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Feldman, Tyler L. ***Implementation of Forecasting Metrics to Improve Customer Service and Inventory Velocity***

Abstract

When important strategic and tactical decisions and operational plans are made based on forecast, it is imperative to have as accurate of a forecast as possible. The purpose of this project was to develop and implement forecast performance metrics to give Company XYZ a measurement tool to determine to the accuracy of the forecast they were using to build plans and make decisions. Additionally, the purpose of the project was to determine if the forecast performance metrics would increase forecast accuracy and if there was a significant correlation between forecast accuracy and inventory/order fulfillment.

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Chapter I: Introduction

Company XYZ, whose organizational name was withheld to ensure confidentiality, began doing business in rural Wisconsin over 100 years ago and continues to grow and expand globally. Originally, they made wooden furniture and wagons. The company has grown from its roots and became an innovation leader in the markets they serve. These markets include worldwide plastic applications in the consumer, commercial, medical, and industrial areas, with products ranging from as large as a tractor bumper to as small as a gas cap. The company is now in its fourth generation of family leadership and has 1,600 employees located in five countries around the world.

The company is made up of three separate divisions. These divisions are called Proprietary, Contract, and ABC, division name was withheld to ensure confidentiality. While the company is growing and experiencing record sales in certain areas, Company XYZ is also experiencing shrinking margins due to increased competition, growing inventory levels, and decreased order fulfillment rates. The Contract and ABC divisions were the hardest hit by these trends. The company made significant investments into these two divisions and was committed to improving the business to make it successful in the long-run. While many improvements were made on the manufacturing floor to increase efficiency, the company has not made any significant investments in the forecasting and demand planning tools or processes in the last 15 years.

The greatest difficulties the Contract and ABC divisions faced were short lead times, small batch sizes, large product offerings, lengthy changeovers, and high demand variability. These difficulties have created conflict between operations, supply chain planning, sales, customer service, and senior management. Customer service and sales advised to not miss customers requested ship dates. Senior management advised to keep inventory levels low and operations advised to produce products in large quantities to reduce changeovers. The planning team needed an accurate forecast to enable them to meet all of the business unit's objectives. A clearer picture of expected future demand could enable the company to produce in larger lot sizes for certain key items, fulfill customer orders on time, and still turn inventory over frequently enough to keep inventory at a comfortable level.

The organization had a demand forecasting tool that was bolted onto a material requirements planning system. However, this forecasting tool was reaching the end of its life cycle and was at risk of no longer being supported by its vendor. There were two individuals who were tasked with the responsibility of forecasting and demand planning for the Contract and ABC divisions. However, forecasting was just part of their responsibilities and they were not solely focused on forecasting. The sales forecast was used for master planning, capacity planning, labor planning, strategic planning, budgeting, and in the case of make to stock products it was used to drive planned requirements. These planned requirements triggered the purchase of raw materials and production to take place even though there may not have been a real customer order.

The Contract and ABC divisions relied heavily on the sales forecast to complete various planning initiatives. However, they did not have any metrics in place to determine the accuracy of the forecast they were using to complete those initiatives.

Statement of the Problem

Company XYZ has been in business for over 100 years and while the business has grown and matured, the forecasting and demand planning systems, methodology, and metrics have not. This has created an environment where decisions were made on data that has not been proven to be accurate. If not improved, the Contract and ABC divisions are at risk of decreased profitability, increased inventory, and poor service to customers.

Purpose of the Study

This study analyzed the implementation of forecast performance metrics and measured the impact it had on reducing inventory levels and improving order fulfillment. Additionally, the forecast performance metrics were used to identify root cause of poor forecast performance so it could be corrected and measured to verify those corrections improved forecast performance.

Significance of the Study

The results of this study have the potential to be replicated across a broader and larger sample, including the other division in the company, in an attempt to further increase control of inventory and order fulfillment for Company XYZ. Improved forecast performance would decrease the demand variability allowing the company to follow just in time practices more closely. Successfully following a just in time model would decrease inventory holding costs, decrease the cash conversion cycle, decrease missed shipments, and create better customer relationships.

Assumptions of the Study

This project included a number of assumptions that relied on data control and manual evaluation to determine when it was appropriate to adjust forecast based historical forecast performance metrics. The first assumption that existed in the study was that were not any changes to the planning parameters for the products in the sample throughout the length of the study. These planning parameters included lead time, safety stock, safety time, and economic batch quantity. This assumption ensured that data remained consistent throughout the study and did not allow it to be a variable that contributed to changes in inventory levels or order fulfillment rates.

Additionally, there was an assumption that the company's material requirements planning (MRP) system would continue to calculate and function identical as it has in the past. MRP systems can use daily, weekly, or even monthly buckets to calculate requirements. Before the study started the company was using daily buckets. Therefore it was assumed that this practice would continue throughout the study.

Lastly, it was assumed that a standard procedure and good judgment was used when determining when to adjust the forecast demand based on the implemented historical forecast performance metrics. This process required manual evaluations by the forecasting personnel that were tasked with reviewing poor performing products with the study to determine what adjustments should be made. It was also assumed that formal demand reviews would take place as they have in the past.

Definition of Terms

The supply chain management terminology used in the study is applicable across many industries besides just the plastic industry. The understanding of these supply chain management terms is critical to understanding the background and applications of this study.

Assemble to order. A production strategy where common components are kept in stock in anticipation of an order and then assembled to customized products upon receipt of an order (Pittman & Atwater, 2016).

Economic order quantity. When a re-order point is reached, this is quantity or size of a purchase orders or production run that minimizes total cost (Pittman & Atwater, 2016).

Electronic data interchange (EDI). **"**The paperless (electronic) exchange of trading documents, such as purchase orders, shipment authorizations, advanced shipment notices, and invoices, using standardized document format" (Pittman & Atwater, 2016, p. 65).

Lead time. An interval measurement between placement of an order and expected delivery (Pittman & Atwater, 2016).

Make to order. A manufacturing process in which manufacturing starts only after a customer's order is received (Pittman & Atwater, 2016).

Make to stock. A production strategy that is used by businesses where goods are finished before customer orders to match production and inventory with consumer demand forecasts (Pittman & Atwater, 2016).

Material requirements planning (MRP). "A set of techniques that uses bill of material data, inventory data, and the master production schedule to calculate requirements for materials" (Pittman & Atwater, 2016, p. 116).

Safety stock. A planned quantity of inventory that is kept to protect against fluctuations in supply or demand (Pittman & Atwater, 2016).

Safety time. A variable quantity of an item in which inventory is held based on forward looking demand trends. (Barry, 2016)

Limitations of the Study

The results of this project were limited to products in the Contract and ABC divisions of Company XYZ. The project could have expanded into the third division of Company XYZ but difficult access of data due to a different database was a limiting factor.

The forecasting and demand planning tool that was used by the company was reaching the end of its life cycle. Therefore, it had limited functionality when compared to many of the new tools that exist. As a result, data needed for the study had to be extracted manually from a database at precise times to ensure data integrity. Consistency with data extract timing was maintained by using a repeatable calendar date and time.

Furthermore, the inventory metric that senior management valued the most was month end inventory dollars. Therefore, this was the metric used in the study to analyze whether increased forecast performance led to decrease inventory. A limitation exists when using this measurement due to the fact that it was a single snap shot in time and may not have reflected the overall inventory performance for the month. For example, a production run could have occurred on the last day of the month so inventory increased over last month but average days in inventory month over month could have went down.

Methodology

As part of the study, three new forecasting performance metrics by unique product number were developed and introduced. These metrics were forecast accuracy, forecast bias, and forecast value-add. Additionally, the forecast accuracy and forecast bias metrics were able to be applied to historical data prior to the start of the study that was stored in one of the company's databases. The forecast value-add metrics unfortunately was not so the metric was only able to be calculated and recorded from December 2018 to February 2019. The other two metrics were calculated and recorded from December 2017 to February 2019.

The remaining data points, inventory dollars and order fulfillment rates, were calculated and recorded from December 2017 to February 2019. Inventory dollars was captured at month end by unique product number. The same methodology that inventory dollars used was applied to order fulfillment rates.

All of the data collected in the study was owned by Company XYZ and approved for use in this study. The study collected and compiled all the data that was used. The study then used the data to calculate the three forecasting performance metrics. The forecasting performance metrics were then shared with the forecasting personnel, which were direct reports to the study, for them to analyze and perform root cause analysis with the study when poor performance was evident.

The sole responsibility for data analysis was with the study. Data analysis was conducted with descriptive and inferential statistics. The first analysis that was done was to determine if there was a significant correlation between an independent and two dependent variables. The independent variable in the study was forecast accuracy and the dependent variables were inventory dollars and order fulfillment. A correlation and regression test, using a P-value of .05, was used to determine if the correlation was significant.

The second data analysis that was done was to determine whether forecast accuracy increased after the forecast performance metrics were introduced. A two tail Z-test using alpha of 0.05 was used. The prior year time frame used was December 2017 – February 2018, the three months prior time frame used was September 2018 – November 2018, and the after time frame was December 2018 – February 2019. Using these time periods would account for seasonality of certain products. The mean forecast accuracy in each of the three time periods was recorded in a table to be analyzed with a Z-test.

Summary

Company XYZ has been in business for over 100 years and has continued to grow and expand. The company was made up of three divisions called Proprietary, Contract, and ABC. The Contract and ABC divisions have been negatively impacted due to increased competition, growing inventory, and decreased order fulfillment rates. These divisions have seen significant investments into the manufacturing processes but little has been done to improve the forecasting and demand planning in these areas. These two divisions have personnel who were tasked with forecasting and demand planning. However, they did not have any metrics in place to determine the accuracy of the forecast they were publishing to the business.

The focus of this project was to develop and implement forecast performance metrics in the Contract and ABC divisions. These metrics were aimed at understanding the impact they had on inventory levels and order fulfillment rates. Additionally, the metrics were developed to provide a starting point for root cause analysis on poor performance so corrections could be made to improve performance.

Chapter II: Literature Review

Organizations are faced with numerous options and strategies that they can use to manage their supply chain from beginning to end. Most of these options and strategies will rely on some sort of predictive data that is forward looking at what expected demand the organization will receive from its customers. In the case of Company XYZ, and more specifically in the Contract and ABC divisions, this data will come from the sales forecast that is reviewed, revised, and published monthly. However, the issue with the sales forecast data is that since forecast performance metrics are not currently used there is no way to verify the accuracy of the data and the impacts it has on these two divisions. If not improved, the Contract and ABC divisions are at risk of decreased profitability, increased inventory, and poor service to customers. This study analyzed the implementation of forecast performance metrics and measured the impact it had on reducing inventory levels and improving order fulfillment. Additionally, the forecast performance metrics were used to identify root cause of poor forecast performance so it could be corrected and analyzed to show if those actions improved forecast performance.

Supply Chain Management Overview

There are multiple explanations of what supply chain management is and why organizations should place a focus on its concepts. Hugos (2018) found "supply chain management is the coordination of production, inventory, location, and transportation among the participants in a supply chain to achieve the best mix of responsiveness and efficiency for the market being served" (p. 4). Supply chain management as a concept began in the 1980s and was a new way of thinking which focused on combining the functions needed to serve customers instead of working in silos (Hugos, 2018). Hong, Zhang, and Ding (2018) found that supply chain management has become one of the largest means for an organization to increase performance by controlling costs.

As the word supply chain implies, it represents a group or network of interrelated linkages. Stadler and Kilger (2008) state that these linkages can be found upstream, downstream, or both from a specific organization. Within an organization, these linkages can come from different business units and even from different sites within the company (Stadler & Kilger, 2018). Also, a network does not flow in a single chain. It is expected that a supply chain will have convergent and divergent flows created from many customer demands all at once (Stadler & Kilger, 2018).

The mix between external and internal flow is what makes supply chain management such a broad practice. Sethi, Yan, and Zhang (2005) states that supply chain management covers vast territory, uses numerous analytical tools, and is highly cross-functional. Competitiveness, customer service, integration, coordination stand as the house of supply chain management but logistics, marketing, operations research organization theory, purchasing, and supply make up the foundation of supply chain management (Stadler & Kilger, 2018). Panayiotou and Aravosis (2011) found that this integration allows the right amount of product to be produced, at the right time to meet planned requirements, at the agreed upon price, and in a way that minimizes cost to the organization.

Forecasting and Demand Planning

Loretto, 2011 found **“**demand planning is an essential process in determining how much product a business will sell to satisfy all customer demand” (p. 3). Therefore, the purpose of demand planning is to work closely with customers to determine how much of what product will need to be sold in a given period in order to meet their demands (Loretto, 2011). This period of time is sometimes referred to as a long-term plan, which could span anywhere from 6-24 months out. An output of the demand planning step is a finalized forecast which is used in subsequent steps in the supply chain planning process. Hugos (2018) found that the demand plan is what a company builds their operational plan around in order to meet customer demands. Demand planning and forecasting is easy if there is just one customer and buys one product but that is rarely the case.

Strategies and techniques. Forecasting and demand planning requires close collaboration with customers and understanding of trends in the market (Loretto, 2011). Therefore, it can be said that the sales and marketing managers have a lot of input into forecasting. However, Lapide (2013) found "these managers primarily focus on maximizing revenue and market share because these are normally the corporate goals placed on them" (p. 17). This creates an environment where forecasting and demand planning can be overlooked. However, Wilson (2017) suggests that demand planners will rely more on automation. Data is more readily available, is more real-time, and it is coming from more places (Wilson, 2017). Organizations will need to better utilize and streamline that data in order to be efficient in the demand planning process.

Collection of any input data from various inputs often adds value when compiling a forecast. Examples of those inputs are previous planning runs, historic customer sales, historic shipments, and any corrections made (Stadtler & Kilger, 2008). This data would then be brought together and a statistical forecast would run using algorithms defined by the user or software. The statistical forecast would then be reviewed by humans to judge the accuracy of the forecast and then they would provide their input to capture things such as promotions (Stadtler & Kilger, 2008). While computed forecast, or statistical forecast, can be effective enough in some situations, it is not intuitive enough to be effective in larger organizations that have significant shifts or demand and changes in business (Lapide, 2013). This is why it is imperative to have some level of customer interaction. The next step would be to consolidate all of the planners forecast and manage any exceptions. Once that is complete, Stadtler and Kilger (2008) found that the forecast should then be reviewed as part of a demand review and subsequently publish to further planning processes.

Another strategy that is used to try and eliminate forecast inaccuracy is by planning at a product group level and not at the product stock keeping unit (SKU). This creates a more aggregated approach and allows for greater accuracy (Hugos, 2018). Many organizations have a large number of SKUs and it would be improbable for individuals to tackle that much information and still maintain accuracy. Another strategy which can be used in certain industries is described by Haberleitner, Meyr, and Taudes (2010) in which they found that it may also be helpful to use differing units such as units, dollars, or pounds. The varying measurements allow easy conversions to be made if needed for other processes.

Forecast metrics. As stated previously, demand planning is essential to the planning process for an organization. Moreover, a high level of forecast accuracy is imperative for the subsequent steps to be proficient and to keep overall costs down (Jain, 2017). Tokle and Krumwiede (2006) found that the average forecasting error of the 218 companies in a survey was 22.3%. High forecast accuracy allows safety stock and inventory levels to remain low. Furseth and Stumbaugh (2017) found that measuring forecast accuracy also allows for a method to identify areas that can be improved upon. This enables financial, strategic, and marketing plans to be made on accurate data.

Jain (2017) states that in order to evaluate the performance of the forecast, metrics must be in place. There are only five metrics that can be used effectively in most businesses. Those five metrics are mean percent error, mean absolute error, weighted mean absolute percent error, forecast bias, and range of error (Jain, 2017). An error is an error when forecasting, whether over or under forecasting. Jain (2017) states using absolute error allows to account for each type of error while being able to ignore the signs. Additionally, bias can also show over or under forecasting. Bias should be measured and investigated when it is above or below an organizations threshold so action can be taken to improve (Jain, 2017).

Sales and Operations Planning

Similar to supply chain management, sales and operations planning first started in the 1980s (Alexander, 2016). The concept of sales and operations planning (S&OP) is to align as an organization on sales and operations output volumes that will be produced and sold for a specific time period. Tinker (2010) found that these meetings were usually held on a monthly basis and had representation from sales, operations, supply chain, and senior management. Ultimately, the meetings are held and plans are put in place to further close the gap between planning and execution (Michel, 2018). Those gaps often exist if plans are made outside of these meetings because individuals may not be aware of all of the constraints that exist. Whereas when a larger team meets to set plan it is more likely someone in the room will be aware of possible constraints such as logistics, labor shortages, material shortages, and machine downtime (Alexander, 2016).

Importance of S&OP. The S&OP process is all about planning for different scenarios (Michel, 2018). Some of the questions that come up just are not able to be answered until you have an entire view of the supply chain (Michel, 2018). This is the importance of the S&OP process. In fact Tinker (2010) found "a S&OP process can produce improvement of 5% to 25%

in such areas as working capital reduction, reduction of obsolete inventory, transportation, production and material costs, time to market, and sales growth" (p. 2). Another importance of this process is aligning on the plan and being creating accountability on the execution (Tinker, 2010). The best plans can be laid out but if no one steps up to execute on those plans they will never be more than just plans.

Strategies and techniques. It is clear that there is a significant importance to S&OP, but the trick is finding a strategy or technique that is beneficial to the managers that are involved. S&OP should be treated as a process not a technology (Michel, 2018). A typical monthly S&OP cycle includes, demand review, supply review, a pre S&OP, and an Executive S&OP (Tinker, 2010). The demand review phase is typically a meeting led by a Vice President of Sales and the goal is to review the unconstrained forecasted demand and come to an agreement on a final plan (Tinker 2010). The demand plan is then used in the supply review phase. During the supply review phase, a Vice President of Operations holds a meeting in which the team will review if the supply plan meets the demand (Tinker, 2010). In the next step, the pre S&OP phase, a plan comes together that fixes any of the constraints between the supply and demand plan and creates an operating plan. The operating plan provides an aggregate view of sales targets, production demands, and inventory projections by month (Tinker, 2010). Last, is the executive S&OP phase. This phase is typically owned by a member of the executive team such as the CEO. It is in this phase that the operating plan is reviewed and the proposal is either confirmed or denied for the plan to be reevaluated (Michel, 2018).

Implementation. Implementation of the S&OP process can be difficult, and as Tinker (2010) found, there are key levers that can go a long way in making implementation easier. The key levers that Tinker (2010) discusses are vision, sponsorship, design, and reports. Alexander

(2016) also found that implementation required leadership commitment or sponsorship. Leadership commitment comes in the form of recognizing the importance of S&OP and giving the team ample time and resources (Alexander, 2016). Vision comes in the form of understanding what S&OP is and what it is not (Tinker, 2010). It is about clearing up any misconceptions that the team might have about S&OP and setting expectations. Implementation of S&OP must also meet the design of the reporting structure of an organization (Tinker, 2010). For example, it should be aligned to the organizational reporting structure and have the right members involved. Reports are also a key component of implementation. The data that is reviewed at each step needs to be accurate, accessible in a timely, manner, and be displayed in an efficient manner (Tinker, 2010). Alexander (2016) found “S&OP as a process requires discipline: sticking to the calendar, communicating decisions in a timely manner, and covering required agendas” (p. 5).

Master Production Scheduling

Master production scheduling (MPS) utilizes outputs from the demand and supply plan of the supply chain planning system. MPS requires an intricate feel for demand and more importantly supply (Stadler & Kilger, 2008). The purpose of MPS is to develop short to mid-term plans on what products and in what quantities will be produced to help meet company objectives. Jonsson & Kjellsdotter Ivert (2015) found “MPS therefore drives operations in terms of what is assembled, manufactured or bought” (p. 1). Additionally, Sahin, Powell Robinson and Gao (2008) found that MPS is an important function to help MRP systems drive calculations early in the planning process.

Importance of master production scheduling. The importance of MPS lies within its ability to make the most economical decision for the organization to meet its strategic initiatives.

MPS also enables decisions to be made such as safety stock level which will help curve demand swings and forecast inaccuracies and allow an organization to maintain acceptable service levels (Feng, Rao, & Raturi, 2011).

Gahm, Dünnwaldd, and Sahamie (2014) also found that MPS is a key decision making step that allows for economical decision to be made and translated into a production plan. This is also an important step because it kicks off the start of the dependent planning tasks. These tasks include distribution planning, capacity planning, production scheduling, material requirements planning and order promising (Gahm et al., 2014).

Although it has been previously highlighted, order promising is of significant importance to an organization. The earlier a company is able to communicate to customer and promise order timing the better (Stadtler & Kilger, 2008). Customers want to know any early indications that they might have material delays. If MPS is not utilized this communication often comes too late and the customer is unable to shift their production or purchasing plan to compensate for the material shortage (Stadtler & Kilger, 2008).

Strategies and techniques. As with the study of supply chain management, the strategies and techniques of MPS are relatively new. One strategy that came to light is the process of freezing the MPS. Ultimately, this technique puts a virtual freeze on the MPS during a specified time interval and changes are not allowed during at that time (Herrera, Belmokhtar, Thomas, & Parada, 2016). In that frozen time, quantities cannot be adjusted without formal approval to the plan that the organization will execute against in the production scheduling step. This technique works best in stochastic environment and is aimed at creating a more stable plan.

MPS relies heavily on data. This data is in the form of forecast, inventory, and capacity. Once all the data is present an unconstrained supply model can be generated, which should ignore any capacities such as production or purchasing (Stadtler & Kilger, 2008). The optimal model, which is defined by the user, should be selected. Next, Stadtler and Kilger (2008) found that the model should then be evaluated to identify areas which have overloaded capacities. If there is not anything that is over capacity this model is complete. However, if there are overloaded capacities the essential resources should be selected and actions should be taken to adjust the model to create an optimal constrained solution (Stadtler & Kilger, 2008). This method will produce a constrained model which will be able to be output to the production scheduling step.

An additional strategy in MPS is the use of lot size calculations to balance the holding cost of inventory, backlogging costs, and the cost of set up on the manufacturing floor. This is a useful strategy when, as Vargas and Metters (2011) found, "faced with conditions such as rolling planning schedules with an infinite planning horizon, frozen portions of the production schedule and having both open production orders and non-zero on hand inventory" (p. 298).

Efficiency gains. Efficiency gains from MPS come in the form of the minimization of production costs, the holding costs of inventory, and set up costs. Herrera et al. (2016) were able to show that through the use of MPS modeling that it allowed for cost degradation. In other studies, Jonsson and Kjellsdotter Ivery (2015) found certain direct relationships between plan feasibility and MPS. If MPS is not used plans are still able to be generated in the short to mid-term window but it is less likely that they will be able to be properly executed at the subsequent processes. An organization using MPS also prevents large increases in schedule instability (Nadaei & Mahlooji, 2014).

Production Scheduling

As the last step in the supply chain planning process before a finished good is produced, this final step in the process has the most interaction with the manufacturing shop floor. In a fully developed supply chain system, this step would use the output from the master production schedule to create production orders and then sort and sequence the work that was defined as being due in weekly buckets (Davis, 2015). Production scheduling includes the planning of manufacturing assets and the resources needed for those assets to produce products (Jozefowska & Zimniak, 2008). Production scheduling has been an ongoing research topic because it is critical to understand the impacts it can have of the manufacturing output and efficiency (Kang & Choi, 2011). Without understanding the true impact that the production schedule is having, an organization could be creating excessive changeovers, increased downtime, waste of resources, and low employee morale.

Importance of production scheduling. Production scheduling is charged with managing numerous complexities including machine constraints, personnel constraints, and changes in customer demands such as expedites or quantity changes. This step, as Kang and Choi (2010) found, "allocates resources over time to these activities, so that production tasks can be accomplished timely and cost-effectively" (p. 3319). If done correctly, production scheduling enables an organization to run more efficiently on the shop floor, optimize use of existing assets, reduce costs, and free up capacity for continued growth (Kang & Choi, 2010). Stadtler and Kilger (2008) describe that while scheduling may not have a maximum cost impact as other areas of supply chain planning might have, it is important to keep in mind the cost that rush orders or penalty charges that could result from poor production scheduling.

Software systems and techniques. The production scheduling function is not only responsible for sorting and sequencing production orders, they also have to manage material flow, machine usage and likely the workforce usage. Enterprise resource planning (ERP) software systems, which almost all organization have some version of, will typically have a module know as material requirements planning (MRP). This module, MRP, is extremely efficient at controlling material flow, machine usage and workforce usage if the system parameters are set up correctly (Stadtler & Kilger, 2008). ERP systems can certainly aid in the management and flow of production scheduling but as Jozefowska and Zimniak (2008) have found they usually do not offer any automation of optimizing the production schedule. Therefore, more dynamic software systems and techniques are often needed in order optimize the requirements that are sent to the production scheduling step from the master production scheduling step.

Scheduling tasks can be done by using staff expertise of the process at each location (Stadtler & Kilger, 2008). However, this can often times lead to risk that subjective decisions could be made and their expertise could be lost due to retirement or other means. This shows the importance to develop a more systematic approach, model, or technique to ensure an optimal schedule is being output to the manufacturing floor to execute on.

Summary

In many organizations, forecasting is the first step in the supply chain planning process. The purpose of demand planning is to work closely with customers to determine how much of what product will need to be sold in a given period in order to meet their demands (Loretto, 2011). Once an organization establishes what will need to be sold is, it can build plans around how to meet demand. The basis for those plans will be the forecast or demand plan. This forecast will then flow through subsequent planning steps so the organization can align. A few of those steps covered in this study were S&OP, master scheduling, and production scheduling. Tinker (2010) found this process can improve working capital reduction by 5% to 25%.

A high level of forecast accuracy is imperative for the subsequent steps to be proficient and to keep overall costs down (Jain, 2017). In order for a company to track forecast accuracy it must have a metric in place. This will allow for a company to track progress and determine if the forecasting efforts are hitting the mark. Furthermore, in order to improve forecast accuracy a company can use different methods of forecast analysis to determine areas that can use improvement. In the end, improving forecast performance is a good step in the right direction to help an organization become more profitable. The subsequent chapters will evaluate the impact of implementing forecast performance metrics on inventory and order fulfillment, which are a few key contributors to profitability.

Chapter III: Methodology

Company XYZ has had a successful past but now is faced with increased competition and decreased margins. Although the organization has grown and matured, the forecasting and demand planning systems, methodology, and metrics have not. This has created an environment where decisions are made on data that has not been proven to be accurate. Therefore, new forecasting performance metrics were be developed and implemented. The forecast performance metrics were used to identify root cause of poor forecast performance so it can be corrected. Additionally, the study sought to find out if improved forecast performance could deliver a significant reduction of work in process and finished goods inventory and improve customer service.

Introduced Metrics

As part of the study, three new forecasting performance metrics were introduced. Two of these metrics, forecast accuracy and forecast bias, were able to be applied to data that was collected from the initial data collection. The third metric, forecast value-add, was only able to be applied to the data set from monthly forecast publishes that were made from December 2018 to February 2019. This was due to the need to capture the difference between the system only forecast and the adjusted monthly forecast that could not be captured in the historical data from December 2017 to November 2018. Forecast accuracy was calculated using the following formula if sales was greater than adjusted forecast, ((1-(|Sales – Adjusted Forecast|) / Sales)) x 100. If sales was less than adjusted forecast then this formula was used instead, ((1-(|Sales – Adjusted Forecast|) / Adjusted Forecast)) x 100. This was done to ensure that if there were large difference between sales and adjusted forecast that the calculated results would not be a negative value. This metric would be the only metric that would be compared to inventory and order fulfillment.

Forecast bias was calculated using the following formula, (Adjusted Forecast – Actual Sales) / (Adjusted Forecast + Actual Sales). Forecast bias measured how far above or below the adjusted forecast was compared to actual sales on a scale of zero to one and zero to negative one. A forecast bias of zero meant there was no bias present and that adjusted forecast was equal to actuals sales. The further away from zero the forecast bias was meant more bias was present. Forecast bias above zero meant that the adjusted forecast was greater than actual sales and below zero meant that adjusted forecast was less than actual sales. This metric would be used to identify root causes of poor forecast accuracy. Adjustments to the forecast were made to correct poor forecast performance when bias existed in the same direction for two straight months.

Lastly, forecast value add is a calculated metric to compare the performance between the statistical forecast and the adjusted forecast. However, in some cases those two forecast values were the same. It was calculated using the following formula, ((|sales – adjusted forecast|) / sales) x 100 - ((|sales – system forecast|) / sales) x 100. This metric was also used to identify root causes of poor forecast accuracy. In this case, the metric was used to determine if the statistical forecast is more accurate than the manually adjusted forecast. If the calculation resulted in a positive number, it showed that the system forecast was closer to the actual sales than the adjusted forecast was. Adjustments to the forecast were made to correct poor forecast performance when the system forecast was more accurate than the adjusted forecast for two straight months.

Data Collection Procedures

Data was collected from the company's business intelligence software, DI Diver. This data source stored all of data points that were needed in this study and could be extracted on an ad hoc basis. There were five data points that were needed for the study. The first data point that was collected was the system statistical monthly forecast by product, given a label of Forecast2. This data point showed what the forecasting software predicted the monthly forecast to be before any manual adjustments. The second data point was the adjusted monthly forecast by product, given a label of Forecast1. This data point differs from the first because it can involve manual human adjustment. It is important to note that the adjusted and statistical forecast would use a one month lag. This would mean that the adjusted and statistical forecast for the month of November would be the forecast for the month of November that was published as part of the October forecasting process. The rest of the data points needed for the study were monthly sales by product, monthly order fulfillment rate by product, and month end inventory levels by product. The time frame that was used to collect data from was from December 2017 to February 2019. For each month a table was created, similar to Table 1, to record the raw data points required.

Table 1

Individual Month Data Points

SKU	Sales	Forecast1	Forecast2	Inventory ($)	Fulfillment (%)
204446	0	0	0	0	0
204576	0	0	0	0	0
204107	0	0	0	0	0

A sample of 40 different products was chosen. All the products were make to stock but had a variation of high volume and low volume. They also had a mix of planning parameters such as lead time, safety stock, and minimum run quantity. These planning parameters were not to be adjusted as part of the study. These products were tracked and each month data points for actual sales, order fulfillment rate, adjusted forecast and month end inventory were recorded for the previous month. This allowed for the forecast accuracy and forecast bias calculations to take occur for the time frame of December 2017 – November 2018. The same process took place from December 2018 – February 2019 except that now statistical forecast was also able to be captured. This change now allowed for the forecast value-add metric to be calculated. The calculations for monthly forecast accuracy, forecast bias, and forecast value add were added in additional columns of Table 1 because Table 1 had all the data points needed for the calculations. Table 2 shows the end result of the data collection and calculations that was completed for each month of the study.

Table 2

Individual Month Data Points and Calculations

SKU	Sales	Forecast1	Forecast2	Inventory	Fulfillment	Accuracy	Bias	Value
204446	0	0	0	0	0	0	0	0
204576	0	0	0	0	0	0	0	0
204107	0	0	0	0	0	0	0	0

The mean forecast accuracy, total inventory dollars, and mean order fulfillment for the sample was then calculated from each monthly data set in an Excel spreadsheet to give an overall monthly mean and total of the sample. The mean and total data for these three data points would be what would be used for data analysis.

Forecast bias and forecast value-add would not use mean monthly data. Instead, the product level detail used for the root cause analysis which may trigger forecast corrections to be made in subsequent month was sorted in a table in an Excel spreadsheet similar to Table 3 and Table 4. This data was pulled directly from each individual month data set and sorted in a manner that allowed for easy interpretation at the product SKU level of poor performance and identification of where forecast needed to be adjusted. When two months in a row had poor performance in the same direction, corrections to the next month forecast for that product SKU were made. Note that Table 3, forecast bias, was kept for two months before the implementation of the forecast performance metrics so it could be used to make forecast adjustments to poor performing products right away.

Table 3

Forecast Bias

SKU	Month 1	Month 2	Month 3	Month 4	Month 5
204446	0	0	0	0	0
204576	0	0	0	0	0
204107	0	0	0	0	0

However, Table 4 was only kept for the months after the forecast performance metrics were implemented, December 2018 – February 2019, because the data was not able to be captured from historical data.

Table 4

Forecast Value Add

SKU	Month 1	Month 2	Month 3
204446	0	0	0
204576	0	0	0
204107	0	0	0

It was expected that there would be a significant correlation between forecast accuracy and inventory/customer order fulfillment. It was also expected that as adjustments to the forecast were made, as part of the root cause analysis from forecast bias and forecast value-add, that forecast accuracy would improve when compared to previous months and previous year.

Data Analysis

This study included multiple different data analysis techniques from the sample. The first technique that used was a correlation and regression test of the values in Table 5, which are mean forecast accuracy, total monthly inventory, and mean customer fulfillment rate by month. The purpose of this test was to determine if there was a significant correlation between forecast accuracy, independent variable, and inventory/order fulfillment, dependent variables. The correlation test was not enough to show whether it was significant or not. Therefore, a regression test was used to further analyze whether the correlation was significant. In the regression test forecast accuracy was used as the independent variable and inventory and order fulfillment were used as the dependent variables. Additionally, 95% was used as the confidence level. Therefore, a P-value of .05 was used to determine if there was a significant correlation or not.

Table 5

Mean Forecast Accuracy, Total Inventory Dollar, and Mean Order Fulfillment

Year-Month	Forecast Accuracy	Inventory ($)	Order Fulfillment (%)
2017-10	0	0	0
2017-11	0	0	0
2018-1	0	0	0

The second technique that was used in data analysis was a two tail Z-test using alpha of 0.05. This test was to compare whether forecast accuracy improved after forecast performance metrics were implemented. Unlike the first test, this test would be done at the product level. The after performance metrics were implemented time frame that was used was December 2018-February 2019. For comparison purposes two before time periods were used for before forecast performance metric implementation. The first was December 2017 – February 2018 or what would be labeled last year. The second was September 2018-November 2018 or what would be labeled as last three prior. The mean forecast accuracy for each product in the specific time frame was calculated and recorded in Table 6 to be analyzed with a Z-test.

Table 6

Forecast Accuracy Comparisons

SKU	After	Three Months Prior	Last Year
204446	0	0	0
204576	0	0	0
204107	0	0	0

For each before and after data set, descriptive statistics were calculated so the reported variances could be used in each of the Z-tests. Once the variances were recorded the Z-test was able to be run on both data sets to determine whether there was a significant difference between forecast accuracy after the implementation of forecast performance metrics when compared to both previous year and last three months.

Summary

The development and implementation of new forecast performance metrics in the Contract and ABC divisions were aimed at understanding the impact those metrics had on inventory levels and order fulfillment. Additionally, the metrics were developed to provide a starting point for root cause analysis on poor performance so corrections could be made to improve performance. Overall, if the study showed a significant correlation between the variables in the first test and the second test showed significant difference when comparing forecast accuracy before and after the implementation it would prove the metrics gave the divisions more accurate data to base decisions on and allow them more control over inventory and order fulfillment.

Chapter IV: Results

The study focused on analyzing the effects of the introduced forecast performance metrics on inventory, order fulfillment, and forecast improvement in the Contact and ABC divisions of Company XYZ. While all planning parameters such as lead time, safety stock, and minimum order quantity remained unchanged, the forecast performance metrics were be used to identify root cause of poor forecast performance so it can be corrected. If the study proved the introduction of the metrics improved forecast accuracy, the company would have more accurate data to use when making important business decisions. Additionally, if the study proved that increased forecast accuracy led to decreased inventory and increased order fulfillment, the company would realize the value in a more refined forecasting process. More accurate forecast would provide a stronger foundation for the demand review, supply review, sales and operations planning, and master planning processes.

Introduced Metrics

As part of the study, three new forecasting performance metrics were introduced. The first metric, forecast accuracy, was calculated using the following formula if sales was greater than adjusted forecast, ((1-(|Sales – Adjusted Forecast|) / Sales)) x 100. If sales was less than adjusted forecast then this formula was used instead, ((1-(|Sales – Adjusted Forecast|) / Adjusted Forecast)) x 100. This was done to ensure that if there were large difference between sales and adjusted forecast that the calculated results would not be a negative value. This metric would be the only metric that would be compared to inventory and order fulfillment. This metric was able to be measured throughout the entire data set because it could be calculated using historical data.

The second metric, forecast bias, was calculated using the following formula, (Adjusted Forecast – Actual Sales) / (Adjusted Forecast + Actual Sales). Forecast bias measured how far above or below the adjusted forecast was compared to actual sales on a scale of zero to one and zero to negative one. A forecast bias of zero meant there was no bias present and that adjusted forecast was equal to actuals sales. The further away from zero the forecast bias was meant more bias was present. Forecast bias above zero meant that the adjusted forecast was greater than actual sales and below zero meant that adjusted forecast was less than actual sales. This metric would be used to identify root causes of poor forecast accuracy. Adjustments to the forecast were made to correct poor forecast performance when bias existed in the same direction for two straight months. As with forecast accuracy, this metric was able to be measured throughout the entire data set because it could be calculated using historical data.

Lastly, forecast value add is a calculated metric to compare the performance between the statistical forecast and the adjusted forecast. However, in some cases those two forecast values were the same. It was calculated using the following formula, ((|sales – adjusted forecast|) / sales) x 100 - ((|sales – system forecast|) / sales) x 100. This metric was also used to identify root causes of poor forecast accuracy. In this case, the metric was used to determine if the statistical forecast is more accurate than the manually adjusted forecast. If the calculation resulted in a positive number, it showed that the statistical forecast was closer to the actual sales than the adjusted forecast was. Adjustments to the forecast were made to correct poor forecast performance when the statistical forecast was more accurate than the adjusted forecast for two straight months. This metric was only able to be calculated after the implementation in December 2018 because historical data did not capture the system forecast needed for the calculation.

Data Collection Procedures

Data was collected from the company's business intelligence software, DI Diver. This data source stored all of data points that were needed in this study and could be extracted on an ad hoc basis. There were five data points that were needed for the study. The first data point that was collected was the system statistical monthly forecast by product, given the label of Forecast2. This data point showed what the forecasting software predicted the monthly forecast to be before any manual adjustments. The second data point was the adjusted monthly forecast by product, given the label of Forecast1. This data point differs from the first because it can involve manual human adjustment. It is important to note that the adjusted and statistical forecast would use a one month lag. This meant that the adjusted and statistical forecast for the month of November would be the forecast for the month of November that was published as part of the October forecasting process. The rest of the data points needed for the study were monthly sales by product, monthly order fulfillment rate by product, and month end inventory levels by product. The time frame that was used to collect data from was from December 2017 to February 2019. For each month a table was created, shown in Table 7, to record the raw data points required. Table 7 shows only six of the 40 product SKUs. Data for all 40 product SKUs can be found in Appendix A.

Table 7

Individual Month Data Points

SKU	Sales	Forecast1	Forecast2	Inventory	Fulfillment
201202	480	600	500	10,938	85%
202070	0	160	160	7,963	100%
202182	4,320	4,320	4,530	27,913	100%
202405	13,696	11,040	12,150	71,603	85%
202711	1,728	4,536	4,536	39,813	100%
202727	5,650	12,050	12,050	54,155	100%

A sample of 40 different products was chosen. All the products were make to stock but had a variation of high volume and low volume. They also had a mix of planning parameters such as lead time, safety stock, and minimum run quantity. These planning parameters were not to be adjusted as part of the study. These products were tracked and each month data points for actual sales, order fulfillment rate, adjusted forecast and month end inventory were recorded for the previous month. This allowed for the forecast accuracy and forecast bias calculations to take occur for the time frame of December 2017 – November 2018. The same process took place from December 2018 – February 2019 except that statistical forecast was also able to be captured. This change allowed for the forecast value-add metric to be calculated. The calculations for monthly forecast accuracy, forecast bias, and forecast value add were added in additional columns of Table 7. Table 8 shows the end result of the data collection and calculations that was completed for each month of the study. Table 8 shows only six of the 40 product SKUs. Data for all 40 product SKUs can be found in Appendix B.

Table 8

Individual Month Data Points and Calculations

SKU	Sales	Forecast1	Forecast2	Inventory	Fulfillment	Accuracy	Bias	Value
201202	480	600	500	10,938	85%	80%	0.1	20.8
202070	0	160	160	7,963	100%	0%	1.0	0.0
202182	4,320	4,320	4,530	27,913	100%	100%	0	-4.9
202405	13,696	11,040	12,150	71,603	85%	81%	-0.1	8.1
202711	1,728	4,536	4,536	39,813	100%	38%	0.4	0.0
202727	5,650	12,050	12,050	54,155	100%	47%	0.4	0.0

The mean forecast accuracy, total inventory dollars, and mean order fulfillment for the sample was then calculated from each monthly data set in to give an overall monthly mean and total of the sample. The mean and total data for these three data points would be what would be used for data analysis.

Forecast bias and forecast value-add did not use mean monthly data. Instead, the product level detail used for the root cause analysis which may trigger forecast corrections to be made in subsequent month was sorted in Table 9 and Table 10. This data was pulled directly from each individual month data set and sorted in a manner that allowed for easy interpretation at the product SKU level of poor performance and identification of where forecast needed to be adjusted. When two months in a row had poor performance in the same direction, corrections to the next month forecast for that product SKU were made. Table 9 shows only six of the 40 product SKUs. Data for all 40 product SKUs can be found in Appendix C.

Table 9

Forecast Bias

SKU	2018-10	2018-11	2018-12	2019-01	2019-02
201202	-0.85	0.39	0.15	0.04	0.33
202070	-0.06	-0.38	-0.88	-0.50	1.00
202182	-0.17	0.05	-0.06	-0.04	0.33
202405	0.00	0.33	0.43	-1.00	0.32
202711	-0.04	-0.52	1.00	-0.74	0.53
202727	-0.35	-0.57	0.69	-0.50	0.39

Note that Table 9 was kept for all months in the study, but Table 10 was only kept for the months after the forecast performance metrics were implemented, December 2018 – February 2019. Table 10 shows only six of the 40 product SKUs. Data for all 40 product SKUs can be found in Appendix D.

Table 10

Forecast Value Add

SKU	2018-12	2019-01	2019-02
201202	-5.0	0.0	20.8
202070	-0.88	-0.50	1.00
202182	-0.9	-5.3	-4.9
202405	-15.6	0.0	8.1
202711	0.0	-4.3	0.0
202727	0.0	0.0	0.0

It was expected that there would be a significant correlation between forecast accuracy and inventory/customer order fulfillment. It was also expected that as adjustments to the forecast were made, as part of the root cause analysis from forecast bias and forecast value-add, that forecast accuracy would improve when compared to previous months and previous year.

Data Analysis

This study included multiple different data analysis techniques from the sample. The first technique that used was a correlation and regression test of the values in Table 11, which are mean forecast accuracy, total monthly inventory, and mean customer fulfillment rate by month.

The purpose of this test was to determine if there was a significant correlation between forecast accuracy, independent variable, and inventory/order fulfillment, dependent variables. The correlation test was not enough to show whether it was significant or not. Therefore, a regression test was used to further analyze whether the correlation was significant. In the regression test forecast accuracy was used as the independent variable and inventory and order fulfillment were used as the dependent variables. Additionally, 95% was used as the confidence level. Therefore, a P-value of .05 was used to determine if there was a significant correlation or not.

Table 11

Mean Forecast Accuracy, Total Inventory Dollar, and Mean Order Fulfillment

Year - Month	Forecast Accuracy	Inventory ($)	Fulfillment (%)
2017-12	53.55%	1,504,585	85.0%
2018-1	54.26%	1,684,910	87.7%
2018-2	51.27%	1,711,147	82.2%
2018-3	75.57%	1,803,601	94.2%
2018-4	66.08%	1,840,531	93.0%
2018-5	60.16%	1,615,215	94.1%
2018-6	59.15%	1,471,090	93.3%
2018-7	62.28%	1,461,945	88.5%
2018-8	54.28%	1,561,690	86.7%
2018-9	55.00%	1,502,022	81.8%
2018-10	59.89%	1,763,620	92.9%
2018-11	59.12%	1,585,155	94.9%
2018-12	57.27%	1,813,255	93.2%
2019-1	61.65%	1,688,612	93.7%
2019-2	66.99%	1,668,978	94.8%

The second technique that was used in data analysis was a two tail z-Test using alpha of 0.05. This test was to compare whether forecast accuracy improved after forecast performance metrics were implemented. Unlike the first test, this test would be done at the product level. The after performance metrics were implemented time frame that was used was December 2018-February 2019. For comparison purposes two before time periods were used for before forecast performance metric implementation. The first was December 2017 – February 2018, or what would be labeled last year. The second, was September 2018-November 2018, or what would be labeled as three months prior. The mean forecast accuracy for each product in the specific time frame was calculated and recorded in Table 12 to be analyzed with a z-Test: two sample for means. Table 12 shows only six of the 40 product SKUs. Data for all 40 product SKUs can be found in Appendix E.

Table 12

Forecast Accuracy Comparisons

SKU	After	Three Months Prior	Last Year
201202	81.6%	26.9%	47.8%
202070	13.2%	75.4%	3.0%
202182	93.6%	79.0%	85.6%
202405	40.1%	72.3%	48.1%
202711	17.8%	59.8%	45.1%
202727	32.8%	46.1%	69.1%

Forecast accuracy impacts. Significant negative correlation between forecast accuracy and inventory dollar and significant positive correlation between forecast accuracy and order fulfillment is critical for improving operational efficiency when decision are made based on forecast.

Analysis. An increase in forecast accuracy would result in decreased inventory dollars and increased order fulfillment percent. Therefore, an analysis of correlation and regression was ran. The data used in the analysis is shown in Appendix D. This analysis was run in Excel by utilizing the data analysis tool pack. A correlation analysis was run to compare both forecast accuracy and inventory dollars and forecast accuracy and order fulfillment percent. Once the correlation analysis was complete, a regression analysis was ran to also compare both forecast accuracy and inventory dollars and forecast accuracy and order fulfillment percent. The regression test would show if the correlation was statistically significant. Both regression analyses were completed using an alpha value of 0.05.

Results. The correlation test showed a positive correlation between forecast accuracy and inventory dollars with a value of 0.3989. The correlation test also showed a positive correlation between forecast accuracy and order fulfillment percent with a value of 0.6683. The correlation test revealed that as forecast accuracy increased so did inventory dollars and order fulfillment percent. Since, this data was not enough to determine if the correlation was statistically significant a regression analysis followed using an alpha value of 0.05. The results of the regression analysis between forecast accuracy and inventory dollars resulted in a p-value of 0.1408. That p-value was greater than the alpha value. This means that the positive correlation between forecast accuracy and inventory dollars was not statistically significant. However, the results of the regression analysis between forecast accuracy and order fulfillment percent resulted in a p-value of 0.0051. In this analysis, the p-value was less than the alpha value. Therefore, the correlation between forecast accuracy and order fulfillment rate was statistically significant.

Forecast accuracy improvement. A significant increase in forecast accuracy after the implementation of forecast performance metrics would prove that the forecast performance metrics were successful in increasing overall forecast accuracy. Increased forecast accuracy would give the organization a more accurate foundation to base planning initiatives on.

Analysis. To test forecast accuracy improvement after the implementation of forecast performance metrics a z-Test: two sample for means was run. The data used in the analysis is shown in Appendix E. This analysis was run in Excel by utilizing the data analysis tool pack. Before a z-Test could be run, descriptive statistics for each data set, after, three months prior, and last year, was run. The descriptive statistics would give values for each data set for mean, standard error, median, standard deviation, sample variance, kurtosis, range, minimum, maximum, sum, and count. The sample variance value from this set was the input needed from each data set which allowed for the z-Test to take place. A z-Test was run to compare last year to after and to compare three months prior to after. Each analysis used an alpha value of 0.05. The results of this test was used to determine if there was a significant change in forecast accuracy after the implementation of new forecast performance metrics and adjustments to the forecast that came from the determinations of poor performance.

Results. The descriptive statistic data point needed for the z-Test was sample variance. The last year data set had a sample variance of 0.08806. The three months prior data set had a sample variance of 0.05433 and the after data set had a sample variance of 0.03733. The result of the first z-Test analysis between the three months prior and after data set, using the reported sample variances from above, resulted in a p-value two tail of 0.29373. In this analysis, the p-value was greater than the alpha value of 0.05. Therefore, there is not a significant difference in forecast accuracy between three months prior and after the implementation of forecast performance metrics. The result of the second z-Test analysis between the last year and after data set, using the reported sample variances from above, resulted in a p-value two tail of 0.02999. In this analysis, the p-value was less than the alpha value of 0.05. Therefore, there is a significant difference in forecast accuracy between last year and after the implementation of forecast performance metrics.

Summary

As the problem statement stated, Company XYZ did not have forecast performance metrics in place and was using data that has not been proven to be accurate. The reason for implementing forecast performance metrics was not only to start measuring performance but also to determine if forecast performance had an impact on inventory dollars and order fulfillment percent. The results of the study show that a positive correlation existed between forecast accuracy and inventory and between forecast accuracy and order fulfillment. However, the only correlation that was statistically significant was the correlation between forecast accuracy and order fulfillment. Therefore, as forecast accuracy increased so did the company's ability to successfully fulfill customer orders.

Additionally, the forecast performance metrics were implemented as a root cause and trend analysis tool to determine where poor performance was taking place so it could be corrected, thus increasing forecast performance. The results of the study show that there was not a significant difference between the forecast accuracy three months prior to implementation and after implementation. However, there was a significant difference between last year's forecast accuracy and the forecast accuracy after implementation of the performance metrics.

Chapter V: Discussion, Conclusion, and Recommendation

This study was conducted at a worldwide plastics applications company to understand how the forecast accuracy could be improved and the impact it had on downstream functions, such as order fulfillment and inventory. The purpose of the study was to develop and implement forecast performance metrics and measure the impact it had on reducing inventory levels and improving order fulfillment. Additionally, the forecast performance metrics were used to identify root cause of poor forecast performance so it could be corrected and measured to verify those corrections improved forecast performance.

The first chapter focused on the background information of the Company XYZ and outlined the problems that the Contract and ABC divisions were experiencing as part of their demand and supply planning process. The more accurate the input, forecast, that flowed into the demand and supply planning process, the more accurate the data would be for the planning personnel to base critical decisions on. Additionally, a gap existed in the organization because there were not any metrics in place to measure forecast performance. Therefore, the organization was unsure how accurate the forecast was and how to improve it.

Literature related to the study was reviewed in the second chapter. The related literature included an overview of supply chain management and a detailed view of the various functions within supply chain management. The functions reviewed included forecasting and demand planning, sales and operations planning, master production scheduling, and production scheduling. Within each function, literature was reviewed to understand what other have found to be successful strategies and techniques. Additionally, the literature review provided insight into the importance of each function and how they interacted with one another and the dependence on forecast. Lastly, the related literature provided examples of what others have found to be valuable forecast performance metrics and how they were calculated.

Chapter III discussed the methodology of the study. First, the data needed for the introduced metrics was discussed. Next, the calculations for the introduced metrics were discussed and the use of each metrics was covered. The sample for the study was selected from 40 random product SKUs that were all make to stock. The product SKUs that were part of the study were not allowed any changes to them in terms of lead time, safety stock, and minimum run quantity. Data was pulled on a monthly basis and necessary calculations were made to complete the forecast performance and root cause metrics. Data was sorted in various tables to allow for data analysis. The use of a correlation test, regression test, and a z-Test were discussed to complete data analysis.

Chapter IV presented the results of the implementation of the forecast performance metrics and the impact they had on order fulfillment, inventory, and forecast accuracy. There was a positive correlation between forecast accuracy and inventory dollars but the regression test showed that it was not statistically significant. However, the positive correlation between forecast accuracy and order fulfillment was proven statistically significant by the regression test. A z-Test showed that there was not a significant difference between forecast accuracy after the implementation of the forecast performance metrics when compared to three months prior to implementation. However, a z-Test did show that there was a significant difference between forecast accuracy after the implementation when compared to the same time period the prior year.

The final chapter will discuss the benefits the study offers to the organization and what can be done with the results. The limitations of the study will be discussed further.

Additionally, the conclusions and recommendations that were drawn from the study will also be discussed.

Limitations

As stated in previous chapters, there were known limitations prior to when the study began. One of those limitations was the forecasting and demand planning tool. This limitation proved to be a difficulty when it came to data extraction. The data needed for the study was not easily accessible from the tool and calculations had to be done outside of the tool. More modern forecasting and demand planning tools have forecast performance metrics built right into them.

The second known limitation prior to the study regarded how inventory data was gathered. The study used reported month end inventory, which only showed a single snap shot in time and may not have reflected the overall performance for the month. In fact, while gathering month end inventory for the study a more in depth look was completed. This showed that for a single product SKU a large production run was completed right at the end of the month and did not ship prior to month end. The rest of that month the inventory level was significantly lower but the way in which inventory was reported did not reflect that.

The last limitation did not become evident until during and after the study was complete. This limitation was mostly due to the short time frame after the forecast performance metrics were introduced. Since the time frame was short the root cause metrics, forecast bias and forecast value add, were acted on to make changes to the forecast after only two months of poor performance in the same direction. If more time was available the study would have been designed to only make changes after three months of poor performance in the same direction.

Conclusions

As part of the study, a statistically significant correlation was found to exist between forecast accuracy and order fulfillment. While forecast accuracy and inventory dollars did have a positive correlation, it was not a statistically significant correlation. The fact that there was a positive correlation and not a negative correlation was a surprise. However, it would be expected that when safety stock and lead times are adjusted that the positive correlation would turn into a negative correlation.

Based on these results, these two divisions can expect that when forecast accuracy is high that inventory will decrease and order fulfillment will be high. On the other hand, it can also be expected that when forecast accuracy is low, inventory will likely rise and order fulfillment will likely decrease. This proves the value that a high forecast accuracy to the business.

Also as part of the study, a statically significant difference between forecast accuracy in the prior year and after the implementation of the forecast performance metrics existed in the study. While there was not a statically significant different between forecast accuracy in the prior three months and after the implementation of the forecast performance metrics, the study still showed that the metrics had an impact that was not based solely on luck or other variables that existed in the study.

Based on these results, these two divisions can expect that the continued use of the forecast performance and root cause metrics will drive increased forecast accuracy. Additionally, things that are not measured will not be improved. Since the study proved forecast accuracy increases inventory and order fulfillment performance, having a metric in place proves valuable.

Recommendations

The study showed that the implemented metrics had a significant impact to the two divisions. Therefore, it should be expanded upon. The Contract and ABC divisions have around 2,000 product SKUs that were currently being forecasted. The study only used a sample of 40 product SKUs, which is only two percent of the division's product SKUs. To continue to improve forecast accuracy and drive order fulfillment rates up and inventory down, the organization should expand the forecast performance metrics that were introduced as part of the study to the rest of the product SKUs in the two divisions.

The data collection procedures and calculations have been documented and standardized to make it easy to implement to a larger data set. While the data set will be larger, it will still be manageable because only poor performing product SKUs will be reviewed for corrections. Work should also be done to expand the techniques and metrics of the study to the third division of the company, Proprietary, that is kept mostly separate from the two included in the study as it does not have shared resources. This division represents an additional 1,200 product SKUs that are currently being forecasted.

The next change that should occur is to use the forecast accuracy metrics to make small step changes to the planning parameters that were not changed as part of the study. The planning parameters were not changed during the study to ensure that the only controllable change to the environment was just the implementation and use of the forecast performance and root cause metrics. When individual product SKUs have increased forecast performance, the organization will be able to make reductions in safety stock and possibly lead time. If the organization can accurately guess what they will sell next month and subsequent months after they will not need as much safety stock or lead time to cover unpredicted order volume. This would be a main driver towards decreased inventory and increased cash flow for the organization.

Lastly, a topic that has not been discussed thus far is the importance to discuss the results of the study with those who can have a significant input into what drove the results. Those individuals could include sales and marketing representatives who have close contact with the customer and have knowledge of promotions that could impact sales. The largest misses in the forecast performance metrics should be shared with those individuals on a monthly basis so a true root cause can be discussed and agreed upon corrections can be determined.

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Appendix A: Individual Month Data Points

SKU	Sales	Forecast1	Forecast2	Inventory	Fulfillment
201202	480	600	500	10,938	85%
202070	0	160	160	7,963	100%
202182	4,320	4,320	4,530	27,913	100%
202405	13,696	11,040	12,150	71,603	85%
202711	1,728	4,536	4,536	39,813	100%
202727	5,650	12,050	12,050	54,155	100%
203403	16,832	18,997	18,100	74,263	100%
203683	15,445	21,175	24,720	37,310	95%
203813	9,600	8,640	9,000	10,465	90%
203863	656,100	519,300	510,300	312,885	95%
203882	18,320	33,302	33,302	33,600	99%
204076	7,500	10,725	12,200	17,255	100%
204106	7,168	5,248	4,780	15,015	100%
204107	9,120	8,791	8,791	25,988	90%
204250	0	5	5	849	100%
204314	9,600	5,400	3,850	16,713	100%
204350	2,592	3,888	2,150	14,613	100%
204388	9,600	9,600	13,350	55,388	100%
204411	3,072	4,608	3,758	12,023	100%
204446	74,880	54,144	54,144	165,148	85%
204447	4,700	11,220	15,960	41,913	100%
204457	12,840	10,920	11,660	48,055	100%
204459	5,280	5,340	5,000	23,153	100%
204462	3,072	702	702	11,620	90%
204499	1,329	1,090	1,270	10,308	100%
204523	11,136	11,520	12,150	74,778	100%
204576	6,480	3,700	2,570	7,490	90%
400041	4,900	4,900	4,900	6,738	100%
400156	20,000	15,000	13,300	84,452	90%
400309	9,000	14,700	14,700	44,910	90%
400478	3,930	6,615	4,870	40,602	100%
400507	0	0	125	1,531	100%
400515	800	1,440	1,050	18,944	100%
400553	2,400	3,040	3,040	40,215	100%
400558	5,000	0	0	11,953	0%
400572	2,480	2,080	1,875	13,055	100%
400584	2,460	4,560	3,780	48,090	100%
400595	0	4,800	4,800	56,945	100%
400600	420	480	480	11,060	100%
400602	420	360	360	11,690	100%
400613	9,180	10,420	11,630	57,585	100%

Appendix B: Individual Month Data Points and Calculations

SKU	Sales	Forecast1	Forecast2	Inventory	Fulfillment	Accuracy	Bias	Value
201202	480	600	500	10,938	85%	80%	0.1	20.8
202070	0	160	160	7,963	100%	0%	1.0	0.0
202182	4,320	4,320	4,530	27,913	100%	100%	0	-4.9
202405	13,696	11,040	12,150	71,603	85%	81%	-0.1	8.1
202711	1,728	4,536	4,536	39,813	100%	38%	0.4	0.0
202727	5,650	12,050	12,050	54,155	100%	47%	0.4	0.0
203403	16,832	18,997	18,100	74,263	100%	89%	0.1	5.3
203683	15,445	21,175	24,720	37,310	95%	73%	0.2	-23.0
203813	9,600	8,640	9,000	10,465	90%	90%	-0.1	3.8
203863	656,100	519,300	510,300	312,885	95%	79%	-0.1	-1.4
203882	18,320	33,302	33,302	33,600	99%	55%	0.3	0.0
204076	7,500	10,725	12,200	17,255	100%	70%	0.2	-19.7
204106	7,168	5,248	4,780	15,015	100%	73%	-0.2	-6.5
204107	9,120	8,791	8,791	25,988	90%	96%	0.0	0.0
204250	0	5	5	849	100%	0%	1.0	0.0
204314	9,600	5,400	3,850	16,713	100%	56%	-0.3	-16.1
204350	2,592	3,888	2,150	14,613	100%	67%	0.2	32.9
204388	9,600	9,600	13,350	55,388	100%	100%	0	-39.1
204411	3,072	4,608	3,758	12,023	100%	67%	0.2	27.7
204446	74,880	54,144	54,144	165,148	85%	72%	-0.2	0.0
204447	4,700	11,220	15,960	41,913	100%	42%	0.4	-100.9
204457	12,840	10,920	11,660	48,055	100%	85%	-0.1	5.8
204459	5,280	5,340	5,000	23,153	100%	99%	0.0	-4.2
204462	3,072	702	702	11,620	90%	23%	-0.6	0.0
204499	1,329	1,090	1,270	10,308	100%	82%	-0.1	13.5
204523	11,136	11,520	12,150	74,778	100%	97%	0.0	-5.7
204576	6,480	3,700	2,570	7,490	90%	57%	-0.3	-17.4
400041	4,900	4,900	4,900	6,738	100%	100%	0	0.0
400156	20,000	15,000	13,300	84,452	90%	75%	-0.1	-8.5
400309	9,000	14,700	14,700	44,910	90%	61%	0.2	0.0
400478	3,930	6,615	4,870	40,602	100%	59%	0.3	44.4
400507	0	0	125	1,531	100%	100%	0	-2.5
400515	800	1,440	1,050	18,944	100%	56%	0.3	48.8
400553	2,400	3,040	3,040	40,215	100%	79%	0.1	0.0
400558	5,000	0	0	11,953	0%	0%	-1.0	0.0
400572	2,480	2,080	1,875	13,055	100%	84%	-0.1	-8.3
400584	2,460	4,560	3,780	48,090	100%	54%	0.3	31.7
400595	0	4,800	4,800	56,945	100%	0%	1.0	0.0
400600	420	480	480	11,060	100%	88%	0.1	0.0
400602	420	360	360	11,690	100%	86%	-0.1	0.0
400613	9,180	10,420	11,630	57,585	100%	88%	0.1	-13.2

Appendix C: Forecast Bias

SKU	2018-10	2018-11	2018-12	2019-01	2019-02
201202	-0.85	0.39	0.15	0.04	0.33
202070	-0.06	-0.38	-0.88	-0.50	1.00
202182	-0.17	0.05	-0.06	-0.04	0.33
202405	0.00	0.33	0.43	-1.00	0.32
202711	-0.04	-0.52	1.00	-0.74	0.53
202727	-0.35	-0.57	0.69	-0.50	0.39
203403	-0.13	0.04	-0.14	0.25	0.36
203683	0.11	0.04	0.20	0.16	0.31
203813	0.11	-0.18	-0.19	0.00	0.06
203863	0.14	0.13	0.01	-1.00	0.49
203882	0.51	-0.36	-0.21	0.48	0.50
204076	0.04	-0.10	-0.14	0.00	0.42
204106	-0.30	0.01	-0.45	0.15	0.03
204107	0.01	-0.42	0.15	-0.23	0.16
204250	-0.95	-0.33	0.40	0.00	1.00
204314	-0.03	-0.37	0.24	-0.03	-0.28
204350	-0.21	0.00	0.12	0.18	0.50
204388	0.11	-0.16	-0.25	0.13	0.33
204411	-0.50	0.00	-0.33	0.00	0.50
204446	-0.35	-0.63	-0.33	-0.03	0.04
204447	-0.82	-0.68	-0.17	-0.87	0.61
204457	0.15	-0.06	0.08	0.09	0.11
204459	-0.02	-0.04	-0.02	-0.39	0.40
204462	1.00	1.00	-0.30	-0.98	-0.63
204499	0.00	0.46	-0.24	0.21	0.19
204523	0.09	-0.30	-0.31	0.04	0.28
204576	-0.33	-0.35	-0.30	-0.21	-0.27
400041	-0.13	0.13	0.11	0.14	0.08
400156	0.02	-0.08	0.22	0.49	0.00
400309	-0.71	-0.32	0.00	-0.41	0.36
400478	0.12	0.05	0.07	0.11	0.36
400507	0.36	-0.22	1.00	-0.43	0.00
400515	-0.25	-0.20	-0.14	-0.20	0.38
400553	-0.12	-0.78	-0.38	-0.09	0.31
400558	1.00	0.00	0.25	0.00	-1.00
400572	-1.00	-0.28	0.02	-0.09	0.02
400584	-0.01	0.10	0.26	0.17	0.39
400600	0.25	0.25	0.25	0.29	0.33
400602	-0.23	0.25	0.08	0.11	0.20
400613	-0.40	1.00	-0.24	0.42	0.06

Appendix D: Forecast Value Add

SKU	2018-12	2019-01	2019-02
201202	-5.0	0.0	20.8
202070	-0.88	-0.50	1.00
202182	-0.9	-5.3	-4.9
202405	-15.6	0.0	8.1
202711	0.0	-4.3	0.0
202727	0.0	0.0	0.0
203403	9.5	11.1	5.3
203683	42.5	15.3	-23.0
203813	6.9	0.0	3.8
203863	-4.3	0.0	-1.4
203882	0.0	0.0	0.0
204076	-3.3	0.0	-19.7
204106	-7.3	-19.8	-6.5
204107	0.0	0.0	0.0
204250	0.0	-2.2	0.0
204314	0.0	3.7	-16.1
204350	22.6	29.9	32.9
204388	-5.0	13.5	-39.1
204411	-6.9	-15.4	27.7
204446	-45.2	0.0	0.0
204447	-5.9	-7.1	-100.9
204457	13.7	-9.3	5.8
204459	3.5	14.4	-4.2
204462	0.0	0.0	0.0
204499	14.5	-18.8	13.5
204523	21.9	-3.9	-5.7
204576	0.0	-23.4	-17.4
400041	0.0	0.0	0.0
400156	-21.0	-30.5	-8.5
400309	0.0	0.0	0.0
400478	4.3	10.0	44.4
400507	2.5	-10.4	-2.5
400515	3.1	13.5	48.8
400553	0.0	0.0	0.0
400558	0.0	0.0	0.0
400572	0.0	-83.3	-8.3
400584	-7.1	33.6	31.7
400600	0.0	0.0	0.0
400602	5.6	20.8	0.0
400613	37.6	-53.4	-13.2

Appendix E: Forecast Accuracy Comparisons

SKU	After	Three Months Prior	Last Year
201202	81.6%	26.9%	47.8%
202070	13.2%	75.4%	3.0%
202182	93.6%	79.0%	85.6%
202405	40.1%	72.3%	48.1%
202711	17.8%	59.8%	45.1%
202727	32.8%	46.1%	69.1%
203403	74.5%	80.3%	66.2%
203683	70.7%	89.8%	8.7%
203813	85.7%	79.2%	79.0%
203863	59.1%	83.3%	55.1%
203882	52.0%	34.7%	53.6%
204076	81.3%	79.4%	79.6%
204106	61.6%	68.2%	84.0%
204107	77.8%	55.9%	66.1%
204250	47.0%	17.6%	42.6%
204314	70.0%	46.9%	60.4%
204350	71.8%	82.9%	2.0%
204388	79.1%	81.3%	37.2%
204411	72.2%	44.4%	83.3%
204446	72.2%	41.4%	86.0%
204447	39.8%	20.8%	0.0%
204457	84.5%	71.6%	0.0%
204459	79.5%	85.3%	66.5%
204462	26.0%	0.0%	33.3%
204499	69.5%	79.1%	45.2%
204523	80.9%	72.5%	33.3%
204576	58.9%	48.4%	0.0%
400041	85.0%	76.9%	81.7%
400156	57.8%	82.5%	78.5%
400309	67.8%	22.8%	81.8%
400478	75.7%	81.2%	75.5%
400507	46.7%	36.8%	16.5%
400515	65.7%	73.0%	69.8%
400553	69.3%	54.1%	40.1%
400558	53.3%	66.7%	30.0%
400572	87.7%	52.1%	89.6%
400584	60.9%	80.6%	91.3%
400600	67.7%	56.7%	13.3%
400602	83.8%	53.6%	95.2%
400613	63.4%	17.6%	47.9%