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A Frame Work and Analysis to Inform the Selection of Piece-level Order-fulfillment Technologies

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XX. A FRAMEWORK AND ANALYSIS TO INFORM THE SELECTION OF PIECE-LEVEL ORDER-FULFILLMENT TECHNOLOGIES

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Abstract

The piece-level order-fulfillment technology selection problem is an important strategic problem that significantly impacts distribution center costs and operations, and is typically solved based on empirical experiences. Given a demand curve and a suite of available piece-level order-fulfillment technologies, we analyze where in the demand curve different order-fulfillment technologies should be applied. To do so, we develop a framework that jointly determines the best combination of piece-level order-fulfillment technologies and the assignment of SKUs to these technologies, which relaxes the sequential-modeling approach of previous research. We validate our methodology with industry data and show that our model provides technology recommendations and SKU assignments that are consistent with successful implementations. Through a set of numerical experiments and statistical analysis, we identify key factors in implementing manual versus automated order-fulfillment technologies and provide observations into the application of different order-fulfillment technology strategies. Finally, we present conclusions and future research directions.

Keywords: Material Handling, Warehouse Design, Facilities Planning

1. Motivation

We study the problem of selecting piece-level order-fulfillment technologies for a distribution center. The selection of order-fulfillment technologies is an important problem, impacting overall distribution center design and lifetime costs, and is challenging because the designer must select amongst a large number of diverse technologies [12].

To illustrate the challenges a distribution center designer faces, consider a major pharmaceutical distributor in Europe who combines automatic and manual picking systems to fulfill customer requirements. The distributor stores 100,000 stock keeping units (SKUs), has short lead time requirements, and makes multiple deliveries per day to customers.

An A-Frame system, which is an automated dispensing technology, is implemented to pick fast-moving SKUs [19]. A-Frame systems are capable of high throughput performance with reduced labor requirements. However, A-Frame systems have high capital costs, require manual replenishment, and are limited in the type of SKUs that can be fulfilled.

Slow-moving SKUs are picked from a picking machine, which is a stock-to-picker technology that consists of two or more pick stations and a common storage area [20, 21]. An integrated closed-loop conveyor decouples the pick stations from the storage area by transporting the needed totes to and from the storage area and the pick stations. A picking machine allows slow-moving SKUs to be picked efficiently as walking and searching times are eliminated. Additionally, the large quantity of slow-moving SKUs are stored such that high-storage densities are achieved.

The remaining SKUs are picked in a manual picking area using a picker-to-stock strategy, where an operator visits fixed locations to make a pick. Radio frequency (RF) picking is employed to reduce the amount of time an operator spends searching for the next pick and to increase picking accuracy. The manual area, which has a high labor requirement, but a low capital investment, consists mainly of SKUs that are requested with a high number of pieces per line and are medium to fast moving.

In such a design, 15% of SKUs are fulfilled from the A-Frame system, 17% from the manual picking area, and 68% from the picking machine. Because of the company's demand curve this allocation of SKUs to technologies results in 75% of lines being fulfilled from the A-Frame system, 17% from the manual process, and 8% from the picking machine. Using these technologies enables the entire order-fulfillment process to be completed within 45 minutes. The selection of these specific order-fulfillment technologies was determined based on past empirical experiences after an analysis and classification of fast-, medium-, and slow-moving SKUs.

In our research, we ask questions such as, "Why are close to 70% of SKUs allocated to the stock-to-picker technology? Why not allocate 50% or 80%? What factors impact piece-level order-fulfillment technology selection? Should SKUs with high demands be fulfilled differently than SKUs with low demands? Which SKUs should be fulfilled using automation?" To answer questions like these, we conduct a statistical analysis to increase the understanding of what factors most contribute to selecting different piece-level order-fulfillment technologies for different SKU characteristics and distribution center environments. To do this, we develop a systematic framework based on optimization that jointly determines the best combination of order-fulfillment technologies, as well as the number and type of the SKUs assigned to the technologies. Our intention is to increase the understanding of facility designers and planners who are considering the implications of selecting among different order-fulfillment technologies and assessing such technologies within a variety of distribution center environments.

In the next section we provide background information on order-fulfillment technologies, demand profiles, and the order-fulfillment technology selection and assignment process.

2. Background

Material handling is the science and art of moving, storing, protecting, and controlling material [25]. The purpose of a material handling system is to provide the "right amount of the right material, in the right condition, at the right place, in the right position, in the right sequence, and for the right cost, by the right method(s)" [25]. A specific kind of material handling technology is order-fulfillment technology. Order-fulfillment encompasses the securing of a customer order and applying resources (inventory, labor, information, etc.) to transfer the set of items in the order to the customer. Order-fulfillment technology is commonly used to reduce labor requirements, increase throughput, increase order accuracy, and decrease lead times. Orders can be fulfilled at different levels, ranging from piece-level, carton-based, or unit-load fulfillment. We focus our research on piece-level order-fulfillment technologies, which involves the most complicated form of order-fulfillment and uses the widest variety of material handling technologies [3]. Piece-level order-fulfillment has been increasing as distribution centers are experiencing an increase in the total volume of orders and a decrease in the number of items per order. Also, customer service initiatives, such as same-day shipping, require short lead times from the receipt of the order to when the order is fulfilled.

A wide range of material handling technologies in general, and piece-level order-fulfillment technologies in particular, exist on the market, with expenditures on warehouse technologies steadily increasing [4]. The number of technologies available is also increasing with the technologies becoming more complex mechanically, electronically, and through the use of more sophisticated identification technologies. Piece-level order-fulfillment technologies available on the market can be classified as picker-to-stock, stock-to-picker, and automated dispensing technologies. Picker-to-stock systems, where the picker travels to the items, require a low capital investment, but are labor intensive. Stock-to-picker systems, which bring the items to the picker, eliminate walking and searching, but require a substantial infrastructure investment. Finally, automated dispensing technologies eliminate picking labor, but require a high capital investment, require manual replenishment, and the type of products that can be fulfilled is limited.

Companies experience demand at the individual SKU level and the demand for individual SKUs can vary widely. A demand profile segments SKUs into different classes depending on the demand for each product. For example, fast-moving, popular items are a small fraction of the total number of SKUs, but account for a large portion of the demand activity. On the other hand, slower-moving products make up a large bulk of the number of SKUs, but constitute only a fraction of the demand activity. Through a demand analysis, we can create demand curves (also known as Pareto curves) to characterize a distribution center's piece-level order-fulfillment activity. The SKUs are ranked in decreasing order based on lines (pieces) of demand and plotted cumulatively. Demand skewness curves display the percentage of SKUs that represent a certain percentage of lines (pieces) processed. For example, a 20/80 order-line demand curve denotes that 20% of the SKUs account for 80% of the order-lines.

To design an effective piece-level order-fulfillment strategy that meets customer requirements while minimizing costs, high-demanded SKUs may be fulfilled differently than low-demanded SKUs. Consequently, more than one order-fulfillment technology is typically required due to the variability in SKU profiles. However, a good implementation attempts to minimize the number of order-fulfillment technologies recommended because of the cost associated with integrating technologies.

Consequently, our research goal is to study the piece-level order-fulfillment technology selection problem. This important strategic decision in facilities planning determines the selection of the types of technologies, the specification of the capacity of each type of technology, and the assignment of SKUs to the selected technologies for a given demand curve and technology parameters.. Through our research, we increase the understanding of the critical factors and enabling conditions for the selection of piece-level order-fulfillment technologies through a statistical analysis.

To facilitate our analysis, we develop an optimization-based framework that jointly determines the best combination of order-fulfillment technologies to select and the allocation of SKUs to the selected technologies. An example solution from our framework is presented in Figure 1 for an 20/80 demand curve with 10,000 total SKUs. For this example, an automated dispensing technology is selected for the 1,800 highest-moving SKUs, a stock-to-picker system is selected for the 6,200 slowest-moving SKUs, and a picker-to-stock system is selected for 2,000 medium-moving SKUs. Because of the skewness of the demand curve, the automated dispensing technology fulfills an average of 43.24 lines per SKU per day, whereas the picker-to-stock system only fulfills an average of 1.54 lines per SKU per day.

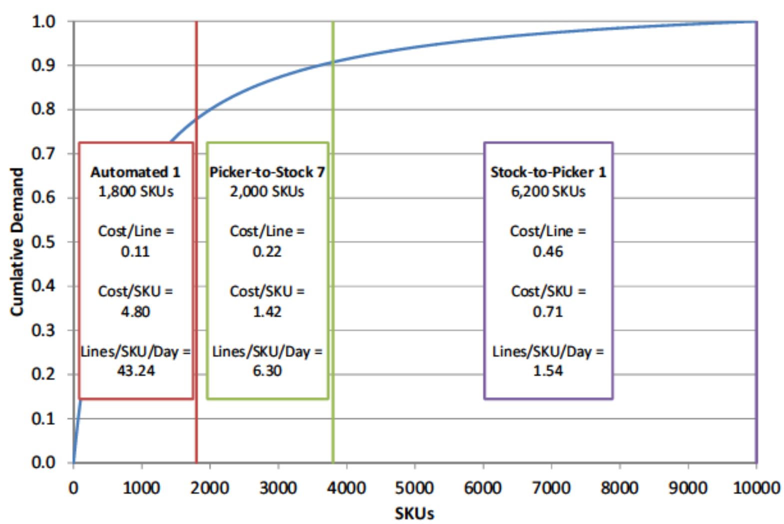

Figure 1: An Example Solution of the Selection of Piece-Level Order-Fulfillment Technology and Assignment of SKUs to the Selected Technologies.

Solving the piece-level order-fulfillment technology selection problem is far from obvious in most cases. As many factors exist to consider, as well as technology combinations, a large number of degrees of freedom are present in the decision process [3]. Due to the lack of decision aids, facility designers tend to solve the order-fulfillment technology selection problem based on their own experiences or rely on the experiences of technology providers [3, 12]. Technology providers currently recommend technologies based on past empirical experience given detailed knowledge about order-fulfillment technology specifications. Currently, most order-fulfillment design decisions are based on insights, experiences, or simulations [10]. A typical planning process begins with a data analysis of the distribution center's operations to identify fast-, medium-, and slow-moving SKUs, as well as SKU characteristics that lead to special fulfillment requirements. Next, order-fulfillment technologies are selected and the capacity and layout of the selected technologies is determined. A detailed cost and operational study is then conducted. Typically, the planning stage is an iterative process with multiple plans and layouts being generated based on design feedback.

In the literature and in practice, the order-fulfillment technology selection problem is solved sequentially by either: (1) partitioning the demand curve and then assigning technologies to the partitions; or (2) determining the technologies to implement in the distribution center and then assigning SKUs to the selected technologies. Consequently, a fundamental assumption of the existing literature is that either the selection of technologies can be accomplished without knowing the assignment of SKUs to the technologies, or the SKUs can be partitioned without knowledge of the technology choices. Our research determines the technologies and the assignment of SKUs to the technologies simultaneously, and thus relaxes this fundamental assumption.

The remainder of this paper is organized as follows. The next section provides a review of the literature in the area of material handling technology selection, noting limitations that do not adequately address the piece-level order-fulfillment technology selection problem. In Section 4 we describe our problem statement and discuss the assumptions of our selection model. In Section 5 we provide a mixed-integer, linear program to determine the selection of order-fulfillment technologies, as well as the assignment of SKU ranges to the selected technologies. Our model is validated using industry implementations and current technology data in Section 6. In Section 7 we perform a set of numerical experiments and statistical analysis to explore characteristics of our modeling approach, to identify the key factors in implementing automated versus manual order-fulfillment technologies, and to provide observations into characteristics that merit selection of different types of order-fulfillment technologies. Finally, in Section 8 we conclude the paper and discuss opportunities for future research.

3. Literature Review

A vast body of literature exists on warehouse design (see Gu et al. [11, 12] and the references therein). However, the majority of the literature focuses on analyzing specific policies or technologies and systematic design procedures are limited [10]. Baker and Canessa [4] review current literature that addresses overall structure of warehouse design methodology and compare the literature with practices from warehouse design companies. The warehouse design methodologies identified are step-by-step procedures with the majority including an empirically-based step for technology selection.

Technology selection literature, in general, has focused on multi-criteria decision models (see [2, 5] and the references therein). Research on material handling technology selection is rare [12] and can be categorized into three major approaches: general frameworks to follow; mathematical models and algorithms; and knowledge-based rules.

3.1 General Frameworks

General frameworks provide guidelines to follow when selecting material handling equipment and tools include decision trees, matrix solution guides, benchmarking assessment, and factor analysis [4]. All existing literature solve the problem sequentially, with [9, 13, 15, 27] first determining the technologies to be selected and then assigning SKUs to the technologies; while [3, 4, 22] first partition the SKUs by demand characteristics and then select the technologies based on the partitions.

Yoon and Sharp [27] develop a procedure for the systematic analysis and design of order-fulfillment systems based on expert opinion and processes that includes an input, selection, and evaluation stage. Chackelson et al. [7] illustrate how a Six Sigma methodology can be incorporated into the procedure developed by Yoon and Sharp [27]. Hassan [13] presents a framework for the selection of material handling transport equipment needed for handling discrete loads in manufacturing and logistics settings. Malmborg et al. [15] develop a computer-based expert system to select industrial trucks by developing a taxonomy and inference mechanism. Chu et al. [9] provide a systematic method for selecting material handling equipment for a production shop using a two-stage approach that recommends a ranked set of equipment based on user input data.

Apple et al. [3] present a formalized design process based on empirical observations that uses matrix solution guides to specify which material handling solution would be best for a combination of parameters. Sharp et al. [22] incorporate storage media assignment to zones as a level in their warehouse workflow.

3.2 Mathematical Models and Algorithms

Mathematical models and algorithms to select material handling equipment are limited. All approaches (except [23]) focus on transport technologies and not order-fulfillment technologies; therefore, the approaches are not applicable to our problem. Hassan et al. [14] develops an integer programming model to select material handling equipment and assign it to departmental moves. The problem is solved using a construction heuristic algorithm assuming a given layout of departments. Welgama and Gibson [26] combine knowledge-based and optimization approaches to select material handling equipment and assignment of moves. They minimize total cost and aisle space requirements using a two-phase algorithm. Noble and Tanchoco [16] develop a framework from which transport material handling systems can be selected using a design justification approach that includes an integer programming formulation to determine system alternatives. However, the selection and actual assignment of material handling equipment to flow paths is conducted by the designer.

Shen et al. [23] provide throughput time models for manual and semi-automated order-fulfillment systems (ignoring the fully-automated case) and then use a genetic algorithm to select technologies based on the smallest picking time for different operational policies. Their methodology is used to select technologies based only on order-picking time (ignoring infrastructure costs) and does not assign SKUs to the selected technologies.

3.3 Knowledge-Based Rules

Knowledge-based rules identify important characteristics to consider when selecting material handling equipment. Dallari et al. [10] conduct an empirical study on order-fulfillment systems based on 68 warehouses in Italy, ignoring the completely automated alternative. They find that the most important parameters for selecting order-fulfillment technologies are the number of order lines picked per day, the number of SKUs in the picking area, and the average order size. The authors incorporate their taxonomy based on these parameters into the methodology of Yoon and Sharp [27]. Noble and Tanchoco [17] explore the impact that different system design parameters have on the selection and specification of material handling systems in a job shop environment. They find that the primary design parameters to consider are shop loading, number of jobs, and unit load size.

3.4 Summary

While the technology selection problem is very important in the sense that it will affect the overall warehouse design and lifetime costs, the existing literature on technology selection is preliminary. In summary, the literature on material handling selection includes: (1) general frameworks for technology selection that are based on empirical experiences; (2) mathematical models and algorithms that are limited to selecting transport technologies; and (3) knowledge-based rules, while helpful, do not completely address our problem statement as defined in Section 4. Specifically, we are aware of no literature that uses mathematical models to simultaneously select piece-level order-fulfillment technologies and allocate demand to the selected technologies. In the next section we provide our problem statement and modeling assumptions.

4. Problem Statement

As noted earlier, the objective of this research is to inform decisions and provide new insights into the piece-level order-fulfillment technology selection problem. To do so, we develop a systematic framework to determine the best combination of order-fulfillment technologies and the assignment of SKUs to the selected technologies. We designed our methodology to capture the primary trade-offs associated with the selection decision while taking into consideration that the input data must be available to designers. The input data required are of two types: distribution center characteristics and technology specifications. Distribution center characteristics include the number of SKUs, the number of order lines and pieces processed per day, error costs, working hours, labor rates, the study period, and the minimum attractive rate of return (MARR). Order-fulfillment technology specifications are modeled in terms of modules and include the technologies' space capacities, throughputs, capital expenditures, accuracy rates, energy costs, maintenance costs, and labor requirements. To calculate labor costs, we require specification of whether a technology requires manual picking or if the picking process is fully automated. We note that order-fulfillment technologies can use automation to aid in the picking process and still require manual picking (i.e., stock-to-picker technologies). We also require order line and piece demand skewness curves, which can be obtained through a demand analysis. We represent demand curves as presented by Bender [6], where the x/y curve indicates that $x\%$ of the SKUs make up $y\%$ of the total lines (pieces) of demand.

In our model we assume that order-fulfillment technology selection can be determined based on a simplified view of the distribution center. We consider only the number of SKUs and the number of lines and pieces of demand requested for each of the SKUs, ignoring other factors such as order-structure and physical product characteristics. Also, we use a single-point estimate (rather than a time-series estimate) to characterize demand patterns. Consequently, we assume demand is constant for the given time of analysis. Typically, strategic design questions are answered using average and peak demand rates, which our model handles.

We only consider SKUs fulfilled using piece-level order-fulfillment technologies and thus remove extremely high demanded SKUs from our analysis. Such SKUs have such high item velocity that they are requested on every couple of orders and are fulfilled via an even more efficient fulfillment process such as pulling cartons from a pallet at the end of the picking area [19].

We assume simplified order-fulfillment technology dynamics. Space capacity is defined as a function of the number of SKUs a module can hold, not based on physical product dimensions. In addition, we assume picker-to-stock technology has a constant throughput rate regardless of the number of SKUs assigned to the technology even though we realize increasing the number of SKUs that a picker is responsible for increases the walking distance [24]. We ignore economies of scale associated with the technologies, assuming technology costs are a linear function of the number of modules deployed.

Because of these assumptions, our methodology is intended as an initial step in the design process, realizing that the outputs from our model will be used as a starting point for more detailed analysis that could include additional physical, economic, operational, and facility considerations. For example, if our model recommends selecting A-Frame technology, a secondary step would be to conduct a detailed slotting analysis to determine which SKUs are capable of being ejected from the technology, the number of channels to assign to each SKU in the A-Frame, as well as a detailed plan of the facility's layout and operational costs. Because selecting order-fulfillment technologies is a strategic decision, we believe our approach provides a good compromise between the cost and effort of data collection and the accuracy of the model's results. Also, our methodology is consistent with approaches in the literature [4]. For example, Yoon and Sharp's [27] design procedure has a selection stage, followed by a detailed evaluation stage.

5. Mathematical Model

We provide a mixed, integer linear mathematical model that minimizes infrastructure, energy, maintenance, error, and labor costs. For a given demand curve, distribution center characteristics, and technology specifications, the decision variables of the model determine the piece-level order-fulfillment technology selection and the SKU assignment to technology (as visually displayed in Figure 1).

Sets:

J demand curve ranges; indexed on j; $j = 0, 1, 2, 3, \ldots, |J|$
T order-fulfillment technologies; indexed on t; $t = 1, 2, 3, \ldots, |T|$
$\mathbb{N}$ natural numbers, $\mathbb{N} = \{0, 1, 2, 3, \ldots\}$

Parameters:

n_s number of SKUs in the distribution center
n_l number of order lines requested per day in the distribution center
n_p number of pieces requested per day in the distribution center
A_l order line demand skewness curve factor for an x/y curve, where $A_l = x(1-y)/(y-x)$
A_p piece demand skewness curve factor for an x/y curve, where $A_p = x(1-y)/(y-x)$
b_j cumulative percentage of SKUs for range j
Δ_j^l cumulative percentage of order lines for range j
Δ_j^p cumulative percentage of pieces for range j
f loaded yearly labor rate for a distribution center employee
g annual given present worth economic factor for the company's MARR and study period, N, calculated as $(\mathrm{MARR}(1+\mathrm{MARR})^N)/((1+\mathrm{MARR})^N - 1)$
v number of shifts per day
h number of working hours per shift
d number of working days per year
a_t 1 if technology t is an automated dispensing technology (i.e., does not require manual picking); 0 if technology t requires a manual picking process
s_t space capacity of one module for technology t in number of SKUs
c_t capital investment expense per module for technology t
k_t picking labor requirements of one module for technology t in fraction of persons
l_t throughput rate for technology t in lines per hour
p_t throughput rate for technology t in pieces per hour
r_t replenishment rate for technology t in pieces per person-hour

i_t identified error rate for automated technology t in errors per line processed
u_t downstream identified picking error rate for technology t in errors per line
q_t identified rework rate for technology t in lines per person-hour
U cost of a downstream identified error
m_t annual maintenance costs per module for technology t
e_t annual energy costs per module for technology t

The parameters Δ_j^l and Δ_j^p are calculated using Bender's Pareto curve [6] and shown below,

$$\Delta_j^l = \frac{(1+A_l)b_j}{(A_l+b_j)}, \tag{1}$$

$$\Delta_j^p = \frac{(1+A_p)b_j}{(A_p+b_j)}. \tag{2}$$

Variables:

w_t = the number of modules selected for technology t
x_{jt} = 1 if range j is assigned to technology t
y_t = the number of employees for technology t required for replenishment and rework

Before presenting our mathematical model, we provide an example of the input data required for each technology in T. Let $t = 1$ denote the picker-to-stock process of retrieving items from shelving using paper pick lists. Because manual picking is performed, $a_1 = 0$. One shelving module that can hold 200 SKUs is priced at \$2200; therefore, $s_1 = 200$ and $c_1 = 2200$. When one picker is responsible for 5 modules ($k_1 = 0.20$), the throughput rates for employees results in $l_1 = 100$ lines per person-hour, $p_1 = 150$ pieces per person-hour, and $r_1 = 600$ pieces per person-hour for replenishment. No quality checks are performed after the items are picked; therefore, the identified error rate and rework rate are both 0 (i.e., $i_1 = q_1 = 0$). However, downstream inspection by the customer identifies 35 errors per 10,000 pieces picked on average, resulting in $u_1 = 0.0035$. The maintenance and energy costs are assumed to be negligible (i.e., $m_1 = e_1 = 0$).

Next, we present our mathematical model formulation.

Model:

$$\begin{aligned} \min \quad & \sum_{t\in T} w_t(gc_t + m_t + e_t) + fv(k_t w_t + y_t) + \\ & \sum_{t\in T}\sum_{j\in J} U u_t d n_l x_{jt}\left(\Delta_j^l - \Delta_{j-1}^l\right) \end{aligned} \tag{3}$$

$$\text{s.t.} \quad \sum_{j=1}^{|J|} x_{jt} \left(b_j - b_{j-1}\right) \frac{n_s}{s_t} \le w_t \qquad \forall t \in T, \tag{4}$$

$$\sum_{j=1}^{|J|} x_{jt} \left(\Delta_j^l - \Delta_{j-1}^l\right) \frac{n_l}{hvl_t} \le w_t \qquad \forall t \in T, \tag{5}$$

$$\sum_{j=1}^{|J|} x_{jt} \left(\Delta_j^p - \Delta_{j-1}^p\right) \frac{n_p}{hvp_t} \le w_t \qquad \forall t \in T, \tag{6}$$

$$\sum_{j=1}^{|J|} x_{jt} \left(\Delta_j^p - \Delta_{j-1}^p\right) \frac{n_p}{hvr_t} + x_{jt} a_t \left(\Delta_j^l - \Delta_{j-1}^l\right) \frac{n_l i_t}{hvq_t} \le y_t \quad \forall t \in T, \tag{7}$$

$$\sum_{t \in T} x_{jt} = 1 \qquad \forall j \in J, \tag{8}$$

$$x_{jt} \in \{0,1\} \qquad \forall j \in J, \forall t \in T, \tag{9}$$

$$w_t \in \mathbb{N} \qquad \forall t \in T, \tag{10}$$

$$y_t \ge 0 \qquad \forall t \in T. \tag{11}$$

As shown above, the selection of order-fulfillment technologies can be modeled as a mixed-integer, linear program. The objective, (3), is to minimize the annual cost of the order-fulfillment process, which is a combination of capital investment, maintenance, and energy costs; labor costs for picking, replenishment, and rework processes; and error costs associated with the selected technologies. In (4), the technologies' capacities must meet the SKU space requirements. Throughput constraints on the number of lines and pieces processed are enforced for each selected technology in (5) and (6), respectively. In (7), the replenishment and rework labor is required to handle at least the number of pieces fulfilled at each selected technology, as well as the identified error rework from automated systems. All demand must be assigned to a technology, as shown in (8). The bounds for the variables are provided in (9)–(11).

The objective function captures a wide range of factors that influence technology selection. However, if the designer does not want to consider (or does not have data on) certain factors, values for these parameters can be set to zero. For example, the cost of a downstream identified error to a customer may be hard to quantify and the selection of order-fulfillment technologies can be determined without considering the cost of downstream identified errors by setting $U = 0$. Additional considerations are presented in Appendix A.

To develop a linear model, we discretize demand curves into ranges. A set of ranges is mapped to the demand curve with our model assigning ranges to selected technologies. Increasing the number of ranges produces solutions with increased granularity; however, the increased granularity is at the expense of increased computational requirements. An exact representation is to have one SKU per range. Modeling the assignment of ranges to technologies (rather than determining the breakpoints in a demand curve) has the advantage of producing a linear model that does not require inputting an ordered set of technologies. This modeling approach also permits a more general assignment of demand to technologies. For example, it is possible to assign the 3rd and 5th range, without assigning the 4th range to a technology. In [18], we analyze the impact of dividing the demand curve into ranges on our model's objective function and computational time. We determine that setting the number of SKUs per range to 100 results in a reasonable trade-off of solution quality and computational time and use this configuration in the remaining analysis.

In the next section we validate our mathematical model with data from industry implementations.

6. Validation with Industry Implementation Data

To determine whether our modeling approach is an accurate representation of the order-fulfillment decision process, we validated our model with inputs and outputs from four real-world cases. These cases represented a wide range of industries (pharmaceutical, fashion, cosmetic, and office), countries (Spain, Great Britain, and Ukraine), and demands patterns. Each case was implemented in practice, with the piece-level order-fulfillment selection problem solved based on the experiences of an order-fulfillment technology provider.

For each case, the information provided was of two types.

Input Data Input data included demand data obtained from the customer's data analysis – the number of SKUs, number of lines fulfilled per day, number of pieces fulfilled per day, and demand curves for lines and pieces. Distribution center operating information was provided on the number of shifts, working hours, and labor rates. Finally, we were provided with technology data for a suite of twelve different order-fulfillment technologies.

Implemented Solution The implemented solution was provided, which included the technologies selected, as well as the number of SKUs, pieces, and lines assigned to each technology.

Using the provided input data, we ran our optimization model and compared the outputs from our model to the implemented solution in terms of technology selected and SKU assignment to the technologies. Table 1 provides the selected technologies, the number of SKUs assigned to the technologies, and the number of lines picked from the technologies, for both solution methodologies. Our model's solutions are comparable to the implemented solutions for the pharmaceutical, fashion, and cosmetic industries. For these cases, both methodologies select similar technologies and assign similar types of SKUs to the technologies. For example, in the pharmaceutical case both methodologies recommended an A-Frame system, picking machine, and manual picking systems, and in the fashion case, both methodologies recommended a picking machine.

However, two main differences exist in the solutions. First, the implemented solutions have a wider variety of manual picking systems, which occurs because of special handling characteristics that our model ignores (i.e., refrigeration requirements, security of products,

Table 1: Comparison of the Implemented and the Model's Technology Selection and SKU Assignment.

	Pharmaceutical				Fashion				Cosmetic				Office			
Technology	Implem. # SKUs	Model # SKUs	Implem. # Lines	Model # Lines	Implem. # SKUs	Model # SKUs	Implem. # Lines	Model # Lines	Implem. # SKUs	Model # SKUs	Implem. # Lines	Model # Lines	Implem. # SKUs	Model # SKUs	Implem. # Lines	Model # Lines
A-Frame System	2,645	3,506	42,030	46,830	-	-	-	-	-	-	-	-	428	8,750	9,235	72,000
Picking Machine	11,920	12,271	4,326	8,988	5,840	5,840	1,400	1,400	-	-	-	-	10,536	8,750	13,309	12,000
Manual Systems (Total)	2,965	1,753	9,644	182	-	-	-	-	1,870	1,870	449,550	449,550	6,536	-	61,456	-
Batch Picking System	1,090	-	4,968	-	-	-	-	-	-	-	-	-	-	-	-	-
Ubay Shelving with PTL	-	-	-	-	-	-	-	-	546	1,870	435,860	449,550	4,714	-	34,887	-
Flow Rack with PTL	-	-	-	-	-	-	-	-	672	-	13,340	-	-	-	-	-
Shelving with RF picking	1,875	1,753	4,676	182	-	-	-	-	652	-	350	-	1,534	-	16,418	-
Palette Picking	-	-	-	-	-	-	-	-	-	-	-	-	288	-	10,151	-
Total	17,530	17,530	56,000	56,000	5,840	5,840	1,400	1,400	1,870	1,870	449,550	449,550	17,500	17,500	84,000	84,000

and oversized products characteristics). The second primary difference is seen in the number of SKUs assigned to the selected technologies. Our model tends to assign more SKUs to the A-Frame system than is actually implemented. Because our model is designed at the strategic level, we ignore slotting constraints. Thus, our model assigns all SKUs in a range to the A-Frame, although not every SKU can be ejected due to physical product constraints.

The office case highlights the limitation of our model for specialized project implementations. Office products have diverse dimensions, weights, and picking requirements. For example, the majority of the product dimensions can not be ejected from the A-Frame system (which explains the disparity in the number of SKUs assigned to the A-Frame). Additionally, unique picking processes exist. Some orders request individual pieces of paper, which must be picked, counted, and placed in a plastic sleeve for delivery. Orders can consist of requests for items at the piece and the full-case levels. Also, heavy products, such as reams of paper, require manual picking processes. These unique picking requirements require a customized solution and selection process that does not lend itself well to the use of our model.

In summary, our model provides technology recommendations and SKU assignments for the pharmaceutical, fashion, and cosmetic industry that are consistent with successful implementations, which validates that our model can be used to add science to the order-fulfillment decision process for similar implementation projects. However, as our model does not consider all dynamics, the model is only a first step in the design process and the provided solution will need to be massaged to obtain a feasible, implementable solution.

Next we conduct a set of numerical experiments and statistical analysis to gain insights into the order-fulfillment selection process.

7. Numerical Experiments and Statistical Analysis

We conduct a set of numerical experiments and statistical analysis to analyze various distribution center factors to determine the effect that these factors have on order-fulfillment technology selection. Our experimental design allows us to explore a wide range of operating environments to identify the key factors in implementing automated versus manual order-fulfillment technologies and provides observations into which characteristics merit selection of which types of order-fulfillment technologies.

We analyze several factors that influence order-fulfillment technology selection. To represent different industries and a wide range of distribution centers, we vary the following factors over the provided values.

1. Number of SKUs (1,000; 10,000; 100,000)
2. Number of Order Lines Processed per Day (10,000; 50,000; 100,000)
3. Average Number of Pieces per Order Line (1; 2; 3)
4. Demand Curves (10/90; 20/80; 20/50)

5. Number of Shifts (1; 2)

6. Yearly Labor Rate (100; 300)

7. Peak Demand Factor (1.0; 1.4; 2.0)

To account for peak demands that occur during a working day, we multiply the average number of lines processed per day by a peak demand factor. We conduct a full-factorial analysis, with the data for all 972 instances provided in [18].

We assume that the line and piece demand curves follow the same distribution. We set the number of working hours per shift to 7.5, the number of working days per year to 200, the cost of a downstream identified error to 0.20 cost units, and the annual worth given present worth economic factor to 0.38629, which assumes a 4-year study period and a 20% MARR. We perform our experimental design using a set of twelve order-fulfillment technology alternatives with technology characteristics provided in Table 2. The alternatives are based on technologies available from an order-fulfillment technology provider; however, to hide proprietary data, technology characteristics have been modified slightly and cost values have been normalized.

To identify the key factors in implementing automated versus manual order-fulfillment technology, we classify our twelve order-fulfillment technologies in terms of manual and automated technologies. For manual technologies, a picker-to-stock strategy is employed with all the order-picking activities completed by a person. Automated solutions include stock-to-picker, as well as automated dispensing strategies. A solution can recommend multiple technologies with a varying number of SKUs and lines being fulfilled from each of the selected technologies. We classify each solution from two perspectives: the percentage of SKUs that are fulfilled using automation (denoted as *SKU automation*) and the percentage of lines that are fulfilled using automation (denoted as *line automation*).

The instances in our experimental design are solved using CPLEX 10.1 and run on a Dell Precision 390 PC with an Intel Core 2 processor at 2.93GHz and with 4.0 GB of RAM and Microsoft Windows 7 as the operating system.

First, we conduct a one-way ANOVA, using a significance level of 0.05, to objectively determine which distribution center characteristics have an influence on SKU and line automation. Table 3 provides the p-values, mean and standard deviation for the seven characteristics. The number of SKUs, number of lines, number of shifts, and labor rate statistically impact both SKU and line automation. In addition, line automation is statistically influenced by the demand curve.

Second, a two-way ANOVA, using a significance level of 0.05, is conducted to explore if interactions between distribution center characteristics influence the levels of automation, with p-values displayed in Table 4. A statistically significant interaction exists with the number of SKUs and the number of lines, demand curve, the number of shifts and the labor rates for both SKU and line automation. Also, an interaction exists between the number of shifts and the labor rate for SKU automation. For line automation, an interaction exists between the number of lines and the number of shifts and the labor rate, as well as between

Table 2: Order-Fulfillment Technology Alternatives

t		s_t	k_t	l_t	p_t	r_t	i_t	q_t	u_t	c_t	m_t	e_t
1	Picker-to-Stock 1	10	0.333	100	200	1500			0.00035	56.3	0.0	0.0
2	Picker-to-Stock 2	100	0.900	500	850	4080			0.00020	348.8	0.0	0.0
3	Picker-to-Stock 3	400	0.800	250	425	6600			0.00020	787.5	2.4	3.9
4	Picker-to-Stock 4	700	1.000	180	300	1050			0.00020	862.8	2.6	3.9
5	Picker-to-Stock 5	415	1.000	250	350	1050			0.00005	926.0	27.8	4.6
6	Picker-to-Stock 6	200	0.200	80	136	600			0.00350	16.8	0.0	0.0
7	Picker-to-Stock 7	200	0.150	100	170	600			0.00035	19.0	0.0	0.0
8	Automated Dispensing 1	60	0.000	300	1500	1000	0.00033	30	0.00010	165.0	5.0	1.2
9	Automated Dispensing 2	24000	0.000	1700	2890	6600	0.00033	30	0.00010	29000.0	870.0	217.5
10	Stock-to-Picker 1	415	1.000	250	350	1050			0.00005	926.0	27.8	4.6
11	Stock-to-Picker 2	10000	1.000	800	1275	6600			0.00005	8700.0	261.0	65.3
12	Stock-to-Picker 3	12500	1.000	600	1275	6600			0.00005	9000.0	270.0	67.5

Table 3: One-Way ANOVA Results for the Percentage of SKUs (Lines) that are Fulfilled with Automation

	SKU Automation			Line Automation		
Number of SKUs	p-value	Mean	StDev	p-value	Mean	StDev
1000	0.000	0.736	0.330	0.000	0.936	0.133
10000		0.296	0.334		0.598	0.360
100000		0.242	0.417		0.293	0.403
Number of Lines	p-value	Mean	StDev	p-value	Mean	StDev
10000	0.000	0.271	0.367	0.000	0.469	0.435
50000		0.471	0.439		0.645	0.400
100000		0.531	0.421		0.713	0.369
Pieces Per Line	p-value	Mean	StDev	p-value	Mean	StDev
1	0.505	0.404	0.426	0.089	0.576	0.426
2		0.427	0.425		0.604	0.418
3		0.443	0.423		0.647	0.398
Demand Curve	p-value	Mean	StDev	p-value	Mean	StDev
10/90	0.726	0.435	0.427	0.000	0.734	0.369
20/80		0.429	0.423		0.498	0.422
20/50		0.409	0.423		0.595	0.419
Number Shifts	p-value	Mean	StDev	p-value	Mean	StDev
1	0.000	0.319	0.387	0.000	0.532	0.429
2		0.530	0.434		0.686	0.386
Labor Rate	p-value	Mean	StDev	p-value	Mean	StDev
100	0.000	0.269	0.367	0.000	0.473	0.427
300		0.580	0.421		0.744	0.355
Peak Demand Rate	p-value	Mean	StDev	p-value	Mean	StDev
1.0	0.086	0.389	0.426	0.118	0.575	0.421
1.4		0.422	0.424		0.609	0.415
2.0		0.463	0.422		0.642	0.408

Table 4: Two-Way ANOVA p-values for SKU and Line Automation

SKU Automation							
	Number of SKUs	Number of Lines	Pieces Per Line	Demand Curve	Number of Shifts	Labor Rate	Peak Rate
Number of SKUs	-	0.000	0.821	0.027	0.000	0.000	0.268
Number of Lines		-	1.000	0.830	0.084	0.090	0.995
Pieces Per Line			-	0.976	0.952	0.978	1.000
Demand Curve				-	0.376	0.467	0.998
Number of Shifts					-	0.000	0.801
Labor Rate						-	0.874
Peak Demand Rate							-
Line Automation							
Number of SKUs	-	0.000	0.665	0.000	0.000	0.000	0.000
Number of Lines		-	0.999	0.991	0.013	0.005	1.000
Pieces Per Line			-	0.962	0.596	0.622	0.999
Demand Curve				-	0.907	0.907	1.000
Number of Shifts					-	0.000	0.786
Labor Rate						-	0.626
Peak Demand Rate							-

the labor rate and the number of shifts. Tables 5 and 6 display SKU and line automation values for the two-way interactions that are statistically significant, respectively.

Our ANOVA analyses provide the following observations, which are in alignment with previous empirical research in [10].

1. Obviously, as labor costs increase, automation (which reduces labor) becomes more attractive. The increase in infrastructure costs can be justified by the higher savings in labor cost and higher labor rates can justify large amounts of automation even when the number of SKUs is large or the number of lines small. Labor rates, which vary by geographical regions, explain why certain regions are more likely to have automated warehouses.

2. As the number of lines fulfilled increases, mechanization and automation become more attractive and the percent of SKUs and lines picked with automation increases.

3. As the demand curve becomes more skewed, a single A-item SKU location has higher technology utilization resulting in increased line automation. An interaction between the number of SKUs and the demand curve exists. When the number of SKUs is small, flat demand curves, which evenly distribute demand to the SKUs, increases SKU automation. On the other hand, when the number of SKUs is large,

Table 5: Average Percentage of SKUs that are Fulfilled with Automation for the Statistically Significant Interactions

SKU Automation										
	Number of Lines			Demand Curve			Number of Shifts		Labor Rate	
Number of SKUs	10000	50000	100000	10/90	20/80	20/50	1	2	100	300
1000	0.321	0.911	0.976	0.687	0.719	0.803	0.767	0.706	0.686	0.786
10000	0.242	0.256	0.388	0.362	0.262	0.263	0.185	0.406	0.118	0.473
100000	0.250	0.246	0.229	0.256	0.248	0.222	0.004	0.479	0.001	0.482
Number of Shifts									100	300
1									0.290	0.348
2									0.248	0.813

Table 6: Average Percentage of Lines that are Fulfilled with Automation for the Statistically Significant Interactions

Line Automation													
	# of Lines			Demand Curve			# of Shifts		Labor Rate		Peak Rate		
# of SKUs	10000	50000	100000	10/90	20/80	20/50	1	2	100	300	1	1.4	2
1000	0.817	0.992	0.999	0.981	0.935	0.892	0.947	0.926	0.913	0.960	0.905	0.938	0.965
10000	0.336	0.641	0.816	0.792	0.591	0.411	0.549	0.646	0.453	0.742	0.535	0.596	0.661
100000	0.252	0.303	0.324	0.430	0.258	0.191	0.101	0.485	0.054	0.531	0.284	0.293	0.301
# of Lines							1	2	100	300			
10000							0.341	0.596	0.280	0.657			
50000							0.581	0.710	0.519	0.772			
100000							0.674	0.751	0.621	0.805			
Labor Rate							1	2					
100							0.474	0.473					
300							0.591	0.898					

Table 7: Average Cost per Line, Cost per SKU Location, and Lines per SKU Location for the Three Technology Strategies

	Picker-to-Stock	Stock-to-Picker	Automated Dispensing
Cost per Line	0.41	0.97	0.09
Cost per SKU	0.48	0.42	5.44
Lines per SKU	2.58	0.71	66.48

a skewed demand curve ensures that high-moving SKUs have enough demand to justify automation.

4. Increasing the number of shifts increases the potential utilization of the fixed capital cost of the technology investment. In general, when the number of shifts increase, a higher percentage of SKUs justify automation (and also represent higher line automation). However, there are limitations to this observation, especially for facilities with a small number of SKUs where the labor required to conduct replenishment activities over two shifts may outweigh the automation benefits.

5. In general, automation is most attractive when the number of SKUs is low, the number of lines is high, the demand curve is skewed, the number of shifts is high, and the labor rate is high.

Third, we analyze SKU characteristics that lead to the selection of different types of order-fulfillment technologies. We categorize the technologies in terms of the three primary strategies: picker-to-stock, stock-to-picker, and automated dispensing technologies. Table 7 displays the average cost per line, cost per SKU location, and the number of lines fulfilled per SKU location for the technology selected in our experimental design. As illustrated in Table 7, automated dispensing systems tend to have a low cost per line picked and a high cost per SKU location because automated dispensing systems are used to fulfill high-moving SKUs that have a high lines-per-SKU ratio. Automation also tends to be implemented with a stock-to-picker strategy for the slow-moving SKUs. Slow moving SKUs make up a large number of the total SKUS (i.e., often over 90% of a retailer's catalog is comprised of slow-moving SKUs with demand in the range of 0.2 to 0.8 units per week [8]). Consequently, slow moving items consume large amounts of space and if fulfilled via a picker-to-stock system will require large travel distances. Stock-to-picker systems provide cost efficiencies for slow-moving SKU fulfillment by eliminating these significant travel costs. Subsequently, automation tends to be used for the few, very fast-moving SKUs and the many, slow-moving SKUs, with a picker-to-stock strategy used for the remaining medium-moving SKUs.

Fourth, we analyze the number of technologies selected. Table 8 displays the percentage of the solutions that implement one, two, three, or four technologies, as well as the average number of implemented technologies by strategy. For example, 48.25% of

Table 8: Percentage of Solutions that Recommend a Specific Number of Technologies and the Average Number Selected by Technology Strategy

		Average Number Selected by Technology Strategy			
# Techn.	% of Solutions	Picker-to-Stock	Stock-to-Picker	Automated Dispensing	Total
1	47.43	0.56	0.10	0.35	1.00
2	48.25	0.93	0.10	0.97	2.00
3	2.88	0.96	1.29	0.75	3.00
4	1.44	1.00	2.00	1.00	4.00

all instances recommend a two-technology solution with the average number of picker-to-stock technologies in a two-technology solution equal to 0.93. When only one technology is selected, the majority of the instances select a picker-to-stock technology. Also, one-technology solutions with an automated dispensing technology are only selected for 1,000-SKU distribution centers; and one-technology solutions with stock-to-picker technologies are only selected for 100,000-SKU distribution centers. For two-technology solutions, the majority of solutions consist of a combination of picker-to-stock and automated dispensing technologies. However, when three or more technologies are implemented, all solutions utilize a stock-to-picker strategy. In practice, there is a cost associated with integrating multiple technologies. Even though our model assumes negligible costs of integration, our model recommends less than 1.5% of solutions with more than three technologies, which illustrates that limiting the number of technologies selected does not significantly impact solution quality.

In the next section we conclude our paper and provide future research directions.

8. Conclusions and Future Research

In summary, we conducted a numerical experiment and statistical analysis to provide insights into the selection of piece-level order-fulfillment technologies. To do so, we developed a systematic framework to solve the order-fulfillment technology selection problem, which jointly selects the types of technologies, the capacity of each type of technology, and the assignment of SKUs to the selected technologies.

Through an experimental design and statistical analysis, we considered important factors involved in the selection and assignment of piece-level order-fulfillment technologies. We discovered observations into the distribution center characteristics that lead to automation being successfully implemented and identified the key factors in implementing automated versus manual technologies.

Our technical contribution is that

> *We developed an optimization model that jointly determines the selection of order-fulfillment technologies and the assignment of SKUs to the technologies,*

which relaxes a fundamental assumption of previous research and provides a beneficial tool to practitioners.

This research contributes to the current body of knowledge by increasing the understanding of what factors most contribute to selecting piece-level order-fulfillment technologies for different segments of the demand curve. Our primary managerial insight is that

Successful order-fulfillment technology implementations tend to employ automation for the few, fast-moving SKUs and the many, slow-moving SKUs.

Our developed model and insights have potential benefits for practitioners, which include reducing the time to develop initial design concepts, providing a formalized basis for evaluating alternative design concepts, reducing the educational time and training expenses for new employees, improving the solutions that new employees recommend, and gaining insights into order-fulfillment technologies and their applications.

The area of order-fulfillment technology selection presents a host of challenging problems. Our primary performance objective is economic, whereas future research could explore additional objectives that include environmental factors, accuracy, risk, or flexibility associated with the selected technologies. In addition, if more detailed SKU data are available, the physical dimensions of products could be incorporated into our analysis. In addition, we assume technology has a constant throughput rate regardless of the number of SKUs assigned to the technology and thus future research could identify different configurations of the same technology. Typically, an overhead cost of implementing a solution exists, which includes the cost of a warehouse control system (WCS), conveyor systems, receiving, and shipping areas. A post-processing step could be incorporated into our analysis to calculate the costs of overhead to provide more comprehensive costing results. Additionally, we focused on piece-level order-fulfillment technologies; however, our methodology could be applied to technology selection and demand assignment throughout the distribution center (i.e., at the pallet or case levels).

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A. Return Processing and A-Frame SKU Inclusion

Product return rates can be substantial, especially for Internet sales because customers cannot try and feel the product before purchase. For example, online apparel retailers experience return rates totaling up to 45% of their orders [1]. Therefore, the handling of returned products, which represent a significant cost to distribution centers, influences the selection of order-fulfillment technologies.

A typical return process includes receiving the returned products, performing a quality check, reconditioning the returned products, and storing the products for reuse and future order picking. Returned products are often treated as separate SKUs, especially when first-in-first-out processing, expiration dates, or lot tracking are enforced. Consequently, return processing is important from a space capacity perspective rather than a technology throughput perspective. Return rates tend to be correlated with error rates of technologies (i.e., the higher the pick error rate the higher the percentage of returned products). Therefore, improving the pick accuracy should decrease return processing costs.

To incorporate the return processing into our mathematical model from Section 5, define ϕ as the percent of pieces returned, and replace (4) with (12),

$$\sum_{j=1}^{|J|} x_{jt} \left(b_j - b_{j-1}\right) \left(\frac{n_s}{s_t} + \phi n_p\right) \leq w_t \qquad \forall t \in T. \tag{12}$$

A-Frame systems are an automated dispensing technology that automatically dispenses items onto a conveyor belt that fills into order totes. A-Frame systems are most suitable when the items to be picked are small in size and can withstand a fall onto a conveyor. For reasons related to the physical nature of the item, such as packaging restrictions or product dimensions, not all items can be ejected from an A-Frame and should not be considered for assignment to A-Frame systems.

To incorporate A-Frame system SKU inclusion, define α as the percent of SKUs that can be ejected from an A-Frame, let $t = t'$ denote an A-Frame system, and add the following constraint to the mathematical model from Section 5,

$$\sum_{j=1}^{|J|} x_{jt'} \left(b_j - b_{j-1}\right) \leq \alpha_{t'}. \tag{13}$$