A DATA DRIVEN INVENTORY SOLUTION FRAMEWORK FOR AN INVENTORY MANAGEMENT PROBLEM

by
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ABSTRACT

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Business Analytics M.Sc. THESIS, JULY 2022

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Keywords: Inventory Management, Data Driven Inventory Management, Textile industry

Demand forecast is the most essential input of the inventory models. In the case of manufacturing processes with a variety of similar products that can use a shared production line and common resources, the total amount of inventory and the itemized inventory levels need to be determined separately, but considering the correlation caused by the shared resources, we propose a framework that calculates the total required inventory levels based on the previous sales and demand forecasts and then determines the maximum amount of a production to be inventoried as a function of each product's forecast, and its previous sales for the period of the inventory. After deriving the max ratio to produce for each product, we propose clustering the products based on this ratio, to facilitate the application in industry. Using these ratios and the forecasts, the amount that need to be produced for each product is calculated. Then a new ratio for each product is calculated by dividing the amount of product to the required inventory for that product. Then the extra capacity is used so lowest ratio will become as high as possible. In our case study, we applied the framework to a tire cord fabric manufacturer (Company K), and after implementation they reported a total inventory decrease from 20 days of service to 10.

ÖZET

BİR ENVANTER YÖNETİM PROBLEMİNE YÖNELİK VERİ DAYALI ENVANTER ÇÖZÜM ÇERÇEVESİ

REZA VALIMORADI

İş Analitiği YÜKSEK LİSANS TEZİ, Temmuz 2022

Tez Danışmanı: Prof. Dr. Raha Akhavan-Tabatabaei
İkinci Tez Danışmanı: Asst. Prof. Dr. Burak Gökgür

Anahtar Kelimeler: Envanter Yönetimi, Veriye Dayalı Envanter Yönetimi, Tekstil sektörü

Talep tahmini, stok modellerinin en önemli girdisidir. Ortak bir üretim hattını ve ortak kaynakları kullanabilen çeşitli benzer ürünlere sahip üretim süreçlerinde, toplam envanter miktarı ve kalemlere ayrılmış envanter seviyelerinin ayrı ayrı belirlenmesi gerekir, ancak paylaşılan kaynakların neden olduğu korelasyon dikkate alındığında, biz önceki satış ve talep tahminlerine dayalı olarak gerekli toplam stok seviyelerini hesaplayan ve ardından her bir ürünün tahmininin bir fonksiyonu olarak stoklanacak maksimum üretim miktarını ve stok dönemi için önceki satışlarını belirleyen bir çerçeve öneririz. Her ürün için üretilecek maksimum oranı elde ettikten sonra, sanayide uygulamayı kolaylaştırmak için ürünleri bu orana göre kümelemeyi öneriyoruz. Bu oranlar ve tahminler kullanılarak her bir ürün için üretilmesi gereken miktar hesaplanır. Daha sonra, ürün miktarı o ürün için gerekli envantere bölünerek her ürün için yeni bir oran hesaplanır. Daha sonra ekstra kapasite kullanılır, böylece en düşük oran mümkün olduğu kadar yüksek olur. Vaka çalışmamızda, çerçeveyi bir lastik kordu kumaş üreticisine (Şirket K) uyguladık ve uygulamadan sonra toplam envanterin 20 günlük hizmetten 10'a düştüğünü bildirdiler.

ACKNOWLEDGEMENTS

I would like to express my sincere gratitude and appreciation to my family, who have been a great source of support. I am deeply grateful to Raha Akhavan-Tabataei and Burak Gökgür, whose guidance and encouragement has been invaluable throughout this study.

Dedication page
I dedicate my dissertation work to my family and many friends.

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1. Introduction

Data generated by manufacturing systems is experiencing an exponential growth and has reached 1000 exabyte annually Yin and Kaynak (2015). New trends in manufacturing around the world such as Industry 4.0 in Germany, Industrial Internet in the US, and Made in China aim at converting data acquired during the product life cycle to intelligence to use the resources more efficiently Tao et al. (2018). These programs are designed to promote the use of new IT technologies in manufacturing processes which is a driver for smart manufacturing. Smart manufacturing's goal is to create a positive impact in all aspects of manufacturing from the data generated throughout the product life cycle Tao and Qi (2017).

These data can be used to improve all aspects of manufacturing and create more efficient product management. One of the aspects that the data can help to improve is finished goods inventory, hereafter to be called Inventory. In different industries, the type of inventory (raw material, work in process (WIP), finished goods) and how much each one matters to the firms in that industry differs. Boute et al. (2007) analyzed 17 industries and showed that average inventory for the textile industry for example, is on average equivalent of 31 days of production.

Manufacturers keep inventory for different reasons such as complying with the promised lead-times, inaccuracy of forecasts, cost of changing the production line, cost of losing sales, etc. The market and the industry that a manufacturer works in, determine the reasons why and the quantity of the inventory that a manufacturer needs to hold. One important attribute in this decision making process is costs. Underage costs, i.e. not having enough inventory to fulfill the demand, differ from industry to industry, and even sometimes from one manufacturer to another in the same industry. Consequently, a general inventory model that applies to all industries loses sight of intrinsic aspects of each industry. Thus, inspired by a case in the industrial textile manufacturing, i.e. a tire cord fabric manufacturer firm, an inventory model that fits the characteristics of this industry was developed.

Textile manufacturing is among the first industries that were affected by the industrial revolution. The underlying reason for it is the repetitive process of manufacturing different types of textiles. In other words, the process to produce fiber, yarn, or fabric is repeated with a few adjustments for different types of products. Hence, with machines that have the capabilities and access to the raw material, any player can join the market. As an example, at the beginning of the pandemic, China was able to increase its face mask production capacity by tenfold in less than two months Gereffi (2020).

The textile industry produces many product groups, as shown in Figure 1. Some of these products such as yarn can be finished goods for a manufacturer, work in process for another one, and raw material for the next. The global textile industry is expected to pass USD 1 Trillion in the coming years with USD 700 billion in fiber, yarn and fabric products Uddin (2019). Figure 1.1 demonstrates textile industry. The part the industry that is covered by this research are the producers whose finished goods products are fiber, yarn, or fabric hence forward will be called textile industry unless explicitly mentioned otherwise.

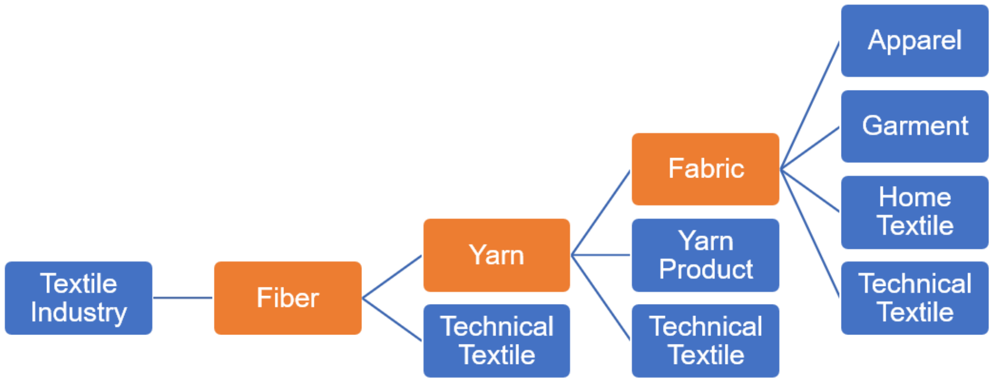

Figure 1.1 Textile industry products Uddin (2019)

Inventory models use forecast or expected demand to plan the inventory. New methods for forecasting use future sales as the dependent variable, and previous sales and other macroeconomic lead indicators such as GDP as independent variables to build a model to forecast it Sagaert et al. (2018). Then using the forecasted sales, inventory for each product is determined and then total inventory will be the sum of them. An issue with the general inventory models is that they do not consider the production process and do not devise the plan based on that. Hence, synergy of the combination of products is not considered in them. In our model, we addressed this issue by focusing on a particular production line and starting with the total required inventory rather than product inventory.

Textile industry has 3 main complexities. First, it uses shared lines. Shared line is defined as a line that can produce a range of products with little adjustments in the machine. This enables manufacturers to use the line to produce different products. It also means a machine does not have to stop working as a particular product is not being produced as all machines are multipurpose and can produce other products. It also enhances inventory management as the manufacturer has more agility to change the product it is producing without stopping the line. Secondly, since shared line allows the production of different products, these manufacturers can produce a large variety of products. Hence, as manufacturers in the textile industry are able to produce many products using same machinery, an inventory model that incorporates variety of products while takes into account the ability to swiftly change production line needs is a complex problem to address. A manufacturer needs good production planning as well as inventory management to use its shared-line production process to decrease its inventory while increasing the product variety.

Third main complexity of textile industry is the difference in the sales forecast accuracy of each product. Nonetheless, the total sales forecast's accuracy can be quite stable as it is in our case company. Consequently, our model uses the total sales' forecast for planning the total inventory required and the shared-line production function which allows changing of products with low to zero costs and using products' forecasts and sales to plan the product basis inventory.

The company that this thesis is built on is a textile manufacturer that works in the tire industry. It will be called company K. It keeps inventory to cover its production lead time and capacity constraints. The focus of this research is developing a new finished goods inventory model that decreases the total inventory, hence lowers the required working capital without affecting the service level.

The rest of this thesis includes the following sections: 2 provides a literature review of inventory planning and textile inventory models. 3 background of company K and problem settings. 4, proposed solution model and testing it. 5 includes the performance analysis of the model and managerial insights. Finally, in 6 conclusion remarks and future research are presented. Auxiliary information is provided at the end.

2. Literature Review

An inventory plan has two parts, namely: Demand and model. in this chapter a review of both and how they contribute to inventory planning is presented. Then where our work comes in and its contribution to the literature will be discussed.

Inventory models were created using the available data to construct the demand distribution with demand stochasticity in mind Ban and Rudin (2019). Initially, the researchers assumed that the demand is known Arrow et al. (1958), and Scarf (1960) and built more simplistic models. Later on, and since research in this field developed further, the uncertainty of demand has been modeled using three approaches: Bayesian, Min-max, and Data-driven. In the Bayesian approach, available information are used and updated previous decision/information as new information became available and the parameters are learned based on the distribution assumption Azoury (1985). In the Min-max approach, given a specific uncertain set of distributions, the decision-maker chooses the best decision among the set Chen et al. (2007), and Gallego and Moon (1993). In the last approach, the Date-Driven approach, sample data from unknown demand is available to the decision-maker. The decision-maker then uses different models such as stochastic gradient algorithm Burnetas and Smith (2000), and Kunnumkal and Topaloglu (2008), and adaptive value estimation method George and Powell (2006) to forecast the demand. One of the latest developments is using machine learning in demand forecasting Ban and Rudin (2019). Using machine learning allows for more accurate forecasts as there is no cap on the number of parameters and their relations. An example of the use of machine learning techniques for forecasting in our industry is done by Sagaert et al. (2018). They used LASSO models and big data and increased the accuracy of the forecast for a company that works in the textile industry by 16.1%.

The second part of the inventory plan is the model. Most of the research for models date back to the 80s. The basic models are developed and presented in the textbooks. For example, Federgruen and Zipkin (1986), and Federgruen and Zipkin (1984) worked on an inventory model when the production capacity is limited and the demand is uncertain. They showed the optimal policy is to hold a base stock in inventory. However, they did not provide an algorithm to calculate the quantity of this base stock. Tayur (1993) worked on the problem and built on it to produce a model to calculate the optimal number. Then Ciarallo et al. (1994)relaxed one of the assumptions and created a model when the capacity is also uncertain. One of the latest and the closest to our research is DeCroix and Arreola-Risa (1998). This paper expands the base stock policy proposed for a multi-product infinite horizon in previous research and proves its optimality. The demand is uncertain, hence one of the additions to the DeCroix and Arreola-Risa (1998) research is modeling the demand and supply as a stochastic process. In other words, even though the supply is limited, the actual amount of supply can differ from one period to the next. Gallego and Hu (2004) incorporated the assumption of stochastic demand and supply and modeled them using Markovian models. DeCroix and Arreola-Risa (1998) model is the corner stone for stochastic supply and demand. This model was expended by Cheng et al. (2004) by incorporating capacity planning with inventory planning.Ohta et al. (2007) created another model by assuming demand arrival distribution follows Poisson distribution and production time for each product follows Erlang distribution. Then they showed which products should be produced as make-to-order and which ones as make-to-stock. Finally, for the products that should be made to stock, a base stock inventory model is proposed. Then Shen (2013) used the assumption of stochastic demand distribution for a multi-product production when the resources are scarce and products have different levels of importance. Demirel et al. (2015) incorporated the production line characteristics into uncertain demand. They model the production for a manufacturer that has one shared line-multipurpose line- and a dedicated line. Products first produced in the shared line and then customized in the dedicated line.

To the best of our knowledge, Even though there has been a vast amount of research on inventory planning, modeling, and forecasting. However, there is little attention paid to the complexities specific to the textile industry. Hence, no inventory model that simultaneously considers the shared line characteristics of textile industry, large variety of products, and the difference in their sales forecast accuracy has not been developed.

Our research addresses the gap between industry characteristics of textile industry and previous research on stochastic demand while considering the equal importance of products, and production capacity constraints.

3. Background & Problem Description

In this chapter, we will explain our case company. The first section is dedicated to the company's background, operations, and current inventory model. The second section will cover the data that the company provided us for the purpose of modeling a more efficient inventory system for them. Finally, in the last section a descriptive analysis of the data is presented.

The information presented in this chapter was gathered during the interviews we had with the global supply chain group of the Company K between January and May 2021. Through these interviews, their practices, models, and processes were mapped. Furthermore, we developed a new inventory model for the finished goods products of the Brazil plant which was tested and confirmed by the Company K global supply chain team.

3.1 Company K

In 1973, Company K was founded. After many expansions, mergers, and acquisitions the company cemented its place as the leader in the reinforcement market. It has 12 plants on 4 continents producing a wide variety of products. Its product categories consist of construction reinforcement, composite reinforcement, and tire reinforcement. Our project focuses on the Brazil plant of the company which will be denoted as the plant from this point on. The plant's main product segment is "tire cord fabrics" (TCF). Approximately, 7-10 percent of the cost of a tire is TCF. TCF is the major product segment of the company such that one out of each three motor vehicle tires, and one in every two aircraft tires in the world in are reinforced by the company's products, mainly TCF. In 2019, TCF Yarn together generated 82.8 percent of the revenue of the company.

3.1.1 Production Process

Production consists of three stages, twisting, weaving and dipping s shown in Figure 3.1. First the raw material goes through the twisting process. In this process raw material are shaped into yarn ropes. In the second stage a weaving machine weaves the yarn ropes and creates yarn ply. Finally, in the third stage a dipping machine creates the tire cord fabric (TCF).

There are two types of raw materials that are used, nylon 66 and polyester. There is a 3-to-4-month lag for the delivery of the raw materials by the suppliers of nylon and polyester. Hence, orders for them are made 5-6 months ahead (Sagaert, 2018). Furthermore, the production lead time from raw material to TCF is 21 days. The company needs to address the demand for a month e.g. July, during that month, e.g. July. However, orders are given to the company during the month. Hence, the company needs to have inventory to address the deviation of sales forecasts and actual demands.

The plant produces 4 different segments of products, namely: greige fabric, yarn, single end cord, and TCF. Yarn and greige fabric are unfinished products that are sometimes sold to customers. Nonetheless, the main product is TCF.

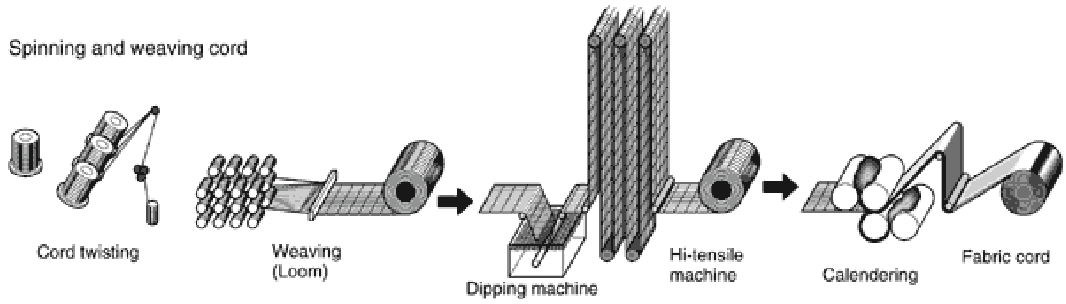

Figure 3.1 TCF production process (www.bridgestone.com)

3.1.2 Products

During the period starting Dec 2018 and ending Dec 2020, the plant produced 96 different SKU. Of these products, 3 were single-end cord, 18 types of yarn, and 2 types of Kratos – a specific product that is produced for one customer and is used for construction reinforcement. The rest of the products (73 SKUs) consisting over 92% of the sales volume for the study period are TCF. This information is presented in Figure 3.2.

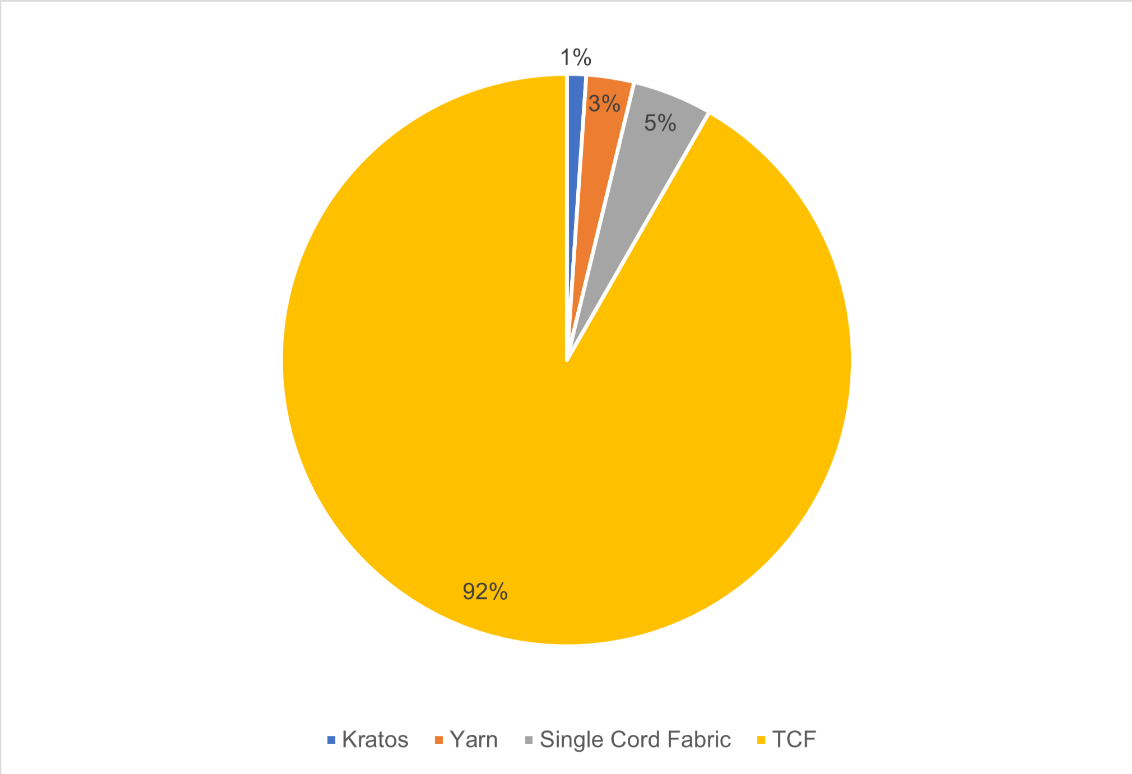

Figure 3.2 Percentage of sales volume of different segments of products for Brazil plant during the study period

3.1.3 Customers

The Brazil plant had 27 different customers during the study period. Company groups the customers (based on the products they buy and the important of the customer to the company) into 6 different segments. The main segment which is called the Big 6 consists of the 6 largest tire producers in the world: Michelin, Bridgestone, Continental, Goodyear, Sumitomo, and Pirelli. This group accounts for over 72% of the sales volume during the study period. Figure 3.3 shows the sales volume to each segment of the customers.

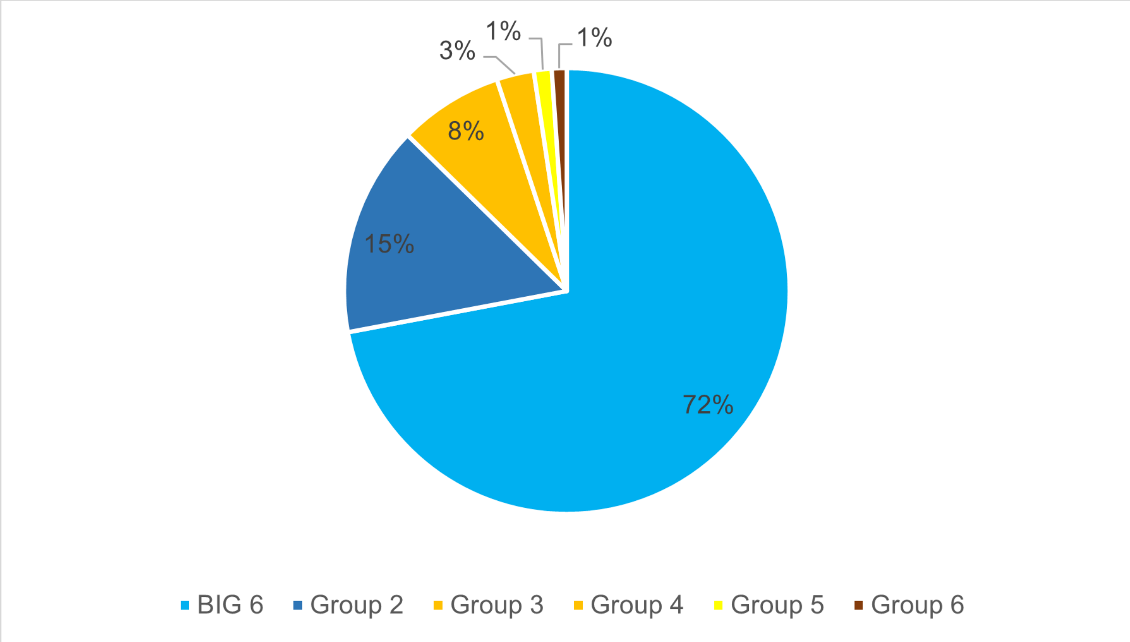

Figure 3.3 Sales volume for each segment of customers during the study period

3.1.4 Forecasts

Forecasts of demand are used for inventory and production planning. For inventory, the company has raw material, work in process, and finished goods inventories. Raw material has the longest lead time, 3 to 4 months. However, other constraints such as the procurement department's requirements, and optimization of the production among different plants around the world require 12 monthly forecasts. Consequently, each month the company forecasts the sales for each SKU to each customer for the next 12 months. At the end of each month, all the forecasts are updated. "Lag 0" forecast means the forecast for the sales of month "A" at the beginning of month "A", and "lag 1" means forecasts for the sales of the month, one month prior to it. For instance, the Lag 1 forecast for period t+1 is the sales forecast for period t+1 at the beginning of period t.

3.1.5 Company K's Current Inventory Model

In the current model, all products are considered similar and on average 20 days of lag 1 forecast for each SKU is kept in the inventory. This amount can vary and for some SKU-customers be up to 30 days of forecasts based on the customer's and SKU's importance.

In their model, the headquarter only determines the monthly production required for each SKU, based on the forecasts and ending inventory. Then the plant managers plan the production schedule.

3.2 Problem Framing

Currently, inventory covers the production lead time as well as capacity constraints. The company wants to lower its inventory without affecting its service level. By decreasing the inventory, company will save on its working capital and lowers financial costs of production. However, if the reduction in the inventory affects its service level, it may lose its customers. Hence, the goal of the project is finding the optimal inventory that does not affect the current service level of the company which is tied to addressing the demand during a month.

3.3 Data

The company stores forecasts and actual sales for all SKU-Customers for all periods and plants. This data is used for operational planning as well as operational and financial performance management. The same data is for the purpose of optimizing the inventory in this research.

3.3.1 Sales Data

The company keeps sales data for each year in a separate file. As this research encompasses three years, 2018, 2019, and 2020; three files were consolidated in one excel sheet. This sheet consists of 34 columns and 450 rows. This sheet is part of the total sales information. It has been filtered based on the plant ID. Hence, all of the data available are for the SKUs produced in the plant. The other two columns that define the information presented in each row are customer and SKU names.

Hence, for each SKU-Customer, there is a row presenting its sales for the 12 months of a specific year (file name). The rest of the information available in this sheet are region, customer segment, country sold to, raw material, product type, local product code, and Dtex and Yarn (material attributes).

For the purpose of this research, the sales information for each SKU was consolidated. The final file had the sales information from December 2018 until December 2020 for 96 SKUs that were produced in this plant. Consequently, the final sales data set had 25 inputs for months of sales for 96 SKUs.

3.3.2 Forecast Data

For each SKU-Customer, the company forecasts the sales for 12 months at the beginning of each month, including the months the forecasts occur, i.e. in July 2022, the company forecast the sale for $SKU_1, Customer_A$ for July 2022, until June 2023. These forecasts are called lag 0-lag 12 forecasts for a month. Hence, $SKU_1, Customer_A$ lag 0 forecast of July 2022, is the forecasted sale of $SKU_1, Customer_A$ during July 2022. Here again, forecasts are aggregated on the SKU level. Consequently, there are 12 forecasted sales for each of the 25 months of data for each SKU. Lag 0 forecasts are used for production planning in the plant, lag 1 forecasts are used for finished goods inventory planning and the rest for raw material and production planning between different plants.

3.3.3 Production Capacity

The other input for the model is the production capacity. As most of the products produced in this plant are TCF, the production capacity for TCF production will be considered as the production capacity of the plant.

To calculate the production capacity of the plant, utilization of the capacity, as well as the total capacity, is provided by the company. The minimum of utilized capacity of the three stages (i.e. twisting, weaving, and dipping as it is presented in figure 2) will be considered as the production capacity of the plant for that given month.

3.4 Descriptive Analysis

In this section analysis of the sales, forecast, and capacity data as well as descriptive insights on them is provided.

Sales data consists of 96 distinctive SKU sales over 25 months. Hence, there are 2400 sales data points in our data set. During this period, the company faced some very high demand volatility due to COVID 19 pandemic. Figure 3.4 shows the total sales volume of all products during the study period.

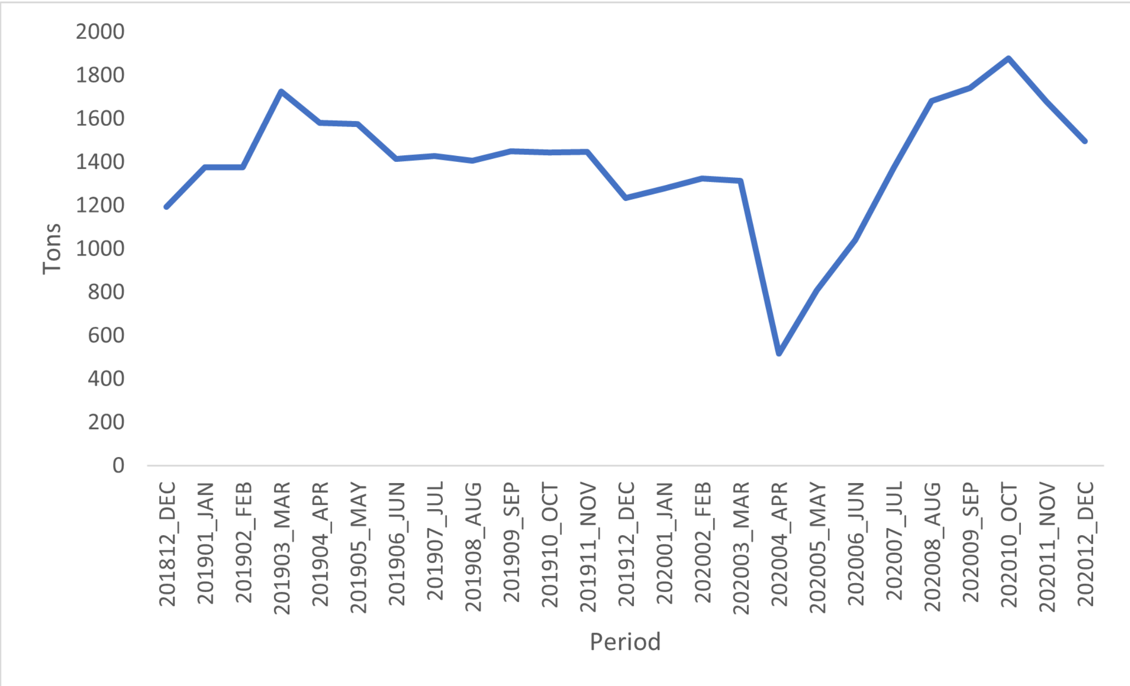

Figure 3.4 Total sales volume during the study period.

The volatility can be the result of changes in the number of SKUs sold during periods or the amount sold per SKU. Figures 3.5 and 3.6 together show that the volatility if the total sales was not due to changes in average sales per SKU or the decrease in the number of SKU sold. However, both of them have changed during the pandemic.

The second input of the model is the forecasts. Forecasts are important as planning is based on them. As for the forecasts, there are 12 lag forecasts for each SKU-Customer. Lag 1 forecasts are used for the finished good inventory. Figure 3.7 shows the total lag 1 forecasts for the period. Lag 1 forecast of period t is the forecasted sales for period t at the beginning of period t-1.

The ratio of total sales to total lag 1 forecast per period demonstrates the changes in forecasts in comparison to changes in the demand. It shows if the changes are

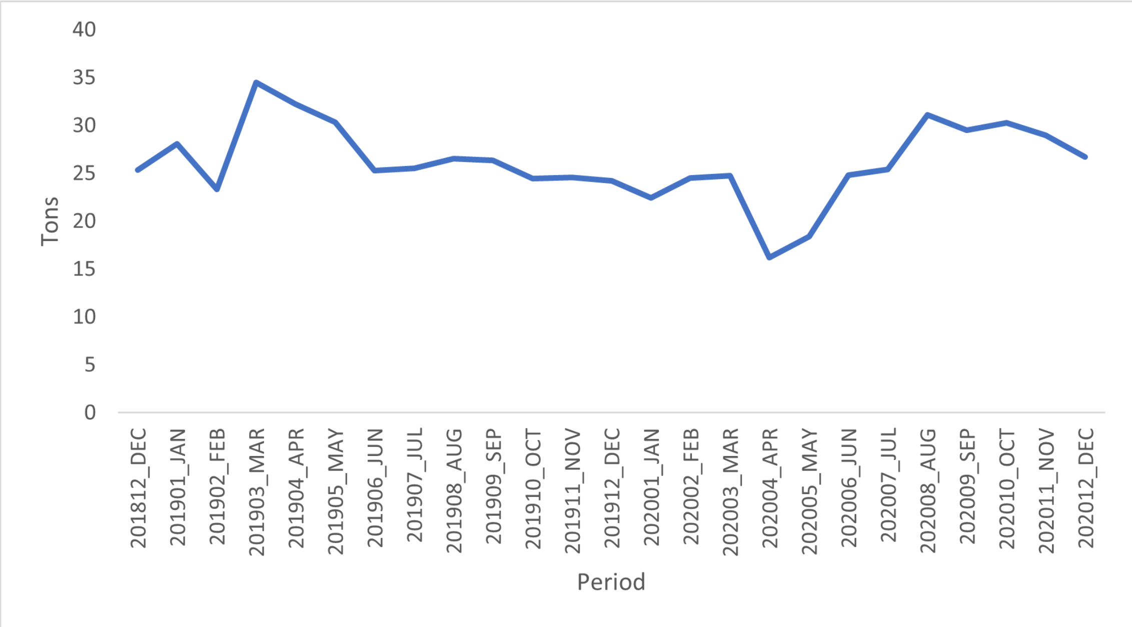

Figure 3.5 Average volume sold per SKU during each period.

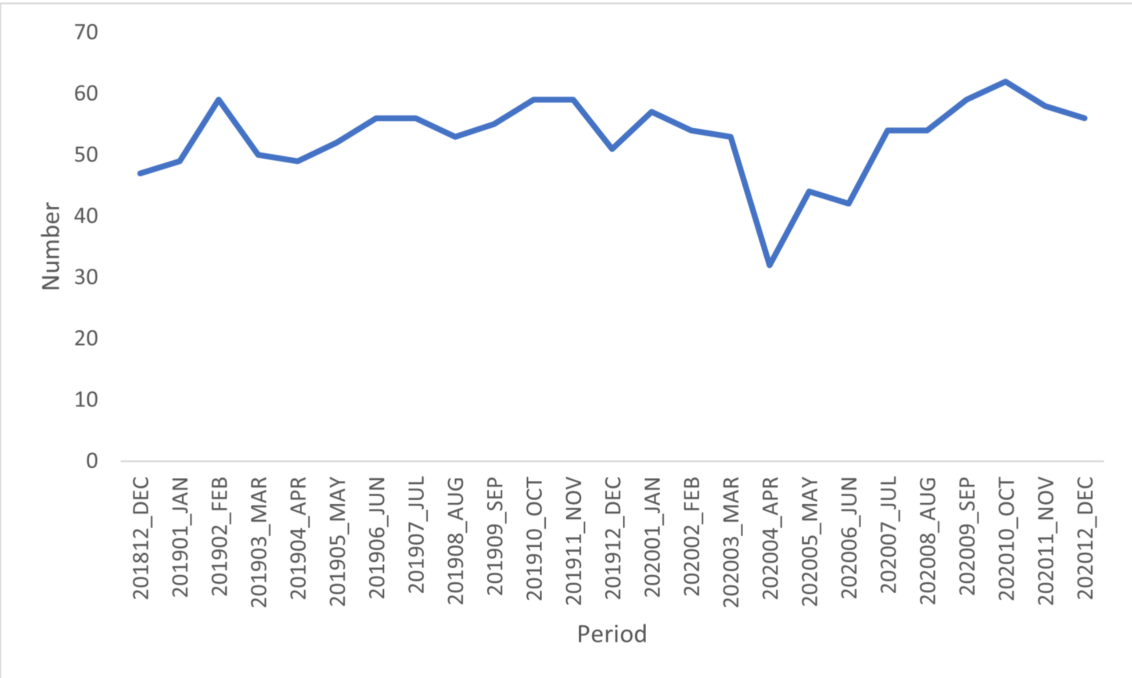

Figure 3.6 Number of SKUs sold during each period.

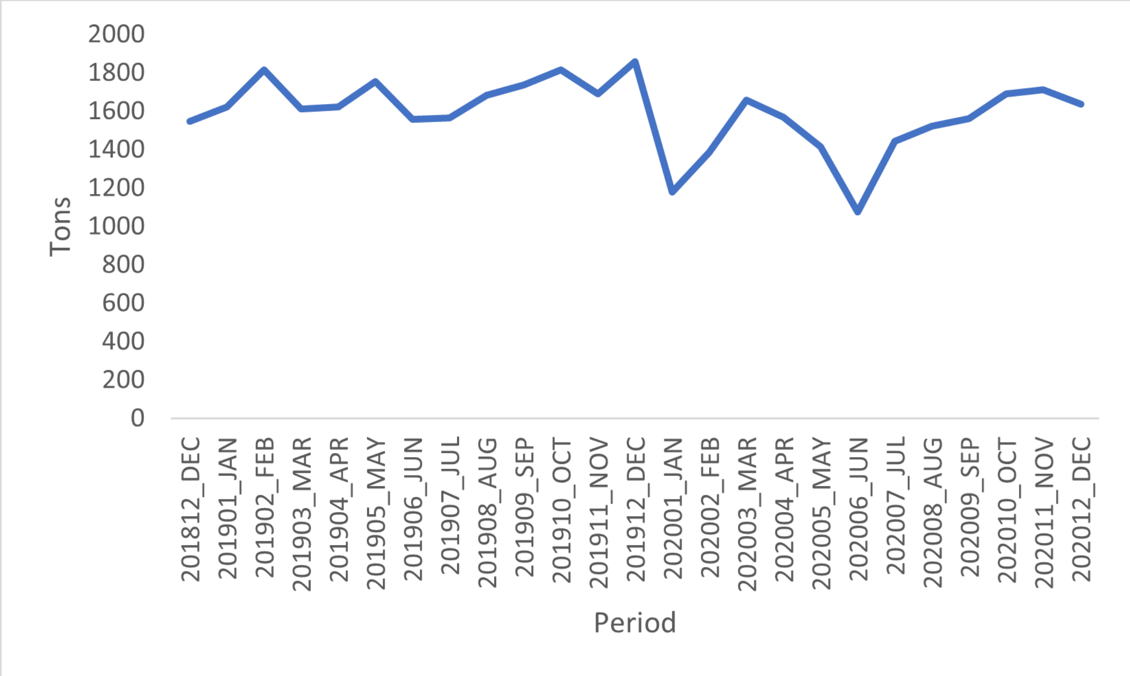

Figure 3.7 Total lag 1 forecast for the study period.

lagging, or if the forecast can foresee how the market will react to conditions such as COVID 19 pandemic. Figure 3.8 illustrates that the forecasts are lagging to adapt to new market conditions. In April 2020 the ratio dropped, meaning the forecasts did not foresee the changes in the market that the pandemic and the restriction imposed on car usage and hence tire market and the TCF. Then the ratio increases and reaches its pinnacle in October 2020. It means the forecasts are lagging and it takes them some months to adapt to the new market conditions.

The last part is the production capacity of the plant for each month. The production capacity is known as utilization capacity which means the actual capacity that is used during a particular month is also known. As the utilization capacity can be the result of downtimes or repairs as well as not having demand to produce more. Hence, as the reason behind utilization capacity is not known to us, we considered the utilization as exogenous. Hence, each production stage utilization was used as it was given to us. Nonetheless, forecast accuracy and inventory may have affected the utilization. For instance, during April 2020, when the pandemic hit the market, the utilization dropped. For the purpose of this study minimum utilized capacity of the three stages was considered equal to total capacity. Figure 3.9 shows the total capacity of the plant for 2019 and 2020.

In the next chapter, we will explain our solution approach and how our model works.

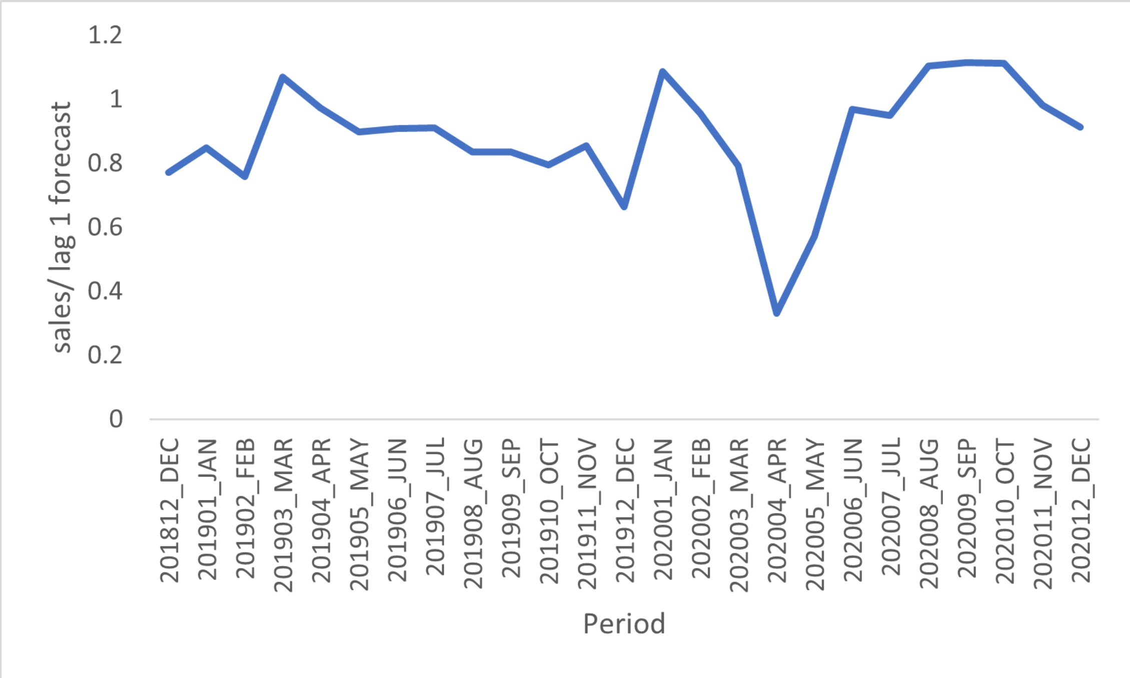

Figure 3.8 Total sales ratio to total lag 1 forecasts per period

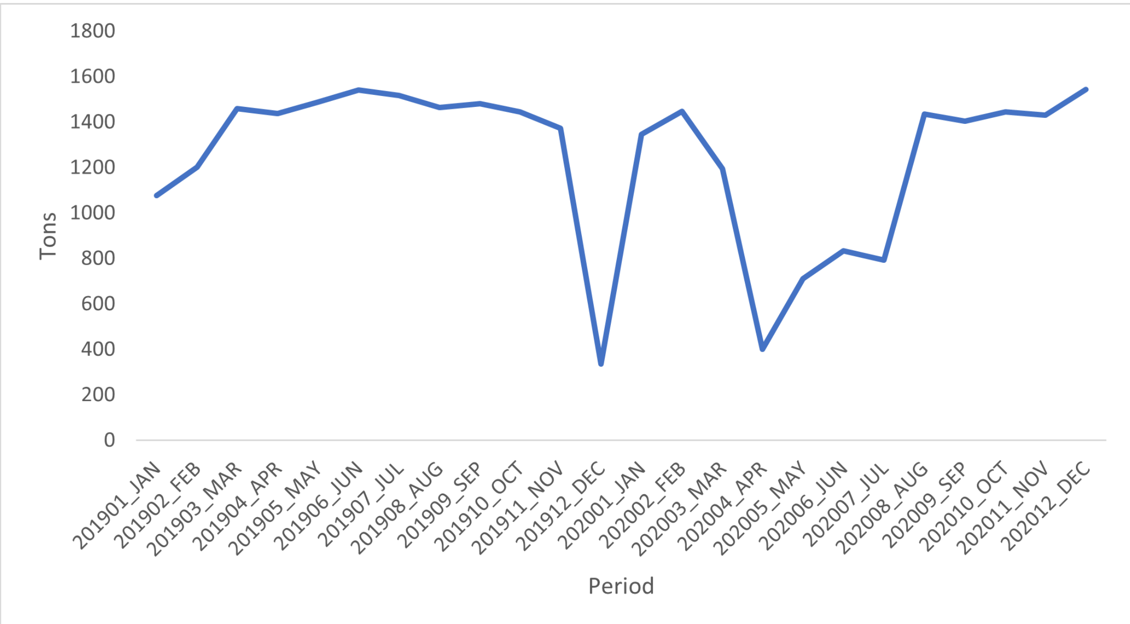

Figure 3.9 Total capacity of the plant during 2019 and 2020.

4. Proposed Solution Approach

In this section first we develop an inventory model for a manufacturer that produces only a single product. Then based on the insights from that model and the data provided to us, we developed an inventory model for textile manufacturers. In the second part of the section a discussion on out of sample testing of the model is presented.

4.1 Model

Our model is a periodic-review framework in which at the beginning of the period the manufacturer decides on how much inventory it will need for the next period and produces that during current period. This is called *"target beginning inventory"* which will be noted as $y_{(t,i)}$ indicating the target inventory for period t of product i. It is the ideal inventory level we want to achieve. However, the manufacturer may not achieve producing the targets due to production capacity limitations. Consequently, the actual amount of inventory that at the beginning of each period which is called *"beginning inventory"* may or may not be equal to *"target beginning inventory"* for that period. Total production capacity is known for each period, and it will be denoted as k_t meaning total capacity for period t. Forecasted sales for product i in period t is called $f_{(t,i)}$ and its actual sales as $s_{(t,i)}$.

The first step is calculating the total inventory which is the sum of inventory for all products for a period. The practice of the company is using days of service as days of the total forecasts. Hence, we use the same method for calculating the total amount of inventory and it is equal to: $\alpha \sum_i f_{(t+1,i)}$. Eq. (1) presents the relation between total inventory, total sales, production capacity and excess capacity denoted as Ek_t.

Eq. (1): *begining inventory*$_t$ + *production capacity*$_t$ - *sales*$_t$ = *excess capacity*$_t$

Eq. (2):$\alpha \sum_i f_{(t+1,i\,)}$ + k$_t$- $\alpha \sum_i s_{(t,i)}$=Ek_t

Negative Ek_t means the sum of inventory and production capacity during period t was not enough to satisfy the demand. Hence, the company needs more inventory. Consequently, in the first step, minimum that results in positive Ek_t for all the t periods is calculated. Appendix 1 shows the flowchart for this step.

The inventory is used to support k_t as it may not be enough to cover the demands for that period. Another reason that manufacturers need inventory even when the capacity of the period is more than enough to cover the demand for that period, is production lead-time. As the products are using the same machines and we do not have the work in process inventory information, it is assumed that the lead-time follows a uniform distribution for all products. Hence, total inventory should also be more than expected lead-time for a product. We assume a product can be in any stage of production when the demand company gets the order for that product. In other words, the probability for the product in any stage is drawn from a uniform distribution. Consequently, the expected lead-time will be equal to half of the lead-time and will be denoted as . After calculating the average lead-time, the minimum total inventory will be the maximum of (α, β) which we denote by θ, where $\theta = max(\alpha, \beta)$.

Now the total beginning inventory for period *t+1* is: $\theta \sum_i \mathrm{f}_{(t+1,i\,)}$. The next step is calculating the inventory for each product based on their previous sales and forecasts. Here, we assume that all products use the same machinery and process as the TCF. The only difference that results in having all those SKUs is the setting of the machine and the raw material used. It is also assumed that there is no material difference in the production time of different products. Another assumption is that the raw material is enough for producing all products and there is no priority between customers and the products.

Our model addresses the inventory problem for a manufacturer that produces the inventory one period ahead of the time it is required. For instance, March's inventory is produced during February. Furthermore, the segment of the industry that this research addresses is B2B producers that do not face selling seasons.

After determining total required inventory for a month, we look to address the question of how much of each SKU should be produced for the inventory of a particular month. In order to determine this amount, sales and forecast of each SKU is analyzed. Since in the ideal case the inventory is used during the next period, we do not want to produce anything that is not going to be used in two consecutive periods. Hence, a new multiplier is created to make sure that the maximum ratio of the forecast that is produced will be used during two consecutive periods. It will be denoted $\gamma_{(t,i)}$, meaning the γ for period t and product i. Equation below shows the ratio between $\gamma_{(t,i)}$, sales and forecasts.

$\gamma_{(t,i)} = (s_{(t,i)} + s_{(t+1,i)})/(f_{(t,i)})$

After calculating $\gamma_{(t,i)}$, minimum $\gamma_{(t,i)}$ for each product will be called $\gamma_{(i)}$ and the amount to be produced as inventory during period t is $\gamma_{(i)} * f_{(t+1,i)}$ which will be the next period's beginning inventory. In each month, the priority of production is as follows:

Demand of the period (s_t) $\gamma_{(i)} * f_{(t+1,i)}$ (Inventory that is needed for the next period)

if $\gamma_{(i)} * f_{(t,i)} - s_{(t,i)} > \gamma_{(i)} * f_{(t+1,i)}$,then:

$\gamma_{(i)} * f_{(t,i)} - s_{(t,i)}$ will be used as inventory for period t+1 for product i

After driving all the $\gamma_{(i)}$ we need to check if $\sum_i(\gamma_{(i)} * f_{(t,i)}) > \theta \sum_i \mathrm{f}_{(t,i)}$. If this condition meets, then we can proceed further and start planning the inventory production using available capacity based on the priority of that was mentioned before. As $\gamma_{(i)}$is based on product i forecast and sales, and independent from the rest of the products, there is variation among $\gamma_{(i)}$s. Hence, production planning of the inventory needs a new ratio which we call $\phi_{(t,i)}$

$\phi_{(t,i)}$= (amount of i in period t)/$(\gamma_{(i)} * f_{(t,i)})$

$\phi_{(t,i)}$ represents the portion of the target inventory that is produced to cover the 2^{nd} priority production, or what is considered as going to be used to cover the sales of *t+1* or the inventory production for *t+2*.

The aim of production is producing enough of each product until all $\phi_{(t,i)}$ reaches 1. However, due to capacity constraints, it may not be feasible to achieve it. Hence, the production starts with the product with the lowest $\phi_{(t,i)}$ until it's $\phi_{(t)}$ reaches the second lowest $\phi_{(t,i)}$ then, the production of both continues until they reach the next one. This continues until all product's ϕ reaches 1.

To make the model easier to use in industry, we propose binning the products based on $\gamma_{(i)}$, into a few groups. Products in each group will have the same $\omega_{(i)}$. $\omega_{(i)}$ will work the same as $\gamma_{(i)}$ for products i and the rest of the steps will be the same as before. The difference here is having the same multiplier for a group of products and decreasing the number of multipliers to make it easier to use. However, for the model to use, the following conditions must be met:

$\sum_i(\omega_{(i)} * f_{(t,i)}) > \theta \sum_i \mathrm{f}_{(t,i)}$

$\forall : \omega_{(i)} \leq \gamma_{(i)}$

4.2 Out of Sample Test

To make sure data mining has not affected our results, we pursued out of sample testing. However, as our data set was limited, we did not divide the data into train and test. In ideal case, we would have been able to test the model with 2021 data. Company K team performed this test and reported that the model is producing same results, this report is available in the appendix. Nonetheless, as we did not have access to that data, we generated our future sample data set to test the model.

4.2.1 Time series

Sales data is known to have time series features inside them. To generate a new sales data set, we used the time series methods in StatTools software. However, sales volatility and scarcity of data impeded the process. The data set that was created had low forecast accuracy and for most of the SKUs, because there were not enough data points, we had to use moving average or simple exponential smoothing which creates identical out of sample forecasts. Figures 4.1 and 4.2 show an example of data created with these methods.

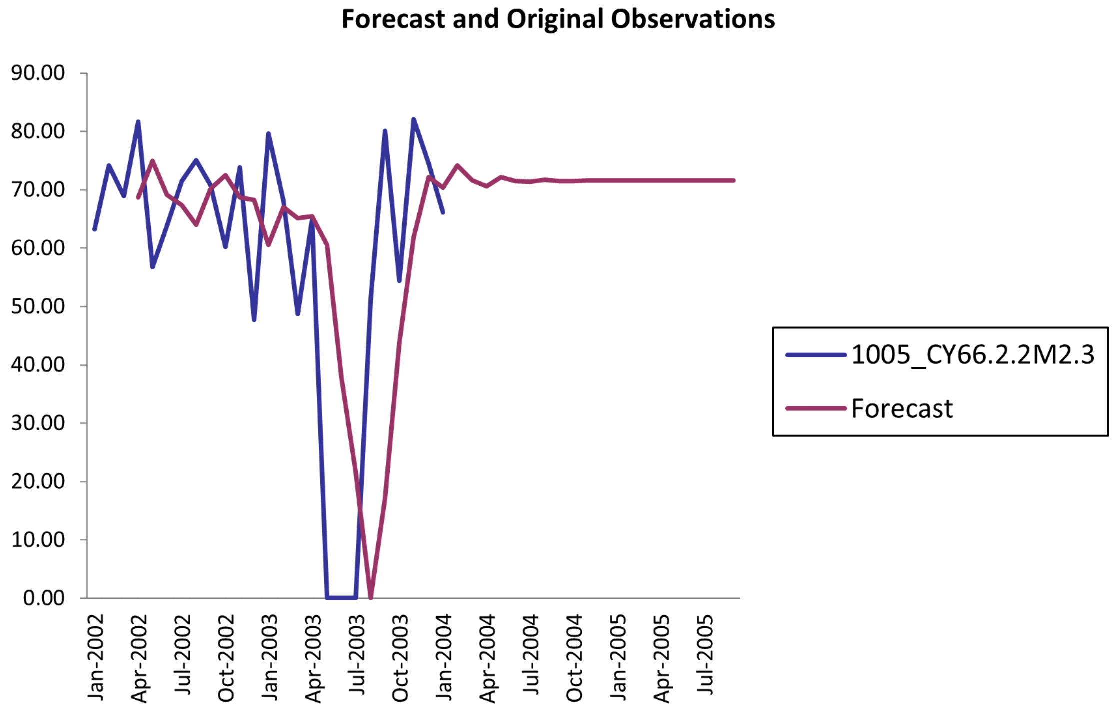

Figure 4.1 Actual sales and forecasted sales using 3 periods moving average for $1005_CY66.2.2M2.3SKU$

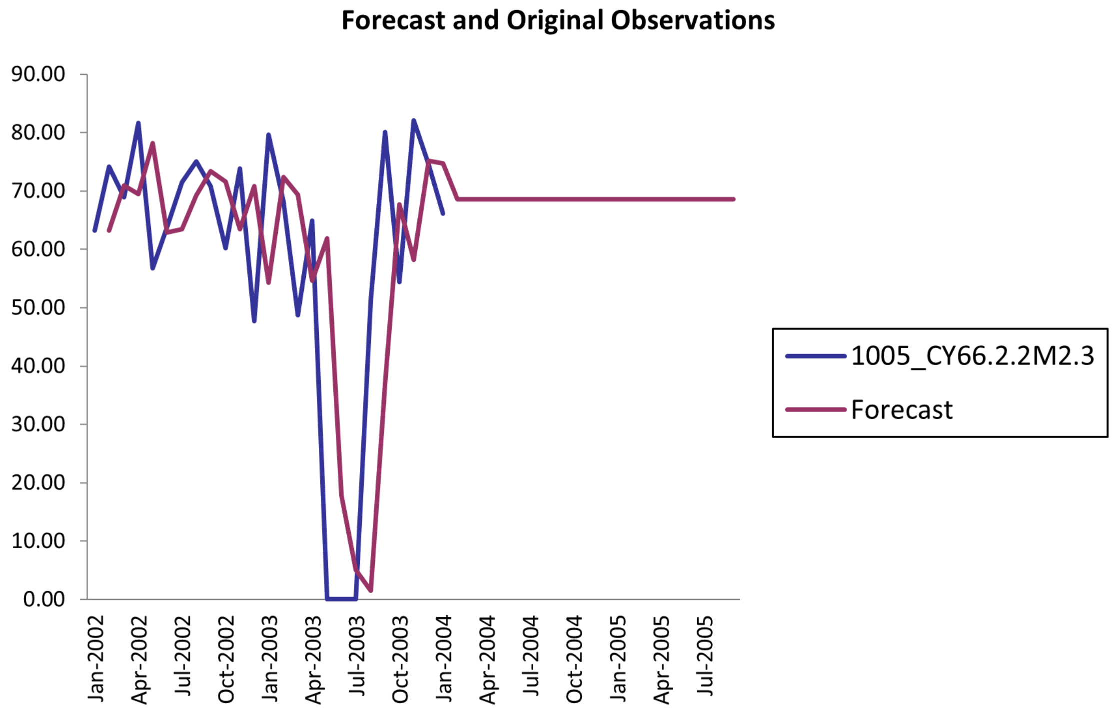

Figure 4.2 Actual sales and forecasted sales using simple exponential smoothing for $1005_CY66.2.2M2.3SKU$

5. Analysis & Results

In this section the results of the implementation of the model on the data set and the saving it would have brought to the company in case they used this model for the study period is presented. Then managerial insights that are drawn from the model are provided.

5.1 Performance

There are two types of performance measures that can be used, performance of the model in the data set that the model is created upon, performance of the model in out of sample data set. As it was mentioned in Section 4.2, we were not able to perform out of sample test. Nonetheless, the company affirmed the model and sent us their report which is available in the Appendix A.4. The model consists of two parts, optimizing the total inventory and then optimizing the SKU based inventory. The second part of the model assures the total inventory follows the assumption of the model and will be used in two consecutive periods. Figure 5.2 Shows the total tons of inventory based on days of forecasts. With using 10 days of forecast instead of 20 days, company could have decreased its total inventory for the 25 months of the study by 12,772 tons.

The second part of the model is to address the issue of volatility of forecast accuracy between SKUs. The figure 17 shows how much extra inventory is needed for each period if the company keeps 10 days of forecast for all of the SKUs. The difference here is the required inventory to address the demand for each SKU based on the total production capacity and 10 days of forecast for each SKUs.

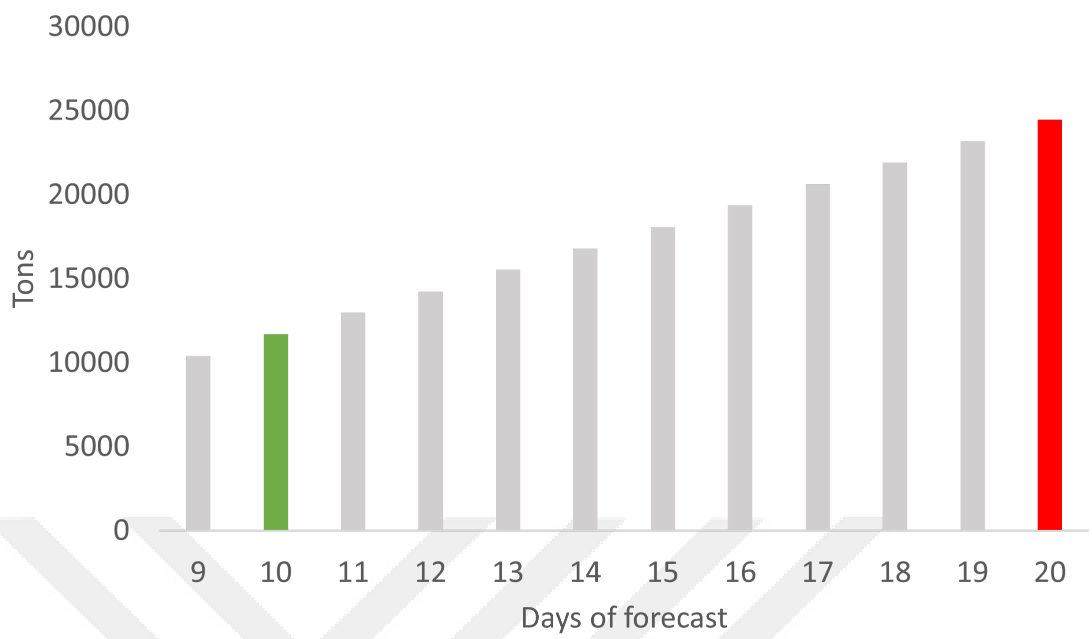

Figure 5.1 Total inventory for the 25 months based on days of forecast used for inventory model

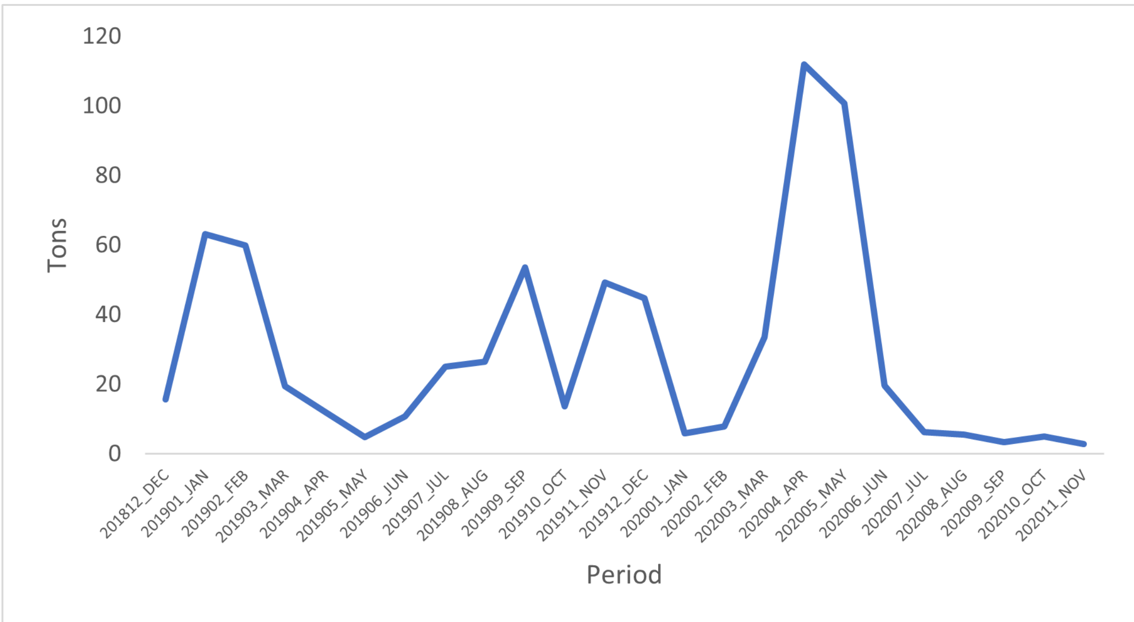

Figure 5.2 Extra tons of inventory required to address the sales of each month in case 10 days of forecast for all products is produced

5.2 Managerial Insights

Inventory is one of the major components of working capital. Hence, improving it not only affects the operations of the firm but also its profitability. As a result, inventory management should not be considered as the sole duty of the operations management team or the plants' managers. Higher managers should give priority to inventory, especially in manufacturing firms such as the company in our case study. More than required inventory increases the costs of the firm and lowers its profitability. On the other hand, low inventory affects the service level and can result in losing customers. Therefore, finding the adequate level of inventory is crucial for a well-functioning company.

Since the importance of inventory and planning is a well-known subject in the industry, managers focus on improving the input of their inventory and planning models which is the demand forecast. However, they might lose sight of improving the inventory model itself based on the new accuracy of the forecasts. Our model showed accuracy and its volatility can affects the total inventory required inventory as well as SKU level inventory. Consequently, it is highly advised to review the inventory model and the forecast model together to incorporate the increase/decrease of the accuracy of the forecast inside the model. In other words, is dependent on the forecast accuracy, hence as forecast methods and its accuracy changes, needs to be adapted to it.

6. Conclusion & Discussion

This research studies a new inventory model to determine the total inventory required for an industrial textile manufacturer that uses shared-line production process for a wide range of products using one production line. This research adds to the lean inventory management literature by devising a data-driven model for manufacturers that operate in the textile industry.

Our model leverages the shared line characteristic of the production process and infinitesimal cost of changing the production line settings to find an optimal level of total inventory and then developing a SKU level inventory that meets the total inventory requirements while keeping the service level intact. First the model determines the total inventory level and brings it down from 20 days of forecast to 10 days. In the next step for each SKU a ratio that shows the percentage of the forecast that should be produced for the inventory is calculated. Finally, based on the amount of each product in the beginning inventory, and target ending inventory, production priority for the products is suggested.

Volatility and accuracy of the aggregate forecasts, production capacity, and actual sales and expected production lead time are used to determine the total required inventory. SKU forecasts and sales of two consecutive periods are used to determine the inventory level for each SKU. Intuitively, it is evident that based on aggregate forecasts, capacity, sales, and production lead time, the total inventory needed to address the demand during the lead time production can be addressed. However, as there are many different SKUs with different forecast accuracy volatilities, it is difficult to assure that this inventory plan works. The second part of the model is built on the intuition that in an ideal inventory model, what is produced for the inventory of the next period should be used during that period. There are two usages for any product during the period, next period's inventory or this period's sales. The former can be at most equal to the sales of that particular SKU during the coming month. Hence, the maximum amount produced for each SKU will be enough to cover two consecutive months of sales.

In our study, we modeled the expected lead time based on a uniform distribution of products in WIP inventory. However, in reality this may not be true and WIP inventory distribution can change the lead time and result in lower or higher finished goods inventory. The second assumption of the model is identical production speed for all settings. This assumption is logical as they are using similar machines and company reports total production capacity without considering which product will be produced during the period. Nonetheless, there might be differences in production speed of different SKUs. The third assumption of the model deals with the production process. As the main product of the plant (%92 of the tons of products produced in the plant) is TCF, its production process is considered as the production process (twisting, weaving, and dipping) for all products. However, %8 of the products may follow a different production process. For instance, yarn only uses twisting. Hence, in a future model, the production capacity can take this feature into account. The last assumption considers the production capacity. Here, we used the actual utilization provided to us from the company. Nevertheless, this may not be the maximum utilization possible for the line during a month. In future studies we can assimilate the line information such as downtimes to calculate the maximum utilization of the line and use that as an input for the model. Inclusion of these concepts can further improve the performance of the inventory model; however, it will make it specialized to a particular producer rather than a part of the textile industry.

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APPENDIX A

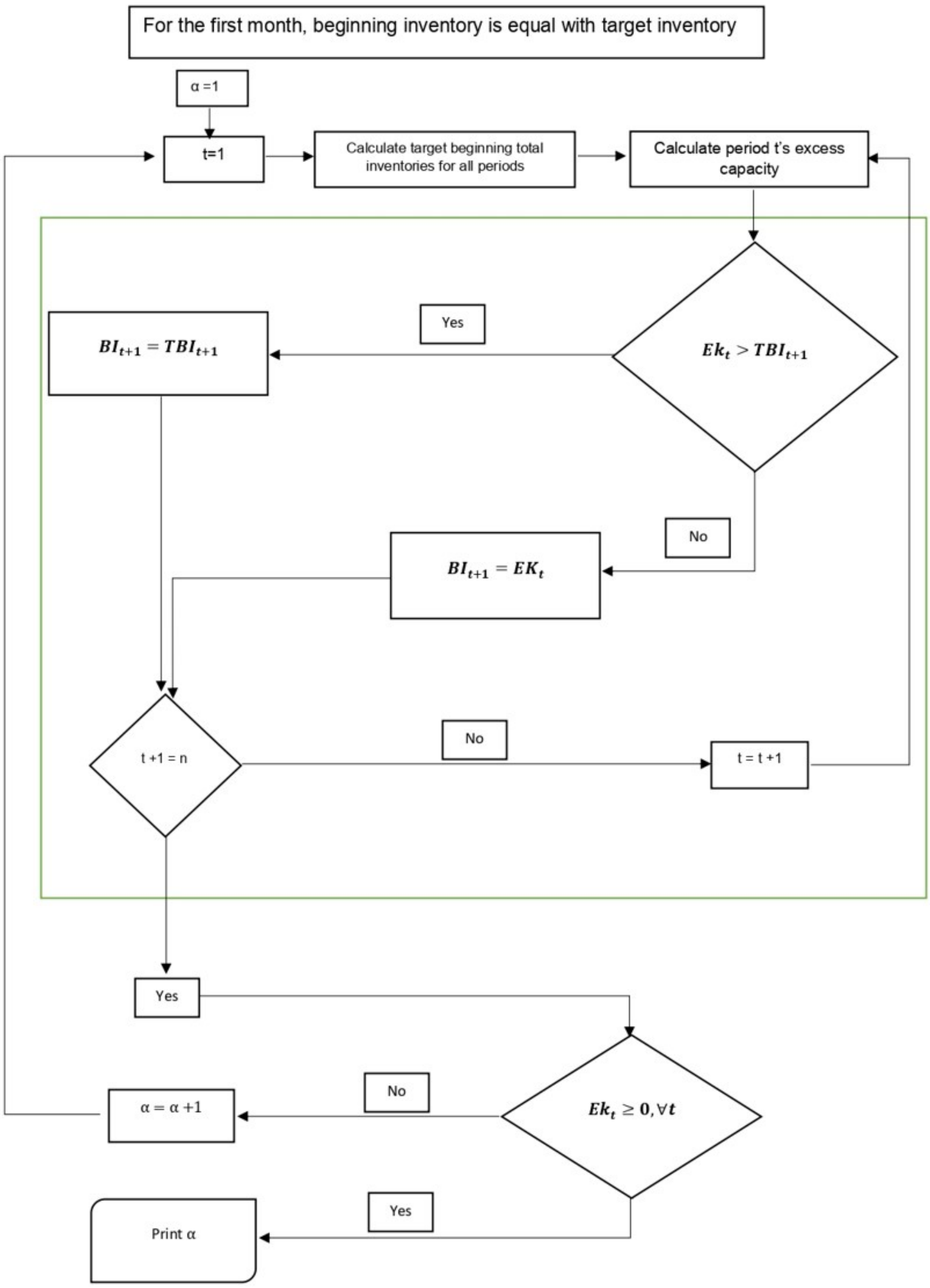
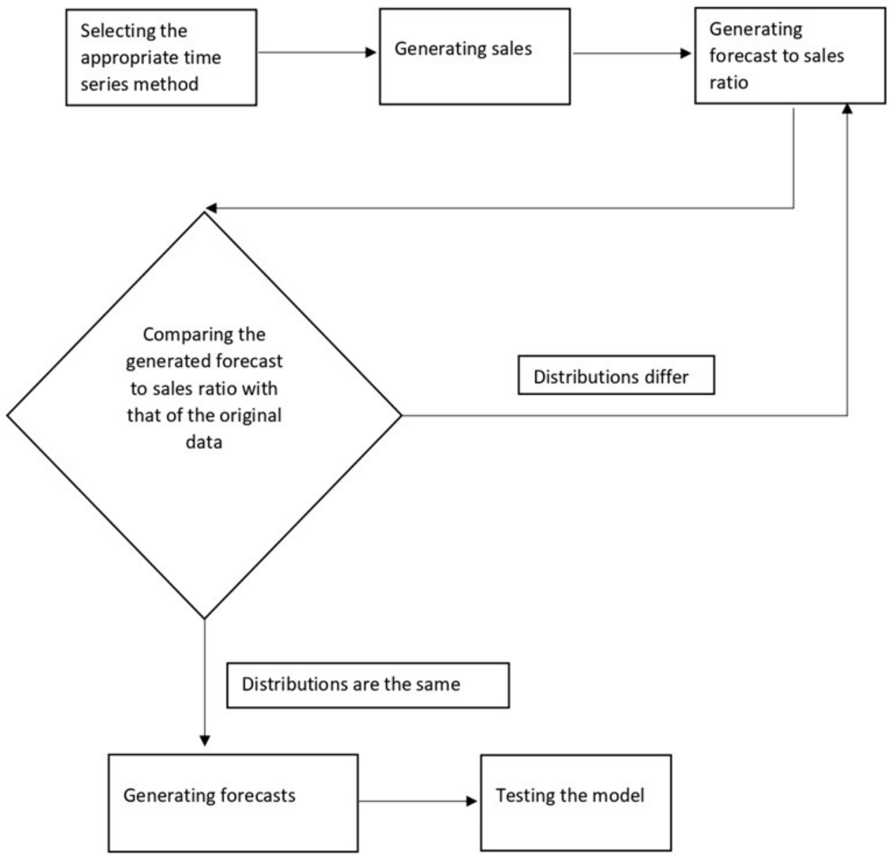


Figure A.1 Selecting the α flowchart



Notes:

Sales have a timeseries nature, hence for generating future sales a time series model is suggested.

Figure A.2 Generating sales forecast using time series methods'flowchart

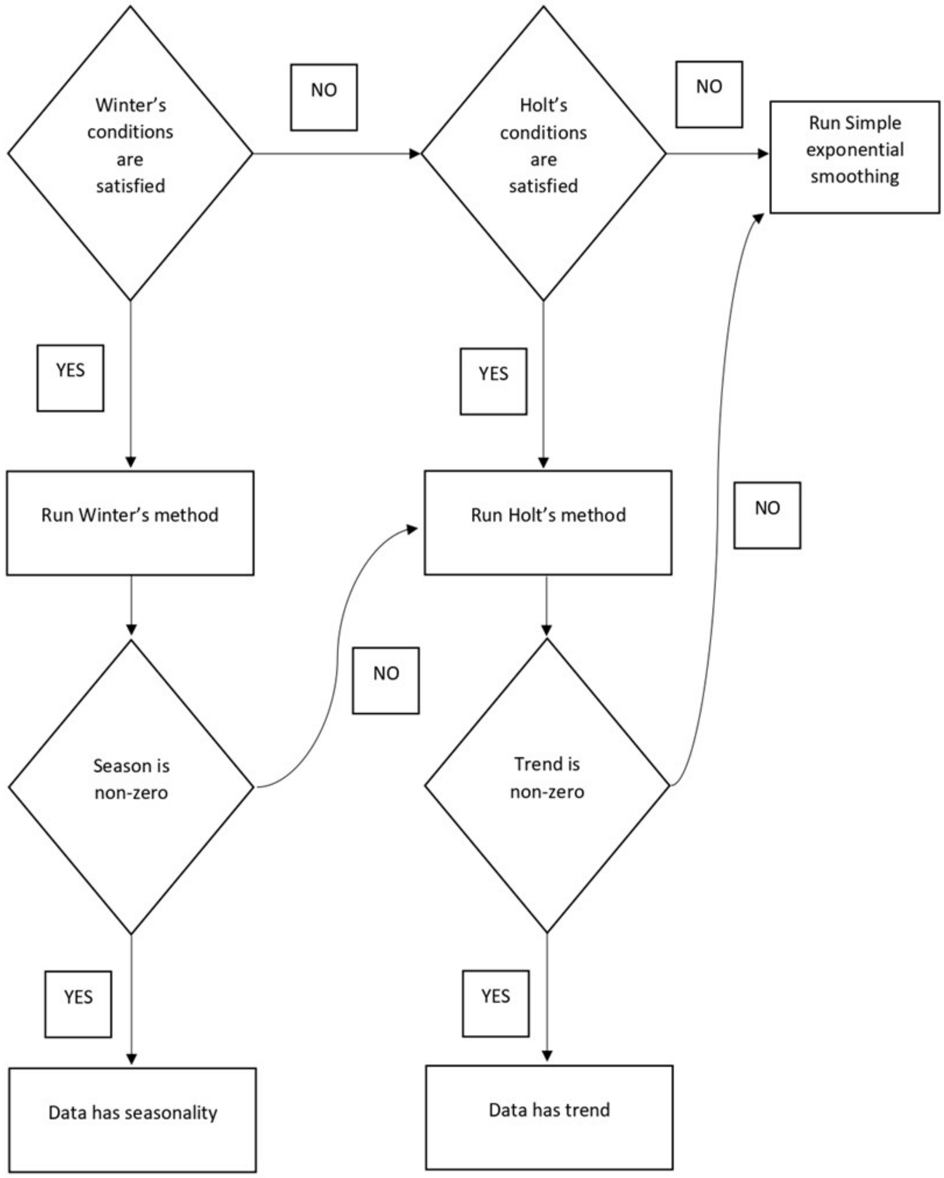


Figure A.3 Selecting the time series method flowchart

Inventory Optimization Project

[redacted] & Sabancı University

2021

Team Members:

Sabancı University : Raha Akhavan, Burak Gokgur, Reza Valimoradi

[redacted] : Ufuk Uzel, Arzu Sevencan, Cansu Yalazı, Sena Korkmaz, Gökçe Erdinç

1- Aim Of the Project

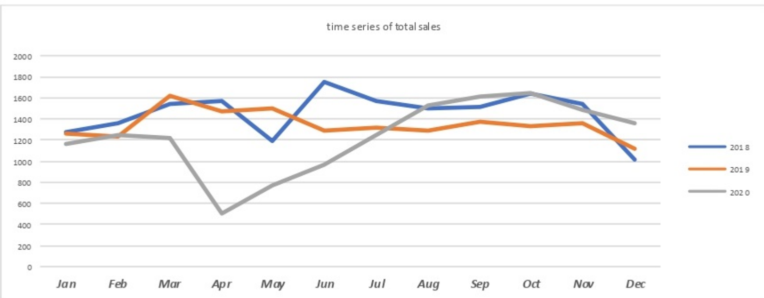
Inventory management is crucial for businesses, particularly in manufacturing businesses such as KordSA. Extra inventory burdens the company with unnecessary high working capital; on the contrary, a decrease in inventory can hurt customer satisfaction by creating delivery delays. Consequently, companies should assiduously decrease the amount of inventory to a level that does not affect the delivery of products. The project aims at finding the optimal policy for the inventory for the KordSA Brazil plant.

2- Sales Analysis

The first step of the project was getting familiar with the sales and forecasts. The volatility of the sales, forecasts, and error term (Actual sales minus the Forecasts) was analyzed. High volatility in sales means the market is volatile. If the forecasts are volatile and the error term is not, it means the forecasts are following the market conditions well. However, when the volatility in the error term is high, it means the accuracy of the forecasts are low.

To measure volatility, "standard deviation", "average", and "coefficient of variation" of forecasts, actual sales, and error terms were calculated. These measures showed that SKU based forecasts and error terms are highly volatile. However, the total forecast per month and its error term is relatively stable. Meaning the scheduling cannot be done beforehand with high accuracy, whereas, the total amount of inventory can be calculated with high level of certainty.

2.a Actual Sales Analysis



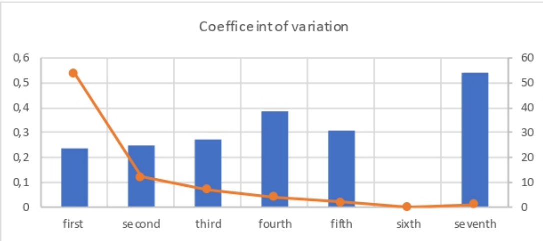
*Analysis is done based on TCF sales

2.b Average of Sales and Coefficient of Variation

TCF data, 80 sku's are analyzed with 2018-2019-2020 sales.

- Variation analyze/ average sales

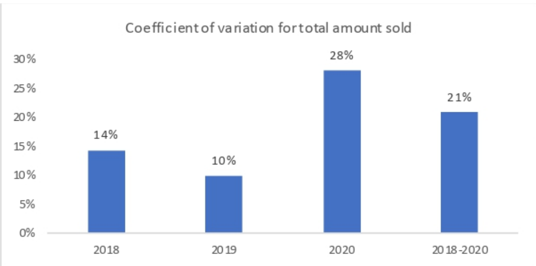
Trend shows that; as the number of SKUs in the group decreased, the CV increase. In another word; increasing sku's are decreasing variation in subtotal of sales.



average less than 21.258	first
average less than 42.258 more than 21.258	second
average less than 63.258 more than 42.258	third
average less than 84.258 more than 63.258	fourth
average less than 105.258 more than 84.258	fifth
average less than 126.258 more than 105.258	sixth
average less than 147.258 more than 126.258	seventh

*Analysis is done based on TCF sales

- Variation analysis by Years



percent of the products that have higher SD/mean than the total sales (sku's rate variating more then sub total)

2018	2019	2020	2018-2020
76%	74%	71%	96%

Total sales are much more stable then sku levels, as found in average analyze; sku's are more variating then subtotal.

2020 was the most volatile year among these three years with an SD/Mean of 0.28. However, the increase in the CV in 2020 shows the effects of the pandemic on the sales by increases in the volatility.

The coefficient of variation (CV) is defined as the ratio of the standard deviation σ *to the mean* μ, $c_v = \frac{\sigma}{\mu}$. *, It shows the extent of variability in relation to the mean of the population.*

3- Inventory Planning

Main Assumption of the study is; we are going to plan month end inventory based on Lag 1 forecast.

So Inventory Analysis is done based on Lag1 forecast.

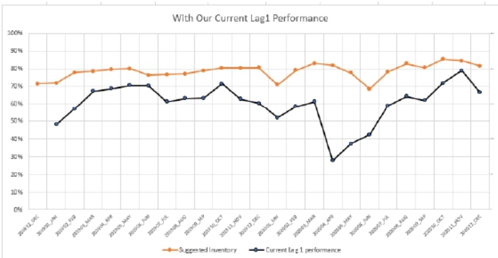
This study is taking into account below inventory model for with Lag1.

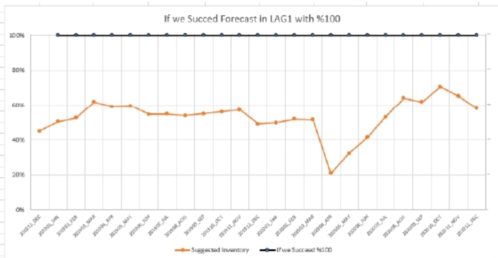
Minimum
- The month's forecast + Average (Actual – Forecast) + α(Standard deviation of (Actual – Forecast))
- Average (Actual) + β(Standard deviation of (Actual))

With above model, suggested inventory with our current Lag1 performance is showed with orange line in left table. If we had option to succeed %100 accuracy in Lag1, as shown in right table suggested inventory improves with average of %33.

Our current Lag 1 performance is; %60, with error of %40.

According to this model; each %10 improvement **in FA in Lag 1;** equals to 200 tons (in average) decreasing possibility in inventory. (For referans sales of 1,6 kt/month)





Not: This study is done based on %99 coverage rate of sales with suggested inventory.

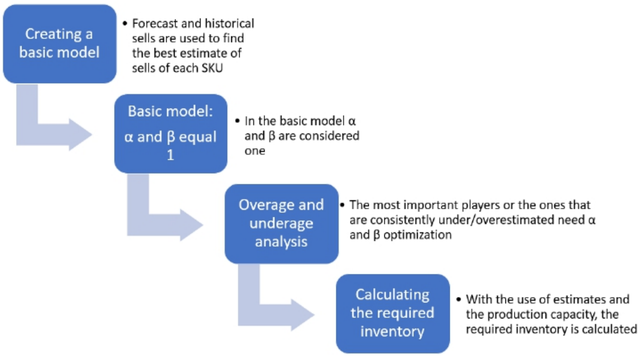
4- Correct Planning for Optimized Inventory

A model was developed to estimate the minimum amount of total inventory needed to supply the demand with the following assumption:

1. All demands must be met during the month.
2. Maximum production capacity is the minimum of the capacities of the three stages of production.
3. Utilization can reach 100%.

4. Inventory of the month will be used to support the month's sales or next month's inventory or next month's sales. In other words, the inventory for each month must be used to support one of the aforementioned items.
5. There is no setup costs.
6. Each month's capacity is only used to produce the month's sales and the next month's inventory.

In order to calculate the min required inventory, first it was assumed that the 4th assumption holds all the time. Based on these assumptions, 10 days of lag 1 forecast met the demand of Dec 2018 till Dec 2020..



Lessons Learned; If we plan all SKU's with 10 dos according to Lag 1; because actualized is lower in some case, this model creates waiting inventory and available capacity does not covers sales on time.

Model is improved with SKU categorization;

During the next stage of the model, SKUs were grouped in three different groups; The first degree, second degree, and third degree sales. Then these groups are used to produce the required inventory of the month.

- First degree sales are the SKUs that 70% of their forecast of each month were always less than the sum of the sales of the two consecutive months. i.e. If the amount of lag 1 forecast of SKU A in Jan is 10 tons, 70% of it, 7 tons, is less than the actual sales of Jan + Feb.
- Second degree sales are remaining SKUs that 40% of their lag 1 forecast were 90% of the times less than the sum of actual sales of the two consecutive months. I.e., if the amount of lag 1 forecast of SKU B in Jan is 10 tons, 40% of it, 6 tons, is less than the actual sales of Jan + Feb in at least 90% of the times.
- Third degree sales are the remaining SKUs. Meaning the high volatility in their sales resulted in very low accuracy of their lag 1 forecast and they should not be made for the inventory. Nonetheless, only the capacity of the month, and not the inventory is used to cover the sales of these SKUs.

With Multi-period model;

- In reality, each month the plant must not only produce the demand of that month but also the required inventory of the next month.
- New variables are added to the independent time frame model

<u>New Assumptions: Excess Sales</u>

- The sum of the positive deviations from the Lag 1 forecasts. In other words, it is the sum of the difference of Actual sales and the Lag 1 forecast for the SKUs that sold more than their Lag1 forecasts

New Assumptions: Excess Forecast

- The negative deviation of sales from forecast. I.e. if an SKU's forecast is 10 tons and its sales is 8 tons, the excess forecast of this SKU will be 2 tons.
- It is assumed that the scheduling is efficient enough not to produce the excess forecast during the month. In other words, the actual sales not the forecast of the month is used to plan production of the month.
- The amount of the Excess Forecast can be used to produce the actual sales of the month or next month's inventory.

New Assumptions: Excess capacity

- In this model the definition of Excess Capacity differs from the previous model as new variables are added to the model.

Excess capacity calculated as:

(Total capacity + Target beginning inventory + Excess Forecast) – (Total forecast + Excess Sales + Target ending inventory)

- Excess capacity can be negative. It means that there is not enough excess capacity to produce all of production required to meet the sales of the month + required inventory of the next month.
- Negative excess capacity does not mean that the model failed. However, it means that next month will start with less than the required inventory.
- The negative excess capacity can be covered by next month's excess capacity. Meaning next month's excess capacity can be used to produce enough products to meet the target ending inventory.
- I.e. Jan's excess capacity is -10, its target ending inventory is 200. It's realized ending inventory will be 190. Feb's target beginning inventory is 200, excess capacity is 30, and target ending inventory is 150. Here as the plant started with less than its target beginning inventory, it has to use 10 tons of its excess capacity to cover this shortage. In other words, the actual Feb's excess capacity will decrease to 20.

Calculation of month end inventory;

0.7 * lag 1 forecast of first degree SKU + up to 0.4 * lag 1 forecast of second degree SKU

Days in the month	31	31	28	31	30	31	30	31	31	30	31	30	31
Row Labels	201812_DEC	201901_JAN	201902_FEB	201903_MAI	201904_APR	201905_MAY	201906_JUN	201907_JUL	201908_AUG	201909_SEP	201910_OCT	201911_NOV	201912_DEC
Total capacity	1670	1670	1508	1670	1616	1670	1616	1670	1670	1616	1670	1616	1670
Total forecast	1545	1623	1817	1611	1624	1756	1557	1566	1682	1735	1815	1692	1858
Target beginning inventory	499	524	649	520	541	567	519	505	543	578	585	564	599
Target ending inventory	524	649	520	541	567	519	505	543	578	585	564	599	380
Excess Sales	162	307	199	295	226	171	182	223	163	169	77	198	94
Excess Forecast	515	552	638	181	270	351	323	362	438	454	447	441	717
excess capacity	452	167	260	-77	10	141	214	204	226	159	246	132	654
Negative deviation from tar	0	0	0	-77	-67	0	0	0	0	0	0	0	0
Ratio (Negative deviation t	0	0	0	0	0	0	0	0	0	0	0	0	0
realized beginning inventor	499	524	649	520	465	500	519	505	543	578	585	564	599
DOS	10	10	10	10	10	10	10	10	10	10	10	10	10

Days in the month	31	29	31	30	31	30	31	31	30	31	30	31
Row Labels	202001_JAN	202002_FEB	202003_MAI	202004_APR	202005_MAY	202006_JUN	202007_JUL	202008_AUG	202009_SEP	202010_OCT	202011_NOV	202012_DEC
Total capacity	1658	1484	1658	1603	1660	1609	1655	1652	1609	1655	1615	1679
Total forecast	1177	1386	1657	1567	1413	1075	1444	1521	1560	1689	1710	1638
Target beginning inventory	380	478	535	522	456	358	466	491	520	545	570	528
Target ending inventory	478	535	522	456	358	466	491	520	545	570	528	
Excess Sales	325	247	165	46	158	296	229	306	379	355	185	205
Excess Forecast	223	308	510	1094	761	330	300	146	198	165	215	346
excess capacity	281	103	358	1151	948	460	257	-59	-157	-249	-22	710
Negative deviation from tar	0	0	0	0	0	0	0	-59	-215	-465	-487	223
Ratio (Negative deviation t	0	0	0	0	0	0	0	0	0	1	1	
realized beginning inventor	380	478	535	522	456	358	466	491	461	330	105	41
DOS	10	10	10	10	10	10	10	10	10	10	10	

To wrap up, first the total amount of inventory in the ideal case that all the inventory is used within two months is calculated. Then 70% of the lag 1 forecast of the first degree sales SKUs is created for the inventory. If it is not enough, up to 40% of the lag 1 forecasts of the second degree sales SKUs is created for the inventory as well. However, inclusion of the second degree sales SKUs increases the risk of unused inventory, meaning the total inventory most increase to make sure the demand can be met.

And with this way 10 dos meets up, sales requirements with optimized planning.

Confidential [redacted]

Figure A.4 Company K's white paper