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Using dynamic demand information and zoning for the storage of non-uniform density stock keeping units

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The warehouse order-picking operation is one of the most labour-intense activities that has an important impact on responsiveness and efficiency of the supply chain. An understanding of the impact of the simultaneous effects of customer demand patterns and order clustering, considering physical restrictions in product storage, is critical for improving operational performance. Storage restrictions may include storing non-uniform density stock keeping units (SKUs) whose dimensions and weight constrain the order-picking operation given that a priority must be followed. In this paper, a heuristic optimisation based on a quadratic integer programming is employed to generate a layout solution that considers customer demand patterns and order clustering. A simulation model is used to investigate the effects of creating and implementing these layout solutions in conjunction with density zones to account for restrictions in non-uniform density SKUs. Results from combining layout optimisation heuristics and density zoning indicate statistical significant differences between assignments that ignore the aforementioned factors and those that recognise it.

Keywords: optimal layout heuristics; optimisation; order-picking; zoning; simulation; logistics

1. Introduction

Imbalances between the demand and the supply create inventory in the supply chain. These inventories serve as buffers that may be employed to meet stochastic fluctuations in customer demand (Stevenson 2012). Warehouses and distribution centres are a class of storage facilities designed to deliberately retain inventory as a reserve that provides protection from the inability to face uncertain demand in a timely fashion and reduces the risk of stock-out while replenishing lead time (Shapiro 2007). Thus, inventory and facilities are critical drivers of supply-demand responsiveness within the supply chain (Chopra and Meindl 2010). However, while these inventories and facilities within the supply chain may be a hedge for handling unexpected fluctuations in demand and support for timely response to varying demand, there are costs associated with storing and retrieving these inventories. Reasonable storage layouts that provide timely access to products are desirable. On the other hand, unsystematic storage, meaning facility layouts that do not consider potential dynamics of the demand as well as product density restrictions, may take advantage of the storage space while also being viewed as wasteful and inefficient with regard to order-picking operations and responsiveness. In this paper, the customer demand is considered dynamic as it seeks to reflect temporal request patterns that reveal variations in the preference of certain products over time, e.g. seasonal items, while reflecting the propensity of these customers to order certain classes of products together.

Density, as well as the size of the stored product, may impact the ease or difficulty in the picking process (Muther and Mogensen 1973; Hwang, Hui Oh, and Nam Cha 2003). The sequence of an order-picking operation may be constrained by significant differences in the density presented by stored products. In a non-uniform SKU warehousing environment, some products may present high, medium, and low levels of density values. A distribution centre, for example, that distributes perishable and non-perishable items from small to medium grocery stores as well as local restaurants may carry different density products such as tomato sauce can cases whose density is highly relative to potato chips bulks whose density is lower. The operation that retrieves these products is constrained by the order in which these items are temporarily stored in the order picker basket during the picking tour. This constraint can be envisioned as density restrictions that restrain the order-picking operation as product retrieval sequences are required to maintain a hierarchical order in which high- to medium-density products are primarily retrieved. This requirement is necessary to preserve the physical integrity of the retrieved products.

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The idea of order clustering involves the combination of items that have a high likelihood of appearing together in an order. For example, there is a high probability that customers order coffee and coffee maker filters together. Seasonal patterns may also affect ordering patterns as the consumption of certain items may increase during a time interval. Managers need to recurrently evaluate order patterns and modify stock location in an effort to respond to such cyclical components. The ordering of seasonal products may relate to other products. For example, in the US during the fall season, gravy and stuffing may both frequently and simultaneously be ordered as Thanksgiving Day, a major national holiday, approaches. Other items that do not present seasonal recurrence may still display a prevalent correlation with other items and, as such, should be also considered in an allocation strategy as well. Nonetheless, numerous of these dependencies cannot be characterised by collectively; a methodical analysis is necessary.

When utilising order clustering, managers must find a balance between the responsiveness that stems from timely inventory access and the costs of implementing systematic retrieving inventory procedures. Responsiveness itself is affected by order-retrieval processes; these have been identified as one of the most critical warehousing operations along the supply chain, contributing between 40 and 60% of warehousing total costs (Goetschalckx and Ashayeri 1989). This process is typically performed by automated guided vehicles or by individuals (De Koster, Le-Duc, and Roodbergen 2007). Most recent order-picking methods include combinations of layout, storage assignments, order clustering, picker routing, order accumulation and zoning. In most cases, these methods assume that the demand for products is random and independent and identically distributed. However, in many instances, the demand for products presents certain dependency patterns in which some products are frequently ordered together with other products (Frazelle and Sharp 1989).

Managers' attempts to balance between responsiveness and efficiency by relying on order-retrieval processes may be negatively affected by substantial swings in the demand produced by the magnified effects of its variability (Kahn 1987; Chen and Lee 2012). This is particularly important to large warehouses that serve multi-item demand markets with case-lot- and less-than-case-lot-quantity stored in gravity-flow racks and whose items may be described as non-uniform density stock keeping units (SKUs). Two successful techniques to improve warehouse performance include optimal storage assignment and family-based grouping (Gu, Goetschalckx, and Mcginnis 2007; Bozer and Kile 2008). Some studies that model order-picking operations consider the dynamics of the demand but largely ignore density restrictions.

The purpose of this paper is to present a method to design storage layouts that improves the performance of order-picking processes for non-uniform density SKUs. The method combines two well-known order-picking techniques, namely warehouse zoning and storage layout that considers family-based grouping. A zero-one non-linear programming model is employed to solve the family-based grouping problem, and a discrete-event simulation model is used to test the performance of designed density zones. The storage layout heuristic takes into consideration the dynamic and dependent nature of customer demands, while zoning allows the grouping of non-uniform density items into sub-zones that categorise products by their density.

The optimal storage layout heuristic formulates the problem as a zero-one quadratic assignment model in which throughput, product correlations and distances relative to the shipping area and between slots are considered in seeking a solution to the assignment problem (e.g. Liu 2004). However, this formulation assumes that products' physical features such as density do not constrain the system, e.g. as is seen with books and DVDs. In many distribution centres though, such as the one studied in this paper, the physical characteristics of the retrieved product play a major role and affect the sequence of retrieval. In particular, retrieval of non-uniform density SKUs is sensitive to the order-picking operation sequence as indicated above.

In a realistic environment, as the one employed to mimic the warehousing operation used in this paper, the order-picking operation itself is not only limited by characteristics of the picked products, but it also presents stochastic components that impact operational performance. This paper uses a discrete-event simulation approach to mimic the behaviour of the order-picking process to consider the probabilistic nature of this environment and design density zones using the storage layout solution as guidance. This allows products to be sequenced considering the order suggested by the storage layout while respecting ranges of density restrictions in each zone. The simulation model developed in this paper is also employed to examine the impact of the solution generated by the method suggested in this study. This method is compared to a pure zoning strategy in which products are randomly assigned to areas that are only restricted by density zones.

The reasons that describe the importance of this study and its results are detailed as follows. First, to the author's knowledge, this is the first formal study of storage layout heuristics that consider dynamics of the customer demand and product clustering along with constraints associated to the storage of non-uniform density SKUs. Second, by combining a non-linear quadratic programming that recognises demand dynamics and zoning that acknowledges the density differences existing among dissimilar class of products, this study provides evidence of potential applications for warehouses that are commonly found in production systems similar to the one studied in this paper. Third, the statistical analysis suggests that the selection of the studied policy variables is critical to the performance of the retrieval operation and may lead to considerable improvements in certain measures while potentially exacerbating others. Fourth, this study highlights the significance of research in this area to assist managers and investigators in familiarising themselves with the properties of these types of order-picking operations as well as the levers that may be used to improve the performance of warehousing layouts.

Section 2 presents the problem statement. Section 3 describes the literature related to order-picking methods. Section 4 describes the heuristic and simulation model that are used. Section 5 presents the results of the simulation. Finally, the last section provides conclusions, discusses the managerial implications, and presents directions for future research.

2. Problem statement

The business operation considered in this paper characterises a large local distribution centre in which order-picking processes are performed by individuals. This operation is performed by order pickers who drive retrieval cars along aisles to physically retrieve SKUs in response to order-batching requirements generated by either internal or external customers. Once the retrieval task is completed, the orders that have filled are positioned in the shipping area where they are lined up to be loaded on trucks that are sent to the final destination. It is presumed that order pickers execute a low-level retrieval process, and cases are stockpiled on the racks consistent with the product ordering frequency (i.e., fast to slow occurrence) and density (high to low). The configuration of the modelled warehouse is restricted by an S-shaped routing scheme in which order pickers enter the first aisle and sequentially travel forward (Figure 1). Routing order pickers using the S-shaped (or traversal) heuristic approach signify that any aisle containing at least one pick is traversed completely. Aisles without picks are not part of the tour. From the last visited aisle, the order picker returns to the depot. Travelling backwards is not allowed in this setting. The extant literature in traversal routing widely discusses the elements that influence the adoption of this routing scheme; in particular, the aisle dimension restrictions may not allow two-way travelling and safety policies. When possible, the retrieval of items comprises a batching process in which two or more orders are processed using a First Come First Served scheme and picked jointly in a single tour. Travelling backward means not back to previous aisle and not turning in the previous aisle and travel back to the shipping area. This restriction is imposed by the serpentine picking operation.

Order-picking operations such as the one described in this study may be found in numerous domains that involve restrictions imposed by the shape, size and density of the picked item. In the setting studied in this paper, the author considers products density restrictions as they constrain the construction of routing schemes using an S-shaped routing structure (for additional references see: Roodbergen and Koster (2001), Henn, Koch, and Wäscher (2012)). This restriction requires to sequentially retrieving SKUs from high- to low-density ranges as the picking tour progresses. The physical integrity of low-density SKUs may be compromised when high-density products are superimposed over

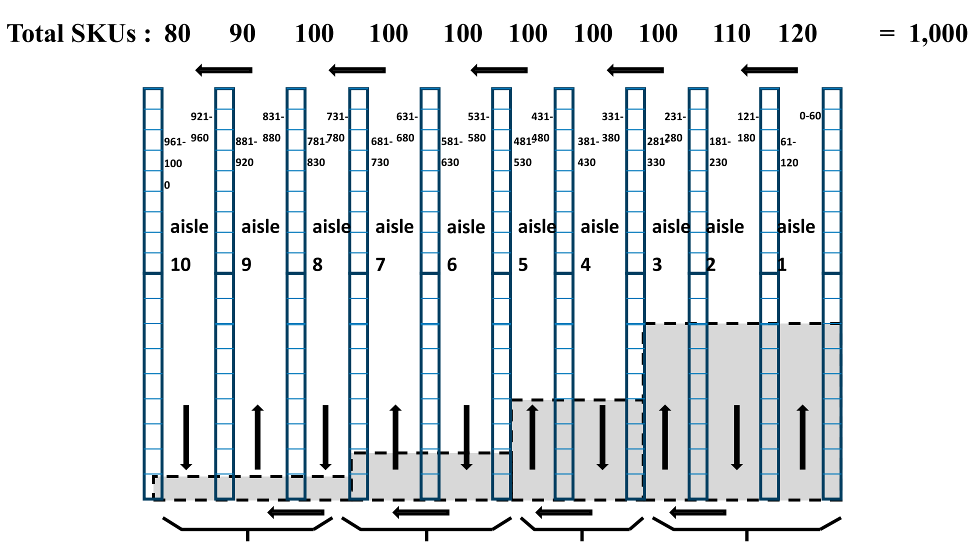

Figure 1. Warehouse configuration and product distribution.

low-density products due to space limitations while performing the picking tour. In a multi-density product environment, it is reasonable to include this restriction when order-picking operators follow a restricted S-shaped route scheme.

The picking method is assumed to follow a Z-type approach in which operators retrieve products on both sides of the aisles. This choice is justified as the studied system resembles a real-world warehousing operation whose aisles are not narrow enough to allow picking from both sides of the aisle without changing position. The aisles are not wide enough to allow two-way traffic either. Thus, Z-type is used in wide aisles where there is a need to move from one side of the aisle to another. The goal of this paper is (1) to propose a storage layout approach that combines a storage assignment model and zoning to improve order-picking operation, (2) to analyse the impact of solutions generated using the heuristic on system performance, and (3) to contrast these solutions with a pure zoning policy used in warehouses that commonly store non-uniform density SKUs. This is accomplished in this paper by minimising the order-picking times and the travel distance.

This paper focuses on employing a heuristic that considers product correlation and zoning restrictions to generate solutions that shed light on a particular class of assignment problems that involves non-uniform density SKUs. Literature that explores the effects of demand patterns and non-uniform density SKUs to store products in rigid environments is limited. To analyse the effectiveness of the proposed method, this paper compares a warehouse that employs the heuristic to that of a traditional warehouse environment in which products are stored using a conventional zoning method that considers density-restricted areas but disregards the behaviour of the demand as well as the stochastic behaviour of the order-picking operation.

3. Literature review

Based on the order-picking operation performed over a warehouse that stores non-uniform SKUs, this paper develops a heuristic that considers the multiple SKU assignment, considers the behaviour of the demand within zones, and recognises the existing differences in mass and volume of the required products. The heuristic is then examined using a simulation to test its efficacy. A simulation model is an efficient mechanism to capture density restrictions per zone as it is capable to evaluate the performance of feasible solutions in conjunction with the aforementioned heuristic. These models permit the consideration of strategies that allow the slot assignment process to be implemented. Weight ranges as well as serpentine path and Z-type picking constraints are characteristics of actual zones that can be properly characterised in the simulation model.

Simulation characterisations have been conventionally used as a mechanism to assess the performance of novel heuristics and to perform scenario and sensitivity analysis (Diaz 2010). In this sense, a particular situation is modelled and then contrasted with novel solutions obtained from normative models. These techniques have also been used as mechanisms to gain insights in current and expected warehousing behaviour; for example, to analyse the impact of specific factors on total travel time (Lee 1992), to show that full-turnover storage outperforms class-based storage (Van Oudheusden and Zhu 1992), and to investigate the effects of the aisle configuration, stocking policy, batching, and zoning (Petersen 2002). Mellema and Smith (1988), De Koster (1994), Petersen, Aase, and Heiser (2004), and Zu and Sun (2015) also use simulation to test solutions that involve variable time windows and stochastic order arrivals. Similar to this study, Diaz (2010) combined optimisation with simulation to build layout solutions that consider stochastic demand behaviour and order batching. Three streams of research, the optimal layout problem, order-picking and zoning are relevant to position this work.

3.1 *Optimal layout problem*

Warehouses' responsiveness is a factor of the accuracy of picking operations and the speed of delivery. Thus, a good facility layout is critical to high performance since it allows adequate stock handling and picking procedures as well as replenishing operations. Trends in the literature indicate the use of metaheuristics to incorporate actual operational constraints as well as to study new classes of problems (e.g. Komarudin and Wong 2010; Chen et al. 2015; Öncan 2015; Pan, Shih, and Wu 2015).

A storage assignment method that considers products' physical configuration is the cube-per-order index (COI) rule (Heskett 1963). COI is ratio of cube (cubic footage of storage space of item) and number of requests (frequency of visiting that item). Extensions of the COI index include return policies and ABC curves (Caron, Marchet, and Perego 1998) as well as class-based storage with S-shaped traversal routing in low-level picker-to-part systems (Rao and Adil 2013). Sharma and Shah (2015) conducted a quality-based cluster analysis to consider closeness among customers and propose algorithm with new layout design, zoning and storage allocation policy. However, most approaches that address the optimal layout problem commonly disregard differences in product densities which have an impact on the sequencing of the order-picking operation. An exception to these trends is the work of Hwang, Hui Oh, and Nam Cha (2003) who, recognising the importance of weights in material handling activities in warehouse, developed a linear programming with the objective of minimising the workload required for order-picking operations. These authors developed the density-turnover index to capture both the density and order frequency of an item and thus solve their linear programming model. Incorporating knowledge of product density may assist in implementing storage layout solutions that improve warehousing performance.

3.2 *Order-picking*

Productivity (pick rate), cycle time (time between items order reception and item shipping) and accuracy (correct items shipped) are the most common influential factors in order-picking operations (Taljanovic, Salihbegovic, and Pandzo 2012). A common goal of order-picking operations is maximisation of the service level (Goetschalckx and Ashayeri 1989; Chen et al. 2000) which contains a variety of factors such as average and variation of order delivery time, order integrity and accuracy (De Koster et al. 2007). This goal is subject to well-known restrictions that include the nature of the SKU, labour and capital (Chen and Lee 2012). This is further complicated by the consideration of alternative routing policies (Qin, Chen, and Ma 2015). The presence of dependency elements in the demand may significantly influence the performance of the supply chain (Diaz and Bailey 2011), and in particular, warehouse operations. Currently, storage assignment techniques tend to disregard the correlations that reflect the propensity of customers to order certain items along with other products over time (Battini et al. 2015).

Family-grouping methods recognise these relationships and suggest placing-related products in the same section of the warehouse (Frazelle and Sharp 1989; Goetschalckx and Ashayeri 1989; Brynzér and Johansson 1996). When certain restrictions such as density apply, the literature suggests placing-related products as closely as possible to each other (De Koster et al. 2007). Two family-based grouping methods include complementary-based and contact-based methods (De Koster et al. 2007). The decision about what class of products may be grouped together is reliant upon a combination of the properties of all products in the group (e.g. Kofler et al. 2015).

Dependency patterns and order frequency have been recognised by some authors (e.g. Accorsi, Manzini, and Maranesi 2014). Liu (1999) considers similarities and throughput while Jane and Laih (2005) consider the problem of assigning products to zones in a synchronised system based on co-appearance of items in the same order. The dynamics of demand has been also considered under a large number of scenarios (e.g. Torres-Soto and Üster 2011; Wu, Wu, and Lin 2011; Gilland and Heese 2013; Lu et al. 2015; Tsamis et al. 2015). Ming-Huang Chiang et al. (2014) propose a based-association rule mining to consider both the intensity and nature of the relationships between products in a distribution centre while picking orders.

Similarities between product demands and the throughput-to-storage ratio combined are considered in the work of Liu (2004). That work is extended in this paper by explicitly considering differences in product densities through integrating a warehousing zoning method in the proposed heuristic.

3.3 *Zoning*

Zoning is an activity that consists of the division or segmentation of the warehouse that considers factors such as storage strategies, product differentiation and order-picking operations (De Koster et al. 2007; Gu, Goetschalckx, and Mcginnis 2007). Order-picking activities are performed within a prearranged constrained zone (e.g. Choy et al. 2014), and in many cases, particular order pickers are assigned to these zones. Zoning assists in reducing the propensity for congestion, thus improving order-picking times (Chen et al. 2014). For example, Roy et al. (2009) study the effects of multiple load/unload points and the trade-off in warehouse zoning on the cycle times (waiting time, travel times and load/unload times). However, zoning may be impractical in environments that strive for efficiency since assigning operators to individual zones may be expensive.

Furthermore, it can be difficult to determine the criteria used to establish zones for products. It is recognised that using both the combination of contact-based method and family-based products has implementation limitations since restriction such as density may interfere with the assignment process. As a general rule, for products that cannot be strictly placed next to one another, it is recommended that they be as close together as possible (Wäscher 2004; De Koster et al. 2007). A mechanism to accomplish this in the setting may involve identifying weight zones in which items are placed following the sequence suggested by the layout assignment previously developed. Weight ranges may be used as criteria to establish these zones. Thus, each zone identifies applicable weight restrictions in which an item's position can be exchanged guided by the storage assignment process. It is beneficial to use zoning as a mechanism to create density zones in which classes of product can be grouped within weight ranges. This mechanism is used to observe restrictions in the storage of non-uniform density products.

4. Methodology

The approach considered in this analysis contains two parts. The first part characterises the optimal layout problem as a zero-one quadratic assignment model. Throughput, correlations among products and distances both relative to the shipping area and between slots are considered in this formulation. The second part of the method builds a discrete-event simulation-based model to implement density zones that consider density restrictions and accommodates the probabilistic nature of the retrieval process.

4.1 *Storage layout assignment*

Mathematical programming models are commonly used to produce solutions to many warehousing and order-picking problems. In this section, the stock location or assignment problem is revisited.

Many techniques presume that the building configuration may be modified to accommodate product layouts. In this study, however, the building configuration as well as the routing policy (serpentine) is assumed to be invariable. Thus, an option to optimising the order-picking process is to concentrate on the placement and arrangement of products. This configuration may benefit from consideration of the dynamic nature of customer demand and the variable tendencies shown in ordering patterns, particularly for customer demands of a certain class of non-uniform density items that recurrently varies with seasons. As indicated, warehouse managers need to occasionally evaluate the orders and correct stock location in response to such seasonal components. As in Liu (2004) and Diaz (2010), the heuristic used in this paper formulates the problem as a zero-one quadratic assignment problem and consists of the three sequential parts that include: ranking, clustering, and interchanging. The optimisation model is characterised using:

(1) Similarity matrix (correlation) measure between SKUs
(2) Throughput-to-storage ratios
(3) The distance from the input/output to storage location, and finally
(4) The relative distance among slots.

To describe this problem, consider:
Minimise

$$z = \frac{1}{2}\sum_{i=1}^{K}\sum_{j=1}^{P}\sum_{k=1}^{K}\sum_{l=1}^{P} t_i s_{ik} d_{jl} x_{ij} x_{kl} + \sum_{i=1}^{K}\sum_{j=1}^{P} t_i r_j x_{ij} \tag{1}$$

Subject to:

$$\sum_{i=1}^{K} x_{ij} = 1 \quad j = 1, \ldots, P \tag{2}$$

$$\sum_{j=1}^{P} x_{ij} = S_i \quad i = 1, \ldots, K \tag{3}$$

$$x_{ij} = 0, 1 \quad i = 1, \ldots, K \quad j = 1, \ldots, P \tag{4}$$

where $\sum_{i=1}^{K} S_i \leq P$; and $K \leq P$.

d_{jl} represents the travel distance between slot j and l on the picking route.
t_i represents the throughput-to-storage ratio for item i.
r_j represents the relative distance of slot j to the input/output area.
x_{ij} (a binary variable) with 1 if item i is assigned to slot j, and 0 otherwise.
K represents the number of products to be allocated.
P represents the number of existing available slots.
S_i represents the storage necessities for item i.
s_{ik} represents the similarity between items i and k.

The objective function (1) gives the expected distance necessary to perform the order-picking operation. If a SKU i is allocated to slot j, it takes r_j distance units to come from the input/output area to slot j. As the total number of slot is j, an operator travels r_j distance units to travel from the input/output area to slot j. Since the total quantity of slots for item i is s_i, for those slots assigned to item i, the likelihood of the picking tour belonging to slot j is $1/S_i$. The total number of picking tours performed per SKU i is T_i. The product of $t_i = T_i/S_i$ and $r_j x_{ij}$ defines the expected distance required to go from the input/ output area to slot j. It is presumed that an order picker can travel from slot j to some other slot during the picking trip. s_{ik} provides the likelihood that an operator traverses a distance d_{jl} from slot j to slot l. Thus, the product of $t_i = T_i/S_i$ and $s_{ik} d_{jl} x_{ij} x_{kl}$ denotes the expected distance from slot j to slot l. The sum of all items and slots results in the total expected distance necessary to conduct the retrieval operations. Finally, constraint (2) guarantees that only one item i is assigned to slot j; constraint (3) assures that the number of slots assigned to item i equals S_i; and restriction (4) constricts the variable values as zero or one. Liu's (2004) mathematical model does not take density restrictions into account.

An alternative to solving this problem simplifies the problem to several sub-formulations at several stages that can be progressively solved. First, in a ranking stage, the correlation or similarity can be assumed to be zero. Consequently, the problem is reduced to a binary assignment problem that considers slot assignments based on stock frequency. In a second stage of clustering, the throughput-to-storage ratios can be omitted, and the clusters are formed based on similarities. Finally, the outcomes from stages one and two are combined in the interchanging stage. An assessment of the objective function of the entire quadratic formulation is solved by iterating between the ranking and the clustering stages (for details of this extensive procedure, see Liu (2004)). Notice that this heuristic does not consider density restrictions.

Travel times and the distances travelled by the operators are the most common objectives to minimise. The order-picking process analysed in this paper employs a storage assignment method restricted by density constraints: heavy products must be placed on the bottom of the pallet, while light products on top during the operation.

4.2 *Zoning*

The second part of the approach suggested in this paper considers developing a discrete-event simulation model to design and implement density zones similar to the simulation model developed by Diaz (2010). In this part, results from the storage layout assignment heuristic are used in conjunction to the simulation model to execute the final slot assignment and test the operational performance of the proposed policy.

The simulation model is used to allocate products per zone guided by the storage layout assignment heuristic. This allows products to be exchanged in each density zone without risking their physical integrity. By applying the heuristic to the simulation model, if certain products are in high demand and related to one another, they are placed at the beginning of the aisle (or entry point of the created zone) so that there are opportunities to retrieve them more quickly as required by the dynamics of demand following a single-block layout.

These zones are sequentially structured such that higher density products may be presented before medium and lower density products while performing the order-picking tour. As a result, higher density products can be placed in the bottom of the picking basket without risking the physical integrity of the picked products when performing the order-picking process. This allows the warehousing manager, as a subject matter expert on average ordered weight and volume per product, the ability to determine the number of weight ranges per zone in which products can be exchanged while maintaining its density consistency. The warehouse manager uses the layout assignment heuristic to distribute the storage of each product per zone. Thus, the simulation model becomes a means to perform this final assignment process that explicitly accounts for differences in products' density.

In a traditional warehouse that stores non-uniform SKUs, the density of each product is assessed and arbitrarily assigned to the corresponding density range zone. On the other hand, this heuristic considers products' turnover ratio and correlation, and assigns fast-moving products to the entry point of the corresponding zone, improving their chance to be picked first in a picking tour. To envision how this method works, a numerical study is conducted and presented in the next sections.

5. Numerical study

The experimental setting in this study involves modelling an order-picking operation with the following characteristics and policy variables:

(1) Orders: 4, 8, 12 products per order.
(2) Batch: 4, 5, 6 orders per batch.
(3) Carts: 5 Units – Max Unit load: 72 items.
(4) Speed: 100 ft/min.
(5) SKUs: 1000 items.

(6) Routing: S-shape (serpentine) without returns (one-way).
(7) Distance per aisle: 90 feet.
(8) Demand: 20/80.
(9) Number of aisles: 10.
(10) Number of weight zones: 4.

The demand 20/80 means that 20% of the items contribute to 80% of the movement. The distribution of this 20% is not random over the warehouse since it is reliant upon the type and density of item stored as well as the temporal relationship between items. The temporal relationship between items reflects dynamic patterns of the demand. Moreover, the contribution of the 20% from the heavy and medium-heavy products stored in aisles 1–3 is 60% as depicted by the shaded areas in Figure 1. The bottom line of Figure 1 indicates how the total percentage of the 20% is distributed. In addition, it is assumed that each slot stores only one product, so the number of slots to be assigned varies per aisle. A close examination of Figure 1 reveals that the number of slots decreases as the number of aisles increases. This reflects constrains observed in the real operation mimicked in this study. The line that begins reading 'Total SKUs' from the top of the figure indicates the number of products to be stored per aisle. The number of SKUs considered in this paper is 1000 items.

A discrete-event simulation model developed in ARENA simulation software is employed to mimic the order-picking operation. Each replication simulates one year of order-picking operations with shifts of 12 h/360 days per year. The interarrival of the historical demand is modelled by employing a stochastic exponential function (5.34 min), while the service time is modelled as the Poisson distribution (0.85 min). The measures of performance include average time spent performing order-picking per batch and miles travelled per year.

Each experimental treatment consists of combinations of SKUs per order and the number of orders per batch. For example, six items per order, and four orders per batch provides a batch of 24 SKUs. A full-factorial experimental design with three levels of items per order and three levels of batch size (3 × 3) results in nine treatments. Twenty replications for each of the nine treatments are run. Figure 1 shows a schematic representation of current warehouse configuration.

The picking Z-type method that retrieves products on both sides of the aisles is assumed. An order picker with several orders or batched picking lists moves from the input/output area to the storage location. The order picker considers the products' sequence retrieval in the picking list, departs from the input area, and enters into the storage area at point aisles 1, 3, 5, 7 and 9; this is represented by the arrows pointing upward in Figure 1. The order picker then performs the picking tour while retrieving products from the racks. Each time that the order picker finds the physical location of a product contained in his or her assigned picking list, he or she stops to retrieve the entire item, places it in the cart, and then continues the tour. Once all products on the picking list have been retrieved, the order picker travels to the shipping area. Finally, the selected items are placed behind the trucks in the input/output area. It is assumed that replenishment of stock items within the order-picking area occurs separately from order-picking operations and that the input/output area has infinite capacity.

The size of density zones is found in conjunction to the number of exit points shown in Figure 1. These exit points' constraint is static when performing a picking tour using a restricted unidirectional serpentine path. The exit points are those points over the invariable serpentine path configuration analysed in this work by which order pickers may exit the picking route to move to the shipping area. This decreases the likelihood of redundant aisle travelling. In the configuration studied in this paper, aisles 2, 4, 6, 8 and 10 contain the exit points where order pickers can depart the storage area and displace to the input/output area. The final number of zones for this experimental arrangement is presumed to be four (heavy, medium heavy, medium and light).

The simulator replicates the behaviour of the order-picking activity as described in Section 2. Grounded on the order history, the order demands are produced using the dynamic characteristics described above in which certain SKUs are regularly requested and are related to other SKUs.

6. Results

To contrast pure zoning methods with the proposed solution developed in this paper, a full-factorial assessment of the variance is employed on the two measures of performance. The confidence level in all of the tests was at least 95%. The power of the analysis reported 99%. The significance analysis of the results presented in Tables 1 and 2. These results are consistent with other results obtained in the literature (Diaz 2010) in terms of the improvement related to the dynamics of the demand (Liu 2004) and reorganising SKUs per zones (Petersen 2002).

The experimental results indicate the relative advantage of employing the information patterns obtained from item correlations combined with throughput-to-store ratio and zoning to attain the final storage layout. In this setting, the obtained improvement leads to a maximum reduction of approximately 27.1% in order-picking time and 57.4% decrease

Table 1. Order-picking times obtained from comparing current and proposed situation.

Number	SKU/order	Batches	Ignore	Use	Percentage improvement (%)
1	4	4	0.759	0.695	9.21
2	4	5	0.868	0.787	10.35
3	4	6	0.988	0.891	10.84
4	8	4	1.138	1.006	13.10
5	8	5	1.259	1.106	13.86
6	8	6	1.377	1.202	14.56
7	12	4	1.647	1.296	27.08
8	12	5	1.697	1.384	22.55
9	12	6	1.804	1.524	18.37

Table 2. Travelled distance by operator when performing the order-picking process obtained from comparing current and proposed situation.

SKUs	Batch size	Ignore	Use	Percentage improvement (%)
4	4	481.16	359.26	33.93
4	5	556.38	425.51	30.75
4	6	666.06	520.55	27.95
8	4	546.01	367.01	48.77
8	5	635.50	439.99	44.43
8	6	762.57	546.43	39.55
12	4	579.51	368.20	57.39
12	5	677.05	441.04	53.51
12	6	817.97	550.23	48.66

in total distance travelled by the operator. Table 1 shows the experiment number followed by SKUs per order, the batch size and the order-picking time using pure zoning. In this sense, each zone either ignores the proposed solution (Ignore) or uses it (Use), and the results from each zone are contrasted to define the percentage of improvement that is achieved by employing the suggested method. The 'Ignore' condition presumes pure zoning considering density restrictions as noticed in the actual setting. Upon the application of the heuristic, up to 40% of the products are reassigned per zone.

A decrease in travel time is noticed as the number of SKUs increases per batch. However, after attaining a threshold, the enhancement becomes less substantial and begins declining. This reflects the law of diminishing returns that defines the decrease in the marginal output as the amount by which a single factor is increased, while all other factors remain constant. The substantial length of the order-picking operation deters any economy of scales obtained.

Table 2 exhibits the simulation results in terms of the average distance travelled by the operators during the order-picking activity. Similar to Table 1, in the leftmost column, the table presents the number of the experiment followed by the number of SKUs per order, the batch size, the distance travelled by the operator when ignoring the proposed solution (Ignore), the distance travelled by the operator using the suggested method (Use) and the enhancement percentage.

Considerable benefits are obtained when the dynamics of the demand and zoning are used together. It is apparent that as the number of SKUs increases in a batch, so does the distance to traverse. The larger the batch size, the higher the probability of visiting remote locations; thus, larger distances are observed. The percentage of improvement increases per batch across groups as the number of SKUs increases. However, within groups of SKUs, the improvement tends to decline. This may be explained by the fact that there are more picking locations to stopover.

The results presented in Tables 1 and 2 are evaluated using a full-factorial model ANOVA (SAS version 9.3). Notice that interactions exist among all of the policy variables in all of the experiments. The results show statistically significant two-way interactions between the order quantities factor and the batch size. There is also a statistically significant difference between experiment means for treatments with all batch sizes and all order quantity factors. All of the main effects and two-way interactions show substantial significance with p-values of less than 0.01. Since this interaction is significance, further analysis is conducted. Thus, multiple comparison tests using the Tukey t-test are performed. As the batch size is incremented, the change between time values for performing the order-picking process becomes statistically significant. This applied to all order quantity levels. Comparable results are obtained for the distance travelled by the order pickers. For lower to higher levels of order quantities and batch sizes, there were statistically significant differences in the distance travelled by the order pickers when they execute the retrieval operation.

7. Conclusions

Warehouses and distribution centres are a class of storage facilities designed to purposely retain inventory as a reserve against the inability to meet uncertain demand in a timely manner. Storage layout optimisation and density zoning are two techniques used to design and assess improvements in the responsiveness and efficiency of warehouses, and therefore, the performance of a firm.

An optimisation heuristic based on a quadratic integer programming to solve the store assignment problem is considered in this paper to improve order-picking operations in a warehouse. The assignment problem considers two aspects of dynamic demand that include throughput-to-storage ratios and ordering similarities (clustering). The heuristic employed in this paper reduces the problem to several sub-formulations that are solved in several stages.

A discrete-event simulation model is constructed to replicate and analyse the behaviour of the warehouse in the presence of a solution that combines storage layout assignment and density zoning. Items are assigned in each zone following the solution produced by the integer quadratic programming model. The allocation process within each zone guarantees the physical integrity of the product while considering the dynamics of the demand and performing the picking operation. Items that have higher throughput-to-storage ratios and high correlation factors are successfully reallocated in each zone, thereby enhancing opportunities to efficiently select items while performing the picking tour. This study resembles an actual medium-sized warehouse, whose certain zones are composed of two or more aisles while its order-picking operation allows flexibly skipping aisles that observe entry and exit points. The improvements obtained in this paper may not be applicable to more restricted operations such those performed in small warehouses that contain less than two aisles, follow a S-shaped tour without backward travelling, and do not contain cross-sections where order pickers may exit the aisle.

The simulation model is extensively replicated in order to contrasts the performance of the treatments that employ the suggested solution method with those that use the pure zoning approach. Information about the total travelled distance and time spent in the process by the operator when executing the order-picking operation is collected. Experimental results suggest that there are considerable and significant differences between experiments that employ the suggested decision rules and experiments that disregard them. The statistical significance of these differences is determined conducting ANOVA tests which report values as less than 0.01.

Future endeavours include investigating the effects of cross-sections where the order picker can exit the S-path without traversing the entire aisle. This analysis can be combined with modelling the situation in which slots are found empty and requires replenishment from upper slots where safety stock may exist. In addition, researchers can expand the setting of this study from one warehouse to multiple facilities while analysing the impact of information sharing through a supply chain network as well as contrasting the other type of dynamic demands using the same setting. Future comparisons between the method suggested in this paper and other methods besides pure zoning will require adapting such methods to acknowledge density constraints. As improvements in the responsiveness and efficiency of a single facility can be replicated through a network of facilities, gains are larger and new challenges are discovered. For example, it remains to be seen to what extent the results of this work can be applied to warehouse configurations that use storage layouts other than serpentine path. At a single-facility level, future endeavours include quantifying the impact of the proposed method using metrics that reflect contributions of the warehouse performance viewed from the green supply chain perspective (e.g., emissions discharges and energy consumption).

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References

Accorsi, R., R. Manzini, and F. Maranesi. 2014. "A Decision-support System for the Design and Management of Warehousing Systems." *Computers in Industry* 65 (1): 175–186.

Battini, D., M. Calzavara, A. Persona, and F. Sgarbossa. 2015. "Order Picking System Design: The Storage Assignment and Travel Distance Estimation (SA&TDE) Joint Method." *International Journal of Production Research* 53 (4): 1077–1093.

Bozer, Y., and J. Kile. 2008. "Order Batching in Walk-and-pick Order Picking Systems." *International Journal of Production Research* 46 (7): 1887–1909.

Brynzér, H., and M. I. Johansson. 1996. "Storage Location Assignment: Using the Product Structure to Reduce Order Picking Times." *International Journal of Production Economics* 46–47: 595–603. http://www.sciencedirect.com/science/article/pii/0925527394000913

Caron, F., G. Marchet, and A. Perego. 1998. "Routing Policies and COI-based Storage Policies in Picker-to-part Systems." *International Journal of Production Research* 36 (3): 713–732.

Chen, L., and H. L. Lee. 2012. "Bullwhip Effect Measurement and Its Implications." *Operations Research* 60 (4): 771–784.

Chen, F., Z. Drezner, J. K. Ryan, and D. Simchi-Levi. 2000. "Quantifying the Bullwhip Effect in a Simple Supply Chain: The Impact of Forecasting, Lead Times, and Information." *Management Science* 46 (3): 436–443.

Chen, F., H. Wang, Y. Xie, and C. Qi. 2014. "An ACO-based Online Routing Method for Multiple Order Pickers with Congestion Consideration in Warehouse." *Journal of Intelligent Manufacturing*: 1–20. doi: 10.1007/s10845-014-0871-1.

Chen, T.-L., C.-Y. Cheng, Y.-Y. Chen, and L.-K. Chan. 2015. "An Efficient Hybrid Algorithm for Integrated Order Batching, Sequencing and Routing Problem." *International Journal of Production Economics* 159: 158–167.

Chopra, S., and P. Meindl. 2010. *Supply Chain Management – Strategy, Planning, and Operation*. NJ: Prentice Hall.

Choy, K., N. Sheng, H. Lam, I. K. Lai, K. Chow, and G. Ho. 2014. "Assess the Effects of Different Operations Policies on Warehousing Reliability." *International Journal of Production Research* 52 (3): 662–678.

De Koster, R. 1994. "Performance Approximation of Pick-to-belt Orderpicking Systems." *European Journal of Operational Research* 72 (3): 558–573. http://www.sciencedirect.com/science/article/pii/0377221794904235

De Koster, R., T. Le-Duc, and K. J. Roodbergen. 2007. "Design and Control of Warehouse Order Picking: A Literature Review." *European Journal of Operational Research* 182 (2): 481–501. http://www.sciencedirect.com/science/article/pii/S0377221706006473

Diaz, R. 2010. "Using Optmization Coupled with Simulation to Construct Layout Solutionsed." In *Proceedings of the 2010 Spring Simulation Multiconference*. Society for Computer Simulation International, 77. Orlando: Florida.

Diaz, R., and M. Bailey. 2011. "Building Knowledge to Improve Enterprise Performance from Inventory Simulation Models." *International Journal of Production Economics* 134 (1): 108–113. http://www.sciencedirect.com/science/article/pii/S0925527311002416

Frazelle, E. A., and G. P. Sharp. 1989. "Correlated Assignment Strategy can Improve any Order-picking Operation." *Industrial Engeneering* 21 (4): 33–37.

Gilland, W. G., and H. S. Heese. 2013. "Sequence Matters: Shelf-Space Allocation under Dynamic Customer-driven Substitution." *Production and Operations Management* 22 (4): 875–887.

Goetschalckx, M., and J. Ashayeri. 1989. "Classification and Design of Order Picking." *Logistics Information Management* 2 (2): 99–106.

Gu, J., M. Goetschalckx, and L. F. Mcginnis. 2007. "Research on Warehouse Operation: A Comprehensive Review." *European Journal of Operational Research* 177 (1): 1–21. http://www.sciencedirect.com/science/article/pii/S0377221706001056

Henn, S., S. Koch, and G. Wäscher. 2012. *Order Batching in Order Picking Warehouses: A Survey of Solution Approaches*. London: Springer.

Heskett, J. L. 1963. "Cube-per-order Index – A Key to Warehouse Stock Location." *Transportation and distribution Management* 3 (1): 27–31.

Hwang, H., Y. Hui Oh, and C. Nam Cha, 2003. "A Stock Location Rule for a Low Level Picker-to-part System." *Engineering Optimization* 35 (3): 285–295.

Jane, C.-C., and Y.-W. Laih. 2005. "A Clustering Algorithm for Item Assignment in a Synchronized Zone Order Picking System." *European Journal of Operational Research* 166 (2): 489–496.

Kahn, J. A. 1987. "Inventories and the Volatility of Production." *The American Economic Review* 77 (4): 667–679.

Kofler, M., A. Beham, S. Wagner, and M. Affenzeller. 2015. "Robust Storage Assignment in Warehouses with Correlated Demand." In *Computational Intelligence and Efficiency in Engineering Systems* edited by G. Borowik, Z. Chaczko, W. Jacak, and T. Luba. 415–428. Springer: International Publishing.

Komarudin, and K. Y. Wong. 2010. "Applying Ant System for solving Unequal Area Facility Layout Problems." *European Journal of Operational Research* 202 (3): 730–746. http://www.sciencedirect.com/science/article/pii/S0377221709004834

Lee, M.-K. 1992. "A Storage Assignment Policy in a Man-on-board Automated Storage/Retrieval System." *International Journal of Production Research* 30 (10): 2281–2292. Accessed September 6, 2013. http://dx.doi.org/10.1080/00207549208948155

Liu, C.-M. 1999. "Clustering Techniques for Stock Location and Order-picking in a Distribution Center." *Computers & Operations Research* 26 (10–11): 989–1002. http://www.sciencedirect.com/science/article/pii/S030505489900026X

Liu, C.-M. 2004. "Optimal Storage Layout and Order Picking for Warehousing." *International Journal of Operations Research* 1 (1): 37–46.

Lu, W., D. Mcfarlane, V. Giannikas, and Q. Zhang. 2016. "An Algorithm for Dynamic Order-picking in Warehouse Operations." *European Journal of Operational Research* 248 (1): 107–122.

Mellema, P. M., and Smith, C. A. 1988. "Simulation Analysis of Narrow-aisle Order Selection Systems." *Proceedings of the 20th Conference on Winter Simulation*. San Diego, CA, United States: ACM, 597–602.

Ming-Huang Chiang, D., C. P. Lin, and M. C. Chen. 2014. "Data Mining based Storage Assignment Heuristics for Travel Distance Reduction." *Expert Systems* 31 (1): 81–90.

Muther, R., and Mogensen, A. H. 1973. *Systematic Layout Planning* Cahners Books: The University of Michigan.

Öncan, T. 2015. "Milp Formulations and an Iterated Local Search Algorithm with Tabu Thresholding for the Order Batching Problem." *European Journal of Operational Research* 243 (1): 142–155.

Pan, J. C.-H., P.-H. Shih, and M.-H. Wu. 2015. "Order Batching in a Pick-and-pass Warehousing System with Group Genetic Algorithm." *Omega* 57 (December): 238–248.

Petersen, C. G. 2002. "Considerations in Order Picking Zone Configuration." *International Journal of Operations & Production Management* 22 (7/8): 793–805. http://proquest.umi.com/pqdweb?did=217493551&Fmt=7&clientId=3505&RQT=309&VName=PQD

Petersen, C. G., G. R. Aase, and D. R. Heiser. 2004. "Improving Order-picking Performance Through the Implementation of Class-based Storage." *International Journal of Physical Distribution & Logistics Management* 34 (7/8): 534–544. http://proquest.umi.com/pqdweb?did=725684861&Fmt=7&clientId=3505&RQT=309&VName=PQD

Qin, K., F. Y. Chen, and L. Ma. 2015. "Cutting Down the Travel Distance of Put Systems at Kunming International Flower Auction Market." *International Journal of Production Research* 53 (12): 3573–3585.

Rao, S. S., and G. K. Adil. 2013. "Class-based Storage with Exact S-shaped Traversal Routeing in Low-level Picker-to-part Systems." *International Journal of Production Research* 51 (16): 4979–4996.

Roodbergen, K. J., and R. Koster. 2001. "Routing Methods for Warehouses with Multiple Cross Aisles." *International Journal of Production Research* 39 (9): 1865–1883.

Roy, D., A. Krishnamurthy, S. Heragu, and C. Malmborg. 2009. "Impact of Zones on Throughput and Cycle Times in Warehouses with Autonomous Vehicles." In *IEEE International Conference on Automation Science and Engineering*, Bangalore, India, 449–454.

Shapiro, J. F. 2007. *Modeling the Supply Chain*. CengageBrain. com.

Sharma, S., and B. Shah. 2015. "A Proposed Hybrid Storage Assignment Framework: A Case Study." *International Journal of Productivity and Performance Management* 64 (6): 870–892.

Stevenson, W. J. 2012. *Operations Management*. 11th ed. New York: McGraw-Hill/Irwin.

Taljanovic, K., A. Salihbegovic, and A. Pandzo. 2012. "A Fast Manual Picking of Small Parts High Volume Orders." *Journal of Communication and Computer* 9: 1097–1103.

Torres-Soto, J. E., and H. Üster. 2011. "Dynamic-demand Capacitated Facility Location Problems with and without Relocation." *International Journal of Production Research* 49 (13): 3979–4005.

Tsamis, N., V. Giannikas, D. Mcfarlane, W. Lu, and J. Strachan. 2015. "Adaptive Storage Location Assignment for Warehouses using Intelligent Products." In *Service Orientation in Holonic and Multi-agent Manufacturing*, edited by T. Borangiu, A.Thomas, D.Trentesaux, 271–279. Springer: International Publishing.

Van Oudheusden, D. L., and W. Zhu. 1992. *Storage Layout of AS/RS Racks based on Recurrent Orders*. *European Journal of Operational Research* 58 (1): 48–56. http://www.sciencedirect.com/science/article/pii/037722179290234Z

Wäscher, G. 2004. "Order Picking: A Survey of Planning Problems and Methods." *Supply Chain Management and Reverse Logistics*: 323–347.

Wu, H.-H., C.-H. Wu, and J. T. Lin. 2011. "Dynamic Selling of Quality-graded Products under Demand Uncertainties." *Computers & Industrial Engineering* 61 (1): 141–149.

Zu, Q., and B. Sun. 2015. "Optimization of Order Picking Work Flow at the e-Commerce Logistics Centers." In *Human Centered Computing*, edited by Q. Zu, B. Hu, N. Gu, 598–608. Springer: International Publishing.