

# SEEKING TRENDS FROM INVOICING DATA

Case: Company X

## Abstract

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Title of publication <b>Seeking trends from invoicing data</b> Case: Company X		
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Abstract <p>In order to survive in highly competitive markets, businesses need to forecast the future. Precise forecasts help businesses to achieve their objectives through historical data, and enable them to increase sales, improve customer service, and maintain efficient business activities. By examining varying trends, businesses can predict future changes more efficiently.</p> <p>The aim of the thesis was to find trends from invoicing data so the case company could forecast future invoicing more precisely. The study included invoicing data from two mills. The invoicing data was gathered from January 2016 until August 2018 by using Company X's internal IT systems. A quantitative research approach was chosen. The data was examined in six months' time series by observing the effects of different invoicing points.</p> <p>The study revealed that trends were found from Company X's invoicing data. However, the trends vary between mills, time series, and invoicing points. Medium-term and long-term trends were found. Some of the trends were more distinctive than others, but fluctuation could be noticed from each time series. If the circumstances remain similar, it can be assumed that the trends presented will also occur in the future.</p> <p>Because the invoicing trends were examined by observing the effects of various invoicing points, further research could focus on examining trends through mathematical calculations. Since the thesis focuses only on a specific company, the results cannot be generalised. However, as trends were found, it can be assumed that Company X's other mills will also have trends in their invoicing data.</p>		
Keywords Forecasting, Trends, Invoicing data		

## Tiivistelmä

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Tiivistelmä <p>Yritysten tulee ennustaa tulevaisuutta, jotta he pärjäävät kilpailukykyisenä markkinoilla. Tarkat ennusteet auttavat yrityksiä saavuttamaan tavoitteensa historiatiedon avulla. Ennusteet mahdollistavat yritysten myynnin lisäämisen, asiakaspalvelun kehittämisen ja tehokkuuden säilyttämisen.</p> <p>Tämän opinnäytetyön tarkoitus oli etsiä trendejä laskutusdatasta, jotta toimeksiantaja pystyisi paremmin ennustamaan tulevaisuuden laskutusta. Tutkimus sisälsi laskutusdataa kahdelta tehtaalta. Laskutusdata kerättiin tammikuun 2016 – elokuun 2018 väliseltä ajalta, Yritys X:n tietojärjestelmien avulla. Tutkimukseen valittiin määrällinen lähestymistapa. Laskutusdataa tutkittiin kuuden kuukauden aikajaksoissa havainnoimalla eri laskutuspisteiden vaikutuksia.</p> <p>Tutkimus paljasti, että Yritys X:n laskutusdatasta löydettiin trendejä. Trendit kuitenkin vaihtelevat tehtaasta, aikajaksosta ja laskutuspisteestä riippuen. Keskipitkiä ja pidempiaikaisia trendejä löydettiin. Osa trendeistä erottui selkeämmin kuin toiset, mutta vaihtelua oli havaittavissa jokaisessa aikajaksossa. Mikäli olosuhteet pysyvät samanlaisina, voidaan olettaa, että esitetyt trendit ilmenevät myös tulevaisuudessa.</p> <p>Mahdollinen jatkotutkimus voisi tarkastella trendejä matemaattisten kaavojen avulla, sillä tässä tutkimuksessa trendejä tarkasteltiin havainnoimalla laskutuspisteiden vaikutuksia. Tutkimus keskittyy ainoastaan tiettyyn yritykseen, joten tuloksia ei voida yleistää muihin yrityksiin. Koska trendejä löydettiin, voidaan olettaa, että Yritys X:n muilla tehtailla on niin ikään havaittavissa trendejä.</p>		
Asiasanat Ennustaminen, trendit, laskutusdata		

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# 1 INTRODUCTION

## 1.1 Background

Forecasting of future events play a critical role in planning and decision-making processes (Montgomery, Jennings & Kulahci 2015, 3). Most businesses rely heavily upon forecasts and therefore, businesses have started to pay more attention to forecasting their future events. Forecasts are needed because in some industries production processes take a long time and customers are not willing to wait. Businesses rely on forecasts, so that they can accurately predict future demand and thus increase sales, improve customer service, and maintain efficient supply chain activities. (Chase Jr. 2013, 25-26.)

Precise forecasts help businesses to achieve their objectives through historical data. When businesses are able to predict what is likely to happen in the future, they can calculate and thus, implement business plans to achieve faster invoiced income (Simić, Simić & Svirčević 2011, 14). As forecasting has become a fundamental process for businesses, it has increased the amount of emerged trends. Developing technologies have brought up new trends, which are likely to have effects on future forecasts. (Rubin 2015a.)

This research will be done as an assignment for a case company. Research focusing on invoicing trends is needed, since the results will give beneficial information for the future. The data included in this research is confidential. Thus, the mandator wants to stay unnamed and it will be called as Company X. Company X does business in domestic and international markets. The data was collected from two different mills, and the mills will be named as Mill 1 and Mill 2. Both of these mills are located in Finland. The mills produce different type of goods, but these goods are mainly exported to the same markets.

This research is limited to Company X and its two mills. Trends will be examined from the invoicing data which has been collected from the past 32 months. The daily invoicing data will be analysed by observing the effects of five different invoicing points.

## 1.2 Research problem and objectives

This research aims to find trends from the invoicing data. The objective of this research is to analyse which factors cause trends in invoicing. Company X wants to find out if there are any frequent fluctuation or trends formed in the invoicing data. If fluctuation or trends can be found, Company X can more precisely forecast how invoicing will occur in the upcoming months. It will also help them to create more precise invoicing forecasts for the

future. If trends are found, factors causing these trends will also be examined. Considering the research problem and objective, the research question was formed as following:

*“What trends occur in the invoicing data?”*

After defining the research objective and question, an appropriate research methodology will be examined. The invoicing data analysed in this research was collected by using Company X's IT system. Invoicing data has been routinely recorded by Company X, but not for research purposes. This means that the data analysed in this research can be defined as secondary data. Sørensen, Sabroe & Olsen (1996, 435) describe secondary data as data, which has not been gathered for research purposes. When considering the research question, a quantitative research approach was chosen, since the main aim in this research is to find phenomena from numerical invoicing data. According to Kananen (2011a, 12), a quantitative research approach is the most appropriate for examining the interaction between various factors and numerical data.

This research will proceed as follows. At first, theory about forecasting and trends are presented in chapter two. In chapter three, the chosen research approach and data collection method are explained. After the data collection process, the invoicing data will be analysed in Excel. Fourth chapter includes the results, which are presented in the form of bar charts and line graphs. In the fifth chapter, results are discussed and reviewed in the light of literature. Recommendations for future and Company X are also presented at the end of this research.

## 2 FORECASTING

In order to survive in highly competitive markets, businesses need to forecast the future. Information concerning future events is critical for businesses. Most of the time, businesses gather information about future through research and development (R&D) and by market segmentation. Information technology (IT) has enabled businesses to collect data and information that their competitors are not able to find (Porter & Millar 1990). In competitive and changing markets, the need for information and data concerning the future has emphasized. As Porter (1985) stated, by generating new ways to overcome their rivals, businesses can achieve competitive advantage. During the years, information technology has strengthen its position within all industries, and it has also established forecasting techniques and models for businesses to predict future business plans.

The main idea in forecasting is to help businesses to estimate the future. Therefore, a forecast can be defined as a prediction of future event. Forecasts help businesses to plan future activities such as sales, demand, raw materials, inventory levels, and acquisitions. By forecasting future demand, businesses can also improve their customer service, logistics, and generally operate more efficiently. (Montgomery et al. 2015, 1-2.) In order for businesses to maintain or strengthen their position in competing markets, they need to think ahead.

Enterprise Resource Planning (ERP) systems are efficient tools for businesses to collect data and information needed in forecasting. The main objective for ERP systems is to gather domain knowledge, which will assist managers to make better decisions (Simić et al. 2011, 14). Stalk Jr. (1988, 47) draws attention to fast information flow inside the company. He describes how the importance of fast lead times and fluent information flow can increase efficiency and cut expenses within the business. IT systems are a natural way to speed up the information transmission. In order to generate faster knowledge movement through the company, ERP systems can be used to collect data and information from both internal and external activities. This will enhance the connection between diverse business activities. ERP systems are often combined with IT based Supply Chain Management (SCM) softwares. These IT systems guide businesses to estimate future actions based on external and internal information (Simić et al. 2011, 15). When combined together, ERP and SCM systems can help businesses to reach higher productiveness, and hence increase lucrativeness (Marinagi, Trivellas & Sakas 2014, 587).

In most industries and businesses, decision making depends on forecasts. Forecasts relieve future uncertainty, and this way they guide decision makers to more accurate

decisions. Successful forecasting can increase businesses' profitability significantly. As businesses have a clear vision about future events, they are able to plan production to match more precisely with customer demand, and thus decrease inventory expenses. Through forecasting, businesses are also able to cut distribution costs. Information concerning future demand allows businesses to acquire adequate amount of raw materials, hence cut costs caused by excessive raw materials. Forecasting is a core of various business activities, and when implemented efficiently it can increase businesses' profit margins. (Singh, Olasky, Cluff & Welch, Jr. 2006, 11.)

With this in mind, a forecast is only a prediction of possible future events. It is important to separate forecasts from business plans or objectives. However, forecasts can be utilized when creating business objectives, plans or goals (Kolassa and Siemsen 2014, 11). In order to establish achievable business objectives, businesses require both historical- and real time information. High quality and easy accessible data combined with various IT systems will help businesses' to develop more realistic plans, budgets, and objectives. (Lyll, Mercier & Gstettner 2018.)

According to Kolassa and Siemsen (2014, 4), it is impossible to create a perfect forecast. They suggest, that the way how a forecast is created, defines whether the forecast is good or bad. Gilliland, Tashman & Sglavo (2015, 111-113) state that by combining forecasts created in different methods has been proven to be more accurate than forecasts created by using only one method. They believe that forecasts created by using different methods are able to include broader set of information which allows data to dispute, and thus increase the accuracy of forecasts. Similarly, Cagdas and Erol (2012, 4) and Samonas (2015, 97), suggest that forecasts are more likely to be precise when different methods are combined. As a result, people inside the businesses should continuously question the ambiguity of forecasts (Kolassa and Siemsen, 2014, 8).

Some future events are easier to predict than others, for example different variations in time horizon will make it more difficult to forecast. Christopher (2011, 91) argues, that businesses operating internationally will find it easier to predict global demand in comparison to forecasting of single markets. This theory is supported by Hugos (2018, 48). He believes that single markets forecasts are more challenging to do. He explains that the accuracy of forecasts are likely to decrease when forecasts are divided into single markets.

Meyr (2008) describes how the utilisation of supply chains defines how businesses benefit from forecasts. In cases which a business utilises make-to-stock supply chain, their stock is produced against a forecast and customers are only served from this stock. As a result,

production capacity, warehouse space, and the acquisition of required raw materials are determined against the forecast. Gilliland et al. (2015, 356) draw attention to distribution and warehousing costs in make-to-stock supply chain. To ensure the required level of customer service, businesses need to forecast future quantities, so they are able to determine transportation modes and quantity of carriers. Chase Jr. (2013, 27) agrees with these theories, and he describes how make-to-order supply chains require demand forecasts, though customers are willing to wait for long time for their products. He also states how imprecise forecasting will eventually decrease the level of customer service and increase the costs of supply chain.

Forecasting can be executed in almost every industry, but it is most used in business and economics. Forecasts are usually divided into three different categories, short-term, medium-term, and long-term forecasts as presented in Figure 1. Short-term forecasts contain events from few days up to several months. Medium-term forecasts usually include events from two years into the future, and long-term forecasts can extend by many years into the future. Short- and medium-term forecasts are often used within managers to determine future activities and plans. Short- and medium-term forecasts are generally based on historical data, which are likely to stay constant in the future. Statistics compiled by a company are essential when creating short- or medium-term forecast. (Montgomery et al. 2015, 1-2.)

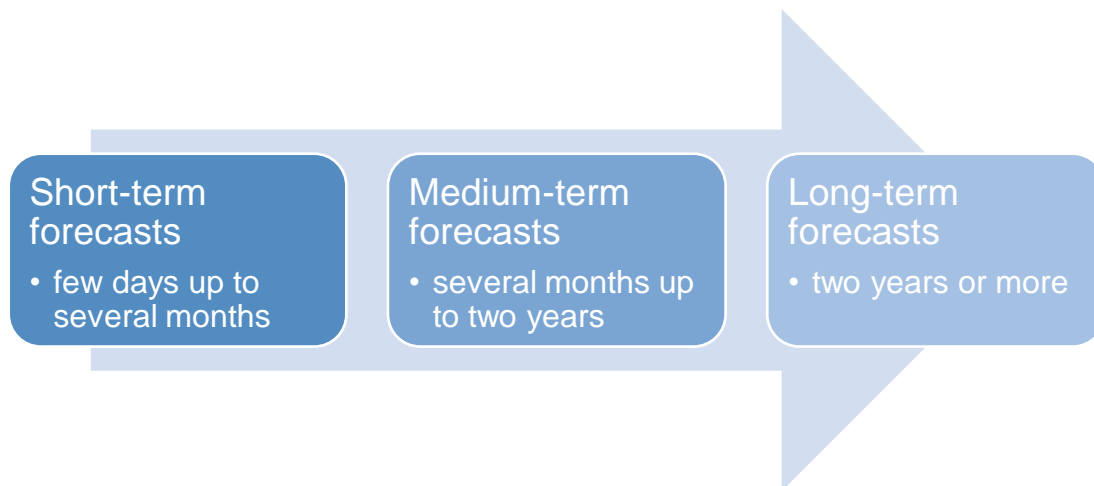


Figure 1. Forecast categories and durations (Montgomery et al. 2015, 1-2.)

Forecasts can be used to predict a certain event in the near future, but in most of the times, they are needed to estimate multiple time-periods ahead (Kolassa and Siemsen 2014, 56). Long-lasting forecasts require a large amount of statistical data, for example sales levels or received orders. In such cases where businesses are not able to gather enough data to predict the future, they must use an approximation from already accumulated data. This can lead to inaccurate forecasts if the assumptions are made by

using an author's intuition. Kolassa and Siemsen (2014, 56), and Bettner (2014, 68) refer that long forecasting horizons are key to productive forecasts, but at the same time, Montgomery et al. (2015, 77) argue that in the long run forecasts are likely to become imprecise. They suggest that external factors, such as new customers, will decrease the accuracy of a forecast. A similar view is held by Chase Jr. (2013, 93). He states that longer timespan forecasts are likely to become inaccurate over the time, due to unexpected factors influencing the price of the product.

Different business activities require a different type of forecast intervals. For example, in production planning, estimates concerning future demand are generally renewed on a monthly basis. Short intervals in production planning are needed, since customers demand vary monthly. This forces businesses to change production cycles and plan deliveries for each month to match customers demand as precisely as possible. However, long-term forecasts can be as precise as short-term forecasts, as long as the forecast interval is kept short. Forecast horizon can extend to the future by several months, but in order to create effective forecasts, the interval should only extend couple of months into the future. (Montgomery et al. 2015, 6.)

Customers are not prepared to wait for goods or services, as they have become accustomed to prompt availability. If a business is not able to respond to customers demand in reasonable time, customers may look for substitutive products elsewhere (Singh et al. 2006, 11). Such phenomena are most likely to occur in markets where switching costs are low. In such cases, where customer decides to look alternative products elsewhere, the information of their future demand is also lost, this makes it challenging for businesses to forecast future demand of lost customers (Gilliland et al. 2015, 82). In high switching cost markets where substitutive products are rare, customers are usually willing to wait for their products.

These functions have enhanced the need that businesses must be aware of future customer behavior, in order to retain high customer satisfaction. This has led to a situation, where businesses have to keep an eye on changing trends and signals found from previous forecasts. Since most forecasts are based on historical data, businesses must store and go through historical data collected from various business activities. Trends and signals appearing on previous data can provide a directional estimate of what the future demand will look like. Therefore, forecasts also help businesses to create faster order handling processes and reach faster customer responses. (Chase Jr. 2013, 47.)

Kolassa and Siemsen (2014, 129) describe how forecasts are beneficial for decision making, but in order to utilize forecasts as efficiently as possible, businesses must

understand the methods required to create a forecast and how to utilize it for decision making. In most cases, a forecast is based on data and assumptions. However, experience gained from different business activities by the author or authors, has been proven to be a critical part of a precise forecast (Chase Jr. 2013, 8). Kolassa and Siemsen (2014, 4) believe that a forecast can be made by using intuitions. Similarly, Chase Jr. (2013, 8) suggests that assumptions gathered from earlier experiences can either strengthen or deteriorate the accuracy of a forecast.

## 2.1 Time series forecasting

Most forecasts are based on historical data. Hugos (2018, 47) refers that historical data and statistics can be efficiently utilized when creating future forecasts. His theory has been supported by Montgomery et al. (2015, 5). They suggest that historical data can be used as a fundamental to create future forecasts.

Time series forecasting is one of the most used forecasting methods. Time series forecast model creates forecasts based only on products or services demand history. Usually historical data includes statistics from different business activities that occur on a monthly basis such as sales, orders, invoicing, and shipment levels (Box, Jenkins, Reinsel & Ljung 2015, 1). In some industries time series can consist continuously stored data such as price movements of raw materials or changes in monthly profits (Chatfield 2003, 1).

Some businesses are not able to gather data from various activities, but in order to generate a time series forecast, at least shipment data and received orders should be collected. Time series forecast can be created by using only shipment and order data, this however, decreases the accuracy of the forecast. (Gilliland et al. 2015, 82.)

Kolassa and Siemsen (2014, 4) emphasizes the importance of information and data. According to them, information and statistics can significantly deteriorate the quandary of the future. They suggest that forecasts should include all data and statistics applicable to a business.

Time series analysis seeks to observe trends or patterns from data, and predicts that these patterns or trends will extend into the future. Samonas (2015, 89) states that usually time series consists of four components that are (1) the trend or pattern, (2) the seasonality, (3) the cyclical contraction and (4) irregular changes. Time series forecasting can help businesses in multiple actions and it can be implemented in various fields, for example in economics and industry (Cagdas and Erol 2012, 3). Time series methods are most beneficial when forecasts focus on steady markets where the changes of trends or seasonality are slight (Hugos, 2018, 47).

Samonas (2015, 88) proposes that forecasts can be made by using three different techniques; extrapolation technique, causative technique, and judgemental technique. Extrapolation technique is similar to time series method. This technique believes that former events and statistics will be a natural sign of the future. However, this technique is most beneficial for sustainable businesses. Causative technique tries to realise the changes of the market combined with vision and presumptions. This technique provide most advantages when transitions are limited in the future. Judgemental techniques may occur in such cases where business are not able to gather historical statistics or information. An author or authors may use their own opinions or feelings to judge the future prediction. In some cases reforming of forecast is required if the forecast was made by using judgmental techniques.

Normally, time series will notice a trend or a pattern in historical data. In some cases, historical data does not include any trends, patterns or seasonality. According to Gilliland et al. (2015, 121) historical data without trends or seasonality will form a flat-line forecast. They also suggest that flat-line forecasts can reliably predict future events. On the contrary, Chase Jr. (2013, 47) argues that forecasts which can precisely point out trends, patterns, or seasonality are more beneficial for businesses. When forecasts can notify differences, they are more sustainable and therefore, allow businesses to react faster to changing customer demand.

Some time series are more predicable than others. Time series that last for years are more difficult to forecast than time series that last for couple of months. Significant changes in historical data complicate the forecasting process. Minimal movements or stable time series allow businesses to generate more accurate forecasts. (Hugos 2018, 47-48.)

## 2.2 Trends, patterns and seasonality in forecasting

When creating forecasts it is needed to examine effects of trends, patterns, and seasonality. Movements in data and statistics can appear to be crucial factors in future events as they can unveil possible future changes. Therefore, it is important for businesses to monitor frequent and continuing trends and patterns. Effects of trends, patterns, and seasonality extend to all industries, but they may vary depending on the industry and markets.

Rubin (2015b) describes a trend as a direction of change. She states that a trend can either be rising, stable, downward, breaking or changing. Rising trends are usually phenomena that are popular among people or industries. For example, digitalization has

been a rising trend during the recent years. Stable trends are likely to stay constant in the future, whereas downward trends will continue to decrease among users. Technologies can invent something new that will overcome the old way of doing things and in such cases, trends can be broken. If the nature of the trend changes suddenly it will cause a changing trend. These trends affect businesses' and their decision making processes.

Logan (2014, 9) holds a similar view, she suggests that trends express the way where the markets are moving. She also points out that trends can be divided into three categories such as forecasts (see Figure 2). Trends that continue from couple of days up to three weeks are defined as short-term trends. Medium-term trends can extend from weeks to month, and in some cases even several months. The medium-term trends are good indicators for showing of the changes within larger trends. Trends that last for a year are described as long-term trends. Sometimes long-term trends can continue into the future by multiple years. The long-term trends reveal the large overview of what is happening in the markets. These three trends can all occur at the same time in data and statistics gathered by the business. Most of the times, short-term-, medium-term-, and long-term trends differ from each other, but there are cases where different trends can move in the same direction.

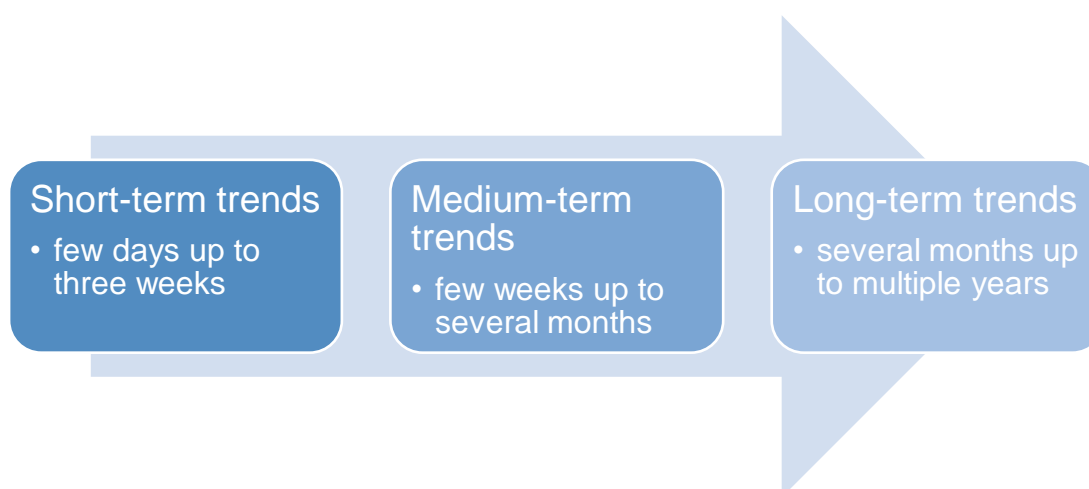


Figure 2. Trend categories and durations (Logan 2014, 9.)

Most of the times, trends are established from external factors. Stock and Watson (1988, 150) refer how new technologies can create emerging trends that will extend to several markets and industries. They also believe that by examining varying trends, businesses can more efficiently predict future changes. Chase Jr. (2013, 27-47) adds that businesses can improve their forecasts if variable trends are being observed. He also refers that effects of trends and other external factors can be predicted by using common sense and previous experiences. He emphasises that even though trends will change over time, the

affects may not be visible instantly. Some customers are neither willing nor able to change their habits over short time. However, in such cases where trends cause more remarkable changes, they may be forced to. For example, if the availability of a certain product has decreased due to emerging trend, customers are likely to adjust their habits and behavior.

Seasonality can have alternating effects on different industries. Some industries suffer more due to consequences of seasonality. Zhang and Qi (2005, 501) describe seasonality as a repetitive cycle. There are several factors that can cause seasonality such as holidays, weather, or frequent marketing of a certain product. Seasonality can create large changes in the demand of certain products or services. For example, the consumption of beverages is higher in summer than in winter. On the other hand, Kolassa and Siemsen (2014, 42) argue that annual data rarely consists seasonality. Seasonality is usually combined with trends. Businesses should pay attention to both of these, as they can have impressive effects on forecasts and thus, on multiple business activities (Zhang & Qi 2005, 501).

Different patterns and signals found from time series are also worth considering, since they can become trends in the future. If businesses can find frequent patterns from their data, they are able to create more advanced forecasts (Hernández, Carro & Lloret 2014, 2). Patterns are likely to change over time as various technologies evolve. According to Christopher (2011, 258), progress of developing markets will create new patterns and enable some markets to strengthen. Hiltunen (2007) draws attention to weak signals. She suggests that weak signals can be defined as an indicator of possible future trends. Weak signals can rise from various actions, for example ideas or trends affecting businesses' operational environment can turn out to be weak signals. She emphasises the importance of analysing weak signals by the fact that businesses can benefit from it. However, it should be mentioned that not all weak signals turn into trends. Small changes today can turn to large trends in the future. If the business can separate possible trends from weak signals, they are able to create head start for themselves. Haslehurst, Randall, Weber & Sullivan (2016) express how future digital trends can be identified. They believe that such trends will increase the level of customer service by creating more intimate customer experience. After the business have gathered several weak signals, they should start examining them. If the business can only find a few weak signals from their data, it is not worth to start analysing them (Hiltunen, 2007).

Chase Jr. (2013, 61) describes how events caused by external factors such as natural disasters or price changes of raw materials can have considerable effects on forecast accuracy. Similarly, Rubin (2015a) states that businesses should continuously examine

their operational environment, because the changes in operational environment will directly affect businesses. Desirability of analysing the surrounding environment increases when businesses are creating forecasts. By examining their operational environment, businesses can recognise possible threats or opportunities. This can increase the accuracy of their forecasts, and also decrease the uncertainty of the future.

### 2.3 Disadvantages of forecasting

Several researches have shown the beneficial effects of forecasting. When forecasts are created and utilized precisely, they will assist businesses in multiple actions. In some cases forecasting can be challenging and create disadvantages for businesses. Usually these disadvantages affect the whole business, not only the department where the possible mistakes were made.

An error made in the forecasting process can cause high excessive costs. Gupta and Maranas (2018, 3) describe how inaccurate medium-term forecasts will increase the production expenses and also lead to dissatisfaction among the customers. A similar stance is taken by Stalk Jr (1988, 47). He expresses how forecasting errors will cause excessive tasks that need to be done and also increase delays in production, which will decrease the efficiency and productivity of the business.

Although the forecast would have been made precisely, it will not directly benefit the business. Makridakis, Wheelwright & Hyndman (1998, 3) draw the attention to the usefulness of forecasts. They describe how decision makers do not always benefit from forecasts, even though the forecasts were made precisely. This can be explained by the fact that forecasts should create links between diverse business departments to allow fluent information flow. In such cases, where forecasts were made by utilizing information gathered by only one department, the advantages for managers are likely to be small. Effective forecasts are able to connect various departments by forming interdependency between them. For example, forecasts regarding marketing projects require information from sales and supply chain.

Effects caused by a forecasting error can last surprisingly long. Customers are likely to seek substitutive products elsewhere if the forecast for certain products was predicted imprecisely. Information concerning their future demand are also lost in this process. Production schedule needs to be renewed after an error in a demand forecast, which will decrease productivity and profits of the business. (Gilliland et al. 2015, 82.)

## 2.4 Prior research

Trends have been examined for years in many industries. However, most prior studies have focused on water or electricity consumption. For example, Zhang, Liu, Xu, Xu & Jiang (2005) research concentrates to detect trends of annual maximum water level and annual maximum streamflow of China's longest river. They collected data from three different gauge stations during the past 130 years. Results of their research show that the trends differ from each gauge station. From the first station they found a decreasing trend, whereas from the second station they found an upward trend. From the third station they found the most significant decreasing trend. Another example by Abdou, Al-Hamoud & Budaiwi (2005) examined trends in mosques energy performance in Saudi Arabia by utilising billing data. The results of their research revealed, that the highest peaks in the data were formed during the summer months.

It was challenging to find relevant researches that focused on invoicing data, since that kind of data can be confidential for companies. Still, the examples mentioned above show that trends can be examined by using historical data regardless the industry or the research topic. Thus, it can be assumed that this research and its data will reveal peaks, fluctuation and or trends.

### 3 RESEARCH METHODS

According to Sekaran and Bougie (2016, 2), a business research can be defined as an effort to examine a problem appearing in the work settings, which needs to be solved. There are various research approaches to solve such problems. However, the research topic usually determines the most suitable approach. This research aims to understand what trends occur in the company X's invoicing data and how these trends affect invoicing forecast. The data is examined in such way that it can be indicated which factors generate trends. A quantitative research approach was chosen since it is the most appropriate approach for examining the interaction between various factors and numerical data (Kananen 2011a, 12).

By quantitative research, relationships between variables can be measured numerically by applying various statistical techniques (Saunders, Lewis & Thornhill 2012, 162).

Quantitative research requires knowledge of researched phenomenon. It is impossible to measure anything if the phenomenon is not known (Kananen 2011a, 12). In most cases, quantitative research includes information, models, and theories of the examined phenomenon (Kananen 2011a, 23). Data and statistics play a crucial role, as the quantitative research is based on numbers and percentages (Heikkilä, 2014). Kananen (2011b, 75) states that in quantitative research the numbers are used to form calculations such as addition, subtraction and multiplication. In order to perform such calculations the objective needs to be known. In other words, the author has to know what is being calculated.

Saunders et al. (2012, 475) suggest that quantitative data can be either categorical or numerical data. They define categorical data as data, which cannot be numerically measured. Numerical data can be defined as values, which can be measured or counted as quantities. Numerical data is often more accurate than categorical as it can be divided by values on a numerical scale. Numerical data can be analysed by utilising wider ranges and statistics. In order to gain benefits from the collected data, it needs to be processed in such way that it creates information. Trends and relationships appearing in the data are easier to examine with different quantitative analysis techniques. These techniques are able to reveal trends and relationships in the data through charts, graphs and statistics (Saunders et al. 2012, 472).

This research includes confidential invoicing data. Therefore, the mandator wants to stay unnamed. Data and statistics analysed in this research have been collected from two different mills. Both of the mills are located in Finland. The mills are producing different products, but these products are mainly sold into the same markets. However, the data

and statistics vary depending on the mill and product. In order to clarify the research, the mills will be referred as Mill 1 and Mill 2. Both mill's data have been collected individually, but they will be analysed together. This helps the analysing process as the mills can easily be compared.

### 3.1 Data collection

All of the data and statistics used in this research are secondary data. Data has been routinely recorded by Company X, but it was not originally recorded for research purposes. According to Sørensen et al. (1996, 435), data which have not been gathered for research purposes can be defined as secondary data. Secondary data is described as an advantage, since it is usually easily accessible and can include important information that can be utilised in the research process. Utilisation of secondary data also decreases the amount of time and expenses consumed in the project. A similar view is held by Saunders et al. (2012, 318). According to them, secondary data will save a significant amount of time and money. They also add that if the data and statistics are gathered beforehand, secondary data allows the author to think theoretical aims and essential issues of the research. More time can be spent analysing the data and statistics when secondary data is being utilised.

Secondary data should be selected precisely, since the disadvantages will increase if unnecessary data or statistics were chosen (Sorensen et al. 1996, 440). It is crucial to assess the suitability of the secondary data (Saunders et al. 2012, 319-321).

The data included in this research has been collected from January 2016 up to August 2018. This time period can reveal short-, medium-, and long-term trends in the data. During this period, the results can also show whether the trends are repetitive or not. Trends will be examined from the data by measuring the effects of multiple variables. IT system used in the data collection process allows author to decide which variables to include in the data file. By choosing the appropriate time period and variables as well as by removing unnecessary data, the coverage of the data will be verified.

The invoicing data collected for this research has been collected by using company X's internal IT systems. The combined data includes information such as buyers, delivery countries, terms of delivery, buyer segments, invoicing dates and invoicing points. As the data includes information from multiple factors, it is easier to indicate and compare which factors have stronger effects to trends than others. The data also includes historical information, since it has been collected starting from January of 2016 up to August of 2018. As mentioned by Hugos (2018, 47), varying trends are easier to point out when data

and statistics are gathered by utilising historical data. Saunders et al. (2012, 494) hold a similar view by suggesting that trends can only be examined from longitudinal data. Longer time periods can more precisely reveal repetitive trends and thus, increase the validity of the research. Microsoft Excel is used to analyse the data and form figures. Kolassa and Siemsen (2014, 7) and Saunders et al. (2012, 473) describe Excel as a complementary tool for analysing data.

### 3.2 Verification of the results

In order to achieve precise and reliable results, only suitable and relevant data should be included. Saunders et al. (2012, 321-322) draw attention to suitability of the secondary data. If the collected data is not able to provide answers for the research, the results will most likely be invalid. Measurement validity is one way to evaluate the secondary data. However, clear solutions to examine measurement validity have not been formed, so such evaluations are often based on author's own evaluations and decisions. Coverage is another way to measure the suitability of the secondary data. Coverage means that the data includes the right time period and variables that provide answers to research questions. Usually two issues are concerned with coverage (1) make sure that unwanted data is separated and (2) ensure that the necessary data remain for analyses (Saunders et al. 2012, 321-322).

Saunders et al. (2012, 323-325) hold a view that data collected by large and well-known companies is reliable, as their existence is dependent on the trustworthiness of their data and information. Data collecting methods in such companies are usually well measured and precise, which most of the times leads to accurate data. The case company is well-known, and it operates internationally. This being said, the invoicing data itself is reliable. In some cases, the IT system creates duplicates or blanks. During the data collection process these will be removed.

### 3.3 Data analysis

The data analysis process aimed to understand which variables create trends and fluctuation in Company X's invoicing data. The data was initially collected by using Company X's IT system. In the data collection process, their IT system allowed to transfer the data directly to Excel. During the data analysis process, the effects of variables and their relationships to trends will be examined. The main variables that will be examined are invoicing points and months.

Even though the data has been collected within the past 32 months, it will be analysed in six months' time periods to examine medium-term trends as well. The first time series will include data from January 2016 until June 2016, second time series includes data from July 2016 until December 2016, third series includes data from January 2017 until June 2017, and fourth time series will include data from July 2017 until December 2017. Only eight months from 2018 are included in this research, so the fifth time series will include data from January 2018 until April 2018, and sixth time series includes data from May 2018 until August 2018.

When the data is analysed in shorter time series, the effects of seasonality can also be taken into consideration. The data will be mostly examined by observing the effects of different invoicing points. By examining invoicing points, it can be seen which of these points create trends or fluctuation in the data. This being said, an invoicing point can be defined as that exact point when the product is being invoiced.

In total, there are five different invoicing points that will be examined. They are delmill, delware, VATdelware, usage, and VATusage. In order to keep this research as compact, VATdelware will be examined together with delware, and VATusage will be examined together with usage.

When invoicing by delmill, it means that products will be delivered directly to the customer. In this case, the products are invoiced at that moment when they are loaded into freight-truck. When invoicing by delware, it means that the products will be delivered to a warehouse where customers can collect the products. In this case, the products are invoiced at that moment when they are collected from the warehouse. VATdelware works in a similar way, only VAT (value added tax) will be added to the initial price. Usage and VATusage mean that the products are being invoiced as they are consumed. However, consumed products are invoiced once a week, on Monday mornings. Only difference between these two is that value added tax will be added when invoicing by VATusage. However, these two invoicing points are only implemented within internal customers. In some cases, a customer can be invoiced by using multiple invoicing points.

Effects of delivery countries and their relationships to trends will be analysed throughout the data analysing process. Time periods will be compared to each other yearly, in order to find out whether the trends are repetitive or not. Mills' results will be compared in order to see how they differ from each other's, and whether they have any similar trends.

Excel is used to analyse the data. At first, pivot tables will be created from the data. Pivot table will be created in a such way that it includes invoicing points in the column section, days in the row section, and the invoiced amount (in kg tons) in value section. By utilising

slicer tools in Excel, the data can be easily divided by mills, invoicing points and time periods. Line graphs and bar charts will be created from the pivot tables to describe the trends. Saunders et al. (2012, 494) suggest that bar charts and line graphs are the most suitable diagrams to show trends between time periods.

## 4 RESULTS

In this section, the effects of variables are presented in the form of bar charts and line graphs. The data will be examined in six time series by observing the effects of two different variables that are invoicing points and months. Presented charts will describe the daily amount of invoiced tons during selected time series. In the figures, there are 31 invoicing days. These days present the total amount of invoiced tons, which have been invoiced in that selected day of the month. For example, day one includes data which has been invoiced in every month's first day. Results from each year will be presented before moving onto another invoicing point. The same model will follow throughout this chapter. As only eight months from 2018 were included in this research, results of 2018 will be presented in two series. Results during the entire time series (January 2016 – August 2018) will be presented at the end of this chapter. In order to make the graphs easy to read, some of them are included in the Appendices. The results of usage during the first time series (January 2016 – June 2016) will be presented first mill by mill.

### 4.1 Usage results

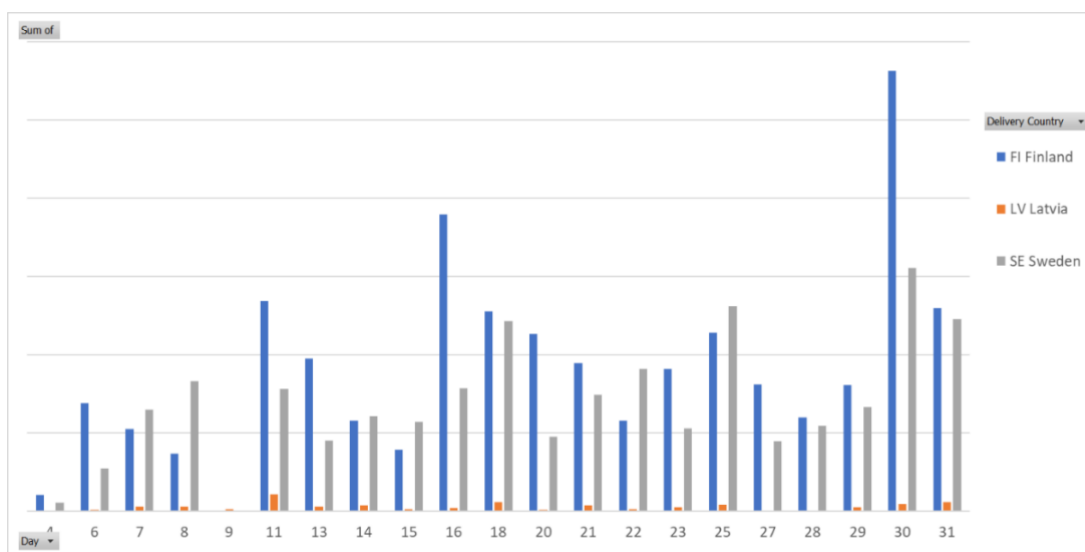


Figure 3. Mill 1 usage data January 2016 – June 2016

As mentioned in chapter 3.3 usage and VAT usage will be examined together. The invoiced total from each day is presented in the vertical axis. However, the scale in the vertical axis is hidden as the values are confidential. Mill number 1's usage data from the first time series can be found from Figure 3. As it can be seen, there is fluctuation between the days. For example, Sweden has distinct peaks on 18th and on 25th. Finland has distinct peaks on 11th, 16th and on 30th. It can also be pointed out, that Finland's and Sweden's highest peaks took place at the end of the month.

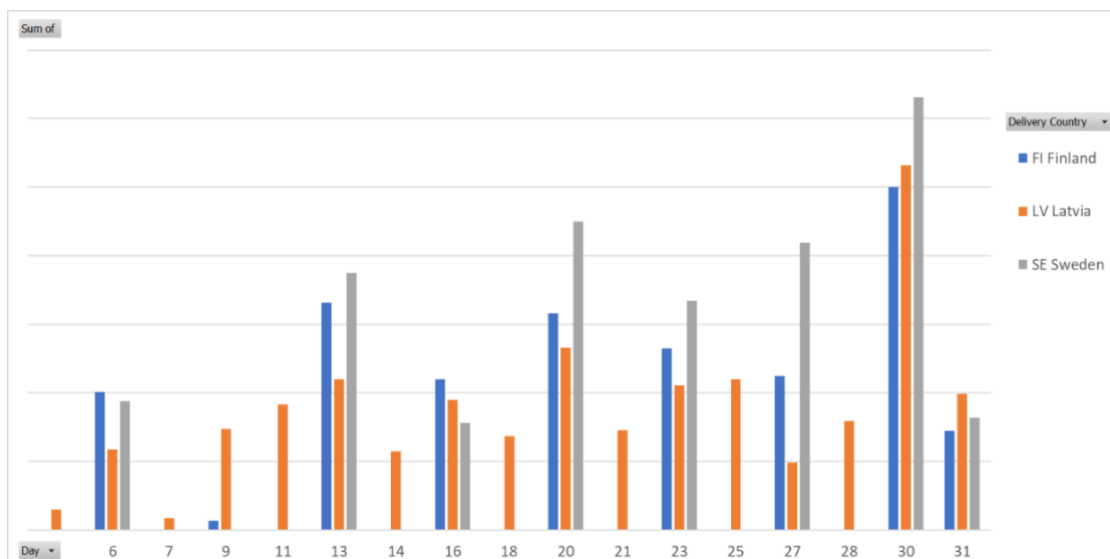


Figure 4. Mill 2 usage data January 2016 - June 2016

Second Mill's usage data from the first time series can be found from Figure 4. As it can be seen, there are significant fluctuation between the days. Distinct peaks especially in Sweden's data can be clearly pointed out on every seven days; on 6th, on 13th, on 20th and on 27th. Finland's and Latvia's data occur likewise Sweden's, but their peaks are not as strong. However, all countries create high peaks in the data at the end of the month. It can also be seen that the quantities rise towards the end of the month.

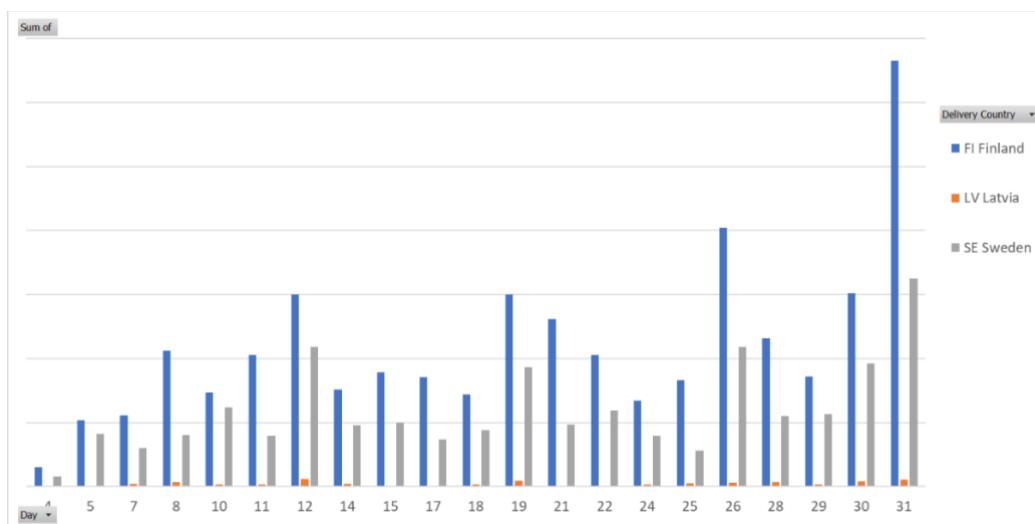


Figure 5. Mill 1 usage data July 2016 – December 2016

First Mill's usage data from the second time series can be found from Figure 5. Fluctuation between the days as well as the high peaks at the end of the month can also be pointed out from this time series. It can be seen that the peaks between every seven

days: on 12th, on 19th and on 26th continue during the second time series as well. The highest peak is formed at the end of the month, similarly than in previous series.

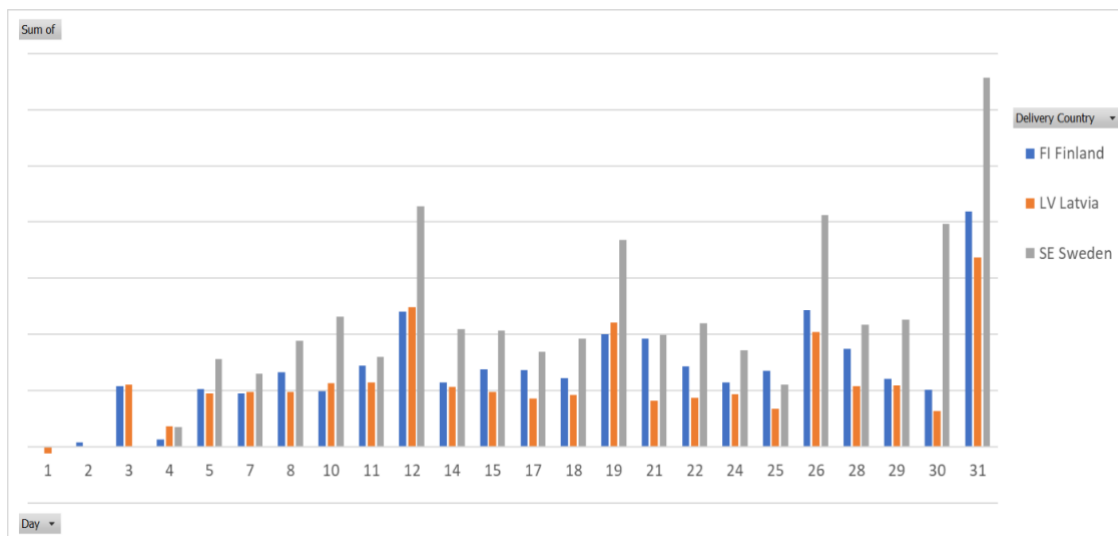


Figure 6. Mill 2 usage data July 2016 – December 2016

Mill 2's usage data from the second time series can be found from Figure 6. As it can be seen, all three countries create distinct peaks in the data on every seven days: on 12th, on 19th and on 26th. Between the peaks the data occurs steadily. The highest peaks can be found at the end of the month.

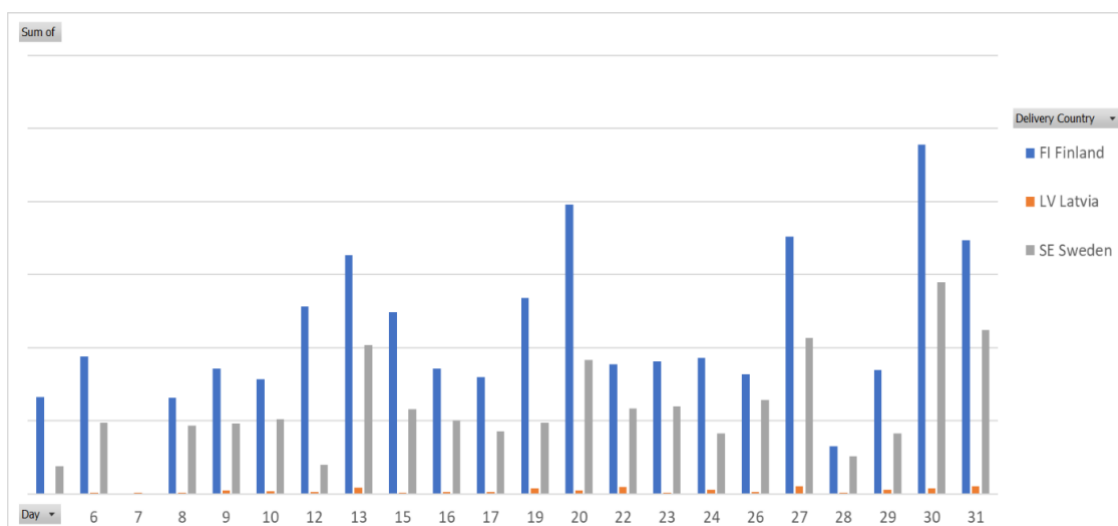


Figure 7. Mill 1 usage data January 2017 – June 2017

Mill 1's usage data during the third time series can be found from Figure 7. As it can be seen, Finland creates peaks on 13th, on 20th, and on 27th, similarly than in previous series. Sweden's data occurs more steadily, only small peaks throughout the days can be seen. Both countries create the highest peaks at the end of the month.

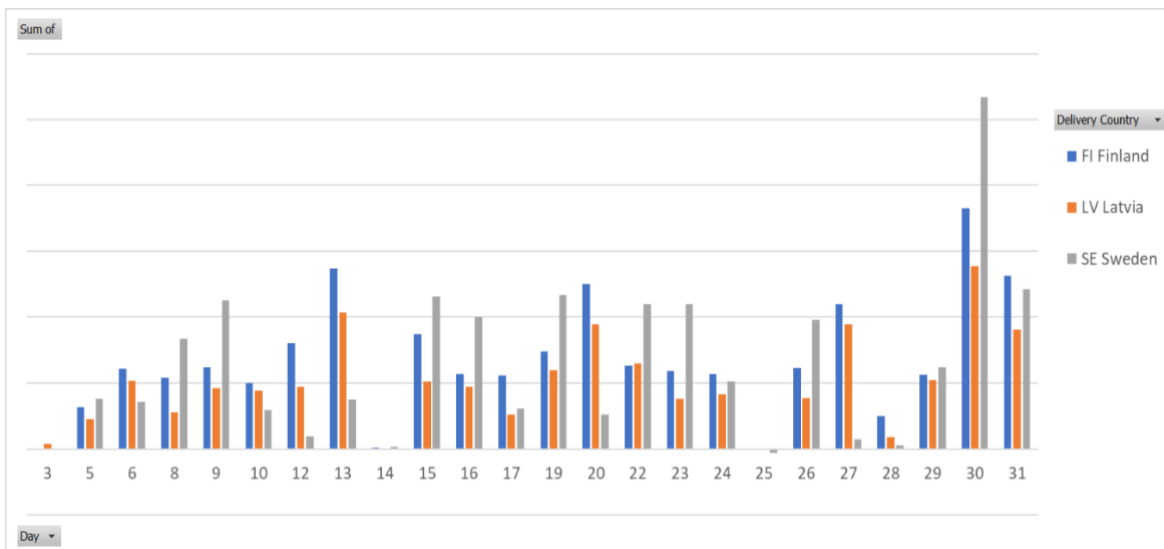


Figure 8. Mill 2 usage data January 2017 – June 2017

Mill number 2's usage data during the third time series can be found from the Figure 8. As it can be seen, peaks in Finland's and Latvia's data are formed on every seven days on 13th, on 20th, and on 27th. Sweden's data stays fairly flat throughout the days, excluding the high peak at the end of the month. Finland's and Latvia's highest peaks take place at the end of the month as in previous series.

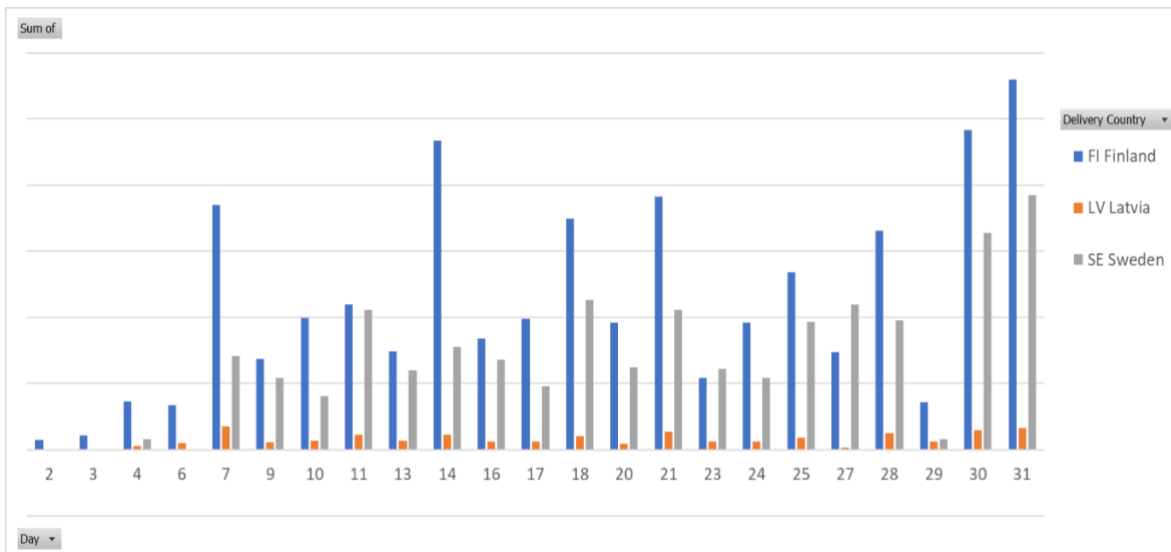


Figure 9. Mill 1 usage data July 2017 – December 2017

First mill's usage data during the fourth time series is presented in Figure 9. As it can be seen, distinct peaks especially in Finland's data are observable on every seven days on 7th, on 14th, on 21st and on 28th. Sweden's data increases slightly towards the end of the month. Differ from previous figures, high peaks formed by Finland and Sweden can be seen on 30th and 31st.

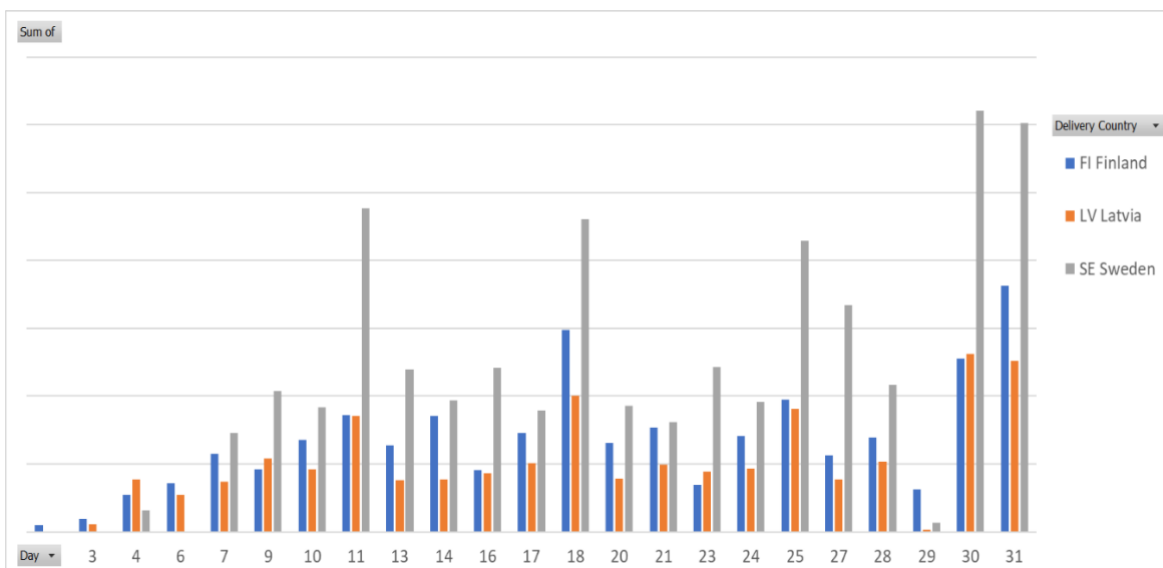


Figure 10. Mill 2 usage data July 2017 – December 2017

As it can be seen from Figure 10, second mill's usage data is consistent with previous time series as Sweden creates distinct peaks on every seven days: on 11th, on 18th, and on 25th. Finland's and Latvia's data occurs fairly stable. However, two equivalent peaks formed by Sweden can be seen at the end of the month, similarly than in Figure 9.

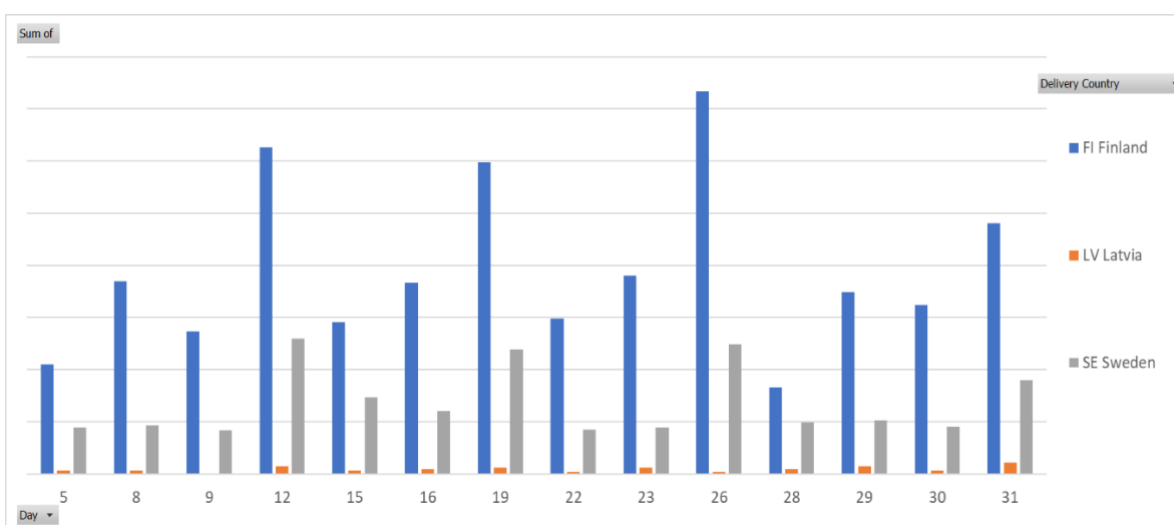


Figure 11. Mill 1 usage data January 2018 – April 2018

As mentioned at the beginning of chapter 4, data from 2018 will be examined in two series. Figure 11 represents Mill 1's usage data during the fifth time series. As it can be seen, peaks are formed in the data between seven days: on 12th, on 19th, and on 26th. However, during this time series Finland's highest peak was formed on 26th, whereas in previous series it was usually formed on 30th or 31st.

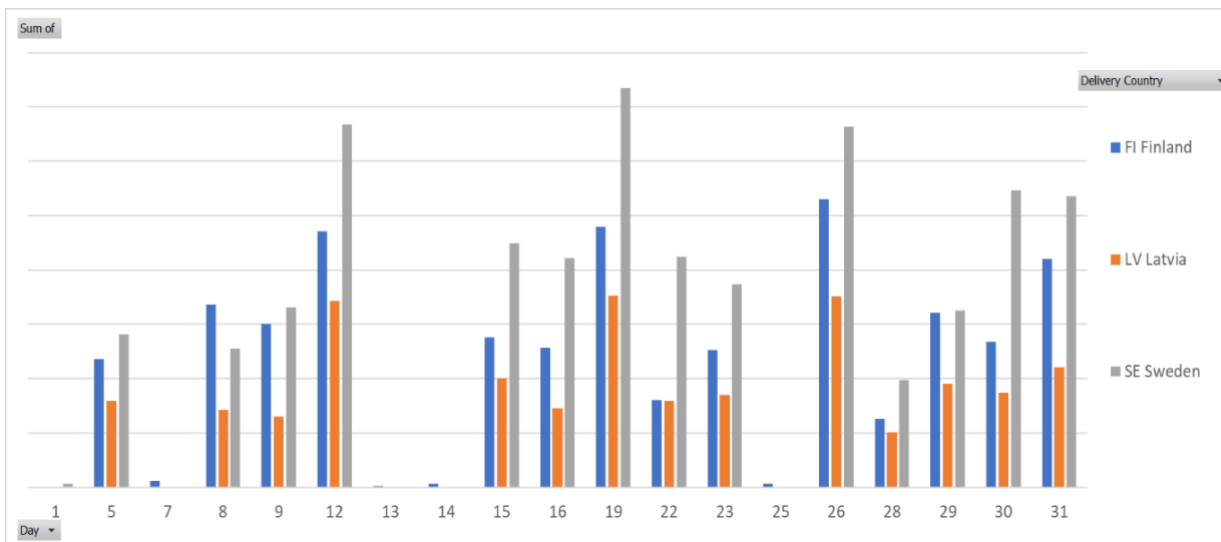


Figure 12. Mill 2 usage data January 2018 – April 2018

Second mill's usage data from the fifth time series can be found from Figure 12. Each of the countries have peaks on every seven days: on 12th, on 19th, and on 26th. Sweden's highest peak was formed on 19th, whereas Finland's and Latvia's highest peaks were formed on 26th. In previous series the highest peaks were formed at the end of the month. However, increase in the data values on 30th and on 31st can be noticed.

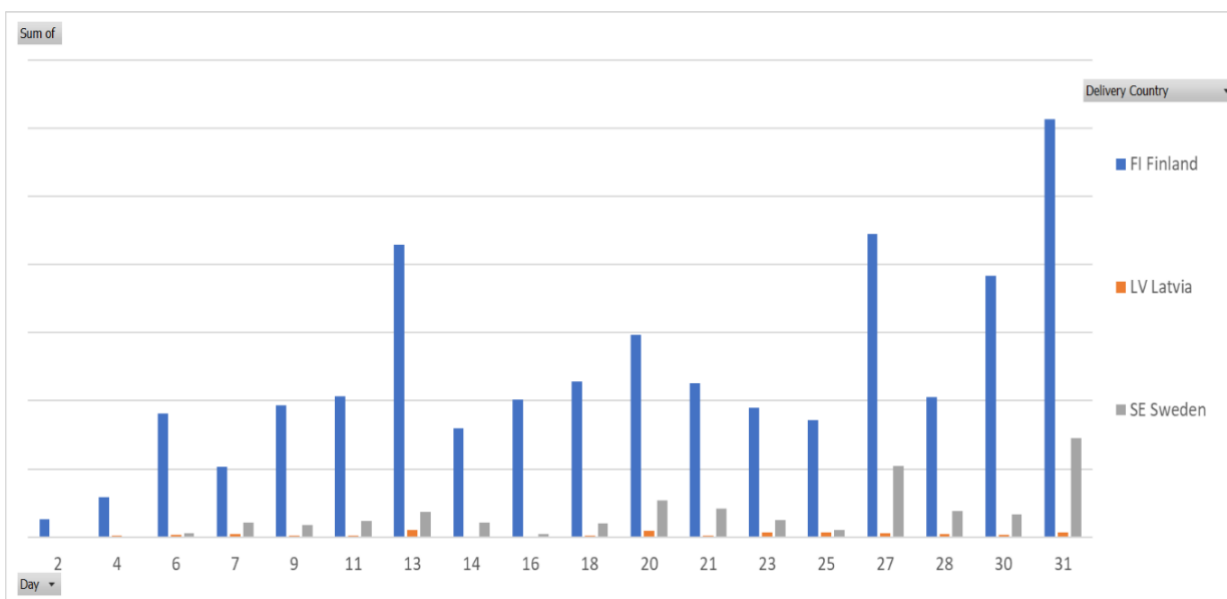


Figure 13. Mill 1 usage data May 2018 – August 2018

Mill 1's usage data during the sixth time series can be found from Figure 13. Peaks on every seven days: on 13th, on 20th, and on 27th apply to this time series as well. Similarly to previous series, the highest peak was formed at the end of the month. It can also be seen, that Sweden's data occurs in lower level compared to previous series.

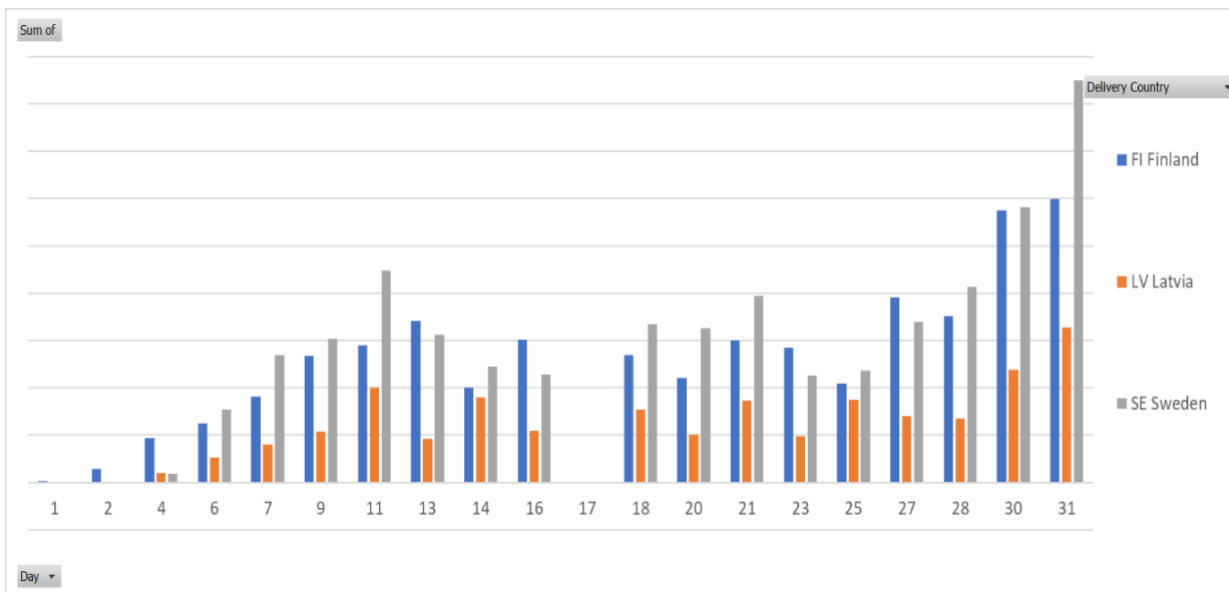


Figure 14. Mill 2 usage data May 2018 – August 2018

Usage data from the Mill number 2 from the sixth time series can be seen from Figure 14. As it can be seen, countries did not form any distinct peaks as seen in previous figures. Data stays fairly flat during the days, excluding the peaks formed on 30th and 31st by all countries. As the results of usage from all six time series have been shown, results of delaware will be examined next.

#### 4.2 Delaware results

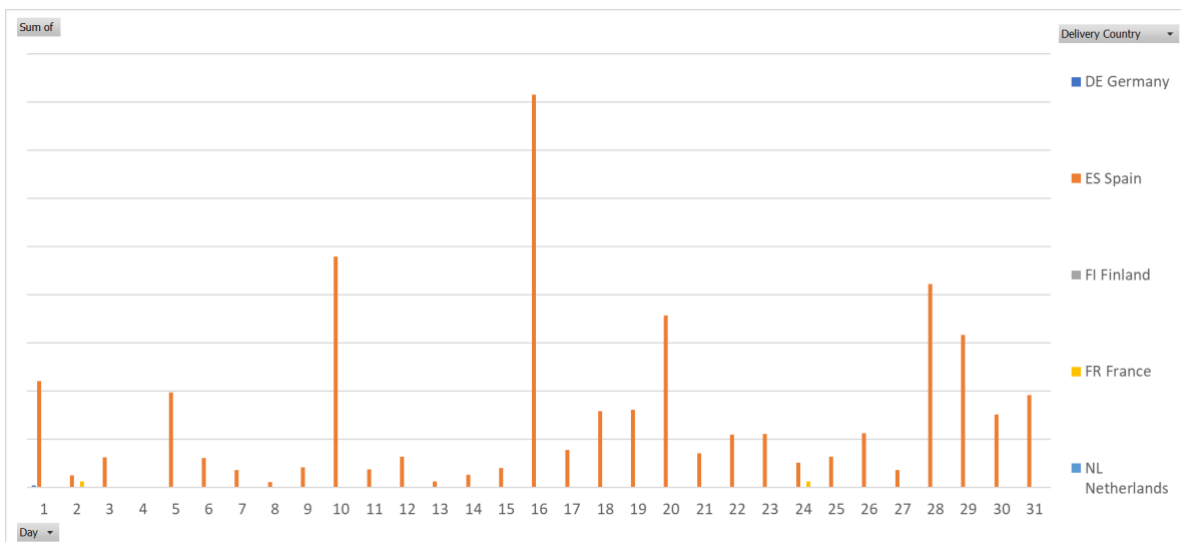


Figure 15. Mill 1 delaware data January 2016 – June 2016

Mill 1’s delaware data from the first time series can be found from Figure 15. As it can be seen, there is fluctuation between the days, and the highest peak was formed on 16<sup>th</sup> by

Spain. Apart from distinct peaks on the first days and last days, the data occurs fairly stable, only small movement can be noticed.

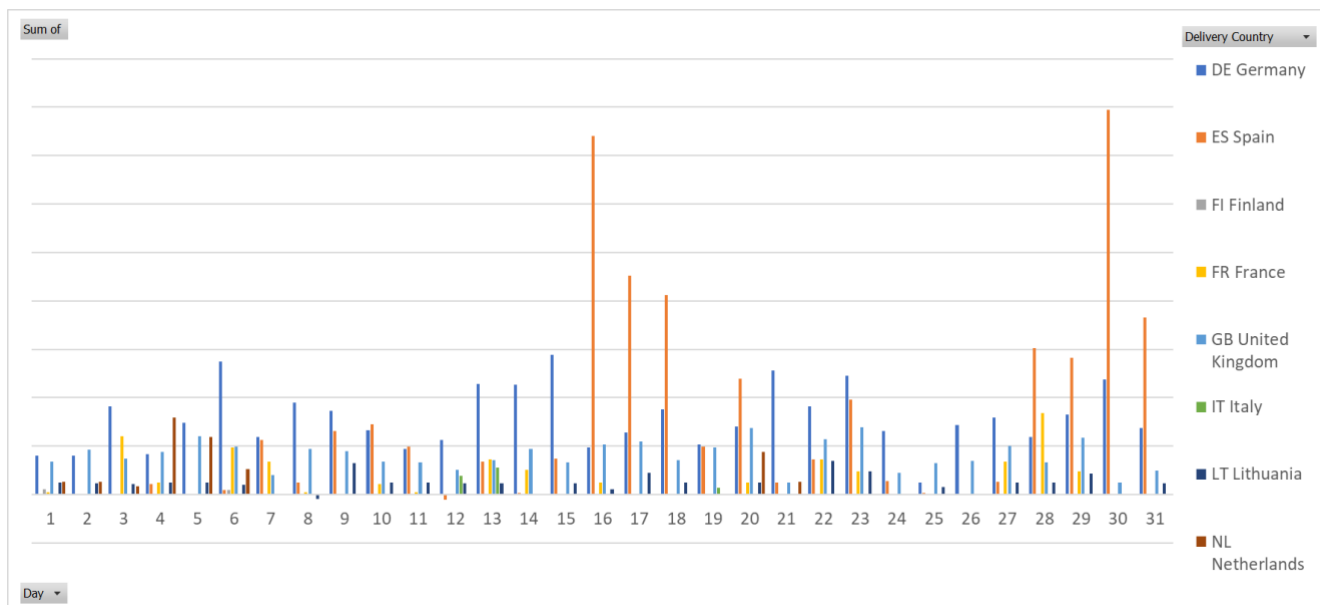


Figure 16. Mill 2 delaware data January 2016 – June 2016

Mill 2's delaware data from the first time series can be found from Figure 16. As it can be seen, Spain forms peaks at the middle and at the end of the month. Besides that, only inconsequential movements among all countries can be noticed.

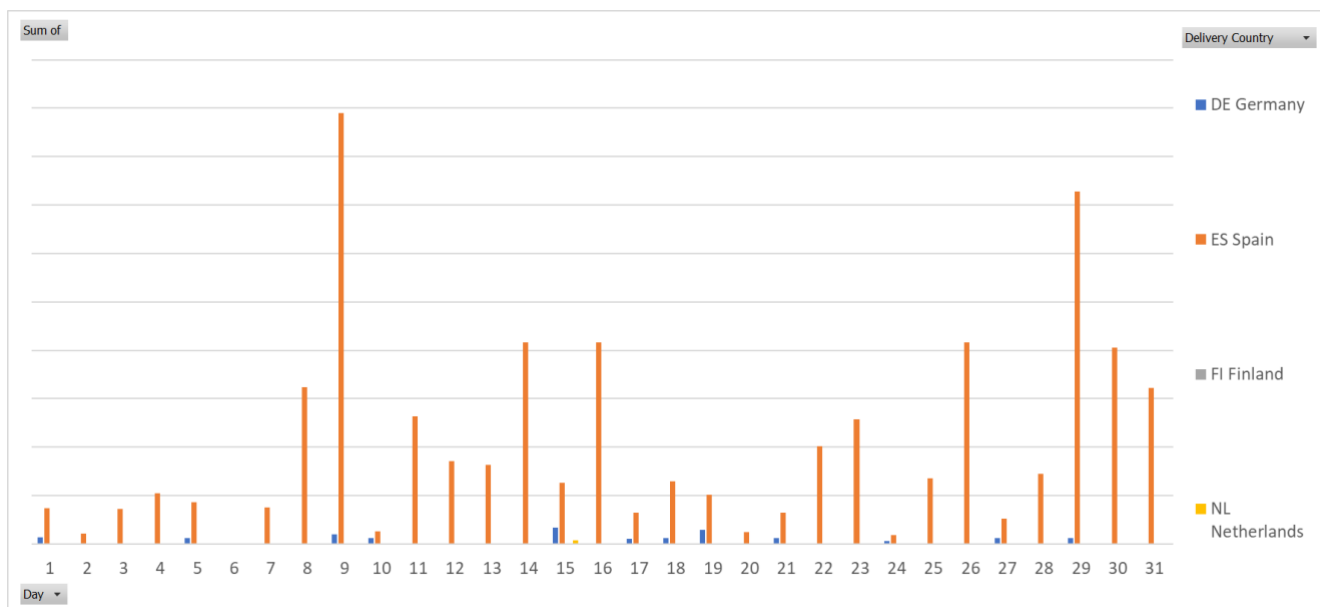


Figure 17. Mill 1 delaware data July 2016 – December 2016

Mill 1's delaware data from the second time series can be seen from Figure 17. Spain forms high peaks on 9<sup>th</sup> and on 29<sup>th</sup>. During the first seven days, only minimal movements

can be seen. Between the peaks, the data occurs fairly stable. Small decrease from 17<sup>th</sup> until 22<sup>nd</sup> can be pointed out.

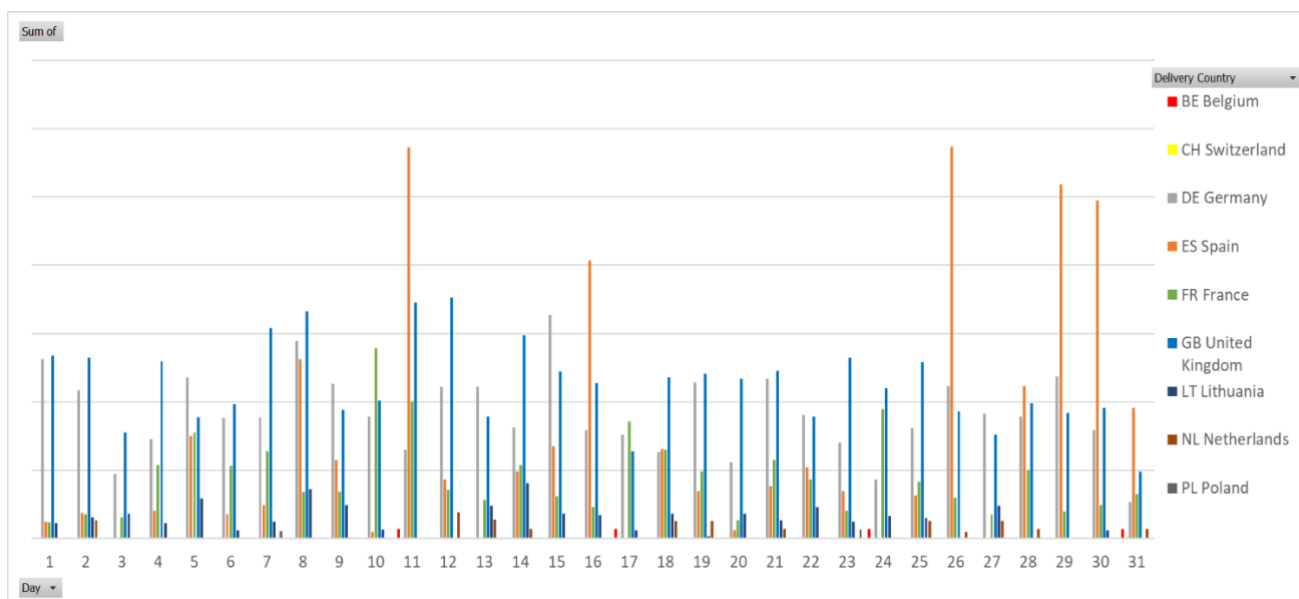


Figure 18. Mill 2 delaware data July 2016 – December 2016

Mill 2's delaware data from the second time series can be found from Figure 18. As it can be seen, Spain creates fluctuation in the data. Distinct peaks on the 11th, on the 16th, and on the 26th day can be pointed out, as well as two similar peaks at the end of the month. Besides that, the data stays relatively stable throughout the days.

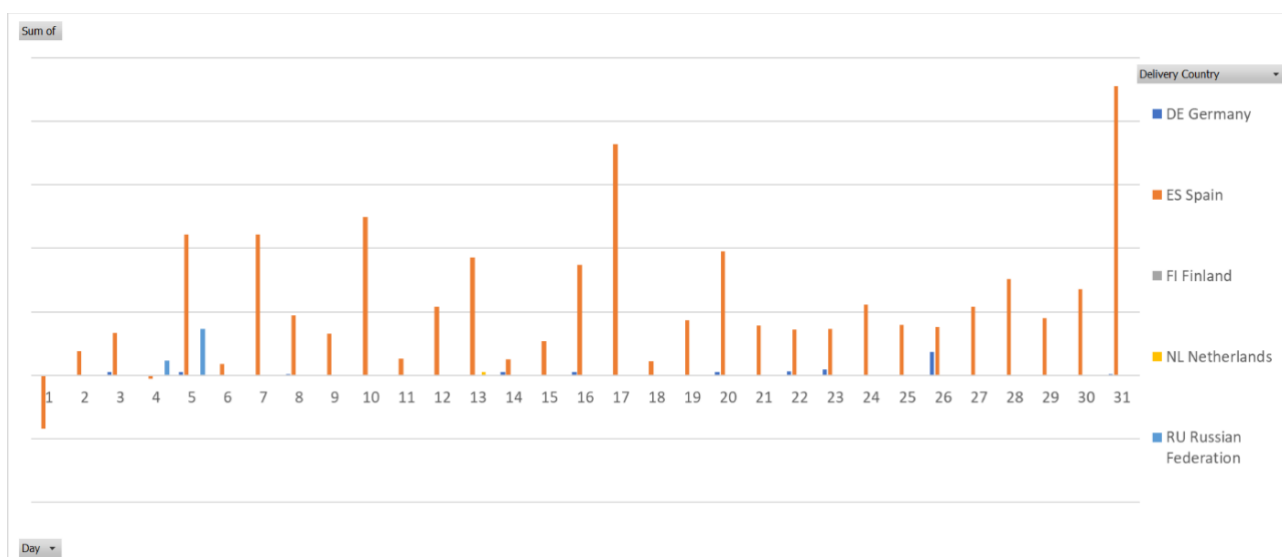


Figure 19. Mill 1 delaware data January 2017 – June 2017

Mill 1's delaware data from the third time series can be found from Figure 19. As it can be seen, Spain creates small fluctuation during the first sixteen days. Two distinct peaks can

be pointed out on 17th and on 31st. Between the peaks, only minimal changes in the data can be seen.

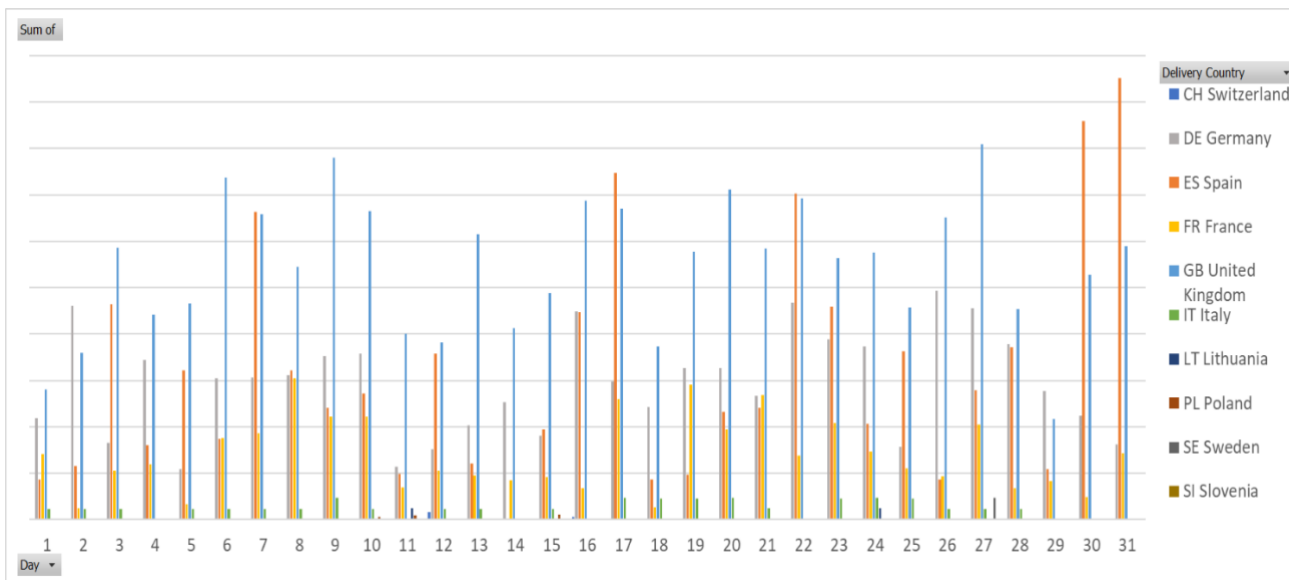


Figure 20. Mill 2 delaware data January 2017 – June 2017

Mill 2’s delaware data from the third time series can be found from Figure 20. As it can be seen, United Kingdom creates small fluctuation almost every other day, whereas Spain forms peaks on 7th, on 17th, and on 22nd. Spain also forms two distinct peaks at the end of the month.

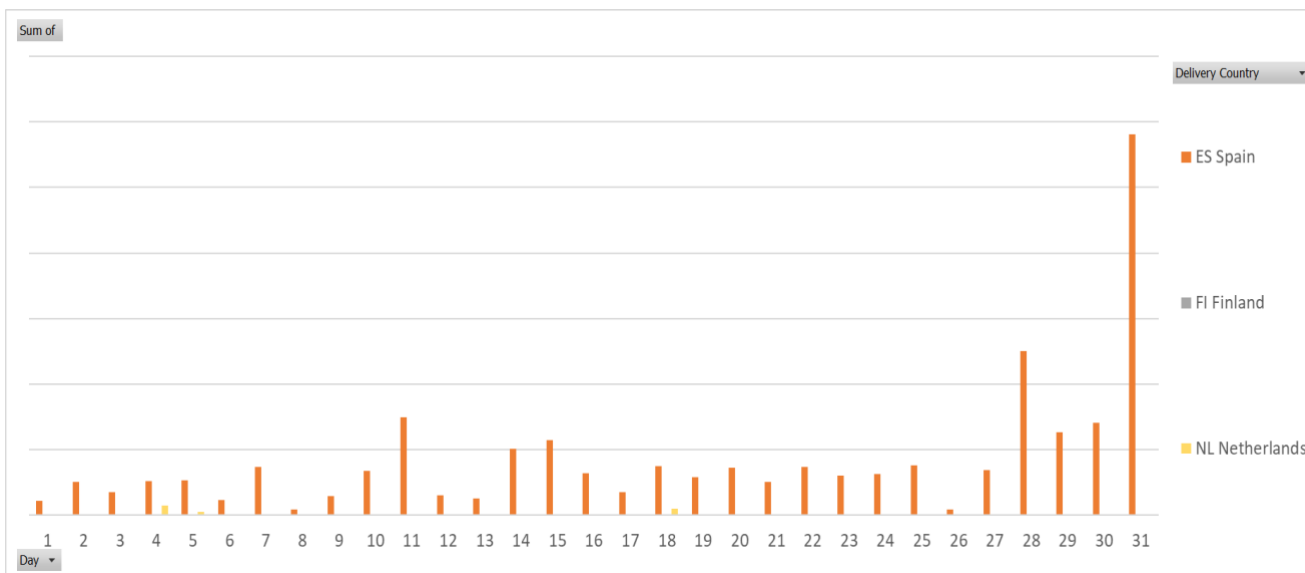


Figure 21. Mill 1 delaware data July 2017 – December 2017

Mill 1’s delware data from the fourth time series can be found from Figure 21. As it can be seen, the data stays stable throughout the days, excluding the peak formed on 31st by Spain.

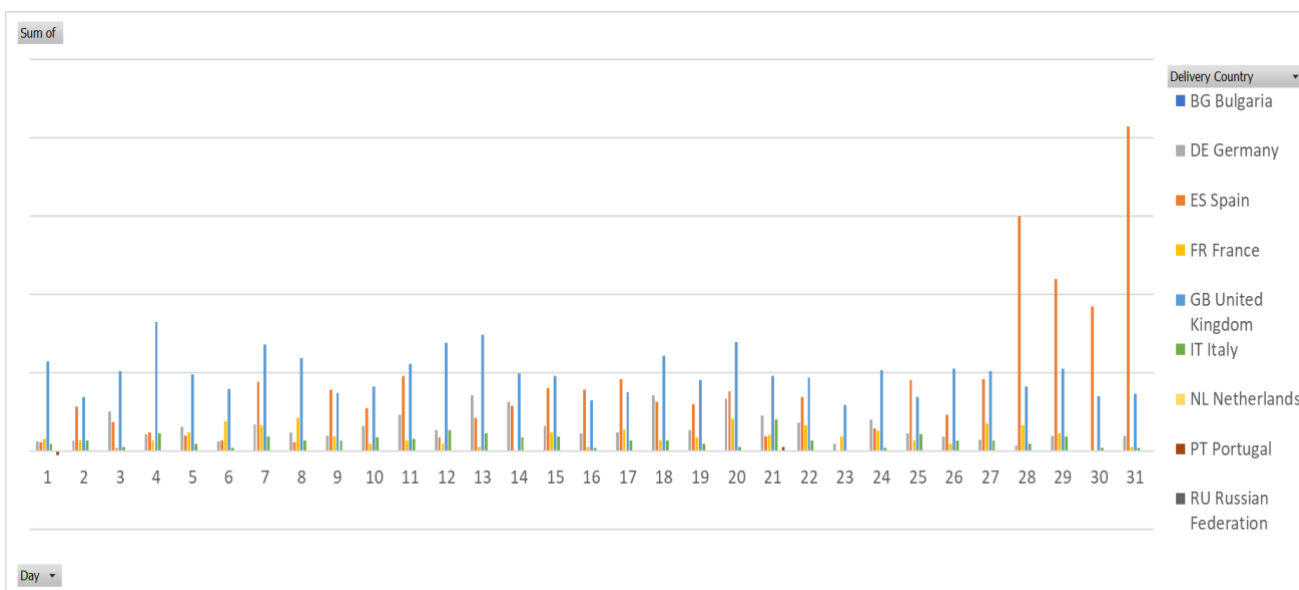


Figure 22. Mill 2 delware data July 2017 – December 2017

Mill 2’s delware data from the fourth time series can be found from Figure 22. Similar to Figure 21, the data stays fairly stable throughout the days. Only Spain’s peaks between the 28th and 31st stand out from the data.

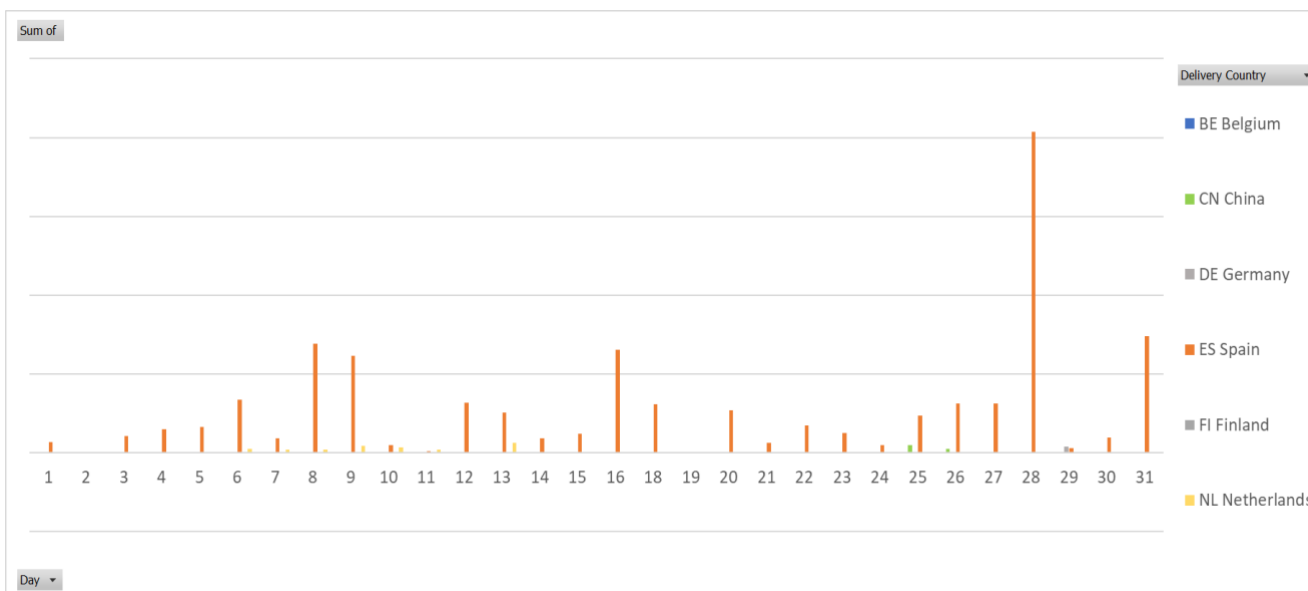


Figure 23. Mill 1 delware data January 2018 – April 2018

Figure 23 presents Mill 1's delaware data from the fifth time series. As it can be seen, Spain has the highest peak at the end of the month, on 28th. Besides that, only small fluctuation during the days can be seen.

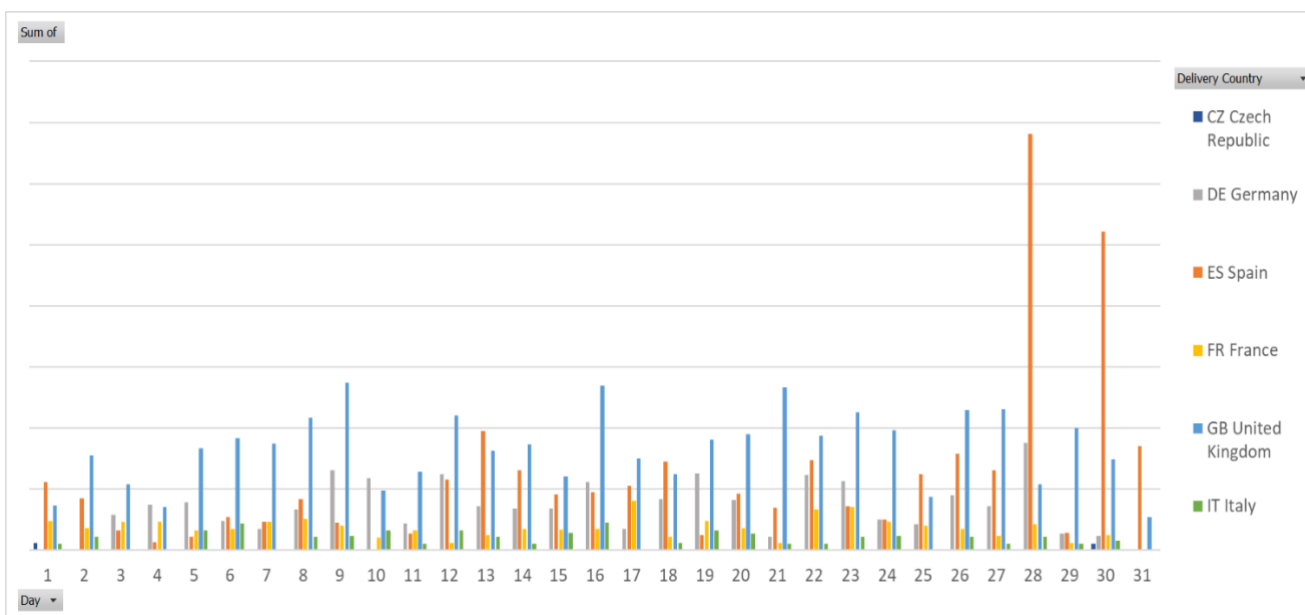


Figure 24. Mill 2 delaware data January 2018 – April 2018

Mill 2's delaware data from the fifth time series can be seen from the Figure 24. Similar to previous series, Spain has distinct peaks at the end of the month: on 28<sup>th</sup> and on 30<sup>th</sup>. Before the peaks, the data occurs relatively stable.

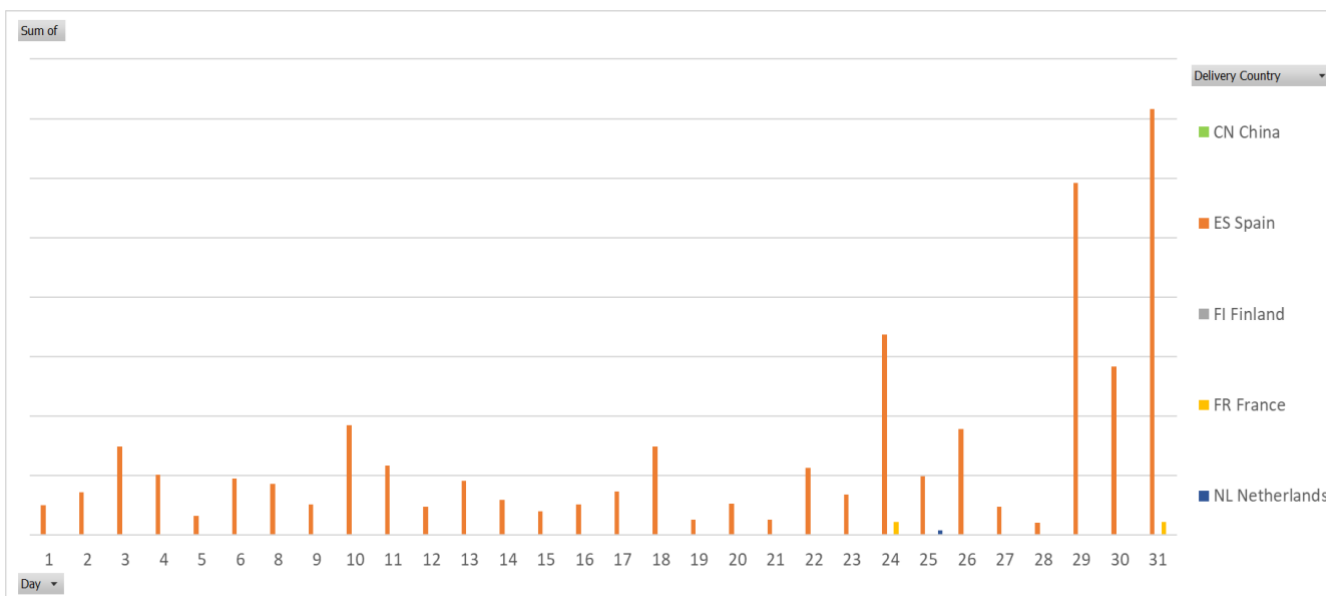


Figure 25. Mill 1 delaware data May 2018 – August 2018

Figure 25 presents Mill 1's delware data from the sixth time series. Similar to previous time series, Spain forms peaks at the end of the month. The data increases towards the end of the month, however, only minimal movement can be noticed.

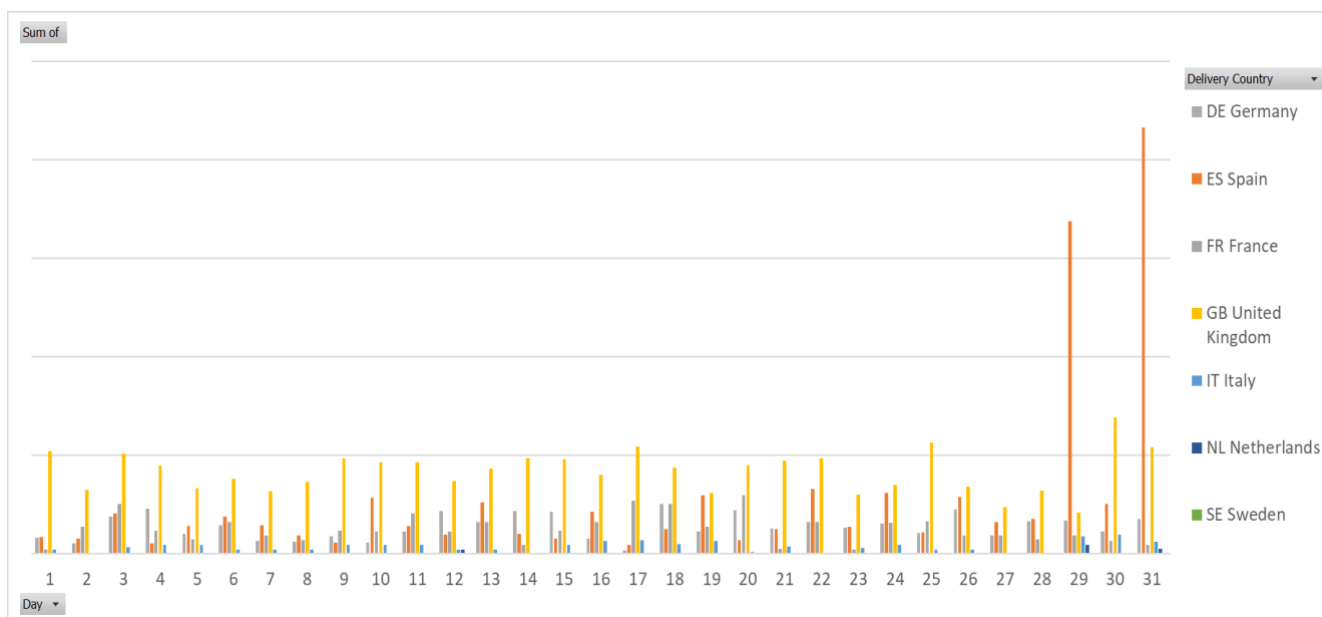


Figure 26. Mill 2 delware data May 2018 – August 2018

Figure 26 presents Mill 2's delware data from the sixth time series. As it can be seen, two distinct peaks on 29th and on 31st are formed by Spain. Only minimal fluctuation can be pointed out before the peaks. All the countries occur stable during the month.

As delware results have been covered, delmill results will be presented next. Figures of delmill data will be presented in the Appendices, since the graphs would be unreadable if included in the text. Delmill data includes various countries, so in order to make them easy to read a line graph will be utilised. Nevertheless, graphs will be described similarly than previously.

#### 4.3 Delmill results

Appendices 1 and 2 present Mills' delmill data from the first time series. As it can be seen from Appendix 1, in Mill 1's data there is clear fluctuation during the first thirteen days. Small peaks on 29th and on 30th can also be pointed out, but at the same time it can be seen that the data decreases towards the end of the month. Appendix 2 presents Mill 2's delmill data from the first time series. Peaks on 1st and on 29th can be seen. Between the peaks the data occurs fairly stable, only small movements at the midway of the month can be pointed out.

Mills' delmill data from the second time series can be found from Appendices 3 and 4. Mill 1's results can be found from Appendix 3. As it can be seen, there are distinct peaks on 9th and on 12th. Small fluctuation on 16th and on 25th can be pointed out as well. Apart from the peaks, the data occurs steadily throughout the days. Mill 2's results can be seen from Appendix 4. Distinct peaks on 4th, on 7th, on 15th, and on 29th can be noticed. Between the peaks, only inconsequential fluctuation can be seen.

Appendices 5 and 6 present Mills' delmill data from the third time series. Mill 1's results can be found from Appendix 5. As it can be noticed, there are distinct peaks on 3rd, on 13th, and on 16th. Line graph also reveals that the data decreases slightly towards the end of the month. Mill 2's results can be found from Appendix 6. As it can be seen, the data stays on higher level during the first ten days of the month. From there, it can be pointed out that the data decreases and creates fluctuation, causing a small peak on 26th.

Mills' delmill data from the fourth time series can be found from Appendices 7 and 8. Mill 1's results can be seen from Appendix 7. It can be pointed out, that there is obvious fluctuation between the days. Peaks at the beginning and at the middle of the month can also be noticed. It is also visible that the data values decrease towards the end of the month. Mill 2's results can be found from Appendix 8. As it can be seen, the data values stay relatively stable during the first twenty-one days, excluding two declines on 9th and on 16th. Small increase at the end of the month can also be noticed.

Appendices 9 and 10 present Mills' delmill data values from the fifth time series. As the data from 2018 was examined in four months' time series, results from the fifth and sixth time series include more visible fluctuation than previous series. Mill 1's results can be found from Appendix 9. As it can be seen, there are several peaks formed in the graph. However, most of these peaks are formed on fairly same level throughout the days. Mill 2's results can be found from Appendix 10. As it can be noticed, at the beginning of the month there are distinct peaks in the data every four days. Towards the end of the month, the data values slightly decrease.

Mills' delmill data from the sixth time series can be found from Appendices 11 and 12. Mill 1's results can be seen from Appendix 11. Obvious fluctuation between the days can be pointed out, similarly than in the first time series of 2018. Peaks stay at the same level throughout the days. Differ from previous time series, the lowest data values can be seen during the first days of the month. Mill 2's results are presented in Appendix 12. During the sixth time series the data occurs relatively stable, small decrease between 10th and 13th as well as declines on 22nd and on 25th can be seen. Differ from previous time series, the highest peak was formed at the end of the month, on 29th.

#### 4.4 Results from the entire time series

Appendices 13 – 18 present invoicing points' data throughout the whole time series from January 2016 until August 2018. Presented charts will describe the daily amount of invoiced tons during selected time series. In the figures, there are 31 invoicing days. These days present the total amount of invoiced tons, which have been invoiced in that selected day of the month. For example, day one includes data which has been invoiced in every month's first day. By examining the whole time series, it can be seen if invoicing points form general trends in the data. Similarly than in previous figures, usage and VATusage will be examined together as well as delware and VATdelware.

Appendices 13 and 14 present Mills' usage data during the whole time series. Mill 1's results can be found from Appendix 13. It can be seen, that both invoicing points form distinct peaks towards the end of the month. VATusage causes more fluctuation during the month, whereas usage occurs relatively stable. Mill 2's results can be seen from Appendix 14. Similar to Mill 1, both invoicing points form peaks at the end of the month. Usage forms a more distinct peak and its data fluctuates more during the month, whereas VATusage forms a smaller peak and its data occurs more stable.

Mills' delware data during the whole time series can be found from Appendices 15 and 16. Appendix 15 present Mill 1's results and as it can be seen, delware data increases towards the end of the month causing a high peak. A small peak at halfway of the month can also be noticed. Mill 2's results can be seen from Appendix 16. A small increase at halfway of the month can be seen from Mill 2's results as well. However, the most distinct increase takes place at the end of the month. VATdelware occurs fairly stable throughout the month, a small decrease towards the end of the month can be noticed.

Appendices 17 and 18 present Mills' delmill data from January 2016 until August 2018. Mill 1's results can be found from Appendix 17. As it can be seen, there are distinct peaks at the beginning of the month. Data slightly decreases towards the end of the month, but fluctuation can still be seen. Mill 2's results can be seen from Appendix 18. A small peak at the beginning of the month can be noticed. After the peak, the data decreases slightly.

## 5 DISCUSSION

The aim of this research was to find out if there were repetitive fluctuation, peaks or trends occurring in the Company X's invoicing data. The objective of this research was to examine which factors caused fluctuation, peaks or trends in the invoicing data.

Considering the research problem and objective, the research question was formed as following:

*“What trends occur in the invoicing data?”*

As Logan (2014, 28) stated, in some cases long-term trends can last over a year or more. When looking the results of usage data throughout all six time series, long-term trends can be noticed from both mills. A weekly trend in both mills data can be found from Figures 4 – 14 where the invoicing total increases and creates a peak on every seven days. Similarly, a long-term trend can be found from Figures 3 – 14 where the invoicing total increases significantly at the end of the month. From Mill 1's results it can be noticed that most of the peaks were created by Finland, whereas Mill 2's peaks were mostly created by Sweden. The differences in invoicing amount between the countries are higher in Mill 1's results when comparing to Mill 2. As already mentioned, when invoicing by usage, the products are invoiced once a week. This explains the peaks on every seven days and at the end of the month. This information comes from Company X's internal processes. Usage results from January 2016 until August 2018 can be found from Appendices 13 and 14. In the bigger picture, the distinct peaks between every seven days are more difficult to notice. However, this time series reveals a long-term trend, that applies to both mills. The total invoicing amount increases significantly at the end of the month, causing a high peak.

The results of delaware reveal long-term trends that applies to both mills. A long-term trend can be seen from Figures 19 – 26 where the invoicing total increases significantly at the end of the months. The results from both mills, show that the peaks were created by Spain. In addition, a medium-term trend can be found from Mill 2's results where the invoicing total increases and creates peak at the midway and at the end of the months. The trend can be seen from Figures 16 and 18. According to Logan (2014, 31), a medium-term trend lasts from few weeks up to several months. In this case, the peaks were also created by Spain. From the results it can be seen, that Mill 2 included broader set of countries than Mill 1. Peaks in Mill 1's data were created by Spain, whereas peaks in Mill 2's data were created by several countries. Delaware results during the entire time series from January 2016 until August 2018 can be found from Appendices 15 and 16. As it can

be seen, in the long run, both mills data occurs quite similarly. The total invoicing amount increases towards the end of the month.

Rubin (2015b) suggests, that trends can sometimes occur in a decreasing form. When looking the results of delmill, it can be noticed that there are not such distinct trends as in previous invoicing points. However, a decreasing trend in Mill 1's results can be found where the daily invoicing total decreases towards the end of the month. This can be seen from Appendices 1, 3, 5, and 7. Similarly, a decreasing trend can be noticed from Mill 2's results where the daily invoicing total decreases towards the end of the month. This can be found from Appendices 6, 8, and 10. Delmill results during the entire time series from January 2016 until August 2018 can be seen from Appendices 17 and 18. As it can be noticed, both mills data has clear fluctuation and a distinct trend is difficult to observe. However, a decreasing trend towards the end of the month can be seen from Mill 2's results.

As different trends were found from the invoicing data, it can be stated that the results provide answers to the research question. This research also focused to reveal which factors create trends in the invoicing data. From the results it can be seen, that delivery countries as a factor created the most distinct trends in the data. As it can be seen from the results, certain countries create peaks and fluctuation in the data. Therefore, it is likely that peaks and fluctuation will occur, as long as products are being sold into these countries. However, it is very likely that customer demand will change monthly, and thus, the total invoicing amount will also change.

To conclude, trends were found from each invoicing point. However, trends differ depending on Mill and/or time series and/or invoicing point. Some of the trends were more distinctive than others, but still, fluctuation can be found from each time series. A long-term trend from each invoicing point was also found during January 2016 – August 2018. In case the circumstances remain similar, it can be assumed that the presented trends will also occur in the future.

### 5.1 Assessment of the results in the light of literature

When comparing the results of this research to prior research done by Zhang et al. (2005) similar results can be found. In the prior research, upward and downward trends were found from the locations included in the research. Even though they utilised data from the past 130 years, the results in the present research are comparable, as increasing and decreasing trends were found. Another similarity was the fact that trends vary between the locations in both researches. (255-265.)

Another prior research provided results that are in line with the present research. Abdou et al. (2005, 165-184) research found peaks from the billing data. Similarly, in the present research peaks were also found from the invoicing data. However, in the prior research, high peaks were formed during the summer months, whereas in the present research high peaks were formed throughout the year.

## 5.2 Limitations of the research

One of the limitations in this research applies to the invoicing data itself. The data was collected from the past 32 months. By utilising historical data even more, the results would be more reliable and generalizable. Saunders et al. (2012, 494) state, that only longitudinal data can reliably present trends. The data collected for this research was enough to reveal long- and medium-term trends as well as a decreasing trend from the data. By increasing the amount of historical data, the results may have been different. However, if a larger data set would have been included, the research would have expanded too much. Since this research did not include interviews or questionnaires, the collected data was in a key role. The data used in this research was high-quality, even though it was secondary data. To increase the validity and reliability of the research, the data collection method and analysing process were precisely chosen and implemented.

The method how trends were examined in this research offers another limitation aspect. There are various prior researches where trends have been mathematically calculated. However, this research only focused to examine trends from the historical data without any mathematical calculations. The results may have been different if trends would have been calculated by utilising various techniques, for example mathematical formulas.

As Kananen (2011a, 85) suggests, a quantitative research provides results which can be often generalised. Since the research focuses only onto a specific company, the results cannot be generalised in another organisations. The invoicing data was collected from each mill individually, so it is impossible to generalize the results, as the data varies between the mills. However, from the results it can be noticed that both mills have trends in their invoicing data, so it can be assumed that Company X's other mills will also have trends in their invoicing data.

## 5.3 Recommendations

Researchers and organisations can use the information received from this research when planning to examine trends from their invoicing data. Author should focus on the quality of the invoicing data, since most of the work concentrates on the data itself. If accessible,

historical data can be efficiently utilised as presented in this research. There are several factors which affect the quality of the invoicing data for example, the data collection method and analysing process. Especially, the data analysing process plays a key role when examining invoicing data, it allows author to delete irrelevant factors from the data.

The most important factor to consider before analysing trends is the data. In order to gain reliable results, longitudinal data should be collected and analysed. Therefore, it is necessary for companies or organisations to collect and store data consistently.

Trends are not limited to a specific industry, they can be found from several industries in different forms. When examining trends for example from invoicing data, it should be noticed that trends may change repeatedly. Therefore, it is important to examine trends regularly so organisations are able to react on emerging trends.

### **Recommendations for Company X**

In this chapter, five recommendations for future research are presented. Firstly, it would be interesting to find out how the results presented in this research would change, if trends would be mathematically calculated. As a second suggestion, invoicing data could be collected and examined from further time series. By utilising longitudinal data, the past fluctuation may reveal new trends. As seen in this research, there are certain countries that create fluctuation in the invoicing data. Therefore, the third suggestion would be to examine only specific countries or markets to find out how their data affects invoicing. Only two mills were included in this research, so as a fourth suggestion, it would be interesting to find out how the invoicing data occurs in other mills. A research where mills from other countries are included and examined could possibly give more insightful results. The results between mills could be compared in order to find out any similarities. In this research, trends were examined by observing the effects of invoicing points. As a fifth suggestion, trends could be examined by analysing the effects of delivery terms. This way it could be seen if specific delivery terms cause movement or trends in the invoicing.

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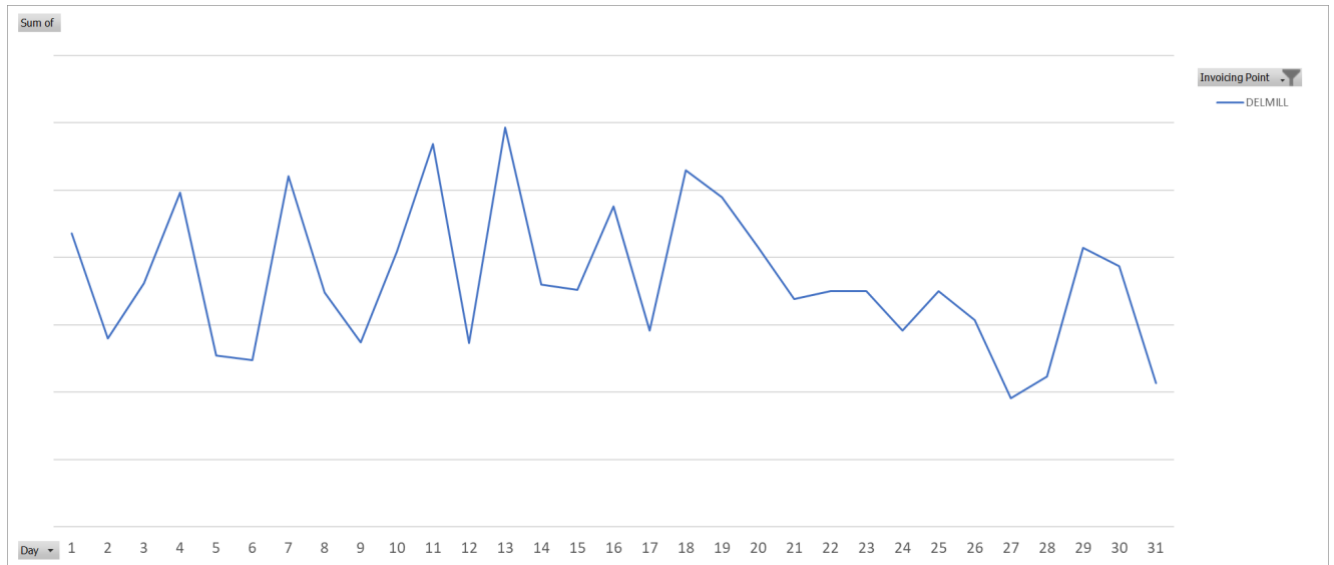
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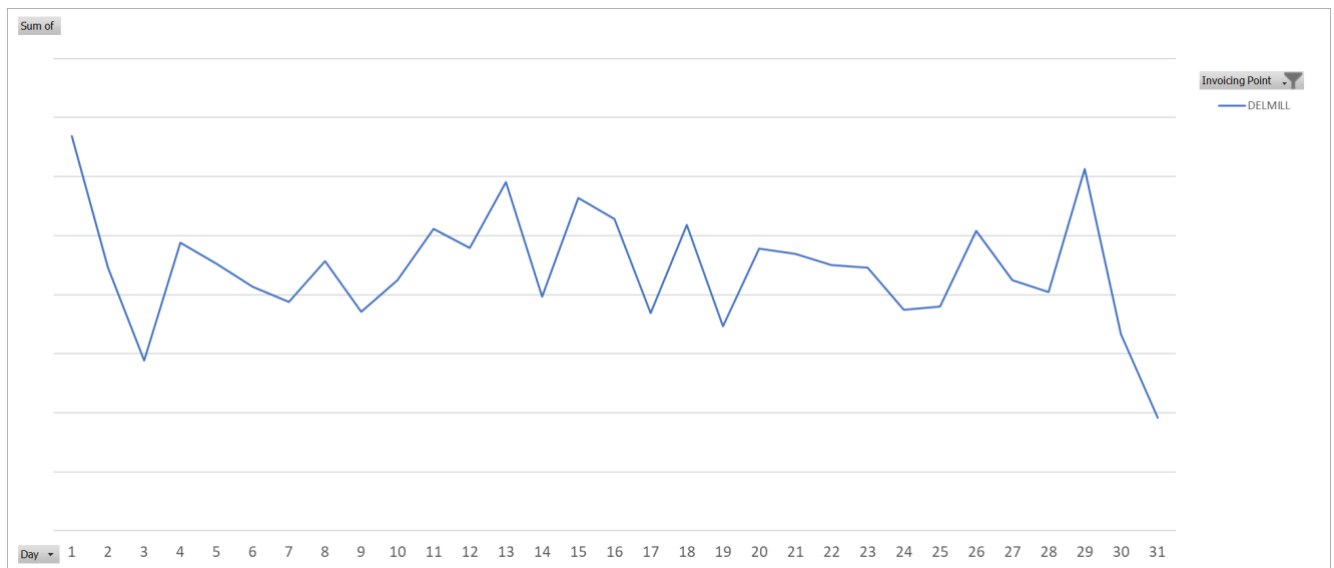
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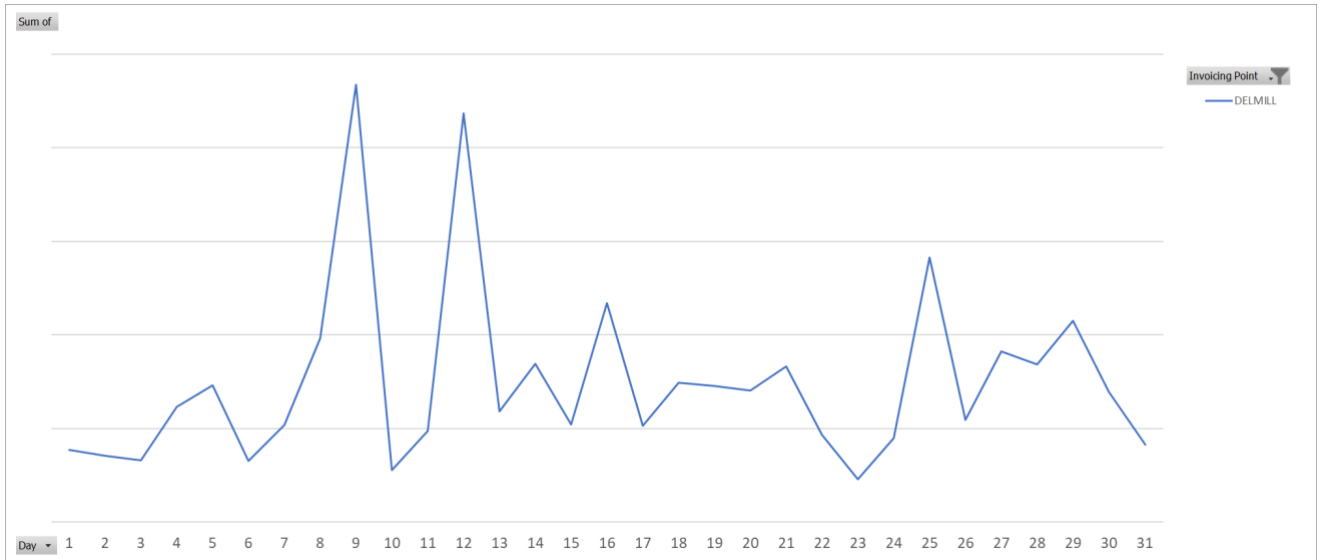
APPENDICES



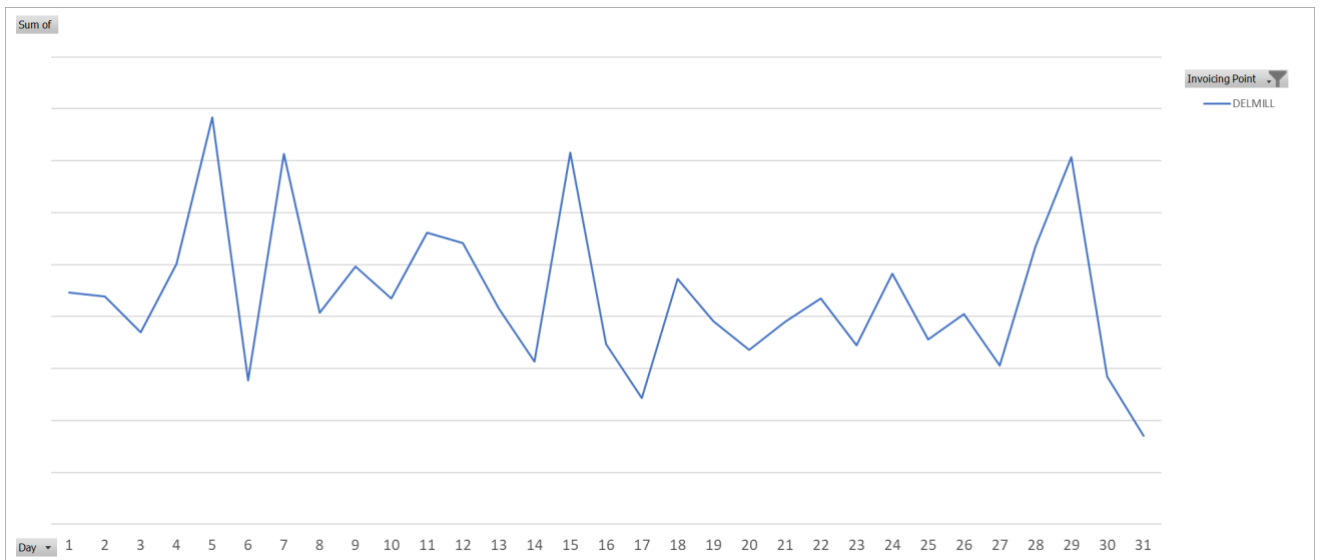
Appendix 1. Mill 1 delmill data January 2016 – June 2016



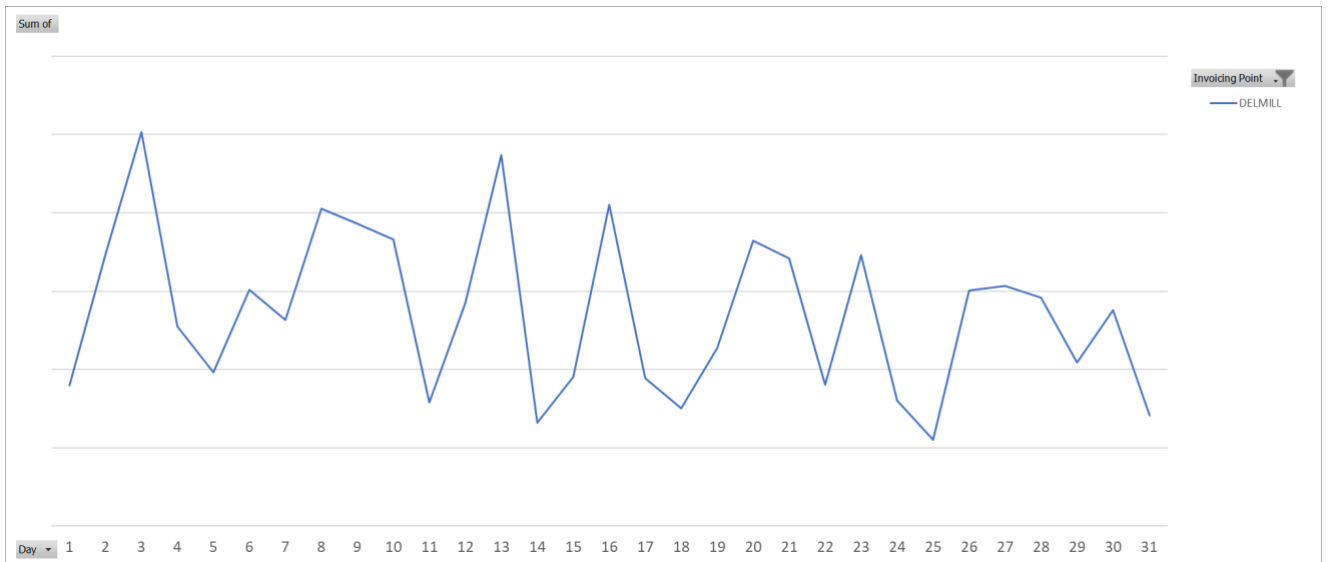
Appendix 2. Mill 2 delmill data January 2016 – June 2016



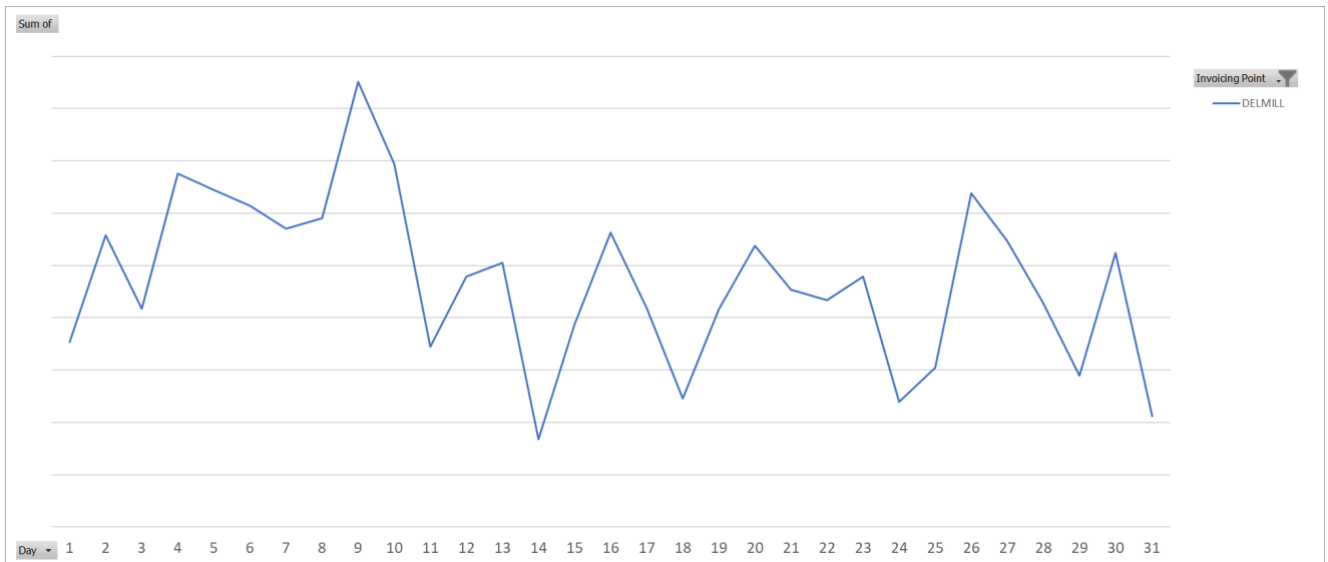
Appendix 3. Mill 1's delmill data July 2016 – December 2016



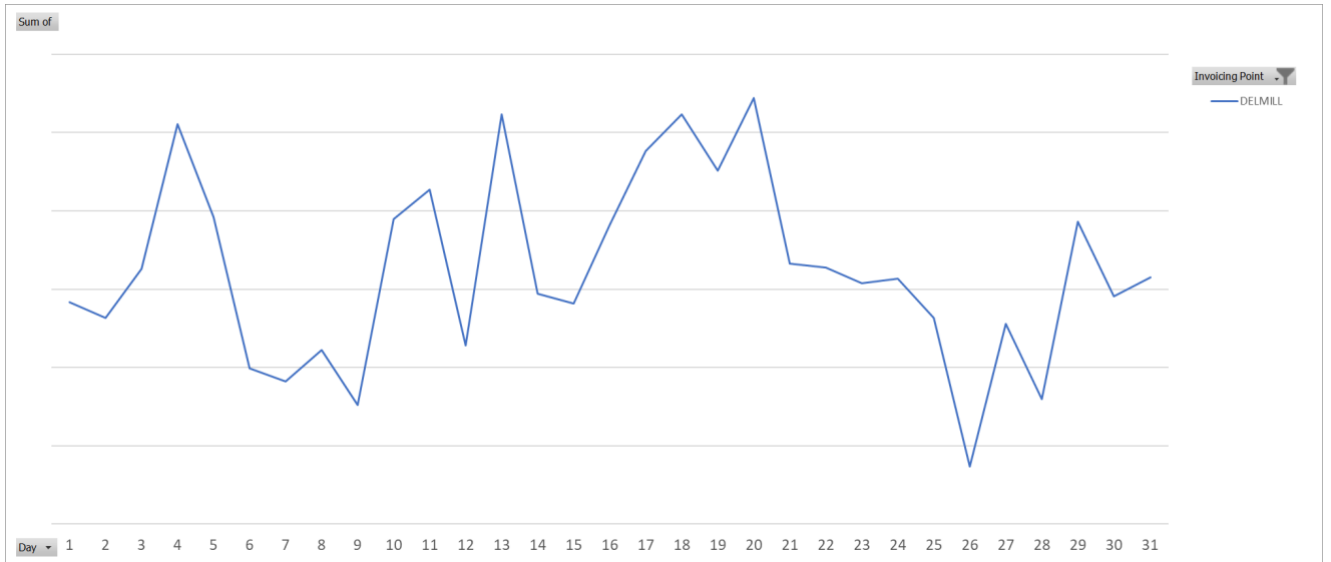
Appendix 4. Mill 2's delmill data July 2016 – December 2016



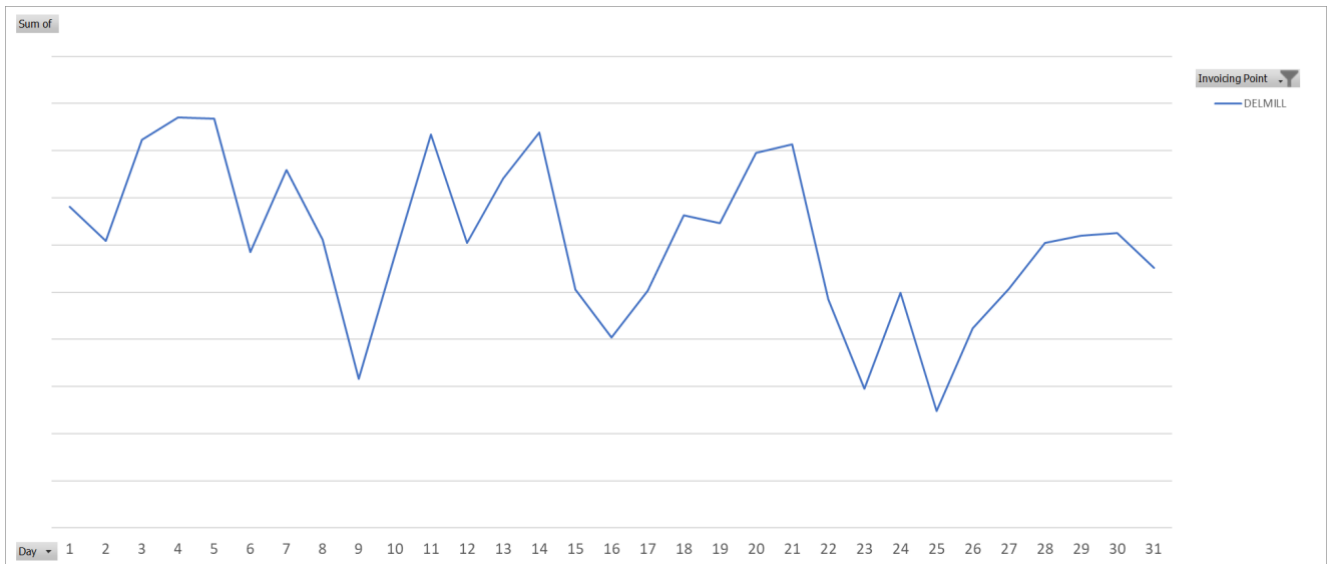
Appendix 5. Mill 1's delmill data January 2017 – June 2017



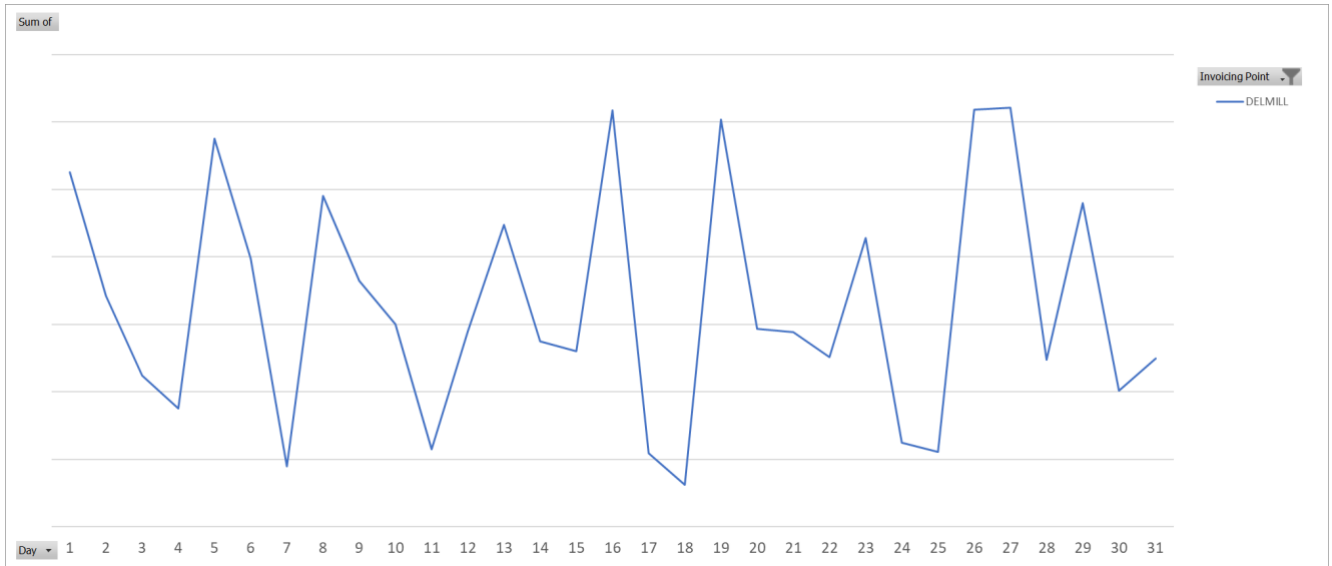
Appendix 6. Mill 2's delmill data January 2017 – June 2017



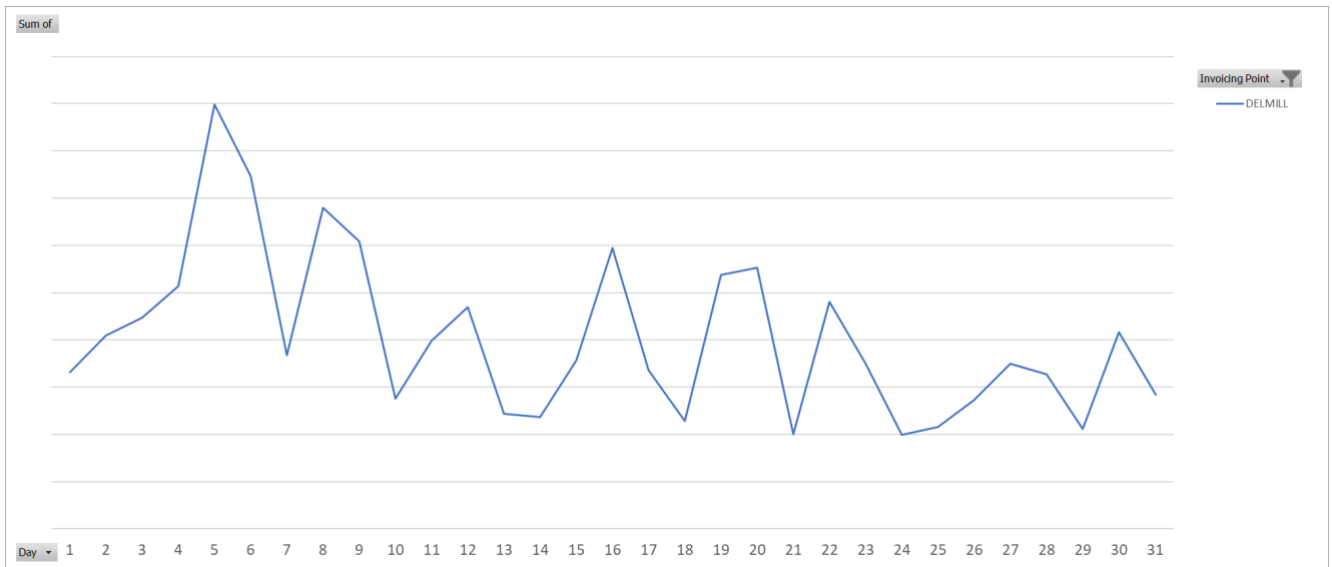
Appendix 7. Mill 1's delmill data July 2017 – December 2017



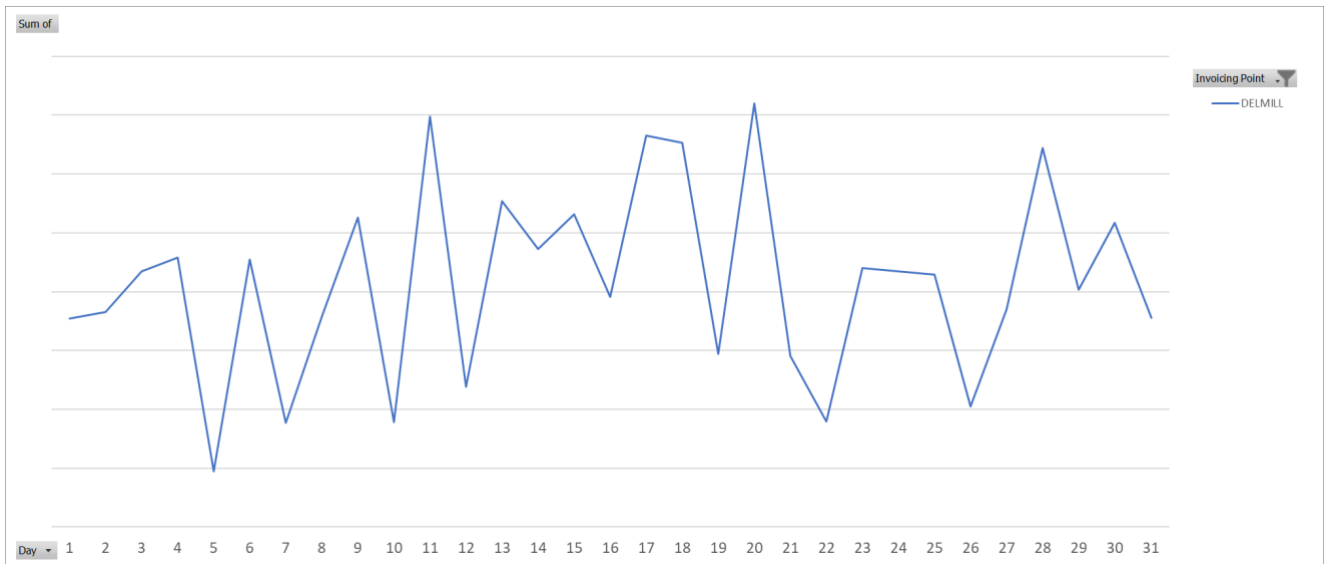
Appendix 8. Mill 2's delmill data July 2017 – December 2017



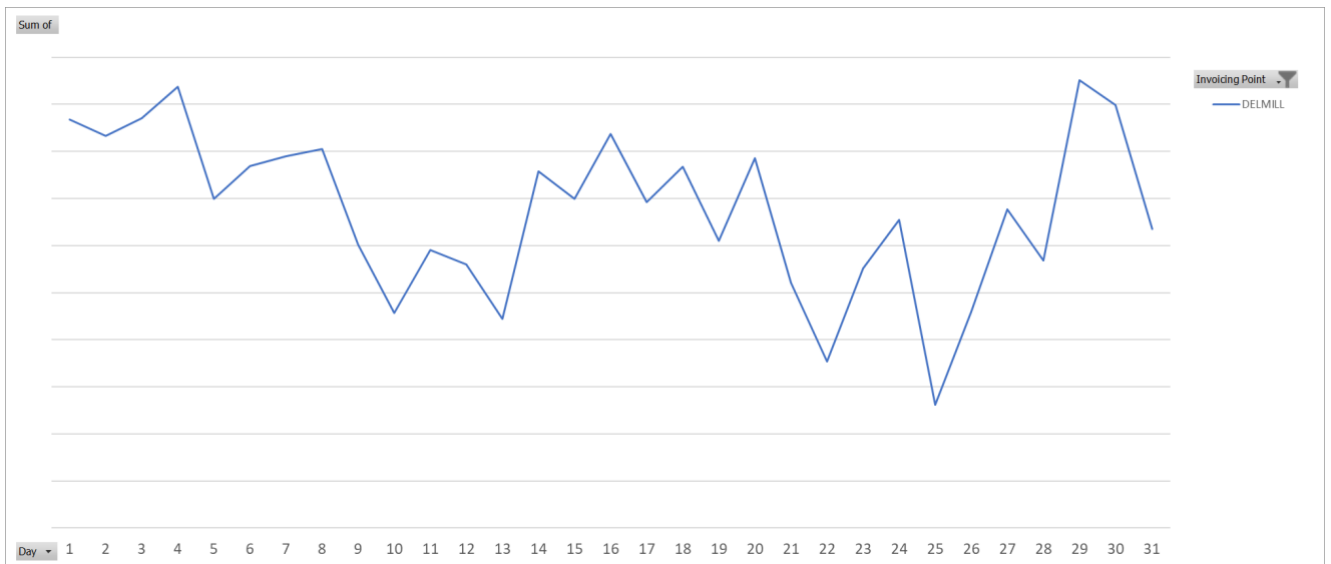
Appendix 9. Mill 1's delmill data January 2018 – April 2018



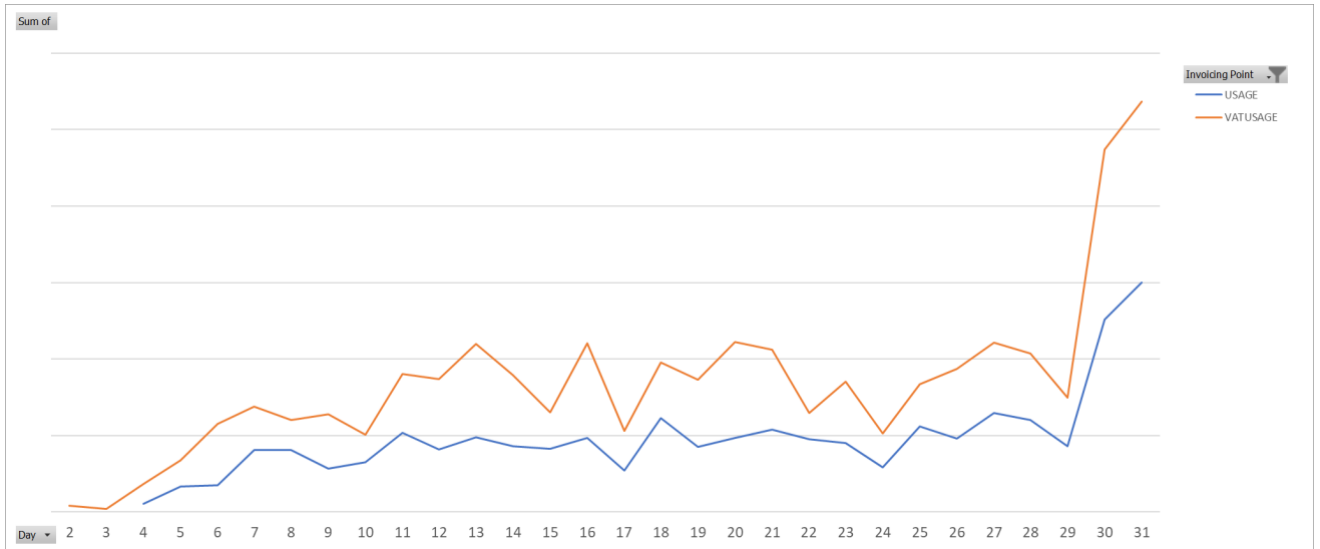
Appendix 10. Mill 2's delmill data January 2018 – April 2018



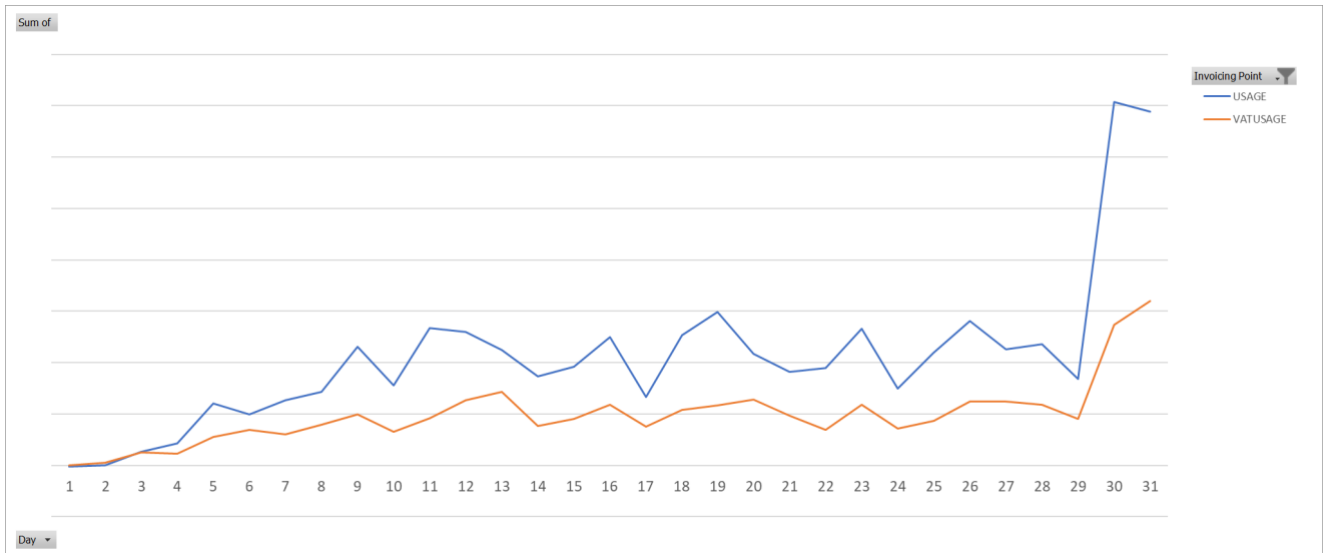
Appendix 11. Mill 1's delmill data May 2018 – August 2018



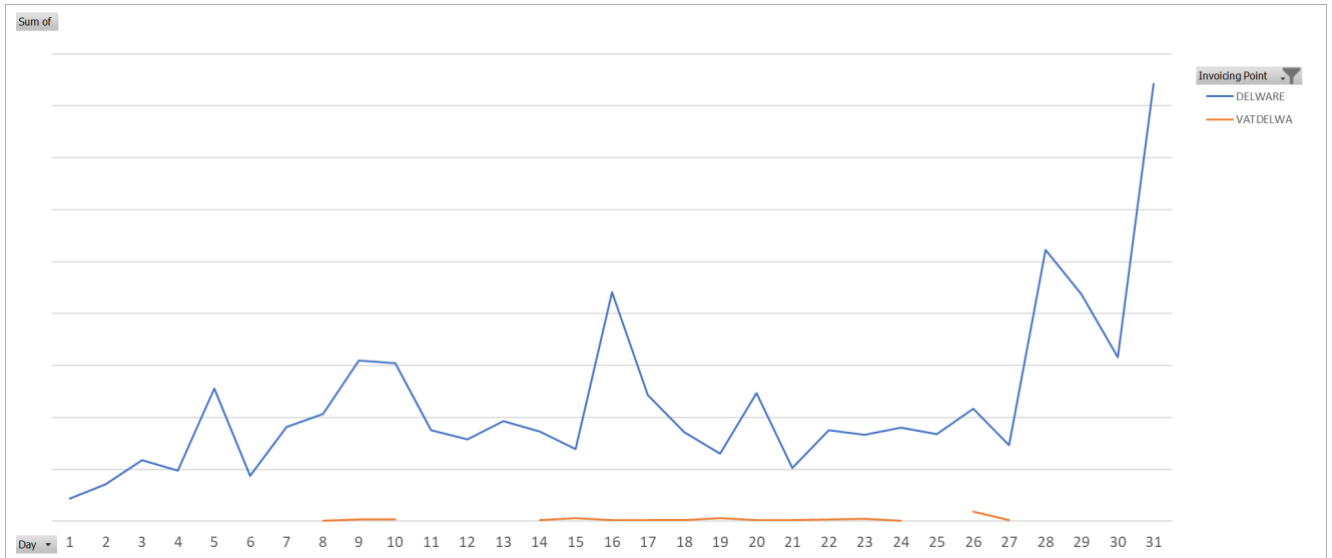
Appendix 12. Mill 2's delmill data May 2018 – August 2018



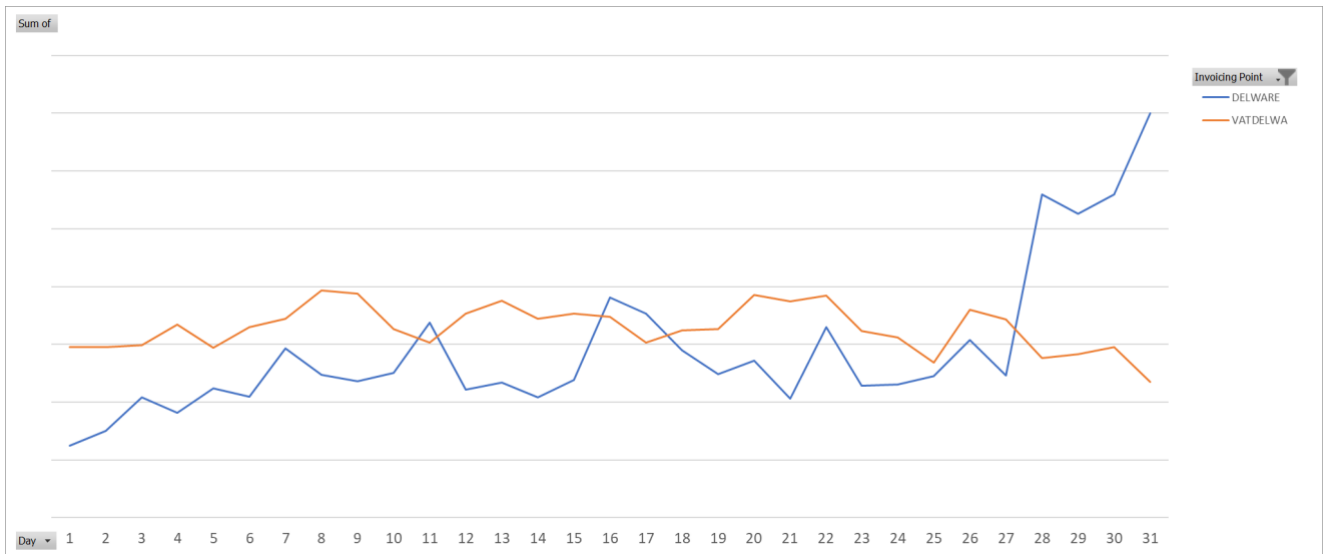
Appendix 13. Mill 1's usage and VATusage data January 2016 – August 2018



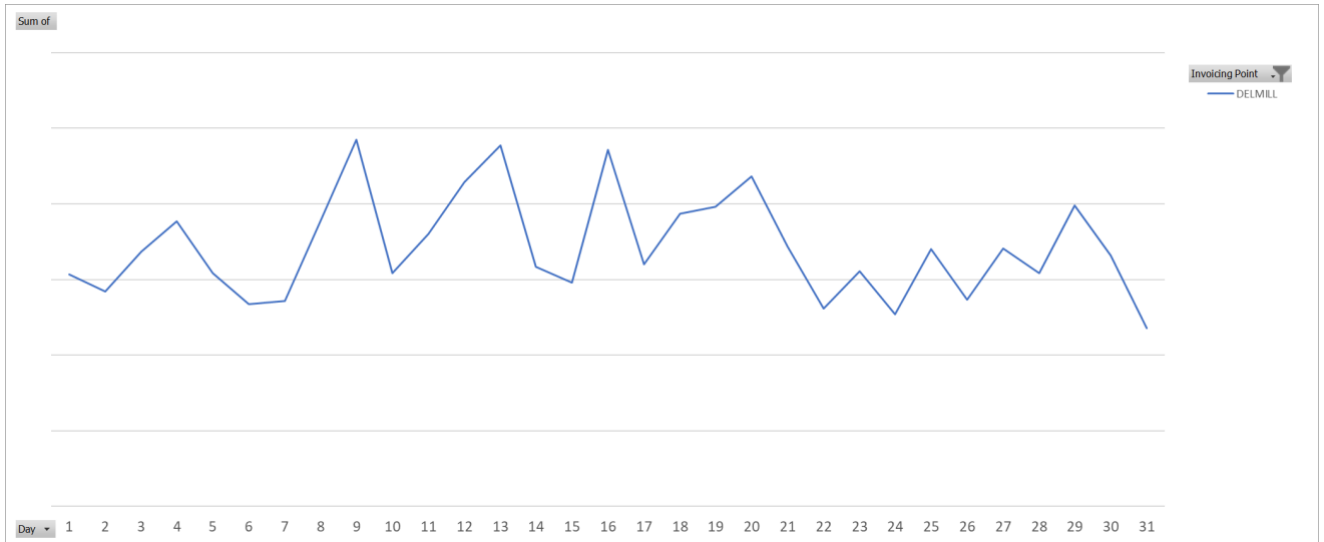
Appendix 14. Mill 2's usage and VATusage data January 2016 – August 2018



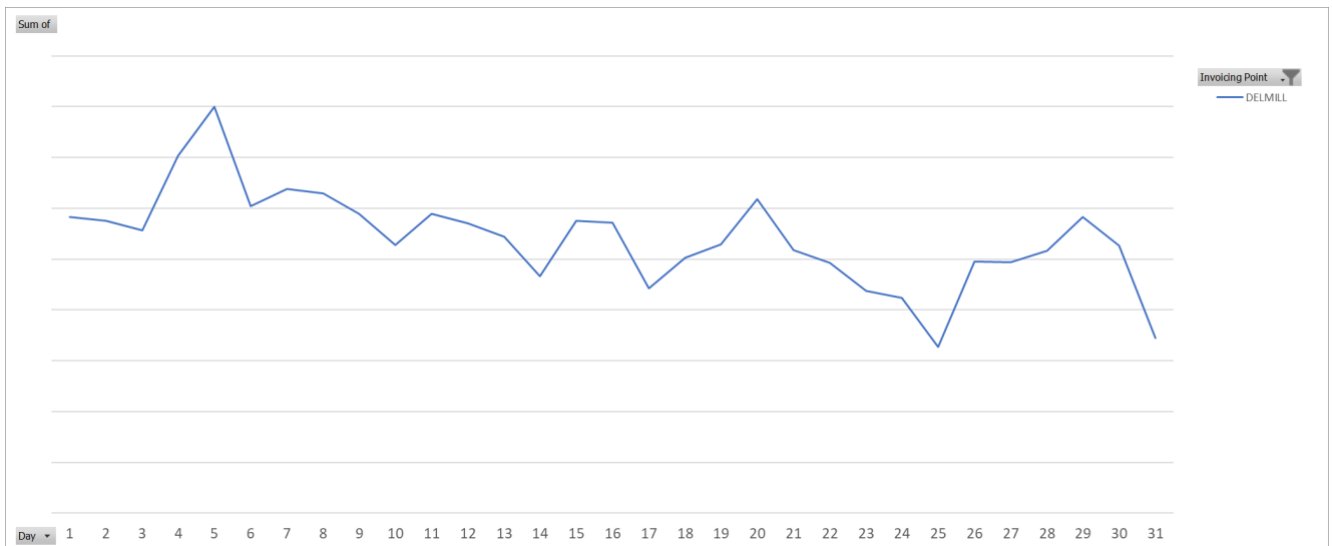
Appendix 15. Mill 1's delware and VATdelware data January 2016 – August 2018



Appendix 16. Mill 2's delware and VATdelware data January 2016 – August 2018



Appendix 17. Mill 1's delmill data January 2016 – August 2018



Appendix 18. Mill 2's delmill data January 2016 – August 2018