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The need of Efficiency along the Pharmaceutical Supply Chain: A case study at a pharmaceutical distributor

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ABSTRACT (ENGLISH)

In recent years, two main aspects are increasingly affecting supply chain performances, namely complexity and uncertainty. Complexity refers to the high number of products offered by companies, whereas product life cycle is reducing and the new product launches become more frequent. Uncertainty is related to the volatile environments where companies compete, reducing forecasts reliability. These problems affect both upstream and downstream parts of supply chains, and are particularly relevant in the case of pharmaceutical supply chains. To handle an uncertain demand, a solution is to improve planning activities. Focusing on downstream supply chains, to increase effectiveness, correctly forecasting the future demand is paramount. Furthermore, inaccuracy in forecasting demand has an impact on operational activities, worsening efficiency by entailing overstock or stockout. This thesis concerns the analysis of an Italian pharmaceutical distributor, which serves customers spread all over Italy purchasing products from both local or foreign manufacturers. It has to deal with the challenging requirements, in terms of service level and delivery speed required from customers, while properly managing thousands of suppliers in order to reach efficiency along the upstream part of the supply chain.

The main objective of this thesis was to identify the most suitable forecast approach, among those available on the company software, that allows for smoothing the effect of an uncertain demand. The expected outcome was to improve effectiveness, modifying the replenishment model not only to support the customer requirements but also to keep costs under control by creating efficiency.

For this purpose, the initial setup was first investigated by the means of single case study research. The methods currently in place were deepened and compared with theories and methods described in literature.

The study's results summarize possible evolution of the models currently used and the development of new ones to support forecasting and replenishment activities. Moreover, they can act as controlling tools about to improve the usage of the current of new models developed. However, the most critical aspect observed was the lack of collaborative vision of the supply chain, which is probably the principal case of inefficiency, both upstream and downstream. Therefore, future detailed study could explore how companies could develop and promote a collaborative culture, identifying what are the barriers in place and how it could be possible to overcome them.

ABSTRACT (ITALIAN)

Negli ultimi anni, incertezza e complessità sono i due principali aspetti che sempre di più influenzano le performance della supply chain. La complessità è dovuta al crescente numero di prodotti offerti, alla riduzione del loro ciclo di vita e alla sempre più frequente introduzione di nuovi prodotti sul mercato da parte delle aziende. L'incertezza è invece causata dalla volatilità dei contesti in cui le aziende competono e dalla conseguente inaffidabilità delle previsioni. Questi problemi si possono riscontrare lungo tutto la catena del valore ed assumono una particolare rilevanza nel caso di supply chain farmaceutiche. Una soluzione per gestire una domanda incerta è migliorare le attività di pianificazione, mentre, per migliorare l'efficacia a valle della filiera, è fondamentale prevedere correttamente la domanda futura. La poca accuratezza previsionale influenza negativamente le attività operative ed aumenta la possibilità di andare in overstock o stockout, creando così inefficienza. Questa tesi analizza un distributore farmaceutico Italiano che acquista i prodotti da produttori sia locali che stranieri e li rivende ai suoi clienti distribuiti sul tutto il territorio Italiano. L'azienda in questione deve soddisfare requisiti impegnativi lungo tutta la filiera. A valle, i clienti esigono consegne rapide ed un alto livello di servizio, parallelamente, a monte, è necessario gestire efficientemente centinaia di fornitori.

L'obiettivo principale di questa tesi è di indentificare, tra i modelli di previsione disponibili sul software aziendale, quello che possa maggiormente mitigare l'incertezza della domanda. Il risultato desiderato è quello di migliore l'efficacia dell'azienda in analisi, modificando anche il modello di approvvigionamento in modo da soddisfare i requisiti dei clienti ma allo stesso tempo tenere i costi sotto controllo creando efficienza.

A tal fine, è stata prima esaminata la configurazione iniziale dell'azienda attraverso lo studio dei modelli attualmente utilizzati, confrontandoli con la teoria e i modelli descritti in letteratura.
I risultati ottenuti sintetizzano sia l'evoluzione dei modelli attualmente utilizzati, che lo sviluppo di nuovi, al fine di migliorare le attività di previsione ed approvvigionamento. Inoltre, le metodologie impiegate durante lo studio possono essere adoperate come strumenti di controllo per perfezionare l'utilizzo sia degli attuali che dei nuovi modelli sviluppati. Ad ogni modo, l'aspetto più critico osservato è la mancanza di visione collaborativa lungo la supply chain, la quale è probabilmente la causa principale di inefficienza. Sarebbe quindi interessante analizzare, in uno studio futuro, come le aziende possano sviluppare una cultura collaborativa, identificando le barriere presenti e come è possibile superarle.

EXECUTIVE SUMMARY

1. INTRODUCTION

Pharmaceutical supply chains are usually considered agile supply chains (Lee, 2002), characterized by a high level of complexity due to its huge responsibility to guarantee people health and safety (Uthayakumar and Priyan, 2013). In addition, today's pharmaceutical supply chains have to deal with huge uncertainties (Wang and Jie, 2019) both, internally and externally. Internal uncertainty is one of the main causes of complexity, since it affects the scheduling and planning of the pharmaceutical supply chain processes (Wang and Jie, 2019). Along the most critical processes, inventory management, reverse logistics and quality management are included (Singh et al., 2016). Regarding external uncertainty, it encompasses supply, demand and environmental uncertainty, relating to all the stakeholders involved along the chain.

In this landscape, a process that links internal and external operations and that increasingly requires to be properly updated is demand forecasting (Nulden, 2017). Demand forecasting is a crucial phase since it is the input for all the planning activities. Also, inventory management is equally important due to the fact that distribution and wholesaling revolve around inventory. Consequently, they are two strongly relevant sources and determinants of uncertainty and complexity, also for a pharmaceutical distributor.

This study aims to investigate two different but linked solutions to improve the supply chain performances of an Italian pharmaceutical distributor, concerning its demand forecasting system and its impact over inventory-sourcing management.

For this purpose, a single case study was conducted taking as unit of analysis one of the largest pharmaceutical distributors in Italy. It collected a turnover of 1.2 billion as of 2019, with more than 700 employees and distributing pharmaceutical drugs to 7.500 pharmacies spread in 17 Italian regions. The distribution network of the company site is composed by almost 750 suppliers, 8 owned distribution centers, and 7,500 customers, i.e. the pharmacies. Taking a supply chain perspective, it is the case of a 1-echelon distribution network in which plants (held by manufacturers/suppliers) replenish the distribution centers, from where goods are delivered to the pharmacies.

As concerns results, the study first identified the most suitable forecast approach for those products that follow the "*standard reorder* ", which means their orders are based on demand forecast. In particular, the analysis, consisted first in evaluating the performances of the forecasting model currently adopted by the company, weighted moving average method. Then, the weighted moving average method and the simple exponential smoothing one, the only two employable models due to company's software limitations, were trained, tested and compared in order to identify the most suitable forecasting model.

Second, the replenishment strategy and the reorder model which have a direct impact on the inventory holding costs were defined. The analysis was performed exploiting a costs and benefits based approach between the AS-IS vs TO-BE situation. In the AS-IS situation the company adopts the fixed reorder interval model by using the same reorder interval (T) for all the range of products. In the TO-BE situation, several ABC analyses were performed to divide the range of products in different groups and assessing to each of them a specific reorder interval (T). The new solution showed that the benefits rising from the TO-BE set-up could largely outweigh the increased cost, in terms of efficiency and service level improvements.
This executive summary is organized as follows. The research methodology is first described, followed by a review of the relevant related literature. Findings and results are then first illustrated, and later discussed. Conclusions are lastly drawn, along with recommendations for future research.

2. RESEARCH METHODOLOGY

The research adopted a single case study approach (Yin, 2014). The case study was conducted in an exploratory manner (Ellram, 1996), to understand how the two processes before mentioned are performed and how it could be possible to improve them. The current state definition was conducted through interviewing experts and operators of the two business areas (i.e., logistics/operations and sales), and by collecting relevant data from the company data base. Relevant documentation was mainly collected through the company ERP-system. Four managers acted as primary informants, including the Chief Operations and Logistics Officer, Stock Specialist Manager, one Buyer and one operator of the Sales and Marketing department. Semi-structured interviews were conducted, having the focus on understanding what forecasting and inventory management models or improvements to current models could be feasible according to the related theory and benchmarking comparable case studies. Lastly, all the possible suitable methods and improvements has been tested and compared with the methods currently adopted at the research site.

Primary first-hand data collected through interviews were triangulated with academic sources, as well as company reports and other web-based sources. To review the academic literature, Google Scholar database was used and the following keywords were applied: “forecast methods”, ”supply chain performance”, “pharmaceutical supply chain”, “ pharmaceutical distributor”, “demand management” and ”inventory control”. Then, the researcher used three over the six possible sources of evidence performing a case study suggested by Yin (2014), documentations, interviews and archival records. In more details, the archival records used in this research refer to data from the ERP-system, as previously acknowledged.

Lastly, a quantitative analysis was performed by using all the relevant numerical data coming from the ERP-system. Its aim was to compare the current models and methods adopted by the company with those investigated in the literature and selecting the most cost-effective alternatives.

3. RELATED LITERATURE

In this section, the conceptual notions underlying the forecasting models used during the research are provided, along with the main performance metrics considered.

3.1 WEIGHTED MOVING AVERAGE METHOD

The weighted moving average is an extension of the moving average method. Like the moving average method, this method produces a forecast composed by the mean of the most recent sales data entries. The weighted moving average allows to assign different weights to the different past demand data which compose the mean (Ghiani et al., 2013).

$$WMA_t(k) = W_1 D_{t-1} + W_2 D_{t-2} + \cdots W_k D_{t-k+1}$$

Where W_i is the weight of the generic period *i*, and

$$\sum_{i=1}^{k} Wi = 1.$$

The forecast expert usually estimates the coefficients according to his knowledge and experience. However, it is possible to understand from the formula that higher is the value of the coefficients assigned to the values close to present, the more the model reacts quickly to demand structural changes (Armstrong, 2001).

3.2 SIMPLE EXPONENTIAL SMOOTHING METHOD

Simple exponential smoothing, also referred to Brown method (Brown, 1963), is an improvement of the moving average method. Given the demand time series D_1, D_2, …., D_t , the forecast for the generic period *t+m* is:

$$P_{t+1} = P_{t+2} = \cdots = P_{t+m} = \alpha Dt + (1-\alpha)Pt$$

Where α is the smoothing coefficient whose value lies between 0 and 1.

The smoothing coefficient α reflects the reactivity of the forecasting model in answering to demand changes. If the demand has an unexpected peak and the smoothing coefficient value is low, the model will have a small reaction (Vandeput, 2018). However, increasing the value of the smoothing coefficient, the model tends to perceive demand peak faster. Usually the value of the smoothing coefficient α is entrusted to forecast experts. Alternatively, it is possible to estimate the value of α through a mathematical model (Rob J Hyndman, 2018).

3.3 FORECAST ACCURACY INDICATORS

3.3.1 Mean Error (ME)

The Mean Error is given by the sum of the errors from period t=1 to n divided by the n number of observations (period evaluated) (Sianesi, 2011):

$$ME = \frac{\sum_{t=1}^{n} E_t}{n}$$

If ME is lower than zero, it means that the forecasting model systematically underestimates the demand. While, if ME is higher than zero, the forecasting model systematically overestimates the demand.

3.3.2 Mean Absolute Deviation (MAD)

The Mean Absolute Deviation measures the accuracy of the forecast by averaging the alleged error (Khair, 2017) (the absolute value of each error). The MAD formula is expressed as follow.

$$MAD = \frac{\sum_{t=1}^{n} |E_t|}{n}$$

3.3.3 Mean Absolute Percent Error (MAPE)

The Mean Absolute Percent Error is the relative version of MAD (Ostergava'́, 2012). In this case, the absolute value of the error at time t (E_t) is divided by the demand value of the same period (D_t).

$$MAPE = \frac{\sum_{t=1}^{n} \frac{|E_t|}{D_t}}{n} 100$$

3.3.4 Mean Square Error (MSE)

Another common indicator used to measure the forecasting errors is the Mean Square Error. In this case, the absolute value of the error is substituted by the squared error (Wallström, 2009).

$$MSE = \frac{\sum_{t=1}^{n} (E_t)^2}{n}$$

3.3.5 Standard Deviation of Error (SDE)

Standard Deviation of Error is also known as standard error. Standard error refers to the estimated root-mean-squared deviation of the error in a parameter estimate or a forecast under repeated sampling (Nau, 2014).

$$SDE = \sqrt{\frac{\sum_{t=1}^{n} (E_t)^2}{n-1}}$$

In this case, there is not the distortion due to the demand squared error and its unit of measure become practical again. However, it provides similar indications of the Mean Square Error (Sianesi, 2011).

3.4 FIXED TIME PERIOD MODEL

In this system, replenishment orders are issued with fixed time interval T, the order quantity varies every time in order to reach the predefined availability level (Objective Level OL) (Sianesi, 2011). According to the Fixed Time Period model, the quantity to order Q is given by the difference between the availability objective level (in units) OL and the actual availability level AAL (Sianesi, 2011).

$$Q = OL - AAL$$

Where the actual availability level is given by

$$AAL = PQ + QO - QC$$

In the formula above, PS corresponds to the quantity physically present in the warehouse, QO is the quantity ordered while QC indicates the quantity already committed (Silver, 2016).

When fixing the availability objective level of inventory, it is necessary that this value allows to cover the average demand during the period LT+T, so the lead time added to the time interval between two orders.

$$OL = D * (LT + T) + SS$$

This system gives the possibility to coordinate the replenishments of related items (Silver, 2016). In addition, this method offers a regular opportunity (every T time interval) to adjust the objective level (OL). However, the main disadvantage is that there is not a continuous control and so the quantity ordered cannot be economical and optimal (Ballou, 1998).

4. FINDINGS AND RESULTS

4.1 FORECAST ANALYSIS

For all the forecasting model selection process 10 products were selected, 5 of them are seasonal products. The sale data exploited to evaluate, train and test the forecasting models belongs to the last 24 periods (weeks) of year 2019. The forecast error indicators used for evaluating all models were ME, MAD, MAPE, MSE and SDE. The two possible investigated alternatives were the optimization of the Weighted Moving Average (WMA) model through the adjustment of the weights value or the implementation of the Simple Exponential Smoothing (SES) model. Once finished the training phase, the two forecasting models were compared on the predictions made for year 2020. According to the literature, two non-linear optimization problems were set in order to uncover the optimal weights for the weighted moving average and the smoothing values for the SES. The objective function consisted for both cases in the minimization of the MSE. The value obtained were 75%, 5%, 5% and 15% for the 4-weeks WMA, while the smoothing factor of SES was 0,78.

In order to test the two models investigated, it was used the demand of the last 24 periods of year 2020. The predictions were made exploiting the values obtained from the training phase and the two following tables, table I and table II, show the result of the two forecasting models, simple exponential smoothing and weighted moving average, respectively.

	SEASONAL PRODUCTS					STABLE PRDUCTS							
	A001	A002	A003	A004	A005	A006	A007	A008	A009	A010	AV. E.	AV. E. SEASONAL	AV. E. STABLE
ME	0	-6	5	14	2	-4	-2	-1	-2	0	0,6	3	-2
MAD	43	80	41	100	20	32	18	14	15	15	38	57	19
MAPE	20%	15%	16%	17%	41%	21%	20%	-	25%	35%	-	22%	-
MSE	3155	16955	2792	13634	638	1439	520	380	342	283	4014	7435	593
SDE	57	133	54	119	26	39	23	20	19	17	51	78	24

Table 5.8 - Forecast accuracy of optimized SES (2020)

	SEASONAL PRODUCTS					STABLE PRDUCTS							
	A001	A002	A003	A004	A005	A006	A007	A008	A009	A010	AV. E.	AV. E. SEASONAL	AV. E. STABLE
ME	1	-7	7	19	3	-4	-2	-1	-2	0	1,3	4	-2
MAD	45	88	43	108	22	31	17	14	14	14	40	61	18
MAPE	21%	16%	16%	18%	43%	20%	20%	-	24%	32%	-	23%	-
MSE	3161	19444	3317	15933	752	1341	461	383	317	239	4535	8522	548
SDE	57	142	59	129	28	37	22	20	18	16	53	83	23

Table 5.9 - Forecast accuracy of optimized WMA (2020)

In order to calculate the improvement of forecast accuracy of the two models analyzed, the forecasts for year 2020 were performed even with the model currently adopted by the company site. This means forecasting by using a weighted moving average method with the not-optimized weights value. The table below shows the percentage reduction of the different average error indicators by comparing the model currently adopted by the company and the two previously investigated models whose parameters were optimized.

	Current model vs Optimized SES	Current model vs Optimized WMA
ME	-86%	-70%
MAD	-24%	-20%
MAPE	-	-
MSE	-43%	-36%
SDE	-20%	-17%

Table 5.11 - Forecasting models comparison

4.2 INVENTORY CONTROL ANALYSIS

The first step of the analysis consisted in the differentiation of the order interval in function of two different product features, turnover generated and number of incoming rows related to the period from April to September 2020. The entire analysis was performed considering one of the eight distribution centers. The analysis output were 3 different categories of suppliers, weekly, biweekly and monthly. Then, the products of weekly suppliers were further divided in weekly, biweekly and monthly products. Once determined the new order frequency, the number of incoming rows was estimated and compared with the one received in the current situation. In this way, it was possible to figure out the effect of this change on the goods entry productivity. Secondly, the quantity and related cost of cycle stocks coming from the new orders division was calculated and compared with the actual values in order to quantify the increase in cost. Finally, the increase in goods entry productivity was transformed in a potential increase in revenue due to the larger amount of stocks available. The value obtained was compared to the increase in cost in order to comprehend if this new solution could be potentially cost effective.

The entire analysis was performed only considering those products that follow the fixed time period model, known, inside the investigated company, as "standard orders". The table below shows the final comparison between the AS-IS and TO-BE situations.

	T (AS-IS)	T (TO-BE)		DELTA	DELTA %
SC value	€ 1.410.408	€ 1.490.019	euro	€ 79.611	6%
Cost of Capital	2%	2%	%/year	-	0%
CS cost	€ 28.208	€ 29.800	euro/year	€ 1.592	6%
Additional rows/semester worked	-	6.264	rows/semester		
Average revenue per row	14	14	euro/rows		
Revenue/semester	€ 45.513.532	€ 45.598.409	euro/semester	€ 84.877	0,2%

Table 5.17 - Costs and benefits comparison

5. DISCUSSION

The results presented in the previous section show that SES slightly better forecast the sales of pharmaceuticals affected by seasonality. On the other hand, both models, SES and WMA are interchangeable forecast models to predict the sales of pharmaceuticals whose demand remains fairly stable. The significant forecast accuracy improvement and the results similarity of the two models is principally given by the high parameter value assigned to closest demand value. In particular, it was 0,78 the value of smoothing coefficient and 0,75 the one assigned to the most recent demand value in the WMA formula. However, having been able to analyze the two forecasting models before mentioned, the area of possible improvements was quite limited.

Concerning the second purpose of this study, the analysis for the customization of the order intervals brought to the conclusion that applying a flexible order interval for each product or supplier can reduce the congestion at the goods entry of the distribution center, by causing a relative low cycle stocks cost increase, proving to be an adoptable solution. Furthermore, the benefits could be even higher if there were more references managed with a fixed time period model since just the 45% of products managed in the investigated DC follow a fixed time period logic. However, since the enlargement of the reorder interval could also entail an increase of safety stocks and their related cost, not considering them makes the analysis only partially completed, while opening interesting future avenues to include safety stocks into a structured analysis.

However, by studying the company, the most critical aspects observed was the lack of a collaborative vision of the supply chain, which is probably the principal cause of inefficiency, both upstream and downstream. Taking a qualitative perspective, this is due to a different business vision between the Board of Directors (BoD) and the managers, and a lack of alignment between the Commercial and Logistics/Operations functions. The first conflicting relationship could be due to the fact that the BoD still sees the target company as it originally was, a cooperative, and so investments and radical management changes are perceived as unnecessary, while managers promote new initiatives to preserve profitability. The second critical relationship is caused by the objectives' diversity pursued by the two functions. The Commercial function aims to increment the contractual bonuses by placing orders that generate overstock, while the Logistics function aims to guarantee a high service level keeping costs under control. It is so lastly suggested to the target company to undertake a challenging path towards the institution of a "collaborative culture" (Barratt, 2004). This means moving away from a collaboration model where, "I win, now you figure out how to win" (Ireland and Bruce, 2000) that currently characterizes the company relationships within and outside its boundaries.

6. CONCLUSION

This thesis aimed to improve efficiency in two different but linked processes for a pharmaceutical distributor, and specifically focused on the development of two models for demand forecasting and management. Regarding the forecast theme, the high weighting coefficients assigned to the last demand period on both models, demonstrate that a dynamic Supply Chain, as the pharmaceutical one, requires a dynamic forecasting model that rapidly reacts to demand variations. Consequently, a pharmaceutical distributor, whose business is focused on service level and efficient inventory management, needs thus a proactive forecasting model.

While, a flexible order interval, customized for different products, proved that despite the enlargement of the order interval entails an increase of the average inventory level and its related costs, it was still possible to reduce the overall costs and to optimize the overall performances. In addition, the analyses performed in this study illustrate that solutions for performance improvement could be rapidly implemented, and if dynamically used, could be employed to check the performances evolution and to change the parameters of the new two models developed.

Nevertheless, some limitations were encountered and must be properly acknowledged. Due to the not updated company software, it was not possible to test other forecasting models that could detect seasonal and trend patters of products demand. Additionally, the unformal procedure of SS definition made not possible to consider them in the analysis and to have so a complete view of the effects of the new demand management model.

These limitations could pave the way for three main themes to be investigated in the future. First, a costs and benefits analysis could be developed concerning the investments in a more sophisticated forecasting technology and all the advantages coming from the latter. Second, it could be interesting to examine how the adoption of safety stock formula could quantitatively affect the performances, also economical, of the company inventory management. Lastly, the most critical issue could regard a detailed study about how the target company could develop and promote a collaborative culture, identifying what are the barriers in place and how it could be possible to overcome them.

1. INTRODUCTION

This chapter provides motivation for this study, illustrating what problems it tackles and why it might be relevant. Demand forecasting and efficient sourcing and inventory management are essential objectives to improve supply chain performances. Pharmaceutical Supply Chain (PSC) is known as one of the most complex supply chains, since it has a high responsibility to provide the right medicine to the right people at the right time. According to the model proposed by Hau Lee (2002), PSC are Agile supply chains. Considering the downstream part of the SC, anything less than 100% service level is unacceptable due to the impact of people health and safety (Uthayakumar and Priyan, 2013). This requires a proper management of the upstream supply chain, which must ensure high products availability through efficient sourcing and inventory strategy.

Anyway, according to the PwC industry report, the pharmaceutical and biotech industry is under severe pressure to ensure pharmaceutical supply chain effectiveness (Wang and Jie, 2019). This is due to globalization, the increased complexity of the network, high customer expectations and shorter product and technology life cycles. Today's pharmaceutical supply chain has to deal with continuous uncertainties (Wang and Jie, 2019). According to supply chain literature, it is possible to classify supply chain uncertainty from the pharmaceutical firms' perspective in two different groups, internal and external uncertainty (Wang and Jie, 2019). Internal uncertainty involves operations, financials and quality-related uncertainty, the external one encompasses supply, demand and environmental uncertainty (Wang and Jie, 2019).

Internal uncertainty is one of the main causes of complexity since it affects the scheduling and planning of the pharmaceutical supply chain processes. The most critical processes for a pharmaceutical supply chain are inventory management, reverse logistics and quality management (Singh et al., 2016). Regarding inventory management, medicines are products affected by a high obsolescence risk even with superior packaging and careful control of environmental conditions. This entails special constraints for inventory management and additional costs for the company (Lainez, 2012). Another source of complexity is the design of a reverse logistics network. In the last decade, national and international regulations about waste management and waste minimization have received increased attention (Kara and Oun, 2010). However, designing a reverse logistic network requires important investments and complex challenges especially in the pharmaceutical sector which is characterizes by a high level of unpredictability in the supply chain (Singh et al., 2016). Moreover, the pharmaceutical industry has very stringent quality standards (Singh et al., 2016). This increases the need of a reverse logistics network as the products are delivered back to the sender if they do not meet the quality standards, and further increases the complexity along the traditional logistics network.

Focusing on external uncertainty for the pharmaceutical industry, one of the main sources is the demand management, especially the demand forecast activities. Demand forecasts stays at the basis of all managerial decisions in logistics and supply chain management (Nulden, 2017). Regardless the configuration of a supply chain system, demand forecasting is the starting point for all planning activities and execution processes (Merkuryeva, 2019). It means that sourcing, transportation and all the operating activities need demand forecast as data input.

Anyway, the relevance and weight that each complexity and uncertainty component has depends on the company and its position and role along the supply chain. This thesis analyses two different topics, inventory-sourcing management and the demand forecasting, which are strongly relevant components of uncertainty and complexity for a pharmaceutical distributor. As mentioned before, demand forecasting is a crucial phase since it is the input for all the planning activities. Inventory management is equally important due to the fact that distribution and wholesaling revolve around inventory.

Deeply related with the inventory management is the concept of product availability. Product availability is considered one of the most important indicator of service level quality (Salam, 2016), especially for a pharmaceutical distributor. In order to provide a high service level, companies have tended towards large stores of inventory, which leads to an increase of immobilized capital. The management of inventories has a direct impact on both profitability and liquidity of a company, especially for distributors who operate in the business of consolidating procurement and minimizing cost for retailers and other businesses. Because distributors work with narrow margins and compete extensively on price, efficient inventory management is essential.

Synthesizing, it is crucial for a distributor to adopt efficient sourcing and inventory strategies as on one hand, excess stock entails an unnecessary freezing of founds, a loss of profit and consequently a liquidity risk. On the other hand, insufficient stock could lead to a reduction of service level, which is unacceptable in the pharmaceutical sector.

2. OBJECTIVES AND METHODOLOGIES

2.1 OBJECTIVES

The project aims to improve the performances of an Italian pharmaceutical distributor by acting on two different but linked processes of its Supply Chain.

The first step consists in identifying the most suitable forecast approach for those products that follow the "*standard reorder ",* which means their orders are based on demand forecast. In the analysis of the business context all the other types of reorder adopted by the company will be explained.

In order to do so, the initial focus was on the forecasting method currently used by the studied company. After evaluated the assumptions and the performances of the current model, a cross analysis between the historical series of the products and the related theory was performed. The historical series analysis aimed to understand the possible demand patterns, trends and seasonality of the whole range of products and selecting a sample of them on which, based on theory, testing different forecast models.

The second objective is to redefine the replenishment strategy and the reorder model which have a direct impact on the inventory holding costs. It is important to know that, according to the Italian law, a pharmaceutical distributor must be the owner of its stocks, so it has to purchase the products from the pharmaceutical producers and resell them to the pharmacies. This entails that the distributors sustain all the risks and costs of owing stocks: cost of cycle stocks, cost of safety stocks, risks of obsolescence, thefts and damages.
Based on what has just been said, the analysis was performed exploiting a costs and benefits based approach between the AS-IS vs TO-BE situation. In the AS-IS situation the company adopts the fixed reorder interval model by using the same reorder interval (T) for all the range of products. On the other hand, in the TO-BE situation an ABC analysis was performed in order to divide the range of products in different groups and assessing to each of them a specific reorder interval (T). The analysis is done to understand if the benefits coming from the TO-BE situation in terms of efficiency and service level outweigh the increased costs.

2.2 METHODOLOGY

This chapter provides information about which research strategy has been adopted for this thesis. In this specific study, the chosen strategy can be defined as a mixed method in with both quantitative and qualitative approach in which the quantitative one has been mainly exploited. The following paragraphs explain the approach of finding theory and related research, followed by how the data in the research was collected and analyzed. This report is focused on two crucial processes of the pharmaceutical supply chain, demand forecasting and sourcing-inventory strategy, as well as identifying improvements or changes of current methods.

2.2.1 RESEARCH STRATEGY

The research had a single case study approach (Yin, 2014), with a pharmaceutical distribution company as case site. The case study was conducted in an exploratory manner in order to understand how the two processes before mentioned are performed and how is possible to improve them (Ellram, 1996). The first step of the case study was the definition of the current methods adopted in the two business areas. This current state definition was conducted interviewing experts and operators of the two areas and by collecting relevant data from the company data base. At the second step, according to the constraints of the managerial software, products' features and company's goals, the focus was understanding which forecasting and inventory management models or improvements to current models could be feasible. This part was conducted exploiting the related theory and benchmarking comparable case studies. Lastly, all the possible suitable methods and improvements has been tested and compared with the methods currently adopted at the research site.

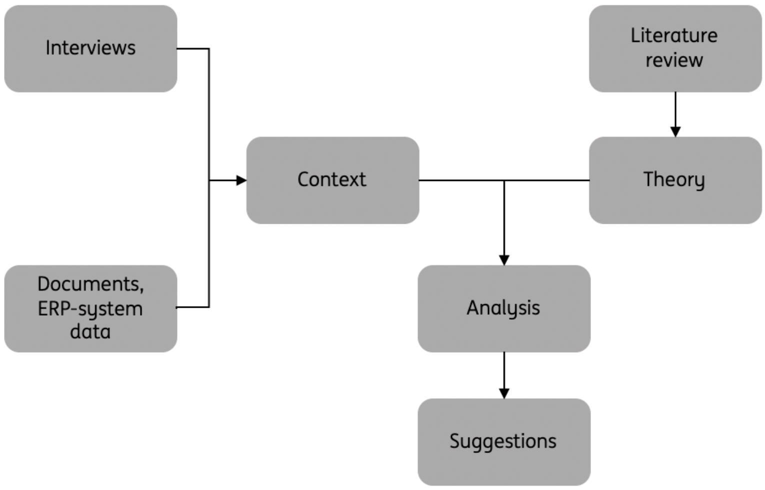

Figure 2.1 - Data analysis approach for the research

The quantitative approach aimed to collect and analyze data from for example sales, number of order rows received, inventory level, forecast and forecast accuracy. This was done in order to distinguish which data to use when performing the analysis of focal areas. The qualitative approach aimed to gather information about the case site's processes and methods.

2.2.2 APPROACH TO LITERATURE SEARCH

The aim of literature search was to understand methods, models and practices could be used for the case site. Before selecting the literature used in the report, a considerable amount of papers, articles and books was read and analyzed in order to understand if it was relevant for this study or not. Several data base has been used to find useful literature, Google scholar, the International Journal of Logistics Management, Journal of Business Logistics, E-Library of Politecnico di Milano. The key words used for literature search were "forecast methods", "supply chain performance", "pharmaceutical supply chain", " pharmaceutical distributor", "demand management" and "inventory control" .

However, a notable part of the literature found was mainly connected to manufacturing and so it is not relevant for the case site since it concerns a pharmaceutical distributor with the core competence within logistics. Anyway, the applicability of each literature documents was benchmarked with the case site, if similar features could be found in the case site the arguments of these documents were considered.

2.2.3 DATA COLLECTION

In this research, different sources of evidence were used to collect relevant data for the project scope. In particular, the researcher used three over the six possible sources of evidence performing a case study suggested by Yin (2014), documentations, interviews and archival records. The documentations used were mainly regarding the manual of the ERP-system of the company in which there are all the forecasting models, formulas and replenishment logics that can be adopted. Concerning the interviews, they were conversational interviews performed in order to get an understanding of the company organization, methods and processes. The participants in the conversational interviews were: Chief Operations and Logistics Officer, Stock Specialist Manager, one Buyer and one operator of the Sales and Marketing department. The archival records used in this research refer to data from the ERP-system. The data from the ERP-system used was historical sales, stock levels at the different DCs, order lines and internal movement of goods.

2.2.4 DATA ANALYSIS

All data collected from documentations, interviews and archival records were analyzed and reported within its contexts. They were mainly exploited to get a picture of the company's supply chain processes, methodologies and practices. Then, according to the business context features, literature helped the researcher to understand which models and methods could be explored, tested and compared to the ones currently adopted. Lastly, a quantitative analysis was performed by using all the relevant numerical data coming from the ERP-system. The quantitative analysis had the purpose of objectively comparing the current models and methods adopted by the company with those investigated in the literature and selecting the most cost-effective alternatives.

3. LITERATURE REVIEW

3.1 FORECASTING

Forecasting is important in many aspects of our lives. As humans, we try to forecast the success in our personal life like in our marriages, jobs and investments. The same happens for Organizations which make huge investments for new products, plants, outlets and software relying on forecasts. Even the Government agencies have to forecast the future behavior of the economy, the environmental impacts and the effects of proposed social programs (Armstrong, 2001).

Forecasts are used to predict the uncertain outcome of a variable (Ghiani et al.,2013). These predictions are made to get an understanding of possible future scenarios which allows for planning in advance for these scenarios (Arnold et al., 2014). Supply chain management and logistics decisions need predictions due to the time lag in matching supply to demand. The typical decision which have to be taken in advance are: facility location, production scheduling, inventory management and transportation planning.

Before proceeding with the literature review is important to make a distinction between *Planning* and *Forecasting.* Planning concerns what the world should look like, while Forecasting is about what it will look like (Armstrong, 2001). It means that Planners exploit forecasting methods to predict the outcome for alternative plans. If the forecast outcome does not satisfy the expectations they can revise the plan and repeat the process.

For pharmaceutical distribution companies obtaining good forecasts of products is even more crucial than other sectors. This is due to the short shelf life of many medicines and the need to control stock levels. As previously mentioned, a good forecast is one of the processes which allows pharmaceutical companies to avoid excessive inventory costs while guaranteeing customer demand satisfaction, and thus decreasing the possibility of loss of customers due to stock obsolescence (Ribeiro et al., 2016).

3.1.2 DEMAND PLANNING PROCESS

The demand planning process sets two objectives (Sianesi, 2011), forecasting future demand by exploiting all the information available (data, commercial actions..) and managing the demand. Managing the demand means from one hand, trying to raise it through specific actions like promotional campaigns and differential price policies aimed to make it more regular over time. On the other hand, managing possible limitations of production and distribution capacity.

This study is focused on the first point the forecast of future demand. In forecasting future demand is crucially important to evaluate (Sianesi, 2011):

- *The forecast object*. It can be the number of orders received, the sales volume or the turnover generated

- *The products aggregation level.* It varies according to the purpose of the forecast. For example, reasoning at family of product level is possible to size the production capacity of plants.

- *Period, horizon and temporal frequency.* The forecast horizon depends on decisions needed to take and the time necessary to apply them. The period or "time bucket" is the unit in which the forecast horizon is divided, typically longer is the horizon longer is the time bucket. The frequency indicates how often the forecasting plan is redefined, usually, if the business is dynamic there will be more frequent updates.

- *Influencing variables.* In many cases the demand can be influenced or explained by several external variables (economic crises, wars, exchange rate fluctuations, political changes, etc.), known as independent variables. The effect of these variables can be immediate or delayed. From a forecasting point of view is better when the effect is delayed since reliable data are already available and is possible to consider it in the forecast.

- *Dependency relationships*. The demand of the finished products coming from the customers is called independent demand which can be affected by the independent variables. The first level of dependent demand is the one which takes in to account the customers demand, the distribution network levels and the average lead time needed to transfer the goods. In this way is possible to know the requirement over the time of finished products. Continuing backwards, there is the second level of dependent demand which consider also the bill of materials and production lead times, so the time occurs to pass from raw materials to WIP and from WIP to finished product. The output will be the requirement of over the time of components and raw materials.

- *Accuracy.* The forecasting process accuracy depends on the aggregation level adopted and the forecast horizon. The aggregation level concerns the time, the products or the geographical areas. Generally, more the data are aggregated lower is the forecast error. Regarding the forecast horizon, shorter it is lower is the forecast error.

3.1.3 CATEGORIZATION OF FORECASTING MODELS

Forecast models can be classified as qualitative or quantitative (Sianesi, 2011). Quantitative methods are based on the historical data of the forecasted variable, so they can be exploited just when data are reliable and available (Ghiani et. al, 2013). Qualitative methods are mainly based on expert judgment or on experimental approaches, however they can also use simple mathematical tools to combine different forecasts. These methods are typically use for long and medium term forecast or when the data available is not sufficient to apply the quantitative methods. For example, for new product launch, political changes or technology upgrades (Ghiani et. al, 2013). Qualitative methods allow the decision maker to consider all those influencing factors which are not happened yet or that have happened but are not present in the historical series. Furthermore, they have the characteristic to generate a widespread consensus on the forecasting process output (Sianesi, 2011). Contrary, since with Qualitative methods is very hard to manipulate large quantities of data, they narrow the quantitative analysis skills. In addition, they entail cost and time-consuming analysis due to the high number of coordination meetings and market researches (Sianesi, 2011). The Qualitative methods analyzed in this thesis are: Delphi method, Jury of expert opinion, Scenario analysis, Sales force composite and Market research.

Quantitative methods make forecast based on mathematical model rather than subjective judgments. These forecasting models have a widespread use among different businesses and industries. Figure 3.1 shows that quantitative methods can be classified as *causal model* and *non-causal models* (Wang, 2011). Non-causal models are also known as *time-series models,* which make the forecast through the extraction and/or analysis from historical time series. Causal models, also known as *cause-and-effect models,* are based on the presence of a causal link between a group of independent variables and the demand.

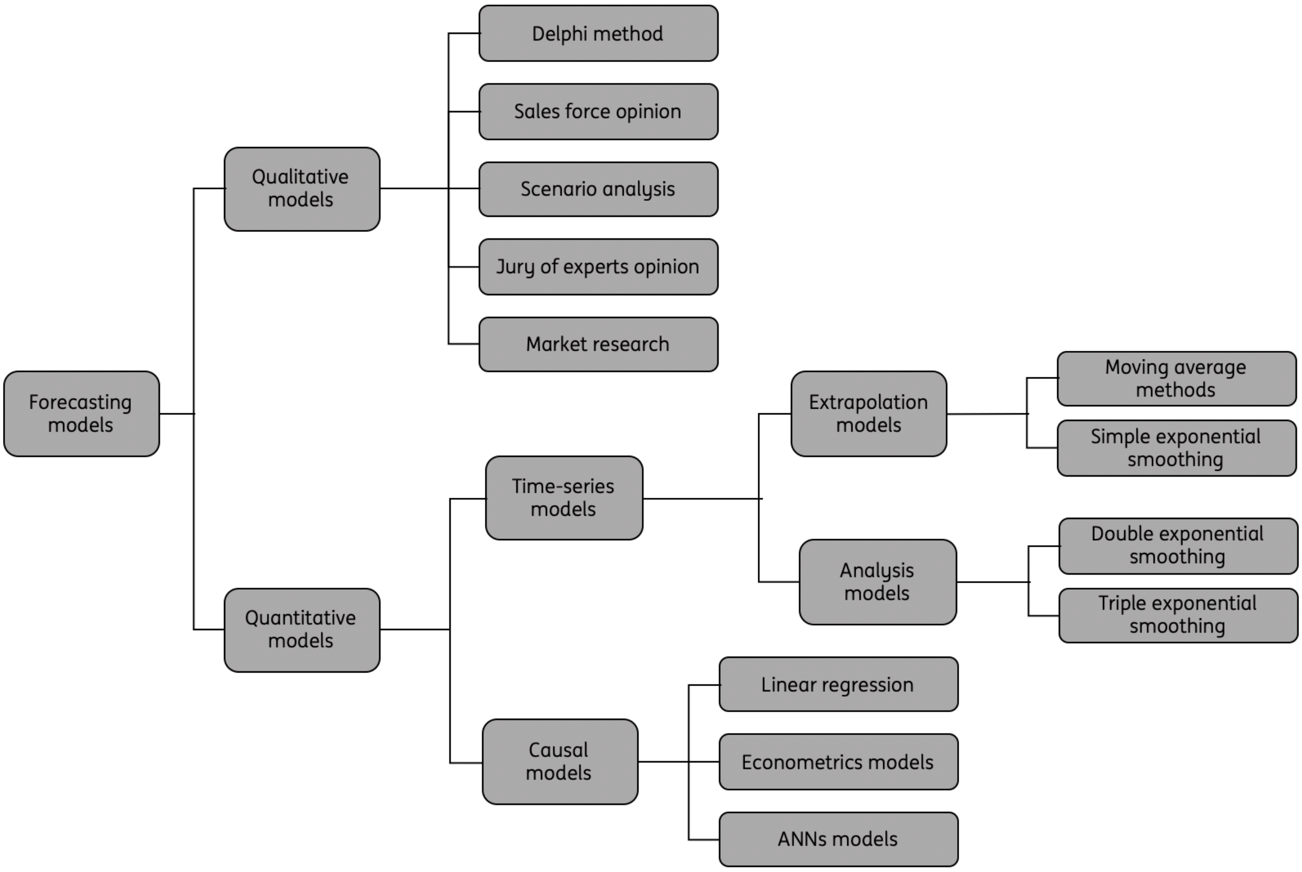

Figure 3.1 – Categorization of forecasting models

Within the time-series models is possible to do a further distinction between the models which do not do any analysis of the past and the ones which do both analysis and extraction of historical time series (Sianesi, 2011). The former, thanks to a mathematical model, are able to extract from the past demand the future one, some examples of these models are: *Moving average*, *Weighted Moving average, simple Exponential smoothing (Brown's model)*. On the other hand, the latter, before making the forecasts, analyze the past time series development in order to find out systematic patters as trend and seasonality, some example are the models of *Holt*, *Winters*.

3.1.4 QALITATIVE MODELS

A number of qualitative forecasting methods have been developed to make good use of qualitative judgments from experts. The most popular qualitative methods are briefly presented in the following.

3.1.4.1 DELPHI METHOD

The Delphi technique was developed during the 1950s by workers at the RAND Corporation while involved on a U.S. Air Force sponsored project. This technique is a procedure to obtain the most reliable consensus of opinion of a group of experts by a series of intensive questionnaires spaced out by opinion feedbacks (Rowe and Wright, 1999). In order to define a procedure as "Delphi", it must have the following four features: anonymity, iteration, controlled feedback, and the statistical aggregation of group response (Rowe and Wright, 1999). Anonymity is achieved thanks to the questionnaires the group members have the possibility to express their opinions privately. The purpose of the iteration is to give to the individuals the opportunity to change their opinions. Between each questionnaire iteration, controlled feedback is provided through which the group members are informed of the opinions of their anonymous colleagues. Often feedback is presented as a simple statistical summary of the group response, usually comprising a mean or median value, such as the average 'group' estimate of the date when an event is forecasted to occur. The Delphi method usually provides more accurate forecasts than face-to-face group discussions since they are often highly influenced by those experts who have more experience, the best interaction and persuasion (Wang, 2011). An application of Delphi method in the pharmaceutical industry is shown by Elizabeth C. S. Swart (2020). The purpose of her article is to find feasible and meaningful outcomes for pharmaceutical value-based contracting in US. The author concludes that Delphi method is a perfect technique to create consensus among the different stakeholders involved in the value-based pharmaceutical contracts (Swart, 2020). Analogously, the same concept can be applied on this case study by substituting the stakeholders involved in the process and the final objective, the future sales.

3.1.4.2 JURY OF EXPERT OPINION METHOD

The jury of expert is a method of generating forecast in which the executives of companies, belonging to different functions, are in charge of formulating the forecasts (Sianesi, 2011). It is also known as the *jury of executive opinion* method. This method is one of the simplest and widely used forecasting methods in business. In the first step the executives acquire all the background information needed to make a forecast. Then in the meeting, the executives write their outputs on a survey paper. The final step is to combine all the options to produce an acceptable result among all the presented ones. The jury of expert opinion method can be considered as an informal variant of the Delphi method. The only difference between them is that the jury of expert opinion method does not prevent the interactions and the mutual influences amongst the meeting participants (Wang, 2011).

3.1.4.3 SALES FORCE OPINION

Sales force can also be an important factor for qualitative forecasting analysis. Based on customers knowledge and initiatives, planned promotion and macroeconomic trends, the sales force arranges and modify the demand forecast. Sales' information is gathered and elaborated through a pyramidal process. The first forecast is made by the lowest level of the pyramid, the sellers, then it is consolidated by passing through the upper levels till reaching the executive of the function. The process is not just a sum of forecasts since the final output is the result of several comparisons between the different level of the pyramid (Sianesi, 2011). A possible disadvantage of this method is that forecasting results of salespeople tend to be too much optimistic. Salespeople may always choose an optimistic prediction since a low estimate could endanger their employment status (Wang, 2011). Furthermore, Sales is just one of departments that composes a company. It is always better to share and discuss the forecast proposal with the other departments in order to avoid possible conflicts at the targets level (Sianesi, 2011).

3.1.4.4 SCENARIO ANALYSIS

Scenario analysis is a systematic process which aims to how different factors can be combined to create possible futures (Wang, 2011). It allows managers to focus on a set of different description of the future, which are explicitly designed to be feasible, but not necessary the most likely (Bunn and Salo, 2011). In contrast to a conceptual future, which represents a hypothetical future state of affairs, a scenario describes the developments, the dynamics, and the moving forces from which a specific conceptual future could result (Kosow 2008). In spite of the multiplicity of scenario techniques, it is possible to identify a recurring methodology in the process development. This methodology divides the process in four sequential phases: identification of the scenario field, identification of key factors, analysis of key factors, scenario generation (Kosow 2008).

1) *Identification of the scenario field.* This part of the process is needed to understand the purpose of the scenarios, the possible limits and all that has to be left out of consideration.

2) *Identification of key factors.* This phase involves working out a description of the scenario fields in terms of its key factors, such as variables, parameters, developments and events, which receive central attention during the further course of the scenario process.

3) *Analysis of key factors.* That is the moment in which all the key factors are subjected to analysis, both individually and together, in order to understand what possible future salient characteristics are conceivable in each case.

4) *Scenario generation.* According to the output of the previous phase, all the different possible scenarios are generated and evaluated. Usually selecting the most sensibly scenarios is a procedure that requires a considerable amount of discussions and debates between the decision makers.

3.1.4.5 MARKET RESEARCH

Market research technique is the systematic, formal and conscious procedure for evolving and testing hypotheses about real markets (Chambers, 1971). It consists in asking customers or possible users how the foresee their future consumption of a product or service. Then the forecast will be based on the answers provided by market. Generally, this technique is adopted for the launch of new products, so when no time series are available. A problem of this method is that the respondents are usually influenced by the trends of the moment. For example, most people have pessimistic opinions during periods of recession and have optimistic opinions in periods of growth and prosperity (Wang, 2011). Furthermore, market researches can be very time and cost consuming before obtaining meaningful results about customers' expectations.

3.1.5 QUANTITATIVE MODELS

As mentioned in paragraph 3.1.2 quantitative forecasting methods exploit sophisticated mathematical models to forecast future demand, they can be classified in two different groups, *time-series models* and *casual models.* The most widespread methods are analyzed and explained in the following sections.

3.1.5.1 CAUSAL MODELS

These models establish a causal relationship between the variable being forecasted and all other related variables. In order to successfully apply these techniques is important to perform the following procedure (Sianesi, 2011):

1) Identifying the independent variables such as price, promotions, weather, time, advertising investments and so on. It is necessary to verify that these variables are not related to each other.

2) Highlighting the functional link (linear, quadratic, exponential equation, etc..) between the variable to forecast (demand) and the independent variables. A function is therefore assumed and tested to verify if it is the best one which describes the relation.

3) Picking out the function parameters

4) The forecast of the dependent variable (demand) is obtained in the face of future estimations or historical data of the independent variables.

The causal models investigated in this thesis are the *simple linear regression model*, *multiple linear regression model, econometric models* and *ANN's models.*

3.1.5.1.1 SIMPLE LINEAR REGRESSION MODEL

The basic concept is that we forecast the time series of interest "*y*" assuming that it has a linear relationship with other time series "*x*". The forecast variable "*y*" is sometimes also called the regressors, dependent or explained variable. The predictor variables "*x*" are sometimes also called the regressors, independent or explanatory variables. The regression model allows a linear relationship between the forecast variable and a single predictor variable (Hyndman and Athanasopoulos, 2018):

$$y_t = a_0 + a_1 x_t + e_t \text{ (1)}$$

From the coefficients a_0 and a_1 is possible to extract the intercept and the slope of line respectively. The intercept a_0 represents the value of y when x is equal to zero. The slope a_1 represents the average predicted change in y resulting from a one unit increase in x.

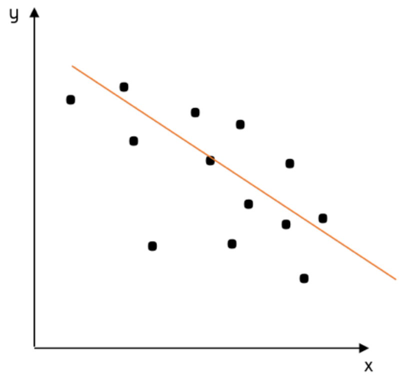

Figure 3.2 – Linear regression line

Notice that the observations do not lie on the straight line but are scattered around it. We can think of each observation y_t as consisting of the explained part of the model, $a_0 + a_1x_t$, and the random "error", e_t. The "error" term does not imply a mistake, but a deviation from the underlying straight-line model. It captures anything that may affect y_t other than x_t. In practice, we have a set of observations but we don't know the value of the coefficients a_0, a_1 . It is possible to estimate these values from the data exploiting the least squares method. The least squares method allows to choose the coefficients by minimizing the sum of the squared errors. It means choosing the values of a_0 and a_1 that minimize variable (Hyndman and Athanasopoulos, 2018):

$$\sum_{t=1}^{T} {e_t}^2 = \sum_{t=1}^{T} (y_t - a_0 - a_1 x_t)^2 \text{ (2)}$$

By applying the partial derivates respectively for a_0 and a_1 is possible to demonstrate that function (2) has minimum when:

$$a_1 = \frac{\sum_{t=1}^{n}(x_t - x_{AV}) * (y_t - y_{AV})}{\sum_{t=1}^{n}(x_t - x_{AV})^2} \text{ (3)}$$

$$a_0 = y_{AV} - a_1 * x_{AV} \text{ (4)}$$

where:

$$x_{AV} = \frac{\sum_{t=1}^{n} x_t}{n} \quad (5)$$

$$y_{AV} = \frac{\sum_{t=1}^{n} y_t}{n} \quad (6)$$

n = number of observations

Furthermore, it is possible to calculate the linear correlation coefficient (Pearson, 1890) which provides information about both the power and the direction of the correlation between the two variables.

$$r = \frac{\sum_{t=1}^{n}(x_t - x_{AV}) * (y_t - y_{AV})}{\sqrt{\sum_{t=1}^{n}(x_t - x_{AV})^2 * \sum_{t=1}^{n}(y_t - y_{AV})^2}} \quad (7)$$

The index will be between the values "-1", which indicates a perfect negative correlation, and "+1" which indicates a perfect positive correlation. Variables are negative correlated when the statistical observations of one variable increase (decrease) as those of the other decrease (increase). While variables are positively correlated when the statistical observations of one variable increase (decrease) as those of the other increase (decrease). Generalizing, the closer the value is zero less strong will be the correlation between the two variables.

However, the validity of linear regression model is based on different assumptions variable (Hyndman and Athanasopoulos, 2018).

- it is assumed that the relationship between the forecast variable and the predictor variables satisfies this linear equation.
- The errors "e_t" have mean zero, they are not autocorrelated and unrelated to the predictor variables
- Each predictor "x" is not a random variable, due to the fact that most data in business and economics is not controllable.

3.1.5.1.2 MULTIPLE LINEAR REGRESSION MODEL

When there are two or more predictor variables, the model is called multiple linear regression model variable (Hyndman and Athanasopoulos, 2018). This model has exactly the same logics of the simple linear regression model where "y " is always the variable to forecast, x1......xk are the k predictor variables and a1.....ak are the coefficients of each variables.

$$y_t = \beta_0 + \beta_1 x_{1,t} + \beta_2 x_{2,t} + \cdots + \beta_k x_{k,t} + e_t \quad (8)$$

The coefficients measure the effect of each predictor variable taking in to account all the other predictors in the model. All the assumptions done in the simple linear regression model are still valid in this model.

An application of multiple linear regression model in the pharmaceutical industry is presented in the experiment conducted by Merkuryeva, Valberga and Smirnov (2019). They performed demand forecasting experiment for a specific pharmaceutical product, by creating a linear regression model with 3 independent variables such as base price, discounted price and a week number of sales for a month. The results showed that multiple linear regression model forecast accuracy and its capacity of reproduce behavior of the demand pattern are better than the moving average method previously performed. However, they added, multiple linear regression model lacks the ability to accurately predict demand peak sales (Merkuryeva, et al., 2019).

3.1.5.1.3 ECONOMETRIC MODELS

In many real cases, the cause-and-effect relationship between dependent and independent variables are not straightforward. The estimated model parameters by the linear regression analysis may become inappropriate due to the highly dynamic relationship between the dependent and independent variables. For example, the interaction of supply and demand jointly determines the equilibrium price and quantity of the product in the market. In such cases, it no longer makes sense to separate dependent and independent variables completely. To handle this problem, a set of simultaneous regression models is necessary to describe dynamics of these systems. The simultaneous regression models are called *econometrics models* in literature, since they are often applied to analyze the relationships between economic variables that should be jointly determined. One can consider that a single regression model is a special case of econometrics models. The general approach of these models is presented below:

The scheme of a system with N equations, N endogenous variables (which influence and are influenced by the other variables) and K predetermined or exogenous variables (which influence but are not influenced by the system) (Gujarati, 2003)is:

$$y_1 = \beta_{1,2} y_2 + \beta_{1,3} y_3 + \ldots + \beta_{1,N} y_N + \gamma_{1,1} x_1 + \ldots + \gamma_{1,K} x_K + u_1$$

$$y_2 = \beta_{2,1} y_1 + \beta_{2,3} y_3 + \ldots + \beta_{2,N} y_N + \gamma_{2,1} x_1 + \ldots + \gamma_{2,K} x_K + u_2$$

$$\ldots$$

$$y_N = \beta_{N,1} y_1 + \ldots + \beta_{N,N-1} y_{N-1} + \gamma_{N,1} x_1 + \ldots + \gamma_{N,K} x_K + u_N \quad (9)$$

where $x_1, x_2, \ldots, x_K$ are exogenous variables, $y_1, y_2, \ldots, y_N$ are endogenous variables, and $u_1, u_2, \ldots, u_N$ are random variables. All these variables are vectors with dimension $d \times 1$, where d is the sample size. The problem is to obtain $\beta_{1,2}$, $\beta_{1,3}$, …, $\beta_{N,N-1}, \gamma_{1,1}, \ldots, \gamma_{N,K}$ from a representative sample of the model. Equation (1) can be represented in matrix form as:

$$BY^T + \Gamma X^T + u^T = 0 \quad (10)$$

where $Y = (y_1 \ . \ . \ . \ y_N)$, $X = (x_1 \ . \ . \ . \ x_K)$, $u = (u_1 \ . \ . \ . \ u_N)$.

The structural model (equation 10) can be expressed in reduced form:

$$Y = X^*\Pi + v \quad (11)$$

with:

$$\Pi^T = -B^{-1}\Gamma, \quad v = -B^{-1}u \quad (12)$$

An equation is identified if the number of parameters in the equation is lower than or equal to $K+1$, in other words, $ni - 1 \leq K - ki$ where ni and ki are the number of endogenous and exogenous variables in equation i. The parameters corresponding to an equation can be calculated only when the equation is identified. Two different matrices can be defined, X ($d \times K$) and Y ($d \times N$), which contain the exogenous and the endogenous variables. Different methods can be used to estimate the parameters of simultaneous regression models such as Indirect Last Squares (ILS) or Two-stage Last Squares (2SLS). Those methods are called *single-equation methods* or *limited information* *methods* (Gujarati,2003), since each equation in the system (of simultaneous equations) is estimated individually, taking in to account any restrictions placed on that equation (such as exclusion of some variables) without worrying about the restrictions on the other equations in the system.

An example of econometric model is presented by Regnier and Ridley (2015) whose conducted an analysis of data concerning entry order and promotional spending from a large sample of drug classes, to estimate peak market share. In order to define the weights of the share of promotional spending, order of entry and time to market on peak market share, they used an ordinary least-squares regression to determine the coefficients in the econometric model. The dependent variable, peak share, was defined as the maximum monthly share reached by a new entrant during the first 4 years on the market (Regnier and Ridley, 2015). While, the independent variables were the share of promotional spending, order of entry, time to market and whether further competitor drugs entered for second entrants (Regnier and Ridley, 2015).

3.1.5.1.4 ARTIFICIAL NEURAL NETWORKS (ANNs) MODEL

Artificial neural networks (ANNs) represent another important form of causal models, which have shown powerful capabilities of modeling complex relationships between inputs and outputs. Artificial neural networks have been developed to mimic the human brain system, composed of a numbers of interconnected processing elements called neurons or nodes. Each node receives "information" from other nodes, processes it locally through a transfer function and produces the output for other nodes. Since each node performs its own function, collectively a network can perform a surprising number of tasks quite efficiently (Reilly and Cooper, 1990). This information processing characteristic makes ANNs a powerful computational device and able to learn from examples and then to generalize to examples never seen before (Zang, 1998).

Currently, ANNs are being used for a wide variety of tasks in many different fields of business, industry and science. One major application area of ANNs is forecasting. Different features allow the use of ANNs to address forecasting tasks. First, ANNs are data-driven self-adaptive methods (Zang, 1998). It means they can learn from examples and capture hidden functional relationships among the data even if the underlying relationships are unknown or hard to describe.

Second, ANNs can generalize (Zang, 1998). Once learned the data presented to them, ANNs can often correctly draw the unseen part of a population even if the sample data contain misleading information. They perfectly suit the purpose of forecasting that predicts the future behavior (the unseen part) from examples of past behavior. Third, ANNs have more flexible functional forms than the traditional statistical methods can effectively deal with. Any forecasting model assumes that exists a relationship between the inputs (the past values of the time series and / or other relevant variables) and the outputs (the future values). ANNs can be a good alternative method to identify this function. Finally, ANNs are nonlinear. Differently from traditional forecasting approaches which assume time series generated by linear processes, ANNs can represent reality in a more precisely way, since real world system are often non-linear (Zang, 1998).

Typically, ANNs have several layers, an input layer, a hidden layer, and an output layer. As a causal model, the inputs to an ANN are independent or explanatory variables, and the outputs are dependent or response variables being forecasted. The functional relationship estimated by the ANN can be written as (Zang, 1998):

$$y = f(x_1, x_2, \ldots, x_p), \quad (13)$$

where $x_1, x_2, \ldots, x_p$ are p independent variables and y is a dependent variable.

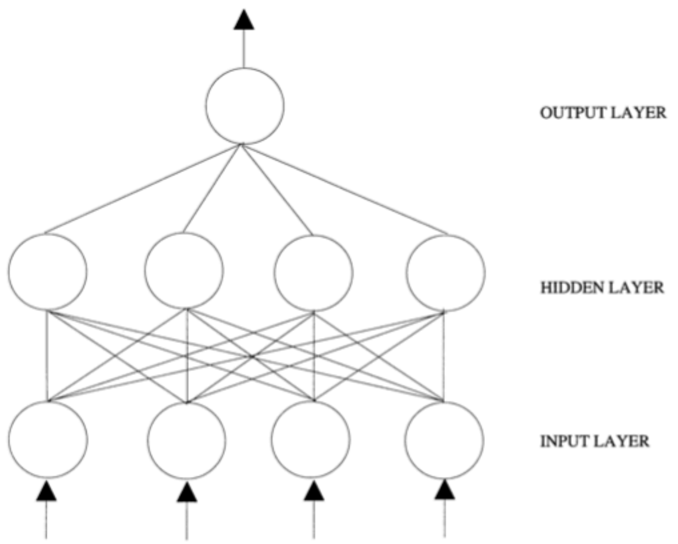

Figure 3.3 – Generic ANNs model

Before an ANN can be used, it has to be trained in order to define the arc weights which are the key elements of an ANN. Once the structure and weights of an ANN are determined, it can be employed to perform forecasting. ANNs have been increasingly used in forecast modeling in the past decade. They are suitable for complicated problems, which are difficult to be mathematically formulated by regression models or econometric models.

In the medical field, the neural networks were mainly applied to improve the quality of diagnosis but were not used very much in the forecast of pharmaceutical products (Fruggiero, 2012). An Artificial Neural Network exploited as forecast model was developed by Chiu (2008) in order to forecast the demand for a specific vaccine. Another ANN model created for this sector has been formulated by Fruggerio (2012). The purpose of the model is to use, as the basis for future needs forecast of pharmacies, personal and diagnostic information of hospital in patients that, after the necessary stay in hospital and with their assigned medical treatment, will determine the real request of medicines at a local level.

3.1.5.2 TIME SERIES MODELS

The demand time series is a sequence of observations D_t (expressed in Kg, €, liters,...), recorded during specific time intervals t, usually equal to each other (days, weeks, months, years,...).

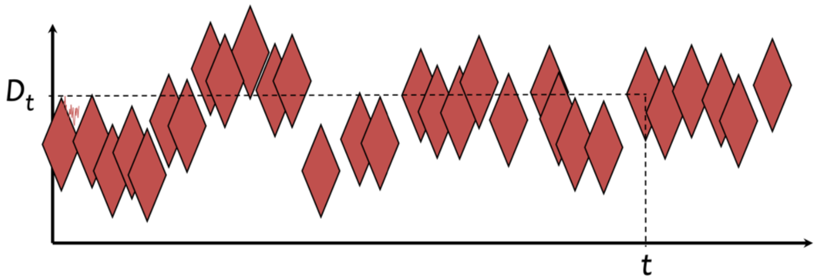

Figure 3.4 – Demand time series

3.1.5.2.1 TIME SERIES ANALYSIS

Before formulating the forecast is necessary to analyze the past demand behavior in order to identify possible trend and seasonality components. In particular, the components that characterize the demand are:

$$D_t = f\,(T_t, S_t, C_t, e_t)$$

3.1.5.2.1.1 TREND

Trend is the increasing or decreasing evolution of demand volume. It may be caused by:

- Changes in the overall volume of product market or the market of a single company. It usually happens during the development phase of products, high demand, or vice versa during the declining phase of the life cycle.

- Changes in the market share of a specific company. For example, due to the competitors, a company can face an increase or decrease in market share.

- Progressive changes of the served geographical market, usually due to an internationalization process

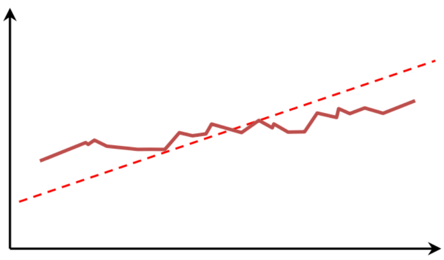

Figure 3.5 – Trend component

3.1.5.2.1.2 SEASONALITY

The causes of seasonality are:

- Climate trend: it entails of products whose cycle depends on the climate. For example, some food or fashion products.

- Customs and traditions: there could be some periods where the demand of some products increases, like the Christmas period.

- Cyclical promotions: they are the typical discounts at the end of the season.

There are also other phenomena which are not strictly seasonal, but are nevertheless relevant. They are defined "*extra-seasonal*":

- Calendar effects: they are usually linked to the working days. Fox example, it is important to take in to account the number of Saturdays and Sundays within the month since it could entail a deviation of the demand which is neither seasonal nor casual. Another example are the movable holidays.

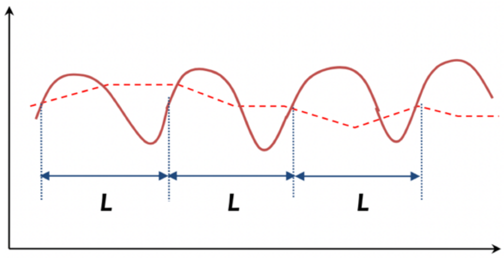

Figure 3.6 – Seasonality component of step L

3.1.5.2.1.3 CYCLICITY

The cyclicity is due to a general economic situation which is able to influence the market of specific goods in the long terms. It is possible to identify different business sectors by comparing their performances according to the cyclicity (Sianesi, 2011):

- Cyclical sectors: they are strongly dependent on the economic cycle. When the economy grows the demand in these sectors grows and vice versa.

- Neutral sectors: they are not heavily dependent on the economic cycle. It usually deals with essential goods (water, food,...).

- Anti-cyclical sectors: they are those sectors which grow when the economic cycle goes into crisis. They refer to the so called “safe heaven”, which are goods with an intrinsic value and result less risky.

3.1.5.2.1.4 TREND ESTIMATION

Through the regression analysis of demand data is possible to identify the trend and quantify it with a function y=f(t) that best approximates the historical data (Sianesi, 2011).

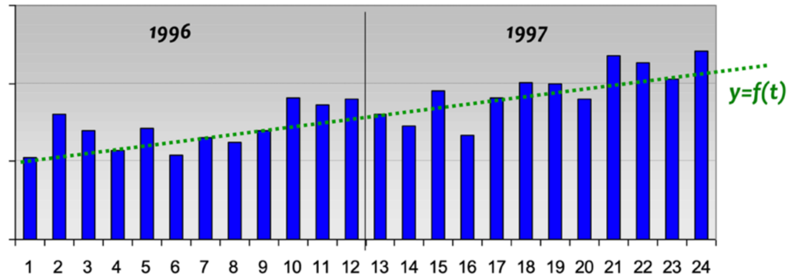

Figure 3.7 – Trend function of 24 demand periods

In order to improve the trend estimation is often convenient filtering the time series. Filtering the time series has the purpose of eliminating and/or smoothing seasonality and the other anomalies present in demand data. A feasible way to filter the demand data is the *centered moving average* (CMA) of order $k = L$ where L is the period in which seasonality and anomalies are sought, usually L = 12 months.

The centered moving average (CMA) represents the arithmetic means of k values such t is the midpoint of the set of instants corresponding to the values:

$$CMA_t(k) = \frac{D_{t-(k-1)/2} + \cdots + D_{t-1} + D_t + D_{t+1} + \cdots D_{t+(k-1)/2}}{k} \quad (14)$$

When k is odd is easy to center the mean in t, on the other hand, when k is even a double recursive procedure is adopted. It is necessary to center the first set of moving averages of order k on the intermediate points of the time intervals, and then calculating a moving average of order k=2 to "temporary realign" the values.

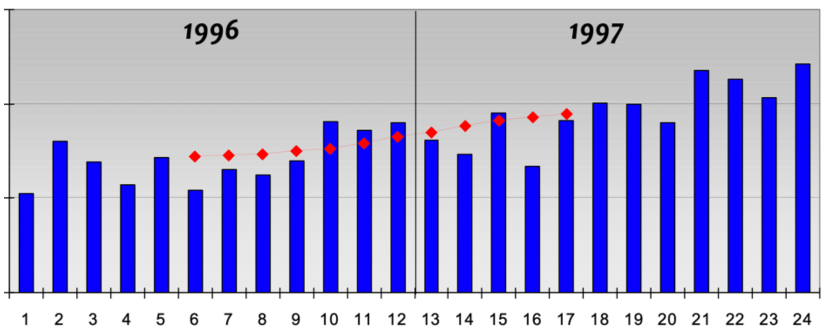

Figure 3.8 – CMA line of 24 demand periods

In the moving average the trend is still present but, as shown in the graph above, it is able to avoid the seasonality since being an average it removes fluctuations and anomalies. Anyway, it is not possible to calculate the centered moving average for all the periods of the time series because the periods at the beginning and at the end of the time series are excluded. This is why, in this case, the centered moving average is used from a mathematical point of view, not from a forecasting point of view.

After filtering the time series, the second step concerns the coefficients that allow to adapt the functional model y=f(t) to the time series. Assuming a linear trend, it is necessary to define the coefficients value of the regression line:

$$y = a + b * t \quad (15)$$

where b [units/period] indicated the slope of the regression line, so the trend. The formulas used to obtain the coefficients a and b are the same presented in the *simple linear regression model*.

Finally, it is feasible to assume that the average demand MT in a specific period t is equal to the regression line calculated at point t. The function y=f(t) detects for each period t the value of the average demand, influenced by the trend component, in that period. This value represents the expected demand at period t if there were no effects of seasonality, cyclicity and random errors.

$$MT_t = y = f(t) \quad (16)$$

3.1.5.2.1.5 SEASONALITY ESTIMATION

Disposing of N historical data (at least two years), it is possible to perform an auto-correlation analysis by calculating the auto-correlation coefficient. The formula of the auto-correlation coefficient is the same of Pearson coefficient (see formula 7). The only difference is that instead of having the dependent and independent variables, X and Y respectively, in the auto-correlation coefficient there is a single variable (demand) but considered as two variables, one describes $year_1$ and the other describes $year_2$.

It is possible to demonstrate that for high values of N (periods) and low values of k (time lag between the periods), the auto-correlation coefficient formula can be simplified as follow (Sianesi, 2011):

$$r = \frac{\sum_{i=0}^{N-k-1}(D_{t-i}-M)*(D_{t-i-k}-M)}{\sum_{i=0}^{N-1}(D_{t-i}-M)^2} \quad (17)$$

Where

$$M = \frac{1}{N}\sum_{i=o}^{N-1} D_{t-i} \quad (18)$$

There is seasonality of step L, where $L=k$, if for k values higher than 2 results a r_k value higher than 0,7. The L seasonal factors are defined one per each seasonal cycle:

$$S_1 \ S_2 \ S_3 \ldots\ldots S_L$$

The seasonal coefficient S_i for a generic period i is attained by the ration between the demand at period i (D_i) and the average value of demand, with trend component, at period i (MT_i).

$$S_i = \frac{D_i}{MT_i} \quad (19)$$

The *"seasonality figure"* is obtained by reporting the seasonality coefficient values on a diagram, where in the x axis there is time and in y axis there are the seasonal coefficients. S_i values higher than 1 means getting forecasting variable values higher than the average, while for S_i values lower than 1 means getting forecasting variable values lower than the average.

3.1.5.2.2 TIME SERIES EXTRAPOLATION MODELS

In the following paragraphs will be adopted the symbology below:

- Effective demand at period t : D_t
- At the end of period t the forecast for the period $t+m$ is: P_{t+m}
- Forecasting horizon: m periods

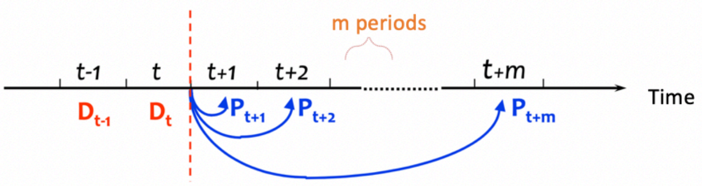

Figure 3.9 – Symbology adopted

Time series extrapolation models are reliable and objective (Armstrong, 2001). They are widely used, especially for inventory and production forecasts, for operational planning for up to two years ahead, and for long-term forecasts in some situations, such as population forecasting (Armstrong, 2001). The extrapolation models investigated in this thesis are the *moving average method, weighted moving average method, simple exponential smoothing methods.* While the investigated models that extrapolate and analysis the time series are *double and triple exponential smoothing methods.*

3.1.5.2.2.1 MOVING AVERAGE METHOD

The concept of moving average is a rough tool to forecast future demand. In this case the mean has not to be centered, the date to take in to account are the ones closer to the period *t*.

Given the demand time series D_1, D_2, ..., D_t, the forecast for period *t+1* is moving average (MA) of order *k* calculated at the end of period *t*. It is therefore possible to assume that the forecast at *t+1* period and of the generic period *t+m* is equal to the moving average at period *t* (Sianesi, 2011).

$$P_{t+1} = P_{t+2} = \cdots = P_{t+m} = MA_t(k) \quad (20)$$

Where

$$MA_t(k) = \frac{D_t + D_{t-1} + D_{t-1} + D_{t-k+1}}{k} \quad (21)$$

With a small number of *k* observations, the forecast is more prone to react to structural changes in the demand but also less resistant to stochastic variation. In extension, such a forecast is likely to mistake random fluctuations in demand for structural changes. In contrast, if a large amount of observations *k* is used to produce the forecast it will act robustly against stochastic fluctuations, but also adapt slowly to changes. (Ghiani et al., 2013).

3.1.5.2.2.2 WEIGHTED MOVING AVERAGE METHOD

The weighted moving average is an extension of the moving average method. Like the moving average method, this method produces a forecast composed by the mean of the most recent sales data entries. In contrast, however, it would be better to consider more the data close the present and less the past ones. The weighted moving average allows to assign different weights to the different past demand data which compose the mean.

$$WMA_t(k) = W_1 D_{t-1} + W_2 D_{t-2} + \cdots W_k D_{t-k+1} \quad (22)$$

Where W_i is the weight of the generic period *i*, and

$$\sum_{i=1}^{k} Wi = 1. \quad (23)$$

The forecast expert usually estimates the coefficient according to his knowledge and experience. However, it is possible to understand from the formula that higher is the value of the coefficients assigned to the values close to present, the more the model reacts quickly to demand structural changes.

3.1.5.2.2.3 SIMPLE EXPONENTIAL SMOOTHING METHOD

Simple exponential smoothing, also referred to Brown method (Brown, 1963), is an improvement of the moving average method. Given the demand time series D_1, D_2, …., D_t , the forecast for the generic period *t+m* is:

$$P_{t+1} = P_{t+2} = \cdots = P_{t+m} = \alpha Dt + (1-\alpha)Pt \quad (24)$$

Where α is the smoothing coefficient whose value lies between 0 and 1.

In other words, the forecast is obtained through a weighted average between the present value of demand D_t and the forecast made in previous period P_t (Sianesi, 2011). The formula can be also re-written in the following way:

$$P_{t+1} = \alpha D_t + P_t - \alpha P_t = P_t + \alpha(D_t - P_t) = P_t + \alpha E_t \quad (25)$$

The difference between demand at period *t* and the forecast at the same period, $(D_t - P_t)$, is the forecasting error (Gardner, 1985). Looking at this formulation, the forecast at period *t+1* is equal to the one made at period *t* corrected by the error made in the previous forecast, smoothed by α coefficient.

Contrary to the moving average method, with the exponential smoothing method the weight that is put on each observation decreases exponentially over time. The most recent observation has the highest weight. Going backwards through the model is possible to demonstrate the exponential smoothing effect (Vandeput, 2018):

at period t: $P_{t+1} = \alpha D_t + (1-\alpha)P_t$ (26)

at period *t-1*: $P_t = \alpha D_{t-1} + (1-\alpha)P_{t-1}$ (27)

at period *t-2* : $P_{t-1} = \alpha D_{t-2} + (1-\alpha)P_{t-2}$ (28)

By substituting:

$$P_{t+1} = \alpha D_t + \alpha(1-\alpha)D_{t-1} + \alpha(1-\alpha)^2 D_{t-2} + \cdots + \alpha(1-\alpha)^i D_{t-i} \quad (29)$$

This formula shows that the forecast P_{t+1} is none other than the last available demand value, multiplied by the α coefficient, added to the demand values of previous periods increasingly smoothed as they move away in time. Therefore, P_{t+1} is the weighted moving average of all past observations.

As with every model, the question comes of the initialization of the first forecast. Since P_0 is unknown, here there are two simple ideas that can be used to initialize the algorithm (Ostertagovà, 2012):

- Initialize the model by setting the first forecast (period 0) equal to the first observation:

$$P_0 = D_0 \quad (30)$$

- Initialize the model by using as first forecast the mean of the first n demand occurrences:

$$P_0 = \frac{1}{n}\sum_{t=o}^{n} D_t \quad (31)$$

Another important aspect of the exponential smoothing method is the estimation of the smoothing coefficient α, since it reflects the reactivity of the forecasting model in answering to demand changes. If the demand has an unexpected peak and the smoothing coefficient value is low, the model will have a small reaction. However, increasing the value of the smoothing coefficient the model tends to perceive demand peak faster. If $\alpha = 1$, the model will predict the same amount of the peak since there would not be smoothing.

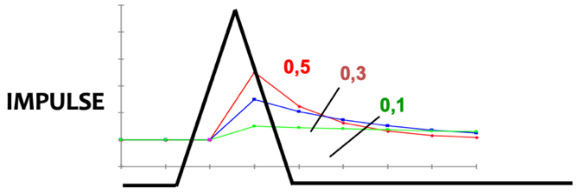

Figure 3.10 – Impulse effect

The same concept can be applied in case of a ramp or step. The higher the value of the smoothing coefficient, the faster the model will react to demand changes.

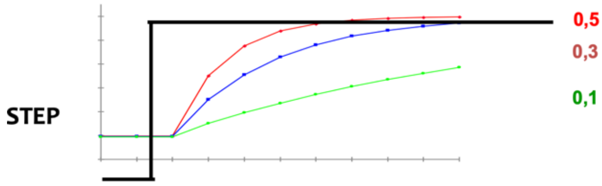

Figure 3.11 – Step effect

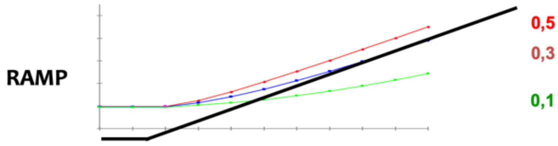

Figure 3.12 - Ramp effect

Usually the value of the smoothing coefficient α is entrusted to forecast experts. Alternatively, it is possible to estimate the value of α through a mathematical model (Hyndman and Athanasopoulos, 2018). It is necessary to set a minimization problem in which the function to minimize is the forecast error and the decision variable is the smoothing coefficient. Some of the possible methods exploited to measure forecast accuracy will be analyzed in another paragraph.

According to what has been said till now, the simple exponential smoothing method can be applied in contexts characterized by the absence of trend and seasonality components. Some of the models that take in to account seasonality and trend will be presented in the following sections.

Gustriansyah, Suhandi, Antony and Sanmorino (2019) tried to predict the sales quantity of multiple products of pharmacy in Palembang city, Indonesia, by using simple exponential smoothing method. After the prediction a MAPE equal to 1.06% was obtained. This means that the accuracy of the predicted sales quantity of pharmaceutical products using the Single exponential smoothing method is high (Gustriansyah et al., 2019). Furthermore, the MAPE value was obtained by forecasting with a smoothing factor α equal to 0,9 (Gustriansyah et al.,2019). This smoothing factor value shows that in a dynamic sector as the pharmaceutical one is needed a reactive model.

3.1.5.2.3 TIME SERIES EXTRAPOLATION AND ANALYSIS MODELS

In the following paragraphs will be adopted the symbology below:

- Effective demand at period t: D_t
- At the end of period t the forecast for the period $t+m$ is: P_{t+m}
- Trend at period t: T_t
- Forecasting horizon: m periods
- Seasonality

3.1.5.2.3.1 DOUBLE EXPONENTIAL SMOOTINIG (HOLT MODEL)

Holt (1957) extended simple exponential smoothing to allow the forecasting of data with a trend. At the end period t, so knowing the effective demand, the forecast of period $t+1$ is given by the mean of period t (M_t), added to the trend at period t (T_t) (Sianesi, 2011).

$$P_{t+1} = M_t + T_t \quad (32)$$

Contrary to simple exponential smoothing method, in this case is possible to extend the forecast to subsequent periods. However, seasonality is still not considered.

$$P_{t+m} = M_t + m * T_t \quad (33)$$

This method involves a forecast equation, as shown above, and two smoothing equations (one for the mean and one for the trend):

$$M_t = \alpha D_t + (1-\alpha)(M_{t-1} + T_{t-1}) \quad (34)$$

$$T_t = \gamma(M_t - M_{t-1}) + (1-\gamma)T_{t-1} \quad (35)$$

As in the Brown's model, α and γ are the smoothing coefficients, respectively of mean and trend, whose values stand between 0 and 1.

In order to calculate the mean, it is necessary to have the demand at the same period and the data of the previous period. It is possible to see the mean formula (M_t) in another way since the data of previous period is none other than the forecast made in the previous period.

$$P_t = M_{t-1} + T_{t-1}. \quad (36)$$

Summing up, the mean is a weighted average of the demand at period *t* and the mean and trend values at the previous period. The previous periods are increasingly smoothed as they move away in time.

The same concept can be applied for the trend formulation. Trend depends on the mean at time *t* *(M_t),* the mean at time *t-1 (M_{t-1})* and the trend at time *t-1 (T_{t-1}).* The trend at time *t* is the weighted average of the increment of the mean *M*, due to the trend, and the trend of the previous period. Even in this case the values of previous are increasingly smoothed as they go away in time.

It is so possible to affirm that in Holt's model, *M* and *T* are the formulas of exponential smoothing of all the data up to period *t* (Sianesi, 2011).

For what concerns the values initialization, there are different methods which can be exploited. Abut the trend some of the possible solutions are (Kelkar, 2004):

- Initialize the first trend value as the increment or difference of the closest two value of demand:

$$T_0 = D_1 - D_0 \quad (37)$$

- Initialize the first trend value as the average increment or difference of the closest values of demand:

$$T_0 = [(D_1 - D_0) + (D_2 - D_1) + \cdots (D_{n+1} - D_n)]\frac{1}{n} \quad (38)$$

- Initialize the first trend value setting it equal to the *b* coefficient of the linear regression line:

$$Y = a + b * x \,; T_0 = b \quad (39\text{-}40)$$

Regarding the mean initialization value, it possible to:

- Set the first value of the mean equal to the last available demand:

$$M_0 = D_0 \quad (41)$$

- Set the first value of the mean equal to the last value identified by the linear regression line:

$$M_0 = a + b * m \quad (42)$$

where a is the intercept, b is the slope (trend) and m are the periods.

As in the simple exponential smoothing, the smoothing coefficients α and γ influence the reactivity of the model. Even in this case, usually, the value of the smoothing coefficients α and γ is entrusted to forecast experts. However, it is feasible to estimate the value of the two coefficients through a minimization problem in which the function to minimize is the forecast error and the decision variables are the smoothing coefficients (Hyndman and Athanasopoulos, 2018).

3.1.5.2.3.2 TRIPLE EXPONENTIAL SMOOTINIG (HOLT-WINTERS MODEL)

Holt (1957) and Winters (1960) extended Holt's method to capture seasonality. The forecast at the end of period t is given by the mean M_t added to the trend of the same period T_t. However, in this case, the cyclical effect of seasonality is taken in to account. The seasonality coefficient S_{t-L} must refer to a comparable period, for example the previous year.

According to the HOLT-WINTERS model, given the time series of demand values $D_1, D_2, \ldots, D_n$, the forecast for period *t+1* is calculated as follow (Winters, 1960):

$$P_{t+1} = (M_t + T_t) * S_{t-L+1} \quad (43)$$

for a generic future period *t+m*:

$$P_{t+m} = (M_t + m * T_t)S_{t-L+m} \quad (44)$$

The Holt-Winters seasonal method comprises the forecast equation and three smoothing equations — one for the mean Mt, one for the trend T_t, and one for the seasonal component S_{t-L}, with corresponding smoothing parameters α, γ *and* β (Fried, 2011). The formulas are similar to

Holt's model ones, the only difference is the presence of seasonality in the mean calculation. The trend formula is exactly the same of the Holt's model:

$$M_t = \alpha \frac{D_t}{S_{t-L}} + (1-\alpha)(M_{t-1} + T_{t-1}) \quad (45)$$

$$T_t = \gamma(M_t - M_{t-1}) + (1-\gamma) * T_{t-1} \quad (46)$$

$$S_t = \beta \frac{D_t}{M_t} + (1-\beta)S_{t-L} \quad (47)$$

Equation number (M_t) shows that the mean at period *t* is the weighted average between the sum of mean and trend if previous period (M_{t+1}+T_{t+1}) and the current seasonally adjusted demand D_t/ S_{t-L}. It is important to note that in deseasonalizing the current demand by D_t/ S_{t-L} , the most recent estimate of the seasonal effect for periods in this position has been used (Winters, 1960). For example, the seasonal factor computed for April last year would be used to seasonally adjust this year's April data.

The novelty of this model lies on the seasonality coefficient formula. In the Holt-Winter model also the seasonality needs to be smoothed. The ratio between the current demand D_t and the current mean M_t is by definition the seasonality. So that the seasonality coefficient is given by the weighted average between the seasonality value at period *t* and the one of previous period *t-1*.

About the initialization of the model, for the firsts values of Trend and Mean is possible to exploit the methods presented for Holt's model. For what concerns the seasonality, it is necessary a minimum of 2 full seasons (or 2L periods) of historical data. A simple solution adopted to calculates the initial value of seasonality (S_0) coefficient is divided in two steps (Ashraf, 2016):

- The first step consists in calculating the seasonality indices of the 2L periods of historical data:

$$S_t = \frac{D_t}{M_t} \qquad t = 1, \dots \dots, 2L \quad (48)$$

- The initialization values, which corresponds to the ones used in the mean equation (M_t), are then calculated through the average of the two seasonal indices corresponding to the same period:

$$S_{t-L} = \frac{S_{t-L} + S_{t-2L}}{2} \quad (49)$$

In literature there are other more complex methods that can be used to calculates the initial value of seasonality coefficient, some of them can be found in the working paper of Trull, García-Díaz and Troncoso (2020).

As in both, the simple exponential smoothing and the Holt's, the smoothing coefficients α, γ, β reflect the reactivity of the model. The value of the smoothing coefficients can be or entrusted to forecast experts or estimated through a minimization problem. Even in this case, the function to minimize is the forecast error and the decision variables are the smoothing coefficients (Winters, 1960).

Anusha, Alok and Shaik (2015) developed a case study in which they seek to understand what forecasting models can better predict stable and seasonal demand of pharmaceuticals. The company investigated is Apollo Pharmacy, one of the largest retail chains in India. The analysis conducted consists in performing the forecasts with all the models, measuring the forecast accuracy by using forecast error indicators and then selecting the right models according to the forecast accuracy. The case study established that Winter's model is the most accurate for seasonal pharmaceuticals, while Moving Average works reliably for stable pharmaceuticals for the chosen Apollo Pharmacy retail (Anusha et al., 2015).

3.1.6 JOINTLY USE OF METHODOLOGIES

Usually, companies prefer to make forecast exploiting different techniques. Ordinarily, companies start with quantitative methods jointly using extrapolative time series techniques and casual methods based on correlations (Sianesi, 2014). The output will be the forecasting plan proposal which has to be analyzed since there could be some critical items. Examples of critical products can be those ones with a high value or which are the beginning or at the end of their life cycle. Anyway, these products have to be submitted to qualitative analysis due to their particular characteristics. After this second step the final forecasting plan is obtained. However, this is not the only scheme which can be follow, there could be some variations depending on the cases.

3.1.7 FORECAST ERRORS AND ACCURACY MEASUREMENT

It fundamental for any SC to understand how to measure and the related impact of forecast errors. The main impacts of forecast errors can be summarized in three categories (Wallastro, 2009):

- *Planning impacts* regards the extra work and the related costs associated to the redesign of the entire plan. This leads to schedule instability.

- *Capacity impacts* which are related to the uneconomical use of capacity

- *Inventory impacts* which include inventory holding cost, obsolescence, lost “sales” cost ecc..

First of all, it is necessary to evaluate the relationship between costs and benefits as accuracy varies. If the forecasting process is performed with low accuracy there will some costs due to the wrong forecasts, such as stock-out costs, stops of production lines or increase in stock costs. In this way, however, the costs of the forecasting process decrease (Sianesi, 2011).

On the other side, if the costs of the forecasting process increase the accuracy increases. it is necessary to build an optimal zone in which the total cost function is minimized. The total cost function is given by the sum between the forecasting process costs and the costs of wrong forecasts.

3.1.7.1 FORECAST ERROR

The forecast error refers to specific time interval which is not further subdivided inside as a “time bucket” (Sianesi, 2011). It is defined as the difference between the effective value of demand at time t (D_t) and the forecasted value at time t (P_t). The error is considered “positive” when the demand is higher than the forecast.

$$E_t = D_t - P_t \quad (50)$$

There are many methods to compute the forecast accuracy, based on the forecasting error e_t. Each measure is calculated for a fixed horizon n which varies according to the planner decision. Shorter is the horizon faster the value will react to deviations from the average, but then it also might fluctuate heavily due to random demand variations (Stadler and Kilger, 2005).

3.1.7.2 FORECAST ERROR MEASURE

It is possible to group the forecast error indicators in three different categories (Sianesi, 2011): *distortion indicators, consistency indicators and tracking signal.*

3.1.7.2.1 DISTORTION INDICATORS

The typical distortion indicator is the mean error ME. It is given by the sum of the errors from period t=1 to n divided by the n number of observations (period evaluated):

$$ME = \frac{\sum_{t=1}^{n} E_t}{n} \quad (51)$$

When it is useful to understand if the forecasting model adopted overestimates or underestimates the demand, it is convenient to calculate the mean (Sianesi, 2011). If ME is lower than zero, it means that the forecasting model systematically underestimates the demand. While, if ME is higher than zero, the forecasting model systematically overestimates the demand. It is important to note that a ME equal to zero is not always a good value since making an average the values of different errors could offset each other.

3.1.7.2.2 CONSISTENCY INDICATORS

Some of the most exploited consistency indicators are: *Mean Absolute Deviation, Mean Absolute Percent Error, Mean Square Error and Standard Deviation of Error.* All of them are presented below.

3.1.7.2.2.1 Mean Absolute Deviation (MAD)

The Mean Absolute Deviation measures the accuracy of the forecast by averaging the alleged error (Khair, 2017) (the absolute value of each error). MAD is often exploited when it is useful to measure the prediction error in the same unit as the original series. The MAD formula is expressed as follow.

$$MAD = \frac{\sum_{t=1}^{n} |E_t|}{n} \quad (52)$$

Thanks to the absolute value, MAD allows to measure the consistency of the errors since the errors with opposite signs do not compensate each other. On the other hand, this is the complementary case to the ME indicator because it is not possible to understand if the forecasting model is overestimating or underestimating the demand (Sianesi, 2011).

3.1.7.2.2.2 Mean Absolute Percent Error (MAPE)

The Mean Absolute Percent Error is the relative version of MAD (Ostertagovà, 2012). In this case, the absolute value of the error at time t (E_t) is divided by the demand value of the same period (D_t).

$$MAPE = \frac{\sum_{t=1}^{n} \frac{|E_t|}{D_t}}{n} 100 \quad (53)$$

The main feature of this indicator is that it allows the comparison of forecasts between different items or products since it measures relative performance. Anyway, given the error in absolute value, MAPE most severely penalizes the errors done at periods when the demand value is low. For example, an error of 1% has a different weight if it refers to a low or high demand value. Furthermore, percentage errors have the disadvantage of being meaningless if the time series includes null demand values (Hyndman and Athanasopoulos, 2018).

3.1.7.2.2.3 Mean Square Error (MSE)

Another common indicator used to measure the forecasting errors is the Mean Square Error. In this case, the absolute value of the error is substituted by the squared error (Sianesi, 2011).

$$MSE = \frac{\sum_{t=1}^{n}(E_t)^2}{n} \quad (54)$$

MSE most severely penalizes the lager errors in absolute value. In addition, the unit of measure of this indicator is not very practical since it deals with squared absolute errors. However, MSE is related to standard deviation of forecast errors and is therefore an appropriate error for mathematical operations (Wallström, 2009). In addition, In the Linear Regression forecasting procedure the MSE is used as the objective function which is minimized. As the error is squared in the formula, large deviations are weighted more heavily than small errors (Stadler and Kilger, 2005).

3.1.7.2.2.4 Standard Deviation of Error (SDE)

Standard Deviation of Error is also known as standard error. Standard error refers to the estimated root-mean-squared deviation of the error in a parameter estimate or a forecast under repeated sampling (Nau, 2014).

$$SDE = \sqrt{\frac{\sum_{t=1}^{n}(E_t)^2}{n-1}} \quad (55)$$

In this case, there is not the distortion due to the demand squared error and its unit of measure become practical again. However, it provides similar indications of the Mean Square Error (Sianesi, 2011).

3.1.7.2.2.5 Tracking Signal (TS)

The object of Tracking signal is to detect systematic change in the demand or a systematic error of the forecast method (Wallström, 2009). The formula of TS is showed as follow.

$$TS = \frac{\sum_{t=1}^{n} E_t}{MAD} \quad (56)$$

TS can vary between +n and -n, the two extremes correspond to:

- If TS = -n, it means the forecast systematically overestimates the demand

- If TS = +n, it means the forecast systematically underestimates the demand

- If TS = 0, the forecasting model neither overestimates nor underestimates the demand

Every time there is a new demand value with its forecast is possible to calculate the error and consequently the tracking signal which can be analyzed over the time. In this way, the TS allows to highlight the deterioration of the forecasting model (Sianesi, 2011). Usually, two thresholds are set and when the TS overtakes one of them an alarm is triggered, so that the users can analyze the deviation causes. The tracking signal is synthetic indicator which gives the possibility to monitor the forecast model over time.

3.1.7.2.2.6 Control charts

Another tool adopted to monitor the forecasts are the control charts. In contrast to tracking signals, control charts can be used to assess each forecast error individually (Palm, 2017). As tracking signal, also control charts exploit control limits in order to detect the deviation causes. Assuming that the forecast error is normally distributed variable with average μ_e and a standard deviation σ_e, it is possible to a confidence interval $\mu_e \pm k\sigma_e$ as control limits.

$$CL = \mu_e \pm k\sigma_e \quad (57)$$

Where

$$\sigma_e = SDE = \sqrt{\frac{\sum_{t=1}^{n}(E_t)^2}{n-1}} \quad (58)$$

K is a parameter which defines the width of the confidence interval.

Control charts allow to study the development of the error (Ghiani et al., 2013). For example, detecting a trend of errors could mean that the demand is rising or falling. While, if the error patter periodically occurs, it could indicate that the demand is affected by seasonality.

3.2 INVENTORY CONTROL

The general goal which lies behind inventory control involves the minimization of all the costs linked to stocks (Ballou, 1998). In details they are:

- Holding costs; they are the costs of keeping inventory in the warehouse which lead to capital immobilization.

- Reorder, setup, transportation... costs

- Disservice costs (delays, stockouts,...); by keeping as inventory big a large amount of stocks the storage costs increases as product availability increases and vice-versa.

In addition, stocks can be classified according to their function. This classification shows the importance of inventory planning:

- *Cycle stocks (CS)*

  The function of cycle stocks is to overcome the discontinuity between the supply and withdrawal of stocks (Sianesi, 2011). Discontinuity can be caused by an anticipated production batch compared to consumption or by a difference between replenishment frequency batch and the withdrawal frequency from the warehouse. The reasons for batch replenishments include: economies of scale (because of large setup costs), quantity discounts in purchase price or freight cost and technological restrictions such as the fixed size of a processing tank in a chemical process (Silver, 2016). The amount of cycle stock on hand at any time depends directly on how frequently orders are placed. This decision is in charge of the management which has to fix the trade-off between the cost of ordering and the cost of having cycle stocks on hand (Silver,2016). However, the formula below represents the calculation of cycle stock.

$$CS = \frac{Q}{2} \quad (59$$

Q is the average order quantity and it is divided by two since cycle stocks is an average between the quantity at the moment in which the order arrives and the quantity when that order has been consumed, so zero. Anyway, cycle stock formula is an assumption since it shows the average amount of inventory present in the warehouse. It does not correspond to exact number.

- *Safety Stocks (SS)*

The function of safety stocks is to cover the variability and uncertainty along the supply chain (Sianesi, 2011). For example, even if the supplier is on time, if the demand unexpectedly increases before the end of the lead time the stock will go below zero without having an additional stock. Specularly, even if the demand were as forecasted, if the supplier is not on time there will be stockout without keeping in the warehouse a safety stock. Demand and lead time variability are two independent phenomenon so companies need safety stock in order to smooth both of them. Increasing the amount of safety stocks lead a greater resilience at the cost of a higher immobilized capital. SS formula is not always the same, it changes in function of the inventory control model. In addition, the level of safety stock is controllable in the sense that this investment is directly related to the desired level of customer service (Silver, 2016)

- *In-transit stock (ITS)*

They include goods in transit between levels of a multi-echelon distribution system or between adjacent work stations in a factory. The ITS of an item between two adjacent locations is proportional to the usage rate of the item and to the transit time between the locations (Silver, 2016). In order to evaluate the in-transit stocks is possible to do hydraulic analogy (Sianesi, 2011).

$$ITS = F * LT \quad (60)$$

Where F is the average flow between a point of origin and a point of destination that can be compared to the flow rate of a fluid. While LT is the average length of the travel associable to the time spent by the fluid to travel the pipe. It is important to know that flow and lead time must have a coherent unit of measure. For example, if the flow is expressed in unit per day the lead time has to expressed in days.

- *Anticipation stocks*

This kind of stocks are usually accumulated in advance of an expected peak of demand (Silver, 2016). When demand is lower than average during a period of the year, it is possible to build excess inventory so that during the period of high requirements the demand can be served from stocks instead of working overtime in the plant.

- *Decoupling stocks*

These stocks are used in a multi-echelon configuration in order to separate the decision making of the different echelons. For example, decoupling inventory allows decentralized decision making at regional warehouses without impacting the decisions at the central warehouse or factory (Silver, 2016).

- *Other stock function*

There are also other typologies of stocks with different scopes. Speculative and opportunistic stocks are linked to discounts and market price development. Stocks linked to transportation allows to reduce the transportation cost thanks to full load shipment. There can be stocks exploited to improve quality of some products like wine or cheese which need to season and age (Sianesi, 2011).

3.2.1 INVENTORY MANAGEMENT MODELS

Inventory management models can be classified or according to continuity of stock level control over time or in function of order quantity (Sianesi, 2011). With periodic review models, the stock level is controlled every T time units, so between two consecutive reviews there may be uncertainty about the stock level value (Silver, 2016). On the other side, with continuous review model is possible to get the same service level requiring less safety stocks. This is because the period over which safety protection is required is longer under periodic review (Silver, 2016). In this thesis, the models analyzed are *fixed reorder interval model (T), fixed order quantity model (EOQ-OP)* and *variable quantity-order point model (Q-OP)* which consists in mix of them. In the first model, the order issue interval is fixed, regular and predefined. While, the order quantity can vary. The second model allows to manage the orders with variable time intervals and it needs a continuous control of the inventory level. When the inventory level reaches a certain point, the order point OP, the order is issued and order quantity is fixed and equal to the economic order quantity EOQ. The third is still continuous review model, like the EOQ-OP, a replenishment is made whenever the inventory position drops to the order point OP. However, in this case the order quantity varies.

3.2.1.1 FIXED ORDER QUANTITY MODEL (EOQ-OP)

Analyzing the dynamic of the inventory, it is possible that when the inventory level falls over the Order Point the order is issued and contemporary the availability of the product ordered will increase by an amount equal to the EOQ. While, in parallel, physical stock decreases continuously over time.

At the end of the replenishment time the economic order quantity arrives and the physical stock realigns with the availability (Slanesi, 2011). However, even if this is a theoretical model there could be possible issues. If the replenishment time increase compared to the forecasted one it could lead to stockout. Similarly, given a replenishment time as forecasted, if the demand unexpectedly increases after the inventory level matches the OP there will be stockout till the economic order quantity arrives. In order to solve the stockout phenomenon the proper solution is holding safety stocks.

3.2.1.1.1 Economic order quantity (EOQ)

The economic order quantity is one of the most widespread optimization models in the supply chain management (Jinn and Teng, 2009). The economic order quantity (EOQ) is the most robust inventory model, it has been introduced for the first time by Ford Whitman Harris in February 1913. Since then, there has been an impressive growth in the number of published papers related to it (Leopoldo, 2014).

The relevant costs considered in this model are (Bartman and Beckmann, 1992):

- *Annual inventory carrying cost* which consists of interest costs, handling costs and rental costs for storage. This cost proportionally and linearly increases as the order size increases.

- *Annual order issuing cost* (if goods are purchased from suppliers) or *annual set-up cost* (if goods are internally produced). This cost decreases as the order size increases.

The total cost is the sum of those two costs mentioned above. Since one has an increasing trend and the other has a decreasing one, the trend of the total cost has a minimum which defines the size of optimal quantity EOQ.

The hypothesis underlying this model are listed as follow (Axsäter, 2009).

- Annual demand is constant D (unit/year)

- Order issuing cost or set-up cost is constant C_O (€/order or €/unit)

- Purchasing cost (or variable production cost) P is constant (€/unit)

- Storage cost C_m is constant (%/year)

- Warehouse storage capacity is not a constraint, it means the model doesn't consider a maximum storage capacity

According to the hypothesis, the objective of the model is to find the order quantity Q which minimize the total cost CTOT. the optimal order quantity Q corresponds to the economic order quantity EOQ. The total cost function is equal to (Sianesi, 2011):

CTOT = Purchasing cost + Order issuing cost + Inventory carrying cost

That can be written in the following shape

$$CTOT(Q) = P * D + \frac{D}{Q} * C_O + \frac{Q}{2} * P * C_m \quad (61)$$

Where $P * D$ is the annual purchasing cost, $\frac{D}{Q}$ is the annual number of orders while $\frac{Q}{2} * P * C_m$ is the quantity deriving from the immobilized capital.

Nullifying the derivate of CTOT with respect to Q is possible to obtain the EOQ formula.

$$EOQ = \sqrt{\frac{2*C_O*D}{P*C_m}} \quad (62)$$

Length of inventory cycle T is a measure that gives a time period how long a batch of EOQ can last in the storage. It is possible to calculate the length of the inventory cycle by assuming the daily consumption d as given (Senthilnathan, 2019).

$$EOQ = T * d \quad (63)$$

$$T = \frac{EOQ}{d} \quad (64)$$

Anyway, the assumptions of this model are very stringent. The classical economic order quantity (EOQ) model assumes that items produced are of perfect quality and that the unit cost of production is independent of demand. However, in realistic situations, product quality is never perfect, but is directly affected by the reliability of the production process (Tripathy, 2003). Several researchers formulated different versions of the EOQ model, Rosenblatt and Lee (1986) have presented two sophisticated models to deal with the EOQ problem with imperfect production, Porteus (1986) analyzed the effect of process quality improvement and set-up cost reduction on optimal lot-sizing. Tapiero (1987) presented a theoretical framework to investigate the trade-offs between pricing, reliability, design and quality control issues operations. Cheng (1989) formulated an EOQ model with an imperfect production process and quality-dependent unit production cost.

3.2.1.1.2 Order Point (OP)

The order point is given by the relationship between the average daily demand D_{day}, the lead time LT and the safety stocks SS (Sianesi, 2011 and Senthilnathan, 2019).

Analytically:

$$OP = D_{LT} + SS \quad (65)$$

where D_{LT} is the average demand during the lead time and is given by the following formula.

$$D_{LT} = D_{day} * LT \quad (66)$$

Regarding the safety stocks, assuming that the demand is affected by variability according to a normal distribution and that the lead time is also affected by variability according to a normal distribution, the safety stocks formula can be written as:

$$SS = k\sqrt{{\sigma_D}^2 * LT + D^2 * {\sigma_{LT}}^2} \quad (67)$$

Where k is constant which defines the required service level. D is the demand, $\sigma_D$is the standard deviation of demand, LT is the lead time and σ_{LT} is the standard deviation of lead time.

The main advantage of the EOQ-OP model is the possibility to have a relative low inventory level in terms of immobilized capital. This is due to the fact that the quantity purchased is the optimal and the inventory level is continuously controlled. On the other side, with this model is quite difficult to plan multi-items ordering since for each item there is an optimal quantity to order in a specific moment. Furthermore, EOQ-OP model is more time and cost consuming a lot of time since it requires a continuous control of the inventory level (Sianesi, 2011). However, thanks to the modern information systems available in the market, it is possible to avoid this issue.

An example of the EOQ-OP model in the pharmaceutical industry is illustrated by Pizano (2019). The object of his work is to quantify the effects of EOQ-OP model adoption over a pharmaceutical retail chain, trying to find the best trade-off between inventory holding cost and service level.
The experiment resulted with an estimated cost savings of 33% in the inventory management derived from inventory reduction. On the other side, it entailed a reduction of service level of 2,53% (Pizano, 2019).

3.2.1.2 VARIABLE QUANITY – ORDER POINT MODEL (Q-OP)

As for the EOQ-OP model, even in the Q-OP model an order is made when the inventory level matches the order point (OP). The difference with the EOQ-OP model is that the order quantity is not fixed but it varies in function of the predefined objective level (OL). It is possible to demonstrate that the Q-OP model's total costs of replenishment, carrying inventory, and shortage are not larger than those of EOQ-OP model (Silver, 2016). However, the computational effort to find the best order point (OP) and objective level (OL) is greater. The main disadvantages of this system are the variability of order quantity, since suppliers could make errors more frequently, and they usually prefer receiving fixed order quantity (Silver, 2016), and the time and cost consuming continuous control of the inventory level.

3.2.1.3 FIXED TIME PERIOD MODEL

This system, also known as a replenishment cycle system, is commonly used in companies without sophisticated computer control. It is also frequently seen when items are ordered from the same supplier, or require resource sharing (Silver, 2016). Replenishment orders are issued with fixed time interval T, the order quantity varies every time in order to reach the predefined availability level (Objective Level OL) (Sianesi, 2011).

Every T intervals an order is issued. As in the previous model, when the order is issued the inventory availability reintegrates instantly while the physical one keeps decreasing till the quantity ordered is delivered. Comparing this model with EOQ-OP one the logic is overturned.
According to the Fixed Time Period model, the quantity to order Q is given by the difference between the availability objective level (in units) OL and the actual availability level AAL (Sianesi, 2011).

$$Q = OL - AAL \quad (68)$$

Where the actual availability level is given by

$$AAL = PQ + QO - QC \quad (69)$$

In the formula above, PS corresponds to the quantity physically present in the warehouse, QO is the quantity ordered while QC indicates the quantity already committed (Silver, 2016).

When fixing the availability objective level of inventory, it is necessary that this value allows to cover the average demand during the period LT+T, so the lead time added to the time interval between two orders.

$$OL = D * (LT + T) + SS \quad (70)$$

In this model, safety stocks have to cover the demand variability during the period T+LT and the variability of the lead time itself. As for the EOQ-OP model, assuming that the demand is affected by variability according to a normal distribution and that the lead time is also affected by variability according to a normal distribution, the safety stocks formula can be written as (Sianesi, 2011):

$$SS = k\sqrt{\sigma_D{}^2 * (LT + T) + D^2 * \sigma_{LT}{}^2} \quad (71)$$

It possible to see that this formula is exactly the one used in the EOQ-OP model where instead of the lead time there is the sum of lead time and time interval between subsequent orders. Since the value of T is fixed and predefined it is not affected by variability.

The positive aspects of this model are the two main drawbacks of the EOQ-OP model. Because of the periodic-review property, this system is much preferred to order point systems in terms of coordinating the replenishments of related items (Silver, 2016). For example, when ordering from the same supplier, the probability to fulfil a shipping container is higher and so is possible to reduce unitary transportation cost. In addition, this method offers a regular opportunity (every T time interval) to adjust the objective level (OL), which is an important feature if the demand pattern is changing with time. However, the main disadvantage is that the average inventory level is higher than EOQ-OP model. This is due to the fact that there is not a continuous control and so the quantity ordered cannot be economical and optimal (Sianesi, 2011).

4. BUSINESS CONTEXT

4.1 BRIEF COMPANY DESCRIPTION

The target company is an Italian pharmaceutical distributor based in Lainate, Lombardy (Italy). Today, it is the second largest distributor in Italy, with a turnover of 1.2 billion as of 2019. The investigated company counts 700 employees, distributes pharmaceutical drugs to 7.500 pharmacies spread in 17 Italian regions and manages a range of products equal to 65.000 unique references. It is a customer-oriented company, whose main goals are to constantly improve the distribution service features according to the market and to create innovative services for the healthcare market. It is important to know that the Board of Director is primarily composed by a group of pharmacists who founded the studied company in 2002 from the merge of the distributive branch of several Italian pharmacists' cooperatives. The purpose of pharmaceutical cooperative is to safeguard the pharmacies that belong to, by holding stocks on pharmacies behalf. In this way, it is possible for pharmacies not to do overstock and at the same time, having a high service level.

4.2 THE DISTRIBUTION NETWORK

The distribution network of the company site is composed by almost 750 suppliers that are manufacturing companies, 8 owned distribution centers, and 7,500 customers, i.e. the pharmacies. Taking a supply chain perspective, it is the case of a 1-echelon distribution network in which plants (held by manufacturers/suppliers) replenish the distribution centers, from where goods are delivered to points the pharmacies. Taking the company site perspective instead, this case represents a direct-shipment scenario since goods are directly delivered from the DCs to the pharmacies.

The distribution centers are located in different cities and widespread in the entire Italy: Rivoli, Novara, Lainate, Nogarole Rocca, Udine, Calderara, Monterotondo and Modugno. Thanks to this wide spread distribution network the considered company is able to perform on average 15.000 delivery per day. The responsibility of the target company starts when the goods arrive at the distribution centers, the inbound transportation, so the flow of goods from manufacturers to the DCs is in charge of the manufacturer. Therefore, the company has to ensure that the inventories at the distribution centers are sufficient to satisfy customers' needs and has to guarantee the fastest possible delivery to the pharmacies. The Information system adopted by the company to integrate the DCs and the transportation is SAP 1998 version.

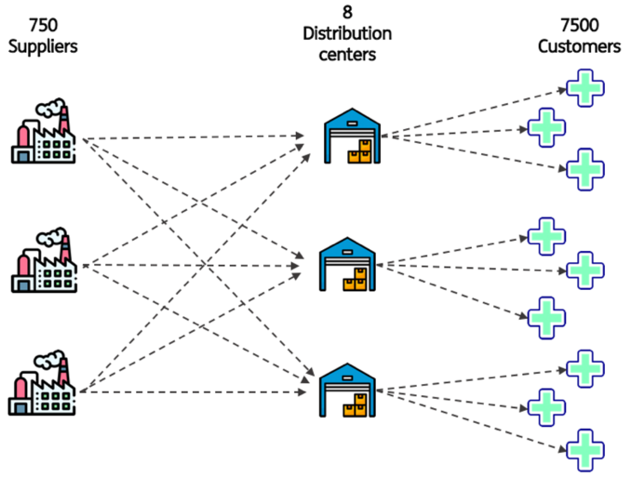

Figure 4.1 – Company supply chain

4.2.1 AN ALTERNATIVE FLOW

In the pharmaceutical industry there is an alternative flow of goods that in the business is known as grey market. Some pharmacies can get a license to become a sort of supplier, so to have the possibility to sell their extra inventories to distributors. This is due to a particular feature of the pharmaceutical market where the manufactures have the possibility to directly sell their products to the pharmacies at a price lower than that proposed to distributors. This strategy promoted by manufacturers is due to the fact that pharmacies have a direct impact on patients purchasing decisions, while distributors do not have a direct contact with the final customer.

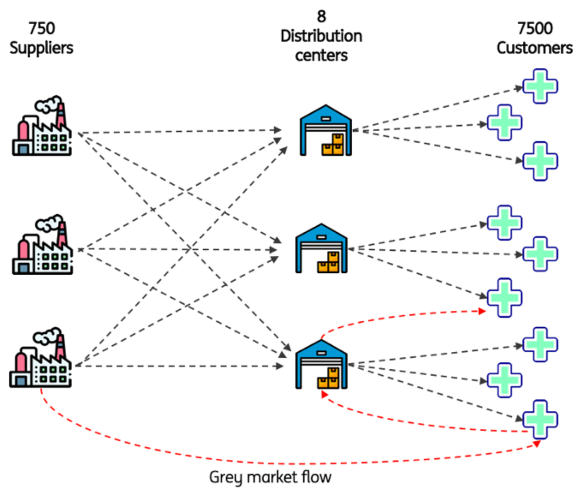

Figure 4.2 – Alternative flow (grey market)

4.3 PRODUCT CATEGORIES

The studied company groups their products in 5 categories: Ethic, Counter Medicines, Para-pharmaceuticals, Homeopathic and Narcotic. Ethic products are those that can be bought just with the prescription. Counter Medicines products are those that can be bought without prescription. Para-pharmaceuticals are all the substances or products that have an adjuvant function compared to the real medicine. For example, material used in medications, hygiene products, cosmetics, dietetic products belong to this category. Homeopathic medicines are products obtained using substance of mineral, chemical, vegetable, animal and biological origin through specific production methods. Lastly, Narcotics are those products, like morphine, which requires a particular and specific prescription to be bought.

4.4 PROCUREMENT ORGANIZATION

The company site has a centralized procurement organization. All the requirements coming from the different distribution centers are aggregated at the headquarter in Lainate. Then, the procurement office of Lainate sends the orders to the suppliers who deliver them directly to the specific DCS, without passing from the headquarter. The matrix below shows the role of the purchasing department inside the organization according to two dimensions, the focus and aim of purchasing.

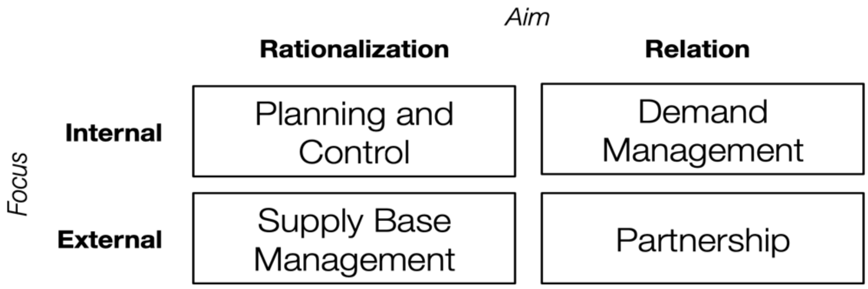

Figure 4.3 – Purchasing department role matrix

The company site can be placed in the up-left quadrant, planning and control, which means the purchasing function tracks the purchasing process and keep company's expenditures under control, by constantly looking for efficiency opportunity through spend management.

4.4.1 INTERNAL ORGANIZATION

Taking an internal point of view, the purchasing function follows a functional grouping criteria based on the order typology. There are 4 different order typologies made by the target company:

- Standard orders

  These types of orders are periodically issued and their main objective of these orders is to satisfy the customers' demand by following the company reorder logics. In this case, the order quantity is suggested by the information system (SAP) according to forecasts, inventory availability and the desired service level. They account for the 68% of the total annual orders.

- Grey market-related orders

  These orders are due to the peculiar characteristic of the pharmaceutical industry which has been previously explained in the distribution network section. Since this typology of orders is directly made at pharmacies, it is not possible to purchase large quantities and this is why they account for the 9% of the total annual orders. Anyway, thanks to the favorable purchasing price of these orders, their main purpose is to lower the average purchasing products price.

- Speculative orders

  Speculative orders have principally a commercial purpose. These orders are based on contractual agreement between the manufacturers and the studied company. If the company site reaches a certain amount of expenditure from a specific supplier, within the fiscal year, then the supplier will reward the company site by an amount of money proportional to the expenditure. Therefore, these orders, which account for the 20% of the total annual orders, are split along year without following any forecasting or inventory policy. They are just based on agreements and negotiations between the company buyers and suppliers. It is important to point out that these orders typically consist in slow moving products orders that consistently increase the inventory level and overload all the warehouse operations. Anyway, the contractual agreement has two main positive aspects. Firstly, receiving a monetary reward at the end of the fiscal year strongly improves the company funds. Secondly, making these contracts reinforces the relationship between the considered company and the manufactures.

- Homeopathic orders

  These orders regard all the Homeopathic products. Even if they follow the same logics of the standard orders, it was decided to manage them separately due to the technical knowledge required to purchase these products. They account for the 3% of the total annual orders.

4.5 PROCESSES FRAMEWORK

This paragraph provides a picture of the current models and practices, adopted by the company site, over the two processes investigated in this theory, forecasting and inventory control management.

The company analyzed employs a fixed-time period model in order to take the inventory under control. The order interval T, fixed and equal for all product portfolio, is equal to 1 week. The formula for definition of the objective level (OB) is equal to the one presented in literature (see formula 70) with a difference on the safety stock calculation. In the company case, safety stock, instead of being analytically calculated through the proper formula (see formula 71), are defined according to the objective number of the "days of coverage" (DoC). The DoC corresponds to the number of days with whom is possible to satisfy the demand just with the inventory. This objective number of coverage's days encompass days of lead time variability, days for goods entry and a number of days which considers the target service level and changes according to the ABC classification of the product. The ABC product classification is based on the rotation index. It is important to point out that the definition process of the DoC is not formalized, it is mainly based on the experience of the decision maker, the Stock Specialist. Anyway, the formula of the DoC is presented as follow.

$$DoC_{days} = LT_{variability}(days) + GoodsEntry(days) + ServiceLevel_{A,B,C}(days) \quad (72)$$

Therefore, the Objective level (OL) is given by

$$OL = D * (LT + T) + D * DoC \quad (73)$$

The forecast model exploited by the company is the weighted moving average (see formula 22). The forecasting time period is equal to 1 week and the model considers 4 past observations differently weighted in order to forecast the next week requirement. The weights, equal for all the product portfolio, are 10% for the closest demand value, 40% for the two past demand values in the middle of the time series and 10% for the furthest demand value. Since the output of forecast is the weekly requirement, it is divided by days per week for the calculation of the OL in order to get a daily requirement.

Lastly, the information system proposes an order quantity based on the formula below.

$$Q = OL - Physical\ Stock - Quantity\ Ordered \quad (74)$$

5. FINDINGS AND RESULTS

5.1 FORECAST ANALYSIS

As previously mentioned, one of two objectives of this study is the evaluation of different forecasting models in order to improve the company performances. The information system employed by the company site offers 4 different forecasting models: weighted moving average, simple exponential smoothing, double exponential smoothing (Holt's model) and triple exponential smoothing (Winters-Holt's model). However, since company software misses different modules whose allow a reliable application of the entire set of forecasting models, only 2 of the 4 present models were tested and compared. The two just mentioned models are the one currently adopted by the company (weighted moving average) and the simple exponential smoothing. Although both models do not require an analysis of the demand time series, it was anyway performed. The aim of the analysis was to distinguish the products whose demand is affected by seasonality from the products with regular demand, in order to understand how and if the seasonality component influences the performances of the two investigated forecasting models.

In this case, the Chief Operations and Logistics Officer (COO) was interviewed with the aim of understanding which product category could be exploited as test subject. According to the COO answer, the demand data exploited to test, compare and evaluate the forecasting models belongs to the category of Ethic products which generates around the 65% of the company turnover.

5.1.1 SEASONALITY ANALYSIS

The seasonality analysis was performed employing class A items of Ethic category that corresponds to 2,470 references. Even in this case, the ABC product classification is based on the rotation index. For all the 2,470 references, 3 years of sales data was analyzed, specifically 2016, 2017 and 2018 data. The data was bi-monthly aggregated in order to emphasize potential seasonal patterns, thus creating a sales time series composed by 18 periods.

The analysis was performed on Microsoft-Excel by searching a seasonal pattern between years 2016 vs 2017 and years 2017 vs 2018 through the use of the auto-correlation coefficient (see formula 17). Table 5.1 shows an extrapolation of the spreadsheet shape on which there are the values of the auto-correlation coefficient.

Period \ Product	A001	A002	A003	A004	A005	A006	A007	A008	A009	A010
Dic/Jan-16vs17	0,57	0,40	0,43	0,31	0,31	0,30	0,00	0,05	0,67	0,42
Feb/Mar-16vs17	-0,13	-0,13	-0,39	-0,27	-0,62	-0,22	-0,11	0,17	0,21	0,07
Apr/May-16vs17	-0,51	-0,29	-0,89	-0,57	-0,71	-0,21	-0,35	-0,29	-0,08	0,67
Jun/Jul-16vs17	-0,21	-0,23	-0,31	-0,39	-0,33	-0,58	-0,21	-0,38	-0,33	0,35
Aug/Set-16vs17	0,76	0,51	0,54	-0,04	0,51	0,17	0,02	-0,15	-0,78	0,06
Oct/Nov-16vs17	0,88	0,87	0,89	0,96	0,94	0,61	0,45	-0,07	-0,96	0,71
Dic/Jan-17vs18	0,33	0,70	0,55	0,64	0,28	0,23	-0,19	-0,22	0,33	-0,24
Feb/Mar-17vs18	-0,27	0,02	-0,34	-0,27	-0,72	-0,65	-0,12	-0,16	0,26	0,09
Apr/May-17vs18	-0,82	-0,05	-0,66	-0,61	-0,67	-0,57	-0,52	0,40	0,01	0,52
Jun/Jul-17vs18	-0,49	0,30	-0,31	-0,29	-0,12	0,25	0,29	0,08	-0,60	-0,52
Aug/Set-17vs18	0,27	0,85	0,55	0,53	0,35	0,48	-0,24	0,25	-0,53	0,64
Oct/Nov-17vs18	0,80	0,94	0,90	0,98	0,84	0,63	0,67	0,28	-0,08	0,25

Table 5.1 – Auto-correlation coefficient value

As mentioned in the literature paragraph, there is seasonality of step L, where L=k, if for k values higher than 2 results a r_k (auto-correlation coefficient) value higher than 0,7. Anyway, the company site business is very dynamic and constantly affected by promotions and discounts that can influence the demand creating illusory cyclicality. In order to avoid this, it was decided to declare a product as seasonal just if the r_k value was higher than 0,7 and positioned at the same seasonality step L in both series of auto-correlation coefficient, respectively 2016vs2017 and 2017vs2018. The first 5 products on table 5.1 are examples of seasonal products with seasonality step L equal to 6. According to this methodology, a list of seasonal products was created and presented to Stock Specialist, who deeply knows the features of the product portfolio, in order to approve the analysis output.

The analysis output brought to the identification of 326 seasonal products whose correspond to the 13% of the entire investigated sample (2,470 references).

5.1.2 FORECASTING MODEL

The first step for the selection of the forecasting model that better fit the products demand was the performances evaluation of the one currently adopted by the company. For all the forecasting model selection process 10 products was selected, 5 of them are seasonal products. The sale data exploited to evaluate, train and test the forecasting models belongs to year 2019 and reported in appendix A. Going into details, the performances evaluation consisted in performing the forecast of the last 24 periods of year 2019, where the forecasting period corresponds to 1 week, by using the present model. Once obtained the forecast values, they were compared to the actual sales data in order to calculate several forecast error indicators. The forecast error indicators used for evaluating all models were ME, MAD, MAPE, MSE and SDE. The results obtained from the current model evaluation are reported in table 5.3, while table 5.2 shows the weights value of the weighted moving average employed to predict.

a	10%
b	40%
c	40%
d	10%

Table 5.2 – Current weights value of WMA

	SEASONAL PRODUCTS					STABLE PRDUCTS							
	A001	A002	A003	A004	A005	A006	A007	A008	A009	A010	AV. E.	AV. E. SEASONAL	AV. E. STABLE
ME	-3	16	39	75	2	-5	-8	1	-1	0	12	26	-3
MAD	58	148	123	257	16	43	30	7	20	11	71	120	22
MAPE	25%	25%	39%	26%	49%	56%	40%	42%	50%	40%	39%	33%	46%
MSE	5734	44017	25124	107696	496	5996	1412	98	690	194	19146	36613	1678
SDE	77	214	162	335	23	79	38	10	27	14	98	162	34

Table 5.3 – Forecast accuracy of WMA (2019)

It is possible to see from the table above that the current model better predicts the stable products demand. All the errors indicators are lower along the stable products column expect the MAPE. Anyway, by comparing MAD and MAPE it is possible to infer that the higher MAPE value is due to the fact that stable products demand is lower than seasonal products one comparing them to their respective absolute errors.

Once the actual model was evaluated, the only two possible alternatives were investigated. The first one was the optimization of the Weighted Moving Average (WMA) model through the adjustment of the weights value. The second one was the implementation of the Simple Exponential Smoothing (SES) model. Both models were trained in order to find all the optimal parameters. For this phase, the same data set of the current model evaluation was used (sales demand 2019). Once finished the training phase, the two forecasting models were compared on the predictions made for year 2020.

5.1.2.1 TRAINING PHASE

This paragraph explains the methodology and process through which the parameters value of both models was found. In detail, these parameters are the 4 weights for what concerns the weighted moving average model and the smoothing coefficient as regards the simple exponential smoothing model.

5.1.2.1.1 *Weighted Moving Average model*

In this case, the objective was to identify the best combination of weights values, applicable for the entire range of products, that can improve the forecasts performances. The data obtained in the current model evaluation phase, reported in table 5.3, was employed in this stage of analysis. According to the literature, a non-linear optimization problem was set in order to uncover the optimal weights. The optimization problem consisted in minimizing the error function, one of the error indicators calculated, and setting as decision variables the 4 weights used in the weighted moving average.

For the selection of the error indicator to minimize, some considerations were done. The MAPE was discarded due to its feature of penalizing the errors done at periods when the demand value is low. This means that minimizing MAPE will likely lead to undershoot the demand. The MAE was even rejected because optimizing it means having a forecast that as often overshoots the demand as undershoots the demand, which means targeting the demand median. Regarding the MSE, it possible to mathematically demonstrate that optimizing this error indicator the forecasting model will have to aim for the total forecast to be equal to the total demand. That is to say that optimizing MSE aims to produce a prediction that is correct on average, therefore this indicator was set as objective function.

It is important to point out that since the weights value has to be equal for the products, the MSE to minimize is the average MSE of all the products investigated. The optimization problem was set on Microsoft-Excel and solved through the Excel solver. The new forecast error values obtained are shown in table 5.5, while table 5.4 displays the optimal weights of the moving average.

a	75%
b	5%
c	5%
d	15%

Table 5.4- Optimized weights value of WMA

	SEASONAL PRODUCTS					STABLE PRDUCTS							
	A001	A002	A003	A004	A005	A006	A007	A008	A009	A010	AV. E.	AV. E. SEASONAL	AV. E. STABLE
ME	-6	4	21	40	1	-9	-6	0	-1	0	4	12	-3
MAD	49	112	106	219	12	36	27	9	18	10	60	100	20
MAPE	21%	19%	30%	22%	38%	50%	33%	64%	43%	35%	36%	26%	45%
MSE	4049	27304	19511	76709	321	2429	1023	151	479	166	13214	25579	850
SDE	65	169	143	283	18	50	33	13	22	13	81	136	26

Table 5.5- Forecast accuracy of optimized WMA (2019)

As expected, all the forecast errors improved, in particular the MSE fell by 31,5%. Regarding the comparison between seasonal and stable products, the same considerations previously done are still valid.

5.1.2.1.2 *Simple Exponential Smoothing model*

As for the previous model, the same procedure was adopted for the simple exponential smoothing model in order to find the optimal exponential smoothing value. The first step was calculating the forecast by assigning a random value to the smoothing coefficient. According to the literature, the first forecast value used to initialize the model was computed making the average of the 4 previous sales periods. Once calculated the forecast values related to the last 24 periods of year 2019, they were compared with the real demand data in order to elaborate the error indicators.

Even in this case, the optimal smoothing value was discovered by setting an optimization problem but with a slight difference from the previous one. Since the decision variable was only the smoothing coefficient, it was possible to create a Data-Table on Excel where on the rows there were all the possible values of the smoothing coefficient and on the columns the average error indicators. Inside this table (table 5.6) there were all the possible indicators values in function of the smoothing coefficient.

α	MAD	MAPE	MSE	SDE
0,02	109,9001553	0,397152646	50045,42299	144,2294544
0,04	101,5564749	0,381238205	42331,09296	133,8957752
0,08	90,29521097	0,370144291	31983,06602	118,5593673
0,11	84,9634767	0,366992853	27565,90857	111,282246
0,14	80,32401451	0,36473203	24068,45921	105,0837574
0,17	76,6213394	0,363401427	21602,07048	100,4134672
0,20	73,60244785	0,362403183	19817,05031	96,83747246
0,23	71,28885966	0,361212196	18492,83772	94,05226745
0,26	69,28487659	0,359708064	17488,66375	91,84772145
0,29	67,85216994	0,359050941	16712,91971	90,07791571
0,32	66,69539727	0,358368772	16104,49173	88,64020568
0,35	65,69935927	0,357692653	15621,46844	87,46100125
0,38	64,77222111	0,356941637	15234,29511	86,48639729
0,41	64,0470794	0,356369708	14921,58232	85,6760732
0,44	63,40478224	0,355621164	14667,49794	84,99931401
0,47	62,80326306	0,354865803	14460,10953	84,43238383
0,50	62,31398914	0,354334155	14290,3043	83,95675848
0,53	61,84626984	0,353836213	14151,06611	83,55790755
0,56	61,53743412	0,353759198	14036,97802	83,22443331
0,59	61,36826764	0,35404664	13943,87007	82,94744539
0,62	61,19395113	0,354343089	13868,56331	82,7200948
0,65	61,01667118	0,354648842	13808,67866	82,53721801
0,68	60,87818238	0,35499434	13762,49072	82,39505856
0,71	60,75480858	0,355476635	13728,81343	82,29104462
0,74	60,63736901	0,355935675	13706,909	82,2236078
0,77	60,58329018	0,356498446	13696,41423	82,19203319
0,80	60,58278164	0,357492114	13697,28036	82,19633385
0,83	60,60554791	0,358914861	13709,72398	82,23714505
0,86	60,66482928	0,360572171	13734,18708	82,31563499
0,89	60,7230126	0,36242406	13771,30533	82,43343022
0,92	60,77072266	0,364302866	13821,88365	82,59255413
0,95	60,82363087	0,366300531	13886,8789	82,79537802
0,98	60,97903843	0,36862167	13967,38935	83,04458407
1,01	61,14057905	0,371106155	14064,65099	83,34314046

Table 5.6– Data table for the smoothing coefficient

In this way, it was possible to find the value of the smoothing coefficient that not only minimizes the MSE but also can be optimal or close to the optimal even for the other error indicators. The final value selected for the smoothing coefficient was 0,78. The results obtained are reported in table 5.7.

	SEASONAL PRODUCTS					STABLE PRDUCTS							
	A001	A002	A003	A004	A005	A006	A007	A008	A009	A010	AV. E.	AV. E. SEASONAL	AV. E. STABLE
ME	-7	0	14	26	0	-11	-5	0	-1	-1	2	7	-4
MAD	52	110	113	220	11	35	28	8	19	10	61	101	20
MAPE	22%	18%	32%	22%	36%	48%	34%	64%	45%	37%	36%	26%	45%
MSE	4347	25351	21485	81062	292	2504	1052	142	537	182	13695	26507	883
SDE	67	163	150	291	17	51	33	12	24	14	82	138	27

Table 5.7 – Forecast accuracy of optimized SES (2019)

As is possible to see from the table above, the values of error indicators are almost identical to the ones resulted from the optimized weighted moving average model. It possible to affirm that from a forecast accuracy point of view the two models analyzed are interchangeable.

The next step had the objective of testing both models, adopting the optimized parameters, in order to select the one that improves the forecast accuracy of the company.

5.1.2.2 TESTING AND SELECTION PHASE

In order to test the two models investigated, it was used a different set of data from the one employed in the training phase. In this case, the two forecasting models predicted the demand of the last 24 periods of year 2020. The reason why was taken the second half of the year instead of the first one is due to the effect of Covid-19 that strongly influenced the demand of pharmaceutical products. However, both models were set with the optimized parameters values got in training phase, 78% was the value of the smoothing coefficient utilized in simple exponential smoothing model while 75%, 5%, 5% and 15% were the weights values employed in the weighted moving average model. The two following tables, table 5.8 and table 5.9, show the result of the two forecasting models, simple exponential smoothing and weighted moving average, respectively.

	SEASONAL PRODUCTS					STABLE PRDUCTS							
	A001	A002	A003	A004	A005	A006	A007	A008	A009	A010	AV. E.	AV. E. SEASONAL	AV. E. STABLE
ME	0	-6	5	14	2	-4	-2	-1	-2	0	0,6	3	-2
MAD	43	80	41	100	20	32	18	14	15	15	38	57	19
MAPE	20%	15%	16%	17%	41%	21%	20%	-	25%	35%	-	22%	-
MSE	3155	16955	2792	13634	638	1439	520	380	342	283	4014	7435	593
SDE	57	133	54	119	26	39	23	20	19	17	51	78	24

Table 5.8 – Forecast accuracy of optimized SES (2020)

	SEASONAL PRODUCTS					STABLE PRDUCTS							
	A001	A002	A003	A004	A005	A006	A007	A008	A009	A010	AV. E.	AV. E. SEASONAL	AV. E. STABLE
ME	1	-7	7	19	3	-4	-2	-1	-2	0	1,3	4	-2
MAD	45	88	43	108	22	31	17	14	14	14	40	61	18
MAPE	21%	16%	16%	18%	43%	20%	20%	-	24%	32%	-	23%	-
MSE	3161	19444	3317	15933	752	1341	461	383	317	239	4535	8522	548
SDE	57	142	59	129	28	37	22	20	18	16	53	83	23

Table 5.9 – Forecast accuracy of optimized WMA (2020)

As shown by the results, it was not possible to calculate the average MAPE since the demand of one stable product was composed by zero values. Anyway, the first observation that can be done by comparing the two tables is that the exponential smoothing model performed lightly better than the weighted moving average one. By splitting the results among seasonal and stable products, it possible to understand that the more suitable forecast accuracy of the simple exponential smoothing problem is due to its better capacity to predict the demand of seasonal products. On the other side, by comparing the two average errors columns of stable products, the results obtained are essentially the same.

With the purpose of getting a complete view of the analysis, a further comparison was performed. In order to quantitative calculate the improvement of forecast accuracy due to the two models previously analyzed, the forecasts for year 2020 were performed even with the model currently adopted by the company site. This means forecasting by using a weighted moving average method with the not-optimized weights value. The following table displays the error indicators value obtained.

	SEASONAL PRODUCTS					STABLE PRDUCTS							
	A001	A002	A003	A004	A005	A006	A007	A008	A009	A010	AV. E.	AV. E. SEASONAL	AV. E. STABLE
ME	4	-6	12	34	6	-6	-1	-1	-2	0	4	10	-2
MAD	53	130	54	140	27	33	21	12	13	14	49	81	18
MAPE	24%	24%	20%	22%	37%	22%	23%	-	21%	33%	-	25%	-
MSE	4532	28845	5117	27929	1313	1547	564	239	264	298	7065	13547	582
SDE	69	173	73	171	37	40	24	16	17	18	64	105	23

Table 5.10– Forecast accuracy of WMA (2020)

Table 5.11 shows the percentage reduction of the different average error indicators acquired thanks to the comparison between the model currently adopted by the company and the two previously investigated models whose parameters were optimized.

	Current model vs Optimized SES	Current model vs Optimized WMA
ME	-86%	-70%
MAD	-24%	-20%
MAPE	-	-
MSE	-43%	-36%
SDE	-20%	-17%

Table 5.11– Forecasting models comparison

5.2 INVENTORY CONTROL ANALYSIS

The second objective of this study aimed to improve the inventory control model employed by the company site. As previously described, the inventory control model currently adopted consists in a fixed time period model with a reorder interval equal to 1 week for the entire products portfolio. Ordering all products with the same time interval mainly produces two different effects. From one side, sending orders each week allows to keep a relatively low amount of stock, both cycle and safety. This is possible thanks to the fact that increasing the order frequency the order quantity is reduced, so the cycle stocks. While, a short time between consecutive orders reduces the variability of the latter, by reducing the safety stocks required. On the other side, sending orders each week means receiving the same good each week, causing congestion at goods entry. Furthermore, ordering frequently reduces the possibility to order boxes instead of pieces thus increasing the time to scan the goods. This second part of the thesis was focused on the two aspects just described. The objective of this analysis was to identify a way to differentiate the order interval according to the products in order to decongest the goods entry and, at the same time, quantifying the effect of this change on the cost and quantity of cycle stocks. Only cycle stocks were taken in consideration within the analysis since safety stock are not mathematically calculated but are mainly based on the decision maker experience.

The first step of the analysis consisted in the differentiation of the order interval in function of two different product features, turnover generated and number of incoming rows related to the period from April to September 2020. Once determined the new order frequency, the number of incoming rows was estimated and compared with the one received in the current situation. In this way, it was possible to figure out the effect of this change on the goods entry productivity. Secondly, the quantity and related cost of cycle stocks coming from the new orders division was calculated and compared with the actual values in order to quantify the increase in cost. Finally, the increase in goods entry productivity was transformed in a potential increase in revenue due to the larger amount of stocks available. The value obtained was compared to the increase in cost in order to comprehend if this new solution could be potentially cost effective.

However, the entire analysis was performed only considering the orders and the amount of inventory coming from those orders that follow the fixed time period model, known, inside the investigated company, as “standard orders”. Moreover, this study was developed considering only one of the 8 Distribution Centers (DC) owned by the company. In particular, the distribution center of Novara where more than 46,000 references are managed.

5.2.1 CUSTOMIZED ORDER FREQUENCY

The first step for the identification of a customized order interval for each product was to aggregate, for each Novara DC suppliers (743), the turnover generated by their respective products. For the entire analysis, the data considered refers to the period from April to September 2020. Once obtained these values, an ABC analysis of the suppliers was performed in order to classify them in 3 different categories, A, B and C.

Class A suppliers were further divided by running a multicriteria ABC analysis. The two criteria evaluated were the turnover again and the number of incoming rows received, during the period analyzed, from each class A supplier. The suppliers marked with “AA”, “AB” and “BA”, where the first letter corresponds to the turnover and the second to the number of rows, were defined as “weekly suppliers”. Weekly suppliers are those whose orders can be placed every week, so they keep the current order interval of 1 week. The other six combinations obtained were defined as “biweekly suppliers” whose orders are placed every two weeks.

For class B suppliers (turnover analysis) was performed exactly the same process done for class A with the difference that in this case, suppliers marked with “AA”, “AB” and “BA” were defined as “biweekly suppliers” while the other combinations as “monthly suppliers”.

Regarding class C suppliers, it was not carried out a further classification and they were directly defined as “monthly suppliers”.

The analysis output brought to have 45 weekly suppliers, 195 biweekly suppliers and 503 monthly suppliers.

However, the 45 weekly suppliers, whose turnover accounts for the 60% of the overall one generated by Novara DC, were further investigated. In order to place weekly orders just for the most relevant products an additional ABC analysis of the products was run for each weekly supplier. Even in this case, the criteria evaluated in the analysis was the turnover generated by each product, while the Pareto rule was exploited the define the three categories. Class A products accounted for the 80% the overall turnover of each supplier, class B for the 15% and class C for remaining 5%. According to this classification, the orders of class A, B and C products are placed with a weekly, biweekly and monthly frequency, respectively. An example of the analysis on suppliers’ products is reported below.

Supplier code	Product	DC	Turnover	Turnover Cumulated	% Turnover cumulated	ABC	T
003510	B01	Novara	€ 267.044	€ 267.044	28,8%	A	weekly
003510	B02	Novara	€ 182.292	€ 449.336	48,5%	A	weekly
003510	B03	Novara	€ 116.342	€ 565.678	61,1%	A	weekly
003510	B04	Novara	€ 68.431	€ 634.109	68,5%	A	weekly
003510	B05	Novara	€ 58.992	€ 693.101	74,8%	A	weekly
003510	B06	Novara	€ 41.070	€ 734.171	79,3%	A	weekly
003510	B07	Novara	€ 30.461	€ 764.633	82,5%	B	biweekly
003510	B08	Novara	€ 26.684	€ 791.316	85,4%	B	biweekly
003510	B09	Novara	€ 20.800	€ 812.117	87,7%	B	biweekly
003510	B10	Novara	€ 20.719	€ 832.835	89,9%	B	biweekly
003510	B11	Novara	€ 18.442	€ 851.277	91,9%	B	biweekly
003510	B12	Novara	€ 13.020	€ 864.297	93,3%	B	biweekly
003510	B13	Novara	€ 12.671	€ 876.968	94,7%	B	biweekly
003510	B14	Novara	€ 11.042	€ 888.011	95,9%	C	monthly
003510	B15	Novara	€ 6.017	€ 894.028	96,5%	C	monthly
003510	B16	Novara	€ 4.907	€ 898.935	97,0%	C	monthly
003510	B17	Novara	€ 4.758	€ 903.693	97,6%	C	monthly
003510	B18	Novara	€ 2.739	€ 906.431	97,8%	C	monthly
003510	B19	Novara	€ 2.658	€ 909.089	98,1%	C	monthly
003510	B20	Novara	€ 2.387	€ 911.477	98,4%	C	monthly
003510	B21	Novara	€ 1.714	€ 913.191	98,6%	C	monthly
003510	B22	Novara	€ 1.704	€ 914.895	98,8%	C	monthly
003510	B23	Novara	€ 1.217	€ 916.112	98,9%	C	monthly
003510	B24	Novara	€ 1.138	€ 917.250	99,0%	C	monthly
003510	B25	Novara	€ 1.099	€ 918.349	99,1%	C	monthly
003510	B26	Novara	€ 997	€ 919.346	99,2%	C	monthly
003510	B27	Novara	€ 935	€ 920.281	99,3%	C	monthly
003510	B28	Novara	€ 875	€ 921.156	99,4%	C	monthly
003510	B29	Novara	€ 684	€ 921.841	99,5%	C	monthly
003510	B30	Novara	€ 683	€ 922.523	99,6%	C	monthly
003510	B31	Novara	€ 659	€ 923.182	99,7%	C	monthly
003510	B32	Novara	€ 559	€ 923.740	99,7%	C	monthly
003510	B33	Novara	€ 456	€ 924.196	99,8%	C	monthly
003510	B34	Novara	€ 373	€ 924.570	99,8%	C	monthly
003510	B35	Novara	€ 363	€ 924.932	99,8%	C	monthly
003510	B36	Novara	€ 333	€ 925.265	99,9%	C	monthly
003510	B37	Novara	€ 265	€ 925.530	99,9%	C	monthly
003510	B38	Novara	€ 262	€ 925.792	99,9%	C	monthly
003510	B39	Novara	€ 242	€ 926.034	100,0%	C	monthly
003510	B40	Novara	€ 199	€ 926.233	100,0%	C	monthly
003510	B41	Novara	€ 88	€ 926.321	100,0%	C	monthly
003510	B42	Novara	€ 59	€ 926.380	100,0%	C	monthly

Table 5.12 – Example of ABC suppliers analysis

5.2.1.1 INCOMING ROWS AND CYCLE STOCKS ESTIMATION

After defining the proper order interval for each supplier or product, the focus moved towards the estimation of new number of incoming rows and the new amount of cycle stocks with its related cost. During the analysis for the customization of the order frequency, it was discovered that the actual number of incoming rows received was considerably lower than the one expected. This was due to the fact that many products, even if their order interval was set as one week, were ordered with a lower order frequency, biweekly or monthly, thus reducing the number of incoming rows received. According to what just said, the calculation of the estimated number of rows coming from the new order frequency was executed in the following way. If a product, in the current situation, was received a number of times lower than the one expected with new order interval, the number of incoming rows considered in the calculation remained the same of the current situation. For example, if a product counted 10 incoming rows, during the six months analyzed and, according to the analysis performed it was defined as a "biweekly product" (thus 12 incoming rows expected), 10 was the number kept in the calculation. On the contrary, when the actual number of rows was higher than the one estimated, the latter was inserted in the calculation. The same concept was adopted at the supplier level for biweekly and monthly suppliers.

Product	customized T	Actual number of rows	Expected rows from customized T	Number used in calculation
A01	weekly	10	24	10
B01	biweekly	22	12	12

Table 5.13 – Example of rows calculation (product level)

Supplier	customized T	Number of Products	Actual number of rows	Expected rows from customized T	Number used in calculation
11400	biweekly	27	227	324	227
11500	monthly	8	54	48	48

Table 5.14 – Example of rows calculation (Supplier level)

Consequently to the estimation of the incoming rows, the valuation of cycle stocks was executed. As reported in the literature, the cycle stocks quantity is given by the quantity ordered divided by two. However, since the quantity ordered can vary, an average order quantity for each product was calculated. The average order quantity was obtained by the ratio between the overall number of pieces purchased and the overall number of incoming rows received during the investigated period, getting so, an average number of pieces per order. Dividing this value by two, the quantity of cycle stocks was attained.

However, for biweekly and monthly suppliers, whose products were not further investigated, was adopted the same logic but, aggregating the values at the supplier level.

Sup.	T custom	Num. of Products	Qt.y received (u)	Qt.y received (€)	Actual number of rows	Actual CS (U)	Actual CS (€)	Exp. Num. rows	Exp. CS (u)	Exp. CS (€)	Num. rows used	CS (u) used	CS (€) used
11400	biweekly	27	5400	35000	227	23,8	154,2	324	16,7	108	227	23,8	154,2
11500	monthly	8	2200	15000	54	40,7	277,8	48	45,8	312,5	48	45,8	312,5

Table 5.15 – Example of CS calculation

5.2.1.2 AS-IS AND TO-BE COMPARISON

Finally, a comparison between the actual situation and the new one obtained from the analysis was performed. The following table shows the results achieved from the analysis by following the calculation logic previously illustrated.

	T AS-IS	T TO-BE			DELTA	DELTA %
CS Quantity	175.839	weekly	111.187	188.728	12.889	7%
		biweekly	65.600			
		monthly	11.940			
CS value	€ 1.410.408	weekly	€ 925.440	€ 1.490.019	79.611	6%
		biweekly	€ 495.155			
		monthly	€ 69.424			
Rows/Semester	95.720	weekly	42.155	89.456	-6.264	-7%
		biweekly	37.308			
		monthly	9.993			
Rows/day	798	745			-52	-7%

Table 5.16 – Analysis output

The CS value was attained by multiplying the CS quantity by the purchasing price. However, as forecasted, the number of incoming rows reduced while the quantity and related value of cycle stocks increased.

Anyway, the number of new incoming rows was expected to be larger, but since not all the products were ordered and received every week, the percentage reduction was only 7%. However, as is possible to see from the table, this 7% reduction corresponds to 52 fewer rows per day to work, that according to the good entry productivity of Novara DC (35,4 rows/hour), are equivalent to 1,47 hours per day. This saved time can so be exploited to work the rows coming from the order typologies such as grey, speculative and homeopathic orders. This means that, reasoning with this logic, there is the possibility to work 52 more rows every day and so, potentially, to increase the overall turnover generated by the distribution center. The table below illustrates the comparison between the just mentioned potential revenues increase and the rise of cycle stock cost.

	T (AS-IS)	T (TO-BE)		DELTA	DELTA %
SC value	€ 1.410.408	€ 1.490.019	euro	€ 79.611	6%
Cost of Capital	2%	2%	%/year	-	0%
CS cost	€ 28.208	€ 29.800	euro/year	€ 1.592	6%
Additional rows/semester worked	-	6.264	rows/semester		
Average revenue per row	14	14	euro/rows		
Revenue/semester	€ 45.513.532	€ 45.598.409	euro/semester	€ 84.877	0,2%

Table 5.17 – Costs and benefits comparison

The cost of cycle stocks was calculated by multiplying their value for the cost of capital. While, the potential revenue increase was given by the additional 6,264 workable rows during the semester multiplied by the average revenue per row, € 14.

6. DISCUSSION

This paragraph aims to discuss the results previously presented, by analyzing and commenting the problems/opportunities met by the researcher. In particular, the discussion mainly includes qualitative observations about how the managerial and corporate approach could affect the performances of the target company.

The first result commented regards the forecast analysis and the related models. As shown by numbers, comparator values indicate that Simple Exponential Smoothing is a superior forecast model to predict sales of pharmaceuticals whose demand fluctuates/varies seasonally. While both models, Simple exponential smoothing and four-weeks weighted moving average are interchangeable forecast models to predict the sales of pharmaceuticals whose demand remains fairly stable. The considerable forecast accuracy improvement shown in table 5.11 is mainly due to the parameters value utilized in the three different models. One of the most relevant aspects extracted from the training phases of the models was the coefficient value assigned to the most recent demand value. In the case of SES, the optimal smoothing coefficient is equal to 0,78, while, regarding the WMA, the optimal weight value assigned to closest demand value is 0,75. This similarity is due to the fact that, as suggested by the literature, a dynamic business as the pharmaceutical one requires, from a statistical point of view, a reactive forecasting model that rapidly reacts to demand variations.

Anyway, it is important to clarify that what was found out from this analysis is just a "local optimum", the area of improvements is still very wide. The adoption of a customized forecasting model according to products demand feature, the use of a forecasting model able to detect the products seasonality and a greater technology employment along the overall forecasting process can undoubtedly simplify the work and enhance company performances and competitiveness. Nowadly and Jung (2020) studied the use of machine learning approaches to improve demand forecasting of a large pharmaceutical manufacturer. They claimed that Artificial Intelligence and machine learning are becoming more ubiquitous in the healthcare industry, more sophisticated forecasting methods emerged. Companies use system dynamics modeling to study how external factors, as diseases progression, to create feedback loops that influence demand forecasts. Another study, published on the Journal of Military and Information Science and performed by Candan, Taşkin and Yazgan (2014) presents a further application of artificial intelligence in

forecasting demand of pharmaceuticals products. In this paper, scholars predicted future demands of a pharmaceutical company considering previous sales quantity and the effects of the external factors by employing a neuro-fuzzy approach, reaching excellent results.
However, machine learning and artificial intelligence are probably the most sophisticated techniques to forecast demand and it is known that the use of these technologies requires a large up-front investment (Nowagly and Jung, 2020). This is the reason why is strongly suggested to the investigated company, to start, through cost-benefits analysis and internal discussion, a path towards the development of a more sophisticated forecasting process, from the data collection and cleaning to the forecasting model output. The most crucial aspect of this modernization process is that it mainly enhances two performance indicators which are important for the entire pharmaceutical sector and even more for a pharmaceutical distributor, service level and overstock. This is possible because, the upgrade of the whole forecasting process allows to improve not only the forecast accuracy, but also several related aspects. Purchasing orders can be based on more realistic data, the costs of inventory can be reduced by a better exploitation of company resources, workforce can be saved and quicker reaction to market changes could be achieved (Candan et al., 2014). In other words, the introduction of technology to support business processes allows to create efficiency.

Strictly related to forecast, the next observation regards inventory management. The analysis performed in this thesis for the customization of the order intervals brought to the conclusion that applying a customized order interval for each product or supplier can reduce the congestion at the goods entry of the distribution center, by causing a relative low cycle stocks cost increase, proving to be an adoptable solution. A direct consequence of the larger amount of stocks is the growth of service level that, as mentioned in the previous chapters, is crucial in the pharmaceutical sector. In addition, the benefits of the order interval customization could be higher if there were more references managed with a fixed time period model. Especially for the Novara distribution network where only 20,569 products, over the 46,000 managed, follow a fixed time period logic.

Anyway, from a theoretical point of view, the fact of not considering safety stocks, makes the analysis partially completed. This is because the enlargement of the reorder interval also involves an increase of safety stocks and their related cost that would certainty affect the analysis results.
The main points of inefficiency detected during the experience at the company site was the extra inventory kept in the distribution centers. Consisted with that, one of the main criticalities that pointed out during the analysis of the inventory management was the process through which the

studied company defines the amount of safety stocks. In this case, the suggestion to the studied company is to formalize the SS definition process by employing the SS formula presented in literature or a customized version. The adoption of SS formula can bring mainly two advantages to company site, one operational and one strategical.

From an operational point view, defining the amount of SS with the formula allows to optimize the quantity of the latter. Krishnamurthy and Prasad (2012) investigated the application effect of a customized safety stock formula for a pharmaceutical company, by achieving an average difference of 30% lower in safety stocks units. This is possible because, first of all, SS formula is based on a statistical model, so certainly more precise than an arbitrary decision. Secondly, the parameters it considers vary along time. In this way, instead of defining a SS quantity that remains constant for the whole year, is possible to optimize it following market changes and variations.

From a strategical point of view, the adoption of the formula allows the company to limit the dependency from the Stock Specialist, the person that actually defines, according to his experience and products knowledge, the amount of safety stocks to keep in all distribution centers.

However, the two just mentioned suggestions aim to improve company performances remaining inside the boundaries of the firm, guaranteeing short-medium term benefits. In order to protect and increase the company profitability in the long term is necessary to adopt a supply chain strategy (Barratt, 2004). During the working experience at the studied company the most critical aspect observed was the lack of a collaborative vision of the supply chain. The absence of collaboration and information sharing is probably the principal cause of inefficiency, both upstream and downstream. Several studies illustrate the benefits gained from the collaboration between the different actors along the entire supply chain. Gavirneni, Kapuscinski and Tayur (1999) studied the use of shared information to improve the supplier's order quantity decisions. They reported that sharing the retailer's demand data reduced the supplier's cost by 1%–35%. Lee, Padmanabhan and Whang (1997) discovered that sharing information reduces the supplier's demand variance, which should benefit the whole supply chain. Aviv (1998) explored the benefits of sharing forecasts between supplier and customer for future demand. The concepts and results presented in these papers can be applied on both sides of the studied company supply chain since it is, at the same time, the supplier of pharmacies and the customer of manufactures. Focusing on pharmaceutical sector, Schwarz and Zhao (2010) examined how the information sharing between a pharmaceutical manufacturer and a pharmaceutical distributor can bring mutual benefits in terms of stocks reduction and production planning optimization. In addition, as suggested before, the

implementation of technology along the value chain can enlarge the magnitude of the benefits coming from the information sharing (Kumar and Pugazhendhi, 2012).
However, once understood the potentiality of supply chain collaboration, it is easily perceivable how information sharing could have positively contributed to the results obtained from the two analyses performed in this thesis. Regarding the forecasting analysis, basing the predictions on sales data that directly comes from pharmacies surely improves the output reliability. While, concerning the customization of the order interval analysis, having the opportunity to involve the suppliers in the order intervals definition can certainly generates substantial and mutual benefits.

Anyway, adopting a collaborative strategy is a challenging task that requires a radical transformation of the company. This implicates moving away from a collaboration model between SC actors where, "I win, now you figure out how to win", in order to go towards a model in which a mutual collaboration aims to create a "win-win" situation (Ireland and Bruce, 2000). In other words, the real challenge for the investigated company is to institute a "collaborative culture" (Barratt, 2004). Creating a collaborative culture is a long process that does not only require a route change on the relationship with the other SC players, so an external change, but also imposes an internal one at both managerial and corporate level (Barratt and Green, 2001). From a qualitative point of view, during the close contact period with the studied company, two different but linked dynamics were emerged that could represent the two main internal obstacles to the change. A different business vision between the Board of Director (BoD) and the managers, and a lack of alignment between the Commercial and Logistics/Operations functions.

As mentioned in chapter 4, the studied company was born from the merge of different Italian cooperatives, and the main aim of cooperatives is to reduce the logistics costs and their related risks of the pharmacies, this means they don't have a profit scope (Calabrese, 2011). The different business vision between the BoD and managers lies right here. The BoD still sees the target company as a cooperative, so investments and radical management changes are perceived as unnecessary efforts in terms of time and costs. On the other side, managers try to promote new initiatives in order to, as any company, improve the profitability. This will certainly be a source of friction for the collaborative culture transition since the BoD focus is not on the supply chain and any collaborative initiatives are likely to be seen as unneeded expenditure (Sabath and Fontanella, 2002).

For what concerns the Commercial and Logistics/Operations functions, their relation can be one of the main obstacles for the collaboration culture construction. The main part of inefficiency comes from the Logistics function, especially, from the consistent amount of overstock kept in the different distribution centers. The greater part of the overstock is generated by the speculative and grey-market related orders which are exclusively managed by the Commercial function. As mentioned before, these kinds of orders are mainly placed to respect contractual agreements and their arrival and related amount is difficult to be planed. In addition, the products contained in these orders are usually slow-moving products, by generating so overstock complicated to work off. This obviously negatively impacts the logistics performances, by increasing inefficiency and its related cost. In this case, the inefficiency is caused by the objectives' diversity pursued by the two functions. The Commercial function aims to improve the commercial relationship with the suppliers and to increment the contractual bonuses at the end of the year. While the Logistics/Operation function aims to guarantee a high service level keeping costs under control. This lack of alignment between these functions can be a problem for the supply chain collaboration because it necessitates adopting a process focus that will involve crossing many functional boundaries (Barratt and Green, 2001). The linkage between the just two mentioned dynamics lies probably on the fact that the BoD does not have a supply chain focus and so it favors to maintain a good commercial relationship with the suppliers at the cost of a low efficiency.

7. CONCLUSION

The pharmaceutical industry is a very dynamic and challenging business characterized by a high degree of uncertainty and accountability since it has a direct impact of people health. These features become even more critical for a pharmaceutical distributor that has to guarantee to its customers, i.e., pharmacies, an outstanding service level and, simultaneously, keeping costs under control in order to preserve its marginality. This can be only achieved through the constant pursuit of efficiency. The objective of this thesis was to explore how to improve efficiency of the considered focal company by acting on both side of its supply chain. The supply chain performances of the target company were then improved through the development of the two models for demand forecasting and management taken from the academic literature and widely analyzed during the study.

The results presented in chapter 5 show how the optimization of both, the forecasting model currently adopted by the company (WMA) and the Simple Exponential Smoothing (SES) model could bring considerable enhancements to company forecast accuracy. The high weighting coefficients assigned to the last demand period on both models, demonstrate that a dynamic Supply Chain, as the pharmaceutical one, requires a dynamic forecasting model that rapidly reacts to demand variations. A pharmaceutical distributor whose business is focused on service level and efficient inventory management, needs thus a proactive forecasting model. Regarding the upstream part of the Supply Chain, a flexible order interval customized for different products allowed for achieving a better utilization of the resources employed at the goods entry, and a consequential benefit in terms of service level. In some cases, despite the enlargement of the order interval entailed an increase of the average inventory level and its related costs, it was still possible to reduce the overall costs. This was enabled by an appropriate method to define order intervals that better acknowledged products characteristics and optimized the overall performances.

From a managerial point view, the analyses performed in this study illustrate that solutions for performances improvement could be rapidly implemented. The same methodologies employed in the analysis could be dynamically used in order to evaluate the performances of the new forecasting and inventory management models and to change their parameters according to market and company needs. It means, on the one hand, measuring the forecast accuracy of the new forecasting methods selected and change their parameters value by optimizing one or more error indicators. On the other hand, it could entail periodically controlling the average amount of stocks and changing the products order interval according to company needs. In addition, this thesis offers a qualitative consideration about how the investigated company could dramatically enhance its performances by working on coordination and alignment, not only internally but also outside its boundaries.

By studying the company site, it emerged that there still are many opportunities for improvement to investigate. The limited use of modern technologies that can simplify and accelerate the company processes and the lack of internal and external collaboration are probably the two most interesting aspects to be deeply analyzed in the future. Furthermore, these two themes entail the greatest opportunities, not only to improve efficiency but also to guarantee the economical sustainability of the studied company in the long term.

Nevertheless, some limitations were encountered and must be properly acknowledge. Regarding the forecasting analysis, due to software constraints, was not possible to test other forecasting models that could detect seasonal and trend patters of products demand. This certainly reduced the potential benefits coming from the analysis. Concerning the order interval customization analysis, the unformal procedure of SS definition made not possible to consider them in the analysis and to have so a complete view of the effects of the new inventory management model. This limitation could pave the way for three main themes to be investigated in future researches. First, a costs and benefits analysis could be developed concerning the investments in a more sophisticated forecasting technology and all the advantages coming from the latter, i.e., forecast accuracy improvements, overstock reduction, better inputs for business planning. Second, it could be interesting to examine how the adoption of safety stock formula could quantitatively affect the performances of the company inventory management, also from an economic perspective. Lastly, the most delicate and decisive issue could regard a detailed study about how the target company could develop and promote a collaborative culture, what are the barriers in place and how it could be possible to overcome them.

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APPENDIX A: Sales values (2019)

Period	A001	A002	A003	A004	A005	A006	A007	A008	A009	A010
week 30	204	516	161	541	15	317	111	41	76	36
week 31	209	458	289	548	14	147	155	5	47	42
week 32	230	429	260	486	8	158	106	31	52	54
week 33	164	278	165	392	7	41	48	13	23	26
week 34	225	305	138	420	11	67	89	23	36	30
week 35	214	378	146	434	20	85	104	24	65	22
week 36	231	501	325	471	50	59	138	11	23	40
week 37	257	464	248	619	53	95	150	11	47	40
week 38	261	519	235	812	69	64	114	8	34	38
week 39	300	618	91	897	61	89	91	11	44	35
week 40	279	578	532	1052	67	58	119	15	61	39
week 41	338	559	552	1201	56	100	111	10	53	47
week 42	256	1000	468	702	59	67	123	12	55	59
week 43	238	1048	596	1395	111	52	123	10	42	32
week 44	247	849	554	1154	87	99	81	11	46	39
week 45	296	990	735	1352	90	93	132	23	67	32
week 46	393	1084	537	1524	84	80	160	13	88	40
week 47	308	1127	665	1230	64	105	126	19	67	36
week 48	268	1105	495	915	71	100	121	15	55	54
week 49	353	1082	604	1501	70	92	115	33	80	38
week 50	367	1133	693	1789	69	79	102	20	113	49
week 51	413	890	805	1774	61	128	120	22	68	59
week 52	284	799	644	1391	47	78	51	17	26	47
week 53	129	392	363	868	11	29	32	10	22	11

APPENDIX B: Forecasts of not optimized WMA (2019)

	A001	A002	A003	A004	A005	A006	A007	A008	A009	A010
week 30	272	530	210	576	14	36	130	7	49	28
week 31	274	506	181	552	13	150	130	11	50	32
week 32	251	497	174	531	14	257	127	21	59	36
week 33	219	481	221	534	14	230	130	22	59	40
week 34	212	434	252	507	11	158	120	20	50	45
week 35	201	359	213	448	9	101	86	20	38	39
week 36	200	314	162	417	10	68	76	20	35	30
week 37	215	351	163	428	18	71	96	21	45	27
week 38	226	429	227	466	34	74	121	17	44	32
week 39	243	476	267	561	50	77	137	12	38	38
week 40	260	505	235	709	60	78	129	10	39	39
week 41	278	559	208	851	64	77	109	10	42	37
week 42	292	586	328	981	64	75	107	12	51	38
week 43	302	617	490	1061	61	79	113	12	56	44
week 44	289	786	521	1006	64	78	118	11	54	50
week 45	256	960	536	1074	82	68	118	11	49	45
week 46	249	958	580	1225	94	76	107	12	47	38
week 47	280	949	629	1294	90	90	114	16	58	36
week 48	331	1027	631	1389	85	90	138	17	73	36
week 49	337	1094	604	1328	75	93	140	17	74	39
week 50	305	1109	578	1161	69	99	126	18	66	44
week 51	316	1101	575	1268	70	95	117	23	72	45
week 52	356	1086	649	1585	69	91	111	25	90	46
week 53	376	997	724	1714	64	100	105	22	83	52

APPENDIX C: Forecasts of optimized WMA (2019)

	A001	A002	A003	A004	A005	A006	A007	A008	A009	A010
week 30	295	488	169	520	12	220	136	8	48	33
week 31	226	526	173	548	15	249	115	33	69	34
week 32	222	472	263	556	14	140	149	7	49	40
week 33	241	445	239	495	9	187	113	27	52	50
week 34	177	334	176	430	9	97	67	18	34	30
week 35	220	336	171	444	11	84	99	20	38	33
week 36	215	379	166	441	17	94	101	25	60	28
week 37	220	450	282	455	40	58	120	13	26	36
week 38	249	437	230	572	44	88	138	14	45	38
week 39	252	494	226	726	59	69	116	11	39	36
week 40	286	588	145	812	59	83	103	11	40	36
week 41	276	560	450	965	65	66	123	14	57	39
week 42	322	558	478	1118	59	92	111	10	50	45
week 43	269	897	415	779	60	72	117	12	54	54
week 44	251	947	579	1299	99	56	122	11	46	35
week 45	263	822	553	1155	82	96	90	11	48	41
week 46	285	991	678	1242	86	87	128	20	63	37
week 47	357	1065	559	1481	89	77	149	13	78	38
week 48	303	1076	646	1242	70	102	121	18	65	37
week 49	282	1090	546	1036	75	98	125	16	59	49
week 50	354	1089	593	1467	72	91	124	28	80	39
week 51	353	1132	676	1645	69	85	108	20	101	47
week 52	385	950	741	1626	64	120	119	21	69	57
week 53	307	869	650	1452	53	83	68	20	41	46

APPENDIX D: Forecasts of optimized SES (2019)

	A001	A002	A003	A004	A005	A006	A007	A008	A009	A010
week 30	300	490	161	512	12	243	133	9	47	34
week 31	225	510	161	535	14	301	116	34	70	36
week 32	213	470	261	545	14	181	146	11	52	41
week 33	226	438	260	499	9	163	115	27	52	51
week 34	178	313	186	416	8	68	63	16	29	32
week 35	215	307	149	419	10	67	83	21	35	30
week 36	214	362	147	431	18	81	99	23	58	24
week 37	227	470	286	462	43	64	130	14	31	36
week 38	250	465	256	584	51	88	145	12	43	39
week 39	259	507	240	762	65	69	121	9	36	38
week 40	291	594	124	867	62	85	98	11	42	36
week 41	282	581	442	1011	66	64	114	14	57	38
week 42	326	564	528	1159	58	92	112	11	54	45
week 43	271	904	481	803	59	73	121	12	55	56
week 44	245	1016	571	1265	100	57	122	10	45	37
week 45	247	886	558	1178	90	90	90	11	46	39
week 46	285	967	696	1314	90	92	123	20	62	33
week 47	369	1058	572	1478	85	83	152	15	82	39
week 48	321	1112	645	1285	69	100	132	18	70	37
week 49	280	1107	528	996	70	100	123	16	58	50
week 50	337	1087	587	1390	70	94	117	29	75	41
week 51	360	1123	670	1701	69	82	105	22	105	47
week 52	401	941	775	1758	63	118	117	22	76	56
week 53	310	830	673	1472	50	87	65	18	37	49

APPENDIX E: Sales values (2020)

	A001	A002	A003	A004	A005	A006	A007	A008	A009	A010
week 30	142	454	107	307	3	188	78	22	52	60
week 31	116	462	98	282	11	188	91	23	70	73
week 32	165	337	114	300	8	154	82	10	78	50
week 33	142	317	106	302	12	113	67	6	59	33
week 34	164	335	104	471	8	132	73	0	61	41
week 35	172	363	133	385	13	188	72	25	82	63
week 36	221	441	168	434	45	191	105	11	81	37
week 37	217	431	148	263	62	187	105	36	64	44
week 38	175	451	137	538	80	157	102	2	72	52
week 39	200	579	148	434	120	153	93	3	74	36
week 40	360	502	195	625	169	194	119	45	83	22
week 41	289	1017	182	682	156	164	106	0	82	48
week 42	331	873	317	839	151	227	128	5	79	34
week 43	283	910	318	931	119	184	138	14	52	51
week 44	257	880	378	1074	105	209	136	0	63	44
week 45	160	722	446	1134	101	137	87	1	76	34
week 46	251	756	371	1022	98	158	115	16	64	59
week 47	249	596	450	947	108	131	123	0	77	74
week 48	334	677	327	841	71	197	81	7	45	41
week 49	314	665	308	825	103	132	67	0	68	28
week 50	261	555	269	734	56	166	73	5	55	33
week 51	278	472	303	808	93	204	103	47	97	46
week 52	204	365	231	663	67	142	114	1	49	64
week 53	174	301	198	592	40	99	58	5	36	41

APPENDIX F: Forecasts of optimized WMA (2020)

	A001	A002	A003	A004	A005	A006	A007	A008	A009	A010
week 30	183	435	120	344	9	179	104	22	81	47
week 31	151	455	109	313	3	192	83	23	58	59
week 32	127	449	101	297	10	190	90	20	66	67
week 33	165	368	115	307	8	162	87	13	77	51
week 34	142	348	106	302	10	131	71	10	60	40
week 35	156	355	104	426	9	141	76	4	63	46
week 36	169	356	128	373	12	177	74	21	79	59
week 37	204	413	154	414	36	176	96	10	77	38
week 38	207	414	142	311	50	179	99	29	65	44
week 39	179	437	139	496	67	165	98	8	74	53
week 40	203	545	151	432	104	161	96	6	75	37
week 41	321	493	183	556	146	190	115	39	79	28
week 42	271	883	174	646	143	164	106	3	80	47
week 43	311	818	278	759	148	211	121	6	79	35
week 44	299	852	293	868	131	187	133	18	60	46
week 45	268	905	342	996	116	202	131	1	66	45
week 46	198	765	417	1077	110	157	99	2	75	35
week 47	252	787	368	1019	102	164	119	14	63	56
week 48	247	657	436	983	107	145	123	1	74	67
week 49	299	686	355	904	79	183	86	6	53	43
week 50	303	678	327	865	101	140	78	3	67	36
week 51	266	575	303	779	67	161	81	4	59	40
week 52	289	519	306	812	88	198	97	36	86	44
week 53	228	428	249	701	74	145	104	3	55	56

APPENDIX G: Forecasts of optimized SES (2020)

	A001	A002	A003	A004	A005	A006	A007	A008	A009	A010
week 30	175	418	112	337	6	189	93	20	73	51
week 31	184	442	121	343	10	180	106	22	81	46
week 32	151	451	110	315	4	186	84	22	58	57
week 33	124	460	101	289	10	188	90	23	67	69
week 34	156	364	111	298	8	161	84	13	76	54
week 35	145	327	107	301	11	124	71	7	63	38
week 36	160	333	105	434	9	130	72	2	61	40
week 37	169	356	127	396	12	175	72	20	77	58
week 38	210	422	159	426	38	188	98	13	80	42
week 39	215	429	150	299	57	187	103	31	68	43
week 40	184	446	140	485	75	164	102	8	71	50
week 41	196	550	146	445	110	155	95	4	73	39
week 42	324	513	184	585	156	185	114	36	81	26
week 43	297	906	182	661	156	169	108	8	82	43
week 44	323	880	287	800	152	214	124	6	80	36
week 45	292	903	311	902	126	191	135	12	58	48
week 46	265	885	363	1036	110	205	136	3	62	45
week 47	183	758	428	1112	103	152	98	1	73	36
week 48	236	756	383	1042	99	157	111	13	66	54
week 49	246	631	435	968	106	137	120	3	75	70
week 50	315	667	351	869	79	184	90	6	52	47
week 51	314	665	317	835	98	143	72	1	64	32
week 52	273	579	280	756	65	161	73	4	57	33
week 53	277	496	298	797	87	195	96	38	88	43

APPENDIX H: E(t)and E(t)^2 values of WVA (2020)

E(t)	A001	A002	A003	A004	A005	A006	A007	A008	A009	A010
week 30	-41	19	-13	-37	-6	9	-26	0	-29	13
week 31	-35	7	-11	-31	8	-4	8	0	12	14
week 32	38	-112	13	3	-2	-36	-8	-10	12	-17
week 33	-23	-51	-9	-5	4	-49	-20	-7	-18	-18
week 34	22	-13	-2	169	-2	1	2	-10	1	1
week 35	16	8	29	-41	4	47	-4	21	19	17
week 36	52	85	40	61	33	14	31	-10	2	-22
week 37	13	18	-6	-151	26	11	9	26	-13	6
week 38	-32	37	-5	227	30	-22	3	-27	7	8
week 39	21	142	9	-62	53	-12	-5	-5	0	-17
week 40	157	-43	44	193	65	33	23	39	8	-15
week 41	-32	524	-1	126	10	-26	-9	-39	3	20
week 42	60	-10	143	193	8	63	22	2	-1	-13
week 43	-28	92	40	172	-29	-27	17	8	-27	16
week 44	-42	28	85	206	-26	22	3	-18	3	-2
week 45	-108	-183	104	138	-15	-65	-44	0	10	-11
week 46	53	-9	-46	-55	-12	1	16	14	-11	24
week 47	-3	-191	82	-72	6	-33	4	-14	14	18
week 48	87	20	-109	-142	-36	52	-42	6	-29	-26
week 49	15	-21	-47	-79	24	-51	-19	-6	15	-15
week 50	-42	-123	-58	-131	-45	26	-5	2	-12	-3
week 51	12	-103	0	29	26	43	22	43	38	6
week 52	-85	-154	-75	-149	-21	-56	17	-35	-37	20
week 53	-54	-127	-51	-109	-34	-46	-46	2	-19	-15

E(t)^2	A001	A002	A003	A004	A005	A006	A007	A008	A009	A010
week 30	1722	352	161	1361	41	73	689	0	832	159
week 31	1244	56	131	950	63	15	63	0	144	210
week 32	1449	12570	166	10	3	1311	61	104	137	280
week 33	536	2563	76	28	13	2361	395	54	335	324
week 34	474	160	6	28396	6	1	5	92	2	1
week 35	261	63	845	1641	19	2180	17	424	349	282
week 36	2657	7196	1635	3746	1092	207	988	90	3	463
week 37	173	308	33	22734	651	118	80	656	164	36
week 38	1036	1359	22	51491	878	488	12	709	43	60
week 39	425	20207	84	3894	2807	156	24	23	0	280
week 40	24512	1851	1937	37325	4275	1070	521	1531	69	239
week 41	1037	274096	1	15930	106	651	80	1557	8	411
week 42	3609	99	20349	37288	59	3933	499	5	2	165
week 43	762	8520	1569	29605	822	737	280	57	717	272
week 44	1728	801	7287	42328	657	475	7	316	10	2
week 45	11603	33506	10794	18973	234	4241	1966	0	92	112
week 46	2773	81	2124	3073	150	0	266	190	117	555
week 47	12	36383	6766	5125	35	1090	20	201	201	328
week 48	7644	417	11819	20051	1293	2676	1779	38	859	662
week 49	222	432	2204	6193	571	2584	359	38	239	212
week 50	1736	15187	3339	17186	2037	695	27	5	140	8
week 51	142	10512	0	820	654	1868	477	1842	1462	40
week 52	7140	23813	5645	22347	459	3129	306	1252	1334	409
week 53	2960	16137	2625	11893	1129	2126	2144	3	354	227

APPENDIX I: |E(t)| and |E(t)|/D(t) values of WVA (2020)

|E(t)|	A001	A002	A003	A004	A005	A006	A007	A008	A009	A010
week 30	41	19	13	37	6	9	26	0	29	13
week 31	35	7	11	31	8	4	8	0	12	14
week 32	38	112	13	3	2	36	8	10	12	17
week 33	23	51	9	5	4	49	20	7	18	18
week 34	22	13	2	169	2	1	2	10	1	1
week 35	16	8	29	41	4	47	4	21	19	17
week 36	52	85	40	61	33	14	31	10	2	22
week 37	13	18	6	151	26	11	9	26	13	6
week 38	32	37	5	227	30	22	3	27	7	8
week 39	21	142	9	62	53	12	5	5	0	17
week 40	157	43	44	193	65	33	23	39	8	15
week 41	32	524	1	126	10	26	9	39	3	20
week 42	60	10	143	193	8	63	22	2	1	13
week 43	28	92	40	172	29	27	17	8	27	16
week 44	42	28	85	206	26	22	3	18	3	2
week 45	108	183	104	138	15	65	44	0	10	11
week 46	53	9	46	55	12	1	16	14	11	24
week 47	3	191	82	72	6	33	4	14	14	18
week 48	87	20	109	142	36	52	42	6	29	26
week 49	15	21	47	79	24	51	19	6	15	15
week 50	42	123	58	131	45	26	5	2	12	3
week 51	12	103	0	29	26	43	22	43	38	6
week 52	85	154	75	149	21	56	17	35	37	20
week 53	54	127	51	109	34	46	46	2	19	15

|E(t)|/D(t)	A001	A002	A003	A004	A005	A006	A007	A008	A009	A010
week 30	29%	4%	12%	12%	213%	5%	34%	1%	55%	21%
week 31	30%	2%	12%	11%	72%	2%	9%	1%	17%	20%
week 32	23%	33%	11%	1%	21%	24%	10%	102%	15%	33%
week 33	16%	16%	8%	2%	30%	43%	30%	122%	31%	55%
week 34	13%	4%	2%	36%	30%	1%	3%	-	2%	2%
week 35	9%	2%	22%	11%	33%	25%	6%	82%	23%	27%
week 36	23%	19%	24%	14%	73%	8%	30%	86%	2%	58%
week 37	6%	4%	4%	57%	41%	6%	9%	71%	20%	14%
week 38	18%	8%	3%	42%	37%	14%	3%	1331%	9%	15%
week 39	10%	25%	6%	14%	44%	8%	5%	159%	0%	46%
week 40	43%	9%	23%	31%	39%	17%	19%	87%	10%	70%
week 41	11%	51%	0%	19%	7%	16%	8%	-	3%	42%
week 42	18%	1%	45%	23%	5%	28%	17%	46%	2%	38%
week 43	10%	10%	12%	18%	24%	15%	12%	54%	51%	32%
week 44	16%	3%	23%	19%	24%	10%	2%	-	5%	4%
week 45	67%	25%	23%	12%	15%	48%	51%	5%	13%	31%
week 46	21%	1%	12%	5%	12%	0%	14%	86%	17%	40%
week 47	1%	32%	18%	8%	5%	25%	4%	-	18%	24%
week 48	26%	3%	33%	17%	51%	26%	52%	88%	65%	63%
week 49	5%	3%	15%	10%	23%	39%	28%	-	23%	52%
week 50	16%	22%	21%	18%	81%	16%	7%	43%	22%	9%
week 51	4%	22%	0%	4%	27%	21%	21%	91%	39%	14%
week 52	41%	42%	33%	23%	32%	39%	15%	3538%	75%	32%
week 53	31%	42%	26%	18%	84%	47%	80%	33%	52%	37%

APPENDIX J: E(t)and E(t)^2 values of SES (2020)

E(t)	A001	A002	A003	A004	A005	A006	A007	A008	A009	A010
week 30	-42	12	-14	-36	-7	8	-28	0	-29	14
week 31	-35	11	-12	-33	7	2	7	1	12	16
week 32	41	-123	13	11	-2	-34	-8	-13	11	-19
week 33	-14	-47	-5	4	4	-48	-17	-7	-17	-21
week 34	19	8	-3	170	-3	8	2	-7	-2	3
week 35	12	30	28	-49	4	58	0	23	21	23
week 36	52	85	41	38	33	16	33	-9	4	-21
week 37	7	9	-11	-163	24	-1	7	23	-16	2
week 38	-40	22	-13	239	23	-30	-1	-29	4	9
week 39	16	133	8	-51	45	-11	-9	-5	3	-14
week 40	164	-48	49	180	59	39	24	41	10	-17
week 41	-35	504	-2	97	0	-21	-8	-36	1	22
week 42	34	-33	135	178	-5	58	20	-3	-3	-9
week 43	-40	30	31	131	-33	-30	14	8	-28	15
week 44	-35	-23	67	172	-21	18	1	-12	5	-4
week 45	-105	-163	83	98	-9	-68	-49	-2	14	-11
week 46	68	-2	-57	-90	-5	6	17	15	-9	23
week 47	13	-160	67	-95	9	-26	12	-13	11	20
week 48	88	46	-108	-127	-35	60	-39	4	-30	-29
week 49	-1	-2	-43	-44	24	-52	-23	-6	16	-19
week 50	-53	-110	-48	-101	-42	23	1	4	-9	1
week 51	5	-107	23	52	28	43	30	43	40	13
week 52	-73	-131	-67	-134	-20	-53	18	-37	-39	21
week 53	-46	-93	-48	-100	-31	-55	-52	-4	-22	-18

E(t)^2	A001	A002	A003	A004	A005	A006	A007	A008	A009	A010
week 30	1724	141	206	1305	46	58	802	0	826	187
week 31	1235	113	148	1086	42	3	46	1	136	256
week 32	1703	15047	178	116	2	1131	56	164	112	379
week 33	194	2208	26	19	13	2342	277	46	278	453
week 34	359	59	10	28887	10	70	5	56	3	11
week 35	148	881	802	2363	18	3345	0	545	426	517
week 36	2670	7145	1700	1467	1085	247	1082	79	13	441
week 37	54	74	119	26430	588	0	52	531	263	6
week 38	1630	479	180	57233	545	907	2	837	20	73
week 39	260	17640	65	2639	2037	113	87	29	9	200
week 40	26747	2283	2379	32292	3473	1495	574	1666	93	293
week 41	1226	254508	5	9319	0	462	60	1297	1	494
week 42	1176	1090	18090	31769	25	3396	412	9	8	83
week 43	1637	884	936	17217	1096	911	209	70	762	225
week 44	1218	550	4453	29538	453	337	1	148	24	14
week 45	10957	26621	6836	9567	75	4619	2376	3	198	117
week 46	4620	4	3227	8187	24	37	299	214	79	512
week 47	168	25734	4422	9007	80	659	139	163	122	399
week 48	7718	2089	11744	16098	1228	3642	1553	18	874	818
week 49	0	4	1835	1928	590	2675	514	37	272	372
week 50	2825	12194	2345	10133	1735	512	1	13	88	1
week 51	28	11512	545	2689	775	1847	913	1832	1595	173
week 52	5305	17058	4471	17847	395	2761	311	1338	1538	437
week 53	2118	8599	2276	10078	984	2977	2716	16	468	339

APPENDIX K: |E(t)| and |E(t)|/D(t) values of SES (2020)

|E(t)|	A001	A002	A003	A004	A005	A006	A007	A008	A009	A010
week 30	42	12	14	36	7	8	28	0	29	14
week 31	35	11	12	33	7	2	7	1	12	16
week 32	41	123	13	11	2	34	8	13	11	19
week 33	14	47	5	4	4	48	17	7	17	21
week 34	19	8	3	170	3	8	2	7	2	3
week 35	12	30	28	49	4	58	0	23	21	23
week 36	52	85	41	38	33	16	33	9	4	21
week 37	7	9	11	163	24	1	7	23	16	2
week 38	40	22	13	239	23	30	1	29	4	9
week 39	16	133	8	51	45	11	9	5	3	14
week 40	164	48	49	180	59	39	24	41	10	17
week 41	35	504	2	97	0	21	8	36	1	22
week 42	34	33	135	178	5	58	20	3	3	9
week 43	40	30	31	131	33	30	14	8	28	15
week 44	35	23	67	172	21	18	1	12	5	4
week 45	105	163	83	98	9	68	49	2	14	11
week 46	68	2	57	90	5	6	17	15	9	23
week 47	13	160	67	95	9	26	12	13	11	20
week 48	88	46	108	127	35	60	39	4	30	29
week 49	1	2	43	44	24	52	23	6	16	19
week 50	53	110	48	101	42	23	1	4	9	1
week 51	5	107	23	52	28	43	30	43	40	13
week 52	73	131	67	134	20	53	18	37	39	21
week 53	46	93	48	100	31	55	52	4	22	18

|E(t)|/D(t)	A001	A002	A003	A004	A005	A006	A007	A008	A009	A010
week 30	29%	3%	13%	12%	226%	4%	36%	1%	55%	23%
week 31	30%	2%	12%	12%	59%	1%	7%	4%	17%	22%
week 32	25%	36%	12%	4%	20%	22%	9%	128%	14%	39%
week 33	10%	15%	5%	1%	30%	43%	25%	114%	28%	65%
week 34	12%	2%	3%	36%	40%	6%	3%	-	3%	8%
week 35	7%	8%	21%	13%	33%	31%	1%	93%	25%	36%
week 36	23%	19%	25%	9%	73%	8%	31%	81%	4%	57%
week 37	3%	2%	7%	62%	39%	0%	7%	64%	25%	5%
week 38	23%	5%	10%	44%	29%	19%	1%	1446%	6%	16%
week 39	8%	23%	5%	12%	38%	7%	10%	179%	4%	39%
week 40	45%	10%	25%	29%	35%	20%	20%	91%	12%	78%
week 41	12%	50%	1%	14%	0%	13%	7%	-	1%	46%
week 42	10%	4%	42%	21%	3%	26%	16%	58%	3%	27%
week 43	14%	3%	10%	14%	28%	16%	10%	60%	53%	29%
week 44	14%	3%	18%	16%	20%	9%	1%	-	8%	8%
week 45	65%	23%	19%	9%	9%	50%	56%	168%	19%	32%
week 46	27%	0%	15%	9%	5%	4%	15%	91%	14%	38%
week 47	5%	27%	15%	10%	8%	20%	10%	-	14%	27%
week 48	26%	7%	33%	15%	49%	31%	49%	60%	66%	70%
week 49	0%	0%	14%	5%	24%	39%	34%	-	24%	69%
week 50	20%	20%	18%	14%	74%	14%	1%	73%	17%	2%
week 51	2%	23%	8%	6%	30%	21%	29%	91%	41%	29%
week 52	36%	36%	29%	20%	30%	37%	15%	3658%	80%	33%
week 53	26%	31%	24%	17%	78%	55%	90%	81%	60%	45%