

Transforming Supply Chain Strategy with Robotics: Measuring the Impact of Utilizing Robotics for
Product Repackaging Operations

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ABSTRACT

The US Bureau of Labor Statistics states that food and beverage manufacturers have experienced annual 0.5% decreases in labor productivity and annual 7% increases in unit labor costs since 2019. These statistics underscore a growing inefficiency in the manufacturing and distribution processes of food products, posing significant challenges to industry players. Our sponsor company, a Fortune 500 food manufacturer, illustrates these challenges in their product repackaging operations. Repackaging operations involve the case-packing of finished goods tailored to the specifications of end customers, typically retailers. The sponsor's product repackaging operation is costly, unscalable, labor-intensive, and outsourced. Our research aims to explore the use of robotic systems to perform the product repackaging operation in-house. Our methodology involves mapping current workflows, understanding demand, capacity, and network flows, formulating a mixed integer linear programming (MILP) model to reimagine the supply chain with repackaging being performed in-house, and conducting scenario analysis to assess the feasibility of insourcing repackaging operations across multiple market scenarios. Our modeling suggests that the most significant annual savings result from the best-case scenario (i.e., 20% increase in customer demand, 20% decrease in transportation cost, and low robotic CapEx), amounting to 56%, and the least annual savings result from the worst-case scenario (i.e., 20% decrease in customer demand, 20% increase in transportation cost and high robotic capex), amounting to 49%. Furthermore, our analysis strengthens the case for embracing robotic automation as it shows that to offset the savings achieved through robotic automation and insourcing repackaging operations, transportation costs would have to surge by nearly 375% (for low CapEx robotics) or 350% (for high CapEx robotics). These findings demonstrate the financial benefits of embracing robotic automation and highlight its indispensable role in ensuring the long-term viability and competitiveness of food manufacturing companies in an increasingly dynamic market landscape.

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Table of Contents

- 1. INTRODUCTION 5**
 - 1.1 OBJECTIVE & RESEARCH QUESTIONS 6**
- 2. STATE OF THE PRACTICE 6**
 - 2.1 STATE OF ROBOTICS IN FOOD MANUFACTURING..... 6**
 - 2.2 OPTIMIZATION IN SUPPLY CHAIN NETWORK DESIGN 8**
- 3. METHODOLOGY 11**
 - 3.1 PHASE 1: SCOPE DEFINITION 12**
 - 3.2 PHASE 2: PROCESS MAPPING 12**
 - 3.3 PHASE 3: DATA COLLECTION & PROCESSING..... 13**
 - 3.4 PHASE 4: MODELING & OPTIMIZATION – DEVELOPING MIXED INTEGER LINEAR PROGRAMMING (MILP) OPTIMIZATION MODEL 14**
 - 3.5 PHASE 5: CASE STUDY & SCENARIO ANALYSIS – RUNNING MILP MODEL UNDER DIFFERENT SCENARIOS AND MEASURING IMPACT..... 19**
- 4. RESULTS 22**
 - 4.1 ROBOTIC VENDOR QUOTATIONS – COST & THROUGHPUT CAPACITY OF ROBOTIC SYSTEMS..... 25**
 - 4.2 BASELINE SCENARIO 27**
 - 4.3 INCREASING ROBOTIC CAPEX BETWEEN 10% AND 40%..... 28**
 - 4.4 WORST-CASE SCENARIO – 20% DECREASE IN CUSTOMER DEMAND, 20% INCREASE IN TRANSPORTATION COST AND HIGH ROBOTIC CAPEX 28**
 - 4.5 BEST-CASE SCENARIO – 20% INCREASE IN CUSTOMER DEMAND, 20% DECREASE IN TRANSPORTATION COST AND LOW ROBOTIC CAPEX 29**
 - 4.6 SUMMARY OF RESULTS..... 30**
 - 4.7 MANAGERIAL INSIGHTS..... 32**
- 5. CONCLUSION & FUTURE RESEARCH..... 33**
- 6. REFERENCES..... 36**

1. INTRODUCTION

The Food and Beverage landscape in the United States has been marked by a concerning trend since 2019. The industry has witnessed a steady annual decline of 0.5% in labor productivity, paralleled by a significant annual increase of 7% in unit labor costs (US Bureau of Labor Statistics, 2023). These statistics underscore a growing inefficiency in the manufacturing and distribution processes of food products, posing significant challenges to industry players.

Our capstone project's sponsor company, a Fortune 500 food manufacturer, illustrates these challenges in their product repackaging operations. Repackaging operations involve the meticulous case-packing of finished goods to the specifications of end customers, typically retailers. This may entail repackaging products into different configurations, sizes, colors, or packaging designs, often to align with specific merchandising or marketing strategies. Currently, our sponsor employs a costly, unscalable, and labor-intensive process for product repackaging, which is outsourced to meet demand. The company is eager to explore insourcing these operations and managing them with robotics systems to scale up and improve heavily manual operations. Bader and Rahimifard (2018) advocate for the adoption of industrial robots to replace inefficient processes within manufacturing systems, particularly those that are bottlenecked, high-risk, repetitive, or involve heavy lifting.

As our sponsor contemplates transitioning to robotics-based systems to replace labor-intensive outsourced repackaging operations, this research aims to assess the viability and potential benefits of this transition. We will do this by identifying appropriate robotic-enhanced repackaging solutions and analyzing the impact of integrating such solutions into the sponsor's supply chain network design, focusing on total supply chain network costs, including storage, transportation, packaging, labor, as well as the fixed costs of maintaining operations of the facilities.

1.1 OBJECTIVE & RESEARCH QUESTIONS

The transition to robotic-based systems can be facilitated by identifying robotics-based systems that will create sustained value, measured by 1) impact on total supply chain network costs and 2) cost-benefit analysis of investing in robotic systems vis-à-vis labor-intensive systems.

Therefore, our research objective is to analyze the cost impact of integrating flexible robot-enhanced repackaging technologies into our sponsor's supply chain network. To do this, we will answer the following questions:

- 1. What robotics-enhanced systems can automate the current manually driven repackaging operations, and how do they vary in cost and throughput?*
- 2. What will be the total system cost savings from integrating the automated repackaging process into the sponsor company's supply chain network design (SCND)?*

2. STATE OF THE PRACTICE

As described in Section 1.1, the project deliverable is an analysis combining the implementation of repackaging processes using innovative, robot-assisted technologies and their corresponding savings in total cost utilizing these robot-assisted technologies in various supply chain network designs (SCND) scenarios. The State of the Practice section thus details the two key areas: 1) state of robotics in food manufacturing and 2) optimization in supply chain network design.

2.1 STATE OF ROBOTICS IN FOOD MANUFACTURING

The International Federation of Robotics (IFR) reported that 15,000 robotics systems were installed by food manufacturers in 2022 (Bill et al., 2023). Mazacheck (2020) states that an increase in industrial robot density led to a growth in productivity across industries. Multiple reasons can explain the popularity of robotics amongst food manufacturers. These are as follows – 1) There have

been increases in the development of cheaper, more easily configurable robotics solutions in the market (Bill et al., 2023). 2) Caldwell (2023) characterized labor in the food industry as less productive than labor across all industries within manufacturing, reinforcing the incentive to implement robotics. The above points support the use of robotics to manage repackaging operations, as the robots would be handling finished food containers with primary packaging already applied in the earlier manufacturing stages.

Küpper et al. (2019) state that advances in robotics can help reduce conversion costs, the sum of direct labor and manufacturing overhead costs incurred to turn raw materials into a finished product, by up to 15%. Furthermore, these robots can also influence structural layout changes, yielding savings of up to 40%. These benefits further bolster our sponsor's focus on leveraging robotics for their repackaging operations. In addition, Koch et al. (2021) used a difference-in-difference method to show that companies that use robots can increase their production by 25% and reduce their labor costs by 7%, which supports the use of robotics.

Bader and Rahimifard (2018) indicated that industrial robotics applications could help achieve benefits, such as reductions in required floor space, increased production rates, improved flexibility and reconfigurability, and an increased competitive advantage due to supply chain responsiveness and the ability to customize and personalize products. This echoes the areas of emphasis of the sponsor company as indicated in the goal and research section.

To further inform our decision on the appropriate robotic repackaging systems, we collaborated with our sponsor and the installers of these systems to determine the best robotics-based solutions regarding configuration, gripper type, and visual guidance system. We also considered the financial implications (Capital Expenditure – CapEx - and Operating Expenditure - OpEx-) and throughput capabilities of these systems.

As we explore the integration of robotics and its far-reaching implications in food manufacturing, we focus on evaluating the strategic implications of incorporating such technology

within our sponsor's existing supply chain network. To do this, Section 2.2 explores how researchers and practitioners have leveraged optimization models to analyze the intricate dynamics of supply chain networks. We aim to study strategies to address supply chain network design optimization and their implications on cost and other tradeoffs. In this way, we can analyze how the efficiency gains achieved through robots will affect the logistics costs of our sponsor company's existing supply chain network.

2.2 OPTIMIZATION IN SUPPLY CHAIN NETWORK DESIGN

We consider approaches taken amongst researchers in academia to formulate prescriptive models that analyze the impact of robotics implementation at the supply chain network level. Finding examples of models that weigh supply chain network costs as a function of robotics systems design and location within the supply chain network would be the most helpful. While little research has been performed on the exact scope of our capstone, researchers have used techniques to estimate total system logistics costs in various other contexts that may be useful. Likewise, studies focusing on unpacking operations, minimizing total system costs in retail and/or distribution contexts, and facility location problems can all inform our methodology.

Belieres et al. (2020) solve a logistics service network design problem with an optimization model that produces a transportation plan that minimizes overall costs in a multi-echelon distribution network. It provides an example of the input parameters to consider when designing a model that minimizes total distribution costs, thus aligning directly with the supply chain network design of our sponsor. Furthermore, the model accounts for both transportation costs (fixed and variable) and storage costs, which inform decision variables about the selection of suppliers, shipment routes, quantities of product moved, product source, etc. Storage limits constrain the warehouse capacity, the throughput of products from suppliers, and the number of vehicles that can be dispatched from the supplier each day. Utilizing these insights, we can build our capstone sponsor's optimization model.

Arslan et al. (2021) develop strategic insights for a cosmetics retailer by modeling an e-commerce distribution network. The model maximizes system profitability in a network that employs multiple order fulfillment strategies. In this study, inventory can be delivered to end customers via a warehouse far from the end customer or through omnichannel-specialized facilities that include physical retail locations and fulfillment centers (FCs) close to the end customer. The outcomes of the model support the use of the omnichannel fulfillment strategies, as the reduced lead time (i.e., same-day delivery) stimulates increased demand to a degree that overcomes the additional transportation, holding, and opening costs. This work helps us define the input parameters we can consider in our sponsor's network to develop scenarios.

Wang et al. (2022) use a joint supply chain network model to define a distribution strategy for multiple manufacturers, owned and outsourced distribution centers (DCs), and retailers. The authors proposed a mixed integer model that minimizes total costs by selecting combinations of manufacturers, third-party logistics (3PLs), and owned DCs with fixed facility opening costs, inventory holding costs, and transportation costs. The results demonstrate that adding 3PLs to the supply chain network can reduce overall system costs, even if the 3PLs have fixed opening costs. This model determines the lowest-cost supply chain network designs and how to use optimization to convey the value of using 3PLs rather than owned facilities, like the case of our sponsor company.

Janjevic et al. (2021) developed a three-echelon capacitated location-routing problem to optimize omnichannel distribution networks, including transshipment points, collection and delivery points (CDPs), hubs, and end customers. Demand is met via at-home deliveries or customer pickup at CDPs. The model takes several parameters into account to make decisions in the network. These decisions are the choice of facility, parcels that are transferred between facility locations, the vehicles used to transfer parcels between facility locations, and the quantity of demand served by a facility via each last-mile distribution service option in a manner that minimizes total system cost. These parameters include travel distance between facilities, cost parameters for routes (which may accrue as a function of distance, time, parcels, or fixed vehicle costs per delivery, per the route cost estimation formulae), facility capacities, vehicle speeds, and demand for home delivery and CDPs in

each demand zone. Likewise, our model considers capacity, throughput, and inventory level constraints at different periods, showing the utility of this study in its application to our model.

Zhao et al. (2023) built an optimization model that reduces total system costs in a supply chain network with suppliers, DCs, and retailers engaging in outbound flows and returns of expired products. The model achieves the lowest total cost by determining the location of unpacking operations and the size of case packs for a broad assortment of SKUs. Parameters such as handling costs, picking costs, return costs, unpacking costs, and reorder size may fluctuate with changing case pack sizes and the location of the unpacking operations, which may occur in either stores or DCs. The authors suggest that the strategies determined by the optimization would generate an estimated 17.3% reduction in unpacking costs compared to actuality for a grocery retailer in China. This research gives us insights into how optimization models can be built to capture total system costs in a labor-intensive environment, helping us determine the optimal location for repackaging operations in our sponsor's supply chain network.

Broekmeulen et al. (2017) studied an optimization model that determines the optimal location of unpacking operations for an assortment of 1,135 products in a European retailer's supply chain network. The model incorporates parameters that capture the cost drivers of unpacking costs. They differ depending on the unpacking location and its workflow. The cost drivers include unpacking costs, store shelf stacking costs, store backroom storage costs, and store replenishment costs, which may increase with larger case packs. The authors assert that the optimized unpacking strategy would yield an 8% cost reduction in unpacking operations. This speaks to the utility of optimization techniques and considering the effect of inventory in a facility location problem, thus being relevant to our sponsor company's objective.

The exploration of such optimization techniques in supply chain network design unveils a rich landscape of methodologies and insights helpful for this capstone project. By studying the approach taken by various research endeavors, we gained valuable strategies to minimize total logistics costs and enhance operational efficiency. From modeling distribution strategies to optimizing facility

locations, each study contributes to our understanding of how robotics implementation intersects with supply chain network design. These findings provide a robust foundation to formulate our optimization model tailored to our sponsor's unique challenges and objectives, empowering us to make informed decisions to enhance their supply chain network.

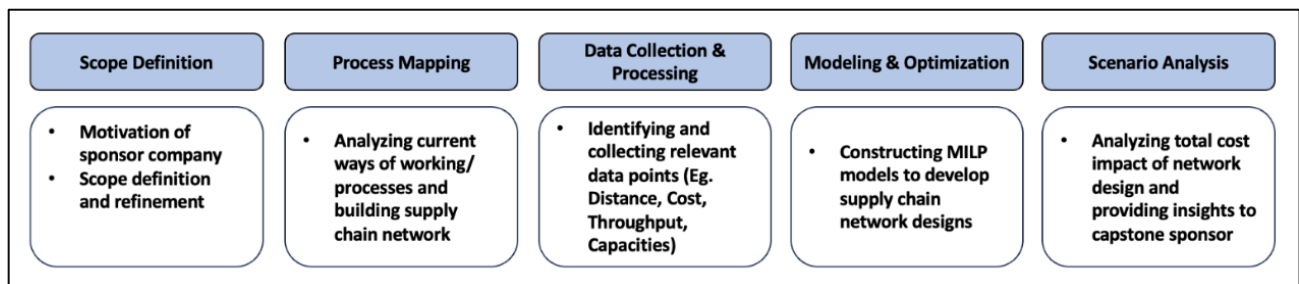
In summary, our state-of-the-practice analysis delved into the intricacies of robotics integration in food manufacturing and supply chain network design optimization. By dissecting the state of robotics adoption and exploring diverse optimization models, we gained deep strategic insight into the symbiotic relationship between robotics and supply chain network design. Utilizing these insights, we crafted a tailored solution that optimized repackaging operations and drove cost efficiencies across our sponsor's supply chain network, propelling them toward sustainable growth and competitiveness in the industry.

3. METHODOLOGY

The methodology for the project consisted of learning about the sponsor company's strategic motivation, mapping the processes involved, collecting relevant data, and developing a Mixed Integer Linear Programming (MILP) model that can run various scenarios to enable leadership decision-making. Each phase of the methodology is outlined in Figure 1, followed by details of each phase.

Figure 1

Methodology Process



3.1 PHASE 1: SCOPE DEFINITION

Our methodology begins with learning the strategic priorities and motivation for this project by our sponsor company. This involves conducting interview calls with the sponsor company's leadership team and site visits to the repackaging facility to better understand the complexity faced in current operations. It also involves discovering our sponsor's reasons for focusing on certain robotic-enhanced repackaging operations. The understanding developed through such visits helps us further refine the scope and narrow it down to the target requirement for the sponsor company that would ultimately allow for strategic decision-making.

As part of this step, we agree with the leadership team that we shall determine the impact of robotics system implementation on the supply chain network costs for one star product within the current assortment of products of the sponsor company. The sponsor company emphasizes that robotic solutions in the form of articulated arms should be considered for the project's scope, attributing their choice to the flexibility and reduced space offered by such solutions. Finally, we agree that the geographical scope of this project would be the sponsor company's entire US supply chain network for the chosen finished product. This supply chain network shall consist of a total of 80 nodes that include a Production Facility, a Repackaging Facility, Mixing Centers, and End-Customers spread across the US geographical landscape.

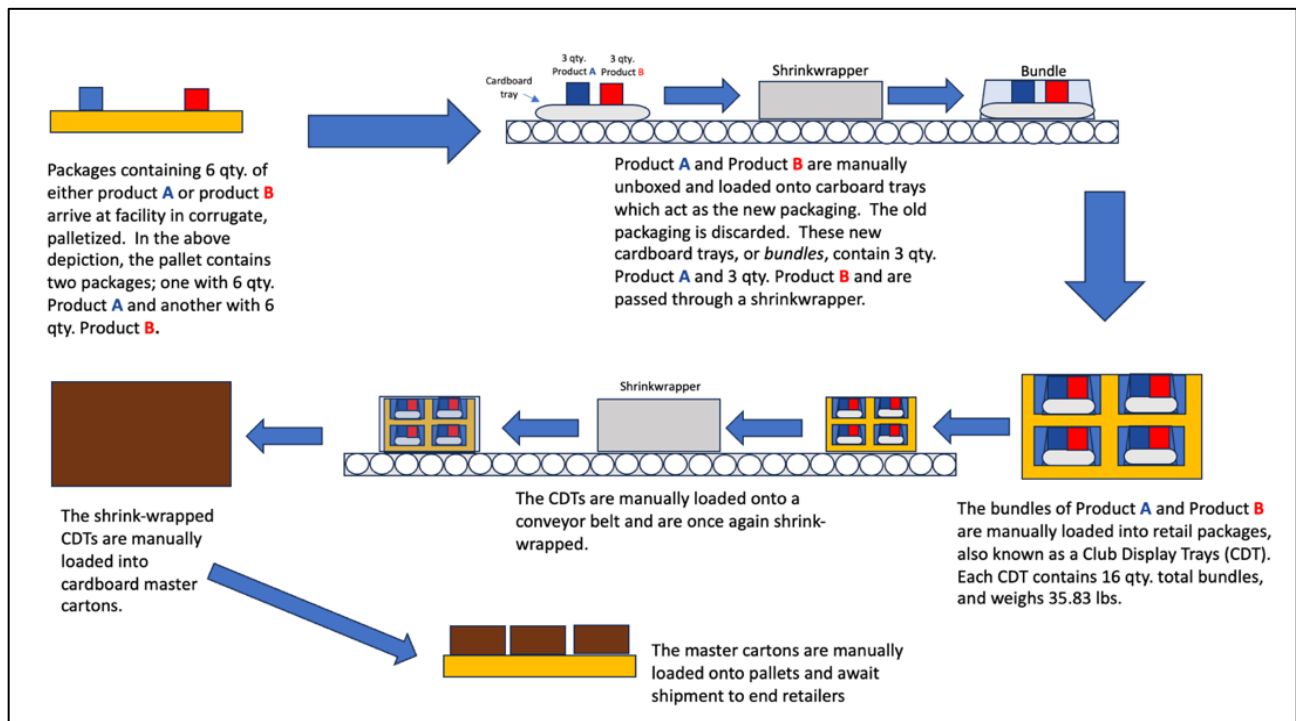
3.2 PHASE 2: PROCESS MAPPING

Next, we deep dive into analyzing existing business processes and their limitations. We interview key stakeholders at the repackaging facility to better understand current working methods and what repackaging means for the sponsor company. Observing the end-to-end repackaging process, we measured the facility's throughput and analyzed potential areas of cost savings (i.e., storage, labor, and packaging costs). Additionally, we asked clarifying questions regarding the specifications of robotic solutions that would help automate the current manual repackaging process.

Figure 2 outlines the repackaging process in the outsourced facility. Descriptions detail the processes that are currently manual and where automation is present. Steps that involve shrink-wrapping have automation in place, but all other touchpoints with the physical product, as it progresses through forms of secondary packaging, are driven by manual operations.

Figure 2

Repackaging Process



3.3 PHASE 3: DATA COLLECTION & PROCESSING

Once we understand the processes, we identify the data needed to develop the optimization model. Here, we partner with our sponsor company to gain data access and learn company-specific terminology and nuances. The data include the dimensions and weight of the product at various stages of the repackaging process. Additionally, we collect data on the end-consumer demand and intra-network material flows within our sponsor's supply chain for 2023, which help inform the demand, throughput, and storage capacity constraints for our model. We also utilized 2023 spot market rates for refrigerated truckloads for our model development, donated by DAT Freight &

Analytics, the largest truckload freight marketplace in North America. The truckload rate is divided amongst the total units shipped in a full truckload, helping us determine trucking cost parameters per unit basis along any node in the sponsor's logistics network.

For example, if a transportation lane (a route connecting two nodes in the supply chain network) is to have an estimated rate of \$2,000, the per unit cost of transportation would be calculated as follows:

$$TC_{ij} = \frac{\$2,000 \text{ cost per truckload}}{7,488 \text{ units per truckload}} = \$0.27 \text{ truckload cost per unit}$$

Clarification: We assume 26 pallets per truckload, 288 units per pallet

Throughput and inventory capacity constraints at the Production Facility, Repackaging Facility and Mixing Centers are benchmarked with intra-network material flow data provided by the sponsor company. This benchmarking ensures that the model is constrained with realistic throughput and capacity constraints. We also organize calls with robotic systems manufacturers to collect inputs on their technologies' cost, space, and throughput requirements.

3.4 PHASE 4: MODELING & OPTIMIZATION – DEVELOPING MIXED INTEGER LINEAR PROGRAMMING (MILP) OPTIMIZATION MODEL

A MILP model consists of four key elements –

1. Parameters – Described in detail in Section 3.3.
2. The Objective Function – In our case, the sum of the total cost of transportation, unitary cost of repackaging (driven by either in-house operations via robotics or outsourced operations), and the cost of robotics are minimized.
3. The Decision Variables – In our case, which nodes of the network will be open, on which node arcs the product will move to arrive at the Mixing Centers and/or End-Customers, how

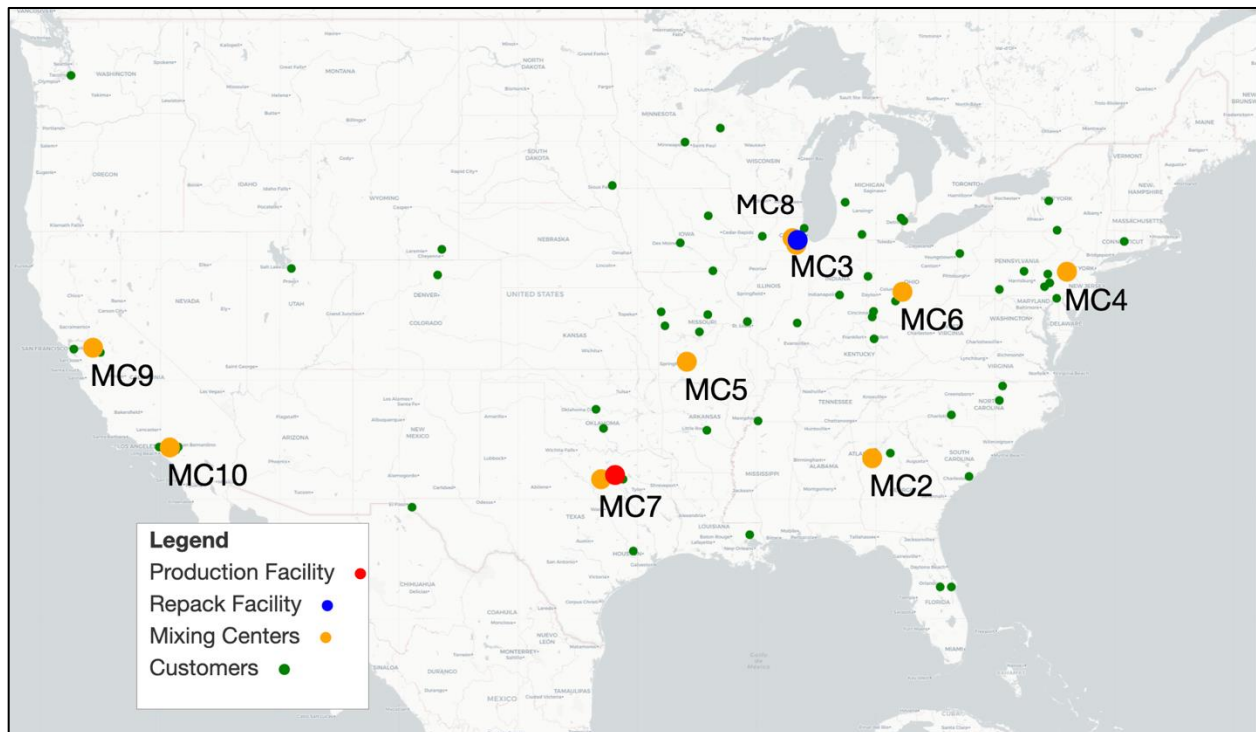
much flow will travel on these arcs, and finally, how much inventory will be managed per facility.

4. Constraints – In our case, the constraints are the Mixing Centers' throughput and inventory storage capacities, the quantity of demand at the end customers, and the production capacity at the production facility.

Figure 3 helps us map the network nodes and develop a visual reference of the flows in the current supply chain network to develop the model. In the figure, the red dot signifies the production facility (where base SKUs are manufactured), the blue dot represents the repackaging facility (where base SKUs are repackaged), and the Mixing Centers (where many different repackaged SKUs are collected and sorted for outbound logistics), and the green dot represents the customers.

Figure 3

Supply Chain Network of Sponsor Company



Utilizing the data received, we developed an optimization model by defining the following Network: $Graph = \{N, A\}$ where $N = Nodes$ and $A = Arcs$. The nodes refer to all logistics facilities, and the arcs denote all feasible connections.

Sets

N Set of all nodes

$N_{pf} = \{0\}$ Set of Production Facilities

$N_{rf} = \{1\}$ Set of Repackaging Facilities

$N_{mc} = \{2, 3, 4, 5, 6, 7, 8, 9, \text{ and } 10\}$ Set of Mixing Centers

$N_{iv} = \{0, 1, 2, 3, 4, 5, 6, 7, 8, 9, \text{ and } 10\}$ Set of Inventory Holding Locations

$N_c = \{11, 12, 13, \dots \dots \dots 79\}$ Set of Customers

$T = \{0, 1, 2, \dots \dots \dots 7\}$ Set of Periods

$Q = \{0, 1, 2, 3, 4, 5, 6, 7, 8, 9, \text{ and } 10\}$ Set of Indexes for Inventory Storage Locations

Parameters

TC_{ij} Costs per transported unit from location i to location j

D_{jt} Demand at customer location j at time t

$Capacity$ Production capacity of the Production Facility

Cap_thro_0 Throughput capacity of the Production Facility

Cap_thro_1 Throughput capacity of the Repackaging Facility

Cap_thro_j Throughput capacity of the Mixing Center j

Cap_inv_i Inventory storage capacity at node i

MCL Unitary labor cost with currently outsourced repackaging operation

MCP Unitary packaging cost with the currently outsourced repackaging operation

MCW Unitary packaging waste cost with the currently outsourced repackaging operation

MCS Unitary storage cost with the currently outsourced repackaging operation

PCP Unitary packaging cost with the insourced robotics-driven repackaging operation

PCL Unitary labor cost with the insourced robotics-driven repackaging operation

RC Robotic-systems capital expenditure

OC Robotic-systems operational expenditure

Variables

X_{ijt} Number of products transported from location i to location j in a given period t

Y_t Quantity of products processed at the production facility at period t

IV_{it} Quantity of inventory held at location i at period t

B_t represents whether the repackaging facility at node 1 is open or not at period t

Objective Function

$$\begin{aligned} \text{Min } Z = & \sum_{(i,j) \in N, t \in T} (TC_{ij} X_{ijt}) + \sum_{t \in T} (X_{01t} \times (MCL + MCP + MCW + MCS)) + ((1 - B_t) \cdot \\ & (RC + OC)) + \sum_{i \in N_{mc}, t \in T} (X_{0it} \times (PCP + PCL)) \end{aligned}$$

Constraints

1. The customer demand must be satisfied exactly.

$$\sum_{i \in N_{mc}} X_{ijt} = D_{jt} \quad \forall j \in N_c, t \in T$$

2. The production capacity must not be exceeded at any period.

$$Y_t \leq \text{Capacity} \quad \forall t \in T$$

3. The production sent from Production Facility (0) to Repackaging Facility (1) must not exceed the throughput capacity of the Production Facility.

$$X_{01t} \leq \text{Cap_thro}_0 \times b \quad \forall t \in T$$

4. The production sent from the Production Facility (0) to mixed centers must not exceed the throughput capacity of the Production Facility.

$$\sum_{j \in N_{mc}} X_{0jt} \leq Cap_thro_0 \times (1 - b) \forall t \in T$$

5. The quantity of inventory received by the Repackaging Facility (1) and the inventory sent to the Mixed Centers in the same period from the Repackaging Facility (1) must not exceed the throughput capacity of the Repackaging Facility (1).

$$X_{01t} + \sum_{i \in N_{mc}} X_{1it} \leq Cap_thro_1 \forall t \in T$$

6. The sum of the amount of inventory received by a Mixing Center from either the production facility (0) or the Repackaging Facility (1) and the inventory shipped to customers by the Mixing Center in the same period must not exceed the throughput capacity of the Mixing Center.

$$X_{0jt} + X_{1jt} + \sum_{i \in N_c} X_{jit} \leq Cap_thro_j \forall j \in N_{mc}, t \in T$$

7. Storage capacity constraints at the Production Facility, Repackaging Facility, and Mixing Centers.

$$IV_{it} \leq Cap_inv_i \forall i \in (N_{pf} \cup N_{rf} \cup N_{mc}), t \in T$$

8. Inventory flow constraints at the Production Facility (0).

$$\begin{aligned} \text{At time 0: } Y_0 - \sum_{i \in (N_{rf} \cup N_{mc})} X_{0i0} &= IV_{00} \\ \text{Time 1 to 7: } IV_{0(t-1)} + Y_t - \sum_{j \in (N_{rf} \cup N_{mc})} X_{0jt} &= IV_{0t} \forall t \in T \end{aligned}$$

9. Inventory flow constraints at the Repackaging Facility (1).

$$\begin{aligned} \text{At time 0: } X_{010} - \sum_{i \in N_{mc}} X_{1i0} &= IV_{10} \\ \text{Time 1 to 7: } IV_{1(t-1)} + X_{01t} - \sum_{i \in N_{mc}} X_{1it} &= IV_{1t} \quad \forall t \in T \end{aligned}$$

10. Inventory flow constraints at the Mixing Centers.

$$\begin{aligned} \text{At time 0: } X_{0j0} + X_{1j0} - \sum_{i \in N_c} X_{ji0} &= IV_{j0} \quad \forall j \in N_{mc} \\ \text{Time 1 to 7: } IV_{j(t-1)} + X_{0jt} + X_{1jt} - \sum_{i \in N_c} X_{jit} &= IV_{jt} \quad \forall j \in N_{mc}, t \in T \end{aligned}$$

11. Domain of variables

$$\begin{aligned} X_{ijt} &\in \mathbb{Z} \quad \forall i \in N, j \in N, t \in T \\ IV_{it} &\in \mathbb{Z} \quad \forall i \in (N_{pf} \cup N_{rf} \cup N_{mc}), t \in T \\ Y_t &\in \mathbb{Z} \quad \forall t \in T \\ B_t &\in \{0,1\} \quad \forall t \in T \end{aligned}$$

3.5 PHASE 5: CASE STUDY & SCENARIO ANALYSIS – RUNNING MILP MODEL UNDER DIFFERENT SCENARIOS AND MEASURING IMPACT

For the case study, the data collected from the robotic vendors (i.e., capital/operating expenditure requirements and throughput of robotics systems) and the sponsor company (i.e., storage and throughput capacities, facility locations, customer demand) parameters are integrated into the MILP model.

The size of the instance used in the model presented earlier is as follows –

- One Production Facility
- One Repackaging Facility
- Nine Mixing Centers
- Sixty-nine End-customers
- Eight Periods (weeks)

We selected an eight-week timeframe for the optimization for a few key reasons. To begin, the customer demand data provided did not include time series data, but rather a log of quantities of products shipped to customers in the year 2023. Demand for any given week for a customer is calculated as the sum of all demand in the year 2023 divided by 52 weeks in a calendar year. An eight-week optimization adequately integrates what is known about customer demand without unnecessarily increasing computational complexity.

When the model is run, it generates thousands of decision variables that determine how inventory should be passed through the network. The model is forced to move inventory through the supply chain efficiently, reflecting the forward flow design of the sponsor company's supply chain. This means the product starts in the production facility (depicted in red in Figure 3), then moves to the outsourced repackaging facility (depicted in blue in Figure 3, if $B_m=1$), then to Mixing Centers (depicted in orange), and finally to end customers (depicted in green). The objective function tasks the model to do this as efficiently as possible, minimizing total costs across the supply chain.

By forcing or relaxing constraints, the model can be used to compare the total cost of the current supply chain, whereby the repackaging is outsourced, versus a new network design, where the repackaging is performed in-house at the production facility and the outsourced repackaging facility node is bypassed (i.e., products ships from the production facility directly to the Mixing Centers, and finally to the customers). Comparing the total system cost in either of these scenarios

gives the savings (or increased total expenditures) associated with the decision to perform the repackaging in-house.

Additional scenarios are run to confirm if the model results in the initial scenarios made with the baseline data and business-as-is are repeated. Each scenario depicts how exogenous factors (i.e., transportation cost and customer demand) impact the differences in total systems cost for the current or reimagined supply chain network designs.

The scenarios of interest include the following –

1. Baseline Scenario – This scenario directly evaluates the feasibility of implementing robotics using transportation costs and customer demand for 2023.
2. Increasing Robotic CapEx between 10% to 40% – This scenario assesses whether unexpected increases in costs of implementing robotics between 10% and 40% put the feasibility of robotic implementation at risk.
3. Worst-case Scenario – This scenario assesses whether unfavorable market conditions of a 20% decrease in customer demand, 20% increase in transportation cost, and high robotic CapEx put the feasibility of robotic implementation at risk.
4. Best-case Scenario – This scenario determines the best possible cost-benefit outcome that could arise after implementing robotics, assuming favorable market conditions of a 20% increase in customer demand, a 20% decrease in transportation cost, and low robotic CapEx.

The scenario analyses holistically incorporate the findings of each of these iterations. Inferences derived from the modeling results are more robust if the same trend withstands multiple scenarios. Mixed outputs under the various scenarios would dampen the conclusiveness of the results. In assessing a robotics implementation and integrating repackaging operations, demonstrating that cost-savings are sustained across multiple or all scenarios would emphasize the

resilience of the initiative. At the same time, mixed results would be informative of threats that inhibit its success.

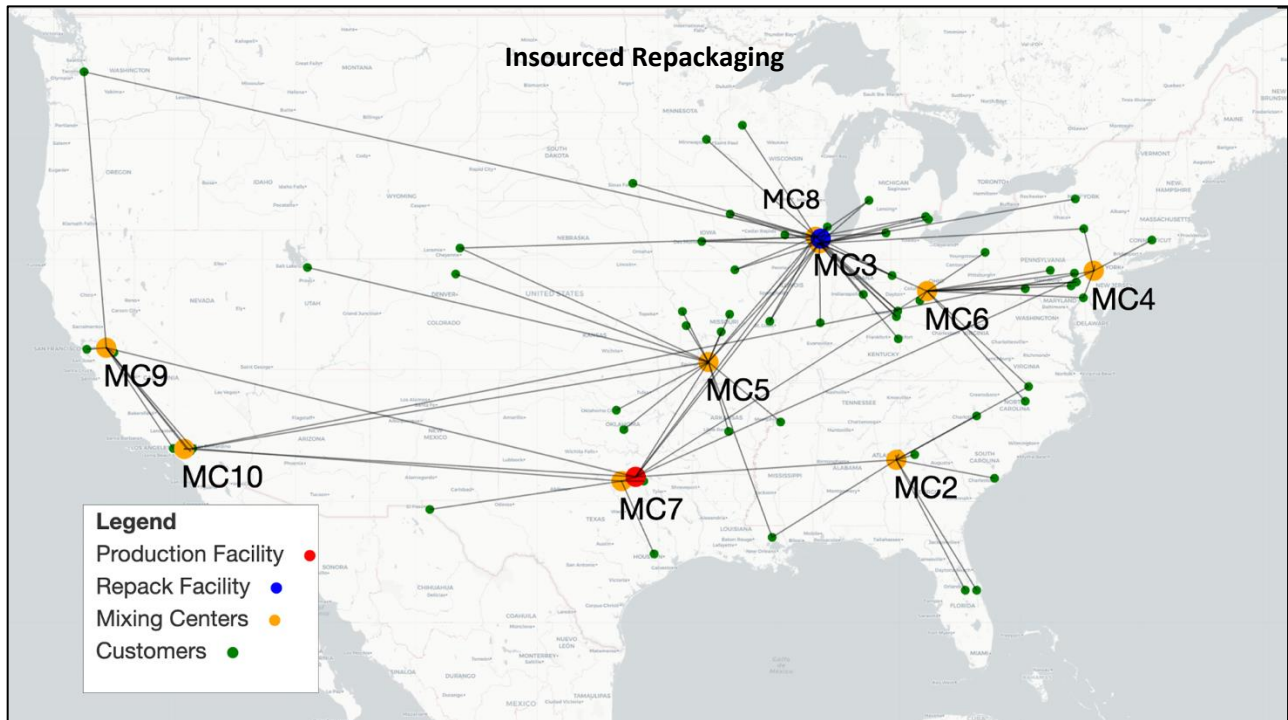
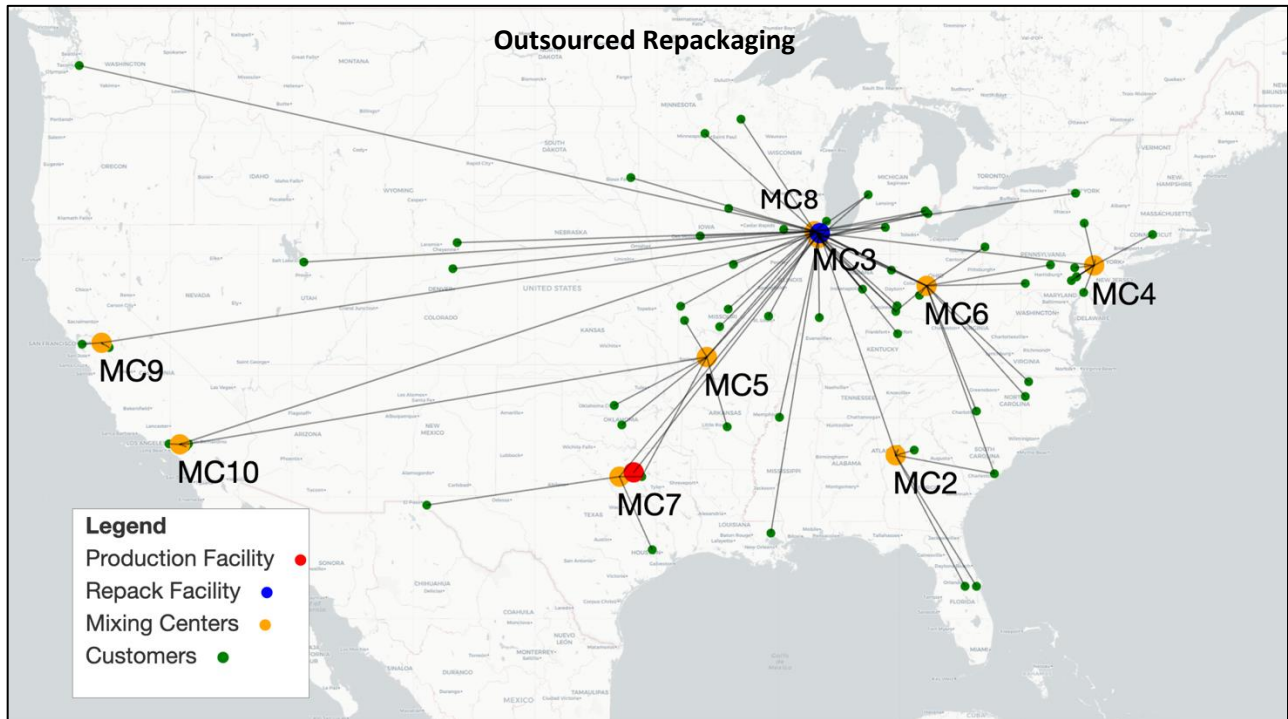
In addition to total system cost, other model outputs are relevant to the supply chain analysis. Total system cost can be broken down into its components (transportation cost, packaging cost, storage cost, packaging waste, labor cost, and capital and operating expenditure) to determine the critical cost drivers of the system. Transportation flows across each supply chain node are calculated, revealing which carrier's lanes will be most impactful on total system cost. Inventory flows through each of the nodes in the supply chain can be determined, informing which mixing centers are most utilized in any of the given scenarios, as some of them may be approaching capacity and bottlenecking the system.

4. RESULTS

This section documents the robotic solution quotations received from the robotic vendors for automating the existing manually driven product repackaging operation. This is followed by the results of our MILP optimization model, which considers multiple scenarios and the business-as-is case. In the business-as-is case, the decision to integrate the repackaging operations forces significant shifts in the flows of the product in the supply chain network. As an example, let us analyze the Chicago area. These shifts can be visualized in Figure 4, which demonstrates how, in outsourced repackaging, all product is shipped to the repackaging partner in the Chicago area once it is manufactured at the production facility, making that area the focal point of distribution. However, in the insourced repackaging (see the second map of Figure 4), we witnessed less product being shipped to the Chicago area and a higher volume of flows from the production facility directly to the Mixing Centers, in orange.

Figure 4

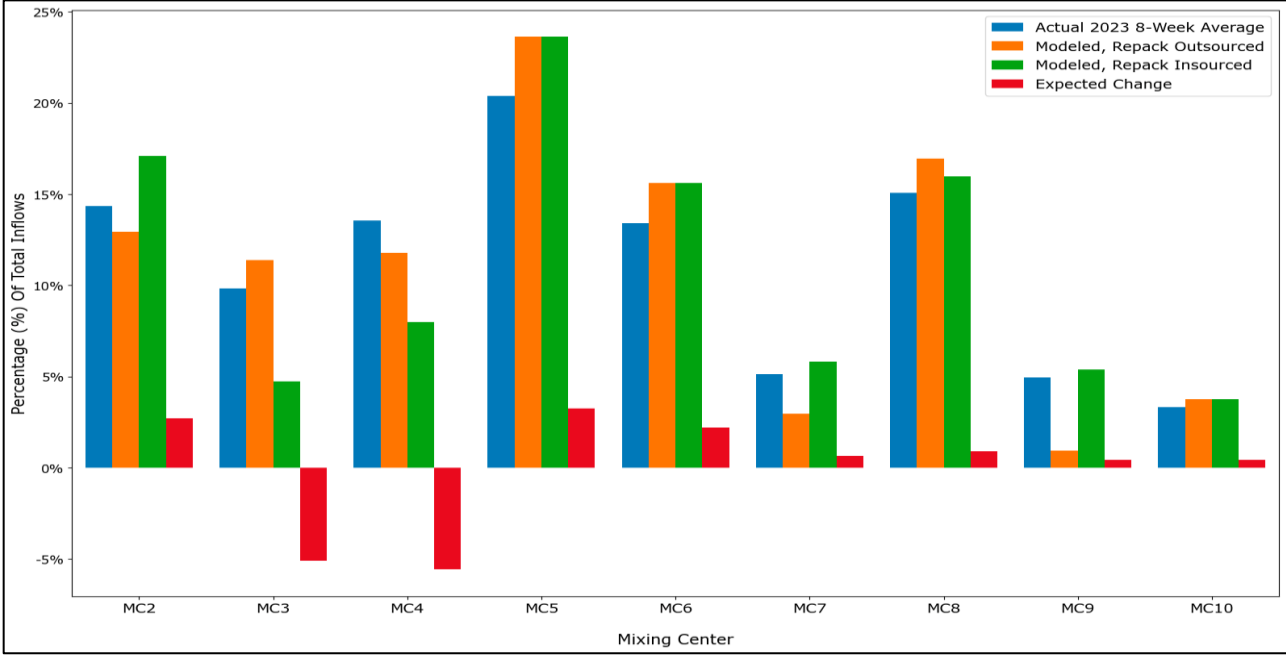
Supply Chain Network with Outsourced Repackaging vs. Insourced Repackaging



Additionally, Figure 5 depicts the impact of insourcing on Mixing Center utilization. In blue, the actual Mixing Center utilization, derived from intra-network material inflows given by the sponsor company, is indicated. The modeled utilization of the Mixing Centers under the baseline scenarios is shown in orange and green. In red, the difference between the actual utilization derived from the sponsor's intra-network inflows and the modeled utilization when repackaging operations are insourced is indicated, showing the expected change in Mixing Center utilization that would be required to achieve the more efficient transportation enabled by insourcing repackaging operations.

The model selects to reduce utilization at Mixing Centers 3 and 4 when insourcing repackaging operations. This can be explained by the large Southern, Southeastern, and Western markets for products. Shipping from the production facility in Texas to Mixing Center 3 in the Chicago region would involve moving the products away from those regions, leading to high transportation costs. The model prefers to serve those customers from Mixing Centers 2 (+4.13%/+15,979 units), 9 (+4.45%/+17,212 units), and 7 (+2.84%/+10,979 units) which are a convenient stop along the way from Texas to their respective markets.

Figure 5
Impact of Insourced Repackaging on Mixing Center Utilization



Section 4.1 explains the robotic vendor quotations, including the cost and throughput capacity of robotic systems. Section 4.2 through 4.5 break down the modeled total systems cost under each scenario of interest, section 4.6 summarizes the results, and section 4.7 provides managerial insights.

4.1 ROBOTIC VENDOR QUOTATIONS – COST & THROUGHPUT CAPACITY OF ROBOTIC SYSTEMS

We collaborated with leading robotic system vendors to understand what robotic system solution can automate the current manually driven repackaging operations. We shared with them the existing product repackaging operation process diagram, i.e., Figure 2, and key data, such as the size of the repacked product at each stage and the system's throughput requirements. This helped the vendors craft solutions that fit the requirements of our sponsor company. Figure 6 depicts the solution given to us by the robotic vendors. With automation and the in-house repackaging operations, de-palletizing and unboxing products A and B is no longer needed. Additionally, the loading of bundles into Club Display Trays (CDTs) and the palletizing of the finished CDTs are automated using the conveyor and articulated arms. With the new solution, the robotic vendors stated that only 1-2 employees would be needed to manage the current scale of operations, a significant reduction in labor requirements compared to the currently outsourced system.

Table 1 showcases the quotations received from the vendors for the cost and throughput capacity associated with the robotic solutions. From these quotations, we see that the throughput capacity of robotic systems is the primary cost driver for such systems.

The costs and labor requirements received from the vendors are utilized in the MILP model for scenario generation. For the model, the costs received from the vendors are adapted to their depreciated values, assuming a 5-year depreciation, as supported by US tax law (IFR, 2020). For example, considering the model's 8-week time period and the quotations from Vendor A, the calculation of the CapEx and OpEx of the robotic systems are as follows –

$$RC = \left(\frac{\$2.5M \text{ Robotic System CapEx}}{52 \text{ Weeks} * 5 \text{ Years}} \right) * 8 \text{ Weeks} = \$76,923 \text{ CapEx for the system}$$

Clarification: We assume a 5 year depreciation

$$OC = \left(\frac{\$2.5M \text{ Robotic System CapEx}}{52 \text{ Weeks} * 5 \text{ Years}} \right) * 8 \text{ Weeks} * 0.05 = \$3,846 \text{ OpEx for the system}$$

Clarification: We multiply by 0.05 as this is the OpEx % for Vendor A

Figure 6

Repackaging Operations With Robotics

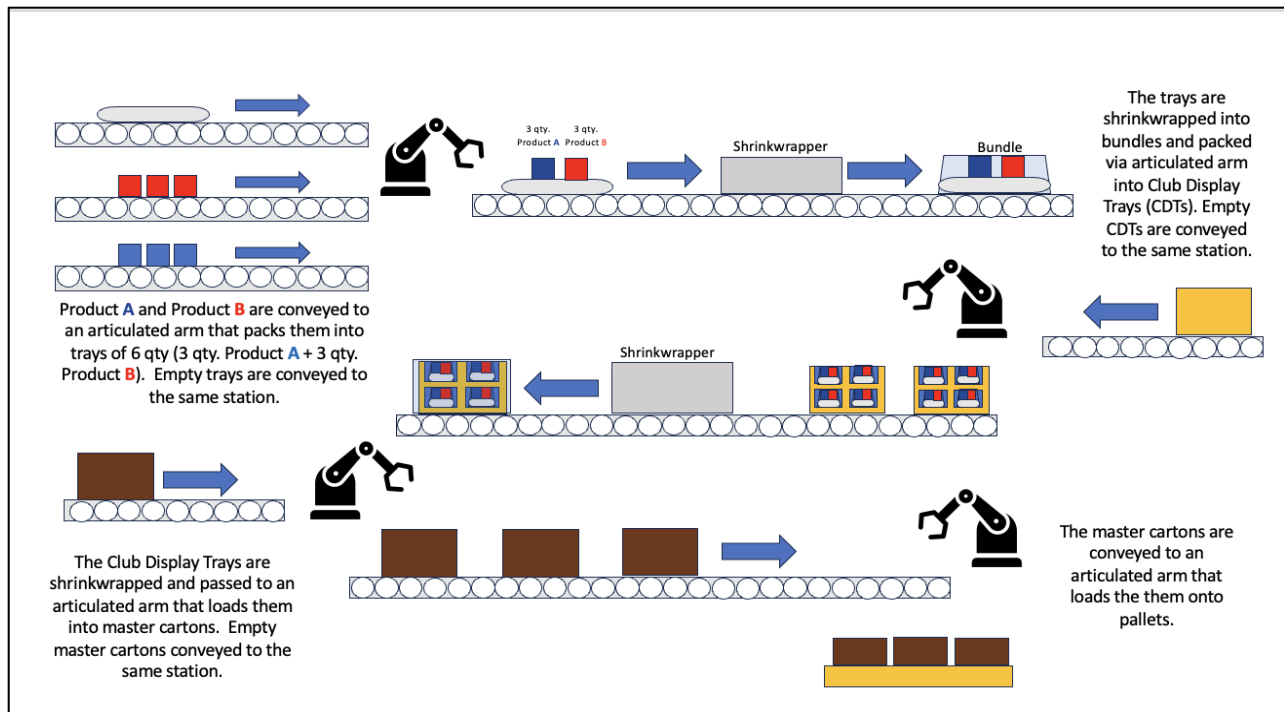


Table 1

Robotic Vendors Quotations – Cost & Throughput Capacity

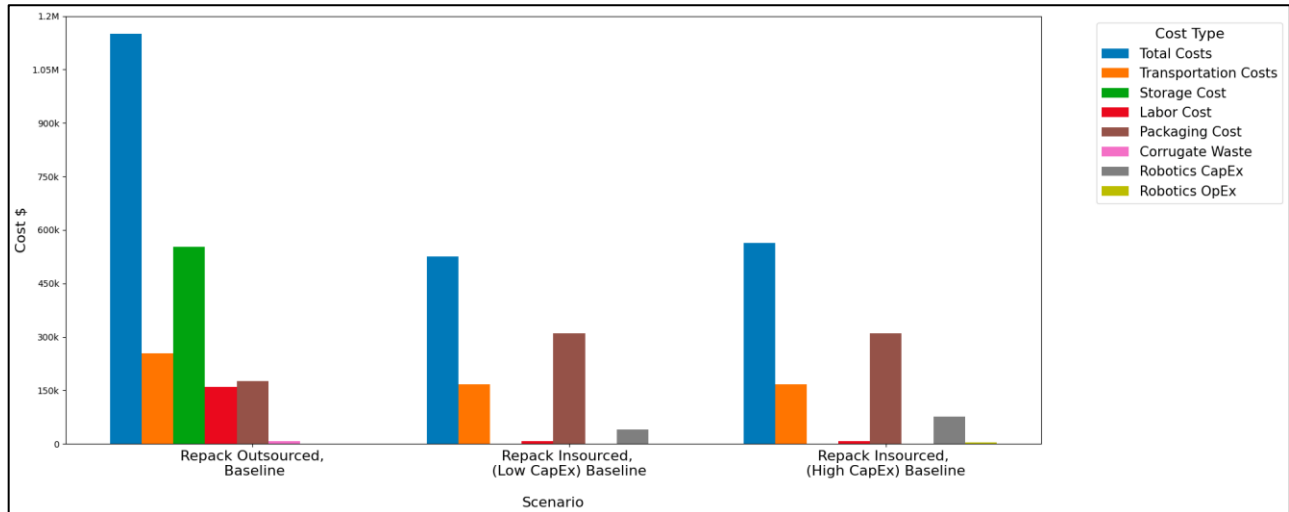
Name of Vendor	CapEx	OpEx	Throughput Capacity
Vendor A	\$2.5M	5% of CapEx	1,800 CDTs/8 Hrs
	\$2.4M		1,500 CDTs/8 Hrs
	\$2M		1,000 CDTs/8 Hrs
Vendor B	\$1.32M	\$10K	1680 CDTs/8 Hrs

4.2 BASELINE SCENARIO

This scenario utilizes the customer demand and transportation rates from 2023 and simulates an environment under realistic market conditions. Under this scenario, two robotic systems are used, namely, low and high CapEx robotic systems, which were gathered from two leading robotic system providers. The cost of the high CapEx robotic system is 47% higher than that of the low CapEx robotic system. Figure 7 shows that the total system cost is reduced by 54% if the low CapEx robotic system is deployed and by 51% when the high CapEx robotic system is deployed. This can be attributed to reductions in transportation (34%), storage (100%, as it is eliminated), and labor costs (95%), which overcome the expectation that packaging costs will increase by 75%. As shown in Figure 7, the model optimizes transportation flows when it is no longer constrained to ship all inventory produced in the production facility directly to the repackaging facility. When the repackaging operation is insourced, the model elects to allocate more inventory to MC2, MC7, and MC9 and less to MC3 and MC4 before shipping to customers, thereby lowering transportation costs.

Figure 7

Total System Costs: Repack Outsourced vs. Insourced

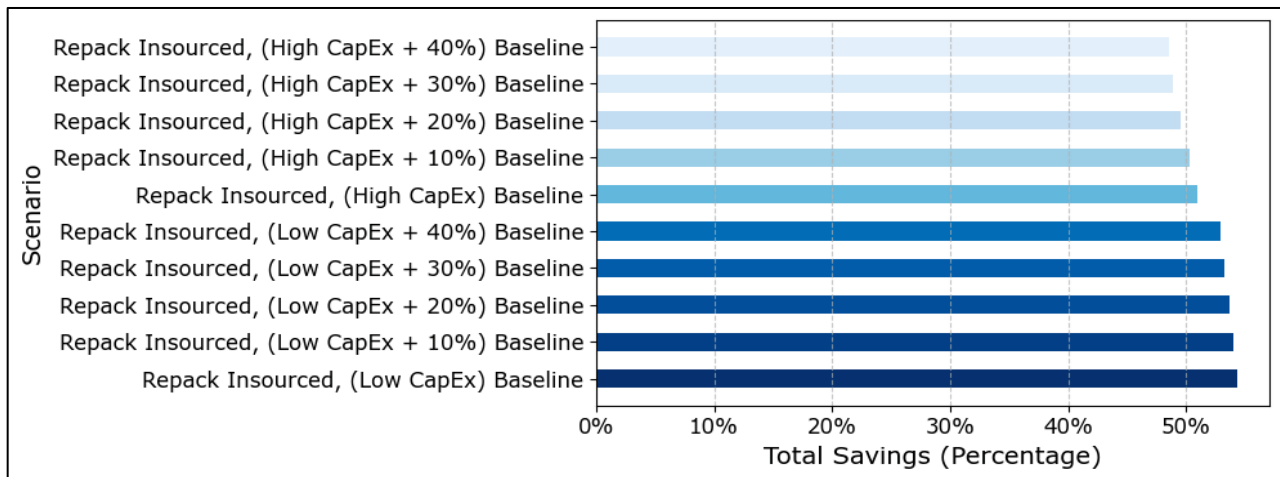


4.3 INCREASING ROBOTIC CAPEX BETWEEN 10% AND 40%

This scenario incorporates incremental increases in CapEx, broadening the analysis to account for uncertainty in the necessary expenditures in case the sponsor company pursues an implementation. During the implementation of robotics, complexities may arise that drive up the total cost associated with the system. Given that the robotic vendors were asked for an estimate of the cost of implementation rather than a detailed proposal, the expenditure may likely increase as implementation unfolds. This analysis allows our sponsor company to plan for such cost increases and thus accordingly plan contingencies that reduce overall risk. In Figure 8, total system savings are evaluated as the CapEx increases in increments of 10%. Total systems savings are reduced to 48.5% when the high CapEx robotics system entails a 40% increase in expenditure.

Figure 8

Cost Savings Outcomes (%) of Baseline Scenario With Increases In CapEx

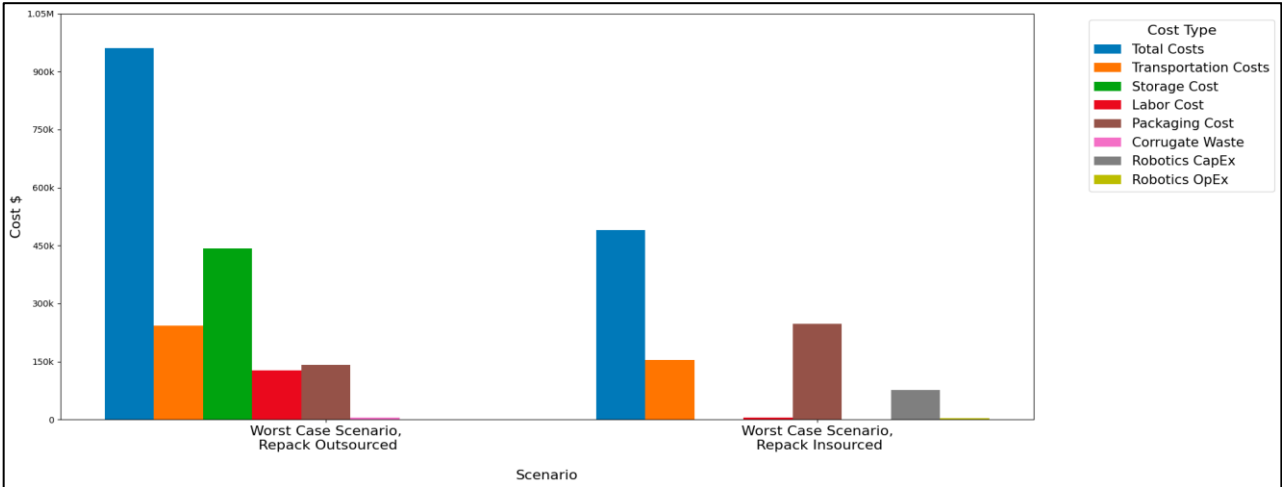


4.4 WORST-CASE SCENARIO – 20% DECREASE IN CUSTOMER DEMAND, 20% INCREASE IN TRANSPORTATION COST AND HIGH ROBOTIC CAPEX

This scenario assesses whether unfavorable market conditions of a 20% decrease in customer demand, a 20% increase in transportation cost, and high robotic CapEx put the feasibility of robotic implementation at risk. Under this scenario, the cost savings from transportation, labor,

and storage are diminished compared to the insourced baseline scenario, given that fewer products are being produced. Thus, there is a diminished benefit from implementing robotics. Furthermore, compared to the insourced baseline scenario, we observe the utilization of MC2, MC5, MC6, MC7, MC9, and MC10 is higher, and MC3, MC4, and MC8 are lower. This suggests an optimal supply chain network would have increased capacity at Mixing Centers with higher utilization. Figure 9 shows that the total system cost still reduces by 49%, even under unfavorable conditions. This reduction can be attributed to reductions in transportation (36%), storage (100%, as it is eliminated), and labor costs (95%).

Figure 9
Worst-case Scenario: Repack Outsourced vs. Insourced



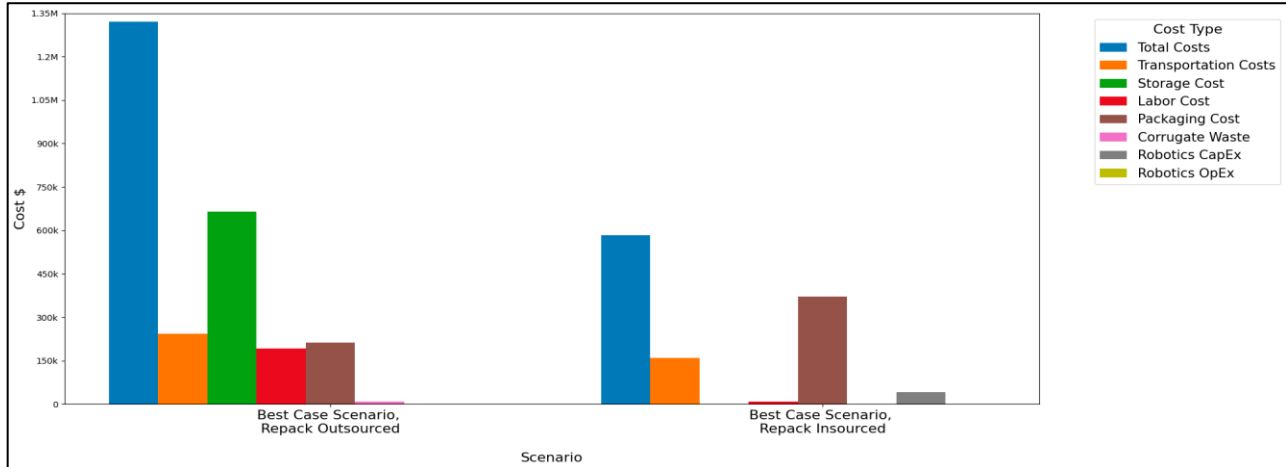
4.5 BEST-CASE SCENARIO – 20% INCREASE IN CUSTOMER DEMAND, 20% DECREASE IN TRANSPORTATION COST AND LOW ROBOTIC CAPEX

This scenario determines the best possible cost-benefit outcome that could arise after implementing robotics, assuming favorable market conditions of a 20% increase in customer demand, a 20% decrease in transportation cost, and low robotic CapEx. Under this scenario, the increase in demand is accommodated by an assumption that a 20% increase in storage and throughput capacities of the system is possible. This was necessary to allow the model to arrive at a feasible solution. Thus, there is no difference in the Mixing Center utilization compared to the

insourced baseline scenario. Figure 10 shows that the total system cost was reduced by 56% under such favorable conditions. This reduction can be attributed to reductions in transportation (34%), storage (100%, as it is eliminated), and labor costs (95%).

Figure 10

Best-case Scenario: Repack Outsourced vs. Insourced

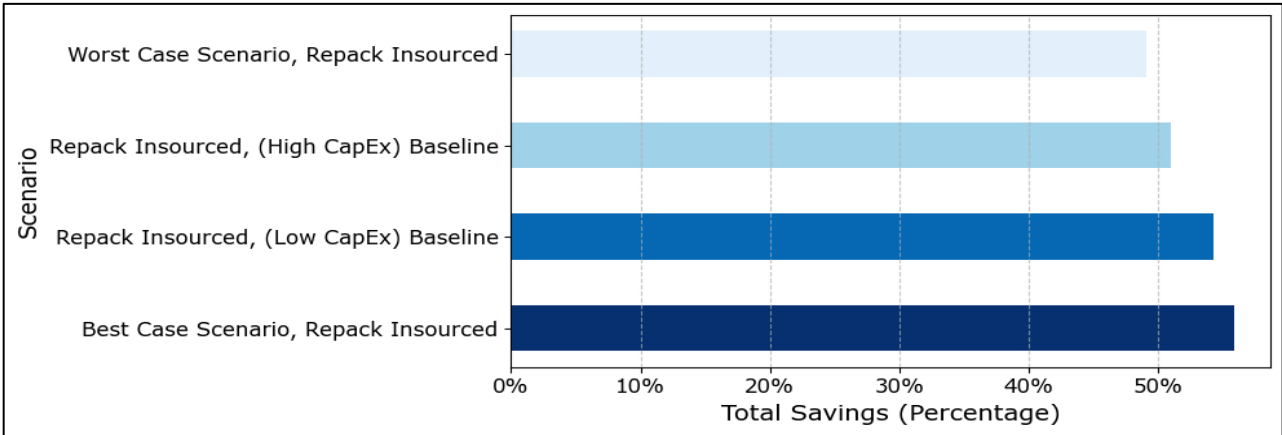


4.6 SUMMARY OF RESULTS

In summary, Figure 11 encapsulates the savings in percentage accomplished by the scenarios depicted in Sections 4.2 through 4.5. It shows that the most significant savings come from the best-case scenario, amounting to 56%, and the least savings come from the worst-case scenario, amounting to 49% in a year. These savings are driven by the reduced per-unit cost of repackaging and transportation of the product due to the insourcing of the repackaging operations using robotics.

Figure 11

Cost Savings Outcomes (%) For Scenario Simulations

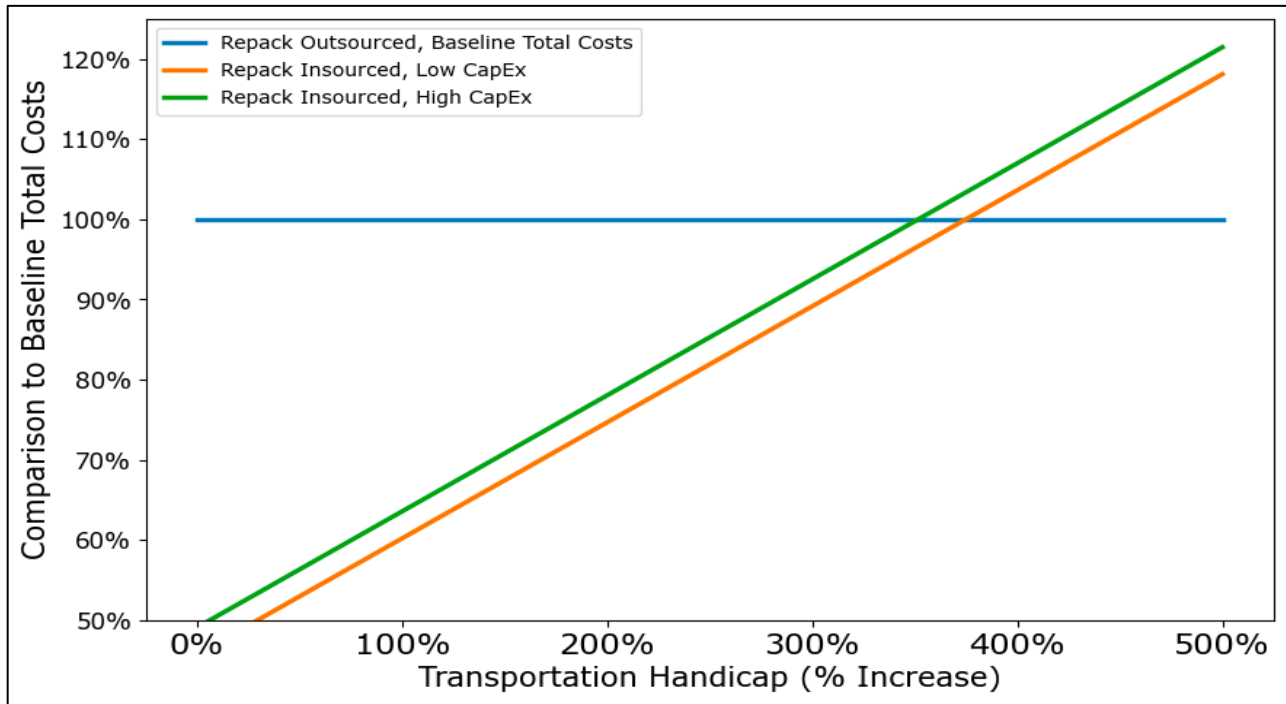


Furthermore, Figure 12 illustrates the degree of cost savings associated with insourcing robotics. The green and orange lines represent the total system cost of the baseline scenarios using high CapEx and low CapEx robotic systems, respectively. The blue line represents the total system cost of the current supply chain network with outsourced repackaging. As we move along the x-axis, the transportation costs generated by the insourced baseline scenarios are augmented with increasing percentages. The point of intersection of the green, orange, and blue lines occurs when conditions are met, which equals the total system cost of the scenarios.

Our findings suggest that the transportation costs would need to be increased by nearly 375% (in the case of low CapEx robotics) or 350% (in the case of high CapEx robotics) to negate the savings associated with insourcing repackaging operations in the baseline scenario. These findings demonstrate the financial benefits of embracing robotic automation and highlight its indispensable role in ensuring the long-term viability and competitiveness of food manufacturing companies in an increasingly dynamic market landscape.

Figure 12

Transportation Cost Handicap Required to Negate Cost Savings of Insourcing Repackaging



4.7 MANAGERIAL INSIGHTS

Implementing robotics and replacing existing outsourced repackaging operations presents a promising avenue for total system cost savings, potentially ranging between 49% and 56%. Furthermore, electing to insource robotics results in a 35% reduction in total trucking kilometers, from 989K kilometers to 645K kilometers over a year, assuming the product is shipped via full truckload. Thus, we recommend that our sponsor company consider insourcing and automating its existing costly, unscalable, labor-intensive, and outsourced product repackaging system with robotic solutions.

Should our sponsor company insource its repackaging operations, another avenue exists for further cost optimization: the procurement cost of the exterior physical packaging of the product. Our sponsor company currently procures and assembles the physical product packaging at a cost

75% higher than the outsourced vendor's. Thus, this avenue is a crucial opportunity to drive down total system costs further and improve operational efficiencies.

However, the transition to insourcing entails substantial changes, including changes in the flow of product and inventory levels at various nodes of the supply chain network. We observed that our product processed at the repackaging facility sat for six weeks before being shipped to the Mixing Centers for further customer distribution. We estimate that the total demand for our product is served via 13,000 full pallets. Insourcing repackaging operations shall result in these 13,000 pallets circulating for six weeks longer in the sponsor's owned facilities in the supply chain network than they are currently. Additionally, the insourcing repackaging operations shall lead to a decrease in utilization by 10.7% across Mixing Centers MC3 and MC4 collectively and an increase by the same amount across the other Mixing Centers MC2, MC5, MC6, MC7, MC8, MC9, and MC10 collectively. This change in utilization must be implemented at the Mixing Centers to realize the savings suggested in the results. This may require further expenditures, such as an increase in these Mixing Centers' storage and handling capacity.

Additionally, streamlining order processes could help reduce the 6-week delay between the production of the base product and the final repackaging product, thereby reducing the impact of the shift in utilization at the Production Facility and Mixing Centers. This could also reduce the repacked product's safety stock and batch sizes. If this can be achieved, it is possible to reduce the throughput requirements of the currently suggested robotic solutions, thus reducing the overall cost of robotics.

5. CONCLUSION & FUTURE RESEARCH

In conclusion, we developed a MILP model that optimizes the total systems costs of the sponsor company's supply chain network. The model considers unitary operating costs and flow constraints contingent upon the positioning of the repackaging operations, be it that they are performed either with the outsourced repackaging facility or in-house at the production facility with robotics-driven systems. It also considers the inventory and throughput capacities of each location

in the network, as well as the unitary trucking costs associated with each of the arcs in the network. With these input parameters and constraints, the model generates thousands of decision variables informing the production timing, the choice of repackaging operation, and the product flows throughout the supply chain network, optimizing them all to generate the most cost-effective outcomes.

The robotic systems that leverage articulated arms and conveyor systems, as explained in section 4.1, fit the requirements of automating our sponsor company's currently manually driven repackaging operations. The robotic solution costs range from \$1.32M to \$2.5M, and throughput capacities range from 1,000 CDTs/8 Hrs to 1,800 CDTs/8 Hrs. Integrating the capital and operational expenditures for those solutions into the model, we observe that the decision to integrate the repackaging operations forces significant shifts in the flows of the product in the supply chain network. Running various scenarios demonstrates the clear benefit of in-sourcing the repackaging operations via robotics. Our modeling suggests that the most significant annual savings result from the best-case scenario, amounting to 56%, and the least annual savings result from the worst-case scenario, amounting to 49%, showcasing the benefits of insourcing repackaging operations and substituting labor driver operations with robotics-based systems.

However, our capstone has a few limitations. It assumes that the robotic systems suggested for automation can adequately fit at the Production Facility. To design an optimal solution, a thorough physical examination by the robotics vendor of the Production Facility is needed to ensure a smooth integration of the robotic system with existing operations. Furthermore, to accommodate our model's need for lane-specific trucking rates, we incorporated actual 2023 trucking rates for select lanes from DAT Freight & Analytics. These rates were the foundation for a linear regression analysis that enabled us to forecast the trucking rates for all other lanes within the network.

A promising area for future research could be to evaluate the viability of deploying the appropriate robotic product repackaging systems within Mixing Centers rather than the existing Production Facility. This shift could streamline operations by consolidating repackaging processes

closer to the end customers, potentially reducing transportation costs and lead times. However, a comprehensive feasibility study is needed, examining factors such as space availability within Mixing Centers, robotics system requirements at those locations, potential impacts on transportation costs, and optimization of inventory management and throughput capacity to ensure no significant disruption to ongoing operations.

Moreover, given that our capstone focuses on one-star product, an intriguing avenue for further research involves expanding the analysis to encompass additional products from the sponsor's product catalog. By incorporating a broader range of products, our sponsor can assess the collective throughput requirements for the robotic repackaging system. Since the cost of robotic systems is directly proportional to their throughput capacities, conducting a comprehensive analysis could be beneficial. This analysis would evaluate the return on investment associated with scaling up the robotic infrastructure to accommodate varied throughput and product repackaging demands across multiple product lines. Additionally, extending the timeframe of the model to cover an entire year rather than eight weeks may provide insight into the total system costs with greater accuracy. Through such an endeavor, our sponsor company could gain valuable insights into the cost-effectiveness and scalability of robotic solutions within the context of diverse product portfolios and operational requirements.

The suggested areas of future research promise to enhance efficiency and agility within the supply chain of our sponsor company while maintaining business continuity. By strategically deploying robotics in Mixing Centers or expanding their throughput capacity, our capstone sponsor could potentially enhance flexibility, responsiveness, and cost-effectiveness throughout the supply chain, helping them gain a competitive advantage and position themselves for sustained success in an increasingly competitive marketplace.

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