A flexible tool for warehouse design and picking optimization

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Abstract: This paper describes the development of a software tool, programmed in Visual Basic for Applications - Microsoft Excel™, to support the design of a new warehouse, e.g. to decide on the number of aisles or cross-aisles as a function of the (expected) order size before the new warehouse is built. The software tool was designed to be flexible enough to reproduce the geometry of any warehouse as a function of its main parameters, i.e. number of blocks, number of cross-aisles, shape factor and total storage capacity. In the same tool, different routing policies have been embodied, including the traditional heuristic strategies (S-shape, return, largest gap and aisle-by-aisle), as well as an “advanced” return policy that allows exploiting the cross-aisles where available. The chosen context of analysis of these policies is that of manual, picker-to-parts, order picker systems. The effectiveness of the tool developed has been tested on a sample warehouse, of fixed storage capacity, where the software was used to compute the travel distance of the picker as a function of the routing policy, shape factors, number of aisles, number of cross-aisles and size of the order picking list. The best policy, i.e. the policy that returned the shortest path, was identified for each warehouse configuration investigated. Besides supporting the design a new warehouse, the proposed software tool is expected to be useful also to test the performance of an existing warehouse and to substantiate operational decisions, e.g. the choice of the routing policy to be implemented.

Keywords: warehouse design; software tool; travel distance; routing.

1. Introduction

The efficiency and effectiveness of logistics activities in general and of distribution networks in particular, is largely determined by the operation of the warehouses, as the nodes of these networks (Zhang & Lai, 2006). The logistics cost relating to warehouse processes, including receiving, storage, order picking and shipping, is often high (Rouwenhorst et al., 2000). Among the different processes, order picking is generally recognized as the most expensive activity, because it tends to be either very labour intensive or capital intensive (Frazelle, 2002). Order picking is the process of selecting a set of items, retrieving them from their storage locations and transporting them to a sorting/consolidation process for order fulfillment and shipment, in response to a customer’s request (Rouwenhorst et al., 2000). The picking process can either be performed manually or (partly) automated. In the case of a manual process, it is estimated that picking operations account for more than 55% of the total cost of warehouse operations (Coyle et al., 1996; Tompkins et al., 1996; Bottani et al., 2015). For this reason, both researchers and logistics managers consider order picking as a promising area for productivity improvement (de Koster et al., 2007). The high cost of picking is mainly due to the fact that approximately 50% of the total order picking time is spent by pickers in (unproductive) travelling. This part of the order picking time is commonly known as the “travel time” of pickers and affects the total order picking time to the largest extent (Tompkins et al., 1996). As the travel time is an increasing function of the travel distance, minimizing this distance is suggested by many authors as the main leverage for optimising the total picking time of warehouses (Jarvis & McDowell, 1991; Hall, 1993; Petersen, 1999; Petersen & Aase, 2004). Reducing the travel distance of pickers has a direct impact on warehouse performance in terms of cost and delivery lead-time, and consequently affects the performance of the whole supply chain. Indeed, the faster items are picked from the warehouse, the shorter the time spent on order fulfilment; hence, the lead-time required for delivering the product to the final customer decreases correspondingly (de Koster et al., 2007; Bottani et al., 2012). Researchers (e.g. Gu et al., 2007 or de Koster et al., 2007) agree that several factors affect the travel distance in an order picking system. These factors include: the overall structure of the warehouse in terms of size and layout (Roodbergen & Vis, 2006; Parikh & Meller, 2010); the use of order picking (Van Nieuwenhuyse & de Koster, 2009; Le-Duc & de Koster, 2007) vs. batch picking (Henn, 2012; Hong et al., 2012); the storage assignment policy (Petersen & Schmenner, 1999; Webster et al., 2012; Bottani et al. 2012); the use of zone picking (Petersen, 2002; Jane & Laih, 2005; de Koster et al. 2012); the picker routing (Petersen & Aase, 2004; Kulak et al., 2012); the use of narrow aisles, because of possible congestions (Pan & Wu, 2012; Chen et al., 2013, 2016; Mowrey & Parikh, 2014).

Although all the factors listed above contribute to the minimization of the travel distance of pickers, researchers typically focus on one or two specific topics to be analysed and optimised, as it is not trivial to investigate all the factors at a time (de Koster et al., 2007; Bottani et al., 2012, 2015; Manzini et al., 2012). In this paper, we attempt to create a software tool that allows the simultaneous analysis of several factors listed above. The
tool has been programmed using visual basic for applications (VBA) under Microsoft Excel™ and has been designed to be flexible enough to reproduce any warehouse layout and routing policy adopted. Consequently, we have tested the effectiveness of the software tool by analysing the relationship between the routing policy and warehouse layout and by assessing their impact on the total distance covered by pickers. This issue has been explored in literature only by Petersen (1997; 1999), who carried out a detailed analysis of variance to examine the interactions of routing policies, warehouse layout and depot location under different operating conditions of a warehouse.

The remainder of the paper is organized as follows. Section 2 describes the software tool developed. In section 3, we analyse the relationship between the routing policy and warehouse layout and their impact on the picking process. Section 4 summarises the main findings of the research, discusses the main implications (both practical and theoretical) and outlines future research directions.

2. Modelling framework

As mentioned, we developed a software tool able to reproduce the layout of a regular (rectangular) warehouse as well as different routing policies that can be adopted by pickers to fulfill an order. As we focus on these elements, the following assumptions hold true:

1. a manual, picker-to-parts order picking strategy is adopted;
2. a random storage of items is applied in the warehouse, meaning that all picking locations have the same probability of being visited by the picker;
3. the warehouse consists of racks and each picking location can contain only one stock keeping unit (SKU). Picking activities involve only low-level storage locations;
4. the input/output (I/O) gate is located at the bottom left corner of the warehouse;
5. the aisle width is not negligible.

The software tool receives, as input, the following parameters that can be set directly by the end-user:

- **shape factor**, i.e. the ratio between the length and width of the warehouse;
- **storage capacity** of the warehouse, i.e. the total amount of storage locations that involve picking activities;
- **number of cross-aisles**;
- **aisle width**;
- **order size**, i.e. maximum number of items included in the picking list;
- **size of the storage locations**, in terms of length and width;
- **routing policy**.

As it is computed as the ratio between the warehouse length and width, the shape factor can vary in a range of possible values; at present, the software tool is able to create warehouse layouts whose shape factors varies from 0.005 to 30 approximately. As far as the order size is concerned, once the user has set the maximum length of the picking list, the software automatically generates random picking lists whose average size is half the maximum length selected. Because the picking lists are generated randomly, in line with assumption (4), to provide statistically significant outcomes the software creates 10,000 picking lists for each scenario analysed.

With respect to the routing policy, the software embodies the traditional return (R) and S-shape (S) policies. Moreover, for both policies an “advanced” strategy has been developed, in an attempt of exploiting the warehouse cross-aisles (where available). These new policies are referred to as advanced return (Radv) and advanced S-shape (Sadv). Their functioning is as described below and compared to the traditional R and S policies.

- **Radv**: when using the traditional R policy, the warehouse cross-aisles are never used, as the picker enters an aisle and leaves it always from the same side. Under the Radv policy, instead, the picker may choose to use a cross-aisle after having picked the item required, to move to a different (adjacent) aisle where further items should be picked. An example of this policy is proposed in Figure 1;
- **Sadv**: in the traditional S policy, the picker enters an aisle from one side and traverses it up to the other side; then, it moves to the next (adjacent) aisle where new items should be picked. Cross-aisles are not exploited with this policy. The Sadv policy has been developed to allow the picker to change aisle exploiting the cross-aisles. An example of this policy is proposed in Figure 2.

As shown in Figures 1 and 2, to exploit the cross-aisle, aisles should be sufficiently width to allow a picker to change directions within them, avoiding congestions. This is the rationale behind assumption (5) of wide aisles.
3. Analysis and results

The four policies described in the previous section were compared in terms of the average travel distance generated, as a function of the warehouse shape factor and maximum size of the order picking list. To carry out the analyses, the following parameters were set:

- storage capacity: 2,400 picking locations;
- size of the storage locations: 1.25 m (length) x 1.00 m (width);
- aisle width: 3 m;
- order size: from 10 to 100 (step 10);
- shape factor: 23 values, from 0.00454 to 30;
- number of cross-aisles: from 1 to 21 (step 1).

Overall, the combination of the above parameters (10x23x21) with the routing policies (4) led to 19,320 scenarios, each of which was analysed by means of 10,000 different picking list generated randomly. For brevity, we limit the presentation of the outcomes to a selection of results obtained for the S and S_{adv} policies and then show the comparison with the R and R_{adv} policies.

Figure 3 shows the results obtained with order size=10 when adopting the S routing policy. From this figure it can be seen that the minimum travel distance is obtained when setting 1 cross-aisle and a warehouse shape factor ranging from 2.13 to 2.29.
The minimum distance covered by the picker as a function of the warehouse shape factor is proposed in Figure 4. This figure shows that the travel distance initially decreases with the increase in the shape factor, reaching a minimum for shape factor between 2.13 and 2.29, as already highlighted. For higher values of the shape factor, the travel distance increases. In general, higher shape factors indicate that the warehouse length is significantly higher than its width, which makes the picking routes longer.

The variation in the number of cross-aisles (Figure 5) has a similar effect on the minimum travel distance. More precisely, as the S policy does not make use of the cross-aisles, their increase in number merely involves an increase in the travel distance, because of the increase in the warehouse size.

Figure 6 shows the combined effect of the shape factor and number of cross-aisles on the travel distance covered by the picker. As this figure shows, although both these parameters affect the minimum travel distance, the effect of the number of cross-aisles is weaker than that of the warehouse shape factor. The “optimal” length of the picking tour is obviously obtained with 1 cross-aisle and shape factor between 2.13 and 2.29.

The analyses proposed above have been carried out also for different values of order size; as an example, Table 1 provides the average distance between two picks and the optimal shape factor of the warehouse for the S routing policy, as a function of the maximum number of items in the order size.
the picking list. As it is reasonable to expect, the average distance between two subsequent picks decreases with the increase in the number of items to be picked. Conversely, the optimal shape factor is constant for a wide range of order sizes (from 20 to 80 items in the picking list), which was not obvious to expect. This result suggests that the optimal shape factor depends mainly on the routing policy applied, while it is less sensitive to the size of the order picking list.

Table 1: average distance between two picks and optimal shape factor as a function of the number of items in the picking list for the S policy.

<table>
<thead>
<tr>
<th>Maximum number of items in the picking list</th>
<th>Average distance between two picks [m]</th>
<th>Optimal shape factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>88.7901</td>
<td>2.2917</td>
</tr>
<tr>
<td>20</td>
<td>64.1303</td>
<td>3.1731</td>
</tr>
<tr>
<td>30</td>
<td>52.1691</td>
<td>3.1731</td>
</tr>
<tr>
<td>40</td>
<td>44.8719</td>
<td>3.1731</td>
</tr>
<tr>
<td>50</td>
<td>39.5691</td>
<td>3.1731</td>
</tr>
<tr>
<td>60</td>
<td>35.2879</td>
<td>3.1731</td>
</tr>
<tr>
<td>70</td>
<td>32.3434</td>
<td>3.1731</td>
</tr>
<tr>
<td>80</td>
<td>29.4878</td>
<td>3.1731</td>
</tr>
<tr>
<td>90</td>
<td>26.9916</td>
<td>2.1290</td>
</tr>
<tr>
<td>100</td>
<td>24.9726</td>
<td>0.0179</td>
</tr>
</tbody>
</table>

Similar analyses were repeated for the remaining policies and in the following we provide some comparative results. As an example, Figure 7 shows the relationships between the optimal shape factor and the maximum number of items in the picking list for all the policies examined in this study. A general consideration from this table is that the optimal shape factor depends on the size of the order picking list; such a dependency should be taken into account when designing a new warehouse, as it could affect the performance of the picking process. However, the S adv policy is somehow an exception in this regard; indeed, when adopting this policy the optimal shape factor remains quite stable around 2-4, regardless the maximum length of the order picking list. This suggests that the S adv routing strategy is robust against possible variations in the length of the picking list. The length of the picking list could always vary in time and in any case, it is somehow out of the control of the warehouse manager, as it depends on the order issued by the customers; therefore, a routing policy that is robust against this factor could be privileged in practical cases.

Additional interesting outcomes can be derived by analysing the relationship between the number of cross-aisles and number of items in the picking list (Figure 8). For both the S and R policies, the optimal number of cross-aisles is 1 (which means that the warehouse includes only the corridor at the end of the rack), because none of these policies actually makes use of the corridors when routing order pickers. Conversely, looking at the S adv and R adv policies, it is easy to see that the optimal number of cross-aisles does not vary significantly as a function of the order size, being quite stable around 3-4 for both policies. This is an interesting outcome, which suggests that, when pondering the adoption of these policies, the number of cross-aisles can be set at 3 or 4 (regardless of the order size) to minimize the travel distance of pickers.

Figure 9 provides a graph representation of the relationships between the average distance between two picks and the number of items in the picking list, as a function of the routing policy adopted. It is easy to see that, with the number of items in the picking list increasing, the average distance between two picks tends to decrease. This was expected because, being the warehouse size fixed, the increase in the number of items in the picking list involves the items to be closer to each other. Looking instead at lower order sizes, from Figure 9 it can be seen that the S and R policies return almost the same distance between two adjacent picks and that the same happens for the S adv and R adv policies. Probably, this is because the two groups of policies make use of the cross-aisles in a similar way, resulting in similar picking tours. Overall, the S adv policy seems to return the shortest path, as the average distance between two subsequent picks is always shorter compared to the remaining policies.

Table 2 and Figure 10 summarise the optimal distance obtained for the different policies, as a function of the
number of items in the picking list. By “optimal” we mean the shortest distance resulting from the set of 10,000 random picking lists when varying the warehouse shape factor and number of cross-aisles. The outcomes in Table 2 and Figure 10 indicate that the S_{adv} policy, with appropriate settings, is able to return a shorter travel distance compared to the remaining policies. The average saving against the R_{adv} policy accounts for 2.73%, while it reaches 27.94% and 22.65% when considering the R or S policies, respectively.

Table 2: optimal distance [m] a function of the number of items in the picking list and of the picking policy.

<table>
<thead>
<tr>
<th>Maximum number of items in the picking list</th>
<th>S</th>
<th>R</th>
<th>S_{adv}</th>
<th>R_{adv}</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>443.95</td>
<td>450.63</td>
<td>339.93</td>
<td>341.26</td>
</tr>
<tr>
<td>20</td>
<td>641.30</td>
<td>660.87</td>
<td>475.58</td>
<td>479.45</td>
</tr>
<tr>
<td>30</td>
<td>782.53</td>
<td>819.06</td>
<td>579.52</td>
<td>588.37</td>
</tr>
<tr>
<td>40</td>
<td>897.43</td>
<td>941.47</td>
<td>671.25</td>
<td>683.72</td>
</tr>
<tr>
<td>50</td>
<td>989.22</td>
<td>1050.40</td>
<td>747.60</td>
<td>768.07</td>
</tr>
<tr>
<td>60</td>
<td>1058.63</td>
<td>1138.31</td>
<td>812.59</td>
<td>843.36</td>
</tr>
<tr>
<td>70</td>
<td>1132.02</td>
<td>1232.67</td>
<td>883.84</td>
<td>919.09</td>
</tr>
<tr>
<td>80</td>
<td>1179.51</td>
<td>1299.90</td>
<td>937.32</td>
<td>974.42</td>
</tr>
<tr>
<td>90</td>
<td>1214.62</td>
<td>1355.13</td>
<td>979.83</td>
<td>1022.31</td>
</tr>
<tr>
<td>100</td>
<td>1248.63</td>
<td>1434.92</td>
<td>1040.64</td>
<td>1091.56</td>
</tr>
</tbody>
</table>

Figure 10: “optimal” distance vs. order size.

4. Conclusions

Although picking could seem a simple process at first glance, there are several different factors that affect this activity. This consideration motivated us to develop a flexible software tool that allows to assess the impact of some of those factors on the performance of the order picking process, in terms of the total distance travelled by the picker to fulfil an order. In this paper, we exploited the model to analyse the presence (and number) of cross-aisles, the warehouse shape factor and the routing policy adopted, and their impact on the picking process. Overall, 483 different scenarios were considered by combining the warehouse shape factor (23 values) and the number of cross aisles (21 values) and evaluated applying 4 routing policy and considering 10 different order size. Results were averaged on a sample of 10,000 picking lists, generated randomly by the software tool.

The outcomes obtained show that in general the routing policies that exploit the warehouse cross-aisles (i.e. R_{adv} or S_{adv}) return better results compared to simple policies (i.e. R and S) which do not make use of the cross-aisles. This was expected, because the presence of cross-aisles allows an order picker to change corridor without travelling it entirely (if not necessary); this allows to select a shorter path and decreases, overall, the total distance covered. A further interesting outcome is that when applying either the R_{adv} or S_{adv} policies, the optimal warehouse shape factor does not change significantly as a function of the order size; this suggests that both policies are sufficiently robust in this respect. Therefore, their adoption should be privileged in practical cases when designing a new warehouse. An additional outcome of this study is that the shape factor is somehow dependent on the size of the order list; conversely, the number of cross-aisles does not seem to depend on this latter parameter. These considerations can be useful too when designing a new warehouse: if the warehouse manager knows (or can estimate) the expected size of the orders to be fulfilled, he/she will also be able to determine the optimal shape factor, thus minimizing the travel distance of pickers.

From a scientific point of view, the literature relating to picking optimization typically consists of mathematical models for routing or storage allocation. Although interesting, such models are not trivial to be extended to the case the warehouse includes more than 2 cross-aisles. Conversely, using our tool we were able to vary the number of cross-aisles from 1 to 21, thus providing innovative results. At the same time, for testing purpose the results presented were limited to a specific warehouse configuration (i.e. storage capacity: 2400 picking locations). Although the size could be representative of a real warehouse, it would be interesting to analyse more warehouse sizes, in terms of storage capacity, to investigate whether the results obtained in this paper are confirmed. This is left for future studies. From a technical point of view the software tool itself could also be improved, by adding further routing policies (e.g. aisle-by-aisle or Combined+), for a more comprehensive evaluation.

References


