Intelligent Product Placement Strategies for Amazon.com's Worldwide Fulfillment Centers

by

Linsey Rubenstein

B.S. Industrial and Systems Engineering, Georgia Institute of Technology (1998)

Submitted to the Sloan School of Management
and the Engineering Systems Division
in Partial Fulfillment of the Requirements for the Degrees of

Master of Business Administration
and
Master of Science in Engineering

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ABSTRACT

Online retail has radically changed traditional supply chain operations by providing a direct-to-consumer model that eliminates the need for traditional brick-and-mortar retail stores. With this new order, retailers have had to design warehouse solutions that fit the changing operational requirements of online retail. Over the last several years, Amazon.com has become a market leader, capturing almost 8% of all online retail sales in 2005. As Amazon grows in size and scope it is faced with unique challenges in warehouse system design and strategy.

A significant portion of Amazon's total fulfillment cost is in the "picking" process which is where associates pick items to fulfill customer orders. Picking costs are directly influenced by the upstream stowing process which determines where to physically store Amazon's retail items. Currently, Amazon's fulfillment centers stow inventory according to "profiling" rules which direct inventory to various locations in the warehouse in order to optimize the space utilization of the facility. However, these profiling rules do not account for the impact of the stowing decisions on the cost to pick and replenish products downstream.

While facility space reaches capacity during peak season, the fulfillment centers are well below their physical space capacity the remainder of the year. Due to the cyclical nature of customer demand at Amazon, the current profiling strategy of optimizing space utilization may be sub-optimal during the low demand periods when space capacity is not a constraint. This thesis will test this hypothesis by exploring alternative product placement strategies for Amazon's fulfillment centers.

Engineering Thesis Advisor: Stanley Gershwin
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CHAPTER 1: INTRODUCTION

1.1 Project Motivation and Goals

Product placement, the method for how inventory is physically stored in a warehouse, is an important operations design decision that impacts the overall productivity and cost of fulfillment. At Amazon, the primary goal of the current product placement methodology is to optimize the space utilization of the warehouse. Many warehouses use this strategy given the high cost of capital and the expense of expanding or introducing new warehouses.

Amazon's Space Management Team, which is responsible for capacity planning and product placement decisions, had concerns that the current methodology may be sub-optimal. First, Amazon's business is highly cyclical with a large portion of sales occurring during the holiday season (Christmas). This means that the current warehouses are well below capacity during the majority of the year. Therefore, a product placement strategy that focuses solely on space utilization may not be optimal. Next, Amazon's major cost driver is the picking operation, which is where associates physically pick orders from the warehouse. The upstream stowing process dictates where products will be physically located thereby influencing the distance and travel time that is required to pick customer orders. The Space Management Team was interested in developing a systems solution that minimized the total costs of both space and labor. This thesis explores alternative product placement strategies for Amazon's retail operations with the overall goal of reducing total fulfillment cost.

1.2 Project Methodology

The following methodology was used to manage the project objectives and scope:

1. Understand current product placement policies and warehouse system design
2. Identify alternative product placement solutions
3. Collaborate with key stakeholders to down-select promising alternatives
4. Model alternatives
5. Analyze alternatives and assess tradeoffs
6. Provide recommendations

1.3 Project Outcome

Two alternative product placement strategies were analyzed as part of the internship project:

1) The Cloud – A product placement strategy that distributes inventory randomly to several different warehouse zones (called clouds). The goal is to create multiple such clouds that would at any given point in time contain all inventory needed for fulfilling all customer orders. The cloud model showed a 10-15% potential annual cost savings.
2) Product Group Affinity – A product placement strategy that directs inventory to virtual warehouse zones based on product group. For example, books would be stowed in one area of the warehouse, music in another area of the warehouse, etc. The model predicted a 4-8% cost savings by implementing an affinity strategy.

Despite the operational benefits and wide use of *product group affinity* in industry, this method did not align well with Amazon's long-term strategic objectives to expand product offerings and stimulate customer orders across multiple product categories. Given the promising operational and financial benefits of the *cloud,* the Amazon Operations Leadership Team selected this product placement strategy to pilot in 2006.

1.4 Thesis Outline

The following outline provides the reader with a general overview of the content and sequence of the thesis chapters.

Chapter 2 will provide an overview of the state of online retail, discussing Amazon's business in the context of the industry as a whole, followed by an overview of the firm's fulfillment center operations.

Chapter 3 will discuss previous research efforts conducted on product placement in academia and at Amazon. This chapter will summarize the various product placement alternatives considered as part of the internship.

Chapter 4 will provide a detailed description of the Lexington facility which was used as a case study for this project. The chapter will discuss Lexington's key attributes, facility layout, labor allocation, and algorithms.

Chapter 5 will present a baseline model of Amazon's current picking performance at the Lexington facility, discussing key drivers and the role of variability in determining pick productivity.

Chapter 6 will introduce the cloud model approach, a product placement concept that disperses inventory to multiple locations, creating a "warehouse-within-a warehouse". The improvement will be quantified utilizing statistical and probability analysis. Both quantitative and qualitative benefits and risks will be discussed.

Chapter 7 will introduce the affinity approach, a product placement concept in which items are stowed based on product groups. Both quantitative and qualitative benefits and risks will be explored.

Chapter 8 will discuss the implications of the cloud and affinity approaches on continuous flow fulfillment centers. Key operational differences will be reviewed as well as the importance of matching product placement strategies with current processes.

Chapter 9 will summarize the thesis recommendations as well as opportunities for future research projects. The thesis will conclude by discussing leadership observations at Amazon.

CHAPTER 2: AMAZON OPERATIONS

2.1 Online Retail Industry

In 2005, the online retail industry entered its tenth year in business, signifying an important milestone in consumer purchasing trends. According to Forrester Research and Shop.org[1], in 2004, U.S. online retail sales increased 23.8% to $109.6 billion (excluding travel and auctions). Online retail sales accounted for 6.5% of all retail sales and are forecasted to continue to grow as a percentage of overall retail revenues[2].

While no one can accurately predict what the future holds for the online retail industry in the next ten years, it is certain that this new channel will play an important role for both buyers and sellers. Large established firms can no longer afford to have only retail stores as shoppers now expect a new service level. These firms are now faced with the difficult task of designing a supply chain and operations strategy that aligns with both their traditional retail channel and their online retail requirements. Some retailers have decided to enter the market head-on (Wal-Mart) while others have decided to outsource their online fulfillment (Target.com) to third party logistics providers. Regardless of their strategy, these established firms have the distinct advantage of a successful brand and the ability to cross-market their products to both of these channels. First-movers in online retail, such as Amazon.com, developed distinct operational and supply chain advantages, but are now recognizing the power of branding in the marketplace. Therefore, these firms are developing strategic alliances that leverage their operational capabilities to gain access to more established brands with strong reputations and customer loyalty. In summary, each of these players, both new and established firms, will play a key role in creating and capturing value from this new retail channel.

2.2 Amazon.com Company Background

Amazon's vision is to have the "earth's greatest selection" and to be the "earth's most customer-centric company." This is a notable shift from the company's original vision of becoming the "earth's largest online bookseller." In 2005, Amazon's online catalog

[1] http://www.technewsworld.com/story/43319.html

[2] http://www.allaboutmarketresearch.com/ind/ind003.htm

consisted of over 1.4 million unique items in over 32 product categories. Amazon now sells everything from diamonds, to Apple iPods, and gourmet food.

Amazon's strategy is based on convenience, selection, and low prices[3]. Historically, in the retail industry, selection and low prices were considered to be at odds with one another. However, Amazon is able to compete on both of these fronts because the firm does not need to hold inventory in multiple retail stores unlike their traditional brick-and-mortar counterparts. This enables Amazon to have lower capital costs, lower inventory costs, and higher inventory turns which translates into their ability to offer greater selection at lower prices.

In order to offer greater selection and enhanced customer service, Amazon has grown their traditional customer base. The firm has formed strategic alliances with large merchants such as Toys 'R Us and Target.com, providing fulfillment and software services in exchange for enhanced product selection and brand recognition. Additionally, Amazon launched Marketplace, enabling third party sellers to offer their merchandise on Amazon's website.

In 2004, Amazon posted their first profit, showing investors that it could survive the dot.com downturn. In 2005, sales grew 23% to $8.4 billion in revenues[4], capturing 8% of all online sales (excluding auctions and travel). Net income for the year was $359 million, down from $588 million in 2004.

As the online market continues to grow, Amazon is faced with increasing competition from traditional retail stores entering the market, such as WalMart.com. In order to compete, Amazon continues to focus on their core competencies, namely their software expertise and operational excellence. The online retailer seeks out the best and brightest software developers in the industry, developing sophisticated proprietary technologies to manage their website and operations. Amazon also continues to make improvements to their fulfillment operations through Six Sigma and warehouse optimization techniques.

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[3] Amazon 2004 Annual Report
[4] Amazon 2005 Annual Report

2.3 Pizza Team Organizational Structure

In order to better understand the motivation for the internship project it is important to understand the organizational structure of the software organization to which the intern was assigned.

The heart of Amazon is their software organization which provides the complex algorithms and optimization programs that run the daily operations of the fulfillment centers. The software organization is divided into many different "pizza teams" which support each of the individual processes within the fulfillment center. For example, there are individual pizza teams for receive, stow, pick, and sort. While the researcher was assigned to the stow pizza team, called Space Management, significant interaction between several pizza teams was necessary in order to achieve the goals of the internship project.

The pizza team concept is to create small, autonomous teams that are responsible and accountable for a defined set of work processes and measurable goals. The overall goal of this structure is to enable speed and innovation in each of Amazon's work processes. In order to achieve this goal, the need for communication across teams must be reduced, by eliminating dependencies in each of the team's processes. In other words, the team must be composed of all of the elements it needs to function on its own, without regard to other team's processes and work functions. In fact, the optimal team at Amazon is one that is composed of only one individual.

Beyond speed and innovation, there is a cultural motivation behind the pizza team concept. The idea being that morale will be improved as software engineers feel a greater sense of ownership and pride in their ability to set their own direction and goals. In some respects, the pizza team concept is a way to keep the entrepreneurial spirit alive as the company moves from being a small start-up to a major player in the retail industry.

While the pizza team concept results in many positive aspects, it is not without problems. While software code can be broken down to independent pieces, the overall warehouse physical processes are inherently tied together. As such, the pizza team structure itself can lead to sub-optimization. Recognizing this, the leader of the Space Management pizza team sought to develop a project that would look across organizational boundaries to find a product placement solution that would not only improve stowing in isolation, rather it would optimize the entire value stream.

2.4 Amazon Fulfillment Operations

Amazon's warehouses are called Fulfillment Centers (FC's). Amazon has operations in several locations throughout the U.S., Canada, Europe, Japan, and most recently China. Each of the FC's has specific capabilities and product lines, enabling the firm to offer a large selection, while leveraging a common platform and meeting the unique requirements of their local markets.

At a tactical level, each FC performs the same basic function. The FC's obtain large shipments from vendors and retail partners, store these items, and then deliver smaller quantities to the end customer, who typically purchases only a few items. The translation of these goods from large incoming shipments to small outgoing deliveries is called the fulfillment process.

This section will describe Amazon's current fulfillment operations from the time the vendor delivers the inventory to the receiving dock to the time the order is shipped to the final customer. The major FC physical processes are as follows: receive, stow/replenish, pick, sort, pack and ship. The following section will describe each of these processes in detail in order to give the reader a deeper understanding of Amazon's operations as well as a context in which to consider the thesis problem. Those readers who are already familiar with Amazon's fulfillment center operations may choose to skip to the next section.

2.4.1 Receive

The first major step in the fulfillment process is the receive operation. Here, items are delivered from thousands of vendors based on Amazon's ordering systems. The critical steps in the receive process are as follows: inspecting shipments to ensure the quantity and content of the cases matches Amazon's order request, "virtually" receiving the items in Amazon's software systems for tracking purposes, and lastly staging the items for the next stow process.

Shipments may be received at the dock or directly at the storage bin (called "direct to bin"). In the former process items must be handled twice, once to receive the item and again when the item is stowed. In the latter process, where items are received directly at the bin, the receive operation and stow operation essentially become one process. "Direct to bin" is typically utilized for Amazon's high quality vendors where accuracy issues are not problematic, thereby minimizing the need for quality inspections.

2.4.2 Stow

The stow process, also called "put-away" in some warehouses, is the method in which products are physically stored in preparation for retrieval in the downstream picking process. As the focus of the project is on alternative storage solutions, the stow process is important for the reader to understand in detail. First I will review Amazon stowing terminology, next the different storage philosophies will be discussed, followed by a review of the storage mechanisms used in Amazon FC's.

In order to discuss stowing in more detail it is important to understand some basic Amazon terminology. A single unit of storage at Amazon is called a "bin." For tracking purposes, each bin has a unique bar-code. Amazon also differentiates each unique inventory item as an ASIN (Amazon Stock Identification Number), similar to a sku. Every ASIN is also assigned a unique numerical bar-code. Therefore, when an ASIN is placed in a bin, the item is both physically and virtually stowed. This tracking capability is essential to Amazon's quality and customer service.

Amazon uses two general storage methods: random and directed.

1. Random storage

In random storage, items are physically stored anywhere that there is available space in the pick area. Therefore, a distinct ASIN will not necessarily be placed in the same bin the next time the item is stowed in the fulfillment center. Once the stower finds an available bin location, they will use an RF scanner to scan the item and the bin location, such that the item is both physically and virtually stored in Amazon's software systems. This will enable the item to be retrieved once an order is placed by a customer.

2. Directed Storage

In the directed storage methodology, an ASIN is assigned to a specific bin location. Every time this ASIN is ordered it will be stowed and picked from the same "address" or location in the FC. Items are directed to various storage types based on their demand velocity. Items with higher demand will be directed to pallet areas, while lower demand items will be placed in smaller storage types (storage types will be discussed next). The velocity thresholds are set by the software engineering team.

Chapter 3 will discuss the tradeoffs between random and directed storage methods as well as alternative methodologies that are currently being used in industry.

Amazon utilizes several different physical storage types to store product. The main storage modes are as follows: library, library deep, case flow, and pallet storage.

1. Library

Library shelves are typically what would be found in a traditional brick and mortar retail bookstore or in a neighborhood library (Figure 1). Library shelves typically hold small items such as books, music, and DVD's that have relatively low demand. Each bin in a library shelve can hold multiple different ASINs.

Figure 1. Library Bins

2. Library deep

Library deep shelves are similar to regular library shelves except they are larger in all three dimensions. Due to the greater size of the bins, this storage method not only holds books, music, and DVD's but also a wide variety of products such as kitchen products, toys, and electronics (Figure 2). Library deep shelves are typically used for products that have a higher demand than those stored in library shelves. Items stored in library deep shelves may be stowed randomly or directed.

Figure 2. Library Deep Bins

3. Case Flow Rack

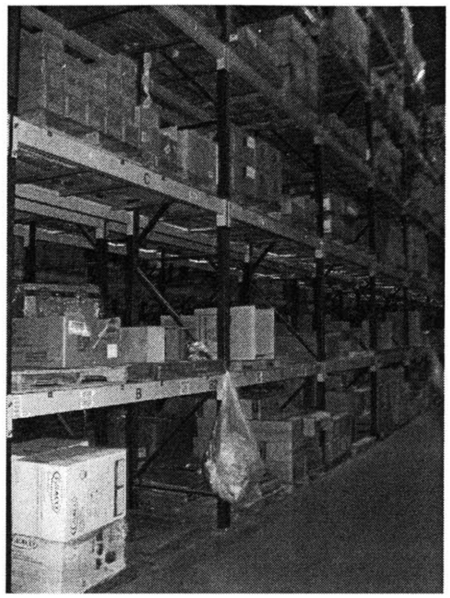
Case flow storage has deep bins which slide downward and are lined with rollers such that when a case is removed gravity pulls the next case forward (Figure 3). Items are stowed from one side of the rack and picked from the other side. This method is typically used for high demand products that come in smaller than pallet quantities. A wide range of products are stored in case flow racks.

Figure 3. Case Flow Rack

4. Pallet rack

Pallet rack storage at Amazon is similar to what can be found in almost any large-scale distribution center. This storage method is used for Amazon's high demand products that are delivered from the vendor in large quantities (Figure 4).

Figure 4. Pallet Rack



To summarize, Amazon utilizes several different storage types to fit their wide range or product types and customer demands. The main storage types are library, library deep, case flow, and pallet rack. The major storage types that will be relevant to the thesis are library and library deep shelving given that approximately 70% of all products are stowed using this storage mode.

2.4.3 Replenishment

As inventory of a particular ASIN is depleted, the inventory must be replenished. Typically, seven days worth of demand is held. Once safety stock levels are reached the inventory is pulled from a "reserve area" and replenished to the major stow areas. The replenishment process itself is essentially the same as the stow operation.

2.4.4 Pick

The pick operation can be visualized as the ubiquitous trip to the grocery store. As a shopper, you have a list of items that you need for the week, and you go through the grocery store in a logical pattern, in order to "pick" each of the goods on your list. At Amazon the shopper is called the "picker." Unlike, a regular shopping list however, the picker follows a computer generated pick list on an RF scanner, and follows a "pick path" which represents the route a picker must follow.

The RF scanner shows the picker the location of the next item on the list. Once the item is found the picker scans the item to ensure that it is the correct ASIN. Then the picker inspects the item for damage and places the item in a tote. The tote is stored on a cart (similar to a grocery store cart). The picker will then move to the next location identified on the RF scanner. Once a tote is deemed full, the picker will place the tote on a conveyor in preparation for the next process, sortation. The tote itself has a bar code such that the items in the tote can be physically tracked throughout the remaining steps of the fulfillment process.

It should be noted here, that at Amazon pickers are not picking all of items for a given customer order (called "pick-to-order"); rather they are picking items that may belong to tens if not hundreds of different orders. Additionally, multiple different pickers may pick items for the same order. This is necessary because for a given customer order, each item in the order may be located in far away locations in the warehouse. In order to minimize travel time between picks, a sophisticated computer algorithm assigns pickers items to items in close proximity. This means that items must later be sorted into their correct orders in the downstream process described in the next section.

2.4.5 Sortation

The major goal of the sortation process is to assemble the items that are in many different totes into their associated customer orders. There are two different methods of sortation at Amazon: automated and manual sortation.

1. Automated Sortation

In the automated sortation method, an operator removes each item from its tote. The item then goes through an induct station where it is directed along a series of conveyors to one of several thousand chutes or lanes where it will eventually meet up with the remainder of the customer order. Once the order is completed, it will go to the pack process.

2. Manual

In the manual sortation method, there are two major operations: tote sortation and rebin. In tote sortation there are distinct staging areas for batches of totes to arrive. A "batch" contains multiple orders which are contained in several different totes. Once the batch of totes arrives in the staging area they are physically moved to the "rebin" step. In the rebin process, each item is removed from the tote, scanned, and directed to a bin in a "rebin station." A rebin station is similar to a library shelving mechanism except it is smaller and portable. Items that belong to the same customer order will "meet" or be assembled in the same bin. Once all of the items in the totes have been placed in the appropriate bin in the rebin station, the rebin station will be moved to the next step in the process, packing.

2.4.6 Pack/Ship

Once the items have been assembled into their customer orders, they are ready to be packed. Packers place the orders into right-sized boxes and the orders are directed to the appropriate location for their shipping destination. The last step in the process is to load the boxes onto trucks for their final delivery to the customer.

CHAPTER 3: PRODUCT PLACEMENT

3.1 Previous Research

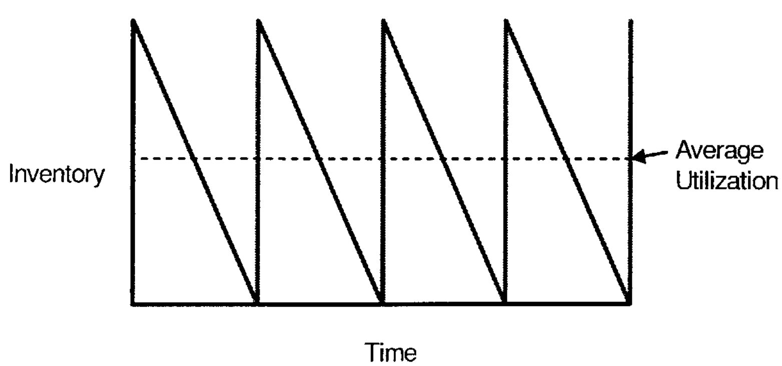
There is a significant amount of research on product placement in warehouse management. Researchers categorize storage schemes broadly as either random or directed (sometimes also referred to as shared versus dedicated storage).

In the directed storage method, items are assigned to a fixed location. This would be similar to visiting your community library. Each book is assigned to a specific location on the library shelf such that visitors can easily find and retrieve the book they are looking for. Benefits of this storage method are as follows[5]:

- Ability to store high volume products in convenient locations, increasing picker productivity
- Ability for associates to learn where products are located
- High degree of accuracy

However, directed storage is not beneficial from a space utilization perspective. As inventory is depleted from the fixed location, the storage unit is under-utilized until inventory is replenished once again. Figure 5 provides an idealized view of this dynamic as presented by Bartholdi and Hackman.

Figure 5. Directed Storage Locations Inventory over Time

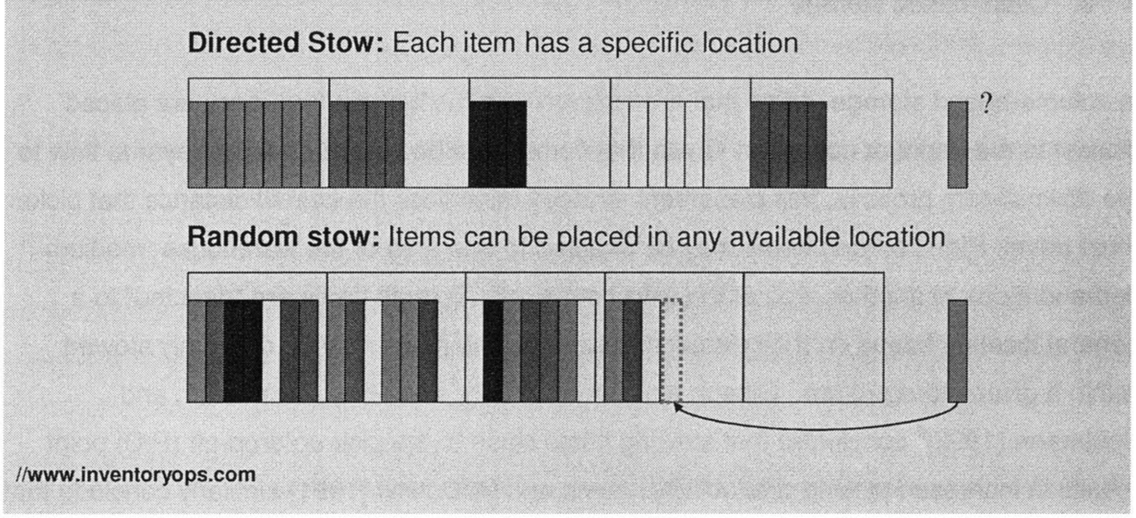


[5] http://www.tli.gatech.edu/whscience/book/wh-sci-0.76.pdf

Theoretically, at any given point in time the storage locations will be half empty on average. For this reason, warehouse managers must make strategic tradeoffs between the benefits of improved productivity due to worker learning, ease of use, and accuracy versus the costs of storage capacity.

In contrast, in the random storage scheme, items are placed in any open storage location. Multiple different products may be placed in the same storage bin. Once a product is removed from the bin a different product may take the place of the original one. Figure 6 compares directed and random storage schemes[6]:

Figure 6. Comparison of Directed versus Random Stow



From a space utilization perspective, the random stow methodology performs much better than directed storage. Bartholdi and Hackman estimate that average capacity utilization for random storage will be approximately 66%. However, there are several drawbacks to this storage methodology:

- Workers are not able to learn where products are located, potentially reducing efficiency
- In some cases, products may take longer to stow as workers search for available space

[6] http://www.inventoryops.com/

- Accuracy issues may arise due to employee error

As such, tradeoffs between random and directed storage must be considered, and operations managers must choose storage philosophies that best fit their products, processes, and people.

While these storage methods represent broad categories, warehouses often use a hybrid of the random and directed storage philosophies. These storage solutions can be classified as follows:

1. Volume-based storage
2. Class-based storage

In volume-based storage, items that are ordered with the highest frequency are placed closest to the depot or conveyor. Given that items must be placed on a conveyor to flow to the downstream process, this placement strategy minimizes the overall distance that pickers must travel. High demand items may be directed to one area of the warehouse, medium demand items to another area of the warehouse, etc. Though items are "directed" to a general location based on their demand frequency, the items may be randomly stowed within a given storage area. Gibson and Sharp (1992)[7] and Gray, Karmarkar, and Seidmann (1992)[8] concluded that stowing items close to the pick-up/drop-off (P/D) point results in increased picking productivity. Jarvis and McDowell (1991) similarly conclude that the optimal storage policy is to stow the highest demand items in the aisle nearest the P/D point and the next highest demand items in the next aisle, and so on[9]. Bartholdi and Hackman (2006) investigate the design and implementation aspects of "fast pick" areas in improving overall pick productivity[10]. Petersen, Siu, and Heiser (2005) recommend placing

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[7] Gibson, D. R., & Sharp, G. P. (1992). Order batching procedures. European Journal of Operational Research, 58, 57-67.

[8] Gray, A. E., Karmarkar, U. S., & Seidmann, A. (1992). Design and operation of an order-consolidation warehouse: Models and application. European Journal of Operational Research, 58, 3-13.

[9] Jarvis, J. M., & McDowell, E. D. (1991). Optimal product layout in an order picking warehouse. IIE Transactions, 23(1), 93-102.

[10] http://www.tli.gatech.edu/whscience/book/wh-sci-0.76.pdf

higher volume items in a "golden zone" area, between the picker's waist and shoulders, in order to increase picker efficiency[11].

In the class-based storage policy, items are stowed by product group or class. For instance products that tend to be ordered together might be placed in the same area. Another way to define a storage class would be by identifying items with similar sizes and dimensions such that storage equipment can be designed to fit unique product needs. Peterson, Aase, and Heiser (2004) compare the efficiency of class-based storage systems to volume-based and random storage policies[12]. This research also considers the impact of the number of storage classes and partition methods on warehouse productivity. Enyan and Rosenblatt (1994) analyze the impact of class-based storage policies for automated storage and retrieval systems[13]. Peterson and Roodbergen (1998) consider how volume-based strategies can work in concert with class-based storage policies[14].

This research differs from prior studies in several ways. First, this thesis identifies storage strategies for e-commerce fulfillment, a topic in which there is minimal prior research. (in the next section I will discuss the prior Amazon research in this area). While previous studies focus on how to stow and pick large quantities of items for delivery to retailers, e-commerce order fulfillment strategies must optimize the delivery of a small number of items to the end customer. In this thesis I will investigate the impact of class-based storage policies on e-commerce order fulfillment productivity. This thesis will also explore a novel storage strategy which disperses unique items to multiple locations in a fulfillment center, creating a "warehouse-within-a-warehouse." This methodology has not been explored in either traditional or e-commerce fulfillment environments.

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[11] Petersen, C.G., Siu, C., & Heiser, D. R. (2005), Improving order picking performance utilizing slotting and golden zone storage, International Journal of Operations & Production Management, Volume 25, Number 10, 997-1012.

[12] Petersen, C.G., Aase, G., & Heiser, D.R., (2004) Improving order-picking performance through the implementation of class-based storage. International Journal of Physical Distribution & Logistics Management.

[13] Enyan, A. & Rosenblatt, M.J. (1994) Establishing zones in single-command class-based rectangular AS/RS. IIE Transactions 30, 469-480.

3.2 Previous Amazon Studies

Two alternative product placement proposals were initiated by previous Amazon interns as follows:

1. Fast Pick Area
2. "3 to 5" approach

The fast pick area, studied by Sarah Marsh, a Harvard Business school intern, utilizes many of the volume-based concepts as presented in the literature. The concept of the fast pick area is to place Amazon's hot sellers in a separate area located next to the receiving dock and conveyors, thereby reducing travel time and increasing picker productivity. Marsh's study concluded that due to Amazon's high turnover rates amongst the most popular titles (approximately 40% per week for the top 500 selling items) that the increased maintenance costs and potential accuracy issues (due to the continuous movement of inventory) outweighed any of the potential benefits gained from increased picking productivity.

The "3 to 5" approach, researched by Charlene Lieu, an MIT Leaders for Manufacturing Fellow, hypothesizes that placement of high demand items on shelves located within the "3 to 5" foot strike zone (also known as the "golden zone"), will result in higher picking productivity. Conceptually, items located within this strike zone are the easiest and most ergonomic to pick from. Given that the picker will have to bend or reach less frequently, labor savings are likely to result. Lieu's analysis estimates that the "3-to-5" approach will result in the reduction of 65 labor hours per picker per year.

3.3 Alternatives Considered

Two alternative product placement strategies were analyzed as part of the internship project:

1. The Cloud
2. Product Group Affinity

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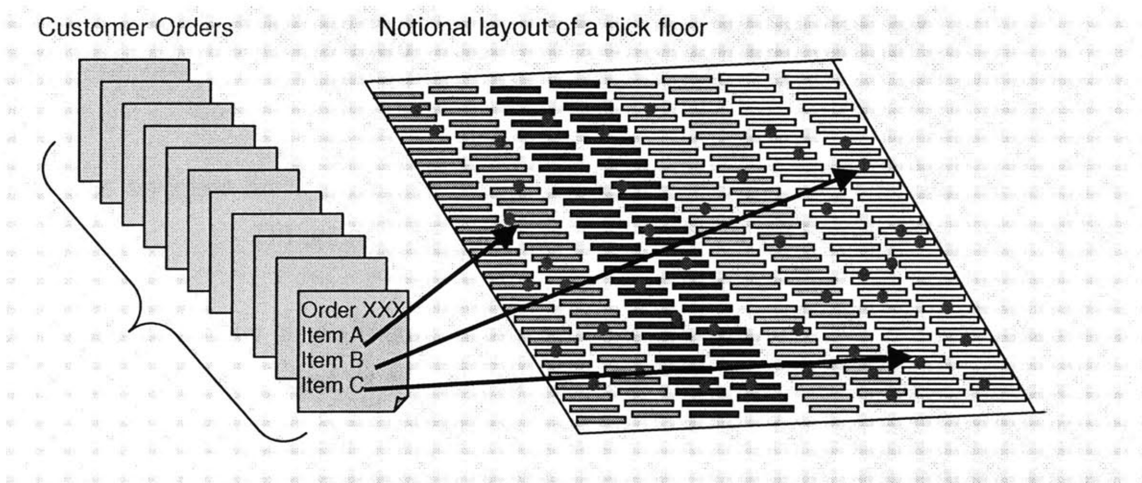
[14] Peterson, C.G. & Roodbergen K.J., Order Picking 401: How to improve order picking efficiency with routing and storage policies, 1-17.

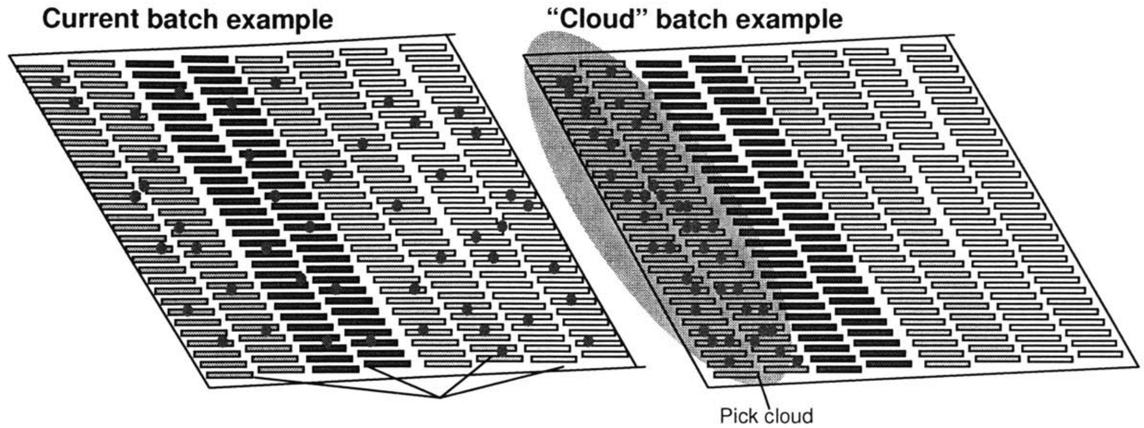
In the "cloud" concept, unique ASIN's are distributed to multiple locations in the FC, creating "clouds" that at any given point in time contain the majority of all inventory necessary to fulfill a customer order. Currently, when inventory of a unique ASIN arrives in the FC it is stowed in one or a few locations. For example, if Amazon orders 30 copies of a CD, these items will most likely be placed in one bin. The result is that customer orders consisting of several different ASIN's, are likely to be located in several different locations dispersed throughout the FC. Figure 7 depicts this dynamic:

Figure 7. Notional Depiction of Order Spread



The cloud concept hypothesizes that by dispersing the inventory to multiple locations customer orders will be able to be picked from one or a few clouds, resulting in increased pick productivity as distance traveled between consecutive picks is minimized. The following graphic compares the current batch picks with the potential "cloud" batch picks.

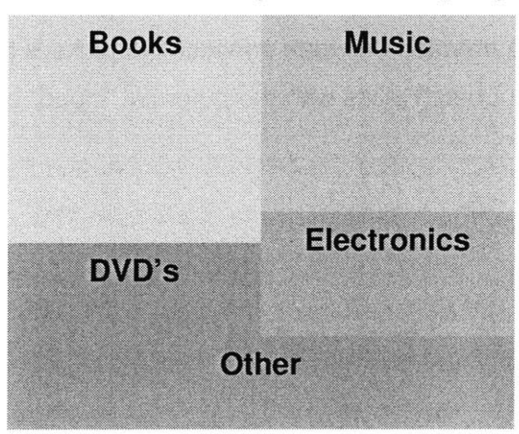
Figure 8. Comparison of Current Batch Picks with Cloud Batch Picks



In the cloud approach, the increased pick productivity gains must be weighed against the additional "cost" to spread the inventory to multiple locations in the FC.

The second alternative studied, the product affinity approach is similar to class-based storage. The concept is that inventory would be stowed to warehouse zones based on product groups. For example, books would be stowed in one zone, music in another zone, DVD's in another zone, and so on. Figure 9 portrays a theoretical product group warehouse layout.

Figure 9. Notional Affinity Product Group Layout



The product affinity approach hypothesizes that since customers tend to order items within a single product group, this placement strategy will enable orders to be in closer proximity to one another, thereby reducing the distance between picks and increasing pick productivity. Additionally, storage equipment can be tailored to the individual product requirements, resulting in additional gains. While products would be directed to their associated warehouse zones, items would be stowed randomly within these zones thereby leveraging the benefits of both the directed and random stow philosophies.

In the next section, I will discuss the LEX1 fulfillment center that was used as a case study to research these alternative product placement concepts.

CHAPTER 4: LEXINGTON FULFILLMENT CENTER

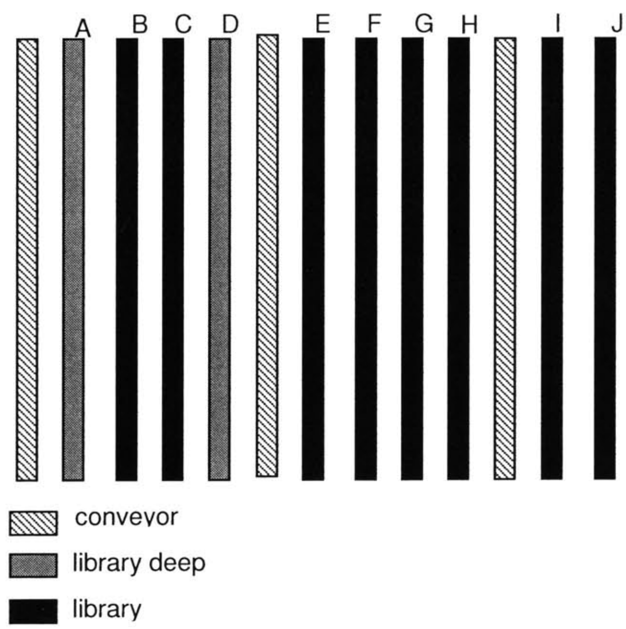
4.1 Key Features

The LEX1 fulfillment center is located in Lexington, Kentucky. The site has the largest product selection in terms of the number of unique ASIN's. The major products that are fulfilled from the FC are books, music, video and DVD's. At the time of the internship, over 90% of the products were randomly stowed to library and library deep bins. Because this particular facility had the lowest pick productivity of all of the FC's, this site was identified as the pilot location for the study. Additionally, as Amazon continues to expand their product selection across the entire network, LEX1 represented a good case study for understanding the impact of product placement on a high variety fulfillment center. In chapter 8, I will discuss how alternative product placement strategies will impact other Amazon FC's.

4.2 Facilities Layout

In order to assess various product placement schemes at LEX1 it is important to understand the layout and pick processes. Figure 10 is a notional depiction of the facility layout:

Figure 10. Notional Facility Layout



This layout represents a typical pick floor at LEX1. There are 10 rows A through J with over 30 aisles per row. Each aisle is approximately 50 feet in length with 4 feet in between each aisle. There are a total of three conveyors in the area. The pickers are assigned to work in a pick area or zone, consisting of several rows. LEX1 has three separate pick floors that represent a combination of library and library deep bins.

4.3 Labor Assignment

The LEX1 site is considered a "batchy" fulfillment center. As stated earlier, a given customer order may be located in multiple different areas spread across the FC. By "batching" or consolidating multiple orders, walking distance between picks can be reduced significantly (the batching algorithm will be discussed in the next section). Multiple pickers will pick items for a given batch. The pickers place each item onto a tote. Once the tote is filled to capacity the picker will place it on one of the three conveyors nearest to them. The pickers retrieve the items one row at a time. For example, a picker will start at row A and pick all of the items in that aisle before moving to row B. Even though orders are part of batches in the LEX1 FC, the order picker works in a continuous fashion as directed by the RF scanner without any awareness of which order(s) he is fulfilling.

Once the totes are placed on the conveyor they go to the sorting area. Here the individual totes are assembled into their assigned batch. Once all of the orders for a given batch reach the sorting area, they move via cart to a "rebin" station where they are broken out into their individual customer orders as directed by an RF scanner.

4.4 Batching Algorithm

In order to understand how pickers are assigned to batches, it is important to get an understanding of the algorithm used to created batches of orders. Initially, the algorithm attempts to find "enough" demands (orders) that reside in a single pick area. The size of the demand differs in each fulfillment center, but generally it is constrained by the capacity of the rebin wall. For example, if a rebin wall has 40 to 50 bins, the demand that would be "enough" would be, 120 to 150 picks (assuming an average order consisting of 3 items). Once there is no longer enough demand in a single pick area, then the algorithm will analyze all pairs of areas. For example, if there are 10 areas in the FC than there would be "10 choose 2" possible combinations. Once there are no longer enough demands to generate pairs, then 3 areas are analyzed, and 4 areas, and so on. This process continues until the algorithm reaches the max_area_combination. The max_area_combination is a setting determined by each fulfillment center. This setting effectively says that once x areas have been reached, stop using the algorithm.

While changes to the current algorithm were not considered as part of the researcher's project, the algorithm has a direct influence on picker productivity and therefore any future changes to stowing policy must be considered within the context of the current software system. In the next section, a baseline model of the current Lexington performance, utilizing the existing algorithm, will be discussed and analyzed.

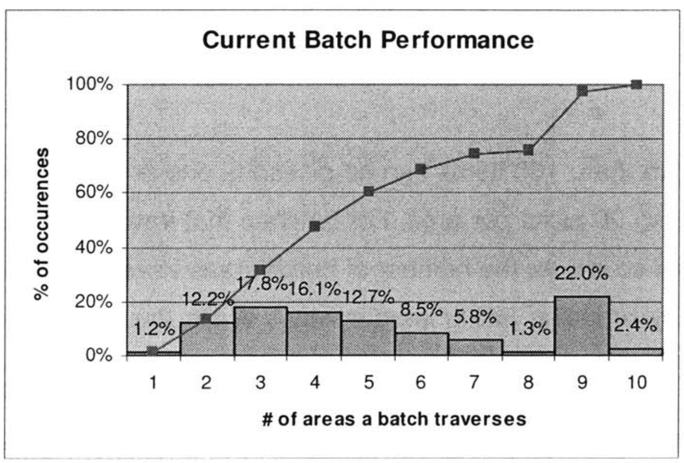
CHAPTER 5: CURRENT PERFORMANCE

5.1 Baseline Model

Before assessing various stowing policies, a baseline model for the Lexington fulfillment center was created. Future product placement scenarios will then be compared to the current performance results. The data utilized in this analysis represents over 18,000 batches.

As discussed earlier, the current batching algorithm attempts to optimize the number of areas a batch traverses. As such, the researcher gathered data to assess how the current algorithm performs. Figure 11 shows the number of pick areas the current batches traverse at LEX1:

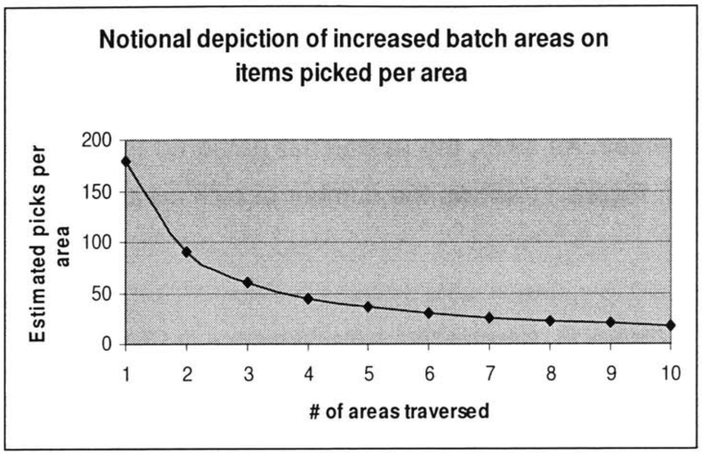
Figure 11. Current Batch Performance at LEX1



From the chart we see that 1.2% of batches are currently contained in a single area, 12.2% traverse two pick areas, 17.8% traverse 3 areas, etc. It should be noted that the number of batches traversing 9 areas is quite significant (22% of all occurrences). These are the clean-up batches that are unable to be optimized due to the nature of the greedy batching algorithm that is used. While not part of the research objectives of this internship, it is unclear whether or not the current algorithms used here could perform better. In the future this may be a promising area for software developers to analyze further.

From this analysis, it is clear that the majority of batches are picked from multiple areas in the FC. Ultimately this means that the pick density, or travel distance between picks is impacted. To illustrate this further consider the following generalized example. Assuming a batch size of 180 items distributed evenly to each pick area, we see the following results:

Figure 12. Notional Impact of Batch Areas on Picks per Area



With only one batch area, 180 items can be picked in one area. For batches that traverse 2 areas, there are only 90 picks per area. For batches that traverse 3 areas, there are only 60 picks per area, and so on. As the number of batch areas traversed increases, picks per area decreases, thereby reducing picker productivity. While the number of picks per area (as produced by the batching algorithm) is highly variable in reality, this example helps us to understand the underlying dynamics of the problem.

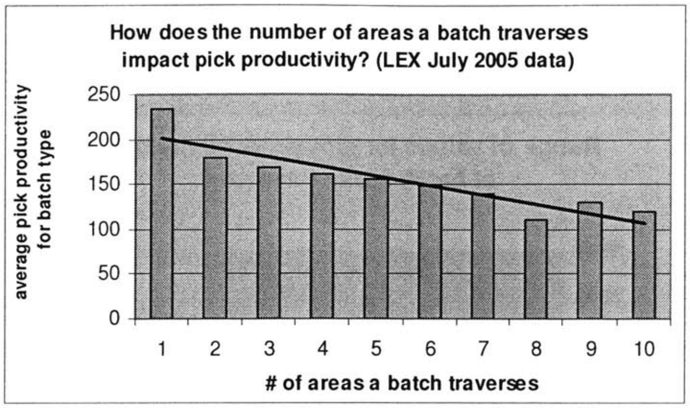
Next, the pick productivity for each batch was compared to the number of areas the batch traverses. Pick productivity, or the pick rate is calculated as follows:

$$\text{Pick rate} = \frac{\text{Number of picks in batch}}{\text{Total time of batch}}$$

This rate is then converted to a per hour rate and does not necessarily suggest that rate was achieved for an entire hour, only that for a given batch this rate was achieved for a period of time.

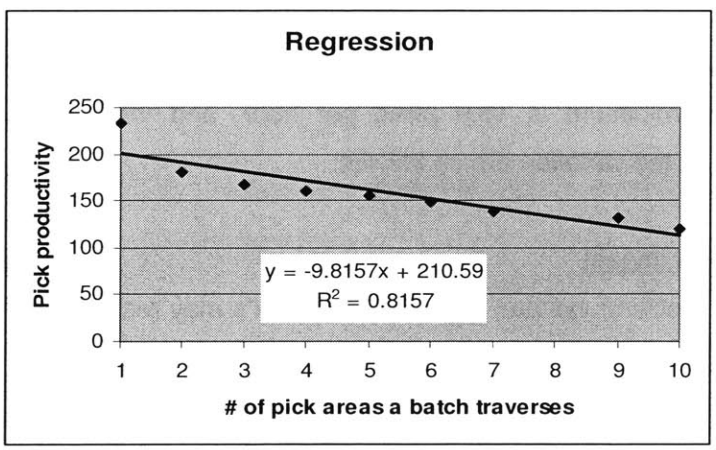
Figure 13 confirms the negative trend between the number of areas a batch traverses and pick productivity.

Figure 13. Impact of Number of Batch Areas and Pick Productivity



Next, a regression analysis is performed. Due to the low sample size of batches that traverse 8 areas this data set is removed.

Figure 14. Regression Analysis

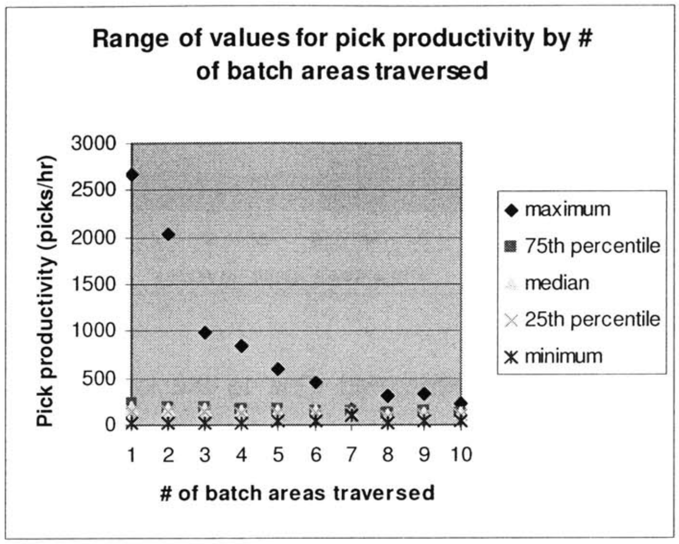


R-squared, a measure of good fit, is approximately 81% which is a fairly good predictor of pick productivity. However, batches that traverse one area appear to be much farther from the regression line than other batches. Given this, the researcher explored the reasons for this discrepancy.

5.2 Role of Variability

Further investigation of the data reveals a significant amount of variability in pick productivity for a given batch area size (batch traversing one area, two areas, etc.). Figure 15 explains this further:

Figure 15. Variability in Pick Productivity



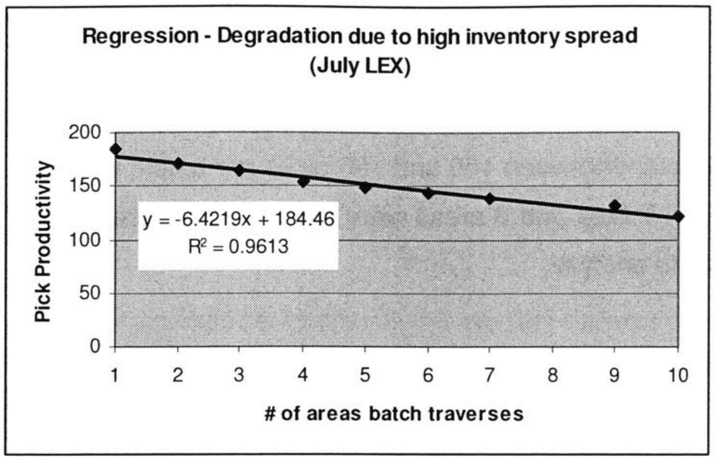
For example, for all batches that traverse 1 pick area only, the maximum pick productivity is 2670 picks/hr, the minimum is 16.9 picks per hour, and the median is 180.56. The underlying causes of the variation are as follows:

<u>1. High velocity ASIN impact</u>

Under our current stocking system, high velocity ASIN's may reside in one or a few bins in large quantities. An example of a high velocity ASIN would be a new release or a best selling novel. The Lexington data indicates that in some cases batches are created that consists of one or a few of these high velocity ASIN's. For example, 100 Harry Potter books may be picked from one bin, resulting in a pick productivity well exceeding a rate of 300 picks per hour. Out of 211 batches that traversed only 1 pick area, 13.7% of batches could be categorized as high velocity batches (picking 20 or more copies in a single aisle).

When we remove the high velocity batches from the data set we see the following trend:

Figure 16. Regression, Degradation due to High Velocity Batches

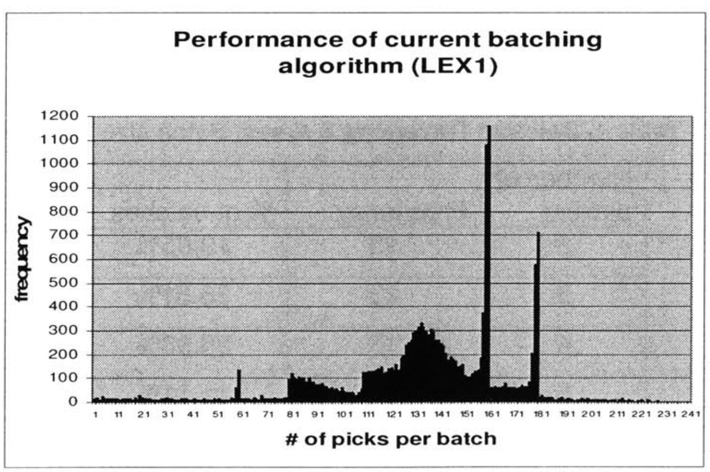


By removing the variability caused by these high velocity batches we see that the pick productivity for one area batches decreases, while R^2 increases to 96%. Thus, the reason why the one area batches appeared to be such an outlier, was due to the prevalence of these high velocity batches.

2. Variation in picks per batch

Another cause of the variation in the data is due to the distribution in the number of picks per batch. Figure 17 shows the distribution of picks per batch.

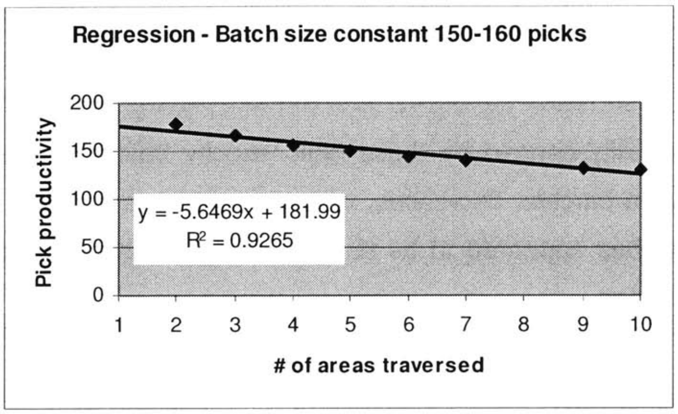
Figure 17. Distribution of Picks per Batch



The majority of batches have between 91 and 180 picks, but clearly there is a non-negligible number of picks that fall in the upper and lower tails. Holding all other factors equal, a batch consisting of 180 picks would perform better than a batch consisting on only 90 picks.

Holding batches constant between 150 and 160 picks per batch, we see the following trend. Batches that traverse 1 area and 8 areas were not included because there was not a large enough sample size to analyze.

Figure 18. Holding Batch Size Constant, 150-160 Picks



3. Labor variability

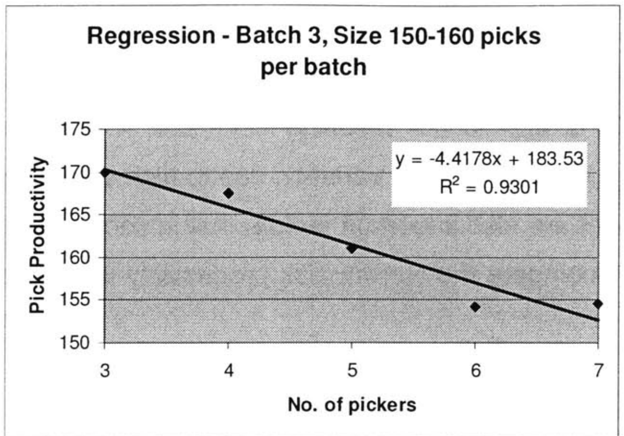
Another cause of variation in the data is due to the impact of labor on pick productivity. For example, for all batches that traverse 3 areas with a batch size of 150-160 picks per hour, we see the following distribution of labor:

Table 1. Batches Traversing 3 Areas, Batch size 150-160

Number of pickers	Frequency	% of batches
2	12	19.05%
3	23	36.51%
4	17	26.98%
5	7	11.11%
6	4	6.35%

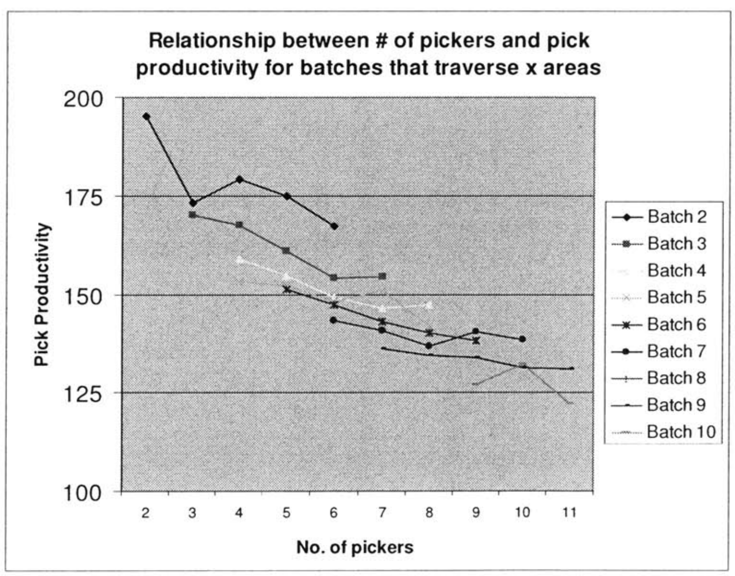
Plotting number of pickers versus pick productivity for batches traversing 3 areas, while holding batch size near constant, we see the following:

Figure 19. Regression Batch Area 3, 150-160 Picks



From the data we see that as the number of pickers increase for a given batch, there is a diminishing return in pick productivity. This makes intuitive sense; as pickers are added to the pick path the workers compete with each other for work, thereby reducing the pick density of the batch. Comparing this data for all batches area sizes we see a similar trend:

Figure 20. Impact of Labor on Picking Productivity



While there is not a large enough sample size for batches traversing one area, the data indicates that there is a steeper slope for batches that traverse a smaller number of areas. Therefore, the impact of adding labor has a more profound impact on the pick rate as the number of batch areas traversed decreases.

In summary, as the number of areas a batch traverses increases, the pick productivity or pick rate decreases. This is due to the resulting decrease in pick density resulting in increased walking distance between picks. Variation due to high velocity batches, picks per batch, and labor assignment are also important factors that impact overall pick productivity. Using these insights, I will compare the current pick productivity with the proposed product placement strategies.

CHAPTER 6: THE CLOUD

6.1 Cloud Model Assumptions

For the purpose of analyzing the cloud, the following data, ground rules, and assumptions were used:

1. Data is taken from the Lexington fulfillment center historical log files.
2. Approximately 18,000 batches were analyzed.
3. ASIN's will be distributed evenly throughout 10 pick areas at LEX1.
4. Layout and shelving requirements are not a constraint.
5. Each of the 10 pick areas is equally sized. The cloud model will not impact the size of the pick areas.

6.2 Pick Productivity Analysis

As stated earlier, the cloud model will enable batches to be picked from a smaller warehouse envelope thereby increasing picks per area and reducing picker travel time. In order to assess the potential performance of the cloud model, an understanding of how orders will be distributed is important. For this analysis it is assumed that inventory will be distributed evenly to 10 pick areas. For example, if there are 20 copies of a book, there will be 2 copies available in each pick area.

Next, it is important to understand how various customer order profiles will be picked in the cloud model. For the purpose of this analysis a single order is defined as a customer order for one item. A multi-order represents a customer order for more than one item. A "high-high" inventory order represents a multi-order where all items in the order have inventory with 10 items or more. A "high-low" inventory order represents a multi-order in which at least one item has at least 10 units in inventory and at least one item in the order has less than 10 units in inventory. Lastly a "low-low" inventory order is a customer order where all items have less than 10 units in inventory.

Table 2 summarizes the options for how various orders profiles will be picked in the cloud model.

Table 2. Cloud Impact on Order Profiles

Order Profile	Analysis
Single orders	Order can be picked from any cloud in which the ASIN is located
Multi-order -> High - High inventory order	Order can be picked from any of the ten clouds
Multi-order -> High - Low inventory order	Order can be picked from the cloud that contains the low inventory ASIN
Multi-order -> Low - Low inventory order	Likelihood that the order will be dispersed in multiple clouds

From this chart, we see that single orders, high-high inventory orders, and high-low inventory orders can be picked from a single cloud or pick area. For example, for a high-high inventory order having two ASIN's, one with 10 copies and one with 20 copies, each of the 10 clouds will have both of these items; therefore, the order can be picked from any of the clouds. On the other hand, low-low inventory multi-orders present a problem. For example, if an order contains 2 ASIN's each with only one in inventory there is a 10% chance this order will be able to be picked from one cloud; conversely, there is a 90% chance that this order will traverse two different clouds.

Given that low-low inventory multi-orders may fall in multiple clouds, it is important to assess the magnitude of orders that are in this category. In order to calculate the percentage of orders that will reside in multiple clouds we must first determine the number of low-low inventory orders. From Appendix A-1 we determine that the number of low-low inventory orders represent 42% of the multi-order shipments. Next we must determine the following: given a low-low inventory order, what is the probability that the order will reside in multiple clouds. Appendix A-2 details these probabilities for each of the low-low inventory orders. Next we determine the percentage of low-low inventory orders that will reside in multiple clouds, using the following calculation:

X = Percentage of orders that reside in multiple clouds
N = Number of occurrences of low-low inventory order
P(O) = Probability order resides in multiple clouds

$$X = \sum (N \times P(O)) \quad \{\text{for all order pairs whose sum is less than 10}\}$$

Using this calculation, we conclude that 25% of multi-orders will fall in multiple clouds (see Appendix A-3). Conversely, 75% of multi-orders will fall in the same cloud. Comparing this with the current performance at Lexington, where less than 2% of orders are contained in a single area, the cloud produces a distinct advantage.

From the regression equation in Figure 16, we predict that one area batches, as produced by the cloud will result in the following pick productivity:

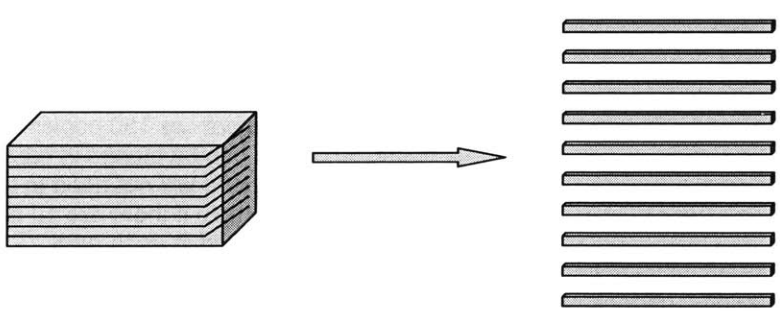
$$Y = -6.4X + 184.5 = (-6.4 \times 1) + 184.5 = 178 \text{ picks per hour}$$

Comparing this estimated pick productivity with the current average of 147 picks per hour, results in a 20% improvement in pick productivity. This is a promising result, especially in an environment where a 5% improvement is considerable. In order to fully understand the impact of the cloud however, the gains in pick productivity must be weighed against the losses in receiving performance. The next section will discuss this further.

6.3 Receiving Analysis

In order to implement the cloud product placement approach, inventory must be dispersed to each of the ten pick areas in the LEX1 FC. This will require that distinct ASINs to be "sorted" prior to being stowed. Figure 21 depicts this change:

Figure 21. Sortation Requirement for Cloud Product Placement



Current: Place 10 copies in one location

Future: Sort copies such that there is 1 copy in each of 10 locations

In order to quantify the cost of this sortation operation it is important to understand the different methods in which items are received at LEX1. As discussed earlier items may be received at the "dock" or at the "bin."

At the dock

There are two different methods in which items can be received at the dock:

1. Pallet quantities are received at the carton level without having to open the carton or scan individual items. Cartons are not opened until they are ready to be picked. Pallet quantities represent less than 10% of receipts.
2. Items are received in smaller quantities called eaches. Every individual carton must be opened, each item scanned and inspected for damage. The majority of items are received in this manner.

At the bin

Items that are received at the bin typically come from reliable vendors and therefore do not have to be individually scanned and inspected. The cartons will go directly to the pick area where the box will be opened and the items randomly stowed.

The following chart summarizes how these receive processes will be impacted by the cloud product placement strategy:

Table 3. Impact of Cloud Product Placement Strategy

Receive Process	Current process	Cloud Impact
At the dock: pallet quantities	ASINs received at carton level	Cartons may need to be opened in order to distribute copies to each pick area. Items do not need to be handled individually, however. For example, if there are 100 copies of an ASIN, 10 copies can be placed in each tote. In some cases, cartons will not need to be opened. For example if there are 10 cartons, 1 carton can be placed in each area.
At the dock: Eaches	ASINs received as eaches; cartons opened and items are individually scanned and inspected	As items are received they will be placed in one of 10 totes.
At the bin	Cartons are opened at the bin where items stowed	Cartons will need to be opened at the dock in order to sort ASINs prior to stowing them at the bin. This will increase the number of touches required.

A previous sortation study conducted in 2005, showed that items could be sorted to six different totes at a rate of 600 per hour. For the purpose of this study, it is assumed that the rate will not change by increasing the number of totes to ten. This rate includes the time it takes to scan each item and place each item in one of the totes. This rate is modified for each of the receive processes as follows:

Table 4. Estimated Sortation Rates by Receive Process

Current Receive Process	Rate Used
At the bin	600 units/hr: Each item will need to be individually scanned and placed into one of 10 totes at the dock.
At the dock: Eaches	1200 units/hr: Receivers are already opening the box and scanning each item; the only additional process is the placement of each ASIN in a separate tote. Assuming that 50% of the time represents opening the box and scanning each item and the remaining 50% represents placing the items in totes, a rate of 1200 units per hour can be expected.
At the dock: Pallet quantities	800 units per hour: It is assumed that since each item will not have to be handled individually that the sortation rate will be better than the "at the bin" receive process, but worse than "at the dock each" receive process.

Using these rates, we determine the number of "sorters" or labor required as a result of this new operation. Figure 22 shows a notional example of this sortation impact:

Figure 22. Notional Example of Sortation Impact

	At bin eaches	At bin pallet qty	At dock
Daily Receiving Volume (Hypothetical)	80,000	5,000	70,000
Sort rate (units/hr)	1,200	800	600
Sort rate per day (Sort rate x 22 working hours per day)	26,400	17,600	13,200
# of Sorters required/day (daily volume/sort rate per day)	3.0	0.3	5.3
Total hours/year (Sorters x 22 hours/day x 365 days/year)	24,333	2,281	42,583
Total hours increase	69,198		

Using actual volumes we estimate a 10% increase in receiving hours. However, given that the total number of receiving hours is less than the total number of picking hours, the net benefit is a 15% reduction in picking hours. Therefore, overall the cloud product placement solution is net positive.

6.4 Concerns

While this study indicates a significant potential savings from implementing a cloud approach, there are several issues that must be addressed in the future in order to validate these results.

1. Sortation requirements are estimations based on a previous pilot study

Amazon's peak season occurred during the time of this study. As such the researcher was unable to conduct a pilot study to assess the true costs of the sortation process for each of the receive processes. In order to estimate the costs, a previous pilot study that was developed for alternative purposes was used as a baseline. While this method is reasonable, it is recommended that Amazon test the sortation process during in order to validate the results provided here.

2. Stowing impact needs to be analyzed

There will be an additional stowing cost associated with implementing the cloud approach. The main cost will be the additional scanning that will be required as copies are spread to more areas. For example, currently when a stower has 30 copies of the same ASIN they can scan one copy and enter "30" into their RF scanner which tells the system that 30 copies are present in the bin. In the cloud approach there will be 3 copies in 10 areas resulting in 10 times the number of scanning operations required. Scanning, however is only a small cost of the entire operation and should not reduce the savings significantly.

3. Inventory spread decisions

In some cases, it may not be optimal to disperse the entire inventory to multiple locations. For example, instructional/educational materials often times are ordered in large quantities. It may make sense to hold these items in one location versus spreading these to multiple locations. Additionally, the FC may want to keep a portion of their high velocity ASIN inventory in a single location. As discussed earlier, high velocity ASIN batches result in extremely high picking productivity. Therefore it may be beneficial to spread some of the inventory to the ten pick areas, while keeping some of the inventory in one location to create these high velocity batches. These hybrid approaches should be studied in more detail in the future.

CHAPTER 7: AFFINITY

7.1 Product Affinity Approach

At the time of the internship there was considerable stakeholder interest in understanding the impact of the product affinity model on pick productivity. It was hypothesized that customers tend to purchase items within a single product line (i.e. customers who purchase a book are more likely to purchase another book as their second order item rather than a DVD). Given the current random stow method, all product groups reside in all pick areas, meaning that even if a customer orders items from a single product group, the likelihood that the order resides in multiple areas is high. On the other hand, if ASINs were stowed to zones based on product group, the number of areas a batch traverses is likely to be reduced, thereby increasing pick productivity. In order to test this hypothesis, the researcher gathered data on customer order buying patterns and used this data to assess the potential pick productivity gains.

7.2 Pick Productivity Analysis

At LEX1, the top three product lines – books, music, and DVD's – make up over 90% of all customer orders. For each of these product lines the researcher gathered data to determine the portion of multi-orders (orders having more than one item) that belonged to a single product group and the portion of orders that belonged to multiple product groups. The following chart summarizes these findings:

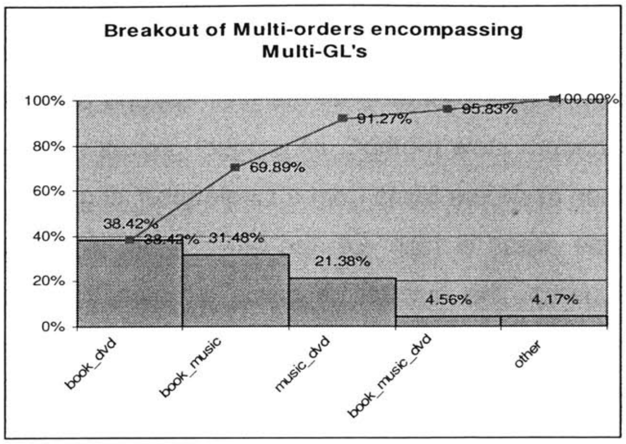
Table 5. Amazon Customer Buying Behavior

Product Group	One Product Group	Multiple Product Groups
Books	> 80%	<20%
DVD	> 50%	<50%
Music	> 50%	<50%

These numbers confirm that more often than not customers tend to order within a single product line. For example, over 80% of book multi-orders consist of books only. Over 50% DVD multi-orders and music multi-orders consists only of these items.

Analyzing the composition of multi-orders that consist of multiple product groups, we see the following:

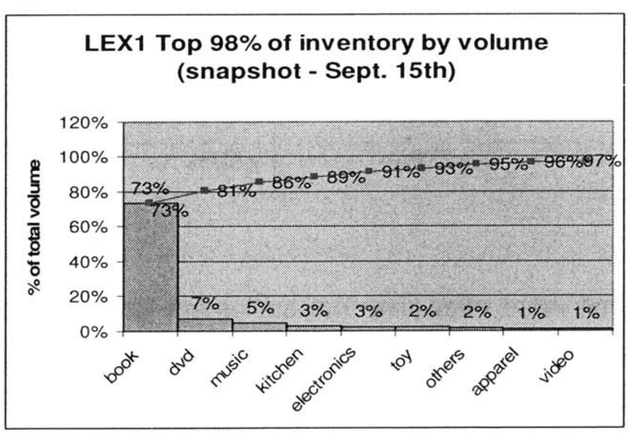
Figure 23. Product Group Breakout for Multi-Orders



The data shows that of multi-orders consisting of multiple product groups, 38% are book/DVD orders, 31% are book/music orders, 21% are music/DVD orders, 4% are books/music/DVD orders, and 4.17% are other product group combinations.

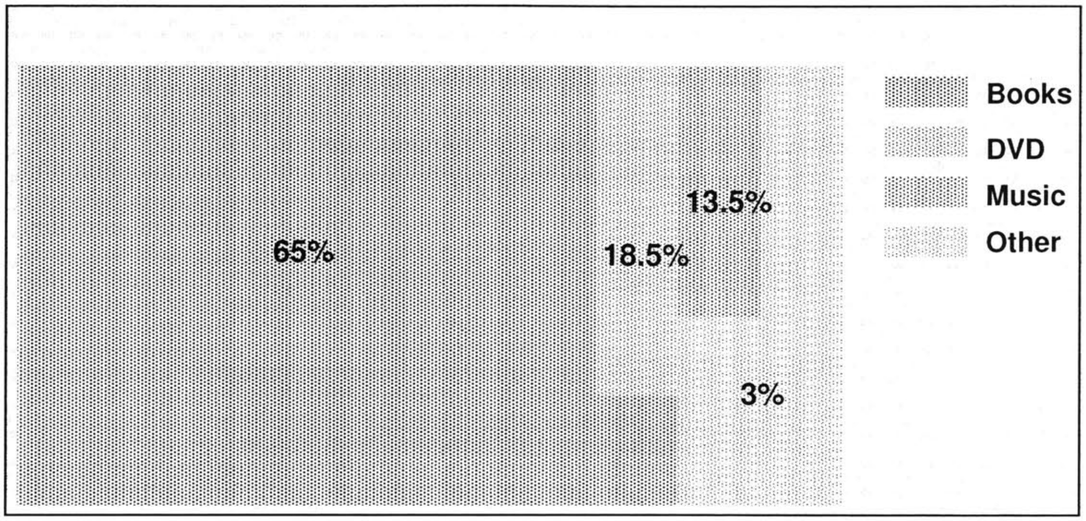
Having determined the profile of customer orders, the next step is to understand the volume or "envelope" each of the product groups takes up in the fulfillment center. Figure 24 shows the volume breakout by product group:

Figure 24. Pareto of Inventory Volume by Product Group



Therefore, assuming a total of ten warehouse areas, books make up approximately 7.3 areas. DVD's and music make up .7 and .5 areas, respectively. Multi-orders consisting of both music and DVD orders will make up 1.2 areas. The remaining product groups if combined would make up 1.5 areas. Figure 25 summarizes the inventory volume versus the percentage of sales for each product group:

Figure 25. Inventory Volume versus Sales

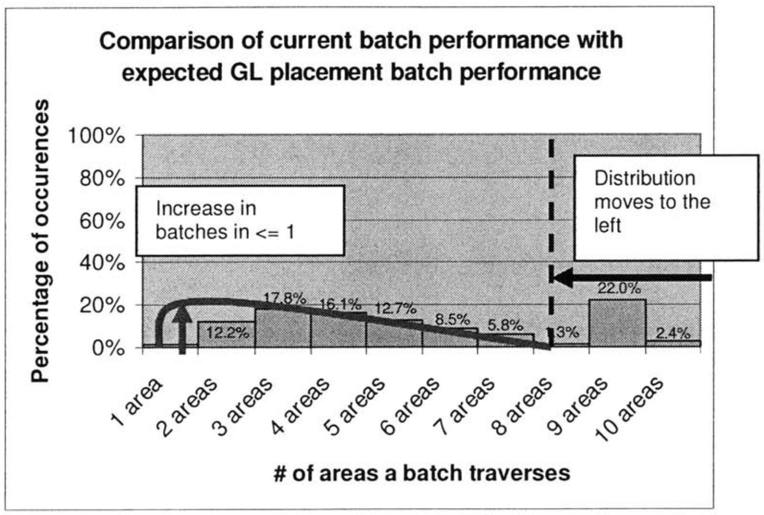


It should be emphasized here that the remaining "other" product groups make up 12% of the total area, but only 3% of sales. Given that these items are slow movers, they are currently taking up space throughout the FC, thereby reducing pick density. Even if no other changes are made, stowing these slow moving products together in a separate zone will result in improved pick productivity and could be accomplished with minimal effort. Music and DVD's on the other hand, take up a small amount of space compared to their percentage of sales. This indicates that product placement by affinity is likely to result in positive gains.

Next, we determine the percentage of orders that will be able to be picked from these product group zones. The data shows that 5.7% of the total customer orders could be picked from the music zone, 6.7% out of the DVD zone, and 3.4% out of both of these zones combined. Reflecting back to the LEX1 baseline study only 1.2% of batches could be picked from a single pick area. Assuming a one-to-one correlation between orders and batches, the product affinity approach would result in 5.7% of batches in .5 areas, 6.7% of batches in .7 areas, and 3.4% of batches in 1.2 areas.

Furthermore, the number of orders or batches traversing 8, 9, and 10 areas should be minimal. Out of 719,887 orders analyzed only 2,877 were multi-orders consisting of books, music, and DVD's and another 2,632 were made up of "other" combinations, representing 1% of total orders. Figure 26 contrasts the current performance with a notional depiction of the expected performance of stowing by product group:

Figure 26. Expected Product Affinity Performance



Using the regression equation and current batching performance we calculate the current pick performance as 150.4 which is a 2% differential from the actual pick performance of 147 picks per hour. In comparison, we estimate that stowing by product group will result in 159.3 picks per hour (See Appendix A-4 for calculations).

This represents a 6% improvement in pick productivity from the current baseline. Of course, this is a point estimate, the actual distribution of batches traversing one to ten areas is unknown. Testing various scenarios for this distribution we see a range of pick productivity improvement between 4-8%.

In summary, product group affinity results in positive pick productivity gains. Given that customers tend to order within a single product group, placement by product line will reduce the number of areas an order is picked from thereby increasing overall pick density. In the next section, I will discuss the potential impact to the upstream stow process that will be required to place items in product group zones.

7.3 Stowing Impact

In order to implement the affinity strategy inventory must be placed in product group zones. However, within a given product group zone, inventory can still be stowed randomly within that zone. Therefore, the actual impact to the stowing process is considered negligible. The implementation process is also fairly straightforward. Rather than transitioning to the new approach all at once, stowers would gradually introduce this scheme by placing inventory into the these zones. As inventory is depleted from the current areas, the zones will migrate over time to these product groupings. Additionally, these zones are "virtual" and therefore, strict zoning rules are not necessary; as long as items are placed close to their product group, improvements will be gained.

Though not studied as part of this analysis, there may also be benefits of the affinity strategy from an equipment storage perspective. If storage bins can be tailored to the unique product groups, this will improve space utilization and possibly picking as items are easier to retrieve from the bins. An indication of this benefit can be found in the Reno FC media center. This media center, which is composed solely of music, using tailored case flow bins, has the highest pick productivity of all of the FC's. This may be an area of interesting study in the future.

7.4 Strategic Issues

Beyond the operational benefits of the affinity approach, several strategic issues should be considered. There are two major business strategies that Amazon is implementing that may reduce the overall benefits of this product placement approach in the future. The first is Amazon's 'Prime' promotion. For an annual fee, Prime allows customers to receive free shipping on all their Amazon orders. The overall goal of the program is to increase consumer purchasing and encourage customers to purchase outside of traditional product lines. Amazon's second strategy is to expand their product offerings by partnering with major retailers such as Toys 'R Us and Target.com. In the long-term, if these strategies are successful, Amazon will become a "one-stop shopping" retailer. Clearly, if consumer purchasing trends change and customers buy items across multiple product lines, the overall benefit of the product affinity approach will be minimized.

In summary, product group affinity has both operational and financial benefits. The implementation of this approach is fairly simple and straight forward, thereby making this proposal very attractive. However, there is weak strategic alignment between the affinity approach and Amazon's business goals due to future product expansion and cross-sell strategies.

CHAPTER 8: IMPLICATIONS FOR CONTINUOUS FLOW FULFILLMENT

8.1 Introduction to Continuous Flow FC's

Thus far, our analysis has focused on "batchy" FC's. Amazon has another category of fulfillment centers, called continuous flow FC's. Continuous flow FC's, as their name suggests, process orders in a continuous fashion rather than having to consolidate orders into batches. Having determined that product placement would have a positive impact in batchy FC's, the Senior Operations Management Team wanted to assess the potential impact on continuous flow FC's. In the next section, I will discuss the key differences between the batchy and continuous flow FC's. For the purpose of this analysis, Reno (RNO1) was used as a model of a continuous flow FC. Next, a comparison of RNO1 and LEX1 pick density will be analyzed. Lastly, I will discuss the implications of the proposed product placement strategies on a continuous flow FC and provide recommendations for aligning stowing policy with operations architecture.

8.2 Batchy versus Continuous Flow

One of the major operational differences between RNO1 and LEX1 is the Crisplant, Amazon's automated sorter. Because LEX1 does not have a Crisplant and uses a manual sortation process, pickers are constrained to picking batches of approximately 60 orders (approximately 120 to 180 items) - the capacity limitation of sortation. As stated earlier, in LEX1, at any point in time pickers are assigned picks in a single area for a single batch. Since the orders are spread over many pick areas the pick density is relatively low. As such, an *order-based placement strategy*, such as the cloud, which enables individual "orders" to be located in the same pick area, has a significant picking advantage. In contrast, the capacity of the Crisplant at RNO1 is upwards of two thousand orders. This means that individual orders do not have to be in the same pick area in order to obtain a high pick density; rather the picking software can route a picker to any of the other two thousand orders (or 6000 + items) that are in close proximity to the picker's current location. In order to understand the magnitude of the Crisplant advantage, the pick density's of RNO1 and LEX1 are compared.

Four weeks of pick data in November was analyzed for pick areas with comparable bin types (compromised primarily of library shelving, random stow) and product size for both RNO1 and LEX1. In this analysis 'picks per aisle' is used as a measure of pick density.

Picks per aisle is calculated by taking the number of picks and dividing it by the number of aisles entered for a single picker in one hour intervals. RNO has between 1.4 picks and 1.6 picks per aisle whereas LEX has between 1.6 and 1.7 picks per aisle. However, RNO's aisles are approximately 11 ft long whereas LEX's aisles are approximately 50 ft long. Converting this to 'feet per pick' we see the following:

Figure 27. Comparison of Pick Density for LEX1 versus RNO1

LEX1 Feet per Pick

	Wk 44	Wk 45	Wk 46	Wk 47
PA2	30.1	31.8	31.6	32.1
PA3	31.3	31.5	31.9	31.8
PA4	34.3	35.4	34.1	34.9
PA5	28.4	28.9	28.6	30.9
PA6	29.5	30.2	31.8	28.9
PA7	27.2	28.7	29.5	30.9
Avg	***30.1***	***31.1***	***31.2***	***31.6***

RNO1 Feet per pick

	Wk 44	Wk 45	Wk 46	Wk 47
PA31	7.6	8.1	8.0	8.0
PA32	7.5	8.1	8.3	8.3
PA34	5.9	6.9	7.5	7.3
PA35	6.7	7.4	7.6	7.8
Avg	***6.9***	***7.6***	***7.9***	***7.8***

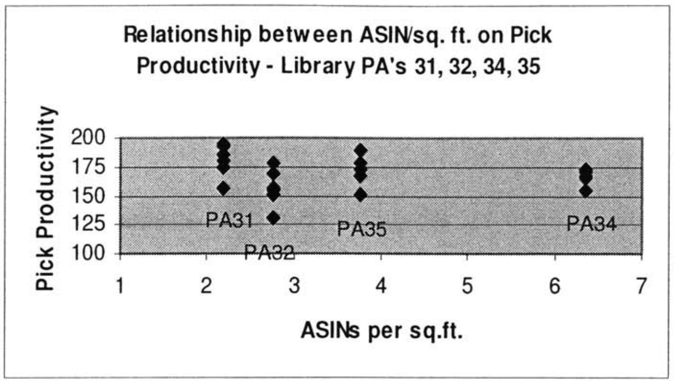
RNO's pick density is substantially higher with approximately 7 to 8 feet per pick (on average) whereas LEX is approximately 30 to 31 feet per pick (on average). Since this metric does not consider between aisle distances it is important to note that "feet per pick" is not a good absolute measure, however it is a good relative measure to use. Clearly, RNO's batch-less process enables the FC to obtain a much higher pick density.

8.3 Implications of Order-Based Strategy

Given that the proximity of individual orders in a pick area is not a requirement for high pick density at RNO1, it is questionable whether an order-based strategy such as the cloud or affinity strategy will have a significant pick productivity impact. While the cloud is expected to increase picking productivity at LEX1 by 147 picks per hour to 178 picks per hour, RNO1 is already achieving these rates for comparable pick areas.

In order to test this hypothesis, four pick areas at RNO1 with similar bin types and product sizes were analyzed to determine how higher ASIN concentration would impact pick productivity. ASIN concentration is measured by the number of distinct ASINs per square foot. In the cloud model, ASIN concentration would increase substantially. If the cloud was to be applicable at RNO1, it would be expected that increased ASIN concentration would increase pick productivity. The following graph contradicts this notion:

Figure 28. Impact of ASIN Concentration on Pick Productivity



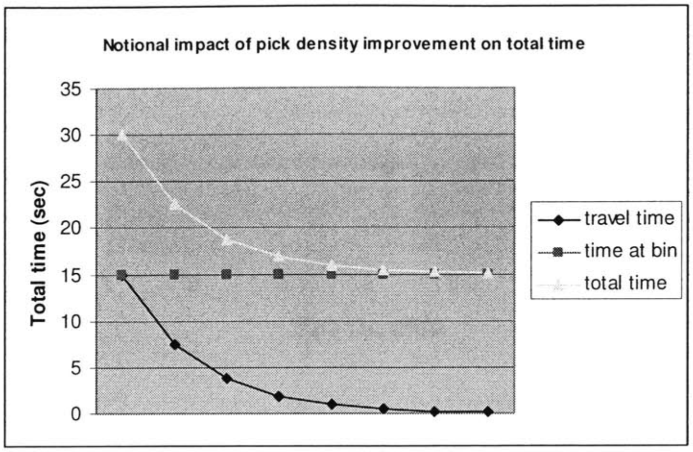
While pick area 34 has 2 to 3.5 times the number of distinct ASINs per square foot as the other areas, there appears to be no impact to pick productivity. There are two potential reasons for this for this outcome: 1) the Crisplant enables dense picks regardless of the number of ASINs per square feet 2) Any additional density created by the number of distinct ASINs in an area is virtually wiped out by 'time at bin,' the time that it takes to search for the product once the aisle is reached. In the case of pick area 34 perhaps the addition of distinct ASINs means there are less copies available increasing time at bin. In the next section we will discuss the impact of 'time at bin' in more detail.

8.4 Time at Bin

It is important to understand the significance of time at bin in terms of its overall impact on picking time. For the purposes of this discussion 'time at bin' represents the time to find the bin once you reach the aisle, plus the time to find the item once you reach the bin, plus the time to scan the item and check for damage. As 'travel time between picks' diminishes the 'time at bin' begins to dominate the total picking time and additional pick density has a negligible impact. For example, let us assume that the average time between picks is 30 seconds with 50% of the time representing travel time and 50% of the time representing time at bin. Assuming that pick density improvements result in a reduction in travel time of 50%, travel time becomes 7.5 seconds and time at bin is 15 sec with total time being 22.5

sec. If we continue to increase pick density reducing travel time by 50% we see the following:

Figure 29. Pick Density Improvement on Total Time



From this chart we see that additional reduction in travel time due to pick density becomes negligible over time. While no data currently exists to track 'time at bin' this relationship provides a useful framework. Given that RNO is already achieving 1.4 to 1.6 picks per 11 foot aisle in the random stow areas it appears that we are reaching a threshold where additional pick density (as produced by the cloud or other means) may not achieve enough pick productivity benefit to outweigh the additional costs required to implement such methods.

8.5 Matching Product Placement with Process

Given that the Crisplant does not require an order-based product placement strategy in order to achieve high pick density it appears that the proposed placement strategies are not a systemic solution for continuous flow FC's. Further, the operational differences at RNO1 and LEX1 suggest that no product placement solution is likely to be universally applicable/ beneficial to both continuous and batchy FC's. Both of these FC's are at different points on the travel time/time at bin curve as exemplified by RNO's significant multiplier in pick density. Additionally these FC's have different picking algorithms; requiring product placement solutions that are aligned and integrated with their individual operations system design. Therefore, it is recommended that Amazon match their product placement strategy with their overall operational processes. In the future, Amazon should research stowing policies that fit the unique requirements of the continuous flow operation.

CHAPTER 9: RECOMMENDATIONS

The purpose of this chapter is to move beyond the specific thesis problem and discuss recommendations for continued research in the future. In many ways this thesis is a starting point for continued improvement and hopefully a springboard for innovate ideas to emerge.

9.1 Further validation of model

Due to the promising financial and operational benefits of the cloud approach, the Senior Operations Leadership Team selected this product placement strategy to pilot in 2006. It is recommended that continued work be completed in the following areas:

1. Develop a pilot study of the sortation process to validate model
2. Assess the stowing cost impact of the cloud approach
3. Investigate hybrid opportunities for distributing inventory

This research will not only help to validate the model, but also will ensure buy-in from those teams that will be affected by the change. As such, it is important that multiple stakeholders from various functions are involved in the data collection and study.

9.2 Opportunities for future projects

My research on product placement strategy led to several key observations on future projects that will help Amazon to improve their operations. These projects may be relevant for future interns and/or current employees.

1. Time at Bin Study for Continuous Flow FC's

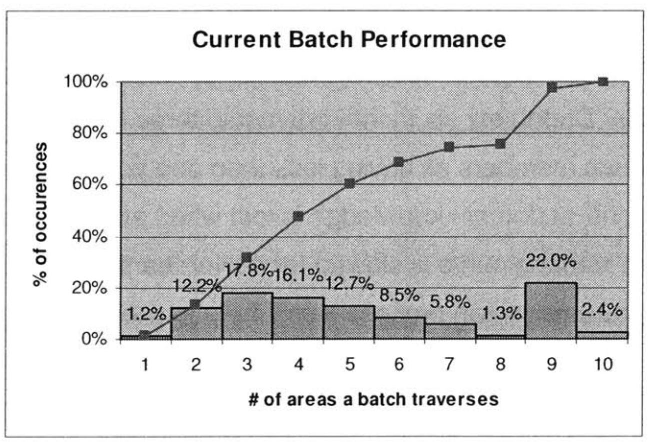
As discussed in Chapter 8, as pick density increases, overall travel time decreases and 'time at bin' becomes a greater portion of overall pick time. Time at bin is defined as time to find the bin once you reach the aisle, plus the time to search for the item once you reach the bin, plus the time to scan the item and check for damage. Future studies should identify the breakout of travel time and time at bin to determine if additional pick density improvements will have a substantial impact on overall picking time in continuous flow FC's. Using this data, a simple model could be constructed to simulate higher density picks in order to determine how this would impact overall pick time. This will enable operations managers to decide where to focus their efforts to maximize potential savings. While pick density projects to increase pick density are always ongoing, future studies should also try to identify opportunities to reduce 'time at bin' through lean techniques, quality improvements, or optimization.

Project deliverables include the following:

- Identify breakout of picking time as follows: walking, searching, handling, scanning, and checking for damage.
- Identify where to focus future efforts based on which time elements will have the greatest contribution towards reducing overall pick time.
- Develop and implement strategies for improving pick productivity based on these findings. These may include optimization, lean techniques, or six sigma strategies.

2. Batching algorithm improvements

As discussed in Chapter 5, the current batching algorithm that is used to batch orders may not be optimal. Referring to figure 11, we find that the large majority of batches traverse multiple areas:



It is unclear whether the current methodology is appropriate for minimizing picker travel time. For example, it may be more optimal to minimize the distribution/variation of the number of areas a batches traverses rather than attempting to create batches that traverse one or two areas. In other words, instead of creating only a few batches that traverse one or two areas, the algorithm could attempt to create more batches that traverse three to five areas, while minimizing the number of batches that traverse more than five areas. Potentially reducing the total variation in batch areas would provide an overall better solution. Additionally, many other algorithms should be tested to determine is a more optimal solution space.

3. Lean/Organizational Improvements

While Amazon is highly skilled at developing algorithms and optimizations, there is minimal effort dedicated towards implementing lean processes and organizational changes in the fulfillment centers and in the software organizations. This may in part be due to the fact that most of the engineers have software backgrounds as opposed to production of manufacturing experience. Additionally there is a cultural tendency at Amazon to focus on the technical aspects of problems versus the "softer" organizational issues that require behavioral changes. I believe that this is an area of great opportunity for improved productivity at Amazon. Several research areas that could be explored are as follows:

Standard Work/Documentation

Within the pizza teams, each team member is responsible and accountable for managing their own projects as they see fit. Often times coding is not well documented and must later be deciphered by an employee other than the originator when changes or improvements are needed. To further exacerbate this issue, there is considerable employee turnover within the software organization. During my six month internship three members transitioned out of the team, leaving four team members all having less than one year of experience at the company. As such, critical domain knowledge is lost when an employee leaves the organization and the learning curve is slowed for newer team members. A disciplined standard work and documentation process would help to alleviate the negative effects of employee turnover while providing for improved team efficiency.

Cross-functional Work Teams

During my internship project it became clear that there was very little cross-functional expertise within the pizza team organizations. While my internship required an understanding of the entire value stream, there were very few employees who understood and could explain the interconnections between each of the organizations, processes, and functions. The pizza teams are fairly homogeneous organizations made up almost entirely of software engineers. Attempts at bringing in process engineering skills have been met with little success. If Amazon wants to move beyond local optimization of individual processes (stow, pick, sort) teams should consist of a mix of process and functional knowledge.

Incentives/ Reward System

During my internship project, I observed that business objectives and individual incentives were not directly aligned in both the FC and Pizza Team organizations. In the FC, performance of pickers is measured every hour, minute, and second of the day. Amazon's computer systems track how many items each employee picks and compares this to expected target performance levels. If an employee performs below a certain threshold they will receive additional training or worst case they will be let go from the company. However, there are no incentives for associates to perform better than the target. Given that higher picking productivity translates directly into bottom line savings (less labor required), Amazon should investigate appropriate incentives to motivate associates to exceed targets. Similarly, in the office environment, the pizza teams are expected to achieve certain performance goals each year. However, there are no incentive schemes for engineers to exceed these targets.

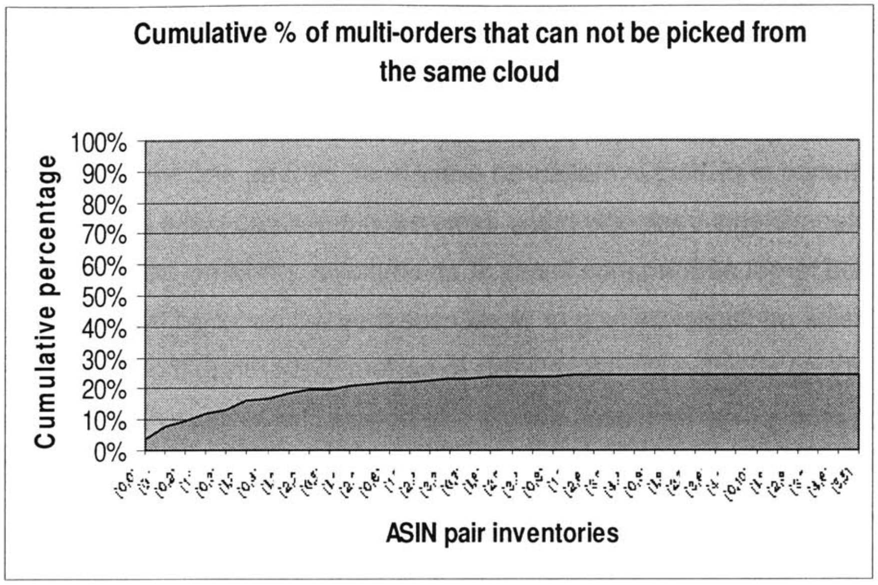
In the future Amazon should broaden their focus from implementing not only software and technical solutions in order to gain productivity improvements, but also by leveraging their greatest asset – their people – in order to change behaviors that would result in bottom line savings. Standard work, cross-functional teams, and incentives are three potential means for achieving improved performance.

9.3 Conclusions

As Amazon continues to expand operations through product line enhancements, strategic partnerships, and by increasing their global presence, warehouse design and strategy will continue to play a critical role in the company's ability to compete and maintain their profitable position. Product placement is one area of warehouse design that can have a real impact on fulfillment costs and as such it should be carefully considered as part of the firm's overall operational strategy. Additionally, as product lines change and expand, current product placement strategies may no longer be optimal. Amazon's ability to compete in the future will depend on their ability to continually change and adapt in order to meet market demands. A robust and flexible warehouse design and strategy will be a key component to ensuring Amazon's success.

APPENDIX A

A-1: Multi-orders in multiple areas



Note: ASINs with "0" quantity most likely had one in inventory when ordered. As the shipment data is historical and the inventory data is current this analysis can be considered conservative.

A-2: Low Inventory Multi-Order Shipment data

qty of rarest ASIN	qty of 2nd rarest ASIN	Total shipments with these multi-order qty's	% of multi-order shipments	Cumulative % of total multi-order shipments
0	0	29775	3.72%	3.72%
0	1	37388	4.67%	8.39%
0	2	22193	2.77%	11.17%
1	1	19493	2.44%	13.60%
0	3	14808	1.85%	15.45%
1	2	26204	3.27%	18.73%
0	4	9784	1.22%	19.95%
1	3	17678	2.21%	22.16%
2	2	11350	1.42%	23.58%
0	5	6387	0.80%	24.38%
1	4	11404	1.43%	25.80%
2	3	16059	2.01%	27.81%
0	6	4789	0.60%	28.41%
1	5	7585	0.95%	29.36%
2	4	10861	1.36%	30.71%
3	3	6833	0.85%	31.57%
0	7	3346	0.42%	31.98%
1	6	5625	0.70%	32.69%
2	5	7386	0.92%	33.61%
3	4	9720	1.21%	34.83%
0	8	2779	0.35%	35.17%
1	7	4012	0.50%	35.67%
2	6	5433	0.68%	36.35%
3	5	6712	0.84%	37.19%
4	4	3939	0.49%	37.68%
0	9	2221	0.28%	37.96%
1	8	3198	0.40%	38.36%
2	7	3834	0.48%	38.84%
3	6	4793	0.60%	39.44%
4	5	5740	0.72%	40.16%
0	10	1747	0.22%	40.38%
1	9	2562	0.32%	40.70%
2	8	3062	0.38%	41.08%
3	7	3370	0.42%	41.50%
4	6	4043	0.51%	42.00%
5	5	2241	0.28%	42.28%

Note: ASINs with "0" quantity most likely had one in inventory when ordered. As the shipment data is historical and the inventory data is current this analysis can be considered conservative.

A-3: Probability Analysis

qty of rarest ASIN	qty of 2nd rarest ASIN	Formula	Probability 2 ASINs located in the same area
1	1	1-(9/10)	10.0%
1	2	1-(8/10)	20.0%
1	3	1-(7/10)	30.0%
1	4	1-(6/10)	40.0%
1	5	1-(5/10)	50.0%
1	6	1-(4/10)	60.0%
1	7	1-(3/10)	70.0%
1	8	1-(2/10)	80.0%
1	9	1-(1/10)	90.0%
2	2	1-((8/10)*(7/9))	37.8%
2	3	1-((7/10)*(6/9))	53.3%
2	4	1-((6/10)*(5/9))	60.0%
2	5	1-((5/10)*(4/9))	77.8%
2	6	1-((4/10)*(3/9))	86.7%
2	7	1-((3/10)*(2/9))	93.3%
2	8	1-((2/10)*(1/9))	97.8%
3	3	1-((7/10)*(6/9)*(5/8))	70.8%
3	4	1-((6/10)*(5/9)*(4/8))	83.3%
3	5	1-((5/10)*(4/9)*(3/8))	91.7%
3	6	1-((4/10)*(3/9)*(2/8))	96.7%
3	7	1-(3/10)*(2/9)*(1/8))	99.2%
4	4	1-((6/10)*(5/9)*(4/8)*(3/7))	92.86%
4	5	1-((5/10)*(4/9)*(3/8)*(2/7))	97.62%
4	6	1-((4/10)*(3/9)*(2/8)*(1/7))	99.52%
5	5	1-((5/10)*(4/9)*(3/8)*(2/7)*(1/6))	99.60%

A-4: Estimation of Affinity Pick Productivity

# of areas a batch traverses	Est. Pick Productivity from regression equation	% of occurrences	Calculated estimate
0.50	181.24905	5.7%	10.28
0.70	179.96467	6.7%	12.02
1.20	176.75372	3.4%	5.96
1	178.0381	1.20%	2.14
2	171.6162	12.00%	20.59
3	165.1943	18.00%	29.73
4	158.7724	16.00%	25.40
5	152.3505	13.00%	19.81
6	145.9286	9.00%	13.13
7	139.5067	6.00%	8.37
8	133.0848	6.00%	7.99
9	126.6629	2%	2.62
10	120.241	1.00%	1.20
Total			159.25

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