Design, Development, and Implementation of a Demand Forecast Model: A case Study to Improve Cargill's Demand Management

Master thesis submitted to Delft University of Technology

in partial fulfilment of the requirements for the degree of

MASTER OF SCIENCE

in **Complex System Engineering and Management**

Faculty of Technology, Policy, and Management

by

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To be defended in public on September 26th, 2022

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Preface

When I arrived in the Netherlands, I was completely amazed by the level and quantity of engineering innovations that were implemented in a such small country. The way how many different transport and infrastructure systems share the limited available space.

During my master's in Complex System and Engineering and Management, I could learn in more detail about these innovations. The time passed by, and I learned a lot. It was incredible and costly of course, the many things I have learned in these two years of the master's. More than I could have imagined before starting it.

I choose the specialization in transport and logistics, because I considered, that among the master elective tracks, this was possibly the track that had the biggest challenges concerning supply chain management, transportation decision making, and technological innovation.

Through this thesis project, I wanted to bring the solution to one of the most pressing problems that were affecting the demand management performance of one of the most important multinational family companies, as is Cargill.

Half a year ago, I started this adventure with the mission to apply the knowledge acquired during my studies at TU Delft. In my graduation committee, I could find the best compass and guidance in moments of doubt and insecurity. For this, I would like to thank them. To Professor Marcel Ludema, who spared no effort and accompanied me from the beginning of this thesis project with very accurate and direct comments. To Professor Lóri Tavasszy, who always gave me solutions and hope to achieve the laborious task, that was this master thesis project. And finally, to Professor Jos Blank, who provided me with useful insights and guidelines for the development of the forecasting model, that now have been materialized in this master thesis report.

I would also like to thank all the Master planning team of Cargill GEOS EMEA, who welcomed in the best way. By providing me from the beginning with all the resources that I required for the development of this thesis project. To Annemarth Bleeker, who gave me the chance to do my thesis project in Cargill GEOS and provided me with the required resources for the task. To Thijs Delzeyne, who shared all his knowledge about the little details of the demand management process that was being carried out at Cargill GEOS. To Yu Han, who was constantly supervising my progress and providing me with feedback about the performance of my forecast model. And to Sushant Singhal, who always provided very good advice in all kinds of matters.

Finally, I would like to thank my sister Anette, my brother-in-law, Jeffrey Nieuwland, and all his family, who supported me economically and emotionally during all my master's studies. I will always be thankful to them for all their help and good advice.

This master thesis project focused on the development of a demand forecast to improve the demand management conditions at Cargill GEOS for the Retailer customers. Who presented a supply chain and production challenge for Cargill GEOS. For this reason, the baseline conditions were analyzed, not only for the development of a proper demand forecast model but also to identify improvement opportunities that could help Cargill to mitigate the impact of volatile demand. For this reason, additionally to the demand forecast developed in this research, a modification to the management of their safety stock was developed based on the insights obtained from the data analysis.

In this way, Cargill's supply chain is now better prepared to meet its customer demand On Time and In Full.

Summary

In this thesis project, the case of **Cargill Global Edible Oil Solutions**, an organization that provides edible oil solutions for industrial and retailer customers is analyzed. Cargill GEOS' supply chain processes are managed in two stages following two production strategies. The first stage encompasses the sourcing and storage of raw oil, which is managed on a Make-to-Stock production strategy based on the aggregated demand of the industrial and retailer customers. The second part of the supply chain is managed following a Make to Forecast (MTF) production strategy for the production planning of the upcoming orders. In the case of the retailer customers, these are served by the Retail Food Services (RFS). Which is the business model through which Cargills offer the production outsourcing service of final goods, ready for the retail market.

For the RFS weekly demand that has a notice time of 7 days, Cargill uses the Make-To Forecast production strategy. Which relies on a demand forecast to estimate the upcoming demand and to generate the production planning. Production delays and forecast errors are compensated by safety stocks to maintain acceptable service levels. The RFS safety stock levels are estimated based on the production lead times and demand variability.

The accuracy of the RFS demand forecast is only about 50%, and for this reason, the safety stocks are managed at a high constant level all year round. Due to this, the internal warehouses are not enough, and Cargill relies on external warehouses. Due to the forecast influence on the production planning process, the main objective of this thesis project is "the design, development, and implementation of a transparent forecast model that can improve the demand management and production planning of Cargill GEOS' Retail Food Services".

For this thesis project, one RFS customer has been selected as a sample, which will be referred to as **"Global Retailer"**. Global Retailer is a corporate RFS customer that has retail stores in different countries of the EMEA region and currently is responsible for 25% of the RFS inventory, the inventor measured in oil liters. Which makes Global Retailer a good representative of the RFS customers' demand. Global Retailer has registered demand for 120 RFS products, these RFS products are aimed at specific countries in the EMEA region, but some of them are distributed in more than one country. Due to this, when the 120 RFS demand datasets are analyzed considering the country demand, when considering the country demand, 166 country-RFS product datasets are obtained.

For the elaboration of this thesis project, the Double Diamond Design (DDD) has been selected for the design of the research (Singh Brar, 2017). Because it provides an orderly and detailed enough structure that fits well with aim of this thesis project. Due to this, the design objective was approached in 4 stages, **Discovery, Define, Develop, and Delivery**. In the first two stages, the 8 design goals for the forecast model were presented. At the end of the second stage, the corresponding technical requirements to achieve these design goals were presented. In the third stage, solutions according to the technical requirements were developed and in the fourth stage, the technical requirements were fulfilled.

In the **Discovery stage**, the baseline conditions of the supply chain and demand management were presented, including the role of the demand forecast in the demand management for Retail Food Services, the demand data management, the forecast elaboration process and its performance, and its overall impact on the customer service levels. In this stage, the design goals for these different aspects were identified.

During the Discovery stage, it was found that two years before this thesis project, Cargill had migrated to an SAP HANA platform for information management, which is referred to as SAP IBP (Färber et al.,

2012). Due to this, the oldest demand record available is from September 2019 and the most recent one considered is from April 2022. This data limitation affected the feasibility of producing a useful forecast and limited considerably the forecasting options, as it can be seen in section 4.3. From the 166 country product demand datasets, only 16 of them had the 32 max possible monthly observations from September 2019 to April 2022. In this way, only two years and half of the demand observations were available.

These demand datasets are the input for the monthly SAP statistical forecast, which is automatically generated based on the moving average. As the moving average can only estimate the time series' current level, the SAP statistical forecast has an average accuracy of 42%, because the demand is not stable enough to be properly forecast using a moving average. This statistical forecast is reviewed and corrected by the demand planner, improving the accuracy to 49%. While the demand forecast is produced at a monthly level, the production planning is performed at a weekly level. For this reason, one of the design goals was to develop a useful forecast that can be as close as possible to the weekly level to match the weekly demand and the production planning.

The production planning is based on a monthly material resource planning process, where the forecasted monthly demand is distributed in the following 5 weeks, then compared with the inventory levels and the required safety stock. The gaps in the inventory are covered through the production planning in the following 5 weeks.

When demand data was analyzed, it was found that the datasets follow seasonal patterns that were repeated in the two years and a half of observations. Also, it was found that some of the new RFS products were the replacement or successors of old inactive RFS products. Which lead to the identification of 2 of the 8 design goals for the forecast model. First, the development of a forecast model that can estimate seasonal patterns, and second, the development of a procedure to identify the demand successors and predecessors of the RFS products. In this way, the new RFS products with less than 8 months in the market will have enough observations to be forecasted. About the safety stock management, these were managed on a constant level all year round, based on the production lead times and the demand variability. This approach has generated excess inventory during the off-peak periods and most of the year, but not enough inventory to satisfy the demand during the demand peak periods. This situation is detailed in section 2.5 and solved in section 5.4.

In the **Define Stage**, 3 literature reviews were performed to determine the technical requirements for the identified design goals. The first literature review was focused on forecast applications in supply chain management. In one of the selected papers, an approach to align the management of the safety stock levels with the demand forecast was developed (Kurawarwala & Matsuo, 1996). The other 2 selected papers showed the importance of determining the right aggregation level to make the most of the forecast model and the data available (R. Hyndman & Kostenko, 2007; Zotteri et al., 2005).

The second literature review was about seasonal forecasting models, there the ARIMA model, the ETS exponential smoothing model, and the STL+ETS model were reviewed. In the third literature review, 2 forecasting software solutions were reviewed and RStudio IDE was selected for the forecast development and testing. Based on these literature reviews, the 8 technical requirements for this thesis project were established. The first 6 were related to the forecast requirements, the 7th requirement aimed to develop a procedure to identify the demand successors in the RFS products to improve the input information, and the 8th requirement aimed to improve the management of the safety stocks based on the forecast and data analysis insights.

In the **Develop Stage**, different solutions for the technical requirements were developed. In the first section, a data aggregation framework, to determine the roadmap to achieve a useful demand forecast as close as possible to the weekly level, was developed. Following the roadmap, the considered forecasting approaches were tested at a monthly level, depending on their performance based on the technical requirements, the best forecast model might be tested at the 3-week level. If the forecast model performance was acceptable, the forecast model will also be tested at the weekly level. Then the forecast performance at different time aggregation levels will be assessed to choose the most suitable one.

In the second section of the Develop stage, the designs of the considered forecasting models were presented, the ARIMA, ETS exponential smoothing, and the STL+ETS. In the third section, 3 datasets with the 32 monthly observations were selected to test the mentioned models at the monthly level, in alignment with the time aggregation roadmap. The results showed that the ARIMA model could not estimate the datasets’ seasonal patterns and collapsed into a moving average model. The ETS exponential smoothing model was also not able to estimate the seasonal patterns and produced a constant level forecast. The case of the STL+ETS model was different because this model is based on the robust STL decomposition, which can estimate seasonal patterns with a minimum of two years of observations (Cleveland et al., 1990). In this way, the STL +ETS model was able to produce a seasonal forecast that matched the observed demand patterns at a monthly level. For this reason, the STL+ETS model was selected as the model to forecast the RFS demand.

In the fourth section, the Demand Shift Tracking (DST) procedure to identify the RFS products' demand successors and predecessors, was developed. This procedure proved to be very useful to aggregate the fragmented demand datasets at the country level and obtain enough data to generate the demand forecast using the STL+ETS model. The DST procedure was applied to each country's group of demand datasets and was based on the demand levels, the seasonal patterns, and the periods of phasing in and out of the new and old products, respectively. The results of this procedure were verified and validated by the sales department. The DST procedure was used to consolidate the 166 country-RFS products datasets into 37 datasets, where 27 of them had the 32 max possible monthly observations, 2 consolidated datasets were rejected by the sales assistant and one of them had less than the 24 monthly observations required for the STL+ETS model. Due to this only 34 datasets were considered for the next steps.

In the fifth section, the monthly STL+ETS model design was extended by including an outlier removal function. This allowed to further increase the accuracy of the STL+ETS model, but as only two years and half of the observations were available, the reliability of the results of the outlier removal function was dubious and the results were verified case by case. Then the forecast results of the extended STL+ETS model were tested by trimming the last 3 months of the datasets to analyze the match between the forecast and the observed demand in the months of February, March, and April 2022. Through this, it was found that the main shortcoming was that the STL+ETS model had problems estimating the changes in the trend component. It required at least 3 observations to capture the changes in the monthly demand levels. But it was also found that this trend estimation problem could be mitigated by using the prediction interval value, which matched better with the observed demand, as the demand forecast.

In the **Delivery stage**, the developed solutions for the forecast model were implemented. In the first section, the extended STL+ETS model was implemented at the monthly level for the 34 datasets of Global Retailer. As the forecast results had a good match with the demand observations, following the time aggregation roadmap, a sample of the 5 best performing datasets was selected to be forecasted at the 3-week level. This sample size was selected, as these were the datasets that performed better and could show more clearly the degradation of the seasonal patterns and loss of accuracy by lowering the time aggregation level. The 3-week forecast results showed that the seasonal patterns were still present, the error level decreased slightly, and the estimation of the trend level was mitigated as more observations became available in the lower time aggregation level. For this reason, the STL+ETS model was also tested at the weekly level with the same 5 best performing datasets, in this case, there was a considerable worsening of the forecast accuracy, and the match between the forecast results and the observed demand. This was due to the demand displacement and variation from year to year at the weekly level. For this reason, the 3-week level was chosen as the right time aggregation level and the first 5 technical requirements were fulfilled.

In the second section, the details to integrate the STL+ETS model into the Cargill GEOS' demand planning process were given. As the STL+ETS model does not exist natively in the SAP HANA environment, where the demand planning process occurs. Guidelines to connect the RStudio IDE, where the STL+ETS model can be executed, with the SAP HANA environment were given. In that way, the sixth and last forecast technical requirement was fulfilled.

In the third section, the details to integrate the Demand Shift Tracking procedure into the demand planning process were given. Different solutions were considered to implement it into the SAP IBP platform. Nevertheless, as the replacement of the products occurred only in some countries, it was not possible to implement it in SAP IBP, as it would create conflicts when the RFS products demand data was aggregated. For this reason, the solution was to implement a shared register, managed between the sales assistant and the demand planner. Because the sales assistant is the first stakeholder to find out about the RFS product replacements and the demand planner is the stakeholder who needs this information to make the corrections in SAP IBP.

In the fourth section, the forecast and data analysis insights were used to develop a seasonal management of the safety stocks. In this way, the safety stock levels can leverage the seasonal demand patterns by having variable levels based on the expected demand during different quarters of the year. The quarters have been defined to match the peak and off-peak periods. As the products have their demand peak periods at different times of the year, this approach allowed to manage the safety stock and storage capacity more efficiently. Increasing and reducing the safety stock of different RFS products in the same quarter according to their registered seasonal demand.

In the fifth section, the impacts of the developed solutions for the RFS demand management the RFS were presented. In the case of the DST procedure, it allowed increasing the number of datasets with 32 monthly observations by 69%. The statistical forecast error was reduced by 60%. The hours per month correcting the statistical forecast by the demand planner would be reduced by 59%. The production planning corrections due to forecast errors would be reduced by 59%. The number of rejected orders and changed orders registered would be reduced by 59%. The safety stock levels as a whole can be reduced by 30% and for specific products, it can be reduced at most by 63%.

The main conclusions were that the Cargill GEOS RFS demand follows marked seasonal patterns, which due to the data limitations could not be leveraged by traditional forecasting models. Nevertheless, the STL-based model due to its low data requirements was able to produce a useful forecast. Second, considering the data availability and the STL+ETS model capabilities the 3-week time aggregation was determined as the most suitable for the forecast of the RFS demand. Third, the implementation of the DST procedure is key for good data management of the RFS demand. Fourth, the make-to-forecast production strategy is a very robust a flexible one, but to make the most of it, it is important to have a useful demand forecast and that the safety stocks are managed based on the insights of the demand forecast.

The main recommendations to keep improving the demand management are first, the improvement of the data management. For example, in the baseline conditions, high fragmentation of the demand data was found, which required the development of a demand shift tracking procedure just to obtain forecastable datasets. Another example of data management that could be improved is the fact the SAP IBP data platform contains many fields to add information on the demand of the products. Nevertheless, in most of the cases, these fields were blank or not updated. Second, in this thesis project, it was determined that the right forecast time aggregation level was the 3-week, mainly because of the data availability. For that reason, if Cargill desires to produce a useful weekly forecast, it is recommended to gather at least 5 years of observations. Third, to improve the forecast accuracy, especially to deal with the demand outliers, it is strongly recommended to keep a register of the events occurring during the appearance of the outliers. In this way, the causal relationships of the demand can be identified, and a better manual correction of the demand forecast can be obtained.

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Glossary of Terms

- **Aggregated demand:** It refers to the sum of the demand from different sources. In this thesis project, the demand stems from the Industrial customers and the Retailer customers. So, the term aggregated demand refers to the sum of the demand of these two kinds of customers.
- **Consolidated Dataset:** it refers to the demand datasets obtained after the application of the demand shift tracking procedure on the initial 166 country product demand datasets.
- **Demand dataset:** it refers to the Time series of the demand. The demand datasets have been used in this research for the management of the RFS products' demand data. Specifically for the management of the RFS products' demand per each country and the aggregated RFS's demand from the different retailer customers.
- **Forecast method**: The forecast method definition is limited to the forecast algorithm or approach required to obtain the point forecast. These approaches do not consider the nature of the forecast error or the prediction intervals (R. Hyndman et al., 2008).
- **Forecast model:** it refers to the forecast method and the analysis framework. That not only considers the point forecast, but analysis of the model suitability, the error term nature, and the prediction intervals (R. Hyndman et al., 2008).
- **Succession relationship**: It refers to the demand transfer or replacement in the demand of the RFS customers. This is due to small changes in the product specifications that cause the change in their SKU code and these to be defined as different products to avoid confusion in the production planning process. As it is explained in sections 2.2 and 2.3.A.
- **Stock Keeping Unit (SKU):** A Stock Keeping Unit represents the smallest unit of a product that can be added, and sold in an inventory control system (Gregersen, 2021). In this thesis project, it refers to the bottled oil that is packaged on boxes and the boxes on a pallet. As the bottled oil comes in different volumes, the oil liters on each Stock Keeping Unit might differ from product to product.
- **Time aggregation level:** it refers to how the demand has been aggregated in the time series for its use on a demand forecast. In the discovery stage of this thesis project, the time aggregation level for forecast demand is managed at a monthly level. This level is changed to 3-week and weekly time aggregation during the delivery stage to determine the time aggregation level that improves the forecast results quality.
- **Time series:** a time series is a set of numeric values that are the result of a process that is observed continuously or at discrete times (R. Hyndman et al., 2008). In this thesis project, the time series analyzed are the demand time series from the observed demand of the different products of the Retail Food Services.
- **Useful forecast:** For this research purpose, the term "useful forecast" will be used to refer to any forecast model that can properly leverage the demand data to generate a representative demand forecast of the observed demand in the RFS.

1. Introduction

In the global market, organizations have taken different strategies to manage how they offer their goods and services. Traditionally, organizations have executed their production processes in-house to have better control of them (Bremen & Oehmen, 2010). But as they have expanded worldwide, the cost of establishing new production facilities in different regions and the cost of transporting their products from overseas has shown to be considerable. For this reason, to minimize costs and maintain an acceptable response time, other strategies were considered, such as production outsourcing (Chen & Xiao, 2015).

Production outsourcing is one of the many strategies that multinational companies can take to optimize their production process cost, time, and flexibility by relying on third parties to take responsibility for some of the production processes (Chen & Xiao, 2015). This is because the third parties involved in these commercial relationships are better established and have more resources and knowledge to execute the required activities in a more cost-efficient way. The production outsourcing can range from the manufacturing of one specific part or intermediate good that is required for the production process to the complete production of final goods with all the customer brand details ready to be sold to the final customer.

Many companies that offer the production outsourcing service do not rely on one or just a few customers for their business success. But they work with many customers that may have different requirements. This is to reduce the risk of depending on a limited number of customers. Which can affect their power relationship (Lee & Johnsen, 2012).

The manufacturing companies manage these commercial relationships with their customers in different ways, according to the customers' requirements. Some customers have specific demand orders for specific periods, which are managed with long enough notice time to prepare them on time with relatively low costs. These kinds of orders are managed following a make-to-order production strategy (Meredith & Akinc, 2007). While other customers have open book contracts that are supervised by account managers. The demand from these customers will arrive on a regular basis and the order details will have a relatively short notice time. These are orders are manageable when the quantities ordered are stable over time. Nevertheless, in the cases when the ordered quantities present a considerable variation in the quantities between periods. It can make production planning a complicated task (Akinc & Meredith, 2015).

The contract terms for these commercial relationships specify a minimum service level, which the manufacturer must maintain to ensure the continuity of the commercial relationship (Katok et al., 2008). To comply with the service levels, the manufacturers can take a variety of production strategies for the production planning and management of their supply chain. The classical ones are the Make-to-Stock and Make-to-Order. The make-to-order is effective when the orders for specific batches of products have long enough notice times. While the Make-to-Stock seems to be useful for products that are required on a regular basis and have very short notice times (Meredith & Akinc, 2007). Nevertheless, when the ordered quantities are not stable over time, using a make-to-stock production strategy will cause an increase in the safety stock levels to maintain the required service level, especially during the demand peak periods. In that situation, it will consume the storage capacity of the producer, which will increase the storage cost and reduce the inventory capacity for the rest of the products (Meredith & Akinc, 2007).

For these reasons, alternative and hybrid production strategies exist, as is the case for the Make-to-Forecast production strategy. The Make to Forecast production strategy relies on two mechanisms, a demand forecast, to estimate the upcoming demand, which is later matched when the customer demand becomes available at the Customer Order Decoupling Point, and the management of safety stock levels to compensate for the forecast errors and unexpected production setbacks (Akinc & Meredith, 2015).

In this way, following the make-to-forecast production strategy, the production planning reliability depends on the quality of the demand forecast. The more reliable the demand forecast and the production planning, the safety stock levels and the storage cost can be reduced, and storage capacity becomes available for other products that might require it. Increasing the supply chain flexibility to meet the customer demand in time according to the agreed service levels (Meredith & Akinc, 2007).

In this thesis project, the Case of the multinational company Cargill will be analyzed. Specifically, their business unit is named Global Edible Oil Solutions (GEOS) which provides the production outsourcing service of bottled oil goods ready for distribution in the retail market (Cargill Inc, 2022a). Where most of Cargill GEOS's customers are retailer chains such as supermarkets. These production outsourcing commercial relationships are grouped under the name of Retail Food Services (RFS) (Cargill Inc, 2022a). For the management of their RFS demand, Cargill GEOS relies on the Make to Forecast production strategy. This is because most of the RFS demand is managed in open book contracts, which present variations in the demanded quantities. Unfortunately, the demand forecast for the RFS is lacking accuracy, which has led to the increase of their safety stock and is currently affecting Cargill GEOS's capacity to deliver the final goods On Time and In Full according to contracted service level goals (Meredith & Akinc, 2007).

Other alternatives have been considered by Cargill to improve the service levels for the RFS, such as the increase of their production and storage capacity, the renegotiation of the commercial relationships with the customers, to increase the orders notice time in exchange for a discount on the production costs (Goldratt, 1984). Nevertheless, Cargill decided that among the different options, the data analysis to improve the forecast accuracy is the most cost-efficient and quick to implement option (G. Wang et al., 2016).

For this reason, in agreement with Cargill before the beginning of the thesis project, the objective of this thesis project was set as *the Design, Development, and Implementation of a Transparent Forecast Model that can Improve the Demand Management and Production Planning of Cargill GEOS' Retail Food Services*. For this thesis project, an RFS customer has been selected as a sample of the RFS demand, which will be referred to as "Global Retailer". Global Retailer is a multinational retailer, which has registered demand for 120 RFS products and currently is responsible for 25% of the RFS inventory, measured in oil liters. Due to this, Global Retailer is a good representative of the RFS customer's demand.

To achieve the thesis project objective in a structured way, the Double Diamond design methodology (Singh Brar, 2017) has been chosen and will be introduced in the following section. In the second section, a brief introduction of the Retail Food Services and the baseline conditions of Cargill's supply chain, including the demand and production planning process, the forecast elaboration and performance, and the resulting service levels will be presented along with most of the identified design goals for this thesis project. In the third section, a literature review will be performed to identify the technical requirements for design goals, the last design goal will be presented and different forecasting models will be reviewed. In the fourth section, the forecasting models will be tested to choose the best-performing one, according to the technical requirements. The selected forecast model will be further tested to improve its design and develop the forecast model for this thesis project objective. In the fifth section, the developed forecast model results will be presented along with some other solutions to improve the demand management and execution of the production strategy at Cargill GEOS. The sixth section will present the conclusions and recommendations of this thesis project. Followed by the References and the appendix section.

1.1. Thesis Project Methodology

For the elaboration of this thesis project, the Double diamond design (DDD) has been selected for the design of the research. This is because the DDD is a flexible and customizable model that provides enough guidelines for the design and development of engineering solutions. Specifically, the double diamond developed by Singh Brar (Singh Brar, 2017) has been used as inspiration, because this one provides an orderly and detailed enough structure that fits well with aim of this thesis research project.

In this way, the double diamond design was not only used to guide the reasoning process development of data-based solutions, but it also helped to present the thesis project storyline and design steps on a clear and coherent way.

A. Design Objective

As it has been stated in the introduction, the RFS demand is being managed following the Make to Forecast production strategy. Which depends on the forecast accuracy and the management of the safety stocks. Unfortunately, the poor performance of the demand forecast has pushed Cargill GEOS to increase the safety stock levels along with storage costs to avoid affecting the customer service level.

Due to this, the main objective of this thesis project has been defined as:

“The Design, Development, and Implementation of a Transparent Forecast Model that can Improve the Demand Management and Production Planning of Cargill Geos’ Retail Food Services”

Considering the problematic situation, Cargill wants to improve their demand management by improving the demand forecast performance to relieve some pressure on the inventory levels.

In consequence increase the level of their customer satisfaction indicator: the On Time in Full percentage (OTIF).

For this reason, the forecast model to be developed must not only have better accuracy than the current statistical forecast. But it must also be based on a white box method to provide useful insights for the management of the RFS demand (Pintelas et al., 2020).

B. CoSEM Relevance

This thesis project approaches the complexity of the management of a multinational company supply chain that offers an outsourcing production service. For this reason, the organization under study needed to adjust its production planning process to meet contracted service levels and customer requirements. The main problems to achieve this task were the short notice times and the demand variability Which makes it difficult to match the production planning with the customer demand. For that purpose, the organization has been relying on mechanisms such as a demand forecast and safety stocks. Nevertheless, due to the low performance of the forecast, the safety stock levels have risen so much that the organization had to rely on external warehouses which have also increased the storage cost. For that reason, this thesis project will focus on the design, development, and implementation of a forecast model, and other solutions to improve demand management in the organization.

The design of the forecast model has taken into consideration the goals and expectations of the relevant stakeholders in the organization, such as the Supply Chain Design Analytics (SCDA) leader, the SCDA coordinator, and the demand planner. As well as the identified challenges to achieve the design goals, which will be used to establish the corresponding technical requirements that were fulfilled to achieve the main design objective.

To accomplish these tasks, thorough statistical analyses of the demand data were carried out, which allowed identifying relevant seasonal patterns, as well as a detailed exploration of the different processes and stakeholders involved in the demand and production planning. In this way, the developed solutions were not only technically feasible and compatible with the pre-existent supply chain processes, but they were also aligned with the stakeholders' goals and expectations. Making this thesis project relevant for the Master of Science in Complex System Engineering and Management objectives (TU Delft Faculty of Technology Policy and Management, 2020).

C. Research Scope

This thesis project scope will cover the baseline conditions from the supply chain management, the data management, the role of the demand forecast in the demand management for Retail Food Services, the forecast elaboration process, the forecast performance, and its overall impact on the customer service levels. Specifically for the selected sample customer “Global retailer”.

> This is to identify the design goals and establish the corresponding technical requirements which will be used to assess the performance of forecasting models and other required solutions. Later, these solutions will be assessed to measure their impact on the RFS demand management.

From a planning perspective, this thesis project scope will be limited to the demand short-term planning process. The short-term planning considers the upcoming demand in the following 5 weeks, which are calculated based on the forecasted quantities obtained every month. The monthly forecast time horizon in the short-term planning is only for the 3 upcoming months. This is reviewed monthly, and the corresponding corrections are applied.

D. Research Design Stages

The Double Diamond Design consists of four stages, Discover, Define, Develop, and Delivery. These 4 stages are guiding steps for the orderly development of the design solutions.

D.1 First Stage - Discover

The first stage of the double diamond model is D**iscover**. This is the stage where most of the baseline information from the stakeholders and supply chain processes is collected. In this way, the Discover stage will aim to explore the baseline conditions of Cargill GEOS’s supply chain and identify the design goals that need to be considered to formulate the model requirements according to their reality. In this way, the objective of the first stage can be summed up in the following question:

What are the baseline conditions and issues of Cargill GEOS’ supply chain that should be considered in the forecast model design?

D.2 Second Stage - Define

The second stage **Define** is where the technical design requirements are defined. For this purpose, the technical requirements to achieve the identified goals will be investigated in the literature. In this way the objective of the second stage can be summed up in the following question:

What are the technical design requirements for the Development and Implementation of a demand forecast model for Cargill GEOS’s Retail Food Services?

D.3 Third Stage - Develop

The third stage of the diamond model, **Develop**, characterizes as the stage where prototypes of the solution approaches are tested and assessed based on the defined technical requirements of the previous section. This stage objective is achieved by answering the following question:

Which of the considered forecasting approaches performs better according to the defined model design technical requirements?

Then the best performing model will be tested and based on the found shortcomings its accuracy will be improved.

D.4 Fourth Stage - Delivery

The fourth and final stage of the double diamond design model, **Delivery**. In this stage, the best-performing model will be used to forecast the RFS demand, and the forecast insights will be used to improve the demand management for Retail Food Services. In this way, the 4th stage objective can be summed up with the following questions:

To what extent the developed model can improve the demand planning process and demand management for Retail food services?

1.2. Thesis Project Outline under the Double Diamond Design

Now that the thesis project design objective and its stages have been presented, the thesis project outline will be introduced:

The next chapter 2 corresponds to the **Discover** stage, the first section will briefly Cargill GEOS Retail Food Services' business model. In the second section, Cargill GEOS' supply chain baseline conditions, including the production strategies, the demand planning process, and the role of the forecast in production planning will be presented. In the third section, the data management and the demand data of Global Retailer will be described. In the fourth section, the baseline monthly forecast performance will be analyzed. In the fifth section, the baseline safety stock management will be presented. The design goals 1 to 7 will be identified in the different sections of the Discovery stage.

Chapter 3 corresponds to the **Define** stage, where 3 brief literature reviews to identify and formulate the technical requirements that must be considered in the design process will be presented. In the first section, a literature review of forecast applications will be presented, where the 8th technical and last identified goal will be presented for the improvement of the safety stock management, along with a review of forecast aggregation level and sample size impact on forecast performance. In the second section, the literature review of the 3 seasonal forecast models will be presented. In the fourth section, the technical requirements based on the design goals and the literature reviews will be established.

Chapter 4 corresponds to the **Develop** stage, where different solutions according to the technical requirements will be developed. In the first section, a data aggregation framework will help to establish the roadmap to take the monthly forecast as close as possible to the weekly level. In the second section, the model designs of the seasonal forecast models considered in the literature review will be presented. In the third section, a sample of Global Retailer demand datasets will be used to assess the seasonal forecasting models based on the technical requirements and the selected forecast model for the rest of the research. In the fourth section, a procedure to improve the data management and leverage the existing relationships between the demand datasets will be developed. In the fifth section, the selected model will be extended and tested to determine its shortcomings to improve the model's accuracy.

Chapter 5 corresponds to the **Delivery stage**, where the technical requirements will be fulfilled by implementing the developed solutions in the previous section. First, the demand forecast will be generated at the monthly, 3-week, and weekly time aggregation levels will be presented to assess them and identify the right aggregation level with the available data. In the second section, the solution to implement the selected forecast model in demand planning will be presented. In the third section, the implementation of the procedure to improve data management in the demand planning process will be presented. In the fourth section, the forecast and data analysis insights will be used to develop seasonal management of the safety stock levels based on their demand variation. In the fifth section, a summary of the impact of the developed solutions on the demand management of the RFS will be presented to conclude the Double Diamond Design.

In chapter 6, the conclusions and recommendations of the thesis project will be presented.

The following figure shows the double diamond design diagram, which summarizes the thesis project outline.

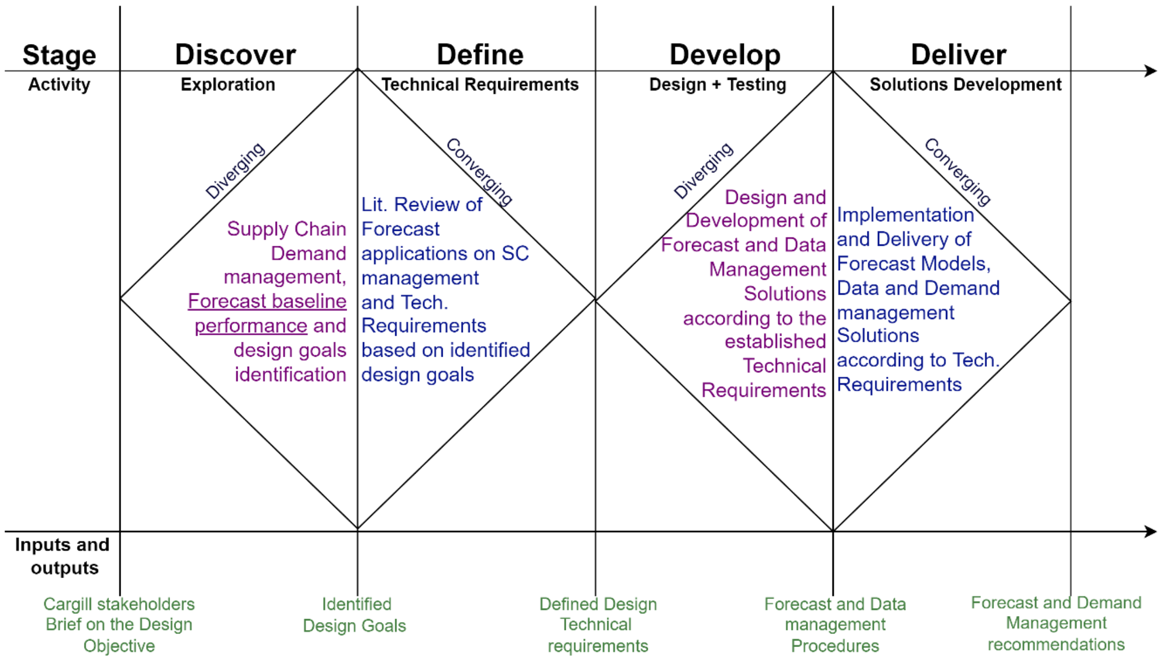
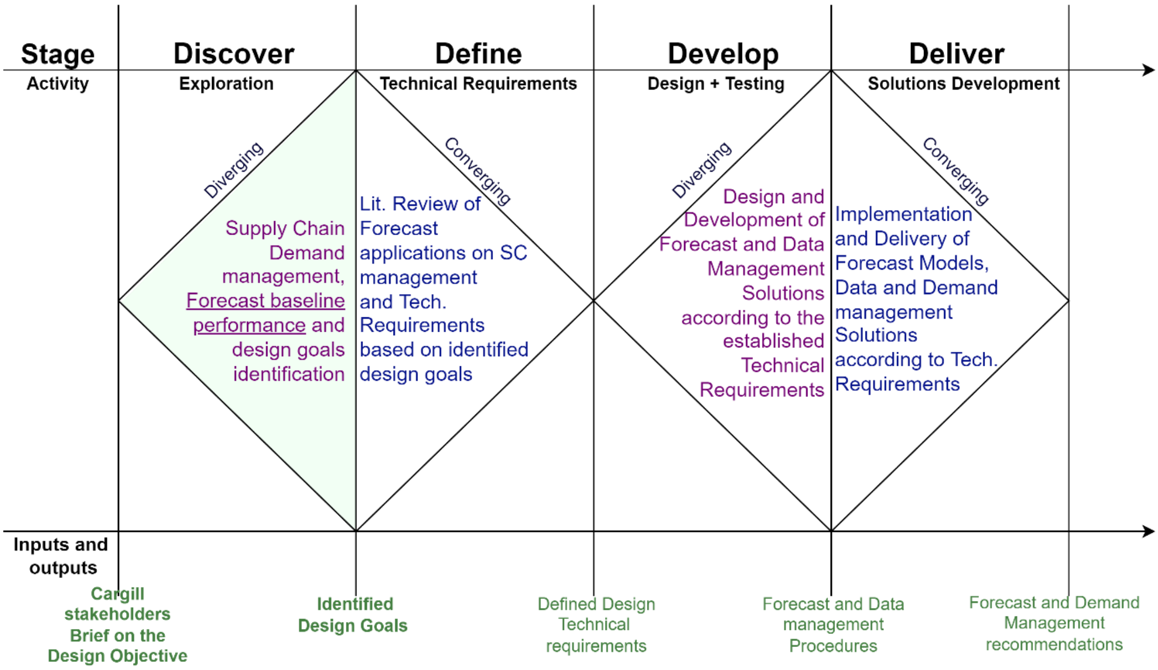


Figure 1 Thesis project Outline Based on The Double Diamond Design Model. Source: developed by the Author.

2. Discover Stage

In this first stage of the Double Diamond Design, the baseline information from the supply chain processes and the stakeholders will be presented. This includes not only the baseline conditions but also the design goals that will be used to formulate the model's technical requirements.



In this first section, the Retail Food Services commercial relationship will be presented. In the second section, the management of Cargill GEOS's supply chain will be presented, including the Cargill Integrated Business Planning (IBP), which is the process through which the supply chain processes are aligned in the long- and short-term planning, and the use of the Make to Forecast production strategy. In the third section, the demand data management process will be presented along with the description of Global Retailer's demand data, which has been sampled for this thesis project. In the fourth section, the baseline forecast performance will establish the conditions and accuracy level to be surpassed by the developed model. The fifth section will present the safety stock levels that are managed to compensate for forecast errors and production setbacks.

2.1. The Retail Food Services

Cargill Global Edible Oil Solutions (GEOS) is an edible oil solutions provider (Cargill Inc, 2022b). Whose services range from the provision of Oil in bulk quantities, for their industrial customers, to the provision of the production outsourcing service, for retailer customers. This thesis project will focus on production outsourcing and retailer customers.

The production outsourcing service that Cargill GEOS offers receives the name **Retail Food Services (RFS)** (Cargill Inc, 2022a). In the RFS, Cargill GEOS engages in Commercial relationships with retailer chains that operate in the EMEA region. These commercial relationships' duration can range between 6 to 24 months, with the possibility of renewal. In the RFS, Cargill takes responsibility for the Oil and material sourcing, production planning, Oil refining, the bottling process, stock management, and delivery of final edible oil goods ready for distribution at the retail market according to the retailer's demand, on an agreed point. The RFS demand arrives weekly with 7 days of notice. A schematization of the RFS commercial relationships is presented in the following figure:

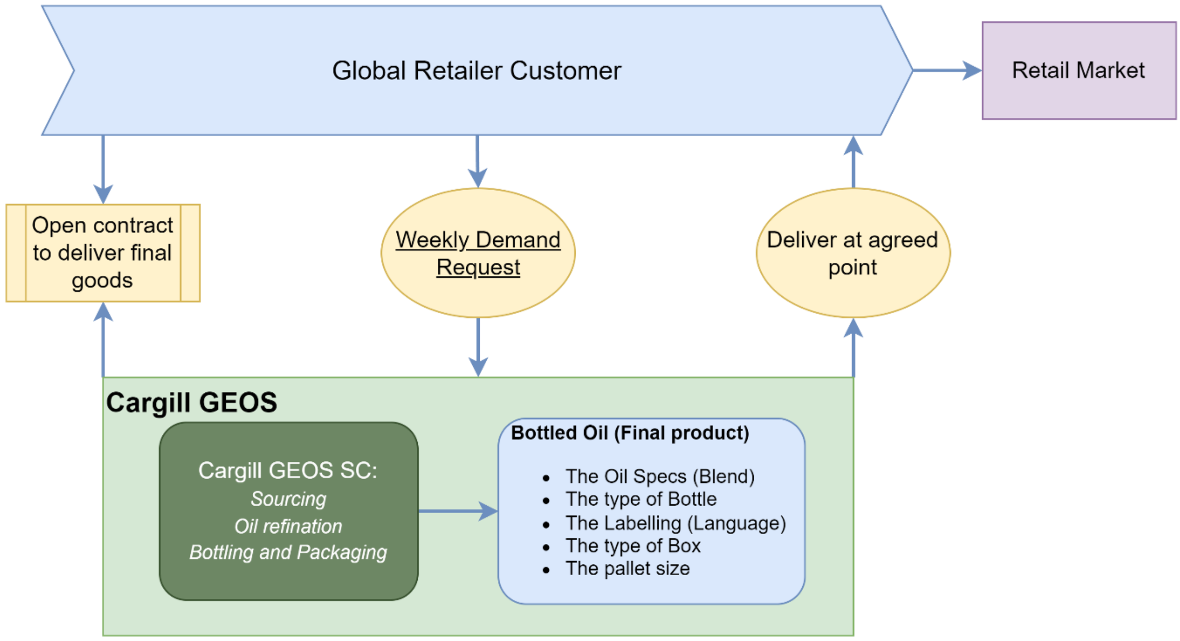


Figure 2 Schematization of the Cargill GEOS's Retail Food Services Business model

The RFS customers rely on Cargill GEOS as an already established manufacturing company with a great production capacity with multiple factories located in the EMEA region. In this way, Cargill due to its production capacity and available resources can deal better with production setbacks offering their RFS customer competitive prices thanks to the economies of scale (Chen & Xiao, 2015).

For the management of the RFS demand, Cargill GEOS follows a Make to Forecast production strategy (Meredith & Akinc, 2007). In this way, Cargill relies on a demand forecast to guide short-term production planning and the use of safety stock levels to compensate for forecast errors and production setbacks. The management of Cargill GEOS's supply chain will be explained in more detail in the following section.

2.2. Cargill Geos' Supply Chain Management

Cargill GEOS Supply chain begins with the procurement process of Tropical oils crude and seeds. This is performed by the inbound logistics department. These commodities are obtained through trading in the Oil and seeds market. As these commodities arrive in containers from overseas, the quantities are on the scale of 24 000 liters and above. The lead time of the sourcing process can range from 2 to 6 months duration. The seeds are sent to the Cargill Agriculture Supply Chain business unit (CASC) plant. Where the seeds are crushed for their oil extraction. The oil is stored to build up stocks for the weekly production planning. Until this point, the supply chain and stocks are managed following a Make-to-Stock production strategy. The stock levels of the 20 basic oils are managed based on the aggregated demand projections from the Industrial and retailer customers, in the long-term planning.

From the refineries onwards, the supply chain is managed on a Make to Forecast production strategy for short-term planning, and it is in the refineries, where the production for the industrial and the retailer customers diverge. The short-term planning has a time horizon of 6 weeks.

The crude oil is sent from the storage tanks to the refineries every week according to the production planning. There the crude oil is refined from impurities, treated, and blended according to the customers' demand specifications. Since the oil is transported to the refineries, to the obtention of the processed oil according to specifications, it can take up to 3 working days.

In the case of industrial customers, the Oil in bulk quantities has a low processing level and it is aimed to be used in the customers’ production processes. As the oil has a low processing level, this can be treated additionally to match the order specifications of another customer in case the original customer does not want it anymore. For this reason, the industrial customer service level is better than for the RFS customers.

In the case of the production for the Retail Food Services (RFS), the recipe for the oil treatments, blending and conditions is specific for each of the 370 active RFS products. The treated and blended oil from the refineries is sent to bottling plants. As the RFS are bottled oil products for the retail market, the oil is filled on specific bottles and labels according to the production description. Then the oil bottles are put into boxes and the boxes into pallets. Each pallet of bottled oil comprises a Stock Keeping Unit (SKU), which is the minimum unit of product for production planning, inventory management, and commercialization. To clarify what is a Stock Keeping Unit, a representation of it can be found in the following figure.

Figure 3 Example of a Stock Keeping Unit (SKU) of bottled oil

As the products come in bottles of different types and volumes, the liters of oil per SKU are not the same for different products. In the same way, to differentiate the GEOS products in demand planning, production planning, inventory management, and customer orders, a numeric code is used to refer to the different stock keeping units, this is the **SKU code**. The following figure some of the specific elements that differentiate the RFS products, how these are managed in the production planning when these are incorporated in the production process.

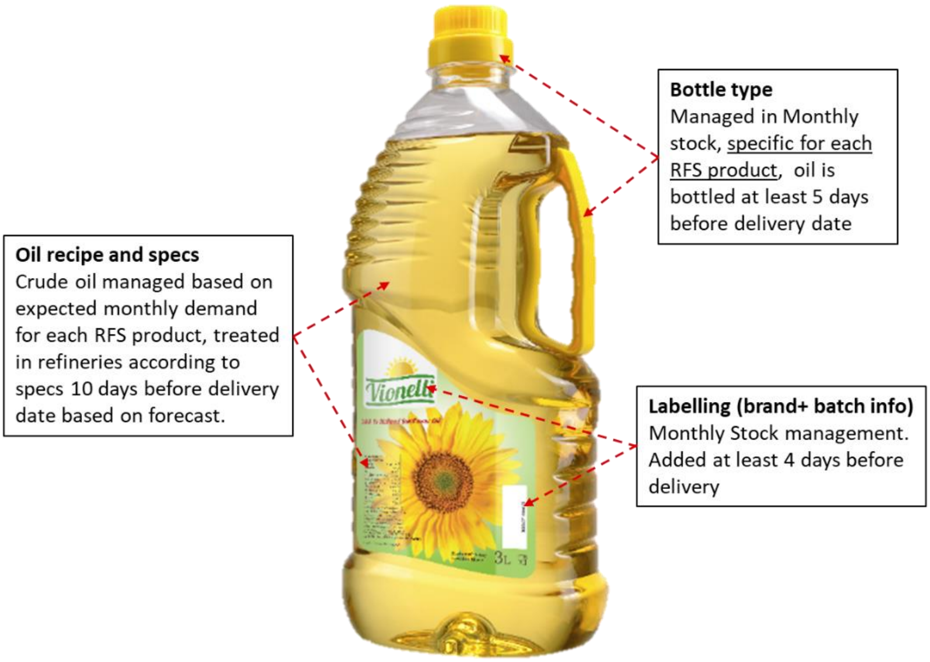


Figure 4 Bottled oil components assembly

After the raw oil is transported to the refineries for its treatment, the Bottling, packaging, and palletization process can take another 4 working days and the delivery to the customer desired location might take up to 2 additional days. Due to this, from the moment the raw oil is transported from the storage tanks to be processed, to the moment the pallets of bottled oil are in the retailer's customer agreed location, the lead time is about 9 to 10 days.

Nevertheless, as it has been explained, the RFS production process requires not only the oil with the right specifications. But also to have all the bottling, labels, and packaging material. The inventory management of these intermediate packaging goods is included in a Material Resource Planning (MRP) process, which is carried out monthly. In the MRP process, the RFS forecasted demand and the existing safety stock levels are reviewed to define the production planning for the 5 following weeks. The MRP process will be explained in more detail during the rest of the section. Then, one week before the delivery time, the RFS orders arrive, and these are matched with the forecasted weekly demand. If there is a gap between them or if there has been any production setback that has affected the weekly production, the safety stock can cover it.

The outline and the management of Cargill GEOS's supply chain can be visualized in the following figure:

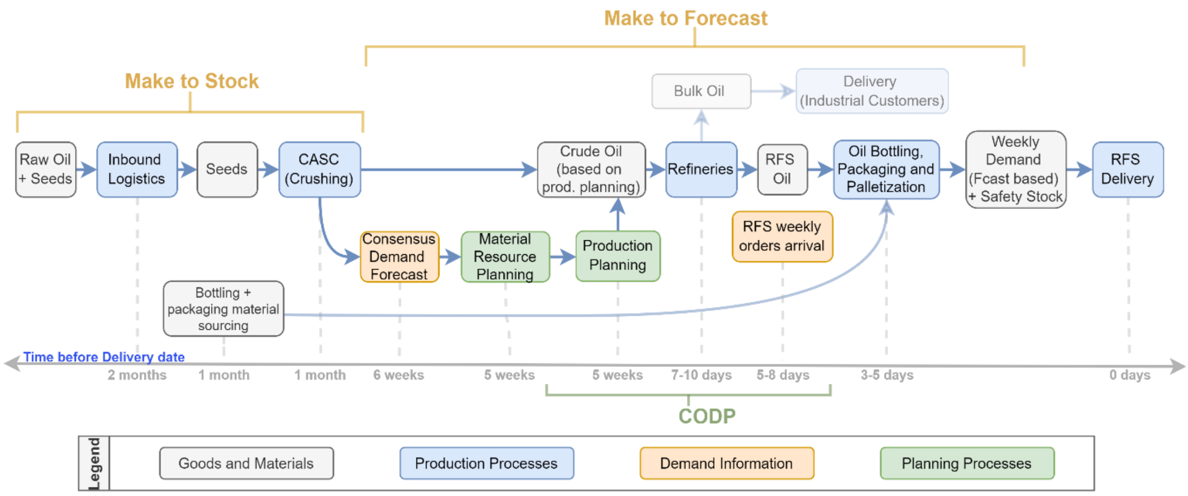


Figure 5 Cargill GEOS' Supply Chain Management Outline

For the management of the RFS in GEOS' supply chain, exist intermediate goods and final good inventories. The first intermediate inventory is located between the crushing process and the refineries. In this inventory, the raw oil stock is managed under the Make to Stock production strategy according to the aggregated demand expected for Cargill GEOS. The second intermediate inventory is for the Bottling and packaging materials that come from an external supplier. This second intermediate inventory is managed under the Make to Forecast production strategy and it is replenished based on the Material Resource Planning process for the RFS, which is based on the demand forecast. The next inventory is the inventory of the RFS final goods. This is composed of the safety stock and the cycle stock that will be used to meet the weekly demand.

A. *Cargill Integrated Business Planning process*

For the management and coordination of the different processes that interact or are part of the supply chain. Cargill follows a Sales and Operation Planning (S&OP) process (Wallace & Stahl, 2008). Which they have named "**Cargill Integrated Business Planning" (CIBP).** This S&OP process has been designed under the Integrated Business Planning approach (IBP) to manage the alignment of the supply chain processes. The IBP approach collects the good practices of a mature S&OP process (Bower, 2012).

In this way, Cargill GEOS coordinates the different supply chain processes as well as the management of the intermediate and final goods inventories to respond timely to customer demand, following the Make To Forecast (MTF) production strategy (Meredith & Akinc, 2007). To guide the Cargill Integrate Business Planning, Cargill relies on the demand planning process, which is based on the demand forecast, which will be detailed in the following section.

The Cargill IBP process is composed of 2 time horizons, the long and the short-term planning. The long-term planning comprises the demand projections from 24 months into the future until the present time. The demand projections are based on the statistical demand forecast obtained from the SAP Integrated Business Planning data management platform (SAP IBP). Based on the demand projections, Cargill GEOS's growth goals are defined and the corresponding plans to achieve them are developed, along with the planning and execution of the procurement process.

The short-term planning starts 6 weeks before the present time, to meet the upcoming demand on a weekly level and it is updated monthly based on the consensus demand forecast. The demand forecast starts with the statistical forecast that is automatically generated in the SAP IBP data management platform. This forecast is reviewed by the demand planner and some corrections are made if the demand planner considers that the forecast is biased or is providing a wrong forecast. This reviewed forecast is also reviewed by the sales department, and it is adjusted if the sales department considers that the forecasted quantities differ from the business outlook. This forecast that has received the input of the demand planner and the sales department, receives the name “consensus demand forecast” and it is the forecast that is used in short-term planning. Based on this forecast, the Material Resource Planning (MRP) process estimates the gap on a weekly level between the inventory levels and the forecasted demand. The production planning is defined to cover the demand gaps in the upcoming 5 weeks. The long and short-term planning will be explained in detail in the following section.

B. The Role of the Demand Forecast in CIBP for Cargill GEOS RFS

To establish the importance of the demand forecast in the management and planning of the supply chain processes, the demand planning process for the Retail Food Services (RFS) will be explained in detail.

The demand forecast elaboration starts with data collection in the SAP IBP system. For the demand forecast elaboration, Cargill GEOS works with delivery data. This is because the RFS customer orders are messy due to cancelled, duplicated, and changed orders in the quantities and the product details. Due to this, the customer request data is not suitable as input data for forecast, because it would require a manual cleaning and validation of the orders, which could be too laborious and time-consuming for the development of the demand forecast. This improvement opportunity has been acknowledged, but due to the time limitations and other challenges that will be presented in the following sections, it has been excluded from thesis project scope. On the other hand, the delivery data is stored automatically in the SAP IBP data management platform each time an order is dispatched for the customers every week. Still there exist some differences between the customer requested delivery date and the real delivery date such as a time lag, along with a small difference in the quantities of the accepted orders and the delivered ones.

> In the case of Global Retailer, the average time lag between the requested delivery date and the real delivery date is about 7 days and the difference between the requested and the delivery quantities is about 5%. This 5% difference seems to be the result of procurement and production problems that are mitigated by Cargill GEOS's effort to maintain the service levels at a minimum of 95% of the requested volumes.

In this way, the RFS products’ delivery data is used for the generation of the automatic statistical forecast in the SAP IBP data platform. This automatic forecast is used for the different RFS product demands, from the bulk oil for industrial customers to the 375 active RFS products for retailers. It is important to mention that all the GEOS demand is reviewed by the only demand planner that works in GEOS. For this reason, the demand forecast must be generated automatically. Otherwise, the workload would be too high for demand planner to have all the product forecasts on time. The algorithm of this automatic forecast has been designed by Deloitte, as a third party, and it is adjusted according to the Demand planner requirements and insights from the data.

> According to the input received from the Supply Chain Design and Analytics (SCDA) leader, who is also responsible for the Cargill Integrated Business Planning. It is key that **the developed forecast can be integrated into the SAP IBP data platform to be used automatically**. Thus, the developed forecast will replace the baseline automatic statistical forecast. **In this way, the design goal number 6 was identified.** *The design goals are not numbered according to their order of appearance, but according to the order of the defined technical requirements in the Define Stage.*

Currently, a simple moving average algorithm is being used for the automatic demand forecast, which in the demand planning process receives the name of “Statistical Demand Forecast”. This statistical forecast is used for the long-term planning and demand projections, as well as for the planning and execution of the Inbound logistics processes. In this way, the stock levels of the 20 basics tropical oils and seeds are managed following the statistical demand forecast.

In **long-term planning**, the monthly demand projections that start 24 months in advance, can only be matched with 50% of the demand contracts. This is because the commercial relationships range from 6 to 24 months in duration. In this way, 6 months before delivery time, most of the contracts have been signed, and the demand projection’s reliability improves.

These demand projections include the aggregated demand from Industrial and retailers (RFS) customers for the planning of the inbound logistics processes. As only 20 basic oils need to be procured for all the Cargill GEOS’ supply chain, these quantities are stable all year round and the forecast accuracy for the basic oils is about 90%. The long-term planning can be seen summed up in the following table:

Table 1 Improvement of the basic oils demand forecast reliability in the long-term planning.

<table>
<tr><th></th><th>Process stage</th><th>Time until delivery</th><th>Time in weeks</th><th>Basic Oils Forecast Reliability level</th></tr>
<tr><td rowspan="4">Long Term planning</td><td>Existing Commercial Relationships in Retail Food Services</td><td>24 months or more</td><td>130</td><td>50.00%</td></tr>
<tr><td>Demand Projections</td><td>12 to 24 months</td><td>104</td><td>60.00%</td></tr>
<tr><td>Open book Contract Signing to supply</td><td>6 to 18 months</td><td>52</td><td>85.00%</td></tr>
<tr><td>Inbound logistics planning</td><td>6 months</td><td>26</td><td>90.00%</td></tr>
</table>

The long-term planning and procurement processes have enough accuracy for Cargill’s standards, but they are not the focus of this thesis project. They have been briefly explained to provide enough context and understanding of Cargill operations and the demand planning process.

The short-term planning comprises the upcoming demand in the following 5 to 6 weeks and the corresponding production planning. As explained at the beginning of this section, in the refineries the production planning process begins following a Make-to-Forecast production strategy and the consensus demand forecast.

While for the Long-term planning and the procurement process of the 20 basics oils, the statistical forecast uses the monthly aggregated demand of all GEOS products. For the Retail Food Services (RFS), the demand for each of the 370 RFS products is forecasted individually. For this reason, the long-term planning forecast average accuracy is 90%, while for the RFS the baseline average forecast accuracy from the statistical demand forecast is only 42% and the demand is measured in liters.

In alignment with the design objective and the research scope, the design goal number 1 was defined as **the developed forecast for the RFS demand must improve the SAP IBP statistical forecast accuracy.** This design goal was approved by the SCDA leader in the month of March 2022.

Cargill classifies the RFS demand data based on the ABC XYZ segmentation (Zenkova & Kabanova, 2018) and its forecastability (FrePPLe, 2018). In this way, the RFS products' monthly demand has been classified based on their number of demand observations and on the Coefficient of Variation (CoV), which is defined as the ratio between the standard deviation and the mean (Arunraj et al., 2016). For this classification, the demand for each RFS product is analyzed on a monthly level and the demand has been counted in liters of oil.

In this way, the demand for RFS products has been classified as smooth (46%), when the demand is regular and the quantities are stable; intermittent (34%), when the demand is stable in the quantities, but not regular; erratic (9%), when the demand is regular, but the quantities are unstable, and Lumpy (11%), when the demand is neither regular nor stable in the quantities. Nevertheless, the ABC XYZ classification is not very useful to explain the statistical forecast performance, because the XYZ classification considers stable any product, whose demand has a **CoV lower than 80%** (Zenkova & Kabanova, 2018).

For these reasons, even if according to the ABC XYZ classification the demand might be classified as stable, it is not stable enough to be forecast by a moving average algorithm, that can at most estimate the demand current level (Johnston et al., 1999). Because the RFS demand varies in the demanded quantities from week to week and month to month. As a result, the monthly <u>Statistical demand forecast has a 42% accuracy</u> level, and it must be reviewed and adjusted monthly by the demand planner. This review and adjustment occur 8 weeks before the delivery date. This reviewed forecast by the demand planner receives the name of “<u>Demand planner input demand forecast”, achieving an average accuracy of 49%.</u>

To keep aligned the demand planner input forecast with the business outlook, 6 weeks before the delivery date. The sales assistants review the demand planner input demand forecast and if some corrections are required, the corresponding adjustments are made. This forecast receives the name “Consensus Demand Forecast”. In the Global Retailer sampled demand, no change was registered between the Demand Planner Input Demand Forecast and the Consensus Demand Forecast.

> The last time that the demand forecast had a considerable adjustment due to the business outlook was during the months of March, April, and May 2022, due to the Ukrainian conflict (Lang & McKee, 2022). In that situation, the demand for seasonal-only RFS products was canceled due to the resulting oil shortage and the seasonal patterns of many other products were disrupted, causing new demand peaks in periods along with demand historical records. In this situation, no automatic statistical forecast algorithm could have estimated the resulting demand, because they are based on past observations (R. Hyndman et al., 2008).

This kind of adjustments to the demand forecast are possible because the moving average algorithm is easily interpretable and the demand planner is aware of its limitations (Johnston et al., 1999). Still, after discussing with the SCDA Leader and the demand planner the features of the model, it was decided that the forecast to be developed had to be based on a transparent or white box model (Pintelas et al., 2020). This is to maintain its interpretability, take the corresponding measures as forecast adjustments when the past observations might not be enough to estimate the upcoming demand during disruption periods. **In this way, the design goal number 3 was defined as the forecast model must be transparent and interpretable to adjust it when it is required.**

The monthly consensus demand forecast is used for the Material Resource Planning (MRP) process that takes place 5 weeks before the delivery date. The MRP process is the process where the weekly production planning for the following 5 weeks is determined.

In the MRP process, on a weekly level for each of the RFS finished goods, the stock keeping units in inventory are compared to the sum of the upcoming weekly demand and the required level of the weekly safety stocks. This calculation is expressed in the following mathematical expression:

$$RFS\ Inventory + \boldsymbol{Weekly\ production} \geq Weekly\ forecasted\ demand + Required\ Safety\ Stock \qquad 2\text{-}1$$

As it can be seen in the mathematical expression 2-1, the weekly production planning is set following the Make to Forecast production strategy. Not only producing for the expected demand but also maintaining a safety stock for each of the RFS products.

In this way, the upcoming weekly demand is calculated by distributing the monthly consensus demand forecast in the following 5 weeks. Due to this, the production planning depends on the input provided by the forecast. Currently, the demand forecast is being estimated on a monthly level. So, to match the time aggregation of the production planning, the monthly forecast is distributed in the 5 following weeks of the MRP process. Due to the time aggregation difference between the forecast and the production planning, at the request of the SCDA leader, **the demand forecast time aggregation level has to be taken from the monthly level to the weekly, to the extent possible**. In this way, the design goal number 2 has been identified.

The second design goal has been phrased in this way because, while the RFS demand shows some stability at the monthly level, which allows the moving average to perform relatively well in the best cases. When the time aggregation level was reduced, the forecast accuracy was reduced, due to the appearance many peaks and valleys caused by the weekly demand variation start appearing (Rostami-Tabar et al., 2014; Zotteri et al., 2005). Which rise the error level and renders the moving average into a useless algorithm for an accurate demand forecasting at lower time aggregation levels.

Besides the adjustments of the demand planner and the sales assistants in the consensus demand forecast, to improve the match between the production planning and the upcoming customer demand. It is possible to make later corrections in the weekly production planning. This is through the input provided by the customer service representatives, who are the first point of contact for the customers. As the make-to-forecast production strategy allows a floating Customer Order Decoupling Point (CODP), which is the point in time where the customer demand becomes available and can be matched with the production planning and demand forecast (Akinc & Meredith, 2015). In the specific case of Cargill GEOS RFS, the customer service input allows to correct the production planning, from the moment it is created, 5 weeks before delivery time to one week before the delivery time. This is because it is in the last week when the customers' orders arrive, and the floating Customer Order Decoupling Point (CODP) concludes.

As it can be seen on the right side of the following figure, most of the production planning correction requests arrive in the last 3 weeks before delivery. In the case of Global Retailer, from January to July 2022, 136 production planning corrections have been registered. 49.2% of them have been attributed to Forecast errors, 16% to production delays, 10% to changes in customer requests, and the rest correspond to other reasons. These corrections take about 25 minutes to solve, through coordination between production planners and customer representatives. This leads to 14 extra hours due to forecast errors.

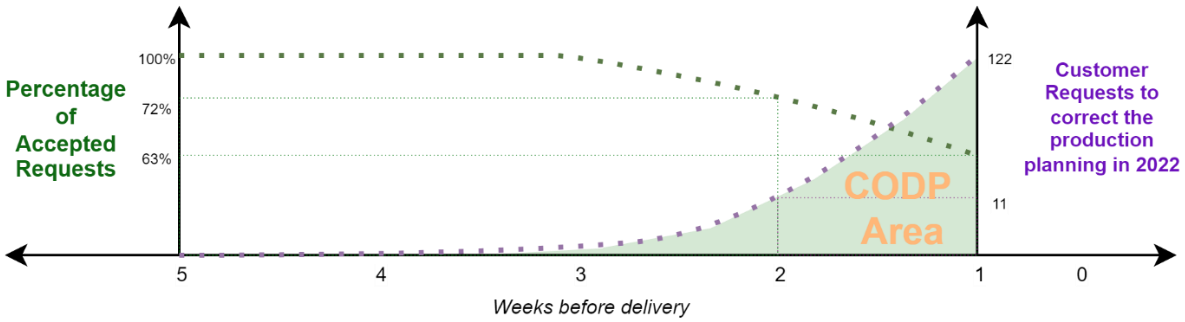


Figure 6 Customer Order Decoupling Point Floating Area

Unfortunately, as can be seen on the left side of the figure above, not all these correction requests can be fulfilled. Because the closer the corrections are to the delivery time, the fewer resources are available to implement them. If the requests arrive at least 3 weeks before the delivery time, 100% of them can be fulfilled. But the closer they are to their delivery, this percentage reduces. This year 33% of these production correction requests have been rejected.

After these many corrections in the forecast, the RFS customer demand arrives one week before the delivery time, as can be seen in the timeline of Figure 5 Cargill GEOS' Supply Chain Management Outline. If there are still gaps between the production planning and the real demand, they can be covered by the safety stocks.

According to the GEOS OTIF report for RFS, from January 2022 to July 2022, Global Retailer has registered 3195 orders, and 62% of orders were delivered On Time and In Full (**62% OTIF level**). Along with this OTIF level for Global Retailer, 1985 changes in the original orders have been registered in the same period. Where 15% of these changes are directly attributed to **Forecast errors, 298 orders**. And 738 rejected orders have been registered, where 294 of them are attributed to forecast errors. At the beginning of the thesis project, it was considered to relate the OTIF indicator to one of the design goals, but after reviewing it in detail with the SCDA coordinator at a meeting at the end of June 2022. The idea was dismissed because there are many factors influencing the OTIF indicator.

The short-term planning activities and the forecast accuracy improvement until the delivery time have been summarized in the following table:

Table 2 Retail Food Services demand forecast in the short-term planning.

	Process stage	Time until delivery	Time in weeks	RFS Forecast Accuracy level
Short term planning	*Automatic Statistical forecast*	3 months	**17**	42.00%
	Demand Planner Input Forecast	8 weeks	**8**	49.00%
	Consensus demand forecast	6 weeks	**6**	49.00%
	MRP Run (Safety stock + Demand production)	5 weeks	**5**	49.00%
	RFS Delivery	0 weeks	**0**	49.00%

An overview of the long-term planning, specifically the demand projections accuracy level for the Basic Oils procurement, and the short-term planning, specifically the demand forecast accuracy for the Retail Food services production planning can be appreciated in the following figure:

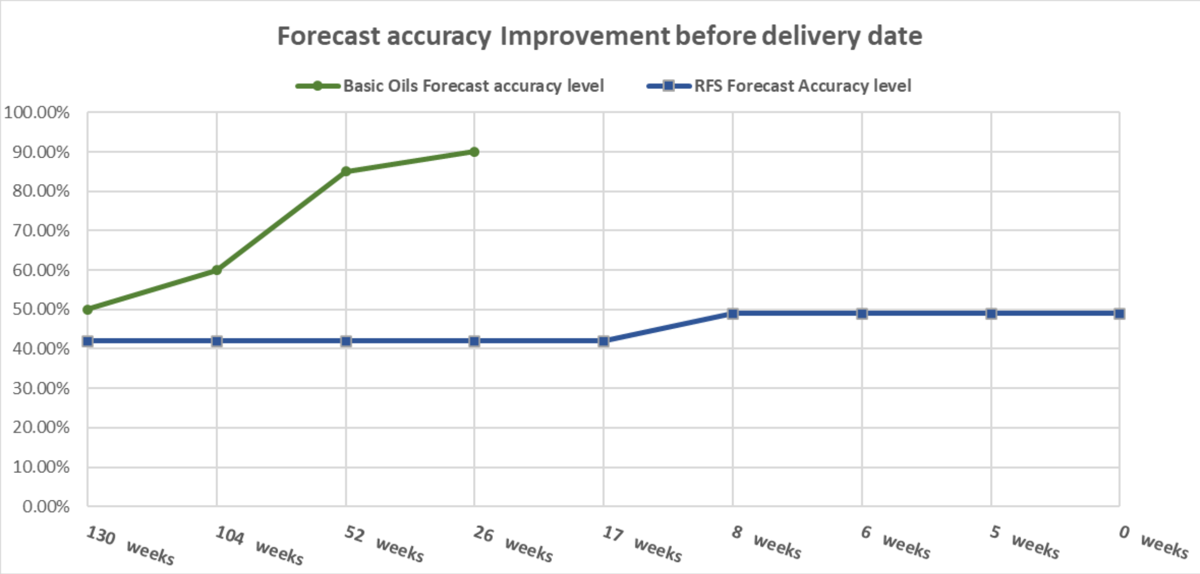


Figure 7 Forecast accuracy evolution during the long- and short-term planning. Source: Developed by the author.

2.3. Demand Data Management

For the data management of the Retail food services products, the Stock Keeping Unit (SKU) code is used. At the beginning of section 2.2, the concept of SKU was explained in detail. As the liters of Oil per SKU is different for each RFS product. In the demand planning process, and the data management in the SAP IBP platform, the RFS products' demand data is managed in liters of oil. Later during the MRP and the production planning process, the liters of oil are converted into the stock-keeping units. During the rest of the thesis project, the terms “SKU” and “RFS” will be used interchangeably to refer to the RFS products and the demand data will be analyzed solely in liters of Oil. For example when referring to the demand datasets.

In the SAP IBP system, information about the RFS products’ demand since September 2019 can be found, for example, the liters of oil sold per RFS product, the product description, the order date, the delivery date, the delivery point, the business name, the country of origin, the country to be delivered and other information that might be relevant for the coordination of the different supply chain processes. Unfortunately, information before September 2019 is not available anymore, because at that time Cargill GEOS migrated to the Current version of the SAP IBP data platform, named TC2. SAP IBP is a platform based on SAP HANA (Färber et al., 2012). For the analysis of the baseline conditions and the demand at the monthly level, the last month considered is April 2022, unless it is indicated otherwise.

A. Global Retailer Demand datasets for the Retail Food services

As stated in the research design scope, only the demand of Global Retailer, a retail chain that operates in the EMEA region, will be considered for the analysis. Global Retailer has registered demand for 120 RFS products, but not all of them are active anymore. These 120 RFS products demand datasets can be identified by their SKU code. Some of these products are distributed in only some countries of the EMEA region, while others in more than one country, when these countries share language, culture, or have similar food legislation. For the production planning process, Cargill only considers the total demand that is later distributed to Global Retailer in different countries as Global Retailer in different countries is defined as separate commercial entities. In this way, when the geographical demand of the products was taken into consideration, 166 country-RFS products demand datasets were obtained.

As mentioned above, Cargill only needs the total demand for the different products, independently of the country's demand behavior. Nevertheless, when the demand datasets and their plots were analyzed thoroughly in Excel. It was found that even if the product total demand datasets show some seasonal patterns. Stronger and more marked seasonal patterns could be identified in the products' datasets when their demand was analyzed at the country level. This was because of two main factors. First, each country had its own seasonal patterns, and second, products that were sold in more than one country were not available during the same period in different countries. For example, one product could be available in Belgium since September 2019, but the same product was only available since October 2020 in the Netherlands. Or a product that was being distributed since September in both countries stopped its distribution in September 2020 in the Netherlands.

Faced with these findings, it was decided that to make the most of the data available, the best approach was to analyze the demand at the country level to estimate better the seasonal patterns of the products with an active demand. Similar reasoning is given by Zotteri (Zotteri et al., 2005), who recommended that data aggregation level should be selected according to the nature of the processes that generate it. In this case study, the demand is generated first at the regional level and it is later aggregated to estimate the total demand to arrange the production planning. But as explained, it is in this way that important information about the demand patterns available at the country level gets dismissed. For this reason, the RFS products demand datasets will be considered at the country level.

These 166 country-SKU datasets present different demand behavior. Some of them are intermittent as they correspond to seasonal-only products, while some others present a short-life demand that lasted about 8 months. Due to the lack of demand observations, especially for the new RFS products. It is difficult to estimate a demand forecast because the SAP IBP forecasting algorithm seems to require at least 12 months of demand observations. The register of the longest demand datasets goes back to September 2019, which makes a max of 32 months until April 2022.

After the country-SKU dataset initial analysis, an interview with the sales assistants was carried out. There it was found that some of the RFS products that had a short market life, about 8 months of demand until they were not demanded anymore, were actually the predecessors and successors of the new and old RFS products, respectively. This second finding about the demand data just reinforces the previous decision of analyzing the demand data at the country level, as these replacements occur in specific countries. These replacements or succession relationships between the RFS products were due to small changes in the product specifications. For example, changes in the oils' recipe, changes in the bottling and labeling materials, as well as in the packaging. Some of these replacements between products were registered by the sales assistants, but this information was not considered in the SAP IBP system or the demand datasets management.

The following figure shows an example of these succession relationships that occurred at the country level. Which is an excel plot that shows the 4 RFS product datasets in the country, that are part of these replacement relationships. As it can be seen in this figure these datasets share a similar demand level, the phasing out and phasing in periods occur simultaneously and more importantly, they maintain the demand seasonal patterns. When these datasets are analyzed as a whole the repetition of these patterns can be appreciated year after year. Presenting a regular demand peak period from November to March and an Off-peak period from April to October.

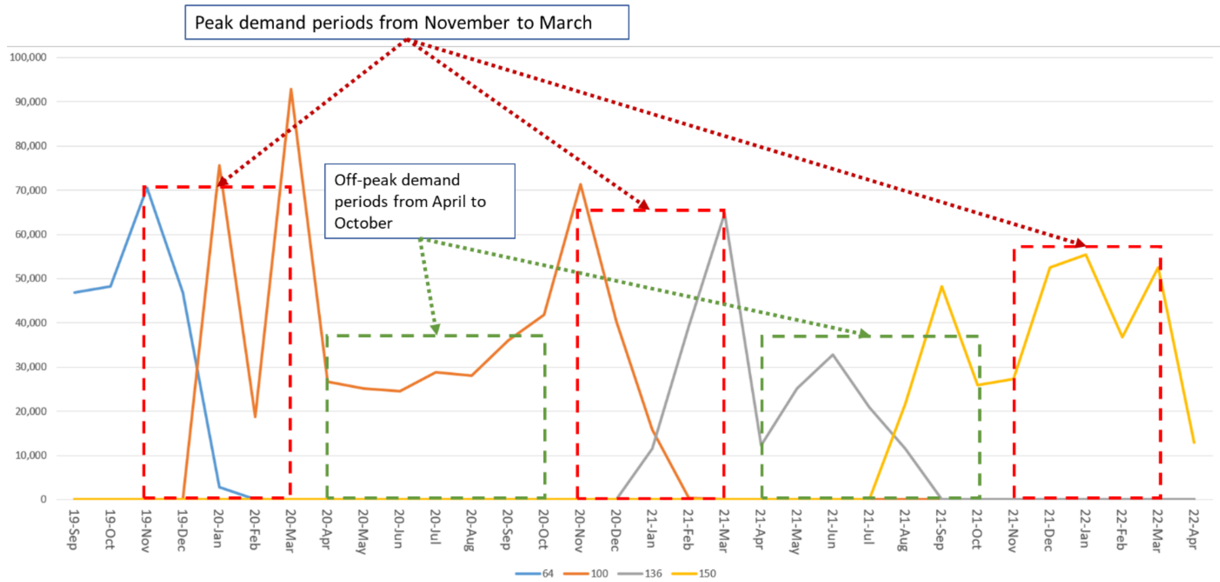


Figure 8 Example of the succession relationship between Retail Food Services products within the same country

Considering that there existed many more replacements between the RFS at the country level that were not properly registered and that there were only about 2 years and half of the demand observations available, which would already limit the forecasting options. The product replacement was brought to the awareness of the SCDA coordinator at a meeting at the end of May. As a result of this meeting, **the design goal number 5 was defined as the forecast model that can produce a useful forecast, even with the data availability limitations,** and **the design goal number 7 was defined as the development of a procedure to objectively identify existing succession relationships between the RFS products.**

B. Demand data description

In the preliminary analysis, all demand datasets were worked on monthly demand level in an excel table, where basic statistical parameters such as the average, the standard deviation, and the number of demand observations per dataset were calculated. As the demand datasets were on an excel table, these could be grouped, filtered, and ordered by country, by SKU code, by type of oil such as rapeseed, sunflower, and blended, and by liters per bottle. In this way, the datasets were organized based on the number of monthly observations from the highest to the lowest, as will be described in the following paragraphs.

The content of this section has been removed due to the confidentiality issues.

The differentiation between the regular and the seasonal-only products has been made because the regular product demands are managed with the Make-to-Forecast production strategy. While seasonal-only products are ordered with two months of notice, and these are produced following a make-to-order production strategy.

The differentiation between the active and the inactive products has been made, because, as it was stated in the previous section, the RFS products that have already been terminated have a chance of being the predecessor of other RFS products. For example, many regular products have less than 20 demand observations at the monthly level. Which might make them not suitable for some forecasting models (R. Hyndman & Kostenko, 2007). Nevertheless, as explained above, from existing product replacements in the RFS, the registered ones are only a fraction of the total.

2.4. The Monthly Demand forecast performance for Global Retailer demand

In this section, the baseline performance of the Statistical demand forecast, the demand planner input forecast, and the consensus demand forecast. For this purpose, the performance of the country-SKU datasets will be reviewed. Nevertheless, as described previously, not all the datasets have the same number of observations which impedes obtaining a demand forecast for them. For that reason, in this section, a sample of 12 of the 21 datasets that have 28 monthly observations or more have been selected. This sample was selected because it will show the performance of the automatic statistical forecast in the best conditions possible, which would be used as a benchmark to compare with the developed forecast model performance in the following stages.

A. Demand Forecast variables

As explained previously in the demand planning process, the RFS products are managed in liters of oil. To evaluate the forecast performance, concerning accuracy and error levels, the Mean Absolute Percentual Error (MAPE) will be used. The MAPE is one of the most popular and easier-to-interpret error level indicators (R. Hyndman et al., 2008).

B. Monthly Forecast time horizon

To assess the performance of the 3 monthly forecasts, all the information available will be considered. In the case of the statistical demand forecast, it requires at least 12 months of demand observations. For that reason and considering that not all the datasets have 32 observations, the time horizon will be of 18 months.

C. Monthly Forecast Performance Results

The datasets in the following table have been arranged based on their Coefficient of Variation (CoV), which is defined as the ratio between the standard deviation and the mean (Arunraj et al., 2016). The CoV is a dispersion measure and to some extent a useful indicator of how difficult it can be to forecast a time series. The enumeration of the sampled Country-SKU datasets corresponds to their consolidated datasets enumeration which is introduced in section 4.4. These datasets were selected because they did not require to be modified by the product replacements or demand aggregation for production planning in the following stages. For better visualization of the forecast performance, they were colored. The best performing datasets forecasts are in green, followed by the forecasts in yellow, the worst performing datasets are colored in red.

Table 3 Baseline Forecast performance

Dataset	Average demand (in liters)	CoV	MAPE statistical Fcast	MAPE Demand planner input Fcast	MAPE Consensus demand Fcast
18	Data removed due to confidentiality Issues	**27.43%**	30.45%	33.93%	33.93%
1		**29.11%**	36.18%	26.87%	26.87%
3		**43.41%**	49.97%	43.29%	43.29%
7		**49.19%**	91.36%	85.92%	85.92%
11		**49.26%**	54.96%	39.75%	39.75%
14		**50.46%**	69.99%	52.70%	52.70%
2		**50.61%**	47.58%	46.77%	46.77%
16		**52.39%**	62.86%	36.89%	36.89%
9		**58.55%**	58.36%	67.67%	67.67%
12		**67.79%**	107.24%	53.02%	53.02%
13		**68.35%**	115.17%	121.42%	121.42%
15		**71.92%**	81.31%	78.62%	78.62%
Average		51.54%	**67.12%**	**57.24%**	**57.24%**
Weighted Average		43.59%	**57.91%**	**50.97%**	**50.97%**
Accuracy levels based on W.A.			42.09%	49.03%	49.03%

As it can be seen in the table, there is a correlation between the CoV and the Error level. This is especially the case for the Statistical Forecast because it fully depends on the moving average algorithm, which performs better when the demand observations present a low variability or dispersion level (Johnston et al., 1999). It can also be seen that with the demand planner input the forecast accuracy improves. But this is mainly the case when the statistical forecast is visibly incorrect, and the error level is considerable. The consensus demand forecast does not present variations from the Demand planner input forecast. As commented previously the last correction in the consensus demand was due to the Ukrainian conflict that affected mainly the demand for the seasonal only products (Lang & McKee, 2022), which are produced on a make-to-order basis. These are not included in this sample due to the fewer demand observations and the lower dependency on the forecasts.

An example of the statistical forecast performance can be seen in the following figure. The figure shows the forecasts for the dataset **3** with Coefficient of Variation 43.41%. The statistical forecast in blue does not show a good match with the actual deliveries in red, remember that stated in 2.2.B, delivery data is used as input for the forecast. For this reason, the demand planner applies the correction and assumes a constant level demand forecast in green. In the case of this dataset, this correction helped to reduce the MAPE from 49.97% to 43.29%. As stated previously, for Global Retailer data, the Consensus demand forecast does not show an improvement with respect the Demand planner Input. For this reason, their lines in the following figure are overlapping and the demand planner is not visible.

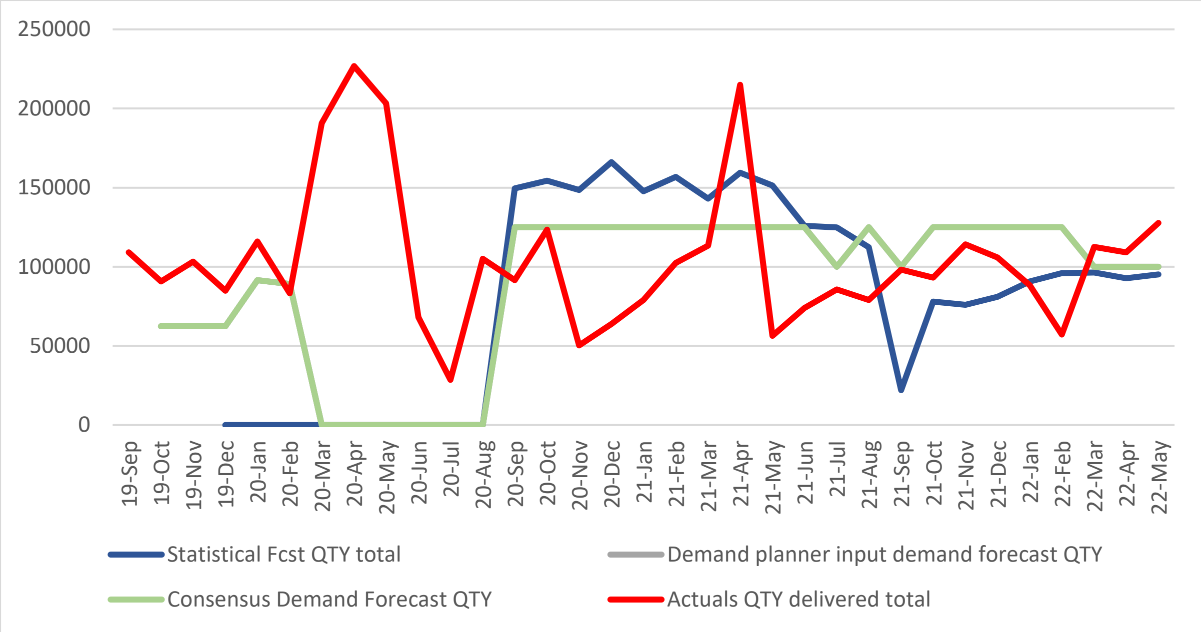


Figure 9 Forecast comparison against real demand for consolidated dataset 3

As stated in previous sections and shown in *Figure 8 Example of the succession relationship between Retail Food Services products within the same country*. Global Retailer's demand presents some degree of seasonality and varies in the demand quantities from month to month. Not showing the same patterns for all the RFS products. But the most common pattern is the presence of two demand peak periods, the first one from February to May, and the second from August to December. This can be seen in the following figure.

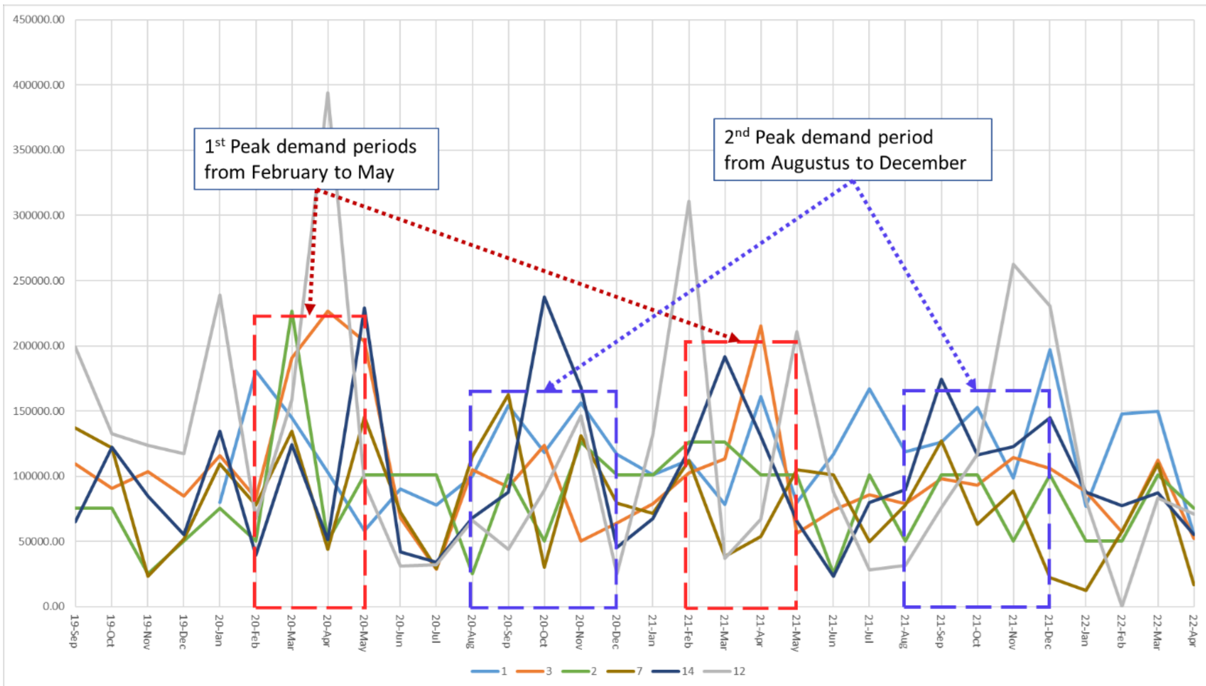


Figure 10 Example of Seasonal demand pattern with two demand peaks per year, one before summer (in red) and the second before the end of the year (blue)

In the case of these seasonal demand patterns, it seems to be influenced by seasonal events as Christmas and Easter. It is difficult to know with certainty, as Cargill does not deal directly with retail market demand, but it satisfy the retailer demand that have their own marketing and commercial strategies (Arunraj et al., 2016). Still these seasonal patterns are repeated in the two years of observations. The main change is on the demand level, but the peaks and valleys show stability at the monthly level. These stable seasonal patterns were communicated to the SCDA coordinator and according to the guidelines of the SCDA leader of developing a transparent forecast model. **The design goal number 4 was defined as the forecast model must be able to capture seasonal demand patterns or others to generate a representative forecast of the observed demand.**

2.5. Safety Stock Management

As stated in section 2.2, Cargill GEOS uses a Make to Forecast (MTF) production strategy for the management of the RFS demand. As part of the MTF, Cargill GEOS also manages safety stocks of finished RFS products to mitigate the forecast errors and production setbacks. This is to meet the contracted service levels, that range between 80% to 95% for the different RFS customers.

For the calculation of the Safety stock levels of each RFS, Cargill GEOS uses the following formula that is based on the **weekly demand** and lead time variability (Thieuleux, 2022), individually for each product:

$$SS = Z \times \sqrt{L \times \sigma_{demand}^2 + \mu_{sales}^2 \times \sigma_{lead\ time}^2} \qquad \text{2-2}$$

This formula assumes that RFS demand follows a normal distribution, in that way the Z indicates the cumulative probability for the standard normal distribution (Little, 2013), that is matched with the desired service level, the L is for the production process Lead time (L), the demand variance (σ_{demand}^2), the average demand for the RFS product (μ_{sales}) and the variance of the lead time of the production process lead time ($\sigma_{lead\ time}^2$).

The corresponding values of Z for the most common service levels can be found in the following table and be calculated with the excel function NORM.S.INV.

Table 4 Service levels and the corresponding number of SD deviations above the mean of the normal distribution

Service Level	80%	90%	95%
Z (#SD)	0.84162123	1.28155157	1.64485363

The production lead times are almost constant for all the RFS products, and in the Safety Stock formula, 1 week has been defined as the average lead time (L) and 0.2 weeks of standard deviation (SD) for the lead times. So, by replacing the lead time values in the safety stock formula 2-3, the following can be obtained:

$$SS = Z \times \sqrt{(Lead\ time) \times SD_{demand}^2 + Avg_{demand}^2 \times SD_{lead\ time}^2} \qquad \text{2-3}$$

$$SS = Z \times \sqrt{1 \times SD_{demand}^2 + 0.04 \times Avg_{demand}^2} \qquad \text{2-4}$$

Then, the demand standard deviation can also be replaced based on the definition of the Coefficient of Variation 2-5:

$$SD = CoV \times Average \qquad \text{2-5}$$

In this way the Safety Stock formula 2-4 can be changed into 2-6:

$$SS = Z \times \sqrt{CoV_{demand}^2 \times Avg_{demand}^2 + 0.04 \times Avg_{demand}^2} \qquad \text{2-6}$$

Then, by factorizing the Avg_{demand}^2 2-7 is obtained:

$$SS = Z \times \sqrt{CoV_{demand}^2 + 0.04} \times Avg_{demand} \qquad \text{2-7}$$

To simplify the principles of the 2-7 formula and considering that the 0.04 lead time weeks only generates a 3% error on the Safety stock, the 0.04 can be omitted and 2-8 can be obtained.

$$SS = Z \times CoV_{demand} \times Avg_{demand} \qquad \text{2-8}$$

In this way, the Safety Stock levels of the RFS of Cargill GEOS depend mainly on the Service level (Z), the Coefficient of Variation of the demand (CoV), and Average demand as can be seen in 2-8.

Based on the 2-8 formula, considering an average demand of 1000 liters, the 3 most common service levels of 80%, 90%, and 95%, and 6 values of the Coefficient of Variation that are representative of the RFS demand. The Safety stock levels for these different parameters can be found in the following table:

Table 5 RFS Safety Stock quantity variation for an Average demand of 1000 liters

		Coefficient of Variation (CoV)					
Service level	Z value (#SD)	20%	40%	60%	80%	100%	120%
80%	0.84162	168.32	**336.65**	**504.97**	673.30	841.62	1009.95
90%	1.28155	256.31	512.62	768.93	1025.24	1281.55	1537.86
95%	1.64485	328.97	657.94	986.91	1315.88	1644.85	1973.82

As it can be seen in the table above, the Safety stock levels duplicate from 80% to a 95% service level, as it follows the cumulative probability of the normal distribution, these service levels can be approached in the contracts with the RFS customers. On the other hand, the Safety Stock levels can match average demand when the CoV is above 100%. Considering that the most common CoV values range between 40% to 60%, that the contracted service level for Global Retailer is 50% and assuming a 1000 liters weekly demand, the safety stock all year round would range from 33% to 50.4% of the weekly demand. As commented previously, the safety stock exists to compensate for forecast errors and production setbacks, but it is the CoV the factor with the biggest influence on the safety stocks. So these additional quantities need to be kept in stock as the forecast does not have enough accuracy to align the safety stocks to it.

To see how this safety stock management approach affects the RFS product demand with real data. The safety stock levels of 3 consolidated datasets with different CoV values have been calculated in the following table.

Table 6 Safety stock levels for the consolidated datasets 18,3 and 13

Dataset	Service Level	Z value (#SD)	CoV	Average Demand	Safety Stock Level	SSL/Avg Demand (%)
18	80%	0.841621234	25.68%	**Data removed due to confidentiality Issues**		21.61%
3	80%	0.841621234	44.37%			37.35%
13	80%	0.841621234	77.60%			65.31%

As stated above, the main problem for the management of demand and the safety stocks is not the service levels by themselves, but the demand variation (CoV) that can substantially increase the required safety stock level for the different products. It is worth emphasizing the fact that the baseline approach for the safety stock levels is more suited for a make-to-stock production strategy than for a Make to forecast (Meredith & Akinc, 2007). This is because, the safety stock levels are being managed on a constant level all year round, independently of the demand forecast, following the demand variation and service levels. Due to this, the demand peak and off-peak periods caused enough variation in the year, that increased the safety stock above what is necessary for most of the year, but below what is needed during the demand peak periods. This situation is depicted in the following figure.

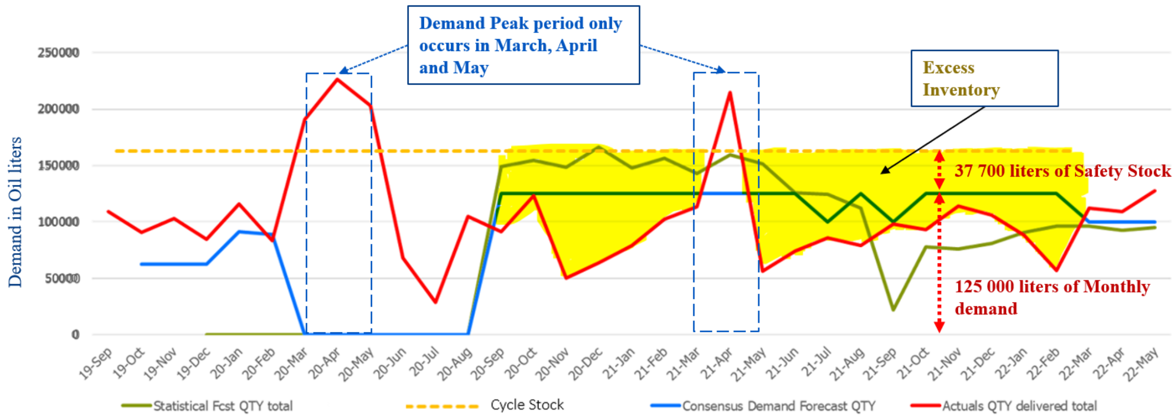


Figure 11 Forecasted demand and safety stock levels in comparison to the observed demand for dataset 3

The baseline management of the safety stock is understandable considering the demand forecast performance, as it calculated using a moving average which achieves an average accuracy of 49%. It is expected that by improving the performance of the demand forecast and the quality of the demand insights, the management of the safety stock levels can be improved. This would be an important improvement because currently, the RFS inventories are above Cargill GEOS's internal warehouses capacity and Cargill has to rely on external warehouses.

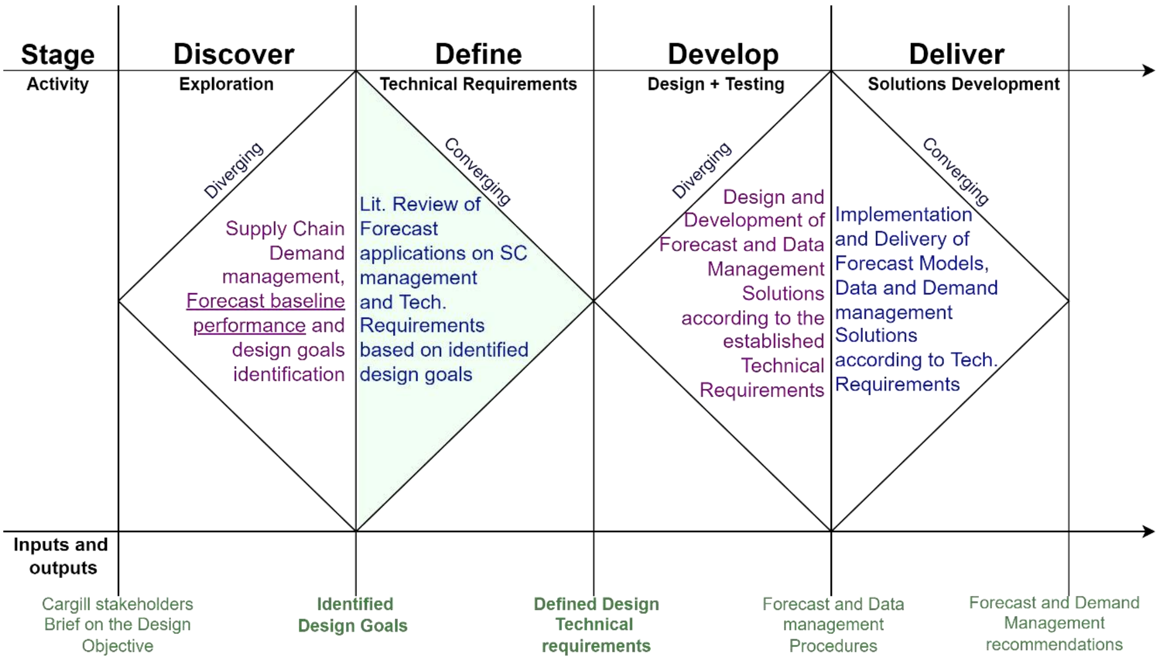
2.6. Discovery Stage Conclusions

As it has been shown in the Discovery stage, the make-to-forecast production strategy allows Cargill GEOS to provide the RFS products to their customers while maintaining the contracted service levels, even though the forecast performance is poor. There are many causes for the low performance of the statistical forecast, the first one is the use of the moving average. Because this is one of the most basic forecasting approaches as it can only provide the time series' current level. Second is the fact that the time series show seasonal patterns, but no action has been taken to leverage this information that is known in the organization. The third is the demand data availability, as the demand show seasonality, to estimate these seasonal patterns properly two years of observations will probably not be enough.

Fourth, the demand fragmentation due to the replacement of RFS products causes even fewer demand observations to be available for the demand forecast, making less feasible the achievement of a useful demand forecast. As Cargill GEOS production processes are planned to follow the make-to-forecast production strategy, the main consequence of low forecast performance has been the rise of the safety stock level, increasing considerably the storage cost as Cargill's internal warehouses are not enough and they had to rely on external ones.

3. Define Stage

In this stage, the design goals, the baseline conditions, and other relevant topics for the thesis project objective were investigated in the literature to determine the technical requirements to achieve them.



In the first section, a brief literature review of the forecast applications in supply chain management is presented along with the design goal number 8. In the second section, a literature review of seasonal forecasts will be presented. Including forecast models such as the ARIMA model, the ETS Exponential Smoothing, and the STL+ETS model. In the third section. The third section presents the statistical platforms considered for the forecast model development, such as RStudio IDE and STATA. The fourth section goes over the different design goals and based on the insights obtained from the literature review, the corresponding technical requirements have been formulated.

3.1. Forecast applications in Supply Chain Management

In this section, a brief literature review of forecast applications in Supply chain management will be presented. The first part presents research for the development of the demand forecast of short-life cycle products, that lack demand observation, along with the policies to improve the management of the inventory levels based on the forecast insights. From the insights of this paper, the design goal number 8 will be introduced. The second part focuses on the demand aggregation levels and the data limitations to achieve a weekly demand forecast.

A. Demand Planning and Forecasting for short life cycle products

Considering the succession relationships between some of the RFS products, as was described in section 2.3, and the fact that more than 80% of the country-SKU datasets a short life. The case study carried out by Kurawarwala (Kurawarwala & Matsuo, 1996) was considered pertinent for this thesis project. In the study, Kurawarwala analyses the case of a computer manufacturer that due to technological improvement must replace his line of products every 12 months.

As the supply chain lead time for these products was about 6 months, there was no demand data available for the production planning of these products. Only about 6 months after that the products have introduced to the market, the demand data was available, but by that time the products were already in their life cycle maturity stage and only had 6 months left of market life (Kurawarwala & Matsuo, 1996).

For this reason, to improve the demand and production planning of the manufacturer, the author studied the demand for previous generations' products. It was found that the demand for these products followed seasonal patterns and were also influenced by the product's market life cycle. With these insights, the author was able to develop a Product Growth model, based on the research of Bass (Bass, 1969). The developed model included the market seasonal demand and the product life cycle influence on the customer demand (Kurawarwala & Matsuo, 1996).

Based on the insights of this demand model, Kurawarwala (Kurawarwala & Matsuo, 1996) was also able to develop an inventory management model and a corresponding optimal procurement policy. The inventory management model considered the lead times, the demand over the product lifetime, and the demand competition between the new and old products, phasing in and out respectively. The insights from the optimal procurement policy suggested building up inventory for the products before and during the life cycle peak period. This stock will be consumed until depletion, giving way for the rise of the next generation product.

B. Forecast Aggregation Level and Sample Size Impact On Forecast Performance

To determine the technical requirements for the design goal number 2 "The forecast time aggregation level must be weekly or as close as possible" two papers were considered:

The first one from Hyndmand (R. Hyndman & Kostenko, 2007) explains the importance of the minimum sample for the obtention of the forecast. The main insight from this paper is that the higher the randomness level in the data more observations will be required. In the case of Global Retailer demand, the demand shows a stable seasonality at the monthly level. But this seasonality decreases at the weekly level, hindering the estimation of the seasonal pattern with available demand data.

The second paper considered was from Zotteri (Zotteri et al., 2005), in his paper Zotteri explains the impact of the aggregation level on the forecast accuracy. This impact depends on the data because not all the data show the same patterns at different aggregation levels and the common scenario shows an increase of parameters and factors to be considered when the forecast is performed at lower aggregation levels.

As it can be seen, both Hyndmand and Zotteri (R. Hyndman & Kostenko, 2007; Zotteri et al., 2005) point into the same direction. When the forecast aggregation level is lowered, the number of parameters and randomness of the data increase. If it is not compensated with additional information, it will only lead to a loss of forecast accuracy and an increase in the error term. In this way, the right aggregation level will fully depend on the available demand information and the increase of the parameters that need to be estimated. Which in terms of Hyndman (R. Hyndman & Kostenko, 2007) is defined as the increase of the randomness at lower aggregation levels.

In the case of Cargill, the demand orders arrive at a weekly level, but they tend to present marked peaks, which hinders the weekly demand forecasting. For that reason, the demand data is aggregated at the monthly level to obtain a smoother and more stable demand, which can be forecasted more easily.

C. Preliminary Conclusion

Kurawarwala's research (Kurawarwala & Matsuo, 1996) shows that by considering the demand seasonality, it is possible to improve inventory management. For that reason, after informing the SCDA coordinator about the possibility to improve the safety stock management based on the seasonal patterns at one of our weekly meetings at the beginning of July. It was decided that **the design goal number 8 in this thesis project will be to improve the RFS inventory management based on the insights obtained from the developed forecast model and the demand data analysis.**

The forecast aggregation insights will be used to formulate the technical requirements of the design goal number 2 and to develop a roadmap to determine the right aggregation level for the RFS demand forecast.

3.2. Forecasting Models

The different forecast models presented in this section are based on statistical methods, which are white methods to comply with the design goal number 3 "the demand forecast must transparent and interpretable to adjust it when it is required". Additionally, all the considered forecast models in this section are capable of estimating the seasonal patterns in the time series. The 3 considered forecasting models are the (S) ARIMA model (Arunraj et al., 2016), which is based on autocorrelation relationships, but in its seasonal versions can include seasonal patterns. The ETS exponential smoothing (R. Hyndman et al., 2008), which is a specialized forecast model for the estimation of seasonal time series by the estimation of the seasonal and trend components. And STL+ETS model (Bergmeir et al., 2016), which is a two parts forecast model based on the STL decomposition and the ETS exponential smoothing.

A. (S)ARIMA model

The ARIMA model is one of the most popular forecasting approaches along with the ETS exponential smoothing (R. Hyndman et al., 2008). The ARIMA models were developed in 1962 by Box in collaboration with Jenkins (Box et al., 2015). This family of models considers the autocorrelation relationships in the time series to estimate a proper model that can replicate the time series patterns. The ARIMA or SARIMA, in its seasonal version, stands for Seasonal Auto-Regressive Integrative Moving Average (Arunraj et al., 2016). One of the basic components is the Moving average, this is a similar approach to the simple moving average. But the ARIMA model considers the Auto Correlation Function (ACF) performance to estimate if the past observations show a strong correlation with the time series moving average to be used as an indicator of future observations (X. Wang et al., 2006).

The integrative part of the model removes the time series trend. This is because the ACF needs to be calculated on stationary conditions, so the trend must be removed first by the Integrative component. The Auto-Regressive part in the name of the model refers to the Partial Auto Correlation Function (PACF). The PACF looks for statistically significant correlations between the present values and past observations, without considering the influence of the neighboring observations (X. Wang et al., 2006).

Considering the different components, the equation of an ARIMA model (p,0,q) of p-th order AR, 0 order I, and q-th order MA, will have the following form (R. Hyndman et al., 2008):

$$y_t = \lambda + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q} \tag{3-1}$$

B. The ETS Exponential Smoothing statistical model

Historically, the exponential smoothing methods and models have been used for forecasting and inventory control. The term "Exponential Smoothing" refers to a family of forecasting methods and models that make use of weighted past observations for forecast estimation. Where the recent observations have a higher weight than older ones. The weight decrease for the older observations occurs in an exponential way (R. Hyndman et al., 2008).

The ETS Exponential Smoothing model is a state space model, where the term State refers to the values that the variables that comprise the model are taking. And the term Space refers to the parametric space that defines and constrains the variables, as well as the equations that are used to estimate the data behavior (R. Hyndman et al., 2008).

The ETS stands for Error, Trend, and Seasonality. This is because, the ETS exponential smoothing model can estimate the Error component and the prediction distribution, given the level of confidence. It can estimate the Trend, which is a combination of the level and the growth term. And it can estimate the seasonal component, which refers to the repetition of patterns in the time series over time (R. Hyndman et al., 2008).

Just considering the Trend and the Seasonal component, the following fifteen exponential methods (Taylor, 2003) to obtain the point forecast can be constructed:

Trend component	Seasonal component		
	N (None)	A (Additive)	M (Multiplicative)
N (None)	N,N	N,A	N,M
A (Additive)	A,N	A,A	A,M
A_d (Additive damped)	A_d,N	A_d,A	A_d,M
M (Multiplicative)	M,N	M,A	M,M
M_d (Multiplicative damped)	M_d,N	M_d,A	M_d,M

Figure 12 The fifteen exponential smoothing methods. Source:(R. Hyndman et al., 2008)

By considering the nature of the error component, the stochastic space models allow not only to estimate the point forecast but also their prediction interval and other properties. This is useful for applications such as inventory, where the expected costs and the estimation of the service levels rely on the prediction intervals of the demand (R. J. Hyndman & Khandakar, 2008).

C. Seasonal Trend Loess Decomposition (STL)

The Seasonal Trend Loess Decomposition is a specialized robust decomposition method that can estimate the de seasonal and trend components of the time series. This method was designed (Cleveland et al., 1990) to be simple as possible, flexible to adapt to different time series, and robust in the sense that can even deal with time series that have gaps and outliers in the observations.

The method works on a cyclical basis, due to this, the method requires at least two cycles to provide a proper estimation. This is because the STL consists of two recursive operations (Cleveland et al., 1990), the inner and the outer loop. The inner loop's purpose is to estimate the Seasonal and Trend components after each cycle. While the outer loop's purpose is to assign weights to the different observations based on their fitness to the estimated Seasonal and Trend components.

For the estimation of the components in the inner loop, the first step is to generate a smoothened version of the time series that can be linear or quadratic depending on the time series behavior. This smoothened function is generated based on the Loess approach, which considers the distance of the neighboring observations for the estimation of each point in the smoothened time series. In this way, the nearest observations will receive a higher weight and the algorithm can deal with data gaps and outliers in the time series (Cleveland et al., 1990). To estimate the seasonal component at the end of each cycle, the model applies again a Loess smoothening, in this way the model can deal with outlier and observations gaps to estimate the seasonal behavior at each point of the cycle. Then the seasonal component is removed from the smoothened time series to estimate and obtain the deseasonalized smoothened time series. This trend component is smoothened again based on Loess. With this, the inner loop concludes.

Then, the original time series is compared with the estimated components to measure the error level, the closer they are to this generated time series the bigger the weight assigned to them. After this, the inner loop is repeated, but the weights estimated in the outer loop are assigned to each observation to obtain the final Seasonal and Trend components. In this way the STL decomposition has the following structure:

$$Y = T + S + R \tag{3-2}$$

Where the time series observation is Y, the trend component is T, the seasonal Component is S, and the Remainder component is R.

D. The STL + ETS Model

Being aware of the data decomposition capacities of the STL method, the research and experimentation to obtain models that can leverage this information have led to the development STL+ETS model (Bergmeir et al., 2016). Considering the robustness of the STL decomposition method that can estimate reliably the seasonal and trend components of different time series due to its double loop design (Cleveland et al., 1990). While the ETS exponential smoothing is a forecasting approach that can take care of the remainder component for the estimation of the time series forecast, based on the seasonal and trend components provided by the STL decomposition (Bergmeir et al., 2016).

The research of Bergmeir (Bergmeir et al., 2016) shows that the STL+ETS model can outperform the traditional ETS exponential smoothing model. The main reason why this forecasting design performs better is because of the two loops design of the STL, which can draw the seasonal and the trend components from the time series with more accuracy and consistency than the method used in the regular ETS exponential smoothing that relies only on the exponential smoothing and the weighted moving average that decreases exponentially (Bergmeir et al., 2016).

E. Preliminary conclusions

The following table provides an overview of the capacities and expectations of the reviewed forecasting models in the literature, which will be tested in the Develop Stage.

Table 7 Forecasting Models Overview

N°	Feature	ARIMA model	ETS exp. smooth.	STL+ETS
1	**Seasonal patterns estimation**	Yes, in its seasonal version (S)ARIMA (Arunraj et al., 2016)	Yes, specifically designed for seasonal time series (R. Hyndman et al., 2008)	Yes, through the Seasonal Trend decomposition based in Loess (Bergmeir et al., 2016)
2	**Data requirements according to literature**	8 years (cycles) to estimate seasonal patterns (Ouyang et al., 2021)	17 months according to the literature, but might be more depending on the randomness level (R. Hyndman & Kostenko, 2007)	2 years (cycles) minimum, due to the STL requirements (Cleveland et al., 1990)
3	**Additional features**	Can estimate other patterns based on the Auto Correlation Function (Arunraj et al., 2016)	None	None
4	**Expectations based on literature review**	All-round model, which can estimate ACF-based patterns and seasonal patterns	Seasonal patterns estimation performance is superior to the ARIMA model, due to specialization	Seasonal patterns estimation performance is superior to the ETS model, according to testing results in the literature

All the explored models in this section can estimate the time series seasonal components. The ARIMA model and the ETS exponential smoothing the more popular. While the ARIMA is capable of estimating more than just seasonal patterns (Arunraj et al., 2016), the ETS exponential smoothing is a model specially designed for the forecast of seasonal time series (R. Hyndman et al., 2008). On the other hand, the STL+ETS is a combined model that according to the literature has shown a better performance than the traditional ETS exponential smoothing (Bergmeir et al., 2016). All these three models will be tested in the Develop stage and based on their performance against the technical requirements, one of them will be chosen for the generation of the demand forecast in the delivery section.

3.3. Software Solutions Considered for the Forecast Development

For the development of the demand forecast model, two alternatives were considered due to their popularity and availability of tutorials. The first one was RStudio, which is an open-source Integrated Development Environment and one of the most used platforms in the scientific community for time series forecasts (RStudio, 2009). The second was STATA which is commercial software developed for the time series forecast and includes models such as the ARIMA and exponential smoothing (Newton, 2005).

A. RStudio – An Integrated Development Environment for R

RStudio is a Statistical open-source platform (Racine, 2012) that provides statistical tools for time series analysis, development, testing of different forecasting models, and additional data treatment. This open-source platform is the result of the open-source R project (Ripley, 2001), RStudio has a very active scientific community active (RStudio, 2009), which works constantly on the experimentation and development of state of art statistical tools such as tests, forecasting algorithms, and others.

Due to this, there is abundant literature, information, and tutorials about the use of the platform, the statistical packages, and solutions that make RStudio IDE a suitable environment for the testing and development of the forecast models.

A.1 RStudio and the "Forecast" estimation Package

Between the packages for time series forecast modeling, the "forecast" package is available at RStudio (R. J. Hyndman & Khandakar, 2008). This package provides RStudio IDE with the statistical model's framework to assess the data and generate different forecasting models. Within the RStudio's time series scientific community, the most relevant forecasting methods are analyzed such as the ARIMA and the ETS exponential smoothing models (R. J. Hyndman & Khandakar, 2008).

The main benefit of the R forecast package is that it provides automatic forecasting algorithms for the estimation of the ARIMA and the ETS exponential smoothing models(R. J. Hyndman & Khandakar, 2008). This makes the Forecast package a good fit for this study, as the use of automatic forecasting algorithms is an already popularized practice that is also included in the design goal number 6. The STL+ETS model was incorporated into the RStudio IDE since version 5.6 of the Forecast package (R. Hyndman, 2014).

B. STATA

Stata is the commercial statistical software developed by Stata Corp for data manipulation, visualization, statistics, and automated reporting (Newton, 2005). As well as RStudio, the interaction with Stata is through a command line interface. Nevertheless, as Stata is a commercial solution its technological progress is limited by the time and money invested by Stata Corp. For example, before its 16th release, Stata did not allow working with more than one dataset at a time (Stata Corp., 2019).

C. Software Selection

When both statistical solutions are compared, RStudio seems to be a better option, due to its flexibility, active community, number of tutorials, and open-source code that allows, not only those scientific developments to be quickly included in its Integrated Development Environment. But that these innovations are directly developed on RStudio (R. J. Hyndman & Khandakar, 2008). As was the case of the STL+ETS forecasting model design, which has been developed in 2016 (Bergmeir et al., 2016). As well as for automatic outliers detecting function which was included in the RStudio forecast package in 2021 (R. J. Hyndman, 2021).

For these reasons, RStudio IDE was selected as the software platform for the development of the forecast model.

3.4. Research Design Technical Requirements

As stated in section 2.2, the design goals were numbered according to the presentation order of the technical requirements. This is because to provide order between the technical requirements these have been in Forecast, Data management, and Demand management. The first 6 are forecast-related requirements. The seventh is a Data management technical requirement and the eighth is a Demand management technical requirement.

The first technical requirement stems from the main design objective of this research. To improve the demand management of Retail Food Services, the design goal number 1 was defined as "the developed forecast for the RFS demand must improve the SAP IBP statistical forecast accuracy". As it has been shown in section 2.4, the monthly statistical demand forecast has a weighted average MAPE of 57.91%. For this reason, the first technical requirement is that the developed forecast model must have a MAPE lower than 50%.

The second technical requirement approaches the design goal number 2, "the demand forecast time aggregation level has to be taken from the monthly level to the weekly, to the extent possible". This is because as it has been stated in section 2.2, the production planning and the safety stock levels for the RFS, are both managed at a weekly level. While the demand forecast is being managed on a monthly aggregation level. However, only 2 years and a half of demand observations might hinder the achievement of a *useful demand forecast* at the weekly level (R. Hyndman & Kostenko, 2007). For these reasons, the second technical requirement is to develop a useful demand forecast, that is as close as possible to the weekly time aggregation level.

> The selection of the time aggregation level is also influenced by the number of demand observations available. But that issue will be approached directly in the 5th technical requirement.

For the third technical requirement, as explained in 2.2.B, the design goal number 3 was defined as "the forecast model must be transparent and interpretable to adjust when it is required". This is for example when the past observations might not be enough to estimate the upcoming demand during disruption periods and allow the demand planner and sales commercial to add their input when it is required. For this reason, the third technical requirement is that the model is based on a white box method (Pintelas et al., 2020).

The fourth technical requirement, in alignment to the design goal number 4 defined in 2.4 as "the forecast model must be able to capture seasonal demand patterns or others to generate a representative forecast of the observed demand" is about forecast model capacities. Because the baseline forecast method is the moving average, that can estimate at most the time series current level (Johnston et al., 1999). But as shown in Figure 10, the RFS demand shows seasonal patterns. For this reason, the fourth requirement is that the developed model must be able to estimate the existing demand patterns and relationships, as well as the demand seasonal components.

For the fifth technical requirement, the design goal number 5 was defined as "the forecast model can produce a useful forecast, even with the data availability limitations" in section 2.3.A. According to Hyndman (R. Hyndman & Kostenko, 2007). To establish seasonal-based forecasts, different forecasting methods have different data requirements to estimate the model parameters and be able to provide useful forecasts. Nevertheless, as explained in 3.1.B the selection of the right model is also influenced by the level of randomness of the data. For this reason, the fifth technical requirement is to develop a demand forecast model that can produce a useful forecast with the available demand data.

The sixth technical requirement, the design goal number 6 was defined as "the developed forecast can be integrated into the SAP IBP data platform to be used automatically" in section 2.2.B. This is because if the model was run manually, the time required to run the models will increase substantially. For this reason, the sixth technical requirement is the forecast model can be integrated with the SAP IBP data platform and be executed in an automated way.

The Seventh technical requirement, the design goal number 6 was defined as "To develop a procedure to objectively identify existing succession relationships between the RFS products" in section 2.3.A. This is to approach the situation of the not registered succession relationships between the RFS products. As this is key to forecasting the demand for the active RFS products of Global Retailer. In this way, the seventh technical requirement is that the developed procedure to identify the succession relationships must be objective and the results must be validated by the sales assistants.

The eighth technical requirement, the design goal number 8 was defined in section 3.1.C as the improvement of the RFS inventory management based on the insights obtained from the developed forecast model, and the demand data analysis. This is because the RFS inventory management is also part of the Make to Forecast production strategy (Meredith & Akinc, 2007) and as it is explained in section 2.5. The safety stock levels are being managed closer to make to stock strategy than a Make to forecast, as the safety stock is being calculated independently from the demand forecast. For this reason, the eighth technical requirement is that the safety stocks must be managed on a variable level based on the insights obtained from the demand forecast and the data analysis.

In this way, the 8 technical requirements for the identified design goals have been established. These will be used to assess the performance of the different solutions developed in the following stage Develop and an overview of them can be found in the following table.

Table 8 Design Goals and Technical Requirements.

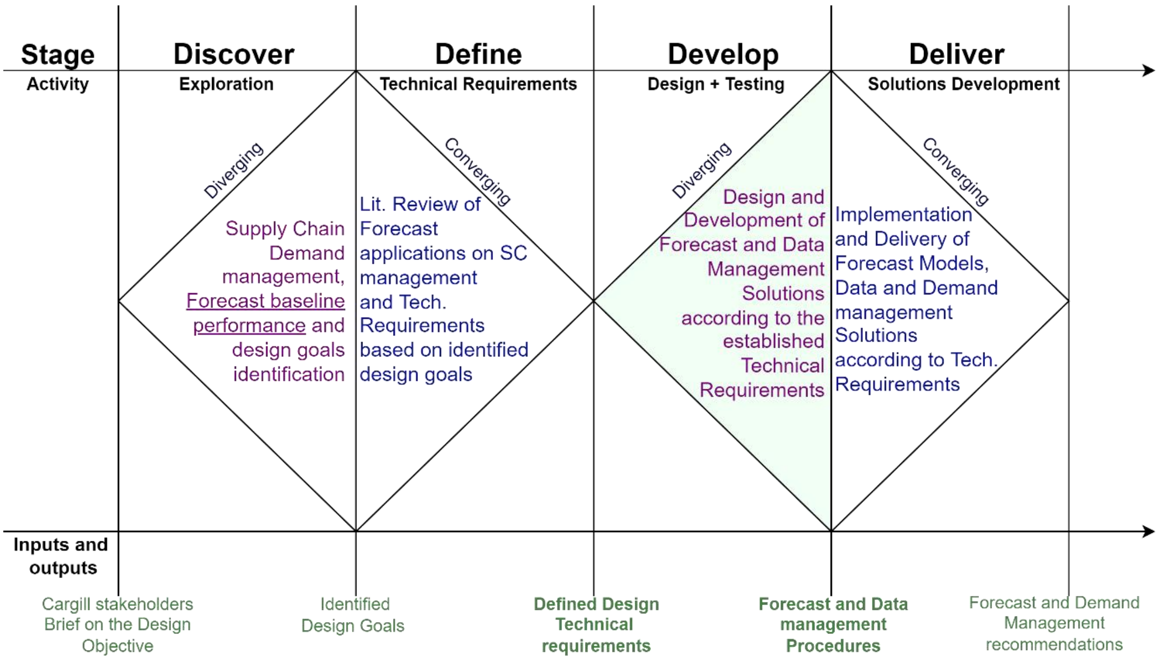
N°	Category	Design Goals (What)	Technical Requirements (How)
1	Forecast	A forecast that improves the SAP IBP statistical forecast accuracy	The developed forecast model must have a MAPE lower than 50%
2	Forecast	The forecast time aggregation level must be weekly or as close as possible.	The Development of a useful demand forecast that is as close as possible to the weekly time aggregation level.
3	Forecast	The demand forecast must transparent and interpretable to adjust it when it is required	The demand forecast must be based on a white box method
4	Forecast	The model must be able to capture seasonal demand patterns or others to generate a representative forecast of the observed demand.	The developed model must be able to estimate the existing demand patterns and relationships, as the demand seasonal components
5	Forecast	The forecast model can produce a useful forecast, even with the data availability limitations	The Demand Forecast Model can produce a useful forecast with the available demand data (two years and a half).
6	Forecast	The developed forecast can be integrated into the SAP IBP data platform to be used automatically	The forecast model can be integrated with the SAP IBP data platform and be executed in an automatical way.
7	Data management	To develop a procedure to objectively identify existing succession relationships between the RFS products.	The developed procedure to identify the succession relationships must be objective and the results must be validated by the sales assistants.
8	Demand management	Improve the RFS inventory management based on the insights obtained from the developed forecast model and demand data analysis	The safety stocks must be managed on a variable level based on the insights obtained from the demand forecast and the data analysis.

3.5. Define Stage Conclusions

In the Define stage, 3 different literature reviews were performed and the Technical requirements have been established. The main conclusions from this stage are first, considering the current management of the safety stock on a constant level all year round and the fact that Cargill GEOS uses the make-to-forecast production strategy, it is possible and even recommended that the insights obtained from the demand forecast must be considered to improve the management of the safety stocks. Second, factors such as the data availability, the data randomness level, and the forecast model capabilities are key for determining the right time aggregation level for the forecast.

4. Develop Stage

Based on the technical requirements, established in the previous stage to achieve the design goals. This stage will focus on the development of the corresponding solutions. In this way, the Develop presents the following outline:



In the first section, a data aggregation framework is presented to elaborate on the feasibility of achieving a weekly demand forecast to develop a roadmap to determine the right time aggregation level considering the available data. The second section presents the design of the forecasting models that was tested for the demand forecast. In the third section, based on the roadmap defined in the data aggregation framework, the forecasting models were tested on a monthly level and assessed based on the defined forecast technical requirements to determine the best-performing forecasting model. In the fourth section, the data management procedure for the seventh technical requirement is introduced. This procedure enables the identification of the demand succession relationships between the predecessors and successors process products in each country's market. In the fifth section, the selected model has been extended to improve its accuracy and to identify the corresponding shortcomings to prepare some strategies to overcome them.

The set of developed solutions has been implemented as a whole in the delivery section to generate the forecast of the developed model along with guidelines for its implementation in the Cargill GEOS demand planning process.

4.1. Data Aggregation Framework

In alignment with the second technical requirement, this framework was developed to assess the feasibility of different aggregation levels forecast.

During the preliminary tests for the different models, it was found that by lowering the aggregation levels the presence of identifiable patterns, as the seasonal demand, in the dataset decreased. For example, as shown in Figure 10, the demand seasonality is so clear at a monthly level that it can be seen without using seasonal analysis statistical tools. But on the weekly level, these seasonal patterns become less visible and even some of the forecasting models in the preliminary analysis were not able to generate any useful forecast.

Due to this, 4 factors were considered for this framework. The first two are the closeness to the weekly aggregation level (usefulness) and the feasibility of developing the forecast models, this is especially important considering that there are only two years of demand observations available. The other two were the weekly demand aggregation and the smoothing requirement. In case of the weekly demand aggregation, it refers to how the weekly demand has been aggregated at different time levels. As explained in section 3.1.B, at higher aggregation levels the data smoothing increases, but at lower aggregation levels more information might be required, if the data patterns are stable in the different aggregation levels a smoothing technique might be required as the STL (Cleveland et al., 1990). These insights are summed up in the following table for different time aggregation levels.

Table 9 Forecast Demand aggregation framework

Forecasting aggregation Level	Usefulness (Design goals)	Feasibility	Weekly Demand aggregation	Smoothing Requirement
Monthly basis	Current state	Medium, data limitations	Good, in 5 to 6 weeks	Low
4 Weekly basis	Small improvement	Medium, data limitations	Good, in 4 weeks	Low
3 Weekly basis	Useful	Low, not enough data	Medium, in 3 weeks	Medium
Bi-weekly basis	Very useful	Low, Seasonal, and other data patterns become less visible	Low, in 2 weeks	High
Weekly basis	Goal	Very low, demand patterns are scattered	None, this is the lowest demand aggregation level	Very High

The main effect that wants to be avoided by lowering the time aggregation level is the degradation of the seasonal pattern due to the demand displacement and the weekly demand variation. From one year to the next one, the demand peaks and valleys do not occur in the exact period. At a monthly level, the demand displacement is low. But the lower the aggregation level, the more demand displacement will hamper the estimation of the seasonal patterns. This effect can be reduced with the use of some smoothing treatment.

Due to this, the forecast models will be tested at a monthly level, and depending on the selected model's performance, the aggregation level will be decreased to a 3-week forecast. Because at the 3-week aggregation level the demand datasets still retain some seasonal patterns. And if the forecast obtained at the 3-week level is accurate enough, the weekly forecast will be tested to review its feasibility.

The reasoning behind the proposed roadmap, which considers the degradation of seasonal patterns as the time aggregation is lowered, is aligned with the findings of the study performed by (Kourentzes et al., 2017) about the temporal aggregation impact on the forecast and prevalence of patterns in demand time series. This study considers this line of reasoning part of the main schools of thought concerning time aggregation and forecast accuracy. This school of thought is based on the determination of the most optimal time aggregation level at which forecasting models can maximize their accuracy.

Considering the applicability of time series in the production planning of different industries, and the simplicity of the developed framework and roadmap to determine the most suitable time aggregation level. This solution can be applicable in almost any organization that needs to optimize its forecast accuracy concerning time aggregation. What is more, Rostami-Tabar (Rostami-Tabar et al., 2014) tested different forecasting models as the ARIMA model and the ETS exponential smoothing, where he concluded that the time aggregation allowed a higher forecast accuracy, following a function of the forecast model parameters. He also recognized the prevalence and degradation of seasonal factors in time series at lower time aggregation levels.

4.2. Basic Models design

As explained in section 3.2, the models considered in this thesis project are all capable of estimating the seasonal patterns in the time series. Their designs are implemented of the statistical forecasting package in RStudio "forecast" (R. J. Hyndman & Khandakar, 2008) where the analysis and operations are mostly fixed automated processes. For this reason, if it is desired to improve the performance of these models, modifications can be done mainly in the inputs and/or the outputs of these models.

A. (S)ARIMA model design

The model design is based on an automatic ARIMA forecast algorithm (R. J. Hyndman & Khandakar, 2008). that determines the model order. This model also includes the seasonal ARIMA within its estimation. In that way, the selected model has the form ARIMA (p,d,q)(P,D,Q)m. Where the lowercase p, d, and q indicate the model order in the basic ARIMA and the uppercase P, D, Q, and the letter m indicated the order of the seasonal ARIMA, and m indicates the seasonal frequency. This is because the full model allows to estimate the patterns within each season (lowercase) and to estimate the relationships that are caused by seasonal patterns (uppercase).

For the selection of the ARIMA model, the algorithm relies on the Akaike Information Criterion (AIC)

$$AIC = -2\log(L) + 2(p + q + P + Q + k) \qquad 4\text{-}1$$

Where k=1 if there is differencing in the data, otherwise k=0. L is the maximized likelihood of the model fitted to the differenced data $(1 - B^m)^D(1 - B)^d y_t$. For the determination of the d parameter, the successive KPSS unit-root test is used and the data is differentiated (d) until the result is insignificant (Kwiatkowski et al., 1992). For the seasonal D, an extended version of the Canova Hansen test is used (Canova & Hansen, 1995). Originally Canova Hansen test tested whether the seasonal pattern can be modeled using fixed dummy variables. But this also shows useful to determine the D order in a strictly ARIMA framework.

A.1 Model implementation

First, D is determined, and the data is seasonally differenced. Then the d parameter is determined on this differenced data and the data is differenced between the consecutive observations. The next step is to determine the p, d, q, and the P, D, Q parameters. For this a stepwise process is applied, where the goal is to minimize the AIC (R. Hyndman et al., 2008).

For the stepwise process, the values of p and q can range from 0 to 3, and for P and Q, they can be 0 or 1. By considering all the possible combinations of p, d, q, P, D, Q, and k; there are **480** models available (R. J. Hyndman & Athanasopoulos, 2013). The first four considered models are the following ones:

- *ARIMA(2; d; 2) if D = 0 and ARIMA(2; d; 2)(1;D; 1) if D ≠ 0*
- *ARIMA(0; d; 0) if D = 0 and ARIMA(0; d; 0)(0;D; 0) if D ≠ 0.*
- *ARIMA(1; d; 0) if D = 0 and ARIMA(1; d; 0)(1;D; 0) if D ≠ 0.*
- *ARIMA(0; d; 1) if D = 0 and ARIMA(0; d; 1)(0;D; 1) if D ≠ 0.*

The model with the lowest AIC is selected and thirteen variations are generated in the following way: One of p, q, P, and Q is allowed to vary by ±1 from the selected model. Both p and q vary by ±1 from the selected model. Both P and Q vary ±1 from the selected model.

From these 13 variations, the mode with the lowest AIC is selected and the procedure is repeated until the AIC does not decrease in the neighborhood of the selected model (R. J. Hyndman & Khandakar, 2008).

B. ETS exponential smoothing model design

Similar to the ARIMA model, the ETS exponential smoothing model is also selected based on AIC. In the case of the ETS model, the likelihood is given by (R. Hyndman et al., 2008):

$$L^*(\theta, x_0) = nlog\left(\sum_{t=1}^{n} \varepsilon_t^2\right) + 2\sum_{t=1}^{n} log|r(x_{t-1})| \qquad \text{4-2}$$

Where θ represents the parameters α, β, γ, and Φ. x_o represents the initial states $l_o, b_o, s_o, s_{-1}, \dots s_{-m+1}$ and n is the number of observations. The initial state parameters can be estimated with the ETS exponential model recursive equations by minimizing $L*$. The initial states x_o are constrained so they sum zero for the additive seasonal models and *m* for the multiplicative seasonal models (R. Hyndman et al., 2008).

The AIC for the ETS exponential smoothing model is given by $AIC = L * (\hat{\theta}, \hat{x}_0) + 2q$ (R. Hyndman et al., 2008). Where q is the number of parameters in θ plus the number of free states in x_o. The model that minimizes the AIC between the appropriate models is selected. While there are 480 ARIMA models, there are only 15 possible algorithms for the ETS exponential and 30 models when the error term is considered. Due to this, the 15 algorithms can be tested each.

From the selected forecast, the point forecast is estimated, and the prediction intervals are estimated following the statistical approach if they are linear or by simulating future sample paths (R. J. Hyndman et al., 2005).

C. STL+ETS model design

This model design is based on the work of Bergmeir (Bergmeir et al., 2016). The STL+ETS modeling approach is based on the high capabilities of the STL decomposition to determine the seasonal and the trend component (Cleveland et al., 1990), but as the STL is not a forecasting method by itself. For this reason, it is complemented with the ETS exponential smoothing model, which takes cares of the remainder component.

In this way, the STL decomposes the time series data on a seasonal, trend, and remainder component, as it was explained in 3.2. The remainder time series component is then bootstrapped using a moving block bootstrap approach (MBB) (Bergmeir et al., 2016). 99 bootstrapped versions of the remainder component are generated and assembled with the seasonal and trend component to generate 99 bootstrapped versions of the original time series. The original time series and the 99 bootstrapped time series are forecasted based on the ETS exponential smoothing model, that was previously described. The resulting 100 time series forecast are combined based on their median, as the median is less sensitive to outliers (Bergmeir et al., 2016).

In this way, the STL decomposition helps to create a family of similar TS, which are later forecasted under the ETS model and combined based on the median values. The outline of the STL+ETS model design can be found in the following diagram:

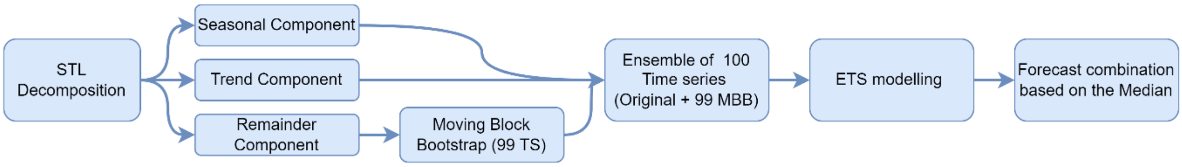


Figure 13 STL+ETS model design Diagram. Source: Developed by the Author.

4.3. Forecast model testing`

In this section, the forecasting models will be tested and assessed based on the 6 technical requirements established in the define stage section, except for the second technical requirement. Because it will be determined after a forecast model is chosen.

A. Demand Datasets

During the preliminary testing of the 3 considered forecasting models, datasets with more than 10 years of observations, which can be found in the Rstudio package “Mcomp” (R. J. Hyndman & Khandakar, 2008), were used. In these cases, the 3 models were able to estimate relevant patterns and generate forecasts that matched the patterns of previous observations.

In the same way, the models were tested with 4 of the 166 country-SKU demand datasets for RFS. These 4 datasets had the 32 monthly max possible observations. Nevertheless, some of these country RFS product datasets were combined later. For that reason, as done in section 2.4.C, 3 RFS products demand datasets, that did not require to be combined or aggregated and belong to the consolidated datasets detailed in section 4.4, have been selected. These 3 datasets have the 32 max possible demand observations. Datasets with the 32 demand observations have been selected to test the model in the best conditions possible and be able to identify any difference in their performance. The results and insights that are presented for these 3 datasets are congruent with the results and observations obtained from the other 4 RFS datasets mentioned. The forecast plots have been considered as part of these observations to analyze how well the models can replicate the seasonal behavior of the demand data. To show the model's performance for the RFS datasets, the 3 sampled datasets have been considered enough. The quantities of the RFS products used in this forecast testing are measured in liters of oil.

Table 10 Dataset Samples for the testing and assessment of the forecast models

Dataset	Customer Group Name	Product ID	#Obs	Average demand (liters)	CoV
18	GL FRANCE	100131670	32	102,193.55	53.07%
13	GL AUSTRIA	100131479	31	22,385.81	69.39%
3	GL FINLAND	100130666	32	70,409.42	53.96%

B. Forecast variables

For the test and comparison of the selected model's performance with the baseline SAP IBP statistical forecast, two indicators have been chosen. the first one is the Mean Absolute Percentual Error (MAPE), which was already introduced in section 2.4. Nevertheless, the main shortcoming of the MAPE is that as it is a percentual error indicator when a demand observation is zero, the MAPE will be infinite or undefined. For that reason, the second indicator that has been selected is the Mean Absolute Scale Error (Mase) (R. J. Hyndman & Koehler, 2006). This error indicator is based on the performance of the Naïve forecast method which considers that the next observation is going to be the same value as the last one. In this way, the MASE measures the analyzed forecast error in comparison to the error generated by the Naïve approach forecast (R. Hyndman et al., 2008). The MASE value is above 1 when the analyzed forecast performs worse than the naïve approach and lower than 1 when it performs better.

C. Monthly Forecast time horizon

For the testing of the models, a time horizon of 12 months will be used. This is to assess the quality of the forecast generated against the established technical requirements during the yearly seasonal period. In this testing, not only the accuracy and error levels will be considered, but also the capabilities of the forecast models to provide a seasonal forecast representative of the observed demand.

D. ARIMA model

As it can be seen in the following figure and table, even if the ARIMA model has achieved a better MAPE performance than the SAP IBP statistical forecast indicated in Table 3, the performance has been below expectations.

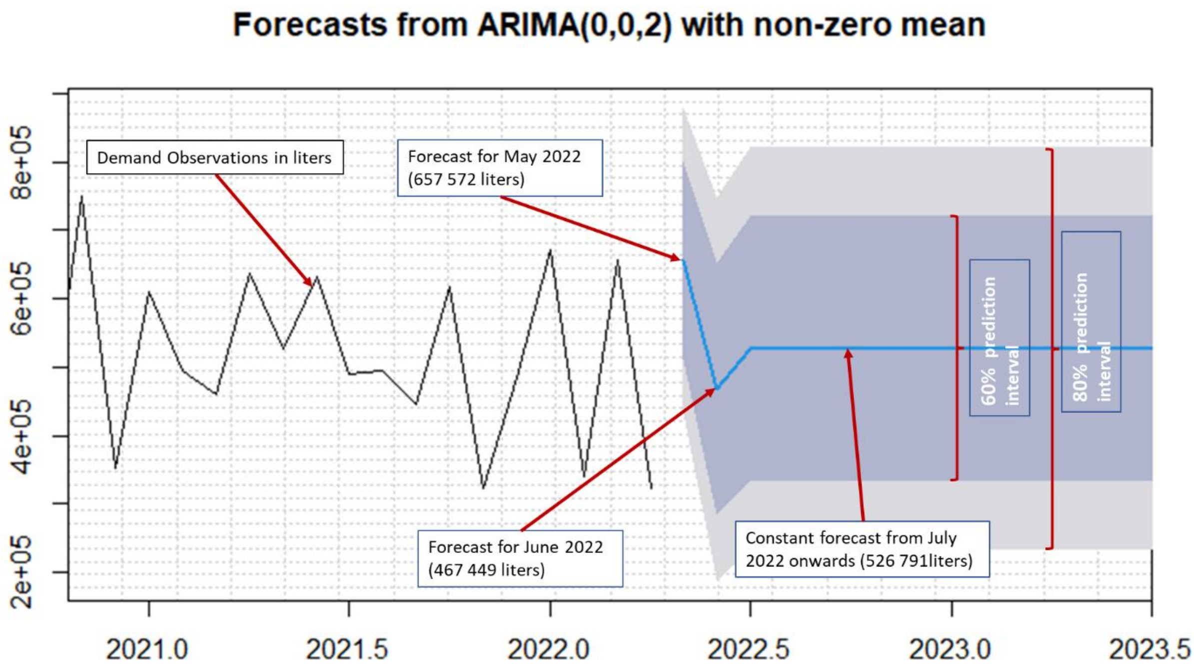


Figure 14 ARIMA model (0,0,2) forecast plot for consolidated dataset 18

This is because as indicated in the following table, the ARIMA model collapsed into a moving average of first or second order (R. Hyndman, 2014). This seems to be due to the lack of demand observations, only two years. Which were not enough observations to capture the seasonal patterns.

Table 11 ARIMA model testing results

Forecast model	Dataset	#Obs	Average demand (liters)	CoV	MAPE	MASE
2. ARIMA model (0,0,2)	18	32	102,193.55	53.07%	**18.11%**	**0.5123**
2. ARIMA model (0,0,1)	13	31	22,385.81	69.39%	**Inf**	**0.5832**
2. ARIMA model (0,0,1)	3	32	70,409.42	53.96%	**35.59%**	**0.7537**

In this way, the ARIMA model only provides a relatively useful forecast in a two-month horizon. After that, the model forecasted a constant level, because it is a 2nd order moving average. The ARIMA model forecast plot of the other two datasets can be found in the appendix. Due to this, the ARIMA model does not provide a useful forecast for demand planning beyond this short term. In the case of dataset 13, the MAPE has been infinite, this is because there are zero values in its demand.

Table 12 ARIMA model technical requirements assessment

N°	Category	Technical Requirements (How)	Assessment
1	Forecast	The developed forecast model must have a MAPE lower than 50%	Good, the MAPE of the ARIMA model has achieved values between 16% to 35%.
3	Forecast	The demand forecast must be based on a white box method	Good, The ARIMA model has collapsed into a 1st and 2nd order moving average forecast, which is easy to interpret.
4	Forecast	The developed model must be able to estimate the existing demand patterns and relationships, as the demand seasonal components	Limited, the ARIMA model has only been able to estimate a moving average, which does not represent substantial progress from the baseline forecast model.
5	Forecast	The Demand Forecast Model can produce a useful forecast with the available demand data (two years and a half).	Limited, the two years of observations were not enough for the ARIMA to estimate seasonal patterns, only a moving average algorithm.
6	Forecast	The forecast model can be integrated with the SAP IBP data platform and be executed in an automated way.	Excellent, the ARIMA model exists natively in the SAP system.

As it has been described in the table above, the ARIMA model could not show a good performance in technical requirements 4 and 5. Besides this, the ARIMA models did not show considerable improvement with the respect to the baseline statistical forecast.

E. ETS Exponential Smoothing

In the case of the ETS Exponential Smoothing model, as can be seen in the following figure, the results were even worse than the ARIMA model. Which is also below the expectations considering that the ETS model is specialized in the forecast of time series based on their trend and seasonal component.

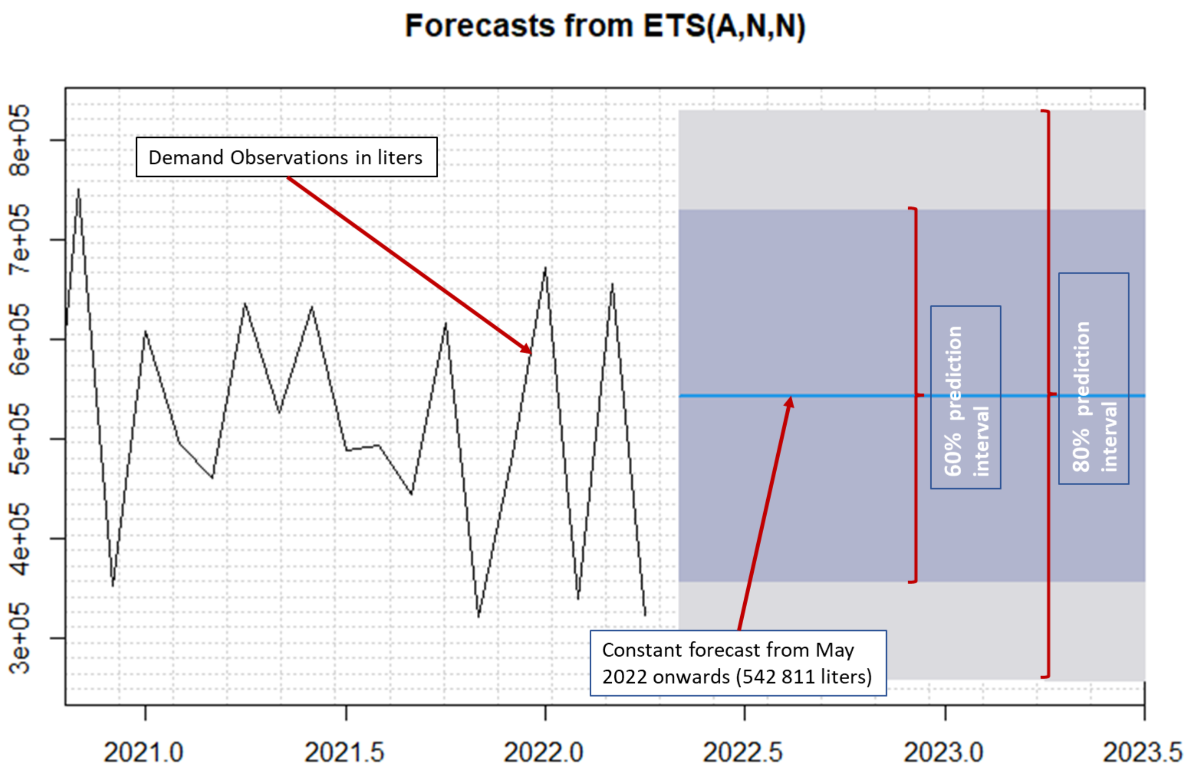


Figure 15 ETS exponential smoothing model (A,N,N) forecast plot for consolidated dataset 18

As can be seen in the following table, the MAPE results were even worse than for the ARIMA model. While the ARIMA model could generate a two-month horizon forecast. The ETS model just forecasted a constant level forecast. The ETS model forecast plot of the other two datasets can be found in the appendix. The performance can be explained by the number of observations. According to Hyndman (R. Hyndman & Kostenko, 2007), the ETS exponential smoothing model requires at least 17 monthly observations. In this case, 32 were used. But Hyndman also mentions that depending on the level of randomness and the number of seasonal changes, this might not be enough. When the ETS components estimation was analyzed, the only output obtained was the level. The Slope and the Seasonal component could not be estimated as the time series observations were not enough for this randomness level (R. J. Hyndman & Khandakar, 2008).

Table 13 ETS Exponential Smoothing model testing results

Forecast model	Dataset	#Obs	Average demand (liters)	CoV	MAPE	MASE
3. ETS Exp. Smooth (A,N,N)	18	32	102,193.55	53.07%	**24.81%**	**0.7196**
3. ETS Exp. Smooth (A,N,N)	13	31	22,385.81	69.39%	**Inf**	**0.6676**
3. ETS Exp. Smooth (M,N,N)	3	32	70,409.42	53.96%	**45.83%**	**0.8758**

The lack of observations also explains why the (S)ARIMA model was not able to estimate seasonal patterns and collapsed into moving average. According to (Ouyang et al., 2021), the ARIMA model needs at least 8 years of observations to be able to estimate the seasonal components in time series. While the ETS model only relies on the seasonal components, it could only provide a constant level forecast.

Table 14 ETS exponential smoothing Technical requirements assessment

N°	Category	Technical Requirements (How)	Assessment
1	Forecast	The developed forecast model must have a MAPE lower than 50%	Limited, even when the results indicate a MAPE error below 50%, the forecast results do not reflect the improvement.
3	Forecast	The demand forecast must be based on a white box method	Very poor, the ETS model forecast has been identical to the Naïve approach, which assumes a constant level.
4	Forecast	The developed model must be able to estimate the existing demand patterns and relationships, as the demand seasonal components	Very poor, the ETS model was not able to estimate any useful pattern or relationship in the demand time series.
5	Forecast	The Demand Forecast Model can produce a useful forecast with the available demand data (two years and a half).	Poor, the two years of observations were not enough for the ETS model to estimate seasonal or other relevant relationships.
6	Forecast	The forecast model can be integrated with the SAP IBP data platform and be executed in an automated way.	Excellent, the ETS model exists natively in the SAP system.

In the case of the ETS exponential smoothing model, the model performance can be considered equal to or even worse than the baseline statistical forecast. It has performed very poorly concerning the technical requirements, except for its integration in the SAP system, because it exists there natively.

F. STL+ETS exponential smoothing model

In the case of the STL + ETS model, the forecast results were the best among the tested models. This can be seen in the two following figures that show the STL decomposition and the forecast plot for dataset 18. In both figures, it can be seen how the STL+ETS model was able to estimate the seasonal patterns of the time series and also able to implement them in the demand forecast.

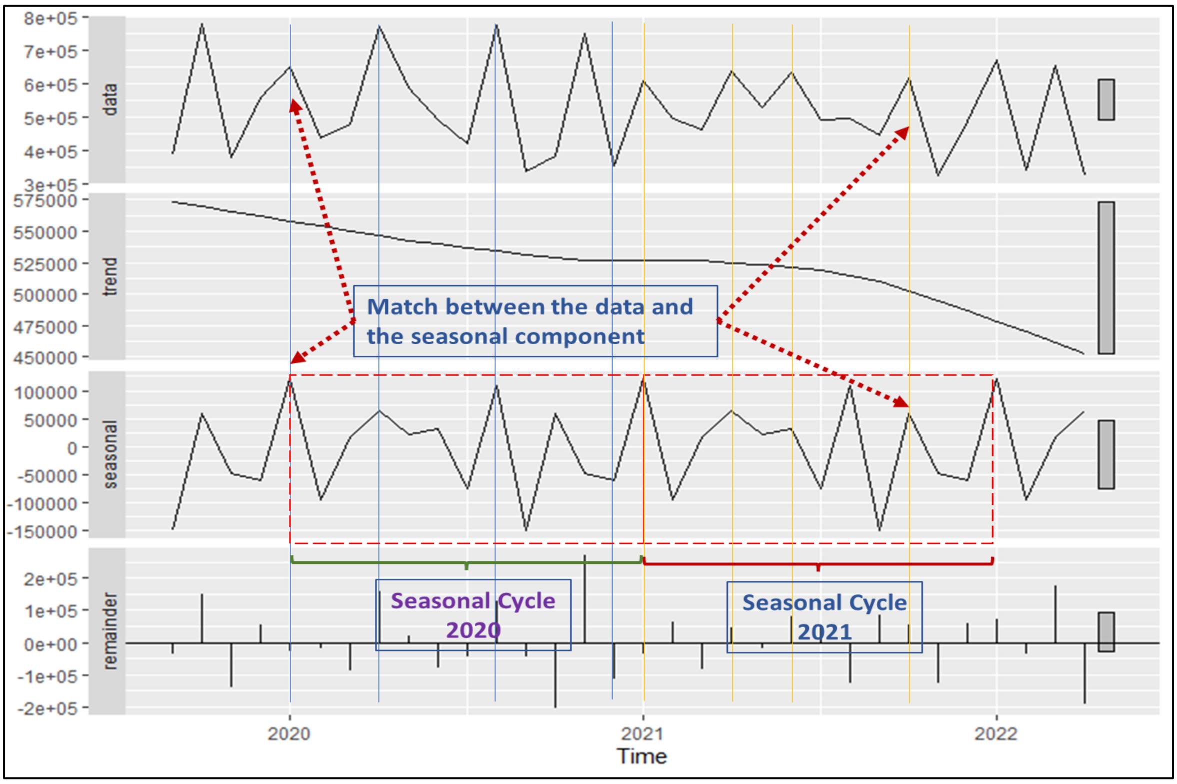


Figure 16 STL decomposition plot for consolidated dataset 18

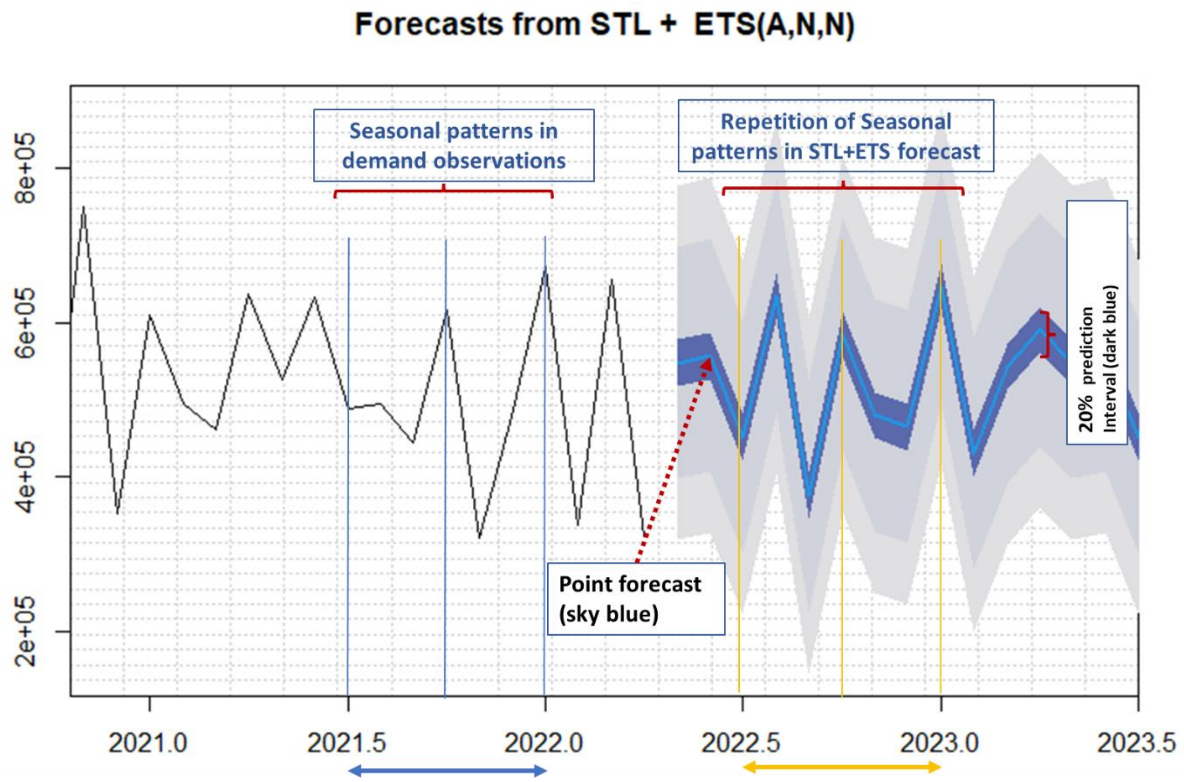


Figure 17 STL+ETS (A,N,N) model forecast plot for consolidated dataset 18

The MAPE results, as shown in the following table, were also the best among the tested models. Which are well supported by the forecast plot results, because the STL+ETS model has been the only model able to generate a useful demand forecast, that represents properly the seasonal patterns of the observed demand. The STL+ETS model forecast plot of the other two datasets can be found in the appendix.

Table 15 STL+ETS model testing results

Forecast model	Dataset	#Obs	Average demand (liters)	CoV	MAPE	MASE
4. STL + ETS exp. smooth (M,N,N)	18	32	102,193.55	53.07%	**16.19%**	**0.5006**
4. STL + ETS exp. smooth (A,N,N)	13	31	22,385.81	69.39%	**Inf**	**0.5815**
4. STL + ETS exp. smooth (A,N,N)	3	32	70,409.42	53.96%	**31.45%**	**0.6228**

It seems to be that the STL decomposition has been the most important factor for the successful implementation of a seasonal model with the 2 years and half of the observations available. This is because the STL decomposition can estimate the seasonal components with a minimum of 2 years of observations (Cleveland et al., 1990).

Table 16 STL+ETS model Technical requirements assessment

N°	Category	Technical Requirements (How)	Assessment
1	Forecast	The developed forecast model must have a MAPE lower than 50%	Excellent, in all the cases the STL+ETS model achieved the lowest MAPE, ranging between 16.19% to 31%
3	Forecast	The demand forecast must be based on a white box method	Excellent, the model has been able to achieve an explainable forecast based on the demand seasonal patterns
4	Forecast	The developed model must be able to estimate the existing demand patterns and relationships, as the demand seasonal components	Excellent, the model has been able to estimate the seasonal, trend, and error components of the demand data to generate a model with its corresponding confidence levels.
5	Forecast	The Demand Forecast Model can produce a useful forecast with the available demand data (two years and a half).	Excellent, the model has been the only one to generate a meaningful and representative forecast, despite the data limitations
6	Forecast	The forecast model can be integrated with the SAP IBP data platform and be executed in an automatical way.	Limited, the model does not exist natively in the SAP system, but it is possible to include it by integrating RStudio with SAP HANA

As has already been mentioned, the STL+ETS model had the best performance among the considered models, and it is the only one that has been able to produce a useful demand forecast. The only issue is that the STL+ETS model does not exist natively in the SAP HANA system, but it is possible to include it by integrating RStudio and SAP HANA, as will be explained in section 5.2.

G. Model Selection

As it can be seen in the following summary table, the STL + ETS is the model that had the best performance. Not only regarding the error indicators but overall in the forecast technical requirements, by providing a seasonal forecast that is representative of the observed demand. Due to this, this will be the model selected to be used during the rest of this research.

Table 17 Model's performance Summary table

Forecast model	Dataset	MAPE	MASE
1. SAP IBP forecast	**18**	32.73%	NA
2. ARIMA model	**18**	18.11%	0.5123
3. ETS Exp. Smooth	**18**	24.81%	0.7196
4. STL + ETS	**18**	**16.19%**	**0.5006**
1. SAP IBP forecast	**13**	123.19%	NA
2. ARIMA model	**13**	Inf	0.5832
3. ETS Exp. Smooth	**13**	Inf	0.6676
4. STL + ETS	**13**	**Inf**	**0.5815**
1. SAP IBP forecast	**3**	59.00%	NA
2. ARIMA model	**3**	35.59%	0.7537
3. ETS Exp. Smooth	**3**	45.83%	0.8758
4. STL + ETS	**3**	**31.45%**	**0.6228**

The obtained testing results are aligned with the research conducted by Ouyang (Ouyang et al., 2021). Ouyang compared the benefits of incorporating the STL decomposition to take care of the seasonal components of the time series. The STL was combined with the ARIMA and the ETS exponential smoothing model. In this study, the traditional and the combined version of the models were tested and compared in different time horizons, ranging from 1 to 24 months. In all the cases, it was the STL+ETS the one that outperformed the rest of them. This was attributed to the STL seasonal algorithm, which showed to be more effective than the seasonal algorithm of the ARIMA and the ETS model.

About the validity of selecting the STL+ETS model as the best option to forecast the RFS products demand. The results have quickly converged towards the STL+ETS model due to the lack of observations that rendered the other forecasting models inadequate. This does not mean that the STL+ETS model will always be the best option for the RFS demand forecasting, but it is under the conditions described in the baseline conditions. Due to this, the analysis performed in this section should be repeated when more data becomes available. In the case of the ETS model, it is difficult to know with certainty how many years of observations it will require. But it is recommended that the analyses are repeated when 5 years of observations are available. In the case of the ARIMA model, according to the literature, it would require at least 8 years of observations to estimate seasonal patterns. For this reason, it is recommended to perform again the analysis, when 8 years of observations are available and then when 10 years of observations become available. Just to control the performance of the different models.

Regarding the applicability of these analyses and results in other industries or studies, it is relevant to emphasize that the forecasting models were selected due to the observed seasonality of the demand. Therefore the applicability of this testing design should be limited to studies where seasonality is a considerable factor in the phenomenon or process under study.

H. Reflection

At the beginning of this thesis project, the ARIMA model was the first and only model considered for the demand forecast of the RFS. Nevertheless, its poor performance could not live up to the expectations. This was because the ARIMA model performed very well on seasonal time series with more than 10 years of observations. But with only two years and half of the demand observations, this was not the case. Due to this the initial scope and the theoretical framework were extended to consider additional forecasting models that could produce a representative demand forecast of the RFS. In the literature, the ETS exponential was well recommended along with the ARIMA (R. Hyndman et al., 2008). Most of the publications of these two models were from Rob Hyndman, a prolific statistician on the topic of time series forecasting (R. J. Hyndman & Athanasopoulos, 2013). Who also took part in the development of the RStudio forecasting package (R. J. Hyndman & Khandakar, 2008). It was during the review of his more recent literature that the STL+ETS model design was found (Bergmeir et al., 2016). This was the only model that with a minimum of 2 years of observations was capable of successfully estimating the seasonal patterns in the time series and was selected for the development of this thesis project.

4.4. Demand Shift Tracking Procedure

In alignment with the 7th technical requirement and the input obtained from the sales assistant presented in section 2.3.A. The developed procedure to identify the RFS product replacement relationships between the 166 country-SKU datasets will be presented.

A. Development of the Demand Shift Tracking Procedure

This procedure was developed on the already validated assumption by the sales assistant, that the SKU code is being replaced every time the RFS customers request a change in the product specifications. This is because as explained in section 2.2, the SKU code is used to track the different specifications of the products, and for production planning and inventory management. From a demand planning perspective, the changes in the SKU code have generated a fragmentation of the products' historical demand registers. The procedure was named “Demand Shift Tracking”.

For the development of the demand shift tracking procedure, the assumptions were taken into consideration:

First, as cooking oil is an essential product, each time a product demand is finished, another product must take on that demand. As the product replacement presents very similar features the final customer does not notice the changes and the demand levels and seasonal patterns of the new products are similar to the predecessors, and phasing in and phasing out periods must be close in time. So the demand can shift swiftly to the new product that is immediately available.

Second, as the product description does not change considerably, by comparing the product description the demand shift or replacement relationships can be verified.

Third, in case the demand shift between two products is still uncertain, some seasonal analyses, such as the “ggsubseriesplot()” function, are available on RStudio IDE. In that way, it can be verified if combining the datasets improves or worsen the seasonal expected values.

Fourth, these results can be verified by the sales assistants, as they are aware of the demand shifts between the SKU datasets in different countries.

**The demand shift tracking procedure can be found in detail in the appendix section.*

B. Datasets merging

Within each country's market, the datasets were identified as predecessors and successors of the different datasets. An example of the succession relationships can be found in Figure 8. All these datasets were assigned the last active product successor code. Because the production planning overlooks the country's market demand distribution and only considers the SKU code. In this way, all the datasets were merged according to their last active successor. **Due to this, from this point onwards, all the datasets will be aggregated to be managed by their product or SKU code, at product level and not country level anymore.** The datasets that could not be matched on any succession relationship and did not have enough observations to be forecasted individually were removed. The rest of the datasets were merged into 37 consolidated datasets, increasing substantially the number of observations, as can be seen in the following figure.

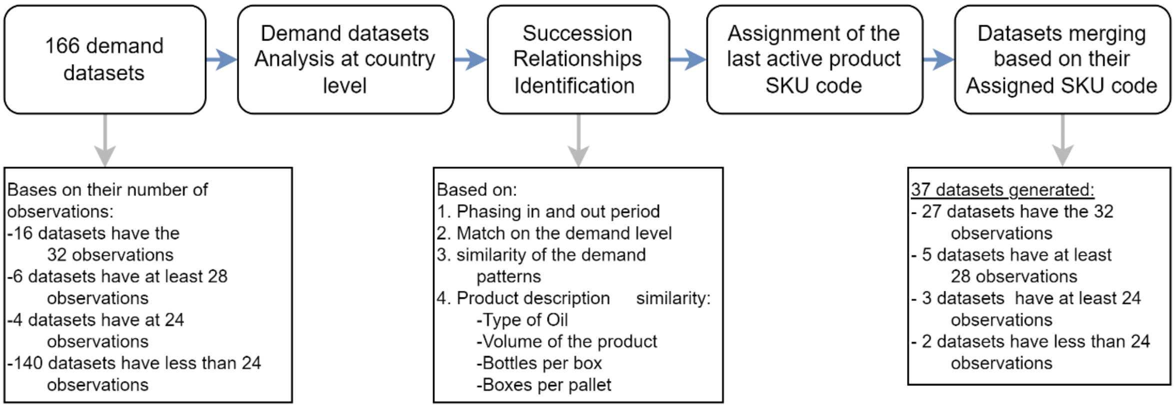


Figure 18 Demand shift tracking procedure and datasets merging outline

C. DST Results Description

From these consolidated 37 datasets. 12 of them are datasets that did not require to be merged, as they represent regular active products that were only delivered in one country market. From the 37, 17 datasets are the result of the DST procedure and are regular products. The last 8 datasets are seasonal-only products, 6 of them are the result of the DST procedure and the other 2 datasets were not merged because presented enough observations and seasonal patterns to be included in the monthly forecast. The

Of the 12 regular product datasets that did not require to be merged, 10 present 32 observations, and the lowest one has 28 observations. The average demand is 119 000 liters. The lowest average demand is 22 000 liters, and the highest average demand is 529 000 liters.

The sampled datasets 3,13 and 18 are part of these 12 regular product datasets. They were selected as a sample because they were constant during the research.

Of the 17 regular product datasets obtained from the DST procedure, 16 have 32 observations and one has 27 observations. The average demand is 321 000 liters. The lowest average demand is 9 000 liters, and the highest average demand is 731 000 liters.

From the 8 seasonal products datasets, only 3 have 32 observations and are part of the consolidated ones. They have an average demand of 71k, 99k, and 129k liters. The next 3 have more than 24 observations, enough observations to be forecasted. Their average demand is 31k, 86k, and 153k liters. The last two have 22 and 21 observations, so they cannot be forecasted. Their average demand is 5k and 174k liters.

The sales assistant responsible for Global Retailer demand received the results of the Demand Shift tracking procedure for their verification. From the consolidated datasets presented, datasets 21 and 34 were rejected, these were seasonal-only products. Additionally, dataset 31 was removed, because the consolidated datasets 21 and 31 had less than 24 monthly observations and the datasets. Thus, they could not be forecasted with the STL+ETS model. In this way, only 34 of the consolidated datasets will be used in the rest of the thesis project.

The applicability of this solution is limited, as it has been developed specifically for the data challenge found in Cargill GEOS. Therefore for this solution to be suitable in other organizations, the manufacturing company should have a similar data fragmentation problem, or the business should be related to a line product that has a short market life. For example in the case of technological products as in the paper of kurawarwala (Kurawarwala & Matsuo, 1996) with personal computers or a more recent case to estimate the smartphones demand projection, as has been depicted by Wang (C. H. Wang & Liu, 2022).

D. Causal relationships and related improvement opportunities in the demand forecast

During the development and application of the demand shift tracking procedure, the concept of the demand group was developed. This refers to the influence of seasonal-only products on the demand for regular products within the country markets. In some demand groups, the influence of the seasonal-only products is so intense that in the periods when the seasonal-only products are demanded, the demand for the regular products can decrease considerably to the point of being nullified. In the literature, this phenomenon is named cannibalization and it is indeed one of the relevant factors described by Arunraj (Arunraj et al., 2016) to improve forecast accuracy by moving from univariable forecast to multivariable forecast.

These multivariable approaches are based on correlations, considering other factors such as weather conditions, or holidays. In the selected seasonal forecast, the effects of holidays have already been captured to some extent in the seasonal forecast. Still, the multivariable approach was indeed considered at the beginning of this thesis project. Nevertheless, this approach requires different datasets with enough observations to determine existing correlations (Arunraj et al., 2016). As it has been shown in 2.3, this was not the case for Cargill RFS demand. Which required the development of the Demand Shift Tracking (DST) just to obtain enough data to produce a useful demand forecast and the development of a time aggregation framework to comply with the second technical requirement.

The data fragmentation and the limited data availability were the main challenges that hampered the development of more advanced forecasting designs (R. Hyndman & Kostenko, 2007; Rostami-Tabar et al., 2014). The development of the DST and the time aggregation framework solutions to solve these issues took about 2 months of the timeline. Still, considering the forecast accuracy and insights obtained, which are described in section 5.1. Additional efforts to implement more advanced solutions would provide small improvements that might not justify the time and effort required for their implementation. Much more considering the available demand data (R. Hyndman & Kostenko, 2007), which could lead to ambiguous or biased results that would require manual verification, hampering its implementation in a big-scale operational context, as is the case of Cargill GEOS. But it is worthy of consideration for further research.

Despite the challenges to develop and implement a forecast design that includes the influence of the weather or the RFS retail market price. Some factors have a more considerable influence on the RFS demand and are easier to implement. As it is the case of the cannibalization between the seasonal-only and the regular products and the geopolitical events that can cause problems on the raw oil availability.

In the case of cannibalization, this occurs at the country level between regular and seasonal only products, and it has been observed during the data analysis for the DST procedure. But it is recommended to address this situation through the forecast manual correction, as the intensity of these relationships is not very clear with the data available. This adjustment is possible because the demand for the seasonal-only product is available two months before delivery time, which makes it feasible to reduce the regular products' forecasted quantities when the seasonal-only products are in demand. In this way, the demand planner and the sales assistant can make better informed manual adjustments in the demand planner input and the consensus demand forecast.

In the case of geopolitical events, attention should be put to these to keep a register of the influence of these on the RFS demand. This will allow an understanding of the influence and causal relationships of different types of disruptions and events on the RFS demand. For example, events that lead to raw oil supply disruptions might affect the oil price, which could lead to an increase in the demand as the RFS customer want to build up stock before the shortage impact, as occurred in the case of the sunflower products during the Ukrainian conflict (Lang & McKee, 2022).

4.5. Extended model design to improve the performance STL+ETS model

As the STL+ETS design has been chosen as the best option among the tested models for the demand forecast. The model design proposed by Bergmeir (Bergmeir et al., 2016) will be extended to improve the model performance and deal better with its shortcomings. As stated in section 4.2, the considered models are almost fixed processes, that can only be improved by improving their inputs and outputs. In this section, an outlier removal function will be presented to improve the data input for the STL+ETS model, and the STL+ETS model will be tested against real demand data to identify some of its shortcomings and provide guidelines to improve the interpretation of the model output.

A. Outlier Replacement Function

As the STL+ETS forecast model relies on automatic algorithms, there is not much room for manual calibration. For that reason, the best way to improve the quality of the output forecast is by improving the input data quality. Considering that the STL+ETS model relies on the demand seasonality and that there are only 33 months of observations available. The detection of the demand outliers becomes a complicated task because there are not many cycles to compare the presumed outliers to the past observations (R. Hyndman & Kostenko, 2007).

A.1 The “tsclean()” function for automatic filtering

For the outlier’s identification and their replacements, the function “tsclean” (R. J. Hyndman, 2021) was used. This function is part of the R Forecast package (R. J. Hyndman & Khandakar, 2008). The outlier detection procedure is based on the outlier’s definition given by Tukey (Tukey, 1976). Tukey defines as outliers, the observations that are outside the interquartile range (IQR$\pm$ 1.5 IQR). Then these values are replaced based on the STL decomposition, which based on locally weighted smoothing (Loess) will determine the replacement value (Cleveland et al., 1990). An example of the outlier identification and the corresponding replacement using the tsclean() function can be appreciated in the following figure:

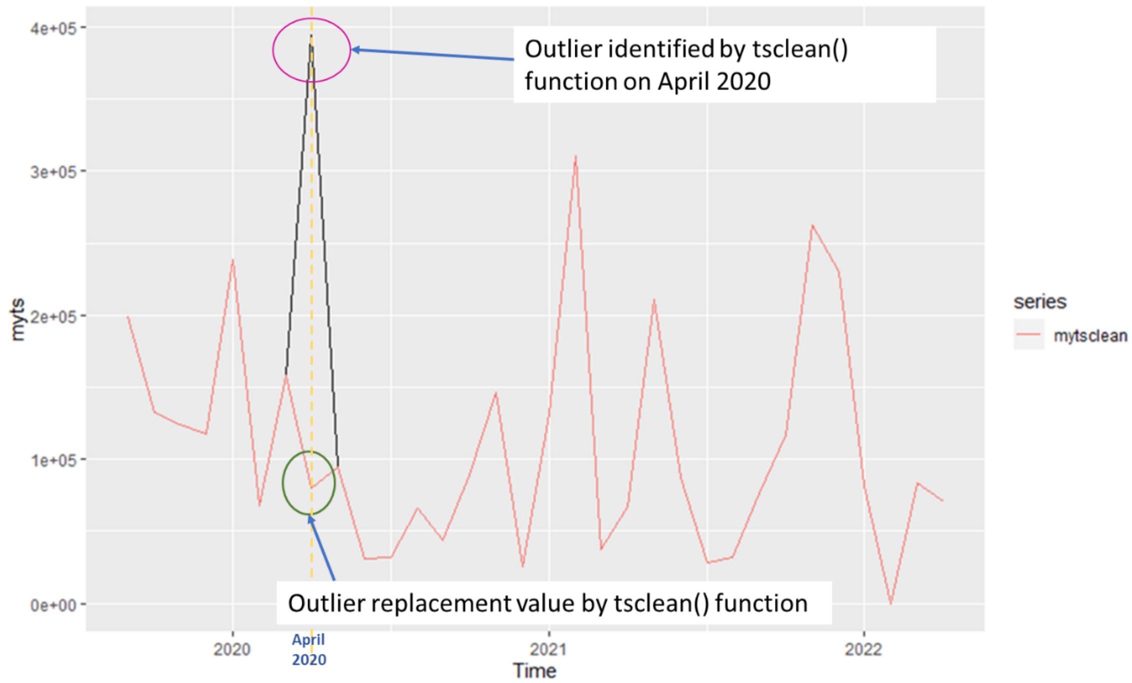


Figure 19 Original time series (Black) and time series after outlier removal (Red), for consolidated dataset 12

A.2 Automatic filtering supervision

As stated at the beginning of the section, due to the limited observations, the reliability of the outlier replacement function tsclean is dubious. For that reason, the results of the "tsclean()" function were reviewed case by case for the different datasets. For this task, seasonal analysis functions such as "ggseasonplot()" and "ggsubseriesplot()" available in the forecast package were used (R. J. Hyndman & Khandakar, 2008). These functions allow to obtain seasonal plots that show the average seasonal values of the time series as can be seen in the Figure 20 and Figure 21, which show the before and after the application of the tsclean function in the consolidated dataset 12:

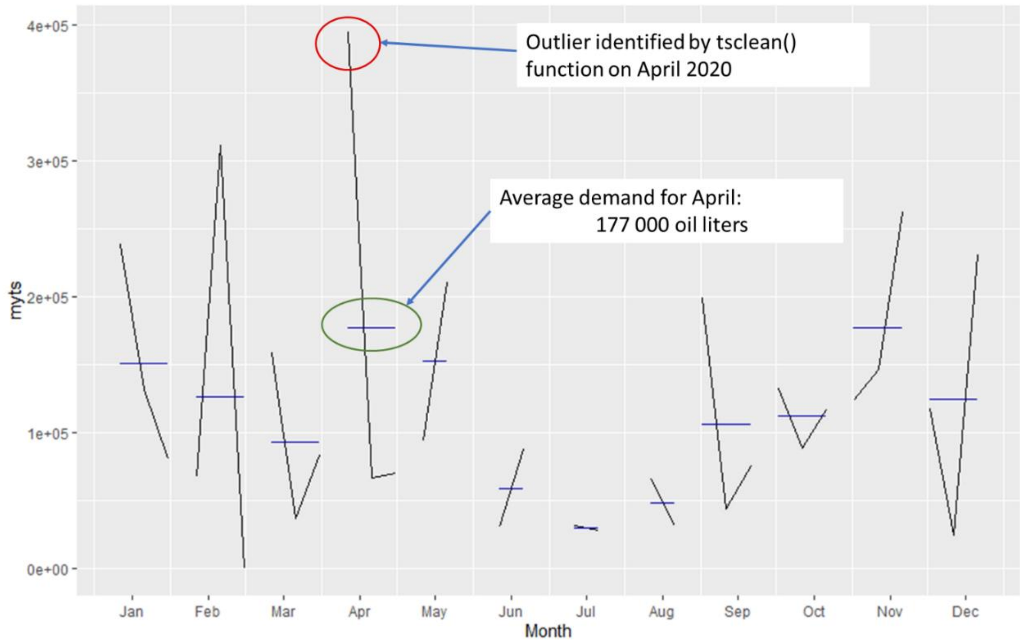


Figure 20 ggsubseriesplot() plot for the consolidated dataset 12, before the outlier removal

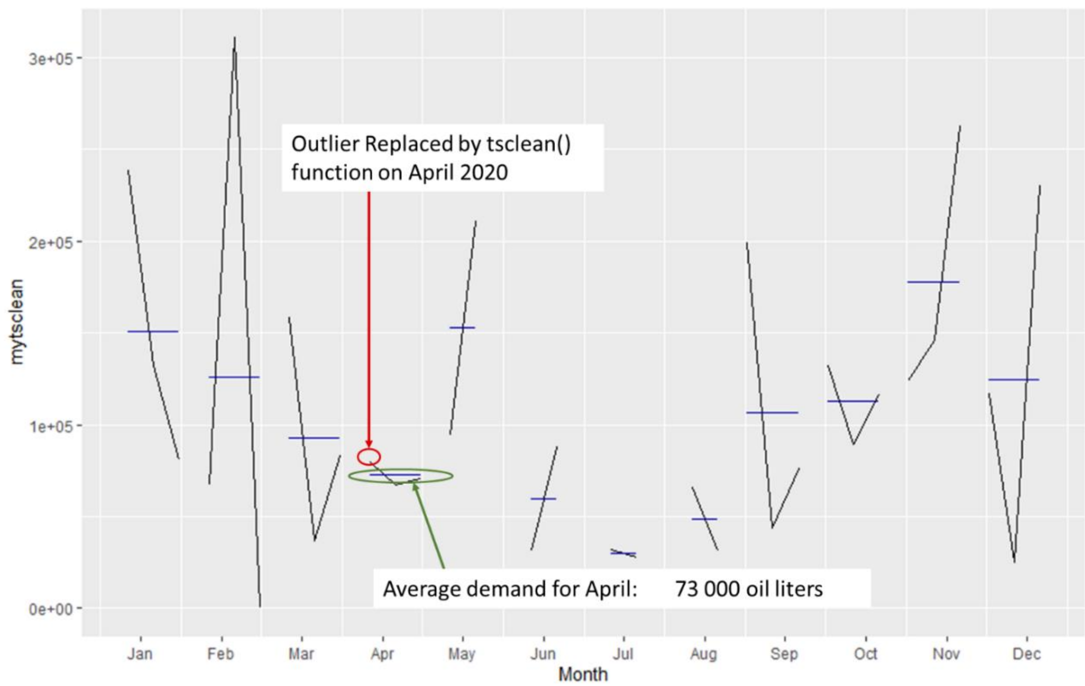


Figure 21 ggsubseriesplot() plot for the consolidated dataset 12, after the outlier removal

As it can be seen in Figure 19, according to the tsclean function, there was an outlier identified in April 2020 in the consolidated dataset 12. The ggsubseriesplot() plots in Figure 20 and Figure 21 allow visualizing the changes in the average seasonal demand for April, after the replacement of the presumed outlier. It can be seen that by removing that outlier, the average demand for the month of April is more aligned with the demand observed for April in the last two years. For that reason, the outlier was removed from the demand dataset.

With the current demand observations, the reliability of the automatic outlier replacement process is low and it is not possible to know with certainty if the presumed outliers are or not. This situation will only be clarified over time as more demand observations become available (R. Hyndman & Kostenko, 2007).

Another way to improve the demand outlier identification process was if there was a register of the events occurring during the outliers generation period. Some better insights could be obtained to understand better the demand influencing factors (Armstrong, 2005). Unfortunately, Cargill GEOS did not keep a register of the events occurring during the appearance of the demand outliers. But it is highly recommended that they start keeping a register of these events to improve the understanding of demand influencing factors.

Up to this point, the extended model design will have the following outline:

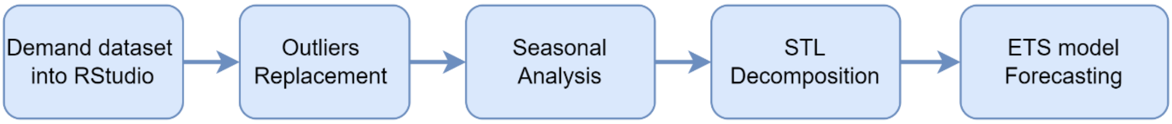


Figure 22 Extended STL+ETS model Design

The first step is to load the demand time series datasets into RStudio IDE. Second, the datasets are analyzed for outliers. The next step is the review of the existing seasonal patterns with the use of the "ggseasonplot()" and "ggsubseriesplot()" functions, as explained above. Then the datasets are decomposed into their seasonal, trend, and remainder components based on Loess. These components as explained in the STL+ETS model design section will be used for the generation of a time series ensemble, which will be forecasted using the ETS exponential smoothing process and then will be combined based on their median values to obtain the STL+ETS forecast, along with the corresponding prediction intervals (Bergmeir et al., 2016).

B. Train Dataset testing to Identify Improvement Opportunities in the STL+ETS Model

To identify shortcomings in the STL+ETS model forecast at the monthly time aggregation level, the model will be tested against real demand data. For this, the last three months of the consolidated datasets that have at least 27 monthly observations were trimmed. At most the datasets can have 32 monthly observations, from September 2019 up to April 2022. The last three months (February, March, and April 2022) will be used to test the STL+ETS model performance. These trimmed datasets will be referred to as train datasets. Chronologically, the testing procedure was developed before the outlier removal. This was because the need to include the outlier removal was identified from the train dataset testing results.

The train dataset testing is summarized in the following outline. First, the time series is trimmed, by defining a new time series on RStudio, based on the full monthly time series but excluding the last 3 observations. Then the time series is reviewed for changes in the seasonal averages with the ggsubseriesplot() function. Then the train dataset STL decomposition plot is compared with the full dataset, to see how the estimation of the components by the STL decomposition might have changed. This STL decomposition is also used as input for the forecast generation. To conclude the forecast plot is compared against the demand observations as can be seen in Figure 24.

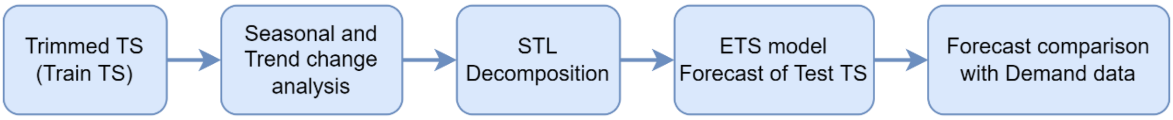


Figure 23 Train dataset forecast comparison with demand data

The testing of the train datasets took place along with the obtention of the STL+ETS monthly forecast (section 5.1.A), based on the extended STL+ETS model schematized in Figure 22. The RStudio code for the Monthly forecast and the train dataset testing can be found in the appendix.

B.1 Forecasting variable

As the objective of train dataset testing is to measure the error level of the STL+ETS forecast over the real demand. The Absolute Percentual Error (APE) will be used to measure the forecast accuracy. The average of the APE is the MAPE that has already been defined in previous sections (R. Hyndman et al., 2008).

B.2 Time horizon

As explained above, the months of February, March, and April 2022 were removed from the demand datasets. To be used as a reference and measure the APE of the STL+ETS forecast model. Due to this, the time horizon considered in this testing is of 3 months.

B.3 Results

In 60% of the cases, the estimated seasonal component for the train datasets was similar to the full datasets, with some exceptions caused by the oil shortage disruption. The main difference was in the trend component, especially for the months of February, March, April, and May 2022. This is because the level for the peak periods tends to change from year to year. Making these months, the least predictable period.

The other 40% of the cases showed a disruption in their seasonal patterns, presenting demand peaks even in months when the demand was at its lowest valleys in previous years. This disruption of the seasonal patterns is attributed to the Ukrainian conflict, the subsequent oil shortage, and the demand shifts from the canceled promotional products, which are normally demanded in March, April, and May(Lang & McKee, 2022). Another possible explanation for seasonal patterns disruption is the customers' speculation to build up their stock levels and ensure themselves a strategic position to take advantage of the situation (Pan et al., 2020).

The trend component estimation has been the most important shortcoming of the STL+ETS model. This is because the model needed at least 3 observations, at the monthly level, to adjust the trend component. Otherwise, it might just consider the changes as non-statistically significant and consider them part of the error component.

For this shortcoming two approaches were proposed, the first one is based on the prediction intervals. As it can be seen in the following figure, by matching the observed demand with the corresponding prediction intervals, in this case, the lowest value of the 60% prediction interval. It is possible to improve the forecast accuracy in this way until the model can adjust the trend component when more observations become available.

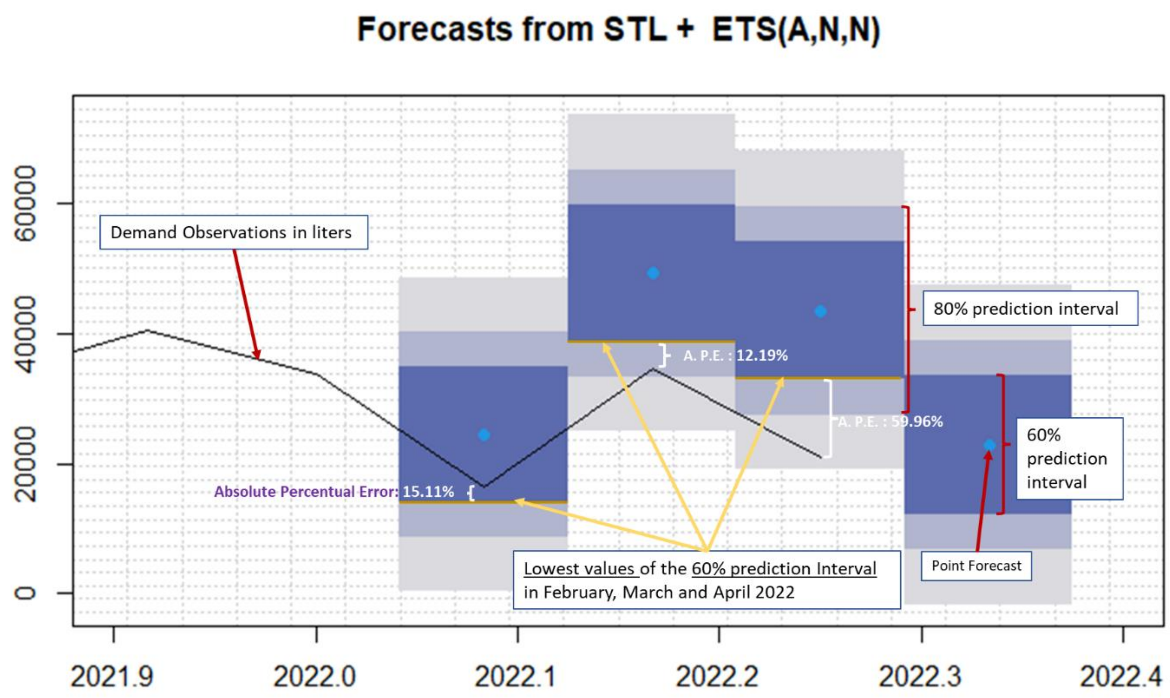


Figure 24 Test dataset forecast plot (in blue) compared to the real demand (in black) for consolidated dataset 11

In the following table, the numeric fitness can be seen in more detail in the following figure. By relying on the low 60 prediction interval, the resulting MAPE is only 29.09%. This is because MAPE for February and March is below 16%, while the MAPE for April is 57%. This shows an overall improvement in the forecast accuracy as explained above.

Table 18 Forecast Absolute Percentual error for the lowest value of 60% of Consolidated dataset 11

Parameters	February	March	April
Forecast Lowest value of 60% prediction interval	14,007.00	38,705.00	32,962.00
Registered Demand	16,500.00	34,500.00	21,000.00
Absolute Percentual Error	15.11%	12.19%	56.96%

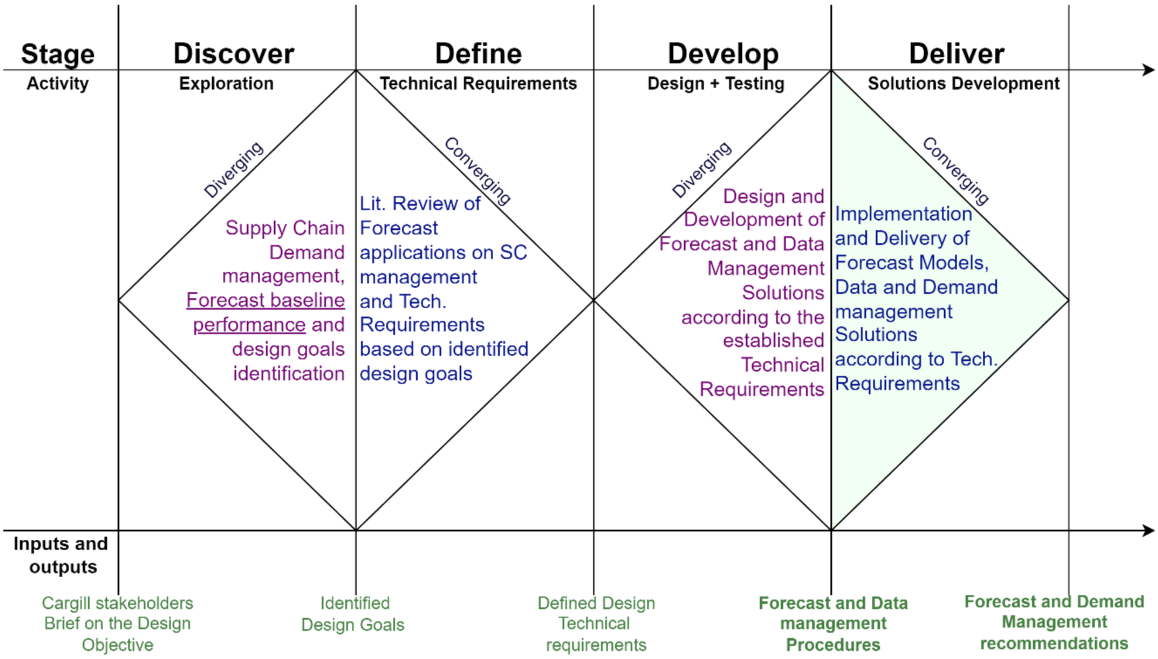
The second approach to improve the estimation of the trend component is by reducing the time aggregation level. As at least 3 observations are required to adjust the trend component, this implies that the forecast will not be able to estimate the level for 3 months. Considering that the production planning occurs on a weekly level, 3 months is too much time. For that reason, a decrease in the time aggregation level has been proposed as a solution. For example, considering the 3-week time aggregation level, the required 3 observations can be obtained in less than two months, more detail of the demand seasonal patterns can be obtained, and the scale of the forecast error will also be reduced.

4.6. Develop Stage Conclusions

In the Develop stage, the time aggregation framework was presented along with the models' design, which were tested. From these, the STL+ETS model was selected as the best option, then the DST procedure was presented and the extended model design to improve the selected forecast model accuracy. In this way, the main conclusions of this stage were first, the time aggregation has provided a structured roadmap to test the forecast models' accuracy at the right level, the monthly level where the demand data is easier to analyze to produce demand forecasts. Second, as stated in the discovery stage the demand seasonality was an important factor to consider in the demand forecast. This has been validated with the selection of the STL+ETS model. A model which high capabilities for the estimation of seasonal patterns even with a limited amount of observations. Third, the DST procedure showed to be very effective and logical, as its results were validated and acknowledged by the different stakeholders in the organization. Fourth, the model extension by including the automatic outlier removal algorithm has shown beneficial for the improvement of the STL+ETS model while maintaining the automatic nature of the forecast model. Fifth, the train dataset testing has been key in the improvement of the STL+ETS model. Allowing not only to identify the need to include an outlier removal algorithm, but also for providing solutions and strategies to compensate for its shortcomings.

5. Delivery Stage

The Delivery stage is the final stage of the Double Diamond Design. In this stage, the developed solutions will be implemented as a package to achieve the thesis project design objective: "The Design , Development and Implementation of a transparent forecast model that can improve the demand management and production planning of Cargill GEOS' Retail Food Services".



In this way, the first section will present the forecast results of the STL+ETS model for the monthly, 3-weekly, and weekly time aggregation levels, in alignment with the 2nd technical requirement the right time aggregation level will be determined for Cargill GEOS RFS. In the second section, the integration guidelines to include the STL+ETS model into the SAP HANA environment, and in that way make it part of the demand planning process, will be given. In the third section, the insights of the forecast results will be used to present the development of a variable safety stock management based on the seasonal behavior of the RFS products. The last section of the delivery stage will present the impacts of the developed solutions in this thesis project on the demand management of the RFS.

5.1. STL+ETS model Forecast Delivery

Now that the STL+ETS model has been extended to deal better with the outliers and the train dataset testing has been developed to verify the forecast accuracy against real data. In this section, the forecast results of the Monthly, 3 weekly, and weekly time aggregation will be presented to meet the first 5 forecast technical requirements.

A. Monthly Forecast

As commented in section 4.4.C from the 37 datasets obtained from the DST, only 34 were eligible to be forecasted. For the monthly forecast, the data was considered from September 2019 to April 2022. The demand datasets in this chapter are on the monthly time aggregation level and their demand is measured in liters of oil.

A.1 Forecast variables

To measure the error level of the different forecasts two indicators were used. These were the Mean Absolute Percentual Error (MAPE) and the Mean Absolute Scaled Error (MASE). As introduced in section 2.4.A and 4.3.B, respectively. The MAPE is easily interpretable as it measures the forecast error relative to the real observation and due to this, it is undefined when one of the data observations is zero. While the MASE measures the error relative to the naïve approach, which allows it to compensate when the MAPE is undefined (R. J. Hyndman & Koehler, 2006).

A.2 Forecast Time Horizon

To assess the extended STL+ETS monthly forecast accuracy not only based on the error levels but also based on real demand observations to see how it would perform in the demand planning process. The train datasets procedure will be included in the monthly forecast results. For this reason, the datasets will be trimmed at their last 3 months and a forecast time horizon of 3 months (February, April, and March 2022) will be considered.

A.3 Monthly Forecast results description

The results of the 34 successfully forecasted datasets with the STL+ETS extended model can be observed in the following table, where the datasets have been arranged based on their Coefficient of Variation (CoV), because it shows a better correlation with the monthly forecast MAPE:

Table 19 STL+ETS model Monthly Forecast Performance

Cons Num Dataset	DST	Average	CoV	MAPE	MASE	Train dataset Assessment
20	**Consolidated**	107,965.48	19.13%	12.82%	0.5845	very poor
5	**Consolidated**	**716,269.32**	**20.82%**	**14.73%**	**0.56**	**Excellent**
24	**Consolidated**	364,018.32	25.18%	15.46%	0.482	Good
29	**Consolidated**	324,227.23	25.21%	13.74%	0.6462	Approx, seasonal pattern change
18	**Complete**	529,240.97	25.68%	18.36%	0.5121	Approx
32	**Consolidated**	379,467.10	27.34%	17.68%	0.543	Good, slight demand displacement
4	**Consolidated**	539,063.19	28.73%	21.57%	0.6114	Approx, trend change
1	Complete	120,881.33	29.47%	19.98%	0.5044	Approx, trend change
19	**Consolidated**	491,477.10	35.27%	26.99%	0.5108	Approx
36	**Consolidated**	720,091.94	36.56%	28.44%	0.5316	Poor
23	**Consolidated**	265,132.26	36.68%	21.87%	0.5466	Poor
37	**Consolidated**	731,744.52	36.82%	27.39%	0.5222	Good, but a trend change
27	**Consolidated**	229,222.45	39.99%	14.93%	0.5214	Approx, demand diplacement+trend change
3	**Complete**	103,645.16	44.37%	31.41%	0.6228	Good, but a trend change
33	**Consolidated**	**41,286.19**	**45.41%**	**25.88%**	**0.5753**	**Good**

2	Complete	84,541.94	47.01%	36.34%	0.5333	Approx
11	Complete	27,846.77	48.75%	25.24%	0.4727	Good, but a trend change
7	Complete	82,377.58	49.40%	54.53%	0.5093	Approx
6	**Consolidated**	**203,219.35**	**52.03%**	**33.88%**	**0.6001**	**Good**
14	Complete	102,193.55	53.07%	39.28%	0.5359	Trend change
16	Complete	70,409.42	53.96%	52.21%	0.4482	Good, slight trend change
28	**Consolidated**	**42,090.19**	**58.15%**	**38.23%**	**0.5325**	**Excellent**
9	**Complete**	36,831.67	64.32%	NA	0.5326	Good
15	**Complete**	**22,385.81**	**69.39%**	**32.33%**	**0.538**	**very good**
12	Complete	119,854.84	76.28%	68.47%	0.5623	Good, but a trend change
13	**Complete**	129,979.84	77.60%	NA	0.5815	Approx
35	**Consolidated**	174,045.97	78.77%	NA	0.5383	Approx
30	**Cons-seasonal**	129,934.84	105.55%	NA	0.5969	Demand canceled
26	**Consolidated**	8,910.58	124.17%	NA	0.5626	Good, but demand displacement
25	**Cons-seasonal**	71,116.94	126.77%	NA	0.5699	Demand canceled
8	**Cons-seasonal**	31,341.72	129.95%	NA	0.6671	Demand canceled
17	**Cons-seasonal**	99,633.87	145.47%	NA	0.5449	Demand canceled
22	**Cons-seasonal**	153,963.75	155.84%	NA	0.5442	Not enough obs to assess
10	**Seasonal**	86,281.80	168.09%	18.36%	0.5121	Not enough obs to assess
Average		***215,902.73***	**63.57%**	**28.40%**	**0.5487**	
Weighted Average			**43.96%**	**23.79%**	**0.5464**	
Accuracy based on W.A.				**76.21%**		

In the table above the datasets are indicated by their consolidation dataset number, their type is also indicated as "complete" for the regular product datasets that did not require to be merged as explained in section 4.4.C, as "consolidated" for the regular product datasets that were the result of the datasets merging, as "seasonal" for the seasonal-only product datasets that did not require to be merged, and as "Cons-seasonal" for the seasonal-only product datasets that were the result of the datasets merging. The highest monthly demand averages for the different products have the darkest red colors, while the lowest averages have the lightest red colors. The CoV, the MAPE, and the MASE are colored with the green, yellow and red color scale, the lowest values have the green color, the next ones have the yellow color, and the highest values have the red color. The last column shows a qualitative assessment of the train dataset testing, to indicate how the generated forecast matched the real demand observations. These were assigned "excellent" when the match was almost perfect, "good" when the forecast generated was very similar to the observations, "good, but…" when the forecast generated was similar to the observations except for the indicated reasons, "approx" when the generated forecast values were wavering around the real observations, "poor" when there was no match, "very poor" when the forecast moved in the opposite direction of the real observations, "demand canceled" when the demand of the products was canceled, this is the case of many seasonal products, and "Not enough obs to assess" when the dataset had less than 27 observations so it could not be trimmed for the train dataset testing.

The cancellation of the seasonal-only products, as explained in section 2.2.B, has been one of the consequences and measures to mitigate the impact of the oil shortage due to the Ukrainian war conflict (Lang & McKee, 2022).

As can be seen in the table Table 19, the CoV is correlated to the MAPE. This is because the more stable demand, the less influencing the seasonal patterns, and there will be fewer opportunities for the STL+ETS model to generate an inaccurate forecast, as it can rely mainly on the trend component. Nevertheless, the fourth technical requirement was the development of a forecast model that can estimate the existing demand patterns and relationships, as the demand seasonal components. In the case of the seasonal time series, a higher CoV value will probably be a better indicator of the seasonality. In those cases, the MASE that measures the error relative to the naïve forecasting approach is a better indicator of the model's capabilities to estimate the seasonal components (R. J. Hyndman & Koehler, 2006). For this reason, despite the high CoV values, the STL+ETS model has been able to obtain relatively low MASE values, and more importantly, the better matching forecast results (train data assessment in green color) do not show a correlation with the MAPE value.

In this way, the STL+ETS model has been able to capture the seasonal components of the RFS datasets achieving a weighted average MAPE value of 23.79%, which fulfills the first technical requirement "The developed forecast model must have a MAPE lower than 50%".

B. The 3-week frequency forecast

In alignment with the second technical requirement and the roadmap defined in 4.1. The 3-week level forecast has been developed. Nevertheless, as not all the datasets had a good performance, only the 5 best-performing datasets were selected to explore the performance of the STL+ETS model at the 3-week level. For the 3-week forecast, demand data from week 37 of 2019 to week 24 of 2022 was considered. In total 50 demand observations were used for each dataset, with a max of 18 demand observations per year. The demand datasets selected were the consolidated datasets 5, 6, 15, 28, and 33. The dataset's demand was measured in liters of oil.

Even If the sample size is relatively small to draw solid generalizable conclusions about the forecast performance at lower time aggregation levels. It is important to emphasize that the monthly forecast results were reviewed in detail to see how they matched the observed demand. Unfortunately, not all the forecasted datasets had a good match with the observed demand. This is because the STL+ETS model relies on the estimation of the seasonal and trend components (Bergmeir et al., 2016). Considering this and that according to literature there is a degradation of the seasonal factors when the time aggregation level is lowered, which in consequence increase the error level (Rostami-Tabar et al., 2014). This degradation effect and impact on the forecast accuracy could not be appreciated in datasets, where the seasonal patterns were not enough to obtain an accurate forecast. For that reason, the 3-week level forecast testing was performed on relatively small sample, but that is of high quality, as it will allow to observe properly the time aggregation level impact on the forecast performance, which will provide generalizable enough conclusions to determine the most suitable time aggregation level that provides enough forecast accuracy, while providing a useful forecast for the RFS production planning.

B.1 Forecast variables

Similar to the monthly time aggregated forecast, the Mean Absolute Percentual Error (MAPE) and the Mean Absolute Scaled Error (MASE) will be used to assess the forecast performance. But in this case, as the MAPE presented undefined values due to the increase of zero-demand observations, the MASE will be the main indicator to assess the error level and accuracy improvement in comparison to the monthly demand forecast.

B.2 Forecast time horizon

Similar to the monthly forecast in the previous part, the 3-week frequency forecast will rely on the train dataset testing procedure, described in section 4.5.B, to assess the performance of the model. In this way, the last 5 observations will be used to assess the forecast performance against real data. This is from week 19 to week 24 of 2022.

B.3 Forecast results description

In the following table, the datasets were ordered based on the 3-week MASE value. In the case of the 3-week forecast, it performed better than expected. Due to the decrease of the time aggregation level, some of the error levels increased. In half of the cases, there was an improvement in MASE value. Overall the match between the forecast and observed demand is still good at the 3-week level as it has been indicated in the “3-week Train dataset Assessment Assessment” and it seems to be correlated with the MASE values (green, yellow and red).

Table 20 3-week forecast performance

Cons Number	3-week Average	3-week CoV	Monthly MAPE	Monthly MASE	3-week MASE	3-week MAPE	Train Dataset Assessment
5	487,099.18	28.3%	15.0%	0.56	**0.5253**	15%	Very good
15	14,479.20	89.0%	32.0%	0.538	**0.5522**	NA	Very good
28	28,212.72	84.1%	38.0%	0.5325	0.5678	NA	Very good
6	137,392.00	65.0%	34.0%	0.6001	**0.5844**	NA	Approximated
33	27,570.24	63.8%	26.0%	0.5753	0.5948	NA	Good
Weighted Average	**138,950.67**	**40.5%**		**0.5670**	**0.5420**		

The main benefit of lowering the time aggregation level is the increase in the demand detail, while the forecast match has not bee considerably affected. This could also be due to the better estimation of the trend component as it was described in section 4.5.B. About the seasonal component, even with the increase of peaks and valleys in the 3-week level, the model has been able capture them in the seasonal component, as it can be seen in the following figure.

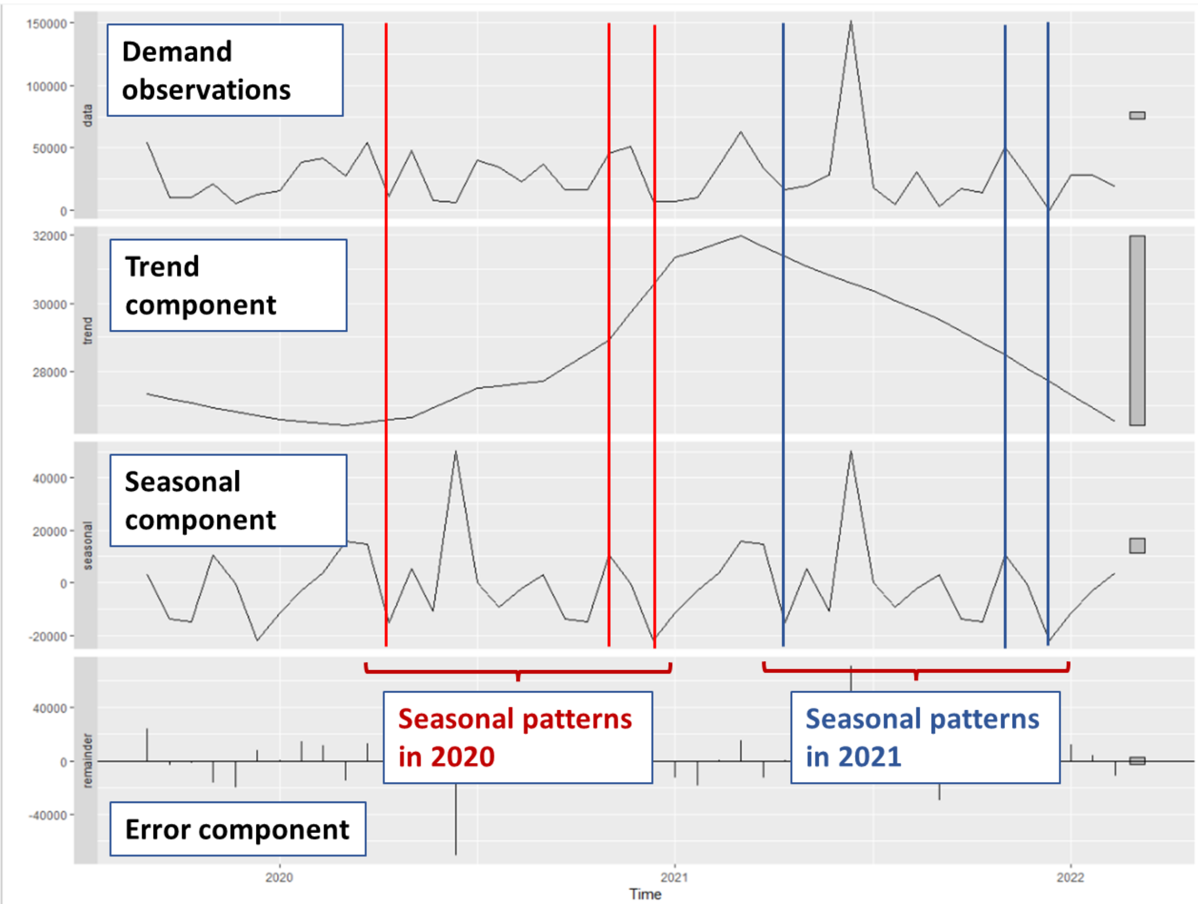


Figure 25 STL decomposition results for the consolidated dataset 28 at the 3-week time aggregation level

The 3-week time aggregation level represents an improvement in comparison to the monthly level because it is closer to the weekly level of production planning. There has been a small increase in some of the error level indicators, but the forecast match with the demand observations at this lower aggregation level compensates for it.

C. *Weekly Forecast*

Due to the good performance of the 3-week level forecast and in alignment with the roadmap described in section 4.1. The same selected datasets for the 3-week level will be forecast at the weekly level. The demand data used was from week 36 of 2019 to week 26 of 2022. The dataset's demand was measured in liters of oil.

C.1 Forecast Variables

For the weekly forecast, the main variable to measure the error level is the Mean Average Scaled Error (MASE). Because the number of zero-demand observations rendered the Mean Average Percentual Error (MAPE) undefined and useless to assess the error level.

C.2 Forecast time horizon

Just as in the two previous time aggregation levels, to measure the weekly level performance the train dataset testing procedure was used to assess the forecast performance against real demand data. The trimmed dataset, for the forecast testing, ranges from week 2019 to week 16 2022. In this way, 148 weekly observations were used for the forecast estimation and the forecast performance was evaluated in comparison to the demand observations from week 17 2022 to week 26 2022. Making a total of 9 weekly demand observations for the forecast assessment.

C.3 Weekly forecast results description

In the following table, the datasets were ordered based on the weekly MASE value. In the case of the weekly forecast, the forecast results were expected. The model was able to improve considerably the estimation of the trend component due to the increase in the frequency of the observation, but the seasonal component estimation was worsened, due to the weekly variation and demand displacements that occur between the years as explained in section 4.1. Overall the match between the forecast and observed demand has worsened as can be seen in Figure 26 and Figure 27 and has been indicated in the “Weekly Train dataset Assessment Assessment”. Still, the match performance seems to be correlated with the MASE values (green, yellow, and red).

Table 21 Weekly Forecast performance

Cons Number	Weekly Average	Weekly CoV	Monthly MASE	3-week MASE	Weekly MASE	Weekly Train dataset Assessment
28	9,775.32	135.27%	0.5325	0.5678	0.5374	Good
5	168,456.18	43.54%	0.56	0.5253	0.5398	Approximated
6	47,268.29	91.77%	0.5753	0.5948	0.5543	Very Good
15	5,076.78	144.13%	0.6001	0.5844	0.5659	Good, with one week demand displacement
33	9,634.19	105.59%	0.538	0.5522	0.5788	Approximated
Weighted Average	**240,210.76**	**61.38%**	**56.19%**	**54.30%**	**54.47%**	

The Figure 26shows the 3-week forecast compared to the real observations as described in section 5.1.B, while the Figure 27 shows the Weekly forecast compared to the real observations.

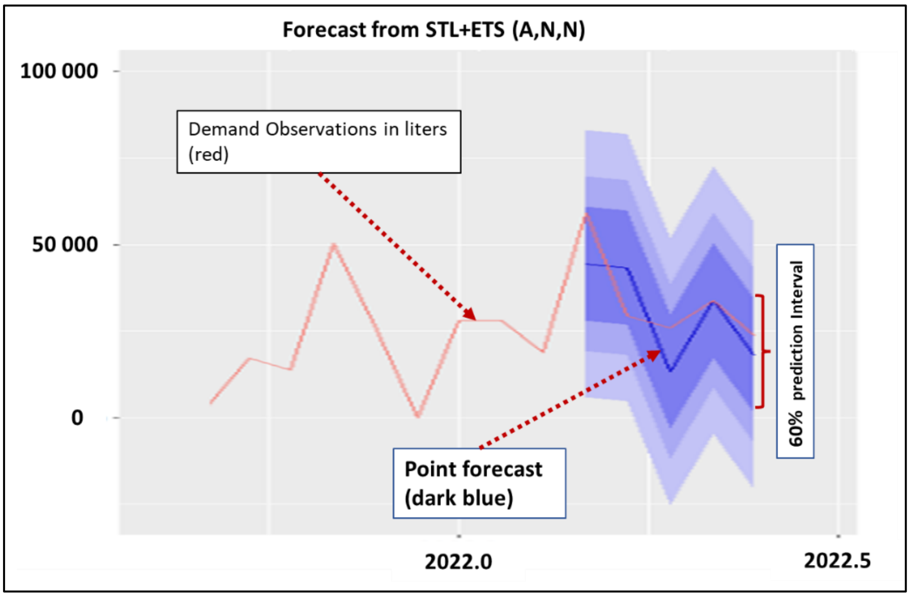


Figure 26 3-week forecast results compared to the demand observations for the consolidated dataset 28

As described above, lowering the time aggregation levels improves the estimation of the trend component. But as can be seen in the weekly forecast, the model is not able to estimate the seasonal patterns. This has been described in sections 3.1.B and 4.1. To lower the time aggregation level without losing accuracy, more observations are required. In this case, 2 years and half of the demand observations are available, to achieve a useful forecast at the weekly level it might be required to have at least 5 years of demand observations.

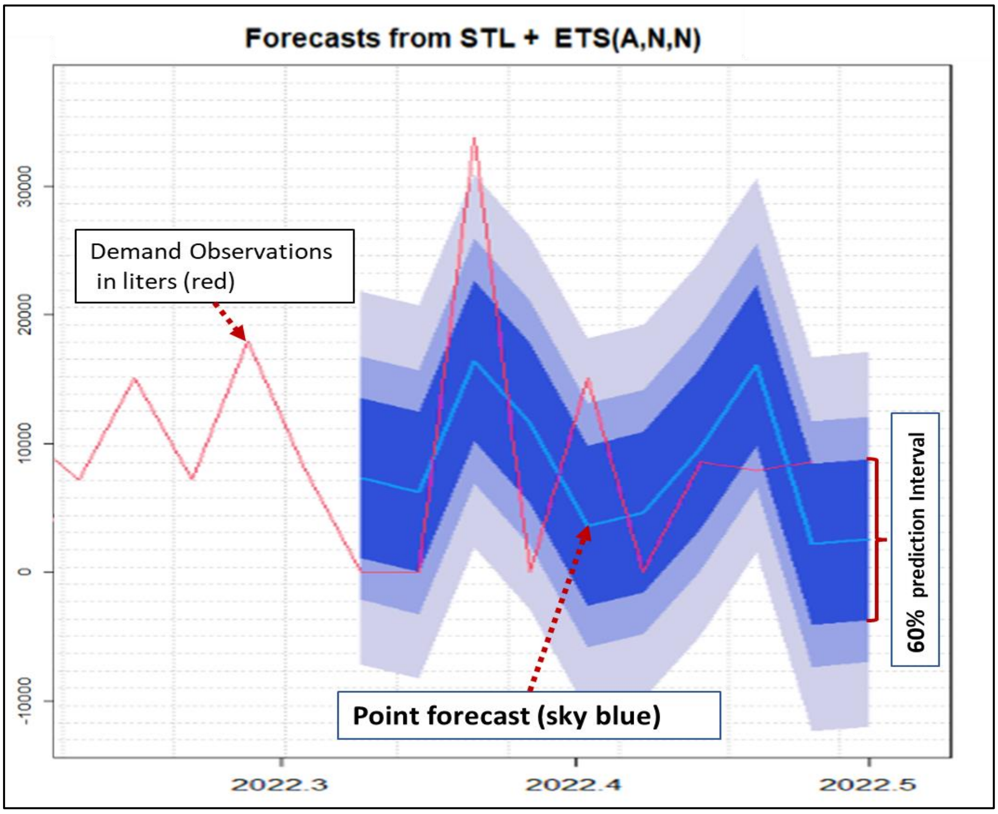


Figure 27 Weekly forecast results compared to the demand observations for the consolidated dataset 28

The Monthly, 3-week, and weekly forecast plots of the 5 selected datasets can be found in the appendix.

D. Selection of the Forecast aggregation level for RFS

Based on the forecast results from the different time aggregation levels and in alignment with the second technical requirement, the 3-week level has been chosen as the right time aggregation level for the forecast of Cargill GEOS RFS demand.

This is because the STL model results at a monthly level were satisfactory, but there was still room for improvement concerning the second technical requirement. For that reason, the 3-week level forecast results were explored. There was found an improvement in the trend component estimation, and the prevalence of the seasonal patterns, which could still be estimated in the seasonal component with the available observations. In this way, the 3-week forecast was considered suitable for the second technical requirement. Nevertheless, considering the good performance of the 3-week level, the weekly level forecast was explored, but overall the match between the forecast and the demand observations worsened.

Table 22 Assessment of Forecast Technical Requirements 1-5

N°	Category	Technical Requirements (How)	Assessment
1	Forecast	The developed forecast model must have a MAPE lower than 50%	Excellent, at the monthly level, the STL+ETS model achieved a weighted average MAPE of 23.79%, and at the 3-week level a weighted average MASE of 0.5420
2	Forecast	The Development of a useful demand forecast that is as close as possible to the weekly time aggregation level.	Very good, in this case, with the available data and the STL+ETS model, the time aggregation level achieved was a 3-week forecast
3	Forecast	The demand forecast must be based on a white box method	Excellent, the forecast is based on a statistical forecast model that is based on the demand data seasonal patterns, which makes it transparent and interpretable to apply adjustments when it is required.
4	Forecast	The developed model must be able to estimate the existing demand patterns and relationships, as the demand seasonal components	Excellent, the model has been able to estimate the seasonal, trend, and error components of the demand data to generate a model with its corresponding prediction intervals, which were used to improve further the forecast accuracy.
5	Forecast	The Demand Forecast Model can produce a useful forecast with the available demand data (two years and a half).	Excellent, the STL+ETS model has been able to estimate successfully the seasonal components of the time series to produce a representative forecast that can match the demand observations.

As it can be seen in the table above, the forecast technical requirements 1 to 5 have been successfully met. In the following sections, the rest of the technical requirements will also be met.

5.2. Integration of the STL+ETS model in SAP HANA

To fulfill the sixth technical requirement “The forecast model can be integrated with the SAP IBP data platform and be executed in an automatical way”. The official website of SAP HANA was reviewed. There it was found that it is possible to connect the RStudio Integrated Development Environment with SAP HANA. As described in sections 2.2 and 2.3, the RFS demand data is managed in the SAP IBP data platform, which is based on the SAP HANA data management solutions developed by SAP SE (Färber et al., 2012).

The integration of SAP HANA and RStudio to be able to obtain the desired forecast is relatively easy to implement. This integration can be done through the Java DataBase Connectivity (JDBC) application programming interface (SAP SE, 2015) as it is described in the SAP community website (Henry, 2016). For this process, it is required to install the following software:

- R Desktop, which is the software environment for statistical computing (Ripley, 2001).

- RStudio Integrated Development Environment (Racine, 2012).
- HANA JDBC Server (SAP SE, 2015).
- The R code for RStudio (Henry, 2016)can be found in the appendix.

All these software solutions are relatively easy to install, as most of them have been already installed in some of Cargill's computers for this thesis project development by Cargill's IT department. Once the software has been installed, RStudio will have the resources and authorizations required to draw the required demand datasets from SAP HANA without requiring to rely on manual preparation of the datasets as it has been done during this project through excel spreadsheets.

The code with the commands and instructions to activate this connection can be found in the Appendix F - R code for integration with SAP HANA. This code has to be run into RStudio console, the code will connect RStudio to the HANA environment to retrieve on smoothly way the desired data for its analysis or forecast in RStudio.

To integrate back the obtained information into SAP HANA environment requires some tailored code according to Cargill SAP IBP data platform requirements. Unfortunately, these details of the data platform were not part of this thesis project scope. Still it is known that Cargill has been able to develop previously data integration solutions in two ways. Once is internally, as it has been in the development of the TC2 system that is currently in operation and the other one is externally. As it is the case with the Deloitte that is responsible of developing and adjusting the current forecast solution for the RFS demand, which is fully integrated into the SAP IBP system. Because the STL+ETS forecast model will replace the forecasting solution described in section 2.4, it is recommended that the implementation of this solution is carried by Deloitte under the supervision and according to the requirements of the Demand planner as it has been done previously.

The economical resources to implement this solution should not be considerable, as this solution will just replace the existing one. About the time for its implementation, with the steps described here, it should not take longer than 3 to 4 working days. But the integration of the information back to SAP IBP should not take longer than a month. This mainly depends on Deloitte capacity to connect the RStudio output back into the SAP IBP data management platform according to the demand planner requirements.

In this way, the sixth technical requirement has been fulfilled as described in the following table.

Table 23 Forecast Technical Requirement #6 Assessment

N°	Category	Technical Requirements (How)	Assessment
6	Forecast	The forecast model can be integrated with the SAP IBP data platform and be executed in an automatical way.	Suitable, the model does not exist natively in the SAP system, but it is possible to include it by integrating RStudio with SAP HANA. From RStudio, it is possible to obtain the datasets forecast results in an automatic way.

5.3. Integration of the Demand Shift Tracking Procedure into the Demand Planning Process

In alignment with the seventh technical requirement, "the developed procedure to identify the succession relationships must be objective and the results must be validated by the sales assistants". The Demand Shift Tracking procedure (DST), which has been described in section 4.4 and can be found in the appendix section, was developed.

Nevertheless to facilitate the inclusion of the Demand Shift Tracking procedure in the demand planning process and avoid demand fragmentation in the future as described in section 4.4. Different alternatives were considered. For example, its inclusion in the TC2 system, which is responsible for Cargill GEOS master data maintenance, and also within the SAP IBP system. Nevertheless, as some products might be replaced only in some country markets and still be active in others, this can create data conflicts when the product demand is analyzed as a whole.

For this reason, after raising the situation to the involved stakeholders, such as the Demand Planner, the Sales Assistants, and the SCDA coordinator. It was decided that the most efficient way to keep track of the succession relationships between the RFS products in each country's market is to maintain a shared register of the identified demand shifts between the products on the Cargill SharePoint cloud. This can be implemented in a shared excel document with the fields indicated in the following table.

Table 24 Recommended Fields for the Demand Shift Tracking register

The table has been removed due to confidentiality issues

The proposed register provides back and forward traceability of the products to identify their successor and predecessor, within each country's market. In this way, the demand planner can retrieve the required demand data to forecast the new SKU code products that have replaced demanded products, due to small changes that required the creation of a new SKU code.

A. Roles and Responsibilities

Similar to the elaboration of the consensus demand forecast described in section 2.2.B. The implementation of the demand shift tracking procedure requires the participation of the Demand planner and the sales assistant. For example, keeping the DST register up to date should be the responsibility of the sales assistant. This is because they are the first ones in the organization to learn about changes in the RFS products specifications and they already have a register of some of the products replacements. Nevertheless, as stated in 2.3 the register is not up to date, and neither was available for the demand planner. The demand planner might also be responsible as the driver to keep the DST register up to date. Particularly in the cases where he is able to identify or suspect the occurrence of a product being replaced by analyzing the demand datasets.

Two moments were identified for the update of the DST register. First, on a routine basis, each time an RFS product with a new SKU code is created. The corresponding successor if it exists should be located in the corresponding country's market and included in the register. Second, each time an existing product is added to the demand of a country. It should be checked if the newly introduced product will be replacing the demand of an already established one.

To facilitate the identification of the demand predecessors and successors the sales assistant and/or the demand planner can also rely on the DST procedure that has been developed in section 4.4 and can be found in the appendix section.

In this way, the seventh technical requirement has been fulfilled successfully, as it is indicated in the following table.

Table 25 Data Management Technical Requirements 7-9

N°	Category	Technical Requirements (How)	Assessment
7	Data management	The developed procedure to identify the succession relationships must be objective and the results must be	Excellent, the developed procedure has been able to identify the existing succession relationships between the RFS products objectively, and the results were validated by the sales assistant, as it has been indicated in section 4.4.C.

		validated by the sales assistants.	

5.4. Forecast Insights for Inventory Management

As it was described in section 2.5. The RFS safety stock levels of Cargill GEOS are being managed closer to a make-to-stock productions strategy than to the make-to-forecast production strategy that Cargill GEOS is currently using. For this reason, a brief literature review was performed in section 3.1.B to identify improvement opportunities for RFS safety stock management. In that way, the eighth technical requirement was formulated as "The safety stocks must be managed on a variable level based on the insights obtained from the demand forecast and the data analysis".

In the baseline described in section 2.5, the safety stock levels are managed at a constant level all year round. Nevertheless, the good performance of the STL+ETS model that relies mainly on the estimation of the seasonal component for the forecast generation, has shown that the RFS demand follows seasonal patterns that are repeated to some extent year after year. For that reason based on the insights obtained from the demand forecast and data analysis in sections 2.3, 4.3, and 5.1. The following seasonal approach has been developed for the management of the RFS safety stock levels.

Table 26 Demand quartes for the management of the Safety Stock levels

Q1	Peak period	Mar - Apr - May
Q2	Off-peak	Jun - Jul - Aug
Q3	Peak period	Sep - Oct - Nov
Q4	Off-peak	Dec - Jan - Feb

As it can be seen in the table above, the annual demand has been split into four quarters, which don't start at the beginning of the year in January but in March. This is because these quarters have been defined based on the monthly observed demand levels, as can be seen in the following figure:

This figure has been removed due to confidentiality issues

Figure 28 Demand seasonal behavior as a whole (in thousand of liters) and its demand levels on each quarter.

The figure above shows the aggregated demand of the "complete" consolidated datasets that were described in section 5.1.A. Their demand was aggregated to show how the RFS demand levels vary as a whole throughout the year. In this way, the first demand peak period occurs in March, April, and May, and the second demand peak period covers from September to November. While the demand off-peak periods occur, first and especially in June, July, and August and the second demand off-peak period occurs from December to February of the following year.

The same formula that was used in the baseline, section 2.5, to determine the annual safety stock levels based on the **weekly demand**, was used for the calculation of the seasonal safety stock levels. This is to provide an improvement in the management of the safety stock levels, without altering the underlying principles used for the management of the safety stock levels. In this way, the formula to estimate the safety stock level on Q1 will be based on the CoV of the weekly demand in Q1, the service level Z, as indicated in table Table 4 in section 2.5, and the Average weekly demand in Q1.

$$SSq1 = Z \times CoV_{demand\ q1} \times Avg_{demand\ q1} \tag{5-1}$$

To examine the impact of managing the safety stocks quarterly, the complete consolidated datasets were used as a sample to calculate their corresponding Safety Stock Levels (SSL) in the following table:

Table 27 Quarter Safety stock levels

This table has been removed due to confidentiality issues

As can be seen in the table, the datasets were ordered considering their average demand level, this was because the CoV did not show any relevant correlation. The average demand and the quarterly safety stock levels, which are expressed as a percentage of the Annual Safety Stock level, are both colored in green for the lowest values, then yellow for the mid values, and red for the highest values.

The last row of the table shows the total annual safety stock and the total safety stocks for each quarter expressed as a percentage of the annual stock. As not all the RFS products have their demand peak periods in the same quarters, their safety stock can be reduced and that additional capacity can be used for the RFS products that have their demand peak periods in that quarter. In this way, the safety stock levels can be managed more efficiently. As there is only a slight increase in the safety stock levels is in the first quarter, while in the second quarter the safety stock levels as a whole can be reduced by a 30%, and for specific RFS products the safety stock reduction can be up to 63%..

This improvement in the management of the safety stock levels was achieved by aggregating the weekly demand on quarters of the year (3 months). But this can also be done monthly or bimonthly. Still, the proposed management in quarters is a good starting point to start exploring the benefits of aligning the safety stock management with the insights obtained from the demand forecast. In this way, the eighth technical requirement has been met successfully.

Table 28 Demand Management Technical Requirements

N°	Category	Technical Requirements (How)	Assessment
10	Demand management	The safety stocks must be managed on a variable level based on the insights obtained from the demand forecast and the data analysis.	Excellent, the forecast has shown the seasonal patterns of the RFS demand, which were used for the development of a quarterly-based safety stock management, that allows managing the RFS products stocks more efficiently.

5.5. Impact on the demand planning process

To conclude the delivery section, the impact of the developed solutions in this thesis project, which had for objective “The Design, Development and Implementation of a transparent forecast model that can improve the demand management and production planning of Cargill GEOS’ Retail Food Services” will be summarized in the following table:

Table 29 Developed measures Impact on the Demand management for the RFS

N°	*Category*	*Measurement*	Baseline	DST + *STL+ETS* (monthly)	Percentual Change
1	1. Demand shift tracking	Monthly demand obs/dataset	9	26	**188.89%**
2	1. Demand shift tracking	# hours invested by sales/ per demand shift	0.25	0.25	**0.00%**
3	1. Demand shift tracking	# hours invested by Demand planner / per demand shift	8	0.25	**-96.88%**
4	2. Statistical Monthly Fcast	Error level (MAPE)	57.91%	23.79%	**-58.92%**
5	2. Statistical Monthly Fcast	Accuracy level (MAPE)	42.09%	76.21%	**81.06%**
6	2. Statistical Monthly Fcast	Error level (MASE)	0.5619	0.5521	**-1.74%**
7	3. Demand planner input Monthly Fcast	Hours invested reviewing Statistical demand Forecast for Customer X (25% volume)	8	3.3	**-58.92%**
8	3. Demand planner input Monthly Fcast	Hours invested reviewing Statistical demand Forecast for RFS	*32*	*13.1*	**-58.92%**
9	3. Demand planner input Monthly Fcast	Error level	50.96%	20.94%	**-58.92%**
10	3. Demand planner input Monthly Fcast	Accuracy level	49.04%	79.06%	**61.23%**
11	4. Customer Order Decoupling Point	Production Planning Correction Requests due to Forecast (in 7 months)	68	28	**-58.92%**
12	4. Customer Order Decoupling Point	Hours invested Production Planning Correction due to Fcast (in7 months)	28	12	**-58.92%**
13	5. Service Level	Order changes due to Forecast errors	298	122	**-58.92%**
14	5. Service Level	Orders rejected due to Forecast errors	294	121	**-58.92%**
15	6. Safety stock management	RFS safety stocks (as a whole) during off peak periods	100%	70.00%	**-30.00%**
16	6. Safety stock management	specific RFS products safety stocks during their off peak periods	100%	37.37%	**-62.63%**

As it can be seen the table has 5 categories, these were ordered based on their order of occurrence in the demand planning process described in section 2.2. For a better estimation of the impact of the solutions developed, the baseline scenario will be compared with the implementation of the developed solutions, but the STL+ETS model will be considered on a monthly forecast.

The first category is the impact of the Demand Shift Tracking (DST) procedure, as explained in section 2.3 many datasets were the product of the demand data fragmentation. In the baseline 166 country-SKU datasets were identified, these datasets presented an average of 9 monthly demand observations and only 16 datasets with the 32 possible monthly demand observations. After the application of the DST procedure, 37 consolidated datasets were generated, two of which were rejected by the sales department. Still the average monthly demand observations have increased by 188%, with 26 monthly observations and 27 datasets were obtained with the 32 possible monthly demand observations.

As detailed in section 5.3, the DST needs to be included in the demand planning process to avoid future fragmentation. Besides the improvement of the data management and the demand forecast, the integration of the DST procedure can reduce the hours invested by the demand planner due to the delayed sales assistants responses by 96%. Because usually when a product replacement occurs, the demand planner is not aware of it and he has to request an update from the sales assistants, from time to time. Until the sales assistant provides the information, the demand planner can be waiting a whole day (8 working hours). But by implementing the DST register described in section 5.3, the demand planner can receive the information on the same day that the product replacement occurs.

The second category is the statistical monthly forecast, as indicated in 2.2.B. The developed forecast model will replace the SAP statistical forecast which is automatically generated based on the moving average algorithm. While the baseline forecast had a MAPE error level of 58%, the developed forecast model achieved a MAPE error of only 24%. This represents a 58% reduction of the forecast error level or a 81% improvement of the statistical forecast accuracy. This has been possible because while the moving average only indicates the time series' current level, the STL+ETS model leveraged the seasonality of the demand observations.

The third category is the “Demand Planner Input” forecast, which is described in section 2.2.B. This forecast is generated from the statistical forecast when the demand planner reviews the forecast performance and applies the corresponding adjustments. Based on the MAPE results for the statistical forecast and the demand planner input forecast. A reduction of the 12% of the MAPE has been attributed to the adjustments of the demand planner. The number of hours invested by the demand planner in the Global Retailer data is of 8 hours per month. Assuming that the hours invested are proportional to the MAPE error level, so the more inaccurate is the generated forecast, the more hours that will be required for its correction. In that way, with the STL+ETS model, only 3.3 hours would have been required for Global Retailer. Then considering that Global retailer represents 25% of the RFS volume, as indicated in section 1. A total of 32 hours are invested monthly by the demand planner in the RFS forecast correction in the baseline scenario. While with the STL+ETS, only 12 hours would have been required. Which is a reduction of 58% of the hours invested the demand planner. As the consensus forecast has not shown an impact on the forecast accuracy improvement, it will be omitted.

The fourth category is the Customer Order Decoupling Point (CODP). In the baseline scenario, section 2.2.B, 68 customer requests were registered in 2022 until the month of July, causing 28 additional working hours between the production planners and the customer service representatives. Assuming that these numbers are proportional to the “Demand planner input” forecast error level (MAPE). In the case the monthly STL+ETS forecast model is implemented, a reduction of the 58% in the production planning corrections would have been registered, as well as in the number of additional working hours to implement these corrections.

The fifth category is the service level, as indicated in section 2.2.B, the main indicator for the service level is the percentage of orders delivered On Time and In Full, according to the customer's initial request. Unfortunately, as there are many factors influencing the service level, the impact of the developed solutions could not be estimated. For that reason, the number of changed orders due to forecast errors, which can imply a change in the quantities or the delivery date, and the number of rejected orders due to forecast errors, which refers to the orders that could not be accepted due to forecast errors and could not be compensated by the safety stock levels, were considered. In the baseline scenario, the changed orders from January to July 2022 were 298 and the Rejected orders were 294. Assuming that these numbers are proportional to the “Demand planner input” forecast error level (MAPE). In the case the monthly STL+ETS forecast model is implemented, but not the seasonal safety stock management, the number of changed orders and the number of rejected orders will be reduced by 58%.

Concerning the improvement of the management of the safety stock levels, as indicated in section 5.4, the safety stock levels can be reduced in general by 30% during the demand off peak periods and for specific RFS products, the safety stock levels can be reduce by 62% during their specific demand off peak periods.

5.6. Delivery Stage Conclusions

In the delivery stage, the solutions to achieve the technical requirement have been implemented, the right forecast time aggregation framework was determined, the guidelines for connecting RStudio to SAP HANA and for integrating the Demand shift tracking procedure into the demand planning process were given, and the impact of the developed solutions was estimated. In this way, the main conclusions of the Delivery stage were first, the train dataset testing played a key role in the determination of the right time aggregation level, as it showed the advantages and shortcomings of developing the STL+ETS forecast model at different time aggregation levels. Second, the integration between SAP HANA and RStudio is a relatively simple process that helps to expand considerably the number of statistical tools available for Cargill or any other organization that relies on SAP HANA solutions for the Enterprise Resource Planning processes. Third, the Demand Shift Tracking procedure was very useful to reduce considerably demand data fragmentation. Nevertheless, its successful implementation and maintenance in the future will be the responsibility of the stakeholders involved.

6. Conclusions and Recommendations

In this section, the lessons learned from the identified design goals, the technical requirements, and the topics investigated throughout the elaboration of the thesis project will be presented. The conclusions will focus on findings and insights obtained from the results and analyses in the different stages. While the recommendations will provide information about improvement opportunities and advice for future research.

6.1. Conclusions

As explained in the **Discovery stage**, Cargill GEOS uses the Make-to-Forecast (MTF) production strategy, which has shown to be a very robust and flexible production strategy for demand management. Especially when the customer demand is uncertain and the notice periods are relatively short. In this case study, a lack of alignment between the demand forecast and the safety stock levels, the main components of the MTF production strategy, was found. The method for the demand forecast was the moving average. This is one of the most basic forecasting approaches, as it only can estimate the time series level. It is presumed that this was the reason why the demand forecast and the safety stocks were not managed coordinately. Because the safety stock was managed closer to a make-to-stock strategy than a make-to-forecast production strategy.

To make the most of the MTF, it is key to understand that the forecast and the safety stock levels must be managed coordinately. This is because the forecast guides the production planning and the safety stock compensates for forecast errors and production setbacks. In that way, it is important to have a useful forecast for the demand planning process and the insights of the demand forecast and data analysis must be considered for the management of the safety stock levels.

Considering that Cargill GEOS plans its production based on the forecast results. Their data management culture shows room for improvement. As it was reported, when two years ago due to the migration to TC2, the current SAP IBP platform for data management, occurred, all the previous RFS demand information was lost and no intention to recover this data was registered.

In the **Develop Stage**, the demand shift tracking procedure was developed and it has shown to be an intuitive and logical way to identify the demand transfers between the Retail Food Services products. The main advantage of this procedure is that it allows identifying the demand transfers objectively by considering the demand characteristics, patterns, and the phasing in and out periods of the products. These identified demand transfers need to be verified by sales assistants, who are aware of these demand transfers but are not carrying out a good register of them.

The results of the demand shift tracking procedure were accurate, especially in the case of the regular products. Where all the identified demand transfers were successfully confirmed by the sales department. In the case of the seasonal only products, these had a more scattered and discontinuous demand which hindered the identification of possible successors and predecessors. Fortunately, as the seasonal only products are produced following a make-to-order production strategy they don’t need to rely on the demand forecast or the demand shift tracking procedure.

In this case study, the STL+ETS model, which is a reliable forecast model was selected. This allowed increasing considerably the forecast accuracy. It is expected that when this model is implemented in the demand planning process the safety stock levels could be decreased, as they would not require to compensate for the forecast's lack of accuracy. Nevertheless, even without the insights from the STL+ETS forecast model, the baseline management of the safety stock levels was simplistic, as it assumed a constant level all year round. Even though Cargill GEOS was aware of the RFS demand seasonality.

The use of the forecast aggregation framework not only allowed to establish a structured approach to determine a suitable demand aggregation level. But it also allowed to include in the early analysis the identified seasonal patterns and how their prevalence was affected as the aggregation level was lowered.

In the **Delivery stage**, the decrease in the prevalence of the seasonal patterns and the increment of the error level as the time aggregation level was lowered, due to the demand displacement from year to year, were indeed important factors to decide the right time aggregation level. Nevertheless, the data available also played an important role. Not only determining the 3-week level as the right time aggregation level according to the technical requirements. But the data availability was also a key factor that tipped the balance towards the selection of the STL+ETS model. As this was the only one of the considered models that could successfully produce a useful demand forecast with the data available.

Based on the insights from the STL+ETS model, which has shown the seasonal behavior of the RFS demand. The fixed safety stock levels can be changed from a fixed level to a quarterly variable safety stock management. This has not only allowed achieving more efficient management of the safety stock, but also a better use of the storage capacity, which can be assigned to other products providing the supply chain with more flexibility. In this way, the safety stocks can become a real support to compensate for forecast errors and demand variability and not being managed blindly on a flat constant level all year round.

To measure the direct impact of the developed solutions on the On Time In Full (OTIF) service level indicator was not possible. Nevertheless, the impact on the service levels is clear considering that half of the production planning correction requests are due to forecast errors, and that from the 3195 registered orders for Global Retailer, the forecast errors are responsible of at least 18% of the orders not delivered On Time and In Full , 298 changed orders and 294 rejected orders.

6.2. Recommendations

In this thesis project, a first step was given to improve the management of the safety stocks, within the framework of the Make to Forecast production strategy. The proposed management of the safety stock levels was based on the observed seasonal patterns in the demand datasets. Which is indeed an improvement from the baseline scenario. Nevertheless, there is still room to improve the alignment between the forecast and the management of the safety stock levels. In this thesis project, improving the management of the safety stock levels was a secondary objective. But based on the forecast performance and the demand variability, the alignment between the forecast and the safety stock levels can be further improved.

Regarding the data management, first ,during the initial data analysis, it was found that Cargill GEOS uses delivery data instead of demand data. This caused a small time lag and a 5% difference between the delivery and the demand data. Second, many product datasets presented different characteristics. Some of them showed intermittent demand, others did not have demand in the last 6 months. Only after gathering more information and through interviews making the right questions, it was found that these features in the datasets were due to the presence of seasonal only products and due to the replacement relationships in the RFS. Still, in Cargill GEOS's SAP IBP data management system exist many fields where information about the different products can be added. Nevertheless, these fields are not updated or are blank. For this reason, it is recommended that more resources are invested in the SAP IBP data management platform. Much more considering that Cargill GEOS manages its production planning process based on a forecast, and the forecast quality depends completely on the available data.

Cargill RFS demand showed marked seasonal patterns, nevertheless due to the data availability and the data fragmentation, even the most used statistical forecasting models were not able to estimate the seasonal patterns to produce a useful forecast. Fortunately, STL-based models only require two years of observations to estimate the time series seasonal patterns, as it was the case for the STL+ETS model. Besides these capacities of the STL+ETS model, the literature has shown that this model is also able to outperform the ARIMA model and the ETS exponential smoothing model. For this reason, it is recommended, that even when Cargill GEOS owns enough observations to obtain a useful forecast from the ARIMA or the ETS exponential smoothing, they should be using the STL+ETS model. Unless testing results prove contrary.

Currently, the selected time aggregation level for the demand forecast is of 3 weeks. But as more demand observations might become available, it will be possible to reduce the aggregation level even further. Before decreasing the aggregation level to 2 weeks. It is recommended to collect at least 4 years of observations, so the model can capture properly the expected demand levels in different periods of the year. And to achieve a weekly forecast, at least 5 years of demand observations would be required. Even in that case, it is still not certain that the forecast accuracy is going to be high enough to use the forecast in the production planning. Because the weekly demand is considerably affected by the weekly demand variations, the demand displacements from year to year, and the recurring presence of demand outliers.

To improve the manual adjustments of the statistical forecast, it is recommended to keep a record of the relevant events that occur when the demand outliers are generated. In this way, it is possible to gain insights into the causal relationships that affect the RFS demand. During the application of the Demand shift tracking, it was found that there existed a strong influence of the seasonal-only products on the demand for the regular products. This was because in the periods when the seasonal products were demanded, there was a considerable decrease in the demand levels of the regular products. In some cases, the replacement was total. Due to this, it is recommended that Cargill is aware of these relationships to improve the quality of manual adjustments in the demand forecast.

In this research, it has been proposed to manage the safety stock levels quarterly. But by managing the safety stock levels at lower aggregation levels, for example bimonthly or in 8-week periods. The management of the safety stock levels can become even more efficient and reduce even more the safety stock levels during the off-peak demand periods of the different products.

6.3. Discussion

In this thesis project, many solutions were developed specifically to achieve the design goals of Cargill GEOS. Nevertheless, this does not mean that their applicability is limited for Cargill GEOS. This is because the supply chain management processes applied in Cargill GEOS are not exclusive of Cargill, but they are common good practices applied in many manufacturing companies, as it was found in the literature.

In this way, any manufacturing company that produces products with a minimum level of customization can serve well from the findings of this thesis project. For example, it has been acknowledged that the Make-To-Forecast (MTF) has shown to be a very robust and flexible production strategy to enable the timely delivery of customer orders on weekly basis, especially when the notice times are relatively short and the demanded quantities have a medium to high variability.

In the case of the developed demand shift tracking procedure developed to improve the data management to obtain enough observations to forecast the active products. This solution was developed specifically considering the demand seasonal patterns and the fact that Cargill GEOS provides essential products that cannot be easily replaced. Without these two minimum conditions, the applicability of this procedure to other organizations is limited.

In the case of the considered forecasting models, the STL+ETS model has shown superior performance in comparison with the ARIMA model and the ETS exponential smoothing model. Nevertheless, this performance is conditioned to the seasonality and the availability of the demand data to be forecasted. This is because the STL+ETS model is a model dependent on the seasonal patterns existing in the analyzed demand data. In the cases where the seasonality of the observations is limited, the ARIMA model could provide a better forecast. This is because even If the ARIMA model can estimate the seasonal patterns, its main capacities lie in the estimation of atemporal patterns through the use of the Auto-Correlation Function (ACF) to identify statistically significant correlations between the recent and past observations.

About the integration between SAP HANA and RStudio through the Java DataBase Connectivity (JDBC) application programming interface. This solution is not only limited to the case of Cargill GEOS. This is because SAP HANA is one of the most used data management platforms for Enterprise Resource Planning. While RStudio is a very useful Integrated Development Environment for the statistical analysis of time series with an active scientific community that is constantly developing new solutions to increase the range of tools provided within it. For these reasons, the relatively easy integration between RStudio and SAP HANA only provides benefits and it is a recommended solution for organizations that want to level up their forecasting capabilities.

In the case of safety stock management, the theoretical foundation to estimate the safety stock levels based on the demand variability and the production lead time is a very solid approach for a make-to-stock production strategy. In this thesis project, the improvement of the safety stock management was a secondary objective. For that reason, the corresponding technical requirement was defined based on the insights of the forecast and data analysis. As stated in the recommendations, there is further room for the improvement of the safety stock levels. For these reasons, the solution of the safety stocks was the alignment with the demand seasonal patterns, it is not the same as the alignment with the forecast itself, but it is a considerable improvement from the baseline conditions. Therefore, this simple yet effective solution for the management of the safety stocks, based on the demand seasonal patterns, can be easily applied to any organization that faces seasonality in their demand and wants to improve the management of their stocks.

6.4. Reflection

For the development of this thesis project, three different forecasting models were considered. Nevertheless, at the beginning of this thesis project, the ARIMA model was the only model considered. This was because, during the initial literature review, the ARIMA model was one of the most common results for forecasting applications in the last 10 years. In the literature, the ARIMA model's capacities the model were well-referred because the ARIMA model can produce a forecast considering the autocorrelation and partial autocorrelation, and additionally, it can also estimate the seasonal patterns to include them in the forecast. For these reasons, the ARIMA model was considered the best solution for the development of a useful forecast.

As the RFS demand data was full of gaps, time series, available in RStudio, were used to experiment with the ARIMA model. Most of these time series were seasonal ones with more than 10 years of observations. In these cases, the ARIMA model had a very good performance, being able to generate a forecast that matched the previously observed patterns. Nevertheless, when the ARIMA model was tested with the most complete RFS datasets at the weekly level, the forecast generated was a constant level one. This result was a considerable drawback for the attainment of the desired weekly level forecast for Cargill GEOS. Despite this, the ARIMA model was tested at a monthly level, because during the initial analysis it was observed that the datasets graphs in excel showed seasonality at the monthly level. At the monthly level, as was seen in the forecast model testing section, the forecast obtained was a moving average. At this point, 4 months have already passed by and the forecast model was not working. These first 3 months were invested in the literature review, defining the thesis project scope, understanding the supply chain productive processes, learning about the demand planning process, and experimenting with Rstudio and the ARIMA model. Still, the ARIMA model was not producing the expected results. As this thesis project was scheduled to be developed during an internship at Cargill GEOS, only 2 months were left for the conclusion of the project according to the original schedule.

To approach the pressing situation, the literature review was quickly expanded to consider other forecasting models. The second most recommended model was the ETS exponential smoothing model, which was described as a forecast model specialized in seasonal patterns and was also available in RStudio. About 4 weeks were invested to understand the concepts behind the ARIMA model and the RStudio. Concepts of the time series, forecasting, statistical correlations, and the autocorrelogram for the autocorrelation function in the ARIMA model. Fortunately, some of these concepts were also applicable to the ETS exponential smoothing model, which allowed a much shorter learning time. However, the results were not even better than the ones obtained for the ARIMA model. In that situation, different tutorials were being reviewed for a better understanding of the models, in case something was being overlooked. Even a manual version of the ARIMA model was considered, but no better performance was obtained. It was during this search of forecasting approaches available at RStudio that the STL+ETS model was discovered.

When the STL+ETS model was tested with the time series available in RStudio, the STL+ETS model performance was comparable to the ARIMA or the ETS model. Nevertheless, when it was tested in the RFS datasets at a monthly level, the model was able to produce a representative forecast of the observed demand. After this, the model was tested with different datasets and it was capable to produce a useful forecast even for the seasonal only products that had an intermittent demand. For these reasons, the STL+ETS model was selected as the forecast model for the RFS demand forecasting. Nevertheless, there was still the problem of the demand datasets that presented few observations. According to the literature and as it was tested, the STL+ETS model could not produce a forecast for datasets with less than 24 monthly observations. To avoid wasting time

Nevertheless, there was a register available that allowed to combine some of the datasets, as some products had replaced other products over time. When the demand for the products was analyzed at a monthly level and per country to find some other possible patterns in the datasets. A pair of datasets, that were not included in the register, showed similar graphs to the replaced products. These similarities were in the demand levels and coincidence of the phasing in and phasing out periods. This case was reported to the SCDA coordinator and to the sales assistant, who confirmed the replacement of these products. Due to this event, the following 3 weeks were invested to develop the Demand Shift Tracking procedure, the results were presented to the sales assistant who confirmed all of them except for two cases of seasonal-only products.

At this point, the data limitation issue was already acknowledged, which was a considerable obstacle to overcome for achieving the weekly forecast level desired by Cargill. For this reason, the feasibility of obtaining a weekly forecast with the data available was analyzed, and the data aggregation framework to determine the right time aggregation level was developed. In this way, the monthly forecast was developed for the 34 consolidated datasets that had a minimum of 24 observations.

To test the STL+ETS forecast model accuracy for the RFS, the train dataset testing procedure in the extended STL+ETS model was developed. In this way, the last 3 months were used to test the forecast accuracy with real data. To improve the forecast accuracy, which was based on the estimation of the seasonal patterns, the data was analyzed for seasonality and the impact of outliers on the identified seasonal patterns by the forecast model. In this way, a manual replacement of presumed outliers was intended on the demand observations on a couple of datasets, this considerably increased the seasonal patterns and allowed to improve the forecast accuracy from an approximated forecasted to an almost perfect matching forecast with the demand observations. Nevertheless, to be applying this outlier replacement on a manual basis took too much time and the identification of outliers based on their visual clarity was not an efficient or objective way. For this reason, being aware of the constant innovations in RStudio, the next task was to find an automatic algorithm that allowed the identification and replacement of outliers in the time series based on the seasonal patterns. It was in this way that the tsclean function for outlier identification and replacement was found. Designed by the same author of the automatic forecasting algorithms in RStudio Rob Hyndman, it was very promising. Then, the theoretical foundation and logic behind this algorithm were reviewed to check its suitability with the intended function. The tsclean() function results were verified based on the seasonal patterns, which were congruent because the function was based on the interquartile definition and the seasonal trend Loess decomposition. Nevertheless, with only two years and half of the observations, it was not very certain which observations were outliers and which were not. For this reason, each outlier proposed by the tsclean function was reviewed case by case. In this way, the forecast accuracy was considerably increased, and the automatic outlier replacement was based on statistical criteria.

As stated, during the discovery stage of the thesis project, the lack of alignment between the safety stock levels and the demand forecast was identified. This was because of the lack of accuracy of the statistical demand forecast, which generated some skepticism in the stakeholders responsible for the safety stock levels management. The baseline management of the safety stock levels was based on the demand variability and the production lead time variability. The structure of the original formula had many factors involved, for that reason as was shown in 2.5. it was simplified to clarify its functioning. In that way became clear that the formula depended mainly on the service levels and the demand variability. During the seasonal data analysis for the forecast, it was found that there were periods of the year when the demand was more stable and lower in quantities. For this reason, to improve the alignment between the developed demand forecast and the safety stock levels, the seasonality and the demand variability in different periods were considered. In that way, the variable safety stock level management was achieved.

These results were presented during the midterm meeting and were well received by my thesis committee. In this way, the beginning of the end of this thesis project finally began.

Many obstacles and setbacks were found during the development of this thesis project. Especially the fact that three different forecasting models had to be tested to obtain a useful forecast due to the data availability limitations. The second problem was the fragmentation of the demand due to the replacement of the products. Providing a solution for this situation added value to this thesis project. But at the same time, it consumed the already scarce time left. Essay writing was not one of my strengths, but it was a skill that I developed during these two years of my master's. For that reason, I would like to thank my first supervisor Marcel for his patience and helpful comments.

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Appendix A - Sap IBP Statistical Forecast Performance

This appendix has been removed due to confidentiality issues.

Appendix B – Testing results of the Monthly Forecast models

A. ARIMA model testing results

A.1 Dataset 18

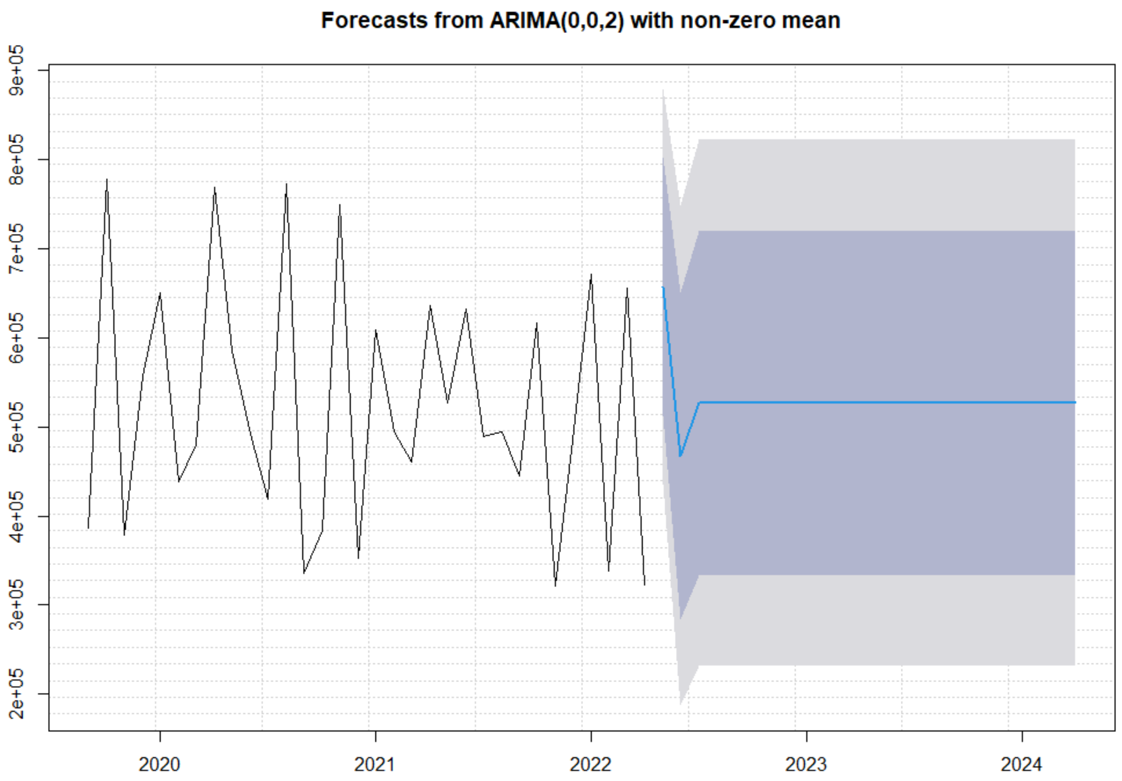

Figure 29 ARIMA model forecast testing results for consolidated dataset 18

A.2 Dataset 13

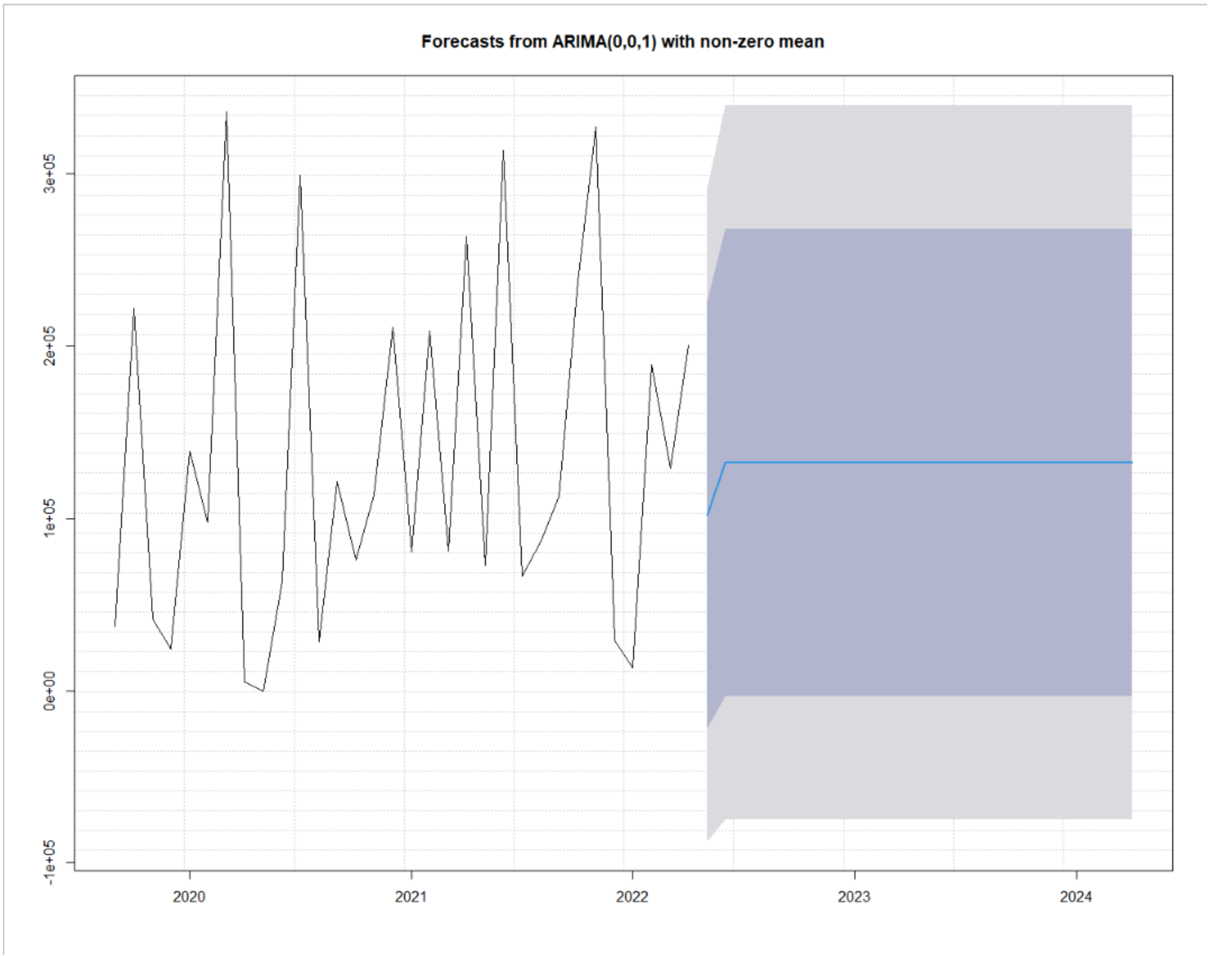

Figure 30 ARIMA model forecast testing results for consolidated dataset 13

A.3 Dataset 3

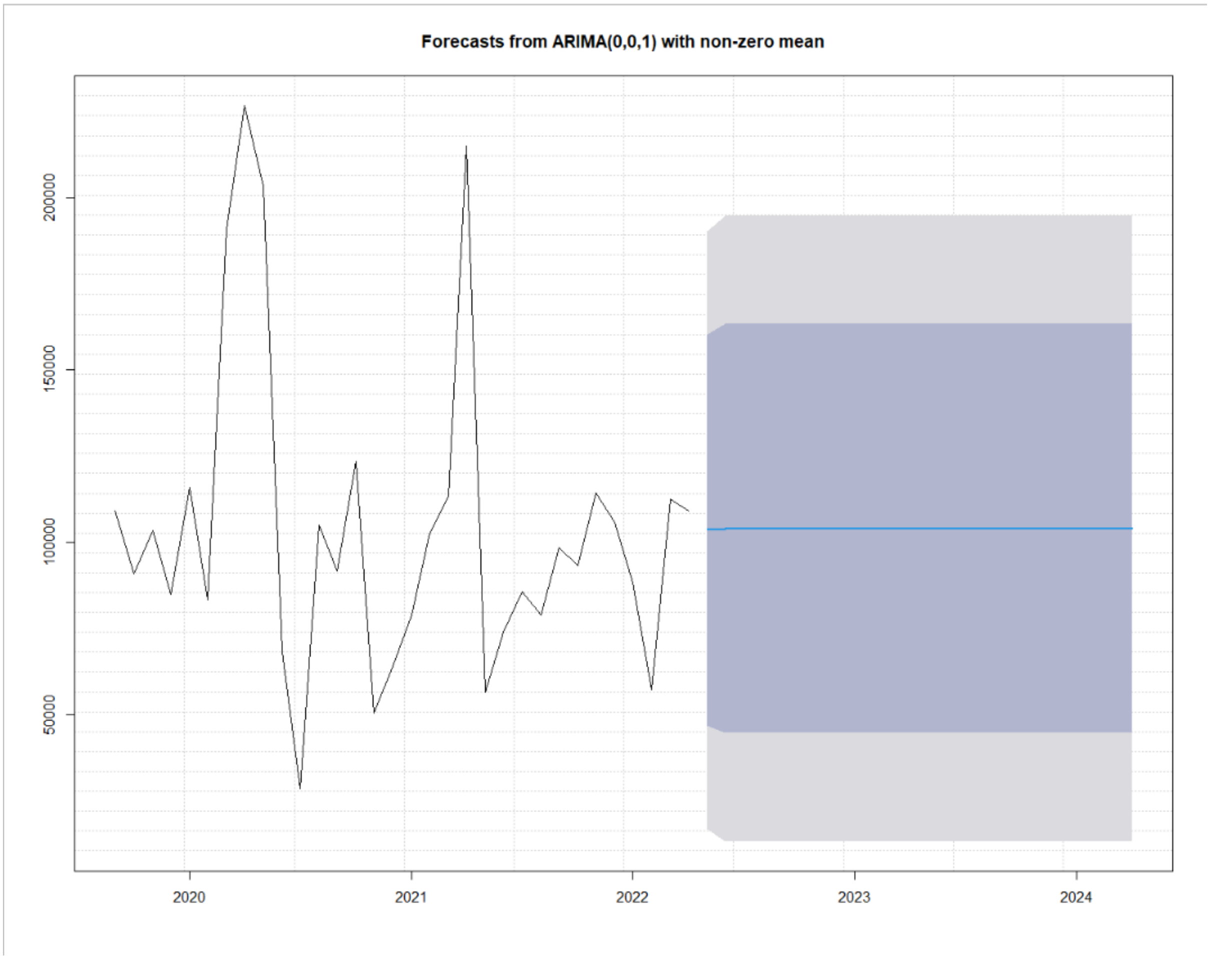

Figure 31 ARIMA model forecast testing results for consolidated dataset 3

B. ETS exponential Smoothing model testing results

B.1 Dataset 18

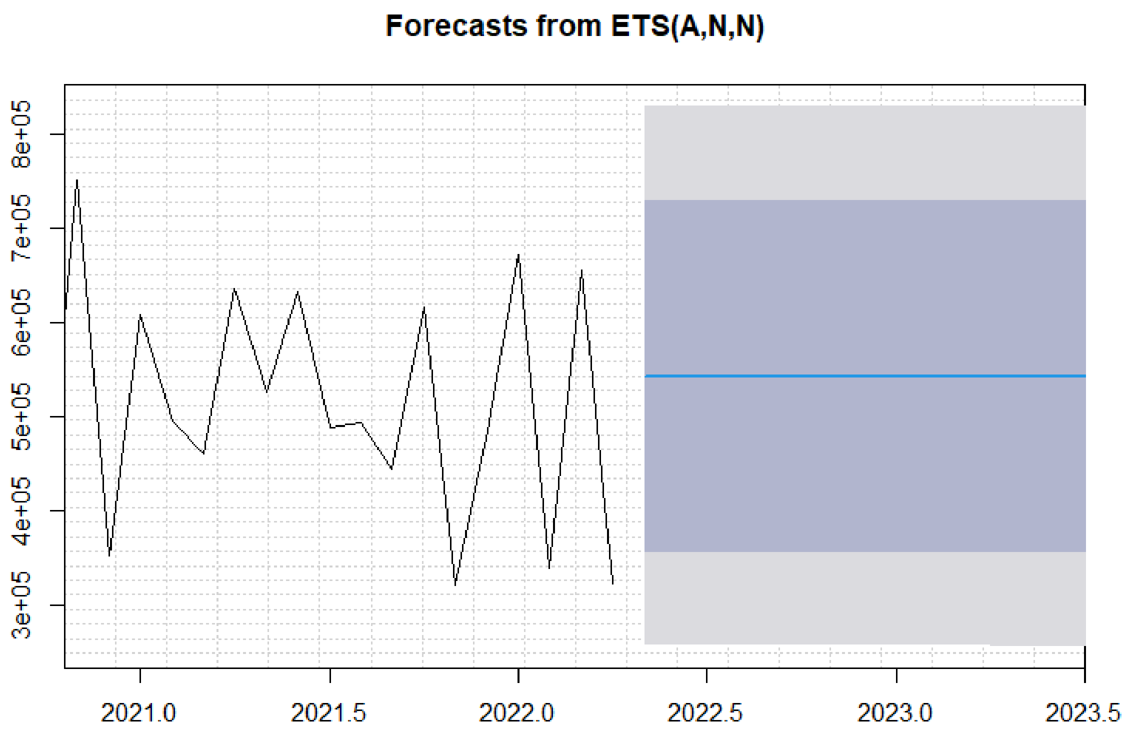

Figure 32 ETS exponential smoothing model forecast testing results for consolidated dataset 18

B.2 Dataset 13

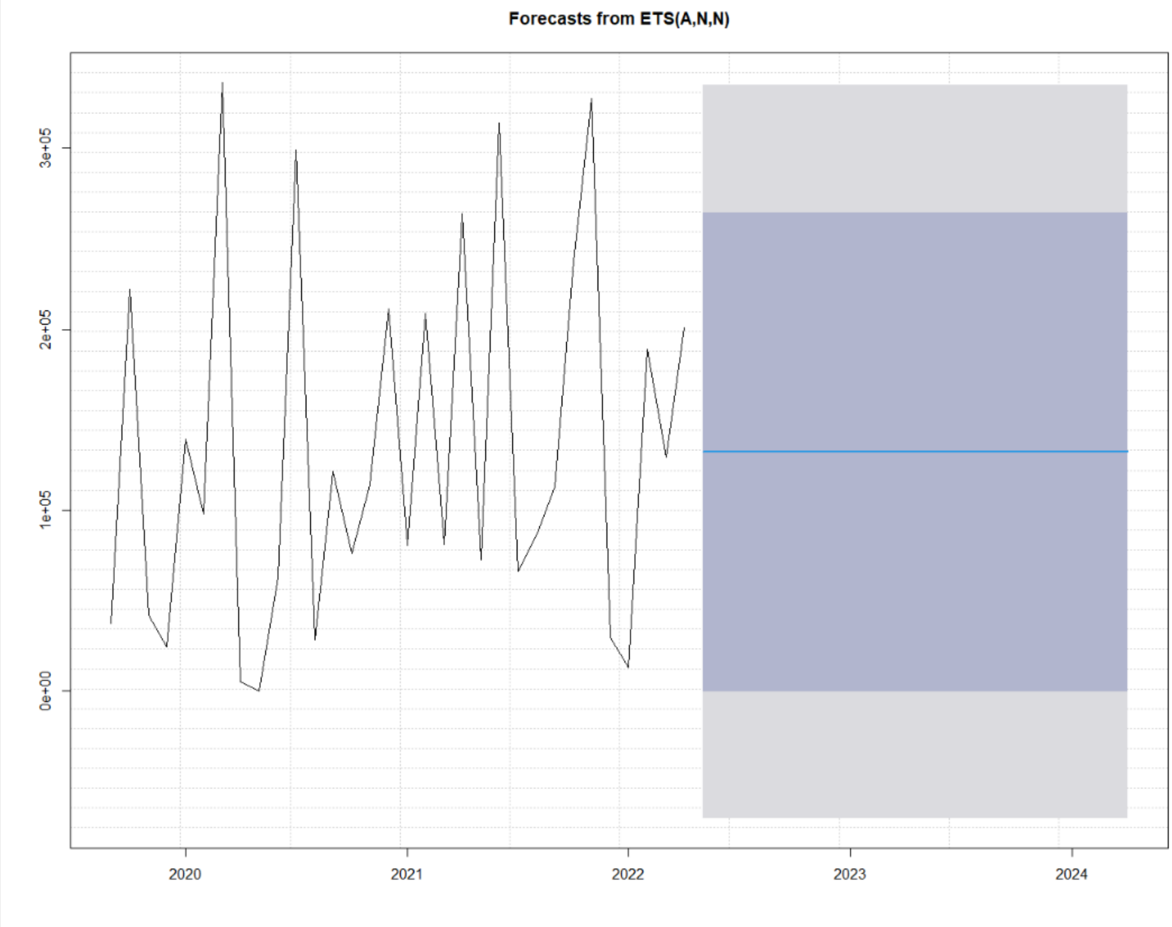

Figure 33 ETS exponential smoothing model forecast testing results for consolidated dataset 13

B.3 Dataset 3

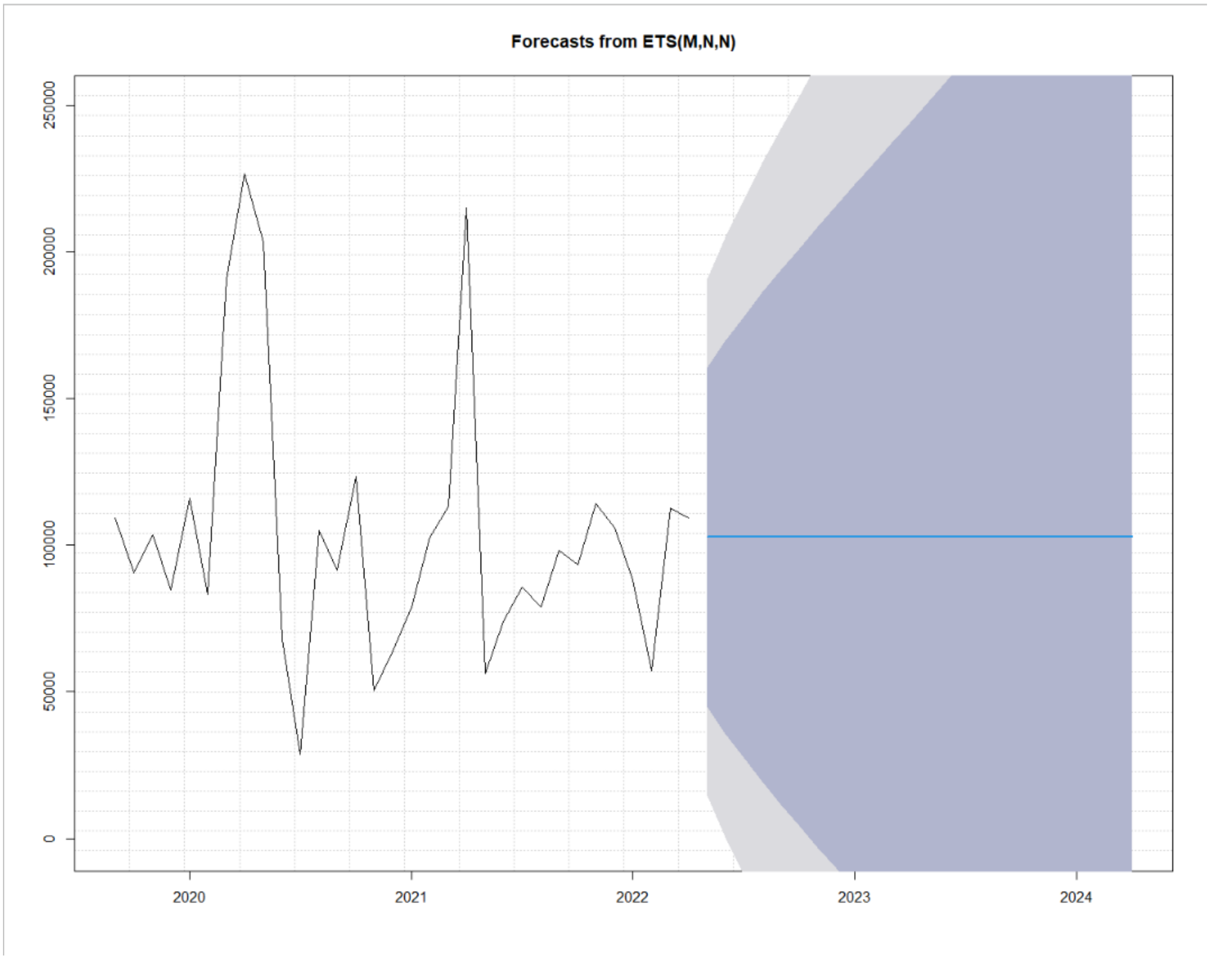

Figure 34 ETS exponential smoothing model forecast testing results for consolidated dataset 3

C. STL+ETS model testing results

C.1 Dataset 18

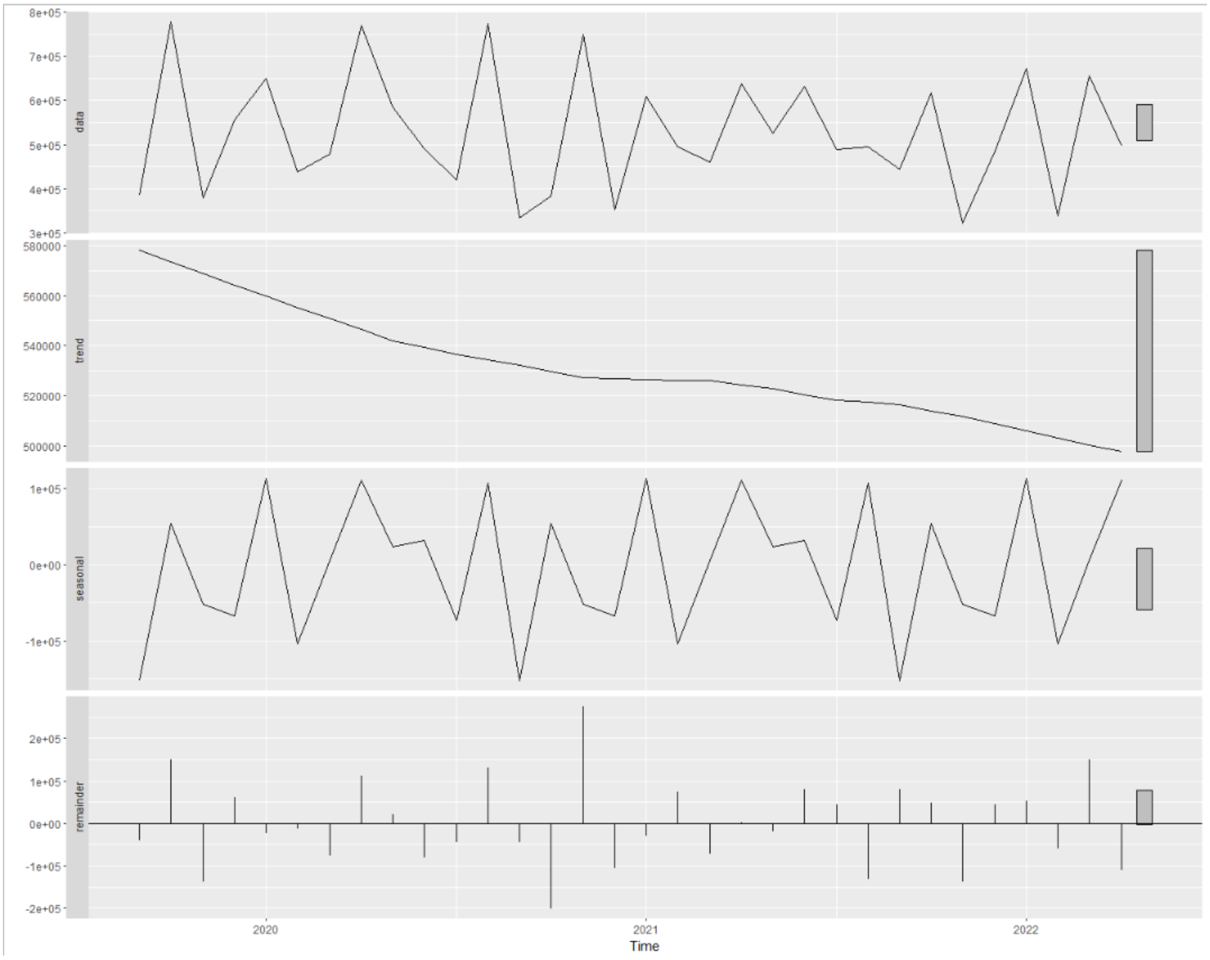

Figure 35 STL Decomposition testing at monthly level for consolidated dataset 18

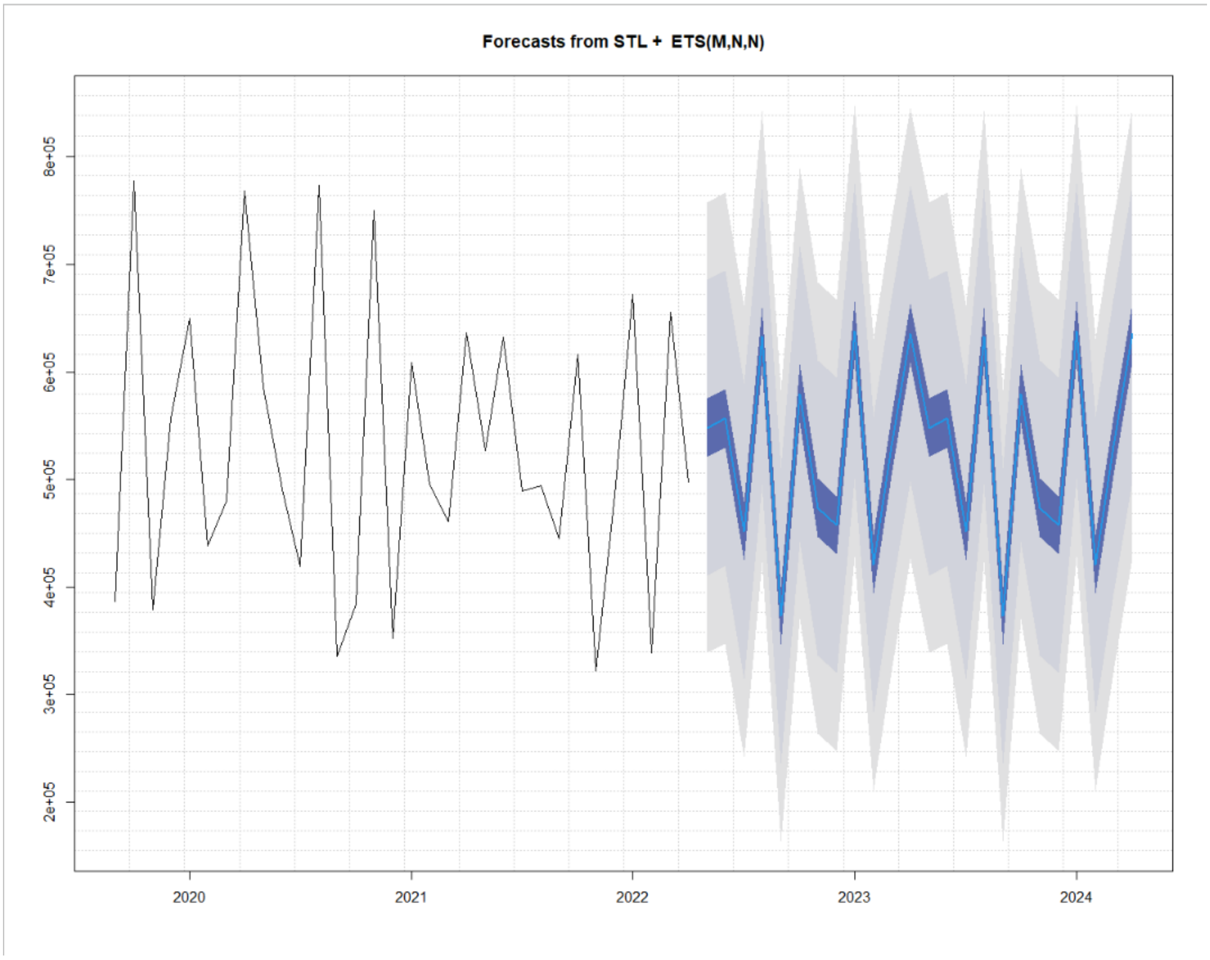

Figure 36 STL+ETS model forecast testing results for consolidated dataset 18

C.2 Dataset 13

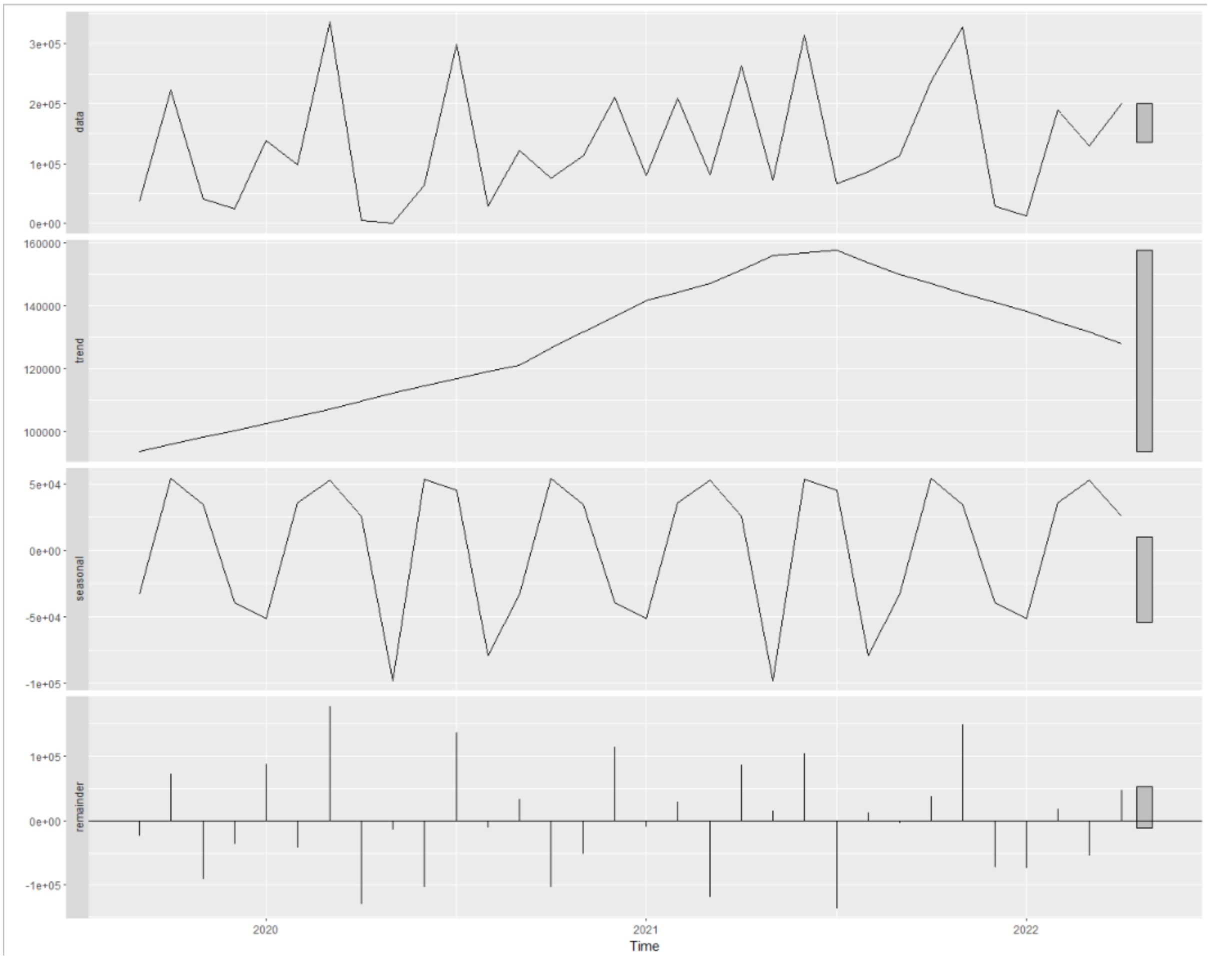

Figure 37 STL Decomposition testing at monthly level for consolidated dataset 13

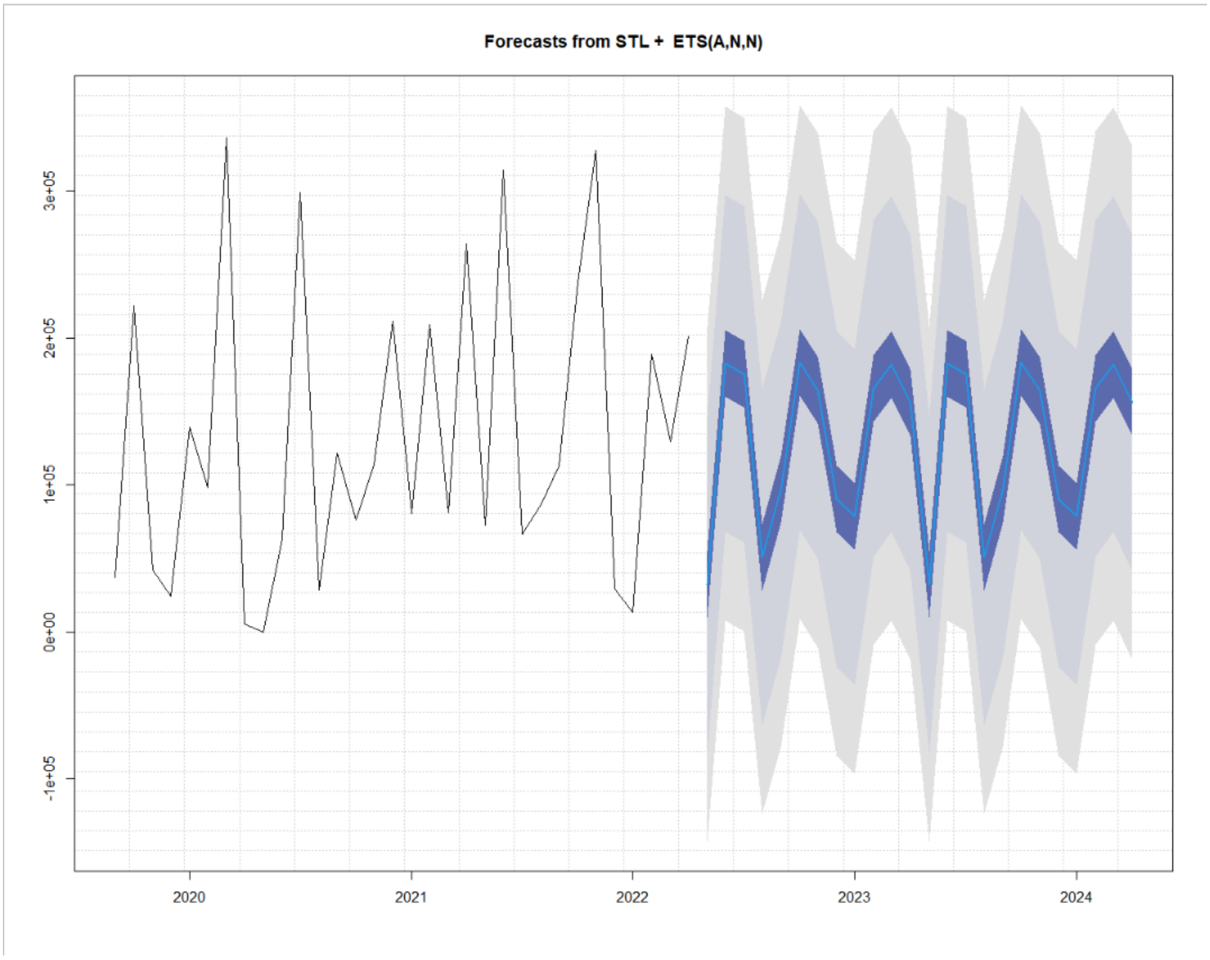

Figure 38 STL+ETS model forecast testing results for consolidated dataset 13

C.3 Dataset 3

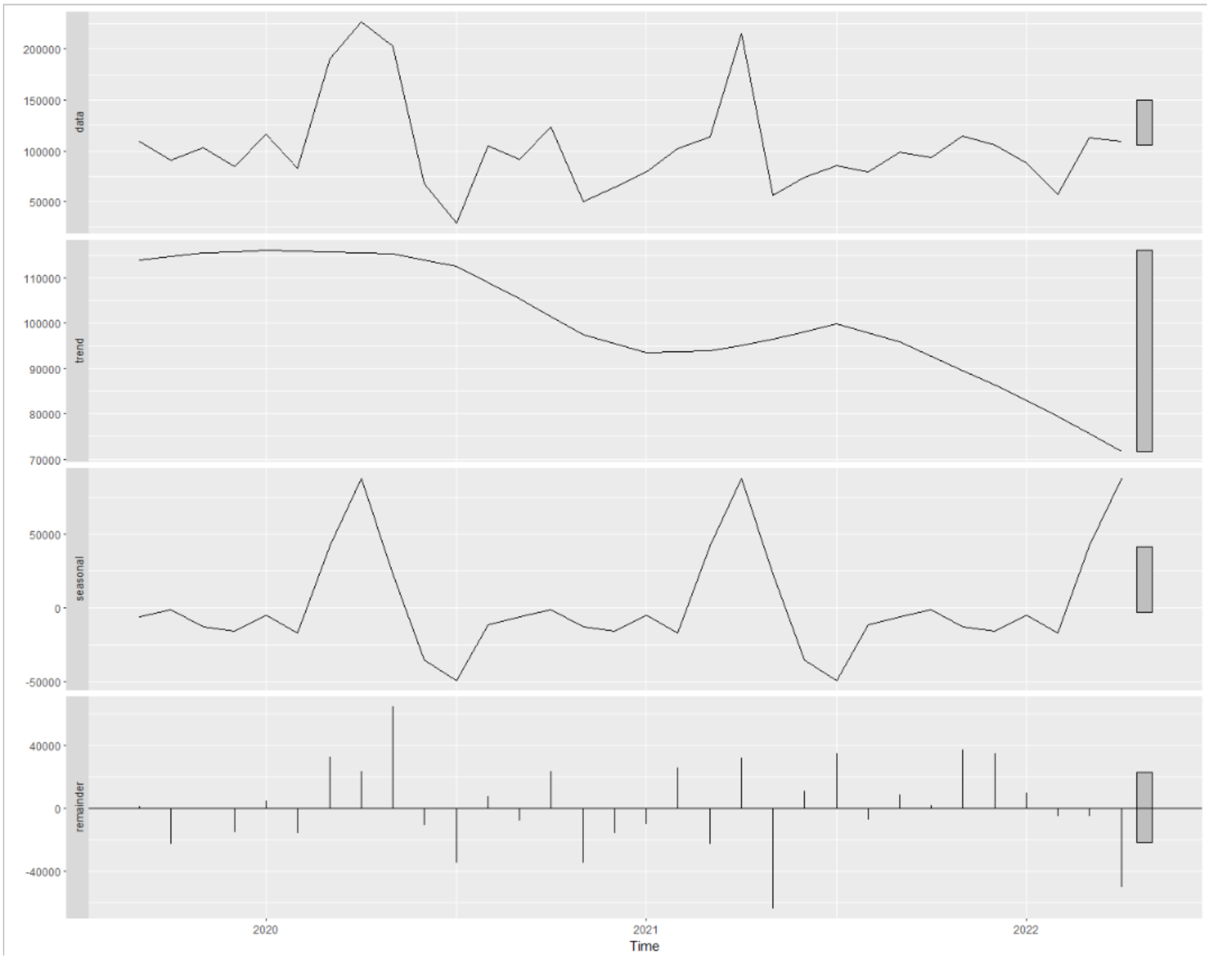

Figure 39 STL Decomposition testing at monthly level for consolidated dataset 3

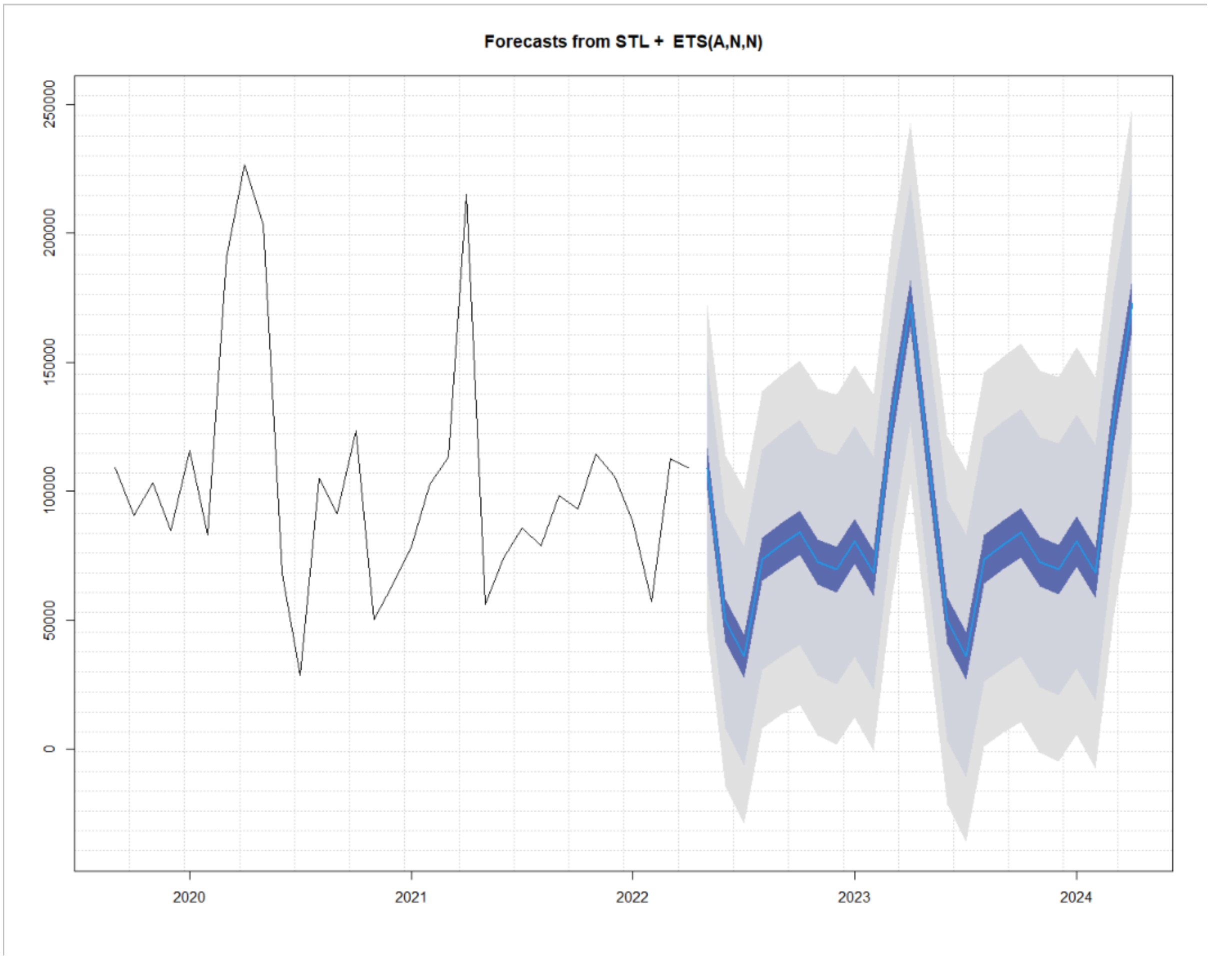

Figure 40 STL+ETS model forecast testing results for consolidated dataset 3

Appendix C - Demand Shift Tracking Procedure

This procedure purpose is to identify the demand shift between the country SKU datasets:

This data management procedure begins the datasets **preliminary analysis**. This analysis is to calculate the available demand observations in the two year period, the Coefficient of Variation, and the existence of the product demand to verify that it is still active. In this way all the datasets information is gathered for a quick analysis.

The second step is to verify **according to the sales assistant list**, which of the products have been recognized to be replaced by another one. The set of replaced and their SKU successor are stated in the list provided by the sales assistant.

As stated in this research, even after the matching of the replaced product datasets listed products to keep track of the demand shift. There are still a lot of products that have a short life time. Due to this, the next is to keep track of this loose demand information to match it to the product corresponding country-SKU dataset.

The demand shift tracking all the analysis will be performed at country level, because the countries represent the markets where the demand of discontinued products should have been replaced. This is because these are essential products, which demand cannot be left unfulfilled.

For purposes of this analysis, we will define demand group as the set of products that have a demand shift relationship. To identify the SKU datasets that belong to the same demand group on each country market, a visual analysis will be used by plotting the demand of the different products for each country. In this way we will look for two main features, products that have a similar demand level and product's demand that suddenly rise up when the suspected previous product's demand decrease suddenly. An additional factor of interest is the seasonality in demand. For example, that these pair of identified products present their demand peaks and valleys on similar periods of the year and on similar quantities. The set of products that are suspected to be part of a demand shift, **must be listed** to keep track of them and be verified during the rest of the demand shift tracking procedure.

The next step is to check their products description. The products description comes after the graphical identification to avoid bias due to the production description. If the graphical analysis has been done well, the product description is similar or identical. But there can be different cases as the following:

a) The first and easiest case is when the product only changes its SKU code, but the production description is the same. Maintaining the same kind of oil, the same volume presentation, 1 to 2l for normal products, and same box and pallet size and type.
b) The second case is when the product changes its pallet size, which can be represented by 40 EA, 50EA or 60EA. But usually the type of oil, volume and box type are still the same.
c) The third case is less common, it is when the product changes the number of bottles per box. This is usually given in the form 15x1l and could change for example to 175x1l.
d) The fourth case can be more difficult to match, this is when the product changes its composition. The usual changes are from a blended oil to a specific type of oil like rapeseed or sunflower or vice versa. By changing from rapeseed to blended. For these cases, it is recommended to put additional emphasis in the following steps.

Another consideration for the demand group identification is that sometimes SKUs of the same demand group can be produced in parallel for a period of time until one takes up all the demand. These cases, as well as the 4th case should be verified with the sales assistant.

In the cases where country customers have too many SKUs, which can hinder the identification of the demand groups. It is recommended to make use of some text filters. This is possible because the products description is almost coded with standardized keywords that describe their features as the type of oil, the bottle size, the number of bottles per box, the pallet size and sometimes the language region.

For the cases where after the product description verification, the results are still inconclusive. Some seasonal statistical analyses can be applied. The software RStudio has functions as the “ggsubseriesplot()". This function allows to plot the observations values along with the monthly average, for frequency equal to 12, or for any defined frequency for the time series. By combining the candidate datasets, the time series seasonality can be visualized as the distance between the observations and the average monthly demand. The smaller the distance, the stronger is the seasonality in the time series.

To conclude, **all of the findings should be verified with the sales assistant**, as they might provide some additional input about the products demand shift and other relationships.

Appendix D - RStudio Code for the Extended STL +ETS Forecast Model Design

---

```
###standard code for data forecast v4
#libraries
library(readxl)
library(forecast)
library(tseries)

##load / Importing excel data
#this can be done with this code, but after the libraries have been
loaded,
#it might be better to do it with the option import dataset
toplot <- read_excel("+Rstudio datasets/toplot.xlsx",
                     +      sheet = "Month")

#Time Series Creation
myts=ts(toplot$delivery,start = c(2019,9),frequency = 12)

myts=ts(toplot
        ,start = c(2019,9),frequency = 12)

#plot

#autoplot(myts)
plot(myts,panel.first = grid(10,40))
myts

############Time series preparation and analysis section
#Remove NA or missing values
```

```
mytsremove=ts(na.remove(myts),start=c(2019,10),frequency = 12)
mytsremove
autoplot(mytsremove)
#myts=mytsremove

#Outlier identification and replacement,

mytsclean=tsclean(myts)
autoplot(myts)+autolayer(mytsclean) #To compare plot of time series

autoplot(myts-mytsclean) #to plot the difference
myts
mytsclean
#myts-mytsclean #to see visualize the difference in values

ggseasonplot(myts) #plots the monthly demand over the years in a same
graph
ggseasonplot(mytsclean)

ggsubseriesplot(myts) #plots the monthly demand average over the years
ggsubseriesplot(mytsclean)


mystlclean=stl(mytsclean,s.window = "periodic") #performs STL
decomposition
mystl=stl(myts,s.window = "periodic")

autoplot(mystl) #plots STL results
autoplot(mystlclean)

#myts=mytsclean

ggtsdisplay(myts) #plots the ACF and PACF in one step, useful for ARIMA

#####plotting code

#autoplot(myts)
#seasonplot(myts,panel.first = grid(12,40))
ggseasonplot(myts)
ggsubseriesplot(myts)

##STL Analysis Plotting
#mystl=stl(myts,s.window = "periodic")
#autoplot(mystl)


###ETS plot for trend change analysis
#ets(myts)
#autoplot(ets(myts))
#ets(train)
#autoplot(ets(train))


#Allows to compare STL seasonal component against the real dataset
autoplot(seasadj(mystl),series="Seas. adj.") +
autolayer(myts,series="Data")
```

```
######STL +ETS Forecast
mystl=stl(myts,s.window = 'periodic')
autoplot(mystl)

#Forecast function automatically selects ETS model to load the STL data
mystlfcst=forecast(mystl,level = c(20,80,95)) #estimate forecast with
confidence levels
plot(mystlfcst,panel.first = grid(20,40)) #plot forecast
summary(mystlfcst) #provides the model parameters along with forecast
results

##To avoid plotting negative values
plot(mystlfcst, ylim = c(-1000,400000),panel.first = grid(20,40))


############################################################
############################################################


####Forecast on train and test datasets

#Spliting data into Train and Test set
train=ts(myts[1:29],start = c(2019,9),frequency = 12)

#train=ts(myts[1:25],start = c(2020,1),frequency = 12) #option for
shorter sets
#To write the values of the train dataset:
train
#class(train) #to verify the object class in RStudio for

########Plots to compare Train vs Full dataset

#seasonal comparison, Assess the monthly average values
ggsubseriesplot(myts)
ggsubseriesplot(train)


#Train STL
mytrainstl=stl(train,s.window = "periodic")

autoplot(mystl)
autoplot(mytrainstl)

#mystl
#mytrainstl
###Train dataset Forecast

mytrainstlfcst=forecast(mytrainstl,level=c(60,80, 95),h=4)
#plot(mytrainstlfcst,panel.first = grid(20,40))

#plotting train forecast against obs from february to April
autoplot(mytrainstlfcst)+autolayer(myts)

summary(mytrainstlfcst)
myts
```

Appendix E - Forecast Results for Monthly, 3-week and Weekly time aggregation levels

A. Dataset 5

A.1 Monthly Fcast

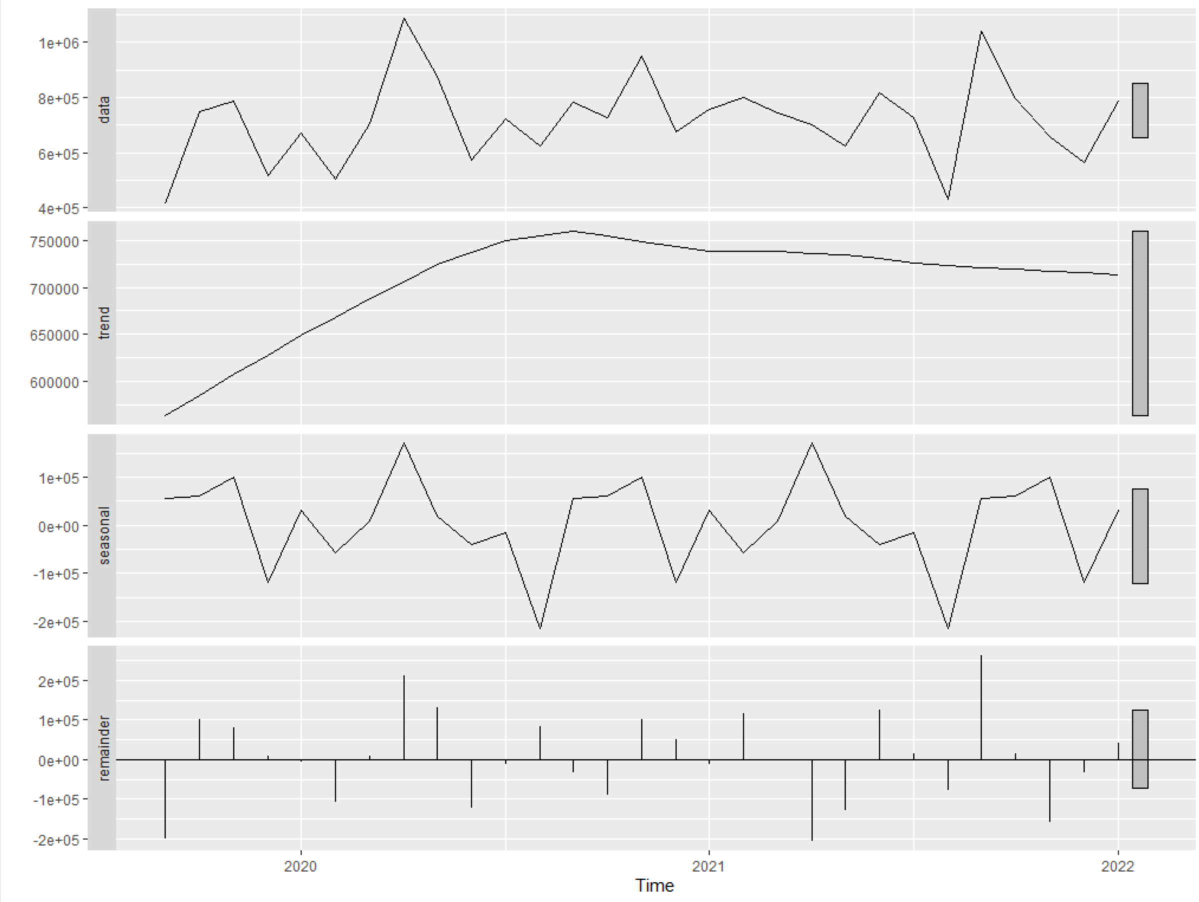

Figure 41 STL Decomposition at monthly level for consolidated dataset 5

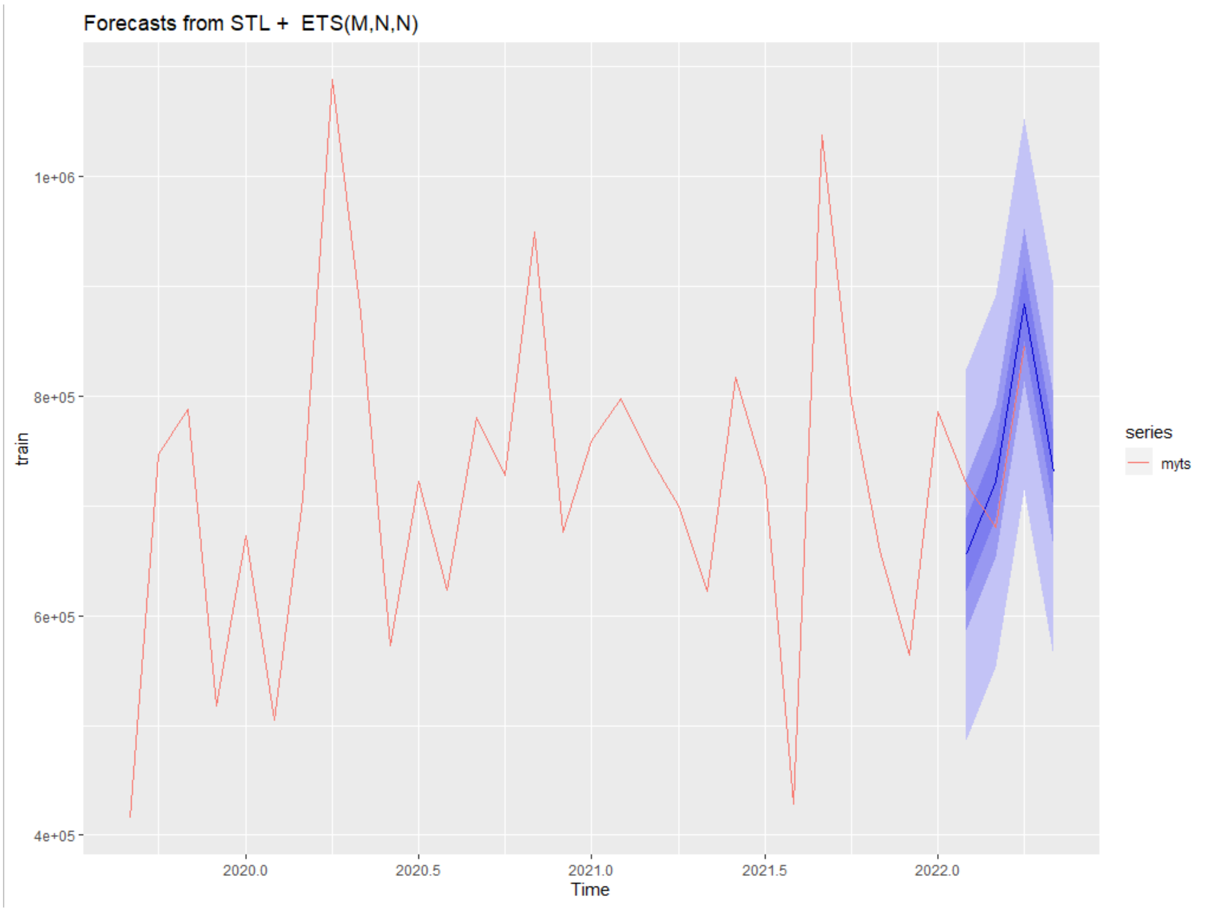

Figure 42 STL+ETS monthly Forecast for consolidated dataset 5

A.2 3-week Fcast

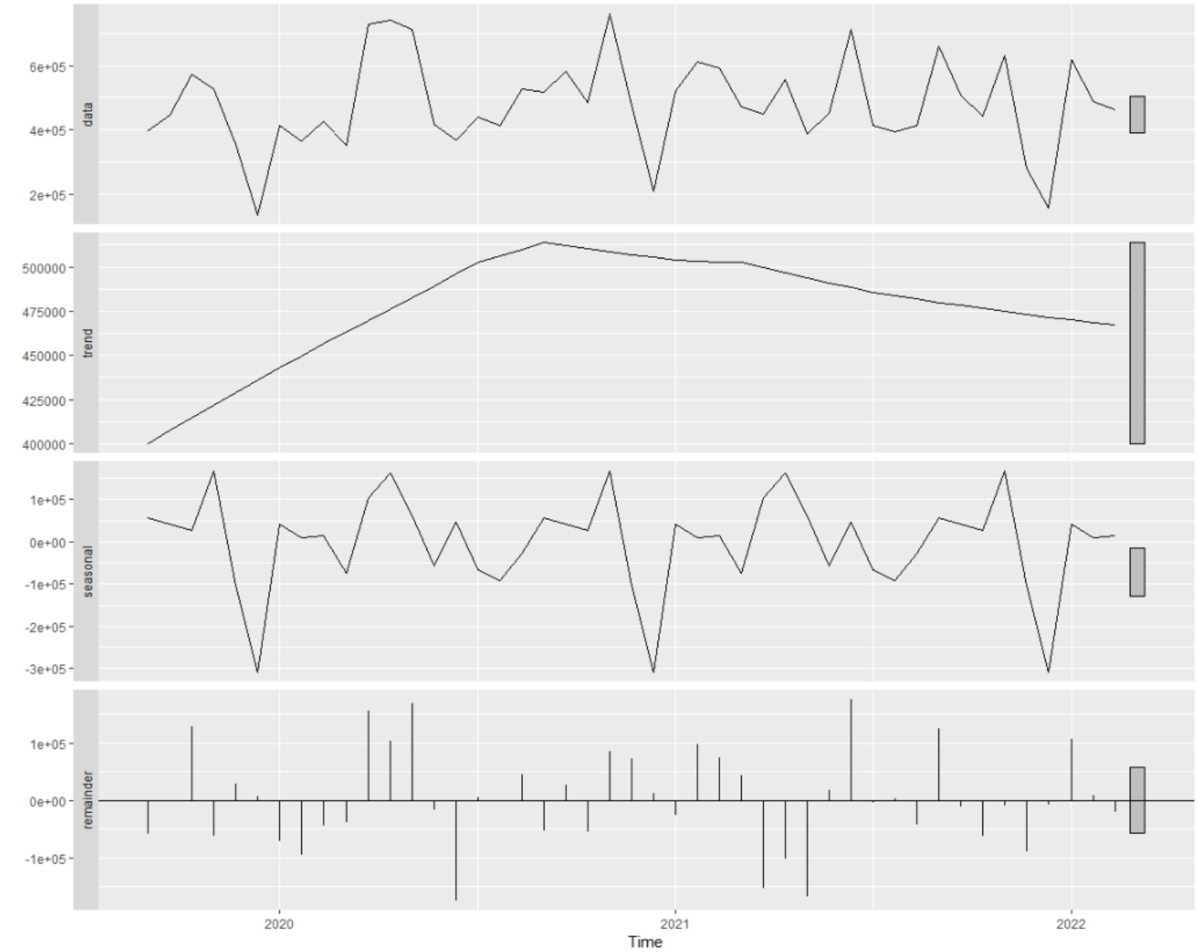

Figure 43 STL Decomposition at 3-week level for consolidated dataset 5

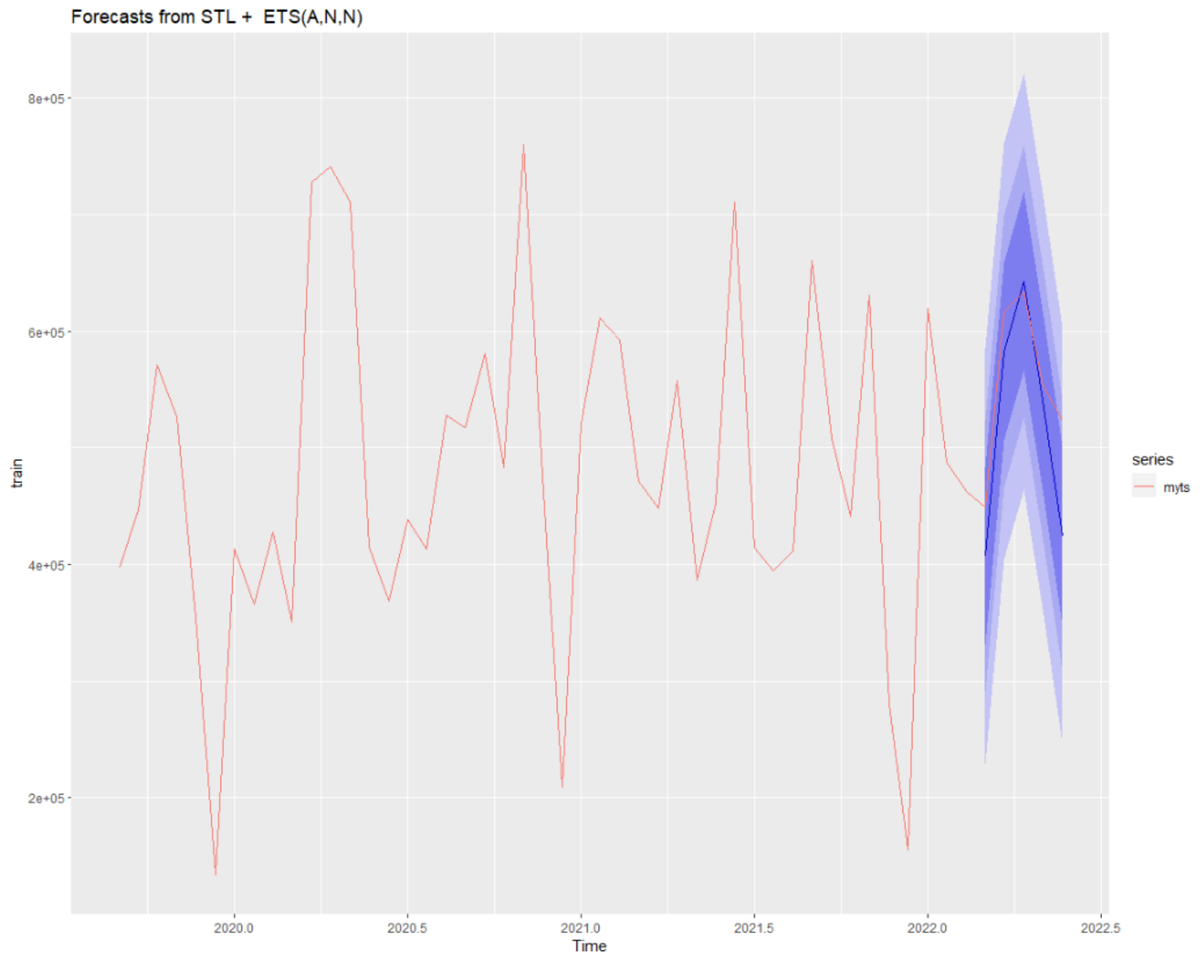

Figure 44 STL+ETS 3-weekly Forecast for consolidated dataset 5

A.3 Weekly forecast

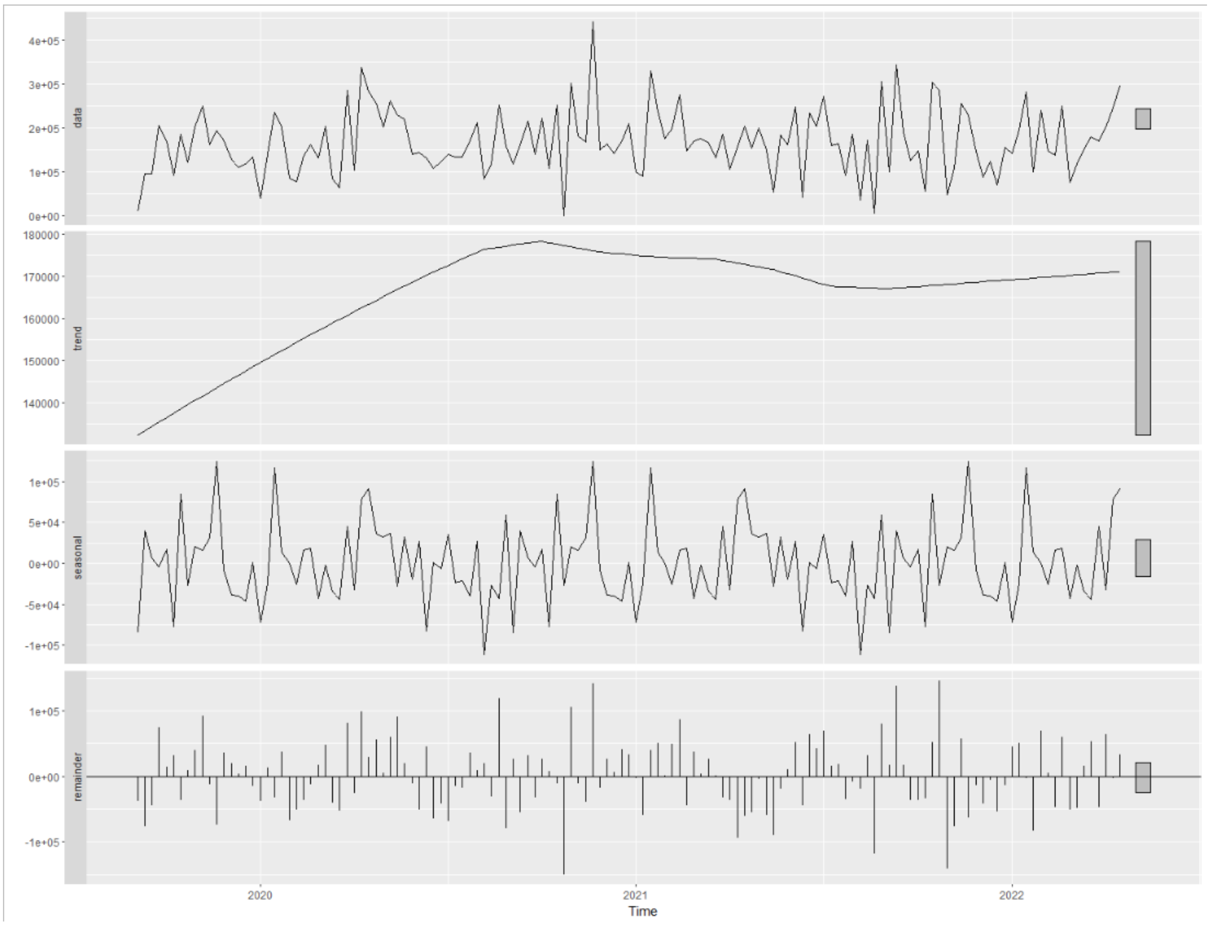

Figure 45 STL Decomposition at Weekly level for consolidated dataset 5

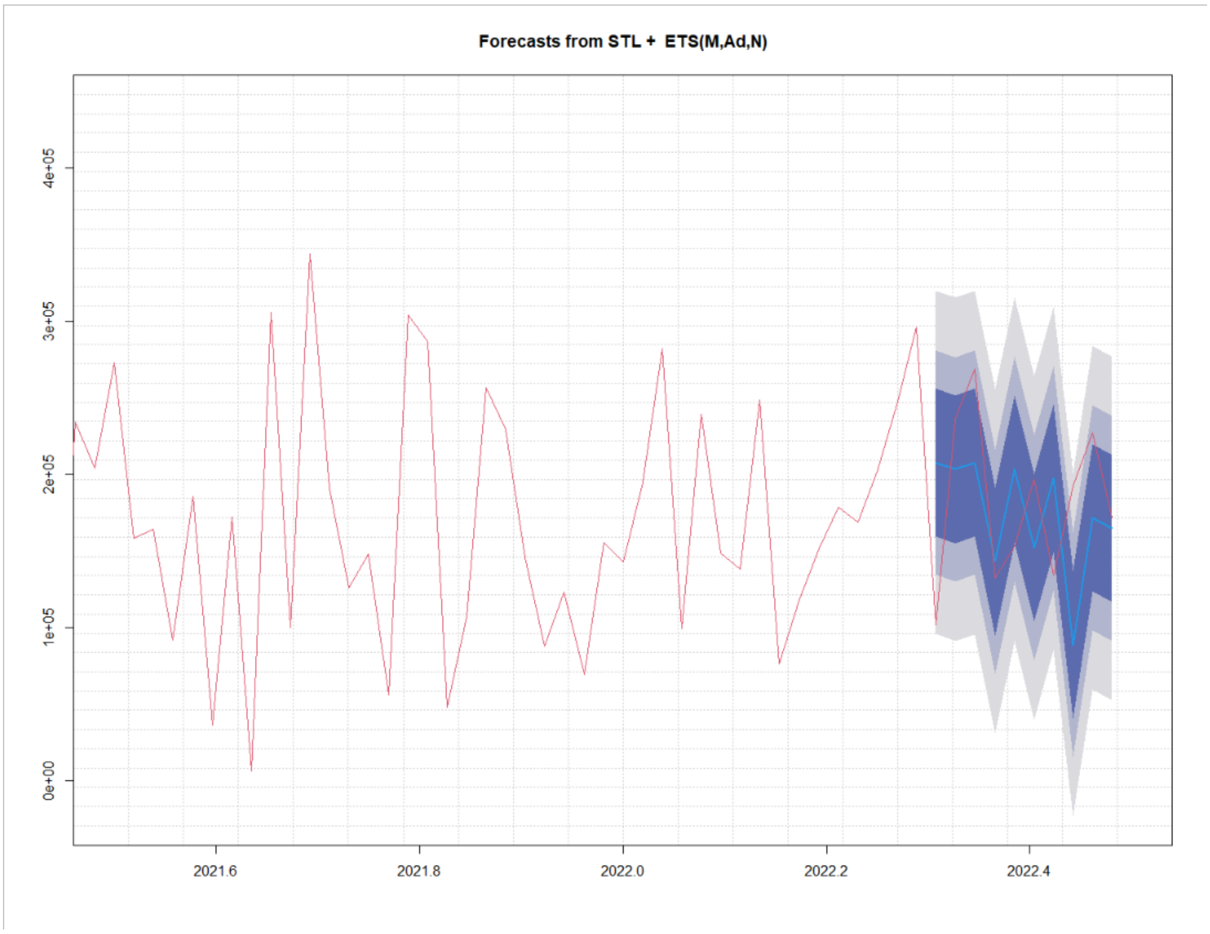

Figure 46 STL+ETS Weekly Forecast for consolidated dataset 5

B. Dataset 6

B.1 Monthly Fcast

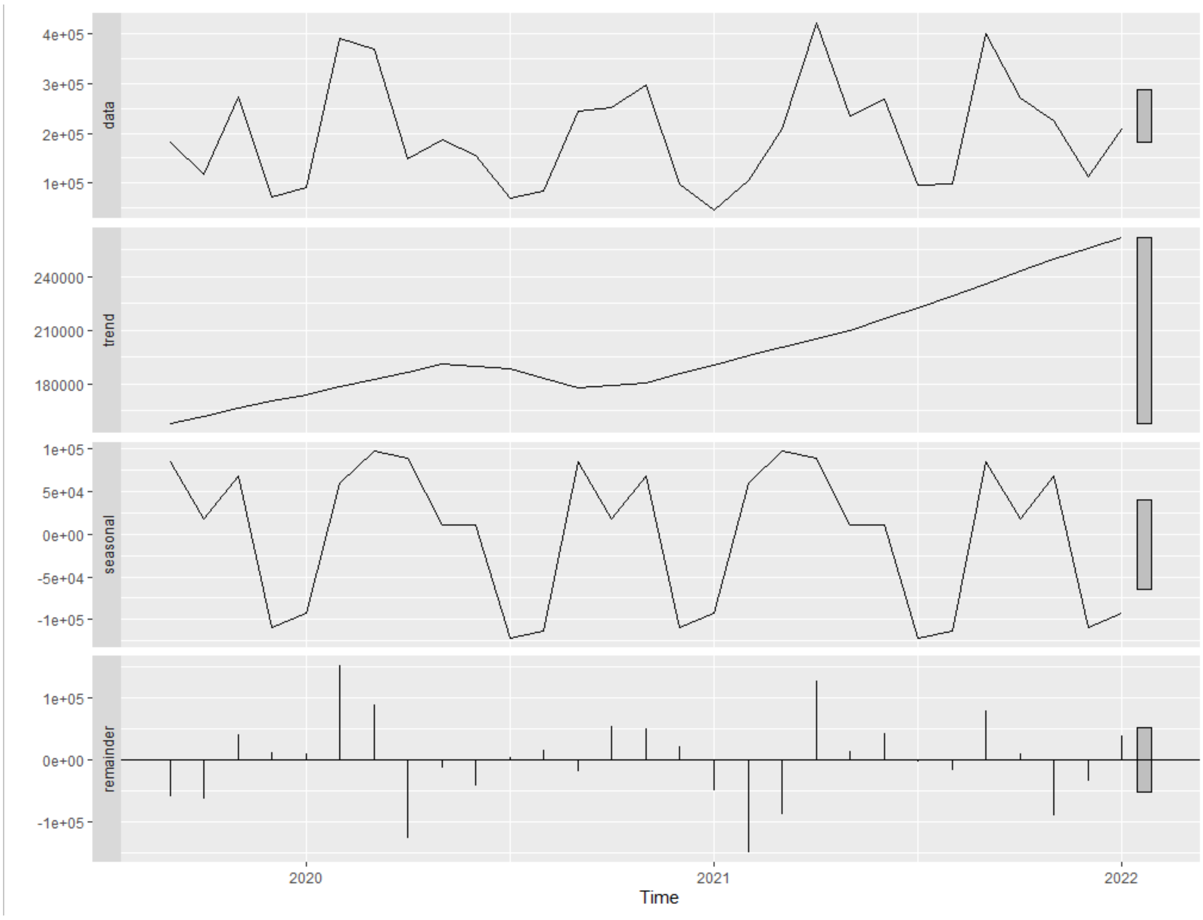

Figure 47 STL Decomposition at monthly level for consolidated dataset 6

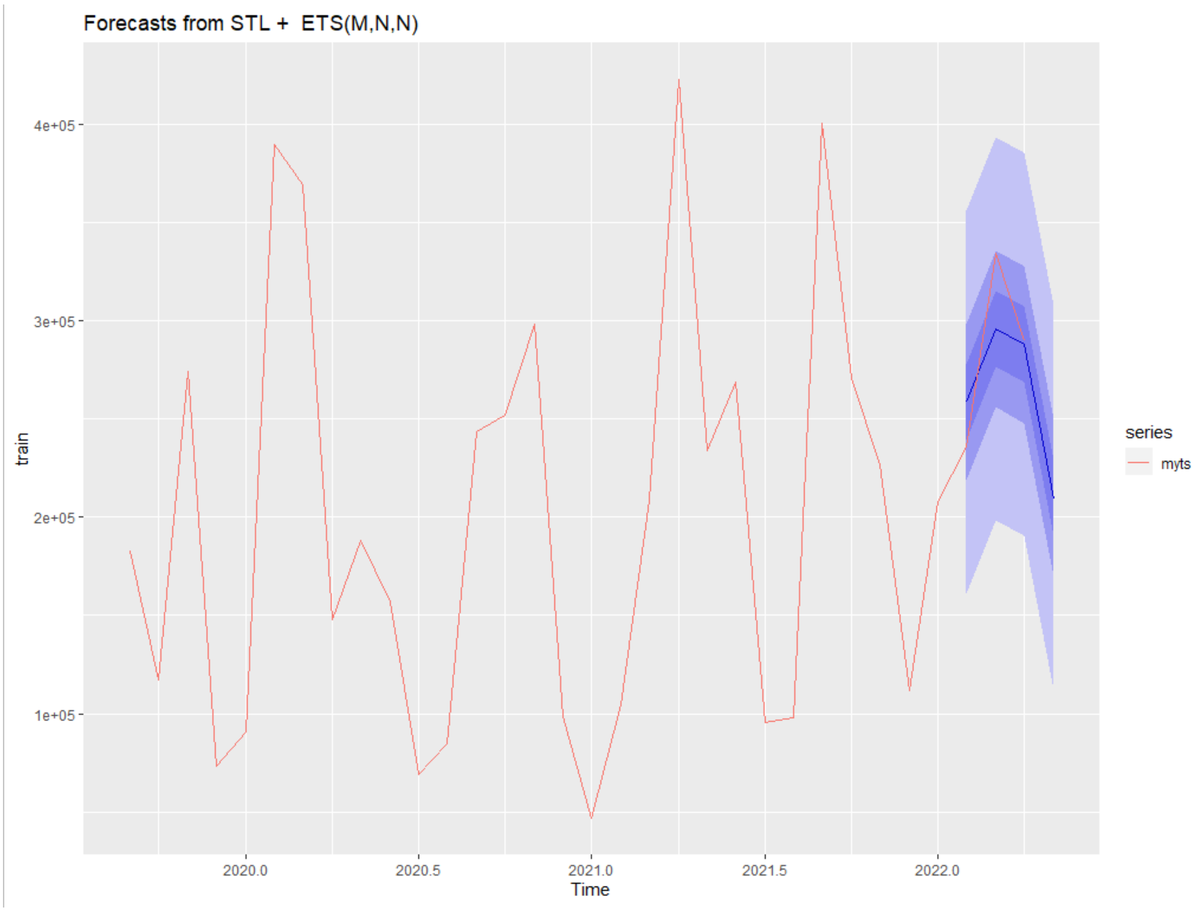

Figure 48 STL+ETS monthly Forecast for consolidated dataset 6

B.2 3-week Fcast

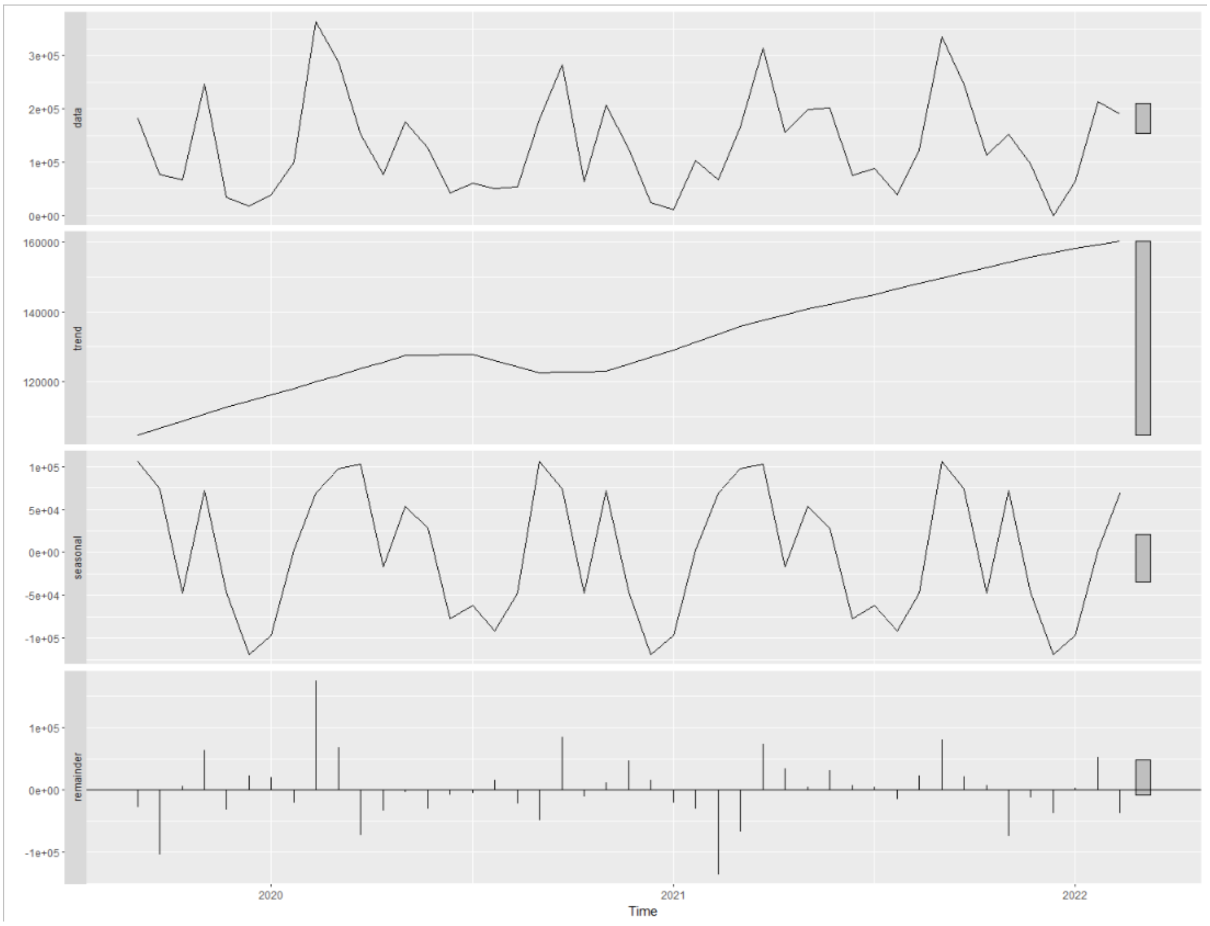

Figure 49 STL Decomposition at 3-week level for consolidated dataset 6

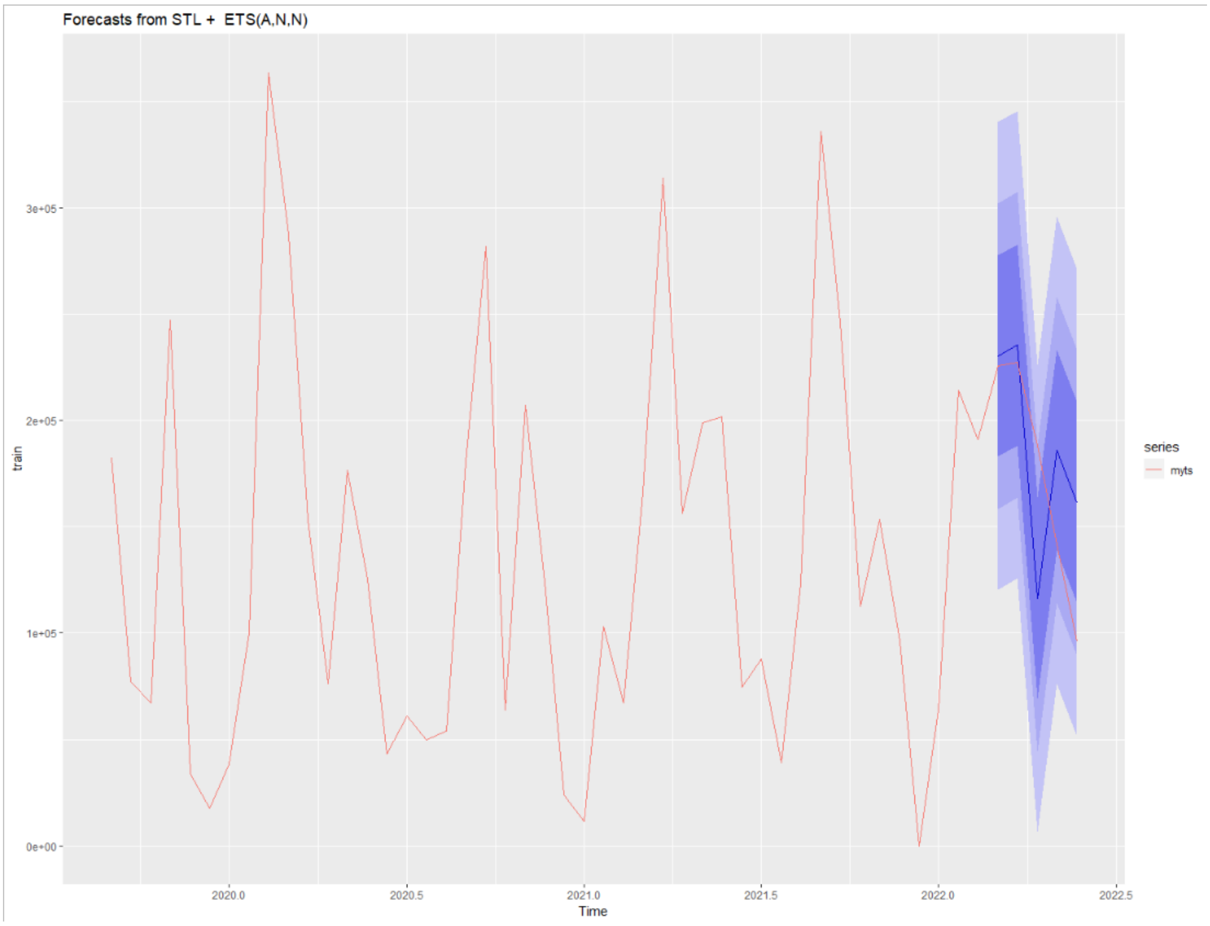

Figure 50 STL+ETS 3-weekly Forecast for consolidated dataset 6

B.3 Weekly Forecast

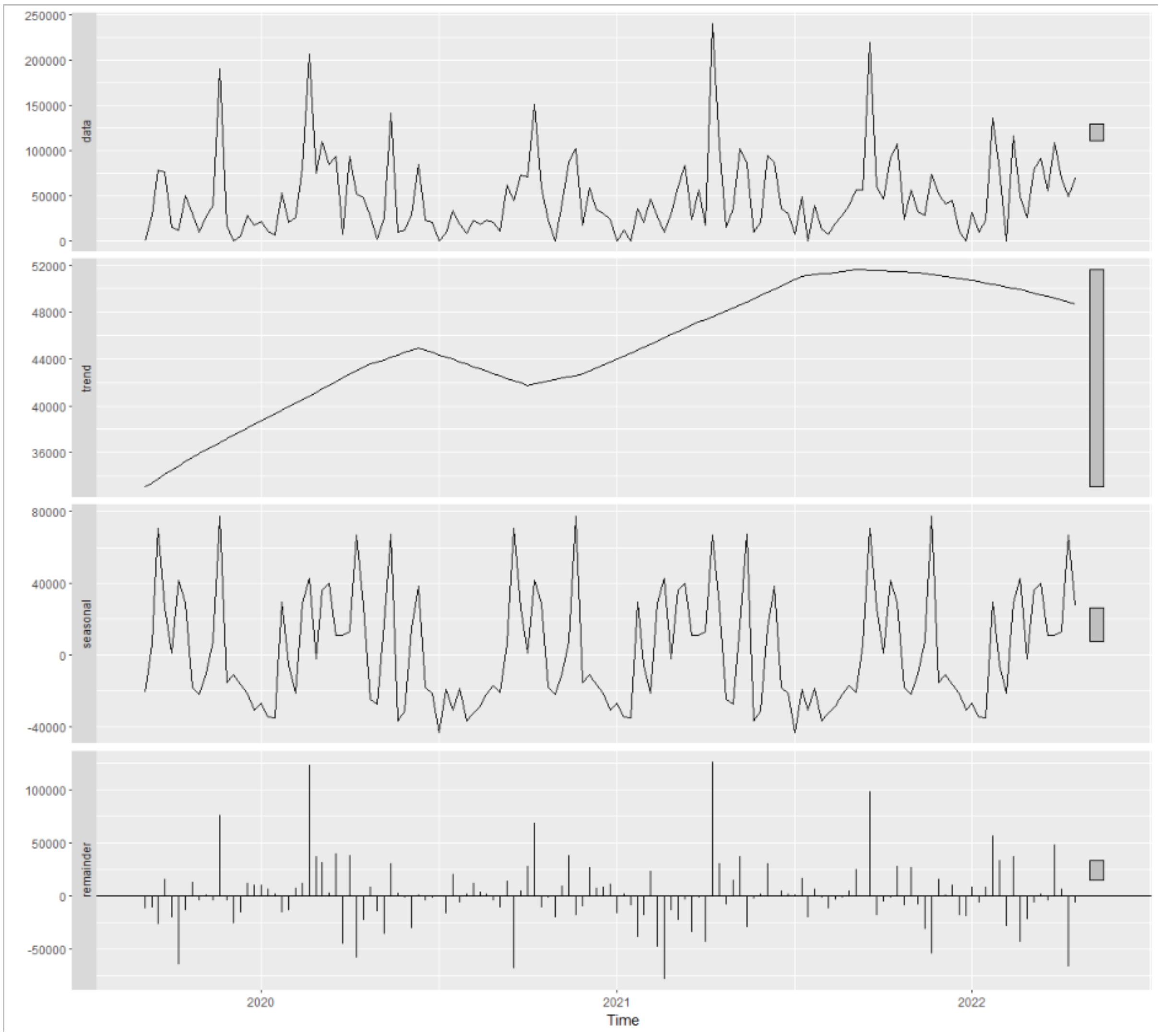

Figure 51 STL Decomposition at Weekly level for consolidated dataset 6

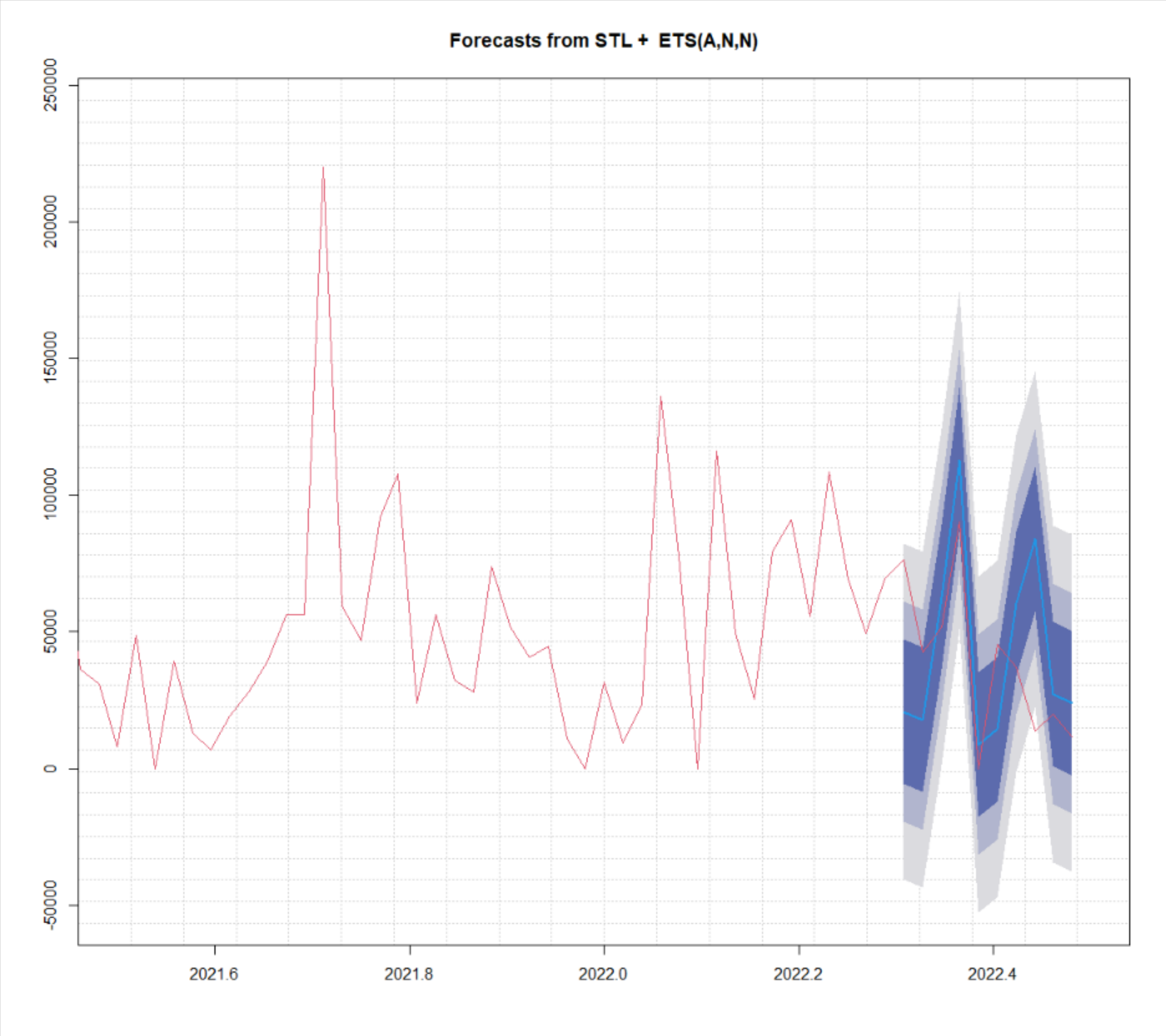

Figure 52 STL+ETS Weekly Forecast for consolidated dataset 6

C. *Dataset 15*

C.1 Monthly Fcast

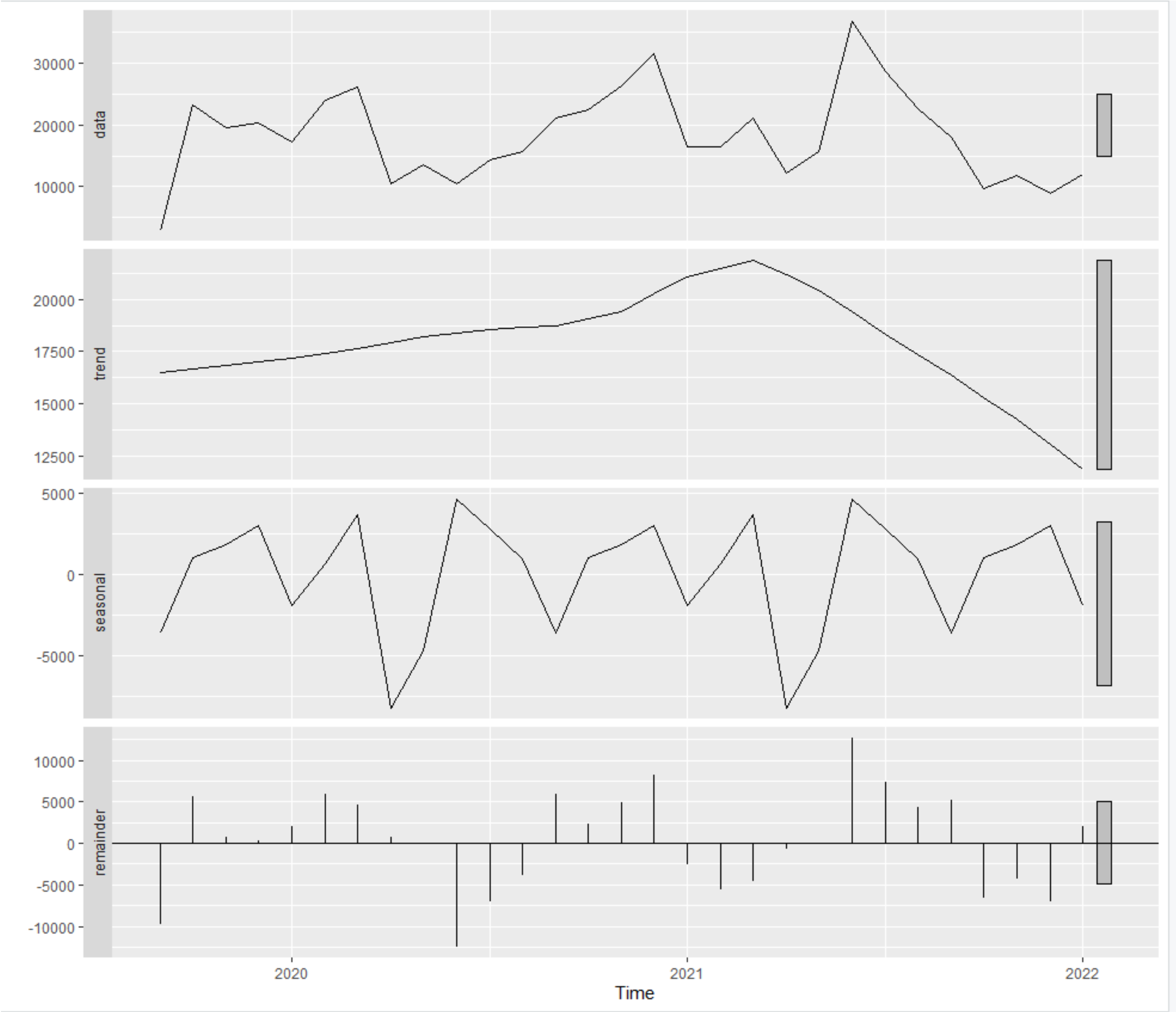

Figure 53 STL Decomposition at monthly level for consolidated dataset 15

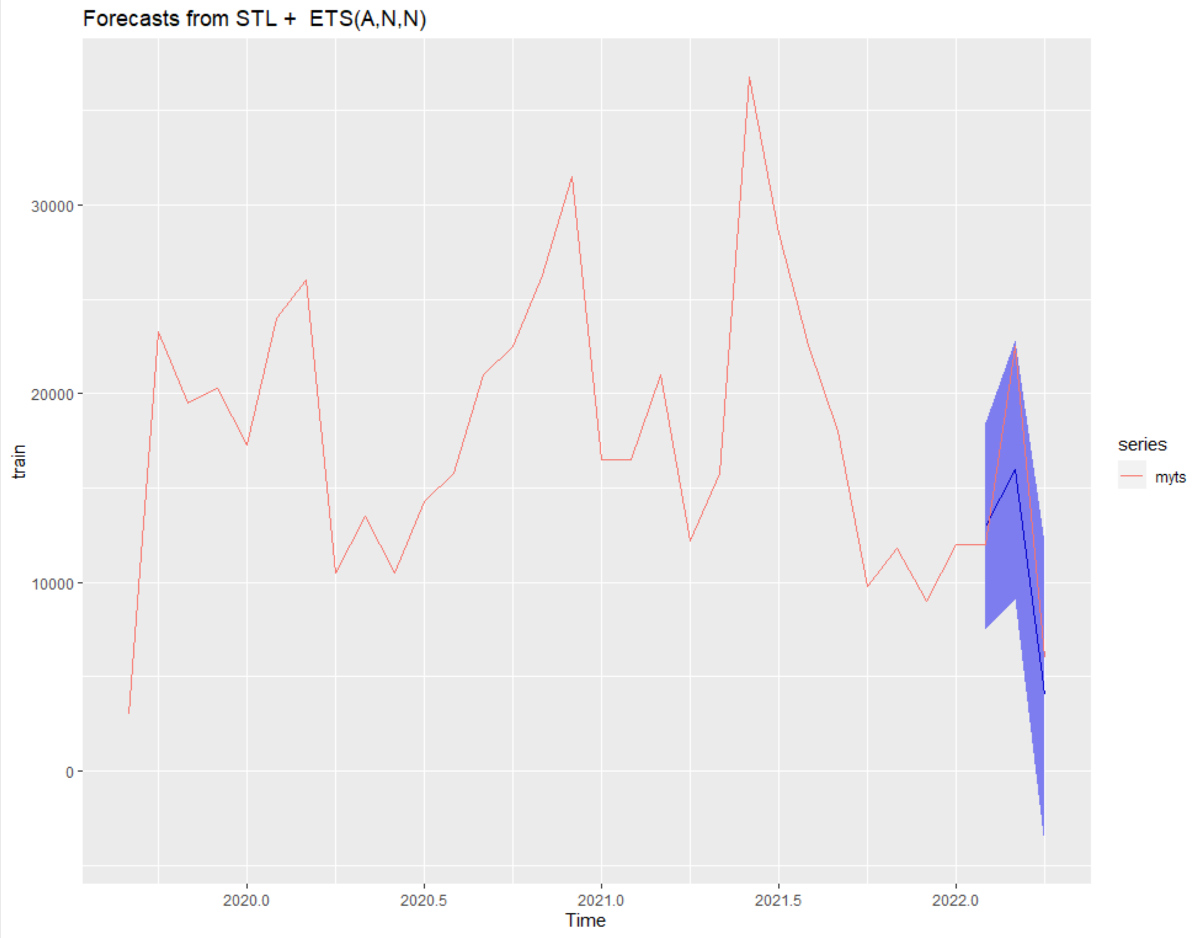

Figure 54 STL+ETS monthly Forecast for consolidated dataset 15

C.2 3-week Fcast

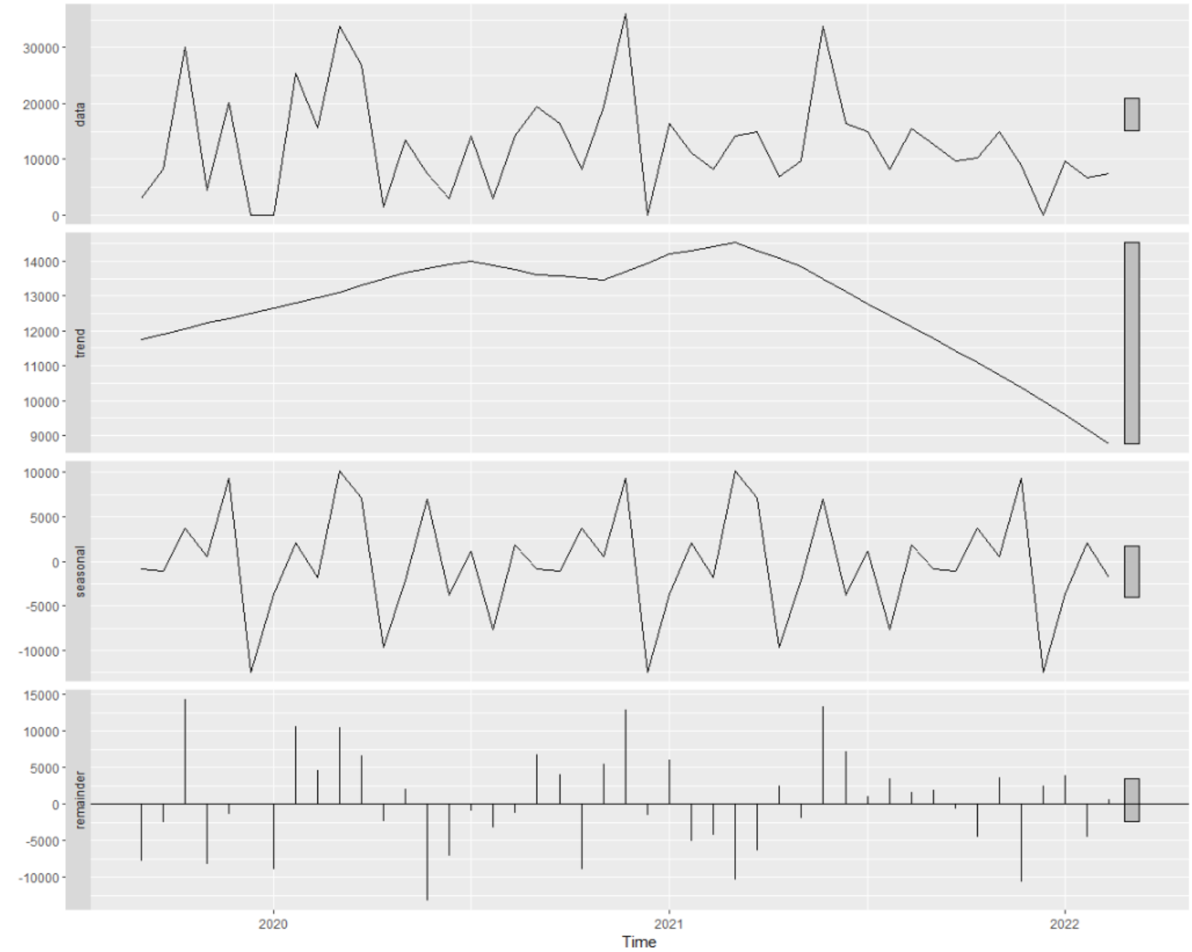

Figure 55 STL Decomposition at 3-week level for consolidated dataset 15

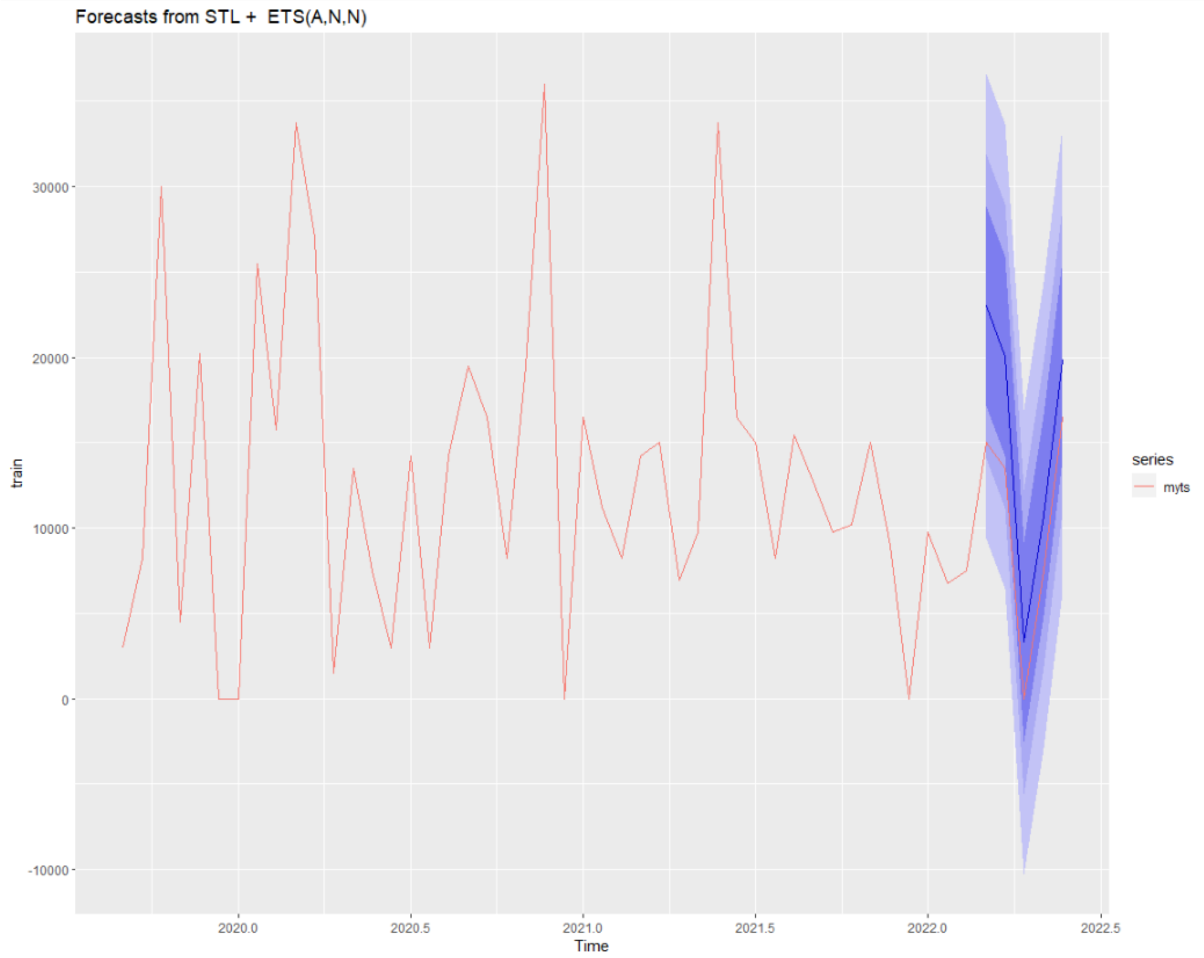

Figure 56 STL+ETS 3-weekly Forecast for consolidated dataset 15

C.3 Weekly Forecast

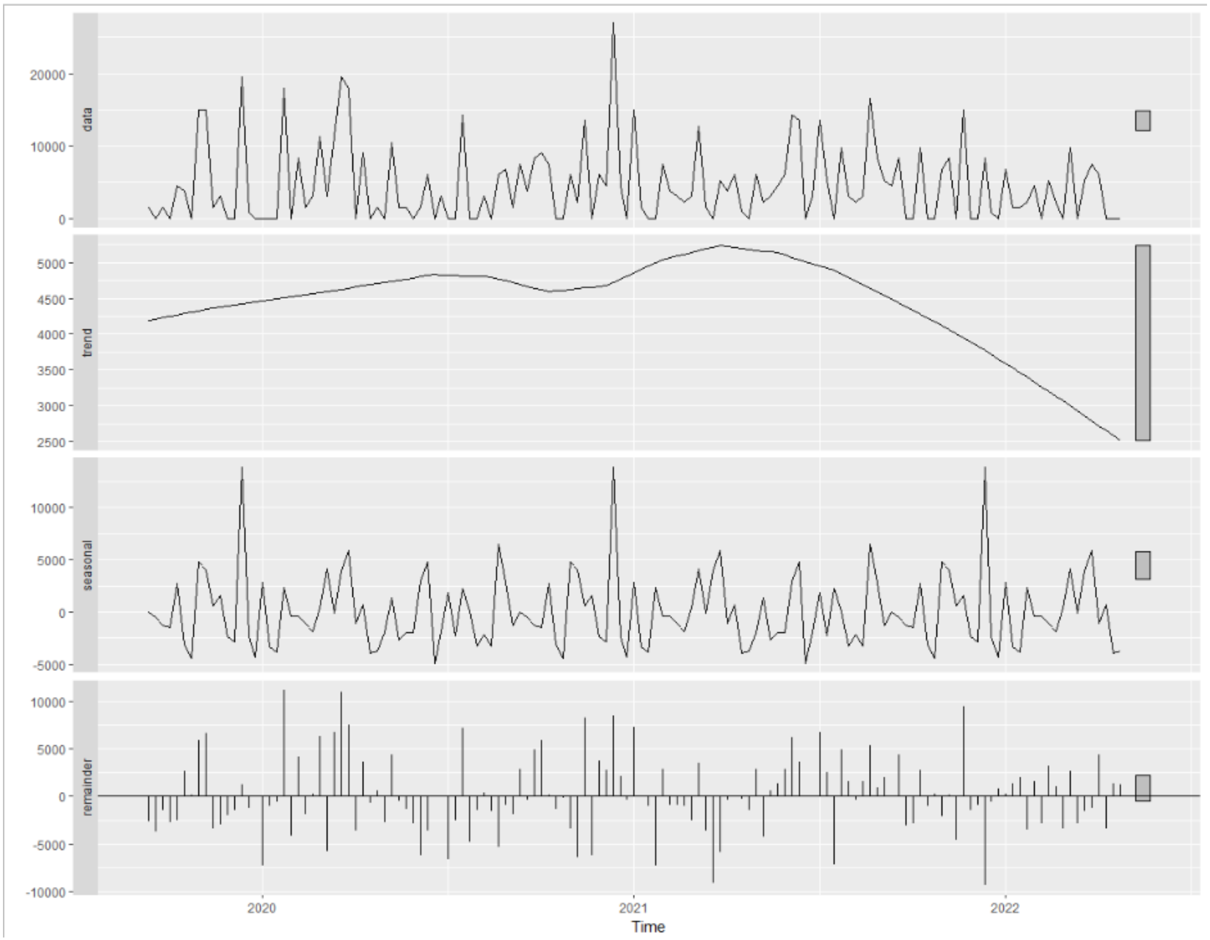

Figure 57 STL Decomposition at Weekly level for consolidated dataset 15

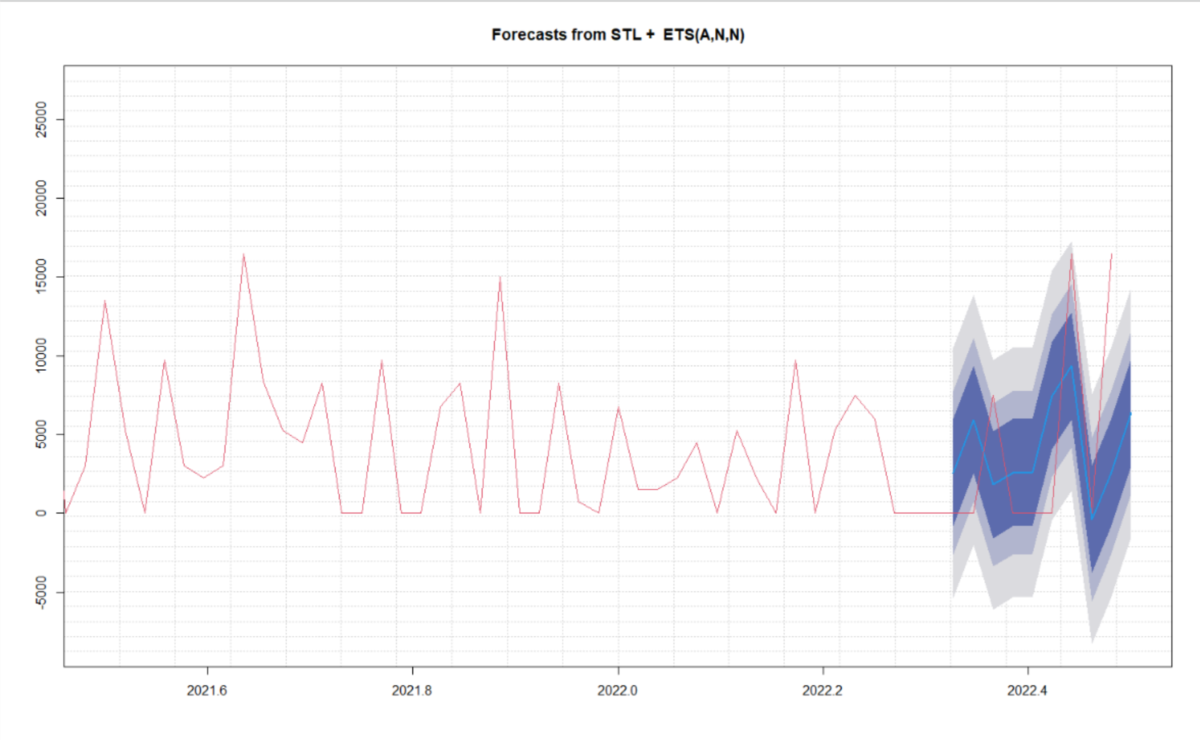

Figure 58 STL+ETS Weekly Forecast for consolidated dataset 15

D. Dataset 28

D.1 Monthly Fcast

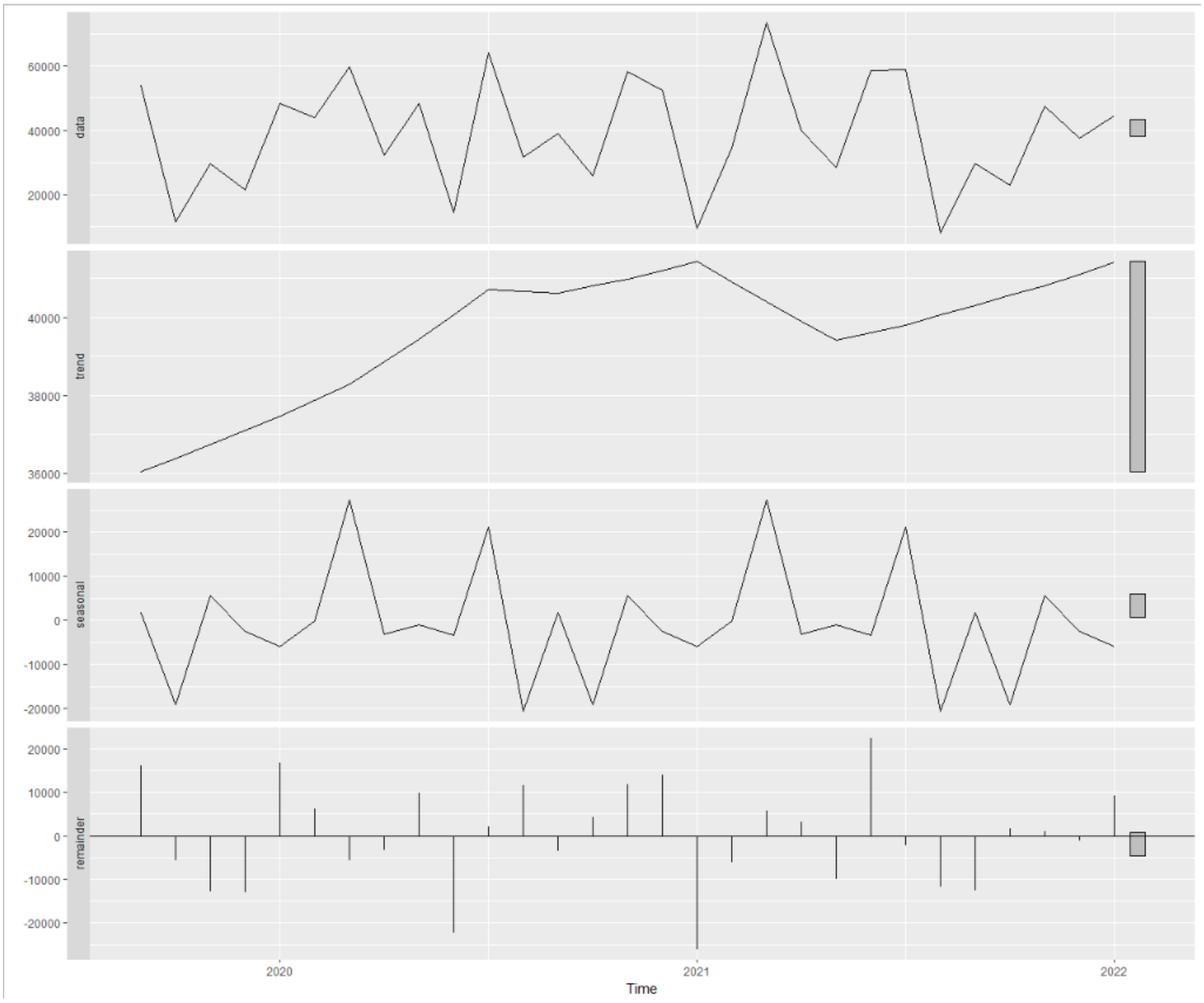

Figure 59 STL Decomposition at monthly level for consolidated dataset 28

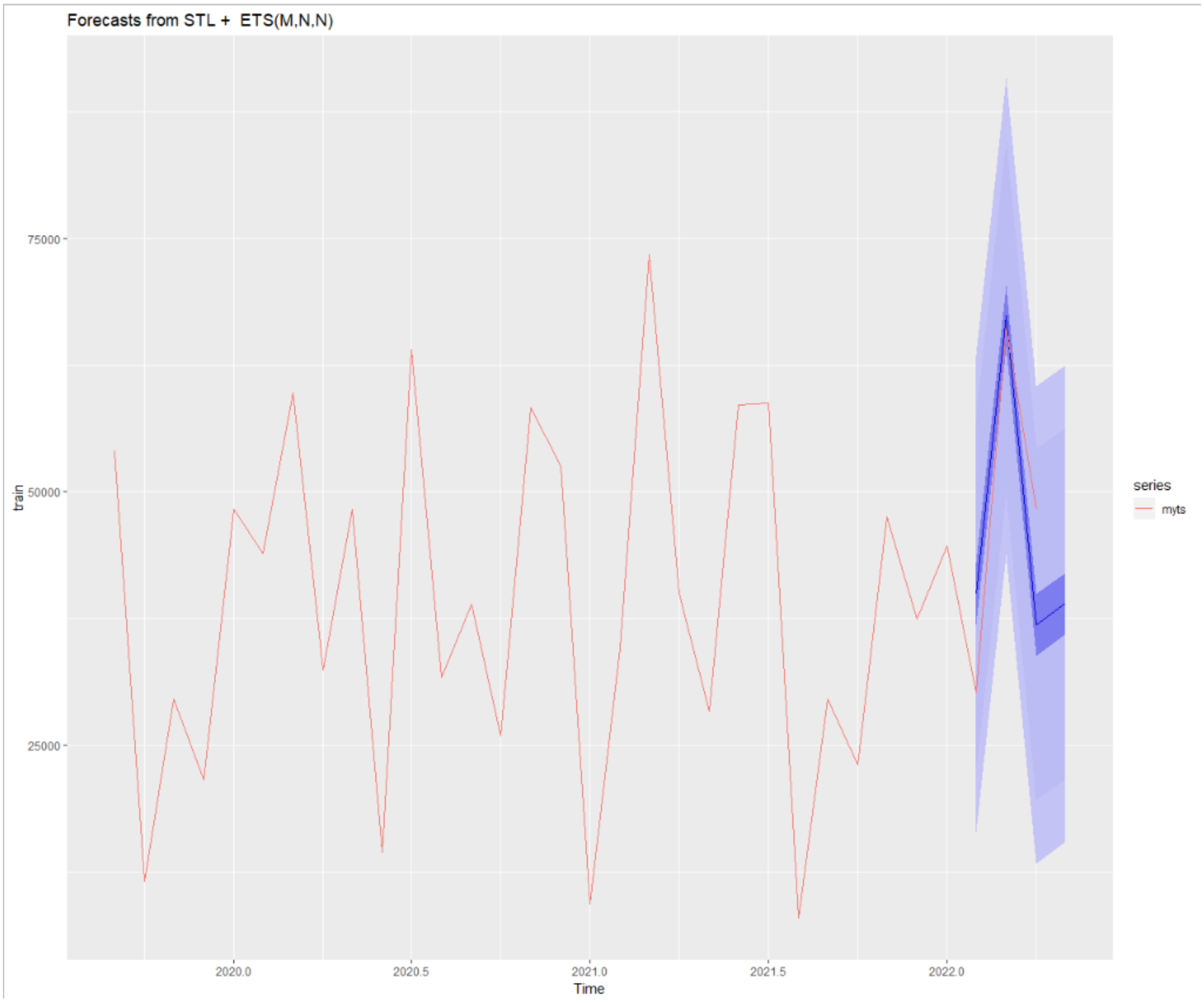

Figure 60 STL+ETS monthly Forecast for consolidated dataset 28

D.2 3-week Fcast

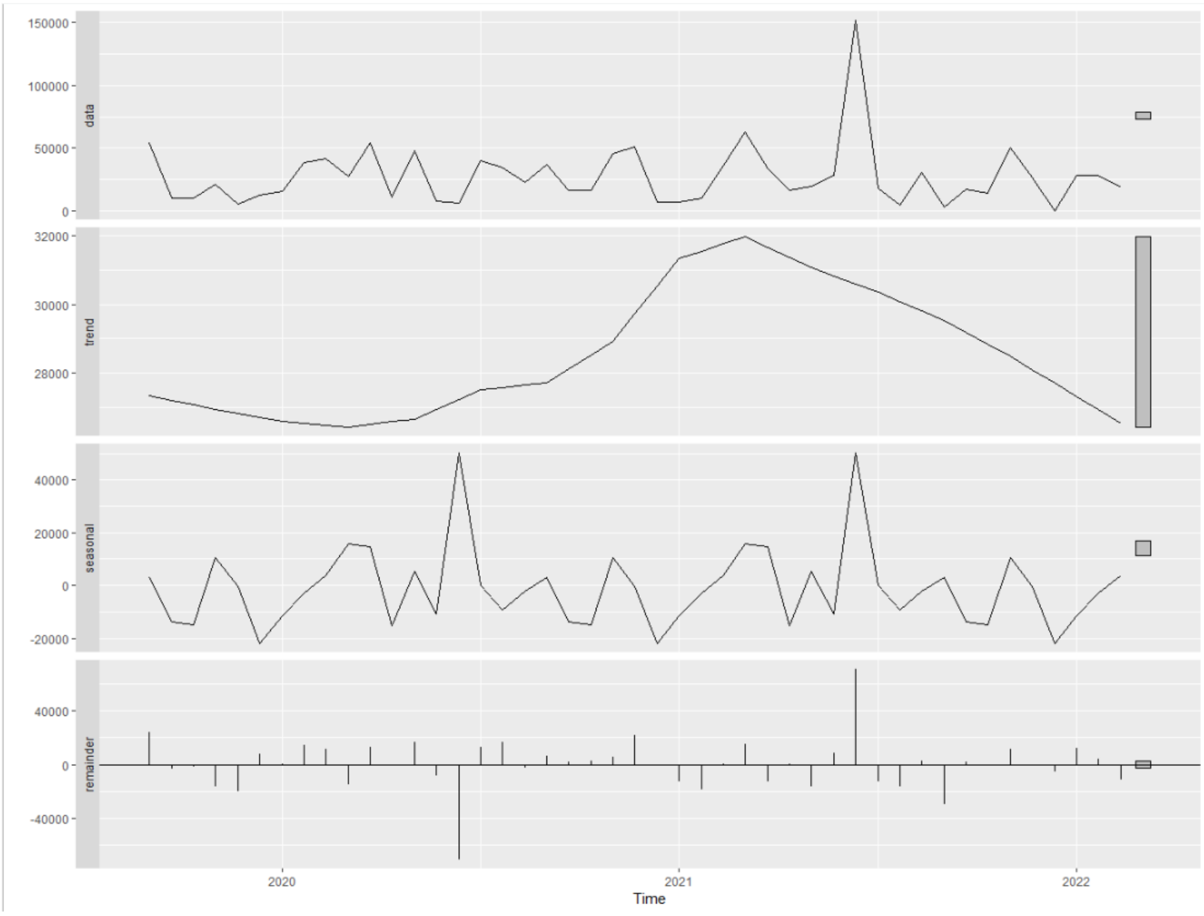

Figure 61 STL Decomposition at 3-week level for consolidated dataset 28

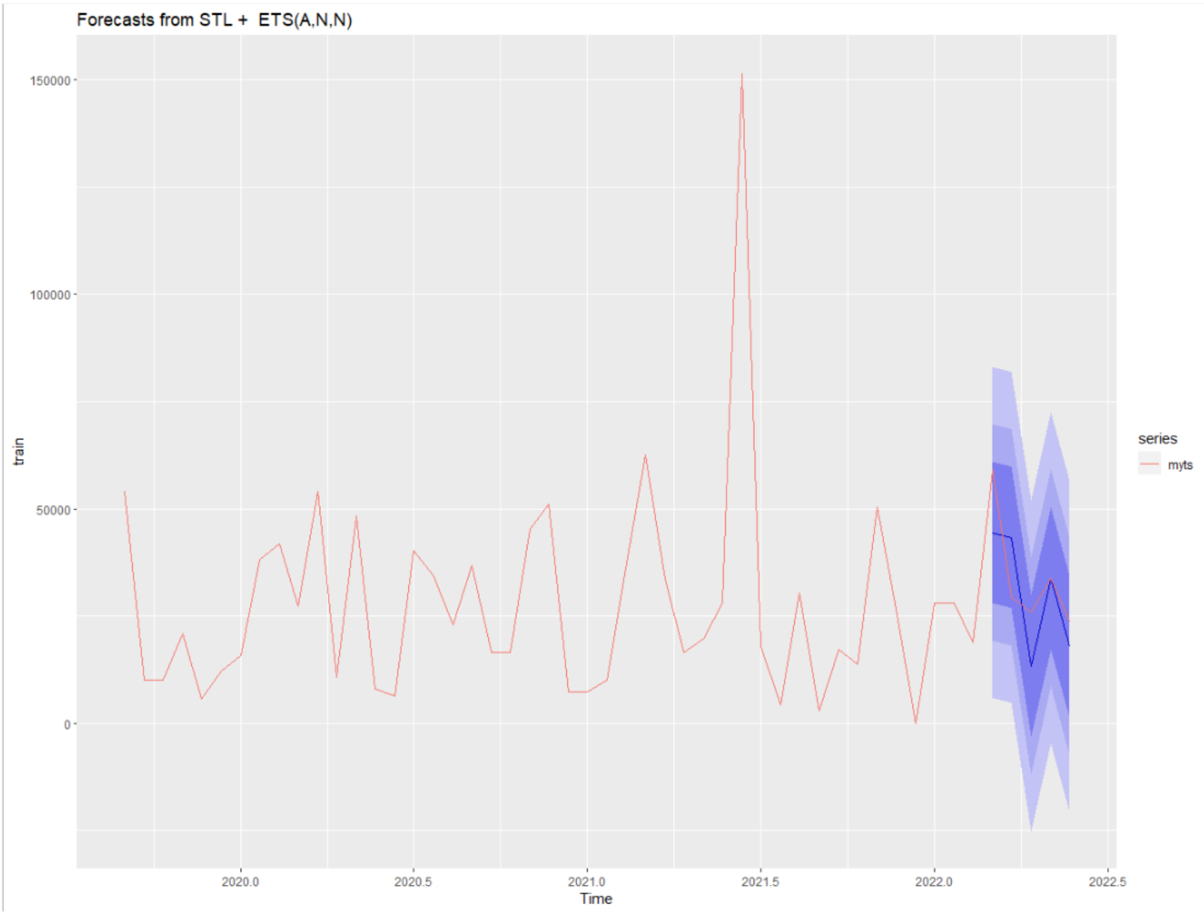

Figure 62 STL+ETS 3-weekly Forecast for consolidated dataset 28

D.3 Weekly Forecast

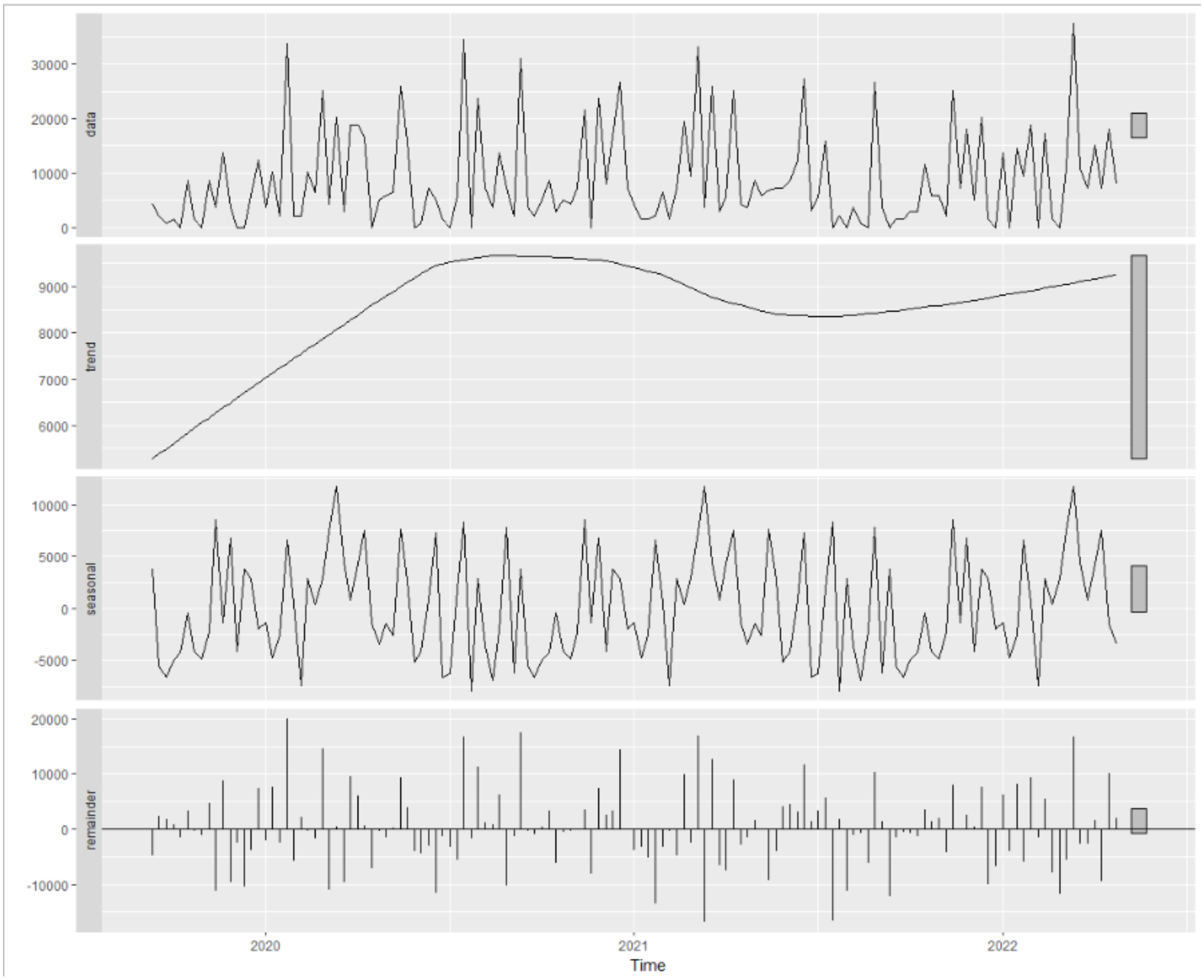

Figure 63 STL Decomposition at Weekly level for consolidated dataset 28

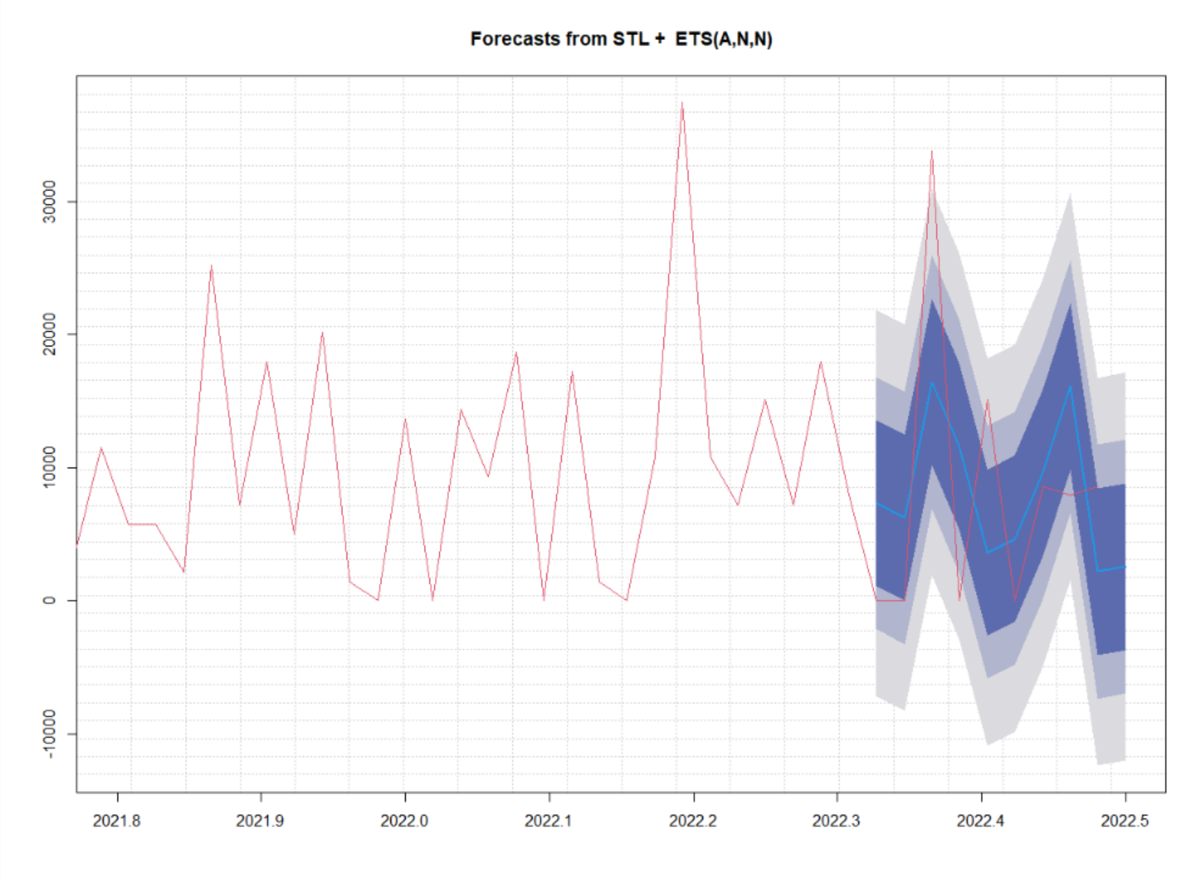

Figure 64 STL+ETS Weekly Forecast for consolidated dataset 28

E. Dataset 33

E.1 Monthly Fcast

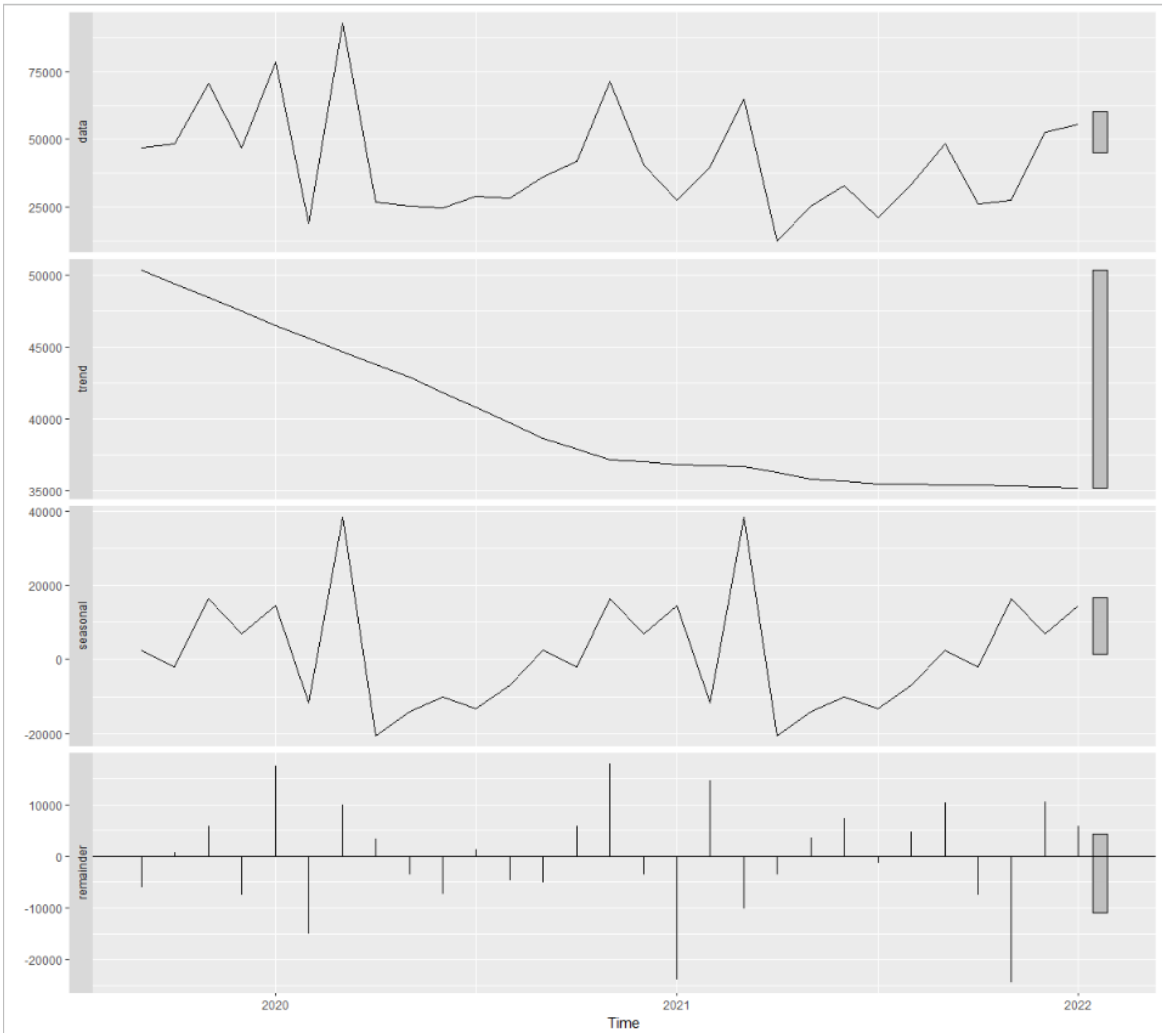

Figure 65 STL Decomposition at monthly level for consolidated dataset 33

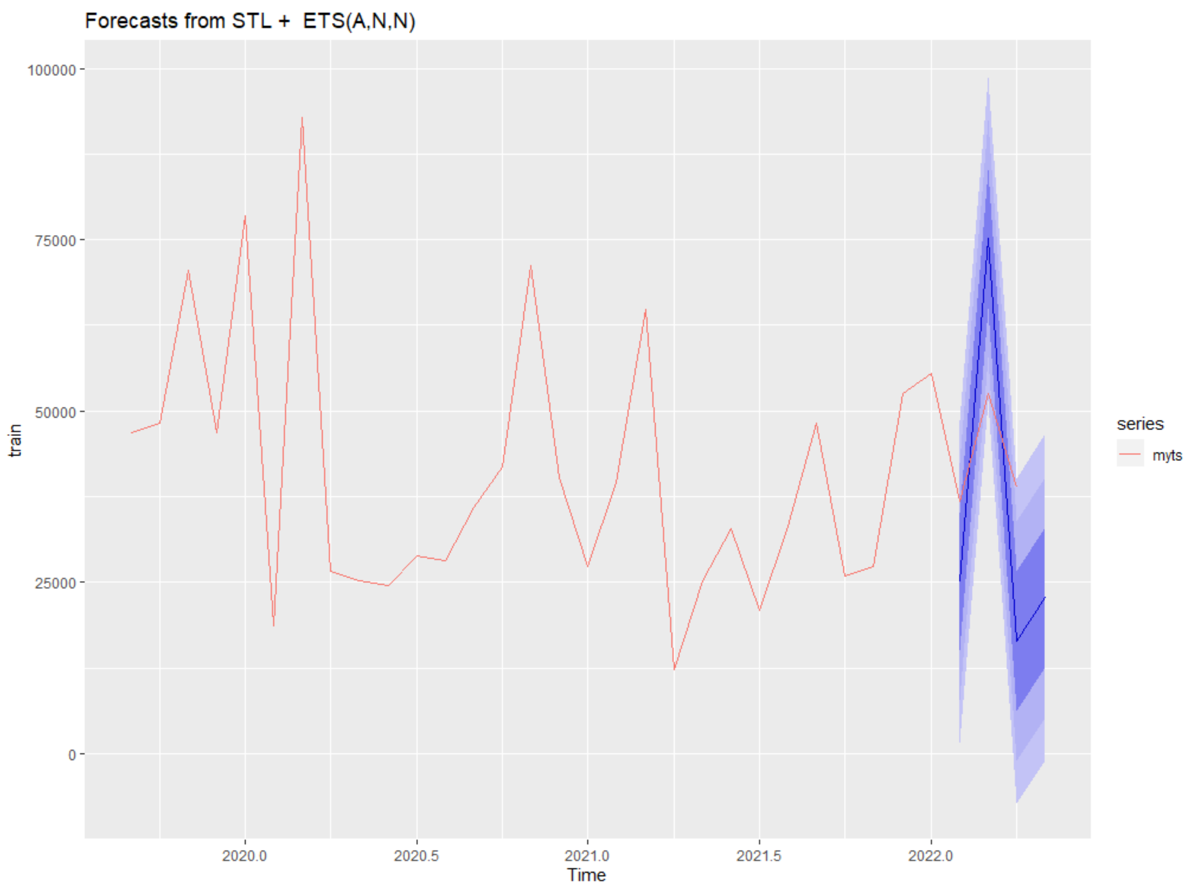

Figure 66 STL+ETS monthly Forecast for consolidated dataset 33

E.2 3-week Fcast

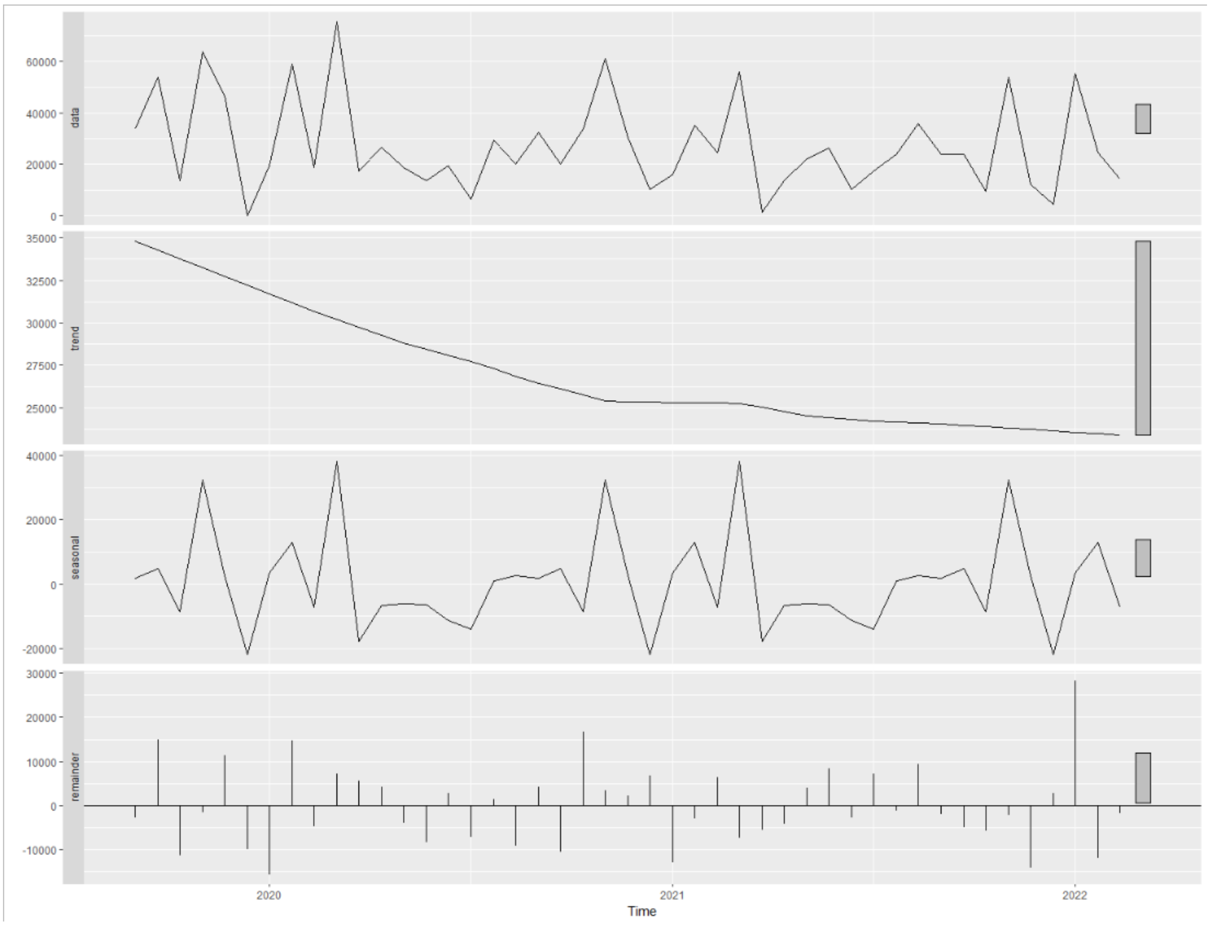

Figure 67 STL Decomposition at 3-week level for consolidated dataset 33

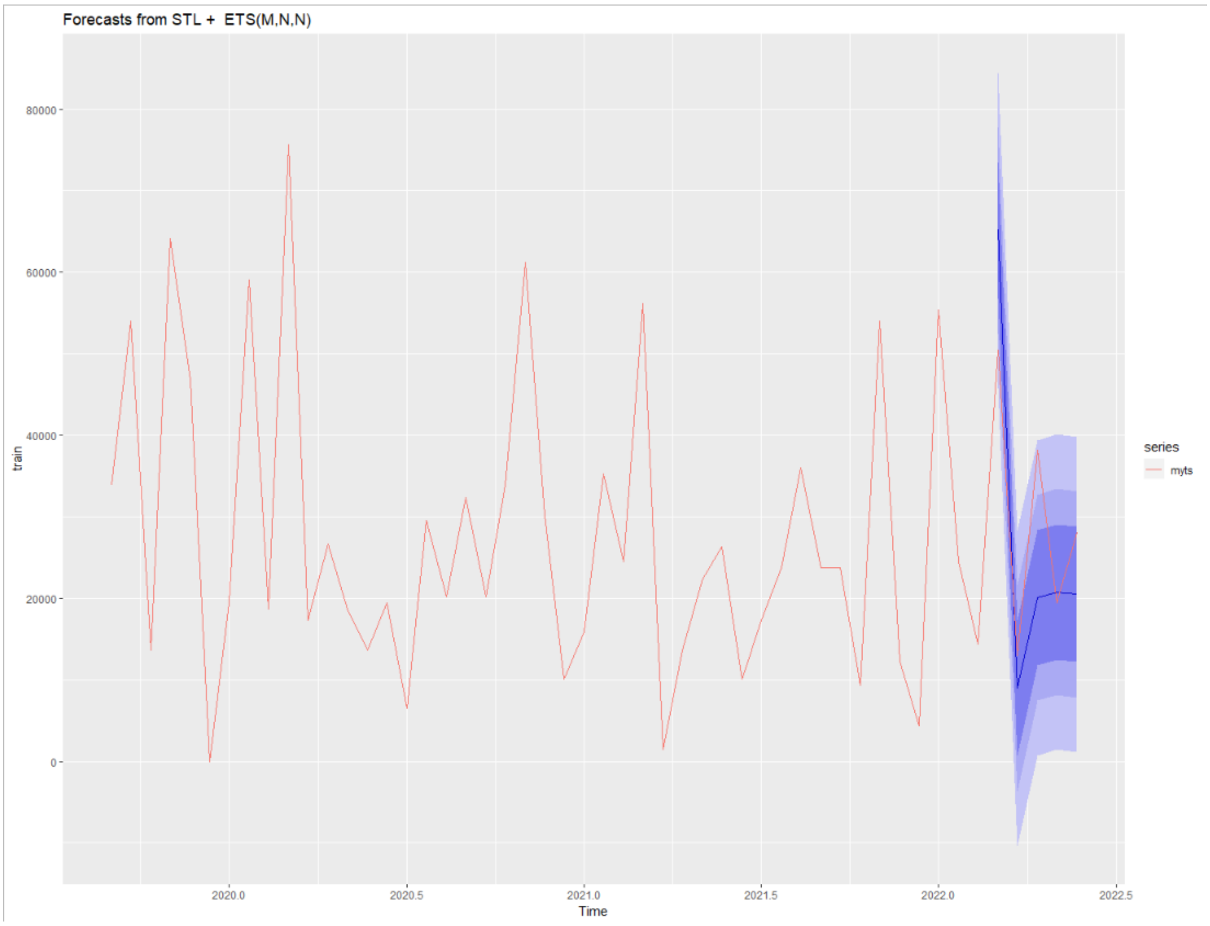

Figure 68 STL+ETS 3-weekly Forecast for consolidated dataset 33

E.3 Weekly Forecast

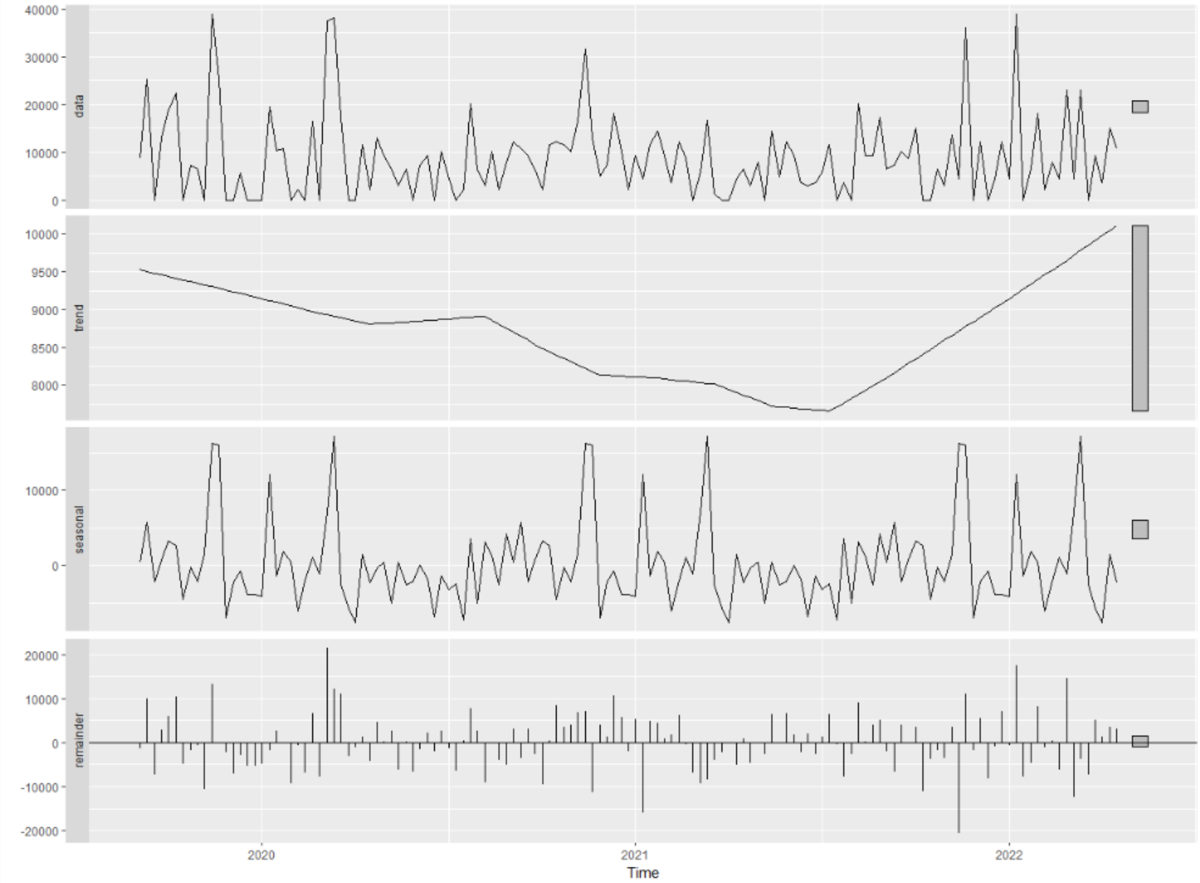

Figure 69 STL Decomposition at Weekly level for consolidated dataset 33

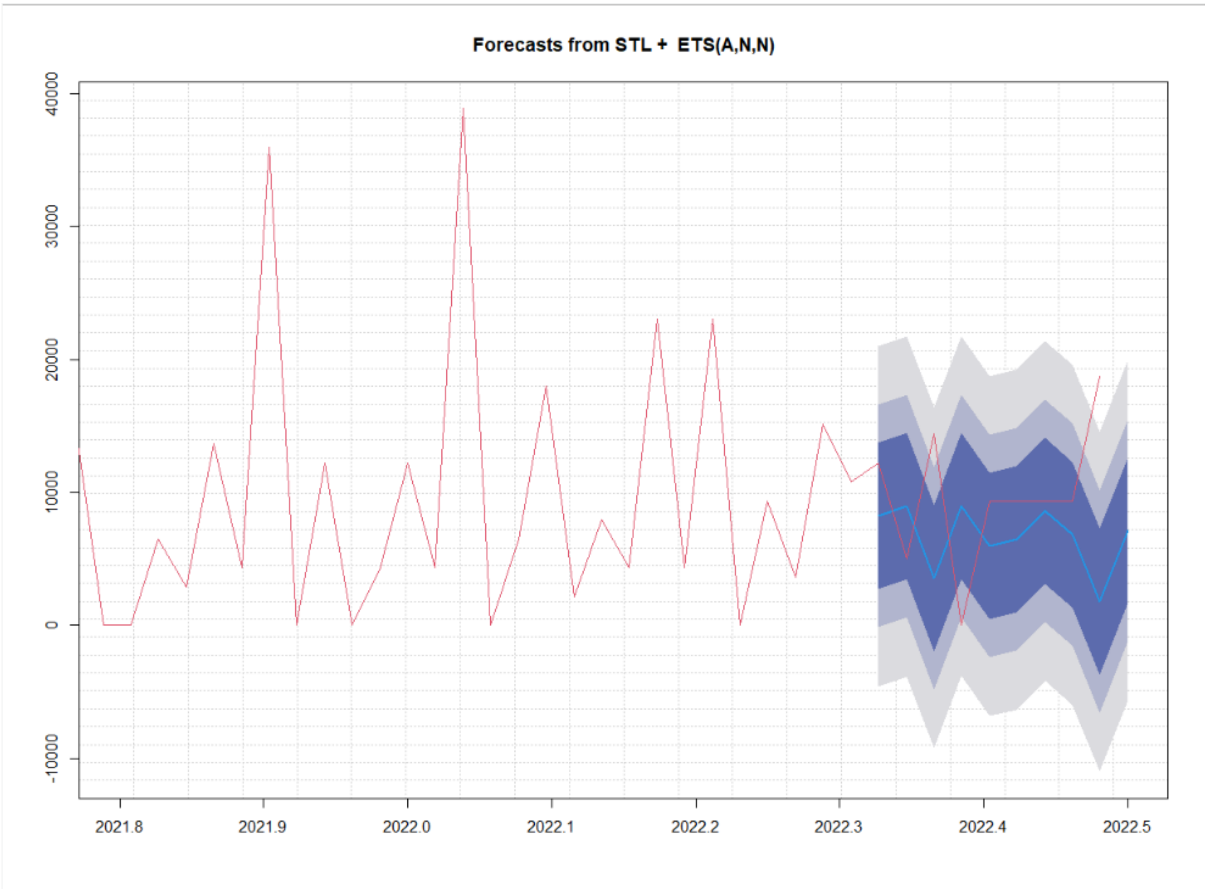

Figure 70 STL+ETS Weekly Forecast for consolidated dataset 33

Appendix F - R code for integration with SAP HANA

The following code has been obtained from https://blogs.sap.com/2016/12/15/connecting-r-studio-to-sap-hana-via-jdbc/ (Henry, 2016).

```
# Things you may need to change:
# - classPath (This needs to Point to the HANA Client JDBC Driver)
# - jdbcDriver (This should remain the same with the HANA Client JDBC driver)
# - hdbuserstore Key, this is the preferred way to connect securely to HANA
# - SAP HANA Host & port name after jdbc:sap://
# - username (HANA DB User)
# - password (HANA DB User Password)
# - dbGetQuery (Change the Select Query, here I selected a 10% Sample of the
CENSUS table in my own schema)

if (!require("RJDBC")) {
  install.packages("RJDBC",repos="http://cran.rstudio.com/")
}

library("RJDBC")

jdbcDriver <- JDBC(driverClass="com.sap.db.jdbc.Driver",
                  classPath=/Applications/sap/hdbclient/ngdbc.jar")

jdbcConnection <- dbConnect(jdbcDriver,  "jdbc:sap:", key="SDI_MONSOON")

jdbcConnection <- dbConnect(jdbcDriver,
                  "jdbc:sap://ukhana.mo.sap.corp:30015/?autocommit=false"
                  ,"username"
                  ,"password")

result <- dbGetQuery(jdbcConnection, "select * from CENSUS TABLESAMPLE SYSTEM
(10)")
print(result)

dbDisconnect(jdbcConnection)
```