POLITECNICO DI TORINO

Master's Degree Thesis

Forecast inbound volumes and workforce needs in a logistics warehouse

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Summary

This thesis explores the forecasting of incoming volumes and workforce requirements in a logistics warehouse. The main objective of the study is to develop a reliable forecasting model based on statistical data to improve resource management and the organisation of goods receiving operations. Through an analysis of historical data, the research aims to identify and quantify patterns, trends and seasonal variations that influence incoming volumes. The thesis consists of two levels: a theoretical discussion of forecasting methodologies and an empirical case study applying these concepts within a distribution centre. Methodological approaches for data collection and analysis are also examined, as well as the development of forecasting algorithms customised to meet the specific operational needs of the logistics centre. The development of the case study will facilitate an examination of the efficacy of forecasting methods that have been specifically designed for a logistics warehouse. By analysing monthly, weekly and daily data, the research will demonstrate how the forecasting model can reduce the costs associated with over- and understaffing, thereby reducing the overall costs of the warehouse.

Acknowledgements

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Acronyms

CAC
: Continental Approval Centre

CAR
: Regional Approval Centre

KPI
: Key Performance Indicator

DC
: Distribution Centre

MA
: Mobile Average

SES
: Simple exponential smoothing

LT
: Lead Time

Chapter 1

Introduction

This study aims to explain the application of a forecast model in a logistics center. The study examines the operational intricacies of logistics management and focuses on forecast modeling methodologies. The research aims to contribute to the academic discourse on logistics optimization. The study aims to provide insights into the interplay between forecast modeling strategies and logistical operational efficiency in a generic logistics center. Due to privacy policies, the name of the logistics center which inspired the case study, is undisclosed.

The work will be approached on two levels. Firstly, will examine theoretical forecasting hints and arrangements within a distribution centre. This is the discourse on logistical optimization and forecasting paradigms. Secondly, it will discuss a case study that uses deliberately modified datasets. This empirical investigation aims to clarify the practical application of forecast methodologies within the operational framework of a distribution centre. The study provides valuable insights into the effectiveness and adaptability of such approaches in real-world scenarios. These two levels will be discussed in parallel. The case study illustrates practical logistic challenges in a distribution center while also addressing broader logistic issues relevant to the industry. This approach aims to provide a balanced understanding of theoretical concepts and their real-world applications, offering insights into effective problem-solving strategies within distribution center logistics.

Furthermore, the study will be divided into distinct parts that outline important aspects of the forecast model's development and application. The first part will focus on dataset creation and the methodology for selecting appropriate data classes for comprehensive data analysis. This segment aims to explain the foundational steps required for robust dataset preparation, which facilitates insightful data-driven decision-making processes. Secondly, the study will examine the process of creating algorithms that are tailored to meet the specific operational requirements of the company under study. This section will explore the conceptualization, development, and refinement of algorithms optimized to address the unique challenges and objectives of the organization. Finally, the study will conclude with an analysis of the results, with a particular focus on optimizing personnel and shift management strategies.

After completing the case study, the results will be thoroughly analysed and discussed to propose potential improvements. The findings, including insights from data analysis, model performance evaluations, and operational observations, will be examined in detail to identify strengths and weaknesses within the existing framework.

During this study, aspects of a logistics center will be thoroughly explored and analyzed. This investigation will encompass various facets such as operational processes, resource management, dataset management relative to inbound volumes. Through a comprehensive examination of these elements, the study aims to provide a holistic understanding of the intricacies and challenges inherent to logistics center operations, thereby facilitating informed decision-making and strategic planning in this domain.

This study will exclusively focus on inbound volumes, abstaining from the analysis of the interplay between inbound and outbound volumes and the corresponding inventory management dynamics. By concentrating solely on inbound volumes, the research aims to delve deeply into the specific challenges, strategies, and implications associated with managing incoming goods data within the distribution center context. This focused approach will facilitate a nuanced exploration of inbound logistics processes and their impact on overall operational efficiency within the DC environment.

1.1 Inventory Management Uncertainty

Distribution centers face significant logistical challenges, particularly when it comes to managing inventory. Uncertainty surrounding inventory management is a major obstacle that must be overcome.

Inventory cost [1] refers to the expenses associated with acquiring, storing, and managing inventory within a business. It encompasses various costs incurred throughout the inventory management process and is a critical component of a company's overall cost structure. Understanding and managing inventory costs effectively is essential for maintaining profitability and optimizing operational efficiency [2].

The inventory levels at a logistics center, located between retail stores and the continental approval centres, are volatile due to the interplay between demand variability and the volume of goods dispatched from the CACs. Anticipating inventory requirements within the logistics center is a challenging task due to this dynamic relationship. It is crucial to maintain optimal stock levels to meet customer demand while avoiding excess inventory and associated costs. To achieve this balance, it is necessary to have strong forecasting models, flexible inventory management strategies, and close collaboration throughout the supply chain to quickly adapt to changing market conditions and effectively mitigate risks. In this case, the forecast should be based on incoming volumes rather than demand.

Another essential point is the stock-out cost which represents an aspect of inventory management, encompassing the expenses and consequences incurred when inventory levels fall below the required thresholds [3]. This includes the financial consequences of missed sales opportunities, potential customer dissatisfaction, rush orders, and expedited shipping costs to replenish depleted stock. Analyzing stock-out costs helps to optimizing inventory control strategies, minimizing financial losses, and enhancing overall operational efficiency within the warehouse center. Furthermore, The lack of clarity regarding inventory levels, demand patterns, and supply chain dynamics complicates the formulation and execution of effective strategies. Without accurate and reliable inventory data, it becomes arduous to allocate resources efficiently, manage the internal organisation and change business strategies [4]. The following analysis examines some of the primary phenomena associated with uncertainty in inventory management

1.1.1 Inventory costs

Lower inventory cost is certain benefit for the organisation that successfully controls the inventory. When making decisions about inventory management, it is important to consider the associated costs. Effective inventory control can significantly reduce costs for an organisation by decreasing the total volume of inventory required to operate [5]. Inventory control involves monitoring inventory levels and proactively managing obsolescence and deterioration by ordering appropriate volumes. The appropriate volumes are ordered to proactively manage inventory and prevent obsolescence and deterioration. Costs must be taken into consideration.

- Holding (or carrying) costs. It generally refers to the costs associated with storing stocks. These costs include taxes, insurance against theft and natural disasters, as well as obsolescence and depreciation of stocked items.
- Setup costs (also known as production change costs). For production to

change from one batch of product to another different batch of product is about acquiring the material needed and organising the production machine for setups and also cleaning out material used from the previous batch.

- Ordering costs. This type of cost is about the administrative costs in dealing with creating a manufacturing or procurement order. Ordering costs take into account all the information, for instance checking the products when delivered, and computing manufacturing or procurement order quantities. A system that deals with tracking of orders is included in this type of cost.
- Shortage costs. In the event of stock shortages, a procurement order may be placed or an existing order may be cancelled, resulting in a delay in receiving the stock. Shortages can result in additional costs due to the need to place new procurement orders or cancel existing ones, leading to delays in receiving the necessary stock. When demand cannot be met, this is known as a stock-out, which can result in cancelled orders or long order waiting periods.

Effective inventory control impacts on storage costs by reducing the costs, which is ordering enough inventories to fulfil the demand of consumers [6].

1.1.2 Uncertain demand

Inventory system models consider both certain and uncertain demand and supply. However, in reality, demand is constantly changing due to order fluctuations, random supplier capacity, and unpredictable events such as weather, machine breakdowns, transportation issues, and human errors [7]. To address uncertainty, safety stock is necessary to cover the possibility of stockouts resulting from uncertain demand [8]. To prevent stock-outs, one solution is to increase the reorder point and maintain extra stock, known as safety stock. This spare inventory is kept to cover potential stock-outs caused by supply or demand variations, as defined by logisticians. Safety stock is an additional planned on-hand inventory that protects against the possibility of stock-outs.

1.1.3 Lead Time

When considering demand uncertainty in inventory management, it is essential to take lead time (LT) into account. Lead time is the duration between placing an order for inventory and receiving it. Accurate demand forecasting becomes increasingly important when the source of supply is distant, resulting in longer lead times.

Longer lead times introduce additional complexity and risk into the inventory management process. With a longer lead time, there is a higher chance of variability and uncertainty in customer demand during the replenishment cycle. Therefore, accurate demand forecasts are crucial in determining the appropriate inventory levels to meet customer needs while avoiding stockouts or excess inventory [9].

Effective demand forecasting is essential in reducing the impact of lead time variability and uncertainty. Accurately predicting future demand patterns and trends enables organizations to proactively adjust inventory levels, reorder points, and safety stock levels to align with anticipated demand during the lead time. This minimizes stockouts, reduces excess inventory holding costs, and optimizes inventory turnover rates.

Furthermore, longer delivery times often require a more comprehensive approach to demand forecasting, taking into account factors such as seasonality, market trends, and supply chain disruptions. The use of advanced prediction techniques, data analysis, and collaborative partnerships along the supply chain can improve the accuracy and reliability of demand forecasts. This allows organizations to more effectively adapt to longer delivery times and fluctuations in customer demand.

1.2 Problem description

This section will primarily focus on analyzing the most significant problems identified in the study. The research aims to uncover the root causes of this key issue and assess its impact on the logistics centre's operations.

The case study discusses a logistic centre that supplies 30 stores in Italy and other countries. In the logistic centre, goods are expedited from centres of continental supply situated in all Europe. The logistic centre faces a significant challenge in the absence of information regarding the arrival times of goods. Information arrive only about two days before by means of an internal software, where it's showed the truck planning. However, it's common for the arrival dates to fluctuate within this software and it poses a significant challenge for managers, who have to plan resources and the management of the stock. Moreover, the lack of efficient communication channels between the upstream and downstream distribution centres exacerbates the uncertainty surrounding inbound volumes. This lack of foresight for stock inbound complicates several operational aspects:

- Inventory Management Uncertainty: The center struggles to predict and manage inventory levels effectively. Without knowing when shipments will arrive, it's challenging to plan for storage space and maintain optimal stock levels. This can lead to inefficiencies, such as stockouts or excess inventory, impacting costs.

- Workforce problem (resource allocation): In the absence of arrival time information, resource allocation becomes a guessing game. The center may overallocate resources during periods of anticipated high inbound traffic or risk being understaffed during unexpected peaks, affecting operational efficiency and service levels. This of the worforce problem, can be seen in part as a consequence of the generic problem described above.
- Unknown stock trends: understanding stock patterns is essential to ensure that inventory levels are adequate to meet demand while minimising overstocking or stock-outs. Accurately identifying patterns such as seasonal fluctuations, trends, and irregularities allows the forecasting model to generate precise predictions that align with inventory needs over time. Furthermore, possessing the capability to assess warehouse efficiency, including stock turnover, order fulfilment rates, and resource utilisation, enables you to strive towards streamlining operations and increasing the overall efficiency of the DC.

1.2.1 Workforce problem

The main focus of this study will analyse and address the challenges of workforce management in distribution centres, in connection with the reception of inbound volumes.

Improving workforce challenges is crucial for enhancing staff satisfaction, operational efficiency, and cost management within a logistics centre. Strategies to mitigate issues such as overtime costs and optimising staffing levels can cultivate a positive work environment, improve productivity, and achieve greater cost-effectiveness. Prioritising workforce management enhances overall operational performance and financial viability while increasing employee satisfaction.

The workforce issue in a logistics centre is crucial as it directly affects costs. Staffing requirements, especially overtime hours, significantly contribute to operational expenses. Furthermore, hiring staff under subordinate employment contracts constitutes a significant cost for a logistics center. In addition to direct wages and benefits, each employment arrangement incurs additional expenses such as taxes, insurance, and administrative overhead. Striking a balance between workforce management strategies, including the use of subordinate employment contracts, is essential for maintaining cost-effectiveness in the logistics center's operational framework.

1.2.2 Problem tree

The use of problem tree analysis proves to be a valuable tool for identifying the causes and effects of a problem situation that one wishes to change. This tool sheds light on the complexity of the situation, identifying other factors that may require intervention through complementary projects to ensure the success of the intervention. It is important to focus on identifying existing problems rather than potential, imagined or future ones. Next, the tree is outlined by identifying the causes and effects of the core problem.

- Trunk (or main problem): The trunk represents the central or main problem that you want to analyze and solve. It is the starting point of the analysis and is positioned at the top of the tree.
- Roots (or causes): Roots are the direct causes or reasons that contribute to the main problem. They develop from the trunk and represent the connections between the core problem and the factors influencing or generating it.
- Leaves (or consequences): The leaves are the consequences or effects of the main problem. They also develop from the trunk, but go in the opposite direction than the roots. Leaves indicate the impacts or consequences that the main problem may generate.

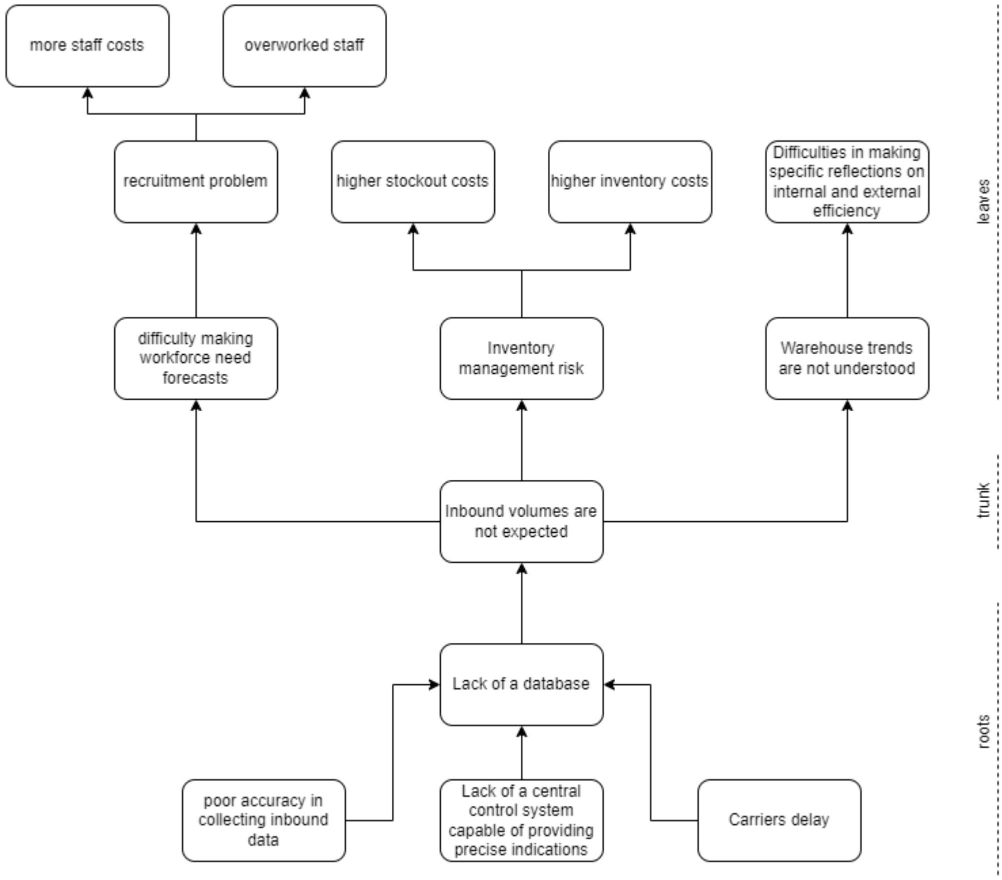

Figure 1.1: Problem tree

1.3 Goal

Once the problems related to the difficulty of obtaining reliable information about the unloading of inbound volumes within the centre were understood, it's possibile to delclare the objective of the study, that is to establish a reliable forecasting framework based on statistical data. Through meticulous analysis and interpretation of historical data trends, the study seeks to develop a robust forecasting model capable of accurately predicting future outcomes. By leveraging statistical methodologies and data-driven insights, the aim is to enhance forecast accuracy, thereby providing stakeholders with dependable projections for informed decision-making and strategic planning within the organization.

The purpose of the case study shown is to create a tool to forecast inbound volumes for the logistics centre. It should be a simple tool that can be used by managers to understand how to plan resources and organise the receipt of goods. The tool must be based on statistical data since the inception of the logistics warehouse, or since the availability of data.

Once the data has been collected, it is necessary to conduct both quantitative and qualitative analysis. Conducting an analysis of data is crucial point because it helps to uncover patterns, trends and seasonal variations, in the volumes over the past years. By studying data managers can gain insights into what influences inbound volumes, such as changes in seasons, market trends and potential growth patterns. This deeper understanding allows them to make forecasts and plan resources effectively ensuring smooth operations and timely receipt of goods.

Moreover data analysis helps identify any unexpected changes, in volumes and enables managers to adjust their strategies accordingly. Ultimately incorporating data analysis into the development of this forecasting tool improves decision making and enhances logistics management efficiency and effectiveness in the warehouse.

After analysing the data and creating a database to aid in forecasting incoming volumes, it is necessary to evaluate the performance of the forecasting algorithm using defined Key Performance Indicators (KPIs). These KPIs serve as quantitative measures to evaluate the accuracy, reliability and effectiveness of the forecasting model in predicting incoming volumes. Metrics such as forecasting error, forecast bias, and forecast accuracy can provide valuable insights into the algorithm's performance. By systematically evaluating the forecasting algorithm against predefined KPIs, it's possible identify areas for improvement and refine forecasting algorith

1.3.1 Solution tree

The transformation of the problem tree into a 'solution tree' or 'goal tree' is a methodological approach. This method involves reformulating all elements of the problem tree in positive and desirable terms, thus creating a vision in which the problem has already been solved.

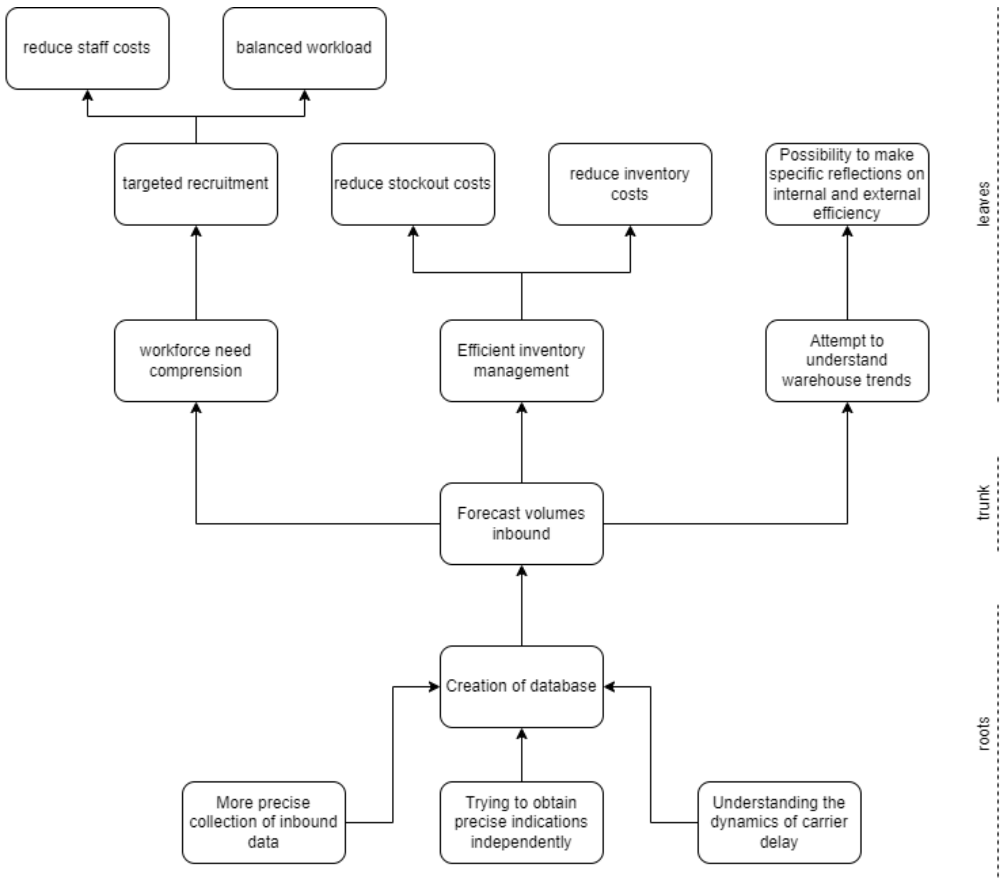

Figure 1.2: Solution Tree

1.3.2 Strategic Selection

From the problem tree and the solution tree, it's possible to see that the principal problem of this case is the inability to make forecasts of volumes inbound. The main reason of that, is the lack of a database where are collected all data relative to the discharges made by trucks in the depot on each individual day. The accuracy of forecasts will increase with the richness of informations of the database.

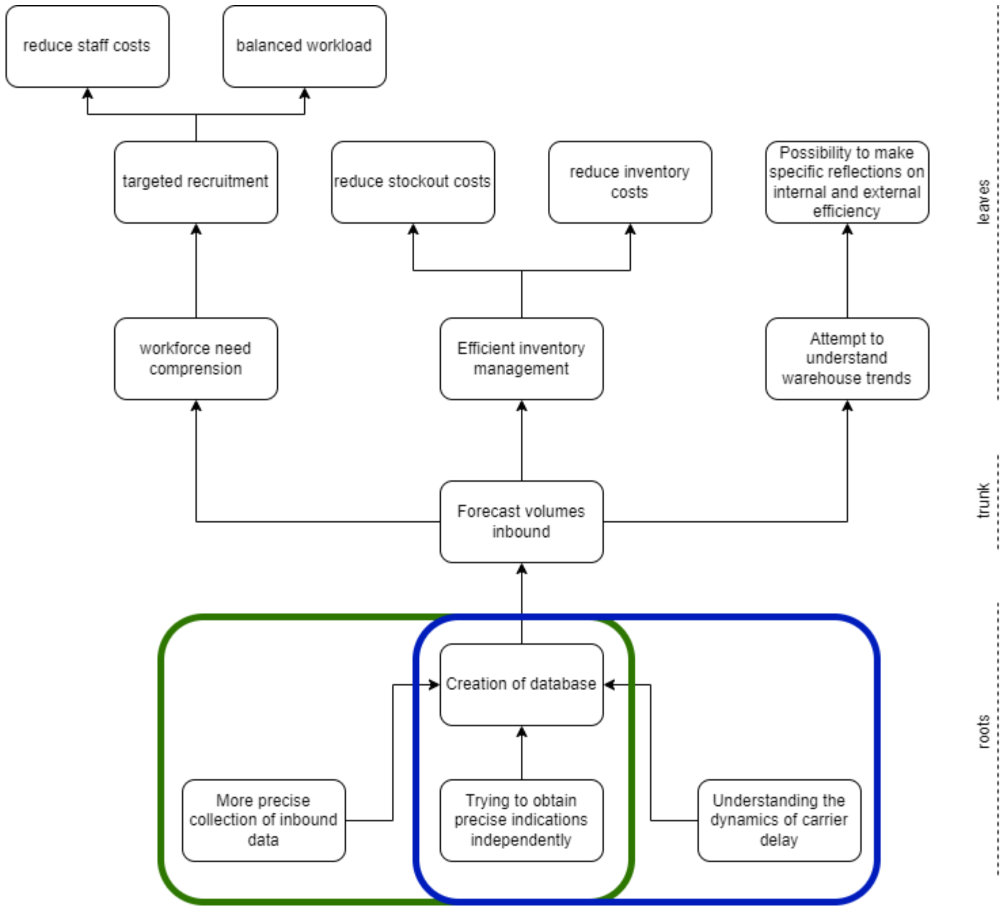

Figure 1.3: Strategy Selection

The proposed strategy involves implementing two distinct action plans, both centred around establishing and utilizing a complete database. The first plan focuses on meticulous data collection practices and the integration and automation of data entry processes within the database infrastructure. This initiative aims to enhance data accuracy and optimize information management procedures, thereby providing a more robust basis for decision-making.

The second action plan aims to use the database to collect data on transporters, allowing for an analysis of their performance and reliability in meeting established delivery times. By evaluating transporter capabilities and track records, the organization can identify and prioritize partnerships with companies that show the highest levels of efficiency and adherence to delivery schedules.

Chapter 2

Data collection

The key challenge addressed in this work is to identify and focus on relevant data that will serve as instrumental inputs to the analysis. Consider the importance of data relevance, i.e. it's necessary to identify and prioritize data sets that are essential to achieving the objectives of the study.

The data collected serves as the basis for fueling the inbound volume prediction algorithm, so the data must be clean and substantial in size. Data cleanliness ensures accuracy and reliability in predicting results, while a large dataset provides the algorithm with sufficient information to effectively identify patterns and trends.

The database should be designed to update automatically with data entered by an operator, which requires a user-friendly process. Simplifying this process reduces the likelihood of errors or delays in updating the database. By implementing intuitive software and tools, operators can seamlessly enter data, allowing the database to be updated in real-time.

For this reason, in the case study, it is chosen to use Excel. It is a simple tool that can be easily used by operators to update unload data. Using Excel as a database has limitations, particularly in terms of scalability and the capacity to perform complex data analysis. Therefore, it can be challenging to handle large amounts of data or develop intricate statistical models. However, to facilitate data entry and adapt the algorithm to the specific needs of the company, this is a viable solution.

In the following sections, we will examine how to organize the database.

2.1 Sectors

Organizing the database involves identifying macro areas into which stocks can be categorized based on dimensions, weight, and shipping priority. This segmentation is useful for storage, as it groups items with similar characteristics or logistical requirements. The database structure should be optimized to support streamlined inventory management processes.

In the case study discussed, we will talk about five different sectors where the goods will be classified:

- 86: These are the most common goods, with standard weight and size and easily stocked on shelves.
- 87: It is a heteroclite, meaning goods that are unusual, atypical or do not conform to normal standards. It refers to an object or product that deviates in size and shape from the norm, which may be difficult to classify or catalog within a specific category.
- 89: Bikes, to which a specific sector is dedicated due to their size and higher sales volumes.
- 90: These are bulky goods, meaning all goods that exceed certain dimensions and weights. They often require specialized machinery for storage at high positions on shelves.
- Transit: These are goods destined for stores. These goods are urgently required and are not stocked on the shelves, but are directly loaded onto the first available truck.

2.2 Data acquisition

To facilitate effective data management within the logistics center, the presence of customized management software tailored to specific business requirements is essential. Such software solutions are designed to align with the unique operational processes and challenges of the logistics center, offering functionalities that cater to inventory management, order processing, transportation coordination, and other critical aspects of logistics operations. By leveraging customized management software, organizations can streamline data entry, enhance data accuracy, automate routine tasks, and gain actionable insights through advanced reporting and analytics capabilities.

The software must be fully customized to eliminate limitations, ensuring it captures crucial data such as goods quantity and their respective sectors within the warehouse.

In order to automate the process, the person responsible for the unloading of the trucks should enter the arrival times of the trucks into the management system in the right moment when operation ends. As a consequence of this level of customization, occasional compilation errors may arise, typically stemming from human oversight or misinterpretation during the implementation process.

Therefore, it is crucial to perform a comprehensive data cleaning process to detect and correct any missing or inaccurate values. By methodically examining the dataset for discrepancies and errors, such as missing or incorrect values, the data's integrity and reliability can be restored.

In the case study data are incorporated into the database using Excel, which is user-friendly and allows for daily and straightforward compilation by the manager of unload department. This approach ensures easy data entry, efficient updates, and minimal complexity in maintaining the database.

2.2.1 Data cleaning

The case study required various forms of data cleaning to ensure data accuracy and reliability during the database creation process.

- Missing values: In the database, the presence of missing values was observed, often stemming from instances where data had not been recorded. This posed a challenge to data completeness and accuracy, requiring efforts to identify and address these gaps. After a meticulous examination of the data, it was decided to replace the missing values with the average values for the current month so as not to alter the veracity of the database.In this specific case, missing values are those values where trucks seem to have arrived, but volume values have not been recorded. Specifically, there were 25 missing values recorded, which were fairly equally distributed, but with a higher concentration in the more distant data.

- Outlier: Outliers are data points that are conspicuously incorrect and can compromise the accuracy of the database. It is necessary to detect and, when possible, correct them by deleting or replacing them. In the study at hand, 9 outliers were identified, mainly represented by unloading values recorded on Sundays, when no unloading takes place at the logistics depot in question on that day. These values were often recorded incorrectly on Sundays, but they actually belonged to neighbouring weekdays such as Saturdays or Mondays. Also, outliers were substituted with the average value of the month.

- Duplication: Only two instances of duplicate data were found. The records in question contained errors in the final data entry. Specifically, the trucks were correctly entered in the file, but the final volumes were those of the previous day.

	Total	Missing Value	Outlier	Duplication	Data cleaned
Value	1565	25	9	2	36
Percentage	100%	1,59%	0,57%	0,13%	2,30%

Table 2.1: Data cleaning

2.3 Class

To prevent the accumulation of redundant data in the database, it is crucial to carefully select the appropriate class of interest. This selection enables consideration of key factors such as carrier punctuality and worker productivity. By focusing on these relevant classes, the database can efficiently capture essential information without unnecessary duplication.

The case study contains examples of useful classes to include in the database:

- Truck reference: This class is essential for tracking and managing the trucks involved in the transportation process. Each truck likely has a unique identifier or reference number associated with it. Storing this information allows tracking of deliveries and monitoring the performance of individual vehicles and carriers.

- Time of arrival - planned time: By recording the exact time when a truck arrives at its destination, the database can provide real-time updates on delivery statuses. Furthermore, by collecting data on planned time, it is possible to analyse the carrier's reliability.

- Status (delivered, never arrived, canceled..): The status of each delivery provides crucial information about the progress of shipments. By categorizing deliveries into different statuses such as delivered, in transit, delayed or canceled it is possible to analyse the actual inbound volumes that arrive in the logistic centre.

- Number of parcels: Tracking the number of parcels associated with each delivery allows for accurate inventory management and allocation of resources. This data gives the driver valuable information to make forecasts.

- Arrival time - End of unloading time: These two classes provide information on the average unloading time and operator efficiency.

- Tiers of prevenience: It can provide information on the efficiency of supply centers. With this data, it is possible to analyse the lead time, the average punctuality of the centre and the preferred type of transport.
- Transport mode: It provides an understanding of the criticality of transport modes. It is possible to understand on which transport routes vehicles are most delayed on average.
- Loading type: Allows understanding of where to address goods in different sectors.

Booking	Truck reference	Transport mode	Loading type	Status	Planned carrier	N° parcel	Tiers name
TRC249646851	Ber/231221/BZ09PRI	road	PRI	Delivered truck	P&O FERRYMASTERS LIMITED	258	CAC Berlin
TRC215334572	SEV/231221/BZ10PRI	sea	PRI	Delivered truck	SMET	702	CAC Seville
TRC125447114	L1/231221/BZ11PAL	road	PAL	Delivered truck	P&O FERRYMASTERS LIMITED	348	CAC Lyon
AU4958337620	ROTT/241221/BZ02PRI	road	PRI	Delivered truck	P&O FERRYMASTERS LIMITED	1008	CAC Rotterdam
AU48503639076	SEV/261221/BZ01PRI	sea	PRI	Delivered truck	SMET	682	CAC Seville

Table 2.2: Qualitative 1

Initial unloading date planned	Truck arrival	Hour of truck arrival	Carrier punctuality	Date of loading	Day of loading	Date of end of loading	Warehouse loading punctuality	N° of loaded parcels
23/12/2021	23/12/2021	13:23	1	23/12/2021	thursday	23/12/2021	1	82
23/12/2021	23/12/2021	15:54	1	23/12/2021	thursday	23/12/2021	0	702
23/12/2021	23/12/2021	14:35	1	23/12/2021	thursday	23/12/2021	0	348
24/12/2021	23/12/2021	16:41	1	24/12/2021	friday	24/12/2021	1	1008
26/12/2021	26/12/2021	09:41	1	26/12/2021	sunday	26/12/2021	0	682

Table 2.3: Qualitative 2

Initial unloading date planned	Truck arrival	Carrier punctuality	Carrier delay	Date of unloading	End date of unloading	Warehouse Delay
27/12/2021	03/01/2022	1	1	03/01/2022	07/01/2022	0
28/12/2021	04/01/2022	1	1	04/01/2022	04/01/2022	1
27/12/2021	10/01/2022	1	1	10/01/2022	10/01/2022	1
31/12/2021	05/01/2022	1	1	05/01/2022	06/01/2022	0
29/12/2021	04/01/2022	1	1	04/01/2022	04/01/2022	0

Table 2.4: Qualitative 3

2.4 Years of statistical interest

The inability to acquire all data from the logistics center's inception stemmed from various factors, including missing data and significant deviations from depot reception trends. These deviations can primarily be attributed to two key factors:

- Covid-19: Impact of Covid-related years, characterized by associated restrictions. The data volumes collected during the covid period, from 2020 until the beginning of 2022, are characterized by violent disruptions and a sharp reduction in volumes due to the total shutdown and closure of shops
- Shifts in supply policies: Changes in supply policies can lead to fluctuations in data patterns. In particular, logistics has changed over the years from a push type of supply system, where goods were pushed to logistics centers resulting in large volumes being concentrated and received, to a pull type system, where goods are shipped according to demand received from stores.

For this reason, it was necessary to make considerations regarding the years of statistical interest. In particular, the Covid years were excluded from the investigation, and a decreasing trend was observed due to changes in company policies, which was considered during algorithm creation.

2.5 Quality and quantity database

As mentioned above, it was decided to establish both a qualitative and a quantitative database in order to comprehensively capture data at the logistics centre. The qualitative database primarily contains information on individual trucks arriving at the centre, providing detailed insight into factors such as origin, destination and transport conditions. Conversely, the quantitative database places greater emphasis on daily volume data, providing a systematic record of inbound volumes over time.

2.5.1 Quality DB

The qualitative database was meticulously constructed by gathering data on individual trucks that arrived at the logistics center over the two years following the Covid period. Prior datasets were excluded from consideration due to challenges in data availability or their limited relevance due to age. This focused approach ensured that the database contained recent and pertinent information, facilitating meaningful analysis and insights into post-Covid operational trends within the logistics center.

For the quality database, careful consideration was given to the selection of appropriate classes to facilitate comprehensive data analysis. Each class was deliberately chosen to match the specific analytical needs of the dataset, ensuring relevance and effectiveness in deriving meaningful insights. By carefully selecting classes that capture essential information relevant to the operations of the logistics centre, such as truck transport route, arrival times and volumes, the database is equipped to support thorough analysis and decision-making processes.

Analysis

The establishment of a qualitative database facilitated the identification of trends and enabled various analyses, including the examination of lead time as outlined below.

Actual LT		*Planned LT*	
Actual LT	Average LT	*Planned LT*	Average LT
CAC Seville	4,00	CAC Seville	3,42
CAC Lyon	1,02	CAC Lyon	1,01
CAC Berlin	5,51	CAC Berlin	3,42
CAC Bruxelles	5,48	CAC Bruxelles	3,30
CAC Dortmund	5,87	CAC Dortmund	3,60
CAC Rotterdam	6,27	CAC Rotterdam	3,69
CAC St.Etienne	1,24	CAC St.Etienne	1,19
CAC Valencia	5,01	CAC Valencia	3,77

Table 2.5: Comparison of Lead Times

As it can see in Table 2.5, it is possible to identify a first indicator of the efficiency of the different continental supply centres. In fact, thanks to the data collected, it is possible to see which centres have the greatest difference between planned and actual lead times.

It is possible to determine the percentage probability of meeting the promised Lead

Tiers name	Compliance with planned LT
CAC Seville	85,31%
CAC Lyon	98,90%
CAC Berlin	62,08%
CAC Bruxelles	60,11%
CAC Dortumund	61,44%
CAC Rotterdam	58,90%
CAC St.Etienne	95,45%
CAC Valencia	75,33%

Table 2.6: Probability of meeting the promised LT

Time. Certain tiers have a higher risk of failing to adhere to the planned LT and it is recommended to mitigate the risk of delay.

Another important aspect to consider is the analysis of the most frequently used transport routes by each supply center. This analysis provides valuable insights into the efficiency and effectiveness of the transportation network. By identifying the commonly used routes by supply centers, logistics managers can optimize transportation planning, streamline route selection, and potentially negotiate better terms with transport providers. Furthermore, this analysis can reveal possible bottlenecks or inefficiencies in the transportation network, allowing for proactive measures to decrease costs.

Tiers name	rail	road	sea
CAC Sevilla	0,12%	12,10%	85,78%
CAC Lyon		99,44%	
CAC Berlin	85,80%	13,60%	0,60%
CAC Bruxelles	61,04%	38,96%	
CAC Dortmund	84,78%	14,75%	0,47%
CAC Rotterdam	15,38%	84,62%	
CAC St.Etienne		100,00%	
CAC Valencia	0,18%	1,26%	98,01%

Table 2.7: Used transport

Furthermore, it is possible to identify the main reasons for delays or cancellations associated with particular transport routes. By examining these correlations, logistics managers can identify recurring problems, such as traffic congestion, adverse weather conditions, or logistical constraints along specific routes. This understanding enables targeted interventions to address the root causes, reduce risks, and improve route efficiency. Implementing proactive measures, such as diversifying routes, using alternative transport modes, or creating contingency plans, can minimise the impact of delays and cancellations.

Status	rail	road	sea
Canceled truck	34,85%	33,71%	31,44%
Canceled truck out delay	19,19%	6,06%	74,75%
Truck never arrived	33,33%	47,22%	19,44%

Table 2.8: Comparison beetween transport mode and status

In this case, it has been observed that cancellations primarily occur when goods are transported by sea. This highlights the vulnerability of maritime transport to various factors, such as adverse weather conditions, port congestion, or unforeseen events like vessel breakdowns.

Generally, the data indicate that sea transport is the mode most prone to delays, followed by road, while rail appears to be the most reliable in terms of timeliness. However, the road has the highest percentage of missed arrivals, which could indicate challenges in managing road deliveries.

In addition, the qualitative database provides information on the haulage companies used by each supply center. This forms the basis for comprehensive analyses aimed at evaluating the effectiveness and performance of these entities in logistical operations.

Tiers name	Carrier punctuality
CAC Sevilla	0,85
CAC Lyon	0,95
CAC Berlin	0,78
CAC Bruxelles	0,61
CAC Dortmund	0,92
CAC Rotterdam	0,83
CAC St.Etienne	0,93
CAC Valencia	0,74

Table 2.9: Carriers punctuality

A basic analytical approach is to examine the average delay experienced by carriers on different routes, thereby identifying patterns and discrepancies in transport efficiency across different logistical pathways.

2.5.2 Quantity DB

When building a quantitative database, it is essential to consider volumes as a critical factor. Volumes are the quantities of goods moving to the distribution centre and serve as a fundamental metric for assessing operational performance and demand patterns.

The inbound volumes arriving at the DC serve as a critical determinant in assessing and addressing workforce-related challenges. Fluctuations in inbound volumes have a direct impact on workload distribution, staffing requirements and operational efficiency within the centre. By analysing inbound volume data, logistics managers can identify peaks in activity, anticipate staffing needs and optimize workforce scheduling accordingly. In addition, the insights gained from volume analysis can inform strategic decisions regarding workforce allocation, training initiatives, and process improvements to mitigate bottlenecks and improve overall productivity within the distribution centre.

Automating the process of recording incoming volumes into the database is a key factor, especially when dealing with daily volume recordings. This automation eliminates the need to manually update the database daily, streamlining data entry processes and reducing the risk of errors or omissions. By implementing automatic collection mechanisms, such as integrating data collection tools with the database system or using sensors for real-time volume tracking, incoming volume data can be seamlessly captured and updated in the database without manual intervention. This ensures that the database is always up to date and reflects the current operational realities within the distribution centre.

Date	Day	N. of week	Day of week	Month	Year	86	87	89	90	Transit	Total
11/12/2023	11	50	2	12	2023	773	44	0	348	298	1463
12/12/2023	12	50	3	12	2023	1732	10	0	108	306	2156
13/12/2023	13	50	4	12	2023	1087	3	0	34	169	1293
14/12/2023	14	50	5	12	2023	854	73	0	455	322	1704
15/12/2023	15	50	6	12	2023	3571	23	0	381	779	4754
16/12/2023	16	50	7	12	2023	848	48	0	7	392	1295
17/12/2023	17	51	1	12	2023	0	0	0	0	0	0

Table 2.10: Example of quantitative database

Chapter 3

Methodical approach and algorithm

This section will explore the process of creating inbound volume forecasting algorithms. We will provide a detailed examination of the methodological approach, along with valuable insights and techniques to improve the reliable of the forecast.

To create an accurate forecast that is tailored to the specific context, it is important to have a good understanding of the different forecasting algorithms available. This includes time series analysis, regression models, and machine learning techniques. Familiarising with these methodologies, it can utilise their strengths and nuances to produce a reliable forecast tailored to your context. Furthermore, investigating possibilities for customization enables the adaptation of these algorithms to consider distinctive factors and complexities inherent to the organisation, ultimately improving the precision and pertinence of the forecast.

As can be observed in Zotteri and Brandimarte's book [10], to begin making a forecast, it is necessary to establish certain parameters:

- Time bucket: The unit of time for which predictions are made, known as the time bucket, significantly impacts forecasting complexity. Forecasting for shorter intervals, such as a day, is typically more complex than forecasting for longer intervals, such as a week or a month.
- Forecasting horizon: The forecast horizon represents the advance with which volume estimates are to be made. For instance, if a time interval of one week is selected, it is important to determine whether to plan for the upcoming week or for week 52.

- Market and product: Having a comprehensive understanding of the market target and the specific products designated for receipt is paramount for accurate forecasting and effective logistics management. By thoroughly analyzing the market segment and product characteristics, including demand patterns, seasonality, and product lifecycle, logistics managers can tailor forecasting models to better anticipate fluctuations in demand and optimise inventory levels accordingly.

Once these parameters are established, it is possible to consider using some of the main forecasting methods.

3.1 Models and formulas

Exponential smoothing, introduced in the late 1950s by Brown, Holt, and Winters [11], remains a cornerstone in forecasting methodology. These methods have proven to be highly successful, providing efficient and reliable forecasts for diverse time series data, a pivotal asset for various industries. Some traditional prediction models are now exposed.

3.1.1 Mobile average (MA)

The moving average model is a useful tool in time series analysis for forecasting future demand trends, particularly when dealing with stationary demand patterns. This model operates on the principle of averaging the most recent k demand observations to derive a forecast for future periods.

$$F_{t,h} = \sum_{i=t}^{t-k+1} \frac{Y_i}{k} \tag{3.1}$$

Essentially, the moving average is the mean of the previous k observations. When selecting the value of k, it is important to consider the balance between a high k, which produces a forecast that is less affected by the most recent observation but may be slow to detect changes in average demand, and a low k, which produces a forecast that is heavily influenced by the most recent observation and is therefore highly responsive to change.

The moving average has a limitation in that it does not consider older observations.

3.1.2 Simple exponential smoothing (SES)

It is a model that proposes to use a weighted average between the last demand observation and the last forecast. This means that past forecasts are updated based on the most recent observations.

$$F_{t+h} = \alpha Y_t + (1-\alpha)F_{t-1,h} \tag{3.2}$$

h: horizon of forecast
α: change-response parameter and noise filtering
F_t: forecast at period t
Y_t: observed value at period t

In this prediction model, the parameter α is crucial in determining the balance between responsiveness and noise filtering. When α is set to a low value, predictions exhibit strong inertia, meaning they are less sensitive to short-term fluctuations or noise in the data. This characteristic makes the model more robust against erratic variations, ensuring that forecasts capture broader trends effectively. Conversely, if α is set to a high value, the model becomes more responsive to recent changes in the data, enabling quicker adaptation to shifts in demand patterns.

The main advantage of the exponential smoothing model is the ability to adapt to new data and refine its predictions over time. By continuously analyzing new data points, the model can dynamically adjust its parameters and update its forecasts to reflect changing patterns and trends in the data.

This model has the limitation of not detecting significant changes in the average level of demand over time.

3.1.3 Exponential smoothing with trend

A first case of non-stationarity in the presence of a positive or negative trend. This model is used when there is a trend of constantly increasing or decreasing inbound volumes [12].

$$F_{t,h} = B_t + hT_t \tag{3.3}$$

$$B_t = \alpha Y_t + (1-\alpha)(B_{t-1} + T_{t-1}) \tag{3.4}$$

$$T_t = \beta(B_t - B_{t-1}) + (1-\beta)(T_{t-1}) \tag{3.5}$$

β: trend-damping coefficient
B_t: the basic level achieved at period t
T_t: trend level achieved at period t

This formula presents a method for forecasting by breaking down the forecast into two crucial elements: a base factor and a trend factor. These factors are closely connected, with each updating process using the previous values of both the base and the trend. This dynamic interplay enables the model to capture the underlying patterns of the data, distinguishing between the baseline level of demand and the directional trend over time.

This model is particularly useful for enhancing the efficiency of inbound volume forecasting when clear downward or upward trends are evident. By capturing and extrapolating these trends, logistics managers can anticipate future fluctuations in inbound volumes with greater accuracy and precision.

The model has limitations when there are trend reversals and the forecast horizon is long.

3.1.4 Exponential smoothing with seasonality (Holt-Winters)

If the dataset shows recurring patterns of increasing or decreasing volumes at specific times of the year, the exponential smoothing model with seasonality can be applied.

To use this model effectively, it is essential to have a comprehensive understanding of both the market dynamics and the specific characteristics of the products being considered. This nuanced knowledge enables a thorough assessment of whether there are any seasonality patterns within the data. By identifying the presence and type of seasonality, such as regular fluctuations in demand linked to particular times of the year or recurring events, the model can be adjusted accordingly to consider these variations [13].

$$F_{t+h} = B_t \cdot S_{t+h-[\frac{h-1}{s}+1]s} \tag{3.6}$$

$$B_t = \alpha \frac{Y_t}{S_{t-s}} + (1-\alpha)B_{t-1} \tag{3.7}$$

$$S_t = \gamma \frac{Y_t}{B_t} + (1-\gamma)S_{t-s} \tag{3.8}$$

S_t: seasonality factor
γ: parameter that dictates the speed at which S_t is updated

The model for exponential damping with seasonality is based on a mechanism that calculates the average percentage decrease or increase for each period of the season. This approach involves analyzing historical data across different seasonal periods to discern underlying patterns of variation. By leveraging exponential damping techniques, the model dynamically adjusts these trends over time, capturing both short-term fluctuations and longer-term seasonality effects. This understanding of the data allows for more accurate forecasting by accounting for the inherent variability and cyclicality observed within seasonal demand patterns.

Although the exponential damping model with seasonality provides powerful forecasting capabilities, it has limitations. Firstly, this method typically requires a large volume of historical data to accurately capture and model seasonal patterns. Without sufficient data points, the model's effectiveness may be compromised, leading to less reliable forecasts. Additionally, the dynamic nature of seasonality presents another limitation. Seasonal patterns can change significantly over time due to various factors, such as shifts in consumer preferences, market trends, or external influences. Therefore, the model's assumptions about seasonality may become outdated or less accurate as time progresses.

3.1.5 Exponential smoothing with seasonality and trend

The following formulas can be used to jointly consider a trend and seasonality factor

$$F_{t+h} = (B_t + h \cdot T_t) \cdot S_{t+h+s\cdot[(h-1)/s+1]} \tag{3.9}$$

$$B_t = \alpha \frac{T_t}{S_{t-s}} + 1(1-\alpha)(B_{t-1} + T_{t-1}) \tag{3.10}$$

The seasonality and trend factors are updated as described above [Equation 3.5 Equation 3.8].

This method integrates the anticipated growth or decline with the base value to adjust the forecast. A multiplication factor tied to seasonality is also factored in to further refine the forecasted values. This dual approach ensures that both the underlying trend and the seasonal variations are adequately accounted for. By considering both aspects, the model can effectively capture the nuanced dynamics of the data and provide more reliable predictions, even in the presence of seasonal fluctuations.

3.2 Performance

To properly assess the effectiveness and reliability of the algorithms under consideration, it is imperative to conduct a comprehensive evaluation of their prediction performance. This evaluation involves analyzing various metrics, such as accuracy, precision, and mean squared error, to gauge how well the algorithms align with the observed data [14].

- BIAS: it refers to the tendency of a model or method to consistently overestimate or underestimate the true value it is trying to predict. The use of a simple average to calculate errors can result in positive and negative errors canceling each other out, which may obscure the overall accuracy of the forecast. BIAS, as a measure of deviation, provides valuable insight into the direction and magnitude of the forecast errors. By summing all errors, BIAS offers a clear indication of whether the forecast tends to overestimate or underestimate actual values, serving as a 'centrality' indicator that highlights the overall tendency of the forecast. This metric is crucial for understanding the systematic bias inherent in the forecasting model

- Mean Absolute Deviation (MAD): in this assessment, the absolute values of forecast errors are utilized. Unlike BIAS, where positive and negative errors may offset each other, the Mean Absolute Deviation (MAD) aggregates both positive and negative errors, offering a comprehensive indicator of forecast accuracy. By summing the absolute values of forecast errors and averaging them, MAD provides a clear measure of errors, regardless of their direction. This metric is invaluable for evaluating the overall accuracy of the forecasting model and identifying areas for improvement

- Root Mean Square Error (RMSE): the RMSE serves as a measure of deviance in forecasting accuracy. It involves squaring the individual forecast errors, thereby considering both positive and negative errors while also providing an estimate of the variance of the volumes. By squaring the errors, RMSE accentuates larger errors, placing greater emphasis on deviations that have a more pronounced impact on inventory management. This weighted approach enables a detailed evaluation of forecast deviation ensuring that significant errors are appropriately accounted for in the evaluation process.

3.3 Forecast month

The initial forecast to be conducted is a one-month forecast. Before starting the forecast, it is essential to analyze the available data set. This includes examining the data's characteristics, such as trends, seasonality, and patterns of variation. This will help determine the most suitable forecasting model based on the dataset's unique attributes.

The dataset provided for the case study shows a clear long-term trend of decreasing inbound volumes over time, as well as a seasonal pattern with higher inbound volumes observed during the summer and winter months. The exponential smoothing method with trend and seasonality [Equation 3.9] was chosen due to the observed downward trend and seasonal pattern in the dataset. By incorporating trend and seasonality components into the forecast, a more accurate representation of the underlying patterns and dynamics observed in the dataset is enabled.

3.3.1 Initialisation

The choice of initialization methods is based on empirical evaluation of forecast reliability, with a primary focus on minimizing RMSE values. This approach enables a comprehensive exploration of various initialization strategies and their respective impacts on forecast performance, ultimately facilitating the selection of the most effective method for achieving reliable forecasts.

In initializing the exponential smoothing method with trend and seasonality, three main factors were considered: the parameters B, T, and S.

- B: it was determined that the most effective approach for initializing the base value is to employ a straightforward method. This involves averaging the values from the first 12 months, which represents the initial year available in the dataset. This method was determined to offer the optimal balance between simplicity and accuracy. It utilizes data from the earliest period to establish a strong foundation for the forecast, while minimizing potential biases introduced by more complex initialization techniques.

- T: for the initialization of the trend factor, a method was employed where the first 12 trends recorded in the dataset were averaged. This approach leverages the trend information from the initial year of data to establish an initial estimate of the underlying trend in the time series. By averaging these trends, the initialization process aims to provide a balanced and representative starting point for capturing the long-term directional movement observed in the data. [10]

$$T_0 = \frac{1}{s}\sum_{i=1}^{s}\frac{Y_{s+i} - Y_i}{s} \tag{3.11}$$

- S: regarding seasonality, the first 12 factors have been initialized differently. The first factor is calculated by adding the first observed value to the first observed value of the following year, from which 13 trend factors T_0 are subtracted, all divided twice by the factor B_0. The others simply making observed month divided by B_0.

$$\begin{cases} S_1 = \frac{Y_1+Y_{13}-13T_0}{2B_0} \\ S_{j-s} = \frac{Y_j}{B_0} & \text{per } j \neq 1 \end{cases}$$

3.3.2 Case study

In the case study, a dynamic adaptation of the forecast was noted over the course of the years, with improvements in accuracy observed in the later periods, particularly in the last year of the dataset. This dynamic nature of the forecast reflects the model's ability to learn and adjust over time, incorporating new information and refining its predictions as more data becomes available.

By including additional years of data, the forecast is expected to benefit from a more comprehensive understanding of the underlying patterns and trends within the dataset. The longer historical time series incorporated into the forecasting model provides insights into a broader range of seasonal variations, trend dynamics, and potential anomalies that may impact inbound volumes. This dataset expansion allows the model to learn more effectively from past patterns and make more informed predictions for future periods. Moreover, the increased volume of data enhances the forecast's robustness, providing greater confidence in the accuracy and reliability of the predicted outcomes.

In the case study, was selected the following values to optimize error values, with a particular focus on RMSE.

alfa	beta	gamma	BIAS	MAD	RMSE
0,40	0,25	0,30	-4166	8989	8,08E+07

Table 3.1: Case study month

The values for bias and RMSE are calculated by averaging the errors of the monthly inbound volume forecasts over the last 12 months. In general, the algorithm performs best with low values of the beta and gamma parameters, and an average value of the alpha parameter. This indicates that the best performance is achieved when attempting to filter out noise caused by fluctuations in the input data of the volumes.

As shown in Table 3.1, a negative BIAS value indicates that the forecast is, on average, higher than the observed values, but not significantly so. Overall, although there may be fluctuations in the inbound volume figures [Figure 3.1], the forecast line reflects the trends observed in the recorded values. This alignment between the forecast and the actual data indicates that the forecasting model effectively captures the underlying patterns and dynamics within the dataset. Despite the inherent variability in inbound volumes, the model's ability to track the recorded values demonstrates its capacity to provide information that will improve in the year.

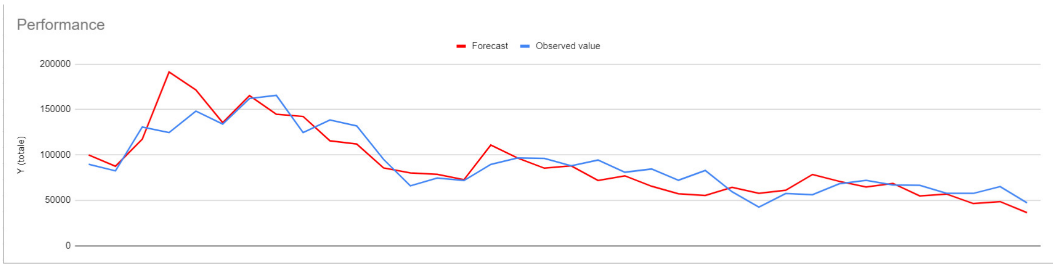

Figure 3.1: Performance Month

3.4 Forecast week

When transitioning to the weekly forecast, the year is divided into 52 weeks, each representing a distinct time interval. A time horizon of five weeks has been designated for the forecast, allowing for a focused analysis of short-term trends and fluctuations in inbound volumes. This narrower time frame allows for a more detailed analysis of the data, making it easier to identify weekly patterns and variations that could affect logistics centre operations.

Furthermore, the weekly forecast provides increased flexibility in responding to quickly changing market conditions and emerging trends, guaranteeing that the logistics centre remains adaptable and responsive to evolving demands.

Following the American model, weeks start on Sunday and end on Saturday. For convenience, the first and last days of the year are merged with the closest weeks, giving a total of exactly 52 weeks per year.

The weekly forecast continues to use the exponential smoothing model with trend and seasonality [Equation 3.9], this approach enables the incorporation of short-term trends and seasonal variations into the prediction process. By using this model, the forecast can effectively capture the dynamic nature of weekly inbound volumes, accounting for underlying trends and periodic fluctuations that may occur throughout the year.

3.4.1 Initialisation

The weekly forecast required the same parameter initialisation as the monthly forecast, using the same forecasting model.

- B: the weekly forecast model has introduced a strategic adjustment to the initialisation of the base value B_0. Previously, the approach was similar to that of the monthly forecast model, which involved averaging the observed value. However, instead of solely considering the values from the first year, the decision was made to calculate the average of all the values spanning the four available years. The modification aimed to capture a broader representation of the underlying patterns and trends observed in the dataset. By incorporating data from multiple years, the initialisation process gained a more comprehensive understanding of the historical inbound volume trends, thereby improving the reliability of the forecasted outcomes.

- T: the T_0 was initialised as it is in the monthly forecast model [Equation 3.11]. Then, the average of the first 52 recorded trend factors is calculated. The T factor is calculated by subtracting the observed value at period t from the value observed at period s+t. For instance, to calculate the T factor for January 2018, subtract the observed value of January 2019 from that of January 2018.

- S: to initialise S_0 in the weekly forecast model, is used the same formula of the month forecast [Equation 3.3.1]. However for seasonality values 1 to 52 a strategic approach was taken. Instead of relying on data from a single year, the averages of individual weeks across all four available years were considered.

3.4.2 Case study

The forecasts produced in the case study generally correspond well with the overall trend observed in the data, effectively capturing the underlying patterns and dynamics. However, it is important to note that there are instances of fluctuations within the data that present difficulties for the forecast model to anticipate accurately. Although the forecasting algorithm incorporates trend and seasonality components, deviations between forecasted and actual values may occur due to unforeseen factors or anomalies. These fluctuations may be influenced by external factors such as sudden changes in market demand, unexpected disruptions in supply chains, or seasonal variations that are not fully accounted for in the model.

Compared to the weekly forecast model, there are minor differences in parameter settings. This is because datasets can react differently and the model requires the ability to adapt and respond to rumors about the dataset.

alfa	beta	gamma	BIAS	MAD	RMSE
0,45	0,10	0,50	-937	1897	5,75E+06

Table 3.2: Case study Week

The Table 3.2 displays insights into the average performance over the last forecast year. Although there is a discernible trend of slightly over-forecasting, the deviations from the actual values are relatively balanced overall. While some forecasts may exceed the observed values, others may fall short, resulting in a distribution of errors that can be characterized as centered around the actual outcomes. The statement implies that the forecasting model may have a slight tendency to overestimate or underestimate inbound volumes in certain periods, but overall it maintains a reasonable level of accuracy in its predictions.

The Figure 3.2 shows that the forecasts generally follow the curve of the observed values, with the exception of a few weeks that experienced significant fluctuations. These fluctuations are likely due to external factors beyond the company's control.

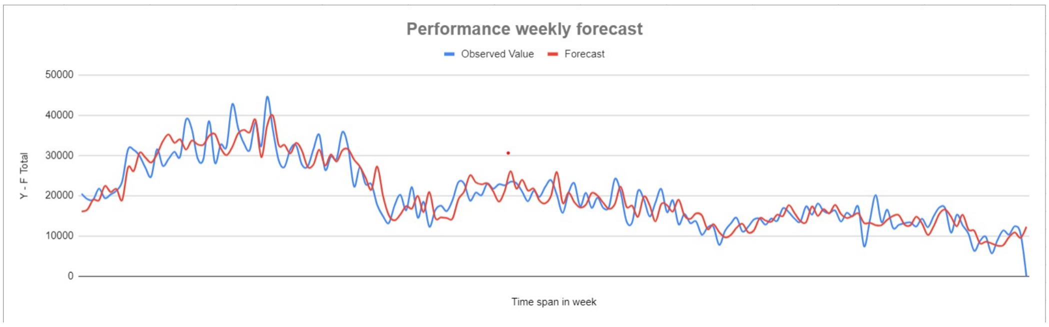

Figure 3.2: Performance Week

3.5 Forecast day

The daily forecast model establishes a forecast horizon of 35 days to provide a detailed projection of inbound volumes over the short term. The prediction algorithm was created using the exponential smoothing model with seasonality. This choice was motivated by the challenge of identifying patterns on a daily basis due to the granularity of the time bucket, which is only one day. The exponential smoothing model with seasonality [Equation 3.6] a suitable framework for capturing short-term fluctuations and seasonal patterns in the dataset. This approach enables the forecast model to adapt dynamically to daily variations in inbound volumes while accounting for recurring patterns over time, enhancing its ability to generate accurate predictions for each day within the 35-day forecast horizon.

For this model, which is a more focused and specific forecast, some considerations had to be made to improve the performance of the forecast.

3.5.1 Weekly seasonality

After analysing the dataset of daily observations, it is clear that there is a consistent trend of higher volumes being received on weekdays, particularly those situated in the middle of the week, as opposed to Mondays and Saturdays. After analysing the dataset of daily observations, it is clear that there is a consistent trend of higher volumes being received on weekdays, particularly those situated in the middle of the week, as opposed to Mondays and Saturdays. It is important to note that this analysis is based on objective observations and not subjective evaluations. This trend may reflect underlying factors such as regular business operations, increased activity levels during weekdays, or specific industry dynamics that influence inbound volumes. Recognising patterns can help optimise resource allocation, schedule staffing levels, and manage inventory effectively in the logistics centre. It is also important to incorporate day-of-week effects into forecasting models to enhance their accuracy and reliability in predicting inbound volumes over different time periods.

This weekly pattern was calculated by analysing the percentage distribution of volumes within each week.

	Sunday	Monday	Tuesday	Wednesday	Thusday	Friday	Saturday
Distribution percentage	0,00%	17,64%	19,39%	16,10%	18,55%	17,78%	10,54%
Weight factor	0,000	1,058	1,163	0,966	1,113	1,067	0,632

Table 3.3: Weekly seasonality

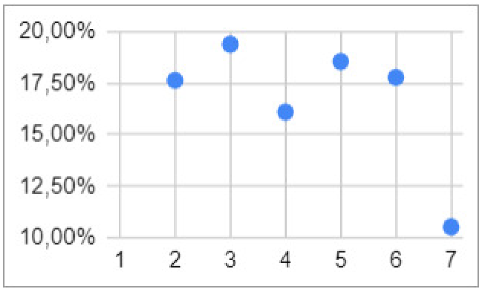

Figure 3.3: weekly seasonality

The Table 3.3 presents a snapshot of volume distribution throughout the week over the past two years. Using data extracted from a simple Excel pivot table analysis, this text clearly illustrates the operational patterns of the DC. One significant observation is the lack of inbound volumes on Sundays, indicating a complete cessation of receiving activities on that day. Furthermore, the data indicates a noticeable decrease in reception levels on Saturdays in comparison to the other days of the week.

In order to improve the algorithm's performance, the weekly trend has been introduced as a multiplicative component. It has been observed that incorporating weekly seasonality is advantageous for enhancing forecast precision. However, instead of relying on the average distribution of the past two years, greater accuracy can be achieved by considering a shorter timeframe, such as the last year or the preceding six months. This adjustment ensures that the forecast model captures recent trends and fluctuations in volume distribution, improving its ability to generate accurate predictions that reflect current operational realities within the distribution center.

3.5.2 Peak

The algorithm's performance was slightly enhanced by incorporating peak detection. Analysis of the data revealed instances where reception volumes significantly deviated from the average, indicating peaks in activity. Following these peak days, a pattern emerged wherein reception volumes tended to exhibit a regression towards the mean. For example, following days of exceptionally high volumes, it was common to observe lower-than-average reception the following day, and vice versa.

To tackle this challenge and reduce the risk of inaccurate predictions, we implemented a strategy to detect peaks whenever the received quantity significantly deviated from a pre-set parameter. When a peak was identified, we decided to halve the alpha value. This adjustment effectively decreased the weight assigned to fluctuations, resulting in a more stable forecast model.

By incorporating the concept of peaks into the forecasting model, the algorithm can dynamically adjust its predictions based on recent deviations from the norm. This adaptive approach enables the model to more accurately capture short-term fluctuations in reception volumes and adjust its forecasts accordingly.

3.5.3 Festive days

Another correction was made by identifying public holidays and forecasting a volume of 0 for those days. This adjustment was necessary because days with no reception could significantly impact the forecast algorithm. By excluding public holidays from the forecast calculations and assigning a predicted volume of 0 for these days, the model's accuracy and stability were improved. This ensures that the algorithm's predictions are not unduly influenced by days where no reception activity occurs, thereby enhancing the overall reliability of the forecasting process.

3.5.4 Initialisation

In this case, the performance of the model was significantly affected by the choice of parameter initialisation, particularly for the S factor:

- B: in the daily forecast model, the B_0 value was initialized by calculating the average of all non-zero values in the dataset. This method ensures a balanced initial value across the entire dataset, using available information to establish a representative starting point for the forecast.
- S: the algorithm's performance was considerably improved by taking into account several considerations during the initialisation of seasonality values. To determine the value of 's', the weekly seasonality's observed values were cleansed depending on the day of the week.

$$S_t = \frac{Y_t}{B_0 \cdot S_{week}} \tag{3.12}$$

  S_{week}: This value refers to the seasonality factor, which is different for each day of the week.

  To stabilize the seasonality component and provide a more consistent representation of seasonal patterns, a weighted approach was adopted to mitigate the fluctuation of the S values. The identified S values were weighted by considering the two previous and two following non-zero values. This strategy incorporates information from adjacent periods, smoothing out any abrupt changes.

3.5.5 Case study

In this scenario, a lower alpha value was selected to achieve optimal performance with an algorithm that effectively filters out noise in variable observations. By selecting a lower alpha value, the algorithm prioritised stability and noise reduction over simply averaging fluctuating observations. By prioritising noise reduction, the algorithm can generate predictions that are less vulnerable to short-term fluctuations and anomalies.

Also in this case, errors are defined based on the average values of the last forecast year.

alfa	gamma	BIAS	MAD	RMSE
0,25	0,30	44	850	1,39E+06

Table 3.4: Case study Day

Although the prediction bias is minimal, indicating a centered forecast, the Mean Absolute Deviation (MAD) may not be equally low, particularly when making daily point forecasts. This discrepancy arises due to the inherent challenges associated with forecasting at a granular level. As the forecasting horizon becomes increasingly narrow, the risk of inaccuracies rises proportionally. The phenomenon of higher sensitivity of short-term forecasts to unforeseen variations and fluctuations in the data is well-established.

Forecasting with a small time bucket entails greater uncertainty and, consequently, a higher likelihood of errors. Despite efforts to minimize bias, the constraints of forecasting at a daily level introduce complexities that can impact the accuracy of point forecasts. Therefore, although the overall forecast may be accurate, the MAD for daily point forecasts may remain relatively high due to the inherent volatility and unpredictability of short-term data.

The Figure 3.4 illustrates that the forecasting strategy prioritises generating predictions based on the average values observed in the data, rather than aiming for precision in day-to-day forecasts.

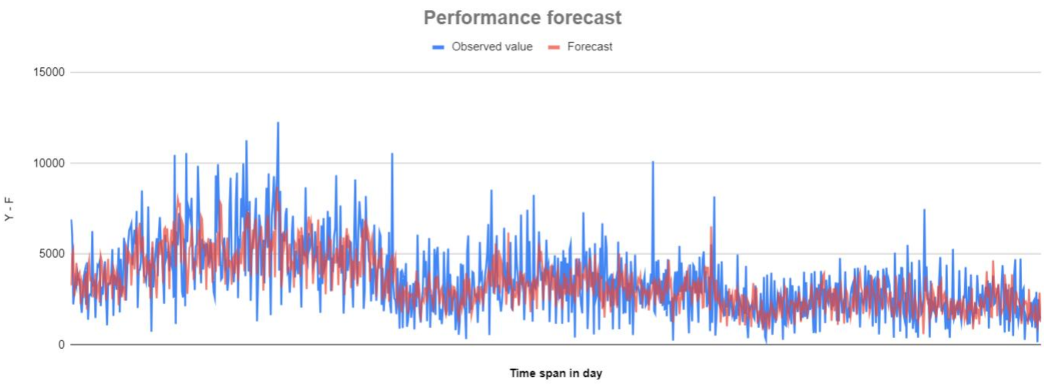

Figure 3.4: Performance Day

Chapter 4

Workforce forecasting

Once the forecast inbound volumes have been collected, it becomes possible to calculate the number of personnel required to efficiently manage the warehouse operations. The following paragraphs will present a comprehensive analysis of the key factors that influence the estimation of required personnel in the warehouse. By thoroughly examining these factors, the aim is to provide a holistic approach to workforce planning that optimises efficiency and meets operational demands, in order to reduce extra costs.

4.1 Worker efficiency

The quantification of worker efficiency necessitates a multifaceted approach, which considers a range of factors, including morale, the working environment, the availability of technology, and more [15].

The following section will identify five critical factors that play a pivotal role in determining staff efficiency within the context of a distribution centre. These factors will be examined in order to gain insights into their impact on workforce productivity and performance.

- Employee engagement: Measure employee engagement, job satisfaction and motivation to assess their impact on productivity and efficiency. Engaged and motivated employees tend to perform better and demonstrate a higher level of commitment to achieving organisational goals.
- Adaptability: It is a crucial aspect of workforce efficiency within the distribution centre, as it enables workers to transition seamlessly between different

roles and tasks as operational needs evolve. Those who demonstrate adaptability are able to fulfil a variety of responsibilities across different departments or functions within the distribution centre. The capacity to be interchangeable in their roles allows for the optimal utilisation of resources and the management of workloads, particularly during peak periods or unforeseen fluctuations in demand.

- Experience: Experienced workers typically demonstrate higher levels of proficiency, productivity, and effectiveness in performing their tasks compared to their less experienced counterparts. This proficiency is the result of accumulated knowledge, skill mastery, and familiarity with operational procedures and equipment, allowing experienced workers to execute tasks with greater speed, accuracy, and confidence. Furthermore, the depot benefits from the availability of personnel with the requisite qualifications to operate warehouse vehicles, given that they hold the requisite licences.

- Organisation: characterised by competent management and well-structured departments, it has a significant impact on the efficiency and morale of DC workers. A competent management team sets clear objectives, provides strategic direction and fosters a supportive working environment, enabling employees to perform at their best and contribute positively to the overall goals of the organisation.

- Productivity metrics: Measure the performance and throughput of individual workers, such as the number of units picked, packed or shipped per hour or shift. Productivity metrics provide tangible indicators of worker performance and efficiency in completing tasks within the DC.

While these elements contribute to overall efficiency, the objective is to develop a methodology to measure worker efficiency within the context of a distribution centre. The methodology will likely encompass objective metrics, productivity indicators, and performance assessments tailored to the specific tasks and responsibilities of workers. By analysing quantitative data and performance metrics, the aim is to provide a quantitative assessment of worker efficiency, while acknowledging the influence of qualitative factors on overall performance.

The focus of this paragraph is on human labour conducted by operators within the distribution centre. It is important to note that discussions related to automated warehouses will be excluded, as the workforce required is significantly reduced due to the extensive use of technology and robotics for handling tasks traditionally performed by human workers.

In order to quantify the efficiency of individual workers, the following formulas are introduced and subsequently explained.

$$Worker\ number = \frac{Number\ of\ parcel}{Capacity \cdot Hours\ in\ a\ working\ day \cdot Efficiency} \tag{4.1}$$

Capacity [4.1]: This coefficient has been calculated specifically for the warehouse in question. In general, the figure represents the number of parcels that a warehouseman can receive in one hour when working at full capacity.

Number of parecls [4.1]: The parcel was selected as the unit of measurement because it is considered the most reliable indicator for estimating incoming quantities. In contrast to other metrics, such as actual volumes or load sizes, parcels offer a consistent and manageable unit of analysis. The actual volumes can vary significantly due to the differing sizes and shapes of the loads, making it challenging to standardise measurements. The same goes for trucks, which cannot be used as a unit of measurement because stuffing would not be taken into account and a clean figure of inbound volumes would not be produced. The utilisation of parcels ensures the representation of quantities being handled is more uniform and accurate. This approach helps to mitigate the uncertainties associated with varying load volumes, thereby providing a more reliable basis for forecasting and planning logistics operations.

Efficiency [4.1]: Efficiency is a parameter that quantifies the actual capacity of a receiving operator. The efficiency is calculated from the actual data history as the ratio of the expected to the actual reception. The efficiency figure may fluctuate over time and encompass all the aforementioned quality factors, as well as any necessary physiological breaks that a worker may have to take.

Hours in a working day [4.1]: In this instance, it is assumed that a single working day. Consequently, the calculation of the requisite number of workers will yield the number of workers required for a single working day. Should one wish to extend the temporal scope, it is sufficient to enter the number of hours corresponding to the desired temporal horizon. To illustrate, if one were to calculate the number of workers required in a given month, one would utilize the figure for the number of parcels scheduled for that month and the number of working hours in that month, without modifying the aforementioned formula.

4.2 Cost of overworking or underworking

Should the projected production figures deviate significantly from the actual figures, there is a substantial risk of incurring additional costs.

In fact, a considerable component of the costs incurred by a warehouse is personnel costs. To better understand this, we will now look at two different types of costs: overworking and underworking costs.

Overworking Costs: When there is a mismatch between the forecasted and actual inbound volumes, leading to an unexpected surge in workload, employees may be required to work overtime. Overtime work typically comes at a premium, increasing the hourly wage and consequently the overall labor costs. Additionally, excessive overtime can lead to employee burnout, decreased morale, and reduced productivity in the long term. Overworking can also result in increased errors, accidents, and the need for temporary workers, further adding to the costs.

Underworking Costs: On the other hand, if the forecasted volumes are significantly higher than the actual volumes, the warehouse may be overstaffed. This leads to paying for idle time, where employees are not fully utilized. Underworking can result in inefficiencies as workers may not be engaged or motivated, potentially leading to higher turnover rates. Furthermore, maintaining a larger workforce than necessary can incur additional costs related to benefits, training, and management.

In both scenarios, the misalignment between forecasted and actual volumes can have a substantial financial impact on warehouse operations. Therefore, accurate forecasting is crucial to balancing the workforce effectively and optimizing personnel costs.

In particular, two phenomena causing higher costs to the warehouse are identified, which should generally be avoided in internal management.

- Overtime: Overtime is a costlier form of work than normal work. In particular, when considering the CCNL contract for the sectors of Goods Distribution, Logistics and Private Services, and simplifying the various cases of overtime, we obtain an average increase in remuneration that can range from 20 to 30 per cent above the normal hourly wage. Furthermore, the number of overtime hours is limited to 250 for year. While overtime hours may be beneficial in certain circumstances, their systematic use to address staff shortages is not a viable solution [16].

- Agency fees: Should it be necessary to recruit workers to fill peaks in demand, relying on an internal agency entails several costs. These costs include administrative expenses for managing the recruitment process, training new hires, and ensuring they are adequately prepared to handle the tasks required. Additionally, the use of an internal agency may involve fees related to advertising the positions, conducting background checks, and processing employment paperwork. Moreover, short-term or temporary workers often require a premium wage due to the nature of their employment, which can further escalate costs. There are also potential productivity losses as new workers acclimate to their roles and the work environment, which can initially reduce overall efficiency. Furthermore, managing a fluctuating workforce requires additional efforts in scheduling, supervision, and maintaining consistent operational standards, all of which contribute to higher operational costs. Furthermore, hiring temporary workers who will not remain stable in the company does not help to consolidate internal know-how at a strategic level. Temporary workers, due to their transient nature, often lack the time to fully integrate into the company culture and processes, which can lead to a loss of valuable knowledge and skills that are developed over time with permanent staff.

4.3 Recruiting time

Prior to embarking upon a detailed examination of the case study, it is imperative to conduct a comprehensive analysis of the various employment contracts that are available within the logistics warehouse. This process entails an in-depth examination of the relative merits and drawbacks of each contract type, with particular attention paid to factors such as cost, flexibility, worker retention, and the impact on internal know-how.

- Full-time employment. Firstly, full-time employment provides stability and reliability. It can be reasonably assumed that full-time employees are less likely to leave their company of employment, thereby reducing the rate of employee turnover and ensuring consistent levels of performance. Such employees are more likely to be committed to and invested in the long-term success of the organisation. Furthermore, full-time employees have greater opportunities for the development and retention of their skills. Over time, employees become more proficient and familiar with the company's processes, which enhances efficiency. The long-term retention of full-time employees facilitates the maintenance of institutional knowledge, which is of paramount importance for the growth and stability of the organisation. Nevertheless, full-time employment is not without its disadvantages. One of the primary disadvantages of full-time employment is the higher cost. The remuneration of full-time employees is typically higher than that of part-time employees, leading to increased labour costs. The provision of benefits such as health insurance and retirement plans contributes to the overall expense. Furthermore, full-time contracts afford less flexibility in adjusting the workforce in response to fluctuating demand, which presents a challenge in adjusting staffing levels during periods of low demand. Another potential issue is the risk of burnout. It is possible that full-time employees may experience burnout as a result of prolonged periods of high workload, which could have an adverse effect on their productivity and morale. Consequently, it is of paramount importance to manage employee well-being in order to prevent burnout and maintain high levels of productivity and job satisfaction.

- Part-time employment offers its own set of advantages. It is generally more cost-effective than full-time employment. Part-time workers typically have lower overall compensation costs, including wages and fewer benefits. This allows employers to reduce labor costs by hiring part-time workers for peak periods without committing to full-time salaries. The flexibility offered by part-time employment is another significant advantage. It allows for easier adjustments in staffing levels based on demand, enabling employers to hire additional staff during busy periods and reduce hours during slower times. Part-time jobs can attract a diverse workforce, including students, parents, and retirees, who value flexible working hours. This diversity can enhance the workplace environment and bring in a range of skills and perspectives. Additionally, part-time employment can help employees achieve a better work-life balance, potentially leading to higher job satisfaction and overall well-being. Hiring part-time workers can also help reduce the need for overtime from full-time employees, effectively managing labor costs and preventing burnout among full-time staff. However, part-time employment also has its disadvantages. Part-time employees might have lower levels of commitment and loyalty compared to full-time workers, leading to higher turnover rates and increased recruitment and training costs. They may also have fewer opportunities for training and professional development, which can limit their skill development and efficiency. Furthermore, part-time employees' varying schedules can lead to inconsistent availability and potential staffing gaps, making coordination and scheduling more complex.

- Internal fixed-term workers: It is possible to employ internal fixed-term workers for a limited period, such as one day or one week. Although this approach is generally more expensive, it allows for a quick reaction to peaks in demand. Nevertheless, the recruitment process for internal fixed-term workers tends to be longer than that for workers hired through a temporary agency. The additional time required for recruitment may prove disadvantageous in situations where immediate workforce adjustments are required.

- Subcontracting fixed-term workers: Similarly, fixed-term workers engaged through subcontracting offer the same benefits as in-house workers, albeit with shorter recruitment times and slightly higher costs.

4.4 Case study

The objective of this case study is to conduct an analysis of the personnel costs associated with unloading activities in the warehouse. This analysis will entail a comparative assessment of two forecasting methods: the traditional approach, which relies on the previous year's data to predict inbound volumes, and the predictive approach that utilises a developed forecasting algorithm. The objective of this analysis is to determine which forecasting technique provides a more accurate and cost-effective solution for managing workforce requirements in the warehouse.

In the calculation of man-hours, certain numerical approximations will be made using the following values as constants.

	Full time	Part time	Staff leasing
Cost	20 €/h	18 €/h	30 €/h
Capacity	80 parcels/h	80 parcels/h	80 parcels/h
Efficiency	80%	70%	70%
Hiring time	6 weeks	6 weeks	3 weeks

Table 4.1: Numerical approximations

It is estimated that the hourly costs of full-time contracts are higher than those of part-time contracts due to the higher benefits provided. Conversely, the costs associated with staff leasing are considerably higher due to the presence of agency costs. It is estimated that efficiency is higher for a permanent employee, lower for part-time and staff leasing, as they are less motivated. In the context of a staff leasing contract, a third party subcontracts resources to work in the warehouse. This type of contract is highly flexible, allowing for the coverage of peaks at a higher cost.

4.4.1 Traditional method

The traditional method involves utilising the previous year's figures as the basis for predicting driving volumes. This approach is currently employed in the warehouse under study. It relies on empirical data and manually adjusted forecasts, which are influenced by the decisions and experience of managers. Parcel data are those actually obtained in the year 2023.

For the purposes of this case study, it is assumed that the use of overtime or a temporary worker is comparable in terms of cost and timing and that it costs 30€/h. The number of staff required is calculated using the above Equation 4.1. The average required quantity of material is calculated, and an allocation of three full-time and four part-time employees is estimated to be convenient in the traditional planning method. A restriction is also created that the number of part-time workers, being four, cannot exceed four workers per day and must be assigned a maximum of 10 times each week, half of the full-time workers.

The data obtained by the traditional method on the first five months of 2024 are listed below.

Table 4.2: Traditional Method

	TRADITIONAL		3	4		
Dates	Parcel	Staff req	Full time	Part time	Det	Costs
01/01/2024	0	0	0	0	0	€ 0
02/01/2024	1455	3	3	1	0	€ 624
03/01/2024	2782	5	3	2	0	€ 887
04/01/2024	4458	9	3	4	1	€ 1.330
05/01/2024	2184	4	3	1	0	€ 697
06/01/2024	2028	4	3	2	0	€ 768
07/01/2024	0	0	0	0	0	€ 0
08/01/2024	4596	9	3	4	1	€ 1.330
09/01/2024	2279	4	3	2	0	€ 768
10/01/2024	1601	3	3	1	0	€ 624
11/01/2024	1634	3	3	0	0	€ 480
12/01/2024	3308	6	3	3	0	€ 912
13/01/2024	2053	4	3	0	1	€ 754
14/01/2024	0	0	0	0	0	€ 0
15/01/2024	2959	6	3	3	0	€ 912
16/01/2024	1580	3	3	0	0	€ 480
17/01/2024	2213	4	3	2	0	€ 768
18/01/2024	2761	5	3	3	0	€ 912
19/01/2024	1708	3	3	0	0	€ 480
20/01/2024	1989	4	3	2	0	€ 768
21/01/2024	0	0	0	0	0	€ 0
22/01/2024	1297	3	3	0	0	€ 480
23/01/2024	1830	4	3	1	0	€ 624
24/01/2024	1418	3	3	2	0	€ 768
25/01/2024	4971	10	3	4	2	€ 1.603
26/01/2024	1587	3	3	1	0	€ 624
27/01/2024	2532	5	3	2	0	€ 768
28/01/2024	0	0	0	0	0	€ 0

Table 4.2: (Continue)

	TRADITIONAL		3	4		
Dates	Parcel	Staff req	Full time	Part time	Det	Costs
29/01/2024	2248	4	3	2	0	€ 768
30/01/2024	1981	4	3	2	0	€ 768
31/01/2024	1249	2	3	1	0	€ 624
01/02/2024	3158	6	3	4	0	€ 1.056
02/02/2024	1702	3	3	1	0	€ 624
03/02/2024	0	0	0	0	0	€ 0
04/02/2024	0	0	0	0	0	€ 0
05/02/2024	4348	8	3	4	1	€ 1.330
06/02/2024	1107	2	3	2	0	€ 768
07/02/2024	363	1	3	1	0	€ 624
08/02/2024	2163	4	3	1	0	€ 624
09/02/2024	1972	4	3	2	0	€ 768
10/02/2024	0	0	0	0	0	€ 0
11/02/2024	0	0	0	0	0	€ 0
12/02/2024	2316	5	3	2	0	€ 768
13/02/2024	1575	3	3	0	0	€ 480
14/02/2024	1432	3	3	1	0	€ 624
15/02/2024	3272	6	3	3	0	€ 912
16/02/2024	3702	7	3	4	0	€ 1.056
17/02/2024	0	0	0	0	0	€ 0
18/02/2024	0	0	0	0	0	€ 0
19/02/2024	943	2	3	1	0	€ 624
20/02/2024	1666	3	3	2	0	€ 768
21/02/2024	901	2	3	2	0	€ 768
22/02/2024	2857	6	3	3	0	€ 912
23/02/2024	1434	3	3	2	0	€ 768
24/02/2024	0	0	0	0	0	€ 0
25/02/2024	0	0	0	0	0	€ 0
26/02/2024	3739	7	3	4	0	€ 1.056
27/02/2024	451	1	3	0	0	€ 480
28/02/2024	1269	2	3	1	0	€ 624
29/02/2024	3866	8	3	4	0	€ 1.056
01/03/2024	1664	3	3	1	0	€ 624
02/03/2024	0	0	0	0	0	€ 0
03/03/2024	0	0	0	0	0	€ 0
04/03/2024	3219	6	3	3	0	€ 912

Table 4.2: (Continue)

	TRADITIONAL		3	4		
Dates	Parcel	Staff req	Full time	Part time	Det	Costs
05/03/2024	3971	8	3	4	0	€ 1.056
06/03/2024	551	1	3	0	0	€ 480
07/03/2024	1599	3	3	0	0	€ 480
08/03/2024	3559	7	3	3	0	€ 912
09/03/2024	0	0	0	0	0	€ 0
10/03/2024	0	0	0	0	0	€ 0
11/03/2024	2346	5	3	2	0	€ 768
12/03/2024	3299	6	3	2	1	€ 1.042
13/03/2024	2933	6	3	2	0	€ 768
14/03/2024	2586	5	3	2	0	€ 768
15/03/2024	2783	5	3	2	0	€ 768
16/03/2024	0	0	0	0	0	€ 0
17/03/2024	0	0	0	0	0	€ 0
18/03/2024	268	1	3	0	0	€ 480
19/03/2024	3687	7	3	4	0	€ 1.056
20/03/2024	2919	6	3	3	0	€ 912
21/03/2024	1054	2	3	0	0	€ 480
22/03/2024	3141	6	3	3	0	€ 912
23/03/2024	0	0	0	0	0	€ 0
24/03/2024	0	0	0	0	0	€ 0
25/03/2024	1637	3	3	1	0	€ 624
26/03/2024	3686	7	3	4	0	€ 1.056
27/03/2024	1132	2	3	1	0	€ 624
28/03/2024	3277	6	3	3	0	€ 912
29/03/2024	1966	4	3	1	0	€ 624
30/03/2024	0	0	0	0	0	€ 0
31/03/2024	0	0	0	0	0	€ 0
01/04/2024	2963	6	3	2	0	€ 768
02/04/2024	2326	5	3	2	0	€ 768
03/04/2024	2402	5	3	2	0	€ 768
04/04/2024	3247	6	3	2	1	€ 1.042
05/04/2024	2446	5	3	2	0	€ 768
06/04/2024	0	0	0	0	0	€ 0
07/04/2024	0	0	0	0	0	€ 0
08/04/2024	2391	5	3	2	0	€ 768
09/04/2024	2083	4	3	1	0	€ 624

Table 4.2: (Continue)

	TRADITIONAL		3	4		
Dates	Parcel	Staff req	Full time	Part time	Det	Costs
10/04/2024	4025	8	3	4	0	€ 1.056
11/04/2024	2035	4	3	1	0	€ 624
12/04/2024	3448	7	3	2	1	€ 1.042
13/04/2024	0	0	0	0	0	€ 0
14/04/2024	0	0	0	0	0	€ 0
15/04/2024	1843	4	3	1	0	€ 624
16/04/2024	2497	5	3	2	0	€ 768
17/04/2024	1917	4	3	1	0	€ 624
18/04/2024	3955	8	3	4	0	€ 1.056
19/04/2024	1979	4	3	2	0	€ 768
20/04/2024	0	0	0	0	0	€ 0
21/04/2024	0	0	0	0	0	€ 0
22/04/2024	4055	8	3	4	0	€ 1.056
23/04/2024	627	1	3	0	0	€ 480
24/04/2024	3143	6	3	2	1	€ 1.042
25/04/2024	2475	5	3	2	0	€ 768
26/04/2024	3347	7	3	2	1	€ 1.042
27/04/2024	0	0	0	0	0	€ 0
28/04/2024	0	0	0	0	0	€ 0
29/04/2024	701	1	3	0	0	€ 480
30/04/2024	4071	8	3	3	1	€ 1.186
01/05/2024	3442	7	3	3	0	€ 912
02/05/2024	2646	5	3	2	0	€ 768
03/05/2024	3100	6	3	2	1	€ 1.042
04/05/2024	0	0	0	0	0	€ 0
05/05/2024	0	0	0	0	0	€ 0
06/05/2024	3586	7	3	3	1	€ 1.186
07/05/2024	2447	5	3	1	0	€ 624
08/05/2024	2773	5	3	1	1	€ 898
09/05/2024	3854	8	3	2	2	€ 1.315
10/05/2024	3438	7	3	3	0	€ 912
11/05/2024	0	0	0	0	0	€ 0
12/05/2024	0	0	0	0	0	€ 0
13/05/2024	2877	6	3	2	0	€ 768
14/05/2024	2714	5	3	1	1	€ 898
15/05/2024	2797	5	3	1	1	€ 898

Table 4.2: (Continue)

	TRADITIONAL		3	4		
Dates	Parcel	Staff req	Full time	Part time	Det	Costs
16/05/2024	3435	7	3	3	0	€ 912
17/05/2024	3418	7	3	3	0	€ 912
18/05/2024	0	0	0	0	0	€ 0
19/05/2024	0	0	0	0	0	€ 0
20/05/2024	1289	3	3	0	0	€ 480
21/05/2024	4779	9	3	4	2	€ 1.603
22/05/2024	2597	5	3	2	0	€ 768
23/05/2024	2431	5	3	2	0	€ 768
24/05/2024	2196	4	3	2	0	€ 768
25/05/2024	0	0	0	0	0	€ 0
26/05/2024	0	0	0	0	0	€ 0
27/05/2024	4047	8	3	4	0	€ 1.056
28/05/2024	2019	4	3	2	0	€ 768
29/05/2024	1221	2	3	1	0	€ 624
30/05/2024	2354	5	3	2	0	€ 768
31/05/2024	1654	3	3	1	0	€ 624

The traditional method was employed to calculate the budgeted personnel costs for the first five months of 2024, which in the sum of section cost of Table 4.2 were found to be €91,857.

4.4.2 Forecast method

In forecasting method, the data obtained from the aforementioned forecast are employed for the drafting of the piloting. In this case study, different forecast data were obtained, taking into account both the trend and seasonality factor [Equation 3.9]. This was the model that best suited the case study.

The average required quantity of material is calculated, and an allocation of two full-time and two part-time employees is estimated to be convenient in the forecast planning method.

The data obtained from the forecast values using the damping method with trend and seasonality are presented in the following table.

Table 4.3: Forecast method

	FORECAST		2	2		
Dates	Parcel	Staff req	Full time	Part time	Det	Costs
01/01/2024	0	0	0	0	0	€ 0
02/01/2024	1537	3	2	1	0	€ 464
03/01/2024	1383	2	2	1	0	€ 464
04/01/2024	2934	5	2	2	1	€ 848
05/01/2024	1508	2	2	1	0	€ 464
06/01/2024	1055	2	2	0	0	€ 320
07/01/2024	0	0	0	0	0	€ 0
08/01/2024	2006	3	2	1	0	€ 464
09/01/2024	2785	5	2	3	0	€ 752
10/01/2024	1160	2	2	0	0	€ 320
11/01/2024	1658	3	2	1	0	€ 464
12/01/2024	1514	2	2	0	0	€ 320
13/01/2024	1449	2	2	0	0	€ 320
14/01/2024	0	0	0	0	0	€ 0
15/01/2024	1602	3	2	1	0	€ 464
16/01/2024	1481	2	2	0	0	€ 320
17/01/2024	1457	2	2	1	0	€ 464
18/01/2024	1575	3	2	1	0	€ 464
19/01/2024	1454	2	2	1	0	€ 464
20/01/2024	854	1	2	1	0	€ 464
21/01/2024	0	0	0	0	0	€ 0
22/01/2024	1494	2	2	0	0	€ 320
23/01/2024	1168	2	2	0	0	€ 320
24/01/2024	2080	4	2	2	0	€ 608

Table 4.3: (Continue)

	FORECAST		2	2		
Dates	Parcel	Staff req	Full time	Part time	Det	Costs
25/01/2024	1706	3	2	1	0	€ 464
26/01/2024	3584	7	2	2	3	€ 1.328
27/01/2024	994	1	2	0	0	€ 320
28/01/2024	0	0	0	0	0	€ 0
29/01/2024	1583	3	2	1	0	€ 464
30/01/2024	1519	2	2	0	0	€ 320
31/01/2024	878	1	2	0	0	€ 320
01/02/2024	1454	2	2	1	0	€ 464
02/02/2024	2394	4	2	2	0	€ 608
03/02/2024	0	0	0	0	0	€ 0
04/02/2024	0	0	0	0	0	€ 0
05/02/2024	2281	4	2	2	0	€ 608
06/02/2024	2371	4	2	2	0	€ 608
07/02/2024	855	1	2	0	0	€ 320
08/02/2024	1300	2	2	1	0	€ 464
09/02/2024	1157	2	2	0	0	€ 320
10/02/2024	0	0	0	0	0	€ 0
11/02/2024	0	0	0	0	0	€ 0
12/02/2024	1355	2	2	0	0	€ 320
13/02/2024	1585	3	2	1	0	€ 464
14/02/2024	1481	2	2	1	0	€ 464
15/02/2024	1753	3	2	1	0	€ 464
16/02/2024	2152	4	2	2	0	€ 608
17/02/2024	0	0	0	0	0	€ 0
18/02/2024	0	0	0	0	0	€ 0
19/02/2024	1894	3	2	1	0	€ 464
20/02/2024	1344	2	2	0	0	€ 320
21/02/2024	1447	2	2	1	0	€ 464
22/02/2024	2042	3	2	1	0	€ 464
23/02/2024	2338	4	2	2	0	€ 608
24/02/2024	0	0	0	0	0	€ 0
25/02/2024	0	0	0	0	0	€ 0
26/02/2024	1960	3	2	1	0	€ 464
27/02/2024	1696	3	2	1	0	€ 464
28/02/2024	806	1	2	1	0	€ 464
29/02/2024	943	1	2	1	0	€ 464

Table 4.3: (Continue)

	FORECAST		2	2		
Dates	Parcel	Staff req	Full time	Part time	Det	Costs
01/03/2024	1392	2	2	1	0	€ 464
02/03/2024	0	0	0	0	0	€ 0
03/03/2024	0	0	0	0	0	€ 0
04/03/2024	1666	3	2	1	0	€ 464
05/03/2024	2147	4	2	2	0	€ 608
06/03/2024	1684	3	2	1	0	€ 464
07/03/2024	946	1	2	1	0	€ 464
08/03/2024	1409	2	2	0	0	€ 320
09/03/2024	0	0	0	0	0	€ 0
10/03/2024	0	0	0	0	0	€ 0
11/03/2024	2679	5	2	2	1	€ 848
12/03/2024	1630	3	2	1	0	€ 464
13/03/2024	1213	2	2	1	0	€ 464
14/03/2024	1734	3	2	1	0	€ 464
15/03/2024	1646	3	2	0	0	€ 320
16/03/2024	0	0	0	0	0	€ 0
17/03/2024	0	0	0	0	0	€ 0
18/03/2024	1837	3	2	1	0	€ 464
19/03/2024	1558	3	2	1	0	€ 464
20/03/2024	1231	2	2	1	0	€ 464
21/03/2024	2005	3	2	1	0	€ 464
22/03/2024	1933	3	2	1	0	€ 464
23/03/2024	0	0	0	0	0	€ 0
24/03/2024	0	0	0	0	0	€ 0
25/03/2024	2003	3	2	1	0	€ 464
26/03/2024	1836	3	2	1	0	€ 464
27/03/2024	1304	2	2	0	0	€ 320
28/03/2024	1683	3	2	1	0	€ 464
29/03/2024	2134	4	2	2	0	€ 608
30/03/2024	0	0	0	0	0	€ 0
31/03/2024	0	0	0	0	0	€ 0
01/04/2024	1774	3	2	1	0	€ 464
02/04/2024	1518	2	2	1	0	€ 464
03/04/2024	980	1	2	1	0	€ 464
04/04/2024	1377	2	2	1	0	€ 464
05/04/2024	1467	2	2	1	0	€ 464

Table 4.3: (Continue)

	FORECAST		2	2		
Dates	Parcel	Staff req	Full time	Part time	Det	Costs
06/04/2024	0	0	0	0	0	€ 0
07/04/2024	0	0	0	0	0	€ 0
08/04/2024	1345	2	2	1	0	€ 464
09/04/2024	1499	2	2	1	0	€ 464
10/04/2024	828	1	2	1	0	€ 464
11/04/2024	1727	3	2	1	0	€ 464
12/04/2024	1556	3	2	1	0	€ 464
13/04/2024	0	0	0	0	0	€ 0
14/04/2024	0	0	0	0	0	€ 0
15/04/2024	1604	3	2	1	0	€ 464
16/04/2024	953	1	2	1	0	€ 464
17/04/2024	702	1	2	1	0	€ 464
18/04/2024	835	1	2	1	0	€ 464
19/04/2024	1700	3	2	1	0	€ 464
20/04/2024	0	0	0	0	0	€ 0
21/04/2024	0	0	0	0	0	€ 0
22/04/2024	902	1	2	1	0	€ 464
23/04/2024	1598	3	2	1	0	€ 464
24/04/2024	606	1	2	1	0	€ 464
25/04/2024	1497	2	2	1	0	€ 464
26/04/2024	1074	2	2	1	0	€ 464
27/04/2024	0	0	0	0	0	€ 0
28/04/2024	0	0	0	0	0	€ 0
29/04/2024	1324	2	2	1	0	€ 464
30/04/2024	1852	3	2	1	0	€ 464
01/05/2024	0	0	0	1	0	€ 144
02/05/2024	1786	3	2	1	0	€ 464
03/05/2024	1351	2	2	1	0	€ 464
04/05/2024	0	0	0	0	0	€ 0
05/05/2024	0	0	0	0	0	€ 0
06/05/2024	1411	2	2	0	0	€ 320
07/05/2024	2431	4	2	1	1	€ 704
08/05/2024	1726	3	2	1	0	€ 464
09/05/2024	1758	3	2	1	0	€ 464
10/05/2024	2086	4	2	2	0	€ 608
11/05/2024	0	0	0	0	0	€ 0

Table 4.3: (Continue)

	FORECAST		2	2		
Dates	Parcel	Staff req	Full time	Part time	Det	Costs
12/05/2024	0	0	0	0	0	€ 0
13/05/2024	1838	3	2	1	0	€ 464
14/05/2024	1913	3	2	1	0	€ 464
15/05/2024	958	1	2	1	0	€ 464
16/05/2024	1721	3	2	1	0	€ 464
17/05/2024	1994	3	2	1	0	€ 464
18/05/2024	0	0	0	0	0	€ 0
19/05/2024	0	0	0	0	0	€ 0
20/05/2024	1638	3	2	1	0	€ 464
21/05/2024	1004	1	2	1	0	€ 464
22/05/2024	1170	2	2	1	0	€ 464
23/05/2024	1407	2	2	1	0	€ 464
24/05/2024	1028	2	2	1	0	€ 464
25/05/2024	0	0	0	0	0	€ 0
26/05/2024	0	0	0	0	0	€ 0
27/05/2024	954	1	2	1	0	€ 464
28/05/2024	1843	3	2	0	0	€ 320
29/05/2024	943	1	2	1	0	€ 464
30/05/2024	1547	3	2	1	0	€ 464
31/05/2024	2345	4	2	2	0	€ 608

The forecast method was employed to calculate the budgeted personnel costs for the initial five months of 2024, which were determined to be the sum of costs in Table 4.3: €52,976.

4.4.3 Comparison between the traditional and forecast method

Once the pilots of the volumes and resources required for reception have been identified, the actual figures obtained in the first five months of 2024 will be presented.

Table 4.4: Extra cost in traditional and forecast method

Real DATE			GAP	Traditional	GAP	Forecast
01/01/2024	0	0	0	€ 0	0	€ 0
02/01/2024	2347	5	1	€ 117	2	€ 317
03/01/2024	2463	5	0	€ 0	2	€ 362
04/01/2024	920	2	0	€ 0	0	€ 0
05/01/2024	2920	6	1	€ 280	3	€ 541
06/01/2024	140	0	0	€ 0	0	€ 0
07/01/2024	0	0	0	€ 0	0	€ 0
08/01/2024	2509	5	0	€ 0	2	€ 380
09/01/2024	1456	3	0	€ 0	0	€ 0
10/01/2024	1558	3	0	€ 0	1	€ 209
11/01/2024	1307	3	0	€ 0	0	€ 0
12/01/2024	2403	5	0	€ 0	3	€ 539
13/01/2024	581	1	0	€ 0	0	€ 0
14/01/2024	0	0	0	€ 0	0	€ 0
15/01/2024	980	2	0	€ 0	0	€ 0
16/01/2024	2056	4	1	€ 203	2	€ 403
17/01/2024	79	0	0	€ 0	0	€ 0
18/01/2024	1711	3	0	€ 0	0	€ 68
19/01/2024	501	1	0	€ 0	0	€ 0
20/01/2024	390	1	0	€ 0	0	€ 0
21/01/2024	0	0	0	€ 0	0	€ 0
22/01/2024	1515	3	0	€ 0	1	€ 192
23/01/2024	3212	6	2	€ 455	4	€ 855
24/01/2024	1178	2	0	€ 0	0	€ 0
25/01/2024	2586	5	0	€ 0	2	€ 410
26/01/2024	0	0	0	€ 0	0	€ 0
27/01/2024	445	1	0	€ 0	0	€ 0
28/01/2024	0	0	0	€ 0	0	€ 0
29/01/2024	3623	7	2	€ 415	4	€ 815
30/01/2024	1858	4	0	€ 0	2	€ 326

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Table 4.4: (continue)

Real DATE			GAP Traditional		GAP Forecast	
31/01/2024	1157	2	0	€ 0	0	€ 52
01/02/2024	2720	5	0	€ 0	2	€ 463
02/02/2024	2048	4	0	€ 0	0	€ 0
03/02/2024	0	0	0	€ 0	0	€ 0
04/02/2024	0	0	0	€ 0	0	€ 0
05/02/2024	3940	8	0	€ 0	4	€ 739
06/02/2024	1128	2	0	€ 0	0	€ 0
07/02/2024	1332	3	0	€ 0	1	€ 120
08/02/2024	1680	3	0	€ 0	0	€ 56
09/02/2024	2290	4	0	€ 0	2	€ 495
10/02/2024	0	0	0	€ 0	0	€ 0
11/02/2024	0	0	0	€ 0	0	€ 0
12/02/2024	4943	10	5	€ 931	8	€ 1.531
13/02/2024	3209	6	3	€ 654	3	€ 654
14/02/2024	1208	2	0	€ 0	0	€ 0
15/02/2024	776	2	0	€ 0	0	€ 0
16/02/2024	2296	4	0	€ 0	0	€ 97
17/02/2024	0	0	0	€ 0	0	€ 0
18/02/2024	0	0	0	€ 0	0	€ 0
19/02/2024	2021	4	0	€ 0	1	€ 189
20/02/2024	3202	6	1	€ 251	4	€ 851
21/02/2024	1271	2	0	€ 0	0	€ 0
22/02/2024	2413	5	0	€ 0	2	€ 343
23/02/2024	1613	3	0	€ 0	0	€ 0
24/02/2024	0	0	0	€ 0	0	€ 0
25/02/2024	0	0	0	€ 0	0	€ 0
26/02/2024	1702	3	0	€ 0	0	€ 65
27/02/2024	1443	3	0	€ 0	0	€ 0
28/02/2024	0	0	0	€ 0	0	€ 0
29/02/2024	2814	5	0	€ 0	2	€ 499
01/03/2024	1791	3	0	€ 0	0	€ 100
02/03/2024	0	0	0	€ 0	0	€ 0
03/03/2024	0	0	0	€ 0	0	€ 0
04/03/2024	3387	7	1	€ 123	4	€ 723
05/03/2024	3690	7	0	€ 41	3	€ 641
06/03/2024	0	0	0	€ 0	0	€ 0

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Table 4.4: (continue)

Real DATE				GAP Traditional		GAP Forecast
07/03/2024	2277	4	1	€ 289	1	€ 289
08/03/2024	2497	5	0	€ 0	3	€ 575
09/03/2024	0	0	0	€ 0	0	€ 0
10/03/2024	0	0	0	€ 0	0	€ 0
11/03/2024	2706	5	0	€ 57	0	€ 57
12/03/2024	1257	2	0	€ 0	0	€ 0
13/03/2024	704	1	0	€ 0	0	€ 0
14/03/2024	3265	6	1	€ 275	3	€ 675
15/03/2024	1777	3	0	€ 0	1	€ 294
16/03/2024	0	0	0	€ 0	0	€ 0
17/03/2024	0	0	0	€ 0	0	€ 0
18/03/2024	3289	6	3	€ 685	3	€ 685
19/03/2024	1600	3	0	€ 0	0	€ 25
20/03/2024	846	2	0	€ 0	0	€ 0
21/03/2024	1658	3	0	€ 48	0	€ 48
22/03/2024	1241	2	0	€ 0	0	€ 0
23/03/2024	0	0	0	€ 0	0	€ 0
24/03/2024	0	0	0	€ 0	0	€ 0
25/03/2024	2678	5	1	€ 246	2	€ 446
26/03/2024	1383	3	0	€ 0	0	€ 0
27/03/2024	799	2	0	€ 0	0	€ 0
28/03/2024	2216	4	0	€ 0	1	€ 266
29/03/2024	2110	4	0	€ 24	0	€ 24
30/03/2024	0	0	0	€ 0	0	€ 0
31/03/2024	0	0	0	€ 0	0	€ 0
01/04/2024	0	0	0	€ 0	0	€ 0
02/04/2024	2694	5	0	€ 52	2	€ 452
03/04/2024	1011	2	0	€ 0	0	€ 0
04/04/2024	398	1	0	€ 0	0	€ 0
05/04/2024	2433	5	0	€ 0	2	€ 350
06/04/2024	0	0	0	€ 0	0	€ 0
07/04/2024	0	0	0	€ 0	0	€ 0
08/04/2024	3087	6	1	€ 206	3	€ 606
09/04/2024	1185	2	0	€ 0	0	€ 0
10/04/2024	1440	3	0	€ 0	0	€ 0
11/04/2024	2037	4	0	€ 0	1	€ 196

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Table 4.4: (continue)

Real DATE				GAP Traditional		GAP Forecast
12/04/2024	781	2	0	€ 0	0	€ 0
13/04/2024	0	0	0	€ 0	0	€ 0
14/04/2024	0	0	0	€ 0	0	€ 0
15/04/2024	1599	3	0	€ 0	0	€ 25
16/04/2024	1494	3	0	€ 0	0	€ 0
17/04/2024	25	0	0	€ 0	0	€ 0
18/04/2024	2834	6	0	€ 0	3	€ 507
19/04/2024	1715	3	0	€ 0	0	€ 70
20/04/2024	0	0	0	€ 0	0	€ 0
21/04/2024	0	0	0	€ 0	0	€ 0
22/04/2024	1695	3	0	€ 0	0	€ 62
23/04/2024	1893	4	1	€ 139	1	€ 139
24/04/2024	828	2	0	€ 0	0	€ 0
25/04/2024	0	0	0	€ 0	0	€ 0
26/04/2024	2847	6	0	€ 0	3	€ 512
27/04/2024	0	0	0	€ 0	0	€ 0
28/04/2024	0	0	0	€ 0	0	€ 0
29/04/2024	3884	8	5	€ 917	5	€ 917
30/04/2024	2138	4	0	€ 0	1	€ 235
01/05/2024	0	0	0	€ 0	0	€ 0
02/05/2024	613	1	0	€ 0	0	€ 0
03/05/2024	1462	3	0	€ 0	0	€ 0
04/05/2024	0	0	0	€ 0	0	€ 0
05/05/2024	0	0	0	€ 0	0	€ 0
06/05/2024	3905	8	0	€ 97	6	€ 1.125
07/05/2024	3428	7	3	€ 539	3	€ 539
08/05/2024	139	0	0	€ 0	0	€ 0
09/05/2024	1208	2	0	€ 0	0	€ 0
10/05/2024	2207	4	0	€ 0	0	€ 62
11/05/2024	0	0	0	€ 0	0	€ 0
12/05/2024	0	0	0	€ 0	0	€ 0
13/05/2024	2633	5	0	€ 29	2	€ 429
14/05/2024	441	1	0	€ 0	0	€ 0
15/05/2024	956	2	0	€ 0	0	€ 0
16/05/2024	2230	4	0	€ 0	1	€ 271
17/05/2024	998	2	0	€ 0	0	€ 0

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Table 4.4: (continue)

Real DATE			GAP	Traditional	GAP	Forecast
18/05/2024	0	0	0	€ 0	0	€ 0
19/05/2024	0	0	0	€ 0	0	€ 0
20/05/2024	2602	5	2	€ 416	2	€ 416
21/05/2024	1394	3	0	€ 0	0	€ 0
22/05/2024	464	1	0	€ 0	0	€ 0
23/05/2024	1568	3	0	€ 0	0	€ 13
24/05/2024	551	1	0	€ 0	0	€ 0
25/05/2024	0	0	0	€ 0	0	€ 0
26/05/2024	0	0	0	€ 0	0	€ 0
27/05/2024	3604	7	0	€ 8	4	€ 808
28/05/2024	1709	3	0	€ 0	1	€ 268
29/05/2024	790	2	0	€ 0	0	€ 0
30/05/2024	1627	3	0	€ 0	0	€ 36
31/05/2024	1987	4	0	€ 0	0	€ 0

The traditional method results in additional costs of €7,498 due to overtime or the use of temporary staff for administrative purposes. In contrast, the forecast method leads to an increase in costs of €24,455.

	Piloting	Extra cost	Total
Traditional	€ 91.857	€ 7.498	€ 99.355
Forecast	€ 52.976	€ 24.455	€ 77.431

Table 4.5: Total cost

The aforementioned example demonstrates that the forecast method results in a 22% reduction in expenditure in the initial five months of 2024 in comparison to the traditional method.

As evidenced by the case study, the forecasting method, which employed a damping formula incorporating trend and seasonality, was able to discern a negative downward trend in volumes. Consequently, it enabled a more effective deployment of resources. This approach allowed for a more accurate determination of the number of personnel to be recruited, aligning more closely with the actual workforce requirements. This precision not only improved operational efficiency but also helped in optimizing personnel costs, ensuring that staffing levels were better matched to the fluctuating demands of the logistics centre.

It can be argued that the forecasting method facilitates a more assertive approach to workforce planning, as evidenced by a reduction in the number of employees hired and an increased reliance on overtime or temporary work. However, had the dataset exhibited an upward trend rather than a downward one, the risk would have been to employ a significantly smaller number of employees than necessary, even with the traditional method.

4.4.4 Month piloting

A further illustration of the efficacy of the forecasting method is the monthly resource planning process. As with the previous daily forecast version, the first five months of 2024 are estimated using both the traditional and the forecast method. For the sake of simplicity and approximation, the formula [Equation 4.1] is employed, with a constant value of 20€/h assigned to the cost of an hour worked by the warehouse operator.

For the purpose of simplification, the cost of overtime is calculated at 30€/h, without consideration of other potential complications or the specific contract types that may vary according to the needs of the warehouse in question.

		Traditional			
Month	Parcel	Staff required	Real	GAP staff	COST
Gen	59452	116	39895	0	€ 18.578,75
Feb	42510	83	41171	0	€ 13.284,38
Mar	57512	112	36018	0	€ 17.972,50
Apr	56233	110	37394	0	€ 17.572,81
May	68214	133	9993	0	€ 21.316,88

Table 4.6: Traditional - month

As illustrated in Table 4.6, the conventional approach fails to account for the decline in the number of parcels shipped, resulting in an overestimation of the required staffing levels by a considerable margin.

The forecasting method Table 4.7 enables the acquisition of lower inbound volume data, thereby facilitating more accurate staff planning. In January, March and May, the savings achieved are particularly noteworthy.

A simplified calculation yields an expenditure amount of €88,725.31 under the traditional method, while the forecast method yields an expenditure amount of

Forecast					
Month	**Parcel**	**Staff required**	**Real**	**GAP staff**	**COST**
Gen	38380	75	39895	3	€ 12.703,91
Feb	45141	88	41171	0	€ 14.106,56
Mar	43394	85	36018	0	€ 13.560,63
Apr	53562	105	37394	0	€ 16.738,13
May	30643	60	9993	0	€ 9.575,94

Table 4.7: Forecast - month

€66,685.16. Once more, the forecasting method results in a reduction of approximately 25% in personnel costs.

Chapter 5

Conclusion

The research presented in this thesis offers substantial advancements in the application of forecasting models for logistics warehouse operations, with a primary focus on predicting inbound volumes and determining workforce requirements. The study emphasises the significance of accurate forecasting in enhancing operational efficiency and optimising resource management, thereby contributing to practical logistics management.

One of the key findings of this research is the effectiveness of the forecast model in identifying trends and seasonality, which facilitated more accurate and efficient workforce planning. The model's ability to predict a downward trend in volumes allowed for better resource allocation and cost management, thereby enhancing overall operational efficiency. However, the study also identified limitations, particularly in the accuracy of daily forecasts and the impact of unforeseen events, such as disruptions in global supply chains.

One illustrative example is the blockade of the Suez Canal by the Houthis, which resulted in a notable slowdown in sea logistics. It is evident that events of this nature cannot be perceived through the lens of statistical data alone. Consequently, it is of paramount importance to subject the data obtained through the algorithm to a human filter in order to ensure the most accurate and reliable outcome. An additional efficacious enhancement would be to enhance communication between the management and the DC, thereby ensuring that any alterations in the direction of management that might affect volume trends are identified in advance. In point of fact, an algorithm based on historical data is unable to ascertain whether distribution flows or other analogous decisions determined by top management will undergo a change.

Despite these challenges, the research demonstrated the importance of continuous refinement of forecasting models to mitigate inaccuracies and adapt to dynamic operational environments. The study's emphasis on avoiding overfitting while optimising forecasting parameters is crucial for maintaining the model's relevance and effectiveness over time. The quality of the data is of paramount importance in feeding the forecasting algorithm. Indeed, maintaining a database containing the stock history will undoubtedly enhance the forecasting performance.

Future research should concentrate on integrating a greater number of comprehensive data points and refining daily forecasting techniques in order to achieve a higher degree of accuracy. The utilisation of advanced machine learning algorithms and the incorporation of real-time data could provide deeper insights and more robust predictive capabilities. Furthermore, extending the scope of the study to include the interplay between inbound and outbound volumes could offer a more holistic view of inventory management and supply chain dynamics.

In conclusion, this thesis makes a significant contribution to the field of logistics optimisation by bridging theoretical concepts with practical applications. The insights gained from this research provide a foundation for ongoing improvements in logistics operations, emphasising the critical role of accurate forecasting in achieving operational excellence. By continuing to refine and adapt these forecasting models, logistics centres can better navigate the complexities of supply chain management, ensuring efficient and effective resource utilisation.

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