Fresher Food Supply: Evaluating the impact of pick-to-zero strategy on freshness of produce using discrete event simulations

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ABSTRACT

Consumers frequently reach behind supermarket shelves to find products with the furthest expiration dates. This instinctive behavior highlights a universal desire for fresh produce. Therefore, the capstone sponsor is eager to deliver fresh produce to maximize customer satisfaction consistently. One innovative approach to increasing freshness is to minimize the duration produce spends in the supply chain by implementing a pick-to-zero strategy. However, can a pick-to-zero strategy improve freshness without significantly increasing costs or excess inventory? This capstone uses discrete event simulation in SimPy to compare the current state and pick-to-zero supply chains (future state) while incorporating uncertainty factors at each facility in the network. The results from the simulation model indicate that a pick-to-zero strategy improves the freshness of produce by 25%, reduces excess inventory by 22%, but roughly increases transportation costs by 35%. However, using a strategically located consolidation center in conjunction with the pick-to-zero strategy reduces transportation costs by 6% compared to daily shipments while increasing freshness by 9%. Furthermore, the results also indicate that products with higher forecast accuracy and lower forecast variance are most suitable for this strategy.

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Our capstone sponsors allowed us to apply our skills, innovate, and delve deeply into the nuances of perishable supply chains possible. Collaborating with such distinguished industry leaders, who generously shared their time, insights, and resources weekly, was both an honor and a cornerstone of our project's success.

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1 Scope definition

1.1 Motivation

Research reveals that individuals make on average approximately two hundred daily food-related decisions (Wansink & Sobal 2007). Thanks to globalization, consumers now enjoy the incredible privilege of relishing a diverse bounty of foods worldwide. The capstone sponsor, a food retailer in the United States, is steadfast in its commitment to offering these global products fresh and accessible to all customers.

The capstone sponsor procures its perishable goods directly from farms or through a network of suppliers. Some of the products sourced are grown in specific regions outside the United States. Therefore, procurement of products such as berries requires an extensive domestic and international network to offer products to customers. Through an extensive distribution center network, the capstone sponsor efficiently replenishes over several thousand retail stores across the US with fresh produce. However, a concern arises when perishable produce arrives from suppliers: the capstone sponsor typically holds from 0.5 to 4+ days, depending on the commodity, of cycle plus safety stock in its distribution centers. (In this document, the words distribution center and warehouse are used interchangeably.) Using First In First Out (FIFO) practices means that such inventory holding diminishes the relative freshness of produce by at least half a day. This decline impacts the customer experience for the capstone sponsor, which prides itself on delivering fresh, and indirectly affects the capstone sponsor's overall business operations. For example, prolonged inventory retention at distribution centers increases the risk of product spoilage and improper handling. Furthermore, elevated inventory levels also escalate working capital and infrastructure requirements. The primary objective of this capstone project is to design and simulate an operating model that reduces the age of perishable inventory while enhancing the flow of perishable goods. The capstone sponsor acknowledges that implementing a just-in-time supply chain for perishables often incurs higher costs. However, through this initiative, the capstone sponsor aims to assess the costs associated with a just-in-time supply chain quantitatively. Hence this evaluation will guide the capstone sponsor in determining whether adopting a just-in-time supply chain is feasible and beneficial to offering fresher products to customers.

1.2 Problem statement & research questions

The key objective of this capstone project is to analyze the impact of adopting a pick-to-zero strategy on freshness, costs, and excess inventory. A pick-to-zero strategy is an order-picking method in which shipments are received, put away, picked, and shipped out all on the same day from a distribution center (DC).

The objective was achieved by developing a quantitative model that factors several variables. Some of the inputs to the model include store order frequency, store order quantity, DC order frequency, DC order quantity, supplier lead times, supplier to DC distance, inventory processing costs and infrastructure capacities. Simulations were run on the model using a subset of the data (split between training and testing data) to measure the effectiveness of the pick-to-zero model. The scope of the capstone is restricted to only three product categories or commodities (used interchangeably): berries, tomatoes, and bagged green salads as set forth by the capstone sponsor. However, these product categories span across ~230 SKUs. Given the scope of the project, the type of quantitative model and the data, the output of the model addressed the following research questions:

1. What key performance indicators (KPIs) will be used to measure the pick-to-zero effectiveness within the DC? What are the current benchmarks and trade-offs?
2. Which node (i.e., facility) of the supply chain network accommodates the safety stock if the DC switches to the pick-to-zero approach?
3. How can the sponsor company achieve a pick-to-zero strategy without using an upstream consolidation center? Can suppliers take on some of the challenges of having to palletize for stores rather than DCs?

1.3 Scope: goals and outcomes

The goal was to reduce the number of days of the inventory when it arrives at the store and ultimately provide fresher produce to consumers. Mathematically, the model evaluated the reduction in age of inventory by eliminating inventory holding at the DC. While the impact on costs was analyzed, costs by itself, was not a constraint or the main criterion in the model.
Key deliverables to the capstone sponsor as part of this project were:

1. A mathematical model to measure the age of inventory, shipment costs and order volumes using pick-to-zero operation.
2. Recommendations on operating methods to achieve pick-to-zero distribution models.
3. Report on the implications of a pick-to-zero operating model on cost, time, waste and distribution efficiencies and the trade-offs with the reduction in the age of inventory.
4. A simulation model to simulate the recommendation is provided.

2 State of the practice

Inventory holding and management constitute the cornerstone of every retailer's business operation. Retailers derive significant advantages from maintaining inventories, primarily rooted in economies of scale. Producing goods in substantial quantities affords retailers discounted purchase prices and optimizes logistic costs. Moreover, inventory holding serves as a buffer against disruptions in production, shielding customers from potential supply and demand shocks. However, these inventory-holding benefits may not always apply to grocery retailers.

Grocery retailers, in particular, face distinctive challenges while managing the supply chain of both fresh perishables with short shelf life, such as vegetables, meat, and dairy and other perishables with long shelf life, such as canned goods, cereals and frozen goods. The inherently extensive range of expiration periods for all commodities accentuates the significance of effective supply chain management. Perishables can be classified as days fresh and weeks fresh (Van Donselaar et al. 2006). Days-fresh are perishable products lasting less than 10 days after harvest. Weeks-fresh are perishable products with a lifetime between 10 and 30 days after harvest. Managing perishables requires multiple touchpoints and quick movement of products from one supply chain node to another. The time spent by products in each segment adds complexity and increases costs. Therefore, managing the time spent in each process and segment plays an instrumental role in maintaining freshness. This capstone aims to evaluate the impact of implementing one such process, pick-to-zero strategy, on freshness, cost and excess inventory. Research was conducted on current trends and challenges in grocery retail and research studies conducted by others in fresh produce handling. The reasons for studying trends and research were:

1. To identify challenges and trends in the retail supply chain
2. To understand How do consumers and retailers measure freshness? Is there a mathematical approximation for freshness?
3. To identify assumptions used by other researchers to quantify costs and inventory position.
4. To identify strategies used to increase freshness that are not limited to picking policy: how does network design or delivery schedule impact freshness?
5. To understand components of a pick-to-zero model.

2.1 Current trends and challenges

One of the challenges retailers face in meeting the demand is to build resilient supply chains that can bring groceries from harvest locations to retail outlets in the least time possible and at the lowest cost. This presents a challenging trade-off for retailers. Consumers receive the best price if the product is delivered at the lowest cost. However, lower costs do not always guarantee fresher products. Deloitte (2023) surveyed 2,000 consumers and employees of 20 large grocery retailers based in the United States. The results of the survey state that fresh food is becoming an obsession for consumers. Roughly 90% of consumers surveyed believe that fresh food is essential to a wholesome diet and therefore makes them happy. Approximately 80% of the respondents think a diet based on fresher food minimizes the risk of chronic health conditions and diseases.

The strong support for fresh food on plates is not only advocated by consumers but also by retailers. Two-thirds of the grocery retail executives who responded to Deloitte's survey believe that fresh food is a crucial pillar of their firm's growth plan over the next three years. In addition, a survey conducted among 10,000 consumers in the USA and Western Europe revealed that access to the best quality fresh products is the most important consideration when choosing where to shop (Broekmeulen & Van Donselaar, 2019). Furthermore, this preference is validated by researcher Joseph Blackburn, who demonstrated that fresh produce, even in a cold chain environment can lose ~20% sucrose within four days of storage, causing the produce to lose sweetness (Blackburn & Scudder, 2009).

Apart from sourcing the best quality product from suppliers through sustainable means, a key component of fresh food supply is the time the product spends in the supply chain. The longer the product takes to get to the store or consumer, the lower the freshness. Consequently, grocers need to implement deeper discounts on fresh products nearing their expiration dates, further eroding profitability. Assessing trade-offs between costs and improving the freshness of the product, i.e., faster movement of product through the supply chain, is the essence of this capstone. Therefore, for grocery retailers, a key area of focus is to bring fresher produce to consumers and retain or gain a competitive advantage.

Wastage of fresh perishables emerges as a substantial concern, exerting a considerable impact on the profitability of grocers globally. Notably, wastage costs grocers nearly 2% of net sales. Reduction in waste can significantly add to a grocery retailer's bottom line considering the industry's thin profit margins (Klingler et al., 2016). Compounding this issue is the discernible decline in consumer willingness to pay as the perceived freshness of commodities diminishes (Tsiros & Heilman, 2005). Furthermore, over 70% of participants shopping for milk in an experiment shuffled through the product rack to find milk with the furthest expiry date, suggesting a strong preference to purchase the freshest items (Shah et al., 2016). In addition to the expiration date, consumers also use sensory characteristics such as look, smell and touch to evaluate the freshness of produce (Barone &

Aschemann-Witzel, 2022). Increasing freshness to improve customer satisfaction is of paramount importance to the capstone sponsor.

After understanding trends and challenges in perishable supply chains, we evaluated methods to quantify freshness. Freshness could be measured differently from the supply chain perspective instead of the customer's perspective. Detailing how long a product spends in the supply chain may not resonate with end consumers. End consumers would perhaps prefer to know the number of days before expiry. Therefore, defining a standard metric for freshness for the scope of this project was essential to compare results between current state and future state with pick-to-zero.

2.2 How to measure freshness

The freshness of a product can be categorized as a function of cost, time and resilience. However, another important factor contributing to freshness is waste. Broekmeulen & Van Donselaar (2019) quantified freshness improvement, food waste and sales by introducing two concepts measuring potential improvements. First is Fresh Case Cover (FCC), defined as the case size divided by the average demand during store shelf life. Second is the Efficient Frontier, defined as the minimum waste required to achieve a particular service level (i.e., On-Shelf Availability). A mathematical expression was developed to evaluate the freshness of a product.

$$\varphi = \left(m - \frac{I}{[z+\beta]}.\frac{1}{\mu}\right)\left(1 + \frac{z}{\beta}\right) \tag{1}$$

where:
j - Remaining Shelf Life (i.e., freshness)
m – Shelf life of product when harvested
z – Relative outdating
b – Fill rate
m – Average daily sales
I – Expected Inventory on hand just before outdating.

The freshness j is given by the shelf life (m) when the product reaches the store minus the time spent in the supply chain multiplied by the products sold to consumers before outdating. The products not sold to consumers due to outdating are accounted for in the equation.

The results of their study reveal five recommendations for improvements:

1. Unpack all cases in the retailer's DC for store quantities, which was set to one unit in their study.
2. Rationalize the SKU assortment by removing the bottom 10% of the slow movers.
3. Categorize the on-shelf availability (OSA) for different assortments. An example given in the study is to reduce OSA by 2% for slow movers and increase by 3% for fast movers.
4. Increase OSA for stores by 1-day increments.
5. Reduce OSA by 2% for all item-location combinations. The OSA targets significantly increase waste. Having a marginally lower OSA can reduce waste and counter the reduction in sales.

Based on the recommendation, a significant improvement in the freshness and waste was observed by increasing the shelf life by one day, resulting in 17% increase in freshness, 43% reduction in waste and a 3.4% increase in OSA. The key takeaway from Broekmeulen & Van Donselaar (2019) is that freshness can be measured as the difference between the initial shelf life, when produce is harvested, and total time taken until the produce is sold. As we cannot control or determine the supplier's harvesting process, the controllable factor in the freshness is the total time taken until the produce is sold. Therefore, the simulation model was built to evaluate the total time taken in the supply chain from supplier to customer. The lower the time, the better the freshness.

If the total time taken must be reduced, processing times of the produce should be reduced at each node of the supply chain network. Further research was conducted on network design, warehouse operations and inventory policy to further understand factors that could influence time taken apart from pick-to-zero.

2.3 Impact of network design and warehouse operations on freshness

A master's thesis done by Gerbecks (2014) is similar to the proposed methodology of the capstone project. However, Gerbecks examined different picking models to arrive at the lowest costs. Gerbecks (2014) explored different supply chain structures for an online retailer to deliver products to consumers effectively. The key focus of the master's thesis was to solve rapid pickup and delivery of perishable products from suppliers to online retailer's pick-up-points using pick-to-zero operations. The pick-to-zero operation was compared to the Estimated Withdrawal and Aging replenishment policy (Broekmeulen & Van Donselaar 2009). An interesting approach was to use a combination of regular and emergency shipments to cater to surges in demand. Rather than assume demand as deterministic, based on forecast values, Gerbecks assumed discrete demand with a Poisson distribution based on Adan, Van Eenige and Resing's (1995) method to formulate a discrete distribution on the first two moments of a non-negative random variable. The demand was fitted against different distributions and Poisson was finally selected based on a chi-squared test. This assumption provides the opportunity to evaluate waste and examine possibilities of suppliers shipping emergency orders.

Since the distribution center (DC) uses pick-to-zero, the pallets can be broken down into cases quickly and shipped to the consumer pickup points within hours. The EWA policy sets the reorder level and time based on the relative outdating for different fixed shelf life. However, the pick-to-zero model developed by Gerbecks uses all customers' aggregate demand as the warehouse's required inventory. Different cost components incorporated by Gerbecks include the cost of lost sales, operational costs, additional transportation costs, and emergency costs in the event that a shipment is requested from the supplier to fulfill a surge in demand. Based on these parameters, Gerbecks simulated demand. He concluded that the pick-to-zero is an optimal strategy for a higher percentage of assortment when demand variability is higher at the retailer DC. When demand increases, the lost sales cost due to pick-to-zero is higher than the relative outdating cost using the EWA policy.

However, the result does not provide insights into freshness potential using pick-to-zero. Another way to improve freshness is to reduce transit times between different legs of the supply chain: Reduce time between supplier and distribution center (DC), and/or reduce the time between DC and store. Liang et al., (2023) quantified freshness improvement using advanced vehicle routing algorithms. The focus was to study the optimization of transportation time using a meta-heuristic algorithm that combined Variable Neighborhood Search (VNS) and Simulated Annealing (SA) as a bi-objective multi-period vehicle routing problem. The bi-objective function captures the trade-offs between customer satisfaction (i.e., freshness) and costs. The results show that more urgent deliveries increase costs and lower the average loading ratio. When the fleet size is smaller, expanding the fleet size effectively increases customer satisfaction.

The heuristic developed by Broekmeulen & Van Donselaar (2009) for managing perishable goods, and the model proposed by Gerbecks (2014), both require demand forecasts. Hence forecast accuracy can impact the results and hence is an important parameter to be analyzed.

2.4 Impact of forecast accuracy on freshness

The heuristic developed by Broekmeulen & Van Donselaar (2009) for managing perishable goods, and the model proposed by Gerbecks (2014), underscore the necessity of accurately forecasting future demand. The accuracy of these forecasts is paramount, particularly when considering operations aimed at minimizing residual inventory, the "pick-to-zero" strategy. Here, the volume of orders is predicted on demand projections. A substantial positive forecast error (where the forecasted demand surpasses actual demand) results in an oversupply, inevitably diminishing inventory freshness due to first-in, first-out (FIFO) inventory practices. Conversely, a negative forecast error (forecasted demand falls short of actual demand) signals potential stockouts, culminating in lost sales. Retailers often mitigate these risks by maintaining safety stock and discounting, yet this approach invariably impinges upon product freshness. Thus, enhancing product freshness and minimizing lost sales are opposing trade-offs mediated by the demand forecasting accuracy.

To dissect forecast accuracy, the actual-to-forecast demand ratio (A/F), a metric introduced by Cachon and Terwiesch (2014), has been used. This ratio serves as a barometer for relative forecast errors, where a ratio of 1 denotes flawless forecast accuracy. Ratios exceeding 1 indicate stockouts, whereas ratios below 1 denote oversupply. Employing this metric facilitates tailored inventory and safety stock policies for each stock keeping unit (SKU), optimizing the balance between product freshness and the mitigation of lost sales. Managing inventory for perishable products has challenges similar to those of the newsvendor inventory management model. Even if forecast accuracies are 100%, orders for inventory must be placed in advance. Hence, a robust inventory policy is required to manage a pick-to-zero strategy.

2.5 Impact of inventory policy on freshness

Broekmeulen & Van Donselaar (2009) developed a heuristic to manage perishable products, called Estimated Withdrawal and Aging (EWA) Replenishment, that modifies the existing periodic review (R,s,n,Q) policy to incorporate relative outdating into reorder level calculations for perishables. Only one product was used for the calculations. Products are replenished using the base policy (R,s,n,Q) and compared against the EWA replenishment policy. The reorder level is set as r, which is the safety stock plus the expected demand next day to the review period and lead time from the supplier. The order quantity should be equal or more than the reorder point but lower than the safety stock plus the total order quantity.

The number of cases (n) is chosen such that the inventory position after replenishment is at or above s, but strictly below s+Q. The inventory withdrawal is evaluated for both First In First Out (FIFO) and Last In First Out (LIFO) withdrawals. Compared to the base policy, the EWA replenishment policy reduces costs by 9.8%. Average freshness increases marginally by 2.4% for EWA replenishment with FIFO withdrawal. Therefore, the EWA policy can yield better results for perishable products. The EWA policy informs of a new method to replenish perishable products. In contrast, previously, all products were replenished using the base (R,s,n,Q) policy, which missed the criticality of aging. Although the EWA policy is not directly applicable to the capstone project because of lack of data for relative outdating, inspiration from the policy to minimize the time produce spends in the supply chain is applicable.

Furthermore, Duan & Liao (2013) developed the old inventory ratio policy (OIR) to supplement a base order-up-to policy for short shelf-life products. Products are first replenished as per base order-up-policy. Then the percentage of old items on hand is calculated. Assumption is that old items are those with remaining shelf life of 1-3 days, but this can be altered on a case-to-case basis. If the proportion of old items on hand exceeds a predetermined threshold, additional replenishment is triggered to account for potential outdated products. Although this inventory policy incorporates freshness in the order-up-to date policy, the policy might not be suitable since data for old items on hand is required.

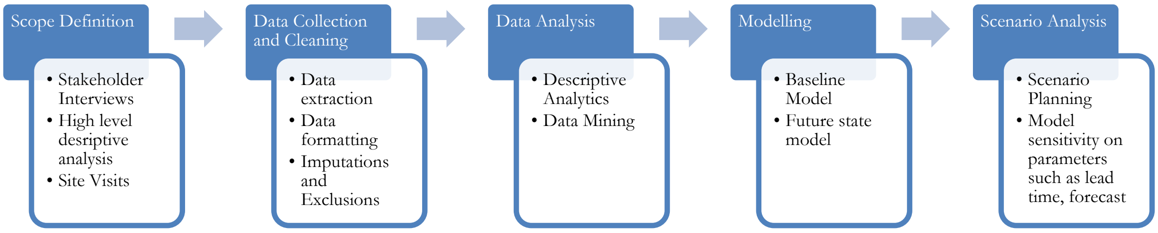
To conclude, this research has highlighted the consumer needs for fresher produce, the challenges faced by retailers to deliver fresher produce and finally the relevant research papers working on similar problems in the field of supply chain management. The capstone project uses this existing research as the bedrock and builds upon the it to evaluate the effects of daily shipment, consolidation centers and forecast accuracy on freshness.

3 Methodology

The overarching objective of this capstone was to strategically redesign supply chain components for perishable items like green salads, berries, and tomatoes. This initiative aimed to curtail discounting practices, reduce excess inventory, enhance freshness, and ultimately elevate the overall customer experience. To redesign supply chain operations, qualitative research based on stakeholder interviews and site visits was conducted. Descriptive analytics of the data was performed to understand best practices and identify drivers to increase freshness. Second, a list of mathematical models that quantify freshness, costs and relative outdating was prepared. Finally, research papers about improving the freshness of products using other methods apart from pick-to-zero or cross-docking strategies were analyzed. The core methodology consisted of five steps (see Figure 1).

Figure 1

Methodology steps



1. *Scope definition* – Define the scope of product categories, warehouse, supply chain network, constraints and understand company processes through site visits and stakeholder interviews to define the data elements required.
2. *Data collection and cleaning* – Gather required data elements, format, process and store in standard templates. Perform data analysis for missing data and corrupted data elements. Impute data elements for missing values and exclude data elements were not required.
    - Collect the data points captured in Figure 2.
    - Remove outliers. Outliers were removed using two methods.
        - Method 1 – Calculated interquartile range and removed left 25% and right 25% for data that are normally distributed.
        - Method 2 – Removed data based on anomalies explained by special events, as enlisted by capstone sponsor. For example, the days of Supply at store were ignored for specific periods of seasonal harvest where the specific SKU is available only one month of the year.
    - Impute data for missing data elements. Data were imputed based on mean of the dataset.
3. *Data analysis* – Analyze data to tie defined processes with actual practices followed. Enlist KPIs and current practices. Understand levels, variability and trends on the data provided by the company.
4. *Modeling* – Build a preliminary quantitative model based on maximum freshness and no additional capital and quantify costs and waste. In the second iteration, more constraints and cost-effective methodologies will be incorporated and the impact on freshness will be measured.
    - The first model is a discrete event simulation model based on demand forecasted between Oct 2023 and Nov 2023. The inventory position and costs will be estimated for the demand. Then, the actual sales will be run to check for model performance.

- In the second iteration, an upstream consolidation center may be considered to aggregate the demand such that daily full truckload shipments from suppliers to DCs are possible.

5. Scenario analysis – Perform sensitivity analysis based on different scenarios that impact freshness and costs when using a pick-to-zero model. Refer to section 4.5 for further details of each scenario.

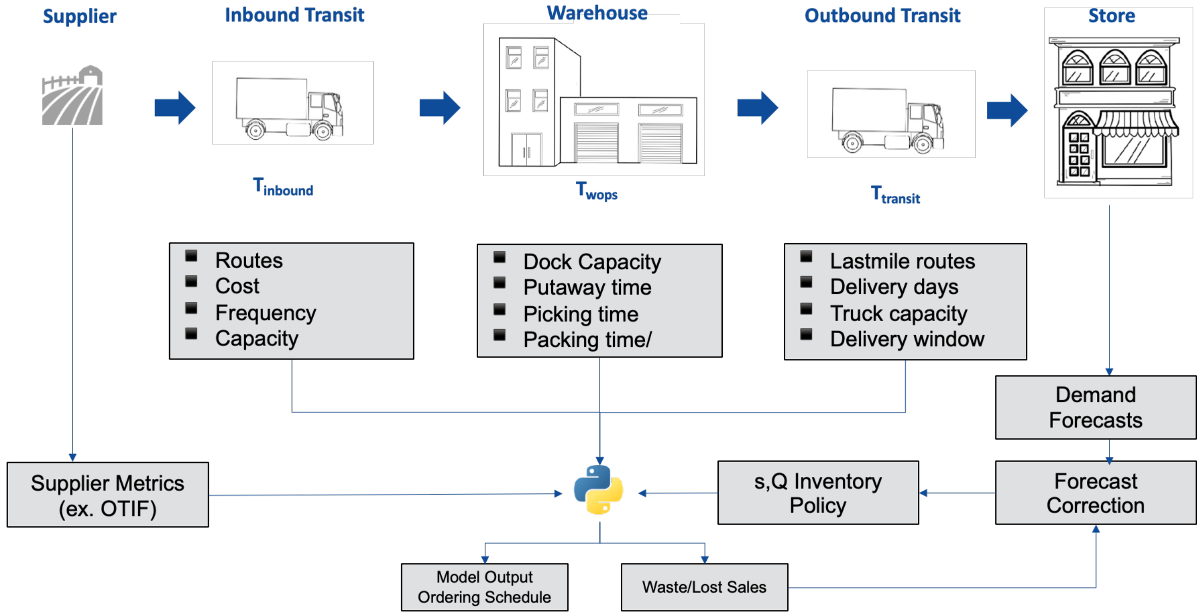
Based on the state of the practice, the pick-to-zero operations would require daily shipments from suppliers to DC and daily shipments from DC to stores to maintain consistent levels of freshness. Certain stores may not have enough daily demand to cube out each truck. Therefore, suppliers may not cube out each truck for daily shipments. This circumstance may require an upstream consolidation center to make the model cost-effective. A deep dive of the various components of the model is captured in Figure 2 in subsection 3.1.

3.1 Simulation framework

The objective was to measure the impact of freshness on time based on the product passing through multiple stages from supplier to store. Hence, the simulation model was built using Discrete Event Simulations (DES) in *SimPy*, as DES follows the process based on time-bound events. Figure 2 captures the various elements of uncertainty in the model to estimate freshness using DES. The model was developed by creating a system state for the current (as-is) process and future state, where pick-to-zero replaces the traditional stock-and-fulfill methodology. Figure 3 highlights the flow chart of operations for the system state.

Figure 2

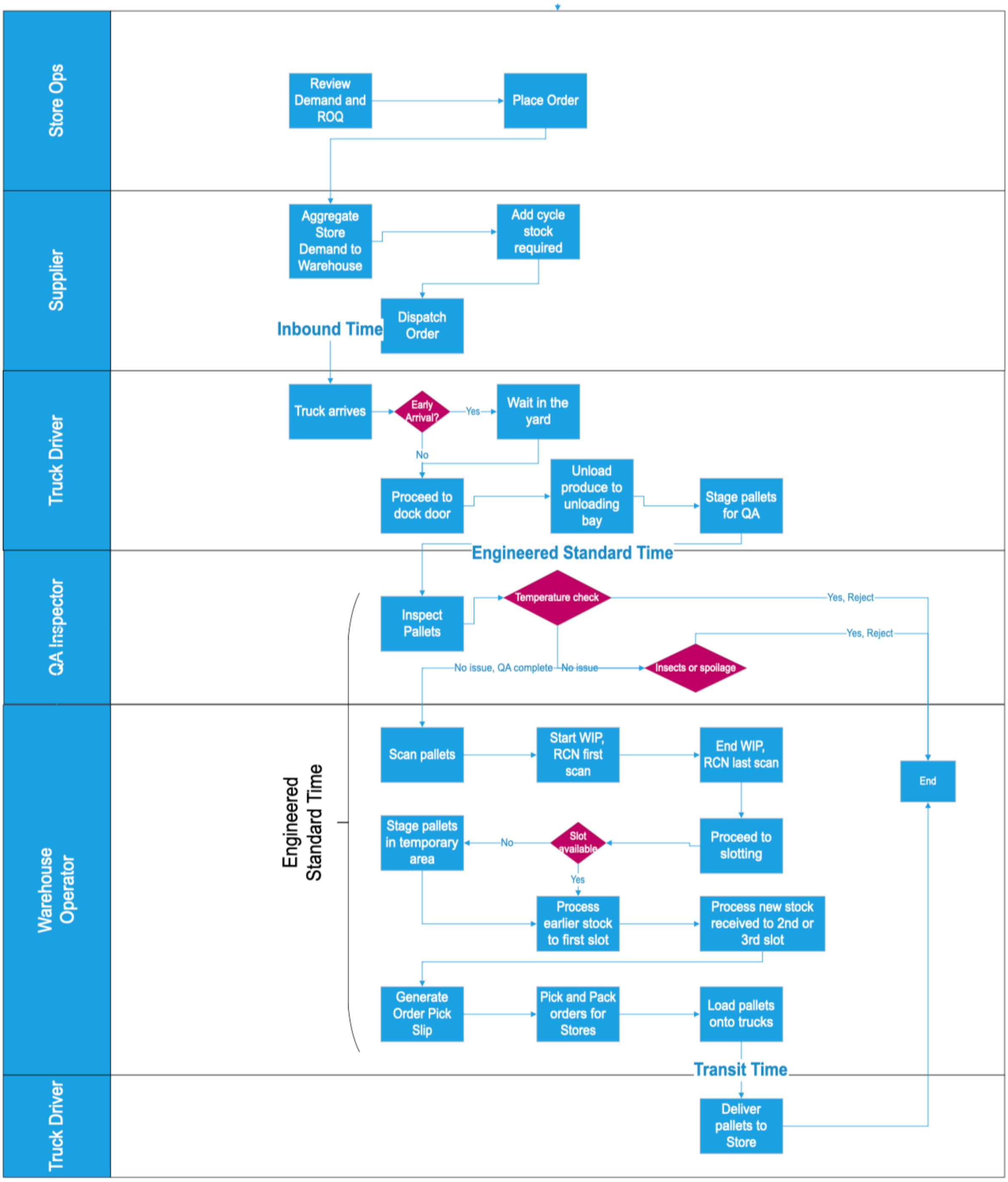
Perishable supply chain with pick-to-zero



Data Points		
Inbound	**DC**	**Outbound**
1. Supplier network 2. Delivery frequency 3. Transportation cost/route 4. On-Time and in-full (OTIF) 5. Quality rejection rate	1. Appointment for arrival time 2. Picking efficiency 3. Labor costs 4. Putaway efficiency 5. Outbound dispatch	1. Store network 2. Store demand per SKU 3. Delivery frequency 4. Transportation cost/route

Figure 3

Process to receive loads, process pallets to slots inside warehouse



3.2 General model considerations

The simulation model was built considering specific scenarios the capstone sponsor wanted to evaluate. The simulation was needed to study the effect of the pick-to-zero strategy given the uncertainties in the supply chain. If all the network components were deterministic, a simple addition of the time taken for each process to move inventory from suppliers to customers would suffice.

However, the uncertainties in the model were introduced at each node of the network based on factors that influence the processing times significantly. The uncertainties and nodes of the supply chain change for each scenario being evaluated. However, certain components remain consistent across all scenarios:

1. *Product categories and SKUs* – Three product categories were selected for testing the model: Tomatoes, Berries, and Bagged Salads. These categories were selected based on their unique supply chain networks and methods to measure product age. Bagged salads are provided with expiry dates by the vendors. Therefore, the remaining shelf life (i.e., freshness) can be measured as the number of days available to the consumer before expiry. However, berries and tomatoes do not have an expiry date; instead, vendors provide the packed date on the cartons. The packed date provides a method to measure the number of days spent in the supply chain network before receiving at the DC. Therefore, freshness for berries and tomatoes was measured by the total time spent in the supply chain from vendor dispatch to store receipt. Each commodity has multiple SKUs. Universal Product Code (UPCs) were used instead of SKUs for the simplicity of model evaluation, and a one-to-one association between UPCs and SKUs was assumed. When considering a unified method to measure freshness across all commodities, Eq. (3) from section 3.3 was used, as the equation captures the total time spent in supply chain. This metric works on all types of commodities as it evaluates the key time-consuming activities all the way from supplier to customer at the store.
2. *Supplier metrics* – Suppliers across the three product categories are located all over the U.S. Certain suppliers who supply berries have multiple sites across the country. Each site fulfills specific SKUs and caters to different seasons. As seasons change, the growing regions switch. Therefore, the location of the supplier creates uncertainty with respect to the travel times from supplier's facility to distribution centers. In a pick-to-zero model, the size of shipments is smaller and more frequent. To emulate a just-in-time approach, the dependence on the smaller but more frequent shipments is high. If shipments are missed, delayed or encounter quality issues, the impact of produce delivery to stores is significantly adverse. Therefore, Fill Rate, On-Time-In-Full (OTIF) and Quality rejection rates were incorporated into the model.
3. *DC warehouse operations time for the pick-to-zero strategy* – The operations are split in two:
   i. Current state – The total warehouse processing time (T_{wops}) for the current state is based on the days of supply held within the warehouse. The inventory is fulfilled to the store using a FIFO withdrawal policy. Therefore, the products are cycled through the warehouse while maintaining a constant cycle and safety stock. The days of supply are tracked in the warehouse

management system (WMS) and are assumed to be the number of days required to process a product when received from the vendor to outbound transit to stores.

ii. Future state – The total time required to process cases in a true pick-to-zero operation is less than 24 hours. The total time required to process produce was split into three events.

Event 1 – Truck inbound receipt, quality check, slotting and put away

Event 2 – Picking

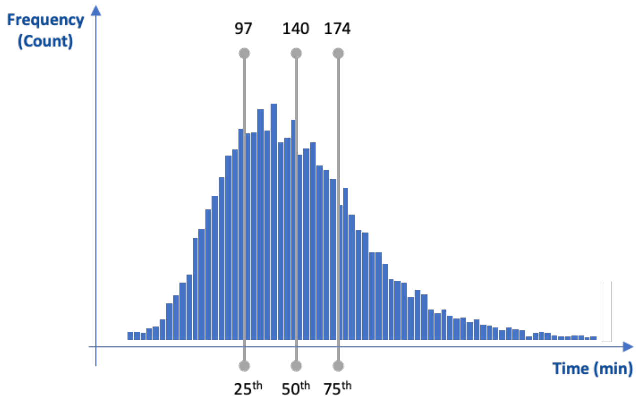
Event 3 – Loading onto trucks.

The enterprise systems captured data on each event for the three product categories in scope. The times for each activity were plotted and times were recorded for 25th and 75th percentile of the distribution. Combining the interquartile range of the three events is the total window of operation for a pick-to-zero approach without operational changes, including automation. Figure 4 captures the window of operation considered for the pick-to-zero strategy.

Figure 4

Pallet scanning and slotting time distribution

First pallet scan – Last pallet scan (By Minutes)



When produce is received at the warehouse, after inspection the first step to scan the inventory into the system starts with the first pallet scan. Here, operators scan each of the cases and check the inventory into the system. Once all pallets of a specific shipment are scanned and slotted, the operator closes the receiver notice with the last pallet scan. Thus, the total time between unloading and slotting is represented by the difference in the first pallet scan and the last pallet scan. The plot of the receiver scan forms a normal distribution. However, some data points represented early arrivals or late arrivals of trucks. The truck arrivals, as a source of uncertainty, is already handled in the model. Therefore, adding the outlier data would double count the uncertainty. Hence, the interquartile range was used to use an acceptable range of receiving times for same type of shipments.

4. *Demand forecast and aggregated demand* – A critical consideration in the model is the forecast for each SKU and store. Units were forecasted by an advanced planning (APS) software for each SKU and store by date for October 2023. However, the forecasts were not generated to the normal distribution, i.e., with a mean and standard deviation. The forecast appeared to already factor in a safety stock (Figure 4). To identify the mean forecast and standard deviation, we follow the steps shown below.

   i. Forecasts were generated using a technique moving average; refer to Table 2 below for example. For each forecast date, the system generates forecasts starting 35 days out. To forecast for SKU and Store on 15th October 2023, forecasts were generated daily between 1st October 2023 and 15th October 2023. In the model, the cycle date (generated date) of the forecast date minus the vendor lead time. Vendor lead time was defined as the minimum vendor lead time to place an order and receive the shipment into a warehouse. For example, if a vendor takes five days to ship orders from when an order was received and another two days in transit, minimum vendor lead time is seven days. The units forecasted for October 15, 2023 were considered based on the cycle date (i.e., day forecast was generated) of October 8, 2023.

   Table 1

   Forecast for UPC 1 for October 15, 2023

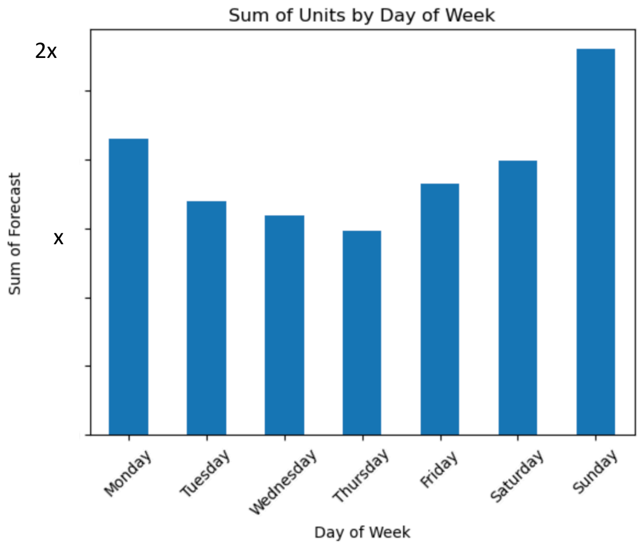
store	cons_upc	cycle_date	forecast_date	forecast
Store 1	UPC 1	20231001	20231015	0.395
Store 1	UPC 1	20231002	20231015	0.396
Store 1	UPC 1	20231003	20231015	0.366
Store 1	UPC 1	20231004	20231015	0.361
Store 1	UPC 1	20231005	20231015	0.372
Store 1	UPC 1	20231006	20231015	0.608
Store 1	UPC 1	20231007	20231015	0.467
Store 1	UPC 1	20231008	20231015	0.552
Store 1	UPC 1	20231009	20231015	0.846
Store 1	UPC 1	20231010	20231015	0.886
Store 1	UPC 1	20231011	20231015	0.193
Store 1	UPC 1	20231012	20231015	0.184
Store 1	UPC 1	20231013	20231015	0.168
Store 1	UPC 1	20231014	20231015	0.553
Store 1	UPC 1	20231015	20231015	1.254

   ii. Due to the small dataset of one month of forecast and sales data, the entire sample could not be used for measuring forecast error. If the entire sample data is used for estimating forecast accuracy and then re-used in simulation, there could be a high chance of data leakage. Therefore, standard deviation was calculated using the forecast and actual sales for the first 15 days of October 2023.

iii. When the sales volume for each SKU was plotted by day of the week, a clear pattern was observed, in which a peak was observed on Sunday, with volumes decreasing throughout the week and increasing again on Friday and Saturday (Figure 5). Then, the standard deviation was calculated for the day of the week for each SKU and Store.

Figure 5

Sum of units sold by day of week



iv. A cycle service level of 95% was assumed for supply planning based on a study by Broekmeulen & Van Donselaar, 2009. From the forecast, 1.64 standard deviations were subtracted to isolate the mean demand. The actual vs. forecast after reducing standard deviations was visually compared and accepted.

5. *Forecast correction* – Forecasts were generated based on historical data. However, if units shipped to the store exceeded forecast units, the excess had to be accounted for in the inventory being shipped the next day. The excess units were cycled through the stores and only forecast minus excess units were shipped from the warehouse.
6. *(s, Q) inventory policy* – Inventory required at the warehouse was calculated based on the continuous review (s, Q) policy with a 95% cycle service level (CSL). This service level is common in the grocery sector (Broekmeulen and Van Donselaar, 2009). In the current state, safety stock is stored within the warehouse. In the future state, the safety stock is shifted to the stores, leaving no inventory in the warehouse after the pick-to-zero strategy is deployed.
7. *Inbound and outbound transportation routes* – In the simulation model, route optimization was not performed for inbound and outbound loads to stores. Loads were assumed to be sent on individual trucks from vendors to DC and DC to store.

Using the considerations described above, quantitative functions were developed to assess performance of the simulation. The three core functions are freshness, cost (including operations and logistics) and excess inventory.

3.3 Quantitative functions of the simulation model

Freshness – The intuition behind the freshness equation is that a product's shelf life decreases not only during transit from vendor to store but also at the store when not sold. If excess units are shipped to stores, the produce would age at the store until sold. For instance, on day one, 10 units are shipped to the store with a seven-day remaining shelf life (RSL) and 2 units are unsold. All the produce are aged at seven days on average. The next day, 8 units are shipped with seven days of RSL. The blended average age would be based on the following function: [(7 days – 1 day) X 2 units and 7 days X 8 units]. If the shipment does not arrive the next day, the unsold product will age the number of days until next shipment. The inspiration to measure freshness as a function of shelf life at harvest minus total time spent in supply chain was from Broekmeulen & Van Donselaar (2019) as given in Equation 1. However, without relative outdating or fill rate data available for considerations, the equation was modified.

Salad Mix – Remaining Shelf Life in number of days available to the customer before expiry using Equation 2.

$$\frac{\left(\kappa - T_{wops} - T_{transit}\right) * I_t + \left(\kappa - T_{wops} - T_{transit} - n\right) * (I_{t-1} - D[i]_{t-1})}{D[i] + (I_{t-1} - D[i]_{t-1})} \tag{2}$$

Berries and Tomatoes – Freshness based on reducing the total time spent in supply chain until receipt at the store using Equation 3.

$$\frac{\left(\gamma + T_{wops} + T_{transit} + T_{inbound}\right) * I_t + \left(\gamma + T_{wops} + T_{transit} + T_{inbound} + n\right) * (I_{t-1} - D[i]_{t-1})}{D[i] + (I_{t-1} - D[i]_{t-1})} \tag{3}$$

Where,

$\kappa = Remaining\ Shelf\ Life\ when\ received\ at\ DC$

$\gamma = Total\ time\ spent\ from\ harvest\ till\ dispatch\ from\ supplier's\ facility$

T_{wops} = $Warehouse\ operations\ time,$

$T_{transit}$ = $Warehouse\ to\ store\ delivery\ time,$

$T_{inbound}$ = Vendor to warehouse $delivery\ time,$

$D[i]_{t-1}$ = $Demand for\ previous\ day,$

$D[i]$ = $Demand\ for$ current time period t,

$n = Number\ of\ days\ before\ next\ shipment\ to\ store,$

I_t = $Inventory\ on$ hand $for\ time\ t,$

I_{t-1} = $Inventory$ on hand $for\ previous\ day,$

Equation 3 represents a better method for estimating the freshness of produce as it incorporates event times all the way from the supplier to the end customer. Strategically, the estimation using equation 3 provides more control over the process improvements in each node of the supply and the ability to measure its impact. The result of the freshness formula is number of days spent in supply chain. Dimension analysis of Equation 3 is calculated below:

$$\frac{Days * \cancel{Units} + Days * \cancel{Units}}{\cancel{Units}}$$

$(\gamma + T_{wops} + T_{transit} + T_{inbound}) - Days$
$(I_{t-1} - D[i]_{t-1}) - Units\ (Eaches)$
$I_t - Units\ (Eaches)$
$D[i] + (I_{t-1} - D[i]_{t-1}) - Units\ (Eaches)$

Labor cost – The capstone sponsor has an incentive-based pay structure for the warehouse operators. The baseline pay is decided based on the number of hours worked per operator and a flat hourly pay rate. In the incentive-based pay, the warehouse operator is given a pick slip with a calculated time for the total time to complete picking (Engineered Standard Time). If the operator completes the pick under the Engineered Standard Time, the pay will be based on an incentive rate multiplied by the number of minutes spent in the picking activity. The greater of the two costs is selected for the operator pay. Equation 4 captures the cost structure for calculating labor costs.

$$C_{ops} = W_{opr} * max\left(\sum \left(\frac{\tau}{\nu}\right) * D[i] + \tau * T_{inb} , \sum \rho * EST_t * O_t \right) \quad (4)$$

$Where,$
$D[i] = Demand\ per\ SKU\ per\ store,$
$T_{inb} = Total\ inward\ time\ in\ hours,$
$q_{case} = Units\ per\ case,$
$\tau = Operator\ Salary\ (\frac{\$}{hr}),$
$\rho = Dollars/min$
$EST_t = Engineered\ Standard\ Time\ (minutes) per\ order,$
$O_t = Orders\ per\ day,$
$W_{opr} = Number\ of\ warehouse\ operators$
$\nu = Operator\ pick\ rate\ (\frac{cases}{hr})$

Cost for Inbound and Outbound Trucks – Inbound and outbound transportation costs are based on the number of trucks being used daily. The number of trucks will depend on the volume and frequency of shipment. A key assumption is that a full truckload can hold 24 pallets. The number is based on historical truck fill rates observed by the capstone sponsor. Equation 5 captures the number of pallets required per order, per SKU for time period t. Based on the value from equation 5, the inbound and outbound costs are calculated based on the number of trucks required using equation 6.

$$Q_{plt} = \sum_{t}\sum_{s}\frac{D[i]}{TI * HI * q_{case}} \quad s \in SKUs,\ time\ period\ t \tag{5}$$

$$C_{inb/oub} = \sum C_{tl} * n \quad \forall\, D[i] > 0 \quad s.t. \quad n = \begin{cases} Q_{plt} > 24, & roundup(\frac{Q_{plt}}{24}) \\ Q_{plt} \leq 24, & 1 \end{cases} \tag{6}$$

$where,$
$Q_{plt} = Quantity\ per\ Pallet,$
$D[i] = Demand\ per\ SKU\ per\ store,$
$C_{tl} = cost\ per\ truck\ for\ forehaul,$
$q_{case} = Units\ per\ case,$
$n = number\ of\ trucks\ per\ day$
$TI = Quantity\ per\ Layer,$
$HI = Layers\ per\ pallet$

Excess inventory – Generally, waste is defined as the amount of inventory disposed of due to outdating. When produce ages at the store and customers do not purchase the product within the set expiry date, the inventory would be discarded. For the scope of this project, rather than studying impacts to waste, the effects of excess inventory were studied. Due to the lack of customer data, there was no accurate way of capturing the expiry date of the produce being sold. Instead, the excess is defined as the amount of inventory held at the warehouse and store in addition to the required inventory to fulfill the demand for a particular day. The focus was to minimize the excess inventory, reduce waste and then stock inventory to a higher service level, such as 90%, to meet uncertainties in demand. Equation 7 represents the excess inventory calculation.

$$e_{inv} = \sum_{t}\sum_{s}\frac{c * q_{case} - S[i]}{S[i]} \quad s \in SKUs,\ time\ period\ t \tag{7}$$

Where,
$q_{case} = Units\ per\ case,$
$c = number\ of\ cases\ per\ day$
$S[i] = Sales\ per\ SKU\ per\ store$

For the purpose of comparison between current state and future state, the main activity drivers were compared rather than calculating actual value for each metric. Table 4 summarizes each metric, activity and driver using an activity-based costing framework. The purpose of the simulations is to evaluate key performance indicators (KPIs) of the business as per current state and future state (with pick-to-zero). To effectively measure performance of the two models, KPIs were defined for freshness, cost and waste based on drivers of each measure.

Table 2

Cost drivers for key activities

SL #	*Metric*	*Activity*	*Key Driver*	*Driver Unit*
1	*Freshness – Salad Mix*	*Remaining shelf life when shipped from vendor minus series of events/stages through which product reaches the store.*	*Total time available to the customer before the product expiry.*	*Remaining Shelf Life (Days)*
2	*Freshness – Berries and Tomatoes*	*Remaining shelf life when shipped from vendor minus series of events/stages through which product reaches the store.*	*Total time spent by product in the supply chain before reaching the customer.*	*Total Time Spent in supply chain (Days)*
3	*Warehouse Operations Cost – Refrigeration Cost*	*Truck arrival at the DC and waiting time before unloading. Ignoring the effect of additional refrigeration required when the truck waits to be served.*	*Time taken until dock door assignment.*	*NA*
4	*Warehouse Operations Cost – Unloading*	*Receiving produce from vendors. It is the labor cost based on time spent.*	*Time taken to unload pallets from the truck.*	*Cases/hour*
5	*Warehouse Operations Cost – Quality Inspection*	*It is the labor cost based on time spent for Quality inspection.*	*Time taken to inspect pallets.*	*Hours/ inspection*
6	*Warehouse Operations Cost – Slotting and Putaway*	*It is the labor cost based on time spent for Slotting and Putaway.*	*Time taken to scan pallets and putaway operations.*	*Cases/hour*
7	*Warehouse Operations Cost - Picking*	*It is the Labor cost based on time spent for Picking and loading for outbound delivery.*	*Time taken to prepare orders.*	*Cases/hour*

4	*Inbound Transportation*	*Number of trucks arriving from vendors based on volume and delivery frequency. Cost incurred is a flat rate charged by carriers per mile for the forehaul + backhaul.*	*Cost per mile travelled by all trucks over time from vendors.*	*Miles traveled*
5	*Outbound Transportation*	*The number of trucks departing DC to individual stores. Cost incurred is a flat rate charged by carriers per mile for the forehaul + backhaul.*	*Cost per mile traveled by all trucks*	*Miles traveled*
6	*Waste*	*Excess units left at the store and the product ages before the customer can purchase.*	*Total excess units left at the end of the period.*	*Units*
7	*Forecast Accuracy*	*NA*	*The deviation of the forecast from the actual sales*	*A/F Ratio*

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In order to measure process improvement initiatives, KPIs and cost drivers need to be defined clearly. Once metrics and measurement units are defined, the current state and future state can be compared on similar terms to arrive at a conclusion of whether the proposed future state process yields better results. A key aspect of measurement is the inventory levels between current state and future state. If the absolute value of inventory movement through the process is the same between current and future state, the comparison would primarily be between the number of touchpoints. However, the hypothesis is that, with a lower lead time, due to more frequent deliveries and continuous review of inventory, the amount of inventory held in the system could be lowered with pick-to-zero and drive towards a Just-In-Time system. Section 3.4 captures the key considerations for inventory calculation.

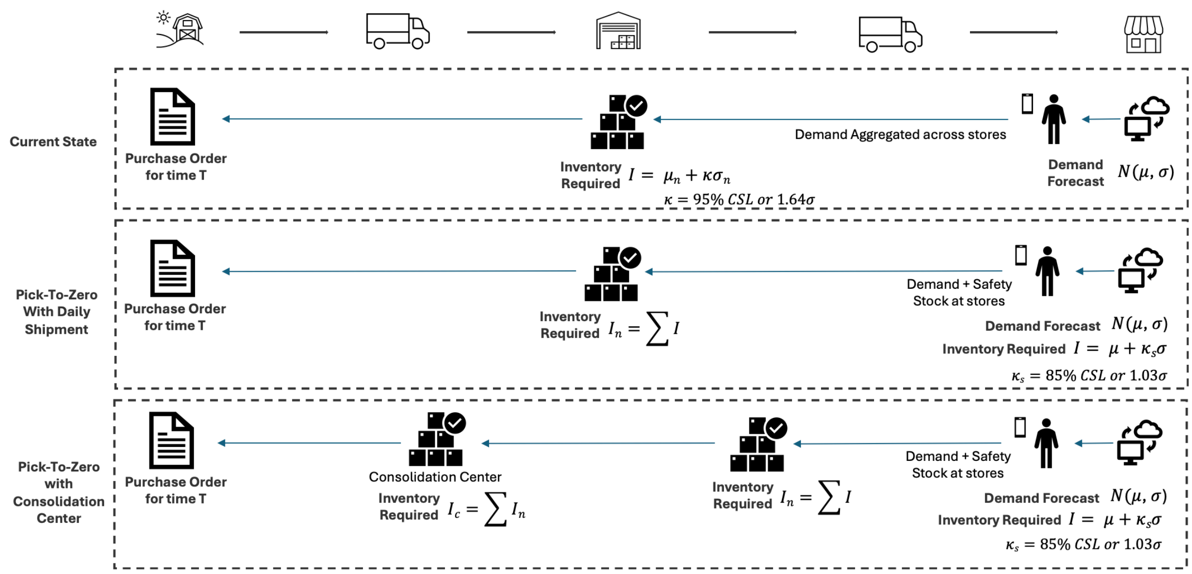
3.4 Inventory calculations

In the current state process, inventory at the store is determined by store managers, who review the forecasts generated for a particular SKU. Based on a quick inventory check at the store and intuition (i.e., experience), the store managers place the store orders, to be fulfilled by the distribution centers. At the distribution center, orders are picked-by-voice through waves generated by the WMS. However, buyers do not directly use the forecasts generated at the stores to replenish the warehouse. They use the warehouse's historical order data for a specific SKU. The disconnect between the store orders and warehouse replenishment orders creates a mismatching in the process that should be analyzed with a discrete event simulation as the timing and factor of one event must lead to the next event to create a continuous workflow.

The capstone sponsor is parallelly working on an initiative to use store forecast data to determine the right amount of inventory required by connecting the forecast and advance planning models. Using this approach, the baseline inventory model was set to a continuous review policy with a fixed re-order point and a cycle service level. Broekmeulen, et al. (2009) considered 90% to 98% a reasonable service for perishable products. In the current state, where safety stock is maintained within the warehouse, the demand is aggregated across multiple stores and a 95% cycle service level (CSL) or 1.64 standard deviations from the mean is taken as the upper limit. In the future state with a pick-to-zero approach and daily shipments, the safety stock moves from the warehouse to the stores with a 95% CSL. However, with a lower lead time the service level can be reduced given that inventory is replenished more frequently. Therefore, the pick-to-zero strategy with daily shipments uses an 85% CSL at the store level. The pick-to-zero approach along with a consolidation center uses 85% CSL at the store and no safety stock at the consolidation center. Demand is aggregated across three distribution centers and 300 stores. Figure 6 summarizes the three approaches.

Figure 6

Inventory calculation method for current state and two future states



The model was built based on the following assumptions:

1. The demand is assumed to follow a normal distribution with a fixed mean and standard deviation. Forecasting will not be performed. The model will be run on forecasts and evaluated against actual sales over one month, starting October 2023.
2. The demand is independent and identically distributed.
3. Orders from suppliers can only be made in multiples of case sizes provided by the supplier for each SKU.
4. Inventory policy is based on a continuous review policy with FIFO withdrawal (Broekmeulen and Van Donselaar, 2009). The effects of LIFO were not studied as the intent of the research is to improve freshness delivered to the end customer by reducing time spent in supply chain. With the use of a LIFO policy, a certain percentage of the inventory that was received the earliest would age more than the newer inventory.
5. Productivity and rates will be constant across product categories and SKUs. Individual SKU productivity and rates can be ignored.
6. For the scope of this study, the effects of forecasting, scheduling and route optimization, supply chain network design and picking process were not considered in the model.

Based on the methodology defined, the possible future state and current state were compared using key business scenarios. The scenarios mimic real-world operations and aim to analyze conditions that need to be true for a pick-to-zero strategy to work. Section 3.5 details the 5 key scenarios analyzed and considerations under each scenario.

3.5 Scenario analysis

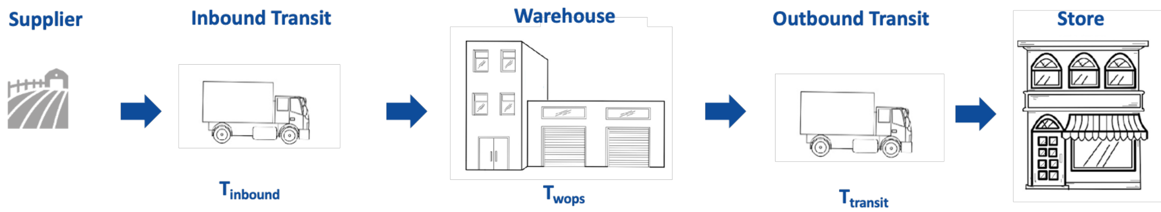
Scenario analysis is a vital component of simulation analysis. Each scenario helps the capstone sponsor understand risks in switching to pick-to-zero and plan for reducing uncertainties by considering multiple future states. Each scenario analyzed in section 3.5 was motivated by key business drivers. Scenario 1 focuses on improving freshness to the highest possible with pick-to-zero, to provide the best customer satisfaction. In Scenario 2, a consolidation center was introduced to drive operation excellence and bring costs down compared to Scenario 1, while maintaining a higher level of freshness. Scenario 3 was developed to understand the impact network design on freshness, without diving deep into an optimization model. Through all the potential changes with a pick-to-zero, a crucial consideration is that each node of the network has sufficient capacity to process goods faster. Scenario 4 was developed to test the capacity hypothesis and analyze potential bottlenecks. Finally, the key driver of uncertainty from the customer is the demand. In a deterministic world, pick-to-zero could be implemented across all commodities. However, forecast accuracy plays a crucial role in maintaining a lean but quick supply chain. Scenario 5 captures the performance of pick-to-zero for a range of forecast accuracy and measures which types of commodities could be best suited for a pick-to-zero model.

3.5.1 Scenario 1: daily inbound and outbound shipments with a pick-to-zero strategy

In the first scenario, improving freshness was explored by introducing daily shipments from vendors to DC and daily shipments from DC to Stores. Figure 7 illustrates the movement of produce through the supply chain network for Scenario 1.

Figure 7

Daily shipment of produce from vendors to DC, and daily outbound shipments from DC to stores.

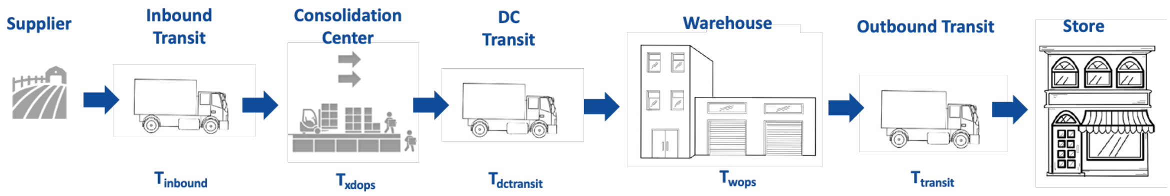


3.5.2 Scenario 2: daily inbound shipments via consolidation center, with pick-to-zero strategy at DC and cross-dock at consolidation center. Outbound shipments as per store delivery schedule.

Daily shipments from vendors and from DC to the stores increases produce's freshness. However, the hypothesis is that the increase in costs would be significant as trucks may not be filled completely. To overcome the excessive number of less-than-truckload trips and increase in miles travelled, the hypothesis is that a consolidation center that aggregates the cargo for multiple DCs could be beneficial. Scenario 2 introduced a consolidation center between the vendor and DC. The consolidation center will serve as a pooling location for two other warehouses of similar volume and size as the DC in scope of this project. The three warehouses combined serve 300+ stores. Vendors ship produce to the consolidation center, which is assumed to operate as a cross-docking facility. Pallets are then shipped from the consolidation center to the DC, and from DC to store. The consolidation center can aggregate inventory, ensuring trucks can be cubed out. The location of the consolidation center is not fixed in Scenario 2. The impact of location was explored in Scenario 3.

Figure 8

Daily shipment of produce from vendors to DC through consolidation center, and daily outbound shipments from DC to stores.



3.5.3 Scenario 3: impact based on consolidation center location.

The freshness of the produce is dependent on the number of transit stages from vendor to store. As the number of stages increases, the amount of time spent in the supply chain increases. Therefore, selecting the consolidation center and the supply chain network design are strategic decisions for freshness improvement. This capstone project explores three options to locate the consolidation center:

Option A) Third-party logistics owns a consolidation center in the "target market".

Option B) Owned consolidation center upstream (i.e., closer to suppliers).

Option C) Owned consolidation center by converting current DC into a consolidation center.

3.5.4 Scenario 4: potential bottlenecks in warehouse operations due to capacity constraints.

The infrastructure in the warehouse has been designed to operate as per the current delivery schedule and volumes. When the delivery schedule from suppliers is changed from four days a week to seven days a week, the volume per shipment would be reduced. However, the number of trucks is expected to increase. The DC operates fresh produce out of 35 dock doors. The hypothesis is that the increase in the number of trucks may create a backlog in the yard for the trucks. Trucks are assigned a dock door on arrival, with an average of 1.5 trucks being processed per dock door per hour. The arrival of trucks in the simulation was modeled based on the distribution of appointment times, observing peak between the 8^{th} and 9^{th} hour of the day (midnight corresponds to the 0^{th} hour). Automation in unloading and slotting can reduce the truck processing times and unlock additional dock capacity.

3.5.5 Scenario 5: forecast accuracy impact on pick-to-zero strategy in DC.

The sponsor company's desire to implement pick-to-zero is to deliver enhanced freshness. However, doing so at the cost of lost sales is an infeasible proposition. Currently, our sponsor company has a budgeted shrinkage percentage (assume a%) due to product expiration across the three product categories in scope. Hence, it can only sell (100-a)%, leading to a loss of sales of a%. These lost sales are caused by inventory holding, leading to the product freshness deterioration. A pick-to-zero strategy will eliminate excessive inventory holding and consequently the loss of sales due to freshness deterioration. However, the pick-to-zero model may introduce lost sales due to reduced safety stock. For the pick-to-zero model to be feasible, lost sales with this approach need to be less than or equal to lost sales with the current model. In the pick-to-zero model, products are reordered based on forecasts. As a result, forecast accuracy is instrumental in ensuring a lost sales factor of less than a particular threshold.

To further understand forecast accuracy, the study leveraged actual sales and forecasted demand data from the sponsor company, spanning four weeks from October to November 2023. Daily forecasts were generated, each aimed at predicting the actual demand for a specific SKU on a forthcoming date. For instance, forecasts were made on October 1st, 2nd, 3rd, and so forth, up to the 15th, each predicting the demand for the 15th. This approach allowed us to assign a "lead" value to each forecast, indicating the number of days in advance a forecast was made; for example, a "lead = 0" means a forecast made on the same day, while "lead = 8" denotes a forecast made eight days prior. This methodology enabled a nuanced forecast accuracy analysis as the lead time approached zero. For the forecast analysis, lead = 8 day: this is a reasonable estimate since freight takes at a maximum three days to travel from the furthest supplier's location to DC's location.

To analyze the forecast accuracy, the metric 'Actual to Forecast Ratio' is used. A/F ratio = Actual Sales/Forecasted Sales. In addition to indicating a forecast's accuracy, this ratio also provided a second dimension which helped in understanding excess or stockout events. For example, an A/F ratio of 1 indicated that the forecast was 100% accurate. An A/F ratio greater than one, for example 1.2, indicated that the actual sales were 20% more than forecasted. An A/F ratio less than one, for example 0.8, indicated that the actual sales were 20% less than forecasted. Assuming that there is no safety stock in the system and stores are replenished using forecast values. A/F ratios greater than 1 indicate stockout events and ratios less than one indicate a buildup of excess inventory. By integrating the forecasted and actual demand data into a singular dataset, the model computed the Actual to Forecast (A/F) ratio for various SKUs having a lead = 0 and a lead = 8, providing a granular view of forecasting accuracy.

To analyze the scenarios in section 3.5, the simulation model compares current-state process (baseline) with future-state process (pick-to-zero). Detailed comparisons and results are presented in section 4.

4 Results

This section summarizes key results from the model as per defined metrics in Table 3. Results have been broken down by product category and scenario. However, for the sake of space, only a few product categories and scenarios are presented. The hypothesis that a pick-to-zero strategy can improve the freshness of produce was backed by a “first principles” approach initially. Currently, produce items are stored within distribution centers as cycle stock and safety stock. If two days of supply are stored within the warehouse, this means the product will take roughly two days to cycle through the warehouse and reach the stores. In a pick-to-zero approach, the two days are reduced to zero, thereby increasing freshness. However, in the pick-to-zero model, if inbound and outbound operations are not changed but the produce is cycled through the warehouse on the same day, the safety and cycle stocks would just be moved from the warehouse to the store. Instead of aging at the warehouse, the produce would age at the stores, offering no freshness improvements to customers.

The inbound and outbound operations were changed to daily shipments to overcome the aforementioned effect. Receiving produce daily and shipping it out daily to stores, the safety and cycle stock requirements were lowered as the review period and lead time were reduced. Therefore, the daily shipments yielded the greatest improvement in freshness, as high as 30% for some SKUs compared to the current state. However, the inbound costs increased by 35% as all vendors do not ship daily in the current state. The outbound logistics costs increased by 20%, as stores that are not receiving shipments daily would be receiving shipments all seven days of the week.

The high total costs can be attributed to high logistics costs and inefficiencies due to incomplete truckloads, thereby increasing cost per case. To overcome the high logistics costs, a consolidation center was introduced. The consolidation center acts as a cross-dock location where multiple vendors can ship full truckloads, and pallets are then transferred to multiple distribution centers located around a specific region. The distribution center then fulfills orders to stores. By aggregating demand across three distribution centers and ~300 stores, the forecast is smoother and safety stock can also be consolidated for multiple facilities by square root law of inventory. Using the consolidation center at a strategically placed location, the freshness can be improved by 10% while reducing costs by 6% compared to daily shipments without consolidation center.

Given that the model does not hold any safety stock at regional distribution centers, forecast accuracy is instrumental in preventing excessive inventory build-up at the store, which degrades freshness, and lost sales events due to stock-outs, which affects company revenues. The analyses further delve into understanding forecast accuracy and variability for different commodities and their

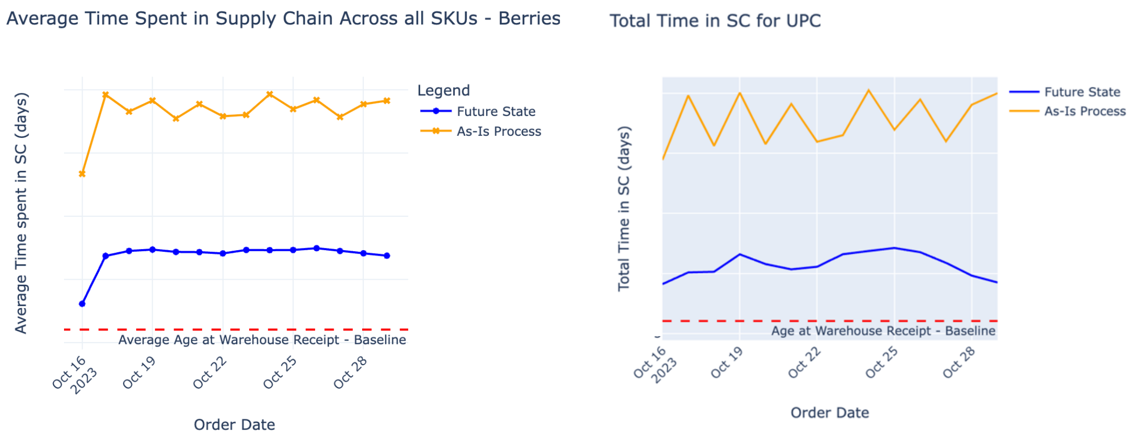
SKUs. Through the analyses, the capstone project identifies characteristics of the SKU, which are most suitable for pick-to-zero models.

4.1 Scenario 1: daily inbound and outbound shipments with a pick-to-zero strategy

Pick-to-zero strategies with daily shipments yield a 25% increase in the freshness for berries. In the current state, across the berries, the warehouse's supply days vary between 1.5 and 2 days. Most vendors of blackberries, strawberries and blueberries supply four days of the week and a few supply three days of the week. In future state, berries are cycled through the warehouse within 8-12 hours and vendors ship all seven days of the week.

Figure 12

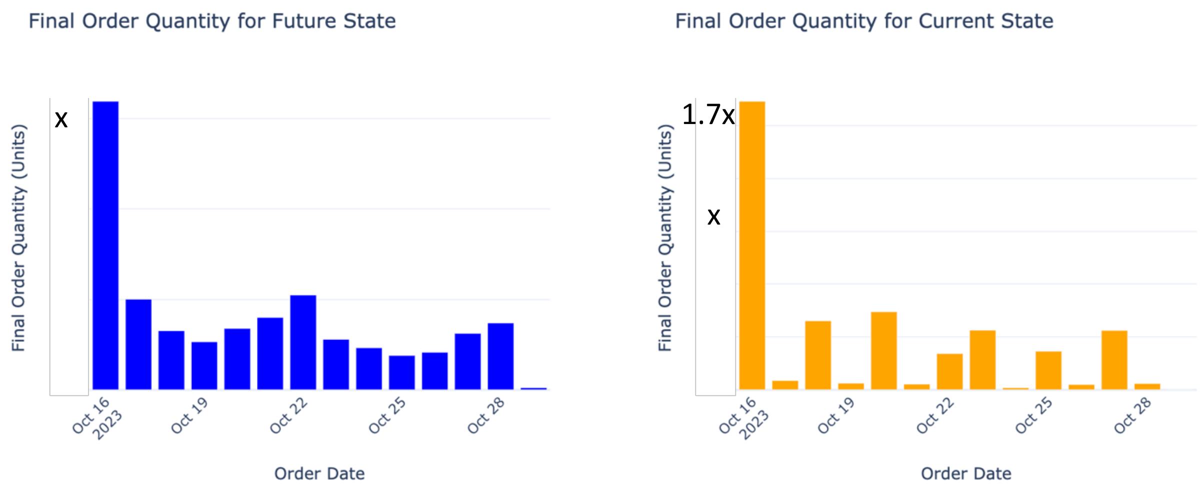
Freshness comparison for berries



Inventory ordered from vendors per day reduces by 22%, owing to daily shipments from vendors. In the current state, order quantity is consolidated for the four days delivered per week; therefore, trucks are cubed out. In the future state, the quantity is ordered irrespective of the truck fill rate. This reduces the quantity ordered, but the ordered quantity variability also reduces over the days.

Figure 13

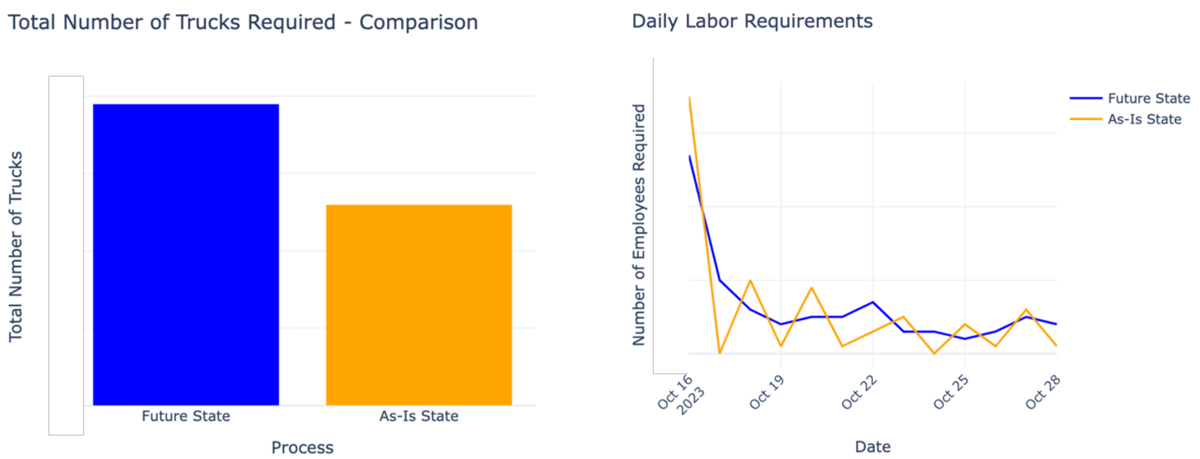
Inbound inventory comparison for berries



The number of trucks required increases by 50% with daily shipments. The total labor required increases by 25% over time. However, the variability in labor needed per day reduces. This result is particularly useful in better planning labor requirements.

Figure 14

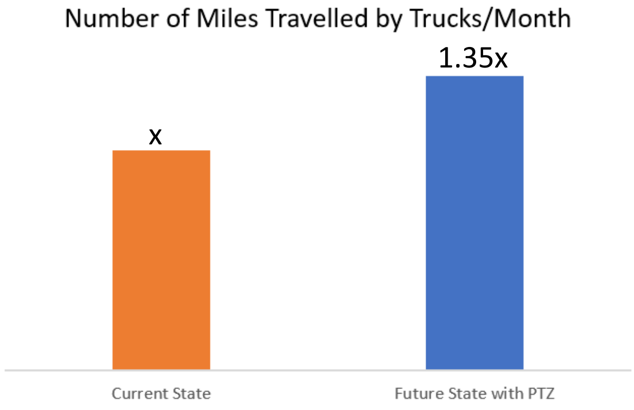
Truck and labor comparison for berries



For a supplier that is currently shipping on a three day schedule, increasing the number of shipments to seven days a week almost doubles the number of miles traveled. In the current state, the supplier ships three days a week due to the low volume. Consolidating three days a week allows the supplier to cube out the truck on most occasions. In the future state, with daily shipments and cube out constraint removed, the truck performs less-than-truckload trips and thereby doubles the number of miles traveled while shipping the same amount of produce.

Figure 15

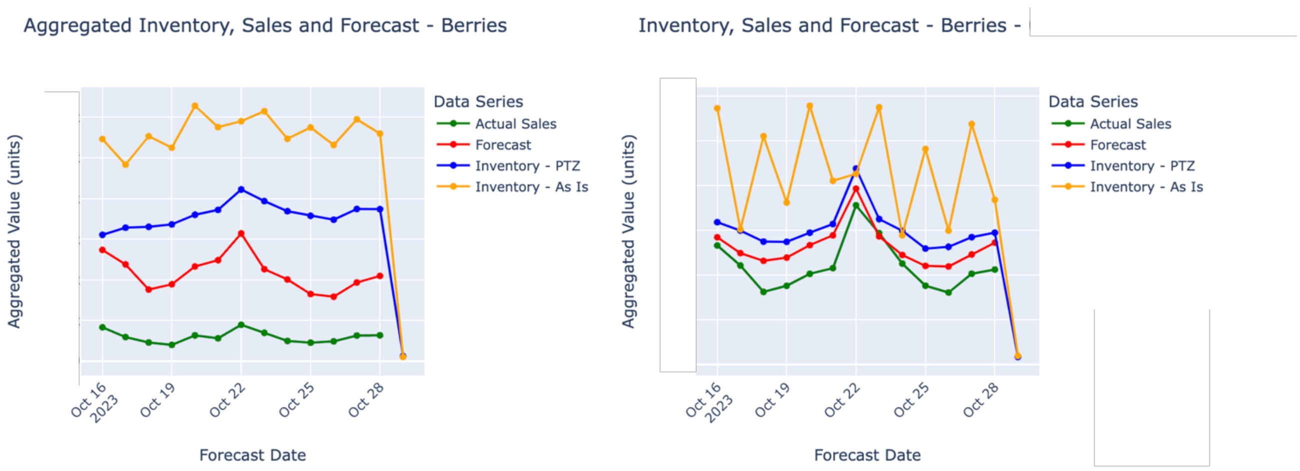
Cost comparison for berries supplier 1



With a lower service level of 85% in pick-to-zero, the total inventory on hand can be reduced by 22%. The frequent deliveries from vendors and quick turnaround at the DC ensures lead times are lower. Therefore, the inventory held within the system can be lowered. Figure 16 compares inventory on hand between current state and pick-to-zero (PTZ) against Actual Sales and Forecast.

Figure 16

Inventory on hand comparison vs forecast and actual sales



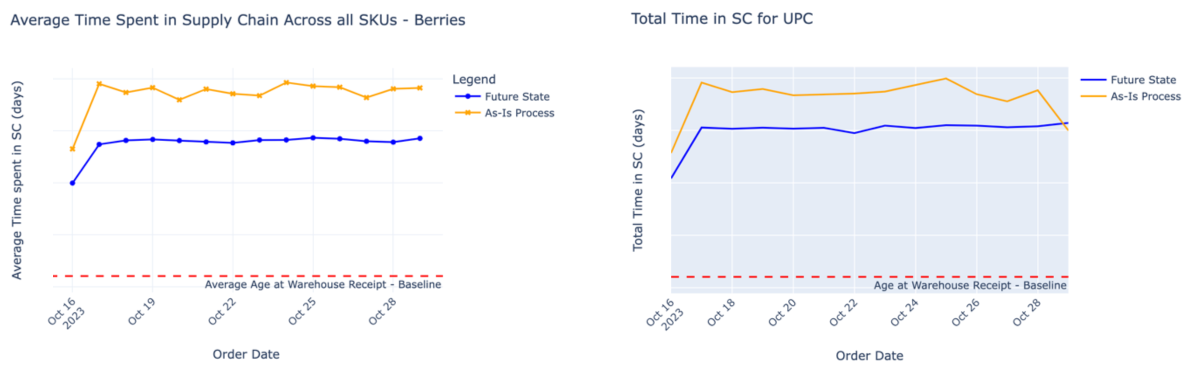
4.2 Scenario 2: daily inbound shipments via consolidation center, with a pick-to-zero strategy at DC and cross-dock at consolidation center.

A consolidation center aims to bring economies of scale in logistics. Using a consolidation center that operates as a cross-dock with less-than-a-day processing times, the produce can be moved from the consolidation center to the distribution within 1.5-2 days. Currently, some vendors ship produce daily as the volume justifies full truckloads daily. For the vendors that cannot cube out a whole truck, the consolidation center provides a means to aggregate orders from multiple distribution centers into a single load. The simulation model was run to increase freshness but maintaining costs per case for inbound logistics using a consolidation center.

The results from the model indicate that a 9% increase in improvement is possible, even with a consolidation center. However, the additional facility required capital expenditure that is not included in the cost calculations. Operational expenses to run the consolidation center have been included, assuming a similar rate of case process per hour by an individual operator. Figure 16 captures the freshness improvement.

Figure 16

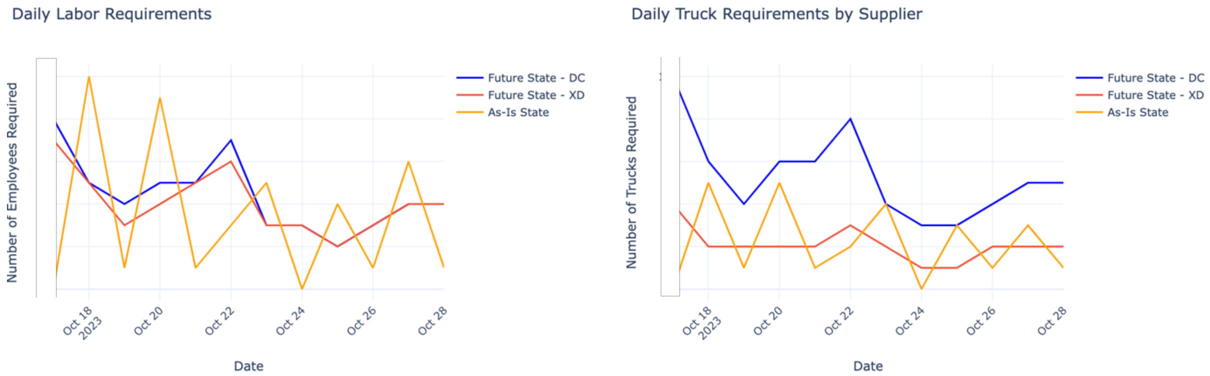
Freshness improvement with consolidation center



Using the consolidation center based in the "target market", the total cost of inbound logistics (from supplier to consolidation center and consolidation center to DC) reduces by 6% compared to daily shipments from suppliers directly to DC (Scenario 1). However, the total logistics costs increases by 27% compared to the current state (baseline). This is attributed to the location of the consolidation center which is not favorable to all suppliers, some of who are located further away from the consolidation center as compared to the DC. Figure 17 captures the labor and trucks comparison.

Figure 17

Cost implications with consolidation center



4.3 Scenario 3: impact based on consolidation center location.

The consolidation center aggregates inventory requirements from three distribution centers (DCs). A single order is placed at the consolidation center, enough to fulfill the three DCs. In the outbound operations from the consolidation center, multiple commodities from multiple suppliers are aggregated and therefore trucks are cubed out before shipping to DCs. The time taken for the operations from supplier to store and costs as a function of miles travelled by trucks depends on the location of the consolidation center. The three locations tested are listed in Table 3. The corresponding freshness is compared to the baseline current state of operation, without pick-to-zero and no daily shipments.

Table 3

Location	***Freshness***
"Target Market"	9% Increase
West Coast with Supplier Site A	1.1% Increase
West Coast with Supplier Site B	10% Decrease
Converting Existing DC Facility to Consolidation Center	25% Increase

Supplier Site A and Supplier Site B represent two facilities of the same vendor that are in different regions.

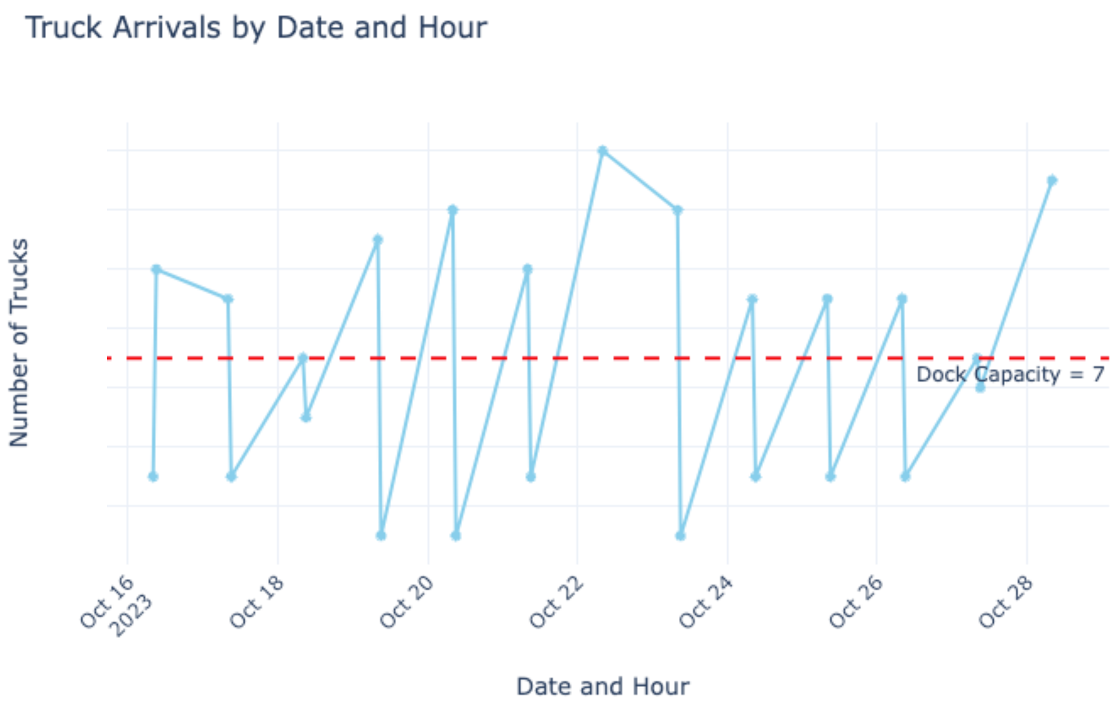
4.4 Scenario 4: potential bottlenecks in warehouse operations due to capacity constraints.

A critical node of operations is the warehouse processing time. In a pick-to-zero model, it is crucial to process goods within a 12-hour window such that the next stages of the process continue without backlogs. The capstone sponsor currently breaks the inbound and outbound operations based on a fixed schedule. Inbound trucks arrive at the warehouse in the morning from 5 AM to afternoon 3PM. Stores are scheduled to receive deliveries between 9 PM and 1 AM. Trucks would need to arrive before 1 PM to meet the store delivery window. If the window is missed beyond 1 PM, the store delivery will be impacted.

Using the model, truck arrivals were simulated to arrive at peak periods between 5 AM and 12PM using Poisson arrival, with a peak at 8 – 9 AM. The facility has in total 35 dock doors. Seven dock doors were assumed to be dedicated docks for fresh produce. Each dock can process 1.5 trucks per hour for unloading and loading. At the arrival rate and processing time, the system would be overloaded at specific times of the day, which could result in the delivery window being missed. Figure 16 captures the truck arrivals by hour and day.

Figure 16

Simulation of truck arrivals per dock door in DC



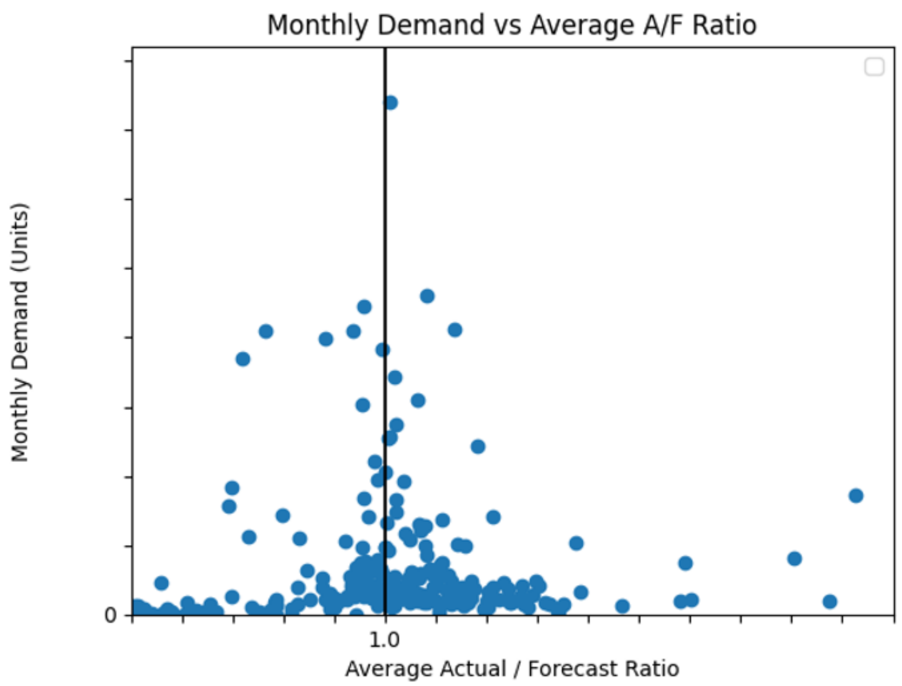
4.5 Scenario 5: impact on lost sales based on the pick-to-zero strategy in DC.

Forecast accuracy

To understand the impact of forecast accuracy on the freshness of the pick-to-zero model, the capstone project analyses the average A/F ratio of all SKUs against their monthly demand. Each dot on the graph in figure 17 represents an individual SKU, with the black line marking an A/F ratio of 1. From the plot below, we see a pattern: The larger the monthly demand, the more accurate the SKU forecast accuracy (A/F ratio closer to 1). Ratios greater than 1 indicate instances of stockouts, while ratios less than 1 indicate oversupply. This section delves deeper into the nuances of forecast accuracy, segmented by product category and lead time. The plots in Figures 18 also reveals an improvement in forecast accuracy as lead approaches zero.

Figure 17

Monthly demand vs A/F ratio

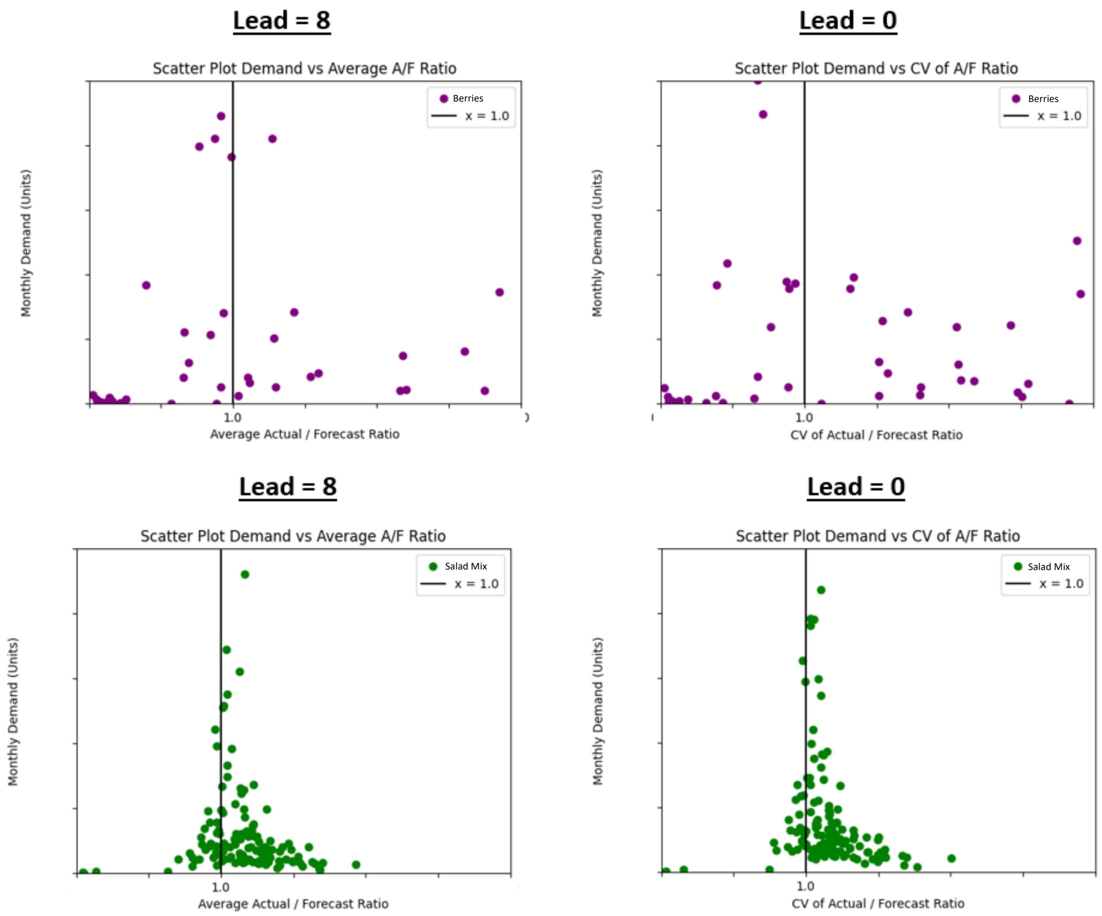


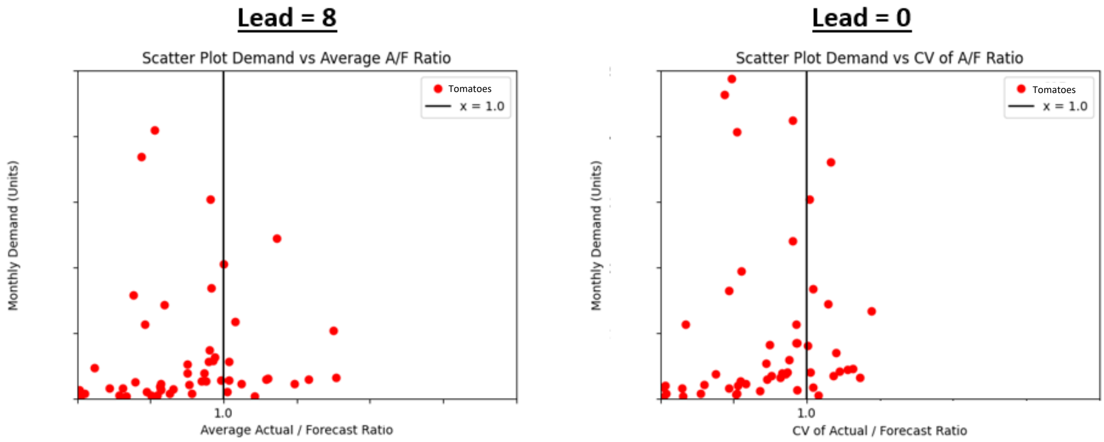
Forecast accuracy by product category

To better understand the forecast accuracy across product categories and lead times, refer to figure 18, which plots the average A/F ratio of all SKUs against their monthly demand for each product category. Figure 18 highlights two trends: First, the higher the monthly demand for SKU, the better the average forecast accuracy (A/F ratio close to 1). This trend is visible in Salad Mix and Tomatoes but absent in Berries. Second, the forecast accuracy improves as lead time approaches zero from eight. This is shown with the dots in the graph “lead = 0” become more concentrated around the A/F ratio = 1.

Figure 18

Monthly demand vs A/F ratio for different review periods



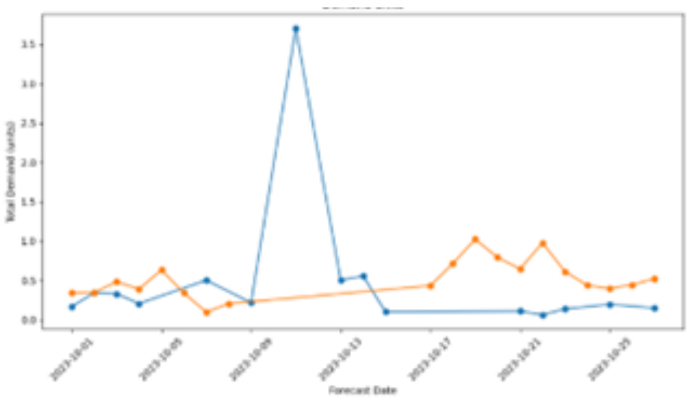


Forecast coefficient of variation

Since average of A/F ratios are calculated over a time horizon, the analysis should consider the effects of variability of A/F ratios for each SKU. Figure 19 demonstrates why variability analysis is important. In Figure 19 the daily A/F ratios are plotted over time for two SKUs having an Average A/F ratio of 1. The yellow and blue lines in the plot below represent a different SKU having the same average A/F ratio. From the plot below it is evident that SKUs having the same average A/F ratios can significantly differ in terms of variability, which in turn can affect the consistency of freshness in the supply chain.

Figure 19

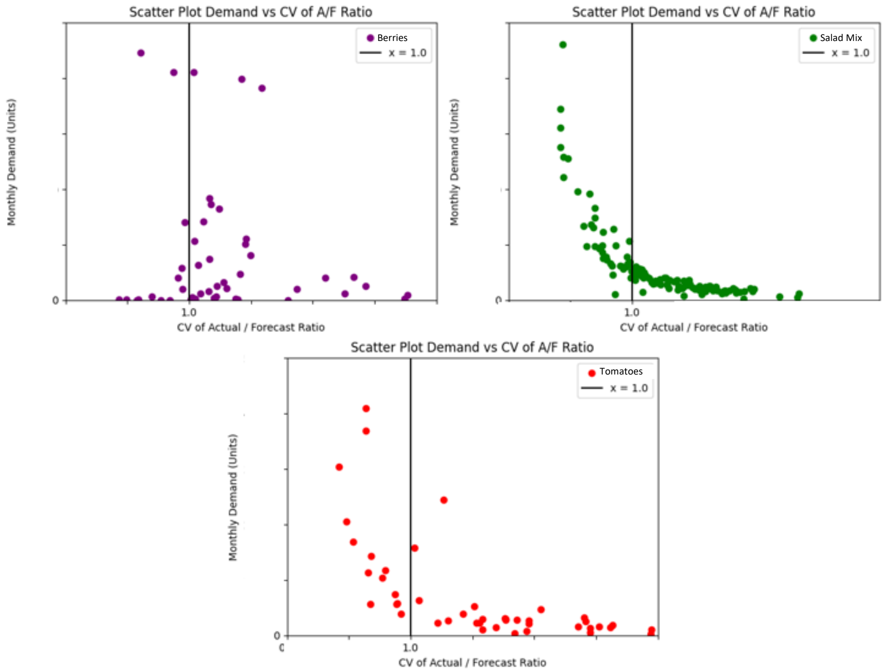
A/F ratio for two SKU's over time



Coefficient of variation (CV) has been calculated to evaluate the variability of A/F ratios by dividing the standard deviation of the SKU's A/F ratio by its average A/F ratio. Figure 20 plots the CV for all the SKUs by commodity against the monthly demand. Figure 20 highlights a pattern: the larger the SKU demand, the smaller the CV. This is a logical outcome since SKUs with lower demand typically have large variability in their forecast.

Figure 20

Monthly demand vs coefficient of variation of A/F ratio



Impact of forecast accuracy on freshness

To understand the impact of forecast accuracy freshness result for SKUs having average A/F ratio 0.5, 1 and 2 are depicted in Figure 21. The results shown in figure 21 are as anticipated: SKUs with A/F ratio 1 has the best average freshness as compared to SKUs with inaccurate forecasts (A/F ratio 0.5 and 2). Hence while choosing SKUs for compatibility with pick-to-zero, SKUs with the best forecast accuracy are recommended.

Figure 21

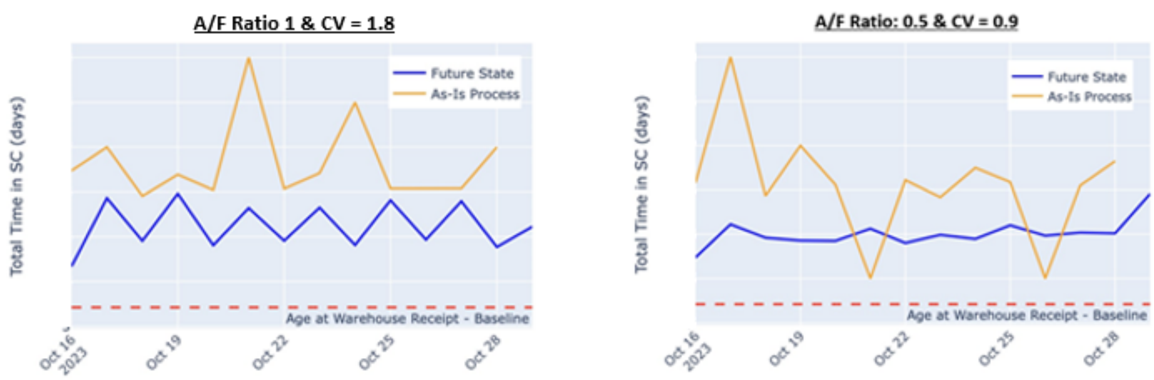
Freshness vs A/F ratio

Coefficient of variation effect on freshness

Since the model recommends choosing SKUs with accurate forecasts, it is essential to understand the effect variability of forecast accuracy on freshness. Figure 22 demonstrates this relationship by plotting the freshness graph of two SKU with approximately equal average A/F ratio but with different CVs of A/F ratio. The results in figure 22 are as anticipated: SKUs with higher CV of A/F ratio have less average freshness and more variability in freshness. Hence, SKUs which also have low CV of A/F ratio are recommended

Figure 22

Freshness vs coefficient of variation of A/F ratio



5 Managerial insights

Based on the results and analysis of system-state there are three key takeaways to operationalize a pick-to-zero model.

1) Daily shipments for improved freshness

When freshness is measured by the reduction of time spent in the supply chain, there are several opportunities to enhance efficiency. Optimizing warehouse operations could increase yield and efficiency. Similarly, re-designing truck routes to minimize travel time could also be beneficial. However, the benefits might not justify the effort. Scheduling shipments from vendors three or four times a week can help in fully utilizing truck space. However, inventory would remain idle in the warehouse or store before becoming available to consumers. Idle inventory represents lost time and decreases inventory turns. Therefore, arranging for daily shipments from vendors, combined with a pick-to-zero strategy in the distribution centers, can enhance the freshness of produce and reduce the amount of inventory held. Nevertheless, this approach can be costly as it may result in trucks not being fully loaded, thus increasing the cost per case.

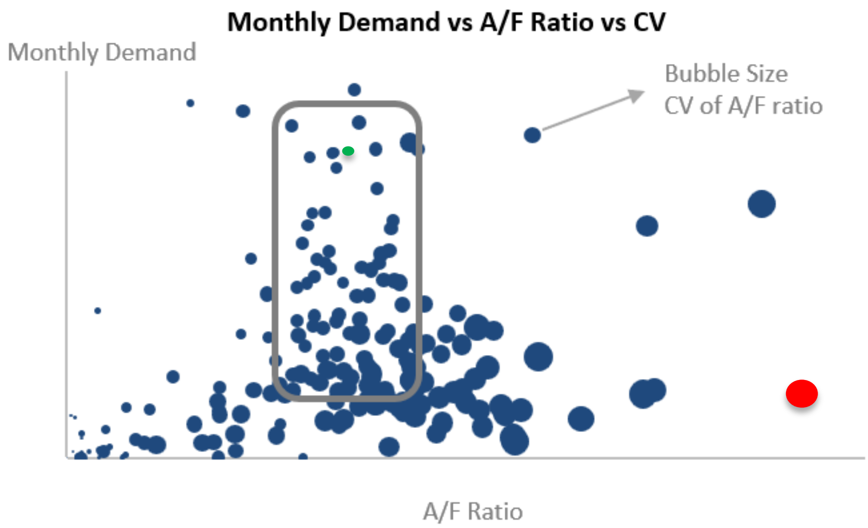
The higher logistics costs could be mitigated by introducing a consolidation center to aggregate inventory requirements across multiple vendors. However, a key challenge in this process is the system's capacity. In addition to internal capabilities, which can be scaled to meet the demands of the new pick-to-zero process, the capabilities of vendors are critical. Vendors located upstream, closer to the harvesting areas, may lack the operational capacity to dispatch multiple trucks daily for a specific retailer. Thus, a strategy combining pick-to-zero, daily shipments, and a consolidation center must also consider vendors as strategic partners in achieving a connected supply chain.

2) Forecast accuracy

As demonstrated in section 4.5, SKUs achieving maximum freshness with the pick-to-zero strategy have high demand, low CV of A/F ratio and A/F ratio between 0.7-1.3. Consequently, SKUs having low demand, high CV of A/F ratio and low accuracy (A/F ratio less than 0.7 or greater than 1.3) have lower freshness on average. SKUs best suited to a pick-to-zero model have been highlighted within figure 23, a bubble chart, using a grey rectangle. In this bubble chart the monthly demand is on y axis, A/F ratio is on x axis and bubble size indicates the CV of A/F ratio. For example, the green dot represents a SKU with high monthly demand, A/F ratio close to 1 and low CV (small bubble size). Hence this is a suitable SKU for the model. Consequently, the red dot has low demand, low forecast accuracy (A/F ratio greater than 1) and high CV (large bubble size). Hence this SKU is not suitable with the model.

Figure 23

Monthly demand vs A/F ratio and CV of A/F ratio



3) Warehouse automation for capacity

The time event analysis of operations performed at the warehouse revealed that the inbound operations that consume the most time are unloading and scanning. Currently each dock door can process 1.5 trucks per hour on average. With the current capacity, the dock doors would be overloaded during certain times of the day, as illustrated in section 4.4, which could negatively impact the pick-to-zero operations. If outbound trucks are not dispatched by a specific time window, they may not arrive within the delivery schedule of the stores (between 9PM and 1AM).

To decrease time spent in unloading and loading at dock doors, an automated skateloader loading system was considered. Pallets can be unloaded or assembled onto the skateloader base, and the system will be rolled into the trailer. A company that specializes in such systems suggested that with a skateloader system 5-6 trucks could be processed per hour as opposed to 1 truck that would take on average 45-60 minutes. The processing times as an aggregate of all dock doors could be analyzed and skateloader systems installed for specific dock doors that would increase the operational capacity of the entire system.

6 Conclusion and future research

This capstone project has analyzed the implications of implementing a pick-to-zero model on freshness, cost and accuracy. The simulations have analyzed the impact on freshness under various conditions. A pick-to-zero model with daily shipments can improve freshness of products by 25% at an additional cost of 34%. However, with the use of a consolidation center total logistics costs can be reduced by 6% compared to daily shipments and freshness improved by 9% compared to current state. Furthermore, SKUs most compatible with the pick-to-zero model are the one with high demand, low CV of A/F ratio and A/F ratio between 0.7-1.3.

Freshness, cost and excess inventory are key metrics that can evaluate effectiveness of a pick-to-zero strategy. Moreover, using time spent in supply chain to measure freshness provides a unified method to measure freshness across all commodities and SKUs. When a pick-to-zero strategy is coupled with daily shipments through a consolidation center, the safety stock at the DC can be eliminated and transferred to the store. However, with more frequent shipments the amount of inventory held as safety stock in stores can be reduced. The simulation model has demonstrated that freshness can be improved using pick-to-zero. Improvements to the pick-to-zero model require additional research in three specific areas:

1) Impact of network design on cargo freshness and cost efficiency: The model achieved transportation cost reductions by integrating consolidation centers into the network. This strategic enhancement not only optimized cost savings but also maintained the freshness of the cargo, even under uncertainty. Analysis on optimal locations for consolidation centers can further help reduce transportation costs for different scenarios.

2) Impact of automation on warehouse operations: The pick-to-zero model with daily shipments requires additional dock capacity. However, since dock doors at the DC are limited so was the operational capacity. Implementing automation could substantially increase operational capacity which is required for a pick-to-zero model

3) Feature engineering for high-variance SKU demand forecasting: Many SKUs in the inventory are currently not suitable for pick-to-zero operations due to the high variability in forecast accuracy. Improvements in forecasting techniques can reduce forecasting variability which can expand the applicability of pick-to-zero operations to these challenging SKUs.

List of abbreviations

PTZ – Pick-To-Zero

DC – Distribution Center

SKU – Stock Keeping Unit

UPC – Universal Product Code

EWA – Estimated Withdrawal and Aging

VNS – Variable Neighborhood Search

SA – Simulated Annealing

s, Q – Continuous Review Policy with reorder point

A/F – Actual vs Forecast Ratio

LIFO – Last In First Out

FIFO – First In First Out

CSL – Cycle Service Level

CV – Coefficient of Variation

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