MULTI-ITEM PICKING METHODOLOGY IN WAREHOUSES

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ABSTRACT

Order picking is the retrieval of items from warehouses to satisfy in-house orders. Recent research shows that order picking counts for more than half of the warehouse operational costs. In this study a storage assignment clustering methodology and computer implementation is developed to reduce the walking required for an order picking operation. The proposed methodology does not consider routing policy, and does not alter the material handling and storage equipment.

The basic principle behind the proposed method is known: items frequently ordered together are clustered in the warehouse. The difference from earlier solutions is in that it avoids full enumeration of the occurrences; a potentially time consuming task. The methodology proposed is based on the transitivity property of implication, allowing for quick computerized processing. The implementation part is potentially the most crucial aspect, as the number of possible clustering combinations is high for construction production systems with thousands of items in the warehouse. Computerised implementation of the population-based enumeration of the occurrences of possible order-combinations is resource-demanding according to computer processing time.

Given the waste elimination through reduced order retrieval time, the method is a potentially valuable tool in a company's 'lean toolbox'. The method is primarily suitable for large construction production systems (for example vessel construction) with variable picking orders, and multiple warehouse distribution systems. That said, the method is equally useful for single-warehouse systems.

The developed demonstrator is expected to be implemented and tested at a leading Norwegian offshore shipbuilder.

KEYWORDS

Lean construction, inventory control, variability, flexible, time compression, storage assignment, order picking.

INTRODUCTION

Order picking is the retrieval of items from warehouses to satisfy in-house orders in the production. Recent research shows that order picking counts for more than half of the warehouse operational costs (Frazelle, 2002; Tompkins et al., 2003; Coyle et al., 1996). One major cause of the large costs is the human aspect. Despite initiations on

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automated order picking, this task is still human resource demanding. Order picking efficiency is influenced by different factors that are mainly studied separately in the literature (Henn et al., 2011). The main factors are: the routing policy, storage strategy (clustering strategies in the warehouse and storage location), warehouse(s) layout, material handling and storage equipment, demand patterns of the stored products, and order batching strategies.

In this study a storage assignment clustering methodology and computer implementation is developed to reduce the walking required for an order picking operation. The proposed methodology does not consider routing policy, and does not alter existing material handling- and storage equipment. The implementation part is potentially the most crucial aspect of two reasons. First, the number of possible clustering combinations is high for construction production systems with thousands of items in the warehouse. Second, computerised implementation of the population-based enumeration of the occurrences of possible order-combinations is resource-demanding according to computer processing time. As such, efficiency and flexibility in the computerised implementation are in focus under the present development.

The basic principle behind the method proposed in this paper is known: items frequently ordered together are clustered in the warehouse. The methodology estimates potential clusters based on the transitivity property of implication; this, allowing for quick computerized processing. As opposed to this, computerised solutions based on full enumeration of the occurrences are regarded as time consuming.

To provide the connection of the proposed method with the construction industry in general, and offshore shipbuilding in particular, it is appropriate to briefly discuss the peculiarities and challenges faced by the Norwegian offshore shipbuilding. Emblemsvåg [3] (2013) acknowledges that the four peculiarities that count in construction projects (as listed by Koskela, 1992) also count in shipbuilding, in addition to a fifth peculiarity that is unique for shipbuilding; which is "the technical complexity and uncertainty of ships combined with steadily shorter lead times dictates that the ships are put into engineering and production before all engineering issues are resolved. It is not uncommon to start engineering with only footprint data available on particular components, with increasing amount of information during the production process". The offshore shipbuilding challenges are largely arising from this fifth peculiarity, with advanced design and engineering taking place concurrently with production, making planning & control (including inventory and warehouse policies) demanding. Kitting policies with standard assembly-sets potentially fails in this dynamic and uncertain environment, and individual item based enumeration of the stock-keeping units is far too time-consuming for these temporary project based organisations. These aspects are potentially explaining the extent of the human resource for the order picking task, but also the necessity of developing solutions that consider the dynamics is such project-based production systems. To adapt Lean production planning & control philosophies with late orders of the components and quick delivery expectations, demand variability and its consequences in the different phases in the construction project (including warehousing) are to be understood. This

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latter is proposed as further research by Ballard et.al. (2007). Given the waste elimination by reduced order retrieval time, the proposed method is a potentially valuable tool in the lean construction toolbox for inventory and warehouse planning. Recall that waste minimization is one of the three fundamental goals of Lean production systems (Koskela, 2000).

PROGRESS IN RELATION TO STATE OF THE ART

The literature on order picking to reduce walking distance is extensive, with two main research streams: routing policies or storage policies. Some initiations on connecting these two major aspects exist though. See Peterson (1999) for a simulation based extrapolation of storage assignments and routing methods. Daniels et al. (1998) develops a solution with multiple locations for each product.

In addition, order batching strategies are considered to affect the order retrieval time. For a review paper on order batching see Henn et al., 2011. These works are based on the assumption that all customer orders are known; a relatively strong and unrealistic assumption in project based production systems facing substantial uncertainty during the production processes (as offshore vessel construction). In such uncertain systems, order batching can be seen as reaction to actual observed customer demand on operational level. The reaction ability (efficiency in order batching) is constrained by the storage clustering methodology defined on a medium-term (tactical) planning level. Concretely, storage clustering policies define the ability to adapt variable customer orders (e.g. flexibility). If we view the order retrieval as a multi-stage problem, in the first stage the storage clusters are defined in light of uncertainty. In the second stage, after revealed customer demand, the orders (or batches of orders) are retrieved. Order batching is an adaptation decision after customer uncertainty is revealed, with the objective to act without increasing the retrieval costs considerably. The conditions to adapt different customer orders are created (or not created) on a higher planning level. This latter is the objective of the present paper.

Route optimisation systems in the warehouse determine the sequence in which products are retrieved from the warehouse with minimal distance. Warehouse route optimisation problems can be found, among others, in Ratcliff and Rosenthal (1983). Alternative to route optimisation is the use of heuristics, where the sequence of the product retrieval varies from fairly simple to complex dynamic patterns. See, among others, Petersen and Schmenner (1999) and Roodbergen (2001). Computerised route optimisation systems to minimize walking time exist; particularly, for automated retrieval of a number of units on the same pick-up route in a warehouse.

Storage policies, with the assignment of the products to warehouse locations, consists of three main groups: (1) random storage locations to empty storage places in the warehouse, (2) dedicated fixed storage location for each product; (3) grouped storage (Hausman et al., 1976). The grouped (clustered) policy takes into consideration the product type, physical volume, frequency of picks and combinations of these. Commonly known grouped-assignment strategies are ABC and XYZ storage policies. See among others Petersen (1999). Both methods are based on the demand frequency of the individual stock keeping units. While the ABC method uses the accumulated monetary value of the items, the XYZ method accumulates the order frequency of the stock keeping units. During the last years, different categorisation methods of the accumulated value have emerged; such as, VED (vital, essential, desirable), FSN (fast, slow moving and non-moving), SDE (scarce, difficult, easy) and HML (high, medium, low); see Kumar, 2006. These methods are based on Pareto analysis of the individual items, and generally group the items in three different ways: highest, medium and minimum. Time series analysis provides, than, a picture on how to efficiently place the items in the warehouse to reduce retrieval costs.

As measure of the order pick-up time, the XYZ policy uses the occurrence frequency of a stock keeping unit (SKU) in picking orders in a defined time period. The demand quantity of an SKU within a specific picking order is not considered directly, as the time used for the retrieval of a quantity of one or 100 units is fairly constant (if we ignore the differences in handling one versus 100 units). The occurrence frequency value indicates the internal transport distance from the storage location to the production location where the product is requested. The XYZ policy groups the SKUs into 3 major categories: Group X, with highest order frequency; Group Y with medium order frequency; Group Z with low order frequency. Similarly to the ABC storage policy, the frequently observed X-units are located within the shortest possible pick-up distance. The occurrence ranges of the X, Y and Z categories are subject to judgemental evaluation, and/or Pareto analysis.

Although the ABC and XYZ policies provide some kind of grouping, these methods work best when the focus is on picking individual items, and are limited in value when multiple products are to be considered in a specific picking order.

In addition to the ABC and XYX methods, bill of material (BOM) based kitting systems are also used for grouping the items to reduce walking distance. A BOM is a hierarchical graph showing the different items/components in a particular product. BOM grouping simplifies the request for assembly parts of a particular product/component, as the operator requests the kit as one single assembly-part. There are both pros and cons of this kind of kitting (see, for example, Corakci 2008). One major disadvantage relates to the occurrence of defect items in a BOM based assembly kit; implying that the operator must replace the defect part from a different kit, which cannot be used without replacing the missing part. A second disadvantage is that an assembly-kit may contain parts that are available in different variants. Such alternatives would be more appropriate not to be grouped into the kit, but to be requested together with the kit. A third disadvantage is when an operator retrieves a kit and in addition requests add-ons which are not naturally part of the kit, but are required to complete the assembly (complementary items). It may be lubricant /oil, filler rod, putty, glue or other supplies purchased for different types of assembly and in greater quantities than the kit assembly needs. Such complementary articles are not necessarily on a BOM list, but grouping them with the kit potentially minimises the walking distance. In summary, although kitting policies are useful in stable production environments, they do not provide flexibility to handle variable picking orders in production systems with frequent changes. See Brynzer and Johansson (1995), and Choobineh and Mohebbi (2004) for more on kitting systems.

In summary, existing order-retrieval approaches are mainly based on full enumeration of the order frequency of single products. The underlying assumption of known customer orders is also unrealistic in construction systems facing a large number of variation orders during the production. Although physical order retrieval (including order batching) is indeed a task to come after the uncertainty of customer orders is revealed, the conditions to adapt variations in these orders are to be created on a higher planning level. If flexibility is not enabled on a higher level, the operational adaptations costs can be unreasonably high. The methodology presented here treats the tactical level planning aspect of order retrieval, and attempts to move state-of-the-art by creating flexibility to adapt variation orders on operational level.

CLUSTERING METHODOLOGY IN WAREHOUSES

The methodology developed here uses the transitivity property of implication to describe the relation between the individual items, to enable efficiency in clustering items to be picked together. The method is an extension of the XYZ policy, in the sense that order frequency in a defined time period is taken as measure for order pick-up time. However, instead of enumerating the frequency of the individual SKU occurrences in picking orders in a defined time period, the frequency is enumerated pairwise. Pairwise enumeration allows for transitivity analysis of the pairs, to define storage clusters (of 2…n SKUs), without the need to describe the frequency of all possible cluster combinations, a time consuming and computationally difficult task.

THE METHODOLOGY

Consider a three-item problem, with SKUs A, B and C, and pairwise enumeration of the occurrence frequency. Transitivity analysis indicates that:

- If (A, B) and (B, C) => (A, B, C) should be grouped together.

The occurrence frequency of pairs (A, B), (A, C) and (B, C) can be decomposed into a common part n, and a variable non-negative part, as follows:

- (A, B) picked together x times, where $x = n + a$ and $a \geq 0$
- (B, C) picked together y times, where $y = n + b$ and $b \geq 0$
- (A, C) picked together z times, where $z = n + c$ and $c \geq 0$
- and $n = \min(x, y, z)$

From the above it follows that *n* is the maximal possible numbers of times the items A, B, C can be picked together within a defined time period. We call ***n*** the transitive implication number (***TIN***). The strength of the *TIN* is defined by the value n, and it indicates the importance of grouping the SKUs together. A high *TIN* value indicates a strong transitive implication and that the items are to be grouped in the warehouse location. A small *TIN* indicates a weaker transitive implication.

For a case with m products, an iterative evaluation of the TIN is suggested, by including pairs into the analysis sequentially, starting with the high frequency pairs. To avoid banal cases, a lower bound threshold value TINα is established beforehand, and the sequential inclusion process stops when this threshold is obtained. The value of TINα is subject to judgmental evaluation, and takes into consideration factors like weight, product family, warehouse capacity, and others.

The multi-item algorithm is as follows:

- **Step 1**: Rank in decreasing order the pairwise order occurrences of the SKUs.
- (A, B) picked together x times, where $x = n + a$ and $a \geq 0$

- (B, C) picked together y times, where $y = n + b$ and $b \geq 0$
- (C, D) picked together z times, where $z = n + c$ and $c \geq 0$
- …
- (L, M) picked together t times, where $t = n + m$
- and $n = \min(x, y, z, \ldots, t)$
- **Step2:** Start the transitive analysis with the highest order frequency pairs, calculate the TIN value and make grouping decision by evaluating the TIN value against the threshold TINα. If (A, B) and (B, C) => (A, B, C) should be grouped together **if** $TIN_{ABC} \geq TIN\alpha$.
- **Step3:** Include the next pair on the ranking list, and evaluate the new TIN value against TINα. If (A, B, C) and (C, D) => (A, B, C, D) should be grouped together **if** $TIN_{ABCD} \geq TIN\alpha$
- **Step 4:** Continue the process until the TIN value of the cluster reaches the lower bound TINα. If (A, B, C, D, …, K) and (K, L) => (A, B, C, D, …, K , L) should be grouped together if $TIN_{ABCD \ldots K} \geq TIN\alpha$. The process is stopped otherwise.
- **Step 5:** Judgmental ex-post evaluation of the defined clusters. In this step, the results from a historical individual item analysis (XYZ) can be used to detect additional important patterns. Particularly, a low TIN value does not automatically indicate that items/components are to be excluded from a cluster. As for ABC analysis, the complementarity of items is to be analysed.

Observe that a 'one-shot' evaluation of the *TIN* across all SKUs will not provide a good decision, as the lowest frequency pair will be constraining for the grouping decisions, and strong pairing indications can be overlooked.

The definition of a time period within which picking orders are analysed depends on the particular production system. In Norwegian shipbuilding the appropriate the time-period is the production system lifecycle of a vessel; about one year.

COMPUTER IMPLEMENTATION

To illustrate the multi-item clustering principles developed, the methodology is implemented in a demonstrator program written in Excel. The program consists of 3 connected worksheets: (1) The PICKING ORDER SCENARIOS worksheet, with demand scenarios of SKUs in picking-orders; (2) The XYZ-worksheet with a traditional XYZ analysis; (3) The CLUSTER worksheet, for cluster output.

Worksheet (1) consists of picking orders in a time-period. One picking order consists of particular SKUs and their demand quantities (see Figure 1, with picking orders defined by the lines, and SKUs by columns).

The proposed method counts first the order frequency of all SKUs within the defined time-period. This is a traditional XYZ analysis, with output on the XYZ-worksheet. The demand quantity of an SKU within a picking order is registered in worksheet (1), but not directly considered in the computerized analysis, as the order frequency (and not the quantity) is taken as measure for the pick-up time. The time used for the retrieval of a quantity of one or 100 units is fairly constant, if we ignore the differences in handling one versus 100 units. That said, the quantity demanded is considered in an ex-post judgemental analysis. For an example, consider the pick-up order on line 12, with the demand quantities 12, 83 and 24 for SKUs C, D and F respectively. The method registers one 'count' for each pair (C, D), (C, F) and (D, F). The process is performed for each order line, and summarized on SKU-pairs level: all identified pairs are summed up by their occurrence frequency in pick-up orders during the time period.

	A	B	C	D	E	F	G	H
1	ORDER LINES: EACH LINE CONTAINS ONE PICKING-ORDER. (The SKU names are the row columns.)							
2				28		58		
3		21			55	53		
4		61			18			
5					37			
6				96				
7				35	12	80		
8				77	61	9		
9			44			37		
10			59	27		83		
11	18					7		
12			12	83		24		

Figure 1: Example of picking orders in the PICKING ORDER SCENARIOS worksheet

The CLUSTER worksheet performs the algorithm presented in the previous section, and presents suggested clusters to adapt variations in pick-up orders based on the pairwise occurrence frequency. Concretely, the pairwise occurrences are model-input real time observations, while the clusters are model output estimations, to handle variations in pick up orders with reduced walking time.

Table 1 summarizes over the observed pairwise occurrences of 6 SKUs (A, B, C, D, E, and F), calculates the TIN values and suggests clusters. Observe that the clusters suggested are ABC and CDE. By analysing the individual SKU occurrences and the type of products, we can additionally improve the decision by evaluating whether these clusters are to be interpolated or whether it is appropriate to establish multiple locations of item C, a solution that provides flexibility. The decision on the location of F has to take into consideration the occurrence frequency of item F in relation to other product groups (not presented here).

Table 1: Example of output summary – Suggested clusters

Pairwise occurrence of SKUs in pick-up orders	Occurrence frequency, ranked in decreasing order	TIN $TIN_{\alpha} = 30$		Suggested clusters
AB	98			
CD	55			
CE	48	TIN_{CDE}	48	**CDE**
AC	30	TIN_{ABC}	30	**ABC**
AE	20	TIN_{ABCE}	20	
BF	5	TIN_{ABCEF}	5	

Figure 2 shows how a subset of the clusters from Table 1 is presented in the demonstrator program. Note that the demonstrator checks all possible clusters, but only displays clusters with *TIN* values over the defined threshold.

	A	B	C	D	E	F	G	H
1	FREQUENCY	PAIRS		TIN	CLUSTERS		TRESHOLD:	30
2	98	AB		48	CDE			
3	55	CD		30	ABC			
4	48	CE		30	ABCDE			
5	30	AC		...				
6	20	AE		5	ABF			

Figure 2: Example from the CLUSTER worksheet

DISCUSSION OF THE METHOD AND CONCLUSIONS

The suggested method is a medium-term planning level (tactical) policy, originated from the commonly known XYZ grouping method; in the sense that the order frequency is taken as measure for order pick-up time. It, however, substantially differs from XYZ policy in that the pairwise order frequency is evaluated, as opposed to individual item order frequency in the XYZ policy. The new method provides a dynamic grouping possibility of any potential combination of the items, and decision support for potentially multiple locations of one specific item. This is particularly interesting in multiple warehouse systems. Multiple locations of an item increase quick response abilities; a crucial aspect in specialized one-of-a-kind offshore vessel production and other complex project based production systems.

In summary, the method provides flexibility with respect to handling variation in the picking orders, without increasing time and costs substantially. The grade of flexibility is evaluated by the strength of the transitivity property of an item in relation to multiple clusters (*TIN*). This information is potentially useful for additional decision support of multiple locations of particular items.

The method is also useful as kitting support. Traditional kitting strategies have the potential to be costly and rigid in non-standardized environments with frequent variation orders. Kitting strategies also fail when the quality of the items in the kit is variable. Quality variations lead to frequent replacements, and trigger the need for individual SKU stocks to avoid replacements from other kits.

In the following, the suggested clustering method is discussed in relation with a bill of material (BOM) list, to illustrate the method's potential value with respect to kitting decisions. Assume the BOM list presented on Figure 3. In is rather intuitive that the BOM-list, in combination with a high *TIN* number for items C, D, E and F, indicates that these items potentially form a kit. Consider now that items A, B, E, F also have a high *TIN* value. The BOM, in addition to the *TIN*, indicates that items A and B should be clustered with the kit (C, D, E, F) but not kitted, unless additional factors are suggesting this. Other important factors to consider can be the use of common tools, and/or common workforce.

Note that under kitting decisions, the estimated replacements/errors of an item, and the occurrence of the item in different structures, are also to be analyzed. In conclusion, the suggested clustering methodology potentially eliminates the need for kitting strategies and provides a more flexible solution. Alternatively, the method is a good decision support for kitting. In order to conclude on this, however, large scale real life tests are required.

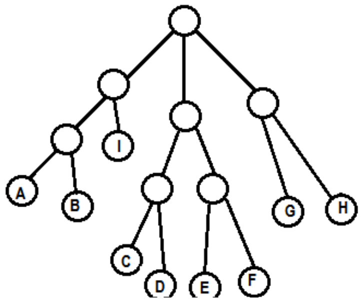

Figure 3: Bill of Material list (BOM)

It is also worth noting that a low *TIN* number does not automatically indicate that particular items/components are to be excluded from a cluster. As for ABC analysis, the complementarity of items is to be evaluated.

One of the most valuable aspects of the suggested method is the quick computerized implementation process, eliminating the need to enumerate the frequency of all possible combinations; a resource demanding process with respect to computer processing time. The prerequisites for such a system to be operational are connected to computerized ways to manage warehouse operations. Although there is still substantial human work in the task of order picking, offshore shipbuilders are now adapting technologies that enable the prerequisites. For validation, the proposed methodology will be implemented and tested at a leading Norwegian offshore shipbuilder, which currently implements a warehouse registration system (named TAG-Manager), including scanning equipment. The proposed grouping algorithm is expected to be implemented as part of this system or as a stand-alone program which access the system's database by a standard ODBC interface.

Concluding the paper, for groups of items a transitive implication number (*TIN*) is computed. In the case of non-zero *TIN* value a transitive implication is identified, indicating the relation between the units in the group. This relation shows the potential to reduce walking distance when multi-items are picked together. The size of the *TIN* indicates the importance of clustering stock keeping units, to reduce order pick up distance (and time).

An ex-post judgmental evaluation of the low *TIN*-value clusters will be needed, to detect complements that are to be clustered within the high *TIN*-value groups.

The proposed methodology combined with BOM-list provides a potentially useful toolset for kitting decisions as well. Ex-post judgmental evaluations of the identified clusters/kits further contributes to improved flexibility in clustering to handle variable requests. The direct result is reduced walking distance in the warehouse.

For detailed description of the demonstrator, please contact one of the authors.

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