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Understanding Worker Blocking and the Design Process

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Abstract

Designing a distribution center (DC) is a complex process that consists of answering dozens of interrelated questions. From our perspective, the penultimate question is one of which picking methodology is optimal. To answer this question requires a full evaluation of picking methodologies in terms of their ability to meet the expected throughput requirements of the system. In manual picking systems, as throughput requirements increase, worker interaction and blocking increase as well. This implies that being able to estimate the amount of worker blocking in a system is critical to a design effort. Most of the prior research in this area addresses this point from an analysis perspective. In this paper we provide a design perspective based on the results from a structured simulation modeling study we conducted. We present our main result — a *design rule ratio* — as well as how this design rule ratio is used within a design process.

1. Introduction

As e-commerce continues to grow, retailers are forced to consider how to increase throughput in their existing picking systems as well as consider whether a different picking methodology is preferred. With manual picking methodologies, as throughput requirements increase, the number of workers required to meet throughput increases. And with more workers, the likelihood for worker interaction, and thus, blocking, increases as well. Therefore, picking systems eventually reach a saturation point where adding an additional worker actually *decreases* the amount of throughput. And, in practice, even before this saturation point, adding additional workers is not cost effective; i.e., it would better to switch to a different picking methodology. We refer to this as the "tipping point."

At Fortna, our Distribution Center Design Methodology is based on understanding this tipping-point phenomenon and being able to predict where it will occur for a given picking operation. Doing so allows us to search through applicable picking methodologies for a given operation and does not require us to analyze each of those operations in detail during the search process.

There are quite a few papers in the literature that focus on worker blocking models, but almost all of them have an analysis focus rather than a design focus. That is, the papers in the literature focus on estimating the amount of worker blocking for a particular instance of a system. Although such information (a particular estimate of the percentage of time a worker is blocked) is valuable, what is needed in the design process is an understanding of the shape of the throughput-versus-worker blocking curve and the parameters that most influence it so that the tipping point can be estimated. This focus was represented in two works in the literature. However, in the design process, the designer will be working with a constraint on the amount of throughput required in the system. This constraint influences where the tipping point occurs as we will discuss later — an observation that we have not encountered in our examination of the literature.

The focus of this research is to determine the parameters that have the greatest impact on blocking and to use the parameters to determine the amount of blocking that can be tolerated to meet a given throughput requirement before the tipping point is encountered. Simulation models are used to estimate worker blocking over a wide range of picking systems and to characterize relationships between the parameters and worker blocking. Our experimentation led us to a ratio that we use to predict the tipping point of a picking system. We present the experimental results with respect to the ratio and illustrate how the ratio can be used in the design process.

2. Literature Review

Research in the area of blocking generally focuses on models to estimate worker blocking. Gue, Meller and Skufca developed a simple throughput model for a narrow-aisle picking system (i.e., the workers cannot pass each other) and modeled two cases of a circular picking area [1]. The first case models two workers as a Markov process where the walk time to pick time ratio is 1:1, and the second case models two workers walking at infinite speed (i.e., the walk time to pick time ratio is 0:1). Simulation models are constructed to address more realistic worker speeds with more than two workers. The authors found that blocking is concave in pick density; that is, worker blocking increases as pick density increases to a point and then decreases with further increases of pick density. This is due to the fact that there is little worker blocking with a low pick density because blocking only occurs when one worker stops to make a pick and there is also little blocking at a high pick density because workers are stopping in unison [1].

Parikh and Meller applied this modeling approach to picking systems with two differences: 1) a wide-aisle picking system, which meant they had to consider blocking when two or more workers required access to the same pick location; 2) the worker may pick multiple copies of the items when they stop to pick [7, 8]. The authors conclude that in a wide-aisle system, significant blocking occurs when multiple picks occur at a given pick point [7]. They also found that significant blocking can occur when there is a high variation in pick density [8]. Hong, Johnson and Peters [3] build on the work of Parikh and Meller [7, 8] by introducing a more efficient closed-form analytical model for a system with multiple picks. The authors find that as pick density increases beyond 0.75 in a two-worker system, the percentage of time blocked converges to 0 when there is a limit on the number of SKUs picked at a pick point. With no limit on the number of picks at a point, blocking converges to $1/(n+1)$, where n is the number of pick points.

Hong, Johnson and Peters address minimizing the blocking in a system by developing a mixed-integer programming model that integrates batching and sequencing in a procedure to minimize the total retrieval time that includes travel time, pick time and delays due to congestion [2]. The authors contend that their model plays an important role in maximizing picker utilization in order to prevent a decrease in worker utilization as the number of pickers increase. Results indicate that the integrated procedure can reduce the total retrieval time by 5% to 15%, primarily due to the reduction in blocking.

Mowrey and Parikh address minimizing the blocking in a system by proposing a variation to traditional aisle layouts in order to address the compromise between space and labor that results from the exclusive use of either wide or narrow aisles [6]. They propose the consideration of mixed-width aisle configurations and develop analytical models for space and travel time to be incorporated into a cost-based optimization model to identify the parameters where mixed-width aisle configurations are preferred.

The above papers are focused on the analysis of a picking system. The authors use the models developed to evaluate how the blocking changes as system parameters change and use that to infer how the design should change. One change that is not considered is how the increase in workers affects blocking, which is what is directly considered by Lüning [5]. Lüning modeled multiple workers in an aisle and directly examined the relationship between the number of workers and worker blocking. The main result of this examination is that, not surprisingly, worker blocking is an increasing function of the number of workers and a non-linear one. In examining his results he recommended at most one worker for every 3 meters of pick face for random storage [5].

Huber extended Lüning's work to multiple aisles by using a closed, zero-buffer queueing network to model throughput in a narrow-aisle manual order picking system

[4]. Experimental results indicated productivity losses of at least 15% as more and more pickers are added to the system. The results also indicate that more congestion occurs in narrow-aisles systems with lower width-to-depth shape factors (fewer, longer aisles).

3. Methodology

The literature suggests that some form of a single-dimensional rule-of-thumb (like, "at most one worker for every 3 meters") is sufficient to address our issue of predicting a tipping point. To explore this further (confirm the result as well as examine the rule's robustness over a variety of typical parameters that we encounter), we developed simulation models to measure throughput and blocking for various aisle configurations and widths (to examine scenarios with, and without, passing). We then evaluated the results from the simulations to gain an understanding of the relationship between input parameters and the amount of blocking in the system.

The results that we present in this paper are based on the picking system shown in Figure 1, which we simplified later to a general layout as shown in Figure 2. We refer to this as a bin aisle layout, where workers push carts through the main aisle and stop at bin picking aisles when there is a pick in that aisle to which they have been assigned. The workers leave their carts in the aisle, travel into a bin aisle to the correct location, execute the pick, and then travel back to the main aisle to deposit the item(s) in the cart. They then proceed. In practice, other workers are blocked if they need access to a bin aisle that is currently occupied or to travel to a point beyond a cart stopped in the picking aisle (i.e., no passing can occur). We present the results related to our simulation model of workers picking in a bin aisle configuration without passing.

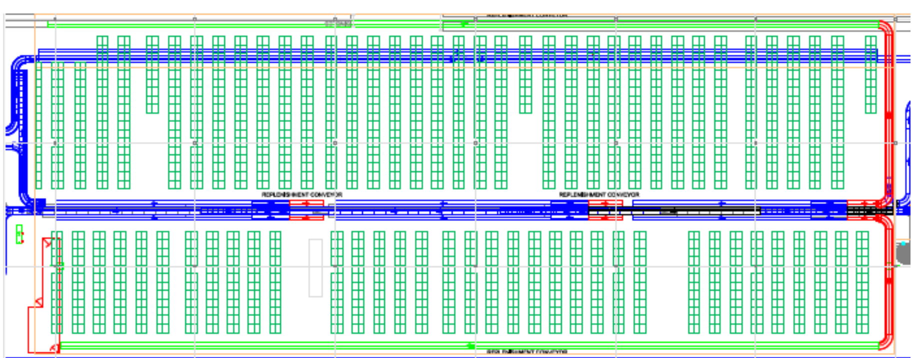

Figure 1: Bin Aisle Configuration in a Distribution Center

For this configuration we held the size of the picking system constant to 40 bin aisles on either side of the main aisle (80 total aisles), with each bin aisle having

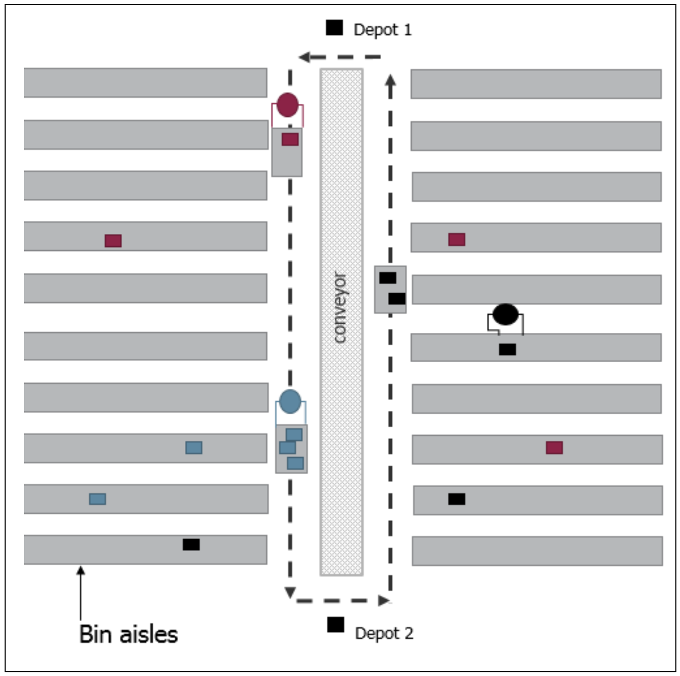

Figure 2: Simplified Bin Aisle Configuration in our Simulation Model

a length of 40 feet, while varying the number of workers from 2 to 50 with order lines ranging from 5 to 12. As indicated in the literature, the number of workers in the system impacts the amount of blocking in a picking system of a given size. Therefore, we first investigate the amount of blocking as a function of the average distance between workers. The results are shown in Figure 3.

As the average distance between workers decreases, the percent of blocking increases. And, similar to previous research results, a non-linear relationship exists between the number of workers in the system and the amount of blocking. That is, the productivity gains (here measured by lines per hour, or LPH) from adding new workers to the system decreases asymptotically. Figure 4 illustrates the productivity loss as workers are added to the system (30 lines per worker tour and 1 to 30 workers). The straight line represents the cumulative lines per hour without blocking, and the curved line represents the actual throughput that includes blocking.

From the results in Figure 3, we observe that the amount of blocking for a particular distance between workers varies by as much as 29%, and, contrary to the conclusions drawn in the literature, it is not clear that this parameter alone will be sufficient to predict the tipping point.

In examining the simulation results for a given number of workers, the lowest point on the curve represents the scenario with the most pick lines. This implies that even in cases where workers are in relatively close proximity, blocking is not an issue if each worker is stopping often. This examination led us to defining a ratio, r, that

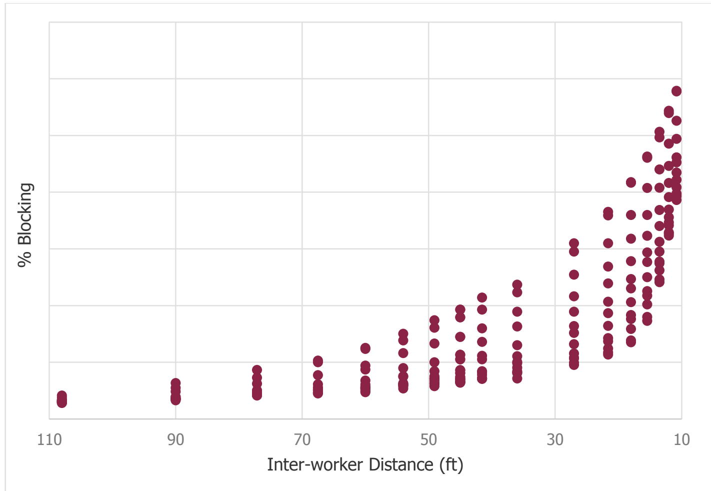

Figure 3: Blocking as a Function of Distance Between Workers

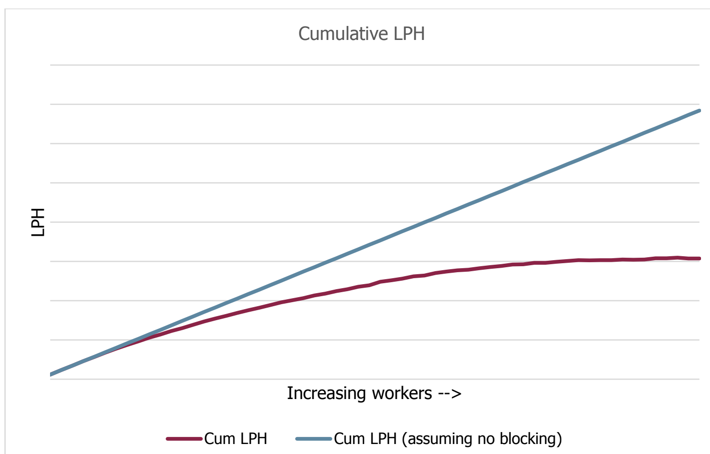

Figure 4: Cumulative Lines per Hour as Workers are Added

considers both the number of workers and the work assigned to each worker:

$$r = \frac{\text{Average distance between workers}}{\text{Average distance between picks for one worker}}.$$

High values of r should represent lower levels of blocking, and conversely, low values should represent higher blocking levels. For example, as r decreases, worker blocking will increase because either the distance between workers is decreasing and/or the distance between picks is increasing, which will make it more likely that a worker will "catch up" to the worker who is currently ahead in the system. We hypothesized that using r would allow us to better predict the tipping point. In Figure 5 we plot the same data points from Figure 3, but with respect to r. (Note: due to proprietary reasons we are purposely not illustrating the values associated with the axes in Figure 5 and the subsequent, related graph.)

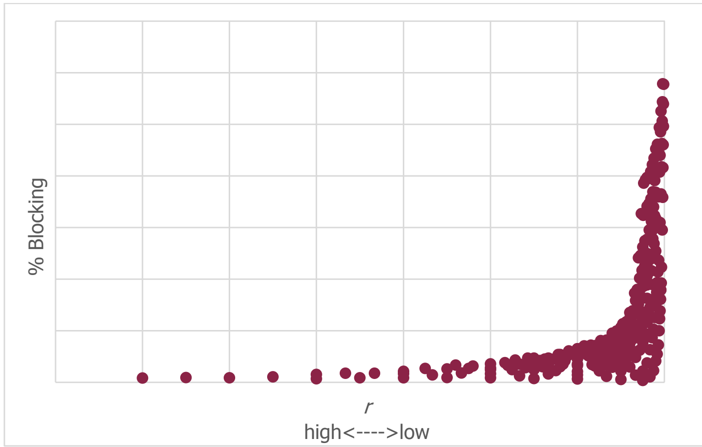

Figure 5: Blocking as a Function of the Ratio of the Average Distance Between Workers and the Average Distance Between Picks for a Worker

In comparing the graphs in Figures 3 and 5, the plot with respect to r represents a better relationship with blocking than considering the distance between workers alone. This is not a surprising result — adding a dimension to a rule-of-thumb will typically improve the predictive value of the rule-of-thumb. However, the strength of the relationship from adding one other, readily available, parameter, was surprising and welcome.

We cannot, however, use the result of Figure 5 from a design perspective because the blocking percentages were determined without holding total throughput fixed. To explain the implication of this statement, consider how the ratio would be calculated in a design problem with an associated design throughput level that needs to be achieved. First, knowing the amount of work that will be assigned to each worker, we can estimate the productivity of a worker with no blocking (implicit in defining this productivity rate is knowing the average distance between picks for a worker, or the denominator of r). This productivity estimate allows us, together with the associated design throughput level, to estimate the number of workers and thus, the average distance between workers (the numerator of r). With r estimated, we can then estimate the amount of blocking in the system. But as this blocking percentage estimate changes (increases), the number of workers in the system will need to change (increases), which will mean that r will change (decreases), which further changes the blocking percentage estimate (increases). This forms the basis for an iterative process to estimate the amount of blocking in the system. In theoretical terms, this process does not converge. In practical terms, as long as the integer number of workers in the picking system does not change from iteration to iteration, we terminate the process.

We applied the iterative process of calculating the number of workers required — explicitly considering blocking — and plotted the corresponding value of r and the blocking percentage. The graph in Figure 6 illustrates the same data points from prior graphs after applying the iterative process.

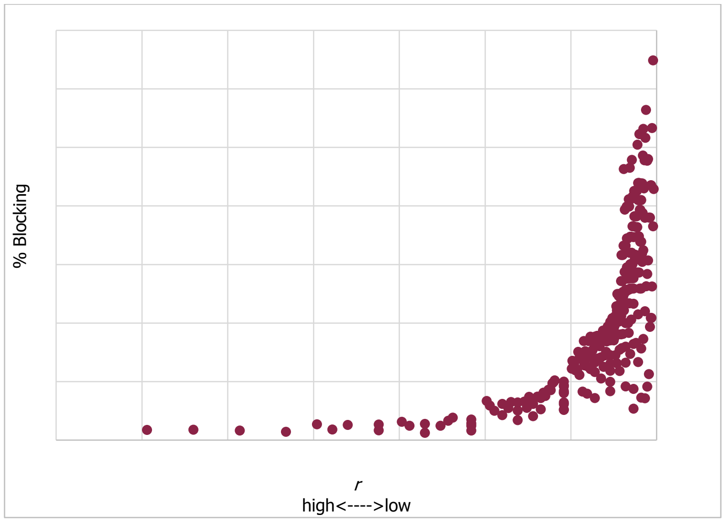

Figure 6: Blocking After Considering Throughput Constraint

The graph in Figure 6 is of a similar shape to the graph in Figure 5, but is shifted left, as expected. And although the strength of the relationship illustrated in Figure 6 is not as strong as in Figure 5, we have concluded that it can be used while concepting a design setting to predict the tipping point of interest. In practice we refer to the value of r that corresponds to the tipping point as r^*. This tipping point changes as the type of picking system changes (e.g., moving from a bin aisle layout to a parallel aisle layout), but we have found that it is fairly robust to typical values for parameters like the number of lines assigned to a worker, their pick times, etc.

4. Conclusions

We have concluded three things through our research. First, a single-dimension rule-of-thumb based on the average distance between workers in a picking system is not sufficient to predict the tipping point where throughput cannot be increased by adding more workers to the system. Second, the ratio that we defined (r) greatly improves our ability to predict the tipping point and the ratio is simple to calculate. Third, from a design perspective, experiments conducted to define the value of the ratio that corresponds to the tipping point in the system (r^*) must be adjusted to account for a design throughput level constraint.

We incorporated the design rule ratio into the Fortna Distribution Center Design Methodology to aid in a quick evaluation of a picking system's feasibility around worker congestion. We believe this problem illustrates how moving from a one-dimensional rule-of-thumb to a multi-dimensional rule-of-thumb (even with only two dimensions) can greatly enhance a designer's ability to quickly understand a system's performance. In addition, when a more detailed evaluation of a picking system is needed, we are able to easily configure the simulation model for such a purpose.

Acknowledgements

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