

# Estimating Travel Distances and Optimizing Product Placement for Dedicated Warehouses with Manual Picking

Uday Venkatadri and Sachin Kubasad

Department of Industrial Engineering  
Dalhousie University  
Halifax, Nova Scotia, B3J 2X4, Canada

## ABSTRACT

*This paper looks at the problem of estimating travel distances for rectangular warehouse sections with manual picking. This study was motivated by a real-life case in the food and beverage industry where case picking occurred in a rectangular section of the warehouse. In particular, we are interested in estimating the distance travelled by an order picker whose picking route begins and ends at a single depot. One of the assumptions in many distance approximation papers is that any location is equally likely to be picked. However, this assumption is unrealistic in the case of dedicated warehouse layout, where products are located strategically in order to minimize total distance.*

*The frequency of accessing a pick location can be estimated from the order history table of a WMS. This in turn can be translated into the probability of accessing certain locations. Under the simplifying assumption that there is no backtracking in the aisles, we build a probability tree to estimate the distance travelled by the order picker.*

*From a placement point of view, we present three product assignment (or order slotting) heuristics in this paper, namely the North-North, North-South, and Nearest Neighbour heuristics. Our study shows that there is very little variation between the heuristics in terms of travel distance.*

## 1. PROBLEM BACKGROUND AND INTRODUCTION

The order picking operation is a labor intensive process and is commonly seen in a wide variety of warehouses and distribution centers. It is quite common in low to mid-volume distribution industries who supply their customers with pallet loads of distributed SKUs. In such cases, a high degree of automation is not easily justifiable. Therefore, warehouse operations managers are very interested in improving their throughput efficiency. A typical measure of picking efficiency is cases picked per hour. Other measures include average time to pick an

order, number of orders with no errors, etc.

In this paper, we look at two problems:

1. The first problem is to estimate travel distances for a rectangular warehouse section with manual picking. Without any loss of generality, we assume that there are several SKUs to be picked in the section. There are dedicated locations to each SKU. The manual picker begins with a pick list which consists of line items and navigates through the warehouse section, aisle-to-aisle, to complete the task. In the context of our paper, we assume that the items picked are in cases and that these cases are stacked on to a pallet which is taken to a depot for shrink wrapping and shipping. The question of interest can be posed as follows: given that a picker has a pick list (list of SKUs to pick), what is the expected travel distance through the aisle set?
2. The second problem is the order slotting problem. Here, the problem is to decide which SKU to assign to which locations. An SKU may need to be assigned to more than one location, depending on turnover. In case it is assigned to several locations, the requirement is usually that the locations be contiguous. Sometimes, many SKUs share the same location. These are details that are somewhat difficult to address fully. Nevertheless, the issue is where to assign which product.

Both problems are important; estimating travel distance is important for managers who are interested in assigning and scheduling workforce. It is also useful for costing purposes. The order slotting problem is important because well slotted warehouses are likely to be more efficient. We became involved in this line of research due in dealing with these questions at a DC in the food and beverage industry sector.

In this paper, we first present the results of a literature review we conducted. We then present our methodology for distance estimation and order slotting. Some results are presented along with our main conclusions. This work has also been presented in Kubasad (2010) and Venkatadri and Kubasad (2009).

## 2. LITERATURE REVIEW

While several models exist in the literature to estimate picking costs for randomized storage, few of the models in the literature specifically deal with dedicated storage. The survey paper by Gu et al (2007) is useful to develop an understanding of the literature.

Hall (1993) presents three routing strategies simple rectangular warehouse sections: traversal, midpoint, and largest gap. The author then develops approximations for expected travel distance for each of these picking strategies. In the traversal strategy, once picking starts on an aisle, the entire aisle is traversed. In the midpoint strategy the aisle is broken into two halves and the halves are accessed from either end. It is used when an aisle contains less than one pick. The largest gap strategy is similar to the midpoint strategy, except that the order picker enters as far as the largest gap between two adjacent picks. One assumption in the research is that the picking locations are randomly distributed, independently and uniformly through the warehouse. This assumption is a restriction for dedicated warehouses, such as the one we were interested in. The author then examines the impact of warehouse shape. He then concludes by discussing the common strategy of assigning products based on turnover, i.e. placing product with the highest turnover closest to the depot.

In their paper, Roodbergen et al. (2008) analyze warehouse order picking operations. This paper also assumes random storage. The paper discusses the factors that affect the efficiency of the picking operation such as layout of the area and the operating principles put in place for picking. A model is presented in the paper to minimize travel distance in the picking areas by identifying an appropriate layout structure consisting of one or more blocks of parallel aisle which is based on a commonly used routing policy, even though it is efficient for some other routing policies as well. An eleven-component estimate for travel distance estimation in warehouse picking operations is presented. The estimate is based on warehouses with any number of rectangular blocks assuming that the S-shaped heuristic is used for routing. The authors then compare the performance of the travel distance estimate with simulation and report that the average error compared to simulation for a test set of 320 layout problems is 0.3% for the S-shape heuristic with a maximum error of 2.9%.

Another relevant article to this research is the one by Sadowsky and Ten Hompel [3] who use an analytical method to calculate travel distance. They assume that the access frequency distribution from the front to the back of each aisle is known. For example, this distribution could follow the exponential distribution, making the probability of picking SKUs at the front of the aisle higher and tailing off towards the end of the aisle. The authors assume that all aisles have the same access frequency, which is a restrictive assumption.

The paper by Le-Duc and De Koster [4] present a probabilistic model that enables us to estimate the average pick travel distance in rectangular warehouse sections with a cross-aisle. One of the assumptions behind this model is class-based storage. They use simulation to show that their model gives good approximate distance. The authors then present a mathematical formulation for the storage-zone optimization problem. Since the exact approach can only solve relatively small problems, they present a heuristic that performs well.

In conclusion, we believe that the probability graph to estimate travel distance overcome the assumptions of random storage (Hall, 1993) and the aisles having the same frequency (Sadowsky, 2008).

### **3. RECTANGULAR-AISLE STRUCTURE AND DEPOT LOCATION**

In this paper, we only look at a single rectangular aisle section of a warehouse. Cross aisles, placed to aid shortcutting are ignored. We also assume that once an aisle is entered, it is fully traversed. While this assumption is somewhat restrictive, it remains the prevalent protocol in many warehouses from the point of view of safety and the desire to reduce congestion. In this paper, we assume a single depot located at the bottom left of the rectangular aisle section from which picking routes begin and end. We also assume that the aisle length is much larger than the rack width as well as the spacing between aisles.

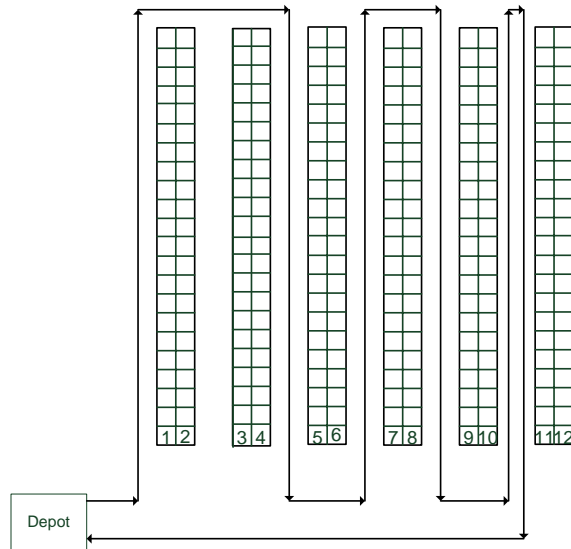


Figure 1: Open-ended aisle configuration allowing picking access from both ends

#### 4. ORDER SLOTTING

Three simple heuristics are presented for order slotting. They are:

1. North-South heuristic or the N-S heuristic
2. North-North heuristic or the N-N heuristic
3. Nearest-Location heuristic or the N-L heuristic

In each of the three heuristics, we do not allow product segmentation. In other words, the assignment of a product is such that it cannot be assigned to two aisles or placed non-contiguously within the same aisle.

The N-S assignment heuristic is described in Figure 2. In this assignment, the highest volume products are allocated along the first aisle in the northerly direction followed by the both sides of the second aisle in the southerly direction and so on.

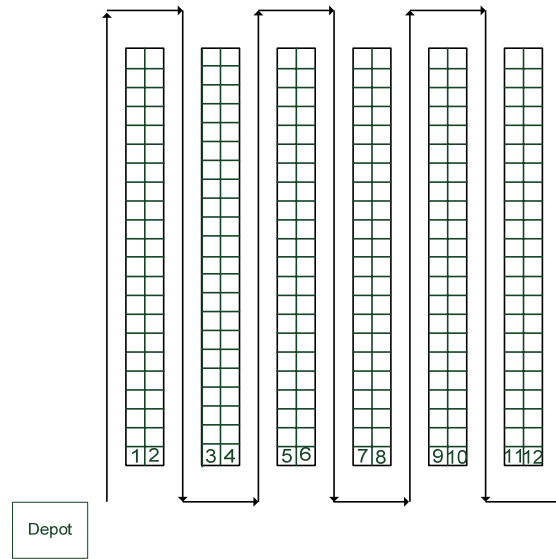


Figure 2: N-S product assignment heuristic

The N-N heuristic is described in Figure 3. With this heuristic, products are assigned in a northerly direction across all aisles. This procedure results in decreasing product demands along racks which is in accordance with one of the assumptions (exponential decrease in frequency of accessing products) in Sadowsky and Ten Hompel (2008). However, the other assumption of equal probability of accessing each aisle is not met in general, because the expected probability of accessing an aisle decreases with the aisle number.

The N-L assignment heuristic is described in Figure 4. Here, products are first sorted in descending order of volume. The slots are sorted in ascending order of distance from the depot. The first product in the product list is assigned slots starting with the closest slot in the slot list where the assignment results in the allocation of product to continuous slots within a single rack. The product is dropped from the product list and the slots from the slot list and the procedure continues.

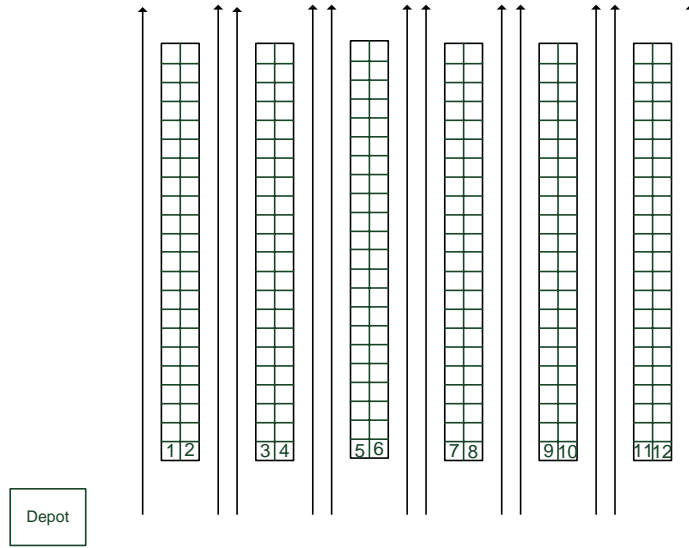


Figure 3: N-N product assignment heuristic

●

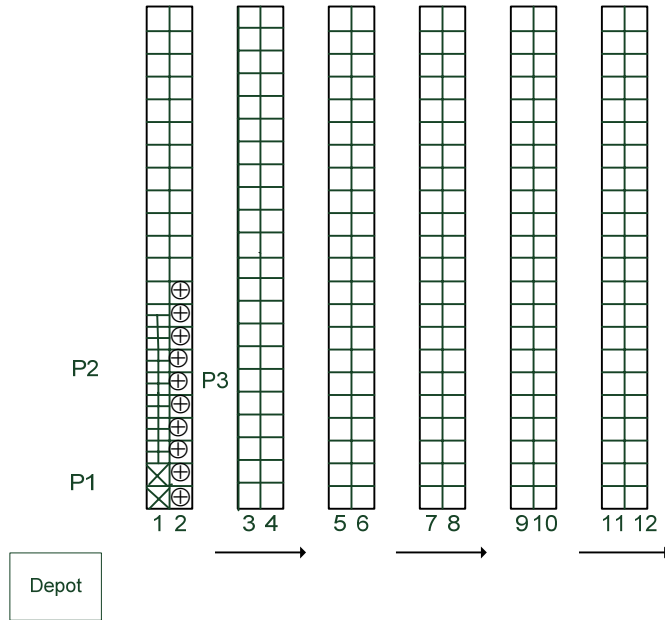


Figure 4: Nearest location product assignment heuristic

In the example illustrated in Figure 4, products P1, P2, and P3 are in decreasing order of volume. Therefore, P1 is first assigned to the slots indicated. P2 is then assigned to slots starting

with the closest available slot, which is the third slot in Rack 1. P3 is assigned next to Rack 2 and this process continues.

The justification of these three heuristics is as follows: The N-S assignment heuristic mimics the S-shaped routing heuristic. Therefore, it is likely to minimize travel distance when an entire aisle has to be traversed when entered. Such would be the case when the aisles are narrow or if in order to avoid collision or congestion, the aisles are designated as one-way. The N-S assignment works well in case of alternating one-way aisles. Note that this heuristic needs adaptation in the presence of cross-aisles or multiple rectangular warehouse sections.

The justification behind the N-N assignment heuristic is that the products are stored close to the depot. If a cross aisle is present, it is our belief that the N-N heuristic will be efficient because it will provide an opportunity to the picker to avoid sections of a long aisle which are infrequently accessed. Note that this heuristic needs adaptation in the presence of cross-aisles or multiple rectangular warehouse sections.

While the aisles closest to the depot are more likely to be accessed in both the N-S and N-N heuristics, the N-L heuristic tends to create wider dispersion of important products across the aisles. However, it also keeps the weighted (by importance) centre-of-gravity of the products closest to the depot. It is expected to work well in the presence of a cross aisle. It is also expected to work well when access is from depots on the South-East and South-West corners of the rectangular section.

## **5. DISTANCE APPROXIMATION USING PROBABILITY GRAPHS**

In this section, we develop distance approximations for the configuration shown in Figure 1. We assume that once the order picker enters the aisle, the entire aisle is traversed. Obviously, this is a simplifying assumption which does not take into account backtracking from an aisle depending on which aisle is entered next and where the next pick occurs.

Let the probability of entering aisle  $j$  be  $P(j)$ . The aisle is entered if any of the SKUs in the aisle need to be picked. Similarly, the aisle is not entered when none of the SKUs need to be picked.



Let  $i$  be the SKU index. It is possible to query a warehouse WMS for the number of orders  $N_i$  that involve a particular SKU  $i$ . Let  $N$  be the total number of orders queried (this should be done over a period of time where the demand has been relatively stable). In this case, the probability of picking product  $i$ ,  $P_i$ , is given by:

$$P_i = \frac{N_i}{N}$$

Let  $Q$  be the set of all products and  $Q_j$  the set of SKUs in aisle  $j$ . Let  $D_i$  be the demand rate of product  $i$ . The aisle is entered if any of the products in the aisle is required. Therefore, the probability of entering aisle  $j$ ,  $P_j$ , is given by:

$$P_j = 1 - \prod_{i \in Q_j} (1 - P_i) \quad (1)$$

Figure 5 shows the critical locations reached in a complete picking path. For the twelve rack configuration shown in the figure, there are 13 locations numbered 0,2,...12 for convenience. Once the picker starts at the depot, he or she has two choices: if Rack 1 needs picking, the picker ends up in location 0c (where c denotes ‘complete’); else, the ending location is 1i. In the former case, the destination node of the picker is labeled 0c because aisle A has been picked at this point. We label the destination node of the picker in the latter case as 1i (i stands for ‘incomplete’) because at this point, racks 2 and 3 (along aisle B) are not yet picked. Obviously, after picking along rack 1, the picker may go back to the start location or move to 2i (when location 2 is reached in this manner, the aisle in front has not been picked and hence the location is labeled 2i). Location 2 may also be reached from location 1 after picking on racks 2 and 3 (along aisle B) and in this case, we label the destination node 2c (where c denotes ‘complete’).

In this manner, it is possible to build the entire probability tree of the picking path (refer to Figure 6). In Figure 6, P(E) represents the probability of entering the corresponding aisle and P(NE) represents the probability of not entering the aisle (the probabilities are calculated from Equation 1). Also, the depot location S is shown on both the left and right sides of the tree for the purpose of convenience.

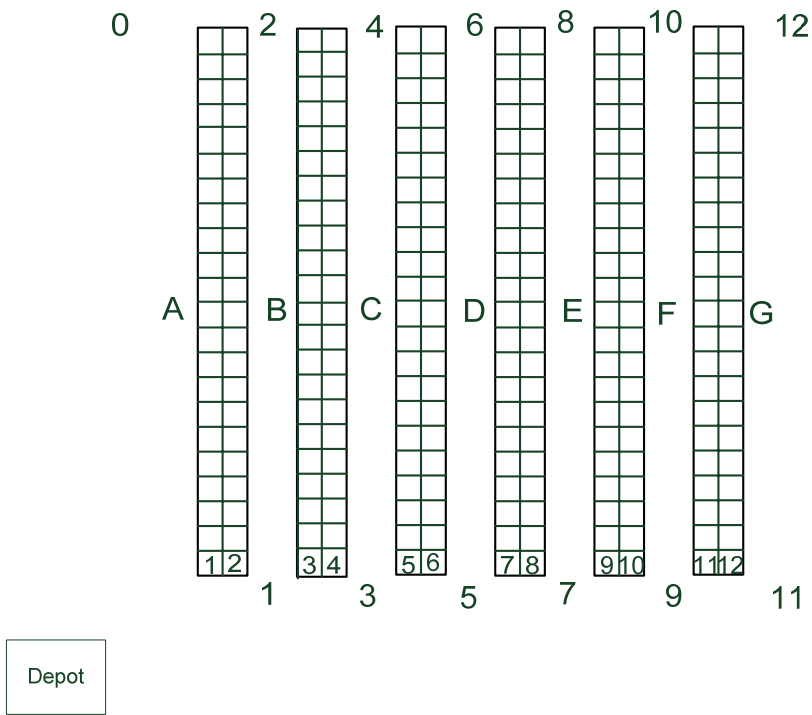


Figure 5: Critical locations in picking path

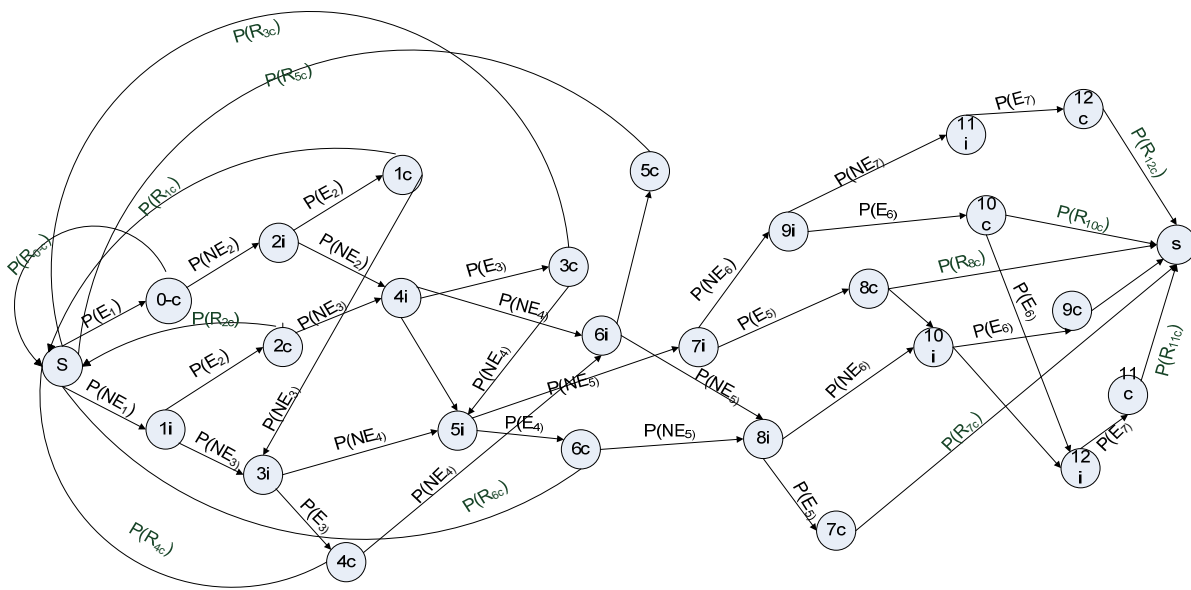


Figure 6: Probability tree of traversal path for the open-ended configuration

Since the distances are known for each location, it is possible to estimate the expected distance by reducing the tree. From S, two locations are possible, 1i and 0c.  $P(S-1i)$  is the probability of going from the depot (location S) to location 1i. The expected distance contribution along this path is  $P(S-1i)D_{S-1i}$ , where  $D_{S-1i}$  is the distance from S to 1i. From 1i, it is possible to go to 2c or 3i and from 0c, S or 2i are the only possible nodes. The expected distance for the entire picking path can be calculated by first finding the probability of entering a node in Figure 6 and multiplying it by the probability of each arc going out of the node and the distance along the arc.

### 3. RESULTS

We used the distance approximation calculations developed in this paper to look at placement strategies for the anonymous industrial partner's distribution center. There were 854 products for assignment in a rectangular section of the DC with the same number of racks and aisles as shown in Figure 6. However, the depth of the racks and aisles were different - there were a total of 933 storage locations in the example with two pallet storage in each location. The demand of products varied significantly. With slot locations proportional to annual demand, the number of slots required for each product varied from 0.3 to 54.7. We assumed that the number of slots required could be fractional, allowing more than one product to share a slot location. In the configuration, the aisle widths were 2.74m with the racks themselves being 51.5m in length. Picking always takes place at the floor level locations, even though storage is 3 levels high.

We first estimated the probability of entering the aisles in the layout (Figure 7). In all cases, the first aisle has the lowest probability of entering. This is because it has only one rack, while all other aisles have two racks. Beyond aisle 2, the probability of entering an aisle is expected to decrease. However, we realized that our order slotting heuristic used volume as the criteria for SKU assignment to locations. In some cases we observed that SKU volume and probability were not completely correlated. There were products with high volumes and low access probabilities, which implied that when they were on a picking list, they were present in high quantities. In discussion with the industrial partner, we were told that in fact, the products with high demand are sometimes ordered more infrequently. Upon reflection, this is indeed what happens when the

EOQ formula is used. Also, assuming that the EOQ formula is used, the item value also has an impact on the volume and frequency of ordering.

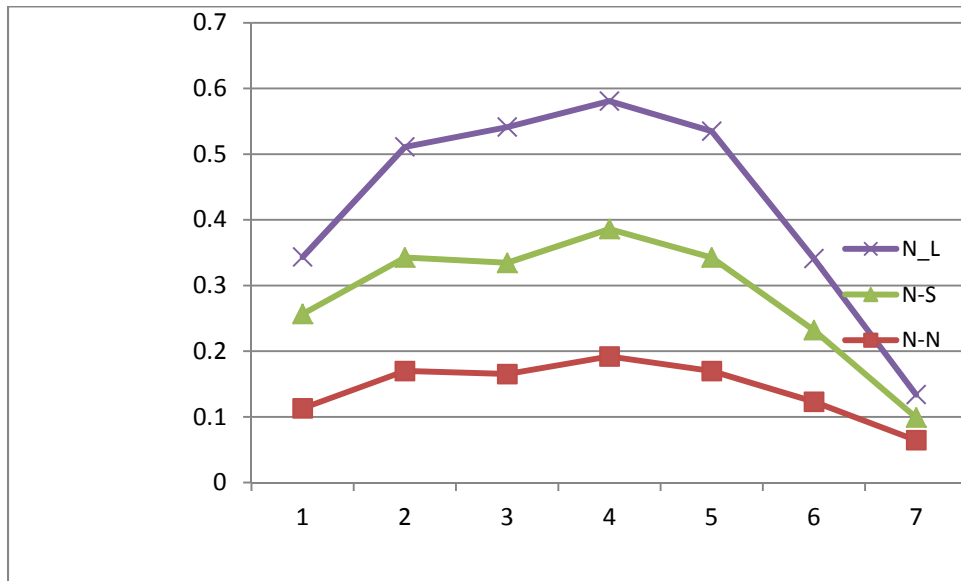


Figure 7: Probability of entering an aisle for the three slotting heuristics

Table 1 below shows the distance approximation calculation results.

Table 1: Distance Approximations (metres)

Assignment heuristic		
N-S	N-N	Nearest-location
459.99	441.16	451.27

As can be seen from the table, the nearest-location performs best overall. However, there is very little difference between this and the other heuristics. In fact, the worst heuristic for this case is the N-S heuristic, whose performance is only 1.93% worse than the nearest-location heuristic. Our speculation is that the nearest-location heuristic keeps the location of frequently picked products as much as possible to the bottom and to the left (i.e., towards the depot). Therefore, it might result in the least expected distance.

#### **4. CONCLUSIONS AND FUTURE RESEARCH**

In this paper, we tried to build a probability graph based costing model for travel distance estimation. We also presented three simple product placement heuristics with very similar travel distance measure.

However, it must be pointed out that our research is still in progress. We are in the process of evaluating the performance of the three heuristics by generating random problems. The heuristics themselves can be modified to rank products by probability of access rather than by volume. A combined measure that takes both probability access and volume into account may also be considered. The calculation of expected distance needs to be refined in many ways. For example, we assumed that once an aisle is accessed, it is traversed completely. This assumption may not hold in many cases. Depending on which products need to be accessed in the next aisle, it may be better to backtrack (as in the largest gap traversal policy presented in Hall, 1993).

We are interested in looking at how cross-aisles help improve picking efficiency. It must be recalled that our assumption is that the entire aisle is travelled when entered. This is obviously an oversimplification. We are in the process of examining what happens if the aisle can be broken up into two or more partitions to improve the distance estimate.

Finally, we are also trying to build a simulation model to gain more insights and validate the expected distance calculations.

#### **5. ACKNOWLEDGEMENTS**

The authors would like to thank the support made available through the National Science and Engineering Research Council of Canada's Discovery and Equipment grants programs. Thanks are also due to an anonymous industrial partner who provided the data and arranged the site visits to facilitate the research.

#### **6. REFERENCES**

- J. Gu, M. Goetschalckx, and L.F. McGinnis (2007), "Research on Warehouse Operation: A Comprehensive Review", *European Journal of Operational Research*, Vol. 177, pp.1-21
- R.W. Hall (1993), "Distance Approximations for Routing Manual Pickers in a Warehouse", *IIE*

Transactions, Vol. 25, No. 4, pp.76-87

- S. Kubasad (2010), "", Unpublished M.Eng project report, Department of Industrial Engineering, Dalhousie University, Halifax, Nova Scotia, Canada
- T. Le-Duc and R.(M.) B.M. De Koster (2005), "Travel Distance Estimation and Storage Zone Optimization in a 2-block Class-based Storage Strategy Warehouse, International Journal of Production Research, Vol. 43, No. 17, pp. 3561–3581.
- K.J. Roodbergen, G.P. Sharp, and I.F.A. Vis (2008), "Designing the Layout Structure of Manual Order Picking Areas in Warehouses", IIE Transactions, Vol. 40, pp.1032-1045, 2008
- V. Sadowsky and M. Ten Homple (2008), "Calculation of the Travel Distance in a Low-Level Picker to Part System Considering any Distribution Function within the Aisles", Progress in Material Handling Research: 2008, Edited by K.Ellis, R. Meller, M.K.Ogle, B.A. Peters, G.D. Taylor, and J.Usher, The Material Handling Industry of America, 2008.
- Uday Venkatadri and Sachin Kubasad (2009), "Optimizing Product Placement for Manual Picking in Warehouses", Proceedings of the 19th International conference on Flexible Automation and Intelligent Manufacturing (FAIM), July 6-July 8, University of Teesside, Middlesbrough,UK