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Collaborative Bots in Distribution Centers

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***Abstract*—This research investigates the business case for using autonomous collaborative robots ("bots") in warehouses. Bots are designed to work collaboratively with human workers in warehouses to fill orders, primarily in e-commerce environments. In order-picking applications, a bot knows the location of every item in the warehouse, and when an item needs to be picked for an order, the bot navigates to that item and waits. Human workers are assigned to patrol specific zones, and when they see a bot waiting, the worker walks to the bot, reads the instructions off the screen, executes the task, and moves on. The bot then drives to the next location, or to a packing or shipping station. Companies that have brought this technology to market advertise these bots as being very efficient systems because human walking is reduced; humans don't have to carry anything or walk around the warehouse to fulfill an order. We investigate conditions where there is good application potential of bots and where there isn't. Analytical models are developed for measuring the work content, productivity, and waiting time by the bot for a worker. A simulation model is built to validate the analytical models. We conclude that with the current pricing structure, the business case for bots is limited to operations with low pick density and throughput requirements that do not lead to excessive congestion or that would favor a more automated solution.**

***Index Terms*—collaborative robotics, cluster picking**

I. Introduction

One of the most significant trends in distribution centers is the increased consideration of using robotics to replace workers or to enhance their capabilities [1]. The motivation is due to many factors. One factor, of course, is the relentless pressure to increase productivity in distribution centers. Another factor is related to the availability of labor to staff distribution centers. To put this bluntly, it is often difficult to hire, train, and retain high-productivity distribution center workers and most distribution center managers find themselves in a constantly revolving carousel to keep their distribution centers staffed appropriately. This has led to thinking about labor as both a cost as well as a potential constraint on the ability to operate a distribution center. Our model focuses exclusively on the tangible, productivity-related advantages, which admittedly is only part of the reason one may choose to deploy bots. Reduced worker training time, worker retention, and hiring costs can also play into the decision.

One robotic application being brought to market to address both of the above factors is autonomous collaborative robots (henceforth referred to as "bots"). Bots are designed to work in close proximity with human workers in the distribution center and to assist with work tasks.

The most-often cited application for bots is to assist workers in the picking function. The bots move the order around the picking area, stopping at every location required to fill the order. The worker still performs all picking functions and once those picking functions are complete, the bot travels to the next location required for the order and the worker travels to another bot. Once the order is complete, the bot travels to a packing area. To aid our discussion, it is actually helpful to think of this as humans assisting bots versus the opposite.

Bot manufacturers tout that bots will reduce worker travel, improve worker efficiency, lower the reliance on labor, increase flexibility, increase order accuracy, improve worker satisfaction, and ease integration with a scalable approach [2]–[4]. In other words, the logic goes that by increasing the productivity of the worker by reducing the walking of the worker and increasing their efficiency in performing the picking task, this will lower the distribution center's need to hire workers, which will reduce the costs associated with hiring, training, and retaining workers as well as potentially circumvent a constraint on the number of workers that can feasibly be hired.

The business case for deploying bots is based on reducing operating expenses by raising capital expenditures (i.e., investing in the bots) or circumventing a labor constraint. To evaluate this business case, we need a throughput model to estimate labor requirements with and without bots as well as a throughput model to estimate the number of bots. As expected, estimating the bots required is dependent on the number of workers in the system. That is, with too few workers to assist the bots, bots will have to wait a long time for a worker, which will lead to even more bots. Likewise, with too many workers, the workers will be starved for work, which will hurt the business case. Our throughput model will need to incorporate this fundamental dynamic.

Given the current bot pricing structure (as of 2018, around $15,000 annually), there needs to be a significant improvement in worker productivity to justify the bot investment. This translates to the need of significantly improving the pick density of the worker by using bots. Thus, in general, non-bot applications with low pick densities will be good candidates for bots and high pick density applications will not.

II. Problem Description

We will model a cluster picking methodology under two scenarios: a traditional, manual system with humans traveling through the picking area and completing the picking operation for multiple orders in the cluster (we will refer to this as the "manual scenario" or "manual application") and a scenario where bots complete the travel and multiple workers assigned across zones (one worker per zone) complete the picking for a cluster or orders (we will refer to this as the "bot scenario" or "bot application"). In the manual application the worker is given a cluster of $N1$ discrete orders. In the bot application the bot is given a cluster of $N2$ discrete orders (where $N2 \leq N1$). In doing so we did not try to exactly mimic any particular bot technology (or for that matter, a comparable smart cart manual system) — our goal was to build a model that was robust in capturing the fundamental dynamics of the system.

Our throughput capacity model must incorporate parameters like,

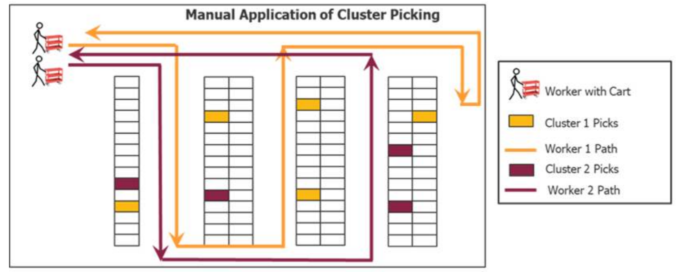
- the size of the picking area (number of aisles, length of aisle),
- the throughput requirements (hourly or daily orders),
- the order profile (lines/order),
- the processing time per line,
- the worker and bot travel speeds, and
- the cluster size (number of lines/pick cycle).

From this model, we will need to determine the number or workers in both scenarios and the number of bots. The latter will be directly dependent on the waiting time of the bot for a worker to assist. This turns out to be the fundamental aspect of our model and we will focus our modeling attention and testing on our ability to estimate the time a bot spends waiting for a worker. Our economic model incorporates bot investment and operating costs in addition to labor costs.

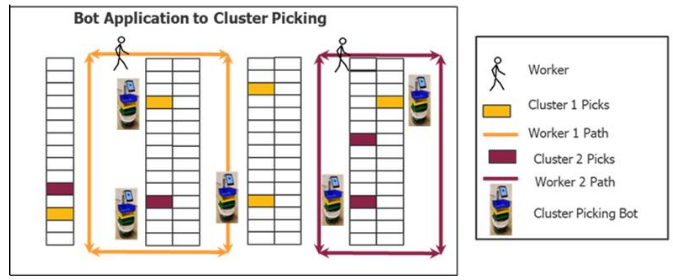
In addition, one of the fundamental challenges for a bot application is that a bot is less efficient at cluster picking than a worker. That is, for a cluster of the same size or smaller, it has at least the same travel when cluster size is the same or more when the cluster size is smaller, and the bot must wait for workers to "find it." Therefore, there will always be more bots in the bot application than workers in the manual application. So, bots can only be applied in situations where congestion would not be an issue in the manual application.

Thus, we must develop a throughput capacity model to estimate the number of workers required to cluster pick a set of orders, a throughput capacity model to estimate the number of bots required to cluster pick a set of orders (being assisted by workers) for a fixed bot waiting time, and a model to estimate the bot waiting time.

The models and analyses we present in this paper are based on a bin aisle layout picking system as shown in Figure 1(a) for the manual application and Figure 1(b) for the bot application.



(a) A manual cluster pick path where workers retrieve carts, traverse aisles with picks, then drop the cart at the end of the pick tour.



(b) Bots traverse the pick path, waiting for a worker to execute the pick. Meanwhile, a worker walks along a designated pick area looking for bots requesting a pick, executes the pick and moves on to the next request/bot. It is possible for a worker to walk the designated area multiple times to execute all the picks, which might decrease the savings implied by the illustration.

Fig. 1. Cluster Picking from a generalized bin aisle layout.

III. Methodology

A. Estimating the Expected Number of Workers in a Manual Cluster Picking Application

We first compute the average cycle time per cluster, which is the average work content in a cluster and includes travel to all relevant pick locations and processing the lines at the pick locations (scanning and confirming). From the cycle time and the lines/cluster, we can compute worker productivity in lines/hour. The ratio of throughput requirement to productivity (adjusted by a personal fatigue and delay allowance, or PF&D) is used to calculate the expected number of workers required to meet throughput. That is,

Expected number of workers needed =

$$\lceil \textit{T-put required}/[(\textit{lines per cycle}/\textit{cycle time})/(1-\textit{PF\&D})] \rceil ,$$

where the cycle time considers both processing time as well as the expected travel time through the area.

Instead of providing this model in detail we present a similar model for the bots. The changes needed should be straightforward for the reader.

B. Estimating the Expected Number of Bots in a Bot Cluster Picking Application

The same approach described above can be applied — without PF&D and adding the time per line that the bot waits for the worker — to estimate the number of bots required to meet throughput. The one critical variable that increases the work content for bots is the amount of time a bot waits at the pick location waiting for a worker to pass by to execute the pick. This wait time adds to the work content, and hence increases the cycle time per cluster for the bots. Estimating it is not straightforward because it depends on the travel pattern for the worker who is searching for a bot. Our model uses an estimated waiting time and we update the estimate in an iterative fashion.

C. Detailed Methodology and Formulas for the Bot Cluster Picking Application

1) Step 1, Bot Throughput Capacity Model: Expected Number of Aisles for a bot picking N lines =

$$E[A] = \left(1 - \left(\frac{A-1}{A}\right)^N\right), \text{where}$$
$$A = \text{number of aisles}$$
$$N = \text{Number of lines per pick cycle;}$$

Across Aisle Travel Distance

$$= 2 \times \frac{C \times A}{2} \times \frac{E[A]}{E[A]+1},$$
$$= C \times A \times \frac{E[A]}{E[A]+1}, \text{where}$$
$$C = \text{center-to-center distance between aisles;}$$

Within Aisle Travel =

$$(E[A] + 0.5) \times L, \text{where}$$
$$L = \text{Aisle depth;}$$

Total Travel Distance for a Bot per Pick Cycle

$$D_B = C \times A \times \frac{E[A]}{E[A]+1} + (E[A]+0.5) \times L;$$

Total Time Required per Pick Cycle

$$E[CT] = \frac{D}{s_B} + (p_l + q_l) \times N, \text{where}$$
$$s_B = \text{bot speed}$$
$$p_l = \text{processing time per line with PF\&D}$$
$$q_l = \text{expected waiting time per line}$$
$$\text{(bot waiting for a worker); and}$$

Required Number of Bots

$$B = \left\lceil TH \times \frac{E[CT]}{N} \right\rceil, \text{where}$$
$$TH = \text{Throughput requirement in Lines per Hour.}$$

As the waiting time depends on the work travel time, we provide the model for that next.

2) Step 2, Worker Travel Model: For our worker travel model, we apply the results of [5] and denote Z = number of zones or workers (assuming one worker per zone).
Expected Number of Aisles in Zone

$$E[A_z] = A_z \times \left[1 - \left(\frac{A_z - 1}{A_z}\right)^{N_z}\right], \text{where}$$
$$A_z = \text{Number of Aisles in a zone, } A_z = A/z$$
$$N_z = \text{Number of Lines in a zone, } N_z = N/z;$$

Travel Distance for worker = D_P;
If $E[A_z]$ is even AND $A_Z - E[A_z] \geq 1$,

$$D_P = E[A_z] \times L + 2 \times A_z \times C \times \frac{E[A_z]}{E[A_z]+1};$$

If $E[A_z]$ is even AND $A_Z - E[A_z] < 1$,

$$D_P = E[A_z] \times L + 2 \times A_z \times C;$$

If $E[A_z]$ is odd AND $A_Z - E[A_z] \geq 1$,

$$D_P = (1 + E[A_z]) \times L + 2 \times A_z \times C \times \frac{E[A_z]}{E[A_z]+1}; \text{and}$$

If $E[A_z]$ is odd AND $A_Z - E[A_z] < 1$,

$$D_P = (1 + E[A_z]) + 2 \times A_z \times C.$$

With a model for the worker travel time, we are now in position to estimate the bot waiting time and provide that model next.

3) Step 3, Estimate Bot Waiting Time:

$$B_Z = \text{Expected bots per zone} = B/Z;$$
$$\text{Expected distance between bots} = D_P/B_Z;$$
$$\text{Expected time for a worker to assist with one line}$$
$$= t_B = \frac{D_P}{B_Z} \times \frac{1}{s_p} + p_l, \text{where}$$
$$s_p = \text{worker speed with PF\&D.}$$

a) Estimating the time a bot waits for a worker, q_l

A bot arriving to a pick location might be processed by the worker right away (assuming the bot's pick location is the closest to the current worker location. However, the bot might be 2^{nd} in queue for the worker, or 3^{rd} in queue, and so forth up to B_Z^{th} in queue. If all these events occur with the same probability, which is $1/B_Z$, the probability distribution of the waiting time of a bot for a worker is:

Expected waiting time

$$q_l = \frac{1}{B_z} \times (1 + 2 + 3 + ... + (B_z - 1))t_B + 0.5t_B;$$
$$q_l = \left(\frac{B_z - 1}{2}\right) t_B + 0.5t_B, \text{using} \sum_{i=1}^{N} \frac{(N)(N+1)}{2};$$
$$q_l = \left(\frac{B_z}{2}\right) t_B.$$

Waiting Time	*Probability*
$0.5t_B{}^*$	$\frac{1}{B_z}$
$0.5t_B + t_B$	$\frac{1}{B_z}$
$0.5t_B + 2t_B$	$\frac{1}{B_z}$
$0.5t_B + 3t_B$	$\frac{1}{B_z}$
$0.5t_B + 4t_B$	$\frac{1}{B_z}$
.	.
.	.
.	.
$0.5t_B + (B_z - 1)t_B$	$\frac{1}{B_z}$

* Assumes the worker needs half of t_B to start processing the first bot in queue

4) Procedure for finding B:

1) We assume a value for q_l
2) Execute Step 1 to estimate B
3) Execute Step 2 to estimate D_P
4) Execute Step 3 to estimate q_l

If assumed q_l is within ϵ seconds of estimated q_l, stop; otherwise, substitute estimated q_l for assumed value and execute Steps 1–3 again.

We assume that this procedure converges, with no evidence to date that it does not.

Our methodology embeds a decision variable; namely, the number of zones, which determines the number of workers. We enumerate the relevant portion of the solution space to finalize our value of B.

IV. Results

A. Testing our Expected Waiting Time Approximation

To explore the accuracy of our waiting time analytical model, we developed a discrete-event simulation model using FlexSim that can be generated automatically for user-defined values for the relevant set of parameters listed in the methodology section (e.g., layout dimensions, lines/order, orders/cluster, etc.). The simulation model captures the dynamics between workers and bots more closely than the analytical model. The analytical model assumes a specific movement pattern for the worker in the designated zone, in which the worker traverses the aisles in the zone sequentially, and executes the picks encountered along this static pick path. The simulation model mimics the actual travel pattern in which the worker traverses the main cross-aisle searching for waiting bots and enters a bin aisle with at least one waiting bot. Sometimes, a bot would arrive to the bin aisle while the worker is executing a pick, in which case the worker might travel back-and-forth in the aisle executing the picks (this back-and-forth movement is not easily captured in a static, analytical model).

We compared the average waiting time per line estimated by the analytical probabilistic model to the simulation's output. We use four scenarios to do so.

- We look at two sizes for the picking area: Small (50 aisles) and Large (200 aisles).
- We also look at a low number of lines per cluster (4) and a higher number of lines per cluster (8).

These combinations, although not exhaustive, allow us to examine the waiting time estimate for situations with a low or high number of SKUs, large or small SKUs, a low or higher number of orders per cluster, a low or higher number of lines per cluster, etc. We hold all other parameter values constant (see Table I for system parameters). Our methodology also requires cost parameters. The cost parameters are provided in Table II [2].

TABLE I
SYSTEM PARAMETER VALUES

Shift Duration	8 hours
Orders/Shift	5,000
Aisle Depth	40 feet
Aisle Center-to-Center Distance	10 feet
Worker Walking Speed with PF&D	150 feet/minute
Bot Walking Speed	150 feet/minute
Average Lines/Order	1.3
Processing Time Per Line	10 seconds

TABLE II
COST PARAMETER VALUES

Loaded Annual Cost per FTE	$40,000
Investment Cost per Bot	$30,000
Bot System Setup Cost	$75,000
Annual maintenance, software, etc. cost	20% of Investment cost
Payback Period	3 years

Tables III–VI below summarize the results of our testing. We provide the results for three values of the number of zones: the value that minimizes the overall costs assuming that our analytical model accurately estimates the number of bots, as well as the number of zones value above and below that assumed, optimal value.

TABLE III
SMALL PICKING AREA – LOW LINES/CLUSTER

Zones	Bots	Average Waiting Time Per Line (Minutes)		
		Analytical	Simulation	Error %
7	33	1.28	1.37	-7%
8	27	0.82	0.94	-13%
9	26	0.73	0.81	-10%

The absolute relative errors in estimating the average waiting time ranged from 0% to 15%, and the only case in which

TABLE IV
SMALL PICKING AREA – HIGHER LINES/CLUSTER

Zones	Bots	Average Waiting Time Per Line (Minutes)		
		Analytical	Simulation	Error %
9	26	1.03	0.89	15%
10	20	0.64	0.65	-1%
11	20	0.60	0.60	0%

TABLE V
LARGE PICKING AREA – LOW LINES/CLUSTER

Zones	Bots	Average Waiting Time Per Line (Minutes)		
		Analytical	Simulation	Error %
11	70	1.91	1.94	-1%
12	63	1.42	1.58	-11%
13	61	1.27	1.42	-11%

the analytical model overestimates the waiting time is the highest pick density scenario, which has a poor business case for the bots. While these relative errors are not as small as we would like them to be, we concluded that the analytical approach tracks the simulation closely enough that we can use the analytical model to narrow the solution space for the optimal bot-worker combination and then simulate the set of combinations around that optimal value to have more confidence in the results.

B. The Key Parameters in the Bots Business Case

After running hundreds of permutations of the design parameters, the results confirm our intuition that beyond the number of shifts, the critical two parameters that determine the business case for bots are the size of the pick area and number of lines that can be picked in parallel by the bot or the worker. Together these two parameters characterize the pick density of a picking operation.

- **Picking Area Size:** All else held constant, as the picking area gets larger, the distance between picks increases. When the distance between picks increases, the number of "unentered aisles in a pick cycle" increases and the worker would walk longer distances along the main aisle, passing by aisles without entering them. A solution that utilizes bots in which a worker is limited to a zone would allow the workers to stay in the aisles with picks and skip walking across aisles with no picks.

TABLE VI
LARGE PICKING AREA – HIGHER LINES/CLUSTER

Zones	Bots	Average Waiting Time Per Line (Minutes)		
		Analytical	Simulation	Error %
13	49	1.55	1.47	6%
14	43	1.13	1.24	-9%
15	41	1.02	1.14	-11%

- **Lines/Pick Cycle:** Similar to the picking area size, as more orders (and lines) are picked simultaneously during a pick cycle, the distance between picks decreases, and the argument above holds.

Thus, the overall result is that the business case for bots is highly dependent on pick density, which itself is dependent on the size of the picking area and the number of lines in a cluster.

With an analytical model that we were comfortable with, we then wanted to look at the financial comparison between the manual and bot scenarios. For the four combinations of picking area size and cluster size, Figure 2 illustrates the number of workers in the manual scenario, the number of workers in the bot scenario, and the number of bots required in the bot scenario, with the latter two values optimized based on the cost parameters provided previously in Table I. Note that the throughput requirements in these combinations was 5,000 orders/day (1 shift/day).

The results conform with our expectations in that the number of workers in the manual scenario is higher than the number of workers in the bot scenario. In addition, the number of bots is higher than the number of workers in the manual scenario. Also, given that we held constant the throughput of the areas, as the size of the area increases, the productivity of the workers and bots decrease (and thus, their numbers increase). And likewise, as we increase the lines per cluster, the productivity of the workers and bots increase and thus, their numbers decrease. Table VII tabulates the results, including the expected costs for each combination over the three-year horizon.

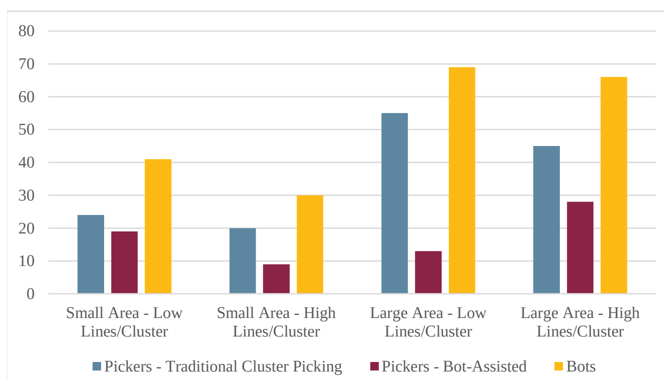


Fig. 2. Estimated values for the number of workers and bots for the two picking scenarios over four combinations of key parameters.

Thus, we can see that for these four combinations only the combination with a large picking area and a low number of lines per cluster is there a positive net benefit for the bot scenario. This is consistent with broader testing. Note: This does not imply that 1 out of 4 (25%) potential application areas are good candidates for bots (or vice versa, that 3 out of 4 (75%) are not).

TABLE VII
RESULTS FROM THE FOUR COMBINATIONS TESTED

<table>
<tr><th rowspan="2">Picking Area</th><th rowspan="2">Scenario</th><th colspan="2">Lines/Cluster</th></tr>
<tr><th>Low (4 Lines/Cluster)</th><th>Higher (8 Lines/Cluster)</th></tr>
<tr><td rowspan="2">Small
(50 Aisles)</td><td>Manual</td><td>Workers Required = 16
3-Year Expected Costs = $1,920,000</td><td>Workers Required = 11
3-Year Expected Costs = $1,320,000</td></tr>
<tr><td>Bot</td><td>Bots Required = 27
Workers to Support Bots = 8
3-Year Expected Costs = $2,331,000
Net Benefit (Loss) = ($411,000)</td><td>Bots Required = 20
Workers to Support Bots = 10
3-Year Expected Costs = $2,235,000
Net Benefit (Loss) = ($915,000)</td></tr>
<tr><td rowspan="2">Large
(200 Aisles)</td><td>Manual</td><td>Workers Required = 43
3-Year Expected Costs = $5,160,000</td><td>Workers Required = 27
3-Year Expected Costs = $3,240,000</td></tr>
<tr><td>Bot</td><td>Bots Required = 63
Workers to Support Bots = 12
3-Year Expected Costs = $4,539,000
Net Benefit (Loss) = $621,000</td><td>Bots Required = 43
Workers to Support Bots = 14
3-Year Expected Costs = $3,819,000
Net Benefit (Loss) = ($579,000)</td></tr>
</table>

C. *Other Business Case Considerations*

In this study we have assumed that the bots and the workers travel at the same speed (after adjusting for PF&D for workers) and the same cluster size. From what we have observed, bots are typically slower than workers, and their load limits restrict their cluster size. In other words, if the bots can travel faster, and if the cluster size carried by the bot can be larger than that carried by a cart pushed by a worker, the business case for the bots will improve. Additionally, multiple-shift operations and distribution centers that rely on temporary labor — which is usually associated with lower picking productivity and a higher hourly costs than permanent labor — would also increase the business case for the bots.

V. CONCLUSIONS

We have concluded two things through our efforts. First, with the current pricing structure and speed capabilities, the business case for bots is limited to operations with low pick density and throughput requirements that do not lead to excessive congestion or that would favor a more automated solution (such as a goods-to-person system). Second, the complexity of estimating worker travel in the bot scenario is quite difficult and would be a good avenue for future research. The dynamics of picker-bot interaction is complex to model analytically. On the other hand, accurately estimating the waiting time is the primary driver in evaluating the business case.

REFERENCES

[1] Material Handling Roadmap, http://www.mhlroadmap.org/, accessed 6/1/2018/.
[2] Locus Robotics, https://www.locusrobotics.com/, accessed 6/1/2018/.
[3] Fetch Robotics, https://fetchrobotics.com/, accessed 6/1/2018/.
[4] Otto Motors, https://ottomotors.com/, accessed 6/1/2018/.
[5] R.W. Hall, "Distance approximations for routing manual pickers in a warehouse," IIE Transactions, vol. 25, pp. 76-87, 1993.