Available online at www.sciencedirect.com
SCIENCE DIRECT
Int. J. Production Economics 92 (2004) 11–19
international journal of production economics
www.elsevier.com/locate/dsw

A comparison of picking, storage, and routing policies in manual order picking

Charles G. Petersen, Gerald Aase*

Department of Operations Management and Information Systems (OMIS), College of Business, Northern Illinois University, DeKalb, IL 60115, USA

Received 1 November 2002; accepted 1 September 2003

Abstract

This article examines the effect of three process decisions (picking, storage, and routing) on order picker travel, which is a major cost component of order fulfillment. The authors use a simulation model based on the operations of a distribution center that is currently picking one order at a time, storing product in a haphazard or random fashion, and using a simplistic procedure for routing pickers. Several picking, storage, and routing policies are evaluated to determine which process decision provides the greatest percent savings relative to the current baseline policies. Several sensitivity analyses are completed to examine the effect of order size, warehouse shape, location of pick-up/drop-off point, and demand distribution on performance. Results show that batching of orders yield the greatest savings particularly when smaller order sizes are common. Results also show the use of either a class-based or volume-based storage policy provides nearly the same level of savings as batching, while being less sensitive to the average order size.

Keywords: Order picking; Warehousing; Storage; Routing; Simulation

1. Introduction

Order picking, the retrieval of stock keeping units (SKUs) from a warehouse to satisfy customer orders, is a vital supply chain component for many companies. Order picking constitutes 50–75% of the total operating costs for a typical warehouse (Coyle et al., 1996). The use of automation is frequently examined as a means for reducing labor costs, but many companies continue using manual order picking due to variability in SKU shape and size, the variability of demand, the seasonality of the products, or the large investment required to automate an order picking system. Existing research addresses various design and operating issues with an objective to reduce order fulfillment costs or to improve overall system performance. The three process decisions considered most often are: (1) how to pick the SKUs, (2) how to store the SKUs, and (3) how to route the pickers in the warehouse.

This research examines several picking, storing, or routing policies simultaneously to determine which process decisions affect performance the most. While some existing research examines these three decisions using a combination of main experiments and sensitivity analyses, published results do not allow managers to determine the

*Corresponding author. Tel.: +1-815-753-6376; fax: +1-815-753-7460.

E-mail address: gaase@niu.edu (G. Aase).

0925-5273/$ - see front matter
doi:10.1016/j.ijpe.2003.09.006

relative importance of the three decisions. This research will facilitate such a comparison with regard to order fulfillment performance. In other words, managers will be able to determine which decision provides the most "bang for our buck". Should a firm implement batching of orders, optimal routing, volume-based storage, or some combination of these policies? The paper concludes by discussing managerial implications concerning the relative importance of the three decisions.

2. Literature review

Order picking has been the topic of much research over the past several decades. The primary focus for most of this research has been identifying more effective picking, storage or routing policies.

Picking policies determine which SKUs are placed on a pick list and subsequently retrieved from their storage locations by a single picker. Strict-order picking is a common policy where pickers complete a tour through the warehouse to pick all SKUs for a single order. This policy is often preferred 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 and 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. Petersen (2000) used this method in his paper to compare picking policies. Based on results found in the bin-packing literature, it is clear that other bin-packing heuristics may yield fewer picking tours. More complex batching techniques that consider both order size and product volumes have been proposed (Ruben and Jacobs, 1999), but the logic for these batching methods are difficult to convey to the employees and were quickly dismissed by the subject firm. Therefore, they are not considered in this research.

Zone picking is another policy that divides the warehouse into zones and allows pickers to retrieve SKUs from within a single zone. Some firms have combined batching and zoning into "wave" picking where each picker is responsible for SKUs in their zone for numerous orders. The benefit for these types of policies become apparent as the size of the warehouse increases, but zone picking requires secondary operations to consolidate orders from the different zones. Results from our study generalize to each zone; therefore, zone and wave picking are not examined directly in this comparison study.

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 and McDowell, 1991; Petersen and Schmenner, 1999). Class-based storage with as few as three storage classes provides nearly the same savings as volume-based storage in an automated storage and retrieval systems (AS/RS) while requiring less data processing (Eynan and Rosenblatt, 1994).

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 may result in confusing routes (Ratliff and Rosenthal, 1983). Heuristics often yield near-optimal solutions while being easy to use (Petersen and Schmenner, 1999; Hall, 1993). Traversal routing, which is widely used in many warehouses because of its simplicity, provides good results when the pick density per picking aisle is large. When using a traversal policy, pickers must completely traverse the entire aisle once it is entered. The combined heuristic combines traversal and return routes to further reduce picker travel to produce near-optimal solutions (Petersen, 1997; Roodbergen and Koster, 2001).

Current research addresses additional topics such as use of technology (Graves et al., 2002), stochastic work levels (Bartholdi et al., 2001), alternate layouts (Caron et al., 2000), and kitting (Brynzer and Johansson, 1995). However, a common feature of this research is that at least two of the three decisions previously discussed (picking, routing and storage) are fixed. In general, most research examines alternative policies for one of the three decisions. The purpose of this research is to examine the effect of these three policy decisions simultaneously in an effort to determine which policy decision has the greatest effect on system performance. De Koster et al. (1999) considers all three decisions, but the focus of several sensitivity analyses is to determine the impact of routing and storage policies on the performance of batching algorithms. Consequently, results are not structured to identify the relative importance of the decision policies.

3. Description of the warehouse simulation model

This section describes the warehouse simulation model used in this research. It is based on the operations of an online/catalog retailer using strict order picking, random storage, and traversal routing at the time of our visit. This scenario serves as a baseline to which different policy combinations are compared. The goal of this experiment is to determine which policy or combination of policies provides the largest reduction in total pick time for all orders in a day. In addition, several sensitivity analyses and extensions to the warehouse model are examined to allow the generalization of results to other warehouse environments.

The specifications for the warehouse simulation model are:

- The warehouse layout has 10 picking aisles with front and back cross-aisles as shown in Fig. 1. The picking aisles are two-sided and are wide enough for two-way travel.
- Each picking tour begins and ends at the p/d point located in the middle of the front cross-aisle.

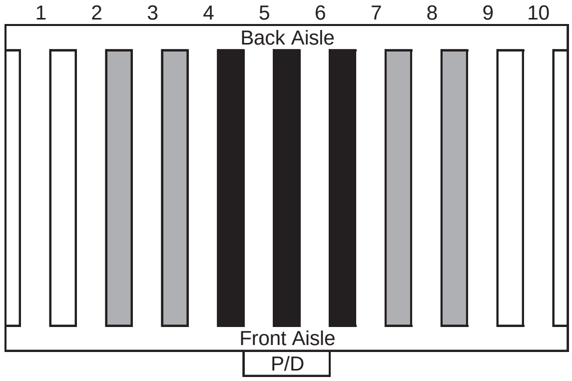


Fig. 1. Warehouse layout.

- The demand for the SKUs is based on an 80–20 distribution so that 20 percent of the SKUs account for 80 percent of the picking activity.
- The picking area uses bin shelving with a total storage capacity of 1000 SKUs
- Each SKU is assigned to only one storage location and every storage location is the same size.
- A picker travel rate of 150 feet per minute and the picking time per SKU of 0.30 minutes are assumed to be constant. The picking time includes all handling of the SKU and administrative time. These estimates are consistent with observations from various picking operations and with the literature (Petersen, 2000; Gray et al., 1992).
- Picking is completed manually using of a picking cart with a capacity of 50 SKUs. If orders are batched, the maximum batch size is set to equal the cart capacity. The picking cart allows multiple orders to be picked, in a manner that maintains order integrity so that no downstream sorting is required. This is commonly referred to as sort-while-pick picking.

4. Experimental design

The purpose of this research is to evaluate several picking, routing, and storage policies to determine which policy or combination of policies will provide the greatest reduction in total picking time when compared to a baseline scenario. The baseline scenario of this experiment corresponds to the current operation of a firm using strict order picking with traversal routing and random storage. Two additional policies are examined for each of the three process decisions, yielding a total of 27 treatments. The experimental design is summarized in Table 1 along with the notation for all factor levels.

The picking policies are strict order (S), FCFS batching (F) (Petersen, 2000), and bin-pack batching (B). Based on a comparison of several bin packing heuristics, this study uses the largest-first heuristic to establish pick list groupings. Preliminary results show that this heuristic is more effective than the FCFS heuristic in reducing the total number of tours required especially when batches are comprised of only a few orders. The routing procedures are traversal (T), combined (K) (Petersen, 1997; Roodbergen and Koster, 2001), and optimal (O) (Ratliff and Rosenthal, 1983). The storage policies are random (R), class-based storage (C) (Eynan and Rosenblatt, 1994), and within-aisle volume-based storage (W) (Jarvis and McDowell, 1991; Petersen and Schmenner, 1999). For class-based storage there are three classes of SKUs: A, B, and C. The A SKUs are the most frequently requested and will be randomly stored within the two picking aisles closest to the p/d point. The B SKUs will be located in the picking aisle on each side of the A SKUs and the C SKUs will occupy the remaining warehouse space.

The treatments resulting from the $3 \times 3 \times 3$ full factorial design are evaluated using data sets generated with a Monte Carlo simulation. By varying the average order sizes for these data sets, results may be generalized more easily across different firms. The average order size for the seven data sets are 5, 10, 15, 20, 25, 30, and 40 SKUs. Since the order sizes for the subject firm are approximately a Poisson distribution and the pick cart is limited to 50 SKUs, a modified Poisson distribution truncated at 50 was used to generate order sizes. In general, the quantity of each SKU in an order is one unit, but there are a few circumstances where the same SKU was randomly generated. Each of the data sets contains 500 randomly generated orders, which corresponds approximately to the number of orders processed during a day at the subject firm. The performance measure of this experiment is the total fulfillment time (total travel and picking time) for the 500 customer orders.

5. Results and discussion

Raw output data for the main experiment are given in Table 2. Comparing the total time for the baseline treatment (STR) to the remaining 26 treatments provides a basis for which the following results are presented.

Fig. 2 shows the average percent reduction in total fulfillment time for each treatment relative to the baseline scenario. Three distinct groupings of policies are apparent. The first group includes all of the three-policy changes and four scenarios involving two-policy changes. Changing all three policies yields an average savings between 27% and 29%. It is interesting to note that similar savings may be attained by using either alternative batching (bin-packing or FCFS) and either alternative storage (within-aisle storage or class-based) policies, while continuing to use the traversal policy.

Table 1
Experimental factors and levels

Factor	Levels	Notation or values
Picking policy	3	Strict order (S), batch FCFS (F), batch bin-pack (B)
Routing policy	3	Traversal (T), combined (K), optimal (O)
Storage policy	3	Random (R), class-based (C), within-aisle (W)
Average order size	7	5, 10, 15, 20, 25, 30, 40 SKUs

Table 2
Total time to fulfill 500 customer orders (minutes)

Order size	STR	STC	STW	SKR	SKC	SKW	SOR	SOC	SOW
5	1849	1345	1329	1674	1268	1236	1537	1191	1173
10	3001	2286	2271	2792	2210	2158	2634	2119	2097
15	3966	3173	3152	3761	3103	3077	3604	2994	2978
20	4852	4019	4000	4677	3958	3933	4517	3844	3823
25	5683	4849	4826	5540	4768	4759	5384	4659	4642
30	6471	5662	5636	6364	5585	5561	6226	5473	5450
40	8000	7274	7244	7951	7189	7163	7843	7071	7047
Average	4304	3556	3536	4135	3482	3457	3983	3380	3361
Order size	FTR	FTC	FTW	FKR	FKC	FKW	FOR	FOC	FOW
5	952	886	880	949	872	871	941	863	859
10	1931	1787	1782	1925	1764	1757	1906	1739	1734
15	2937	2702	2692	2924	2665	2659	2891	2629	2623
20	3995	3641	3626	3964	3594	3585	3915	3537	3531
25	5088	4582	4571	5037	4524	4513	4956	4448	4439
30	6325	5596	5569	6240	5524	5500	6119	5419	5397
40	8000	7274	7244	7951	7189	7163	7843	7071	7047
Average	3538	3199	3187	3507	3157	3148	3455	3106	3097
Order size	BTR	BTC	BTW	BKR	BKC	BKW	BOR	BOC	BOW
5	944	880	880	941	872	868	933	861	858
10	1891	1765	1761	1886	1749	1740	1874	1723	1718
15	2856	2662	2657	2846	2630	2621	2824	2597	2592
20	3837	3577	3563	3827	3531	3519	3791	3481	3472
25	4757	4435	4429	4745	4389	4375	4709	4332	4321
30	6122	5517	5490	6064	5438	5420	5969	5350	5330
40	7989	7269	7239	7942	7185	7158	7834	7067	7043
Average	3401	3139	3130	3385	3101	3090	3350	3057	3048

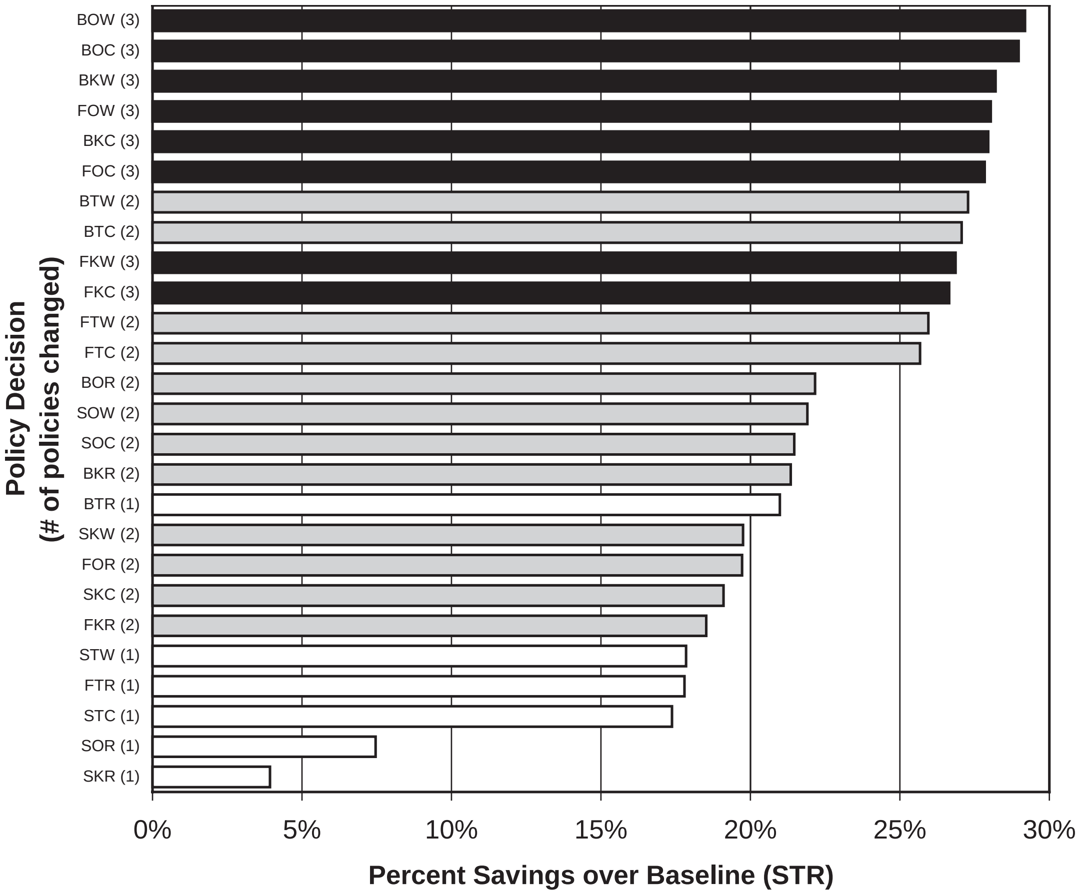
Note: Refer to Table 1 for a guide to notation.

The second grouping contains the remaining two-policy changes and several one-policy changes. Results indicate that a warehouse manager could reduce total fulfillment time between 17% and 22% by batching orders or by using either volume-based or class-based storage. The last grouping entails two scenarios that change only the routing policy.

The implications are clear that managers should attempt to use some form of batching technique in conjunction with either a class-based or volume-based storage policy. This seems to show that the use of a sophisticated routing heuristic or even optimal routing does not result in savings comparable to those achieved by either batching or some form of class-based or volume-based storage. In other words, alternative routing techniques should only be used if these other polices have been put into effect.

5.1. Sensitivity analyses

Further analyses were completed to examine the sensitivity of results to various levels of several input parameters including average order size, warehouse shape, pick-up/drop-off (p/d) point location, and demand distribution of SKUs. By considering results from these sensitivity analyses, the insights gained from the main experiment may be generalized more easily for use by other companies. In general, this sensitivity analysis reveals that the average order size will influence



Note: Refer to Table 1 for a guide to notation.

Fig. 2. Performance Relative to Baseline Policy (STR).

which decision policies should be considered more carefully. The remaining sensitivity analyses support research findings previously reported, showing that warehouse shape, p/d location and demand distribution have a negligible effect on results.

5.1.1. Average order size

Fig. 3 shows the effect of the average order size on performance when changing only one of the three policy decisions. As the average order size increases, the percent savings diminishes for all three types of policy decisions. However, the percent savings is significantly more sensitive to the average order size when the picking policy (i.e., using a batching policy) is the only one changed. This observation is reasonable because the opportunities for combining orders is eliminated as the average order size approaches the maximum batch size of 50 SKUs. Table 3 confirms this notion, showing that the bin-packing and FCFS batching procedures yield only a slight reduction in picking tours for larger order sizes. This insight may explain why some firms believe strict order picking is better than batch picking.

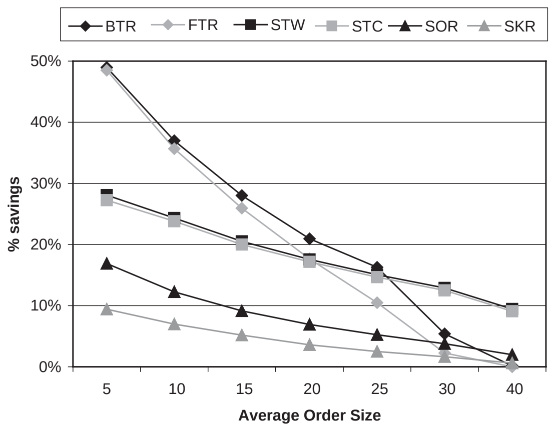
Further analysis of Fig. 3 reveals a slight interaction between the batching procedures and the average order size. While both batching procedures result in similar savings when average order sizes are either small or large, the bin-packing policy performs much better than the

FCFS policy when the average order size is between 20 and 30. Again, this difference in performance corresponds to situations when the bin-packing heuristic is significantly more effective at reducing the number of picking tours as shown in Table 3.

While the use of either batching technique alone (BTR and FTR) is more important for smaller order sizes, the use of either alternative storage policy (STW and STC) will yield greater savings when the average order size exceeds 25 items. It is also interesting to note that the difference in performance for within-aisle volume-based and class-based storage is less than 1% across all order sizes.

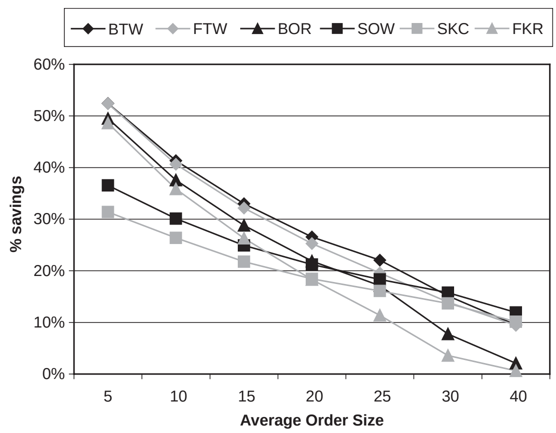
Fig. 3 also illustrates several important observations concerning routing policies. Fig. 3 supports the findings of the main experiment indicating that the use of a more complex routing policy alone will yield minimal improvements. This is particularly true for larger order sizes because the density of SKUs picked from each aisle increases. Consequently, the optimal and combined routing policies tend to form traversal routes.

Fig. 4 shows the performance for six of the twelve scenarios when two policy decisions are changed. The remaining six scenarios have been omitted for the sake of clarity without a loss of pertinent results. When the average order size is greater than 25 SKUs, all scenarios using the random storage policy while changing the remaining two policies suffer poor performance. This insight reflects the ineffectiveness of the picking and routing policies, as seen in Fig. 3, when pick densities are large as much as it indicates a hidden strength of the alternative storage polices. Therefore, it is essential to use either volume-based or class-based storage under



Note: Refer to Table 1 for a guide to notation. The baseline scenario corresponds to STR policies.

Fig. 3. Percent savings in total fulfillment time when changing one policy decision.



Note: Refer to Table 1 for a guide to notation. The baseline scenario corresponds to STR policies.

Fig. 4. Percent savings in total fulfillment time when changing two policy decisions.

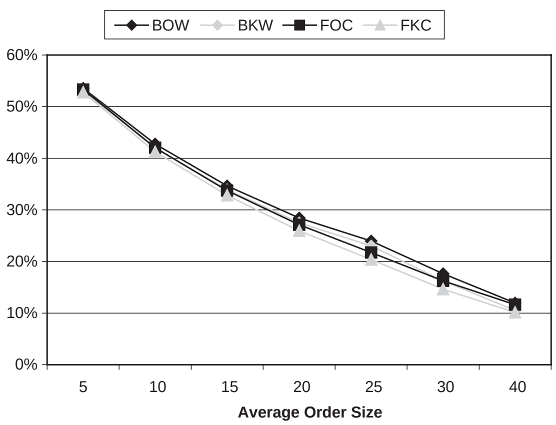
Table 3
Number of picking tours formed by the batching policies (500 orders)

Mean Order Size	5	10	15	20	25	30	40
FCFS	52	110	174	251	338	461	500
Bin-packing	50	100	154	211	254	408	497
Difference	2	10	20	40	84	53	3

those conditions to achieve an improvement in performance.

When the average order size is less than 25 SKUs, the use of either batching technique yields superior savings over two policy change combinations that employ a strict order policy. Combinations involving either batching policy with either volume-based or class-based storage (BTW, BTC, FTW and FTC) provide the most promising savings that range between 20% and 50% depending on the average order size. The implication to warehouse managers is that without regard to average order size, they can reduce picking time by nearly 20% by changing any two of the three decision policies. This finding is powerful because it provides warehouse managers the flexibility to choose a new picking, storage and/or routing policy that fits their unique business situation.

Fig. 5 displays the performance for half of the eight scenarios involving three policy changes. Again, the remaining four scenarios have been omitted without losing any insights. The savings for an order of 5 SKUs is between 53% and 54% and the savings for an order of 40 SKUs is between 10% and 12%. The only notable difference in performance (up to 4%) is between the bin-pack and FCFS batching policies when the average order size is between 15 and 30 SKUs.



Note: Refer to Table 1 for a guide to notation. The baseline scenario corresponds to STR policies.

Fig. 5. Percent savings in total fulfillment time when changing all policy decisions.

5.1.2. Warehouse shape

This sensitivity analysis examined whether the shape of the warehouse affects results when the warehouse capacity is held constant. The baseline warehouse in this paper had a (2×1) shape, where the width of the warehouse was twice as long as the depth. Other shapes investigated were (1×1), (1×2), and (3×1). Except for the (3×1) warehouse, the other warehouse shapes resulting in a minimal increase (less than 1.3%) in fulfillment time. Supporting the findings of previous research (Petersen, 1997), this result is beneficial to warehouse managers because the shape of an existing warehouse is usually difficult and expensive to change.

5.1.3. P/D location

This research assumed that the p/d point was located in the middle of the front cross-aisle. This additional analysis examined the effect of moving the p/d point to the left, front corner of the warehouse (the high volume SKUs were also moved to the picking aisles closest to the new p/d). This corner p/d resulted in a minimal increase of only 0.8% in picking time, although scenarios using strict order picking had an average increase of 4.8% for an order size of 5 SKUs, 1.6% for 10 SKUs, but less than 0.4% for all order sizes above 15 SKUs. This result is consistent with De Koster et al. (1999) and Petersen (1997).

5.1.4. Demand distribution of the SKUs

This research assumed an 80–20 distribution of the SKUs, meaning that 20% of the SKUs have 80% of the pick activity. To examine the effect of demand distributions, a sensitivity analysis was conducted to evaluate a 60–20 distribution of the SKUs. As expected, this change had no impact on the results when using random storage. When one of the batching techniques was used, fulfillment time only increased 3.2%. The greatest impact of approximately 6% was observed when using strict order picking and/or traversal routing.

6. Concluding remarks

This paper evaluates the effect of picking, routing, and storage policies on a manual bin-shelving order picking operation. Results of the simulation experiment show that batching has the largest impact on reducing total fulfillment time, particularly when small order sizes are common. In this paper we assume that the picking cart has separate compartments to maintain individual order integrity and to eliminate additional sorting efforts before order shipments. If this option is not practical, any benefits gained with batch picking may quickly disappear due to the need for additional sorting operations.

The simulation experiment clearly shows that within-aisle volume-based and class-based storage also requires significantly less picker travel than random storage. However, a random storage policy generally utilizes the entire picking area more evenly and reduces worker congestion. Volume-based and class-based storage may require periodic movement of SKUs to reflect the demand distribution of the SKUs during the year. These policies may also increase picker congestion within aisles containing the most popular SKUs. Furthermore, the additional savings that result from using volume-based storage over class-based storage with three storage classes is less than 1%. This is an important observation for warehouse managers because it shows that simple class-based storage policy can significantly reduce total fulfillment time nearly as much as a more information intensive volume-based storage policy.

Finally, results show that switching from traversal to optimal routing does offer a reduction in picker travel, but this reduction is significantly less than changing picking or storage policies. Discussions with several firms also revealed that simple routing heuristics, such as the traversal policy, were considered much more acceptable because they tend to form more consistent routes when compared to routes generated by optimal procedures. This issue should not be overlooked because more complex routes cause more confusion, which in turn will increase picker time and errors.

References

Bartholdi, J.J., Eisenstein, D.D., Foley, R.D., 2001. Performance of bucket brigades when work is stochastic. Operations Research 49 (5), 710–719.

Brynzer, H., Johansson, M.I., 1995. Design and performance of kitting and order picking systems. International Journal of Production Economics 41, 115–125.

Caron, F., Marchet, G., Perego, A., 2000. Optimal layout in low-level picker-to-part systems. International Journal of Production Research 38 (1), 101–117.

Coyle, J.J., Bardi, E.J., Langley, C.J., 1996. The Management of Business Logistics, 6th Edition. West Publishing, St. Paul, MN.

De Koster, M.B.M., Van der Poort, E.S., Wolters, M., 1999. Efficient orderbatching methods in warehouses. International Journal of Production Research 37 (7), 1479–1504.

Eynan, A., Rosenblatt, M.J., 1994. Establishing zones in single-command class-based rectangular AS/RS. IIE Transactions 26 (1), 38–46.

Gibson, D.R., Sharp, G.P., 1992. Order batching procedures. European Journal of Operational Research 58, 57–67.

Graves, R.J., Heragu, S.S., St Onge, A., 2002. Intelligent agent modeling of an industrial warehousing problem. IIE Transactions 34 (7), 601–612.

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

Hall, R.W., 1993. Distance approximations for routing manual pickers in a warehouse. IIE Transactions 25 (4), 76–87.

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

Petersen, C.G., 1997. An evaluation of order picking routing policies. International Journal of Operations & Production Management 17 (1), 1096–1111.

Petersen, C.G., 2000. An evaluation of order picking policies for mail order companies. Production and Operations Management 9 (4), 319–335.

Petersen, C.G., Schmenner, R.W., 1999. An evaluation of routing and volume-based storage policies in an order picking operation. Decision Sciences 30 (2), 481–501.

Ratliff, H.D., Rosenthal, A.S., 1983. Order-picking in a rectangular warehouse: A solvable case of the traveling salesman problem. Operations Research 31 (3), 507–521.

Roodbergen, K.J., Koster, R., 2001. Routing methods for warehouses with multiple cross aisles. International Journal of Production Research 39 (9), 1865–1883.

Ruben, R.A., Jacobs, F.R., 1999. Batch construction heuristics and storage assignment strategies for walk/ride and pick systems. Management Science 45 (4), 575–596.