Open Journal of Business and Management, 2022, 10, 1923-1935
https://www.scirp.org/journal/ojbm
ISSN Online: 2329-3292
ISSN Print: 2329-3284

A Decision Support System for Re-Slotting a Case Pick Distribution Center

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How to cite this paper: Aase, G. R., & Petersen, C. G. (2022). A Decision Support System for Re-Slotting a Case Pick Distribution Center. *Open Journal of Business and Management, 10,* 1923-1935.
https://doi.org/10.4236/ojbm.2022.104099

Received: June 15, 2022
Accepted: July 25, 2022
Published: July 28, 2022

Abstract

This research presents a class-based re-slotting procedure that re-assigns stock-keeping units (SKUs) in a warehouse secondary storage area to new locations based on the SKU activity. The general notion of re-slotting is to place high activity SKUs in premium locations near the pickup/drop-off points of shipping and receiving. This simulation study examines the performance of an ABC class-based rule for guiding SKU swaps between the front and rear sections using case pick data provided by a large regional pharmaceutical distributor. The simulation results show this class-based case pick re-slotting heuristic provides significant savings in picker travel.

Keywords

Distribution, Warehousing, Re-Slotting, Order Picking, Supply Chain, Stock Keeping Units (SKUs)

1. Introduction

A warehouse, or distribution center (DC), stocks products that are redistributed to various customers including: wholesalers, retailers, and end consumers. The primary warehouse operations are often classified as either inbound or outbound. Receiving and putaway are the main inbound activities, whereas order picking and shipping are considered the main outbound activities. Receiving products, or stock keeping units (SKUs), involves many activities but the primary focus is moving the product off the trucks into the warehouse receiving area. The putaway operation then moves the individual SKUs to the proper location in the warehouse. Once orders are received from customers, order pickers gather the SKUs from the warehouse and deliver them to a designated area for packing and shipping. DCs play a critical role in a supply chain by delivering the right products to the right place at the right time in a cost-effective manner. The relationship of these warehouse activities is shown in Figure 1.

Today's competitive environment and supply chain integration initiatives have put enormous pressure on warehouse managers to increase the throughput rate while lowering operating costs of their operations (Frazelle, 2002). Order picking constitutes 50% - 75% of the total operating costs for a typical warehouse (Bozer et al., 2010; Coyle et al., 2003), though it is not clear if this includes the costs for other warehouse operations such as putaway. Nonetheless, these operations are the primary focus for most cost reduction efforts in practice. The use of automation is frequently examined as a means for reducing labor costs associated with picking, but most companies continue using manual order picking for a variety of reasons pertaining to SKU shape and size variability, demand variability, product seasonality, or the large investment required to automate an order picking system. An abundance of research addresses design and operating issues with an objective to reduce order fulfillment costs. Three broad issues are most prominent: 1) how to pick the SKUs, 2) how to route the pickers in the warehouse and 3) how or where to store the SKUs

This research explores the third issue more closely based on an inquiry from a pharmaceutical distribution company. More specifically, this research explores how re-slotting SKUs reduces travel distance, or labor costs, associated with the order picking operations. Slotting, which involves the assignment of SKUs to specific warehouse locations, is a critical warehouse design decision that is often overlooked after the initial design despite managers and consultants reporting how re-slotting can reduce annual costs by 8% - 12% (Trebilcock, 2011). Published research supports these claims by showing how slotting affects labor costs or operator travel associated with the picking process (Renaud & Ruiz, 2008). However, no research has shown the overall effect of re-slotting to reduce operator travel for order picking operations. This study will extend the existing research by studying the effect of slotting rules that use information about order picking operations. A Microsoft Access-based Decision Support System (DSS) is presented for the re-slotting rule based on the number of times a SKU is picked. This research presents results from a simulation-based experimental design using picks made during the past month as primary input measure. The authors then conclude the paper by discussing managerial implications for other DCs using manual picking processes.

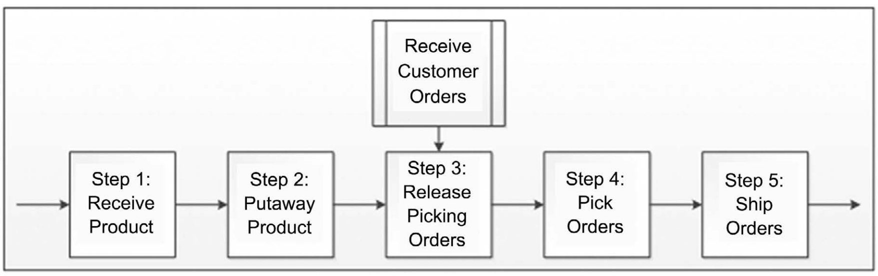

Figure 1. Warehouse processes.

2. Literature Review

The push to lower costs and improve customer service through faster response is leading many managers to implement new approaches in their warehouse and distribution facilities. Due to the significant labor costs associated with order picking, this activity has been the topic of much research. The primary focus of most research in this area has been identifying more effective picking, routing, or storage policies.

2.1. Order Picking Policies

Picking policies determine which SKUs are placed on a pick list and subsequently retrieved from their storage locations by a single picker during a pick tour. Strict-order picking is a common policy where pickers tour the warehouse to pick all line items or SKUs on a single order. This policy is viewed favorably by practitioners because it is easily implemented, and order integrity is always maintained. Combining several orders into batches is an alternative policy that has been shown to reduce total picking time significantly (Gibson & Sharp, 1992; Petersen, 2000; De Koster et al., 1999). First-come-first-served (FCFS) batching combines orders as they arrive until the maximum batch size has been reached. Based on results found in the bin-packing literature, it is clear that other heuristics will yield fewer picking tours, which is critical for reducing total travel time across all pick tours. More complex batching techniques that consider both order size and production volumes have been proposed (Ruben & Jacobs, 1999), but the logic for these batching methods exceeds the capabilities of most warehouse management systems.

Zone picking is another policy that divides the warehouse into zones and allows pickers to retrieve SKUs from within a single zone (Jane, 2000; Petersen, 2000; Petersen, Aase, & Heiser, 2004). Some firms have combined batching and zoning into "wave" picking where a picker is responsible for SKUs in their zone. The benefit for these types of policies becomes apparent as the size of the warehouse increases, but zone picking requires secondary operations to consolidate SKUs picked from the different zones. The subject firm designed and implemented a custom zone picking policy to release pick waves that consider delivery routes containing many orders. The simplicity of their policy was easy to implement, has been well received by employees, and has proven quite effective at minimizing pick tours and travel distance.

2.2. Routing Policies

Routing policies determine the picking sequence of SKUs on the pick list. Using simple heuristics or optimal procedures, the goal of routing policies is to minimize the distance traveled by the picker. Optimal procedures offer the best solution, but they may result in confusing routes (Ratliff & Rosenthal, 1983). Heuristics often yield near-optimal solutions while being easy to use (Petersen &

Schmenner, 1999; Hall, 1993). Traversal routing, which is widely used in many warehouses because of its simplicity, provides good results particularly when the pick density per picking aisle increases. When using a traversal policy, pickers must completely traverse the entire aisle once it is entered. A composite heuristic combining traversal and return routes to further reduce picker travel produced near-optimal solutions (Roodbergen & De Koster, 2001). The later approach reflects the routing policy used by the subject firm.

2.3. Storage Policies

Storage policies, which assign SKUs to storage locations, generally fall into three broad categories. SKUs may be assigned randomly, grouped into classes with similar SKUs that are placed in the same area of the warehouse, or assigned to a location based on demand or volume. Random storage is widely used in many warehouses because it is simple to use, often requires less space than other storage methods, and results in a more level utilization of all picking aisles. Volume-based storage policies assign SKUs with the largest demand to locations near the pick-up/drop-off (p/d) point. Research shows that a within-aisle implementation of volume-based storage significantly reduces travel time (Jarvis & McDowell, 1991; Petersen & Schmenner, 1999). Class-based storage with as few as three storage classes was shown to provide nearly the same savings as volume-based storage in an automated storage and retrieval systems (AS/RS) while requiring less data processing (Hausman et al., 1976; Rosenblatt & Eynan, 1989; Eynan & Rosenblatt, 1994). While research involving automated retrieval systems is rather extensive, most warehouses utilize manual picking methods (Frazelle, 2002).

The effect of class-based storage in a manual picking environment was introduced using a sensitivity analysis (Gibson & Sharp, 1992), but the focus of their research was on batching techniques to reduce picker travel. A comparative study of a manual order picking warehouse revealed that class-based storage reduces picker travel when compared to random storage and offers similar performance as the more complex volume-based storage (Petersen, Aase, & Heiser, 2004). Their research showed class-based storage policies are effective across all conditions by changing factor levels in a simulated warehouse environment, but no research documents the benefit by replicating an existing operation. This current research will test these findings using actual data provided by the subject firm.

2.4. Current Research Extension

This research extends the slotting problem by exploring the importance of re-slotting a warehouse on a regular basis as product offerings and demand changes. While consultants and practitioners publish expected labor savings of 8% - 12% annually, most published research only considers slotting greenfield projects. An adaptive re-slotting approach was proposed using data mining techniques and a binary integer programming technique to assign new products to vacant locations (Chiang, Lin, & Chen, 2011). However, the subject firm requested a simple heuristic technique that will help reduce operator travel and hence operating costs. Since their product offering has reasonably stable demand that follows a normal product lifecycle, the subject firm rarely experiences vacant locations. Therefore, the proposed procedures must consider re-organizing the SKUs location assignments. This may be accomplished by classifying SKUs into storage classes by applying the ABC analysis concepts commonly associated with inventory management, but none of the existing studies document the benefits for using such policies. This research will introduce a simple pairwise exchange heuristic that applies the well-known Pareto concept for assigning SKUs to a class based on their case pick activity.

The following sections provide a general description of the warehouse operation for the subject firm which we replicate using a simulation model, present the details for our experimental design, and then share results of the simulation study. This paper concludes with a summary of important managerial implications.

3. Warehouse Operation Overview

This research is motivated by a pharmaceutical distribution center located in the Chicago, Illinois area that requested assistance for developing a new re-slotting process. Specifically, they asked to determine if re-slotting their secondary storage area will reduce operator travel time for the case pick operations and to identify best practices for guiding their re-slotting process. This section summarizes key aspects of the subject firm operation including the facility layout and key business operating rules. This section also presents details for the class-based re-slotting heuristic.

3.1. Layout and Fulfillment Process Overview

Figure 2 shares the facility layout for the DC examined in this study. While secondary storage is the primary focus of this research, this image illustrates additional areas that are found within many DC facilities. This DC facility is fairly unique since it performs both individual piece picking to provide any piece quantity and a separate operation for case picking full cases. Further details of the piece-picking processes are omitted since it falls outside the scope of this study. The remainder of this paper will focus on the secondary storage area where the case picking occurs.

The secondary storage area holds full unopened cases for approximately half the active SKUs handled within the DC. The remaining SKUs are stored in flow racks or standard hand stack shelves located in the manual and semi-automated piece picking areas. SKUs located in secondary storage are packaged in cardboard boxes and picked in full case quantities where each case contains from 1 to 540 individual pieces. Full cases are picked by operators from the secondary storage locations using tugs and carts, though a few full pallet picks are used for

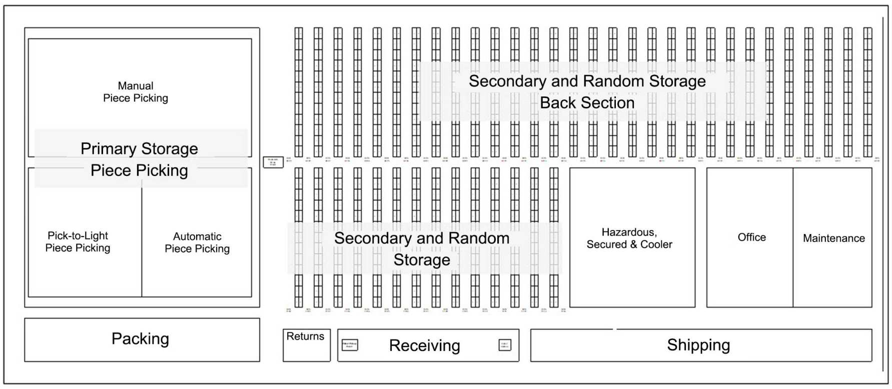

Figure 2. Warehouse layout.

large orders sent to other regional DCs. Once the operators complete their assigned picking tour, the carts are delivered to the shipping area where they are packed and wrapped on a shipping pallet. Individual piece parts involving partial cases are always picked from one of the three piece picking areas. Again, the travel distance associated with piece picking operations is outside the scope of this research. It is also worth noting that the WMS system will often split a customer order into a full case pick order and a second piece pick order. For example, a customer order for 15 bottles of aspirins will likely be released as one case pick order and a second piece pick order of three bottles assuming the full case contains 12 bottles.

The following list summarizes information about the warehouse modeled in this research:

- The Secondary and Random Storage Area has 44 picking aisles each containing 12 or 13 bays on a side. There are front and back cross-aisles and a third cross-aisle located approximately halfway back that partitions the area into a front section and a back section (see Figure 2).
- The picking aisles have racks on each side and are wide enough for two-way travel.
- Racks are approximately 25 feet tall with the secondary storage locations assigned to the lower seven to nine feet. The remaining space located above the secondary storage is designated as random pallet storage. Operations associated with random storage are used for temporary storage of pallets and are outside the scope of this project.
- The rack design within an aisle is identical for each bay, but the racking design varies between aisles. In general, aisles are designed to handle either 1) full pallets, 2) half pallets with a two-foot hand-stack shelf, 3) four hand-stack shelves, or 4) five flow racks.
- Flow racks are seven feet deep by spanning across two racks located back-to-back from adjacent aisles. Full cases are loaded into a flow rack from the back side of the flow rack. This configuration is generally used for smaller, high-velocity SKUs.
- Three pallets are assigned within each bay. Each hand-stack level for a bay

has six locations and each flow rack level has eight locations.
- The case capacity of a location depends on the bay configuration and the size of the full manufacturing case for the SKU assigned to the location.
- Each case picking tour begins at the label station located at the right-hand side in the receiving area and ends at the drop point located in the middle of shipping.
- Case picking is done manually using pallets, mixed pallets or tugs/carts depending on the cubic volume and quantity of cases for each SKU. Case picking is only done from the secondary storage areas. No cases are picked from the piece picking area or random storage area.
- Each SKU is assigned to only one secondary storage location, but several adjacent locations may be grouped together as designated as a single location for a SKU.
- Each storage location is assigned only one SKU.
- There are ten wave releases each night that corresponds to distinct delivery routes. An FTL trailer assigned to each route is located in a unique shipping bay.
- The SKU demands generally follow the 80 - 20 rule in that a few items account for most of the cases demanded. The number of SKU 'hits' for case pick also follow this principle. A "hit" is defined as the number of times a location is visited and it also corresponds to an order line item.
- Current practices of the subject firm involve re-slotting SKUs with large annual cubic volumes due to the attention drawn to moving full pallets. They also re-slot the 25 - 50 SKUs having the highest annual dollar volume for security reasons and SKUs with demands that are rapidly increasing.

3.1.1. SKU Classification Strategy

To operationalize the re-slotting heuristic, SKUs are first assigned to one of four classes (A, B, C & D) using the Pareto "ABC" concept commonly applied to inventory management practices. For this re-slotting problem, high-activity case pick SKUs during the prior month are assigned to the "A" class. SKU activity or "hits" is defined as the number of times a SKU appears as a line item on an order pick list. This also corresponds to the number of times a SKU location is visited during the case picking operation. This differs from other ABC classifications which commonly use total annual units sold or total annual dollar value for the SKUs. The classification strategy for this research uses "hits" because the number of location visits has a stronger correlation to operator travel than the quantity picked. Warehouse managers generally use this measure of "hits" because subsequent items picked on the same pick tour costs very little. Table 1 summarizes the number of SKUs and Total Monthly Hits. For the subject firm of this research, a SKU visited more than 40 times for the case pick operation corresponds to a very high-activity SKU picked two or more times per weekday assuming there are approximately four weeks or 20 weekdays per month.

Table 1. SKU classification summary.

Class	Monthly Hits	SKUs	SKUs %	Total Hits	Hits %
A	>40	311	3.1%	41,997	62.9%
B	20 - 39	298	2.9%	8222	12.3%
C	2 - 19	2541	25.1%	15,815	23.7%
D	0 - 1	6967	68.9%	719	1.1%
Totals		10,117		66,753	

3.1.2. Pairwise Exchange Heuristic

The proposed heuristic uses a pairwise exchange strategy, where high-activity SKUs located in the back of the warehouse are moved into the Front Section. This is a similar logic used by the volume-based and class-based storage policies presented in the current literature where SKUs with the highest demand are located near the pick-up/drop-off (p/d) points. For the case pick operation, this entails moving the A, B and C SKUs from the back section to the front section of the *Secondary Storage area*.

Step 1: Prepare Data—Acquire data providing the current SKU locations and released case pick orders for the past month. Confirm the case pick data is not aggregated across multiple picks. Determine the activity of each SKU, and then apply the ABC SKU classification strategy to determine which SKUS are A, B, C or Ds.

Step 2: Pairwise Exchange—This step involves exchanging a high-activity SKU currently located in the back section with a low-activity SKU located in the front section. On occasion, there may be an open location in front which should be filled with a high-activity SKU currently located in the back section, but this does not happen frequently for the subject firm.

The pairwise exchange heuristic may be characterized as having three sub-steps as shown in **Figure 3**. Using the ABC classification generated during Step 1, Step 2.1 identifies a SKU in the rear section having an "A" classification or the next highest designation. Step 2.2 then identifies a location in the front section having a SKU with a "D" designation or the lowest possible designation. Substep 2.3 involves the pairwise swap, and it also provides a stopping criterion. If the SKU moving forward has a higher ABC designation than the SKU moving back, accept the pairwise exchange and repeat step 2. In other words, a SKU in the back section having a "C" designation would be swapped with a SKU in the front section having a "D" designation. However, it won't be swapped with a SKU in the front section having a "C" designation. The later scenario reflects the stopping criteria where no further attempt is made to identify a pairwise exchange. Step 3 involves preparing a report listing all exchanges identified during Step 2.

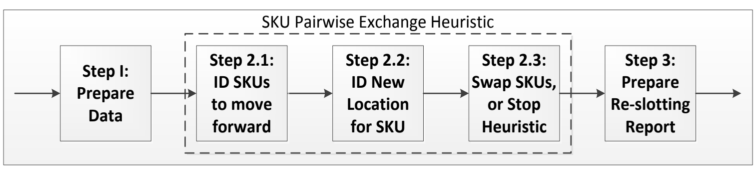

Figure 3. Re-slotting procedure flowchart.

4. Experimental Design

The primary goal of this research is to determine if using the pairwise exchange heuristic to re-slotting the secondary storage area will reduce operator travel time for the case pick operation.

The simulation model was created using structured queries on a SQL Server that had direct access to actual data from the subject firm including item master data, case pick orders, and the wave release times for SKUs located in the secondary storage area. This simulation model replicated the subject firm's operations using actual data for one month with data for 20 regular-crew weekdays. This baseline trail also included five Saturdays using a skeleton crew to fulfill same-day emergency orders. The primary performance metric tracked by this study is total operator travel. Results are reported based on the type of equipment used: forklifts for full one SKU pallets and tugs with carts for mixed SKUs. Additional secondary metrics reported include: 1) number of tours, 2) number of aisles visited, and 3) cubic volume.

The simulation study is replicated twice, where each trial has a sample size of 25 operating days. The Baseline trial uses the current slotting configuration and actual SKU locations. The other trial involves re-slotting the warehouse using the pairwise exchange heuristic with the ABC classification rule for case pick hits.

5. Results

Results for the Baseline Trial shared in Table 2 are reported separately for forklifts and tugs since the two equipment methods commonly used within many DCs have unique implications with regard to labor usage. Forklifts are used when an order contains larger pallet quantities of a single SKU. Whereas the tugs involve some manual movement of SKUs involving fewer cases of a product, casual observation of the Baseline Trail results reveals several insights worth noting. First, the travel distance for the case pick operation is weighted more heavily toward the use of tugs with carts. This is expected for a pharmaceutical distributor because more of their daily business entails small frequent orders to many customers. Therefore, most of the orders are picked by operators using a tug with 3 - 4 carts in tow. Second, mixed pallets are not used for this operation because 98.6% of the case pick orders (65,818 of 66,753) involve fewer than 12 cases. Of the remaining 953 lines, 290 lines required 349 tours or full pallet picks. Therefore, this data supports the logic used by the subject firm for using only tugs with carts when case pick orders do not involve full pallet picks.

Results in Table 3 summarize the performance the Case Pick Rule Trial compared to the Baseline Trial. While the Case Pick Rule only reduces the number of tours by 5.5%, it reduces the number of aisles visited by 31.7% and more importantly the travel distance by 25.1%. These findings are significant since this supports the anecdotal results suggested throughout the business literature indicating a 10% - 12% improvement is expected. This reduction in travel distance is significant and represents meaningful labor savings for any business.

Table 2. Baseline trial summary statistics.

	Pallet w/1 Item	Tug w/Carts	Combined Total
Lines	290	66,463	66,753
Tours	349	555	904
Aisles	290	2381	2671
Volume (Ft3)	20,596	57,791	78,387
Travel (Ft)	258,676	630,766	889,442

Table 3. Simulation study summary statistics.

	Baseline Trial	Case Pick Rule Trial	% Reduction
Tours	904	854	5.5%
Aisles	2671	1825	31.7%
Travel (Ft)	889,442	665,757	25.1%

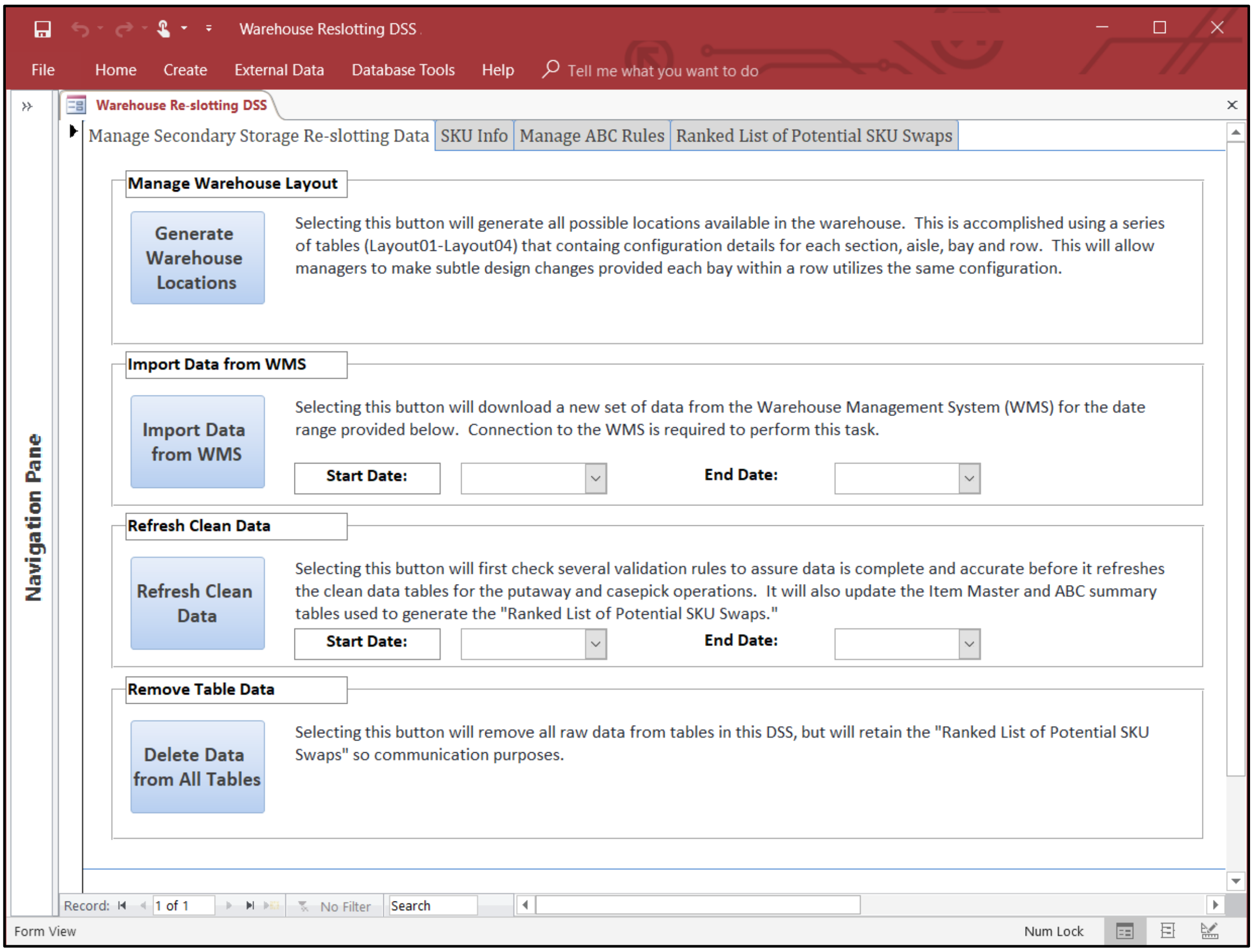

Figure 4. Warehouse Re-slotting DSS using access database.

Implementation of the re-slotting procedure is beyond the primary focus of this study, but several comments are worth noting. The interface shown in **Figure 4** depicts an initial design of a decision support system (DSS) presented to the subject firm, who after some minor changes utilize the DSS on a regular basis. Warehouse operators evaluate the "Ranked List" to identify SKUs they wish to preclude from the list due to special circumstances before they print final report of "Planned Re-slotting Swaps" they can complete during unproductive idle at the end of a picking shift. To reduce the time required to move items, swaps are generally limited to pairs where the SKU (A, B or C) being moved from the back section to the front section has a planned put-away during the following dayshift. Therefore, this creates a situation where a slow-moving item is moved to the back section, while moving very few units of the "A" item from the back section to the front section. The key notions include: 1) swap locations when the high activity items have little or no inventory remaining in the secondary storage area, and 2) allow warehouse operators to move items as time allows during end-of-shift idle time. Therefore, this may result in performing several swaps on one day, no swaps the next day, and many swaps on a slow day. Regardless of the number of swaps, the subject firm completes the activity before operators arrive to work in the morning to begin the receiving and put-away operations.

6. Concluding Remarks

This study has explored using ABC analysis and a class-based storage strategy to re-slot the secondary storage area of a major pharmaceutical distributor. The results show significant reduction in travel distance for case pick operations. The level of improvement supports the claims made in the business literature. Assuming operator travel accounts for approximately 60% of the case picking operations, managers should expect a labor-saving of approximately 15% (60% × 25.1%).

The results of this study naturally have some limitations since they are based on the data for one operation. However, detailed analysis not included in this paper reveals meaningful improvements are expected for the different equipment configurations whether businesses use forklifts to handle pallets or tugs and carts that traverse the aisles in an orderly manner. These observations certainly suggest more detailed studies are justified to explore the re-slotting problem for various operating environments.

This study clearly shows that the pairwise exchange heuristic was effective for re-slotting the secondary storage area of the subject firm. While these results are not compared to an optimal solution, performance metrics provided by managers of the subject firm suggested they were one of the more efficient DCs for the corporation. Nevertheless, the findings of this initial study suggest further detailed studies are warranted to compare results of class-based, volume-based, and optimal re-slotting procedures.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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