and the levels/categories within the attributes are explained in Appendix H. The attributes used in the results sections and the values of those attributes will be explicitly mentioned in those parts.

Four-way analysis of variance (ANOVA)

An initial analysis on the attributes and the close-out supply in Appendix H shows that there exist differences between the different levels of the attributes in close-out supply. However, this should be validated by a statistical test, which is called analysis of variance (ANOVA). An ANOVA test is conducted to assess whether means on a dependent variable are significantly different among groups (Green and Salkind, 2004). The dependent variable which will be investigated is the percentage close-out supply per material compared to the buy quantity. The different groups are the different levels in the attributes, which have been explained before. Green and Salkind (2004) have defined multiple assumptions which should be satisfied to be able to use ANOVA:

- The dependent variable is normally distributed for all populations
- The variances of the dependent variable are the same for all populations
- The cases represent random samples from the populations and the scores on the test variable are independent of each other.

If these assumptions are violated, the resulting P value (which defines if a hypothesis is found to be significant) for the overall F test is inaccurate or unreliable. The third assumption is satisfied, since there is no dependency between scores on the test variable and a random sample has been selected from the close-out supply. The second assumption can be tested using the software program SPSS for windows, and if this assumption is violated other methods can be proposed. The test which is used to assess whether the second assumption is violated is Levene's test of Equality of Error Variances. If the resulting F-value of that test is significant the variances do differ for populations.

Significance level is chosen as 0.05. An independent divided sample of 25000 materials has been chosen over all seasons to include in the ANOVA.

A four-way analysis of variance was conducted to evaluate the relationship between the prices, sizes, silhouettes and colors of the materials and the percentage close-out compared to buy quantity of these materials. The results of Levene's test of Equality Error Variances shows however that variances are not equal among populations. The results are shown in Table 13. Therefore, it cannot be assumed that variances are equal among the three groups. If the variances are different, it is appropriate to choose one of the four methods available for conducting post hoc multiple comparison tests that do not assume that the population variances are equal (Green and Salkind, 2004). Green and Salkind (2004) propose to use the Dunnett's C procedure in cases where the variances are unequal.

Table 13 Levene's Test of Equality of Error Variances

Levene's Test of Equality of Error Variances[a]			
Dependent Variable:Perc100			
F	df1	df2	Sig.
7.787	278	24721	.000

The use of Dunnett's C procedure has as disadvantage that each attribute should be analyzed separately, due to limitations in SPSS when variances are not equal. Therefore the results for each attribute separately using the Dunnett's C procedure will be shown next.

One-way analysis of variance for each attribute

Size

A one-way analysis of variance was conducted to evaluate the relationship between the size of the materials and the percentage of materials that end up in close out inventory. The size is a nominal variable with 10 different categories. Descriptive statistics are given in Appendix I. It is clear that percentages close-out supply of initial buy quantity are lower for more regular sizes. Since variances are not equal among categories, Dunnett's C has been applied. Results are shown in Appendix I, since for each category 9 comparisons have been applied. The significant differences among categories are summarized in Figure 12.

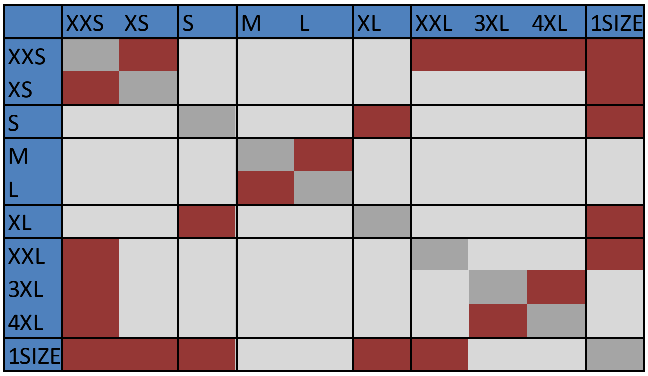


Figure 12 Matrix with significant differences among size categories

Grey boxes show a significant difference, red boxes show the not significant differences. It can be concluded that sizes M and L, which can be regarded as regular sizes, differ from all other sizes. These regular sizes are in percentage significant less present in close-out supply than in the buy quantity. Sizes S and XL differ significantly from the more odd sizes and from the regular sizes M and L. The only disturbing size category is 1SIZE, which does not differ from the sizes XXS, XS, S, XL and XXL. If 1SIZE would be removed from analysis, since it is an exception in the nominal variable size, three significantly different categories can be identified. Thus, this ANOVA shows that more regular sizes have significantly lower close-out supply as a percentage of initial buy quantity.

Price

A one-way analysis of variance was conducted to evaluate the relationship between the price of the materials and the percentage of the materials that ends up in close-out inventory. The price is a nominal variable with three different categories, which are prices in the ranges \$0-\$17, \$18-\$28 and \$29-\$382. Descriptive statistics are given in Appendix I, which show that means are increasing for higher price levels. Dunnett's C procedure has been applied and results are presented in Table 14.

Table 14 Dunnett's C procedure on price level influence on close-out percentage

Multiple Comparisons					
Dunnett C					
				Interval	
(I) PriceCat	(J) PriceCat	Mean Difference (I-J)	Std. Error	Lower Bound	Upper Bound
1	2	-2,301676*	.4402470	-3.333663	-1.269689
	3	-3,312389*	.4443480	-4.353994	-2.270783
2	1	2,301676*	.4402470	1.269689	3.333663
	3	-1.010712	.4650641	-2.100888	.079463
3	1	3,312389*	.4443480	2.270783	4.353994
	2	1.010712	.4650641	-.079463	2.100888

The results of Dunnett's C procedure show that there exist significant differences between category 1 and the other two categories (significant difference if the column Mean Difference (I-J) shows an asterix). There is no significant difference between level 2 and 3. Therefore, it can be concluded that lower prices (up to \$17) have significantly lower close-out supply as a percentage of initial buy quantity than prices above \$18.

Silhouette

A one-way analysis of variance was conducted to evaluate the relationship between the silhouette of the materials and the percentage of the materials that ends up in close-out inventory. Silhouette is an ordinal variable with three different categories; top, bottom and others. The results of applying Dunnett's C procedure on the influence of silhouette category on the percentage close-out supply is presented in Table 15.

Table 15 Results of Dunnett's C procedure on silhouette category influence on close-out supply percentage

Multiple Comparisons					
Dunnett C					
				Interval	
(I) SilhNumeric	(J) SilhNumeric	Mean Difference (I-J)	Std. Error	Lower Bound	Upper Bound
Tops	Bottoms	-.774903	.4303864	-1.783800	.233994
	Other	-4,156613*	1.2100794	-6.998146	-1.315079
Bottoms	Tops	.774903	.4303864	-.233994	1.783800
	Other	-3,381710*	1.2485848	-6.313375	-.450045
Other	Tops	4,156613*	1.2100794	1.315079	6.998146
	Bottoms	3,381710*	1.2485848	.450045	6.313375

The results show that silhouette category 'other' has significantly more close-out supply as percentage of buy quantity than the other two categories.

Color

A one-way analysis of variance was conducted to evaluate the relationship between the color of the materials and the percentage of the materials that ends up in close-out inventory. Color is an ordinal variable with four different levels; black/grey, white, blue and the rest. Descriptive statistics of the different price categories over the percentage close-out is given in Appendix I. The results of applying Dunnett's C procedure on the influence of color category on the percentage close-out supply is presented in Table 16.

Table 16 Results of Dunnett's C procedure on color category influence on close-out supply percentage

Multiple Comparisons					
Dunnett C					
				Interval	
(I) Color	(J) Color	Mean Difference (I-J)	Std. Error	Lower Bound	Upper Bound
Black/grey	White	-.044993	.5519777	-1.463540	1.373555
	Blue	1,409632*	.4995855	.125827	2.693436
	Rest	1,910056*	.4664896	.711348	3.108763
White	Black/grey	.044993	.5519777	-1.373555	1.463540
	Blue	1.454625	.6161357	-.128859	3.038108
	Rest	1,955048*	.5896187	.439738	3.470359
Blue	Black/grey	-1,409632*	.4995855	-2.693436	-.125827
	White	-1.454625	.6161357	-3.038108	.128859
	Rest	.500424	.5408848	-.889555	1.890403
Rest	Black/grey	-1,910056*	.4664896	-3.108763	-.711348
	White	-1,955048*	.5896187	-3.470359	-.439738
	Blue	-.500424	.5408848	-1.890403	.889555

The results from applying Dunnett's C procedure on the influence of color codes on the percentage close-out supply compared to initial buy quantity, show that there exist a few differences. Black/grey has significantly higher close-out supply percentage compared to blue and the rest, while the rest has significantly lower close-out supply percentage compared to black/grey and white. Therefore, we can conclude that less fashionable colors like black/grey have significantly more close-out in percentage than more fashionable colors like yellow.

Conclusion and hypotheses testing

The results from the four-way ANOVA have shown that variances are not equal among categories and therefore regular four-way ANOVA could not be applied. Dunnett's C procedure was applied, since this method does not assume homogeneity of variances. Multiple hypotheses were stated regarding the design phase of the project, relating to the differences between attributes, which have been tested statistically.

Hypothesis 1: Extreme large and small sizes (odd sizes) drop significantly more in close-out than more regular sizes.

Since planners need to buy a certain percentage of the odd sizes (extreme small and large sizes) to avoid out of stocks, which are more expensive than leftover stock, it was expected that close-out inventory would contain more odd sizes than regular sizes. Those odd sizes have less demand, but a certain quantity needs to be bought to ensure sufficient supply. The results in Figure 12 show that odd sizes are significantly more present in close-out inventory than that these are present in the initial buy quantity. Therefore, hypothesis 1 can be accepted.

Hypothesis 2: Higher priced products drop significantly more in close-out than lower priced products.
The most important input/fact for this hypothesis is that planners do not adjust their buying behavior according to prices. Thus, they do not buy more carefully for higher priced products. Therefore, it is expected that higher priced products are more sensitive to demand and that these will drop significantly more in close-out inventory. The results in Table 14 confirm this expectation and hypothesis 2 can be accepted.

Hypothesis 3: More fashionable colors will drop significantly more in close-out than more standard colors like black/white and blue.

The expectation was that more fashionable colors are more sensitive in demand than more regular colors are. However, results show that less fashionable colors like black/grey and white drop significantly more in close-out inventory. That is contradicting to hypothesis 3, which will therefore be rejected.

Attribute forecasting: Proof of concept

The ANOVA showed that attribute forecasting is a possibility which could improve close-out forecast performance, since there exist significant differences between attribute values. Therefore, a simplified model will be created which will predict close-out supply based on attributes. Time constraints for the design will limit the immediate usefulness of such a model, but a proof of concept will be created to show the benefits of a model based on attribute forecasting. First, a general description of attribute forecasting definitions and the model will be given, then the model will be explained. Fisher and Vaidyanathan (2009) describe three types of attributes, on which the attributes chosen for this research can be identified:

- Functional fit – attributes that define whether a given product works or not for a particular consumer need
- Price/value – this attribute has a logical ordering in that the closer the price of a product to a customer's preferred price/value point, the more preferred it is as a substitute. The utility of customers has an influence for this type of attribute.
- Taste – which has to do with fashion trends

Size and silhouette belong to the type functional fit, since consumers are searching for particular sizes/silhouettes which fit their needs. Wholesale price belongs to price/value and color can be identified as attribute type taste. Fisher and Vaidyanathan (2009) formalize the notion of describing a SKU as a bundle of attribute values. T is defined as the number of attributes and Ω is the set of T attributes. $\emptyset_t$ is the number of values for attribute t, while Φ_t is the set of values for attribute t. The variable f_i is defined as the fraction of customers whose first choice is product I, and f_{tit} is the fraction of customers whose first choice on attribute t is the value i_t. This can be applied on the attributes which will be used to create a model for predicting the close-out supply.

This model will predict the percentage close-out supply existence for each unique bundle of attribute values. That means that if total close-out supply value is known, the fraction for each unique bundle of attribute values can be calculated. These values will give the NFS more insight in the expected close-out supply and they can adjust their rebuys based on what types of products will drop into close-out. The proof of concept will be given for the attributes size and color. Therefore, the description of each SKU as a bundle of attribute values can be given: T=2, Ω = {size, color}, Φ_{size}={S,M,L,XL}, Φ_{color}={Black/grey, white, blue, red, rest}. If these attribute values of size and color are combined, 20 unique sets can be identified. It is clear that only a functional fit and taste attribute have been selected, and not a price/value attribute. The price/value attribute would complicate the model, because substitution effects might be involved, like Fisher and Vaidyanathan (2009) also show in their model.

Binary logistic regression

The model (which is considered a proof of concept) will be created using binary logistic regression. First binary logistic regression will be described, afterwards the final model and underlying reasons why binary logistic regression is chosen will be explained. Binary logistic regression model is a statistical method which requires fewer assumptions than other statistical methods, i.e. it does not presume normal distribution for model variables, but a logistic distribution (Muzir, 2011). Muzir (2011) explains that a dependent variable is predicted with two discrete outcomes by one or more prediciting variables. The final equation calculates the likelihood scores which will be used to classify the different attribute combinations (Muzir, 2011). The final probability scores will be compared to a threshold that yields the probabilities for each z, which is the regression score for that particular combination of the independent variables:

$$P(Z) = \frac{1}{(1 + e^{z})}$$

It is obvious that the outcome of this formula is between 0 and 1. The Z in this equation constitutes the scores of interim equation, like presented in the following equation:

$$Z_{123} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon$$

With Z the regression score, β_0 the regression constant, the β_i the regression coefficients, X_i is the i^{th} independent variable and ε the error term. Z_{123} is defined as the Z value for the values 1,2 and 3 for the first three independent variables added. The logistic (logit) function transforms the outcome variable using the natural log of the odds, which leads to the logistic regression model (O'Connel, 2006). This is also shown in Figure 13, which shows the logistic function. It is clear that this logistic function ranges between 0 and 1, which is the output of the model (described as P(Z), using the Z as input). This P(Z) is the probability of a outcome (close-out or not). The variable Z shows how much all independent variables contribute to the model. As O'Connel (2006) states, "logistic analyses for binary outcomes attempt to model the odds of an event's occurrence and to estimate the effects of independent variables on these odds".

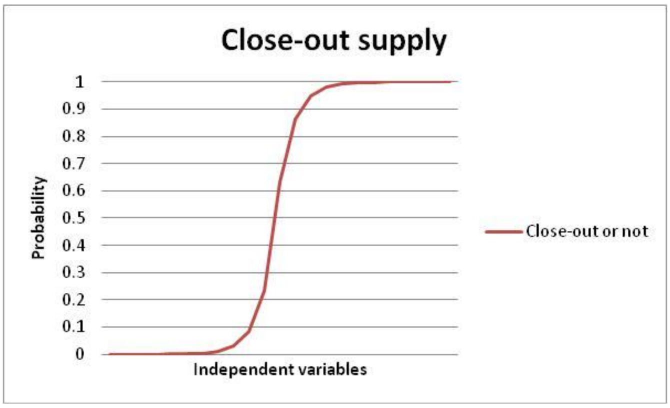


Figure 13 Logistic function

The probability outcomes of this logistic function will later on be used to define the close-out supply quantities per unique combination of attributes values. In other words, the probabilities will be translated using an aggregate forecast to quantities for each combination of size and color. The model for attribute forecasting will thus be created using a binary logistic regression in SPSS. This regression will have as dependent variable percentage close-out, which is the percentage close-out of total close-out for that particular bundle of attribute values. In a binary logistic regression, the dependent variable has either value 0 or 1, which can be explained by the fact that products either drop into close-out or not. The independent categorical variables are size and color, which have the values as described earlier. First it will be explained why logistic regression is the best method to achieve a significant model for attribute forecasting. (Another form of logistic regression is multinomial, which is not considered as model here, since it uses multiple dependent variables, while only close-out supply is the dependent variable here).

A binary logistic regression is the best solution for this model. Building the ANOVA showed difficulties with the distributions and logistic regression ignores these underlying distributions. It must be recognized that the proportions have a binomial distribution, which does not require independent mean and variance, according to Tranmer and Elliot (2008). The mean is denoted by P and the variance by P*(1-P)/n, where n is the number of observations. When there is a proportion as a response, “the logistic transformation is used to link the dependent variable to a set of explanatory variables” (Tranmer and Elliot, 2008). This is the case for close-out inventory, which is the dependent variable and is a proportion as a response.

Another reason for choosing binary logistic regression is stated by O’Connel (2006). Logistic regression does not presume the multiple requirements of the linear regression model (O’Connel, 2006). Binary logistic has been chosen since it has the capability to take any value (negative or positive), while the output is always between 0 and 1. Since materials either drop in close-out or do not drop in close-out, values of 0 and 1 indicate this behavior. The logit function ranges from negative infinity to positive infinity, which eliminates the boundary problems of the probability. Furthermore, logistic regression has certain advantages over linear regression when the dependent variable is dichotomous, which is the case with close-out inventory (O’Connel, 2006). Therefore, it can be concluded that close-out supply using attribute forecasting can be best approached by using binary logistic regression. This will show all attributes as variable in the model (in the equation for Z), while the result is the probability of close-out between 0 and 1. That is what will finally be used to determine the close-out supply per combination of attributes. The sum of these proportions should finally add up to 1, since that will represent total close-out supply. That means that buy quantity is not involved in this model, but this model in combination with the buy quantity will lead to a prediction of close-out supply for a future period.

Data adjustment

Data had to be rewritten to be able to use it for binary logistic regression. Current data is available for each unique combination of material code (MatCd), size and color, which is illustrated in Appendix J. The first step was to determine the percentage existence of each unique combination of color and size for each unique material code. This will give an overview of the percentage existence of each unique combination of size and color in the close-out supply data. Therefore, next step in adjusting the data was to create a table which showed the percentage existence for all 20 unique combinations of size and color. In total, this will sum up to the number of SKUs taken into account in the analysis, since the sum of all percentages is 1 for each SKU. After this step, data is appropriate to define the close-out supply as a binary variable, which is either 0 or 1. Data is available on the numbers of occurrence for each unique combination of size and color in total close-out supply. With this information it is possible to create a list for each size and color with dependent variable close-out which is either 0 or 1. The final result is shown in Appendix J. The values for size are in the range {S, M, L and XL}, while the values for color are between 1 and 5 {1=rest, 2=white, 3=blue, 4=red, 5=black}. Dependent variable close-out supply is thus either 0 or 1, depending on the fact if it would be presented in close-out (1) or not (0).

SPSS model

The final model which will be created using SPSS will have the following format:

$$Z_{ij} = \beta_0 + \beta_i Size_i + \beta_j Color_j + \varepsilon$$

The result will thus be a list for each unique combination of i and j with the values for the β for i and j. Z_{ij} is defined as the Z-value for value i of attribute size and value j of attribute color. For each combination i and j there is a Z-value. Since it is logistic regression, the final result Z will be used in the previous explained probability equation to obtain the probability. Thus, it will be used in the logit transformation to get the proportion close-out supply. Therefore, the model for each i and j (i the size and j the color) will be described as:

$$P_{ij} = \frac{1}{(1 + e^{\beta_0 + \beta_i Size_i + \beta_j Color_j + \varepsilon})}$$

The final result will therefore be a list for each i and j with the probability of this combination to drop in close-out inventory. An important notification is that the model has to be created for each i and j separately, to obtain an attribute forecasting model. SPSS for Windows is used to execute the analysis, which is called binary logistic regression in SPSS as well. Dependent variable is close-out supply, while independent variables are size and color, which are both chosen as categorical variables. An intercept is included in the model. Since only the material codes with values for the 20 unique combinations are taken into account, 20000 cases are included in the analysis. The enter, backward and forward stepwise regression will be tested to obtain the best model with significant predictors. These different approaches have different methods to add the variables to the model, but if the model is significant, each of these approaches will show the same final model.

Binary logistic regression required that the data was rewritten, since only two levels of the dependent variable are allowed. Categorical variable coding is done automatically, in which either the last variable gets the value zero, which is shown in Appendix J. For each attribute, (n-1) variables will be created, since the last variable is attached the value zero. That is the reference variable, against which the scores for the other variables are measured.

Multiple blocks with dependent variable close-out supply and independent categorical variables Size and Color were created. These blocks differ between which variable is first entered in the model and which method is used (enter, forward or backward). All blocks show the same model, the backward stepwise model with conditional choosing of variables is selected. Before the model will be presented some tests are shown to validate that the model is appropriate. Hosmer and Lemeshow tests shows that results are appropriate for logistic regression (Green and Salkind, 2004), as is illustrated in Table 17. The significance, which can range between 0 and 1, should be as high as possible. Therefore, 0.996 is a more than sufficient result to continue with the current model. Contingency table for this test is shown in Appendix J as well.

Table 17 Hosmer en Lemeshow test

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	1.298	8	.996

It is most important that all variables entered in the model are significant, so these can be seen as significant predictors of the close-out supply. In Appendix J it is proved that all variables are significant. The model summary in Table 18 shows the R squares. These should be as high as possible (ranging between 0 and 1), since these show how well the binary regression approximates the data. These values are not as required, but these are adjusted R squares and it is more important that all variables are significant. Further research should try to obtain a model with higher R squares.

Table 18 Model Summary

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	15756.047[a]	.003	.010

In Appendix J the intercept and the values for β for each different attribute value are shown. These variables in the equation are the basis for the model which is created. These results can be incorporated into a regression model which predicts the existence for each unique combination of attribute values in the close-out supply. The results are shown in Table 19, which shows for each unique set of attributes (20 in total) the total existence in close-out supply for each material code. For example, it is expected that of 100 materials of the same material code dropped in close-out, 8 of these materials have size M and have color black. All variables are significant, leading to the result that the model is valid with these colors/sizes.

Table 19 Results of the model

Size	Color	Z	Exp(Z)	Prob
XL	Rest	-3.42682	0.032	0.03
XL	Black	-2.99736	0.050	0.05
XL	White	-3.35122	0.035	0.03
XL	Blue	-3.29906	0.037	0.04
XL	Red	-3.37681	0.034	0.03
L	Rest	-2.96832	0.051	0.05
L	Black	-2.53885	0.079	0.07
L	White	-2.89271	0.055	0.05
L	Blue	-2.84055	0.058	0.06
L	Red	-2.9183	0.054	0.05
M	Rest	-2.85178	0.058	0.05
M	Black	-2.42232	0.089	0.08
M	White	-2.77618	0.062	0.06
M	Blue	-2.72402	0.066	0.06
M	Red	-2.80177	0.061	0.06
S	Rest	-3.20267	0.041	0.04
S	Black	-2.77321	0.062	0.06
S	White	-3.12707	0.044	0.04
S	Blue	-3.07491	0.046	0.04
S	Red	-3.15266	0.043	0.04

The probabilities from

Table 19 show what the expected close-out material supply is on lower material levels when the aggregate close-out supply forecast is known. Then the planners for the NFS can plan their rebuys effectively, because they know the expected content of the close-out supply. This list with probabilities will be entered into another data set, which will show if this prediction is accurate. If that prediction is accurate, attribute forecasting is considered as a realistic option to improve forecast accuracy on lower material levels at Nike.

Implementation

The probabilities from Table 19 will be related to an aggregate forecast to get quantities per unique combination of attributes values. The probabilities in Table 19 add up to 1 now, so that the aggregate forecast is reached. However, if a material does not have one of the attribute values (i.e. no red t-shirts are produced for that particular material code), the probabilities should be rescaled so that they add up to 1(without the probabilities for the red t-shirts). This also shows the advantage of this model, since for all 20 unique combinations, there are probabilities. If one of the combinations would not exist, it would be possible to rewrite the scores so that it would add up to 1. It can be expected that for some materials, particular combinations of size and color do not occur.

To validate that this attribute forecasting improves close-out supply forecasting SU11 data will be used to show how the probabilities can be used to create a forecast. A material code from SU11 which has 20 instances will be used. The result of this implementation is in Table 20.

Table 20 Results implemented for one material code

MatCd	Size	Color	SU11Actual	Probability	CalculatedQty	MAPE	MAD
329337	L	Black	275	0.073178986	341	0.24	66
329337	L	White	192	0.052515084	244	0.27	52
329337	L	Blue	484	0.055171684	257	0.47	227
329337	L	Red	172	0.051256307	239	0.39	67
329337	L	Rest	157	0.048877938	228	0.45	71
329337	M	Black	288	0.081486406	379	0.32	91
329337	M	White	182	0.058625079	273	0.50	91
329337	M	Blue	559	0.061570681	287	0.49	272
329337	M	Red	208	0.057228692	266	0.28	58
329337	M	Rest	214	0.054589142	254	0.19	40
329337	S	Black	172	0.058789261	274	0.59	102
329337	S	White	186	0.042004502	196	0.05	10
329337	S	Blue	201	0.044154177	206	0.02	5
329337	S	Red	72	0.040986763	191	1.00	119
329337	S	Rest	140	0.039065296	182	0.30	42
329337	XL	Black	167	0.047545346	221	0.33	54
329337	XL	White	80	0.033855335	158	0.97	78
329337	XL	Blue	588	0.035603457	166	0.72	422
329337	XL	Red	180	0.033028237	154	0.15	26
329337	XL	Rest	138	0.031467624	146	0.06	8
					Average	0.39	95

The results in Table 20 show an average MAPE of 39% (0.39). That is an improvement compared to the category, gender and silhouette level forecasts created by using distribution analysis, which was considered best method on lower material levels (50% for category, 105% gender and 108% for silhouette, which are even higher material levels). Therefore, we can conclude that attribute forecasting is an opportunity for further research. However, it should be noted that this is only a proof of concept. Not all possible attributes and attribute values are incorporated in the model. Only the material codes with 20 instances for both size and color were selected. Therefore, it is not possible to generalize this result and conclude that it will improve forecast performance with these values. However, it has shown that attribute forecasting is a promising method which should be investigated more extensively. Future research will need to address which attributes and values to take into account for close-out supply attribute forecasting. All attribute values should then be involved in the model, which should also be created for the PEs FTW and EQM.

Conclusion

Objective of this research project was to investigate whether it is possible to improve close-out forecast performance on medium-term (6 to 9 months out). Therefore, first all origins of close-out supply were identified and a process diagram was created. This has contributed to the overview of the complicated close-out process and all different flows leading to close-out inventory destinations.

Current forecast performance was measured for each product engine, including forecast bias. Close-out forecast performance has an inaccuracy of 15% on average over all three product engines over forecast horizons of 1, 3, 6 and 9 months. FTW is the best performing product engine in close-out supply forecasting, which can be related to the standardized processes/facts within that product engine. Forecast performance increases when forecast horizons decreases, since more information becomes available closer to the close-out drop. Furthermore, the forecast bias was measured and it can be concluded that forecasts were constantly too high compared to actuals.

The major objective was to improve close-out supply on lower material levels, like category, gender and eventually silhouette. However, results using traditional forecast heuristics showed this was impossible, due to data limitations and predictability of these time series. The process overview and the analysis of the close-out supply origins has shown the complicated close-out supply process with the unquantifiable flows. The multiple departments involved in the close-out supply process make visibility low. Furthermore, products are introduced each season; causing limited historical information is available for new product introductions since these have never been sold to the market before. Therefore, data was not available on material level for using traditional forecast heuristics. Concluding; the complicated, unpredictable process involving multiple unquantifiable origins makes forecasting using traditional methods on lower material levels impossible.

An analysis on the reflection of the distribution among categories in the buy category on the aggregate close-out supply forecast showed that this was a sufficient predictor for lower material levels. This method has been applied before, so that will not be time and resource consuming for implementation. The distribution among product types (categories, gender and silhouette types) was reflected on the aggregate close-out supply forecast.

Another opportunity to improve the forecast is the use of attribute forecasting, which assumes that forecasts can be given based on certain attributes of materials. An analysis of variance was performed to see whether certain product attributes differ across close-out supply. This showed that close-out supply is significant higher for more expensive products (compared to cheaper products), tail-end sizes (compared to medium sizes), regular colors like black and grey (compared to more fashionable colors) and for a certain part of silhouette codes. The distribution among close-out supply is thus different from the distribution in the buy quantity, showing the disadvantage of using distribution analysis.

This attribute analysis was an opportunity for further research, since products are new introductions each season and no sales data is available for these new introductions. Therefore, a proof of concept was created showing how close-out supply could be predicted using attribute forecasting. Only the predicting attributes color and size (with limited attribute values) were used, but the result was a model with high predictability and significant predictors. Binary logistic regression has been used, since that does not require multiple constraining assumptions, and representing the dependent variable as binary (close-out or not, 1 or 0) showed to be a useful way. Close-out forecast performance on SKU level, which is not even the required level, showed an average inaccuracy (MAPE) of 39%. If this forecast can be aggregated for multiple SKUs within a category, performance will increase. Therefore, it can be concluded that attribute forecasting is a promising method to improve close-out forecast at lower material levels. Drawback is that this model is only a proof of concept. Therefore, further research should prove if an extensive attribute forecasting model shows the same promising results.

At this moment in time, we can therefore conclude that attribute forecasting is the preferred method for improving close-out supply forecast performance, while using the distribution of the buy quantity on an aggregate close-out supply forecast does also yield quite sufficient results and is less difficult to implement. Traditional methods have proven to be not applicable, since the close-out supply process is complex and historical data is not available since each quarter the majority of the products are new product introductions.

Recommendations

Limited data availability on close-out supply on lower material levels has constrained this research, since not enough data was available in time length. Therefore, the most important recommendation is to keep tracking close-out supply on material level to obtain a useful database of close-out supply. It is not sufficient to track it on category or gender level, since material level offers the opportunity to analyze the data more thoroughly if necessary. It will request more space in Nike databases, but since NFS are a growing business and efforts on NFS are increasing, it is necessary to gather data and information on this topic. Currently, close-out supply is gathered on material level and this should be continued to offer more opportunities in the future.

Close-out supply forecast was not tracked before the start of this project on medium-term. Currently close-out forecast accuracy is measured on short-term by the business analysts, but monitoring on longer horizons should also be done. That shows when errors were made and what adjustments over time have changed to the forecasts. These figures will gain insight for improvements in forecasting over time. The percentage analysis has resulted in the conclusion that product engines are totally different. Simultaneously with this project, a lot of effort has been exposed in aligning the product engines and results are already visible. Aligning the product engines will increase efficiency within the organization and will support the transformation towards a category distinction. However, this process is already in progress, so the benefits of this approach will be visible on a short term.

The creation of the close-out supply process has given insight in all the flows, but it became immediately clear that these flows are unquantifiable. Therefore, it is an opportunity to investigate how to track the exact origins of all close-out products. Currently, the visibility on origins is limited, since all information on previous flows (i.e. returns/cancellations/Diverts) is not monitored when products move to close-out. If these flows can be identified and data can be gathered, better forecasts can be created for close-out supply using this data of these flows.

Attribute analysis has shown that this is an opportunity for further research, as well for close-out prediction as for regular demand forecasts. Limited information is available on new product introductions, and product attributes can provide insight into what type of product a new introduction is. The significant differences between attribute levels has indicated that a model can be created which predict the close-out supply of a new product introduction given the initial buy quantity and its attributes. The existing model should be used as a benchmark for the development of a more extensive attribute forecasting model, which should be able to predict close-out supply on lower material levels. Another opportunity regarding attribute forecasting is to apply this method on the regular demand forecasting. This process is less complex and the benefits of attribute forecasting should be easily visible in that process.

Another recommendation is to investigate the opportunities regarding visibility of the close-out supply. The low visibility on the close-out supply process constrains decision making at this moment in time. Multiple origins are unquantifiable. Therefore, the opportunity to change decision making moments in the close-out supply process should be investigated. The most obvious way to achieve this improvement, lead time reduction, can although be considered as impossible.

This report has shown that it is possible to improve close-out supply forecast on lower material levels by using attribute forecasting. However, a more extensive model should be created based on the current proof of concept, which includes all possible attributes and values for all product engines. Therefore, for current implementation it is recommended to use the distribution of the buy quantity as a projection of the distribution within the aggregate close-out supply. That method will improve close-out forecast on a shorter term with fewer resources.

Abbreviations and terminology

ACT	Active
AF	Air Freight
ANOVA	Analysis of Variance
APP	Apparel
ATP	Available to Promise inventory
BuyQty	Buy Quantity, the materials that are planned at the manufacturers
CEE	Eastern Europe
CFS	Customer Financial Services
CO ATP	Available to Promise inventory close-out products
CO	Close-out
ELC	Distribution Center
DP	Demand Planning
DP Forecast	Demand Planning Forecast
DRS	Direct Shipment
EFOD	End Future Offer Date
EHQ	European Headquarters
ELC	European Logistics Center
EPOD	End Product Offer Date
EPR	Early Price Reduction
EQM	Equipment
FA	Fall (July-September)
FPOD	Future Product Offer Date
FTW	Footwear
FY	Fiscal Year
HO	Holiday (October-December)
IAC	Inactive
IM	Inventory Management
MA	Moving Average
MAD	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MASE	Mean Absolute Scaled Error
MSE	Mean Square Error
NFS/FOS	Nike Factory Stores
PE	Product Engine
PO	Purchase Order
Reserved qty	Inventory assigned to customers
RMSE	Root Mean Squared Error
RSO	Returned Sales Order
SKU	Stock Keeping Unit
SO	Sales Order
SP	Spring (January-March)
SU	Summer (April-June)
VAS	Value Added Services
WE	Western Europe
WHQ	World Headquarters
X-PE	Cross Product Engine

References

Alon, I., Qi, M. and Sadowski, R.J. (2001), Forecasting aggregate retail sales: a comparison of artificial neural networks and traditional methods. *Journal of Retailing and Consumer Services.* Vol. 8 pg. 147-156.

Fisher, M. and Raman, A. (2010). The New Science of Retailing: How Analytics are Transforming the Supply Chain and Improving Performance. *Harvard Business Press*. First Edition.

Fisher, M.L. and Vaidyanathan, R. (2009) An Algorithm and Demand Estimation Procedure for Retail Assortment Optimization. *Working paper.*

Green, S.B., and Salkind, N.J. (2004). Using SPSS for Windows and Macintosh; Analyzing and Understanding Data. *Pearson Prentice Hall.* Fourth Edition.

Hyndman, R.J. and Koehler, A.N. (2006) Another look at measures of forecast accuracy. *International Journal of Forecasting.* Vol. 22 (4) pg. 679-688.

Montgomery, D.C. and Runger, G.C. (2002). Applied statistics and probability for engineers. 3rd edition. *John Wiley & Sons, Inc.*

Muzir, E. (2011) Triangle relationship among firm size, capital structure choice and financial performance: some evidence from Turkey. *Journal of Management Research*. Vol 11 pg. 87

O'Connel, A.A. (2006) Logistic regression models for ordinal response variables*. SAGE Publications*

Silver, E.A., Pyke, D.F. and Peterson, R. (1998), Inventory Management and Production Planning and Scheduling. *Wiley*. Third Edition.

Tranmer, M. and Elliot, M. (2008) Binary logistic regression. *Catie Marsh for Census and Survey Research, Paper 20,* 2008.

Wong, W.K. and Guo, Z.X. (2010). A hybrid intelligent model for medium-term sales forecasting in fashion retail supply chains using extreme learning machine and harmony search algorithm. *International Journal of Production Economics*. Vol. 128 pg. 614-624

Zhang, P.G. and Qi, M. (2005), Neural network forecasting for seasonal and trend time series. *European Journal of Operations Research.* Vol.160 pp. 501-514.

Appendix

Appendix A: Close-out supply facts

Confidential.

Appendix B: Data sources

Confidential.

Appendix C: Percentage analysis between product engines

Confidential.

Appendix D: Current forecast performance

Confidential.

Appendix E: Traditional methods on aggregate level – 6 month horizon

6-month forecast horizon

Table 21 shows a summary of the 6-month forecast horizon as was measured in the chapter on forecast performance.

Table 21 Current forecast performance 6 month horizon for all PEs

Current6	MAPE	MAD
FTW	14%	172,274
APP	36%	592,052
EQM	47%	174,250
XPE	16%	682,982

Table 22 shows the optimal methods and forecast accuracy for each product engine. It should be mentioned that Winters and WintersDT give the same forecast for both the 9 and 6 month horizon, since all information from the past is taken from the same season in the previous year, therefore it is a 12-month horizon.

Table 22 Optimized forecast performance for the 6 month horizon for all PEs

Heuristic6	Method	MAPE	MAD	CurrentMAPE
FTW	Winters	13%	185,706	14%
FTW_opt	Winters	11%	157,312	
APP	WintersDT	29%	674,935	36%
APP_opt	WintersDT	19%	425,227	
EQM	MA2	14%	56,406	47%
EQM_opt	ExpSmthDT	12%	49,488	
XPE	WintersDT	23%	905,333	16%
XPE_opt	WintersDT	15%	573,529	

It is clear that for the 6 month horizon forecast, the Winters method does slightly improve FTW and APP and that EQM MAPE can also be improved by using either a 2-period moving average (seasons) or exponential smoothing with damped trend (when optimizing α). However, for all product engines (XPE) no (significant) improvements can be made when applying these forecast heuristics. Therefore, the heuristics show that Winters' method is the best to use for FTW, APP and XPE forecast calculation and that using this heuristic does improve forecast accuracy. This would imply that using a forecast with both trend and seasonality is essential for improving forecast accuracy.

The best results are shown in Table 22, but these are the best results selected from multiple options. These selected options with best forecast performance are highlighted in green in Table 23 and Table 24. With these tables it is possible to compare among all possible techniques and it is possible to get an overview of the results of all applied heuristics.

Table 23 Traditional forecast heuristic results - best results in green

FTW9	MAPE	MAD	MASE	FTW6	MAPE	MAD	MASE
MA4	20%	232,484	1.23	MA4	28%	291,667	1.53
MA2	26%	302,223	1.54	MA2	33%	351,866	1.80
MA_All	23%	253,211	1.32	MA_All	30%	304,870	1.58
WMA	30%	303,998	1.58	WMA	26%	269,040	1.39
LinRegr	38%	421,573	2.18	LinRegr	30%	334,768	1.74
ExpSmth	25%	261,004	1.37	ExpSmth	23%	248,539	1.30
ExpSmthT	38%	382,808	2.04	ExpSmthT	36%	368,594	1.96
ExpSmthD	30%	317,276	1.67	ExpSmthD	30%	317,276	1.67
Winters	9%	111,426	0.59	Winters	9%	111,426	0.59
WintersD	15%	163,159	0.79	WintersD	15%	163,159	0.79
APP9	**MAPE**	**MAD**	**MASE**	**APP6**	**MAPE**	**MAD**	**MASE**
MA4	41%	770,176	1.44	MA4	53%	911,134	1.61
MA2	44%	870,429	1.67	MA2	55%	975,205	1.77
MA_All	41%	739,939	1.36	MA_All	56%	931,390	1.63
WMA	49%	814,812	1.43	WMA	39%	652,964	1.14
LinRegr	62%	1,393,042	2.51	LinRegr	52%	1,041,406	1.89
ExpSmth	79%	1,262,082	2.04	ExpSmth	64%	1,007,210	1.61
ExpSmthT	60%	1,292,970	2.46	ExpSmthT	69%	1,451,537	2.76
ExpSmthD	47%	795,275	1.35	ExpSmthD	48%	796,965	1.32
Winters	48%	1,098,056	2.09	Winters	48%	1,098,056	2.09
WintersD	38%	842,841	1.57	WintersD	38%	842,841	1.57
EQ9	**MAPE**	**MAD**	**MASE**	**EQ6**	**MAPE**	**MAD**	**MASE**
MA4	27%	98,602	0.33	MA4	24%	88,014	0.28
MA2	24%	89,343	0.30	MA2	14%	56,406	0.19
MA_All	33%	105,118	0.35	MA_All	32%	104,641	0.34
WMA	26%	91,542	0.30	WMA	23%	84,662	0.28
LinRegr	76%	324,919	0.93	LinRegr	46%	176,463	0.53
ExpSmth	56%	184,092	0.53	ExpSmth	40%	131,901	0.39
ExpSmthT	83%	331,906	1.08	ExpSmthT	100%	384,768	1.21
ExpSmthD	32%	119,393	0.37	ExpSmthD	18%	67,369	0.22
Winters	47%	214,821	0.74	Winters	47%	214,821	0.74
WintersD	26%	1,065,253	1.49	WintersD	26%	126,192	0.43
XPE9	**MAPE**	**MAD**	**MASE**	**XPE6**	**MAPE**	**MAD**	**MASE**
MA4	32%	1,045,583	1.49	MA4	40%	1,246,271	1.68
MA2	34%	1,183,698	1.72	MA2	41%	1,320,840	1.82
MA_All	29%	917,590	1.27	MA_All	40%	1,196,359	1.57
WMA	36%	1,088,925	1.45	WMA	30%	914,573	1.22
LinRegr	52%	2,047,583	2.80	LinRegr	36%	1,311,535	1.81
ExpSmth	53%	1,582,389	1.96	ExpSmth	45%	1,326,792	1.64
ExpSmthT	44%	1,653,519	2.35	ExpSmthT	44%	1,654,984	2.39
ExpSmthD	36%	1,121,313	1.46	ExpSmthD	36%	1,103,566	1.41
Winters	36%	1,394,712	1.99	Winters	36%	1,394,712	1.99
WintersD	28%	1,065,253	1.49	WintersD	28%	1,065,253	1.49

Table 24 Traditional forecast heuristics results, optimized parameters - best results in green

FTW9	MAPE	MAD	MASE	OptAlpha	FTW6	MAPE	MAD	MASE	OptAlpha
MA4	20%	232,484	1.23		MA4	28%	291,667	1.53	
MA2	26%	302,223	1.54		MA2	33%	351,866	1.80	
MA_All	23%	253,211	1.32		MA_All	30%	304,870	1.58	
WMA	30%	303,998	1.58		WMA	26%	269,040	1.39	
LinRegr	38%	421,573	2.18		LinRegr	30%	334,768	1.74	
ExpSmth	25%	255,381	1.33	0.01	ExpSmth	23%	246,697	1.29	0.35
ExpSmthT	36%	370,483	1.98	0.34	ExpSmthT	33%	352,997	1.85	0.36
ExpSmthD	29%	305,095	1.62	0.25	ExpSmthD	25%	266,351	1.40	0.28
Winters	9%	111,228	0.58	0.29	Winters	9%	111,228	0.58	0.29
WintersDT	9%	112,011	0.59	0.23	WintersDT	9%	112,011	0.59	0.23

APP9	MAPE	MAD	MASE	Opt Alpha	APP6	MAPE	MAD	MASE	OptAlpha
MA4	41%	770,176	1.44		MA4	53%	911,134	1.61	
MA2	44%	870,429	1.67		MA2	55%	975,205	1.77	
MA_All	41%	739,939	1.36		MA_All	56%	931,390	1.63	
WMA	49%	814,812	1.43		WMA	39%	652,964	1.14	
LinRegr	62%	1,393,042	2.51		LinRegr	52%	1,041,406	1.89	
ExpSmth	67%	1,159,772	1.96	1.00	ExpSmth	60%	961,853	1.54	0.91
ExpSmthT	49%	1,068,264	2.02	0.61	ExpSmthT	49%	1,044,829	1.99	0.46
ExpSmthD	47%	795,362	1.36	0.30	ExpSmthD	48%	774,450	1.26	0.25
Winters	36%	780,108	1.45	0.01	Winters	36%	780,108	1.45	0.01
WintersDT	32%	693,271	1.27	0.06	WintersDT	32%	693,271	1.27	0.06

EQ9	MAPE	MAD	MASE	OptAlpha	EQ6	MAPE	MAD	MASE	OptAlpha
MA4	27%	98,602	0.33		MA4	24%	88,014	0.28	
MA2	24%	89,343	0.30		MA2	14%	56,406	0.19	
MA_All	33%	105,118	0.35		MA_All	32%	104,641	0.34	
WMA	26%	91,542	0.30		WMA	23%	84,662	0.28	
LinRegr	76%	324,919	0.93		LinRegr	46%	176,463	0.53	
ExpSmth	48%	160,328	0.47	0.52	ExpSmth	14%	54,012	0.17	0.68
ExpSmthT	50%	200,082	0.61	0.72	ExpSmthT	25%	85,383	0.24	0.73
ExpSmthD	28%	90,072	0.28	0.15	ExpSmthD	12%	49,488	0.17	0.35
Winters	26%	124,527	0.42	0.75	Winters	26%	124,527	0.42	0.75
WintersDT	25%	120,525	0.41	0.19	WintersDT	25%	120,525	0.41	0.19

XPE9	MAPE	MAD	MASE	OptAlpha	XPE6	MAPE	MAD	MASE	OptAlpha
MA4	32%	1,045,583	1.49		MA4	40%	1,246,271	1.68	
MA2	34%	1,183,698	1.72		MA2	41%	1,320,840	1.82	
MA_All	29%	917,590	1.27		MA_All	40%	1,196,359	1.57	
WMA	36%	1,088,925	1.45		WMA	30%	914,573	1.22	
LinRegr	52%	2,047,583	2.80		LinRegr	36%	1,311,535	1.81	
ExpSmth	49%	1,516,809	1.93	0.57	ExpSmth	32%	1,036,944	1.31	1.00
ExpSmthT	40%	1,514,615	2.15	0.46	ExpSmthT	39%	1,309,791	1.74	0.77
ExpSmthD	36%	1,123,785	1.47	0.30	ExpSmthD	32%	1,071,949	1.40	0.52
Winters	25%	948,751	1.31	0.01	Winters	25%	948,751	1.31	0.01
WintersDT	21%	796,028	1.08	0.09	WintersDT	21%	796,028	1.08	0.09

Appendix F: Multiple time series forecasting techniques (FTW)

In this part the result of applying multiple time series forecasting techniques at Nike will be described. Multiple time series forecasting techniques involve interactions between time series of variables. There will be independent and dependent variables involved. The dependent variable, which is possibly influenced by the independent variables, is the close-out supply. The close-out supply data which will be used for this analysis is the inventory snapshot data extracted from Brio, which consists of close-out supply information on lower material levels.

The independent variables are:

- The Buy Quantity (BuyQty), which is the quantity materials which is bought for the selling season by the Inventory Planners. The majority of these materials which will not be shipped out during the season, will drop into close-out after this selling season and will thus be included in the close-out drop of next season.
  - Buy Quantity is done approximately 6 months before selling season, so that means it is done 9 months before the close-out supply of that selling season
  - Data received in Excelfile at material level from the Inventory Planners
- The Demand Planning Forecast (DPForecast), which is the forecast, based on sales orders and history, given 9 months out (of the selling season) by the Demand Planners to the Inventory Planners on the expected demand during the selling season. Based on this Demand Planning Forecast and all Sales Orders which are already entered, the Inventory Planners finally take the decision on the Buy Quantity.
  - Demand Planning Forecast is send through approximately 9 months before selling season, so that means it is send through 12 months before close-out supply
  - Data extracted from Brio on material level with help of Demand Planning department

Since the BuyQty and DPForecast of a particular season possibly influence the close-out supply of the next season, analysis should be conducted on a possible correlation between the BuyQty and DPForecast of season t-1 on the close-out supply in season t. Therefore, the time series for the BuyQty and DPForecast are shifted one period in time to keep a clear overview on the data. This is illustrated graphically in Figure 10.

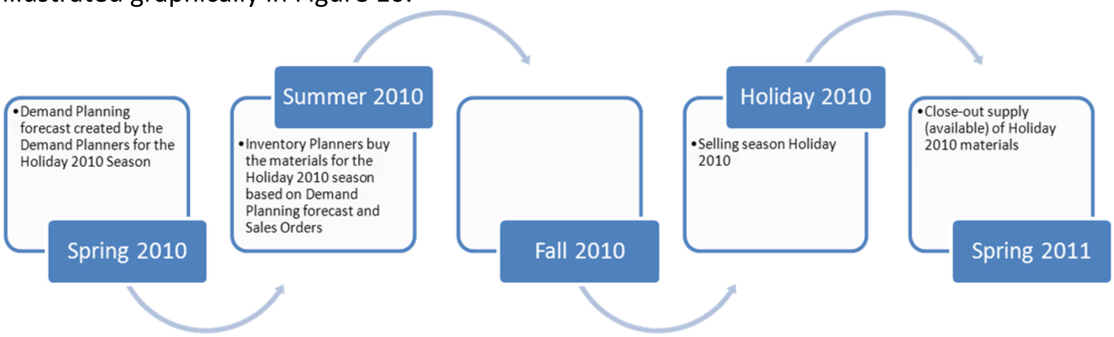


Figure 14 Graphical overview of timeline Buy Quantity, Demand Planning Forecast and the final close-out supply

The analysis which is carried out is a linear regression analysis which is a statistical method used to investigate the relationship between a dependent variable *y* and one or more independent variables *x* (Montgomery and Runger, 2002). The mean of the random variable *Y* is related to *x* (with n independent variables) by the following straight-line relationship: $Y = a + b_1 * x_1 + \dots + b_n * x_n$. The regression analysis is executed using the software program SPSS for Windows and SPSS will return a regression model with the values *a* and *b* and the significance α of this model. If significance is less than 0.05, the model is considered as an accurate representation of the relationship between the variables (Green and Salkind, 2004).

The results from the regression analysis carried out on the close-out supply, buy quantity and demand planning forecast on aggregate and category level are represented in Table 25. Three types of regression models were tested, with close-out supply as dependent variable:

- BuyQty as independent variable
- DPForecast as independent variable
- BuyQty and DPForecast as independent variables

The R^2 gives the square of the correlation coefficient, which is the strength of the correlation between the variables. Alpha is the significance and the intercept and slope together create the final regression model. Last column shows the amount of categories that were significant for the same test on correlation between the dependent and independent variable.

Table 25 Results of regression analysis FTW

Variables							
Dependent	Independent	Alpha	R2	Intercept	Slope	Model	Significance on categorylevel
Close-out supply	BuyQty	0.020	0.694	(135,842.99)	0.055	135,842.99+BuyQty*0.055	3/9 CatCd
Close-out supply	DPForecast	0.051	No significant model				1/9 CatCd
Close-out supply	BuyQty, DPForecast	0.179	No significant model				0/9 CatCd

These results implicate that the only significant relationship is between the BuyQty and the close-out supply on aggregate level (product engine FTW). The model is given in Table 25. There is no significant relationship in the other two models and almost no models on category level were found to be significant. Therefore, it can be concluded that BuyQty is the only factor significantly influencing the close-out supply, and that this model can only be applied on aggregate level.

Appendix G: Distribution buy quantity as predictor

Apparel

Category level

Same analysis, using distributions of close-out supply, buy quantity and demand planning, has been conducted on APP data. The aggregate forecast on which the percentages are applied is the Winters' method with damped trend, since that heuristics performed best on aggregate level. Different compared to FTW is that APP data consist of one season extra (so FA10, HO10, SP11 and SU11) and that APP will also be carried out on silhouette level. Table 26 shows the results for the APP category level analysis.

Table 26 APP category level close-out prediction using distribution analysis

Category level	Aggregate forecast: Winters Damped Trend			
Percentage based on	Average with horizon	Same period, horizon	MAPE	MAD
CO supply		12 months	56%	102,408
CO supply	9 months		60%	80,934
CO supply	6 months		60%	99,721
Buy Quantity		9 months	50%	93,236
Buy Quantity	9 months		50%	79,706
Buy Quantity	6 months		50%	95,080
DP Forecast		12 months	51%	93,595
DP Forecast	9 months		51%	79,584
DP Forecast	6 months		51%	96,964

It is clear that the buy quantity is the best predictor on category level. However, inaccuracy is 50%, which is quite high compared to FTW.

Gender and silhouette level

Applying the method with distribution analysis on gender level and silhouette level for APP were only done using distributions of the close-out supply and the buy quantity. The demand planning distribution delivered worse results compared to buy quantity, which can be easily explained. Results for gender are given in Table 27 and results on silhouette level are given in Table 28.

Table 27 APP gender level close-out prediction using distribution analysis

Gender level	Aggregate forecast: Winters Damped Trend			
Percentage based on	Average with horizon	Same period horizon	MAPE	MAD
CO supply		12 months	235%	62,762
CO supply	9 months		177%	65,888
CO supply	6 months		140%	65,488
Buy Quantity		9 months	122%	67,547
Buy Quantity	9 months		123%	65,534
Buy Quantity	6 months		115%	65,353

The results on gender level show that close-out prediction using distribution analysis are best predicted when using the distribution of the buy quantity, as all previous analyses did. Inaccuracy increasing to more than 100% leads to the conclusion that forecasting at gender level will be very difficult and does not add value. However, the majority of these values above 100% can be explained by the existence of extreme high deviations in the range 1000-15000%. These are the result of high forecasts compared to actuals close to zero but not actually zero. In that case, better insight is gathered when investigating the MAD, which gives the absolute deviation and does not take into account the actual result.

Table 28 APP silhouette level close-out prediction using distribution analysis

Silhouette level	Aggregate forecast: Winters Damped Trend			
Percentage based on	Average with horizon	Same period horizon	MAPE	MAD
CO supply		12 months	108%	29,646
CO supply	9 months		141%	29,722
CO supply	6 months		149%	28,591
Buy Quantity		9 months	132%	23,643
Buy Quantity	9 months		154%	25,097
Buy Quantity	6 months		152%	24,338

Silhouette level results show the same high percentage deviation as the gender level close-out prediction did for the distribution/percentage method. The only difference with all previous results is that the distribution of previous years forecast for the investigated season leads to the best results in terms of MAPE. In terms of MAD, buy quantity distribution of the same season does deliver the best results. It is very difficult to draw conclusions with a lot of actual close-out supply values close to zero. However, all analysis on category and gender level using distributions showed that buy quantity is the best predictor for the distribution of the close-out supply.

Appendix H: Description of the attributes in attribute forecasting

Confidential.

Appendix I: ANOVA attribute forecasting

First part of this Appendix is confidential.

Table 29 Dunnett's C procedure on influence of attribute size on close-out supply (1/2)

(I) SizeNumeric	(J) SizeNumeric	Mean Difference (I-J)	Std. Error	95% Confidence Interval	
				Lower Bound	Upper Bound
1,00	2,00	26.649854	8.7283453	-3.552177	56.851885
	3,00	34,190359*	8.7019180	4.064339	64.316379
	4,00	36,847545*	8.6999444	6.727187	66.967902
	5,00	37,498839*	8.6991650	7.380717	67.616961
	6,00	33,511693*	8.7017391	3.386187	63.637200
	7,00	22.794613	8.7203310	-7.384305	52.973531
	8,00	13.182159	8.8861333	-17.478948	43.843267
	9,00	-.401207	10.6149700	-36.624219	35.821805
	10,00	25.617094	9.0986724	-5.682976	56.917164
2,00	1,00	-26.649854	8.7283453	-56.851885	3.552177
	3,00	7,540505*	.8865481	4.732603	10.348407
	4,00	10,197691*	.8669623	7.451752	12.943630
	5,00	10,848985*	.8591056	8.127900	13.570070
	6,00	6,861839*	.8847906	4.059498	9.664181
	7,00	-3,855241*	1.0520287	-7.187228	-.523254
	8,00	-13,467695*	2.0064786	-19.843980	-7.091409
	9,00	-27,051060*	6.1433036	-47.372598	-6.729523
	10,00	-1.032760	2.8015050	-10.000892	7.935373
3,00	1,00	-34,190359*	8.7019180	-64.316379	-4.064339
	2,00	-7,540505*	.8865481	-10.348407	-4.732603
	4,00	2,657186*	.5394332	.949803	4.364568
	5,00	3,308480*	.5267134	1.641363	4.975597
	6,00	-.678666	.5676433	-2.475355	1.118023
	7,00	-11,395746*	.8038214	-13.940763	-8.850729
	8,00	-21,008200*	1.8882057	-27.010868	-15.005531
	9,00	-34,591566*	6.1056977	-54.799210	-14.383921
	10,00	-8.573265	2.7180498	-17.279750	.133220
4,00	1,00	-36,847545*	8.6999444	-66.967902	-6.727187
	2,00	-10,197691*	.8669623	-12.943630	-7.451752
	3,00	-2,657186*	.5394332	-4.364568	-.949803
	5,00	.651294	.4930346	-.909201	2.211789
	6,00	-3,335851*	.5365398	-5.034073	-1.637630
	7,00	-14,052931*	.7821668	-16.529416	-11.576447
	8,00	-23,665385*	1.8790894	-29.639321	-17.691450
	9,00	-37,248751*	6.1028846	-57.447897	-17.049606
	10,00	-11,230451*	2.7117247	-19.917153	-2.543748
5,00	1,00	-37,498839*	8.6991650	-67.616961	-7.380717
	2,00	-10,848985*	.8591056	-13.570070	-8.127900
	3,00	-3,308480*	.5267134	-4.975597	-1.641363
	4,00	-.651294	.4930346	-2.211789	.909201
	6,00	-3,987146*	.5237498	-5.644880	-2.329412
	7,00	-14,704226*	.7734493	-17.153124	-12.255328
	8,00	-24,316680*	1.8754775	-30.279232	-18.354128
	9,00	-37,900046*	6.1017734	-58.095834	-17.704257
	10,00	-11,881745*	2.7092231	-20.560624	-3.202866

Table 30 Dunnett's C procedure on influence of attribute size on close-out supply (2/2)

(I) SizeNumeric	(J) SizeNumeric	Mean Difference (I-J)	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
6,00	1,00	-33,511693*	8.7017391	-63.637200	-3.386187
	2,00	-6,861839*	.8847906	-9.664181	-4.059498
	3,00	.678666	.5676433	-1.118023	2.475355
	4,00	3,335851*	.5365398	1.637630	5.034073
	5,00	3,987146*	.5237498	2.329412	5.644880
	7,00	-10,717080*	.8018826	-13.255960	-8.178200
	8,00	-20,329534*	1.8873812	-26.329603	-14.329465
	9,00	-33,912900*	6.1054427	-54.119774	-13.706026
	10,00	-7.894599	2.7174770	-16.599293	.810095
7,00	1,00	-22.794613	8.7203310	-52.973531	7.384305
	2,00	3,855241*	1.0520287	.523254	7.187228
	3,00	11,395746*	.8038214	8.850729	13.940763
	4,00	14,052931*	.7821668	11.576447	16.529416
	5,00	14,704226*	.7734493	12.255328	17.153124
	6,00	10,717080*	.8018826	8.178200	13.255960
	8,00	-9,612454*	1.9713238	-15.877421	-3.347487
	9,00	-23,195820*	6.1319117	-43.482768	-2.908872
	10,00	2.822481	2.7764350	-6.066856	11.711818
8,00	1,00	-13.182159	8.8861333	-43.843267	17.478948
	2,00	13,467695*	2.0064786	7.091409	19.843980
	3,00	21,008200*	1.8882057	15.005531	27.010868
	4,00	23,665385*	1.8790894	17.691450	29.639321
	5,00	24,316680*	1.8754775	18.354128	30.279232
	6,00	20,329534*	1.8873812	14.329465	26.329603
	7,00	9,612454*	1.9713238	3.347487	15.877421
	9,00	-13.583366	6.3654955	-34.585079	7.418347
	10,00	12,434935*	3.2600281	2.015025	22.854845
9,00	1,00	.401207	10.6149700	-35.821805	36.624219
	2,00	27,051060*	6.1433036	6.729523	47.372598
	3,00	34,591566*	6.1056977	14.383921	54.799210
	4,00	37,248751*	6.1028846	17.049606	57.447897
	5,00	37,900046*	6.1017734	17.704257	58.095834
	6,00	33,912900*	6.1054427	13.706026	54.119774
	7,00	23,195820*	6.1319117	2.908872	43.482768
	8,00	13.583366	6.3654955	-7.418347	34.585079
	10,00	26,018301*	6.6589794	4.090512	47.946090
10,00	1,00	-25.617094	9.0986724	-56.917164	5.682976
	2,00	1.032760	2.8015050	-7.935373	10.000892
	3,00	8.573265	2.7180498	-.133220	17.279750
	4,00	11,230451*	2.7117247	2.543748	19.917153
	5,00	11,881745*	2.7092231	3.202866	20.560624
	6,00	7.894599	2.7174770	-.810095	16.599293
	7,00	-2.822481	2.7764350	-11.711818	6.066856
	8,00	-12,434935*	3.2600281	-22.854845	-2.015025
	9,00	-26,018301*	6.6589794	-47.946090	-4.090512

Appendix J: Attribute forecasting: proof of concept

Table 31 shows the current data layout which is rewritten to include in the proof of concept.

Table 31 Current data layout

MatCode	Size	Color	Close-out supply	Count
184772	L	1	101	20
184772	L	2	12	20
184772	L	3	434	20
184772	L	4	20	20
184772	L	5	184	20
184772	M	1	16	20
184772	M	2	12	20
184772	M	3	320	20
184772	M	4	37	20
184772	M	5	126	20
184772	S	1	19	20
184772	S	2	7	20
184772	S	3	171	20
184772	S	4	7	20
184772	S	5	52	20
184772	XL	1	56	20
184772	XL	2	8	20
184772	XL	3	381	20
184772	XL	4	10	20
184772	XL	5	118	20
211646	L	1	852	20

The column "Close-out supply" shows the close-out supply for that material code with the unique combination of size and color. Last column ("Count") shows the number of occurrences of each unique material code in the data set of close-out supply. If this value is 20, it means that all combinations of size and color per material code are present. First step in adjusting the data was selecting only the material codes which existed 20 times, because these provide the model with complete information. It has to be noted that in an optimized model, all material codes should be selected.

The final data layout after adjustment is provided in Table 32. For multiple instances of size and color, there can be a value of 1 or 0, meaning either there exists close-out supply or there does not exist any close-out supply.

Table 32 Close-out supply as binary variable

Size	ColorCode	Close-out supply
L	1	1
L	2	1
L	2	0
…	…	…
M	4	1
M	4	1
M	4	0
M	4	0
…	…	…
S	1	1
S	1	0
S	1	0

Table 33 shows the categorical variable codings automatically created by SPSS, including one dummy variable for each independent predicting variable.

Table 33 Categorical variable codings

Categorical Variables Codings

			Parameter coding			
		Frequency	(1)	(2)	(3)	(4)
ColorCode	1	8000	1.000	0.000	0.000	0.000
	2	8000	0.000	1.000	0.000	0.000
	3	8000	0.000	0.000	1.000	0.000
	4	8000	0.000	0.000	0.000	1.000
	5	8000	0.000	0.000	0.000	0.000
Size	L	10000	1.000	0.000	0.000	
	M	10000	0.000	1.000	0.000	
	S	10000	0.000	0.000	1.000	
	XL	10000	0.000	0.000	0.000	

Table 34 shows the contingency table for the Hosmer and Lemeshow test, showing that the observed and predicted values are actually extremely close. Predictability of the model can be considered high.

Table 34 Contingency table for Hosmer and Lemeshow test

Contingency Table for Hosmer and Lemeshow Test

		Close-out supply = 0		Close-out supply = 1		
		Observed	Expected	Observed	Expected	Total
Step 1	1	3872	3871.008	128	128.992	4000
	2	3859	3861.082	141	138.918	4000
	3	3832	3839.896	168	160.104	4000
	4	3836	3827.683	164	172.317	4000
	5	3813	3807.153	187	192.847	4000
	6	3795	3792.457	205	207.543	4000
	7	3774	3780.478	226	219.522	4000
	8	3767	3768.292	233	231.708	4000
	9	3760	3759.280	240	240.720	4000
	10	3690	3690.669	310	309.331	4000

Table 35 shows the final results for the variables to be included in the equation. The β_i for each attribute value is given in the column B, with in the last row the intercept or constant. Table 35 is the most important table in the results section, since it shows the parameters which will be entered in the Z equation, which will finally be translated using a logit function to retrieve values between 0 and 1. However, it is shown in Appendix since most important information is extracted in a table with more overview on variables (SPSS assigns codes to variables). It is clear that all variables entered are significant. However, this significance shows to which extent variables overlap the reference variable. If another Color or Size variable was chosen as reference variable, it might have indicated that variables are not significant. The last two columns, showing the 95% confidence interval, show that some variables overlap. This is not an issue, since these overlap not taking into account the other variable. Therefore, the β for each variable and the constant β can be considered predictors of a significant model.

Table 35 Variables in the equation

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	Size			85.469	3	.000			
	Size(1)	.459	.069	44.264	1	.000	1.582	1.382	1.810
	Size(2)	.575	.068	72.425	1	.000	1.777	1.557	2.029
	Size(3)	.224	.072	9.679	1	.002	1.251	1.086	1.441
	ColorCode			50.959	4	.000			
	ColorCode(1)	-.429	.071	36.413	1	.000	.651	.566	.748
	ColorCode(2)	-.354	.070	25.734	1	.000	.702	.612	.805
	ColorCode(3)	-.302	.069	19.216	1	.000	.740	.646	.846
	ColorCode(4)	-.379	.070	29.195	1	.000	.684	.596	.785
	Constant	-2.997	.066	2051.645	1	0.000	.050		

a. Variable(s) entered on step 1: Size, ColorCode.

Table 36 shows the test of significance for all variables, which can be regarded as sufficient as well, since all models are significant.

Table 36 Significance of the variables

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	136.948	7	.000
	Block	136.948	7	.000
	Model	136.948	7	.000