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Simon Hummelshøj Sloth, Magnus Abildsten Bøgh, Christian Møller Nielsen, Konstantinos Panagiotis Konstantinidis, and Inkyung Sung[0000-0002-7045-8143]

Department of Materials and Production,
Aalborg University, Aalborg, Denmark
{ssloth16, mbagh16, cmni16, kkonst19}@student.aau.dk,
inkyung_sung@mp.aau.dk

**Abstract.** Designing the operating policies of picking systems, which connect inventory and production/assembly lines in a manufacturing system, involves determining replenishment methods for individual items. These replenishment methods affect the overall labor cost and flexibility of the picking system by determining the frequency and quantity of item picking. To design the replenishment method, in this paper, we propose a data-driven decision support framework that provides guidance in comprehending features in a picking system based on demand, size, and value of individual items. The proposed framework is then applied to a real-world case for validation.

**Keywords:** Order picking · Continuous replenishment · Replenishment methods · Data-driven decision support · Principal component analysis

## 1 Introduction

Many companies, especially manufacturers, have seen increasing pressures on cost reduction during the past decades. To cope with this, they often focus on efficient production processes to reduce the operating cost. Furthermore, manufacturing systems have been increasingly challenged by short product life cycles, frequent product introductions and ever changing product mix. These trends force manufacturing companies to focus on a flexible and responsive manufacturing system [1].

One of the system elements contributing to the desired production and manufacturing systems is a picking system, which conducts the process of retrieving items from storage and fulfilling the order of internal or external customers. By nature, the picking system plays a key role as an interface between inventory and production. Importantly, the picking system accounts for a large part of operating costs related to inventory due to the labor-intensive nature of the activities involved in the system. In general, labor cost accounts for upwards of 55% of the total inventory operating cost [2], therefore, the cost for inventory operations can be reduced dramatically by designing an efficient picking system.

The complexity of picking system design is mainly determined by the target system characteristics. These include mechanization level of a system, information availability, scale of operations, and organizational/operating policies for storage, routing, batching and order release [3]. In this paper, we focus on designing an operating policy especially for a replenishment method that governs overall picking processes. Specifically, a replenishment method specifies (1) how a picking order for a specific item is generated, (2) how the picking orders are batched, (3) how the items are picked, and (4) how the items are delivered.

A replenishment method is generally designed by following the conventional discrete order picking (COP) method or the continuous replenishment (CR) method. In the COP method, the items are picked to an order generated with a fixed time interval, whereas in the CR method, the items are continuously picked by re-order point logic following a pull type control mechanism [3–6]. While the CR method lowers picking labor cost and increases the picking flexibility in general [6], the performance of the methods varies depending on the characteristics of the item to be picked [7].

Let us note that the replenishment method choice is not straightforward due to the complicated relationships involved in a picking system and picking operations. For example, human factors such as learning, fatigue and ergonomics [8] are critical to the choice but difficult to measure. The real-life conditions, e.g. safety constraints and picker blocking [9], also increase the complexity of relevant planning problems including the replenishment method choice. As a result, an analytical framework for the replenishment method choice in a picking system has not yet materialized properly and the choice often relies on human expertise in practice.

To address the issue, we propose a data-driven replenishment method choice framework that guides a manager to identify a suitable replenishment method for an item, i.e. whether an item is replenished by the COP method or the CR method. Given a data set containing various items and their specifications, we first determine the attributes of the items that explain the data set, and classify the items based on their replenishment methods (COP or CR), resulting in two data clusters. Given an item of interest, closeness of the item to the clusters of the replenishment methods is evaluated with respect to the attributes determined and, finally, the corresponding replenishment method of the cluster with higher closeness to the item is proposed for the item.

## 2 Proposed Replenishment Method Choice Framework

In this section, the proposed framework is explained with connection to its implementation in a large Danish manufacturing company. The framework consists of six steps as visualized in Fig. 1.

***Step 1*** is to identify the attributes of items that would affect the replenishment method choice. Through interviews with the relevant decision-makers in the manufacturing company and considering the commonly available attributes of an item in the database of companies, we identify the following attributes of

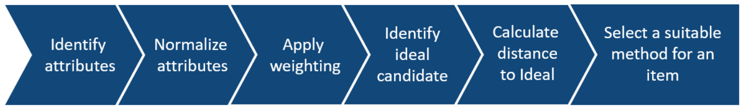


Fig. 1: Visualization of the replenishment method choice framework

an item, which will be used to classify the replenishment method of the item: *size, weight, price* and *demand*.

For a physical item to be picked, it is critical to consider its *size* to evaluate if the item violates space constraints in the picking system. Similarly, the *weight* of an item is essential for the replenishment method choice as the total weight of items carried on a shelf or a pallet is limited. The size and weight of an item are also important as they are closely linked with ergonomic challenges for system operators.

*Price* is another attribute that affects the desired replenishment method for an item. Note that the CR method tends to pick an item in larger batches, allowing the following assembly or production process to stock the item for convenience. However, this practice could increase the risk of the item being lost or damaged during the stock period. Therefore, the COP approach that would reduce the batch size of the item will be suitable for an expensive and valuable item.

Last, the *demand* of an item, and in particular the demand rate of the item, are keys to sustain a flow of items in a system. Obviously, an item with low demands is not suitable to be managed by the CR method. We further consider the *demand variation*, which affects the safety stock level of an item.

It should be noted that the impact of the selected attributes of an item on the replenishment method choice would vary depending on the picking system of interest. To address this issue, further analysis can be performed to see how well the picking item data of the system is explained by the selected attributes.

For this purpose, the principal component analysis (PCA) can be used to evaluate whether the identified attributes are able to explain the variation between the replenishment method choices of items. The PCA is a tool for dimension reduction with the aim of reducing several variables into fewer principal components (PC) that captures a decreasing amount of the variation between the given observations [10].

A Danish manufacturing company investigates their choice of replenishment method for the items to be picked in relation to their internal logistics between inventories and several assembly lines. At the time of investigation, 1777 items and 274 items are being replenished by the COP and CR methods, respectively.

Considering the item attributes proposed in the framework, the company set the *weight, price, yearly demand,* and *demand variation* of an item as the attributes of interest for the replenishment method choice.

To verify the attributes identified, the PCA is performed on the data set of the items, which contains all the attribute values of the items covered in the picking system. The result shows that the selected attributes are able to explain the variation between the items. The PCA result is summarized in Table 1. The PC 1, which is the direction of the data where the most variation in the data is explained, is mainly contributed by the weight, price and the coefficient of variation (CV) of demand.

Table 1: Cumulative variation explained by the principle components

| **Attribute** | **PC 1** | **PC 2** | **PC 3** | **PC 4** |
|---|---|---|---|---|
| Yearly Demand | 0.041 | 0.984 | 0.174 | 0.001 |
| Unit Price | -0.661 | 0.064 | -0.201 | -0.720 |
| Unit Weight | -0.641 | 0.085 | -0.330 | 0.688 |
| CV | -0.388 | -0.144 | 0.906 | 0.091 |
| Cumulative Proportion | 0.513 | 0.764 | 0.968 | 1.000 |

In ***Step 2***, after identifying the attributes, they are normalized to a range between 0 and 1 to eliminate the impact of units of measurement on the replenishment method choice.

In ***Step 3***, weights can be applied to the attributes to scale the importance of them, thereby emphasizing parameters with high impacts on the replenishment method choice. The weights can be guided by the loading scores from the principal components of the PCA (see Table 1) or by the experience of a manager of the target picking system.

In ***Step 4***, ideal candidate items, which represent items most suitable for the COP and CR methods, respectively, are found based on the current replenishment method choices for the items. One feasible way of finding the ideal candidate item is to examine the items that are currently replenished by the same method (COP or CR). Specifically, given the item cluster grouped based on their replenishment method choice, an item positioned in the center of the cluster can be considered as the ideal item for the method. Following the idea, with $k$ item attributes, the centroid $\mathcal{C}$ of $n$ items in a cluster can be calculated by

$$\mathcal{C} = \left( \frac{\sum_{i=1}^{n} x_{i1}}{n}, \frac{\sum_{i=1}^{n} x_{i2}}{n}, \dots, \frac{\sum_{i=1}^{n} x_{ik}}{n} \right), \tag{1}$$

where $x_{ik}$ is the $k$th attribute value of item $i$.

The company groups all items in the picking system according to the replenishment method of the items (COP or CR) and the centroids of the groups are calculated accordingly. To visualize the grouping, the PCA result is re-called. Fig. 2 shows the plot where all items are presented with respect to the first and second PC of the analysis with a log-transformation applied for better visualization of data. In the figure, the items are color coded according to their methods and the vectors (arrows) represent the directions the values of the attributes are varied along.

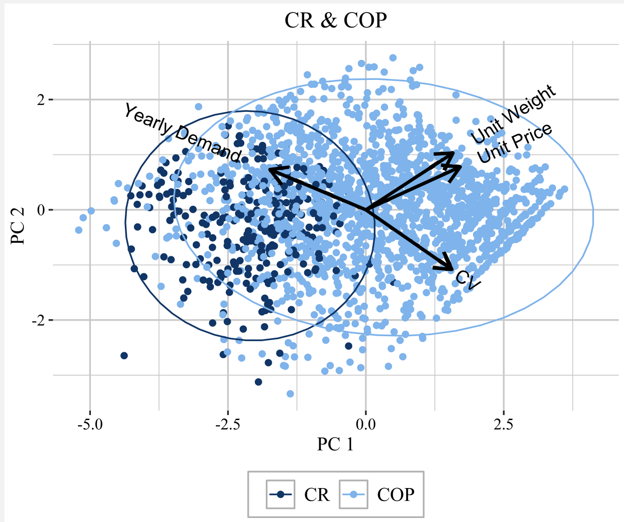


Fig. 2: Log-transformed biplot of PC 1 and PC 2 with confidence ellipses containing 95% of observations

From the figure, it is first observed that in the picking system of the company an item with high demand, a low price, a low weight and a low CV tends to be managed by the CR method, aligned with common practice. Moreover, it is also observed that items with a PC 1 value greater then 0 are most likely managed by the COP method.

In ***Step 5***, after identifying the ideal candidate item for a replenishment method in Step 4, the relevance of an item of interest to a replenishment method is measured. For measuring, the weighted Euclidean distance between the item of interest and the ideal item of the method (the centroid of the data cluster of the method) can be calculated by

$$\sqrt{w_1 \cdot (x_1 - c_1)^2 + w_2 \cdot (x_2 - c_2)^2 + \cdots + w_k \cdot (x_k - c_k)^2}, \quad (2)$$

where $w_k$ is the weight of the $k$th attribute determined in Step 3, and $x_k$ and $c_k$ are the $k$th attribute value of the target item and the ideal item, respectively.

In ***Step 6***, based on the distance measured, the replenishment method of an item is determined. If the distance of an item to the centroid of a certain replenishment method is close enough, the item might can be replenished by the method.

Note that the replenishment method choice made based on the distance should be used as a guidance because the suitable replenishment method for an item would depend on picking system- and item-specific characteristics and other practical conditions. However, such a guidance dramatically lessens the burden of a manager, especially when there are many items and attributes of the items to consider for the replenishment method choice.

The distances of all the items in the picking system to the centroids of the COP and CR method clusters are measured by equation (2). Based on the distances, 67 items, currently replenished by the COP method, are identified as potential items to be replenished by the CR method. From our analysis, it was estimated that replenishing the 67 items by the CR method would yield a reduction in the total number of picks by 3.8% for the three-month period assessed.

## 3 Concluding Remarks

The objective of this study is to support the replenishment method choice in a picking system, which is often done manually. For this, we designed a framework that investigates common attributes of the items replenished by the same method (steps 1–3) and suggests a replenishment method for an item based on its attribute values (steps 4–6). We believe that the proposed framework can provide evidence to validate the practice in the replenishment method choice in a picking system and further increase the automation level of decision-making.

Future research could include extending the framework to contain a predictive function, so that the framework is able to analyze the changes on items over time. This could be done by adding a time dimension to the attribute set of an item. Also, the possibility of extending the outcome of the proposed framework, i.e. supporting additional replenishment methods including the COP and CR methods, can be tested for the generalization of the proposed framework.

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