Sherveer Singh Pannu

Dynamic Classification Of Fast-Moving Consumer Goods in Warehouses Using Forecasting For A Third-Party Logistics Provider

Master's thesis in Engineering and ICT
Supervisor: Anita Romsdal
Co-supervisor: Fabio Sgarbossa
June 2021

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S.S.P

Abstract

This thesis investigates if forecast-based classification can outperform naive classification based on last year's data. The model developed uses an ARIMA forecast to use as the basis for a traditional ABC classification. The model is applied to a case study of Leman, a Small-Medium-sized Enterprise third-party logistics provider working with fast-moving consumer goods in cooperation with the Brynild group, a Norwegian family-owned confectionery manufacturer.

The results show that the forecast-based classifications out-performs the outperform naive classification based on last year's data. It is not at the level of the actual data, but it is in the right direction. Further research and development of the model can give better results.

Sammendrag

Denne oppgaven undersøker om prognosebasert klassifisering kan overgå naiv klassifisering basert på fjorårets data. Den utviklede modellen bruker en ARIMA-prognose som brukes som grunnlag for en tradisjonell ABC-klassifisering. Modellen brukes på en case-studie av Leman, en tredjeparts logistikkleverandør som defineres som en liten eller mellomstore bedrifter som jobber med forbruksvarer i sammenheng med Brynild gruppen, en norsk familieeid godteri produsent.

Resultatene viser at de prognosebaserte klassifiseringene utkonkurrerer den naive klassifiseringen basert på fjorårets data. Resultatene er ikke på nivået med de faktiske dataene, men de peker i riktig retning. Videre forskning og utvikling av modellen kan gi bedre resultater.

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Chapter 1

Introduction

Third-party logistic providers specialize in providing warehouse services and are an essential part of the supply chain. Their main objectives are to store and distribute the goods to customers. Essential tasks in warehouse management are keeping control of goods in inventory, packaging goods, and providing a high level of customer service. Warehouse operations include receiving goods, assigning a storage location for the goods, order picking, and shipping (Bartholdi and Hackman, 2019). Order picking is the most time-consuming of operations, and in general, traveling is the main source of waste in a warehouse(Kofler et al., 2015). Traveling to and from storage locations is a time-consuming task. If a Stock Keeping Unit (SKU) is stored far away from the shipping or receiving area, The warehouse employees will spend much time transporting the product within the warehouse. If this product also is frequently picked for orders, this results in a longer processing time for the warehouse operations. The frequency in which SKUs are picked should be reflected in which storage location they are assigned.

To find out where to place incoming goods, storage assignment policies are used. A storage assignment policy is a set of rules that determines the storage locations of pallets (Ang et al., 2012). There are several well-known assignment policies that warehouses can use. Each policy has multiple methods that The warehouse can use to implement the rules. The effectiveness of storage policy and criterion depends on many factors (Lorenc and Lerher, 2019). The policy and method need to be chosen based on the type of warehouse, the warehouse goods, and the supply chain characteristics.

The Fast-Moving Consumer Goods supply chain involves products with short life cycles, high demand, and low-profit margins on individual products. The business is very competitive, with retailers constantly pressuring manufacturers to lower product prices while maintaining a high service level(Christopher and Towill, 2001).

1.1 Background

This thesis is a part of the DigiMat project. The DigiMat project is a collaborative innovation project, including companies part of Norwegian supply chains. This project's motivation is that there is much competition between large international companies in the Norwegian market. To survive, the Norwegian actors need to be smarter and leaner than their competitors. The DigiMat project wants to automate and optimize the food supply chain processes using advanced technology and supporting ICT systems. Industry 4.0 and the digital revolution now enables companies to do big data analysis to do quick and smart processing and data analysis for different objectives across the supply chain. Large amounts of data are generated at many points of the supply chain. By using the possibilities of the recent advancements in technology, companies can gain an edge over competitors by creating innovative solutions.

1.2 Problem description

This thesis will examine how a third-party logistics provider with FMCG can cut costs and person-hours transporting goods in a warehouse. One of the ways to do this can be to use a dynamic classification system to shorten the transportation time.

This thesis will perform a literature study on warehousing to better understand the background and characterize of the problems warehouses face. There will then be performed a literature study on dynamic storage methods, forecasting, and classification. This will help find methods and classifications that can be used to develop a model to do forecast-based classification for an SME 3PL. This model can then be applied to the case study of Leman. The results will then be discussed and analyzed.

This is an ongoing project, and there have been several master's theses' written about this subject for Leman. These studies will be reviewed and used to understand Leman and the issues they face.

This project will use the case study of Leman, a 3PL provider for Brynild, responsible for the storage and transport of Brynild's products. The project will look at research papers to find what methods can help Leman with their classification.

The research objective is to Investigating of how forecasting can be used in ABC classification for 3PL. The goal is to find a way to use dynamic classification based on a forecast to improve the order picking process in the warehouse and help save money, time, and resources.

This will be done by trying to answer these research questions.

RQ1: *How can the forecasting of fast-moving consumer goods be done.*

RQ2: *How can forecasting using historical order data improve storage classification.*

RQ3: *What is the effect of forecast-based classification, and how can forecast-based classification improve warehouse performance?*

1.3 Research scope

The main objective of this thesis is to investigate if forecast-based classification can outperform naive classification based on last year's data.

The problem is quite complex and needs to be restricted and more clearly defined to work with. The thesis will only look at full pallet picking and will use ABC classification and ARIMA forecasting. This is to simplify the problem to get results easier.

1.4 Structure of the thesis

Table 1.1 shows the structure of the thesis. The purpose of the table is to give a general overview of the paper to the reader.

Chapter	Description
Introduction	Describes the background for the thesis, the problem statement, the research objective, and the structure of the thesis
Research methodology	Describes the methodology used in the research for the thesis and how the paper gathered the research information
Theoretical Background	Investigates existing literature and explains key theoretical takeaways to understand the fundamentals of the thesis. It starts with describing supply chains and fast-moving-consumer-goods, 3PL, warehousing, dynamic storage policies, and forecasting
Model	This chapter describes the model developed to do dynamic classification based on forecasting.
Case Study	This chapter investigates the Leman in detail and describes their warehouse layout, operations, principles, and WMS.
Results	The Results looks at the effect of the model on the case study.
Discussion	The Discussion combines the theoretical background, the model, and the case study to discuss how principles and methods from the research and model are used in the case, the implications, and the issues.
Conclusion	The conclusion summarizes the paper's key takeaways and looks at the research objective.

Table 1.1: Thesis structure

Chapter 2

Research methodology

The research methodologies in this thesis consist of both a literature study and a case study.

2.1 Literature study

The literature study started with a wide scope to gain insight into various methods and general knowledge on storage policies, warehousing, forecasting, and classification. The gained insight helped narrow down the scope and focused the study on specific methods and policies.

In the study, we collected secondary quantitative data primarily through reviewing a set of peer-review articles published in scientific journals. Additionally, two textbooks published by experts in the field of warehousing were used as support. Peer-reviewing strengthens the validity and reliability claim of the articles. To further ensure additional validity in the research study and increase reliability, several papers covering the same topics were selected for review wherever possible. The research is also focused on selecting highly cited papers.

Backward and forward-searching were used to broaden the initial search further. All past references and citations of papers from the initial search were investigated and analyzed. The research was also done on additional papers discussing the relevant topics for review.

The primary literature search was conducted using Web of Science, Scopus, and Science Direct. We used other search engines to find papers discovered in the backward and forwards searches that did not exist in the aforementioned databases.

primary search words	additional search words
Supply chain	flexibility
	Fast moving consumer goods
Third-party logistics	Challenges
	Warehousing
Warehouse	Operations
	Storage policies
Forecasting	Time series
	Evaluation
Dynamic assignment	Storage policies
	Classification
Classification	ABC
	Fast moving consumer goods

Table 2.1: Search terms for the literature study

Abbreviations, acronyms, and synonyms with wildcards of the keywords mentioned 2.1were used to do the searches as wide as possible and exclude missing out on relevant articles because of formulation and wording differences. Using boolean operators in between the keywords ensured that the search terms filtered out most irrelevant articles. Relevant papers were selected by studying the abstract of each result from the query.

2.2 Case study

To better understand warehousing and the effects of dynamic classification, a case study is done of an SME-3PL provider called Leman. The study focuses on their department in

Vestby and only on the goods connected to The Brynild group. The reason for this is that both Leman and Brynild are a part of the Digimat, so through them, we can access information about Brynild's products stored at Lemans.

A single case study has been conducted in this thesis; this type of study has a couple of advantages and disadvantages. A single case study is not as time-consuming as multiple case studies. It allows us to dig deeper and have a better understanding of the case. With a single case study, we can investigate phenomena and describe them in more general detail. With a multi-study, it is possible to understand the differences and similarities in the cases. It will also create a more convincing theory when dealing with empirical evidence with multiple cases(Gustafsson, 2017). In our case, the main reason for not choosing a multi-case study is the time limitation and the limitation of available information.

The information we have used for this case study consists of both primary and secondary data. The primary data we have collected used is from talking to key personnel in both Brynild and Leaman. We have had several meetings with Brynild and Leman about some of their issues and their available data. They have also sent picking orders from 2019 and 2020 to use in the thesis.

The secondary data that has been gathered is, to a larger degree, collected from previous masters thesis performed on Leman connected to the Digimat project. We have relied heavily on this information as we haven't visited Leman because of covid restrictions. The master thesis we have relied on for a better understanding of Leman are Myhr, 2020 and Jorsala et al., 2019.

Chapter 3

Theoretical Background

Some parts of the theoretical background are taken from the specialization project

3.1 Supply Chains

In modern-day businesses, consumer-facing companies are usually part of a more extensive supply chain. A supply chain is defined as the collaborative effort involved in producing and delivering a final product to an end customer. It starts from an initial supplier of raw materials (Lummus and Duclos, 2004). Different types of goods require different supply chain settings. Nevertheless, actors commonly found in most supply chains are a supplier, a manufacturer, a distributor, and a retailer (Manders et al., 2017).To secure that the products are available for purchase by customers when requested, the entire supply chain needs to function efficiently at a high service level. Not only are companies competing with each other, but the different supply chains within the same sectors are also competing for custumers(Christopher and Towill, 2001). Supply chains strive to match supply to demand while keeping operational costs as low as accurately as possible. However, as the demand for goods is often highly volatile and uncertain, supply chains need to account for the unpredictability. Sudden changes in demand require a rapid response from the supply chain to keep service levels high.

Two well-known strategies in modern-day supply chain management are the agile and the lean approaches. A lean approach focuses on removing waste by eliminating non-value-added processes. The supply chain will be as streamlined as possible and requires a stable and predictable demand to operate at a high service level. Production and logistics are made to handle large volumes while keeping unnecessary material movement and handling at a minimum.

The agile approach is suited for supply chains required to be flexible and responsive. Flexibility is required when products themselves and the volume of the material flow change. Responsiveness is an important aspect of adapting to change caused by factors like demand variability (Agarwal et al., 2006).

3.1.1 Fast-Moving Consumer Goods Supply chain

Fast-moving consumer goods (FMCG) are sold frequently at a relatively low price to a large customer base. The demand for the products is generally great, and goods have high turnover rates. Goods of this category have a short lifespan and are consumed rapidly. Profit margins on individual products are low, and producers and retailers rely on economies of scale to be profitable. Compared to most other markets, the business is very competitive, and the customer base is disloyal. Retailers are continuously fighting for their market share by providing low prices and good availability of products. The demand for individual products is highly variable and may have seasonal variations as well. Both producers and wholesalers are always seeking to increase their market share through promotional campaigns and new products. With such a disloyal customer base, a stockout of a particular product will probably result in the consumer purchasing a similar product from a competitive brand. All these factors require the supply chain to be flexible and responsive. Lead times need to be short to guarantee product availability for customers, while the variability in demand poses difficulties in determining producers' production quantities. To compensate for the demand variability, maintaining a safety stock is often advantageous. Keeping a safety stock helps provide availability for customers at the expense of increased storage and material handling.

(Bala and Kumar, 2011) highlights a few issues commonly faced by FMCG supply chains:

- Supply chains include several production plants, including co-manufacturers and co-packaging firms, which increases the complexity of the supply chain.
- Distribution and logistics are handled by third-party specialized firms, further increasing the complexity of the supply chain. Transporting and warehousing are the opera-

tions most commonly outsourced.

- The retail sector constantly pressures manufacturers and suppliers to provide products at lower costs and decrease response times.

These issues are common research subjects, and several studies aim to improve these issues by increasing inter-company collaboration. Supply chains should take advantage of the electronic information sharing and other big data analysis opportunities made possible by the last decade's technological advancements to enhance current practices (Manders et al., 2017, Fayezi et al., 2017).

3.2 Third-Party Logistics Providers

Third-party logistics providers are companies specializing in providing operations such as warehousing and transportation for supply chains. Producers outsourcing logistics to 3PL firms allow them to focus on their core competencies, which are producing goods for consumers (Cheong, 2004). 3PL providers are employed to provide services, adding more value to a client's business than they can achieve alone. They offer a competitive advantage by providing storage space and an established logistics network to facilitate the distribution of goods (Marchet et al., 2017). Using the same warehouse or operating joint transportation for several clients enables the 3PL provider to achieve economies of scale and profitability (Berglund et al., 1999). One of the issues 3pl have is the limited information they have from across the supply chain.

3.3 Warehousing

Warehousing is the storing of goods at one or several points in the supply chain. Keeping an inventory of goods increases availability and lowers lead time on consumer orders. Warehouses cause a buffering effect crucial for supply chains and producers operating with uncertain and volatile demand. The buffering effect allows producers to smoothen production plans and increase batch sizes on production.

Each unique product stored in a warehouse is called a stock-keeping unit (SKU). Units of SKUs are stored in storage locations or slots in the warehouse. Each storage location is assigned a unique address, and multiple units of the same SKU may be stored in the same location if there is enough capacity.

The warehouse management system (WMS) is a software system for enabling real-time control over inventory and warehouse processes. The system keeps a logical representation of the warehouses' layout, SKUs handled in the warehouse, and their storage locations.

3.3.1 Warehouse operations

Two common functions of a warehouse are the reorganization and repackaging of products. As products move downwards in the value chain, the size of the handling unit generally gets smaller. The smaller the size of the handling unit, the larger the cost of material handling is. In an FMCG supply chain, products typically leave the producers on full pallets, where each pallet holds only one type of product. At the end of the value chain, the consumers purchase products in quantities of pieces or eaches. The repacking of goods happens at different stages in the value chain, and warehouses frequently handle units in pallet and carton quantities. Downstream warehouses and distribution centers usually take products of smaller unit sizes than upstream ones (Bartholdi and Hackman, 2019).

In this paper, unit-load warehouses in manual picker-to-parts systems are considered. In a unit-load warehouse, pallets are the handling units, and each pallet contains the same kind of product. They are typically found upstream in the supply chain close to the production facilities (Ang et al., 2012). Manuel picker-to-parts systems involve the worker walking or driving to storage locations to retrieve and put away products. Other methods, like parts-to-pickers systems, including automated storage and retrieval systems, are widely studied in literature but are outside the scope of this thesis (De Koster et al., 2007).

Receiving

Receiving involves activities related to the arrival of goods. More specifically, this involves the processes of assigning a dock to the arriving carrier, unloading the shipment, controlling the contents, and registering the goods into the WMS (Baruffaldi et al., 2020). Units are staged in preparation for the put-away process and sorted or repackaged if needed (Kay, 2015).

Put-away

The put-away process includes the assignment and movement of goods to a storage location (Baruffaldi et al., 2020). Storage location assignment is handled by the WMS using a predefined algorithm or decision rule. The efficiency of subsequent warehouse operations is highly dependant on the assignment policy, and various criteria such as turnover rate, product affinity, and product value are typically considered in the decision algorithm (Kay, 2015).

Picking

Picking is the process of retrieving items from storage locations to fulfill a customer's order. It is considered the most costly warehouse operation, accounting for 55% of the total operational costs. It is also the most critical operation for meeting customer expectations, and thus value creation (Kay, 2015).

The process is initiated when an incoming order triggers the WMS to construct a picking list containing the products and quantities of the order and the goods' storage locations (Baruffaldi et al., 2020). The picking job is assigned to and executed by warehouse personnel.

A forward picking area containing high-demand goods located close to the shipping area can be used to make the order picking process more efficient (Kay, 2015). Products located in the forward picking area are replenished from a reserve storage area.

The order picking process includes:

- Traveling to and from storage locations. Travelling makes up about 55% of the order picking process (Bartholdi and Hackman, 2019).
- Searching for the item to retrieve.
- Retrieving the item from the storage location.
- The administrative time it takes to process the order through the system, assigning the order to a picker, and the time it takes for the order picker to receive and deposit the order.

Shipping

Shipping involves staging completed orders for shipping and assigning a dock for the carrier of the outgoing shipment. The outgoing shipments are registered to the WMS, and inventory levels are updated.

3.3.2 Evaluating warehouse performance

The performance of a warehouse can be measured in several ways. The two main ways presented by (Bartholdi and Hackman, 2019) are to either compare it to an idealistic model expressed as a mathematical formulation or compare it to other actual warehouses to obtain a relative measure of performance. Comparing a warehouse to other warehouses requires that other actors, often competitors, share their policies and practices. This is unlikely to happen in any competitive business, so the first method is the approach that most studies take.

Evaluating a warehouse's performance in terms of cost, throughput, service level, and resource efficiency is essential to understand how well policies and design choices perform relative to the requirements. A good performance evaluation model helps determine how the current practices can be improved and compared to alternative strategies. Simulation is the most common technique for performance evaluation in research. Other methods include benchmarking and analytical models (Gu et al., 2007).

3.4 Dynamic storage policies

Dynamic storage policies are well-established research topics, but most publications focus on static variants (Gu et al., 2007). They usually do not consider the cost of implementing a new storage assignment, fluctuational order patterns, incoming and outgoing material, or re-locations (Kofler et al., 2015). An optimal storage assignment might become outdated due to demand fluctuations, modifications in the picking line, changes in the infrastructure, or variations in the order mix (Kofler et al., 2014). Warehouses can use some processes or methods to make Storage location assignment(SLAP) more dynamic such as re-warehousing, healing, and dynamic classification. The aim is to minimize the total travel time for each warehouse operator while still having a better cost-benefit analysis than the order picking savings.

Some other things need to be considered when investigating SLAP from a dynamic perspective. For instance, with static SLAP, it can be acceptable to have all of the most desirable storage locations filled up. Still, under dynamic conditions, such dense packaging can limit incoming goods' placement with high turnover rates. Since all the desirable storage locations are filled up, they place them in less desirable areas.

Another way to have a more dynamic storage strategy is by using dynamic classifications by dynamically changing SKUs' classification in class-based storage because of the fluctuating nature of demand patterns. One of the ways to do this is by having a dynamic variant of the ABC storage policy.

The ABC storage policy is based on Pareto analysis (Bulfin and Sipper, 1998), a statistical technique for prioritizing a small number of actions that produce the best overall benefit. The Pareto analysis takes advantage of the phenomenon found in various contexts called the Pareto principle, which states that 80% of outcomes are generated by 20% of causes (Bartholdi and Hackman, 2019). The Pareto principle can be applied to several scenarios in warehousing logistics, such as 20% of the SKUs generating 80% of the traffic or 80% of operational costs from handling 20% of the items (Rushton et al., 2000). There are many variants of the ABC analysis; one of the distributions looks like this Wild, 2002:

- A = 10 percent of stock numbers, giving 65 percent of turnover.
- B = 20 percent of stock numbers, giving 25 percent of turnover.
- C = 70 percent of stock numbers, giving 10 percent of turnover

The ABC analysis does not need to be based on turnover; it is merely one way to do it. The classification can be done on pick rate, dollar volume, or other parametersBartholdi and Hackman, 2019. No relation between action and effects strictly conforms to the Pareto principle. Still, in warehousing, the general rule of a minority of the items generating a majority of the traffic is applicable.

The ABC storage policy is class-based and consists of dividing items into classes according to their demand rates. A small fraction of items with the highest demands are classified as A-items and designated to a storage zone close to the receiving and shipping areas. B-items will constitute a larger fraction of items with medium demand. However, most items will be classified as C-items and stored the furthest away from input/output areas (Pierre et al., 2003).

In his paper, Pierre (Pierre et al., 2003) introduces a dynamic variant of the traditional ABC storage policy in manual order picking warehouses, which changes the classification of items based on the daily number of order lines. Following changes in classification, the items need to be relocated to the storage area corresponding to their new class. If the re-locations are considered feasible, i.e., they uphold each storage zone's storage capacity constraints, the estimated time to perform the rearranging does not exceed the time capacity. The iterative procedure of reviewing and reassigning classifications with the primary goal of reducing the average working time per day. Observations from a simulation using data from a case study indicate that when reshuffling time increases, the order picking time decreases, and vice versa.

Another way to do the ABC-analysis is suggested by Zuou (Zhou et al., 2020) in his paper. He suggests using K-means clustering for classification based on a broad set of features that allows for higher precision classification than previous methods. By utilizing data mining techniques, improvements to the traditional ABC class-based storage policy are made. Furthermore, the improved classification policy is used to optimize storage location assignments.

Kheybari proposes a slightly different approach in his paper. Kheybari (Kheybari et al., 2019) examines how traditional use of ABC classification considers demand value as the only criteria. However, many other factors influence a product's importance, such as demand, leadtime, and availability. Using several decision factors requires methods designed to incorporate multiple criteria into the classification process. Multi-criteria decision-making (MCDM) is a family of methods for solving decision and planning problems considering multiple criteria to support decision-makers (Dowlatshahi and 0had, 2010). The proposed method involves identifying criteria for the ABC analysis, determining each criterion's weight, determining each inventory item's value, and clustering items into the three classes. The first step, criterion identification, is done by studying the decision-making environment to identify the classification criteria. Shannon's entropy is used to determine the weight and relative importance of each criterion. TOPSIS is used to evaluate and rank each item according to the criteria and corresponding weights. In the last step, goal programming clusters items into the three classes A, B, and C.

3.5 Forecasting

Demand forecasting is the art of predicting the level of demand which might occur at some future point or period of time (Archer, 1987). One common way to do demand forecasting is to use Time series forecasting. Time series forecasting uses quantitative information of historical patterns forecasting to predicting the level of values that might occur in the future. Because of the difficulty in assessing the exact nature of a time series, it is often considered challenging to generate appropriate forecasts (Khandelwal et al., 2015). Over the years, many different forecasting models have been developed, ARIMA and ANNs(Artificial Neural Networks) are quite popular.

3.5.1 Forecasting Model

The ARIMA models were developed Box and Jenkins(Box and Jenkins, 1970). The models are based on the fundamental principle that the future values of a time series are generated from a linear function of white noise terms and past observations. ARIMA stands for Auto-Regressive Integrated Moving Average and consists of 3 parts, Auto Regression (AR), Integration(I), and Moving Average(MA). These parts are adjusted after the parameters given in the ARIMA model. These parameters are p, d, and q and are non-negative integers; p is the order in the autoregressive model (AR), d is the degree of differencing (I), and q is the order of the moving average model (MA).

When a value X_t is correlated with a previous value of X_{t-k}, it is called autocorrelation, and this is what the AR part of ARIMA uses. By looking at the correlation between X_t and previous values to forecast. AR(x) means x lagged error terms will be used in the ARIMA model and represented by p.

The Auto Regression and Moving Average only work on stationary time series. A time series is called stationary when the value of time series is not dependent on time, and this means that the time series can not be affected by trends or seasonality. The integration part of ARIMA is to make non-stationary time series stationary and is done by differencing. Differencing series is the change between consecutive data points in the series. Differencing of order d is used to convert non-stationary time series to stationary time series (Kotu and Deshpande, 2019).

The Moving average in ARIMA is used to remove error terms of previous time points and predict current and future observations. Moving Average removes non-determinism or random movements from a time series. The value of q is here the number of previous observations used to calculate the current observation.

ARIMA(p, d, q) is a generalist model. The combination of p, d, and q can give very different models; some are mathematically equivalent to other forecasting models. For example:

- ARIMA(0, 1, 0) is the same as the Random Walk model
- ARIMA(0, 0, 0) is a white noise model.
- ARIMA(0, 1, 2) is a Damped Holt's model
- ARIMA(0, 1, 1) without constant is an exponential smoothing model
- ARIMA(0, 1, 2) double exponential smoothing

The ARIMA model can mathematically be expressed as the following:

$$\phi\ B\ 1-B^{d}\ y_t = \theta\ B\ \varepsilon_t$$

Here, y_t and ϵ_t are the actual observation and white noise at time t, respectively. The term d represents the degree of ordinary differencing applied to make the series stationary(Khandelwal et al., 2015).

$$\phi\ B = \ 1-\phi_1 B-\phi_2 B^2-\cdots-\phi_p B^p$$

$$\theta\ B = \ 1-\theta_1 B-\theta_2 B^2-\cdots-\theta_q B^q$$

θB and ϕB are the lag polynomials,and B is the lag operator so that:

$$B y_t = y_{t-1}$$

The constants p, and q are the model orders, whereas the model parameters are:

$$\phi_i, \theta_j \ \ i = 1,2,\dots,p \ \ j = 1,2,\dots,q$$

There are also other variants of ARIMA that are better suited for seasonal forecasting such as SARIMAX.

3.5.2 Model Evaluation

Model evaluation tries to estimate the generalization accuracy of a model on future data that is out of the sample (Raschka, 2018). One method that we can be used in the evaluation step is the Akaike information criterion.

The Akaike information criterion (AIC) was developed by the Japanese statistician Hirotugu Akaike. It is an estimator of prediction error and thereby the relative quality of statistical models for a given set of data(Profillidis and Botzoris, 2019). AIC estimates the amount of information a model loses, the less information the model loses, the better the quality of the model. AIC also looks at the complexity of the model and tries to find a simplistic model with the highest quality. This helps both with overfitting and underfitting.

If we have a statistical model and want to find the AIC score, the AIC model would look like this:

$$AIC = -2log(\widehat{L}) + 2k$$

Here k is the number of estimated parameters in the model, $\widehat{L}$ is the maximum value of the likelihood function for the model(Burnham. and Anderson, 1998). Given a set of potential models, the preferred model will be the model with the lowest AIC value. The likelihood function helps make sure the model has a high quality. A higher number of estimated parameters usually means higher quality, but we can see that the higher number of estimated parameters, the higher penalty for the AIC score. This is how the AIC model can help find the optimal model with high quality that is not overfitted.

3.5.3 Forecasting Evaluation

The accuracy of a forecasting model is evaluated by comparing the original series to the series of forecast values (Hanke et al., 2001)

There is no common consensus among researchers as to which measure is most beneficial for determining the most appropriate forecasting method (Levine and Stephan, 1999). Some of the common indicators used to evaluate accuracy are mean squared error, mean absolute deviation, mean absolute percentage error, mean percentage error, root mean squared error and U-statistic. Regardless of the measure being used, the lowest value generated indicates the most accurate forecasting model.

If we look at the mean squared error(MSE), the equation is:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_t - F_t)^2$$

Here the MSE is calculated using Y_t, F_t, and n, where. Y_t = the actual value in time period t, F_t = the forecast value in time period t, and n = the number of periods

Chapter 4

Model

4.1 Background

The model constructed for this thesis is based on forecasting and ABC classification. The idea is that using a forecast as the basis of the storage assignment/SKU classification can be more dynamic and better reflect how the SKUs will flow through the warehouse. By changing the classification of certain SKUs once a week or once a month, the order picking process can be improved as there will be less time transporting goods and fewer person-hours required to complete picking operations.

The picking strategy for FMCG is often First Expire First Out (FEFO) because of their relatively short shelf life. In real life, this means that if an SKU is ordered, all old units in the warehouse need to be picked before the warehouse operators will pick a new product with updated classifications. This is why the forecast is essential. Without the forecast, the new classification will hit some time after the increase or decrease of orders.

The importance and impact of the model will depend on the accuracy of the forecast, how many SKUs have seasonal demand or trends.

Predictive problem solving

4.2 Setup

The model uses picking orders in a warehouse as its fundament. The order data is then cleaned and prepared so that the model can use it to generate a forecast.

The dataset is first filtered on full pallets as those are the focus for this master. Then the data is reduced to numbers of full pallets pr date pr SKU. To do this, the model uses Spark, a unified analytics engine for large-scale data processing. The data is then transferred to a Pandas data frame to be easier to handle. The data is then turned into a time series and split based on SKU. Then it is feed into Statsmodels ARIMA model. Here each time series is again divided into a training set and a test set. The training set is used to train the model. The parameters in the ARIMA model are changed to find the best fit. The parameters affect how the combination of the autoregression, the integration, and the moving average will work together. The different models are then compared using the AIC score of each model with the different parameters. The best model is picked, and the predictions from this model are used further.

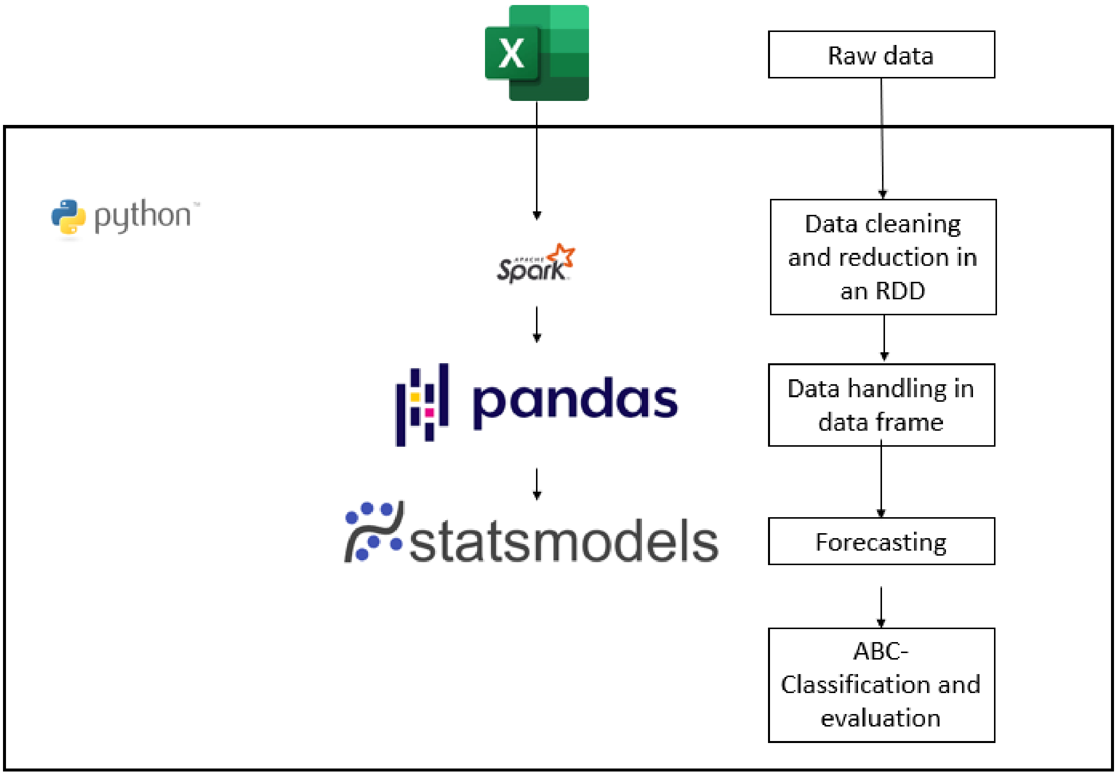

Figure 4.1: Setup and environment of the model

The test set is then compared to the predictions to see how good the forecast model is.

The predictions are then used to make the ABC classification. The classification is done using ABC classification with the distributing picking orders from the warehouse. The classification is based on the theory that 10% of the SKUs stand for 65% of the orders, the next 20% stand for 25% of the orders, and the last 70% stand for 10% of the orders.

To calculate the time used given the new classifications, the average time to retrieve an SKU from each zone in the warehouse is multiplied by the number of orders of that SKU in the test period. This is done for each SKU and then summed into one sum: the total time used for picking pallets. To find the average time used to pick an SKU from a zone, the information is either requested from the warehouse or calculated based on the size of the warehouse and the picking device.

Chapter 5

Case study

Some parts of the Case study are taken from the specialization project.

5.1 Brynild

The Brynild Groupe Is a Norwegian family-owned confectionery manufacturer. The company is owned and managed by the Brynildsen family. Brynild Gruppen operates within the segment of fast-moving consumer goods, confectionery (sweets), such as chocolate, and snacks (nuts and dried fruits). The Brynild groups have product families in all these categories, such as Den Lille Nøttefabrkken (Nuts), Minde (Chocolate), Dent (Hard candy), and Brynild(Confectionary). They also distribute NIVEA in Norway for Beiersdorf AS.

5.1.1 The demand for Brynild's products

Brynild has a broad portfolio of fast-moving consumer goods. There are a lot of categories of goods that all have different demand patterns. The demand for these products can be presented as four types.

New product introduction: The sales are anticipated based on Brynilds knowledge, and the supply chain is filled with approx two months of supply.

Regular demand: Regular demand consists of regular sales products; these have a relatively steady demand around the year; the production is based on historical and currently available information. There is an order lead time of 2-day for these products, and they are made to stock.

Campaign demand: Agreement between supplier and sales. There is a 4-10 week order lead time. These are often sold in display stands or 1/3 pallets.

Seasonal demand: The extra demand for seasonal and regular products during the holiday seasons. These can be produced and stored in mothers before they are sold in the store. The volume is decided four months before.

5.1.2 The distribution

The Brynild group has a production facility located in Fredrikstad. Some of the production of goods has been outsourced to foreign suppliers. All of Brynilds products are stored at Leman's warehouse in Vestby. Brynilds largest customers are wholesalers, such as "COOP AS, "Reitan-Gruppen," and "Norges-Gruppen." These companies contribute to approximately 90% of Brynild's sales. The wholesalers have their own regional and central distribution centers.

Figure 5.1: Overview of the distribution

Leman receives orders from the wholesalers and has a 1-2-day lead time to prepare the orders before the wholesalers come to retrieve the goods. Brynilds products are sold on full pallets, mixed picking pallets or filled sales displays produced filled with predefined products assembled by Leman. After receiving Leman's goods, the wholesaler distributes Brynilds products to grocery stores and kiosks where end-customers can purchase them.

5.2 Leman

Leman is a 3PL provider from Denmark with 25 departments in 7 different countries. They have 2 departments in Norway, one in Drammen and one in Vestby(hereby referred to as Leman). This case study will focus on the one in Vestby as that is where Brynilds products are stored. Leman is a small-medium enterprise (SME) and has 25 employees.

Leman provides multiple services for their customers. They do warehousing, transportation, and customs clearance. They have multiple clients in different industries, such as Brynild Gruppen A/S, Jensen A/S, Kavli AS, and Nutricia A/S. Each client has a separate storage area where their SKUs are stored. Leman's business strategy focuses on long-term contracts with sustainable over-the-market profitable growth combined with strategic "best-fit" acquisitions.

5.2.1 Warehouse layout

Brynilds section in the Leman warehouse consists of 15 aisles with eight levels. The aisles have a single rack depth. The warehouse has an in-and outbound area where the goods are received and delivered. There are approximately 7800 storage locations assigned to Brynild. The bottom shelves are used for carton packing, and the upper ones are used for full pallet picking.

The storage area is divided into four zones, A+, A, B, and C. The storage locations that are the most accessible and take the shortest time to retrieve and place goods in are labeled as A+. This is used for carton picking.

There are six lanes in the I/O area used for storing in-going and outgoing deliveries before they are ready to be stored or shipped. There is also an area set off to packing mixed pallets in front of aisle 25.

Every warehouse's storage location has a unique identification number and a barcode to ensure traceability in the warehouse. The warehouse operators are equipped with forklifts with supportive tools, such as barcode scanners, a display linked to the WMS, and a printer to print labels. The aisles are set wide enough that the forklifts can turn within them.

5.2.2 Warehouse operations

Leman receives a truckload of shipment approximately 3-4 times a day. The truckloads are unloaded in the in-and outbound area, where the order information is uploaded to Lemans WMS. It is then assigned a storage location by the WMS. A warehouse operator then transports the different SKUs to the assigned storage location.

Order picking is more complex; picking lists are generated based on the customer order and assigned to an order picker. The order picking can be divided into two main categories. Picking mixed pallets and picking full pallets. When picking full pallets, the pallets are picked from their storage location and transported to the in-and outbound area. When picking mixed pallets, the order pickers have to pick cartons from different pallets and put them together. The mixed pallets separate the different SKUs from each other pallets. The mixed pallets must be wrapped in plastic wrapping and given a new label before it is shipped. It is, therefore, more labor-intensive to pick mixed pallets than full pallets.

Brynild also sells sales displays made out of cardboard. These are repacked in a mezzanine in the warehouse. The required unit loads are transported from the racks to Leman's mezzanine; then, a non-profit organization packs the SKUs onto the sales displays. The sales displays are then put on pallets and transported to the I/O area for shipping.

5.2.3 Warehouse principles

Leman divides its storage into zones and uses a class-based storage system. They use pick frequency to assign each SKU a class. The SKUs with the highest pick frequency are assigned to the A-class, and the SKUs with the lowest are assigned to the C-class. The storage is divided into zones based on the distance from the I/O point to the storage position. The storage locations that are low and close are reserved for A-SKUs. The storage locations that are further away or are stored higher in the racks are in the B and C Zone and are reserved for B and C-SKUs.

The warehouse operates on the FEFO(First-expired-first-out) principle. This implies that the SKUs with the earliest expire data in the picking list will be picked first in the order picking. This is done to avoid expired SKUs. This also results in that each picking line can only be fulfilled by one production batch. This is to maintain traceability in the supply chain.

There are some exemptions when the warehouse operators overrule the principles. When a pallet is seen as unstable but is assigned to a high altitude position, some operators might choose to place it on a lower shelf to avoid the risk of the pallet falling. Warehouse operators often place unit loads together if they put away two unit loads at the same time. When warehouse operators arrive at a full location because of discrepancies in the WMS, they place their unit load in another storage location.

5.2.4 WMS

The warehouse management(WMS) that Leman uses is called Consafe. The WMS has a central role in the warehouse. When a shipment arrives at the warehouse, the WMS assigns a storage location to the incoming SKUs. The storage location system is based on the WMS internal logic system, information of the incoming unit load, and the warehouse's status. The warehouse operators can also override the suggestions made by the WMS. The WMS allows you to choose between 3 different alternatives on how to manage the automatic location selection in each storage area:

- "Location automatic": Location automatic requires some logic to work and is usually defined by the preferred storage zone and preferred to pick storage zone. Location automatic then gives suggestions on where to place the SKUs.
- "Auto, prompt rack." The warehouse operators have to press next to request another rack to place the goods and get a new search in the put functionality.
- "Auto same aisles as pick area." A storage location is looked for in the same area as where the picking location reduces travel time when a picking location is empty.

The storage areas can also choose how they want to spread their unit loads across the warehouse.

5.3 The model applied to the case study

The model uses data received from Leman's warehouse about orders and transfers of SKUs in the warehouse. To use the data obtained, it needs to be cleaned and prepared. The Dataset contains 85790 rows and 61 columns with order data from 2019 and 2020. The extracted data is order type, the date, the nr of goods, and the SKU nr. Then it follows the recipe in the Model section. To get the average time used for picking an SKU in each storage location for each zone. It is assumed that the forklifts have an average speed of 2 m/s in the warehouse, a vertical velocity of 0,4 m/s, the shelf size is 2 meters, the distance between the ails is 5 meters, the height coefficient for dealing with higher pallets is 1,2. Using these assumptions, the average picking time pr zone is calculated to be 83 seconds for zone A, 167 seconds for zone B, and 275 seconds for zone C.

Chapter 6

Results

6.1 Forecasting

The Results of the forecasting differ from SKU to SKU. The picking order pattern of SKUs also varies a lot, some have a stationary demand pattern, and some are more seasonal. They are also affected by promotions and campaigns, so that the demand pattern can seem quite random without this information.

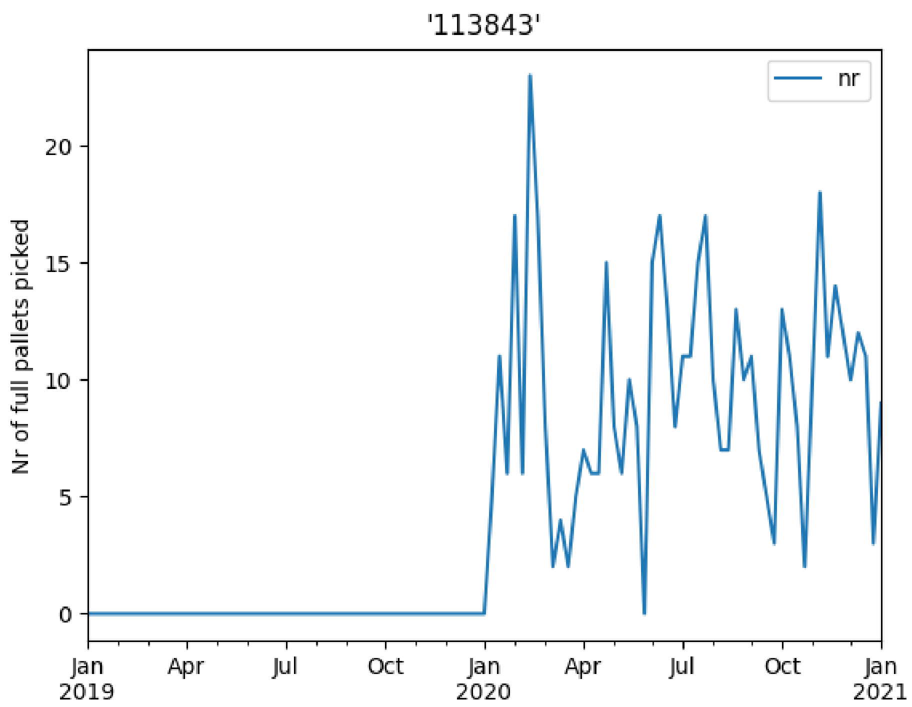

Figure 6.1: Showing the order history of full pallets of SKU 113843 picked in 2019 and 2020

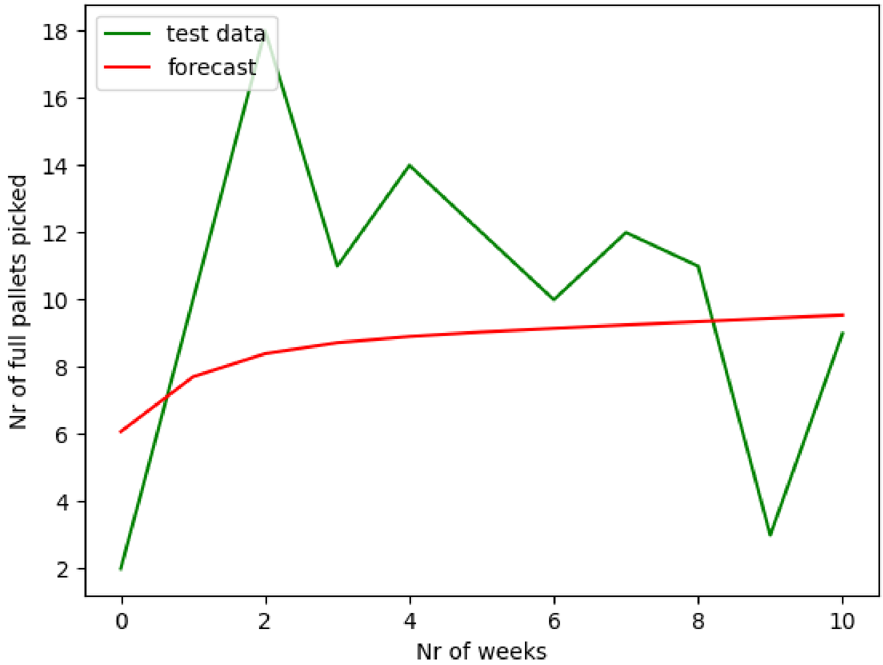

Figure 6.2: Showing the forecast compared to the actual order data of SKU 113843 the last 10 weeks of 2020

Here the MSE of the forecast of SKU 113843 is 18.80. The average MSE is 33.43, and the min is $2.74*10^{-9}$, the max is 10579, and the median is 0.2450.

6.2 Classification

There are multiple ways of doing ABC classification, as discussed in the theory chapter. Here are the results of The ABC analysis done for the case study.

The red line is the ABC classification based on the actual picking orders of the ten last weeks of 2020 and is the ideal ABC classification for this period. The two other ABC classifications will be compared. The green line is the ABC classification based on the order data from the 12 last months form before ten last weeks of 2020, from week 42 in 2019 to week 42 in week 2020. The blue line is the ABC classification based on the forecasted picking orders of the ten last weeks of 2020.

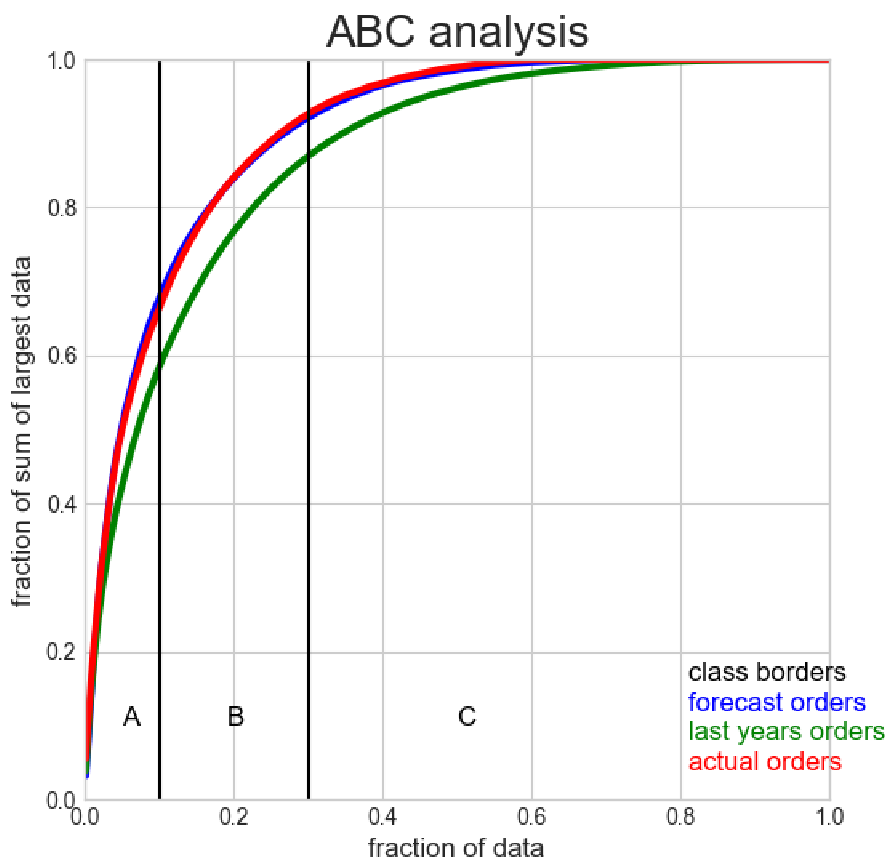

Figure 6.3: Showing the ABC-distribution SKUs using 3 different data sets

6.3 Performance

To see how efficient the classifications have been, we need to compare them and see how much time potentially can be saved. First of we can see how many of the SKUs were classified correctly compared to the actual picking orders ABC classification. Then calculate the time it will take.

By multiplying the number of full pallets getting picked in the last ten weeks of 2020 with the average retrieving time from each zone using the different classifications, we see how much time can be saved using the other classifications. Using the classification from the actual order data, we get **887154 seconds or 246 hours and 26 min** of transportation time retrieving the goods. Using the classification from the forecast order data we can save **26822 seconds or 7 hr 27 min** compered to the naive classification based on last years data.

	A	B	C	Total
Actual	54 / 54	108 / 108	379 / 379	541 / 541
Forecast	38 / 54	68 / 108	346 / 379	452 / 541
Last year	35 / 54	60 / 108	345 / 379	440 / 541

Table 6.1: Classification accuracy

	Time	Time difference
Actual	887154 seconds (246 hours and 26 min)	0
Forecast	973170 seconds (270 hours and 20 min)	+ 86016 sec (23 hours and 54 min)
Last year	1000062 seconds (277 hours and 48 min)	+ 112908 sec (31 hours and 22 min)

Table 6.2: Time used with the new classifications

Chapter 7

Discussion

The objective of this thesis is to see if there is a positive effect of using forecasting in classification.

RQ1: *How can the forecasting of fast-moving consumer goods be done.*

The chosen model for the case study was the ARIMA model. The ARIMA model has a lot of advantages as it is easy to implement and gives good results. We see that the mean MSE for the SKUs is 33.431. This is relatively high, but as we see, the max value is also very high compared to the median, so that some high outliers can affect the results. On the other hand, inspecting the order data, over 300 SKUs of 680 SKUs are not ordered in the last ten weeks. These will probably be easier to forecast than the others and have a better MSE score. The results are not perfect but good enough to indicate how future picking orders will look.

On the other side, it is not the most complected forecasting as it only uses historical order data to make predictions. Several other factors could help improve forecasting. Having access to Point of sales data and using this data forecast can help with more accurate forecasting. In the case of Leman, there is also the question of how to deal with the POS data as they do not have any information on how much stock the regional and central wholesalers warehouses have. However, it can still have a positive effect.

Production and promotion data is also valuable information that can help with the forecast. Without any data on product promotions, the demand pattern can seem random. Having information on why there are sudden increases and drops in orders can be helpful in the accuracy of the forecast. Having information on how future planned promotions will also help the accuracy of the forecast. The same goes for production data; knowing the number of goods coming into the warehouse can indicate products going out, and how many available storage locations are available.

These are some issues with being a 3pl, and the information is not spread throughout the supply chain. But ff all this information is available and is to be used, then the ARIMA model will be insufficient, and other methods that can forecast based on multivariable input might be better. Here ANNs and SARIMAX can be valuable contributions and should be tried out. The classification will be better if the forecast is better, and the better the classification, the better performance.

RQ2: *How can forecasting using historical order data improve storage classification.*

Using forecasting can help classification by being able to pick up on upcoming trends and seasonality. To classify goods correctly, they have to be given the correct classification when they arrive at the warehouse. To know how to classify the goods, we should see how the demand pattern will look when the goods are picked. To know this, we need a forecast.

As seen in the results, we see that the classification based on forecasting outperforms the classification based on last year's data. It classified 452/541 correctly compared to 440/541. The difference is significant and does help lessen the workload for the warehouse.

There are still some issues with the classification model. To compare the classifications, the classes need to be the same number of SKUs in each class. This does not necessarily give the best classification, but a worse classification will be better just because it has more SKUs in the A-category if not done this way. To combat this, find the max amount of goods in each class section in the warehouse and use this as the limiting factor in the classification.

The next step is to try to use a multi-variable classification to improve the classification. The additional variables that the classification can use are the average stay time of each SKU and the stock level in the warehouse of each SKU. The average stay length can indicate if it is worth the placement. Kheybari's Multi-criteria decision-making could be a great fit for this classification; the same can be said for Zuou's classification using clustering and k-means.

RQ3: *What is the effect of forecast-based classification, and how can forecast-based classification improve warehouse performance?*

Forecast-based classification can help lessen the workload and optimize the warehouse. As shown in the results the model can save up to 4 hours and 19 min compared to the last year's data. We see that there is still a way to reach the optimal classification, but it will improve with a better forecast.

So the proposed model does work and improves the situation as it is now. The question is if it is worth it. An improved model can help, but even if the forecast is perfect, the time saved is 31 hours and 22 min. According to the lean methodology, the warehouses should eliminate all waste. The impact of forecast-based classification is greater the larger the warehouse is. In the case study, we have only looked at Brynild's part of Lehman's warehouse. Using forecast-based classification can give an even greater effect if it is to be used in the whole warehouse.

There is also a question of what the warehouse should be optimized against. If the goal is to be better to deal with peak demand or if it is to reduce the average picking time, the classification should be changed accordingly. The goal then also depends on the warehouse's issues and the demand pattern of their goods.

The forecast can also be used in other areas of the warehouse, such as workload planning.

There is also the question of how long the forward is to forecast and how often to change classification. The longer the forecast, the more uncertain it becomes, but it also gives a better foundation for the classification. The rapid changes give a more dynamic classification that can quickly pick up on new trends. On the other hand, if the classification changes too often, it can bring unnecessary changes and confusion. This thesis has tried to use a 10-week forecast as its foundation for classification once. The result is promising and should be further researched to find the forecasting length and classification change.

Chapter 8

Conclusion

The main objective of this thesis was to investigate if forecast based classification can outperform naive classification based on last years data. The results show that the forecast based classifications out-preforms the outperform naive classification based on last years data. It is not at the level of the actual data, but it is in the right direction.

It looks like the principles in the thesis are good, but the execution can be better. Using a more accurate forecasting model and more intelligent classification system the effect could be even better than presented in this thesis.

Areas that can be further explored is the integration of new data like POS and warehouse stock levels can help with both forecasting and classification. The test of ANNs and Multi variable classification can aslo give good results.

Appendix A

Acronyms

List of all abbreviations:

3PL providers Third-Party Logistics Providers

AIC Akaike information criterion

ANN Artificial neural network

ARIMA Autoregressive integrated moving average

FEFO First expire first out

FMCG Fast Moving Consumer Goods

I/O area In-and Outbound Area

ICT Information and Communication Technology

MCDM Multi-criteria decision-making

MSE Mean squared error

POS Point of sale

SKU Stock keeping unit

SLAP Storage Location Assignment Problem

SME Small-Medium-sized Enterprise

WMS Warehouse Management System

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