Evaluation of Automated Storage and Retrieval in a Distribution Center

By

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Abstract

In the face of ecommerce growth and rising customer delivery expectations, companies must adapt to meet shorter contract shipping requirements with existing infrastructures. The “Amazon effect”, an evolution resulting in increased online shopping and direct-to-consumer order fulfillment, is reverberating through the retail industry and requiring manufacturers to evaluate their existing supply chain networks to meet two- and one-day shipping from their distribution centers (DC). This thesis evaluates speed and execution improvements using automated storage and retrieval systems (ASRS) in DCs. Adopting ASRS can provide the essential capability upgrades to reduce material processing time and meet direct-to-consumer deliveries.

The ASRS analysis reviews current DC metrics, future throughput and inventory requirements, comparisons of ASRS technologies utilized today, expected impact of ASRS inside of an existing DC, and sizing and selection of an ASRS. Analysis of the DC evaluated showed that the primary cause of delays in shipping time was due to high variability in task completion time, rather than a high average completion time, causing extended wait times to propagate throughout the DC. While methods to reduce task time variation can be implemented, a warehouse logic upgrade would allow for real-time sequencing to get products shipped in the correct order based on factors like shipping method, customer, or priority. Implementation of ASRS in the DC evaluated could decrease processing time in storage and retrieval by 67% and total processing time through the DC by 37% due to ideal sequencing, diminished downstream variability, and reduced work in progress. The payback period for ASRS is projected to be 4 to 5 years.

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The author wishes to acknowledge her family for their relentless encouragement of her endeavors, no matter how crazy, and her fellow Leaders for Global Operations classmates for their continuous support over the past two years.

Note on Nike Proprietary Information

In order to protect information that is proprietary to Nike, Inc., the data presented throughout this thesis has been modified and does not represent actual values. Data labels have been altered, converted, or removed in order to protect competitive information, while still conveying the findings of this project.

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Acronyms

ASRS – automated storage and retrieval system

CSR – case storage

DC – distribution center

FIFO – first-in-first-out

INT1 – full case to sorter

INT2 – full case to shipping

INT3 – units coming out of picking

INT9 – full case to picking

PFD – process flow diagram

PSR – pallet storage

ROI – return on investment

SKU – stock keeping unit

SRS – storage and retrieval

VAS – value added services

WCS – warehouse control system

WES – warehouse execution system

WIP – work in progress

WMS – warehouse management system

1. Introduction

1.1 Thesis Objective

The need for speed – or the reduction in cycle time to get product to customers faster – is reverberating across the apparel industry. A shift in consumer tendencies to use digital platforms is causing companies to rethink their logistic networks and invest in supply chain capabilities to capture market value and get products to the customer faster. Existing distribution centers (DC), built for wholesale and factory store fulfillment, are evolving into hubs that can service existing customers in digital and direct-to-consumer markets. This thesis investigates the use of automation in the storage and retrieval area of a DC to reduce cycle time. The research in this thesis was conducted in collaboration with Nike at a DC in Memphis, Tennessee.

This thesis reviews the steps required to decide if the time savings and cost impacts of automating the storage and retrieval (SRS) area of a DC are impactful, including data analysis of the distribution center flow, inventory quantity and size, and existing DC infrastructure. The DC referenced in this thesis primarily serves wholesale customers, but the analysis steps can be performed for any DC. The work in this thesis is a continuation of MIT LGO graduates Wallach "Reducing Wave Cycle Time at a Multi-Channel Distribution Center" and Greenlee "Standardization of Workflow in a Large Distribution Center". The recommendations that Greenlee gives on wave dynamics, described in Section 2.2, are examples of ways that orders can be better released into the DC. This thesis identifies how to better perform work after it has been released into the DC.

Section 1 begins with a company overview and problem statement. The DC current operation is described in Section 2. Section 3 reviews literature of current automated storage and retrieval (ASRS) hardware and software technologies on the market. Section 4 goes through the methodology of how to determine if ASRS is the correct fit for a DC, including current and future state DC parameters, expected ASRS impact, sensitivity analyses, and results. The thesis concludes with key findings and recommendations when automating a DC with ASRS.

1.2 Nike, Inc. Organization

1.2.1 Nike Overview

Founded in 1964, Nike is a global sportswear brand that designs, manufactures, and sells shoes, apparel, and equipment. Product design occurs at headquarters in Beaverton, Oregon, while manufacturing occurs primarily in Asia and distribution is performed worldwide. Nike owns a handful of DCs and partners with third party logistics providers (3PL) to operate the remaining DCs. These Nike DCs service wholesale customers, like Footlocker or Dick's Sporting Goods, Nike direct stores, and consumers directly via Nike.com. Products stocked in the DCs are from brands Nike, Jordan, Hurley, and Converse.

Nike's revenue in 2019 exceeded $39 billion (Investor News Details, 2019), making it the largest athletic apparel company in the world and placing it 90th on the Fortune 500 list (Fortune 500, 2018).

1.2.2 Nike Strategy

In 2017, Nike launched the consumer direct offence strategy to boost revenues from 7% to 8% year over year growth (Nike, Inc, 2017). The goal of the consumer direct offence is to double product innovation, double speed of delivery, and double direct sales to consumers. Adoption of this strategy, specifically in speed of delivery, resulted in an in depth look of how Nike DCs operate and how to make them faster.

1.2.3 Project Definition

Currently, Nike has the capability to process orders of various service levels, but is looking to ship faster with rising customer expectations. This means that the distribution center must reduce its *cycle time*, defined as the total time it takes from when an order is released into the DC until it is packaged and ready to be shipped on the shipping dock. Because packages are shipped by truckload, the wait time of the order from when it is processed through the DC until it leaves on the truck is not considered cycle time. Nike foresees its digital channel, and overall wholesale demand, growing over the next 5 years, extenuating the need to upgrade DC infrastructure to meet customer demand and shipping speed.

The data in this thesis comes from the operations in a large DC that houses footwear and equipment and is designed for wholesale customer fulfillment. Increasing direct-to-consumer shipments as well as smaller, more frequent wholesale orders introduce to the DC smaller overall fulfillment quantities. To adapt to the digital market and ship faster, the building is going through multiple retrofits, one of which is an analysis of storage and retrieval (SRS). In the DC evaluated, every product received at the DC is stored and later retrieved when an order is placed. The current forklift and manual labor processes result in variable task completion times, which can be detrimental to on-time delivery.

Multiple projects have been conducted to speed up and reduce variability in SRS. For example, work areas have been reassigned to limit excess forklift driving, and the number of items that can be retrieved before driving to the closest conveyer belt, also called the throwline, have been reduced. Inherent constraints in the process, like safety requirements only allowing one forklift per aisle, have resulted in a throughput threshold that makes it challenging to speed up the SRS process. Nike is looking for a solution to improve first-in-first-out (FIFO) sequencing and create more of a continuous flow through the facility. Wallach and Greenlee, along with other Nike employees, focused on creating uniform work distribution through standardizing “waves”, or order releases to the floor (Greenlee, 2019) (Wallach, 2018). This thesis instead addresses the question of how work can be executed with less variability.

ASRS is a highly automated solution that many warehouse distribution centers employ. Initial analysis and case studies of ASRS indicate that automation can propel Nike DCs towards two-day and next-day shipments. This thesis covers a high level ASRS overview, including an analysis of existing shipping capabilities and future projections to identify ASRS impacts and important system requirements. ASRS is an expensive investment but could be the solution to staying ahead of customer demand and meeting delivery expectations.

2. Distribution Current State

Chapter 2 will discuss the material flow of the distribution center analyzed, including receiving, storage, retrieval, picking, sorting, and shipping. The process of order waving is introduced and key metrics are discussed.

2.1 Distribution Center Material Flow

Product moving through the distribution center can exist in cases, totes, or as an each.

- A case is a box containing same SKU items. A SKU is a specific size, color, and style of product. Depending on the SKU, a case can hold various unit quantities; for example, a case can consist of six pairs of shoes or thirty backpacks. Cases also come in different sized boxes depending on the manufacturer and origin.
- A tote is a plastic container or bin with a volume of approximately 300 gallons that eaches can be put into for consolidation. Totes ensure that a group of eaches, which could be different SKU items on the same order or going to the same processing step, travel together on a conveyer belt.
- An each is a singular unit: one pair of shoes or one t-shirt. When a case is opened, the units inside become eaches. In the DC evaluated, eaches exist in the picking area; in primarily ecommerce facilities, eaches can be the only flow of material.

The flow of an item through the DC goes through six main steps: receiving, storage, retrieval, picking, sorting, and shipping. The processes are described below. A process flow diagram (PFD) is shown in Figure 1. The black lines indicate overlapping flows while the colored lines indicate segmented flows, referenced in the key in Figure 1.

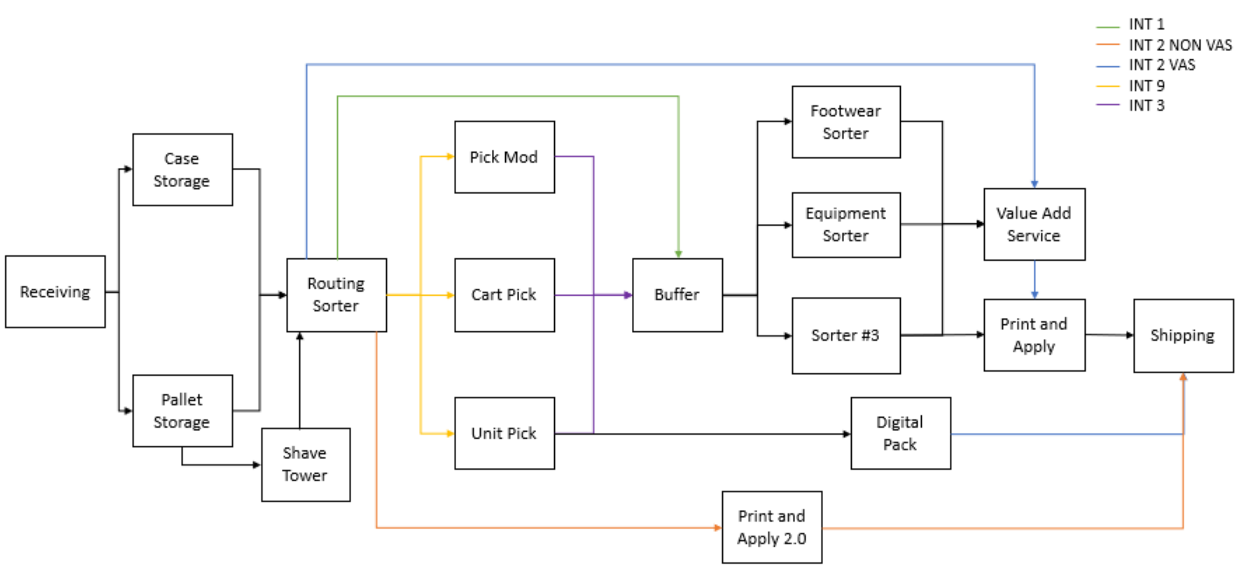

Figure 1: DC Basic flow diagram

Receiving - When trucks arrive at the unloading docks, cases are moved from the truck to a conveyer belt and received into the building. Cases are boxes containing multiple units of one SKU. A receiving sortation mechanism will consolidate cases of the same SKU down the same chute to be moved to the storage area.

Storage – Cases can be stored in either pallet (PSR) or case storage (CSR). Both areas have scaffolding enclosed in the building that reaches to the roof, approximately 40 feet high. PSR stocks same-SKU cases placed on a pallet with a 4-foot by 4-foot footprint. Full pallets have cases stacked 5-foot tall while half pallets are 2.5-foot tall. Four of the five buildings in the DC are allocated to PSR with the last building housing CSR, which stores individual cases distributed randomly throughout the scaffolding. Each slot has a number and barcode assigned to the location. CSR locations can hold multiple cases of a single SKU, depending on the physical dimensions of a case. In general, CSR accounts for 15% and PSR 85% of total inventory in the DC.

After a case is received, same-SKU cases wait in designated chutes. An associate will manually palletize cases onto a pallet if there are more than 4 same-SKU cases. Once a pallet is complete, an employee on a turret truck will pick up the pallet and take it to the first available location dictated by the warehouse management system (WMS). The employee will then scan the location barcode and store the inventory location in WMS. For smaller quantity same-SKU cases in receiving, the boxes will route on the conveyer straight to CSR. An associate will place individual cases on an order picker and store the inventory randomly in CSR, scanning the bar code location to link its location to WMS. Every item that goes through this DC flows through receiving and storage as described above, and subsequently retrieval as described next.

Retrieval – Once an order, or a wave of orders, is released to the DC by the planning team, demand is created in WMS driving a retrieval task. A retrieval task can be a case picked from CSR, a case picked off a pallet in PSR, or an entire pallet removed from PSR. Employees use a combination of order pickers, turret trucks, and reach trucks to drive down aisles, pick cases, and place cases on the back of the truck. WMS will dictate how many cases to retrieve, usually ranging between 2 and 12, before an associate will drive to the conveyer and move cases onto the conveyer belt.

Full pallet pulls can occur if an order requires every case on that pallet, or more commonly, is to move the pallet to the shave tower. The shave tower is a 3-level structure in the pallet area with the purpose to get faster moving SKUs, or product more commonly ordered by customers, to the throwline faster. The throwline is the drop-off point where cases can be added onto the conveyer belt. In the shave tower, associates can walk down aisles on each level and place cases directly to a conveyer belt without using trucks. Most pallets go first to PSR before the shave tower, but a few high-volume SKUs can go straight from receiving to the shave tower.

Routing Sorter - Once on the throwline, a routing sorter can send a case to one of three destinations: picking, sorting, or shipping. The location of the case is dictated by WMS based on order quantity and value-added services (VAS). The four main routes are listed below:

1. INT1 – Full case to sorter
2. INT2 – Full case to shipping
3. INT3 – Units picked from picking area
4. INT9 – Full case to picking replenishment

For example, if a customer orders a quantity 10 of the SKU A, and the associated case contains 6 units of SKU A, there are two options:

1. Two cases of SKU A will be pulled from either case or pallet storage (depending on where the case is located). One case will be sent as an INT2 straight to shipping while the second case will go to picking replenishment as an INT9 to be opened and stocked as units. The remaining four units will be picked as an INT3.
2. Four or more units of SKU A are already slotted in the picking area. One case will be pulled from case or pallet storage and sent as an INT2 to shipping while four units are picked as an INT3.

INT distributions are discussed in detail in Section 4.4.

Picking – There are 3 picking areas: Cart pick, unit pick, and pick module. Table 1 discusses the difference between the picking areas. Cart and unit pick are manual processes while pick module is semi-automated, and all areas are in different areas in the DC. The first step is replenishment; the INT9 case is opened, changing the material flow from case to eaches. The eaches are then placed into a dynamic location. This means that once the eaches are depleted, any SKU can take its place as slots are not designated for a certain SKU. Like case and pallet storage, picking slots are ordered randomly. The second step is picking; a picker will select eaches, according to WMS, and place them into a tote. The tote is then sent off on an outbound conveyer.

Table 1: Comparison of picking areas at the DC

Cart Pick	Unit Pick	Pick Module
• Employees use 3 level carts with totes on top to walk through aisles and pick items • Case replenishment is on the North side and tote drop off is on the South • Stocks only shoes	• Same process as cart pick • Case replenishment and tote drop off are on the same side • Stocks only shoes	• Semi-automated process • Tote travels on a conveyer belt in the center of the picking area and stops at the next item pick location. • All equipment is stored here

The group of picked eaches in totes will enter the buffer, or a waiting area, to consolidate the INT1 and INT3 items within the group, or wave, before proceeding to the sorter.

Sorting – There are 3 sorters: 1 dedicated to footwear only and 2 that can sort all products. Cases or totes are slotted into chutes, where an associate will package the units into shipping boxes to be sent to the customer. At the associate's station, WMS will display the required items and box size for that customer on a screen. This serves as the packing step unless the customer requires value added service (VAS). Examples of VAS include packing slip additions, custom sticker application, or hangars. If an item requires VAS, the box will be sent to a digital pack station where VAS is performed by an associate manually.

Shipping – The completed boxes will go through print and apply, an automated process where the shipping label and taping is completed, and then moved to shipping. Orders will be loaded onto a truck based on its shipping method and leave the DC.

2.2 Waving

Work is introduced into the DC using waves. Waves are a compilation of orders that are grouped together by ship date, shipping carrier, or customer, to name a few. Waves are sized by the planning team based on the overall or product sorter capacity, as defined above. WMS does not allocate INT types until waves have been created, meaning that the distribution of INT types varies wave to wave, which can cause variance in wave completion time. The flow team receives the wave from planning and will release the wave at 12am, 6am, 10am, 4pm 5pm, 7pm, 8pm, or 9pm. In general, we refer to "priority" waves as digital or next day shipments, while "regular" waves are wholesale or standard shipments. Priority waves will release at 12am or as soon as possible while regular waves will release at any time of day. Greenlee goes into detail on wave dynamics in his thesis "Standardization of Workflow in a Large Distribution Center" (Greenlee, 2019).

Greenlee addresses an ideal state where a maximum of 3 waves are worked on at a time, and wave size is decided based on a 2-hour work load in an area instead of the sorter capacity. Currently, there can be up to 30 waves worked on at a given time in the DC. Implementation of Greenlee's work would lead to smaller waves that take 6 hours to complete and fewer waves in progress. This is described further in Section 4.2. Figure 2 shows an example of wave cycle time during a week at the DC. The data is normalized, where a value of 1 means that the wave met the cycle time goal, and values above 100% indicate that flow time was longer than the goal. This data includes day, night, and weekend shifts. In this example, the wave time goal was met 13 times out of 53.

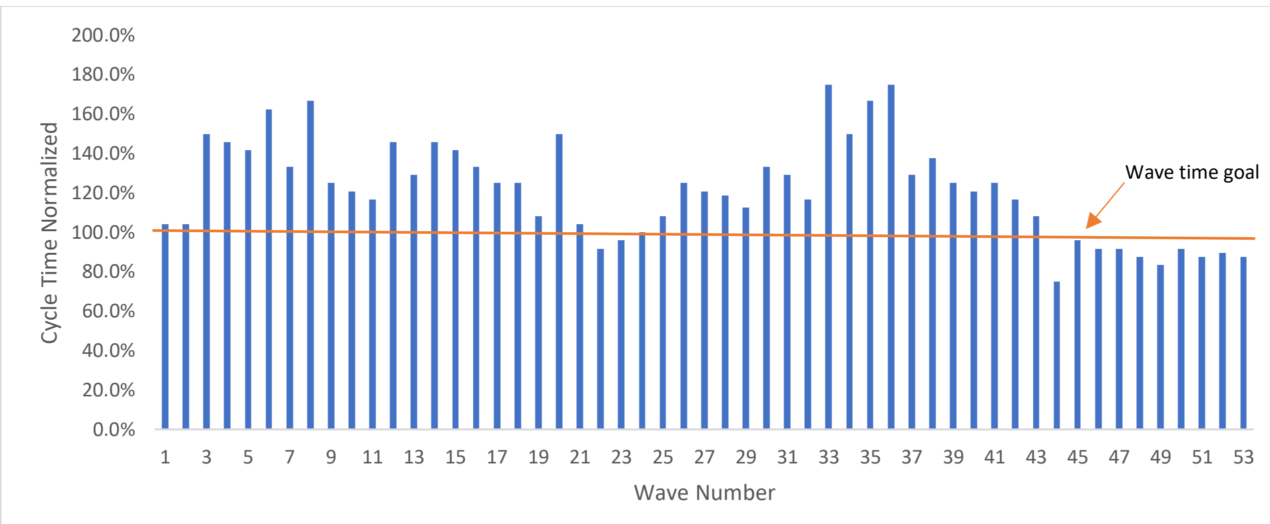

Figure 2: Wave cycle time for a given week in the DC, normalized where 100% is the wave cycle goal.

When evaluating the bottleneck in a DC, it is important to consider the inherent batch nature that waves present. If you were to ask ten employees where the bottleneck in the facility is, you are likely to get ten different responses. This is because the bottleneck now is different than it was an hour ago because of the non-continuity of work. New waves are released on the hour marks listed above instead of when tasks are completed in the DC. Therefore, the actual capacity of the building is hard to quantify due to how the waves are released. The distribution of work and wave dynamics affect the throughput and cycle time for the DC, and are important to consider when evaluating an automated process.

While Greenlee's thesis addresses how to optimize waves to reduce cycle time, this thesis will address how to manage waves in SRS after they have been introduced into the DC.

2.3 Key Metrics

Wave cycle time: This is the total time it takes to complete a wave from when the wave was released by the planning team to when it reaches shipping.

Wave-on-time: This metric is internal to the DC and evaluates if a wave met its set goal. It takes the wave cycle time and compares it to an internal goal, which could be different for priority versus non-priority waves.

Ship-on-time: This metric indicates whether the order made it out the door on time based on the carrier – truck, train, air – departure time. There are instances when wave-on-time is not met but ship-on-time is met if the wave was released days in advance, and vice versa if the wave was released too late.

Pallet density: This is the percent of space used on a pallet versus space available in a pallet slot. As cases are pulled off pallets in PSR, the pallet density goes down. Items received are compiled on new pallets, so older pallets can take up space if not moved to CSR or consolidated with other low-density pallets.

Daily shipments versus goal shipments: This compares the projected or goal shipments to the actual daily shipments. Daily values can be below the goal if the capacity was insufficient, or if the projected sales were less than actual sales.

Full case versus Repack: This would be the INT2 versus the INT1 and INT9 flows, with INT2 defined as "full case" and INT1 and INT9 together defined as "repack". Repack refers to any time the case is opened, which in this case is both in picking and sorting.

2.4 Focusing on SRS in the DC

This thesis will focus on the SRS area, which includes the flows into and out of SRS as well as the inventory storage areas in case and pallet storage shown in Figure 1. The focus on SRS is important because:

1. All items that are processed in the DC are stored and retrieved, so increased throughput in SRS will speed up all wave cycle times.
2. The storage process uses the majority of space in the DC, which is consistent across all DCs. Improvements in SRS will result in less picking movement, higher storage density, and overall lower wave cycle times.
3. SRS throughput is limited. Factors including number of employees, vehicle maintenance, vehicle safety restrictions (one per aisle), and storage accuracy set an inherent limit on pallets or cases per hour that can enter and exit SRS.
4. Compared to the other areas of the DC, accidents occurring in SRS were 12 times larger than accidents experienced by picking in 2018 (Figure 3). An in depth look at SRS should improve workers' well-being and reduce physical stress.

The main focus areas in SRS include improvements in inventory accuracy, pallet and case storage density, storage and retrieval throughput, and SKU organization.

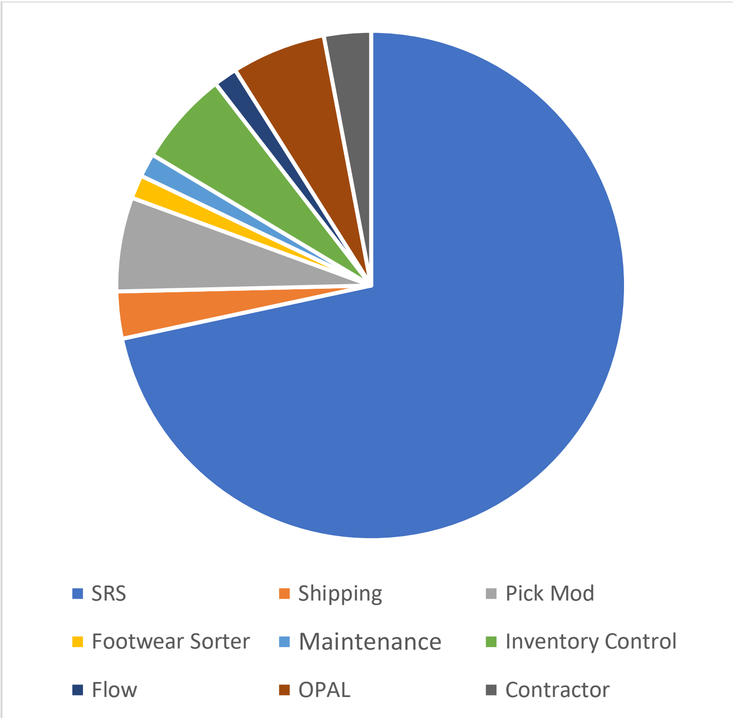

Figure 3: SRS accidents in the DC accounted for 72% of total accidents in 2018

Because previous process improvements did not yield time savings in SRS, automation became a logical consideration. Automating SRS has the potential to solve the current issues revolving around SRS:

- There are throughput limitations built into current process.
- There are issues with Inventory accuracy and lost products.
- SRS was identified as a bottleneck in the DC by many employees. By improving throughput and designing the bottleneck downstream, the process can be controlled and time completion volatility can be reduced.
- Warehouse management system (WMS) logic optimization can be upgraded to a warehouse execution system (WES), discussed further in Section 3.3.
- Reduction in accident rates,

3. Literature Review

This chapter will discuss trends towards ecommerce affecting shipping expectations in the retail industry. Automated storage and retrieval systems are introduced with a focus on pallet, miniload, and shuttle ASRS, Autostore, and autonomous guided vehicles. The chapter concludes with ASRS sizing parameters and a comparison of warehouse management and control software.

3.1 Robotic Trends in the Warehouse Industry

Over the last 10 years, ecommerce sales have grown from nearly non-existent to 14.3% of total retail sales in 2018. (Ali, 2019) Ecommerce has grown 15% per year over the last five years, which is five times the growth rate of total retail sales growth (Figure 4).

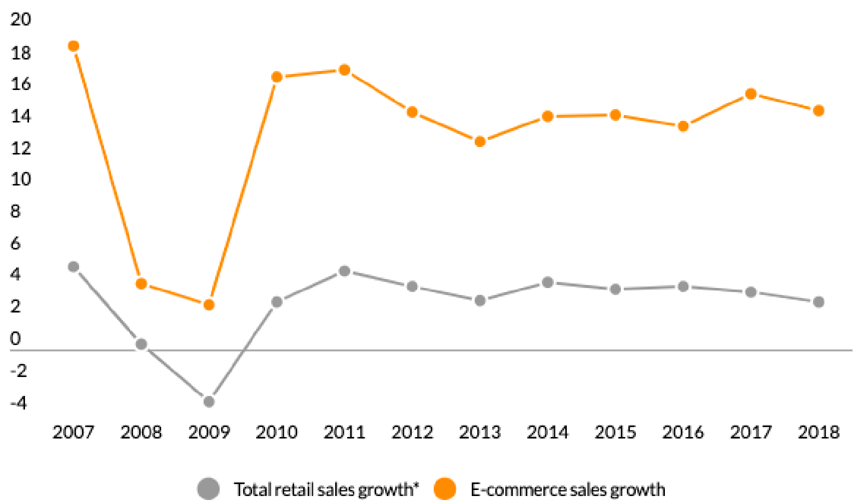

Figure 4: Ecommerce and retail growth in the US over the last 10 years (Ali, 2019)

The growth of ecommerce has challenged manufacturers and distributors to meet sales using existing assets. In a 2018 Warehouse / Distribution Center survey conducted by Logistics Management, the warehouse industry cited an increase in average SKU number, warehouse employment, and use of 3PL facilities due to the demand to meet customer orders. The average square footage of a distribution center increased from 472,400 in 2017 to 672,080 in 2018, present in both larger median square footage and building height, to accommodate increasing inventory volumes and SKU distributions (Michel, 2018). Distribution center sizes are expected to continue increasing; 87% of companies stated that they are in the process of or planning to increase their warehouse footprint by 2024 (Zebra Technologies, 2019).

Larger inventories and warehouse storage space are not the only concerns that warehouse managers have. In 2016, 41% of warehouse managers expressed concern about attracting and retaining a skilled workforce (Trottmann & Zhang, 2017). Increasing customer expectations, smaller complex orders, rising labor and land cost, and labor availability are pushing companies to consider alternative solutions to their warehouse problems. Not only are larger square footage facilities more expensive to own and operate, they introduce internal logistic complexities that could affect performance. Therefore, the ecommerce trend is resulting in a shift towards automation.

Automation in warehouses is shooting upwards. In 2018, approximately 4,000 warehouses used automation. ABI Research projects that by 2025, over 50,000 warehouses will utilize automation, with the overall robot usage increasing by 15 times from 2017 to 2022 (ABI Research, 2019). The goal of automation is to reduce warehouse size and labor costs while maintaining flexibility, increasing efficiency, and optimizing fast turnaround and delivery to the customer. There are a handful of companies that have displayed the value of automation, indicated by their ecommerce sales. Figure 5 identifies the top ten US ecommerce companies in 2019.

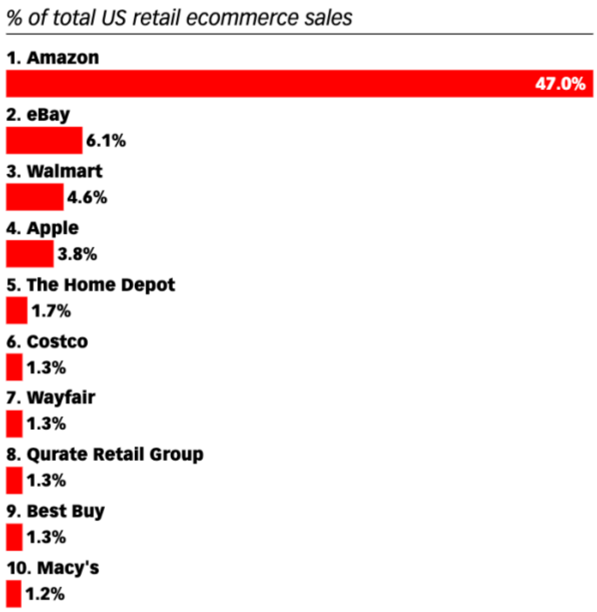

Figure 5: Top 10 US companies as a percent of ecommerce sales in 2019 (eMarketer, 2019)

Amazon, the leader in ecommerce revenue by over 40% compared to its closest competitor, has a heavy investment in robotics starting with their acquisition of Kiva Systems in 2012. Since then, their fulfillment strategy has been unrivaled as they lead the way in fast and cheap deliveries for the customer. This leaves competitors constantly trying to keep up; Walmart (number 3 in ecommerce sales) committed to reach 1-day shipping to 75% of US customers by the end of 2019 (Lore, 2019). All of the retail companies in Figure 5 have invested in warehouse automation to compete with Amazon and will continue to finance additional technologies to capture market share. The level of automation in warehouses ranges from conveyers, human-assisted systems, and full automation. This thesis will only explore five types of ASRS specifically for inventory storage and optimization.

3.2 Automated Storage & Retrieval Systems

ASRS systems were introduced in the 1960s to address heavy pallet loads. Technologies have advanced in the last ten years to span more than just heavy loads as companies aim to process goods and ship product faster to customers. The major types of systems investigated in this study are pallet ASRS, miniload, shuttle, autostore, and autonomous guided vehicles (AGV):

1. Pallet ASRS

Pallet systems, also called unit load ASRS, use cranes running down aisles and have the highest density of all ASRS types. Multiple units or boxes can be stored on a pallet in a single or double deep system. A single system means one pallet per slot, whereas a double deep system means there is a pallet located behind another pallet. Based on vendor conversations, throughput estimates are 85 cycles per hour per crane for single deep and 60 cycles per hour per crane for double deep. Pallet systems can hold weights ranging from 500 to 4,000 pounds and are ideal for heavy loads (AS/RS, 2019). Pallet ASRS is generally tall; systems can be built to a maximum height of 164 ft. All pallet configurations are end of aisle since the pallet must be stored again once retrieved from the ASRS. Therefore, this system is ideal for low throughput and high inventory density or weight requirements.

It is possible to stock multiple SKUs onto one pallet. A robotic arm can be used to consolidate pallets and the software can store where items are located on the pallet. Pallets can be used in conjunction with other ASRS types, like shuttle or miniload, to feed inventory downstream.

There are many vendors that provide pallet systems, including SSI Schaefer, Dematic, Westfalia, and Swisslog. PAS Powerstore (Swisslog) is the only pallet storage system that can be configured inside an existing building. All other pallet systems will need to have the building constructed around the system.

2. Miniload

A miniload ASRS operates similarly to a pallet ASRS but stores either totes or boxes. There is one crane per aisle and boxes or totes can be stored from single-deep up to quadruple-deep, depending on the tote or box size. A storage location in a single deep system can fit one load, which is either a tote or a box. Moving up to quadruple-deep, the locations become longer to accommodate four loads stacked behind eachother. Quadruple-deep systems rival pallet ASRS in inventory density, but triple and quadruple deep systems are rare. Totes can be filled with boxes or individual units, so miniload can be used for ecommerce or omnichannel applications. Cases or totes are not stored by SKU. In general, same-SKU containers are separated across aisles so one aisle is not overwhelmed. Because there is a maximum of one crane per aisle, it is possible that a few aisles will be retrieving while other cranes are not moving. In these lower throughput situations, aisle changing cranes would work well.

Throughput estimates range from 120 to 200 cycles per hour per crane, depending on how deep the inventory is stacked. Loads must be under 500 lbs. Miniload systems have higher installation but lower capital costs than shuttle systems while operational costs are relatively similar.

3. Shuttle

Shuttle systems are single or double-deep, store boxes or totes, and have more shuttles than aisles. The number of shuttles is dictated by the throughput required. Shuttle systems are chosen because the system needs extremely high throughput, estimated to be 500 cycles per hour per aisle. There are many vendors in this space, and the technology has advanced significantly, but the vendor that leads shuttles is SSI Schaefer. They have a patented network design with shuttle lifts in the center of the system that allows it to move shuttles faster than competitors. The number of lifts and shuttles will be decided by the vendor to meet throughput and inventory values.

Shuttle systems are the most expensive ASRS which scales significantly with system size. Loads must be below 200 lbs.

4. Autostore

Autostore is one of the newer emerging unit-based ASRS technologies. An Autostore grid can be 4-16 bins deep and is modular; more grids and robots can be added onto the system. The grid utilizes the same size totes with same SKU units in each tote.

Since totes are stacked upon one another, slower moving SKUs will inherently move towards the bottom and faster moving SKUs will remain at the top. The software system will prioritize when a tote needs to be picked and bring the tote directly to a packing station to be compiled with other units by an employee or a robotic arm into a shipping box. This type of system incorporates storage, retrieval, and picking processes into one step. The system throughput can be increased by adding more robots, but there is a maximum number of robots per surface area and therefore a maximum capacity of the system. The robot parameters indicate a maximum lifting speed of 5.2ft/s and 30 bins/hour/robot (AutoStore, 2019). Thus, Autostore would be ideal for relatively small throughput systems, small facilities, and ecommerce.

Major benefits include high storage density, space reduction, flexible layout, modular system, high performance, goods-to-person, easy to adjust inventory based on season. One notable customer is Puma, who uses this system in their Torrance e-commerce facility.

5. Autonomous guided vehicles (AGV)

AGVs can be used to replace current manual processes, like reach trucks. A fleet management system coordinates vehicle movement with continuous path optimization. There is an automated unit charging schedule for the machines. AGVs can retrieve and store pallets or boxes but cannot pick a box off a pallet. Throughput is approximately the same as that of a manual forklift.

Subsets of AGV include collaborative robots and Kiva. Collaborative robots will follow a worker to reduce the pick path. The worker will place items on the robot, and it will depart towards its delivery destination. Collaborative robots require human interaction to place and pick up items, but act as a delivery mechanism. Vendors in this space include 6 River Systems and Locus and customers include Office Depot and Medline (6 River Systems, Inc, 2019).

Kiva robots, used in Amazon fulfillment centers, also reduce the human pick path, but by moving the entire racking system to a person. The two types of Kiva robots can carry 1,000lbs and 3,000lbs respectively to handle pallets or shelf bays. Elumalai investigates the design parameters that a Kiva robot must have, including the material, size, drive, and electronics (Elumalai, 2018). Collaborative and Kiva robots are ideal for the picking process but can be used in conjunction with storage and retrieval.

A basic delineation of ASRS options is shown in Figure 6. This section will cover the "crane" and "handling" segments as they pertain to the storage and retrieval process in a distribution center.

Roodbergen and Vis defines the terms in Figure 6 as:

Aisle captive in a crane system means that cranes cannot transfer between aisles. These types of ASRS have 1 crane per aisle. *Aisle changing* cranes can move between more than one aisle. This is possible with a drive belt that wraps around aisles. These systems are cheaper because there are less cranes but have a lower throughput than aisle captive systems. Aisle captive and changing systems are applicable to pallet and miniload systems.

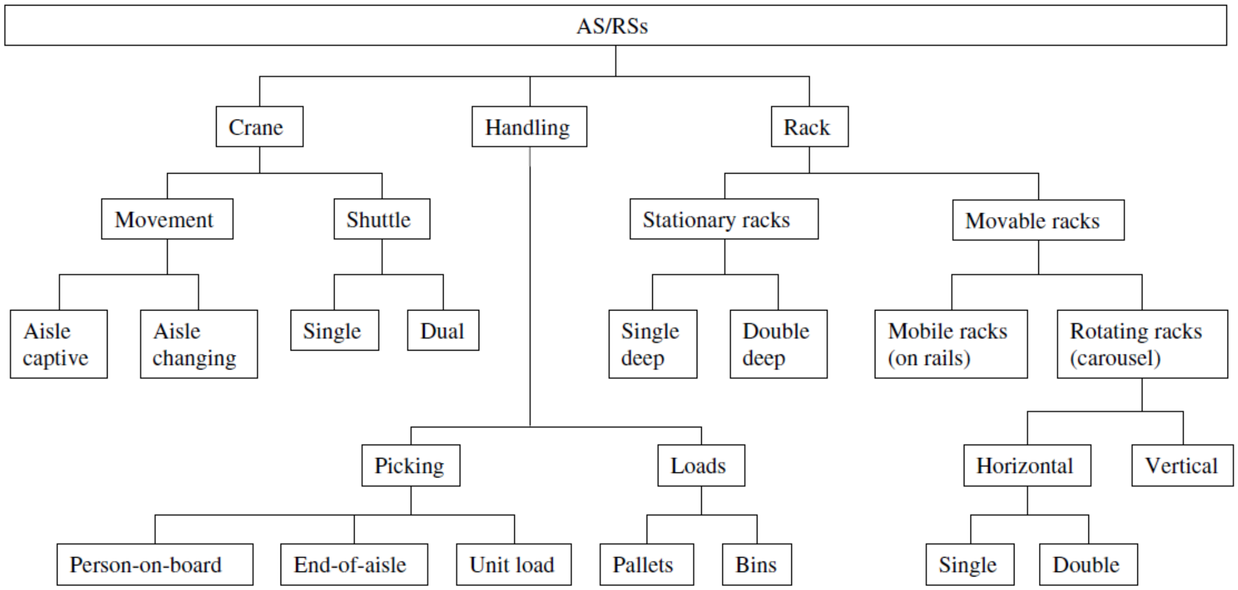

Figure 6: ASRS Functional Tree (Kees Jan Roodbergen, 2006)

Storage methods can range from single to quadruple deep. A *single deep* system will have the unit load directly accessible by a shuttle or crane to the left or right. A *double deep* system will have two-unit loads stacked behind one another, such that the crane or shuttle must shuffle inventory to reach the inner load. The deeper the storage method, the higher the storage density but lower the throughput. Shuttle and pallet systems can go up to double deep while in rare cases miniload systems can reach quadruple deep.

An *end of aisle* system is when a load, for example a pallet, is pulled from storage, brought to the end of the aisle for picking, and returned to its pallet storage location. This can occur in pallet, miniload, or shuttle ASRS types depending on the medium stored. End of aisle does not occur for parts that are removed from ASRS and never put back into the system, like full cases or individual units, called "eaches". Most systems operate in set number of cycles per hour, so end of aisle is important to understand the unit rate of ASRS.

Dual-shuttle cranes are systems capable of transporting two loads at once. This enables a crane to retrieve and store loads at the same time and reduces overall travel time. Most systems operate with dual-shuttle cranes, but single-shuttle cranes can be seen if loads are too heavy. *Dual command cycle* is the software that allows for storage and retrieval requests to be performed at the same time and can occur in both dual-l and single-shuttle cranes. For single-shuttle cranes, the dual command cycle is limited because the logic only applies when a crane stores a pallet and moves to a location for retrieval. *Single command cycles* have a separate retrieval and storage processes. Han et al analyze retrieval time and throughput improvements in sequencing dual command cycles (Min-Hong Han, 1987). Software capabilities are provided by ASRS vendors and is discussed further in Section 3.3.

3.2 ASRS Sizing Parameters

There is no one size fits all when it comes to ASRS. An ASRS must be sized correctly for the process and paired with the right control parameters to operate efficiently. Figure 7 shows the relationship between the control platform and ASRS hardware.

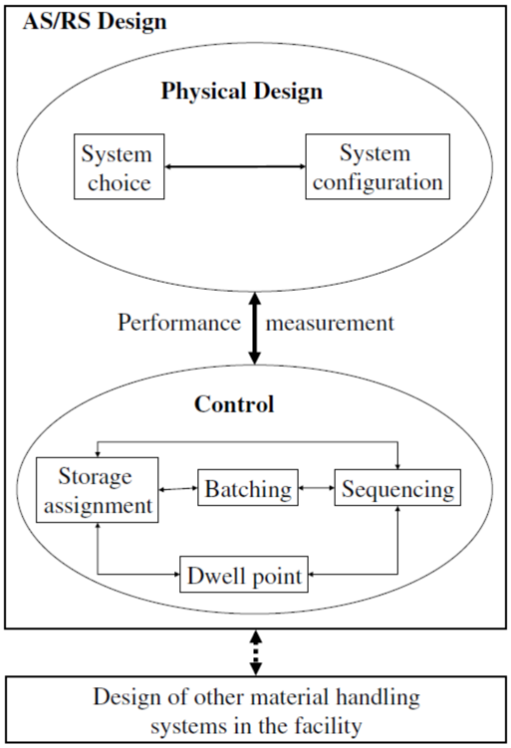

Figure 7: ASRS physical design and performance measurement (Kees Jan Roodbergen, 2006)

Roodbergen et al. identify 6 key design parameters to ensure a successful design:

1. Building capacity requirements

When evaluating both a retrofit or new building, inherent requirements like historical and forecasted data, required throughput, inventory, and storage space help dictate the correct ASRS type. Optional information includes product characteristics, budget, and available land space.

2. System configuration

This includes the physical attributes of the system, like number and length of aisles, aisle captive or changing cranes, quantity and location of inlet and outlet points, and buffer inclusion. Many of these decisions are dictated by inventory quantity and storage method of the building, listed above. If necessary, configuration considerations should evaluate expansion or modification of the existing building.

3. Storage assignment

The storage method, like randomized or by storage class, can come into play with the hardware and software. A randomized system might have additional crane or shuttle movement compared to distinct storage locations. The number and positioning of storage classes, like low, medium, and high moving product, can affect retrieval movement and time.

4. Batching

Bunching orders together, also called waving, affects the software allocation of pick tasks. Combining orders to a specific crane tour, such that the system can store and retrieve in a dual command cycle, can reduce retrieval time. Batching orders requires selection rules for the system to prioritize task allocation.

5. Sequencing

The software can order tasks through the ASRS based on restrictions like due date, shipping method, or customer. The ordering protocols can dictate a type of operation, like single versus dual command cycles, depending on if the order needs to ship immediately. Finally, sequencing orders can be done dynamically such that a new task can be put into the lineup in real time.

6. Dwell-point

The dwell-point is where the crane or shuttle waits when it does not have a task. The goal is to minimize the expected travel time to the next location. Its position can be static or dynamic.

Section 3.3 discusses the ASRS software in more detail.

3.3 Warehouse Management Software

Modern warehouses use either one or multiple software management tools to operate their facilities. Software on the market fall into three buckets: Warehouse management system (WMS), warehouse control system (WCS), and warehouse execution system (WES) (Klappich, 2018). Currently, warehouses must have WMS as a base and can add WCS or WES for added control. WES, the logic that ASRS uses, has introduced “smart factory” capabilities and presented the ability to release orders prioritized by customer type, ship date, or other parameters. Table 2 compares the three systems and their capabilities.

WMS handles people-driven operations. This is the original software tool in distribution centers and focuses on inventory as well as labor and resource management. WCS acts as a bridge between WMS and Programmable Logic Control (PLCs). PLCs are used in many automated systems, including conveyers, motors, carousels, sorters, and scales, to name a few. The WCS works in conjunction with WMS to transmit directions to the PLCs based on the most efficient route for the specific product.

WES is like WCS but with upgraded logic. The upgraded software can make decisions on its own instead of having to relay back to the WMS for instructions. Therefore, the demand is in the WES, which allows the software to complete tasks like real-time item and order picking, re-ordering and prioritization, and waveless (or batchless) order profiles. WES operates in conjunction with WMS and can operate with WCS, though most of WCS logic is already incorporated in WES.

Table 2: Comparison of WMS, WCS, and WES capabilities (Klappich, 2018)

Key Modules	WMS	WCS	WES
Ecosystem Management			
External (Store) Replenishment			
Global View of Inventory			
Multichannel Fulfillment			
Multisite Warehouse Management			
Receiving & Put Away			
ASN			
Receiving & Put Away			
Cross Docking			
Inspection/Quality Control			
Value-Added Services (Receipt)			
Put Away			
Inventory Management			
Multilocation Inventory Control			
Location Replenishments			
Cycle Counting			
Location Management			
Shipping & Dock Management			
Yard Management			
Dock/Appointment Scheduling			
Document Management/Manifesting			
Order Staging			
Shipment Preparation and Execution			
Multicarrier Parcel Management			
TMS Integration			
Order Fulfillment			
Bulk/Case Picking			
Discrete Order Picking			
Zone Picking			
Batch Picking			
Cluster Picking			
Wave Picking			
Zone-Batch Picking			
Zone-Wave Picking			
Zone-Batch-Wave Picking			
Waveless Picking			
Forward Picking Replenishment			
Pallet Picking			

Typically part of the solution

May be part of the solution

Pick to Cart			
Each Picking			
Voice Picking			
Pick and Pass			
Planning			
Slotting Optimization			
Cartonization Optimization			
Order Waving			
Order Routing			
Inventory Management			
Labor Planning			
Labor Forecasting			
Miscellaneous			
Value Added Services (Order)			
DOM Integration			
Task Interleaving			
Labeling			
Third-Party Billing			
Cartonization			
Packing and Palletization			
Quality Management			
Inspection Management			
Labor Management			
Automation Control			
Pick to Light			
Carousel Picking			
Automated Storage & Retrieve Control			
PLC Control System			
Conveyor Sortation Control			
Automation Analytics			
Pick Sequencing and Control			
Sorting Optimization			
Order Release Sequencing/Optimization			
Put Wall Optimization			
AGV/AMR Integration			
AGV/AMR Fleet Management/SWARM			
Peripheral Control			
Analytics & Visibility			
Reporting, Monitoring & Analysis			
Resource/Automation Monitoring			

Predictive Maintenance			
Problem Detection and Alerting			
Use Interface			
Mobile/RF Solutions			
Voice Solutions			
Mobile Tablet Supervisory Use			
AR/VR			
Back-Office Desktop			
Web Portals			

WES was not utilized in DCs before ASRS increased in popularity. Few DCs use WES without an automated system; the WES will sequence orders and allocate tasks to workers. Using manual labor with WES is possible, but it will result in a lower throughput than using a WMS because it may require longer pick paths and forklift driving. Overall, WES in ASRS is one of the main factors that sets ASRS apart from manual processes. In the future, the industry will transition completely to WES over WMS, but for now it is required for both to operate in conjunction with one another.

4. Method and Findings

This chapter will detail an in-depth review of the DC current state, containing current task time completion, SKU distribution, and inventory parameters. ASRS projected impact on the current DC is analyzed, resulting in a 67%-time savings in SRS alone and an improvement from 25% to 79% wave-on-time averages. Finally, the sensitivity analysis discusses situations in which a DC should consider using unit, case, or pallet ASRS based on current takt time and similar SKUs per order affecting pallet consolidation. A comparison of six ASRS types are evaluated based on inventory capacity and throughput for a given DC space. Finally, a discussion of when a DC should and should not automate is presented.

4.1 Current State Analysis

In addition to the DC current state flow described in Section 2, supplementary metrics are required to determine an optimal ASRS type. Based on literature review and vendor correspondence, box size, current task time, and inventory are key factors and are further investigated below.

Box Size

Cases, or boxes with multiple units in them, are received at the DC from factories. Depending on the SKU, cases can come in different sizes and contain different quantities. ASRS can accommodate a variety of box sizes, but it is difficult if box sizes exceed the shuttle or crane size. Vendors will make “heat maps” to determine what the most common case dimension ranges are and what crane or shuttle systems can accommodate the most cases (Table 3). The size of the cases, and thus the equipment and aisle size, can impact the amount of inventory the ASRS can hold. It is suggested to use the same size cases or place inventory into totes to standardize storage space.

Table 3: Case size heat map showing inventory percentage covered by each length, width, and height.

	Length 1 Height 1	Length 2 Height 2	Length 3 Height 3
Width 1	5%	20%	7%
Width 2	10%	40%	15%
Width 3	2%	0%	1%

Current Task Time

A time-based study was performed to analyze process times prior to the buffer. Tasks before the buffer were analyzed because wait times in the buffer ranged between 2 and 10 hours, indicating process fluctuations and variance occurs upstream from the buffer. Time data, which corresponded to when an employee was assigned a task to when he or she completed it, was pulled from the WMS for SRS and picking areas. The data pulled included worker name, task start time and date, task end time and date, working area, and vehicle used. By using task completion time, a task can be inferred to have the same start and end point in the process and can therefore be compared amongst one another. Figure 8 indicates average, standard deviation, and maximum task time completion in terms of case flow for a standard week in the DC. When evaluating a DC, it is suggested to analyze time data uniformly, or by unit if possible. In Figure 8, the term “abandoned task” refers to when an employee is assigned a task and the task is left incomplete, for example due to a shift change, or returned back into WMS as an unidentifiable or lost item. All other steps are identical to the flow map in Figure 1.

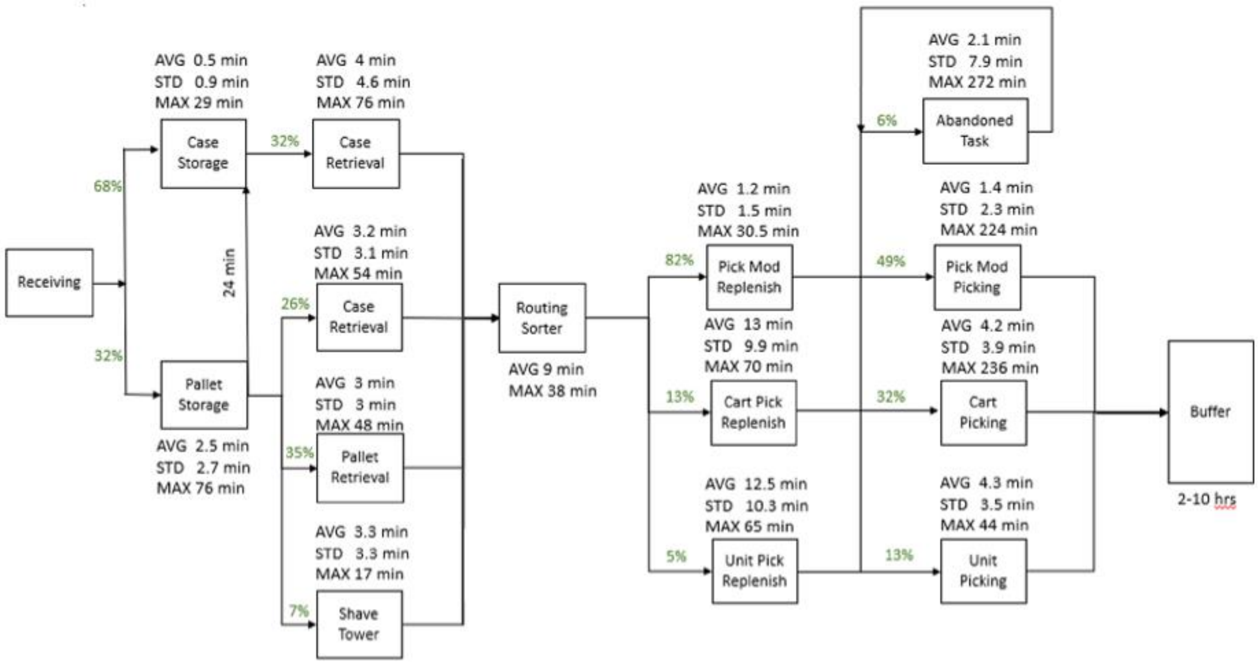

Figure 8: Task completion times over a standard week (average, standard deviation, and maximums).

While Figure 8 outlines task completion times, it does not encompass the wait times between tasks. The WMS evaluated did not have the capability to link tasks between SRS and picking, so wait times between steps could not be evaluated and maximum task times shown in Figure 8 could include wait times. If each item was subject to the maximum task time completion and assuming maximum wait time of 10 hours in the buffer, delays could vary between 33% and 66% of the flow from SRS to the buffer shown in Figure 8.

The distribution of tasks, shown in Figure 8 in green, indicate what areas were more populated with tasks in a given week. The original hypothesis was to improve wave-on-time, average task times would need to get faster. Instead, the data in Figure 8 presents a new hypothesis that it is not the average time it takes to complete a task, but the variations that cumulate to an extensive buffer wait time. For example, in case storage, the average time to complete a task was 30 seconds but the maximum time was 29 minutes. The other SRS and picking areas have similar results. The average time it takes for a case to move from SRS to the buffer is 19.5 minutes, found by multiplying the percent of flow in green by the average time per task and summing the values. In contrast, if we take the average time plus one standard deviation, a case takes 30.9 minutes, 158% longer than the average. In the situation that a case takes the maximum time to complete every task, it would take 383 minutes, 1960% the average! These deviations from the average indicate that the variation in task completion time is causing downstream delays in the buffer.

Let's go back to the process to understand why the flow time fluctuates so much. A wave of orders is released to the floor, which triggers the WMS to request from SRS and picking. To ensure that products do not get lost and the wave ships together, items from SRS and picking will be held in the buffer until at least 90% of the items in a wave are present. If not all items from a wave arrive in the buffer, the wave will either need to be manually released from the buffer on to the sorters or the missing items will be located or start from SRS or picking again. Wait times in the buffer are very long and range from 2 to 10 hours, based on the data depicted in Figure 8. We hypothesize that the wait time in the buffer is due to cases arriving variably due to different paths, task completion times, and multiple waves worked on at once. Since wait times are subject to the longest task completion time, reducing the maximum completion times instead of the average task times will more significantly reduce buffer wait times.

Histograms of task completion times extenuate the hypothesis that improvements in the average task completion time are minimal compared to task completion variance. The data simulates a skewed right distribution curve; Figure 9 shows an example from case retrieval in PSR. This plot was compiled from 34,474 tasks over the course of a week. In this case, there were 643 events, almost 1.9% of all tasks, that took over 3 standard deviations to complete. Figure 10 shows a zoomed in version of Figure 9 focused on these outliers. In a traditional normal distribution curve, these outliers should account for 0.1% of the data. The reason that these events are so important is because the DC uses waving. If a wave has one case inside of the 643 events referenced above, the entire wave must wait at the buffer. Additionally, there are 5 steps with outliers that cases must go through, multiplying the chance that a case will be delayed to the buffer.

Because tasks could account for different case quantities, and cases hold different unit quantities, it is difficult to determine the current takt time per unit. The time study instead shows that the outliers, or tasks that exist beyond 3 standard deviations of the average, are the areas of concern. This study supports Greenlee's findings in wave variation and bottleneck discrepancies at this DC.

As discussed above, a combination of outliers, wait time between tasks, and buffer delay leads to longer wave times. The identification of these parameters presents the question: how can automation significantly reduce the wait times and relationships between these parameters?

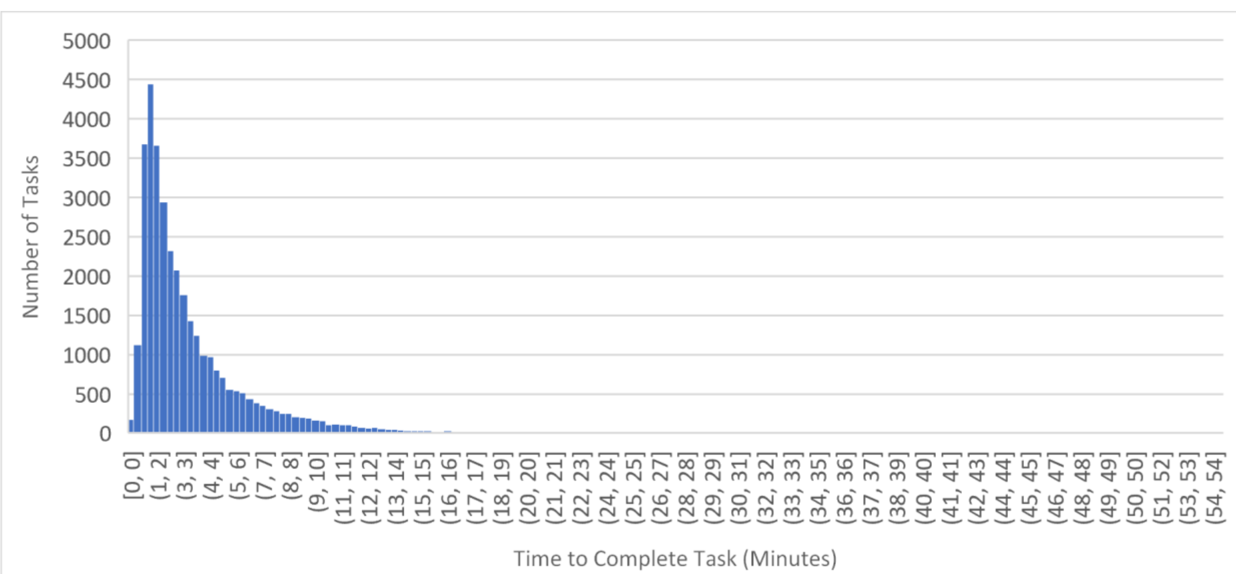

Figure 9: Histogram of task time duration in case retrieval from pallet storage. Data set was taken over one week and consisted of 34,474 data points.

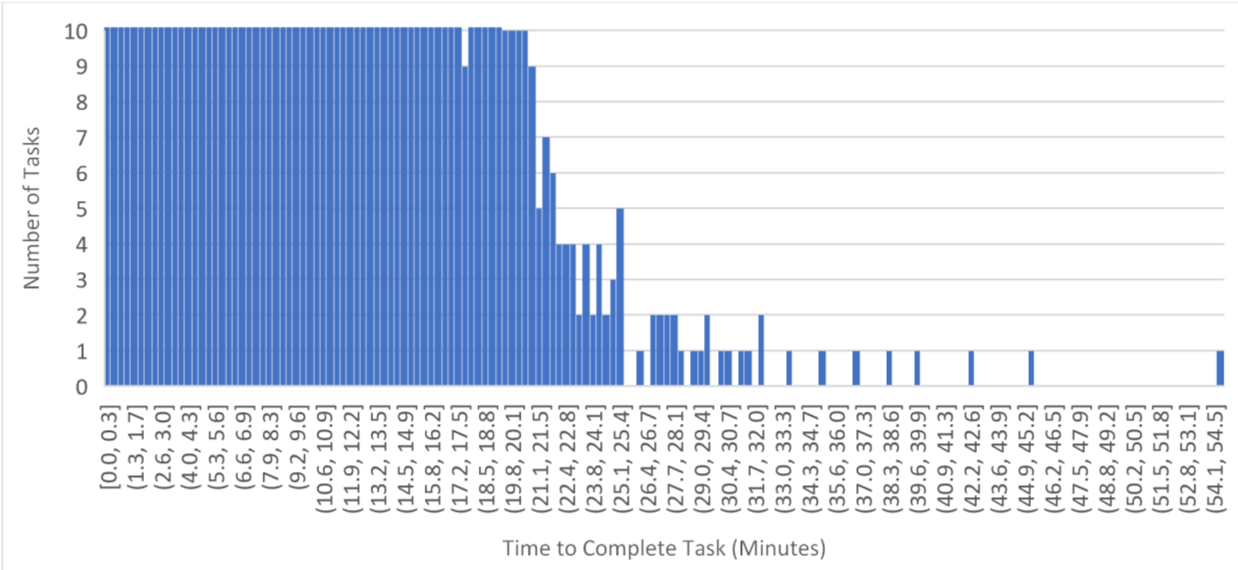

Figure 10: Figure 9 rescaled; over 643 events occurred outside of 3 standard deviations of the mean in case retrieval from pallet storage.

To reduce wait time in the buffer, which will result in shorter waves times, a root cause analysis was performed to identify reasons outliers can exist:

1. Cases and pallets are stored randomly in the DC.

By randomizing the receiving methods of SKUs, SRS drivers may have to cover more ground than if cases and pallets were stored by SKU distribution. For example, faster moving SKUs could be stored in the same location or closer to the ground, reducing the amount of movement required from a driver. This would help reduce picker movement as well.

2. Inventory accuracy

Inventory was often misplaced or stored in the wrong location as what was recorded in WMS. This happened many times in the shave tower, as employees could grab boxes and place them on an adjacent pallet without notifying the system.

3. Drivers and pickers are allocated to zones instead of workflows.

Assume a wave randomly required inventory from one specific aisle, which is allocated to one driver. Since employees are assigned to service an area, and only one vehicle is allowed per aisle for safety reasons, the throughput for that wave is equal to the throughput of one person. The WMS does not have the capability to reassign workers to a new area.

4. The first case pulled waits on a truck until the last case is pulled; at that point, all cases are placed on the throwline together.

If the WMS allocated 20 pulls for the driver before sending cases to the throwline, then case 1 will have to wait for all of the cases to be retrieved from SRS before reaching the throwline. A lean program was piloted, reducing tasks from 20 to 10 to reduce wait time for the first case, but this resulted in additional driving for workers and lower employee productivity (see point 5). Resulting time savings were not quantifiable.

5. Employees are graded by task productivity using a labor management system.

Workers are allocated to areas on the floor, described in point 3. WMS will tell the workers what the next task in their allocated zone is, but this does not necessarily correspond to FIFO. Since workers are graded based on their productivity, they are incentivized to pick as many cases as they can in an hour. If a FIFO system were allocated, this could result in less cases picked per hour because the resulting next pick could be a further drive distance away than what the system would allocate now. This issue is exacerbated when multiple waves have been released at one point in time; the WMS will not allocate work to pickers based on wave, just by location. Therefore, employees being incentivized by picking productivity coupled with numerous waves released to the WMS causes increased WIP and buffer wait times.

The labor management performance tracker and wave-on-time metric conflict with one another; the first system requires a maximum throughput whereas the latter tracks on time delivery. Since waves must move through the DC at the same time, it is the processing speed of the entire wave, from pick 1 to the last pick, and the product accuracy that matters.

ASRS and its software can address and improve the 5 root causes listed above. This is explained in Section 4.3.

Inventory

In an ideal state, all inventory would fit inside the same ASRS. The slots taken by slower moving SKUs will cost more money to hold than for faster moving SKUs. This becomes a debate between how much inventory is necessary to put in the ASRS to meet the business needs and the minimization of touches. A throughput versus inventory analysis is presented in Section 4.4. In general, systems with a large amount of inventory and moderate to low throughput can use a combination of manual pallet or case storage with ASRS to reduce cost. Key metrics to consider when evaluating inventory include:

1. Total SKUs
2. SKU Distribution
3. Inventory quantity with respect to SKU

Total SKUs

For a company that wants instant availability for all of its SKUs, there should be at least one location per SKU in the ASRS. This approach can be taken to assess a conservative situation, since 62.6% of SKUs account for 99% of total volume (Table 4). In the DC studied, we can assume there are 100,000 SKUs. Faster moving SKUs should have more inventory and therefore more slots, so we can expect ASRS locations to exceed 100,000 slots. We must look at the order profile, or SKU distribution with respect to unit volume, to determine how many more slots are necessary. The software can determine when to replenish from pallet or case storage certain SKUs in the ASRS.

SKU Distribution

We are interested in how many SKUs make up most of the shipment volume. The time frame evaluated can vary business to business. In the DC evaluated, a year and a half was evaluated since much of the inventory includes non-seasonal standard product. Industries with short cycle time products should look at a shorter time span. The data below was taken from January 2018 to May 2019. Table 4 and Figure 11 show that 13% of SKUs made up 80% of the unit volume in this period. The distribution exhibits similarities with a logarithmic fit more than the power law with R^2 values of 0.9703 and 0.9252, respectively.

Table 4: SKU percent as a representation of unit volume.

SKU %	Volume %
13.4	80
26	90
38.5	95
62.6	99

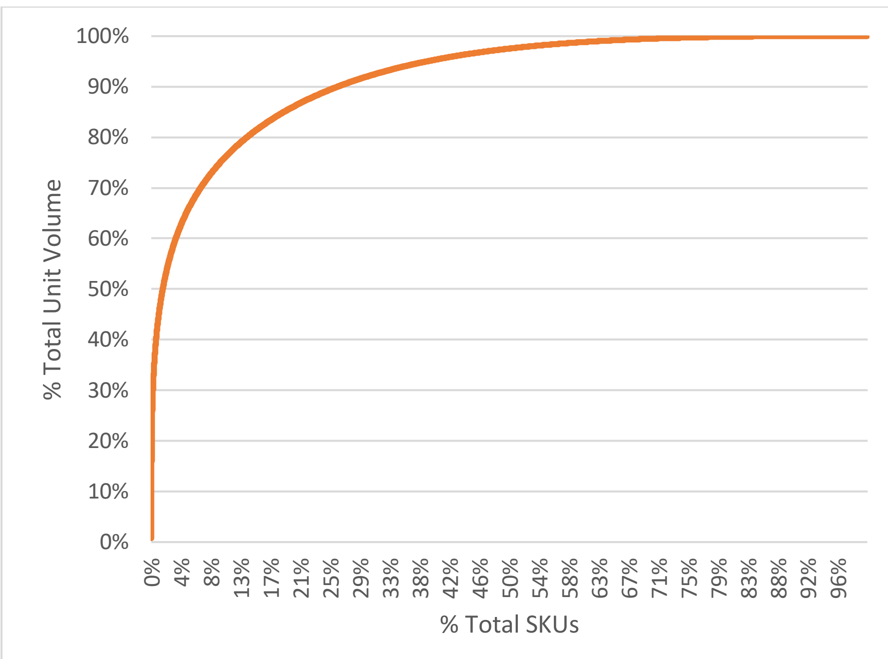

Figure 11: Standard SKU distribution relationship as a percent of volume out of the DC.

The aim is to get the faster moving SKUs into an ASRS to reduce the system size and overall costs. The volume percent an ASRS should target depends on the industry, risk evaluation, and storage volumes discussed in the next section.

Inventory Quantity

Higher moving SKUs will have more inventory; in the DC evaluated, 18% of SKUs have 25 or more cases in stock (Figure 12). Let's assume that we want to size a single-deep miniload ASRS, where each location can take one case, for the 80% volume. From Table 4, 80% volume correlates to 13.4% of SKUs. These high movers fall within the inventory that has 25 or more cases in stock. Therefore, we can size a system such that 13.4% of SKUs have 25 locations and the remaining 86.6% of SKUs have one location. With a total of 100,000 SKUs, the minimum ASRS locations required would be approximately 421,600. This value will increase if we want to include more inventory volume and reduce risk.

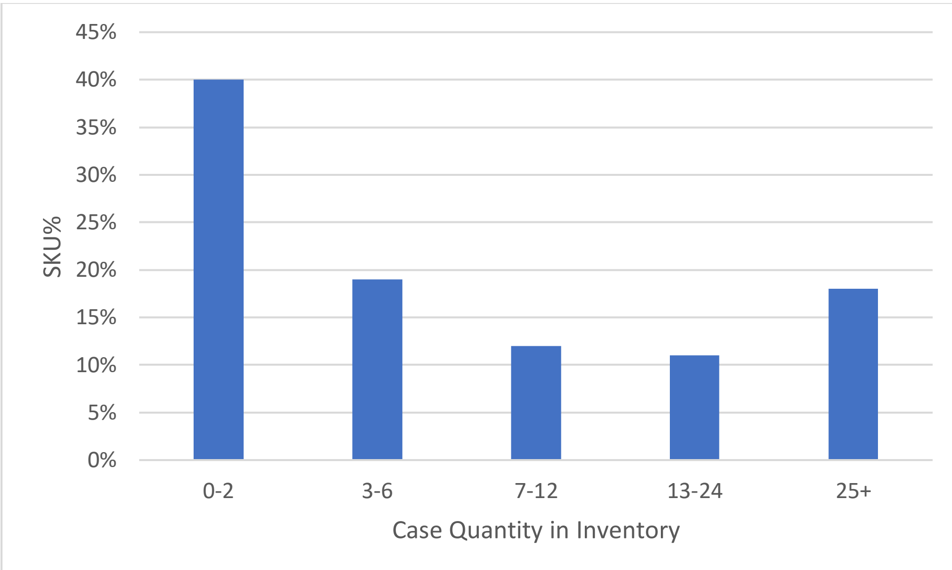

Figure 12: Average inventory in cases of each SKU in the DC.

Evaluating how each DC operates from time studies to incoming and outgoing box sizes and order profiles is essential to determine how and what type of ASRS can help. The next step in determining whether to automate is defining future throughput task time requirements.

4.2 Future State Analysis

Although most ASRS are modular, we want to size an ASRS based on a 5 to 10-year projection. There are three key design parameters that affect system selection: inventory quantity, which was discussed above, retrieval time, and throughput.

Retrieval time is how long it takes for the crane or shuttle to grab a case and place it in storage or retrieve a case from storage to a conveyor. In the DC studied, the outlier events that took over 3 standard deviations from the mean retrieval time were the target, but other facilities may need retrieval times to speed up as well. Retrieval and putaway times depend on the system (like miniload versus shuttle), how large the ASRS is (travel time), and how often non-value-added work is performed like restoring or consolidation.

Throughput is how many cases (or units) per hour the system can move and is closely related to retrieval time. Section 4.4 discusses methods to analyze throughput for different ASRS types. Determining the required throughput can be done by taking 5- or 10-year shipment projection and backing out case or unit per day requirements. At DCs, throughput can vary based on work allocation in a given hour. An ASRS will create more continuous flow, but the system should be sized for peak hours. This requires a look at holidays and more specifically, peak hours on those days.

The DC studied had a peak day that was 180% of an average day in 2018. In addition, peak hours on a standard day constituted 180% of the average hour (Figure 13). The required ASRS throughput would then be scaled for future shipment projections as well as daily and hourly peaks.

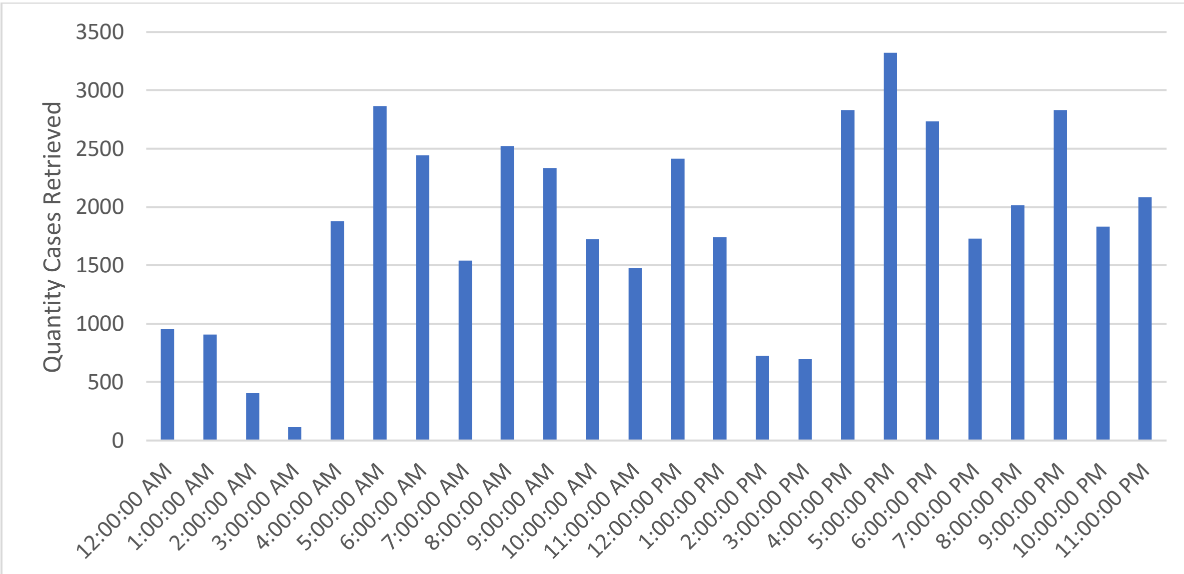

Figure 13: Average cases retrieved from SRS per hour averaged over a 45-day period (not including holiday time)

4.3 Automated Storage and Retrieval Impact

ASRS comes with an array of benefits:

1. Improved Safety: At the DC studied, driving related accidents accounted for over 70% of total incidents in the DC.
2. Built-in Quality and Inventory Accuracy: Eliminates the requirement to perform audit checks and reduces time spent finding lost inventory.
3. Increased Speed of Delivery: This includes higher throughput capacity, ability to perform non-value-added work during down time, continuous flow, and perfect sequencing.

A sequencing study was performed at the DC and is outlined below.

Sequencing Analysis in SRS

Perfect sequencing is defined as ordering case retrieval out of SRS such that one wave is completed before the next wave can be worked on. Currently, workers allocated to a zone, discussed in Section 4.1, makes it not possible to have perfect sequencing. The WMS will tell a worker what the next task is in his or her zone rather than where the next case is to maintain FIFO. The labor management performance metrics conflicts with maintaining FIFO, as workers will continue to grab items in their area to keep productivity high. This results in an increased volume of cases moving through the DC, or WIP, and higher wait times downstream.

WES, the logic control used by ASRS (Section 3.3), can set priority and re-order WIP flowing through the DC based on a specified parameter, like customer ship date or outbound delivery type. This sequencing study will follow a priority specification, outlined in Table 5, so that no more than three waves are worked on in SRS at one time.

Table 5: DC wave priority sequence

	Priority 1	Priority 2	Priority 3	Priority 4	Priority 5
Wave 1	INT9	INT1	INT2		
Wave 2		INT9	INT1	INT2	
Wave 3			INT9	INT1	INT2

Tasks in waves are released based on total flow time from SRS to shipping in 3 groups: INT9, INT1, and INT2. INT9s take the longest, as they must go through picking. INT1s meet INT9s at the sorter, and INT2s meet the INT9 and INT1 mixture at shipping. Reference Figure 1 flow diagram in Section 2.1. The goal is to release each INT type such that the work meets the remaining wave at the sorter and shipping. Let's assume that in the current process up to 40 waves can be worked on at one point in time, when an ideal configuration would have only three waves worked on at once. This results in high WIP and wait times in the buffer or at shipping for the last remaining items in its respective wave to arrive. The intent of perfect sequencing is to reduce WIP and the wait times by sending the correct products in the correct order downstream.

The sequencing study described below used a data set from the DC's WMS consisting of a list of tasks in PSR or CSR and its associated INT type, wave number, start time, and completion time. We developed a simulation to compare current processes to perfect sequencing. The steps for the simulation are as follows:

1. **Task Duration**: The task duration was calculated by subtracting the task completion time from the task start time. In the data, a task was how long it took for a driver to accept a job and drop all of the items on the throwline. This could vary between two and 12 cases pulled.
2. **Pull Time**: Because there were different case quantities associated with each task duration, the data was normalized to find the time to pull (or retrieve) one case. This allows task durations to be comparable amongst one another in seconds per case. Each pull within a task was assumed to take the same amount of time. Therefore, the pull time is task duration divided by the number of cases pulled.
3. **Current Pull Order**: The data was assigned sequential numbers from first to last based on actual task completion time.
4. **Wave Order**: Wave numbers were assigned an order number based on their current order. For example, wave 1 was assigned "1" and wave 2 assigned "2".
5. **Priority Number**: Numbers were assigned in the same sequence as Table 5 based on wave and INT number. Each priority number included at most 3 waves.
6. **Actual INT Completion Time per Wave**: The INT9 completion time per wave was computed to be the difference between the first Wave 1 INT 9 start time and the last Wave 1 INT 9 end time, based on current pull order. This was performed for each wave and INT type separately.
7. **Simulated INT Completion Time per Wave**: Current simulated time was found by adding all pull times from the first Wave 1 INT 9 to the last. This could include pull times that are not associated to that wave. The reason these are simulated is because in reality, there are over 20

workers pulling cases whereas the data assumed that each task was done one after another. This value is compared to Actual INT completion time per wave in step 11.

8. **Sequenced Order**: The data set was filtered by priority number. New sequential numbers were assigned to each pull from start to end to indicate what the new sequence would be.
9. **Sequenced INT Completion Time per Wave**: Based on the new sequence, the pull times from start to finish of a specific wave and INT type were taken, just like step 6 but for the sequenced order.
10. **Percent Time Savings**: Sequenced and simulated INT completion times were compared using a percent time savings between associated waves and INT types.
11. **Result Time Savings**: To associate the sequencing time savings from simulated to actual, the percent time savings was multiplied by the actual INT completion time per wave. Recall that the simulation assumed that each case pull was performed one after another, so this step accounts for multiple drivers working at the same time.

Note that because SRS is manual, there are multiple people working tasks concurrently. This is why the actual time to complete a wave is different than the simulated time. This simulation looks at what the time savings would be for one person to complete every task in the right order; it does not have the ability to account for many workers in SRS. The percent time savings can be translated back into real time data to show real time savings. This simulation could also change based on ASRS type; the shuttle system will have higher throughput over a miniload because there are more shuttles than cranes.

Over two days in the DC, 12 waves, which makes up 25% of weekly wave volume, were analyzed. Four waves from this analysis are shown in Figure 14. Using the sequencing technique described above, the average time savings per wave in SRS only after combining all INT time savings together was 2 hours 52 minutes, with a maximum of 6 hours 52 minutes and a minimum of 19 minutes; this correlates to an average time savings of 67% and a standard deviation of 23%. The sequenced simulation resulted in time savings in SRS for all 12 waves evaluated, indicating that for the sample size addressed, sequencing was a better solution than real time data. There is a possibility that simulated time could increase wave completion time if tasks were truly randomized. For example, priority 3 in Table 5 has tasks from three different waves. If all these tasks are randomized, the time to complete those tasks would be approximately the same as the task to complete all of priority 3. Overall, the total time savings from sequencing should overcome the minimal time increases that result from the randomization of tasks in a priority bucket.

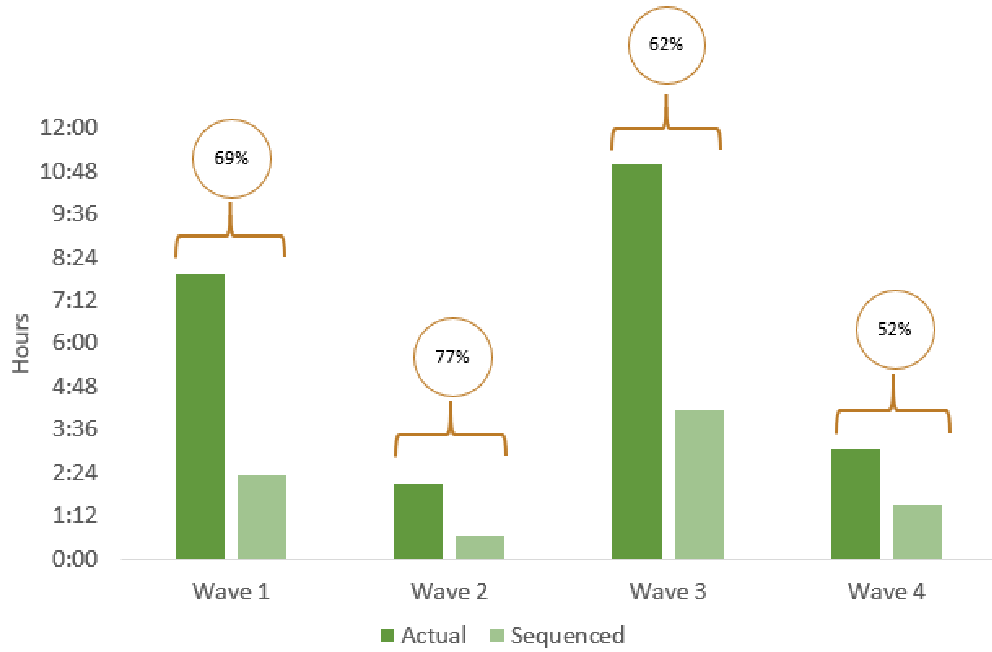

Figure 14: Sequencing simulation resulted in a 67%-time savings in SRS

Total Impact of Sequencing on the DC

Sequencing through SRS is only one area that ASRS can impact. By creating sequenced flow upstream, we can expect downstream operations to run smoother because tasks are implemented in wave order, allowing less items to get lost or misplaced in picking, sorting, and shipping. From Little's Law, by reducing downstream WIP and processing time, the natural variation of the system should decrease.

Another simulation was performed to analyze the impact of ASRS sequencing throughout the entire DC given inherent reduced DC variation and wait times. Table 6 lists values used in the DC simulation, including sequencing results described in the previous section, buffer wait times analyzed in Figure 8, and variation reduction assumptions selected as reasonable expectations in the DC. The simulation assumes that all time savings come from sequencing, buffer wait time, and variation reduction. This is meant to be a starting point to understand what type of wave times we can expect in the DC.

Table 6: Minimum, maximum, standard deviation, and average time savings used in the total impact simulation for select downstream processes.

	Minimum	Maximum	Standard Deviation	Average
Sequencing	19 min	6 hr 52 min	2 hr 53 min	2 hr 15 min
Buffer wait time	2 hr	10 hr	2 hr	6 hr
Variation Reduction	0 hr	5 hr	1.25 hr	1.5 hr

Using these values, potential time reductions per wave were calculated randomly by combining the three factor's expected time savings based off of the minimum, maximum, standard deviation, and average time listed in Table 6. The steps for performing the simulation are listed below:

1) Gather wave time data for a given week from when the wave is released in the DC to when the wave ships.
2) Using the average and standard deviation values in Table 6, create a normal randomized time savings for sequencing, buffer wait time, and variation reduction separately.
3) Average this process over 10,000 iterations.
4) Obtain a simulated wave time value by subtracting the normal randomized time savings from real wave time data.

Figure 15 shows the result of the DC sequencing wave time reduction described above. The blue line indicates current wave times over a given week while the orange line depicts the resulting simulated wave times after subtracting the normalization of expected time savings. The black line defines a current wave time goal of 24 hours to evaluate the performance of the current compared to simulated wave times.

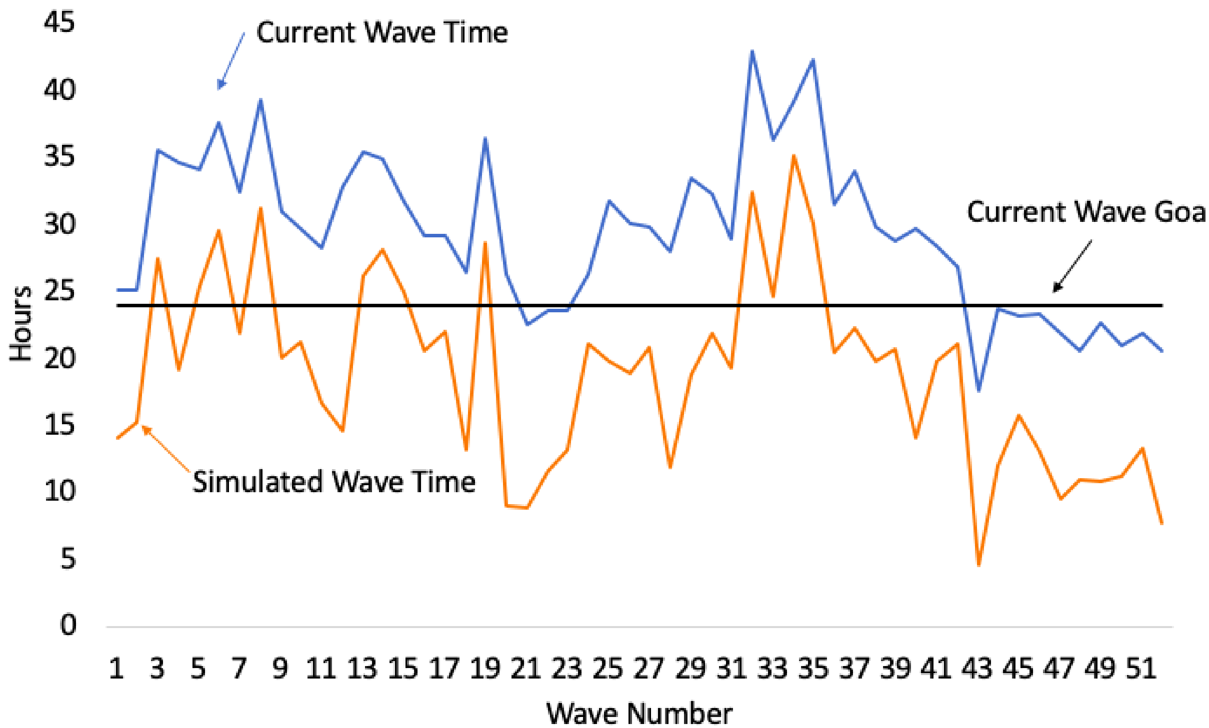

Figure 15: ASRS simulated time reduction. Results averaged over 10,000 wave iterations.

The overall DC simulation in Figure 15 was performed over 10,000 wave iterations and resulted in a total of 558 working hours saved per week, found by summing the difference between the current and simulated wave times. While 25% of actual waves met the current goal, 79% of simulated waves met or surpassed the current goal. Using logic and sequencing, ASRS reduces the wait time in SRS, the routing sorter, and the buffer. By reducing overall wait time, the current DC infrastructure can be utilized at a higher capacity to increase processing volume. Not only could the time savings from ASRS logic reduce wave time, the working hours saved per week can be utilized towards increasing DC throughput by 158% in SRS, given that downstream processes can accommodate an increase in volume).

This is a first look at how ASRS can affect a DC, but additional system dynamics come into play with complex processes. The next step in simulating process time with ASRS is correlating wait time and current process time. For example, a task with above average completion times should be correlated to longer wait times downstream. Additional data analysis and advanced simulation techniques can project realistic expectations when ASRS is implemented.

4.4 Sensitivity Analysis

Although the DC evaluated supplies primarily wholesale markets, many wholesale vendors stock unit instead of case inventory in an effort to efficiently capture rising ecommerce trends. By looking at total flow time through the building for the current DC manual storage process, case ASRS, and unit ASRS, a sensitivity analysis can be performed comparing the three methods. The results of this sensitivity analysis can be used to identify when a distribution center should automate with inventory as a case or unit based on full-case shipment, open-case processing, digital order make-up, total inventory capacity, and required throughput.

ASRS Assumptions

A list of assumptions that are important in comparing ASRS types in terms of throughput and capacity is shown in Table 7. This information was accumulated as a baseline from vendor suggestions and example system parameters, but does not reflect actual system values.

Some notable factors in Table 7 include:

- Expected throughput for miniload, shuttle, pallet, and Autostore, which is a unitized ASRS.
- Required aisle dimensions for each type of ASRS.
- Building parameters, including required clearances and pallet dimensions.
- Programmable system parameters like pallet density and pallet consolidation logic.

These assumptions will come into play later in this section under “Comparing ASRS Types” and are used to compare six different ASRS types based on inventory capacity versus throughput in Figure 21.

Table 7: Assumptions for sizing ASRS in an existing building.

ASRS Throughput			
Case or Unit Storage	Miniload	120	cycle/hr/aisle
	Shuttle	400	cycle/hr/aisle
Pallet Storage	Shuttle	160	cycle/hr/aisle
	Crane (multi-deep)	60	cycle/hr/aisle
	Crane (single-deep)	85	cycle/hr/aisle
Unit Storage (Autostore)	Autostore throughput	25	bins/hr/robot
	Maximum robots	800	robots
	220mm bin	0.37	Bin/ft3
	330mm bin	0.2481	Bin/ft3
	425mm bin	0.2016	Bin/ft3
	Maximum height	17.7	ft
Dimensions			
Shuttle Aisle Width		2.5	ft (length)/aisle

Crane Aisle Width	2	ft (length)/aisle
Pallet Aisle Width	5	ft (length)/aisle
Cases on a Pallet	2	Qty length
	2	Qty width
	4	Qty height
Case height clearance	4	inches
Case width clearance	6	inches
Pallet to pallet clearance	2	inches
ASRS to roof building clearance	2	ft
ASRS to front building clearance	6	ft
ASRS to back building clearance	6	ft
ASRS to side building clearance	1	ft
System Parameters		
Shuttle versus miniload double deep storage locations	80	%
Pallet consolidation occurs when cases are equal to or less than	4	cases
Target pallet density	75	%

Unit versus Case Storage Throughput

Let's assume that the DC has distributions of 20% INT9, 30% INT1, and 50% INT2. The different INTs go through different flows, which cause them to have different processing times:

- INT9: Receiving → SRS → Picking → Sorters → Shipping
- INT1: Receiving → SRS → Sorters → Shipping
- INT2: Receiving → SRS → Shipping

Table 8 shows the time it takes for each INT type to go through the process currently. In this scenario, the current average case processing time is 92.4 seconds.

Table 8: Current process flow time for INT9, INT1, and INT2 in seconds

	INT9 (sec)	INT1 (sec)	INT2 (sec)
Storage	12.4	12.4	12.4
Retrieval	17	17	17
Replenishment	34.5	0	0
Picking	69.6	0	0
Sorters	20.1	20.1	0
VAS	15.9	15.9	15.9
Shipping	16.7	16.7	16.7
Total	186.2	82.1	62

$$0.2(186.8) + 0.3(82.1) + 0.5(62) = 92.4$$

Suppose that a case ASRS will reduce SRS time by 17.4 seconds per case. Since all INT types go through SRS, the total flow time for all INTs will decrease by 17.4 seconds. Table 9 shows the processing time in a case ASRS scenario. By multiplying the INT distribution by the new case flow time, the average case processing time is 75.6 seconds.

Table 9: Case ASRS process flow time for INT9, INT1, and INT2 in seconds

	INT9	INT1	INT2
Storage	6	6	6
Retrieval	6	6	6
Replenishment	34.5	0	0
Picking	69.6	0	0
Sorters	20.1	20.1	0
VAS	15.9	15.9	15.9
Shipping	16.7	16.7	16.7
Total	168.8	64.7	44.6

$$0.2(169.4) + 0.3(64.7) + 0.5(44.6) = 75.6$$

Now, consider a unit ASRS. This new process would require all cases received to be opened, units removed from the case and placed into a tote, and the totes stored into a unitized ASRS (Figure 16). All orders are now pulled as units instead of cases. This will result in the current INT types, which are utilized to reduce excess labor for full case orders, to disappear. In unit ASRS, units are retrieved, sorted, and shipped, meaning that wholesale and digital are processed the same. Therefore, flow times for unit ASRS will be the same regardless of INT type. Table 10 shows the expected process flow time for a unit ASRS.

Table 10: Unit ASRS process flow time for INT9, INT1, and INT2 in seconds

	INT9	INT1	INT2
Storage	20	20	20
Retrieval	0	0	0
Replenishment	0	0	0
Picking	20	20	20
Sorters	18.4	18.4	18.4
VAS	15.9	15.9	15.9
Shipping	16.7	16.7	16.7
Total	91	91	91

With the assumption that storage and picking will take 20 seconds each, the overall processing time ends up being 91 seconds for all items through the DC with unit ASRS. Table 11 compares the current process, case ASRS, and unit ASRS process flow times by INT type.

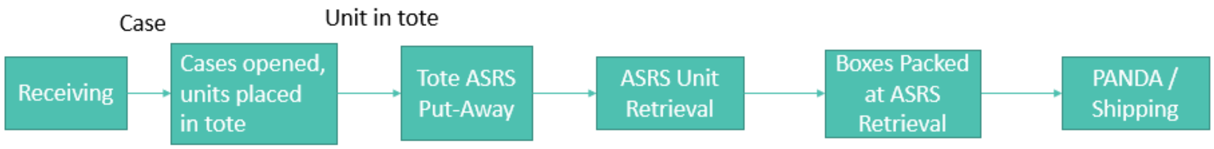

Figure 16: Unit ASRS flow map

Table 11: Flow time of each INT type using different ASRS techniques in seconds

	INT9	INT1	INT2	Average Processing Time
Order Distribution	20%	30%	50%	
Current Process Flow Time (s)	186.8	82.1	62	92.4
Case ASRS Flow Time (s)	168.8	64.7	44.6	75.6
Unit ASRS Flow Time (s)	91	91	91	91

With the data in Table 11, a comparison between unit and case ASRS based off the average processing time shows the trade-off between how inventory should be stocked, shown in Equation 1.

$$168.8y + 64.7(1 - x - y) + 44.6x = 91$$

$$x \leq 1, y \leq 1$$

$$1 - x - y \geq 0$$

Equation 1: Case versus unit ASRS breakeven equation based on Table 11

Where x is the percent of items shipped in a full case and y is the percent of items sent to picking. This equation results in a line indicating percent distributions for full case and picking flows that result in equal average processing times, which indicates the "breakeven" point between case and unit ASRS. A sensitivity diagram was constructed showing when a DC should utilize case or unit ASRS (Figure 17). Note that every DC will have different breakeven parameters based on the current material flow in the building and process flow time assumptions for storage and retrieval on case and unit ASRS. Only two INT types were graphed because this equation only has two degrees of freedom.

The red line in Figure 17 is the resulting "breakeven" point, ending at 62% full case where there are no feasible unit ASRS solutions due to the shorter processing time for INT2. The black triangle region indicates the unfeasible region as the sum of all INT types cannot exceed 100%.

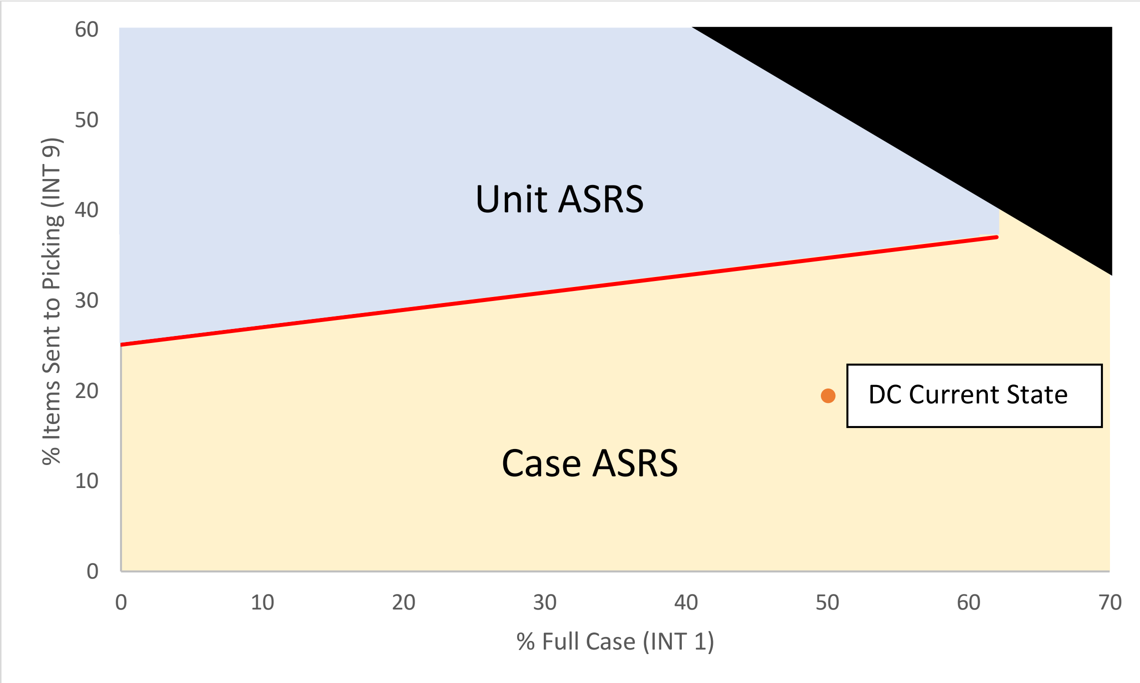

Figure 17: Breakeven line shows the tradeoff based on task time completion for when to stock items in a unit or case method.

This analysis considers the assumptions discussed in this section and does not consider factors outside of the flow time listed in Table 11. The orange dot is the DC current state. In this example, the DC should use case over unit storage because the full case, or wholesale, outbound is significant. If items sent to picking, or orders smaller than a caseload, increases above the red line, the DC should consider moving to unit storage. This comparison is between flow times of the two storage methods and does not indicate if one is better for the process beyond touch time.

These equations cannot be performed with the current process because there are no feasible solutions where manual forklifts are faster than ASRS. The analysis is meant to decide between unit and case ASRS storage methods, not whether automation or the cost of ASRS is the appropriate action for a facility.

Conversely, Figure 17 can be visualized in a full case versus digital volume percent. The vast majority of digital orders require a case to be opened since customers ordering online generally do not buy 6 of the same size and style of shoe. If we assume that wholesale order profiles remain consistent, meaning that the increase in opened cases (INT9) is fully due to digital volume, the data in Table 11 can be analyzed to see at what digital percent unit storage would provide faster flow times.

If we assume that digital volumes are eaches and an increase in digital volume directly increases INT9, we can take Equation 1 and add in a factor for Δd, which stands for the change in digital volume from the initial digital percent in Table 11. Let's assume that the current state conditions are 5% digital and 95% wholesale volume in the DC.

$$168.8(y + \Delta d) + 64.7(1 - x - y - \Delta d) + 44.6x = 91$$

Equation 2: Case versus unit ASRS for digital volume changes

Using Equation 2, a new plot of percent full case versus percent digital is constructed representing another version of case versus unit ASRS (Figure 18). The orange dot represents the DC current state, depicted as 5% digital and 50% full case. Assuming the same full case percent outbound shipments, if digital increases from 5 to 20%, the DC should consider unit storage. This representation is accurate if the full case order profile depicted in Table 11 remain consistent, but if digital increases we would expect the wholesale customers to order in smaller quantities, which could decrease full case orders. With the expectation that digital fulfillment is rising, the DC is trending towards unit storage but still remains in the case ASRS area. The same trend can be seen in Figure 17; a decrease in full case and an increase in items sent to picking will send the current state dot towards the breakeven line.

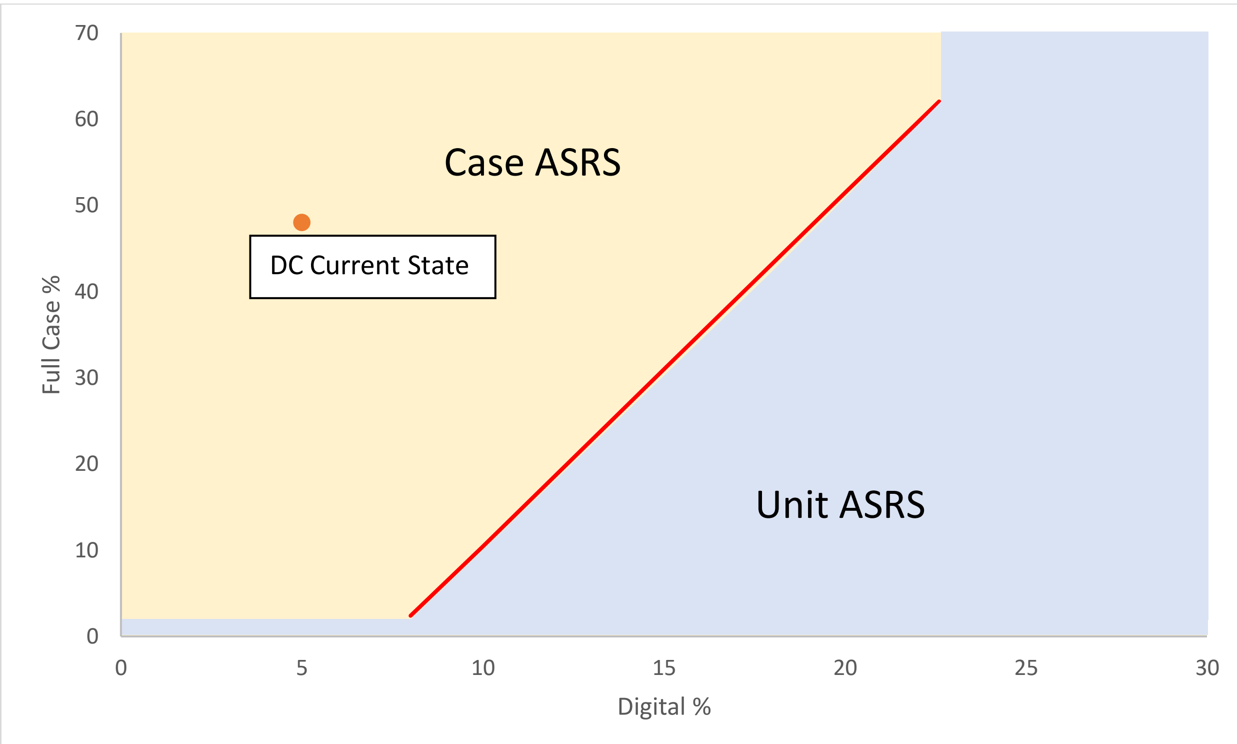

Figure 18: Storage method selection based on full case versus digital flows through the DC.

Miniload Case versus Pallet Storage Throughput

Let's assume that the unit versus case analysis resulted in case storage, like shown in Figure 17 and 18. Case storage can consist of either a case slotted in case storage, like miniload or shuttle ASRS, or a case placed on a pallet, like pallet ASRS. The difference between the two is inventory capacity versus throughput. In this analysis, a miniload and pallet ASRS are compared. They are both assumed to have one crane per aisle and fit inside the same dimensional space.

Figure 19 shows the flow of a case for a miniload system and Figure 20 for a pallet system. Crane travel is dependent on software instructions, inbound, and outbound locations. For example, if inbound and outbound conveyors are on the same side of the ASRS, the crane can immediately drop and pick up a case one after another. This analysis assumes that the case and pallet configurations store full cases, have similar crane set-ups, and only differ by case movement.

For a miniload case ASRS, the process steps are:

1. Storage
    a. Crane travels to the inbound area and retrieves case
    b. Crane travels to storage location and deposits case
2. Retrieval
    a. Crane travels to storage location and collects case
    b. Crane travels to outbound area and deposits case

Because the system only requires storage and retrieval, we can deduce that the case throughput for a miniload system is equal to the miniload throughput:

$$c_{T,m} = m$$

Equation 3: Miniload ASRS throughput in case per hour per aisle

Figure 19: Miniload case flow

Pallet ASRS requires additional movement to store and retrieve a case. In addition to case storage and retrieval, the pallet ASRS will have a consolidation step to increase pallet density. Although there are more flows for a case in pallet ASRS, the inventory storage capacity is higher than miniload or shuttle. The process steps are:

1. Storage
    a. Same SKU pallet retrieved by crane and brought to retrieval area
    b. Case added to pallet by employee or robot
    c. Pallet returned to storage by crane
2. Retrieval
    a. Pallet retrieved by crane and brought to outbound area
    b. Case removed from pallet by employee or robot
    c. Pallet returned to storage by crane
3. Consolidation
    a. (Two) pallets retrieved from storage by cranes
    b. Cases moved from one pallet to another
    c. Full pallet returned to storage

The storage and retrieval motions are each one cycle while consolidation will occur a fraction of the time, depending on when pallets reach a minimum pallet density specified by the company. Overall, the case throughput will be over two times less than the available throughput from the mechanical system. Therefore, a case throughput equation for pallet ASRS is:

$$c_{T,p} = \frac{pT}{2 + c_f}$$

Equation 4: Pallet ASRS throughput in case per hour per aisle

Where p_T is the pallet throughput in cycles/hour (dictated by ASRS manufacturers) and c_f is the consolidation factor, or how often pallet consolidation occurs in a system. The factor of two in the denominator is because for every miniload crane, a pallet crane will have to move twice as much because pallet cranes must retrieve and put away full pallets.

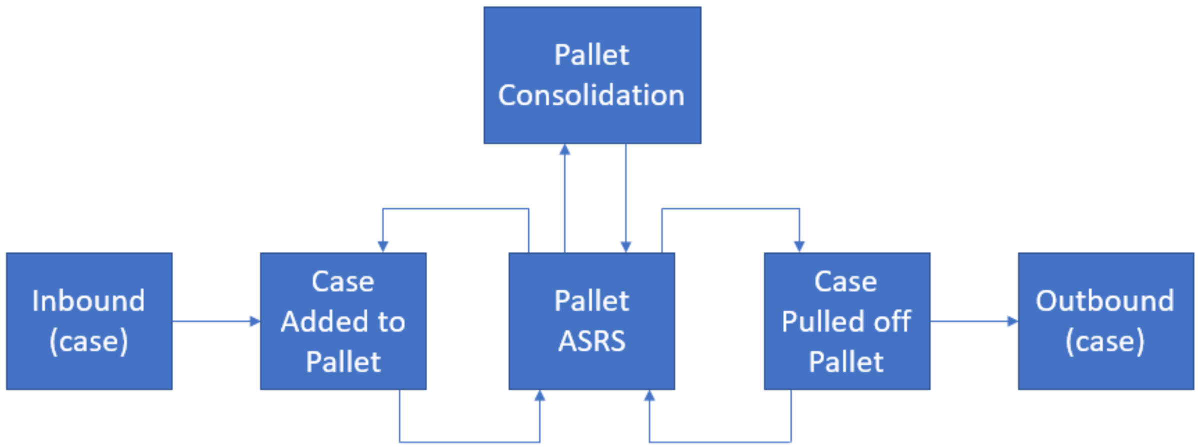

Figure 20: Pallet case flow

Consolidation factor c_f

Let's assume ρ, is the percent of pallet that is utilized (also called pallet density), *min* is the number of cases remaining on a pallet for consolidation to occur, and x is the average outbound cases per SKU per order.

The maximum boxes per pallet is dictated by the case size and pallet size, rounded down to the closest case:

$$\frac{box}{pallet}_{max} = \frac{l_p w_p h_p}{l_c w_c h_c}$$

$$\frac{1}{c_f} = \frac{\rho \frac{box}{pallet}_{max} - min}{x}$$

Equation 5: Consolidation factor for pallet ASRS to maintain high pallet density

Example: If a pallet can hold a maximum of 20 cases, pallet density is 80%, 2 cases are pulled per order, and pallets are consolidated at or below 4 cases, then our equation is:

$$\frac{1}{c_f} = \frac{(0.8)(20\ cases) - 4\ cases}{2\ cases/pull}$$

Consolidation will occur every 6 pulls, so c_f is 0.17.

Breakeven value

There are a few variables that can be altered to analyze the sensitivity of a case versus pallet ASRS. Box size, pallet size, target pallet density, minimum cases for consolidation, and outbound cases/SKU/order all affect the consolidation factor, but building size and ROI also factor into the decision. For a given building size, there will be more miniload aisles than pallet aisles because pallet storage is denser than case. We can find an optimal cases/SKU/order value that dictates, from a throughput standpoint, that miniload and pallet are fast enough for the application. By setting the miniload and pallet throughputs equal to one another:

$$ma_m = \frac{pa_p x}{2 + c_f}$$

Where m is the miniload throughput in cycles/hr/aisle, a_m is the number of miniload aisles for a given building, p is the pallet throughput in cycles/hr/aisle, and a_p is the number of pallet aisles for a given building. a_m will always be larger than a_p, and can be found with knowledge or assumptions of building size, case size, distance between aisles, and staging area. x is the cases/SKU/order, meaning that over this value, a pallet ASRS would have a faster throughput than a miniload ASRS. Solving for x gives:

$$x = \frac{2ma_m(\rho \frac{box}{pallet}_{max} - \min)}{pa_p - ma_m}$$

Equation 6: Breakeven cases/SKU/order that makes pallet and miniload ASRS throughput the same

Using the assumptions in Table 7, the breakeven value between miniload single, miniload double, pallet single, and pallet double deep is shown in Table 12. This means that if there are five cases from the same SKU pulled at the same time, a single deep pallet ASRS would have an equivalent throughput to a single deep miniload ASRS because the high number of cases only requires one pallet pull versus five miniload crane movements.

Table 12: Breakeven cases/SKU/order such that pallet and miniload configurations have equal throughputs

	Pallet Single Deep	**Pallet Double Deep**
Miniload Single Deep	5 case/SKU/order	7.4 case/SKU/order
Miniload Double Deep	4 case/SKU/order	5.8 case/SKU/order

The analysis completed thus far only focus on throughput differences between ASRS. The next comparison will involve throughput and inventory quantity comparisons.

Comparing ASRS Types by Throughput and Inventory

Let's assume that we have a building of 500' x 300' x 60' and are considering any type of ASRS.

The equations listed above dictate the throughput capacity of each system on a case per aisle basis. To find the optimal inventory, the assumptions of clearance height, width, depth as well as average case size, clearance between cases, and ASRS aisle width are used to geometrically calculate the number of aisles that can fit into the building. Using the assumptions stated in Table 7, the number of aisles that can fit in the building for each ASRS type can be calculated. The resulting aisles will dictate the available inventory capacity and the expected throughput for six different systems: pallet double deep, pallet single deep, miniload double deep, miniload single deep, shuttle, and Autostore. An inventory versus throughput plot was constructed to compare ASRS model capabilities (Figure 21).

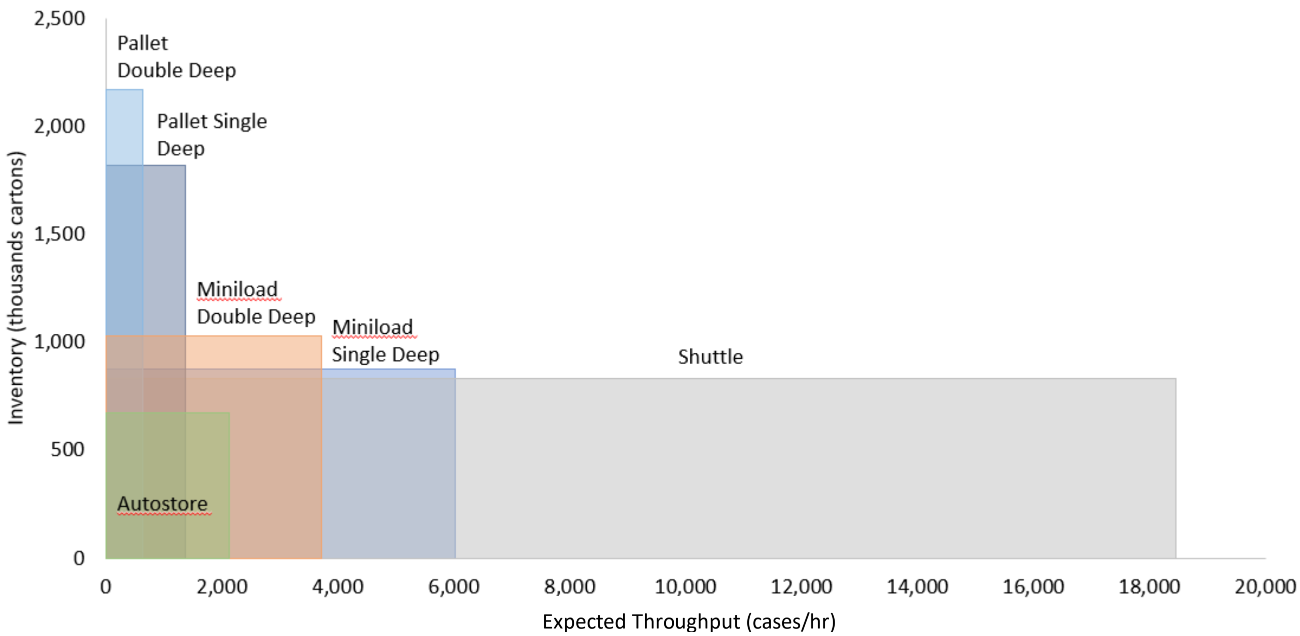

Figure 21: Expected throughput and inventory capacity of different ASRS in a 500' x 300' x 60' building.

The x-axis of this plot shows the expected throughput of the ASRS while the y-axis shows the maximum inventory capacity of the system. Figure 21 shows that pallet double deep has the highest inventory capacity but lowest throughput, while a shuttle system has the fastest throughput but moderate inventory capacity. The overlapping boxes indicate that multiple systems can meet the required inventory and throughput of the system.

While the trends observed in Figure 21 remain consistent across ASRS types, the throughput and inventory values change based on the building size and the assumptions listed in Table 11. For example, if pallet consolidation would occur less often (at say 2 instead of 4 cases remaining), we can expect total throughput to increase because the ASRS can use the extra throughput to accommodate orders. And if the shuttle aisle width was larger, the inventory capacity would be smaller than estimated in Figure 21.

4.5 When to Automate a Distribution Center

Debates surrounding when to automate cover moral and ethical notions around modern labor practices. This thesis will discuss a handful of quantifiable parameters for when automation does and does not make sense. The following section does not encompass a holistic view of ethics but outlines three reasons to automate and one example of when not to automate.

When to automate:

1. The capacity needs of the building cannot be met by adding more people.

There are inherent capacity limitations inside of the walls of a building. As more workers are added, the maximum capacity will eventually taper off to a throughput plateau. One example of this is at the DC analyzed, only one forklift driver could be in an aisle at a time due to safety regulations. This meant that there was a maximum number of drivers and therefore a maximum number of boxes that could be pulled per hour. For a brownfield DC, the maximum capacity is dictated by the number of aisles and average throughput per person. If the maximum capacity cannot be met with labor, then ASRS should be considered.

For a greenfield DC, there is a tradeoff between how large the building needs to be to meet the inventory and throughput requirements and land or labor cost. A building can either be sized to meet the inventory volume by expanding outwards or upwards. The maximum height for a manual building is 40 feet since that is the height that forklifts can reach. Using this method, an estimation of number of aisles required and maximum number of employees can be reached. Conversely, a specified capacity per square foot per person can be established to reach the same result. Not that most DCs are less than 1 million square feet in footprint to reduce product flow path and statistical fluctuations; if a greenfield DC suggests a larger DC, further consideration is required.

2. Automate if the ROI is within reason.

Good payback for ASRS are under 5 years. If the ROI for ASRS is under this, there might be areas in the DC that could be substantially improved with automation. Factors influencing ROI include:

- Inventory accuracy
- Labor and land cost
- Training and turnover cost
- Forklift maintenance cost
- Building costs, like electricity (ASRS does not require lights)
- ASRS maintenance cost
- ASRS total cost
- Building retrofit requirements, including concrete or wall upgrades
- Percent of late orders
- Other time reduction calculations, counting time saved from ASRS logic sequencing versus the current state

3. Low storage density

Consolidating inventory can take time, but without consolidation inventory density suffers. A good time to automate is when storage density is low and there are not enough resources to allocate towards non-value-added work like consolidation. ASRS can consolidate SKUs and even store multiple SKUs on the same pallet. Some consolidation methods include a pallet to a miniload or shuttle ASRS to maintain full pallets, or an automated arm that moves pallets from one area to another.

When not to automate:

An example of when not to automate is when throughput is not uniform within each storage aisle. For a miniload ASRS, each crane has a throughput capacity. Total capacity can then be calculated by adding together throughput from all the cranes. If demand for specific SKUs is coming from one specific aisle, then the one crane capacity cannot meet the required demand. To overcome these situations, a shuttle system could mitigate the demand profiles as shuttles can move between aisles. Also, the software can be updated to ensure that higher moving SKUs are not placed in the same aisle. Avoiding random slotting and accurate forecasting are important for ensuring the best mobility of an ASRS.

5. Conclusion and Recommendations

5.1 Key Results

ASRS has advanced in hardware, but more significantly software, over the last ten years. While miniload and pallet ASRS are still like older models, new ASRS developments like shuttle and Autostore are captivating the market to better accommodate e-commerce. An increasing number of companies, including Puma (PUMA Attacks Peak Season with AutoStore, 2019), Kohls, Varner (Varner, Sweden (Swisslog retail reference), 2019), Footlocker, and REI (REI Goodyear Arizona, 2017), are adopting ASRS to better manage their warehouse operations. Vendors and integrators are popping up globally to support the increase in ASRS business.

Every ASRS is designed and built custom to the DC. While the systems may remain unique, newer designs have added modularity and features for the digital market. The main decision factor between ASRS types is the tradeoff between inventory and throughput, but the sequencing and reduced work in process that ASRS software can offer is the most important factor of an ASRS. Table 13 gives a final comparison of ASRS models analyzed in this paper in terms of inventory capacity, throughput, modularity, maintenance, and cost. The rankings range from 1 to 5, with 5 representing the highest storage capacity, highest throughput, most modular, least maintenance, and cheapest. The cost aspect takes into consideration capital expenditures and assumes that operational costs are relatively the same. The final sum shows that all the systems rank relatively equal in the ASRS matrix but have their own individual benefits.

Table 13: ASRS Comparison Matrix

	Inventory Capacity	Throughput	Modularity	Maintenance	Cost	Sum
Manual	2	1	5	5	5	18
Autostore	1	2	4	4	4	15
Miniload	4	4	2	2	3	15
Shuttle	3	5	3	3	1	15
Pallet ASRS	5	3	1	1	2	12

The decision method for sizing ASRS follows the below process:

1. What speed increase is needed in the DC?
2. Can process improvements meet this speed capacity, or is automation necessary?
3. What are the current state conditions of the DC, including receiving and shipping rates, box size, SKU distribution, and material flow in the DC.
4. What is the required inventory and throughput in the DC?
5. Is ASRS suitable for the DC infrastructure?
6. How can modularity be designed into the system to accommodate for future modifications?

The ASRS models discussed in this thesis cover storage and retrieval areas, but many other types of automation exist for warehouse operations. If ASRS is not a suitable solution for the DC, goods to person solutions or alternative robots, like collaborative robotics, can be evaluated.

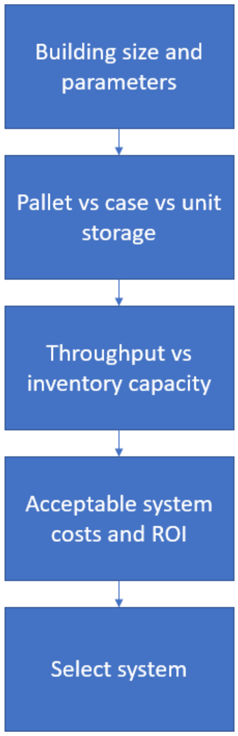

Figure 22: ASRS selection flow

If ASRS is feasible for the process, the decision process discussed in Section 4 follows the flow shown in Figure 22. First, the current state building size and DC parameters described in Section 4.1 are collected. From this information, the storage method can be determined between pallet, case, or unit, depending on the material flow and full case or picking processes outlined in Section 4.4. Once the storage method is decided, the required throughput and inventory capacity will dictate which ASRS are acceptable for the application. The acceptable systems can be sized for the existing building, quoted for pricing, and evaluated based on ROI by considering labor cost, time savings, inventory accuracy, write-offs, chargebacks, safety, maintenance, among other factors. Finally, the system can be selected.

Making the decision to automate a facility is challenging and requires significant monetary and infrastructure investment. A thorough understanding of the future of retail is important before committing to ASRS, but advancement in logistics is required for companies to remain competitive in retail. As the "Amazon Effect" continues to propagate throughout the retail industry, evaluating DCs and existing capabilities in conjunction with ASRS will be essential for digital success in the future.

5.2 Recommendations and Next Steps

Final recommendations for the DC are split into process improvement and capital investments.

Process improvement:

1. Employee performance metrics should be updated to incentivize performing the right tasks instead of volume of work.
2. Reordering pallets in PSR so faster SKUs are closer to the ground and lower SKUs are up high.
3. Multiple SKUs placed on a pallet to increase storage density.
4. Evaluate SKU locations and sales trends weekly.

Capital Investments:

1. Upgrade WMS to incorporate WES so that order sequencing is possible.
2. Install miniload double deep ASRS to accommodate high moving SKUs.

Next Steps:

1. Identify high moving SKUs and the total volume required for an ASRS; how big does the system need to be to meet 1 month of forecast? How many SKUs must fit into an ASRS to meet customer demand?
2. Investigate goods to person solutions for both wholesale and digital channels.
3. Create a more detailed ASRS design.
4. Continue to measure sequencing results on wave time to understand the effects of ASRS.

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