CBA Beverage Manufacturer: Supply Chain Responsiveness Metrics

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ABSTRACT

This research delves into the strategies employed by a company, a leading entity in the beverage sector, to enhance the responsiveness of its supply chain to fluctuating market demands. By understanding the company's usage of key performance indicators, such as lead times across various stages of its supply chain, the study evaluates the company’s capacity to adapt to market shifts and operational changes. Additionally, the research explores the application of random forest and ridge regression to predict delivery delays, identifying the feature importance that contributes to such inefficiencies. The findings gave light on the company's adeptness at meeting customer demands and pinpointed the principal elements that create supply chain responsiveness. Identified the departments in their internal supply chain contributing the most to the company’s irresponsiveness and the main features driving late deliveries. This case study enriches the discussion on supply chain responsiveness, strategies for businesses aiming to succeed in dynamic market conditions.

Capstone Advisor: Inma Borrella

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1. INTRODUCTION

1.1 Motivation

"Getting the right product, at the right price, at the right time to the consumer is not only the linchpin to competitive success but also the key to survival" (Chase et al., 2000, p. 299). As this comment suggests, the key to having competitive success in a company is to have supply chain responsiveness. Supply chain responsiveness can be defined as an organization's ability to adapt quickly and effectively to changes in customer demand, market conditions, and other external factors. It encompasses the speed and flexibility with which an organization can adjust its supply chain processes to meet fluctuating demands and seize new opportunities. As the competitive environment changes to a more global, customer-driven, and data-oriented environment, customers demand higher quality, faster response, and greater reliability of products and services. The main success factor is to focus on speed of response, lead time, and flexibility to create a competitive advantage for the firm in the global marketplace.

Our partner, CBA Beverage Manufacturer, possesses a significant competitive edge due to its high-speed manufacturing lines, which not only enable rapid responses to customer demand but also allow the business to operate with minimal inventory. Their ability to efficiently run their operations with minimal inventory is a testament to their streamlined supply chain and manufacturing processes. In today's global and technologically driven competitive environment, being responsive and agile is paramount. Therefore, the company is keen to assess the responsiveness of its supply chain by measuring the time it takes from the moment an order is placed to the moment it is delivered. Currently, however, the company lacks a means to measure the responsiveness of its supply chain and aims to establish suitable metrics for evaluating this.

1.2 Problem Statement & Research Questions

In this project, we have defined supply chain responsiveness as the response time, which is the duration from when an order is received from the customer to when it is delivered to the customer. This metric is important as it directly impacts customer satisfaction, and it is essential for the company to optimize this and maintain a competitive edge in the global marketplace. The primary success factors include focusing on reducing lead times, enhancing flexibility, and accelerating response speeds.

The CBA Beverage Manufacturer currently lacks a means of evaluating the end-to-end responsiveness of its supply chain. They are focused on understanding several critical factors: how quickly they can secure delivery appointments, the variability of their scheduling processes, and which metrics are most effective for assessing their response times to customers. The company needs to determine the current state of its metrics and identify areas for improvement.

During our visit to the company, we interviewed various teams involved in the order-to-delivery cycle, including those in customer management, procurement, planning, and logistics. We found that each team has its own method for measuring performance and response times, tailored to their specific functions. This interdependence among the teams provided insights into their collective workflow. Such interconnectedness aligns with the concept of system dynamics, suggesting that the company's overall responsiveness is influenced not just by individual teams, but by their combined performance.

For instance, the load planning team calculates responsiveness by measuring the time elapsed between order pickup and shipment. This metric is dependent on the production team's speed in preparing orders for dispatch. Understanding this entire process is vital for accurately assessing the company's overall responsiveness.

In contrast, the production planning team faces challenges in measuring their response time due to a lack of suitable tools, relying instead on fill rate as their key performance indicator (KPI). Additionally, the company's use of an ERP system, named Logility, for production planning, which is operating outside of their central ERP system, complicates the tracking of time for each process step. This disparity in metrics across teams highlights the complexity of accurately gauging the company's responsiveness.

Despite the complexity of defining responsiveness in different departments, the objective is to help the company's leadership understand their status. Our interview with the VP of Supply Chain Solutions indicated that the key reason to study this concept is to adapt to ongoing changes, effectively address challenges, and contribute value across various functions and workflows in an ever-changing business environment.

This capstone project will address the research questions listed below:

- How can supply chain processes be systematically mapped to identify critical touchpoints and potential bottlenecks affecting responsiveness at the CBA Beverage Manufacturer?
- How can we quantify and calculate response time through each process step in the internal supply chain?
- How can we leverage machine learning tools to provide a predictive outcome of the features that contribute the most to late orders?
- What metrics should be used to evaluate and monitor end-to-end supply chain responsiveness?

2. STATE OF THE PRACTICE

In this section, we delve into important factors of supply chain management, exploring topics such as Supply Chain Responsiveness, Supply Chain Processes under Order-to-Delivery (OTD) Flows, Production Planning, Load Planning, and Delivery Appointment Scheduling. These areas were researched as they form the backbone of efficient operations within any supply chain framework. Understanding Supply Chain

Responsiveness Metrics is vital for measuring performance and adopting strategies to meet market demands. Moreover, methodologies like the Balanced Scorecard, SCOR Model, and Value Stream Mapping provides invaluable insights into optimizing processes, enhancing efficiency, and achieving organizational objectives.

2.1 Supply Chain Responsiveness

The term "supply chain responsiveness" carries diverse meanings, contingent on the specific focus area. Whether in the context of time-based competition, performance metrics, or manufacturing, each domain possesses distinct capabilities for measuring response time. Supply chain responsiveness, broadly defined, reflects a supply chain's capacity to react, interpret, and adapt to changes in market signals. As highlighted by Gomez (2005), a good supply chain exhibits three key qualities. Firstly, it quickly reacts to fluctuations in supply or demand. Secondly, it demonstrates adaptability over time in response to evolving market strategies. Thirdly, it effectively aligned interests within the company network, optimizing the supply chain's performance to maximize overall outcomes.

In the literature on performance metrics, an understanding has emerged regarding the evaluation and measurement of responsiveness, revealing variations based on the specific priorities of individual managers. The assessment of responsiveness is derived from four primary components: awareness, stimuli, capabilities, and goals. These components form the basis for a set of performance tools, designed to assist managers in identifying the necessary actions for ensuring the accurate and effective completion of their tasks. This paper focuses on the development of responsiveness metrics, as what can be measured can be managed.

2.2 Supply Chain Processes under Order-to-Delivery (OTD) Flows

2.2.1 Production Planning

In this project, our focus is on the complete lifecycle of an order, from the initial customer request to delivery. This process commences with numerous crucial steps, commencing with the establishment of a tentative purchase order and a preliminary promise date, and concluding with the successful delivery of the order followed by payment from the customer.

Our scope in this initial stage is specifically tailored to the operations that are within the control of the company's operational capabilities. This means that our study will primarily concentrate on the internal supply chain from the order-to-delivery process. This process is critical, as once an order is confirmed and passed to the production team, the company is responsible for the overall timing. A shorter lead time not only improves customer experience but also allows other teams to prepare shipments earlier with sufficient inventory.

Therefore, our objective is to delve into a more accurate estimation of lead time in production planning. We aim to identify areas for improvement through a dual approach: quantitative analysis based on analytics and qualitative analysis drawn from interview feedback. By doing so, we hope to pinpoint specific aspects of the production process that can be optimized for better efficiency and customer satisfaction.

To better understand and improve our methods, we explored agile methodologies, Industry 4.0, and Quick Response Manufacturing (QRM). These approaches are key to helping companies like this CBA Beverage Manufacturer quickly adjust to new demands and custom orders. The company's emphasis on quick manufacturing and ongoing investment in plant automation shows its dedication to these modern strategies. A notable contribution in this field is from Ericksen et al. (2007), who introduced a scientific method to quantify manufacturing lead time in QRM systems. Central to this approach is the Manufacturing Critical-path Time (MCT), defined as the typical time from when a customer places an order to the delivery of the first piece of that order. MCT aims to comprehensively represent lead times in manufacturing. It is calculated by adding the longest durations of specific activities like order processing, material planning, scheduling, manufacturing operations, and logistics. MCT begins with the initiation of an unplanned order and includes time spent in all stages of material processing, from raw materials to work-in-process (WIP) and finished goods. The main objective of MCT is to quantify the lead times of key value-adding activities to reduce inefficiencies across the system and improve responsiveness in the supply chain.

In the article "Manufacturing Critical-path Time (MCT): The QRM Metric for Lead Time" (Ericksen 2007), a detailed breakdown of the Manufacturing Critical-path Time (MCT) is provided with six components. As we have synthesized from the article, MCT can be summarized in a simplified formula as follows:

$$MCT = T_{order} + T_{process} + T_{materials} + T_{scheduling} + T_{manufacturing} + T_{logistics}$$

Where:

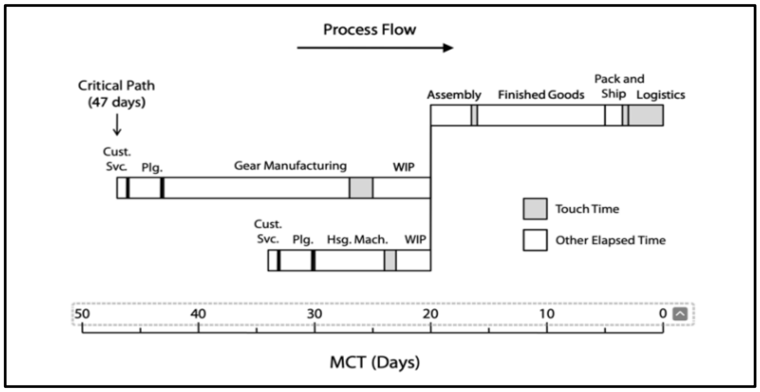
- T_{order} = Time from when a customer creates an unplanned order
- $T_{process}$ = Time taken for order processing
- $T_{materials}$ = Time involved in materials planning
- $T_{scheduling}$ = Time for scheduling activities
- $T_{manufacturing}$ = Manufacturing operations time
- $T_{logistics}$ = Time taken for logistics and delivery to the customer

In the supplementary article, "Tips for Calculating MCT," (Suri, 2010) builds on the foundational work of Ericksen by presenting a detailed examination of the manufacturing process at BadgerTran, a vehicle transmission manufacturer. This company is recognized for its lengthy lead times in both operations and supply chain management. Suri's uses BadgerTran as a practical example, focusing on the calculation of the Manufacturing Critical-path Time (MCT) for specific parts of their manufacturing operations. The purpose of this analysis (Suri, 2010) is to uncover opportunities for reducing lead times, offering a framework that can help to identify the inefficiency in manufacturing environments similar to BadgerTran's.

The process flow chart from figure 1 effectively demonstrates the multiple steps in delivering a final product. This is reflected in the operations at this CBA Beverage Manufacturer, where the production process unfolds sequentially, starting with the creation of pre-foam and caps, and leading up to the final assembly. Subsequently, the process includes an automated line for filling bottles with purified water, concluding with the final packing and storage. Understanding the intricacies of these steps and the time each one consumes is essential for accurately calculating the Manufacturing Critical-path Time (MCT).

Figure 1

MCT Map of Transmission Production at BadgerTran



Studying the case (Suri, 2010) above has provided us with a more structured method to assess the Manufacturing Cycle Time (MCT) in the context of production planning at the CBA Beverage Manufacturer. In the next phase, we conducted an evaluation of important manufacturing steps, informed by feedback from interviews. Subsequently, we developed a dedicated MCT model tailored to their production planning steps. This development was followed by a more comprehensive quantitative analysis with the newest data sources from the company that align with our final MCT model. Therefore, we leveraged this concept to determine the most effective approach, balancing qualitative and quantitative methods.

2.2.2 Load Planning

Within the order-to-delivery framework, our focus includes load planning, an essential workflow that comes after production. Once an order is finished on the production line, it usually spends a short time in the warehouse. In make-to-order scenarios, quick responses are crucial once the finished bulk goods are ready for delivery. The team at the company is constantly engaged in improving delivery appointments, scheduling and coordinating loading times with carriers. The ability to respond quickly when a scheduled order is ready for pickup is key, as it speeds up the entire order-to-delivery process for all customers.

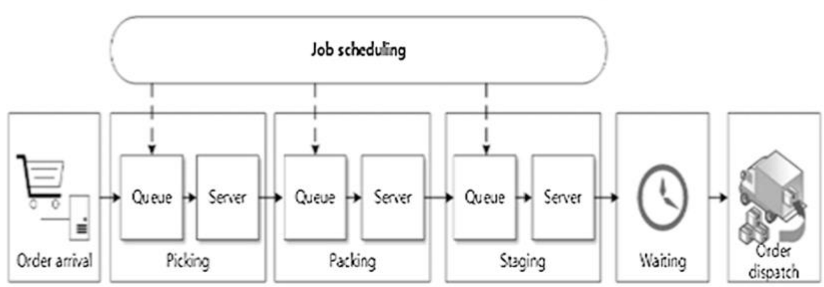
With that in mind, we examined the commonly used methods for assessing response times in load planning. Our objective will be to assess the lead time of load planning and diagnose whether it affects the order-to-delivery cycle in a positive way. Therefore, provides actionable plans to improve the existing workflows.

Continuing this exploration, it's important to consider the specific steps involved in load planning from moving finished goods inventory inside the warehouses to the appropriate loading dock. This process often requires the logistics department to strategically select and interact with contract carriers, or in some cases, resort to the spot market to balance urgent demands. To understand how warehouse operations impact load planning behind the scenes, especially in terms of their reaction time, Kim (2020) reviews the challenges and methods for enhancing warehouse efficiency in the article "Improving Warehouse Responsiveness by Job Priority Management: A European Distribution Centre Field Study." This study focuses on the use of priority-based job scheduling, comparing it to the conventional first-in-first-out approach in load scheduling. The primary aim of Kim's research is to boost responsiveness to market demands for rapid delivery from a warehouse perspective. It investigates how warehouses can efficiently manage order peaks and compressed response times through advanced scheduling methods.

In the context of this article, Figure 2 below depicts the order fulfillment process for retailers, who are the primary focus of the article. However, in real-life applications, this process typically caters to individual customers of the company. It begins with the arrival of an order, progressing through picking, packing, staging, and culminating in the queuing for dispatch. As these steps are interconnected, they can be susceptible to increased waiting times when workforce capacity is exceeded. Thus, employing an efficient job-scheduling system and proactively identifying system bottlenecks are vital for optimizing load planning. This approach ensures that the flow of goods from warehouse to delivery is streamlined and responsive, aligning with the dynamic demands of order fulfillment for both individual and retail customers.

Figure 2

Schematic Diagram of Warehouse Operations and Queue Management



warehouse process (left) and queuing model (right).

Note. *The figure illustrates a warehouse order fulfillment process with three stages: picking, packing, and staging. The model includes automated and manual processes managed via a Warehouse Management System (WMS). From "Improving warehouse responsiveness by job priority management: A European distribution center field study," by T. Y. Kim, 2020, Computers & Industrial Engineering, 139, 105564. https://doi.org/10.1016/j.cie.2018.12.011.*

During our interview at one of the company's most technologically advanced production facilities, we observed that inventory is moved using Laser Guided Vehicles (LGVs) and then stored in an automated racking system. At this stage, the company's loading process relies heavily on system algorithms that prioritize truckloads based on customer orders. However, the team currently measures their performance using cost and service Key Performance Indicators (KPIs), such as the percentage of mispicking or the average cost per truckload. But it does not fully address how quickly they respond to scheduled pickup orders.

Recognizing this gap in their performance metrics, we collaborated with the teams in data mining using their Warehouse Management System (WMS). This effort pinpointed the datasets that can help us better understand the lead time for picking orders.

2.2.3 Delivery Appointment Scheduling

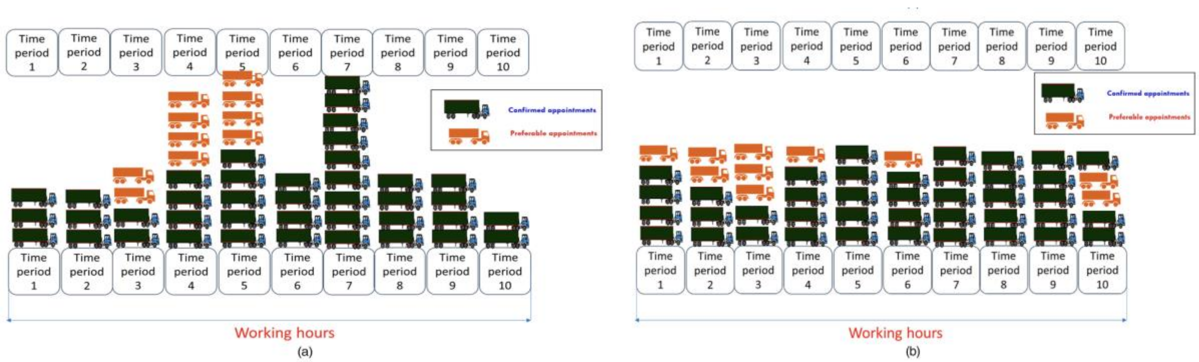
Besides undergoing a traditional supply chain process, which includes plant facilities, the overall efficiency of an order-to-delivery process also hinges on the logistics team's ability to promptly secure an initial delivery time with carriers. This means that an approximate pickup time should be established before production and loading, as the team manages aspects beyond the typical physical flows.

In their article (Abdelmagid, 2022), the author conducted a comprehensive review of the models covering the topic of truck appointment scheduling at ports. The study primarily focused on enhancing the efficiency and responsiveness of these scheduling systems by pinpointing critical factors that affect trucks' arrival and pickup times.

Figure 3 underscores the significance of an appointment system in managing incoming traffic by introducing a truck appointment system. As shown in Figure 3, without such a system, there can be an excessive workload during peak hours, affecting the efficiency of pick-up operations under limited capacity. Simultaneously, it can lead to underutilization of assets during off-peak periods. Therefore, balancing truck delivery appointment time windows is crucial for optimal performance (Abdelmagid 2022)

Figure 3

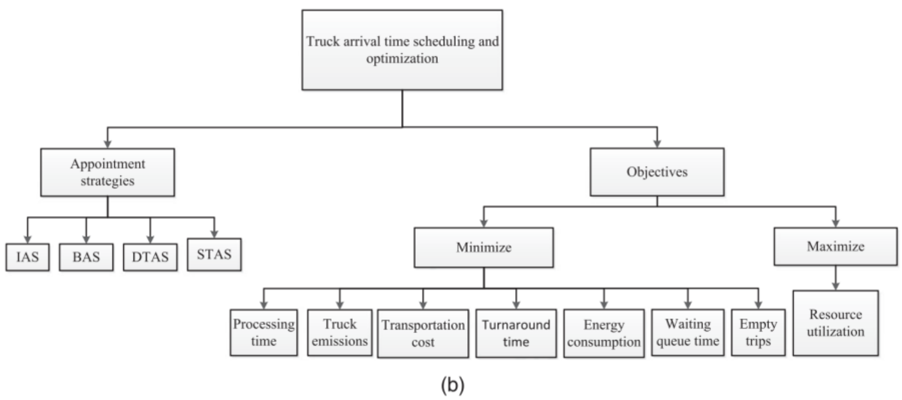
Appointment of trucks (a) before and (b) after applying a truck appointment system



The study (Abdelmagid, 2022) also suggests a structured approach to optimizing the lead time for scheduling an order's appointment, focusing on the study of truck arrival time scheduling. As highlighted in Figure 4, achieving more efficient arrival time scheduling involves reducing processing time, turnaround time, waiting time in queues, and the number of empty trips. In our studies, while we lack detailed records of each step the team takes in contacting carriers, interview feedback allows us to gauge their typical response time. This is done by observing the first tender time, which marks the moment a trucking company accepts a request and comparing it to the final agreed time. To supplement this, we collaborated with the data team to explore potential sources of information from their Service Cloud platform. This platform, currently used by the team to assign workload for every order, could provide new insights into the order-to-delivery process.

Figure 4

Classification of Truck appointment time scheduling



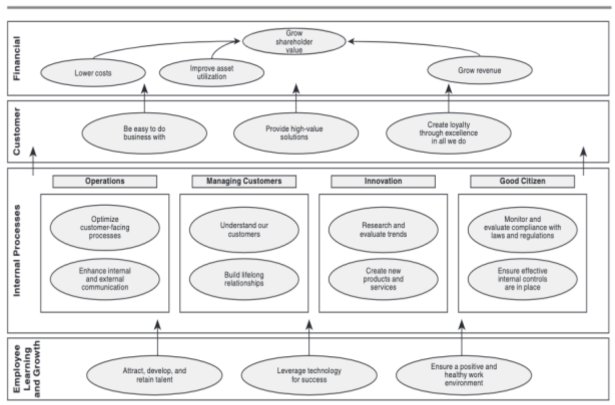
2.3 Supply Chain Responsiveness Metrics

"Measuring supply chain responsiveness performance is the first step for managers to improve any responsive decision-making process in a company. Without understanding the current performance, there is no baseline for managers to set up an improvement plan."(Gómez, 2005). In the supply chain industry, there is one main performance metric systems: the Balanced Scorecard (BSC). The Balanced Scorecard serves as a management tool, offering a framework for companies to translate their vision and strategy into a cohesive set of performance indicators. It strives to balance short-term and long-term objectives, providing a holistic perspective on an organization's performance. This performance metric system guides us in generating a comprehensive set of metrics to accurately measure the responsiveness of the company's current internal supply chain (Order-to-Delivery system).

As described by (Niven, 2006), the Balanced Scorecard is defined as a set of quantifiable measures derived from the organization's strategy. These selected measures serve as a tool for managers or leaders to communicate to external stakeholders the performance drivers by which the organization will achieve its mission and strategic objectives. Niven identifies this tool as having three primary functions: a communication tool, a measurement system, and a strategic management system. The Balanced Scorecard incorporates four perspectives—customer, internal process, employee learning and growth, and financial perspective. Figure 5 illustrates a sample strategy map, effectively segregating the four distinct yet interconnected perspectives of performance.

Figure 5

The Balanced Scorecard Example



From "Assessing Supply Chain Responsiveness in the Telecom Industry" by Gómez Fernández, M, 2005, ZARAGOZA LOGISTICS CENTER. http://hdl.handle.net/1721.1/102759

2.4 Process Mapping

Process mapping is a useful tool for companies as it provides a visual representation of the company's workflows, enabling a deeper understanding of business processes and their components. This understanding is important for identifying inefficiencies, redundancies, and bottlenecks within or between processes. By mapping out processes, the company can standardize operations and streamline workflows, leading to enhanced overall performance. Therefore, we decided to research Value Stream Mapping (VSM) to measure and enhance the internal supply chain's efficiency and responsiveness. VSM is particularly suited for this purpose as it provides a visual representation of the flow of materials and information from the initial customer order to the final delivery. This method allows for the identification of inefficiencies throughout the supply chain, helping pinpoint areas for improvement.

Value Stream Mapping

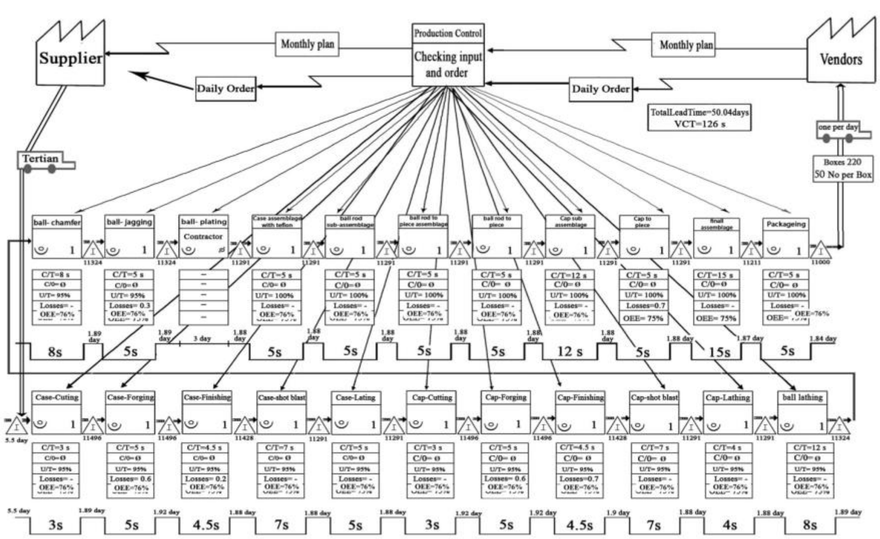
We have recently studied the Balanced Scorecard (BSC) model and the Supply Chain Operations Reference (SCOR) model as potential tools to integrate strategy and operations with performance metrics. Research indicates that an effective methodology for measuring the company’s supply chain responsiveness metrics could also be through Value Stream Mapping (VSM). Value Stream Mapping is an information flow mapping method that assesses the current state of processes involved in taking a product from inception to the customer. VSM identifies value-adding activities from raw material to the delivery of the final product and aims to eliminate any losses within the value stream.

According to [Dadashnejada, A. 2019] the analysis facilitated by VSM helps in recognizing all losses throughout the value stream and developing strategies for their removal. In a Value Stream Map, the question is consistent across all supply chain steps: Does this step add value to the final product from the customer's perspective? Each step should enhance performance effectiveness. Therefore, it categorizes VSM into three groups: value-adding activities, non-value-adding but required activities, and non-value-adding and unnecessary activities. Figure 6 illustrates an example of what our analysis would resemble after constructing this model for the company. This depiction offers valuable insights into distinguishing essential processes from non-essential ones, aiding our comprehension and improvement of their supply chain response times.

The integration of Value Stream Mapping into the company's supply chain management framework emerges as a crucial strategy for improving operational efficiency by identifying the bottlenecks. As demonstrated by Dadashnejada (2019), VSM serves as a powerful tool for identifying and eliminating losses throughout the value stream, thereby streamlining processes, and improving overall performance. The categorization of activities into value-adding, required non-value-adding, and unnecessary non-value-adding activities provides a structured approach for optimizing operations. As illustrated in Figure 6, the visual representation of this analysis offers actionable insights that will guide the company in refining their supply chain response times, leading to greater competitiveness in the market. The company will be able to navigate towards a more agile and efficient supply chain by meeting the fast-changing demand.

Figure 6

Value Stream Map Example



Note. *From "Investigating the Effect of Value Stream Mapping on Overall Equipment Effectiveness: A Case Study." by Dadashnejad, Ali-Asghar, and Changiz Valmohammadi, 2019, Total Quality Management & Business Excellence, vol. 30, no. 3–4, 2019, pp. 466–82, https://doi.org/10.1080/14783363.2017.1308821.*

3. METHODOLOGY

The methodology section describes a structured approach to analyze the company's process flowchart, focusing on characterizing responsiveness in the order-to-delivery flow system. It involves detailed data collection, transformation, and lead time estimation using Python to analyze supply chain efficiency and responsiveness.

3.1 Process mapping

After conducting a comprehensive analysis, we have chosen to delve into the company's process flowchart. This strategic decision is aimed at gaining an understanding of the activities spanning from the initiation of an order to the delivery of that order. The goal is to measure the time it takes each part of the process. We believe that by adopting this approach, we can establish the appropriate metrics to measure company's response time accurately.

We initiated this project by gaining insights into the company's internal supply chain approach mapping their process flowchart, as seen in Figure 7, ensuring that our proposed responsiveness metrics align with the company's strategy. The creation of the process flowchart was essential in providing a comprehensive overview of the journey an order goes within the order-to-delivery flow system. This understanding was crucial in pinpointing the initial stages for data analysis and identifying the reasons for the company's lack of supply chain responsiveness.

The process flowchart shown in Figure 7 illustrates the steps of an order through various departments, each represented by a distinct color, highlighting the order-to-delivery flow system of the company. This color-coded flowchart provides a visual representation of the internal pathways and departmental interactions involved in processing an order.

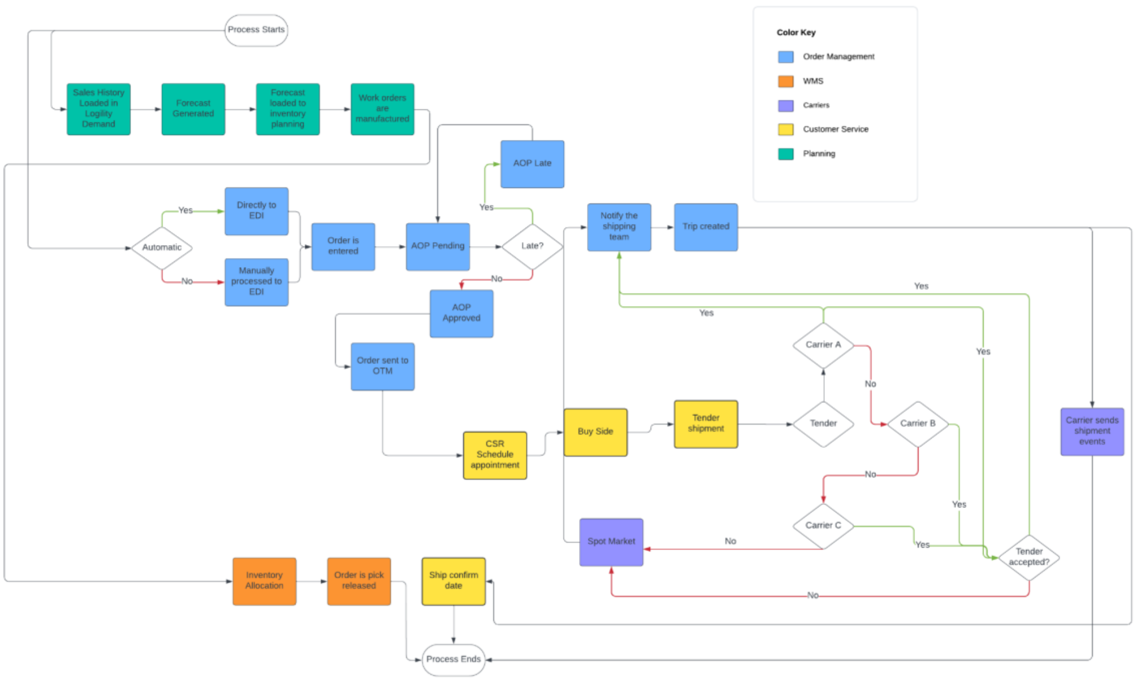
- Green - Planning Department: The primary responsibility of this department is to generate accurate forecasting models. These models are important for maintaining appropriate inventory levels and safety stock at the manufacturing plants, ensuring that the distribution to clients is timely.
- Blue - Order Management Team: The blue section belongs the Order Management team. This team's main function is to confirm customer orders, acting as an information flow hub within the company. Their role is important in the initial stages of the order processing cycle.
- Yellow - Customer Service Team: Highlighted in yellow, the Customer Service team plays an important role in communicating directly with the clients. They must schedule delivery times and making necessary adjustments in response to any unforeseen events, thereby directly affecting whether

if an order was on time or late.

- Orange - WMS Department: The department marked in orange is responsible for Warehouse Management System (WMS) operations. Their key duties include inventory allocation and preparing the orders for delivery to clients,
- Purple - Carriers: This group is essential for transporting the inventory from manufacturing plants to the clients. They ensure that the delivery is not only timely but also meets the standards expected by the clients.

Figure 7

The CBA Beverage Manufacture's Process Flowchart

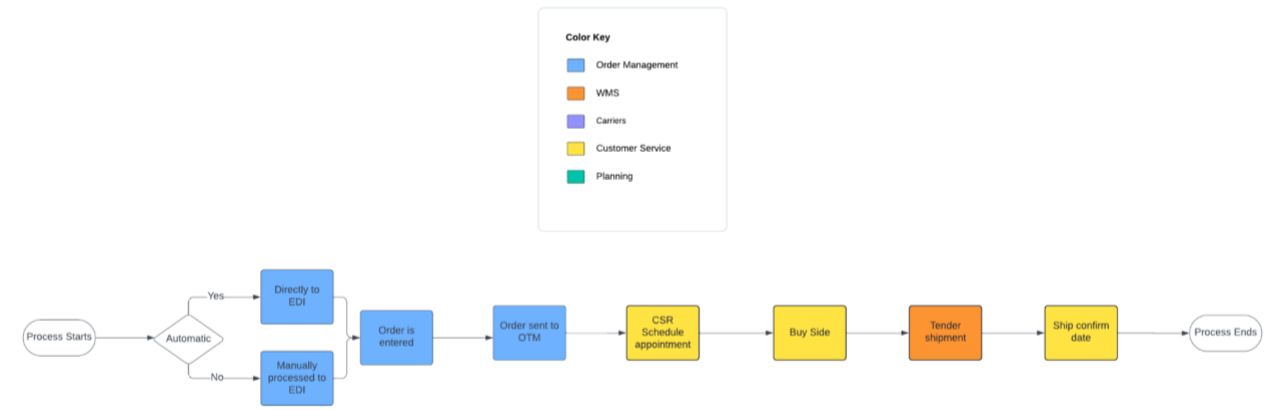


Drawing from the process mapping developed through interview notes and the company's internal documentation on system flows, we streamlined the critical steps for all the order activities. Our primary approach involves understanding the figure 7 flowchart, to illustrate the complete lifecycle of an order, from its entry to delivery. Before proceeding to the most detailed analysis, our method ensures the accurate documentation of essential date and time information for each step, as depicted in Figure 8.

Figure 7 shows the holistic process flow of an order from its entry to delivery, capturing all the steps involved. However, not all these steps were directly quantifiable within the data files provided by the company, needing further analysis to determine relevant timeframes for our study. Therefore, Figure 8 was developed to see what were the specific data points that could be extracted from the company's data frames. This step enabled us to perform calculations and identify areas of inefficiency within the process. In the following section on results, we go deeper into how these identified data points were utilized in our analysis.

Figure 8

Critical Steps of Order-to-Delivery Process



Our approach to data collection and analysis is methodically organized into several steps:

- Data Collection and data preparation
- Data analysis

3.2 Data Collection and data preparation

In the initial phase of collection, we gathered data from multiple sources within the company's decentralized IT systems, operated by various departments. For instance, we obtained the carrier scoreboard data, which encompasses all activities for each delivery number, from the initial tender shipment to the final delivery. We also reviewed the main service metric data file provided directly by the company, capturing all critical timestamps from order creation to the final delivery appointment. Concurrently, we requested additional files not directly linked to delivery numbers but still potentially indicative of the steps the team must navigate within the order-to-delivery cycle. Access to these supporting documents enabled us to assess the overall efficiency and response times of various departments contributing to the company's service delivery framework.

The initial dataset contained multiple activities associated with each delivery number, along with varying datetime formats. To facilitate a deeper analysis of the timing associated with each step, we undertook data manipulation to resolve several datetime formatting issues, converting them into a unified standard format. We then developed an aggregate function to select the most recent information for every delivery number across all activities, such as the latest order release date and first confirmation date. This transformation of the dataset provided us with a detailed overview of the timing recorded for each delivery.

Data Sources

Category	Data Element
Service-Metrics	Order Creation, Order Scheduling, Order Release, Order Arrival, etc.
Carrier Scoreboard	Shipment Start, Source Departure, Tender Time, Tender Response Time

3.3 Data Analysis

To calculate the lead time between each step of the process (Figure 8), we utilized Python to read a consecutive five weeks of order activities from the data files. Then we performed data cleaning and formatting as well as a quality check to come up with a cleaned data table. Next, we selected key datetime data points, as identified through Figure 10, to estimate the gap between two activities for each order and converted that into day format as the actual lead time for each step. For instance, we subtracted the order creation date from the final delivery date to determine the total order-to-delivery time for a specific order. We incorporated more specific datetime information from the carrier and other departments as necessary. Lastly, we estimated the time difference to reveal the duration of each process and associated this with specific departments for further diagnostics.

4. Results

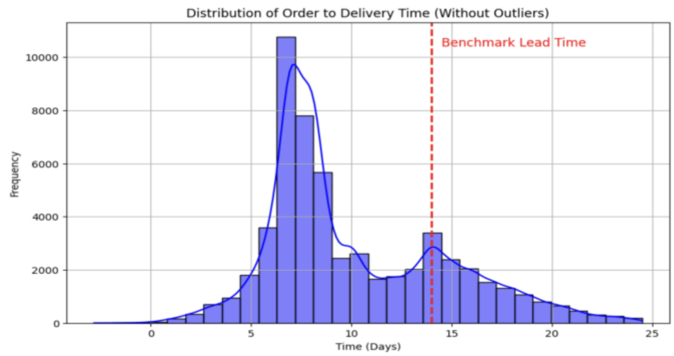
This chapter delves into a detailed analysis of order-to-delivery lead times within the company, examining overall lead times and the specific internal process steps that influence them. Initial sections assess lead times from order placement to dispatch, highlighting key areas of delay. Subsequent sections provide granular insights into how different supply chain regions and key customers impact these times. Advanced analytical methods, including machine learning and root cause analysis, are used to identify and address significant bottlenecks, ultimately aiming to enhance supply chain efficiency and customer satisfaction.

4.1 Order-to-delivery Lead Time analysis

The analysis began by estimating the average lead time for orders the company received over five calendar weeks. This was achieved by analyzing the time from when an order was placed to when it was dispatched. This data collection provided insights into the duration required for the company to fulfill orders across different regions, customers, and carriers. In Figure 9, we depicted the distribution of all the orders we studied. The visualization highlights that the company typically delivers orders within a 7-to-9-day window, which corresponds to the first peak in the chart. However, it also reveals a shortfall, where 20% of orders exceeded the 14-day delivery benchmark, a standard expectation among key customers. This finding suggests the need for an in-depth examination of each step in the internal process to identify and address the causes of delays. In the next phase of our analysis, we will delve deeper into specific processes, as outlined in the diagrams as explained in Section 3.2.

Figure 9

Distribution of Order-to-Delivery Time (Without Outliers)



4.1.1 Lead Time Based on Internal Process Steps - Part 1

The service metrics file provides specific data points that map out the time taken for each process step to be completed. By computing the mean, median, standard deviation, maximum value, and minimum value of these time durations, we can analyze fluctuations and pinpoint bottlenecks as shown in Table 1.

Our data analysis focuses on understanding order processing within the business context. Initially, it selects relevant datetime columns from the aggregated data and converts them into datetime format. Then, it calculates various time differences, such as those for order creation, release, scheduling, confirmation, and shipment. These differences are measured in days and stored in corresponding Data frame columns.

Additionally, the code computes the mean and median values of these time differences, summarizing them for further analysis. This approach offers insights into average durations and the distribution of processing times at each stage of order fulfillment. Such insights can guide decision-making and optimization efforts within the business.

Table 1

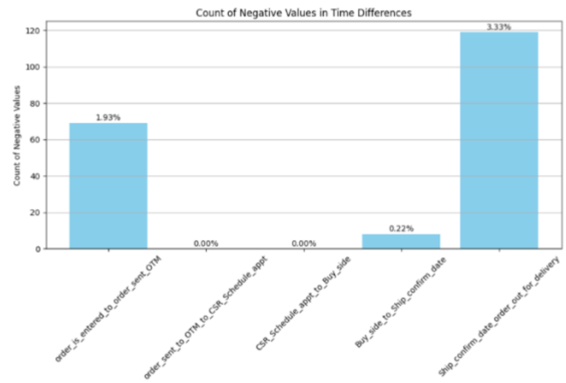
Time each process step takes (Days)

	Mean	Median	STD	MAX	MIN
order_is_entered_to_order_sent_OTM	0.93	0.73	2.73	59.62	(32.29)
order_sent_to_OTM_to_CSR_Schedule_appt	0.51	0.13	2.32	33.00	0.01
CSR_Schedule_appt_to_Buy_side	3.76	1.20	5.24	37.34	0.02
Buy_side_to_Ship_confirm_date	5.23	5.57	2.97	16.55	(0.03)
Ship_confirm_date_order_out_for_delivery	0.44	0.27	5.11	304.75	(14.93)

Following the initial calculations, we investigated the presence of negative values within the dataset. Upon examination, we identified several instances of human errors made by the company. Consequently, we undertook data cleaning measures to rectify these inaccuracies by removing the negative values, as shown in Figure 10. Then, we reran the calculations to ensure a more precise representation of the potential bottleneck at a more granular level.

Figure 10

Count of Negative Values in Time Differences



Once we removed the negative values from the dataset, we conducted a new analysis, which yielded new results. These results offered a clearer and more focused perspective on the actual bottleneck in Table 2.

Table 2

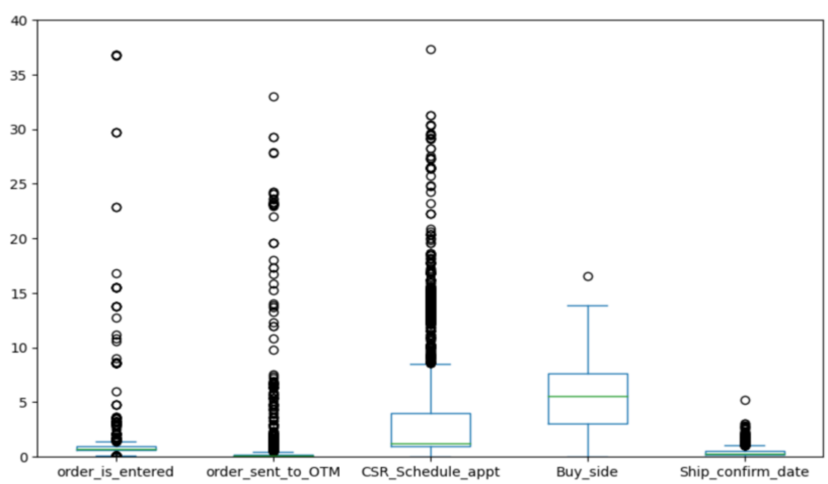
Time each process step takes without negative values (Days)

	Mean	Median	STD	MAX	MIN
order_is_entered_to_order_sent_OTM	1.01	0.73	2.56	59.62	0.00
order_sent_to_OTM_to_CSR_Schedule_appt	0.51	0.13	2.32	33.00	0.01
CSR_Schedule_appt_to_Buy_side	3.76	1.20	5.24	37.34	0.02
Buy_side_to_Ship_confirm_date	5.25	5.58	2.96	16.55	0.03
Ship_confirm_date_order_out_for_delivery	0.47	0.29	5.19	304.75	0.00

We constructed a box plot in Figure 11 to depict the outliers and mean of the data. This visualization allowed us to observe the behavior of the standard deviation in relation to these data points. Through this analysis, we successfully identified the corresponding attributes, providing valuable insights for the company.

Figure 11

Box Plot of the cycle time in each process



The process step labeled "CSR_Schedule_appt_to_Buy_side" exhibited the highest outliers in the boxplot analysis, indicating that it could be a key driver of the total lead time within the company's operations. To address this situation, we sought to identify the attributes associated with the top 10 contributors to this bottleneck, aiming to offer actionable insights. From our analysis, we pinpointed certain attributes as significant contributors to the process step that had a high number of outliers from the Customer Service department.

We have identified certain patterns that significantly influence the main data point. Specifically, six key customers are responsible for driving the outliers, as shown in Figure 12, while another six primary carriers are causing delays in deliveries to six different states in Figure 13. With these findings, we can now formulate recommendations aimed at optimizing the company's supply chain responsiveness, focusing on the targeted departments, customers, carriers, and states mentioned.

Figure 12

Number of orders by Customer based on Most delayed Schedule Appointments

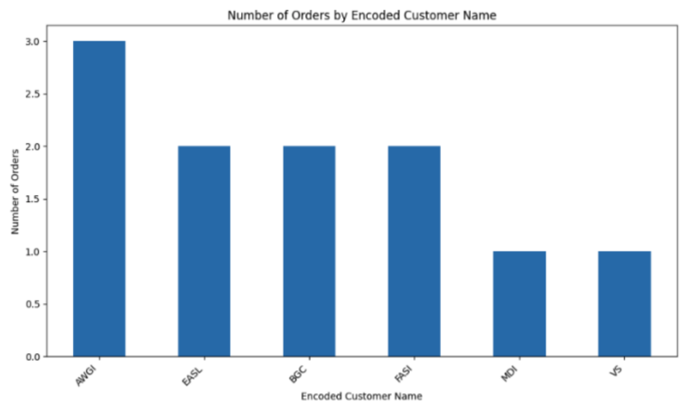


Figure 13

Number of orders by Carrier Name based on Most delayed Schedule Appointments

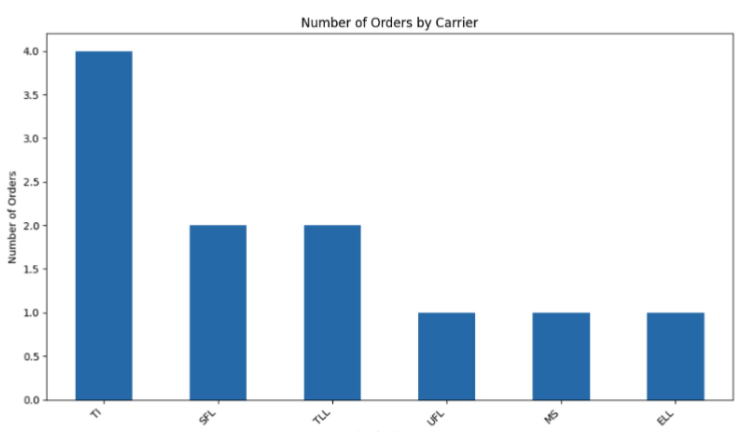
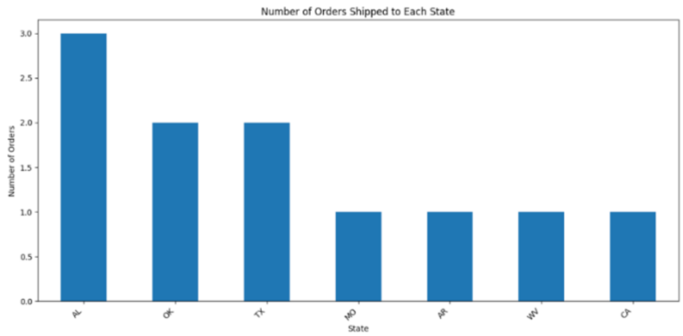


Figure 14

Number of Orders Shipped to Each State based on Most delayed Schedule Appointments



4.1.2 Lead Time based on Internal Process Steps - Part 2 (Carrier Activities)

The second part of the study follows the methodology as described in Section 3, but focuses on data from the scoreboard, which tracks all activities related to carriers and the responses at the end of the order-to-delivery process. In Table 3, the average tendering time is around 10 hours, and it takes approximately an average of 1.5 hours from when the shipment starts to when it completes at the customer's facility. However, the presence of many negative values in the data could bias and undermine the accuracy of the results.

Table 3

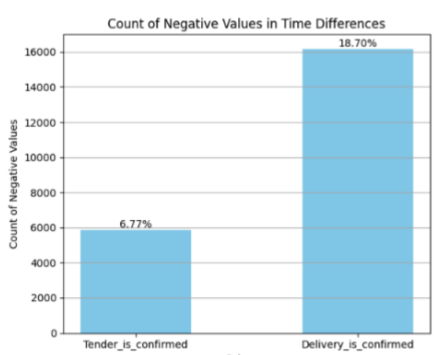
Time each process step takes (Days)

	mean	median	STD	Max	Min
Tender_is_confirmed	0.41	0.02	1.36	29.24	-0.12
Delivery_is_confirmed	0.06	0.07	2.28	7.3	-273.21

In Figure 15, the chart showcases the number of negative values in the scoreboard data. Although both activities contain thousands of negative values, their proportions are relatively low, at approximately 7% and 19%. Consequently, we decided to exclude these values from the summary for estimating lead time.

Figure 15

Count and Percentage of Negative Time Differences in Total Orders



After adjusting for negative values, we re-ran the summary. According to Table 4, the average tender time has increased to 11 hours. Additionally, from the moment it starts, delivery typically takes 4.3 hours to complete. The revised results indicate that the tendering time with the carrier involves more lead time and exhibits a higher standard deviation compared to the final delivery phase.

Table 4

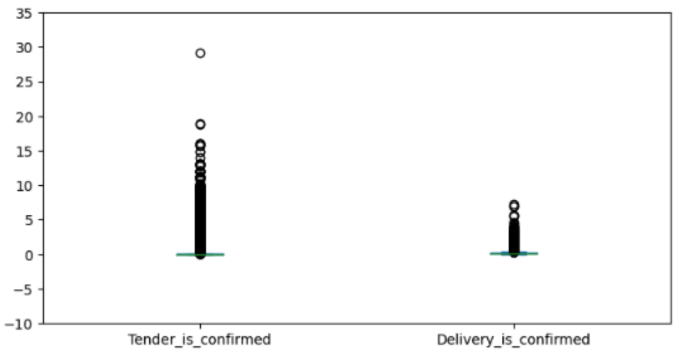
Time each process step takes without negative values (Days)

	mean	median	STD	Max	Min
Tender_is_confirmed	0.46	0.03	1.43	29.24	0
Delivery_is_confirmed	0.18	0.08	0.31	7.3	0

Following our previous analysis, we created a box plot for the two activities recorded in the carrier scoreboard data. This visual further supports the observation that tender time experiences more variability than delivery time. This outcome suggests the need for an in-depth review of how tender time affects the internal processes from the buy-side to the ship-confirm date.

Figure 16

Box Plot of the cycle time in each process



As shown in Figure 16, longer tender times lead to greater variation and extended lead times, primarily due to outliers. We conducted a thorough analysis of the top 30 delivery instances with the longest tender times. Figure 17 illustrates that EAW, COWE, LS, MS, and ME are the top customers for the CBA Beverage Manufacturer, with the longest tender response times. Among them, EAW stands out with the highest number of cases. This indicates the company should focus on addressing the underlying issues related to this customer.

Figure 17

Number of Orders by Customer based on Most delayed Tender Time

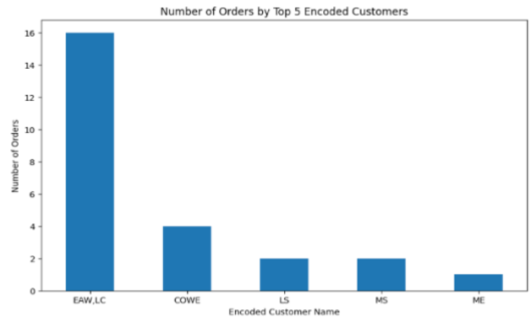


Figure 18 also highlights the regions within the supply chain that have the highest tender times. Also, the west region has the longest tender response time, followed by the South Atlantic and Southwest. This suggests that company should prioritize increasing capacity and improving operational efficiency accordingly.

Figure 18

Number of Orders by Supply Chain Regions based on Most delayed Tender Time

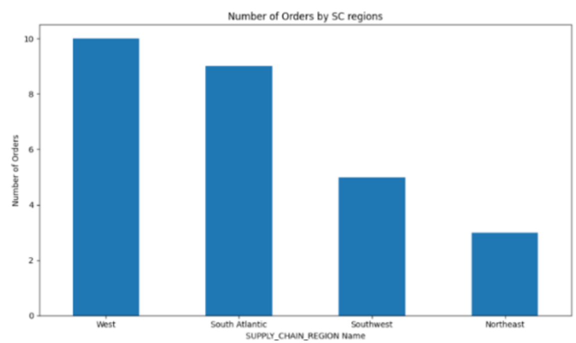
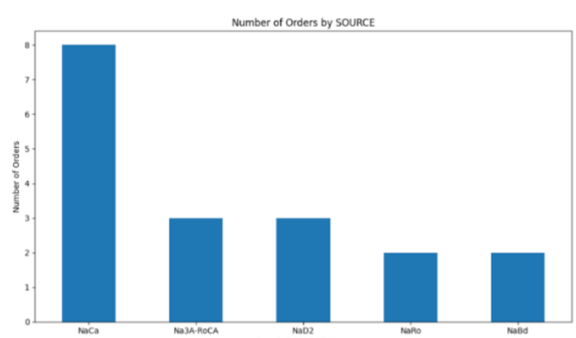


Figure 19 also summarizes the top sources of extended tender times, with the company's facility locations standing out as the primary contributor. For instance, NaCa, Na3A-RoCA, and NaD2 are identified as the top three locations with the longest tender times. This highlights the importance of conducting further operational assessments of the carrier team specifically related to these three locations.

Figure 19

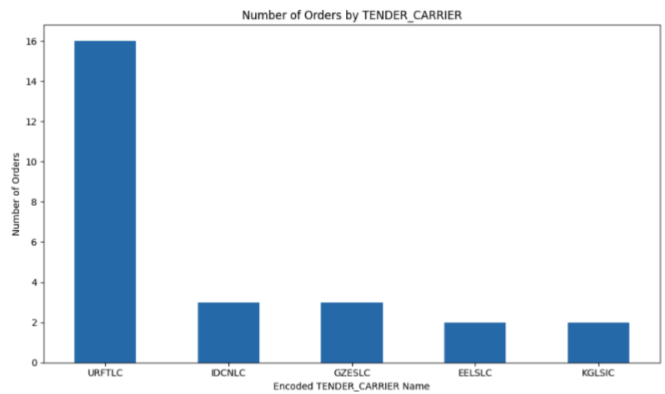
Number of Orders by Source Locations based on Most delayed Tender Time



In Figure 20, the top tender carriers with the longest tender times are visualized. Considering that carriers drive the performance of this activity once the company sends the request, reevaluating the use of URFTLC, IDCNLC, and GZESLC Enterprises could lead to faster tender times.

Figure 20

Number of Orders by Tender Carriers based on Most delayed Tender Time



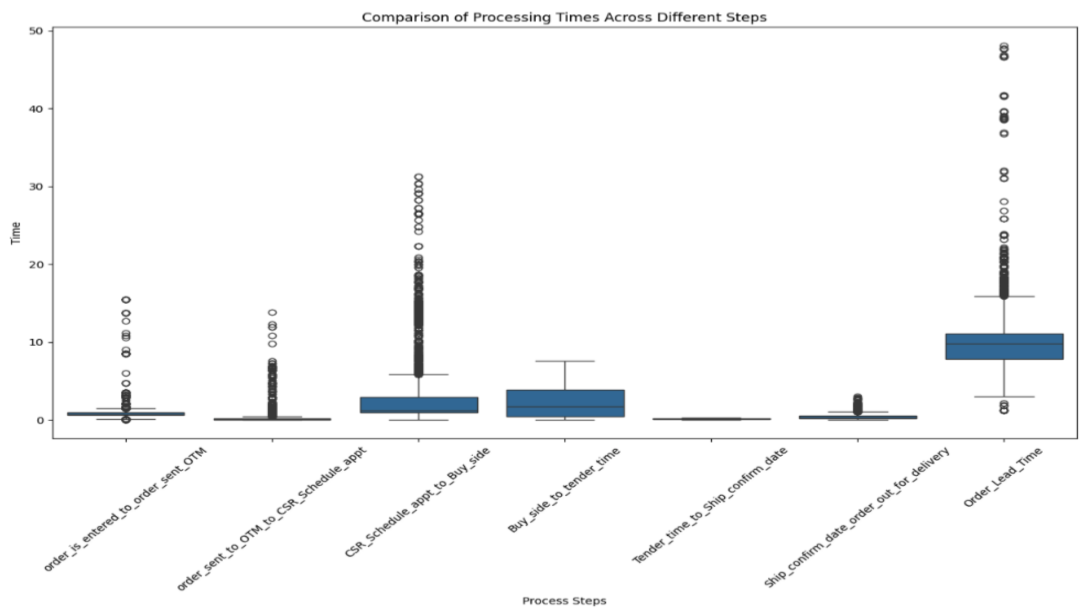
4.1.3 Lead Time of Internal Process with Carrier Activity

To summarize the findings from Sections 4.1.1 and 4.1.2, we employed Python to integrate two disparate data sources. This is depicted in Figure 21, where 'tender time' has been incorporated as an intermediary step between 'buy_side' and 'ship_confirm_date.' Analysis reveals that the lead time from buy side to tender time is substantially longer than from tender time to ship confirm date. Moreover, the process 'CSR_Schedule_appt_to_Buy_side' has been identified as the second most time-consuming step.

For clarity, the steps 'Buy_side_to_tender_time' and 'Tender_time_to_Ship_Confirm_date' are illustrated using only 265 data points, reflecting the accuracy discrepancies across different systems. Conversely, the remaining five process steps are supported by a more substantial dataset of 3,578 data points. Additionally, we have refined the data quality by eliminating any outliers exceeding six standard deviations from the mean for each process step. This approach ensures the reliability and precision of our analysis to diagnose the key drivers of the lead time across multiple stages of the order-to-delivery cycle.

Figure 21

Comparison of all Internal Processes with Total Lead Time



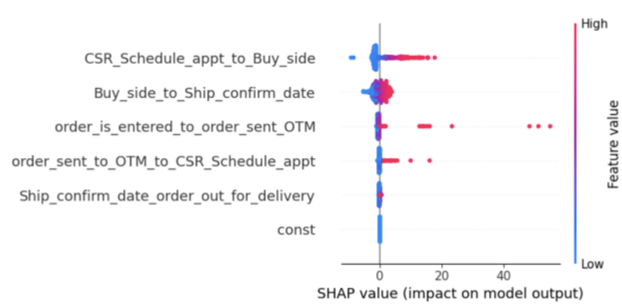
4.2 Drivers of longer lead times

4.2.1 Permutation Approach on Feature Importance

We used Python to implement a machine learning approach to understand which process most significantly influences the total lead time, specifically SHAP value analysis. This method helps visualize the impact of each process on lead time, determining whether it is positive or negative. As shown in Figure 25, the chart indicates that "CSR_Schedule_appt_to_Buy_side" has a positive impact on total lead time in terms of both density and magnitude. Additionally, the process "Order_is_entered_to_order_sent_OTM" also significantly affects lead time, with certain instances dramatically spiking the degree of impact. Consequently, it is crucial for the internal team to manage edge cases within this process and to initially prioritize increasing capacity in the "CSR_Schedule_appt_to_Buy_side" process. This strategic focus will enhance overall efficiency and effectiveness, transforming towards a more responsive supply chain.

Figure 25

SHAP Value Plot of Feature Importance towards Lead Time



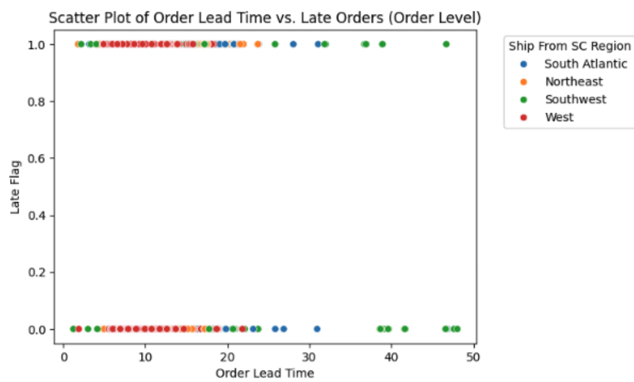
4.2.2 Lead Time versus Late Orders by Supply Chain Operating Regions

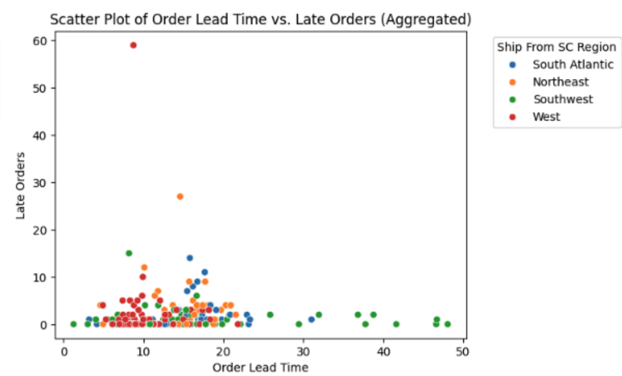
In addition to Section 4.2.1, we delve into how different supply chain operating teams, categorized by regions, perform in terms of their lead time and order lateness distribution. Figure 26 illustrates the distribution of each region across all 3,578 data points over a consecutive five-week period. It highlights that the Southwest region has the highest number of orders with significantly longer lead times, followed by the South Atlantic region. This clearly indicates that these two regions need to improve their efficiency to achieve faster lead times, regardless of order lateness.

Conversely, we aggregate the order-level results to show how lead times correspond to accumulated late orders across all four regions. Figure 27 reveals that the Southwest region experiences the longest lead times, while the South Atlantic region generally faces more issues with lateness.

Figure 26 & 27

Scatter Plot of Order Lead Time versus Late Order at Order and Aggregated Levels



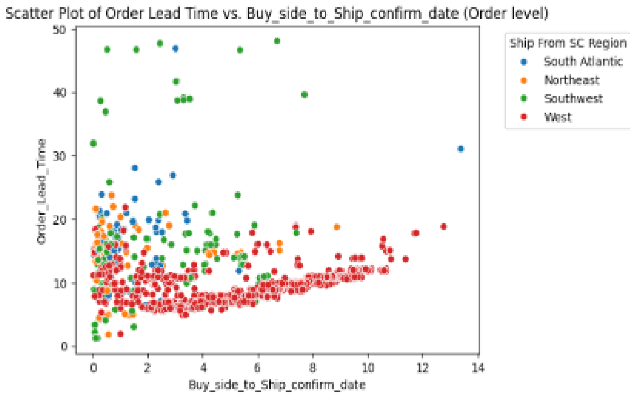


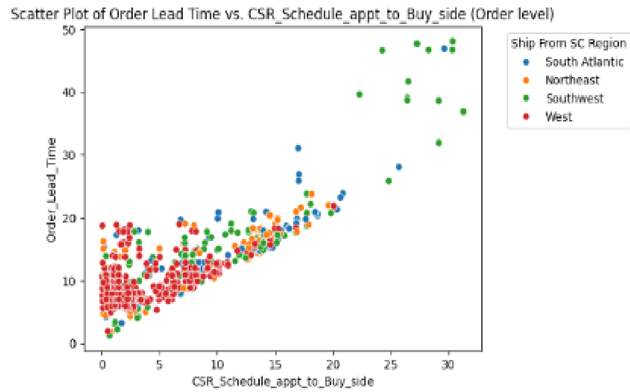
4.2.3 Lead Time versus Internal Process Steps across by Supply Chain Operating Regions

To understand the internal processes driving extended lead times, we analyzed the distribution of all 3,578 orders, focusing on two activities labeled on the x-axis in the charts below. Figure 28 illustrates that "Buy_side_to_Ship_confirm_date" generally correlates positively with total lead time, except in the Southwest region. We then examined how "CSR_Schedule_appt_to_Buy_side" affects lead times, as shown in Figure 29. The findings reveal that the Southwest region experiences significantly longer lead times due to this activity. Therefore, we began to investigate the potential root causes of this inefficiency within the Southwest operations teams.

Figure 28 & 29

Scatter Plot of Order Lead Time versus Late Order at Order and Aggregated Levels



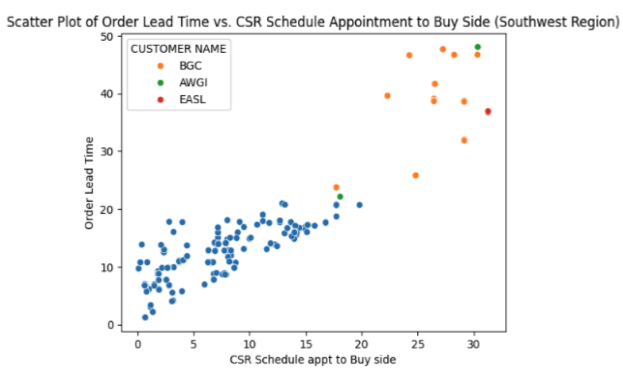


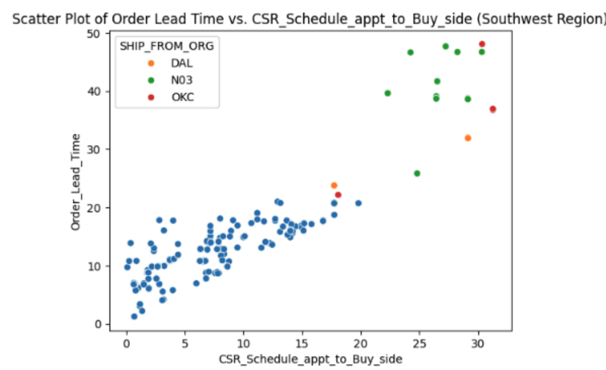
4.2.4 Lead Time versus Internal Process Steps across by Customers & Plants

Based on our analysis in Section 4.2.3, which identified the bottleneck, the subsequent visualizations highlight the key Customers and Plants associated with long lead times. Figure 30 shows that a customer, marked in yellow, is a frequent contributor to longer lead times. This suggests that the company should reassess their cooperation with this client and evaluate potential opportunities to reduce the lead times for these customers. Figure 31 indicates that a Plant, marked in green, is the most common location resulting in longer lead times. While there is no clear information on the association between the highlighted customer and plant, it is evident that the company should develop strategies to monitor and improve performance in these areas to make the supply chain more responsive.

Figure 30 & 31

Scatter Plot of Lead Time versus CSR_Schedule_appt_to_Buy_side by Customers & Plants





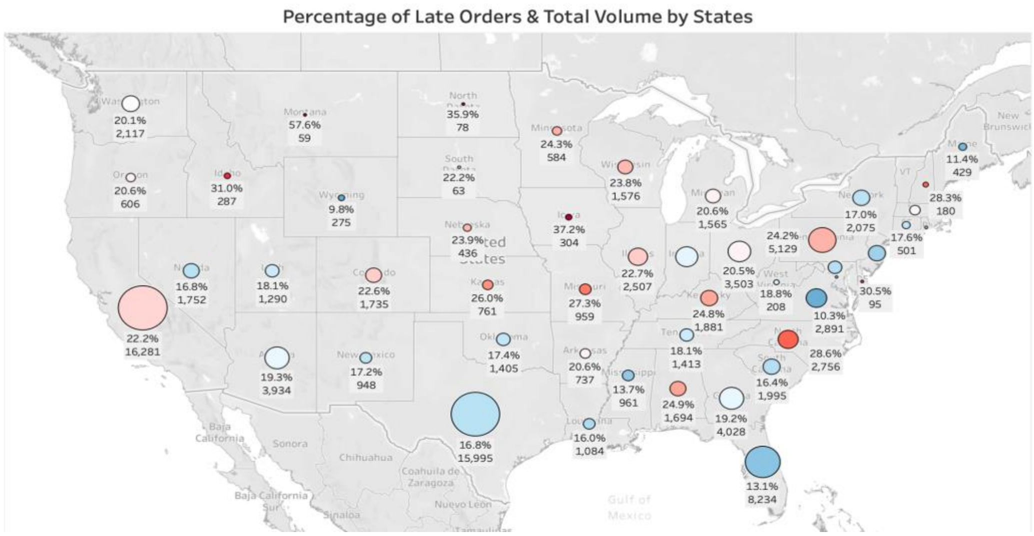
4.3 Characterization of late orders

4.3.1 Countrywide Late Order Distribution

In our exploratory analysis, we also investigated the incidence of lateness in addition to longer lead times, as customer satisfaction is influenced not only by the duration of waiting but also by the company's ability to fulfill its commitments. To assess the company's efficiency in delivery accuracy, we calculated the percentage of late orders and their ratio to the total orders by state. In Figure 32, the size of the circles reflects the business volume, while the color indicates the percentage of late orders. The figure shows that California, Texas, and Florida are the top three states with significant business volumes for this company. The analysis revealed that many Midwestern and Southern states have a notably higher likelihood of late deliveries, whereas California's performance is slightly below the national average.

Figure 32

Percentage of Late Orders with Total Volume

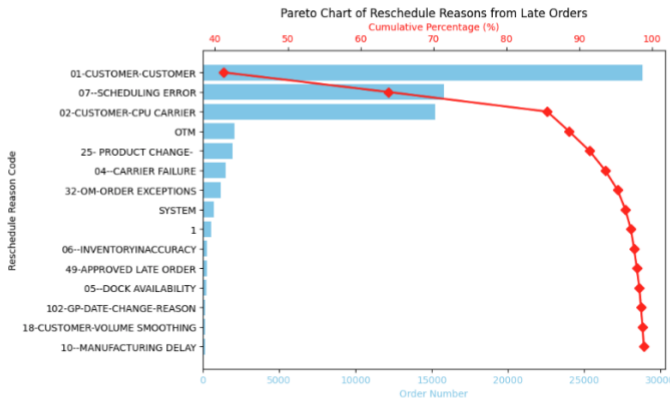


4.3.2 Rescheduling Reason Code Over Late Orders

Figure 33 highlights the primary causes of delivery delays, utilizing reason codes for analysis. The top reasons for lateness include customer-driven issues, scheduling errors, and date changes due to Automated-Order-Processing (AOP) adjustments, all largely beyond the company's control due to external factors and system errors. The analysis then focuses on the fifth major cause: carrier failure. By examining the cycle times for each internal process using carrier scoreboard data, additional insights associated with carrier-related delays are provided.

Figure 33

Pareto Chart of Rescheduling Reason Code from Late Orders

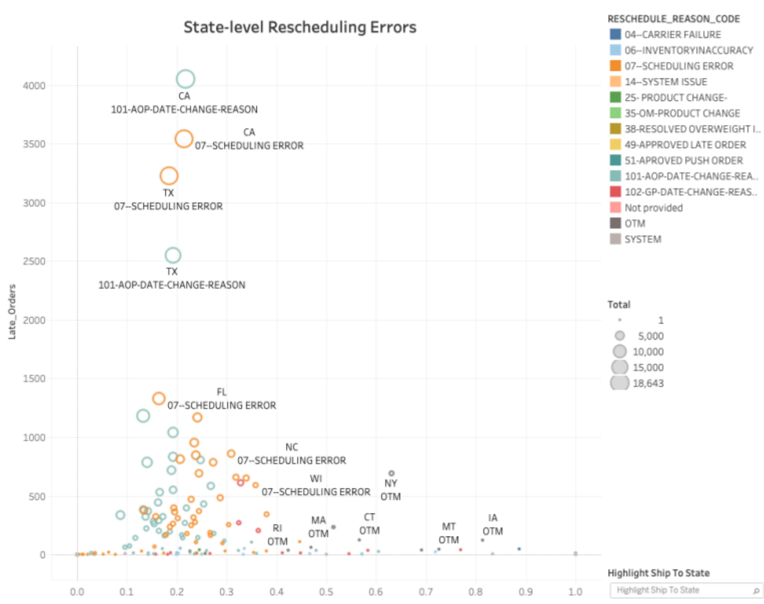


4.3.3 State-level Rescheduling Reason Code for Lateness

To delve into the nuances at the state level, we examined how different reasons for rescheduling are influenced by specific processes or functions. As illustrated in Figure 34, California and Texas exhibit the highest number of late orders, largely attributed to their business size. However, this doesn't necessarily imply underperformance by the regional team. Conversely, certain states show significantly higher late order percentages despite having smaller business volumes. For instance, Indiana and Montana have relatively high percentages of orders that consistently result in delays. This not only extends lead times but also impacts customer experience by failing to meet commitments. Therefore, the company should consider optimizing processes or increasing capacity for business operations, particularly in the regions highlighted on the right-hand side of Figure 34.

Figure 34

State-level Late order distribution with Key Rescheduling reason codes



4.4 Predictive Model of Key Factors Influencing Order Delays

In this project, we used regularized regression techniques—linear, lasso, ridge, and elastic net—to develop a predictive model for determining whether a delivery would be on time or late, as shown in Figure 22. Each of these methods incorporates a penalty term to the loss function to prevent overfitting, with lasso and elastic net adding sparsity to the model by reducing the coefficients of less important variables to zero. After evaluating the performance of each model based on the R-squared (R^2) value, which measures the proportion of variance in the dependent variable that is predictable from the independent variables, we found that the ridge regression model provided the highest R^2. This indicated that it was the most effective at capturing the variance in our delivery timeliness data without overfitting, thanks to its ability to shrink the coefficients towards zero but not exactly to zero, thus maintaining all features in the model.

Figure 22

Model Accuracy Comparison

Linear Regression Training R2: 0.483 Test R2: -2.6216814674377533e+20 --------------------------- Test dataset error metrics MSE: 5.1908273737269174e+19 RMSE: 7204739671.720 MAE: 145796283.479	**Lasso Regression** Training R2 0.105 Test R2: 0.105 --------------------------- Test dataset error metrics MSE: 0.177 RMSE: 0.420 MAE: 0.374
Elasticnet Regression Training R2: 0.270 Test R2: 0.267 --------------------------- Test dataset error metrics MSE: 0.144 RMSE: 0.380 MAE: 0.325	**Ridge Regression** Training R2: 0.483 Test R2: 0.44 --------------------------- Test dataset error metrics MSE: 0.109 RMSE: 0.331 MAE: 0.219

Figure 23

Feature Importance in Ridge Regression

Feature Importance	Coef
CARRIER_NAME_DENSE_GENERIC	0.218
CUSTOMER_NAME_DENSE_CBA_BEVERAGE	0.093
CUSTOMER_NAME_DENSE_CW	0.057
CARRIER_NAME_DENSE_KLG	0.038
CARRIER_NAME_DENSE_PEP	0.035
CARRIER_NAME_DENSE_LS	0.034
CUSTOMER_NAME_DENSE_FM	0.028
CUSTOMER_NAME_DENSE_OTHER	0.025
CUSTOMER_NAME_DENSE_PSM	0.025

Following this, we constructed a second machine learning model using the Random Forest algorithm to further analyze our data. We split our dataset into a training set and a test set with a 70-30 ratio, respectively. The Random Forest model, known for its robustness and ability to handle non-linear data, allowed us to identify and rank the importance of various features in predicting delivery timeliness. This model works by constructing multiple decision trees during training time and outputting the class that is the mode of the classes (classification) of the individual trees. The feature importance derived from this model provided us with insights into which variables most significantly impact whether a delivery will be late or on time, enabling us to focus on these key areas for operational improvements.

Train/Test Split

$$X_{train}, X_{test}, y_{train}, y_{test} = train\_test\_split(X, y, test\_size = 0.25, random\_state = 16)$$

Define Model

$$model = RandomForestClassifier(n\_estimators = 100, random\_state = 42)$$

Fit the Model

$$model.fit(X\_train, y\_train)$$

Predicting Parameter

$$y\_pred = model.predict(X\_test)$$

Accuracy of the model: 85%

MSE: 0.14233

Figure 24

Feature Importance in Random Forest

Feature Importance	Coef
CARRIER_NAME_DENSE_GENERIC	0.321
CARRIER_NAME_DENSE_BLS	0.076
SHIP_TO_STATE_DENSE_CA	0.074
CARRIER_NAME_DENSE_US1L	0.050
SHIP_FROM_SC_REGION_Brand	0.047
SHIP_FROM_SC_REGION_West	0.041
SHIP_FROM_SC_REGION_South Atlantic	0.038
SHIP_FROM_SC_REGION_Northeast	0.037
SHIP_TO_STATE_DENSE_PA	0.030

5. DISCUSSION AND RECOMMENDATIONS

This chapter outlines findings and recommendations to support supply chain efficiency, focusing on identifying bottlenecks, enhancing regional performance, improving data quality, and using predictive modeling to ensure timely deliveries.

5.1 Implementing Manufacturing Critical-path Time (MCT) Calculations

Manufacturing Critical-path Time (MCT) is a comprehensive metric used to quantify the total lead time in a manufacturing or service process, from the moment an order is placed until the first piece of that order is delivered to the customer. MCT is important in identifying inefficiencies and areas for improvement within the supply chain, ultimately helping improve responsiveness.

By mapping out the entire process from order placement to delivery. We saw the sequence of steps that constitutes the longest path through the process, known as the critical path. "CSR_Schedule_appt_to_Buy_side" contributes the most inefficiencies in the company's response times as seen in table 2. Replicating the calculation for these steps to all the process steps within the company will provide enough insight to the company to streamline operations and provide a better service to internal and external stakeholders.

5.1.1 Recommended Calculations:

Columns
ORDER_CREATION_DATE_PST
ORDER_RELEASE_INSERT_DATE_PST
SCHEDULE_INSERT_DATE_PST
SCHEDULE_INSERT_DATE
TENDER_TIME
SHIP_CONFIRM_DATE_PST
DESTINATION_DEPARTURE214

- $Order\ entered\ to\ order\ sent\ to\ OTM = ORDER\ RELEASE\ INSERT\ DATE - ORDER\ CREATION\ DATE$
- $Order\ sent\ to\ OTM\ to\ CSR\ Schedule\ appt = SCHEDULE\ INSERT\ DATE - ORDER\ RELEASE\ INSERT\ DATE$
- $CSR\ Schedule\ appt\ to\ Buy\ Side = SCHEDULE\ INSERT\ DATE - SCHEDULE\ INSERT\ DATE\ PST$
- $Buy\ Side\ to\ Tender\ time = TENDER\ TIME - SCHEDULE\ INSERT\ DATE$
- $Tender\ time\ to\ Ship\ confirm\ date = SHIP\ CONFIRM\ DATE\ PST - TENDER\ TIME$
- $Ship\ confirm\ date\ to\ Out\ for\ delivery = DESTINATION\ DEPARTURE\ 214 - SHIP\ CONFIRM\ DATE\ PST$

5.1.2 Scenario: Southwest Region

a) **Process Mapping**: Create a process map for orders specific to the Southwest region, identifying steps that differ from the general company process due to regional variations.

b) **Calculate Regional MCT**: Apply the MCT calculation method as seen above to the regional process map, summing the times for all steps along the critical path.

c) **Analysis and Improvement:** Analyze the regional MCT to identify steps with extensive lead time.

MCT is a powerful metric for identifying inefficiencies within the manufacturing or service process. By calculating MCT for the overall company and applying it to specific scenarios, organizations can pinpoint areas for improvement, streamline operations, and enhance overall responsiveness. Continuous monitoring and recalculating of MCT after implementing changes are crucial for measuring improvement and maintaining an efficient, responsive supply chain.

5.2 Bottleneck Identification and Process Optimization

We employed advanced analytical tools, including machine learning and root cause analysis, to uncover and address inefficiencies within specific process steps. Particular attention should be given to the "CSR_Schedule_appt_to_Buy_side" step, which has been identified as a major contributor to extended lead times. Efforts to enhance the efficiency of this and other critical steps are essential. Data analysis has revealed that certain customers, carriers, and regions significantly impact delivery schedules. It is advisable to create customized strategies to improve interactions with these departments.

Primary Focus should be mainly to the Southwest Region. Prioritize the Southwest region by allocating additional resources as an increase in headcount to the CSR team and highly recommend in introducing automation in load planning and delivery scheduling to reduce lead times in their process steps.

Secondary Focus should be on carrier performance. After addressing issues in the Southwest, the next focus should be on improving carrier performance. Implementing stricter service level agreements and regular performance reviews can drive improvements ensuring that the client will receive their orders in a timely manner.

Tertiary Focus should be on production planning by improving the production planning process by integrating it with the central ERP system to improve data visibility and response times.

This could involve optimizing scheduling processes, enhancing communication channels, and implementing more robust service level agreements to ensure timely deliveries. By analyzing the patterns and trends associated with these key customers, carriers and regions, the company can better anticipate potential causes of delays or long lead times, and then proactively implement solutions. Fostering stronger partnerships with carriers and customers can lead to more collaborative problem-solving and improved supply chain resilience.

5.3 Regional Supply Chain Enhancement

The performance assessment across different supply chain regions has identified opportunities for improvement, particularly in regions with longer lead times such as the Southwest and South Atlantic. It is recommended to allocate resources strategically and implement initiatives to address these inefficiencies. This includes investing in the infrastructure, technology, and training to help aid the main regions that are causing the company's unresponsiveness therefore increasing the efficiency of the supply chain in these regions. Also, regional optimization should consider the unique challenges and opportunities present in each area, such as local market conditions, transportation networks, and regulatory environments. By tailoring initiatives to the specific needs of each region, the company can achieve more consistent and reliable lead times across its entire supply chain network.

5.4 Data Quality Improvement

Develop a more robust data analytics framework that can provide deeper insights into each step of the supply chain. This should include real-time tracking and predictive analytics to foresee potential delays and dynamically adjust operations. To ensure that decision-making is based on accurate and reliable data, it is crucial to implement measures that improve data quality. This includes identifying and rectifying instances of human error (negative values), as well as ensuring that data analysis methods are robust enough to account for outliers and inaccuracies. By improving data quality, the company can gain more reliable insights that will inform strategic decisions and process improvements.

5.5 Predictive Modeling for Delivery Timeliness

The use of machine learning techniques for predictive modeling can provide valuable foresight into delivery timeliness. By developing models that can predict potential delays, the company can identify key factors influencing on-time deliveries and optimize operational strategies accordingly. These models can also be used to simulate different scenarios and assess the impact of various process changes before they are implemented. This proactive approach to managing the supply chain can help minimize delays and improve the company's ability to meet customer expectations.

6. CONCLUSION

Our project analyzed the time it takes for the company to fulfill orders and investigated the causes of prolonged delivery times. We found that approximately one in five orders did not meet the expected benchmark lead time. By using analytical tools to examine the data, we identified specific aspects of the delivery process that contribute to these delays. To address this issue, the company should focus on the slowest steps in the process and explore ways to improve their efficiency. Furthermore, we discovered that certain regions, particularly the Southwest and South Atlantic, along with large customers, are more likely to experience late orders. It is essential to closely collaborate with these key customers and the associated teams in scheduling and buyside, considering an increase in team size or streamlining current operational processes to enhance delivery mechanisms in these areas.

Looking forward, this project lays the groundwork for future research opportunities, such as integrating real-time data analytics, assessing the impact of sustainability on supply chain efficiency, and adopting emerging technologies. Continuous improvement is a crucial component of the company's culture. By leveraging the insights from this analysis and maintaining a focus on innovation and collaboration, the company can further refine its supply chain operations. This will not only enhance customer satisfaction but also maintain its competitive edge in the industry.

REFERENCES

Dadashnejad, Ali-Asghar, and Changiz Valmohammadi. "Investigating the Effect of Value Stream Mapping on Overall Equipment Effectiveness: A Case Study." Total Quality Management & Business Excellence, vol. 30, no. 3–4, 2019, pp. 466–82, https://doi.org/10.1080/14783363.2017.1308821.

Ericksen, P. D., Stoflet, N. J., & Suri, R. (n.d.). *Manufacturing Critical-path Time (MCT): The QRM Metric for Lead Time*.

Gómez Fernández, M. (2005). Assessing Supply Chain Responsiveness in the Telecom Industry [ZARAGOZA LOGISTICS CENTER]. http://hdl.handle.net/1721.1/102759.

Hausman, W. H. (2004). Supply Chain Performance Metrics. In The Practice of Supply Chain Management: Where Theory and Application Converge (Vol. 62, pp. 61–73). Springer-Verlag. https://doi.org/10.1007/0-387-27275-5_4.

Kellermayr-Scheucher, Marike, et al. "Applications and Perceptions of Workforce Management Systems for Warehouse Operation - Results and Findings from Expert Interviews." Procedia Computer Science, vol. 219, 2023, pp. 255–62, https://doi.org/10.1016/j.procs.2023.01.288.

Kim, T. Y. (2020). Improving warehouse responsiveness by job priority management: A European distribution centre field study. Computers & Industrial Engineering, 139, 105564. https://doi.org/10.1016/j.cie.2018.12.011.

Niven, Paul R. Balanced Scorecard Step-by-Step: Maximizing Performance and Maintaining Results. 2. Aufl., Wiley, 2006, https://doi.org/10.1002/9781119205081.

Suri, R. (2010). *It's about time: The competitive advantage of quick response manufacturing*. Productivity Press.

THATTE, A. A. (2007). Competitive Advantage of a Firm through Supply Chain Responsiveness and SCM Practices [Doctoral dissertation, University of Toledo]. OhioLINK Electronic Theses and Dissertations Center. http://rave.ohiolink.edu/etdc/view?acc_num=toledo1176401773.

Zhou, Honggeng, et al. "Supply Chain Integration and the SCOR Model." Journal of Business Logistics, vol. 32, no. 4, 2011, pp. 332–44, https://doi.org/10.1111/j.0000-0000.2011.01029.x.

Abdelmagid, A. M., Gheith, M. S., & Eltawil, A. B. (2022). A comprehensive review of the truck appointment scheduling models and directions for future research. *Transport Reviews*, *42*(1), 102–126. https://doi.org/10.1080/01441647.2021.1955034

APPENDIX A

A-1

Supply Chain Operations Reference Model (SCOR)