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Build Next-Gen Warehouse: Boost Efficiency & Customer Satisfaction with Automated Order Picking

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Problem of practice:

Online shopping demand has outpaced the development of supporting infrastructure and resources. This might seem to be a good problem for e-tailers and warehouses. However, if this demand is not fulfilled efficiently, it can have costly consequences, even for the biggest and best brands. Order delays and errors mean customer satisfaction suffers, and costs inflate – a combination which squeezes an organization's bottom line. This increasing pressure on efficient order fulfillment has led to advances in warehouse design and automation. However, new research suggests that warehousing efficiencies can be increased a further 20% or more by using an algorithm that combines two datasets – demand for a product, and its affinity to be ordered with other products. This research, by Masoud Mirzaei, Nima Zaerpour and Rene de Koster, found these gains in warehouses that use automated order picking – where robots bring entire racks with products to human operatives.[1] We believe that the core insight can change the game for all warehouses – regardless of the degree of automation – by reducing order-picking time, enabling faster delivery times and improving space utilization

[1]Featured in the February 2021 issue of the *Transportation Research Part E: Logistics and Transportation Review*, authors Masoud Mirzaei, Nima Zaerpour, and Rene de Koster in their article: 'The impact of integrated cluster-based storage allocation on parts-to-picker warehouse performance' talk about how the use automated order picking can reduce order-picking time, enable faster delivery times, and improve space utilization

The E-commerce revolution

Over the last two decades, online shopping has led customers to expect improved choice, competitive pricing, and convenience, leading to continued growth in e-commerce.[2] In 2022, global retail e-commerce sales amounted to approximately US $5.7 trillion and by 2026, this number is expected to rise to $8.1 trillion.[3] As online shopping grows in importance, so does e-commerce order fulfillment. For a typical e-commerce distribution center, almost 55% of the total cost of order fulfillment is taken up by order-picking activities.[4] The research by Mirzaei and team has the potential to bring down order fulfillment time, cost associated with storage, as well as errors in order picking, by simply changing how items are stored in the warehouse.

We believe that this insight can also help e-tailers not only in developed markets like the US and China, but also in developing market contexts such as India which is one of the fastest-growing e-commerce markets.[5] These large values indicate that there is a need for better and faster service and order turnaround. It is here that warehousing efficiencies can add immense value both in developing markets and the world over.

Warehouse tradition

In any large e-commerce fulfillment warehouse, every order's items need to be retrieved from storage and brought to an order assembly station, where the items can be prepared for dispatch. Depending on the level of automation, the product retrieval from storage could be completely handled by robots, or by workers with or without mechanical assistance (e.g. forklifts). With higher levels of automation, an entire storage bin or pod is lifted and moved to the order assembly station (*as shown in Figure 1*), where the relevant items are taken out for packaging and dispatch.

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Figure 1: A storage pod being transported within a warehouse

Source: Geni. Amazon Warehouse Robot 2020. July 10, 2023. Photograph, 4624 × 3412 px.

In developing countries like India, there are some warehouses that still follow traditional storage methods such as Random Storage Policy. Under this method, the manager allocates products to any available storage location. But such a method can prove disastrous if a high-demand item gets stuck deep in storage, which, in turn, slows down item retrieval, thus delaying order delivery, for which the company stands to lose money due to slower item turnover.

A better policy – but not necessarily the best – is the famous ABC or **Class-Based Storage Policy** (CBS). In this method, products in the warehouse are arranged based on demand (typical turnover of a product) and required storage space. Here, warehouse managers categorize all stored items into classes named A, B, C and so on. The method recommends storing items with higher demand turnover in an area closer to the assembly station (from where the order is put together and dispatched) so that it takes less time to move it through the warehouse during order retrieval. Using a similar logic, lower-demand turnover products should be stored further away. Class-based storage system significantly reduces the turnaround time of order picking in a warehouse but as e-commerce is evolving, this method is also in need of an upgrade.

Warehouse evolution

As e-commerce evolved, e-tailers noticed that customers often order multiple products together. For instance, when ordering a smartphone online, customers might often also order earbuds, and/or a charging cable. Such an order pattern suggested a need to evolve warehouse storage beyond just a single-item or stock keeping unit (SKU) demand. Why? Because the *affinity* between two SKUs was found to impact order fulfillment time. Affinity can be defined as how often the two items are ordered together. Mirzaei and team tested the traditional CBS method against methods that incorporated product affinity as well as individual product demand.

We illustrate the comparison between storage methods with an example that may be typical for e-commerce warehouse orders during the festive season. A warehouse manager, let's call her Sara, notices that smartphones (S) are flying off the shelves – they have a *high demand turnover*. Sara also notices that customers who purchase smartphones often also order earbuds (E) and/or a charging cable (C) and/or a power adapter (P) on some occasions together. *Figure 2* summarizes this pattern of demand, and how Sara might mine the data. This data-mining exercise yields crucial insight into different storage strategies. Sara now

needs to allocate storage of smartphones and the relevant accessories to her two available pods, one close (pod 1) to the order assembly point, and the other (pod 2) further away (*see Figure 3*). Two constraints apply to Sara's situation, which might be similar to real-world constraints: 1) Each pod can store the entire quantity of any two SKUs at a time. The right quantity ensures that the SKUs in all 11 orders in *Figure 2* are covered. 2) Items of each SKU are placed entirely in a single pod and cannot be shared between pods.

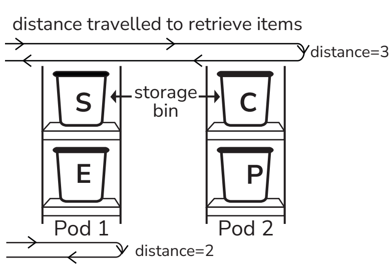
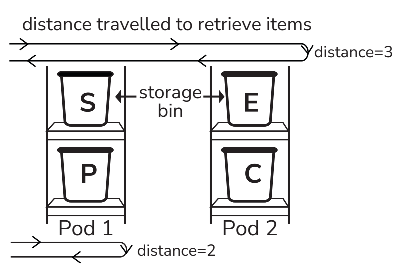
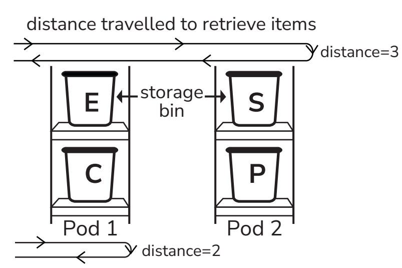
Figure 2: Illustrative Order Pattern for Smartphone and Accessories

Order Data	Demand Turnover Analysis			Affinity Analysis		
#1: S, C						
#2: S, E, P						
#3: E, C	Top-Rank	SKU	Turnover	Top-Rank	Correlation	Instances
#4: S, P						
#5: S, E, P	i	S	8		S&E	4
#6: S, C	ii	E	7		S&C	2
#7: E, C	iii	C	5	I	S&P	5
#8: S, E	iii	P	5	ii	E&C	3
#9: E, C					E&P	3
#10: S, P					C&P	0
#11: S, E, P						

Source: Adapted by the authors based on the article by Mirzaei and team.

Once the data is mined, Sara can compare the classic CBS approach with two approaches that incorporate the affinity factor: **Sequential Turnover-Affinity Storage** (STAS) and **Integrated Cluster Allocation Storage** (ICAS). Depending on which SKUs are stored in which pods, these comparisons are summarized in *Figure 3*.

Figure 3: Storage Policies Compared

	CBS	STAS	ICAS
How it works	Using this method, Sara would store Smartphones (S) along with Earbuds (E) in the location nearest to the order assembly (pod 1), as these items have the highest turnover – 8 and 7 respectively. The remaining two items – charging cable (C) and earbuds (E) – go to the more distant pod (pod 2).	In this strategy, a high turnover item is placed with a highly correlated item in sequence. Thus, Sara would place Smartphones (S) in the closest pod as it has the highest demand turnover. But then, Sara would place the product having the highest affinity with S – power adapters (P) in the same pod (pod 1). Sara would continue this sequential process of assigning SKUs for the distant storage pod. This sequential approach conforms to a human intuition: "There is no point in allocating higher correlated SKUs that don't have a healthy demand turnover."	For this technique, Sara would depend on the optimization algorithm to make storage decisions by considering turnover and affinity in a combined fashion rather than sequentially. ICAS uses a linear, binary integer optimization algorithm, which is a bit of a black-box, but yields very powerful, counter-intuitive storage efficiency results. By the above integrated algorithmic approach, Sara finds that the closest pod should store Earphones (E) and a Charger (C). This is a counterintuitive idea as (E) and (C) neither have the highest turnover SKUs nor they highest affinity from the list.
Graphic depiction			
Distance traveled[a]	52[b]	43[c]	42[d]

Source: Developed by the authors based on the article by Mirzaei and collaborators

[a] *To retrieve an item from storage: Lesser distance implies lower cost and better time efficiency*

[b] *Distance travelled for CBS scenario can be calculated as: 52 = {SC(5)+SEP(5)+EC(5)+SP(5)+SEP(5)+SC(5)+EC(5)+ SE(2)+EC(5)+SP(5)+SEP(5)} where SC(5) = represents the distance travelled for order with items S and C. In case of CBS, SKU S needs pod 1 to travel to the assembly station (AS) so the distance is 2 and SKU C needs pod 2 to travel to the AS so the distance is 3 with a total of 5*

[c] *Distance travelled for STAS scenario can be calculated as: 43 = {SC(5)+SEP(5)+EC(3)+SP(2)+ SEP(5)+SC(5)+EC(3)+ SE(5)+EC(3)+SP(2)+SEP(5)} where the terms have a similar meaning as above*

[d] *Distance travelled for ICAS scenario can be calculated as: 42 = {SC(5)+SEP(5)+EC(2)+SP(3)+SEP(5)+SC(5)+EC(2)+ SE(5)+EC(2)+SP(3)+SEP(5)} where the terms have a similar meaning as above*

Given that the distance is minimized under ICAS, that should be the option Sara selects. But what about the thousands of warehouse managers around the world? Should they all switch to the integrated algorithmic ICAS approach? Or are there conditions under which other storage strategies are better?

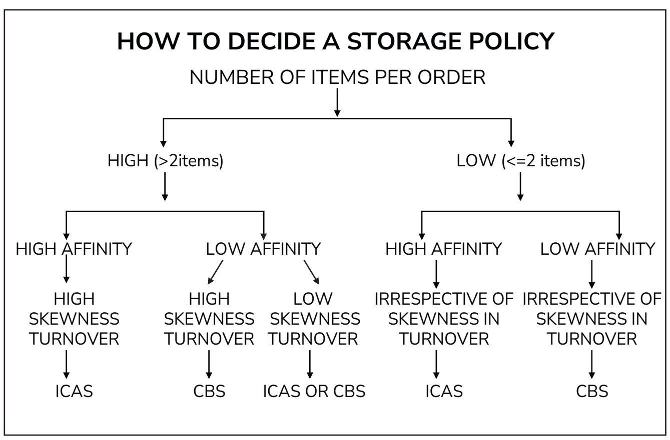
Storage policy considerations

As a warehouse or logistics manager, a key question is **when** to use **which** storage method. While the above example of smartphones and accessories is easy to follow, your actual patterns in demand data could suggest a different policy. Let's take the base case – if extensive order history data is unavailable, e.g. in the case of a new market or new SKUs, then we recommend using CBS policy until sufficient data is gathered post mining. And then, only consider an ICAS or any other integrated storage approach, if the affinity factor across products is high.

We summarize the decision-making drivers for storage policy in *Figure 4*. Note that we have not included STAS policy as this method is similar to ICAS.

Apart from the demand and affinity discussed above, *Figure 4* also takes into account the skewness of the turnover of all SKUs while opting for a storage method. Generally, high skewness in turnover occurs when at most 20% of the SKUs in a warehouse account for 80% of the demand turnover (Pareto's Law). Such high skewness is generally seen in fashion, apparel, and lifestyle items, where trendy items get ordered more frequently than the rest. Low skewness in turnover is generally seen in orders for daily necessities such as groceries or household items. Another consideration for warehouse managers is the mix of number of items in orders (*see Figure 4*). Most online e-commerce transactions, as seen in Amazon or Flipkart, have a low number of items (two or fewer) in a single order. [6]

Figure 4: Decision Parameters for Warehouse Storage Method



Source: Developed by the authors based on the article by Mirzaei and team

Another key consideration to deploy ICAS or any other advanced storage allocation policy is cost considerations. Clearly, a 20% increase in efficiency that accompanies such a policy would offset a one-time cost of upgrading your warehouse storage management system to a pod assembly with robots where the mobile bots essentially carry pods to an assembly station. The investment depends on your current level of automation and nature of customer orders and warehouse picking data.

To sum up...

As e-commerce volumes ramp up globally, e-tailers can garner higher savings from improved warehouse storage policies. We have highlighted how a new technique – that takes into account affinity of items within your order history – is a key to faster order turnaround. The ICAS policy is the best of the current crop of solutions, and with machine learning, even better results can be anticipated. Artificial intelligence could even predict changes in order patterns and adjust storage policy dynamically. To realize maximum benefit of these algorithms, e-tailers, especially in developing markets, should consider upgrading their level of automation to human-supervised robots. The quick win here is to adopt a rational policy based on existing order patterns that can reap huge benefits in cost savings and customer satisfaction.

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