

Benchmarking Warehouse Performance

**Initial Results for Internet-based
Data Envelopment Analysis for
Warehousing (iDEAs-W 1.0)**



**Leon F. McGinnis
Wen-Chih Chen
Paul Griffin
Gunter Sharp
T. Govindaraj
Doug Bodner**

Executive Summary

How good is your warehouse performance? Do you have a lot of room for improvement, or are you very close to "best in class?" Until now, these questions have been impossible to answer without expensive benchmarking studies, because traditional performance metrics simply don't contain enough information to support comparisons over time or across sites.

Data envelopment analysis (DEA) is a relatively new approach to evaluating system performance. DEA enables one warehouse to be compared to a cohort of "peer" warehouses, not based on averages, but based on "best performance." DEA has been implemented in an internet-based tool, iDEAs-W.

iDEAs-W allows warehouse managers to compare their warehouse operations to a large set of other warehouses. iDEAs-W requires only a modest data input effort, and provides a "system efficiency" score. It has been used by over 150 warehouses in the past two years, and has been featured in a number of trade publications.

Analysis of the data for these 150 warehouses reveals that, for almost every segment of the warehousing industry, fewer than 20% to 30% of the warehouses are "efficient." For the vast majority of warehouses, it appears there are significant opportunities for improvement in operational efficiency.

Based on the success of iDEAs-W, an improved and extended tool is being developed, with the goal of determining not only the relative level of operational performance, but also identifying those technologies and practices that are consistent markers of high operational efficiency.

Acknowledgements

The work reported here has benefited from the generous support of a number of organizations. The W. M. Keck Foundation is the founding sponsor of the Keck Virtual Factory Lab, which provided both financial support and computing facilities for this work. The Material Handling Industries of America (MHIA) has supported this work through a variety of promotional efforts, including providing booth space at both ProMat and the North American Material Handling Show, and travel support for the iDEAs-W team to both events. The Progress Group has given generously of their professional expertise in many discussions with the iDEAs-W team regarding performance assessment. The Logistics Institute at Georgia Tech has provided some release time and graduate student support through a grant from the Progress Group.

Accessing iDEAs-W

iDEAs-W may be accessed through the following url:

<http://www.isye.gatech.edu/ideas>

Contacting iDEAs-W team:

Contact Leon McGinnis

Leon.mcginis@isye.gatech.edu

Ph: 404-894-2312

Measuring Warehouse Performance

Can your warehouse operational performance be improved?

In order to answer that question, you need to assess your warehouse's operational performance, relative to an achievable "standard" or "benchmark." There are two problems: measurement and benchmarks.

The measurement problem

Warehouses use resources (facilities, equipment, inventory investment, labor, etc), to produce an economically valuable service (customer orders shipped). Traditionally, warehouse performance has been measured using a host of *single factor performance* and *single factor productivity metrics*. Single factor performance metrics include, for example, lines shipped and fill rate. Simply put, a single factor productivity metric is a ratio of some *system output* quantity to some *resource input* quantity. For example, the output could be lines picked and the input could be labor hours, yielding the labor productivity, or lines per hour. The output could be pallets stored and the input could be total storage slots, yielding the storage utilization. Sometimes the ratio is inverted, for example, packing cost per order shipped.

Single factor metrics are critical for detailed analysis of operations, and can be reported in a manner consistent with standard financial and managerial cost data.

The benchmark problem

There are, however, some drawbacks to single factor metrics. Suppose the value for lines picked per hour this month was 67 and last month was 64. Has performance improved? The answer is "It depends." One must know something about the nature of the orders picked and hours worked, for example the sku spread, the proportions of "fast movers" and "slow movers" picked, and how well the total picking requirements matched the labor hours available in both months. In other words, to interpret a particular single factor metric, or to compare two values, one must have a considerable amount of additional information.

Single factor metrics are difficult to compare over time for a single facility, or across multiple facilities, when conditions are changing. And of course, in the contemporary warehousing environment, change is the only constant! "Rules of thumb" for key performance indicators, such as picks per hour from a particular storage medium, really are too crude to be of much value in detailed performance assessment.

In addition, warehouse performance is rarely judged on one single metric. For example, suppose lines/hour and fill rate are important in judging performance. In comparing two different months, the value of lines/hour may have gone up, while the fill rate may have gone down. We can't really say which month was "better" without assigning "relative values" to the two metrics.

So, while single factor metrics are easy to calculate, and easy to understand, they are not easy to use in assessing warehouse system performance. We need something more powerful.

A new approach

What we need is a way to assess warehouse performance that overcomes the limitations of single factor metrics, by considering all the relevant resource inputs and production outputs simultaneously. A method that might be appropriate is called *data envelopment analysis*, or DEA (see, e.g., Charnes, Cooper, and Rhodes (1978), or Charnes, et al (1994)).

In the context of warehouse performance assessment, DEA would allow a particular warehouse--let's call it the *candidate warehouse*--to be compared to a large set of other warehouses. DEA would construct a hypothetical *composite warehouse* from the input and output data for all other warehouses, and this composite warehouse would be compared to the candidate warehouse. The composite would be constructed in such a way that it produces at least as much output as the candidate warehouse, but uses the minimum possible resources. In this sense, it would be a hypothetical "best practices" warehouse.

The DEA "score" for the candidate warehouse would be reported as a percentage. Suppose the score was 75%. The interpretation would be that the composite warehouse used no more than 75% of any single resource used by the candidate warehouse. In other words, based on the "best practices" composite warehouse, it could be argued the candidate warehouse could reduce its resource usage by 25%.

DEA has the potential to answer the question "How well is my warehouse performing, overall?"

There are some caveats and limitations to the use of DEA. An important caveat is that all the warehouses compared should be "similar enough" so that they are comparable. It may not make sense to compare a warehouse that does only broken case picking from an inventory of 100,000 skus to a warehouse that does only pallet picking from an inventory of 1,000 skus.

To work effectively, DEA requires a considerable number of warehouses for comparison; it is recommended that at least three or four times as many warehouses should be in the database as there are individual inputs and outputs in the DEA model. Also, when DEA was first proposed, it required computational analysis that was not widely available. These pragmatic considerations have limited the application of DEA, until now.

An Internet-Based Self Assessment Tool

The rapid evolution of information technology, especially the internet and microcomputer systems, has created an opportunity to deploy DEA in a way that was not possible thirty years ago. The mathematical analysis required by DEA now can be computed using any one of a number of commercially available software packages.

Perhaps more important is the evolution of the world wide web with secure servers and client browser technology, and especially development systems for application service providers, or ASPs. These new technologies make it possible to have potential users provide their own data through a standard browser-based interface.

iDEAs-W (Internet-based Data Envelopment Analysis for Warehousing) implements DEA to permit the self-assessment--or benchmarking--of individual warehouses using internet technology. With a standard web browser, a prospective user connects to the iDEAs-W website, registers and creates a password, then provides a relatively small amount of data. Once the data have been entered, iDEAs-W computes the DEA score and reports it back to the user. The entire process of entering data takes from 15 to 45 minutes, depending on the proficiency of the user. Computing the DEA score requires only a few seconds of server time, and the response time to the user is usually less than one minute, depending on network traffic. iDEAs-W provides capability for "what-if" analyses by the user, by modifying the resource and output values to see the impact on DEA score.

iDEAs-W has been implemented using the WebObjects™ development platform from Apple, MySQL™ database from MySQLAB, and AMPL™ optimization package from Paragon Decision Technology. The service currently is offered at no cost from the Keck Virtual Factory Lab in the School of Industrial & Systems Engineering at Georgia Tech.

There has been significant industry interest in iDEAs-W. The iDEAs-W team has been encouraged and assisted by the Logistics Execution Systems Association, and the Order Selection, Staging, and Storage Council, both Material Handling Institute organizations, and has been invited to both ProMat 2001 and NAMHS 2002 to present their work to trade show attendees. iDEAs-W has been featured in a number of trade publications, including MHove, WERCSheet, and The Distributor's and Wholesaler's Advisor.

Data Requirements

The initial implementation of iDEAs-W is based on a DEA model developed in the early-nineties by Hackman and Frazelle (1993), and analyzed in detail in Hackman, *et al* (2001). The original on-site data collection involved 55 warehouses and the proposed DEA model had the resource inputs and production outputs identified in Table 1. The Hackman, *et al* DEA model (which has been incorporated in iDEAs-W) had a very limited number of inputs and outputs because they had a limited number of warehouses in their study.

Table 1. DEA Model Inputs and Outputs

Resource Inputs	Production Outputs
Total labor hours	Lines shipped
Warehouse area	Accumulation
Equipment replacement cost	Storage function

The data elements are:

Total labor hours includes both direct and indirect labor that is specifically associated with the warehouse function. In this version of iDEAs-W, value-adding processes are not considered.

Warehouse area is just the floor space actually assigned to the warehouse function.

Equipment replacement cost is determined by applying a "standard cost" to each category of equipment in the user's warehouse. Since we are interested in *operational* performance rather than *financial* performance, this approach allows us to characterize the total equipment portfolio in a consistent manner for all warehouses. It avoids the potentially very tedious and difficult problem of determining the "true" investment value of equipment in each warehouse.

Lines shipped is simply the total number of lines over all orders. It does not include information about the quantity shipped.

Accumulation is defined as the total lines shipped minus the total orders shipped, and is a measure of the extent of accumulation/sortation required. It's an "output" because it "assembles" customer orders.

Storage function is the least "obvious" of the output measures. It is intended to characterize both the mix of storage types and the space actually needed for storage; it is computed by iDEAs-W from user supplied values for the number of broken case SKUs (B), number of pallet locations (P), and proportion of broken case lines. The exact form of the calculation of the storage function (S) performed by iDEAs-W is:

$$S = a \cdot \sqrt{B} + (1-a) \cdot [\sqrt{25 \cdot P} + \sqrt{\text{floor storage sq ft}}]$$

where $a = (\text{broken case lines picked}) / (\text{total lines picked})$.

Appendix A lists all the additional data that are requested from the users in the current version of iDEAs-W. Some of the data items requested are not used directly in computing the DEA score, but are used to determine "affinity groups" within which the user's warehouse should be compared.

User registration is essential. The iDEAs-W team routinely examines the data to detect "outlier" values that may indicate a misunderstanding of data definitions, or even a data entry error. By contacting the user, the team can verify that the data represent a real warehouse, can validate data values, and can work directly with users to resolve inconsistent data.

Security of user data is a paramount concern of the iDEAs-W team. The only access to the raw data allowed is for the iDEAs-W team.

Who are the iDEAs-W users?

On March 1, 2002, there were 159 validated user records in the iDEAs-W database. Figure 1 illustrates the breakdown of warehouses by type.

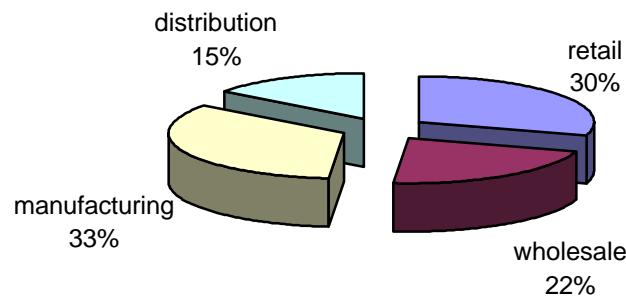


Figure 1. Distribution of Warehouses by Operation Type

The warehouses vary significantly in terms of size, equipment replacement cost, and total labor hours, as illustrated in figures 2, 3, and 4, respectively.

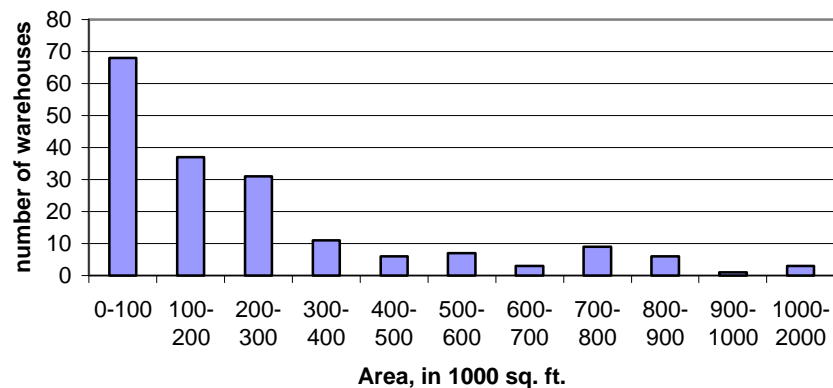


Figure 2. Distribution of Warehouses by Size

Most of the warehouses are smaller than 250,000 sq. ft. in area, although several are larger than 1 million sq. ft.

As figure 3 shows, over 85% of the warehouses have a standardized equipment replacement cost less than \$2 million, although there are a few highly capitalized warehouses, with standardized equipment costs exceeding \$10 million.

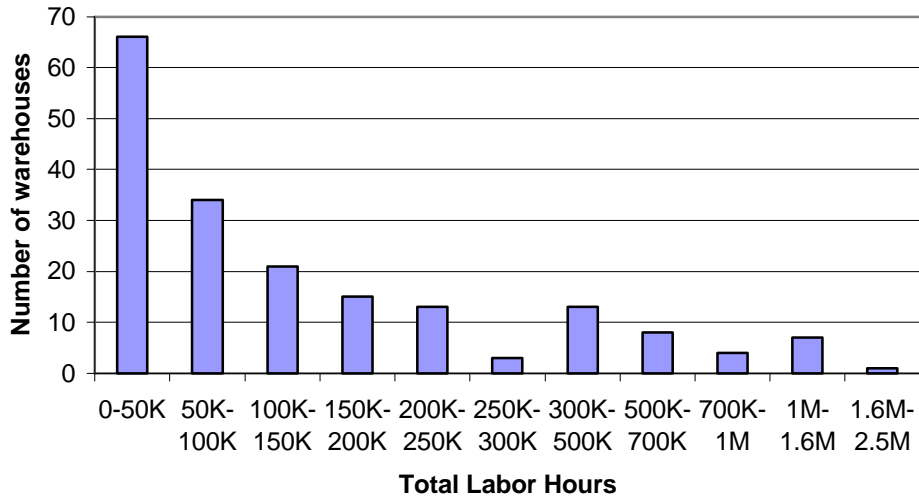


Figure 3. Distribution of Equipment Replacement Cost

Approximately 75% of the warehouses have total labor equivalent to 75 or fewer full time employees (devoted to warehousing functions). There are, however, over a dozen warehouses in the sample with the equivalent of 350 or more full time employees.

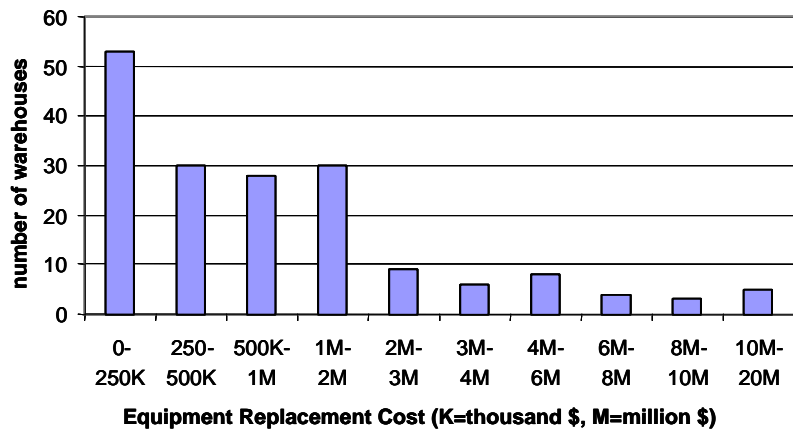


Figure 4. Distribution of Warehouses by Total Labor Hours

It is often assumed that a large investment in equipment implies a high degree of automation, and therefore a relatively lower labor cost. To see if this conjecture is true for the 159 warehouses in the iDEAs-W database, we constructed a scatter plot showing investment and labor cost. Interestingly, Figure 5 does not support the "common wisdom" that capital and labor are traded off against each other. In fact, those warehouses in the sample which have a large equipment investment also tend to have a large labor cost. The correlation between these two attributes is positive.

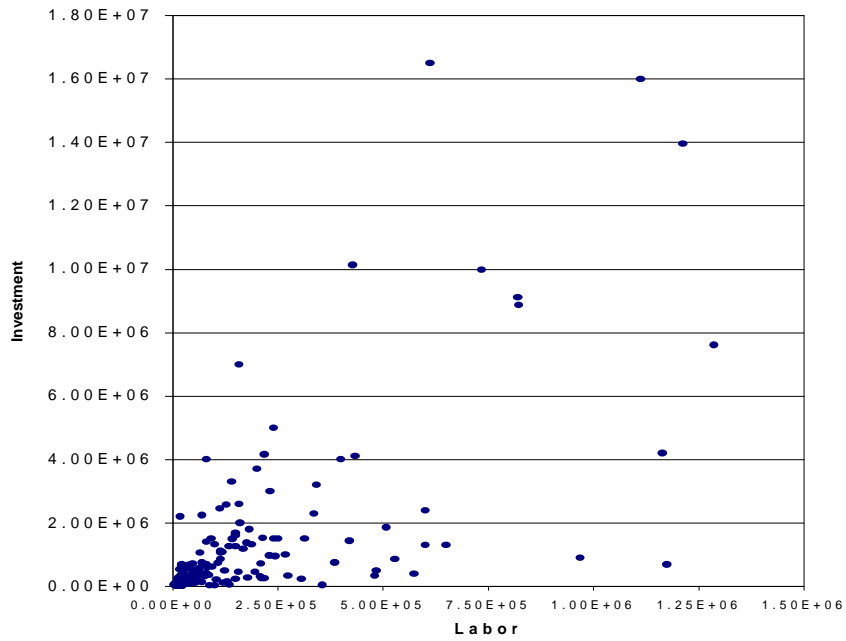


Figure 5. Warehouse Investment versus Labor

Figure 6 shows the distribution of lines picked per labor hour. Note that this includes all lines--full pallet, case, and broken case--and does not consider the quantity per line. Note also that labor includes all warehousing labor in the warehouse, not just order pickers. It should not include non-warehousing labor, such as value adding services.

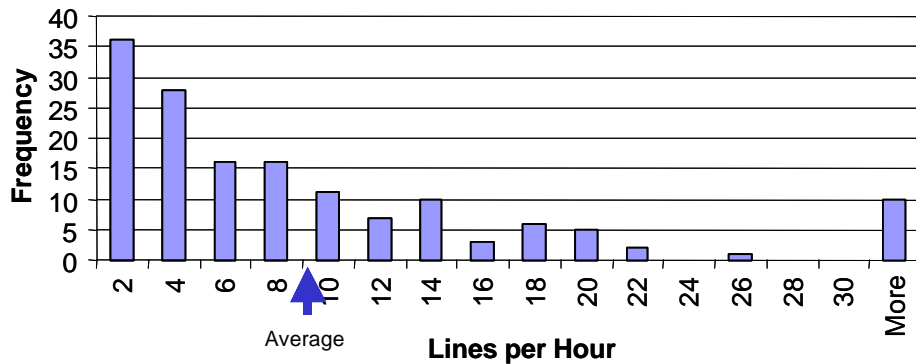


Figure 6. Distribution of Lines per Labor Hour

The data collected by Frazelle and Hackman have been analyzed in several ways (see Frazelle, et al (2001)). The key conclusions from those analyses were:

- Smaller warehouses tend to be more efficient than larger warehouses
- Warehouses using lower levels of automation tend to be more efficient, and the association is more pronounced for smaller firms

Unionization is not negatively correlated with efficiency, and in fact may contribute to higher efficiency.

In the next section, we will see if the iDEAs-W user data confirms the earlier Frazelle, et al conclusions.

Warehouse Performance Analysis

Individual warehouse managers may benefit from DEA analysis simply by learning how their performance compares to the hypothetical "best practice" performance. However, there is another source of benefit from a large-scale DEA study--learning what characteristics of warehouses seem to be correlated with good performance.

Figure 7 is the histogram of efficiency scores when each candidate warehouse is compared against a composite constructed from all 158 "other" warehouses.

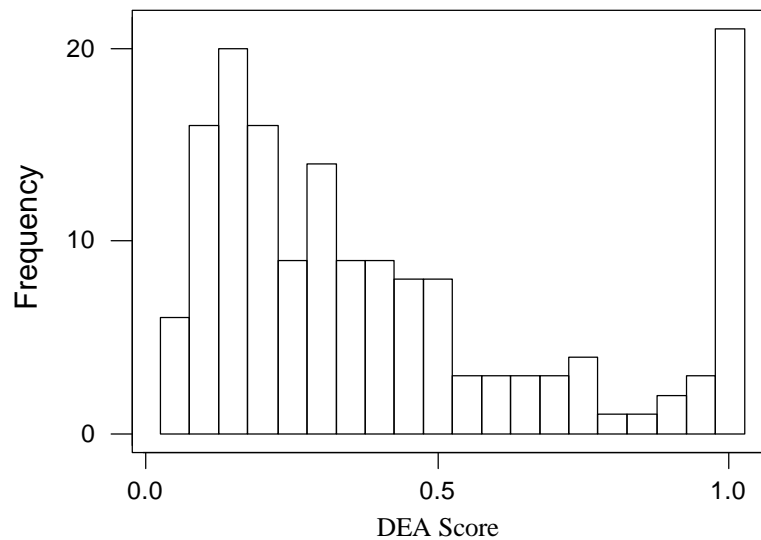


Figure 7. Distribution of Efficiency Scores, All Warehouses Considered

The distribution of efficiency scores indicates that slightly more than 10% of the warehouses are "efficient," i.e., have scores very close to 1. On the other hand, over two-thirds of the warehouses have efficiency scores less than 50%, indicating a potential opportunity to reduce resource inputs by as much as 50%.

Of course, Figure 7 lumps together all four types of warehouse operations (manufacturing, distribution, wholesale, and retail), as well as all industry segments, and all sizes of warehouse. What we really want to see is results where the sample is *segmented* so that warehouses are compared to other warehouses that are similar in some important way.

Resource-Oriented Segmentation

One approach to segmenting our sample of 159 warehouses is to use similarity of resource inputs in terms of magnitude or mix of resources. To better understand the relationship between resources used and DEA scores, we performed statistical analyses of the correlations. For this particular sample of 159 warehouses, and this particular DEA model, what we concluded is:

- Investment is negatively correlated with DEA score, and this effect is statistically significant. As investment in equipment goes up, system efficiency goes down.
- Labor is negatively correlated with DEA score, and this effect is statistically significant, though not as strong as the effect of capital. As headcount goes up, system efficiency goes down.
- Area is positively correlated with DEA score, and this effect is statistically significant, though not as strong as the effect of labor. As the space in the warehouse goes up, system efficiency goes up.

Because investment has the strongest correlation with DEA score, statistically speaking, we used investment to illustrate resource-oriented segmentation of the sample; we created three groups:

- Small investment, less than \$650,000
- Medium investment, between \$650,000 and \$4,000,000
- Large investment, greater than \$4,000,000

Figure 8 shows the distribution of DEA scores for the small investment warehouses, both compared to all other warehouses, and compared only within the segment of 87 small warehouses. Two observations are worth noting. First, the distributions in Figure 8 look very similar to the distribution in Figure 7, i.e., there are some efficient warehouses (DEA scores close to 1) but a very large portion of warehouses with DEA scores below 0.5. Second, the shapes of the two

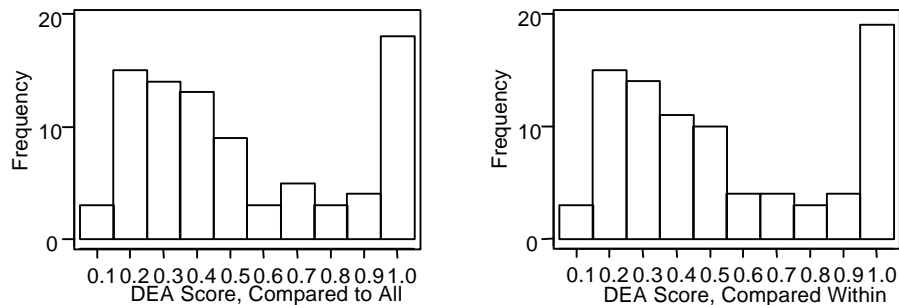


Figure 8. Distribution of Scores for Low Investment (87 Warehouses)

distributions in Figure 8 are almost identical, i.e., it makes little difference if the

low investment warehouses are compared to all warehouses or just within their segment.

The same information is presented in Figure 9 for the 54 medium investment warehouses, and in Figure 10 for the 18 large investment warehouse. Note that Figure 9 is quite different from Figure 8--the "compared to all distribution" is

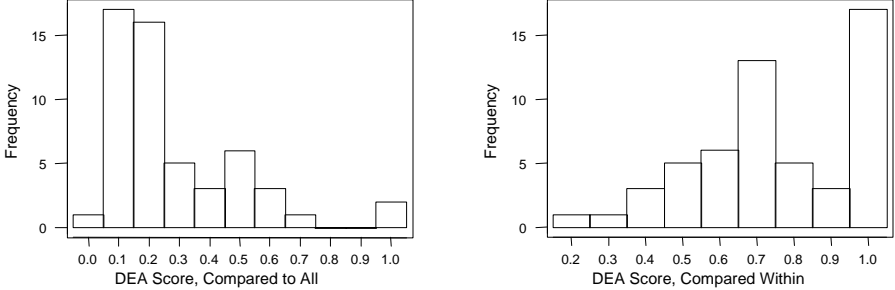


Figure 9. Distribution of Scores for Medium Investment (54 Warehouses)

heavily weighted toward low scores, while the "compared within" distribution is shifted significantly toward the higher scores. In other words, the medium warehouses have bad system efficiency scores when compared to all other warehouses, but their efficiency scores are much better, as a group, when they are compared only within their segment.

This same phenomenon is observed in Figure 10, although the sample size is really too small for us to draw a strong conclusion.

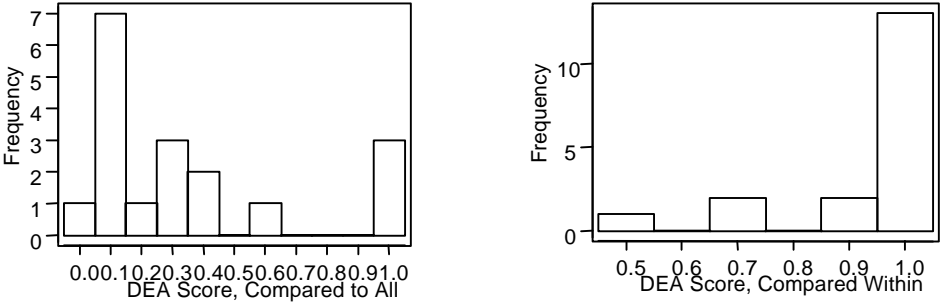


Figure 10. Distribution of Scores for High Investment (18 Warehouses)

Output-Oriented Segmentation

An alternative approach to segmenting our sample is to group warehouses that are similar in terms of their outputs. This could be done by size or by mix, or both. Since the DEA analysis already accounts for "scale of operation," we will focus on output mix.

Consider two warehouses that have the same number of orders, lines, and accumulation, but one ships only full pallets and the other ships only broken case quantities. It does not seem reasonable to expect them to have similar resource requirements, and so they may not be "comparable" in a DEA analysis.

Figure 11 below indicates that thirteen warehouses in our sample do almost exclusively full pallet picking. Warehouses that do exclusively or predominantly pallet picking should be comparable with regard to the DEA analysis.

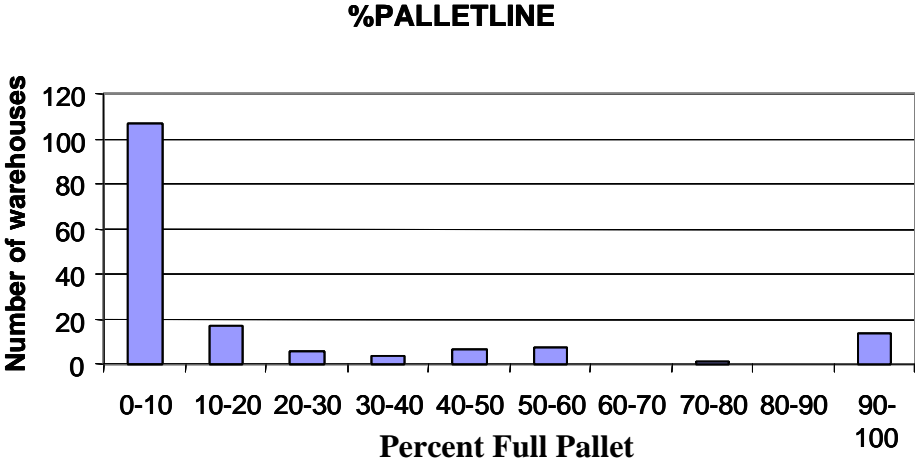


Figure 11. Distribution of Percent Full Pallet Lines

A similar analysis is presented in Figure 12 for full case picking and in Figure 13 for broken case picking. Thirty-two warehouses in our sample do exclusively or predominantly full case picking (defined as 80% or more of the order lines). Forty-nine warehouses do exclusively or predominantly broken case picking.

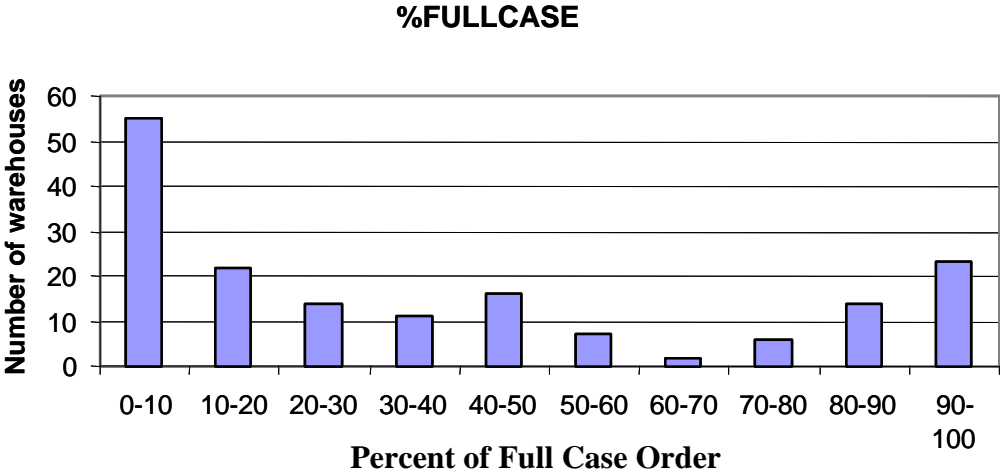


Figure 12. Distribution of Percent Full Case Order Lines

For the remaining sixty-five warehouses, there is no predominance of one type of picking, and so those warehouses do mixed picking.

Suppose we segment our sample of 159 warehouses into four groups, based on the nature of the picking, i.e., full pallet, case, broken case, and mixed. Will the distribution of DEA scores within one of these smaller groups (of more similar warehouses) be significantly different from the distribution shown in Figure 7?

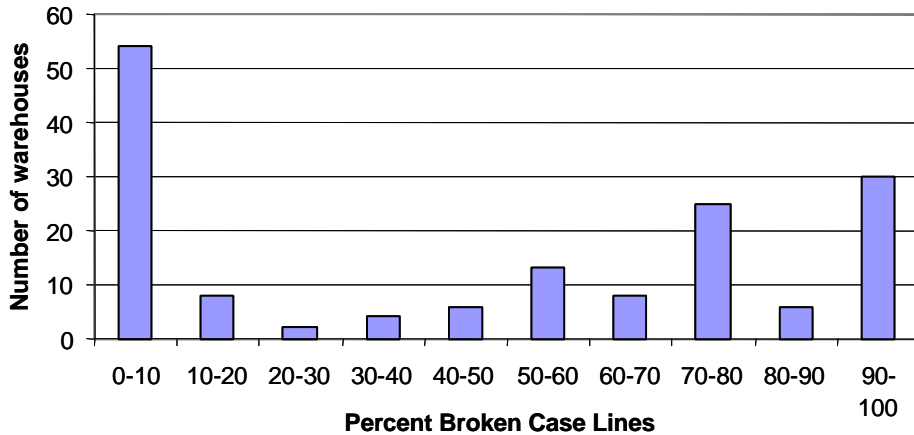


Figure 13. Distribution of Percent Broken Case Lines

Figure 14 shows the distribution of DEA scores for predominantly broken case warehouses. When they are compared to "all" warehouses, the basic shape of the distribution resembles the distribution in Figure 7. When they are compared only within the group of broken case warehouses, the distribution has shifted in a

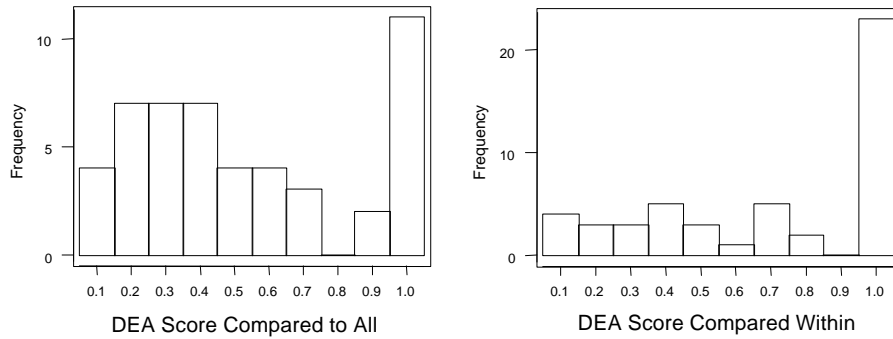


Figure 14. Distribution of Scores for Broken Case Picking (49 Warehouses)

significant way-- almost twice as many warehouses are "efficient," i.e., have a DEA score close to 1. This is to be expected. For a specific warehouse, the DEA score can only go down as more warehouses are added to the comparison set.

While the shape of the "within" distribution in Figure 14 is very different from the distribution in Figure 7 (all warehouses together), this may well be due to the much smaller sample. In other words, as more and more broken case warehouses are added to the sample, it is entirely plausible that the "within" distribution in Figure 14 would start to look more and more like the distribution in Figure 7, because fewer and fewer of the additional warehouses will be "efficient."

The comparable results for case picking, pallet picking, and mixed picking are presented in Figures 15, 16 and 17, respectively.

For full case picking, a much smaller percent of warehouse are "efficient" than was true for broken case picking. This may reflect a greater diversity of operations among broken case picking warehouses. Also, distributions for full

case picking seem to be more heavily weighted toward the low scores, indicating a generally greater opportunity for improvement. Finally, the distribution of scores within the full case picking sample does resemble the distribution in Figure 7, where each warehouse is compared to all other warehouses.

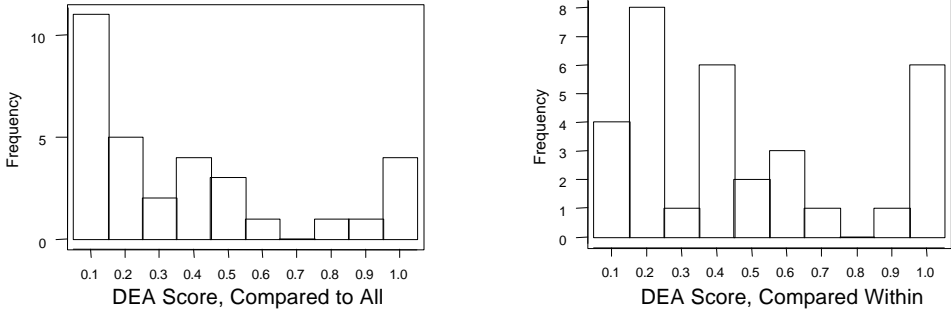


Figure 15. Distribution of Scores for Full Case Picking (32 Warehouses)

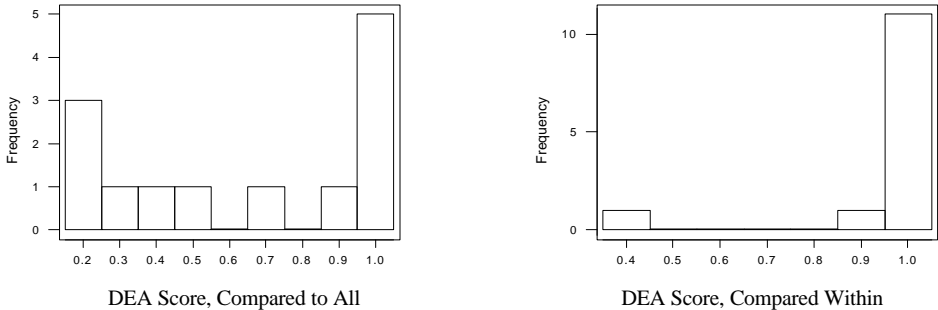


Figure 16. Distribution of Scores for Full Pallet Picking (13 Warehouses)

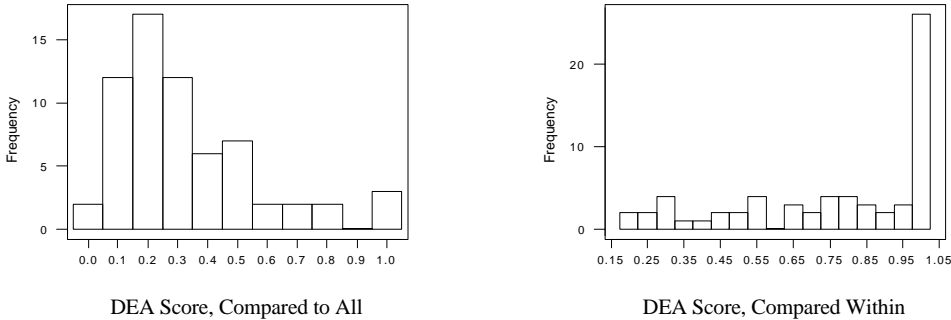


Figure 17. Distribution of Scores for Mixed Picking (65 Warehouses)

The number of predominantly pallet picking warehouses in our sample is too small to support a detailed DEA analysis. The result of applying DEA within such a small sample is illustrated in Figure 16--almost all the warehouses appear to be "efficient" when compared within the subgroup. What we would expect to see as the number of full pallet warehouses increased is a distribution resembling that in Figure 15.

The results for mixed picking warehouses shown in Figure 17 resemble the results for broken case picking, but are even more exaggerated. A large fraction of the

warehouses are "efficient" in the "within" comparison, perhaps reflecting the great diversity of operations. As with broken case picking, as more warehouses are added to the sample, we would expect the distribution to grow more like the distribution in Figure 7, rather than retaining the shape it has now.

Conclusions

Any conclusions we might draw at this point must be considered preliminary. The DEA model we've used is a "legacy" model, and there are aspects of it that we would like to see improved. The sample size we have at this point is smaller than we would like, especially for full pallet picking warehouses.

Recognizing the preliminary nature of the conclusions, however, there are some interesting observations we can make.

1. Bigger is not always better, at least with regard to equipment and labor. There is, however, some evidence that more warehouse space leads to better system efficiency.
2. Labor hours was not found to be a significant factor, by itself, in predicting system efficiency. However, the interaction of labor with investment was found to be significant in the sense that labor hours mitigates the effect of investment (in other words, though high investment warehouses tended to be less efficient than low investment warehouses, the differences becomes less prominent the higher the labor hours).
3. The interaction of investment and area was found to be significant. This means that high investment warehouses are even less efficient if they are also large.
4. No matter how we segment the data, a very large proportion of warehouses are operating at or below 50% system efficiency. While this may reflect seasonal fluctuations in customer orders, it still represents a very significant opportunity for improvement.
5. The opportunity for improvement seems largest for the segment of warehouses doing predominantly full case picking. In that segment, a smaller proportion of the warehouses are "efficient" than in any other segment, and a larger proportion are operating below 50% efficiency.

In comparing these results to the earlier Frazelle, et al (2001) conclusions, there is strong agreement. Both analyses agree that lower levels of capitalization and lower levels of labor are correlated with higher efficiency. However, the current iDEAs-W data seem to indicate that there is a small positive correlation between space and efficiency. We have not yet examined the issue of unionization for the iDEAs-W data.

*

* This page left blank intentionally

Where do we go from here?

Our experience with iDEAs-W 1.0 has been very encouraging. We've demonstrated that it is feasible to collect warehouse benchmark data using internet technology. We've demonstrated that the DEA methodology can be deployed for assessing warehouse system efficiency. We've even learned some interesting things about the current state of warehousing, if we are willing to extrapolate from our sample.

So where do we go from here?

The next challenge is to use the iDEAs-W platform to not only assess relative performance, but also to identify the "best practices" that are markers for high levels of system efficiency. Meeting this challenge will require:

- Enhancing the current DEA model to make it conform better to the realities of contemporary warehousing. In particular, a better set of resource and output definitions is needed. For example, we need to be able to deal with warehouse service levels and value added services, two key factors that are not included in the current model.
- Cataloging the specific technologies, practices, and methods that potentially are highly correlated with either good performance or poor performance. This "auxiliary" information will be the basis for identifying the best practices (and perhaps worst practices) that are the real goal of benchmarking.
- Enhancing the user interface to make it easier for users to create the data records, and to understand the results of our analysis.
- Greatly expanding the number of participating warehouses. The statistical approach to identifying best practices will be successful only if a large number of warehouses participates--somewhere between ten and one hundred times as many warehouses as in our current sample.

With a more robust DEA model, a more complete set of warehouse "attributes," and a much larger database of participating warehouses, it will be possible to identify, for specific categories of warehouses, the particular practices that lead to high levels of system efficiency. Knowing what works for particular types of warehouses, industry segments, and warehouse configurations (size, capitalization, picking type, sku mix, etc), individual warehouses can determine what technologies and practices to adopt, based on their individual economic situation, such as existing facilities, local labor pool and prevailing wage rates, etc.

We finally will have a formal, data-driven way to answer the question, "How well is my warehouse performing?"

iDEAs-W 1.0 has demonstrated the feasibility on-line self-assessment of warehouse performance. The next challenge in deploying this technology will be to enlist thousands of warehouses to participate in the second generation assessment tool. The payoff for them, individually, will be learning the specific "best practices" appropriate for their operation. The payoff for the industry is a significant improvement in warehousing operations.

References

1. "Benchmark Your Operation," in WERCSheet, December 2001.
2. "Real-Time On-line Benchmarking of Warehousing Gathers Steam"
http://www.mhia.org/E-Mhove/display_news.cfm?objectid=4D653E90-5CDE-11D4-89B400D0B7444F12&keywords=benchmark
3. Charnes, A., W.W. Cooper, A.Y. Lewin, and L.M. Seiford, Data Envelopment Analysis: Theory, Methodology, and Application, Kluwer Academic Publishers, Boston, 1994.
4. Charnes, A., W.W. cooper, and E. Rhodes, "Measuring the Efficiency of Decision Making Units," European Journal of Operations Research, 2 (1978), 429-444.
5. Cohen, M.A., Y.S. Zheng, and V. Agrawal, "Service Parts Logistics: A Benchmark Analysis," IIE Transactions, 29 (1997), 627-639
6. Dyckman, Susan (editor), "On-line Assessment Tool for Better Warehousing," in The Distributor's & Wholesaler's Advisor, volume 13, No.1 8, April 15, 2001.
7. Frazelle, E.H., and S.T. Hackman, "the Warehouse Performance Index: A single Point Metric for Benchmarking Warehouse Performance," Material Handling Research Center Technical Report TR-93-14, Georgia Institute of Technology, Atlanta, GA.
8. Hackman Steven T., Edward H., Frazelle, Paul M. Griffin, Susan O. Griffin, and Dimitri A. Vlatsa, "Benchmarking Warehousing and Distribution Operations: An Input-Output Approach," Journal of Productivity Analysis, 16 (2001), 79-100.
9. Griffin, Paul M., and Paul H. Kvam, "A Quantile-Based Approach for Relative Efficiency Measurement," Managerial and Decision Economics, 20 (1999), 403-410.

*

* This page left blank intentionally

Appendix

iDEAs-W Data Requirements

iDEAs-W asks for two kinds of data: those data describing the warehouse inputs and outputs; and those data describing the warehouse scenario, methods, and technologies. The DEA score itself requires only the input and output information. However, in order to be able to assess "best practices" and other markers of high efficiency iDEAs-W needs additional information about the warehouse.

Efficiency Score Information

- Total orders for the 12-month period
- Lines shipped for the 12-month period
 - Broken case lines shipped for the 12-month period
 - Full case lines shipped for the 12-month period
 - Pallet lines shipped for the 12-month period
- Number of broken case pick slots in the warehouse
- Sq. ft. of floor stacking in the warehouse
- Number of pallet rack locations in the warehouse
- Total area associated with the receiving, storage and shipping operations: (sq. ft.)
- Total annual labor hours: (we use the approximation that each full-time equivalent person worked 2,000 hours per year.)
 - Equivalent Full time direct labor headcount:
 - Equivalent Full time indirect labor headcount:

Labor hours is determined by counting the people performing all operations necessary for receiving, putaway, storing, order picking and shipping. Hours spent on maintenance, supervision and management constitute the category of indirect hours. Labor hours does not include the specialized inspections and the indirect hours devoted to operations such as security, customer satisfaction, traffic, value-adding services, or personnel.

Identify the amount of the material handling and storage equipment list below:

Vehicle

- | | | |
|--|--|---|
| <input type="checkbox"/> Pallet Trucks | <input type="checkbox"/> Walkie Stackers | <input type="checkbox"/> Straddle Trucks |
| <input type="checkbox"/> Turret Trucks | <input type="checkbox"/> Hybrid Trucks | <input type="checkbox"/> Side-loader Trucks |
| <input type="checkbox"/> Straddle Reach Trucks | <input type="checkbox"/> Pallet ASRS Machines | <input type="checkbox"/> AGVs |
| <input type="checkbox"/> Sit-down Counterbalance | <input type="checkbox"/> Stand-up Counterbalance | |
| <input type="checkbox"/> Wire-guided Order Pickers | <input type="checkbox"/> Rail-guided Order Pickers | |

Storage Systems

- | | | |
|---|---|---|
| <input type="checkbox"/> Vertical Carousels | <input type="checkbox"/> Horizontal Carousels | <input type="checkbox"/> A-Frame Dispensers |
| <input type="checkbox"/> Person-abord ASRS Aisles | <input type="checkbox"/> Miniload ASRS Aisles | |

Conveyor Systems (in feet)

- | | | |
|---|---|---|
| <input type="checkbox"/> Non-Powered Roller | <input type="checkbox"/> Powered Roller | <input type="checkbox"/> Powered Belt |
| <input type="checkbox"/> Skate Wheel | <input type="checkbox"/> Tow Line | <input type="checkbox"/> Tilt-Tray Sorter |
| <input type="checkbox"/> Pallet Conveyor | | |

Warehouse Description Information

- What type warehouse operation? (e.g. retail, wholesale, manufacturing)
- What Industry? (e.g. automotive, electronics, grocery)
- Total number of item types (skus) in storage in the previous 12 months:
- Lines per order:
Minimum: Average: Maximum:
- How far in advance can you plan warehouse operations? (ignoring rush order)
(eg: Less than a day, One to three days, or More than three days)
- Seasonality is defined as (Volume in the peak month / Average volume per month)
What is the seasonality based on orders:
What is the seasonality based on lines:
What is the seasonality based onpieces:
What is the most common seasonality measure you use?
- Describe the detail dimension of your warehouse:

(eg: receving / shipping : 1,000 sq ft x 16 ft;
high-bay pallet: 50,000 sq ft x 36 ft;
pallet: 80,000 sq ft x 21ft;
item pick and pack (2-level): 58,000 sq ft x 24 ft)

- Check off all the storage technology you use
 - AS/RS
 - Vertical Carousel
 - Horizontal Carousel
 - Miniload
 - Drawer System
 - Bin Shelves
 - Pallet Rack
 - Floor Stacking
 - Deep Lane Pallet
 - Carton Flow Rack
 - Other :
- Do you use a sortation conveyor or other automated sortation?
- What is the dominant mode of operation?
 1. Warehouse PUSHES material to customers based on analysis of customer need, or
 2. Customers PULL material from warehouse based on order entry
- What is the dominant order picking mode?
 1. Single order pick
 2. Single order pick by zone with sortation / accumulation
 3. Batch pick
 4. Batch pick by zone with sortation / accumulation
- Do you use a computerized warehouse management system (WMS)?
- If "YES", it is supplied by:
- How much do you invest in WMS (software + hardware)? (in thousand)
- What is your average storage capacity utilization? (%)
- Describe the definition of storage capacity utilization you use:
- Do you use velocity-based slotting?
- Do you interleave put-away, relocate, and retrieve operations?
- Check any of the following that you use:
 - Pick-to-light
 - Voice recognition
 - RF dispatching
 - Bar-code location verification for put-away and/or retrieval
- Fraction of orders that are rush orders: (%)
- Fraction of lines that are rush orders: (%)
- Do you perform value-adding operation?
- For what percent of value? (%)
- Describe the most common value-adding operation:
- Do you perform crossdocking?
- If "yes", for what percent of physical volume? (%)
- What performance metrics do you routinely track? (check all that apply)
 - Order fill rate
 - Line error rate
 - Inventory accuracy
 - Cost to fill a line
 - Cost to fill an order
 - Cost to fill a carton
 - Cartons/order average
 - Cartons/order distribution
 List other metrics you use: