Expected Travel Distance Models for Retail Store Order Fulfillment

Ning Zhang and Jennifer Pazour
Industrial & Systems Engineering; Rensselaer Polytechnic Institute; Troy, NY 12180, USA
zhangn6@rpi.edu pazouj@rpi.edu
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Abstract

Order-online-pickup-in-store is a new option for customers to order items online but pick them up at a brick-and-mortar store. This provides convenience to customers but requires store employees to conduct order fulfillment operations at retail stores. Although many retailers have implemented pick-up in stores policies, challenges exist in estimating labor requirements and evaluating where to place the pick-up and backroom locations. Reviewing previous literature on order fulfillment and layout designs in warehouses and distribution centers, quantitative models for order fulfillment processes in retail stores are lacking. To fill this research gap, we combine ideas from omni-channel retailing and warehouse expected travel models to derive new travel distance models for retail store order fulfillment. Capturing different placements of pick-up locations and backrooms, multiple models compute the expected efforts employees spend picking single-line orders. We quantify the influences on the sales clerks’ expected travel efforts due to different placements of items, the backroom, and the pick-up location, and varying item demand skewness.

Keywords
order fulfillment, retail stores, quantitative models, expected efforts, order online pick-up in store

1. Introduction

Electronic commerce (e-commerce) is the fastest growing retail market in North America, Eastern Asia and Europe [1]. Based on the U.S. Census Bureau News, e-commerce’s share of total retail sales has grown from 0.64% in the third quarter of 1999 to 9.8% during the same time period of 2018 [2]. In recent years, the United States has experienced $340 billion in annual online sales, while Chinese annual online sales are $672 billion [3]. This global trend, which coincides with the rise of giant e-commerce retailers, such as Amazon, Alibaba and eBay, has enabled people worldwide to make purchases in a much more convenient way. The biggest convenience of e-commerce is that it saves time for customers, who can shop from their homes or offices online instead of spending time in traffic driving and shopping in crowded stores. Another advantage is that e-commerce retailers usually provide a wider assortment of products than physical stores because the latter have limited shelf space.

However, e-commerce has created new issues that need to be addressed. First, home delivery has high last-mile delivery costs. Second, customers can have bad experiences with e-commerce orders being delivered to their homes, such as damaged-in-transit items, as well as missing and stolen packages. To address these concerns, while still providing customers with convenience, an alternative distribution strategy – order-online-pickup-in-store - has become popular with retailers. Also known as “Click and Collect”, this omnichannel strategy connects the retailer’s online store with its physical store channel and combines the benefits of both channels [4]. Consequently, retailers from a wide range of industries have implemented this order-online-pickup-in-store strategy, including Apple, Best Buy, CVS, Uniqlo, Macy’s, and Walmart [5]. A recent survey found that “by 2021, 90% of retailers will offer Buy Online/Pick Up In Store (BOPIS)” [6]. From a customer’s perspective, this strategy allows customers to order items online and then drive to their neighborhood store to pick up the items, which are available at a designated pickup location. From the retailer’s perspective, retailers do not need to invest in costly last-mile delivery services. However, an order-online-pickup-in-store policy requires store employees to conduct order fulfillment within a brick-and-mortar store. That is, store employees are notified that a pickup order needs to be fulfilled (this typically occurs in a centralized location such as the backroom). Next, a store employee travels the aisles of the brick-and-mortar store to pick the requested items contained in the same storage racks in-store customers shop from, and then travels to drop the picked items off at the designated pickup location. Challenges for retailers include the store being designed for a pleasant shopping experience and not explicitly designed for order fulfillment; this has led to inefficient order picking
procedures. Additionally, such a policy requires retailers to plan ahead to determine labor requirements and costs of this policy. This paper focuses on deriving the expected travel distances an employee would spend picking single-line orders within the retail store. Different pickup and backroom locations are considered. Combined together the models developed can provide recommendations on where best to locate the pickup and backroom locations, and as starting point to estimate expected labor for order-fulfillment within a retail store.

2. Literature Review
The incredible growth of the e-commerce market has inspired researchers. Most material handling research has focused on order fulfillment processes and design in warehouses and distribution centers [7,8]. We contribute to research on analytical travel models for manual operations, and thus focus our review there. Pohl, Meller and Gue [9] studied dual-command operations for three common warehouse design layouts, named A, B and C. They derived expected dual-command travel distance equations for random storage in the three layouts, which all have a single pickup/drop-off point. Using those developed travel time models, layouts B and C are best at minimizing expected travel distance, but trade-offs exist based on the warehouse size. Our work is similar to theirs in that we also (1) assume a given layout, albeit we focus on a retail store, whereas their focus is on a warehouse, and (2) are interested in deriving similar performance measures, that is, expected travel distances for single line requests. However, our work varies from their work in two important ways. First, their work assumed a single pickup/drop off location in the center of the facility, whereas we consider a retail store environment, in which the entry (backroom) and exit (pickup location) points do not exist in the same location. We consider location combinations on the same side of the facility, the opposite sides of the facility, and are not necessarily parallel to the rack aisles. Secondly, Pohl, Meller and Gue [9] assumed random storage, whereas we model discrete rack locations in a store, which allows us to explore performance for different skewness levels. Similarly, Tutam and White [10] also developed travel distance models within unit-load warehouses for both single-command and double-command situations. Their novelty is in capturing three scenarios with multiple dock door placements. They determined optimal shape factors, defined as the ratio of warehouse width to its depth, that minimize the expected travel distance for each multiple dock door scenario. While the distances between the dock doors vary in each of the three scenarios, all of the dock doors are assumed located on the bottom of the facility and thus parallel to the aisles. This is in contrast to our work, which considers that the pickup and drop-off locations can occur more generally. For example, we capture the backroom and pickup locations placed on opposite sides of the facility and on locations perpendicular to the aisle structure. Other research derives travel time models for single and dual command travel in automated storage and retrieval systems [11]. While most consider a single input/output point; exceptions include work that derives travel time models when there are multiple different output points [12]. However, because the travel dynamics vary, the models derived are not applicable to our problem.

A few works consider the layout of retail brick-and-mortar stores for in-store shopping experiences. For example, Yapicioglu and Smith [13] determined how to layout departments in retail stores with a racetrack aisle network. Mowrey, C., Parikh, P. J., and Gue, K. R. [14] considered aisle placement in retail stores. The focus of this set of literature is on layout of either departments or aisles. None looked at travel requirements of e-commerce orders being fulfilled in a brick-and-mortar store.

A literature classification has identified a shortage of omni-channel literature, although recently, research on omni-channel logistics has increased [4]. A recent review by Kembro, Norman, and Eriksson [15] described how an omni-channel retail strategy impacts warehouse operations and design. Other work has qualitatively studied the impact of order-online-pickup-instore strategies. For example, Hüblner, Alexander, Heinrich and Johannes [16] studied the last mile order fulfillment issues in the Omni-Channel Grocery Retailing. They developed a holistic logistics planning framework for the last mile order fulfillment in omni-channel grocery retailing, in which they consider retail store fulfillment, however, their approach is qualitative, and lacks mathematical models.

In summary, literature on order fulfillment and layout designs in warehouses and distribution centers exist, however, quantitative models for order fulfillment processes in retail stores are lacking. To fill this research gap, we combine ideas from omni-channel retailing and warehouse expected travel models to derive new expected travel distance models for retail store order fulfillment.

3. Expected Travel Distance Models
We derive expected travel distance models for four different retail store layouts. The four studied layouts are different in their placements of the backroom (BR) and the pickup (PUL) locations. Our focus is on understanding the changes
on expected travel distances under these four situations when a single item is requested from a brick-and-mortar store’s shopping area, which contains inventory placed on a set of racks. To do so, we use “m” to represent the layout model number. We delineate the four models within a rectangular coordinate system, in which the origin (0,0) is set as the bottom left corner of the store. We assume a single item is requested. We model item placement and selection at the storage rack level instead of at the individual item level within the racks. That is, our formulations only take the coordinates of the storage rack the requested item is located, rather than the specific locations of an item within the storage rack. The store employee starts at the backroom, travels to pick up the item located in a rack in the store and then travels to the pickup location. The store employee is assumed then to find other work from the Pickup location. We assume all products are vertically reachable by the store employee and thus capture only x and y travel distance. The time for the employee to extract the item from the rack is assumed negligible.

As illustrated in Figure 1, in the first model, \( m=1 \), the Backroom and the Pickup locations are located diagonally across the retail store, one on the top and the other on the bottom. The second model has the Backroom and the Pickup locations on the same side of the store, close to each other, either on the top or bottom of the store. When \( m=3 \), the model has the Backroom and the Pickup locations aligned on the opposite sides of the facility and parallel to the store’s aisle structure. The Backroom and the Pickup locations, in the fourth model, are again located on the opposite sides of the facility, parallel to aisles. However, their placements do not need to be directly across from each other. Instead, the backroom and pickup locations can be located anywhere along the width of the aisles.

![Figure 1: The locations of the backroom (BR #) and the pickup location (PUL #) in each of the four model layouts.](image)

We assume the retail store shopping area consists of a set of racks, \( L \), indexed on \( l = 1, 2 \ldots |L| \). Each rack \( l \) has a coordinate, \( l_i \) and \( l_j \) which represent the rack’s column and row, respectively. To derive the expected travel distance models, the following input parameters and notation are used.

**Input Parameters:**

- \( B_{0x} \): the x-distance between the y-axis and the Backroom location in layout 1 & 2
- \( B_{0y} \): the y-distance between the Backroom and the top of the store in layout 3 & 4
- \( B_1 \): the x-distance between the Backroom and the left edge of the aisles
- \( P_0 \): the y-distance between the Pickup location and the bottom of the retail store
- \( H_1 \): the y-distance between the top of aisles and the top of the store
- \( H_2 \): the y-distance between the bottom of aisles and the bottom of the store
- \( W \): the length of each rack
- \( Z \): the width of each rack
- \( K \): the x-distance between the Pickup location and the edge of the aisles that is nearest to it
- \( v \): marginal aisle distance of each rack, which allows in-store shoppers and employees to access the rack locations
- \( n \): given number of rows of racks
- \( \sigma \): the length-width rack ratio, which is the number of columns to number of rows
P_l: the probability that an e-commerce order needs an item in location l

For each layout model \( m \), we derive the expected travel efforts for an employee to retrieve an item within the retail stores, which we denote as \( E^m \) (employee’s efforts) and define in (1).

\[
E^m \text{ (employee’s efforts)} = \sum_{l \in L} R^m_l \cdot P_l
\]  

(1)

For each rack \( l \in L \), \( R^m_l \) denotes the travel distance of an employee traveling from the backroom to rack \( l \), and then from rack \( l \) to the pickup location, given the backroom and pickup locations are based on model \( m \). \( R^m_l \) is defined in (2).

\[
R^m_l = \text{distance (Backroom}_m, \text{pick rack } l) + \text{distance (pick rack } l, \text{Pickup location}_m) 
\]  

(2)

Model \( m=1 \):

\[
R^1(l, l_j) = B_1 + H_1 + H_2 + K + n \times (W \times \sigma + Z)
\]  

(3)

The backroom and the pick-up locations in model \( m=1 \) are located diagonally across the retail store, one on the top and the other on the bottom. Therefore, the travel efforts remain the same regardless of the requested items l’s \( i \) and \( j \) coordinates. Therefore, \( l_i \) and \( l_j \) are not involved in the calculation.

Model \( m=2 \):

\[
R^2(l, l_j) = B_1 + 2(H_1 + K + v - Z) + 2(W \times l_i + Z \times l_j)
\]  

(4)

The backroom and the pickup locations in model \( m=2 \) are located close to each other, on either the top or the bottom of the facility. Consequently, both indexes \( l_i \) and \( l_j \) are included, and the location of the requested item influences the employee’s efforts.

Model \( m=3 \):

\[
R^3(l, l_j) = B_1 + K + 2(v - Z) + W \times \sigma n + 2Z \times l_j
\]  

(5)

In \( m=3 \), the backroom and the pickup locations are placed on the opposite sides, as well as are aligned and parallel to the aisles of the facility. Thus, the index \( l_i \) of the desired rack does not influence travel distance. However, the travel distance in the y direction does depend on the requested item’s \( l_j \) value.

Model \( m=4 \):

\[
R^4(l, l_j) = -B_0y + B_1 + H_1 - H_2 + K + P_0 + 2(v - Z) + Z \times (2l_j - n) + W \times \sigma n
\]  

(6)

In model \( m=4 \), the backroom and the pickup locations can be placed anywhere along the width of the aisles, however, they are still located on the opposite sides of the retail store. Therefore, similar to the situation of model \( m=3 \), \( l_j \) is the only coordinate that appears in the function.

4. Experiment Results

In this section, we apply our expected travel models to understand the impact on employee’s travel distances when the backroom and pickup locations change. We set our input parameters to mimic a big box retail store size, in which the regular size of Wal-Mart or Home Depot is between 60,000 and 140,000 square feet [17]. Each side of the target retail store is approximately 80 meters (263 feet) long, therefore, we can change the values of \( n \) and \( \sigma \) parameters such that the total length is within 80 meters. We estimate \( P_l \) using the Bender’s Pareto Demand Curve, which allows us to capture X/Y curves, in which X\% of rack locations make up Y\% of total demand [18]. Four different X/Y curves, namely, 10/90, 20/80, 30/70, and 40/60 curves are considered in this experiment. We provide bounds on expected travel distance performance for each of the models by assigning items to rack locations that provide the best- and the worst-case performances. That is, for a descending ranked-list of rack locations based on \( R_l \) values, we assign items to racks, using both an ascending and descending ranked-list of items’ demand probability, \( P_l \), values. In other words, we assign the most-demanded rack to the most-convenient location, and vice versa. In Table 1, we provide the lower and upper bound values for each of the four models when \( n \) equals to 4, 8, and 16 and \( \sigma \) is 0.5, 1, and 2 respectively. The best lower and upper bound performance among the four models is shaded as red, which occurs for Model 4 regardless of \( n \), \( \sigma \) and demand curve values. As \( n \) and \( \sigma \) gets larger, the store size increases, and expected effort for all the models increase. As expected, the best upper bound occurs with the most skewed demand (i.e., the 10/90 curve), and the best lower bound occurs with the least skewed demand (i.e., the 40/60 curve).
Table 1: Expected Employee’s Efforts for the four layouts with varying number of rows, ratios, and demand curves

<table>
<thead>
<tr>
<th>Value of σ</th>
<th>Value of n</th>
<th>Model m=1</th>
<th>Model m=2</th>
<th>Model m=3</th>
<th>Model m=4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Lower Bound</td>
<td>Upper Bound</td>
<td>Lower Bound</td>
<td>Upper Bound</td>
</tr>
<tr>
<td>σ = 1/2</td>
<td>n = 4</td>
<td>0.1/0.9</td>
<td>120.25</td>
<td>120.25</td>
<td>105.35</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.2/0.8</td>
<td>120.25</td>
<td>120.25</td>
<td>106.60</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.3/0.7</td>
<td>120.25</td>
<td>120.25</td>
<td>108.39</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.4/0.6</td>
<td>120.25</td>
<td>120.25</td>
<td>110.38</td>
</tr>
<tr>
<td>σ = 1</td>
<td>n = 8</td>
<td>0.1/0.9</td>
<td>125.25</td>
<td>125.25</td>
<td>106.85</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.2/0.8</td>
<td>125.25</td>
<td>125.25</td>
<td>110.93</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.3/0.7</td>
<td>125.25</td>
<td>125.25</td>
<td>115.33</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.4/0.6</td>
<td>125.25</td>
<td>125.25</td>
<td>119.69</td>
</tr>
<tr>
<td>σ = 2</td>
<td>n = 16</td>
<td>0.1/0.9</td>
<td>135.25</td>
<td>135.25</td>
<td>111.21</td>
</tr>
<tr>
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<td></td>
<td>0.2/0.8</td>
<td>135.25</td>
<td>135.25</td>
<td>114.89</td>
</tr>
<tr>
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<td>0.3/0.7</td>
<td>135.25</td>
<td>135.25</td>
<td>121.34</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.4/0.6</td>
<td>135.25</td>
<td>135.25</td>
<td>127.70</td>
</tr>
</tbody>
</table>

As shown in the summary table above, we find model m=4 is the best layout among the four models as it provides the smallest value of expected employee’s effort within the retail store for all values of the ratio σ and number of aisles n tested. As a consequence, retail stores wanting to minimize expected travel to pick a single item are suggested to place the Backroom and the Pickup locations on opposite sides of the facility and move them along the width of the aisles array as necessary.

5. Conclusions and Future Research

This work derives expected travel distance models for retrieving a single item in a retail store with four different placements of the backroom and pickup location. According to the experiment results shown after changing the parameter n and the ratio σ, we find out the fourth model requires less expected travel efforts for the store employees to pick an item. Given travel effort dominates order-fulfillment tasks, these models are a starting point to understand placement of pickup locations for pick-up-in-store operations. However, a number of future research directions exist. First, additional considerations beyond travel distance can be incorporated (e.g., waiting time due to congestion of
shoppers, time to search and extract the items, packing time) and then used to estimate throughput times. Second, more complicated objective functions can be explored. For example, both the employee’s efforts and the customer’s efforts can be accounted for in the objective function. Future research is needed to derive the expected travel distances when a set of items are requested and for different retail store layouts. In addition, higher fidelity models are needed to capture an employee may have multiple tasks combined together, for example helping in-store customers or restocking racks, while picking online customers orders. Future research also includes exploring whether to have dedicated employees assigned to online order fulfillment or to have cross-trained employees. Finally, operational design questions around if and how to batch orders, how to route employees, how to assign products to store locations, etc. should be explored for click-and-collect operations in conjunction with in-store shopping.

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References