# Improving Forecasting using Imperfect Advanced Demand Information

Jonathan Nicklin

University of Twente

Faculty of Behavioural Management and Social Sciences

*Industrial Engineering and Management*

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**Author:**
J. Nicklin (Jonathan)
j.m.nicklin@student.utwente.nl

**University of Twente**
Drienerlolaan 5
7522NB Enschede

**Supervisors University of Twente**
Dr. D. Prak (Dennis)
Dr. P. B. Rogetzer (Patricia)

## Preface

Dear reader,

I am writing this note after what can only be described as a formative experience. Before this, I had never dedicated so much of my time dedicated to a single document, been employed by a company to undertake a project, or even felt a continuous force of motivation and drive to complete a project like this. Being able to work independently for an extended period of time is something that at first seemed daunting and challenging, but the process of creating this work has been better than I could have ever anticipated.

Working independently, however, does not mean that I did not have meaningful and impactful connections with those around me. Specifically, I want to give my appreciation to those who have helped me along this journey of mine. Firstly, I would like to thank Dennis for his continued commitment and precise comments – of which I have no doubt increased the quality of this work beyond what it would be without him. Furthermore, I would like to thank my company supervisor and his team for the unrelenting trust and commitment to the project and I wish to take meaningful lessons from those I interacted with. I'd also like to take the time to give my appreciation to my close network, whom were always there to support me if and when I needed.

Finally, for those who have come and gone in my life over the course of my Bachelor degree – I also thank you.

Jonathan

## Executive Summary

Delivering demand when the longest lead time of a product is larger than the agreed time before delivery requires companies to pre-empt demand in the form of generating forecasts. These estimates of demand can be created using various methods, each formulated for a particular business case - be it reduced holding costs for a smooth demand pattern or otherwise. In some cases, however, demand is hard to predict and there is a consensus of striving to achieve a high service level. In these scenarios, communicating with customers to better understand order quantities is facilitated in the form of advanced demand information.

Forecasts that are purely based on imperfect advanced information on demand, however, are inaccurate and can lead to inefficiencies, especially considering holding surplus inventory, and generally rely on the accuracy of those providing the information on demand. In practice, some customer companies tend to be more accurate in providing advanced demand information, and the customers that provide poor insights are treated in the same way.

Therefore, rather than having one source of information to base forecasts on, a systematic combination of two inputs for demand forecasting is presented in this work. The guiding principle suggests that those who are more accurate in predicting upcoming demand will see their advanced demand indication integrated with greater importance in relation to a fitting time series forecasting method. Therefore, by tapping into a wealth of information not yet used in synchrony, companies are both able to improve the overall efficiency of the forecasts, but also maintain the business strategy of a high service level.

Testing various forecasting methodologies in an empirical study suggested that using advanced demand information in any capacity seemingly performed better when the penalty for unmet demand was high. In contrast, time series forecasting methods outperformed when the cost of having surplus stock on hand was high. Interestingly, time series forecasting methods proved to have a greater overall accuracy, yet the most accurate method was determined to be the technique which utilised a suitable time series forecast and advanced demand information simultaneously.

Additionally when tested, there was no indication that advanced demand information accuracy improves with time. This observation is perhaps contrary to intuition as one would expect to see a learning curve as a product matures.

The outcomes of this research suggest that there is an opportunity to create more effective methods at forecasting demand with the prospect of achieving a high service level by combining multiple inputs. In any case, companies that focus on service level should strive to use advanced demand information to forecast demand.

## Contents

## Abbreviation List

ADI – Advanced Demand Information

CAGR – Compound Annual Growth Rate

MRP – Material Requirements Planning

ERP – Enterprise Resource Planner

JIT – Just In Time

LSTM – Long Short Term Memory

MTO – Make-to-Order

MOQ – Minimum Order Quantity

MSE – Mean Squared Error

SES – Simple Exponential Smoothing

SBA – Syntetos-Boylan Approximation

SVR - Support Vector Regression

TSB – Teunter-Syntetos-Babai (Method)

SPEC – Stock-keeping-oriented Prediction Error Costs

MAPE – Mean Average Percentage Error

RMSE – Root Mean Squared Error

MAE – Mean Absolute Error

MdAE – Median Absolute Error

MdAPE – Median Absolute Percentage Error

RMSPE – Root Mean Square Percentage Error

SMAPE – Symmetric Mean Absolute Percentage Error

MASE – Mean Absolute Scaled Error

RMSSE – Root Mean Square Standardised Effect

# 1. Introduction

Uncertainty in demand is a characteristic that all businesses aim to reduce. Improved certainty allows companies to arrange their supply chains for greater responsiveness and efficiency (Chopra, 2019). This improvement can not only be beneficial for a company but also mutually beneficial for its suppliers and customers. Benefits for suppliers include a greater demand transparency, whilst customers experience a reduction in unmet orders. As such, extensive effort is put into predicting future demand.

A common method to gain pre-emptive information on demand, and thus reducing demand uncertainty, is through forecasting based on historical data. Data on past orders predominantly give insights into demand quantities and the times in which these quantities occur. Therefore, information on level, trend, seasonality, and variation in demand quantities of smooth time series (Chopra, 2019), and demand frequency for intermittent demand series data (Syntetos et al., 2005) can be extracted. Understanding these characteristics is important as not all demand can effectively be forecasted using the same method. Deciding on a suitable forecasting method, therefore, can be guided using an analysis of demand attributes.

Another method of predicting future demand is to communicate openly between buyer and seller to understand prospective order amounts. Such advanced demand information (ADI) can be infrequent and realised order amounts are subject to change. Due to these characteristics, ADI should be considered in most cases to be imperfect. While the benefits of increased awareness and predictability for the supplier are evident, the customer gains should not be underestimated. Improved communication between buyer and seller can greatly decrease the risk of unmet orders (Tan, 2008), thus foreseeably enabling an enriched buyer-supplier relationship. In a market with volatile and intermittent demand, the potential of these benefits are only enhanced.

Interestingly, though, limited effort has been placed into incorporating ADI into demand forecasts (Tan, 2008). Businesses in practice tend to depend on one method for forecasting demand, although an integration of both historical data forecasting and ADI could aid resource planners in making better decisions on the amount of inventory the company should carry to efficiently meet demand.

Presented in this work, therefore, is a method which sets out to systematically combine imperfect ADI with a suitable time series forecasting method to produce a more accurate indication on demand ahead of its realisation. The method comprises of integrating ADI and a time series forecasting algorithm, depending on the relative performance, which will later be tested using an empirical case study from a producer of food bars for companies around the globe. While ADI and time series methods may not be accurate in separation and over a large set of products, in combination, they have the ability to provide different viewpoints of the same demand. In addition, there will be companies that are better predictors of future demand than others, thus alluding to how ADI in such a case should be seen as more beneficial.

Accordingly, the remainder of this section is dedicated to understanding the context necessary to achieve the aim of analysing demand to find the most suitable time series method to combine with ADI, and to proposing methods to increase forecast accuracy. This is achieved by discussing the company within the context of its industry, its specific challenges, and deciding which of the challenges to tackle in greater detail.

### *1.1 Introduction of Industry Sector*

Nutritional bars formerly have been seen as food for top athletes who aim to ingest the proper nutrients to support their body through performance and recovery. More recently, however, nutritional bars have been seen as a solution for the fast-paced and health-conscious modern lifestyle, where consumers tend to value time as a premium. Due to diverse customer needs, bars aimed at nutrition come in many shapes and sizes; meal replacement, low carb, low calorie, energy, recovery, and high protein bars. Increased interest in bars has also led to an increase in the industry sector's value. Experts suggest the nutritional bar is set to be to be one of the fastest growing sectors, attributing a compound annual growth rate (CAGR) of 4.3-8.43% for the eight years leading up to 2030 (Straits Research Pvt. Ltd, 2021; Data Bridge Market Research, 2022).

Evidently, whilst currently being a prosperous and growing industry, it is imperative that the company does not lose a foothold as a major market-player. As a service- and quality-oriented company, it finds importance in not only maintaining, but improving service level and quality to its customers. As such, this work will look to contribute to the collective goal of service level improvement by analysing customer ADI and realised demand and combining them as one to create a more accurate forecast. Thereafter, results of this study will serve as a basis for continued effort towards improved service quality within the company.

## *1.2 Context of company*

The following sections will work to understand the company, enabling a better understanding of the requirements for forecasting methods, and the system into which the forecasts will be incorporated.

### *1.2.1 Ordering Process*

Once customer businesses establish a contractual agreement, customers can request sale orders to be approved within 72 hours. For a sales order to be approved, it should be reasonably possible to produce the proposed quantity shortly before the suggested date. Contractually, the company must be able to produce between 90-110% of the desired order amount for the demand to be considered met. Sales orders are final and should not be amended before production.

The ordering process of final sales order is instigated by the customer specifying the amount of a product to be delivered for a chosen week. Later, this request is reviewed internally to decide whether the company is able to deliver the requested demand on time by checking capacity and materials requirements. Subsequently, after sales gives feedback on the quantity and timeframe, with an intent of making an agreement with the customer. Finally, where possible, an agreement is reached and any purchase orders which should be made are completed and the customer is notified.

Increasing global lead times, however, have put a strain on which orders the company is able to accept or decline. With lead time durations having been extended, the time necessary between ordering and receiving input materials readily exceeds the eight weeks prior to production that customers can place an order, the company ask brands to indicate future demand for each product. Receiving ADI from customers allows not only pre-emptive figures on sales over a horizon, but also increases the ability to accept sales order requests.

Providing ADI is not common practice in the industry sector, therefore to encourage participation, any ADI is non-binding. The non-binding nature of ADI offers uncertainty to supply chain planners who must base their raw materials orders from it. Considering an acclaimed 80% of procurement is based on ADI, its accuracy is considered to be extremely important.

The company has limited input into customer ADI, and currently accepts what the customer states to be the prospective order amount. In the case a customer's ADI is believed to be largely deviant from the actual order amount, the company will request a feedback meeting to constructively give input to strive for more accurate information. Similar to the acceptability of delivered sales orders, the company consider ADI to be accurate if realised demand is between 90-110% of the forecasted amount.

### 1.2.2 Lead Time

Procurement processes enable the acquisition of raw material required for complete production of a given order. Such processes are not only dependent on external lead times, but also internal lead times. External lead times are defined as the quantity of time needed from the point of agreement with supplier until the fulfilment of the agreement. Internal lead time is the time necessary from the point that all materials for production are present, until the delivery of the finished goods to the customer. Internal lead time begins directly after the external lead time finishes. An example of such a processes are depicted in Figure 1.

Figure 1 shows that procuring each raw material for manufacturing takes much forethought and planning. Different ingredients such as chocolate or sunflower oil, shown in the various examples, require more preparation particularly if their external lead time is longer. Accurate predictions of demand well in advance of the sales order date are imperative, due to how in cases of long external lead time durations, it is the only piece of information available.

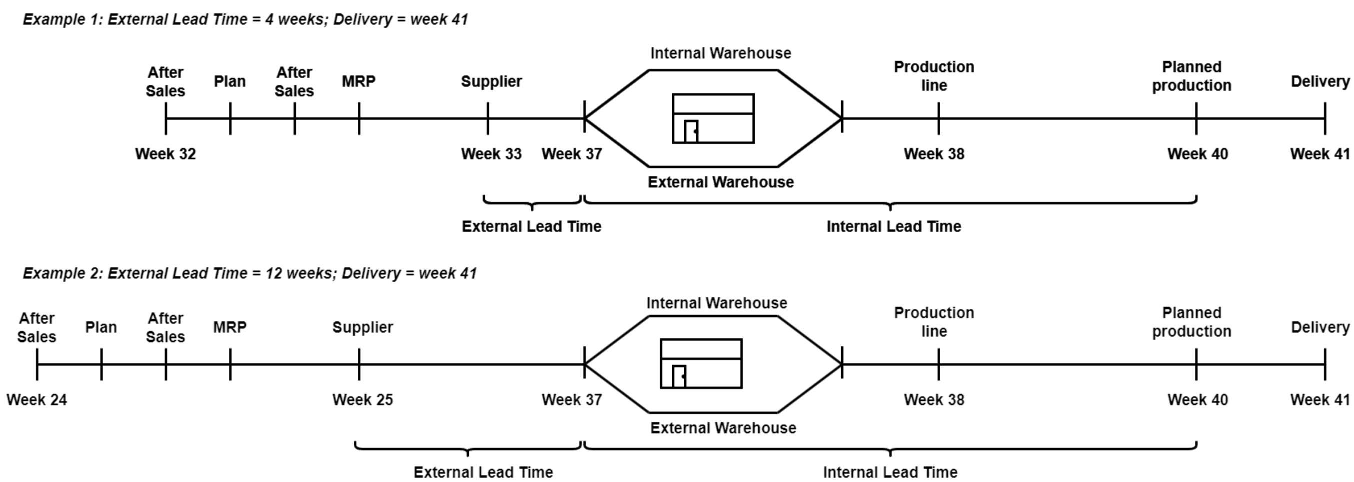


*Figure 1: Impact of External Lead Time Duration*

### 1.2.3 Inventory

The company has on-site and off-site storage capabilities. Their on-site facility is fully utilised with ingredients, packaging and finished products. As it is a smaller warehouse, ingredients and packaging from the larger, off-site storage facility are moved according to the upcoming production schedule. Additionally, the company endeavours to ensure that all of its products, which are stored in the on-site facility directly after production, are picked up by the customer within three days. For certain customers, they aim for a just in time (JIT) delivery due to the restricted space when large orders are produced. The company does not stock finished products in advance, as they work based on a make-to-order (MTO) strategy. The decision to produce on a MTO strategy is motivated by a standardised agreement with every customer that the product will be no more than two weeks post production at the time of arranged pickup. A short window for pickup not only reduces the amount of finished product on hand, thus reducing storage costs, but also limits food waste by forwarding on perishable food products.

Currently, however, the company have an unstructured method for keeping safety stocks of raw materials. Material requirements planning (MRP) planners operate to ensure they order enough stock such that the number of sales orders correctly forecast and satisfied fall within their targets. A continuous review inventory system makes sure that before stock is diminished, enough stock is replenished to at least satisfy the next upcoming production runs. As such, if the realised order is much more than forecasted, the company run the risk of not having enough raw materials on hand to promptly satisfy demand. With various customers experiencing a surge in demand for certain products, the company is also looking to implement safety stock of raw materials, but lack sufficient information on upcoming demand to ensure that they are able to provide these goods according to their target service level.

Note that orders to suppliers may also be subject to minimum order quantity (MOQ) constraints where the minimum amount that can be ordered from the supplier supersedes the amount deemed necessary. In such a case, which is typical for cans of aromas, the company order the minimum amount.

#### *1.2.4 Planning and Production*

Planning is the necessary step before production which sets a schedule for what will be produced in the upcoming week. Production is divided among seven production lines, each with the ability to produce various different types of bars. In weekly production planning review meetings, the production plan for the upcoming fortnight is discussed to determine any immediate steps that should be taken to ensure uninterrupted production.

An uninterrupted production, which cannot always be assured, has the aim of reducing the amount of downtime for any line. Downtime is considered wasted time, where no revenue can be generated as no bars are being produced. As such, the company reduce the number of changeovers between bars. Changeovers, which account for roughly 20% of production time, describe the process of cleaning, setting up the line itself and preparing input materials and kits for the upcoming production run.

Reducing the number of changeovers, and thus reducing the number of production runs of any bar in a given time period, has the undesired knock-on effect of demand intermittency due to how the company deal with placed orders. Typically, large orders are placed, followed by smaller top-up orders which ultimately get bundled together as one order come production to effectively induce an intermittent demand pattern. An intermittent demand pattern, however, makes it difficult to apply classical forecasting and measurement techniques to analyse and leverage demand data. To counter this effect, longer review periods can be taken, or alternative forecasting and measurement techniques can be applied. Alternate forecasting methods include an adapted version of exponential smoothing, machine learning and deep learning.

In lessening the impact of intermittent demand, the company uses larger periods (months instead of weeks) to forecast and plan. In addition, the company places greater importance with category A customers, who tend to order more consistently and at larger levels in comparison to either category B or C customers. Customer categories are sporadically reassigned according to a customer's size and growth potential.

### *1.3 Inhibiting Problems*

Prior to the global pandemic, difference between expected and realised demand was made up for with short lead time durations. At this moment in time, similar response times are not possible. In the wake of COVID-19, global supplies dwindled and lead time durations have lengthened due to production being scaled down. For producers, this has had various ramifications. The company, for instance, have noticed a consequential decrease in service level.

As such, an encouragement for customers to give an indication of demand in advance, months prior to sales orders being placed is made, to better prepare for incoming sales orders. In practice, volatile deviations between ADI and actual order quantities per company are observed. Amplified volatility is also observed at a product level. Inaccuracy between indicated order amounts and actual order amounts, however, make it hard to optimise the relationship between service, quality and cost.

Subsequently, form the above, 3 key areas of interest emerge: forecasting, customer agreements, and external events.

*1.3.1 Forecasting using ADI*

Customers sign long-term contracts where they are encouraged to provide ADI two to six months in advance. Consequently, the company uses this ADI as the single indicator to forecast order sizes customers will request for a given month. Pre-emptive information on demand, however, is often said to be imperfect - especially for newly introduced products and growing customers. As evidenced by discussions with employees of the company, it is said that customer companies are inexperienced in providing ADI to producers. Understandably, as giving advanced information on demand in the industry sector has not been common practice, effort has been put into communicating the mutual benefits created by accurately forecasting demand. Adding further incentive to produce timely indications, the company does not yet bind companies in any degree to ADI. As this could result in ill-thought and thus inaccurate forecasts, the company reserve the right to reject sales orders that they are unable to fulfil.

To add to the matter, further volatility is witnessed with order quantities per product – the actual driver for supply chains. Differences in forecasted and actual demand for individual products mean that unique, unaggregated input materials such as packaging have an exaggerated over or under demand. This causes an issue, especially considering that the lead times for items of packaging reach as high as seven months in extreme cases in the current market. Naturally, unless the customer is placing orders over seven months in advance in such a case, there will be issues in fulfilling this demand on time. For most items, however, ADI in principle bridges the gap between longer lead times and accurately predicting demand.

An interview with an MRP planner reiterated and expanded the issue to say that roughly 80% of raw material orders were based off customer ADI. Understandably with extended lead time durations, MRP planners are having to base almost all procurement from the pre-emptive information on demand they have been given. As such, the company encourage customers to update ADI as the day of the sales order draws nearer, with an aim of greater accuracy. Not all customers, however, comply with providing a revised forecast closer to placing a sales order. An example of the updating procedure is shown in Figure 2.


*Figure 2: ADI Updating*

Although in the foreseeable future lead times are likely set to reduce and stabilise once more, consequently lessening the company's dependency on ADI, the current state of affairs exemplify how a certain robustness should be built into the system. Although during pre-pandemic times the difference in forecasted demand and actual demand was opposed by short lead time durations, it should not suggest that lessons should not be taken.

*1.3.2 Customer Agreements*

Customers each have different contractual agreements which can include price, pick-up arrangements, and storage of packaging to name a few. Understandably, there is no one-size-fits-all model for an arrangement, especially for an international company producing tailor-made items of food. Additionally, as the company is a very service-oriented business, it is important that each of the agreements is upheld to the best of its ability. An approach biased towards being very customer-focused, however, makes it difficult to standardise and streamline processes.

An example of this can be found in ADI provided by customers. As mentioned earlier, external events have exacerbated the issue of variability in demand. Therefore, customers have recently been asked to provide a non-binding forecast in order to better combat such variations. Due to the non-binding nature of the forecast, companies are not held accountable for any deviations in order sizes between their indicated and actual demand. From the perspective of the customer, the performance of the company is judged based on the ability to fulfil sales orders. Given that large differences of indicated and realised demand can readily be in excess of 50%, the perception of performance consequently declines.

### *1.3.3 External Events*

Social, ecological, or environmental disasters are a few reasons why the supply of inputs to the company's production processes may be interrupted. Shipping container misalignment, a misfortunate soy harvest, and COVID-19 are such examples. These types of events are often hard to foresee, meaning there is little companies can do to prevent risk associated with unmet demand, other than through stockpiling and taking position in the market. The former is difficult when inventory, such as ingredients, are perishable.

If the company, however, become aware that such external events are having or will have an impact on the market, measures which negate any negative impacts can be put in place. Alleviating the impact of external events would be limited if there was a lack of understanding as to what demand could foreseeably be in the upcoming horizon. Using a more suitable method to estimate future demand can help the company account for future orders more accurately to put appropriate measures in place to handle demand although external events would have been set to interrupt business.

### *1.3.4 Issues in Summary*

Evidently, the company is facing challenges in being able to meet demand according to the high standards internally set. Although the company is evolving its strategies which include altering customer agreements and taking positions in the market for key ingredients, little has been done to take care of the driver of most of the processes – the forecast. Defining a new way to forecast demand could have direct positive implications for both supplier and customer in that more demand will be able to be met on time – without imposing any new agreements with the customer, or not taking too deep of a position in the market ending in costly consequences.

### *1.3.5 Problem Cluster and Core Problem*

According to the themes above, a problem cluster can be constructed to visualise the nexus of problems (Figure 3). Noticeably, there seems to be a cascade where core problems contribute to the effect that the company are feeling, be it a reduced service level, high storage costs or high obsolescence. Heerkens & Van Winden (2017) suggest that an optimal issue to tackle should be one which is fundamental and influenceable – and that if any problems are remaining the most important should be chosen.

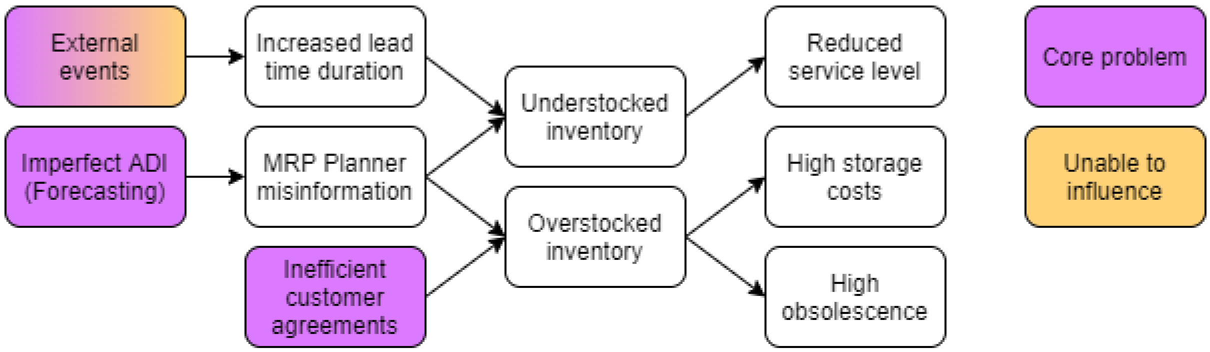


*Figure 3: Problem Cluster*

As such, leftover problem veins contain imperfect ADI and inefficient contract agreements. After a high-level cost-benefit analysis, an investigation into contract agreements seems futile. Often when dealing with contracts in a given industry, there are tenets that the industry readily promotes. Tenets such as the customer owning the packaging of a product yet to be produced are not uncommon in the industry sector, despite being seemingly inefficient. Additionally, understanding a customer's needs is an intricate task, especially when interacting with international businesses. These difficulties make it challenging to implement a solution in a novel way. Accordingly, forecasting using imperfect ADI was chosen as the problem best suited to tackle. The goal of this research, therefore, is to determine an improved way to forecast demand which results in less error than if they company were to continue using ADI as a forecast.

### *1.4 Research*

The following sub-sections lay out the steps and procedures undertaken in the research, namely in its approach, design and outcomes listed as deliverables.

#### *1.4.1 Problem Approach*

In order to best tackle any problem, it is important to gather detailed knowledge about the issue at hand. In this context, the company have dashboards that are set up to visually understand the data and various informed employees to whom questions can be referred to. In addition to secondary sources of information, access to the enterprise resource planning (ERP) system allows observation of primary data. Doing so would not only allow multiple perspectives on the issue, but also aid in data interpretation and signposting which information is available to leverage as part of a solution.

Using these resources, information indicating demand type will be gathered in order to procure a suitable method to forecast product demand. Therefore, this investigation sets out to understand the characteristics of customer demand by answering the following questions:

1. To what extent does advanced information on demand deviate from realised demand?

An initial high-level analysis to determine the current inaccuracy of ADI – the company's forecasting method of choice – will be conducted to visualise and consider patterns in its quality. As such, histograms comparing deviations in accuracy and the corresponding frequency of occurrence will be judged. This will help determine if there is a general pattern to either over or under forecast.

Currently, however, the company is experiencing timing errors in its data. The error occurs when a company delays an order marginally into the subsequent or antecedent period, or if order data is misaligned. Calculating an error between realised and forecasted demand, therefore, can induce large deviations which are not representative of reality. Thus, to answer questions on the performance of ADI as a forecast, the timing error will also be corrected.

2. Does advanced information on demand improve as a product matures?

The company is curious whether newly introduced bars show large variations between forecasted and realised demand. If present, early differences between forecasted and realised demand, for example, can offset accuracy. To judge the hypothesis that customer ADI improves as the bar matures, a regression between the maturity of a bar and its forecast accuracy will be conducted to determine if there is any relationship between the two. This insight will also serve as important when judging the applicability and suitability of the proposed method, which combines ADI and time series forecasting methods.

3. Are there improved ways in which demand can be forecasted?

After the analysis into ADI, an analysis of trend and seasonality of demand will be conducted in line with insights generated from the literature review to ensure that the methods presented are suitable to forecast the type of demand present. An investigation into the two factors is important as forecasts are generated using a time series method. If the algorithm fails to properly account for seasonal demand variation, or general demand growth trends for a product, then the forecast method is rendered unsuitable.

Subsequently, another forecasting method will be developed and investigated such that ADI will be considered congruently to time series forecasting methods with the goal of increased accuracy. Once all forecasting methods have been considered, each will be compared and contrasted using the empirical data provided by the company to determine their usefulness. Usefulness of a forecasting method will be determined to be the technique rendering the least error in its prediction. Accordingly, the error of each forecasting method will be determined, and consequently each of the methods are compared. An overview of the research procedure can be found in Appendix 1.

### *1.4.2 Research Design*

Research into the project takes a combination of various methods. Initially, to understand the issues in greater depth, interviews with company experts were held. Conducted in person for greater effect - questions about origins, perception of the problem and other related matters were discussed. Furthermore, as the company have been gathering a wealth of information, observation of trends in dashboards are also a useful tool in the exploratory phase of research. Data for use in this research has already been established, but was in need of arranging into a usable document for analysis. Variables such as forecast amounts, realised quantities, time period, and customer names have already been established as points of data over recent years, and have been directly exported from an enterprise resource planning system. Analysing information and trends from self-made research are also conducted to explore and understand which methods are appropriate to use later on in the research.

Insights gained from these discussions and analyses are used to guide research into the literature surrounding the topics highlighted. Relevant literature will be considered in the scope of the project, and where pertinent, forwarded to supervisors of the project to hear their feedback in a session of co-reflection in order to gain valuable insights and direction.

### *1.4.3 Deliverables*

The main outputs of this research can be categorised threefold. First, a summary of demand characteristics will be established. This summary will be comprised of answers regarding the magnitude of forecasting deviations, whether forecast accuracy develops the longer the bar is being produced, and whether there is a trend or seasonality in demand. Subsequent results will set the ground for suitable forecasting methods.

Additionally, an inquest into whether ADI accuracy improves with time-gone-by since initial bar production is conducted, adding further context to ADI and if it matures. Lastly, a revised forecasting method, which includes ADI alongside historical forecasting techniques, will be developed and tried. These forecast methods will be presented, along with results on their accuracy based off real-life data. A conclusion and recommendation to the company follow, depicting the results from a comparison between the methods.

Subsequently, chapter 2 on context analysis is dedicated to understanding the company and how it operates – necessary in order to find a suitable solution. Thereafter, chapter 3 is a literature review that was conducted to investigate applicable forecasting methods, demand categorisations, and forecast accuracy measures necessary to build towards a solution. Next, chapter 4 outlines the methodology used to reach the results, including a novel method which uses ADI and historical forecasts in synchrony, with the aim of achieving a forecast of greater accuracy. The subsequent results will then be reported and evaluated in chapter 5 before conclusions and recommendations are finally presented in chapter 6.

# 2. Current Situation

This section sets out to describe the current state of the system, firstly by describing how the data is collected, along with any case-specific nuances. Further, data explaining demand patterns will be examined to see which types of demand are present in the study. For each demand type instance investigated, its corresponding ADI will be explored to gain an impression about the performance of ADI in predicting demand. Lastly, the section is concluded with a general overview of ADI performance for each of the bars included within this segment of the research.

## *2.1 Data*

For data to be used effectively, it must be collected and sorted properly. Additionally, understanding the nuances in the data which could cause improper readings help to ensure they do not cloud the value of information gained from research.

### *2.1.1 Data Collection*

Despite demand data for the company being available as far back as 2018, matching forecast data has only been available since the second month of 2021. To judge forecast accuracy, therefore, only data from the second month of 2021 onward is appropriate to use. Furthermore, for a more meaningful impression, only bars from category A customers are considered. Not only is this choice beneficial due to how ADI is more regularly associated with orders from larger customers, but it accounts for a large portion of overall demand from the most important customers.

As the ERP system continuously handles data, snapshots in time must be taken to gain a static impression of the data. Snapshots of data from the ERP system, therefore, are directly saved in a worksheet on a consistent basis. Such snapshots of primary data contain all available information of demand for that calendar year, combined with any values of ADI customers haven given. An example of how information of an order can evolve with time is shown in Figure 4.

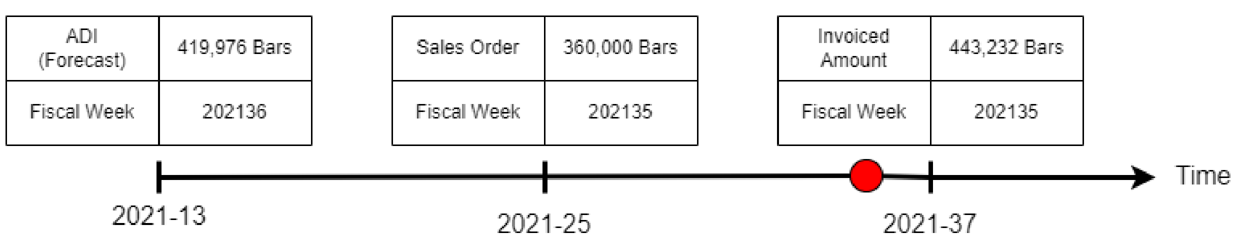


*Figure 4: Timeline of Information Across an Order*

Depicted are three separate snapshots of an order from a large customer, namely from fiscal weeks 2021-13, 2021-25, and 2021-37. In each snapshot, in this case twelve weeks apart, show how the status of an order develops over time. Initially, the system stores demand that the customer has indicated for a certain fiscal week. As mentioned earlier, this indication is considered as the forecast. Later, once the sales order has come in, its quantity replaces the forecast. Lastly, once the product has been produced (indicated by the red dot) and delivered, the units produced are invoiced to the customer. Accordingly, forecast accuracy is measured using the relationship between the forecasted and invoiced amounts.

Noticeably, the sales order is much smaller than the ADI or invoiced amount. This can be attributed to how in practice there tends to be a large order topped up with smaller orders, which are later conglomerated into the final order size eight weeks before production.

Forecasting and sales order data are manually entered, following email communication. Data for the number of invoiced units are manually entered based on the quantity produced.

Note that although data is observed and consequently stored in terms of fiscal weeks, each data point is later converted into months. This conversion aids the processing of information during the research, and is also suitable as planning for demand is possible at a monthly level.

#### *2.1.2 Timing Error*

Notice how in Figure 4, the fiscal week from the first data point differs to those in the second and third. Although a difference of a single week, this error is vastly misleading when judging the accuracy of ADI provided. Such an error is not uncommon within the set of data provided. Its cause seemingly relates to how financial and planning calendar misalignment, meaning that even if an order was on time and matched to the correct fiscal week it could be incorrectly uncorrelated. Due to this error, it is hard to suggest how much of the information is distorted, and how much is due to customers opting to order for a later point in time. Additionally, not all data points are affected, so a simple solution of shifting the weeks could not be done. In any case, as deemed necessary, the timing of orders is tackled later in the research (See section 4.3).

#### *2.1.3 Data Handling*

Unique identifier combinations for a given demand or forecast can be generated using prospective order time, product identification, and status of a given bar. Snapshots in time of such a combination can be aligned in sequence to observe demand and the development of ADI (Appendices 2-3).

Demand for a given order was found by finding the maximum value across the snapshots of data. Using the maximum number found in the snapshot ensured that the true value of the number of units invoiced was retrieved. Unlike demand, ADI for the number of invoiced units can change over time. ADI for a given unique combination was found by using the most recent value across the snapshots of data. This would ensure that the correct number of units indicated by the customer was chosen. If there were no ADI present in any of the snapshots, the formula returns “NF” denoting no ADI was given. Each of the results were condensed into a table, giving the most recent ADI and invoiced demand for each product in a given week.

### *2.2 Demand Types*

As previously discussed, different demand types require to be handled in alternate ways. Accordingly, patterns of demand can be classified according to variation in quantity and frequencies of orders. Likely, not all demand a company would deal with will pertain to one of the demand pattern classifications. The system in place to deal with demand, therefore, should cater to optimally meeting the required quantities at the correct moments in time.

Using a categorisation method later presented in Section 3.1, demand can be classified into four categories, depending on the variation in quantity and frequency of orders. Using this categorisation method, demand is categorised as being erratic, smooth, lumpy or intermittent A large proportion of the demand studied is classified as either lumpy or intermittent, as shown in Table 1. This would indicate that demand is sporadic with multiple periods of zero demand. The finding has direct implications into which forecasting methods are useful, and which methods should best be used to judge the accuracy of these forecasts.

| *Demand Pattern* | *# Products* | *Percentage* |
|---|---|---|
| Erratic | 2 | 1.1% |
| Smooth | 9 | 5.1% |
| Lumpy | 19 | 10.7% |
| Intermittent | 148 | 83.1% |

*Table 1: Investigation into Demand Patterns*

Notably, each of the demand types are present in the dataset, each showing remarkably different patterns between them. In giving an indication about the patterns each of the types of demand represent, Figure 5 takes examples of every demand category from the dataset.

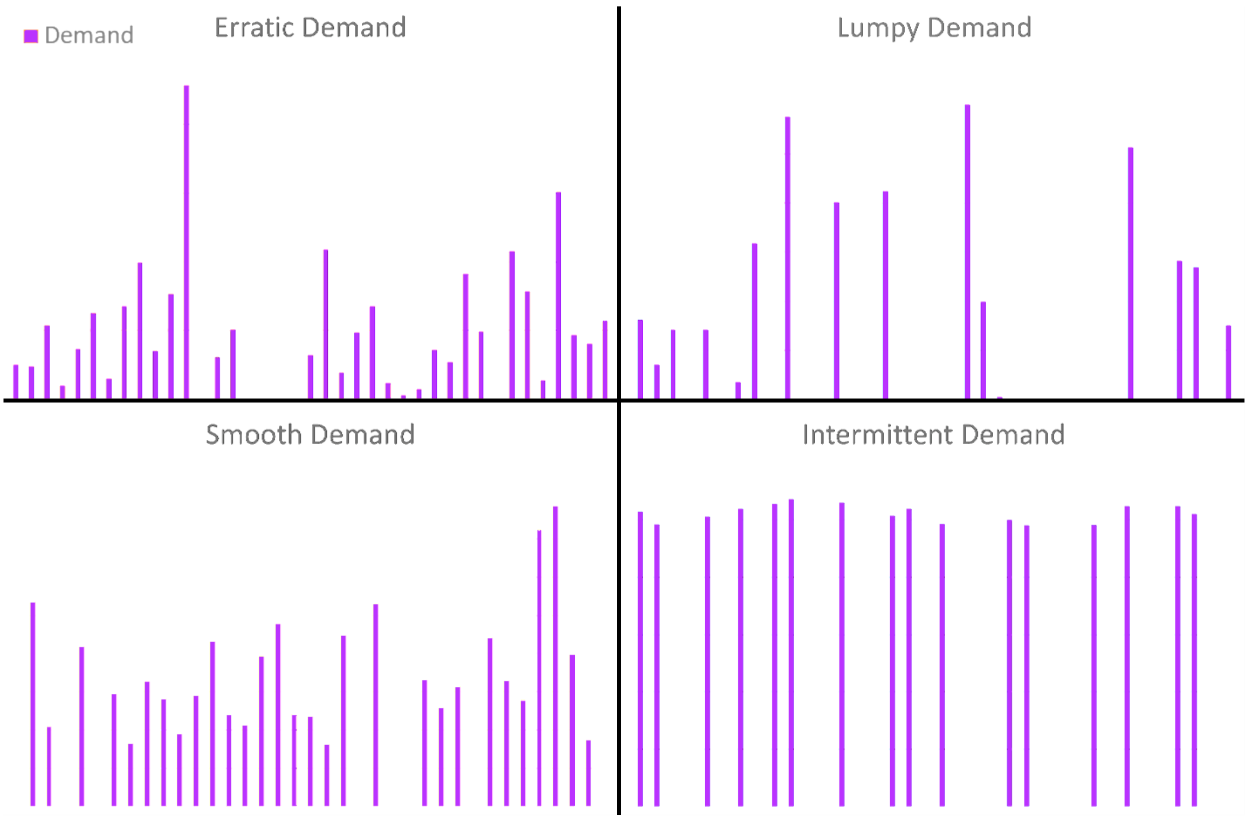


*Figure 5: Demand Patterns within Data*

Each bar represents demand that was realised in a given month, and its height gives a relative idea of how demand for the same product compares over multiple months. Patterns to the left both exhibit more months of demand, and demand plots on the top show a more varied quantity of demand. Understandably, more varied quantities of demand can attribute lessened confidence about the magnitude of a given order, and infrequency can lead to not knowing if and when an order will be placed.

### *2.3 Advanced Demand Information (ADI)*

As a solution for determining future demand, the company have implemented ADI as a forecast so the companies can pre-emptively give information about their demand so that they can best prepare. Therefore, especially for lumpy demand patterns, an impression of future demand would in principle aid the satisfaction of both supplier and customer as demand can more readily be met.

Gong as far back as the second month of 2021, a limited subset of data on customer ADI can be presented alongside realised demand for the corresponding month to gain an impression of accuracy (Figure 6). Each of the examples of demand patterns from earlier are used for the respective months where data on ADI is available.

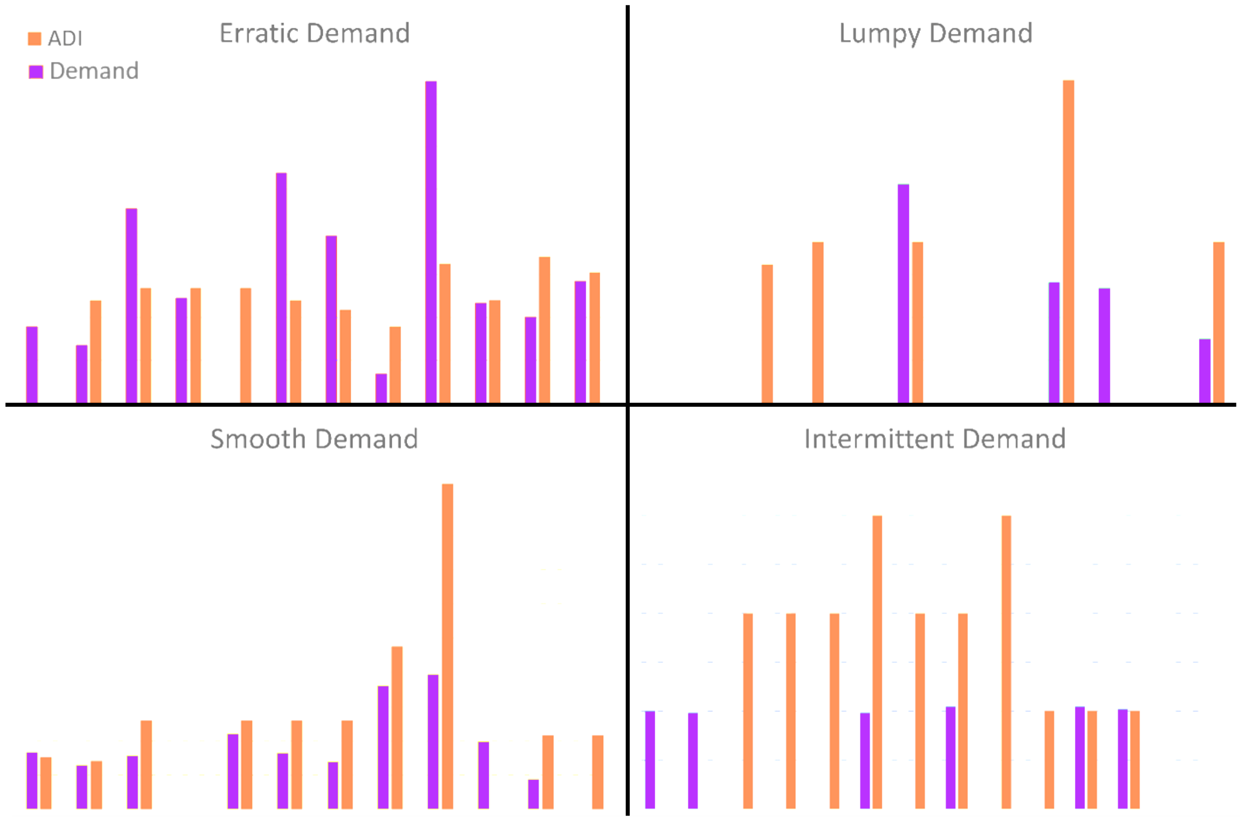


*Figure 6: ADI Predicting Demand Patterns*

Evidently, there are cases in which demand is predicted well by ADI, but also months where ADI was not a good indicator of demand. Interestingly, not all ADI match the demand pattern they are predicting. Looking at demand that is categorised as smooth, a large increase in demand was predicted while the realised demand proved to be responsible for less than half of the anticipated amount. Conversely, demand that is considered erratic provides ADI that seems to be more smooth. Additionally, in each of the plots there are months where demand has been anticipated and no sales orders have materialised, and vice versa.

The plots above, however, only represent a small subsection of the total data for each of the 178 different bars applicable to this study, which collectively make up circa 35-40% of all demand. Therefore, to better gauge how well ADI predicts demand, a more comprehensive overview with all of the bars studied is created.

### *2.4 ADI Accuracy*

The data for all eligible bars can be visualised using a histogram, where the $x$-axis represents the error in ADI from actual demand and the $y$-axis notes the frequency that the variation occurs, to determine if there are any patterns in the data distribution. Gaining a comprehensive picture of deviation, however, requires not only an analysis into differences, but also how large those deviations are from the original amount. As such, Figure 7 depicts quantity errors in forecasting, and Figures 8 shows the forecasting percentage error.

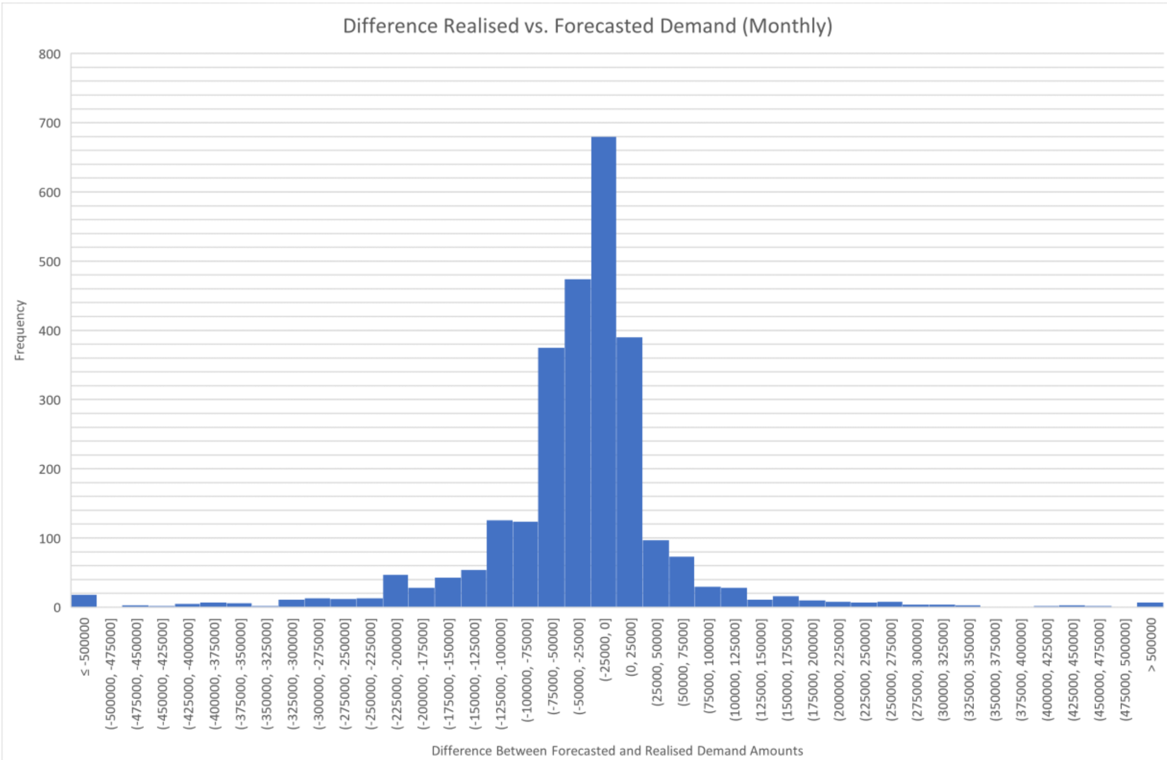


*Figure 7: Unadjusted Forecasting Deviation Error*

Figure 7 displays the distribution of 1,852 points of demand error data if an error of zero is removed. Data points with no error are removed due to how it in all but a few cases represents a month where there was both no demand or sale. When considering the accuracy of forecasts, data which displays complete accuracy when there has been no forecast and no demand placed in a very lumpy and intermittent environment is misleading. Additionally, when production runs consist of producing a large quantity of units, the exact number units produced matching the number of units ordered is rare. The company expect that when producing the bars there will be an over or under production due to factoring in waste and efficiency, where between 90% and 110% of the ordered amount can be produced and invoiced to the customer.

Noticeably, there seems to be a distribution that closely resembles a bell curve with a slight skew to the left. Having the graph skewed slightly to the left would suggest that ADI often over-forecasts the order amount placed by the customer. Another point of interest are the relatively large extrema, which show the count of the number of ADI instances that differ from demand by +/- 500,000 units or greater. Considering that the mean order sizes of the bars studied is about 120,000 units, such large deviations should be thought as anomalous. In general, a distribution that exhibits a bell curve is to be expected, however, to get a better picture on how ADI is currently performing, percentage error of ADI should be examined.

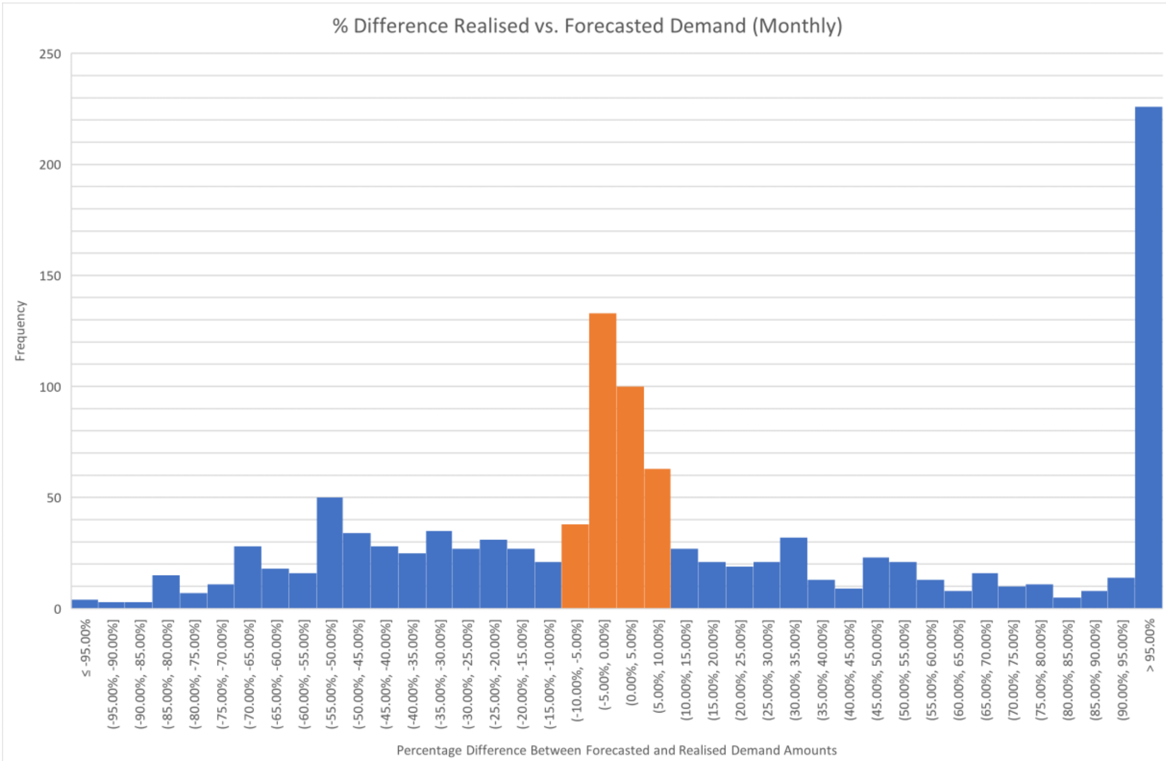


*Figure 8: Unadjusted Forecasting Deviation Percentage Error*

Similar to how no ADI from customers led to an error in the previous graph, errors of -100% were removed due to not being representative of reality. Additionally, the number of observations between the two graphs differ, with the former exhibiting more data points. This is because if there was no forecast or demand, the quotient calculating the percentage difference would have a division by zero error. The central orange segment, depicting the acceptable order deviation can also be explained by a difference in the number of units produced.

Comparing the two graphs a completely different shape is witnessed. The peak in the previous graph is now shadowed by the number of orders that are at least 95% larger than ADI suggested. Catering for demand that is at least 95% larger than expected is a difficult task to manage, which unless surplus stock is carried is also hard to fulfil.

Observing the two graphs in combination, it is highly likely that these deviations in demand come from smaller orders, which would seemingly be easier to handle, as opposed to larger orders. Additionally, when comparing the graphs once more, the latter exhibits a much larger spread of deviation and if the rightmost bar is ignored, a slight skew to the left suggesting over forecasting can once more be argued.

### *2.4.1 Company-specific ADI Accuracy*

Naturally, as different companies set out to provide ADI, its accuracy can be expected to vary depending on which company is providing it. Inherently, this brings up another issue in taking ADI directly as a forecast without considering the specific that the ADI is originating from. Some companies that offer a high accuracy in ADI would be considered more reliable and more trust should be attributed to the figures presented to the company. Companies that are less accurate, however, have the potential to stain the reputation of using ADI as a forecasting indicator for the collective of customers representing the customers of the company.

Therefore, in order to judge and compare, a method later introduced in Section 3.7 sets out to measure the error in using a given forecasting method to predict demand. The average error per bar is collected, along with the average number of bars ordered. Thereafter, the quotient of average error per bar and average order amounts is determined for each customer to give an impression of the relative magnitude of error associated with the ADI provided (Table 2).

| Company | ADI Accuracy Factor |
|---|---|
| 023 | 2.087 |
| 024 | 2.217 |
| 025 | 3.505 |
| 038 | 3.291 |
| 052 | 0.756 |
| 063 | 7.042 |
| 073 | 0.907 |
| 103 | 5.673 |
| 107 | 0.613 |
| 141 | 0.745 |
| 188 | 1.919 |
| 335 | 0.574 |
| 351 | 2.944 |

*Table 2: Company ADI Accuracy Factor*

Notably, if ADI was observed to be of similar quality between each of the customers, values for the ADI accuracy factor would be expected to all be around the same value. As the values mentioned Table 2, however, are generated using a quotient it is evident that the values are quite well spread. The wide range of accuracy factor values for ADI indicate that companies offer hugely varied accuracies when providing demand information to the company.

### *2.5 Context Analysis Summary*

First by exploring the available data, Section 2 has outlined the ways in which demand, and its correlated accuracy can be measured and generated. Although a timing error is present, this will later be solved in the research. Additionally, various demand types including lumpy, intermittent, smooth and erratic have been found within the empirical data provided by the company. Each with its specific characteristics have an impact on how it is handled later on in the study.

Plotting the demand data revealed that ADI seems to be an inefficient predictor of demand. Its incapability to effectively determine demand firstly seemed to be how ADI did not seem to reflect the certain demand type of the product. Furthermore when the demand accuracy is observed for a wide range of products, there seems to be a relatively large difference between forecasted and realised demand amounts. In turn, the source of the accuracy was brought into question, and accordingly an investigation into the accuracy of ADI provided by specific companies was conducted which revealed a large difference in proficiency for providing accurate ADI.

As such, the findings motivate an inquest into alternate methods to predict demand for the wide benefit of the company. Understanding the accuracy of ADI compared to other existing methods and the extension developed later on in this work is later understood, with an intent of improving demand estimates.

## 3. Literature Review

Evidently, ADI has proved to show inaccuracies when forecasting demand, and so an investigation into alternative methods is due. Another technique for predicting future demand should be suitable for use with lumpy and intermittent demand, as it is evident that the demand patterns presented predominantly tend to either one or the other.

As such, an investigation into the available core topics is presented first by the introduction of a method used to smooth the data to rid the aforementioned misalignment. Next, ADI and its benefits are discussed before looking into alternate ways to forecast demand using time series forecasting methods. Finally, the method used to eventually evaluate the accuracy of each is described along with its benefits over other more conventional metrics.

### *3.1 Data Misalignment*

Data that is misaligned makes the task of managing data with the aim of extracting information of quality more difficult. During a time where data wealth is gaining greater importance, collecting data correctly and effectively should be a priority. Although considered harmless (Kerkkänen et al., 2009), data with a misalignment in time can cause issues especially as due to the amount of data typically collected by companies.

Accordingly, to tackle an essentially similar issue of timing errors Kerkkänen et al. (2009) mention a time-smoothing method which works to find the most appropriate enumeration of a forecasted value – in this case ADI.

$$E_A = (S_n + S_{n+1}) - (F_{n-1} + F_n) \qquad (1)$$

$$E_B = (S_{n-1} + S_n) - (F_n + F_{n+1}) \qquad (2)$$

$$E_C = S_n - F_n \qquad (3)$$

$$|SE| = min\{|E_A|, |E_B|, |E_C|\} \qquad (4)$$

Where $F_n$ represents the forecast for period $n$; $S_n$ represents the demand for period $n$; $E$ represents the forecast error for period $n$; and $SE$ represents the smoothed forecast error for period $n$. Equation 1 presents a smaller error if sales lag behind forecasts by one period, equation 2 presents a smaller error if forecasts leg behind sales by one period, and equation 3 gives the error without any lag. The minimum absolute error between all the methods is then considered the smoothed absolute forecast error for the given period (Equation 4). These equations can also be converted to percentage difference errors in order to gain an understanding of the ratio of the error (Equation 5).

$$\frac{demand - forecast}{forecast} \qquad (5)$$

### *3.2 Advanced Demand Information (ADI)*

In many business-to-business settings, judgemental forecasts are preferred to historical forecasting methods due to the highly volatile and non-stationary nature of demand (Tan, 2008). Accordingly, ADI is a judgemental forecasting method which enables a collaborative way of generating demand forecasts through communication. In theory, ADI looks to be able to counteract a seeming randomness in data patterns, with the intention of reducing the risk of unmet orders (Tan, 2008). In addition, ADI has two subsets; perfect and imperfect ADI. The former refers to how realised order amounts do not deviate from the ADI provided, while the latter suggests that the demand is not required to exactly equal the indication (Tan, 2008).

Its widespread applicability, however, cannot be guaranteed. The accuracy of ADI is enabled by a business-to-business environment in which customers have an advanced idea about their requirements as it should align with other related business processes (Tan, 2008).

### *3.3 Intermittent and Lumpy Demand Forecasting*

Various techniques have been developed to forecast intermittent or lumpy time series data. More traditional methods include Holt-Winter and Croston exponential smoothing, both of which statistically weight more recent historical observations with more importance according to a given smoothing constant, without disregarding past observations. Croston's method in particular has widely been used for forecasting intermittent demand series, but it is not without its critics, despite superior performance in prior empirical studies (Syntetos & Boylan, 2001; Kiefer et al., 2021).

More recently, however, new techniques to forecast intermittent and lumpy demand have attempted to gain prevalence. Namely, these can be categorised as machine learning and deep learning methods, including Random Forest, Auto-Support Vector Regression (SVR), and Long Short Term Memory (LSTM). To understand the relative performance of each, Kiefer et al. (2021) compared nine forecasting methods for intermittent and lumpy demand. Results suggested that for each test on different types of dataset, Croston's statistical method consistently and considerably outperformed other techniques.

Importantly, although understanding which method should be preferred when forecasting intermittent or lumpy demand series, knowing when to apply such methods is equally important. Prior studies worked with particular empirical cases to arbitrarily determine boundaries which defined different types of demand (Syntetos et al., 2005). Recognising this, Syntetos et al. (2005) worked towards definitive and universal boundaries to describe patterns of demand according to the accuracy of Croston and the associated Syntetos-Boylan Approximation method (Figure 9).

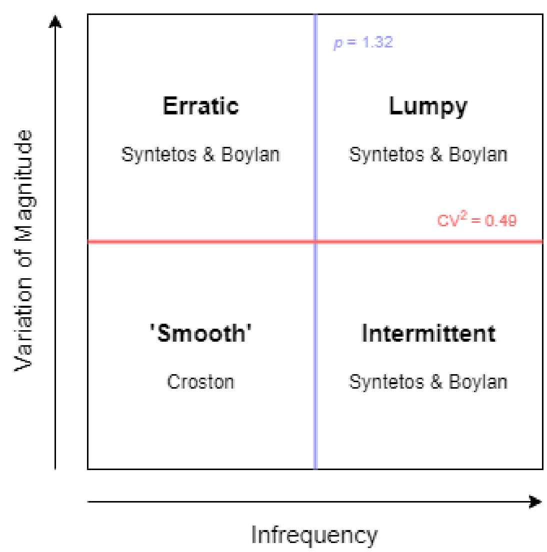


*Figure 9: Demand Pattern Matrix (Syntetos et al., 2005)*

To quantify variation of magnitude in demand, the squared coefficient of variation is calculated by considering the quotient of standard deviation and mean of a population (Equation 6). Infrequency in demand is determined using periodicity of demand, namely by dividing the total number of observations by the number of non-zero demand instances (Equation 7).

$$CV^2 = \left(\frac{\sigma}{\mu}\right)^2 \qquad (6)$$

$$p = \frac{number\ of\ observations}{number\ of\ demand\ instances} \qquad (7)$$

The exact points in which the boundaries between the different types of demand were established by comparing the instances in which mean squared error (MSE) mathematically suggested one forecasting measure to be more accurate than the other. Namely, SBA is said to be a more accurate estimator of future demand than Croston's method if either $CV^2 > 0.49$ or $p > 1.32$.

### *3.4 Croston's Method*

Having noticed deficiencies in exponential smoothing forecast methods as surplus stock due to intermittent demand patterns, Croston devised an improved technique. Croston's technique can be split into two components, namely demand size and inter-demand interval. The size of demand is assumed to be independently distributed with a normal distribution $N(\mu, \sigma^2)$ (Croston, 1972). Additionally, the arrival of demand is generated by a Bernoulli process, where the probability of arrival is $1/p$ (Croston, 1972). Expected inter-demand interval time, therefore, is geometrically distributed with mean $p$ (Syntentos & Boylan, 2005). The resulting quotient of estimated demand size and inter-demand interval serves as the forecast, $Y'_t$.

$p'_t =$ the exponentially smoothed inter-demand interval, updated only if demand occurs in period $t$
$\quad = p'_{t-1} + \alpha(p_t - p'_t)$ and
$z'_t =$ the exponentially smoothed size of demand, updated only if demand occurs in period $t$
$\quad = z'_{t-1} + \alpha(z_t - z'_t)$ then
$Y'_t = {z'_t}/{p'_t}$ is the forecast for the subsequent period

[1] $var(Y'_t) \approx \left[\frac{p(p-1)}{p^4}\left(\mu^2 + \frac{\alpha}{2-\alpha}\sigma^2\right) + \frac{\sigma^2}{p^2}\right]\frac{\alpha}{2-\alpha}$

A benefit of Croston's method is that it can successfully be applied to a wide array of demand types. If periodicity approaches 1, then the forecasting method exactly matches simple exponential smoothing (SES), a common method for forecasting smooth demand. Limitations, however, suggest that the method is unsuited for dealing with obsolescence, as the mean size of demand and inter-demand interval may only be updated when a non-zero demand instance occurs (Teunter et al., 2011). Therefore, the forecast itself does not update when there is no demand. Additionally, a mathematical error in the derivation of the method results in a positive bias, which can be estimated with Equation 8 (Syntetos & Boylan, 2005).

$$\text{Croston's estimated bias} = \frac{\alpha}{\alpha-2}\mu\frac{(p-1)}{p^2} \qquad (8)$$

[1] As corrected by Syntetos et al. (2005)

### *3.5 Syntetos-Boylan Approximation (SBA)*

To correct the error, Syntetos and Boylan (2005) applied a deflation factor to the original Croston method when calculating the forecast for the upcoming period. The implementation of this deflation factor allows SBA to achieve greater forecasting accuracy due to the removal of the positive bias. A slight negative bias, however, still remains and evidence suggests that there are cases in which SBA is more biased than Croston's tool (Teunter et al., 2011). Teunter et al. (2011) also question how this amendment renders the method less intuitive, potentially restricting its implementation in a practical setting.

$p'_t =$ the exponentially smoothed inter-demand interval, updated only if demand occurs in period $t$
$\quad = p'_{t-1} + \alpha(p_t - p'_t)$ and
$z'_t =$ the exponentially smoothed size of demand, updated only if demand occurs in period $t$
$\quad = z'_{t-1} + \alpha(z_t - z'_t)$ then
$Y'_t = \left(1 - \frac{\alpha}{2}\right) {z'_t}/{p'_t}$ is the forecast for the subsequent period

$$var(Y'_t) \approx \left(1 - \frac{\alpha}{2}\right)^2 \cdot \left[\frac{p(p-1)}{p^4}\left(\mu^2 + \frac{\alpha}{2-\alpha}\sigma^2\right) + \frac{\sigma^2}{p^2}\right]\frac{\alpha}{2-\alpha}$$

### *3.6 Teunter-Syntetos-Babai Method (TSB)*

The other limitation of Croston's method, however, was in dealing with obsolescent products. Namely, for long periods of no demand, a stock-keeping unit (SKU) would pertain to the same level of forecast. Teunter et al. (2011) therefore suggest that instead of using periodicity, that the probability of demand should be used. Although a minor change, it allows for the forecast to be updated every period with or without an occurrence of non-zero demand instance. For a forecast to be established using TSB, demand should also be stationary.

As the bias of the previous methods stemmed from the calculation of expected periodicity, opting to use the probability of demand occurring removes any bias. Teunter et al. (2011) stress, however, that the value of the smoothing constants must be chosen with care as values that are too large lead to poor performance.

$D'_t =$ the exponentially smoothed size of demand
$\quad = D'_{t-1} + \beta(0 - D'_t)$ when there is no demand and
$\quad = D'_{t-1} + \beta(1 - z'_t)$ when there is demand
$z'_t =$ the exponentially smoothed size of demand, updated only if demand occurs in period $t$
$\quad = z'_{t-1} + \alpha(z_t - z'_t)$ then
$Y'_t = z'_t \cdot D'_t$ is the forecast for the subsequent period

$$var(Y'_t) \approx \frac{\alpha}{2-\alpha}\frac{\beta}{2-\beta}\sigma^2 p(1-p) + \frac{\alpha}{2-\alpha}\sigma^2 p^2 + \frac{\beta}{2-\beta}\mu^2 p(1-p)$$

### *3.7 Stock-Keeping-Oriented Production Error Costs (SPEC)*

Not only is it important to develop methods to forecast demand; equally important is an understanding of how well a given forecast performs. Opting for a suitable metric and ensuring error to be correctly assessed allows for the forecasting method to be correctly calibrated and optimised (Martin et al., 2020). Current metrics for assessing forecast accuracy such as mean average percentage error (MAPE) and root mean squared error (RMSE) are not suitable, especially when considering intermittent or lumpy demand patterns (Martin et al., 2020). As such, most metrics can only be applied in certain best-suiting situations. Martin et al. (2020) describe six categories in which forecast accuracy measures have deficiencies, namely; scale independency, division by zero, outlier insensitivity, symmetry, interpretability and economic considerations (Table 3).

| | statistical aspects | | | | business aspects | |
|---|---|---|---|---|---|---|
| | scale independency | no division by zero | outlier insensitivity | symmetry | interpretability | economical considerations |
| Absolute Errors | | | | | | |
| - MAE / MdAE | ○ | ● | ○ | ● | ● | ○ |
| - MSE | ○ | ● | ○ | ● | ◐ | ○ |
| - RMSE | ○ | ● | ○ | ● | ◐ | ○ |
| Percentage Errors | | | | | | |
| - MAPE / MdAPE | ● | ○ | ○ | ○ | ● | ○ |
| - RMSPE | ● | ○ | ○ | ○ | ◐ | ○ |
| Symmetric Errors | | | | | | |
| - sMAPE | ● | ○ | ○ | ○ | ○ | ○ |
| Scaled Errors | | | | | | |
| - MASE | ○ | ○ | ● | ● | ◐ | ○ |
| - RMSSE | ○ | ○ | ● | ● | ◐ | ○ |
| SPEC | ● | ● | ◐ | ● | ● | ● |

*Table 3: Properties of Traditional Metrics and SPEC (Martin et al., 2020)*

Noticing this, Martin et al. (2020) developed a novel forecast accuracy measure for diverse application. Different to other methods listed, SPEC is a cost function which looks to determine the costs involved with inaccurate forecasting over a specified time horizon $n$. SPEC utilises the assumptions that forecasts $f_t$ represent deliveries and consequent storage of goods, and demand $y_t$ represents departures of material leaving the system in a specified period (Martin et al., 2020). Accordingly, the total costs incurred from both underestimating demand $\gamma_1$and overestimating demand $\gamma_2$ are calculated at every time point $t$ according to Equation 9.

$$SPEC_{\gamma_1,\gamma_2} = \frac{1}{n}\sum_{t=1}^{n}\sum_{i=1}^{t}\left( max\left[\left[0; min\left[y_i; \sum_{k=1}^{i} y_k - \sum_{j=1}^{t} f_j\right]\cdot \gamma_1; min\left[f_i; \sum_{k=1}^{i} f_k - \sum_{j=1}^{t} y_j\right]\cdot \gamma_2\right]\cdot (t-i+1)\right]\right) \tag{9}$$

Martin et al. (2020) suggest that values for $\gamma_1$ and $\gamma_2$ should sum to 1. Putting a greater weight towards unmet demand returns a score according to being service oriented, and a greater weight towards over-stocking gives a score relating to how much surplus stock is left in warehouses. If the two costs are equal, this would give an indication on the overall accuracy of the forecast.

# 4. Methodology

To apply and judge forecasting methods, first a suitable subset of data has been chosen. Choosing a suitable set of data with the intention to compare accuracy to the current system requires there to be consistent forecasting. Kerkkänen et al. (2009) also suggest a greater importance should be placed on judging the forecasting accuracy of higher-volume customers. In combination, higher-volume customers with more consistent ADI mean that that category A customers are further analysed. Historically in the context of the company, ADI has been regarded as the forecast for category A customers, thus forecasting based on ADI alone will serve as the control. Additionally, each product should still be considered actively in production at least for the first period of demand forecasting, and historical data on prior demand and forecasts should be present. In its absence, no statistical forecast can be generated.

### *4.1 Managing Data*

As mentioned, the company has been collecting data since 2018 and has since accumulated a wealth of usable data for this research. Due to the nature of how the data is collected, however, it must be sorted so that its processing becomes a manageable task. As part of processing the given data, condensed data sheets will be created, which contain time periods, realised demand, and any forecasted amount.

### *4.2 Timing Error Resolution*

To properly judge data, it should be a true representation of reality. Taking particular note of the timing error in the data mentioned in section 2.5.2, data points recorded using different time periods inherently cause error in accuracy measures due to its misalignment. Although, as described earlier, a way to mitigate most of this error is by converting the time aspect of data from fiscal weeks to months. Errors in the data, however, would still persist and so the remaining error in timing should still be rectified.

Intermittent and correctly timed demand, however, foreseeably causes shortcomings in the error smoothing formula. In the case that in month $n+1$ there is forecasted demand $F_{n+1}$ and subsequent realised demand in month $S_{n+1}$, or in month $n-1$ a forecasted demand of $F_{n-1}$ and subsequent realised demand in month $S_{n-1}$, the formulae would present different errors (Tables 4 & 5).

| *Example:* | $F_n$ | $S_n$ | $F_{n-1}$ | $F_{n+1}$ | $S_{n-1}$ | $S_{n+1}$ | $E_A$ | $E_B$ | $E_C$ | ***SE*** |
|---|---|---|---|---|---|---|---|---|---|---|
| No timing error (past) | 0 | 0 | 70560 | 0 | 56448 | 0 | -70560 | 56448 | 0 | **0** |
| No timing error (future) | 0 | 0 | 0 | 100005 | 0 | 100920 | 100920 | -100005 | 0 | **0** |

*Table 4: Example Intermittent Forecasting and Demand Error*

| *Example:* | $F_n$ | $S_n$ | $F_{n-1}$ | $F_{n+1}$ | $S_{n-1}$ | $S_{n+1}$ | $PE_A$ | $PE_B$ | $PE_C$ | ***SPE*** |
|---|---|---|---|---|---|---|---|---|---|---|
| No timing error (past) | 0 | 0 | 70560 | 0 | 56448 | 0 | -100% | NF | NF | **-100%** |
| No timing error (future) | 0 | 0 | 0 | 100005 | 0 | 100920 | -100% | NF | NF | **-100%** |

*Table 5: Example Intermittent Forecasting and Demand Percentage Error*

In each case, deviations between forecasts and reality are misrepresented. The former suggests that the data is more accurate than reality, and considerably less accurate for the latter. Due to the beneficial nature of the formulae, however, this error was noted and similar instances were disregarded from analyses due to the inaccurate portrayal of reality. As such, histograms for forecast accuracy are created to compare smoothed and unsmoothed time series data to visualise its effect on forecast accuracy. Examples of the calculations completed can be found in Appendix 4.

### *4.3 Improvement of customer ADI with time*

For an improved context, an analysis into whether ADI improves with time takes place using linear regression. Percentage error of the forecast is plotted against the duration the specific bar has been in production to determine if there is any meaningful relationship. Results of this test will suggest if more significance should be placed on ADI as production of a bar matures.

### *4.4 Forecasting based on ADI*

Firstly, and to act as the control, the forecast that purely uses customer ADI according to what the company would have used is mimicked. No additional information from historical insights, therefore, contributes towards the forecasts.

Due to the timing error within the dataset, Kerkkänen's smoothing method highlighted in the previous section will be used. Accordingly, the forecast corresponding to the least error (see Equations 1-4) will be chosen as the most representative forecast, and each of the prospective order amounts will be placed in a table (Appendix 5).

### *4.5 Trend and Seasonality*

Using this data, and to ensure that the data is applicable to the statistical forecasting methods, trend and seasonality need to be assessed. While non-stationary demand is acceptable to the aforementioned forecasting methods, seasonality within the data would lead to inaccuracies as seasonal factors are not incorporated into demand estimations.

Determining seasonality, however, first requires an understanding of level and trend. Accordingly, level and trend of a product is found by de-seasonalising demand. De-seasonalised demand can be achieved by finding the average of demand half a season into the past, and half a season into the future at a given point in time (Equation 10). Using linear regression with the resulting intercept as the level, and gradient as the trend (Equation 11), de-seasonalised demand can be found for other periods by extrapolating (Chopra, 2019).

$$\overline{D_t} = \begin{cases} \left[D_{t-(p/2)} + D_{t+(p/2)} + \sum_{i=t+1-(p/2)}^{t-1+(p/2)} 2D_i\right] \Big/ 2p & \text{for } p \text{ even} \\ \sum_{i=t+1-[(p-1)/2]}^{t-1+[(p-1)/2]} D_i \Big/ p & \text{for } p \text{ odd} \end{cases} \tag{10}$$

$$\overline{D_t} = L + T_t \tag{11}$$

As de-seasonalised demand $\overline{D_t}$ is now known for each period, seasonality for a given period can now be established using the quotient of observed demand at a certain time period $D_t$ over de-seasonalised demand (Equation 12). Finally, a seasonal factor describing seasonality across all similar periods is calculated by finding the average seasonality for a select part of the cycle (Equation 13).

$$\overline{s_t} = \frac{D_t}{\overline{D_t}} \tag{12}$$

$$S_i = \frac{\sum_{j=0}^{r-1} \bar{S}_{jp+i}}{r} \tag{13}$$

### *4.6 Forecasting using Time Series Methods*

Using time series methods, any advanced information regarding demand is ignored. Accordingly, historical data as far back as the first month of 2019 is used to establish and gain further forecast accuracy. Using information on demand quantities and the corresponding time of the demand instances, forecasts using Croston, SBA and TSB methods described in Sections 3.2-3.4 are separately established using smoothing constants of less than 0.2, which are commonly found within industry (Chopra, 2019). Excerpts from the resulting calculations are illustrated in Appendices 6-9.

In addition to establishing forecasts, patterns of demand earlier categorised by Syntetos et al. (2005) are determined so that a forecast of greater effectiveness can be generated. Combining Croston's method with SBA will be conducted according to the research conducted by Syntetos et al. (2005).

### *4.7 Combined Forecasting*

While Croston's method and its adaptations have proven valuable with the test of time, its method is highly restricted by not being able to incorporate ADI if present. Notably, a customer which exhibits a good understanding of upcoming demand, and thus offers a sufficiently accurate ADI, should not be constrained to time series information on demand. Heavily relying on ADI, however, especially if the customer is considered unreliable, should be taken with caution. The question then becomes 'to what extent should the company rely on ADI received from its customers?'. Combining the two predictions, therefore, should be considered and tested.

Using ADI and the Croston/SBA method, a revised forecast can be made. The reason for using the Croston/SBA method alongside ADI resides with how the latter should account for obsolescence if and when, assuming the customer puts apt thought into the matter, the customer does not expect to order any units. As such $n$ past observations $O$ at points in time $t$ of the performance of time series forecast $Y'$ and $ADI$ can be combined in such a way which allows greater significance to the most accurate indicator of demand. Equation 14 presents a formula for determining a forecast for demand in the subsequent time period, utilising both ADI and time series forecasting methods.

$$Forecast_{t+1} = \left(\frac{1}{n}\sum_{i=0}^{n-1} O_{t-i}\right) \cdot Y'_{t+1} + \left(\frac{1}{n}\sum_{i=0}^{n-1}[1 - O_{t-i}]\right) \cdot ADI_{t+1} \quad (14)$$

Where if

$$Y'_t > ADI_t \text{ and } Y'_t < D_t;\ O_t = 1$$

$$Y'_t < ADI_t \text{ and } Y'_t > D_t;\ O_t = 1$$

$$Y'_t > ADI_t \text{ and } Y'_t > D_t;\ O_t = \frac{D_t - ADI_t}{ADI_t - Y'_t}$$

$$Y'_t < ADI_t \text{ and } Y'_t < D_t;\ O_t = \frac{D_t - Y'_t}{Y'_t - ADI_t}$$

$$Y'_t = ADI_t;\ O_t = 0.5$$

Otherwise

$$O_t = 0$$

In essence, to apply the effect proposed, observations on how well ADI compared to its historical time series forecast counterpart is determined. As such, the accuracy of the time series forecasting method is deduced. If the observed value of demand is greater than the time series forecast, which is also greater than the ADI, the time series forecasting method is thought to outperform ADI and thus is assigned the value 1 (Figure 10). The same effect occurs when the observed value of demand is smaller than the time series forecast, which is also smaller than the corresponding ADI. If ADI outperformed time series methods a value of zero will be assigned.

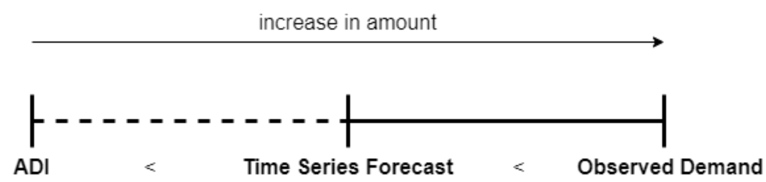


*Figure 10: Visualisation of Value Comparison*

When the value of observed demand falls between the time series forecast and ADI, however, the accuracy of the time series forecasting method is found by normalising the realised demand with respect to the corresponding time series forecast and ADI, depending on which of the two predictions is larger.

To ensure there is no artificial inflation or deflation applied to the forecasts, all weights from each time observation add to 1. Therefore, to determine the coefficient of accuracy for the ADI forecast, the coefficient for the time series forecast can be subtracted from 1.

Generating coefficients using this method ensures that revised forecasting technique can be more or less reactive according to whether the time series forecast improves over time. For the formula to be more reactive to recent performances in ADI and time series methods, a smaller number of observations can be used. Appendix 10 shows the table of forecasts generated using this method.

### *4.8 SPEC Evaluation*

After the various forecasts have been established, the accuracy of each should be considered using the SPEC equation (Equation 9). As such, the forecasted values from each of the methods and the quantity of realised demand are put into an array. These arrays serve as an input into a python code initially authored by Martin et al. (2020), adapted such that information from an excel sheet can be directly imported and the corresponding calculations can be performed (Appendix 11). Accordingly, calculations are made for varying opportunity and storage costs, as well as smoothing constants used in the time series forecasting methods.

# 5. Results

According to methods outlined in the previous sections, resulting graphs and tables are presented. In tandem with the figures, additional context for the further understanding the context and derivations are set out. Further, a high-level analysis into shapes and patterns found in the graphs and numbers are mentioned along with reasoning for its occurrence. The detailed analysis and interpretation of the results will be noted in a later section.

### *5.1 Trend and Seasonality Results*

In conducting the proposed research set out in Section 4, the analysis on the available data shows that bars which were produced for A category customers between January 2018 and March 2021 exhibit a negligible trend (Figure 11).

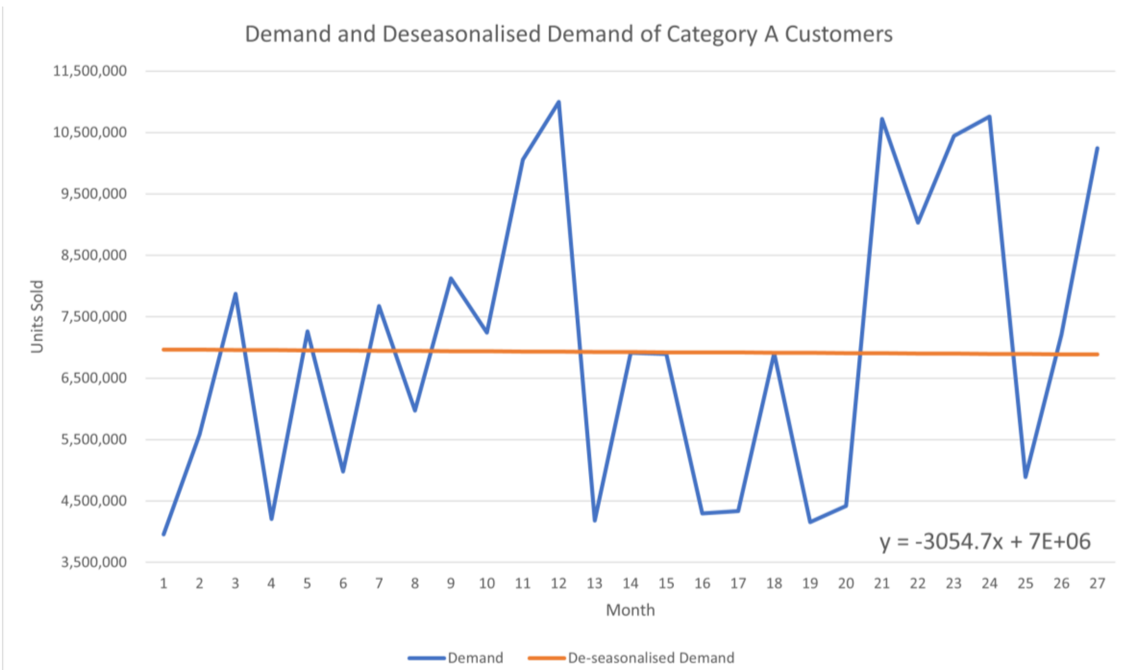


*Figure 11: De-seasonalised Demand*

The stationary nature of the orange line representing de-seasonalised demand suggests that a steady demand of circa 7 million of the considered bars can be expected each month. The blue line representing total demand in the given month, however, seems in contrast to be rather erratic. Difference between lines of demand de-seasonalised demand can typically be due to factors describing seasonality. The average ratio between the demand and de-seasonalised demand points (Equations 12 and 13) subsequently have the ability to estimate seasonality factors. Seasonality factors for each of the months is calculated and set out in line graph (Figure 12). If there is no seasonality, a flat line is expected.

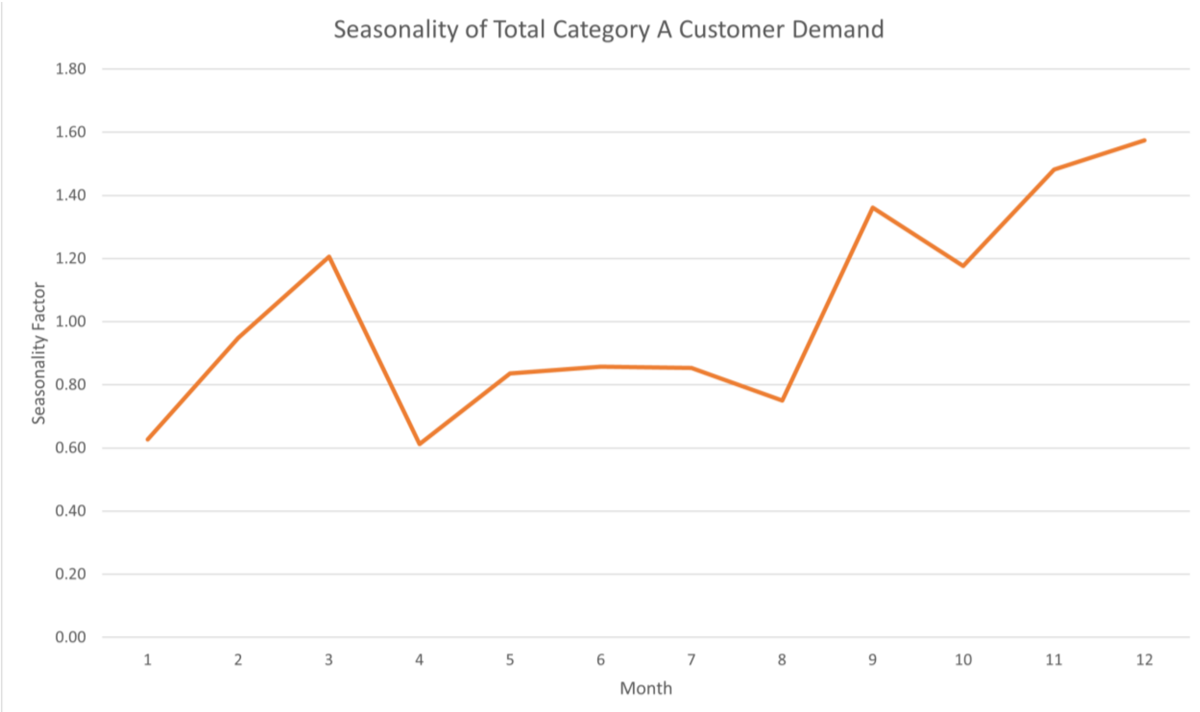


*Figure 12: Seasonality of Total Demand*

Figure 12 seems to suggest that there is a seasonality in the total number of bars ordered per month, as the line exhibits a variation between the different months. As this measure does not consider seasonality of a single bar at a time, however, the test for seasonality is all but conclusive. It is still plausible that there are seasons that more customer orders of different bars are accepted rather than noticing a difference in order size, the latter of which is of importance when investigating intermittent demand. Therefore, a linear regression between the number of orders and the seasonality is performed to determine if there is any correlation (Figure 13).


*Figure 13: Regression Between Seasonality and Number of Orders*

The outcome shows a weak positive relationship, suggesting that it is possible that the seasonality depicted in the data corresponds to a greater number of orders being placed, instead of larger order sizes. As such for the purpose of this study, order size will be considered to have no seasonality.

### *5.2 Timing Adjustment Results*

To correct the timing of ADI in such a way that enables a suitable analysis of suggested demands, time adjustment is completed (see Section 4.3). By using the time adjustment, when the financial and production schedules are not overlapping, ADI will be met with the corresponding demand. Due to large amounts of demand intermittency, more often than not, forecasts and demands from subsequent periods will not be combined, thereby re-coupling correct ADI and demand instances. Comparing Figures 7 against 14, and 8 against 15 shows the influence of the time smoothing equations. In both cases, deviation in observations are presented as more accurate, with values tending towards zero. In any case, this should be expected as Equation 4 suggests the selection of error method attaining the minimum error.

Each of the graphs adjusted for the timing error gain an improved resemblance to a bell curve with a left-sided skew. Once more, order deviations weighted towards the left side of the graph suggest that companies have a tendency to overestimate order amounts at the time of providing ADI. Importantly, the large bar to the right of Figure 15 persists, albeit less in relative magnitude. As it is still prevalent, this would suggest that such a large error is not caused by timing, but from customers ordering considerably larger relative amounts than initially indicated by ADI.

Notably, the adjusted percentage error graph alludes to an increase in the number of observations, namely due to the decreased likelihood of the -100% error found using the percentage change quotient. To account for instances where there was no realised demand but ADI was provided (thus -100% error is accurate), the number of instances of a positive ADI but no demand are counted. From a total of 1852 observations, 346 (≈18.7%) consist of ADI which were not realised to any degree. This insight only exacerbates the impression that customers have a tendency to overestimate ADI.

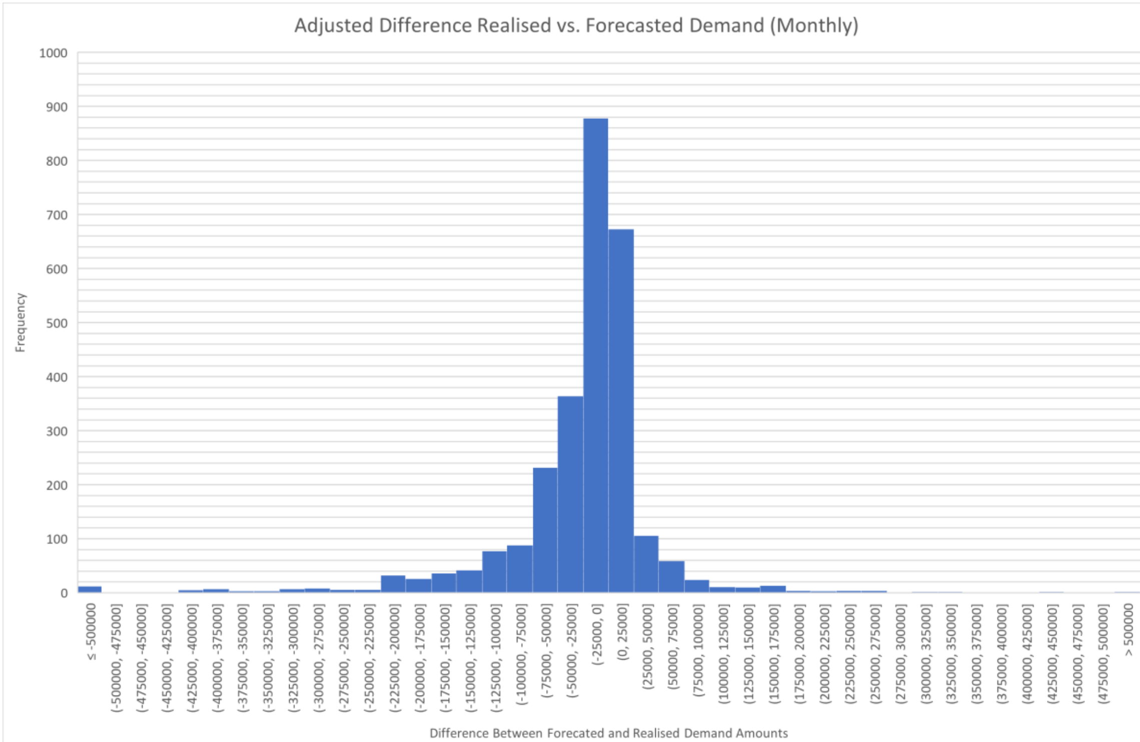


*Figure 14: Adjusted Forecasting Deviation Error*

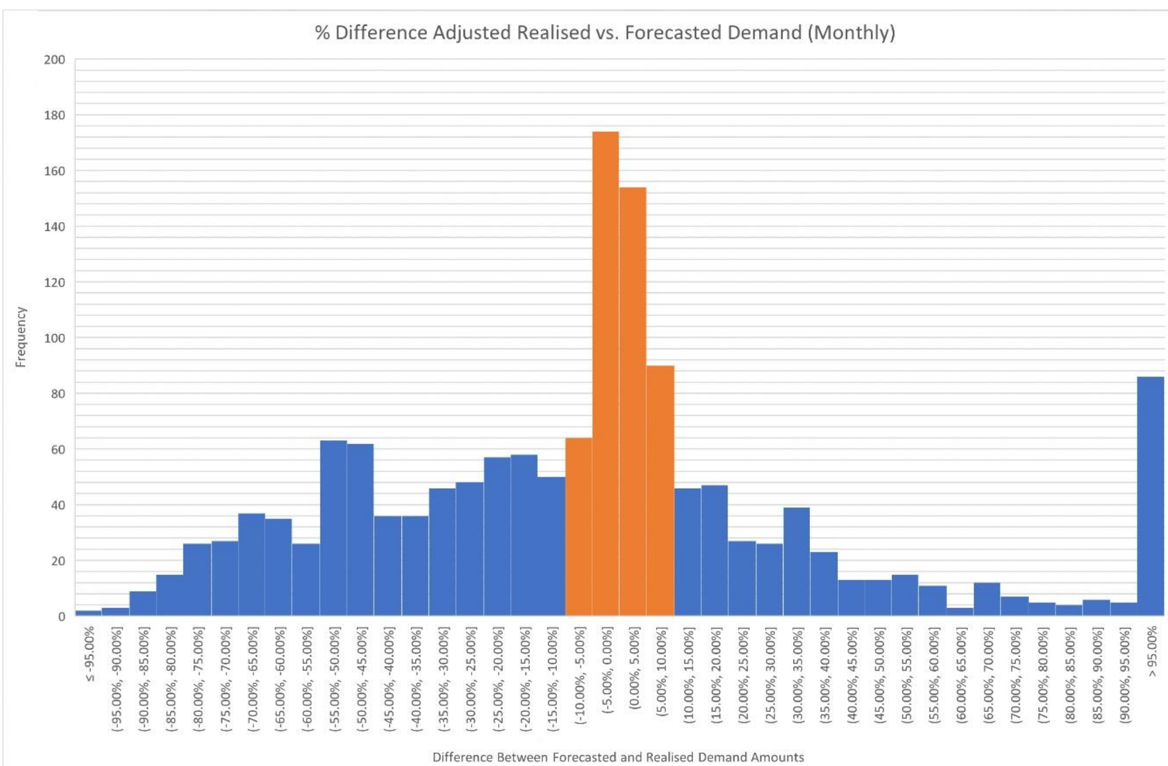


*Figure 15: Adjusted Forecasting Deviation Percentage Error*

ADI which does not at all come to fruition can lead to over-stocked inventories, especially if there is no other source of information to gauge what order amounts can be expected. Considering that the average size of an order is about 120,000 bars, of which most of the materials to produce the bars is bought in advance to a sales order, it can be a hard task to manage. The company maintains the right to reject orders if they are unable to fulfil them according to available capacity, however, so some of this error can likely be attributed to rejecting sales orders.

### *5.3 Improvement of ADI with Time*

Serving as an important insight into the forecasting methods which use ADI as an input, a regression between the number of months a bar has been in production and the associated ADI accuracy is made to determine if ADI improves over time (Figure 16). Interestingly, and rather counter-intuitively, ADI accuracy shows a tendency to under-forecast demand towards the beginning of production. Later, as the bar has been produced for longer, ADI tends to over-forecast demand. The combination of these observations would see the regression line take a negative slope. Overall, however, there seems to be a large spread of accuracy values.

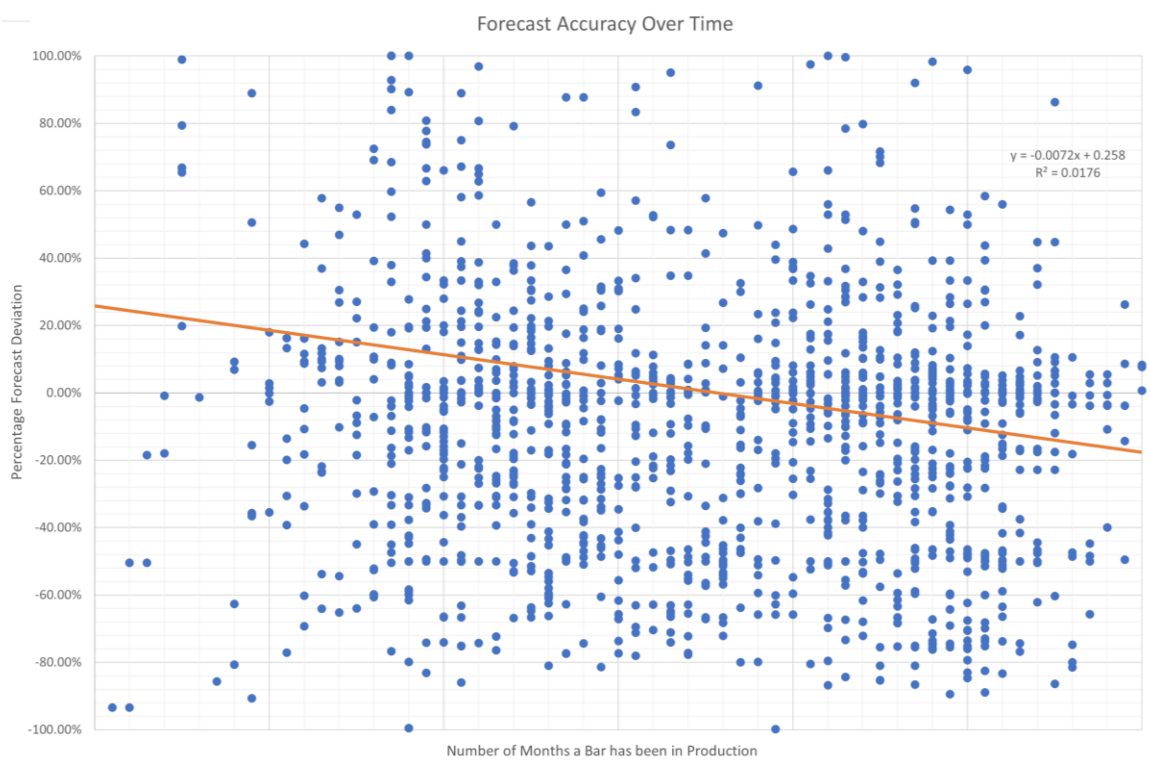


*Figure 16: Development of ADI with Bar Maturity*

### *5.4 Forecasting Results*

As shown in the literature review and methodology sections, there are various different ways to predict future demand. Deciding which of the methods is most suitable intuitively describes the method which obtains the least error. Each of the forecasting methods, therefore, are first established using empirical data provided by the company in such a way which results in all of the forecasts being generated as if they were used by the company (See Appendices 5-10). Later by using the SPEC formula at various opportunity costs ($\gamma_1$), storage costs ($\gamma_2$), and smoothing constants ($\alpha$, $\beta$) – the variables are changed so that a more comprehensive image of the results is established. Notably, not all of the smoothing constants are linked to each of the forecasting methods. Each of the methods aside from ADI make use of the smoothing constant α, while only the TSB method makes use of the secondary smoothing constant β.

Of the forecasts generated, only the ADI and Extension methods mentioned in Tables 6-8 seek to utilise ADI to any agree, where the latter refers to the method derived from this work. On the other hand, ADI is the only method not to make use of any historical forecasting to any degree, and therefore only the Extension method uses both ADI and time series forecasting as inputs.

Tables 6-8 list the relative average loss per month compared to the existing method used by the company (ADI) for each of the forecasting methods by utilising Equation 5. Using values of error in relation to ADI allows the direct comparison of ADI to the other methods presented. Additionally, as the values of error are in this case only scalar, the direct values obtained by the formula are less relevant.

The ranking of each of the methods in each test is listed below, where the best-ranked of the methods is indicated further using a grey highlighted area. Note that due to a lack of data, the forecasting method presented in this work takes advantage of nine observations as opposed to 12. Additionally, the Croston/SBA method referred to in Tables 6-8 refer to the method combining Croston and SBA depending on the type of demand (See Section 3.3).

| | *ADI* | *Croston* | *SBA* | *Croston/SBA* | *TSB* | *Extension*[2] |
|---|---|---|---|---|---|---|
| α= 0.1 (β=0.1) | 1.000 (+0.0%) 2 | 1.301 (+30.1%) 3 | 1.373 (+37.3%) 5 | 1.365 (+36.5%) 4 | 1.883 (+88.3%) 6 | 0.860 (-14.0%) 1 |
| α= 0.1 (β=0.05) | 1.000 (+0.0%) 2 | 1.304 (+30.4%) 3 | 1.373 (+37.3%) 5 | 1.371 (+37.1%) 4 | 2.298 (+129.8%) 6 | 0.863 (-13.7%) 1 |
| α= 0.15 (β=0.1) | 1.000 (+0.0%) 2 | 1.279 (+27.9%) 3 | 1.360 (+36.0%) 5 | 1.347 (+34.7%) 4 | 1.626 (+62.6%) 6 | 0.852 (-14.8%) 1 |
| α= 0.15 (β=0.05) | 1.00 (+0.0%) 2 | 1.325 (+32.5%) 3 | 1.387 (+38.7%) 4 | 1.392 (+39.2%) 5 | 2.088 (+108.8%) 6 | 0.857 (-14.3%) 1 |

*Table 6: Forecast Accuracy SPEC ($\gamma_1$=0.75; $\gamma_2$=0.25)*

[2] The number of prior observations used to calculate the coefficients is three

| | *ADI* | *Croston* | *SBA* | *Croston/SBA* | *TSB* | *Extension* |
|---|---|---|---|---|---|---|
| α= 0.1 (β=0.1) | 1.000 (+0.0%) 5 | 0.837 (-16.3%) 4 | 0.858 (-14.2%) 3 | 0.854 (-14.6%) 2 | 1.015 (+1.5%) 6 | 0.733 (-26.7%) 1 |
| α= 0.1 (β=0.05) | 1.000 (+0.0%) 5 | 0.843 (-15.7%) 2 | 0.858 (-14.2%) 4 | 0.857 (-14.3%) 3 | 1.220 (+22.0%) 6 | 0.732 (-26.8%) 1 |
| α= 0.15 (β=0.1) | 1.000 (+0.0%) 6 | 0.929 (-7.1%) 4 | 0.926 (-7.4%) 3 | 0.920 (-8.0%) 2 | 0.929 (-7.1%) 5 | 0.727 (-27.3%) 1 |
| α= 0.15 (β=0.05) | 1.000 (+0.0%) 5 | 0.864 (-13.6%) 2 | 0.867 (-13.3%) 4 | 0.869 (-13.1%) 3 | 1.127 (+12.7%) 6 | 0.727 (-27.3%) 1 |

*Table 7: Forecast Accuracy SPEC ($\gamma_1$=0.50; $\gamma_2$=0.50)*

| | *ADI* | *Croston* | *SBA* | *Croston/SBA* | *TSB* | *Extension* |
|---|---|---|---|---|---|---|
| α= 0.1 (β=0.1) | 1.000 (+0.0%) 5 | 0.849 (-15.1%) 4 | 0.832 (-16.8%) 3 | 0.829 (-17.1%) 2 | 0.730 (-27.0%) 1 | 1.018 (+1.8%) 6 |
| α= 0.1 (β=0.05) | 1.000 (+0.0%) 5 | 0.862 (-13.8%) 4 | 0.832 (-16.8%) 2 | 0.831 (-16.9%) 1 | 0.842 (-15.8%) 3 | 1.011 (+1.1%) 6 |
| α= 0.15 (β=0.1) | 1.000 (+0.0%) 5 | 0.880 (-11.0%) 4 | 0.840 (-16.0%) 3 | 0.839 (-16.1%) 2 | 0.712 (-28.8%) 1 | 1.012 (+1.2%) 6 |
| α= 0.15 (β=0.05) | 1.000 (+0.0%) 5 | 0.895 (-10.5%) 4 | 0.840 (-16.0%) 2 | 0.842 (-15.8%) 3 | 0.813 (-18.7%) 1 | 1.005 (+0.5%) 6 |

*Table 8: Forecast Accuracy SPEC ($\gamma_1$=0.25; $\gamma_2$=0.75)*

Using cost coefficients which puts greater loss to opportunity cost, Table 6 represents the scenario that the business prefers to be service-oriented rather than cost-cutting, such is the mentality of the company. The results of this test show that for each of the various smoothing coefficients, the extended method which includes ADI and time series forecasting information outperforms each of the other methods consistently. Notably, the second most apt method for a service-oriented forecast is using ADI, the current technique being used by the company.

Conversely, time series methods for predicting demand did not fare well if the cost of unmet demand was so large. Of the remaining methods, Croston showed to be most effective, likely due to its positive bias. Furthermore, TSB showed to be the least effective technique which can be attributed to how the method is focused on reducing stock on hand in an event of no demand. Overall, Table 6 suggests that if a business were to aim to be service-oriented in a setting where the majority of demand is lumpy or intermittent, forecasts which have ADI as an input are recommended.

In determining which of the methods had the greatest overall accuracy, the cost of unmet demand and stock-keeping costs are made to be equal (Table 7). Once more, the extension proposed in this work shows to be a superior predictor of demand when compared to established methods. In juxtaposition to Table 6, however, using ADI as a forecasting method proves to be equally inefficient when overall forecast accuracy is the aim. As expected, each of the time series forecasting methods, apart from TSB, continue to exhibit very similar levels of accuracy, while TSB is once more proving to be a poor indicator of future demand.

Opposite to Table 6, Table 8 applies more cost on keeping surplus stock than not being able to meet demand based on stock. Unsurprisingly, the methods which performed best when the cost of over-stocking is low, perform worst when over-stocking costs are high and vice versa. Evidence further confirming the effects of improved accuracy highlighted by Syntetos et al. (2005) are present where the Croston/SBA method almost consistently outperforms its constituting methods, suggesting that the improvement in using this combined technique works to optimise a reduced inventory level, rather than a better overall forecast accuracy. Table 8, therefore, brings up the argument of how time series forecasting methods are less applicable to companies that value a high service level, and do not mind keeping surplus stock to make sure that as much demand as possible can be met.

# 6. Conclusion and Recommendations

## *6.1 Conclusion*

Deviation of varying degrees between realised and forecasted demand should be anticipated, especially in the case where most demand patterns are not smooth. Planning for demand, therefore, can be a difficult task. To aid in the challenge of dealing with the idiosyncratic nature of demand, ways of gaining information on upcoming demand have been established. Two such methods are by improved customer-supplier communication and analysing historic demand. Typically not thought of as acting in tandem, supply chain managers ultimately face the task of determining which method should be used to more accurately estimate future demand in such a way that allows demand to be met most cost-effectively for the seller.

Perceived costs of meeting demand and keeping surplus stock differ depending on the overarching goals of the organisation. A company carrying expensive items which require a great deal of care to maintain, for example, can foreseeably attribute more expense in keeping stock rather than failing to meet most demand. Similarly, there is no one-size-fits all forecasting method to optimise the demand-meeting and stock-keeping process. Likewise, by using the SPEC metric, forecast accuracy was judged according to the weighted loss for failing to provide demand and overestimating demand.

During this study, the various suitable time series forecasting methods, ADI, and an extended method combining the two were compared to ascertain the best estimator of future demand. Results suggest that in similar cases, where the supplying company has a focus on service and demand appears to be highly intermittent and lumpy, customer ADI should be sought out. In each of the sensitivity tests, the methods incorporating ADI to various degrees appear to be the most efficient methods at reducing perceived overall cost. The next best method in the tests was Croston's method, seemingly due to its positive bias when estimating demand. Conversely, techniques that did not factor in any kind of ADI had an improved performance when the goal was to minimise the costs of stock-keeping. In particular, as a method which seeks to reduce obsolescence, TSB showed to be the most effective method. As alluded to in its original work, differing levels of performance were observed when smoothing constant $\beta$ varied.

Comparing each of the methods when the unmet demand and stock-keeping costs are equal, thus measuring the overall accuracy of the measure, presented interesting outcomes. Namely, the extended technique using both ADI and historical demand as an input proved to significantly outperform its counterparts. This would suggest that either there are customers which are better at providing ADI, or customers which go through phases of accurate advanced demand indications. In any case, this result hints towards the inefficiency of judging upcoming demand using a single indicator.

Surprisingly, the method using only ADI as a forecast proved to be the joint worst performer alongside TSB. Notably, each of these methods can, in the context of this investigation, be considered the extremes – one employs a method to wholly cater for the customer, and the other significantly reduces the amount of stock on hand. Therefore, these methods should be used with care, and in scenarios where they are best suited.

## *6.2 Discussion*

While the results seem rather clear-cut, it is important to note the various characteristics attributed to each method. Not only is the value of the forecast important for a business, but also the variance (Chopra, 2019). As a measure of how much a value can be expected to change, understanding variance can give procurement managers differing levels of confidence that demand will agree with the forecasted amount. Time series forecasting methods not only can gather a best information on demand, but also provide an enumeration of variance. ADI, however, as it typically comes from customers in the form of a standalone value, misses out on this valuable insight. Given a value of ADI, therefore, the receiving company have no idea if the customer is expecting that the number provided could massively vary or not. Thus, any incorporation of ADI into forecasting would forego an understanding of variation.

Additionally, the assumption that procuring the specified forecast in each month can be satisfied with incoming order amounts can at times be flawed. In the case that MOQs are present, the order amount which would be specified may not be possible, resulting in higher holding costs than predicted. Further, in the common case that procurement managers consider ADI as a guideline rather than a rule, greater or fewer units can be ordered. Numerous studies have found such judgemental decisions to perform inefficiently, hindering the ability for analysts to measure, evaluate and improve the current system.

SPEC metric is built on the assumption that demand that cannot immediately be met from stock is considered a lost sale. In reality, businesses can agree on backorders of stock, or demand can be made up by ordering additional supplies to produce an adequate number of units for the customer. Further, it does not account for loss of stock in the event of an accident, or a product exceeding its expiration date.

Finally, forecasting methods inherently suggest that suppliers have little control over influencing and managing demand. Elasticity between price and demand, for example, can be explored to better manage months of higher load, so that a more predictable stream of demand is achievable.

### *6.3 Recommendations*

Considering the results in the context of the company, it is clear that as a service-oriented company, using ADI as a form of forecast is by far the most efficient single-input method for reducing the amount of unmet demand. Additionally, in most cases, as ADI is available months in advance, it allows procurement managers within the company to make informed decisions about prospective demand. This is important for when the critical path of a product is greater than the eight weeks before production where sales orders must be finalised.

Shortcomings of using ADI as the sole forecast methodology, however, should be acknowledged and managed accordingly. Firstly, due to the high instances of ADI studied which are not at all materialised ($\approx$18.7%), an inquest into introducing binding forecasts to some degree should be undertaken. Although amending forecasts to be binding could result in lost business, the gains of better understanding future demand would likely outweigh the costs. Due to the increased risk for customer companies, however, the company could look to modify prices accordingly to lessen the impact of this decision on relationship. Doing so, could foreseeably create a scenario of greater pareto efficiency.

Another suggestion would be to implement a time series forecasting method. Time series methods presented in this work only require one data point: demand of an item in a given month. Even if the implementation of this technique is not incorporated into the forecast of a product, it can give valuable secondary information regarding what magnitude of demand can be expected from a customer, an estimate of the number of months between demand, and the variance of demand. This information can even be collated into a profile of a bar or customer for easy access of information.

In a better optimised case, and due to the positive outcomes of this research, the extended forecasting method which combines ADI and time series techniques should concurrently be tested using the extension provided. With results suggesting that this method both pertains to the business' strategic goals and heavily contributes to the overall forecast effectiveness, implementing this method should be seriously considered.

Finally, this paper strongly suggests using SPEC as the guiding metric in understanding the accuracy of forecasts within the business context. Other forecasting accuracy measures, in comparison, each seem to have their niche and offer little tangible business insight for practitioners. For SPEC to gain full effectiveness, estimates of opportunity and storage costs should be established at a bar level. Using these estimates, the direct costs of an inaccurate forecast, or cost of inaccurate forecasts over a horizon, can be calculated. Knowing the cost of inaccurate forecasts can serve as an input into guiding the discussion of how to orchestrate binding forecasts.

### *6.4 Limitations and Further Work*

Knowing the true values for demand in this study can be challenging. Due to how the company operates, sales orders go through an after sales process in which the order quantity and time aspects are discussed and agreed. This means that the invoiced amount could be misleading with regard to the number of units a customer would have agreed if there was no restriction. One would imagine, therefore, that the way of measuring demand used in this study could undervalue the real amount of demand depending on the influence of after sales on demand.

Due to its promise, further research into methods which combine various different streams of information to better predict demand should be investigated. Namely, finding an improved method in combining ADI and time series forecasting methods should be tried. Additionally, the extended technique outlined in this research should be tested against other empirical scenarios to determine its performance against existing methods to further determine its validity. Further types of demand should also be tested with the extended forecasting method to judge its performance with demand which is predominantly erratic or smooth.

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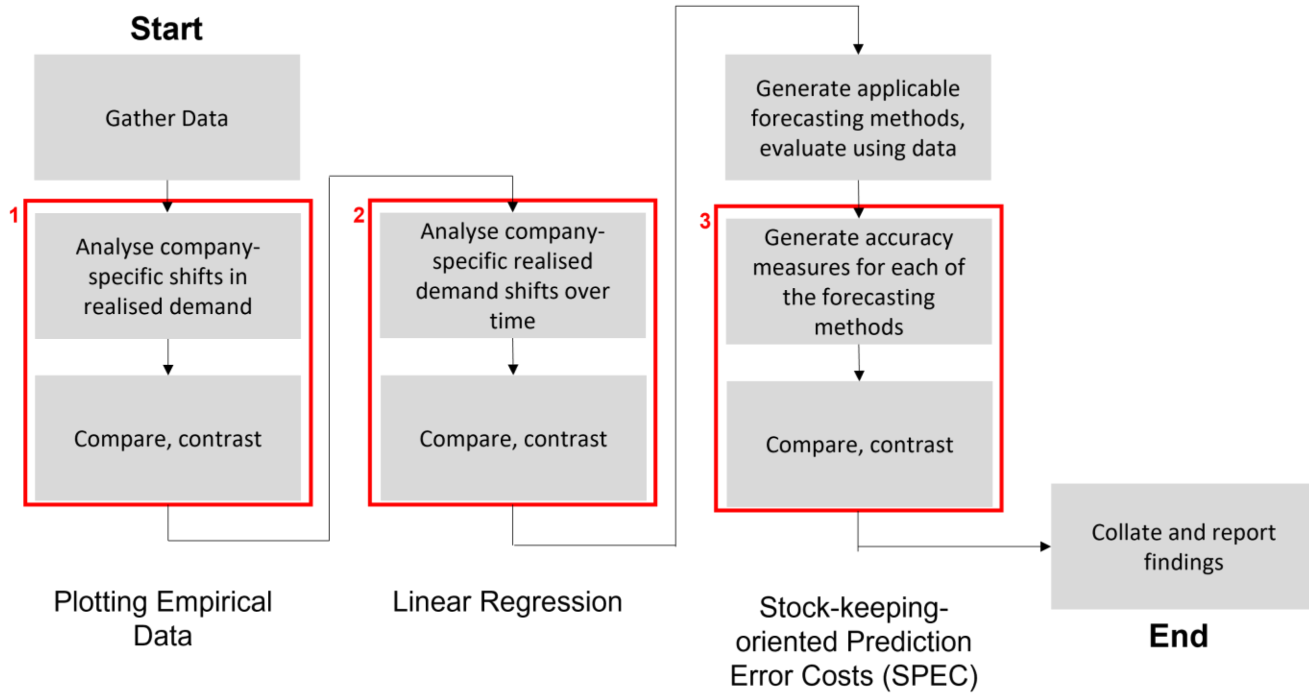
# 8. Appendices

*Appendix 1: Problem Solving Approach*




1: Testing assumption that there are deviations in actual and forecasted demand
2: Testing assumption that ADI accuracy improves as the bar matures
3: Testing whether an improved method to forecast demand can suitably be determined

*Appendix 2: Handling Primary Data (Forecasting)*

| ***Identifier*** | **21-wk6** | **21-wk8** | **21-wk10** | **21-wk12** | **21-wk14** | **21-wk16** | **21-wk18** | **21-wk20** | **21-wk22** | **21-wk24** | **21-wk26** | **21-wk28** | **21-wk30** | **21-wk32** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2021490861955Forecast | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 2021490131963Invoice | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 2021490131963Forecast | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 2021490131965Invoice | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 2021490131965Forecast | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 2021490481966Invoice | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 2021490481966Forecast | - | - | - | - | - | - | - | 50008 | 50008 | 50008 | 50008 | 50008 | 50008 | 50008 |
| 2021490731967Invoice | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 2021490731967Forecast | - | - | - | - | - | - | - | - | - | - | - | - | - | |
| 2021490731968Invoice | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 2021490731968Forecast | - | - | - | - | - | - | - | - | - | - | - | - | - | |
| 2021491611969Invoice | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 2021491611969Forecast | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 2021490731970Invoice | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 2021490731970Forecast | 300024 | 300024 | 300024 | 239976 | 239976 | 239976 | 239976 | 239976 | 239976 | 239976 | 239976 | 120024 | 120024 | 120024 |
| 2021491611987Invoice | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 2021491611987Forecast | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 2021490731988Invoice | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 2021490731988Forecast | 50040 | 50040 | 50040 | 27216 | 27216 | 27216 | 27216 | 27216 | 27216 | 27216 | 27216 | 326592 | 27216 | 27216 |
| 2021490731989Invoice | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 2021490731989Forecast | 50040 | 50040 | 50040 | 27216 | 27216 | 27216 | 27216 | 27216 | 27216 | 27216 | 27216 | 326592 | 27216 | 27216 - |
| 2021490731990Invoice | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 2021490731990Forecast | 50040 | 50040 | 50040 | 18144 | 18144 | 18144 | 18144 | 18144 | 18144 | 18144 | 18144 | 217728 | 18144 | 18144 - |
| 2021490731991Invoice | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 2021490731991Forecast | 50040 | 50040 | 50040 | 36288 | 36288 | 36288 | 36288 | 36288 | 36288 | 36288 | 36288 | 435456 | 36288 | 36288 - |

*Appendix 3: Handling Primary Data (Demand)*

| ***Identifier*** | 21-wk50 | 21-wk52 | 22-wk02 | 22-wk04 | 22-wk06 | 22-wk08 | 22-wk10 | 22-wk12 | 22-wk14 | 22-wk16 | 22-wk18 | 22-wk20 | 22-wk22 | 22-wk24 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2021490861955Forecast | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 2021490131963Invoice | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 2021490131963Forecast | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 2021490131965Invoice | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 2021490131965Forecast | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 2021490481966Invoice | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 2021490481966Forecast | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 2021490731967Invoice | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 2021490731967Forecast | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 2021490731968Invoice | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 2021490731968Forecast | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 2021491611969Invoice | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 2021491611969Forecast | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 2021490731970Invoice | 244944 | 244944 | 244944 | 244944 | 244944 | 244944 | 244944 | 244944 | 244944 | 244944 | 244944 | 244944 | 244944 | 244944 |
| 2021490731970Forecast | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 2021491611987Invoice | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 2021491611987Forecast | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 2021490731988Invoice | 81648 | 81648 | 81648 | 81648 | 81648 | 81648 | 81648 | 81648 | 81648 | 81648 | 81648 | 81648 | 81648 | 81648 |
| 2021490731988Forecast | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 2021490731989Invoice | 82224 | 82224 | 82224 | 82224 | 82224 | 82224 | 82224 | 82224 | 82224 | 82224 | 82224 | 82224 | 82224 | 82224 |
| 2021490731989Forecast | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 2021490731990Invoice | 72576 | 72576 | 72576 | 72576 | 72576 | 72576 | 72576 | 72576 | 72576 | 72576 | 72576 | 72576 | 72576 | 72576 |
| 2021490731990Forecast | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 2021490731991Invoice | 152856 | 152856 | 152856 | 152856 | 152856 | 152856 | 152856 | 152856 | 152856 | 152856 | 152856 | 152856 | 152856 | 152856 |
| 2021490731991Forecast | - | - | - | - | - | - | - | - | - | - | - | - | - | - |

*Appendix 4: Forecast Error Worksheet*

| Identifier | Forecast | Demand | Ec | Ea | Eb | AdjForecastAccuracy | Forecast-1 | Forecast+1 | Sales-1 | Sales+1 |
|---|---|---|---|---|---|---|---|---|---|---|
| 2021030762505 | NF | 0 | 0 | 0 | 0 | 0 | NF | NF | 0 | 0 |
| 2021030762506 | NF | 0 | 0 | 0 | 0 | 0 | NF | NF | 0 | 0 |
| 2021032922513 | NF | 0 | 0 | 0 | 6720 | 0 | NF | NF | 6720 | 0 |
| 2021032922514 | NF | 34128 | 34128 | 34128 | 172728 | 34128 | NF | NF | 138600 | 0 |
| 2021032922516 | NF | 12672 | 12672 | 12672 | 12672 | 12672 | NF | NF | 0 | 0 |
| 2021032922509 | NF | 45504 | 45504 | 45504 | 175536 | 45504 | NF | NF | 130032 | 0 |
| 2021032922511 | NF | 0 | 0 | 0 | 6720 | 0 | NF | NF | 6720 | 0 |
| 2021032922517 | NF | 42336 | 42336 | 42336 | 42336 | 42336 | NF | NF | 0 | 0 |
| 2021032922510 | NF | 0 | 0 | 0 | 133560 | 0 | NF | NF | 133560 | 0 |
| 2021032922512 | NF | 0 | 0 | 33600 | 13440 | 0 | NF | NF | 13440 | 33600 |
| 2021032922515 | NF | 12096 | 12096 | 12096 | 69192 | 12096 | NF | NF | 57096 | 0 |
| 2021030242518 | NF | 105135 | 105135 | 105135 | 105135 | 105135 | NF | NF | 0 | 0 |
| 2021030242519 | NF | 104670 | 104670 | 104670 | 104670 | 104670 | NF | NF | 0 | 0 |
| 2021033402520 | NF | 119232 | 119232 | 269568 | 19200 | 19200 | NF | 100032 | 0 | 150336 |
| 2021033402521 | NF | 0 | 0 | 105024 | -100032 | 0 | NF | 100032 | 0 | 105024 |
| 2021033402522 | NF | 85440 | 85440 | 198528 | -14592 | -14592 | NF | 100032 | 0 | 113088 |
| 2021033402523 | NF | 121152 | 121152 | 279552 | 21120 | 21120 | NF | 100032 | 0 | 158400 |
| 2021032942526 | NF | 0 | 0 | 0 | 0 | 0 | NF | NF | 0 | 0 |
| 2021032942527 | NF | 17475 | 17475 | 17475 | 17475 | 17475 | NF | NF | 0 | 0 |

*Appendix 5: Forecasts based on ADI (Excerpt)*

| Material | Customer | 202104 | 202105 | 202106 | 202107 | 202108 | 202109 | 202110 | 202111 | 202112 |
|---|---|---|---|---|---|---|---|---|---|---|
| 1734 | 024 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0040 | 052 | 0 | 0 | 0 | 0 | 100,032 | 0 | 100,032 | 0 | 100,032 |
| 0078 | 141 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 30,000 | 0 |
| 0083 | 063 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0094 | 052 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 50,016 |
| 0096 | 052 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 50,016 |
| 0104 | 025 | 0 | 14,112 | 21,168 | 28,224 | 63,504 | 28,224 | 42,336 | 28,224 | 42,336 |
| 0137 | 024 | 0 | 0 | 0 | 0 | 0 | 59,994 | 0 | 0 | 59,994 |
| 0158 | 023 | 64,800 | 64,800 | 244,800 | 0 | 108,000 | 108,000 | 108,000 | 108,000 | 432,000 |
| 0179 | 023 | 97,200 | 151,200 | 0 | 151,200 | 151,200 | 151,200 | 453,600 | 248,400 | 453,600 |
| 0182 | 024 | 0 | 0 | 165,600 | 0 | 0 | 0 | 50,040 | 0 | 50,040 |
| 0200 | 141 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 34,995 | 0 |
| 0213 | 141 | 0 | 0 | 0 | 0 | 30,000 | 0 | 0 | 0 | 0 |
| 0349 | 052 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 50,016 | 0 |
| 0354 | 025 | 0 | 14,112 | 14,112 | 28,224 | 28,224 | 42,336 | 14,112 | 14,112 | 14,112 |
| 0375 | 025 | 0 | 0 | 0 | 0 | 338,688 | 536,256 | 874,944 | 515,088 | 536,256 |
| 0392 | 141 | 0 | 0 | 0 | 0 | 30,000 | 0 | 0 | 0 | 0 |
| 0415 | 025 | 0 | 0 | 0 | 119,952 | 91,728 | 105,840 | 105,840 | 105,840 | 70,560 |
| 0419 | 052 | 0 | 0 | 0 | 0 | 0 | 0 | 50,016 | 0 | 0 |
| 0447 | 141 | 0 | 49,995 | 0 | 0 | 0 | 0 | 0 | 75,000 | 0 |
| 0462 | 052 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0477 | 141 | 0 | 0 | 0 | 0 | 30,000 | 0 | 0 | 0 | 0 |
| 0510 | 141 | 0 | 0 | 0 | 0 | 0 | 70,005 | 0 | 0 | 0 |
| 0541 | 024 | 0 | 0 | 105,000 | 0 | 140,000 | 62,500 | 35,000 | 35,000 | 35,000 |
| 0559 | 023 | 0 | 75,600 | 0 | 151,200 | 75,600 | 151,200 | 75,600 | 205,200 | 194,400 |
| 0617 | 052 | 0 | 0 | 0 | 60,000 | 0 | 0 | 0 | 9,984 | 30,000 |
| 0626 | 052 | 0 | 0 | 0 | 0 | 50,016 | 0 | 0 | 0 | 50,016 |
| 0636 | 141 | 0 | 0 | 0 | 0 | 100,005 | 0 | 0 | 100,005 | 100,005 |
| 0674 | 025 | 0 | 14,112 | 14,112 | 14,112 | 14,112 | 14,112 | 14,112 | 14,112 | 14,112 |
| 0687 | 023 | 151,200 | 140,400 | 259,200 | 0 | 259,200 | 259,200 | 259,200 | 475,200 | 950,400 |
| 0786 | 023 | 75,600 | 0 | 151,200 | 0 | 75,600 | 151,200 | 0 | 129,600 | 248,400 |
| 0796 | 052 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 50,016 | 50,016 |
| 0799 | 023 | 64,800 | 0 | 54,000 | 0 | 0 | 54,000 | 54,000 | 54,000 | 108,000 |
| 0828 | 103 | 0 | 0 | 200,016 | 200,016 | 200,016 | 300,024 | 200,016 | 200,016 | 300,024 |
| 0834 | 025 | 0 | 35,280 | 14,112 | 28,224 | 91,728 | 42,336 | 105,840 | 105,840 | 84,672 |
| 0893 | 052 | 0 | 0 | 0 | 0 | 50,016 | 0 | 50,016 | 0 | 50,016 |
| 0909 | 141 | 0 | 0 | 0 | 0 | 0 | 0 | 70,005 | 0 | 0 |
| 0921 | 024 | 0 | 137,160 | 137,160 | 137,160 | 200,160 | 0 | 63,000 | 50,040 | 50,040 |
| 0958 | 103 | 0 | 100,008 | 100,008 | 200,016 | 200,016 | 200,016 | 200,016 | 400,032 | 200,016 |

*Appendix 6: Forecasting using Croston's Method (Excerpt)*

| Material | Customer | 202104 | 202105 | 202106 | 202107 | 202108 | 202109 | 202110 | 202111 | 202112 |
|---|---|---|---|---|---|---|---|---|---|---|
| 1734 | 024 | 9,200 | 9,200 | 9,200 | 9,200 | 9,200 | 9,200 | 9,200 | 9,200 | 9,200 |
| 0040 | 052 | 42,003 | 42,537 | 42,537 | 42,537 | 45,830 | 50,531 | 50,531 | 50,531 | 50,531 |
| 0078 | 141 | 8,793 | 8,793 | 8,793 | 8,793 | 8,793 | 8,793 | 7,958 | 7,958 | 7,958 |
| 0083 | 063 | 47,668 | 47,584 | 47,584 | 47,584 | 47,584 | 47,584 | 47,584 | 47,584 | 34,742 |
| 0094 | 052 | 26,693 | 26,693 | 26,693 | 26,693 | 21,229 | 21,229 | 21,229 | 21,229 | 21,229 |
| 0096 | 052 | 30,227 | 30,227 | 30,227 | 30,227 | 24,591 | 24,591 | 24,591 | 24,591 | 24,591 |
| 0104 | 025 | 25,852 | 20,529 | 20,529 | 28,828 | 30,835 | 30,835 | 42,983 | 42,983 | 36,555 |
| 0137 | 024 | 24,880 | 24,880 | 21,740 | 23,050 | 23,050 | 23,050 | 23,050 | 21,031 | 21,031 |
| 0158 | 023 | 54,164 | 54,164 | 54,164 | 47,829 | 47,829 | 72,575 | 72,575 | 80,794 | 80,794 |
| 0179 | 023 | 96,926 | 91,803 | 88,758 | 95,899 | 95,899 | 95,899 | 95,899 | 111,388 | 103,370 |
| 0182 | 024 | 51,706 | 51,706 | 42,238 | 41,821 | 43,598 | 43,018 | 39,570 | 47,153 | 47,289 |
| 0200 | 141 | 3,637 | 3,637 | 3,637 | 3,637 | 3,637 | 3,637 | 3,637 | 3,637 | 3,637 |
| 0213 | 141 | 5,519 | 5,519 | 5,519 | 5,519 | 5,519 | 5,299 | 5,299 | 5,299 | 5,299 |
| 0349 | 052 | 19,147 | 19,147 | 19,147 | 17,071 | 17,071 | 17,071 | 17,071 | 17,071 | 17,071 |
| 0354 | 025 | 183,440 | 183,440 | 183,440 | 183,440 | 183,440 | 183,440 | 136,265 | 136,265 | 136,265 |
| 0375 | 025 | 263,767 | 263,767 | 263,767 | 263,767 | 263,767 | 263,767 | 263,767 | 169,670 | 163,010 |
| 0392 | 141 | 5,378 | 5,378 | 5,378 | 5,378 | 5,378 | 5,378 | 5,041 | 5,041 | 5,041 |
| 0415 | 025 | 19,140 | 19,140 | 19,140 | 19,140 | 19,140 | 19,140 | 7,962 | 7,962 | 7,962 |
| 0419 | 052 | 18,947 | 18,947 | 18,947 | 17,373 | 17,373 | 17,373 | 17,373 | 17,373 | 17,373 |
| 0447 | 141 | 7,871 | 7,871 | 7,871 | 7,952 | 7,952 | 7,952 | 7,952 | 7,952 | 7,952 |
| 0462 | 052 | 4,357 | 4,357 | 4,357 | 4,357 | 4,357 | 4,357 | 4,357 | 4,357 | 4,357 |
| 0477 | 141 | 6,863 | 6,863 | 6,863 | 6,863 | 6,863 | 6,396 | 6,396 | 6,396 | 6,396 |
| 0510 | 141 | 14,618 | 14,618 | 14,618 | 14,618 | 14,618 | 14,618 | 14,618 | 12,761 | 12,761 |
| 0541 | 024 | 13,587 | 13,587 | 13,587 | 12,322 | 12,322 | 12,322 | 12,394 | 13,528 | 13,528 |
| 0559 | 023 | 44,805 | 48,068 | 48,068 | 48,068 | 48,068 | 48,068 | 39,297 | 39,297 | 52,782 |
| 0617 | 052 | 14,147 | 14,147 | 14,147 | 14,147 | 12,884 | 12,884 | 12,884 | 12,884 | 13,143 |
| 0626 | 052 | 11,119 | 11,119 | 11,119 | 11,358 | 11,358 | 11,358 | 11,358 | 11,835 | 13,531 |
| 0636 | 141 | 18,528 | 20,375 | 20,375 | 20,375 | 20,375 | 22,655 | 22,655 | 22,655 | 24,240 |
| 0674 | 025 | 8,255 | 7,702 | 7,702 | 7,702 | 7,184 | 7,184 | 7,184 | 7,674 | 7,674 |
| 0687 | 023 | 143,340 | 133,595 | 131,759 | 133,666 | 133,666 | 132,441 | 134,925 | 134,058 | 161,346 |
| 0786 | 023 | 37,869 | 38,190 | 38,190 | 38,190 | 38,190 | 31,517 | 36,802 | 36,802 | 40,606 |
| 0796 | 052 | 24,197 | 24,197 | 24,197 | 24,442 | 24,442 | 24,442 | 24,442 | 24,442 | 21,451 |
| 0799 | 023 | 27,900 | 27,900 | 27,900 | 15,518 | 15,518 | 15,518 | 15,518 | 15,518 | 15,190 |
| 0828 | 103 | 54,324 | 51,098 | 53,937 | 53,937 | 53,937 | 53,937 | 48,079 | 48,079 | 48,776 |
| 0834 | 025 | 43,886 | 35,852 | 35,852 | 35,852 | 35,852 | 35,852 | 35,852 | 35,852 | 25,934 |
| 0893 | 052 | 23,721 | 23,721 | 23,721 | 20,069 | 20,069 | 20,069 | 19,685 | 19,685 | 19,941 |
| 0909 | 141 | 16,009 | 16,591 | 16,591 | 16,591 | 16,591 | 16,591 | 16,700 | 16,700 | 16,700 |
| 0921 | 024 | 72,710 | 72,710 | 72,710 | 64,412 | 62,066 | 70,466 | 70,466 | 77,531 | 74,532 |
| 0958 | 103 | 65,848 | 59,925 | 62,430 | 64,894 | 64,894 | 62,616 | 67,677 | 80,342 | 80,342 |

*Appendix 7: Forecasting based on SBA (Excerpt)*

| Material | Customer | 202104 | 202105 | 202106 | 202107 | 202108 | 202109 | 202110 | 202111 | 202112 |
|---|---|---|---|---|---|---|---|---|---|---|
| 1734 | 024 | 8,510 | 8,510 | 8,510 | 8,510 | 8,510 | 8,510 | 8,510 | 8,510 | 8,510 |
| 0040 | 052 | 38,853 | 39,974 | 39,974 | 39,974 | 40,774 | 45,982 | 45,982 | 45,982 | 45,982 |
| 0078 | 141 | 8,133 | 8,133 | 8,133 | 8,133 | 8,133 | 8,133 | 7,027 | 7,027 | 7,027 |
| 0083 | 063 | 44,093 | 42,804 | 42,804 | 42,804 | 42,804 | 42,804 | 42,804 | 42,804 | 27,544 |
| 0094 | 052 | 24,691 | 24,691 | 24,691 | 24,691 | 17,894 | 17,894 | 17,894 | 17,894 | 17,894 |
| 0096 | 052 | 27,960 | 27,960 | 27,960 | 27,960 | 21,099 | 21,099 | 21,099 | 21,099 | 21,099 |
| 0104 | 025 | 23,913 | 17,766 | 17,766 | 24,708 | 27,048 | 27,048 | 37,281 | 37,281 | 31,497 |
| 0137 | 024 | 23,014 | 23,014 | 18,866 | 20,708 | 20,708 | 20,708 | 20,708 | 18,310 | 18,310 |
| 0158 | 023 | 50,102 | 50,102 | 50,102 | 43,316 | 43,316 | 64,799 | 64,799 | 71,465 | 71,465 |
| 0179 | 023 | 89,657 | 82,616 | 81,168 | 88,864 | 88,864 | 88,864 | 88,864 | 94,759 | 90,315 |
| 0182 | 024 | 47,828 | 47,828 | 36,424 | 37,111 | 39,662 | 39,972 | 37,426 | 45,252 | 45,912 |
| 0200 | 141 | 3,364 | 3,364 | 3,364 | 3,364 | 3,364 | 3,364 | 3,364 | 3,364 | 3,364 |
| 0213 | 141 | 5,105 | 5,105 | 5,105 | 5,105 | 5,105 | 4,543 | 4,543 | 4,543 | 4,543 |
| 0349 | 052 | 17,711 | 17,711 | 17,711 | 14,732 | 14,732 | 14,732 | 14,732 | 14,732 | 14,732 |
| 0354 | 025 | 169,682 | 169,682 | 169,682 | 169,682 | 169,682 | 169,682 | 117,534 | 117,534 | 117,534 |
| 0375 | 025 | 243,984 | 243,984 | 243,984 | 243,984 | 243,984 | 243,984 | 243,984 | 130,546 | 130,529 |
| 0392 | 141 | 4,975 | 4,975 | 4,975 | 4,975 | 4,975 | 4,975 | 4,276 | 4,276 | 4,276 |
| 0415 | 025 | 17,705 | 17,705 | 17,705 | 17,705 | 17,705 | 17,705 | 5,502 | 5,502 | 5,502 |
| 0419 | 052 | 17,526 | 17,526 | 17,526 | 15,126 | 15,126 | 15,126 | 15,126 | 15,126 | 15,126 |
| 0447 | 141 | 7,281 | 7,281 | 7,281 | 7,263 | 7,263 | 7,263 | 7,263 | 7,263 | 7,263 |
| 0462 | 052 | 4,030 | 4,030 | 4,030 | 4,030 | 4,030 | 4,030 | 4,030 | 4,030 | 4,030 |
| 0477 | 141 | 6,348 | 6,348 | 6,348 | 6,348 | 6,348 | 5,454 | 5,454 | 5,454 | 5,454 |
| 0510 | 141 | 13,522 | 13,522 | 13,522 | 13,522 | 13,522 | 13,522 | 13,522 | 10,632 | 10,632 |
| 0541 | 024 | 12,568 | 12,568 | 12,568 | 10,709 | 10,709 | 10,709 | 10,740 | 12,149 | 12,149 |
| 0559 | 023 | 41,444 | 43,682 | 43,682 | 43,682 | 43,682 | 43,682 | 32,866 | 32,866 | 44,664 |
| 0617 | 052 | 13,086 | 13,086 | 13,086 | 13,086 | 10,929 | 10,929 | 10,929 | 10,929 | 11,156 |
| 0626 | 052 | 10,285 | 10,285 | 10,285 | 10,109 | 10,109 | 10,109 | 10,109 | 10,427 | 12,398 |
| 0636 | 141 | 17,139 | 18,493 | 18,493 | 18,493 | 18,493 | 20,299 | 20,299 | 20,299 | 21,848 |
| 0674 | 025 | 7,636 | 7,016 | 7,016 | 7,016 | 6,476 | 6,476 | 6,476 | 6,868 | 6,868 |
| 0687 | 023 | 132,589 | 119,459 | 119,467 | 122,588 | 122,588 | 117,943 | 122,032 | 122,811 | 149,359 |
| 0786 | 023 | 35,029 | 34,991 | 34,991 | 34,991 | 34,991 | 27,338 | 32,925 | 32,925 | 36,368 |
| 0796 | 052 | 22,382 | 22,382 | 22,382 | 21,236 | 21,236 | 21,236 | 21,236 | 21,236 | 18,016 |
| 0799 | 023 | 25,808 | 25,808 | 25,808 | 11,777 | 11,777 | 11,777 | 11,777 | 11,777 | 11,510 |
| 0828 | 103 | 50,250 | 45,639 | 49,494 | 49,494 | 49,494 | 49,494 | 41,826 | 41,826 | 42,788 |
| 0834 | 025 | 40,594 | 31,730 | 31,730 | 31,730 | 31,730 | 31,730 | 31,730 | 31,730 | 20,840 |
| 0893 | 052 | 21,942 | 21,942 | 21,942 | 17,316 | 17,316 | 17,316 | 17,054 | 17,054 | 17,627 |
| 0909 | 141 | 14,808 | 15,115 | 15,115 | 15,115 | 15,115 | 15,115 | 14,848 | 14,848 | 14,848 |
| 0921 | 024 | 67,257 | 67,257 | 67,257 | 56,533 | 56,199 | 65,575 | 65,575 | 71,758 | 70,682 |
| 0958 | 103 | 60,909 | 52,606 | 56,096 | 59,476 | 59,476 | 56,401 | 62,177 | 75,039 | 75,039 |

*Appendix 8: Forecasting based on Croston/SBA (Excerpt)*

| Material | Customer | 202104 | 202105 | 202106 | 202107 | 202108 | 202109 | 202110 | 202111 | 202112 |
|---|---|---|---|---|---|---|---|---|---|---|
| 1734 | 024 | 8,510 | 8,510 | 8,510 | 8,510 | 8,510 | 8,510 | 8,510 | 8,510 | 8,510 |
| 0040 | 052 | 38,853 | 39,974 | 39,974 | 39,974 | 40,774 | 45,982 | 45,982 | 45,982 | 45,982 |
| 0078 | 141 | 8,133 | 8,133 | 8,133 | 8,133 | 8,133 | 8,133 | 7,027 | 7,027 | 7,027 |
| 0083 | 063 | 44,093 | 42,804 | 42,804 | 42,804 | 42,804 | 42,804 | 42,804 | 42,804 | 27,544 |
| 0094 | 052 | 24,691 | 24,691 | 24,691 | 24,691 | 17,894 | 17,894 | 17,894 | 17,894 | 17,894 |
| 0096 | 052 | 27,960 | 27,960 | 27,960 | 27,960 | 21,099 | 21,099 | 21,099 | 21,099 | 21,099 |
| 0104 | 025 | 23,913 | 17,766 | 17,766 | 24,708 | 27,048 | 27,048 | 37,281 | 37,281 | 31,497 |
| 0137 | 024 | 23,014 | 23,014 | 18,866 | 20,708 | 20,708 | 20,708 | 20,708 | 18,310 | 18,310 |
| 0158 | 023 | 50,102 | 50,102 | 50,102 | 43,316 | 43,316 | 64,799 | 64,799 | 71,465 | 71,465 |
| 0179 | 023 | 89,657 | 82,616 | 81,168 | 88,864 | 88,864 | 88,864 | 88,864 | 94,759 | 90,315 |
| 0182 | 024 | 47,828 | 47,828 | 36,424 | 37,111 | 39,662 | 39,972 | 37,426 | 45,252 | 45,912 |
| 0200 | 141 | 3,364 | 3,364 | 3,364 | 3,364 | 3,364 | 3,364 | 3,364 | 3,364 | 3,364 |
| 0213 | 141 | 5,105 | 5,105 | 5,105 | 5,105 | 5,105 | 4,543 | 4,543 | 4,543 | 4,543 |
| 0349 | 052 | 17,711 | 17,711 | 17,711 | 14,732 | 14,732 | 14,732 | 14,732 | 14,732 | 14,732 |
| 0354 | 025 | 169,682 | 169,682 | 169,682 | 169,682 | 169,682 | 169,682 | 117,534 | 117,534 | 117,534 |
| 0375 | 025 | 243,984 | 243,984 | 243,984 | 243,984 | 243,984 | 243,984 | 243,984 | 130,546 | 130,529 |
| 0392 | 141 | 4,975 | 4,975 | 4,975 | 4,975 | 4,975 | 4,975 | 4,276 | 4,276 | 4,276 |
| 0415 | 025 | 17,705 | 17,705 | 17,705 | 17,705 | 17,705 | 17,705 | 5,502 | 5,502 | 5,502 |
| 0419 | 052 | 17,526 | 17,526 | 17,526 | 15,126 | 15,126 | 15,126 | 15,126 | 15,126 | 15,126 |
| 0447 | 141 | 7,281 | 7,281 | 7,281 | 7,263 | 7,263 | 7,263 | 7,263 | 7,263 | 7,263 |
| 0462 | 052 | 4,030 | 4,030 | 4,030 | 4,030 | 4,030 | 4,030 | 4,030 | 4,030 | 4,030 |
| 0477 | 141 | 6,348 | 6,348 | 6,348 | 6,348 | 6,348 | 5,454 | 5,454 | 5,454 | 5,454 |
| 0510 | 141 | 13,522 | 13,522 | 13,522 | 13,522 | 13,522 | 13,522 | 13,522 | 10,632 | 10,632 |
| 0541 | 024 | 12,568 | 12,568 | 12,568 | 10,709 | 10,709 | 10,709 | 10,740 | 12,149 | 12,149 |
| 0559 | 023 | 41,444 | 43,682 | 43,682 | 43,682 | 43,682 | 43,682 | 32,866 | 32,866 | 44,664 |
| 0617 | 052 | 13,086 | 13,086 | 13,086 | 13,086 | 10,929 | 10,929 | 10,929 | 10,929 | 11,156 |
| 0626 | 052 | 10,285 | 10,285 | 10,285 | 10,109 | 10,109 | 10,109 | 10,109 | 10,427 | 12,398 |
| 0636 | 141 | 17,139 | 18,493 | 18,493 | 18,493 | 18,493 | 20,299 | 20,299 | 20,299 | 21,848 |
| 0674 | 025 | 7,636 | 7,016 | 7,016 | 7,016 | 6,476 | 6,476 | 6,476 | 6,868 | 6,868 |
| 0687 | 023 | 143,340 | 133,595 | 131,759 | 133,666 | 133,666 | 132,441 | 134,925 | 134,058 | 161,346 |
| 0786 | 023 | 35,029 | 34,991 | 34,991 | 34,991 | 34,991 | 27,338 | 32,925 | 32,925 | 36,368 |
| 0796 | 052 | 22,382 | 22,382 | 22,382 | 21,236 | 21,236 | 21,236 | 21,236 | 21,236 | 18,016 |
| 0799 | 023 | 25,808 | 25,808 | 25,808 | 11,777 | 11,777 | 11,777 | 11,777 | 11,777 | 11,510 |
| 0828 | 103 | 50,250 | 45,639 | 49,494 | 49,494 | 49,494 | 49,494 | 41,826 | 41,826 | 42,788 |
| 0834 | 025 | 40,594 | 31,730 | 31,730 | 31,730 | 31,730 | 31,730 | 31,730 | 31,730 | 20,840 |
| 0893 | 052 | 21,942 | 21,942 | 21,942 | 17,316 | 17,316 | 17,316 | 17,054 | 17,054 | 17,627 |
| 0909 | 141 | 14,808 | 15,115 | 15,115 | 15,115 | 15,115 | 15,115 | 14,848 | 14,848 | 14,848 |
| 0921 | 024 | 67,257 | 67,257 | 67,257 | 56,533 | 56,199 | 65,575 | 65,575 | 71,758 | 70,682 |
| 0958 | 103 | 60,909 | 52,606 | 56,096 | 59,476 | 59,476 | 56,401 | 62,177 | 75,039 | 75,039 |

*Appendix 9: Forecasting based on TSB (Excerpt)*

| Material | Customer | 202104 | 202105 | 202106 | 202107 | 202108 | 202109 | 202110 | 202111 | 202112 |
|---|---|---|---|---|---|---|---|---|---|---|
| 1734 | 024 | 3,119 | 2,807 | 2,526 | 2,274 | 2,046 | 1,842 | 1,657 | 1,492 | 1,343 |
| 0040 | 052 | 33,249 | 35,963 | 31,780 | 28,602 | 31,670 | 41,373 | 39,591 | 35,632 | 32,069 |
| 0078 | 141 | 3,257 | 2,931 | 2,638 | 2,374 | 2,137 | 1,923 | 4,729 | 4,258 | 3,832 |
| 0083 | 063 | 33,773 | 36,356 | 34,621 | 31,159 | 28,043 | 25,239 | 22,715 | 20,443 | 24,705 |
| 0094 | 052 | 13,753 | 12,378 | 11,140 | 10,026 | 14,489 | 12,879 | 11,591 | 10,432 | 9,389 |
| 0096 | 052 | 17,458 | 15,712 | 14,141 | 12,727 | 17,817 | 15,459 | 13,913 | 12,522 | 11,270 |
| 0104 | 025 | 16,632 | 17,955 | 14,881 | 16,144 | 25,461 | 23,802 | 25,632 | 33,652 | 36,428 |
| 0137 | 024 | 13,078 | 11,770 | 15,532 | 19,041 | 17,147 | 15,432 | 13,889 | 17,474 | 15,574 |
| 0158 | 023 | 47,740 | 45,619 | 41,057 | 44,441 | 36,895 | 40,114 | 56,889 | 62,086 | 64,279 |
| 0179 | 023 | 71,106 | 76,187 | 81,005 | 80,258 | 76,247 | 68,623 | 61,760 | 67,754 | 103,246 |
| 0182 | 024 | 32,213 | 28,991 | 33,753 | 36,355 | 37,969 | 41,157 | 41,789 | 39,251 | 47,485 |
| 0200 | 141 | 1,330 | 1,197 | 1,077 | 969 | 872 | 785 | 707 | 636 | 572 |
| 0213 | 141 | 1,942 | 1,748 | 1,573 | 1,416 | 1,274 | 2,682 | 2,752 | 2,477 | 2,229 |
| 0349 | 052 | 9,048 | 8,143 | 7,329 | 10,886 | 10,201 | 9,181 | 8,263 | 7,436 | 6,693 |
| 0354 | 025 | 106,622 | 149,615 | 134,654 | 121,188 | 109,070 | 98,163 | 122,396 | 95,687 | 86,118 |
| 0375 | 025 | 171,488 | 154,339 | 138,905 | 125,015 | 112,513 | 101,262 | 91,136 | 112,493 | 142,262 |
| 0392 | 141 | 1,877 | 1,690 | 1,521 | 1,369 | 1,232 | 1,109 | 2,504 | 2,580 | 2,322 |
| 0415 | 025 | 1,452 | 1,307 | 1,176 | 1,058 | 953 | 857 | 2,687 | 3,117 | 2,805 |
| 0419 | 052 | 11,012 | 9,911 | 8,920 | 11,932 | 11,251 | 10,126 | 9,113 | 8,202 | 7,382 |
| 0447 | 141 | 3,405 | 3,065 | 2,758 | 4,981 | 4,646 | 4,182 | 3,763 | 3,387 | 3,048 |
| 0462 | 052 | 300 | 270 | 243 | 219 | 197 | 177 | 160 | 144 | 129 |
| 0477 | 141 | 1,761 | 1,585 | 1,426 | 1,284 | 1,155 | 3,071 | 3,102 | 2,791 | 2,512 |
| 0510 | 141 | 5,737 | 5,163 | 4,647 | 4,182 | 3,764 | 3,387 | 3,049 | 6,560 | 6,613 |
| 0541 | 024 | 8,078 | 7,271 | 6,544 | 8,632 | 8,086 | 7,278 | 9,405 | 11,721 | 10,845 |
| 0559 | 023 | 31,531 | 34,915 | 34,963 | 31,466 | 28,320 | 25,488 | 30,212 | 27,352 | 31,933 |
| 0617 | 052 | 5,176 | 4,658 | 4,192 | 3,773 | 6,922 | 6,927 | 6,235 | 5,611 | 8,971 |
| 0626 | 052 | 5,283 | 4,755 | 4,279 | 6,852 | 6,837 | 6,153 | 5,538 | 8,310 | 11,671 |
| 0636 | 141 | 6,235 | 10,915 | 11,232 | 10,109 | 9,098 | 14,252 | 14,752 | 13,277 | 18,924 |
| 0674 | 025 | 4,619 | 6,037 | 5,230 | 4,707 | 6,046 | 5,216 | 4,694 | 5,960 | 5,868 |
| 0687 | 023 | 106,513 | 112,336 | 117,694 | 118,441 | 106,255 | 111,534 | 123,065 | 127,213 | 127,873 |
| 0786 | 023 | 26,592 | 30,272 | 28,011 | 25,210 | 22,689 | 26,937 | 28,797 | 28,801 | 32,701 |
| 0796 | 052 | 14,390 | 12,951 | 11,656 | 15,358 | 16,036 | 14,433 | 12,989 | 11,690 | 16,169 |
| 0799 | 023 | 7,876 | 7,089 | 6,380 | 9,236 | 8,222 | 7,399 | 6,660 | 5,994 | 8,850 |
| 0828 | 103 | 34,048 | 39,863 | 45,674 | 41,426 | 37,283 | 33,555 | 39,610 | 35,885 | 41,769 |
| 0834 | 025 | 28,184 | 31,972 | 25,841 | 23,257 | 20,931 | 18,838 | 16,954 | 15,259 | 19,666 |
| 0893 | 052 | 11,679 | 10,511 | 9,460 | 13,817 | 12,292 | 11,063 | 15,199 | 13,617 | 17,473 |
| 0909 | 141 | 4,908 | 9,283 | 8,932 | 8,039 | 7,235 | 6,512 | 11,062 | 10,618 | 9,556 |
| 0921 | 024 | 50,919 | 45,827 | 41,245 | 50,288 | 58,015 | 59,718 | 58,085 | 65,202 | 79,498 |
| 0958 | 103 | 41,996 | 46,763 | 52,051 | 56,318 | 50,995 | 55,147 | 59,107 | 65,332 | 67,687 |

*Appendix 10: Forecasting based on Extension (Excerpt)*

| Material | Customer | 202104 | 202105 | 202106 | 202107 | 202108 | 202109 | 202110 | 202111 | 202112 |
|---|---|---|---|---|---|---|---|---|---|---|
| 1734 | 024 | - | - | - | 0 | 0 | 0 | 0 | 0 | 0 |
| 0040 | 052 | - | - | - | 13,325 | 80,279 | 15,327 | 82,015 | 15,327 | 82,015 |
| 0078 | 141 | - | - | - | 0 | 0 | 0 | 2,342 | 22,342 | 4,684 |
| 0083 | 063 | - | - | - | 14,268 | 0 | 0 | 0 | 0 | 9,181 |
| 0094 | 052 | - | - | - | 0 | 5,965 | 5,965 | 5,965 | 0 | 50,016 |
| 0096 | 052 | - | - | - | 0 | 7,033 | 7,033 | 7,033 | 0 | 50,016 |
| 0104 | 025 | - | - | - | 27,532 | 63,504 | 27,832 | 40,651 | 34,262 | 38,723 |
| 0137 | 024 | - | - | - | 13,806 | 13,806 | 46,899 | 6,903 | 12,206 | 32,204 |
| 0158 | 023 | - | - | - | 43,316 | 64,878 | 93,600 | 93,600 | 95,822 | 191,643 |
| 0179 | 023 | - | - | - | 109,643 | 88,864 | 88,864 | 88,864 | 145,973 | 211,410 |
| 0182 | 024 | - | - | - | 13,474 | 27,621 | 27,837 | 39,881 | 21,360 | 48,092 |
| 0200 | 141 | - | - | - | 0 | 0 | 0 | 0 | 34,995 | 1,121 |
| 0213 | 141 | - | - | - | 0 | 30,000 | 1,497 | 1,497 | 1,497 | 0 |
| 0349 | 052 | - | - | - | 4,911 | 4,911 | 4,911 | 0 | 50,016 | 4,911 |
| 0354 | 025 | - | - | - | 28,224 | 28,224 | 42,336 | 14,112 | 14,112 | 14,112 |
| 0375 | 025 | - | - | - | 0 | 338,688 | 438,832 | 454,304 | 213,345 | 349,501 |
| 0392 | 141 | - | - | - | 0 | 30,000 | 1,658 | 2,850 | 2,850 | 1,425 |
| 0415 | 025 | - | - | - | 119,952 | 67,054 | 47,083 | 24,405 | 24,405 | 17,758 |
| 0419 | 052 | - | - | - | 5,042 | 5,042 | 5,042 | 50,016 | 5,042 | 5,042 |
| 0447 | 141 | - | - | - | 4,842 | 4,842 | 2,421 | 0 | 75,000 | 2,421 |
| 0462 | 052 | - | - | - | 0 | 0 | 0 | 0 | 0 | 0 |
| 0477 | 141 | - | - | - | 0 | 30,000 | 0 | 0 | 0 | 0 |
| 0510 | 141 | - | - | - | 0 | 0 | 70,005 | 4,507 | 7,088 | 7,088 |
| 0541 | 024 | - | - | - | 862 | 129,588 | 41,066 | 23,074 | 23,766 | 23,766 |
| 0559 | 023 | - | - | - | 79,521 | 54,321 | 79,521 | 42,882 | 73,257 | 129,671 |
| 0617 | 052 | - | - | - | 60,000 | 0 | 0 | 0 | 9,984 | 23,719 |
| 0626 | 052 | - | - | - | 3,370 | 36,714 | 6,739 | 3,370 | 6,952 | 24,938 |
| 0636 | 141 | - | - | - | 6,164 | 100,005 | 0 | 0 | 100,005 | 100,005 |
| 0674 | 025 | - | - | - | 7,016 | 6,838 | 6,838 | 6,838 | 9,283 | 9,283 |
| 0687 | 023 | - | - | - | 53,083 | 209,346 | 221,765 | 219,787 | 363,426 | 699,039 |
| 0786 | 023 | - | - | - | 23,233 | 62,064 | 107,423 | 7,655 | 107,124 | 140,584 |
| 0796 | 052 | - | - | - | 7,079 | 7,079 | 7,079 | 0 | 50,016 | 39,776 |
| 0799 | 023 | - | - | - | 4,844 | 918 | 50,709 | 39,926 | 25,851 | 43,673 |
| 0828 | 103 | - | - | - | 49,494 | 49,494 | 49,494 | 84,293 | 84,293 | 163,425 |
| 0834 | 025 | - | - | - | 30,002 | 71,729 | 38,801 | 56,433 | 31,730 | 39,073 |
| 0893 | 052 | - | - | - | 5,772 | 39,116 | 11,544 | 28,042 | 17,054 | 17,627 |
| 0909 | 141 | - | - | - | 5,038 | 0 | 0 | 51,619 | 9,899 | 9,899 |
| 0921 | 024 | - | - | - | 87,893 | 64,206 | 59,468 | 64,620 | 63,704 | 61,415 |
| 0958 | 103 | - | - | - | 69,018 | 69,018 | 96,934 | 121,805 | 219,609 | 99,460 |

*Appendix 11: Python code used to calculate forecast accuracy*

```
# Authors:       Dominik Martin <martin@kit.edu>
#                Philipp Spitzer <office@ksri.kit.edu>
#                Niklas Kühl <kuehl@kit.edu>
# Modified by:   Jonathan Nicklin <j.m.nicklin@student.utwente.nl>

import numpy as np
import pandas as pd

#information from excel is imported into python
df = pd.read_excel (r'C:[path of excel file on device]')
df = df.reset_index()

#opportunity costs (a1) and storage costs (a2) are defined
a1=0.5
a2=0.5

#information from excel is converted from "#, #, #, #,…" into a format that can be handled within python
for i, row in df.iterrows():
   y_true=row['y_true']
   y_pred=row['y_pred']
   y_true = y_true.split(',')
   y_pred = y_pred.split(',')
   y_true_float=[]
   for i in y_true:
      y_true_float.append(float(i))
   y_pred_float=[]
   for i in y_pred:
      y_pred_float.append(float(i))
   y_true=y_true_float
   y_pred=y_pred_float

#Metric for forecast accuracy is calculated according to input arrays and pre-defined costs
   sum_n = 0
   for t in range(1, len(y_true) + 1):
      sum_t = 0
      for i in range(1, t + 1):
         delta1 = np.sum([y_k for y_k in y_true[:i]]) - np.sum([f_j for f_j in y_pred[:t]])
         delta2 = np.sum([f_k for f_k in y_pred[:i]]) - np.sum([y_j for y_j in y_true[:t]])

         sum_t = sum_t + np.max([0, a1 * np.min([y_true[i - 1], delta1]), a2 * np.min([y_pred[i - 1], delta2])])
         * (t - i + 1)
      sum_n = sum_n + sum_t
   print(sum_n / len(y_true))
```