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Simulation analysis of narrow-aisle order selection systems

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ABSTRACT

Selection of items to fill customer orders from systems of pallet rack or shelving arranged in rows with access by means of narrow aisles is becoming commonplace in many distribution centers.

Such systems offer significant advantages in terms of space savings and utilization of the "cube" in distribution facilities. Narrow-aisle high-density order selection systems may tend, however, to have an adverse effect on selection productivity if not planned properly.

This paper is a case study in the use of simulation as a tool for making informed decisions about the design of a narrow-aisle order selection system. Using hypothetical data, and a set of models developed in the SIMAN simulation language for one of the world's largest parts distribution centers, it examines the effect on selection productivity of three key factors in the design of a selection system:

System Configuration
Stocking policy
Selection policy

1. DESIGN ISSUES

A company has decided to consolidate the small parts in its distribution center in a high-density storage system with 10,000 bins. Given the sizes of the parts involved, a bin size of 12" high x 36" wide x 24" deep has been selected. The system is being installed in an existing warehouse, and since the clear height in this building is just over 25', the shelving system is being limited to 25 levels (Figure 1).

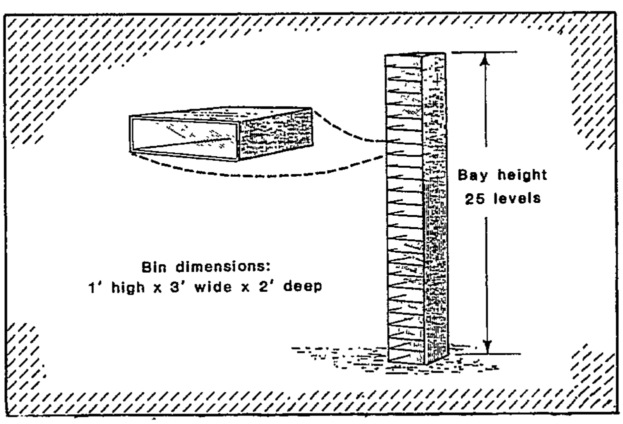

Figure 1: Bay Height and Bin Dimensions

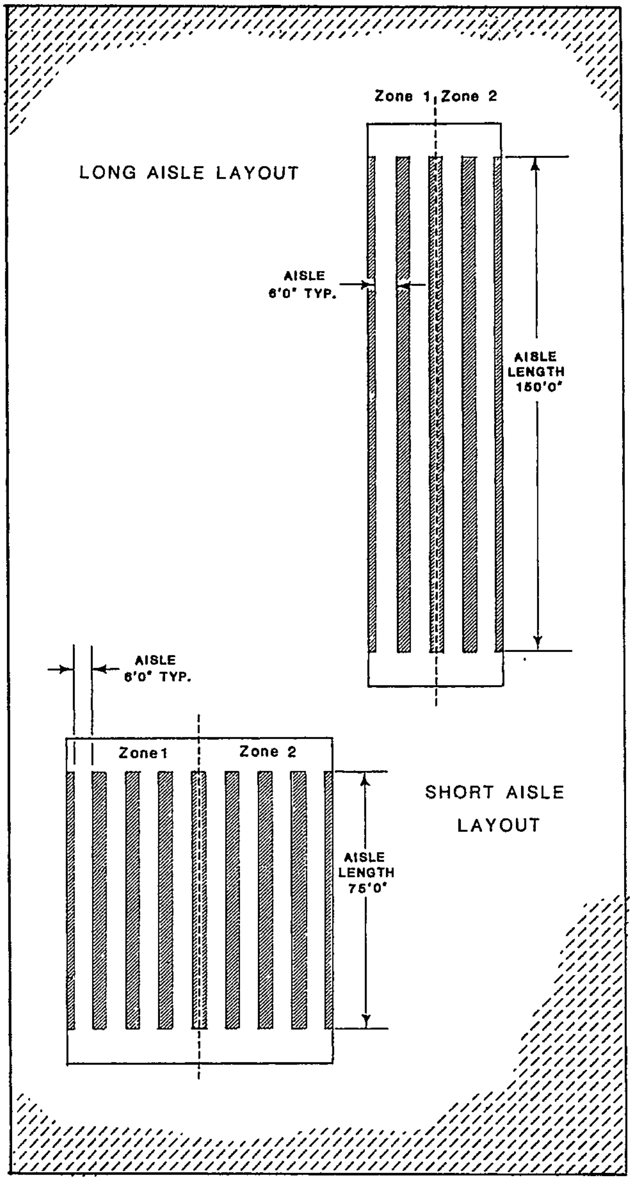

Figure 2: System Configuration Alternatives

There are two candidate locations for the shelving system. One of these locations is a long, narrow area that would accommodate 10,000 bins in four aisles, each 150' long, while the other is more nearly square, and would permit eight 75' aisles (Figure 2). For convenience of reference, we will call these alternative system configurations the long-aisle and the short-aisle layouts. One of the objectives of our simulation was to assess what effect, if any, *system configuration* (aisle length) has on picking productivity.

Orders for parts held in the shelving system will be picked by two wire-guided orderpickers (Figure 3). These vehicles are driven by human operators, and move from one aisle to another under manual control. Once an orderpicker enters an aisle, the operator switches to automatic control. This enables guidance from a wire embedded in the floor of the aisle which keeps the vehicle centered. The operator therefore needs only to control the vertical movement of the carriage, and the horizontal travel of the vehicle down the aisle.

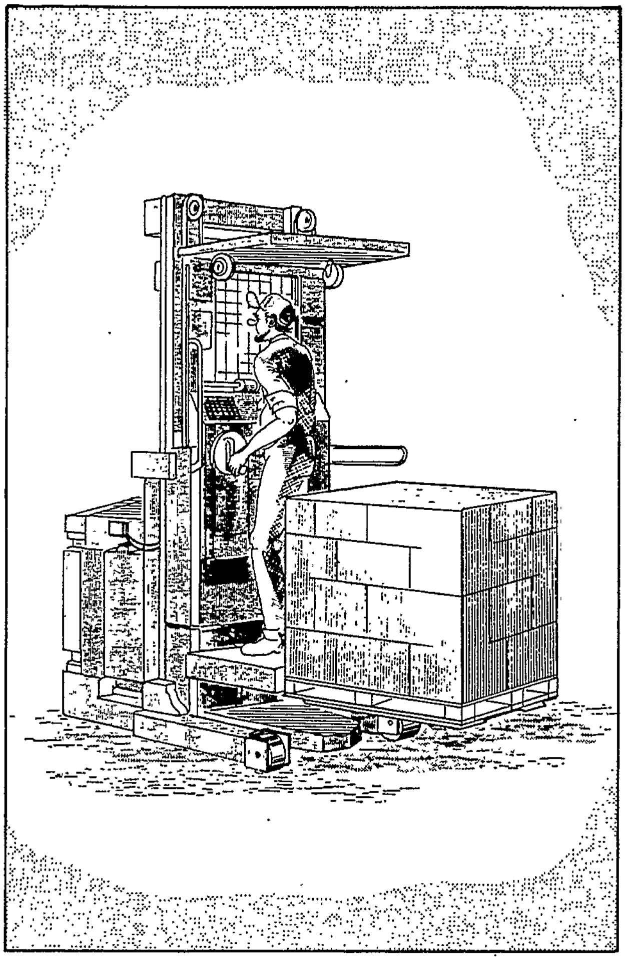

Figure 3: An Orderpicker

An orderpicker is capable of raising an operator and payload to a height of 20' or more, but as the carriage moves up in this range, the danger increases that the vehicle or load will topple over in the event of a sudden stop. To avoid this, an orderpicker has a control system that senses the height of the carriage, and limits horizontal speed accordingly: the higher the carriage, the lower the top horizontal speed.

Because an orderpicker can move faster with its carriage down than with its carriage up, it may be advantageous in some systems to concentrate fast-moving parts in the lower levels of the shelving structure. In other systems, however, the extra effort required by this discipline may yield little or no improvement in picking productivity.

Hereafter, we will refer to this policy as sweet-zone stocking. Figure 1 shows the sweet-zone stocking arrangement contemplated, where 80% of the picks are made from the lower 20% of the shelving structure. An alternative to sweet-zone stocking is random stocking, in which the level where a part is kept is independent of the frequency or size of orders for that part. The second objective of our simulation analysis was to determine whether the sweet-zone *stocking policy* offers significantly greater picking productivity than random stocking.

The sequence of operations for picking an order is as follows:

1. Drive to a dispatch location and get a pick list and empty container.

2. Pick the items on the pick list, in the order in which they appear.

3. Deliver the on-board container to a drop station whenever it fills up, or when all picks on the list have been completed.

Activities 1 and 3 in this sequence may be considered overhead: order selection productivity tends to increase if the time spent dropping containers and getting dispatch lists can be minimized.

To reduce the risk of collisions, an operator is not allowed to enter an aisle that is already occupied. This fact, together with the requirement that picks be made in the order given on the pick list, brings about an additional overhead factor: If operator A's next pick is in an aisle currently occupied by operator B, then A cannot enter and begin picking in that aisle until B departs.

One way to eliminate waiting for aisles is to divide the shelving system into zones of approximately equal size, one for each orderpicker, as shown in Figure 2. Since all aisles in a zone are assigned exclusively to a single operator, an operator is always assured immediate entry into the aisle containing the next pick.

Though zoned picking eliminates competition for aisles, it may increase the time spent delivering full containers and fetching new pick lists: In a zoned system with two operators, each one is responsible for picking only about half of each order. On completing a pick list that is only half as long as before, the operator must deliver a partially filled container to a drop station and go get another pick list.

It may be possible to reduce this disadvantage of zoned picking by subdividing the on-board container, and picking a batch of several orders on each pass through a zone, rather than picking only one order at a time. The dividers in the on-board container provide a way to maintain separation between goods belonging to different orders. Figure 4 shows a picking container divided into 16 compartments for batch picking, as well as a container without dividers for use in picking single orders.

The third objective that we hoped to accomplish with our simulation analysis, then, was to determine whether the

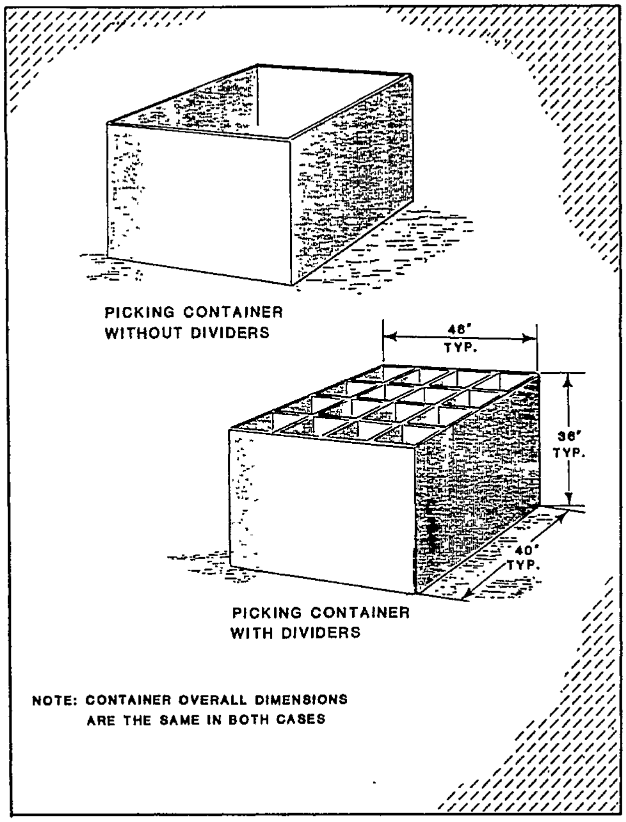

Figure 4: Picking Container Alternatives

selection policy of zoned picking of batched orders yielded higher picking productivity than full-range picking of single orders. (In this case study, each batch consisted of four orders.)

We have now identified three design factors: system configuration, stocking policy, and selection policy. For each design factor, two alternatives are under consideration, giving a total of eight distinct system designs to be tested in a 2 x 2 x 2 full factorial experimental design.

The primary performance measure used in our analysis was picking productivity, measured as pieces picked per man-hour. The model was also structured to keep track of the utilization of the operators, i.e. the percentage of their time spent in the aisles picking orders.

2. ASSUMPTIONS

In order to develop a model of an order selection system and measure the number of pieces picked per man-hour, one must make a number of assumptions not implied by a particular choice of values for the three design factors. This section lays out the assumptions made in this case study.

First, one must make some assumptions about the size of the orders (and the parts) to be picked. Table 1 defines the order characteristics assumed in this paper. Note that the volume of the part being picked, together with the number of pieces found in each location, affects the number of locations an operator must visit in order to fill a given line item. The number of line items on an order, and the number of locations visited to fill a line item, in turn affects the frequency of trips to drop off completed orders and pick up new pick lists.

Table 1: Order Characteristics

Order characteristic	Type of distribution
Line items per order	Triangular; min. 1, mode 6, max. 18
Pieces per line item	Triangular; min. 1,mode 12, max. 38
Cu. in. per piece	Exponential; mean 216

A pick list is a list of the locations that must be visited to pick a given (batch of) customer order(s). A location is defined in terms of four variables: an aisle, a bay, a level, and the side of the aisle from which pieces are to be picked. Aisle side was assumed to have no significant effect on the time required for picking and was excluded from the models.

Table 2 defines the probability distributions used in selecting the aisle, bay, and level for a given pick. Four points deserve comment. First, we assume that the quantity of parts required for each line item can be picked from a single aisle. Second, sweet-zone stocking was distinguished from random stocking by the probability distribution used to determine the level for a pick location. Random stocking made all levels equally probable, whereas sweet-zone stocking applied a kind of "80-20" rule when assigning levels to picks, i.e. 80% of the picks were made from the lower 20% of the levels in the shelving system.

Table 2: Pick Locations

Dimension	Probability distribution
Aisle	All aisles equiprobable
Bay	All bays equiprobable
Level (random)	All levels equiprobable
Level (sweet zone)	Levels 1- 5: 0.8 Levels 6-25: 0.2

Third, pick lists were sorted by aisle, bay, and level, so that all picks in an aisle were together in ascending sequence by bay, and all picks from the same bay in an aisle were in ascending sequence by level. Finally, we assumed that every bin was 80% full. Given the volume of the item being picked (see Table 1), and the size of the bins (see Figure 1), this made it possible to calculate the number of pieces available at each pick location, and hence the number of location visits needed to fill a given line item. In the vast majority of cases, a single bin location contained all the pieces needed to complete a line item.

Table 3: Operating Characteristics

Carriage elevation	Orderpicker speed
0"- 60"	7.0 fps
60"-150"	3.5 fps
> 150"	1.0 fps

Orderpicker acceleration: 1 fpss (vertical as well as horizontal)

Operator Activity	Time required
Pick one piece	5.0 sec.
Drop a container	3.5 min.
Get a new pick list	5.2 min.

The assumptions given in Tables 1 and 2 enabled us to determine how many picks there were on each pick list, and where those picks were located. To complete this overview of model assumptions, we need to describe the operating characteristics of the orderpickers and operators. The models used these characteristics in calculating the time required to travel from one pick location to another, pick the required number of pieces, deliver the completed order to a drop station, and visit the dispatcher to get a new pick list. Table 3 defines these assumptions about the characteristics of the operators and their equipment.

3. RESULTS

Models were prepared for the eight system alternatives called for by the experimental design, and statistics were taken from ten replications of each model. Each replication consisted of a two-hour stabilization period, followed by a ten-hour statistical reporting period. (Statistics from the stabilization periods were discarded to avoid contamination from start-up effects.)

Table 4 gives the performance measure means and standard deviations over the ten replications for each of the eight models, while Table 5 reports observations on operator utilization.

Table 4 shows that zoned picking of batched orders yields considerably higher productivity than full-range picking of single orders. Sweet-zone stocking seems conducive to somewhat higher picking productivity than random stocking, and long aisles also yield slightly higher picking rates than short aisles.

Selection policy also has a strong influence on utilization of the orderpickers (Table 5), but neither stocking policy nor system configuration seem to have much effect on utilization.

Table 4: Pieces Picked Per Man-Hour

Full range picking of single orders

	Random stocking	Sweet-zone stocking	
Short aisles	304.2 8.1	316.8 12.3	Mean SD
Long aisles	314.7 9.5	321.3 15.4	Mean SD

Zoned picking of orders in batches

	Random stocking	Sweet-zone stocking	
Short aisles	434.0 6.3	447.6 8.2	Mean SD
Long aisles	444.9 7.9	452.4 7.9	Mean SD

Table 5. Operator Utilization

Full range picking of single orders

	Random stocking	Sweet-zone stocking	
Short aisles	56% 2%	56% 2%	Mean SD
Long aisles	58% 2%	58% 2%	Mean SD

Zoned picking of orders in batches

	Random stocking	Sweet-zone stocking	
Short aisles	74% 1%	73% 2%	Mean SD
Long aisles	74% 1%	74% 1%	Mean SD

In Table 6 we quantify these general impressions of Tables 4 and 5 by giving approximate 90% confidence intervals for the main effects on productivity and utilization of the three factors in our experimental design (see Law and Kelton 1982, p. 376; we omitted the confidence intervals for two-way interaction effects because all these intervals included zero.)

This table shows that the effect of selection policy on productivity was about 13 times as strong as the effect of stocking policy, and selection policy's effect on utilization was nearly 17 times stronger than that of configuration.

Table 6: Effects of Experimental Factors

Effects on Productivity (Pieces per Man-hour)

Factor	Lower 90% confidence limit	Mean effect	Upper 90% confidence limit
Selection	+117.7	+130.5	+143.3
Stocking	+ 1.2	+ 10.1	+ 19.0
Configuration	+ 2.6	+ 7.7	+ 12.8

Effects on Utilization

Factor	Lower 90% confidence limit	Mean effect	Upper 90% confidence limit
Selection	+16.0%	+16.7%	+17.4%
Configuration	+ 0.6%	+ 1.0%	+ 1.4%
Stocking	- 0.5%	+ 0.1%	+ 0.7%

4. CONCLUDING OBSERVATIONS

In conclusion, we wish to make two observations regarding this case study.

First, we have calculated confidence intervals for the effects of the design factors, but managers may (without irrationality) make decisions contrary to those one would recommend on the basis of a narrow interpretation of the statistics.

For example, use of sweet-zone stocking has a beneficial effect on productivity, but the cost of developing software to implement this policy, and the cost of continually updating the list of "fast movers," and re-stocking parts may outweigh the benefits of this policy.

Configuration, on the other hand, has a weaker effect on productivity than stocking policy, but the long-aisle layout also occupies about 10% less floor space than the short-aisle layout, so a manager might opt for long aisles in spite of the weakness of the statistical support for this configuration.

Conway et al. (1987), writing about the application of statistical hypothesis testing in simulation work, proposed the following Axiom of Significance in Simulation:

If you can't see it with the naked eye, forget it.

We believe that a manager faced with the results presented here would probably do well to act on this advice. In fact, we would go further. Even zoned picking of batched orders may not be justified, though the strength of its effects *are* obvious to the naked eye. Under this policy, it might be necessary to install additional equipment and hire additional personnel to consolidate the various containers making up each order, whereas the improvement in picking productivity might not be large enough to outweigh these additional costs.

Second, the reader would be ill-advised to act on the results presented in this paper, unless there happens to be an excellent match between the attributes of the system being planned and the assumptions presented in sections 1 and 2 above. There is no such thing as a system design that satisfies every set of requirements in an optimal way.

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