Modeling Order Guidelines to Improve Truckload Utilization

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Summary: Freight vehicle capacity, whether it be road, ocean or air transport, is highly under-utilized. This thesis describes the impact of ordering guidelines on the trucking efficiency of a large firm and how those guidelines and associated practices can be changed in order to gain better efficiency.

KEY INSIGHTS

1. Order fulfillment guidelines and practices play an important role in achieving better truckload efficiency.
2. Implementation of linear programming can lead to potential reduction in the number of shipments through the better mixing of trucks.
3. Categorization of the SKUs as cube-constrained, neutral, and volume-constrained can be used to develop heuristic mixing models.

Introduction

An astonishing 24% of all freight vehicles in the European Union (EU) run empty according to a study by the World Economic Forum (2009). The average load factor for the remaining vehicles is only about 57%, resulting in just 43% overall efficiency for European trucks. While the aggregate trucking statistics for the United States are not readily available, we assume that they are not significantly better than Europe’s. The implication, then, is that a great opportunity lies in optimally utilizing available trucking capacity.

To improve truckload utilization, three different research areas can be explored: fill optimization, volume efficiency, and transport. They can be thought of as loading, pre-loading, and post-loading, respectively. Fill optimization focuses on achieving better weight and volume fill for a truck, and it has the most direct impact, of the three, on truck loading decisions. Volume efficiency focuses on aspects of product design and packaging. These changes are more fundamental and, in most companies, are more interconnected with marketing than operations. Lastly, transport includes all aspects of the actual on-the-ground operations of trucks, such as route analysis, network optimization, and drivers’ skills. These measures are only applicable to post-loading and are more focused on obtaining better driving efficiency. Amongst these three, we focus on fill
optimization because, more than the other two, it provides us the opportunity of discovering immediate, as opposed to long-term, improvements.

To achieve greater fill optimization, we focus on ordering guidelines and operating practices. The order fulfillment process (OFP) encompasses three key steps: order promising, warehousing, and transportation. Our focus is on the first step of OFP, order promising, because this is where the decisions that shape a truckload are made. Our objective is to improve these guidelines to help “Shipper” - a multi-national firm - achieve greater efficiency in their transportation activities throughout the United States.

Analysis

This analysis is based on sample shipment data of Shipper, which covers a limited time period and includes extensive shipment data such as SKU information, origin-destination, weight, and volume.

Metric Evaluation

Shipper uses three metrics, volume, floor position, and weight, to determine whether a truck meets their minimum shipping requirements. The benchmarks for these parameters are based on the dimensions of a standard trailer and a given region of operations. Once any one metric is reached, the truck can be shipped. As an operating heuristic, each metric carries equal weight under this framework. After exploring the data, we’ve discovered evidence that floor position has a strong correlation with volume, as shown in Figure 1.

The explanation for this high correlation lies in the fact that volume inherently includes floor position. Thus, Shipper may be able to simplify their operating metrics, and still fill floor positions, if the company eliminates their floor position metric. The contingency table below (Table 1) expands on this, highlighting anomalies that hit floor position but do not meet volume. To prove that volume and floor position are not statistically independent, we conduct a chi-square independence test. At a 99% confidence level, this test shows statistical dependence between the two variables.

<table>
<thead>
<tr>
<th></th>
<th>Does not hit FP</th>
<th>Hits FP</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Does not hit Vol.</td>
<td>790</td>
<td>661</td>
<td>1451</td>
</tr>
<tr>
<td>Hits Vol.</td>
<td>6</td>
<td>521</td>
<td>527</td>
</tr>
<tr>
<td>Total</td>
<td>796</td>
<td>1182</td>
<td>1978</td>
</tr>
</tbody>
</table>

Table 1: Contingency table

Truck mixing

When deciding what products to put on a truck, one must account for the capacity constraints of weight, cube, and floor position. In short, this is the classic bin-packing problem. The bin packing problem is based on a principle of running various possible combinations until a global or local optimum is reached. In logistics, the bin packing problem addresses the loading of freight by packing a finite number of items into the smallest number of bins. There are often conflicting criteria in this optimization process. We have implemented a simple version of the bin packing problem with our linear programming model.

First, we set our objective function as a linearly weighted sum of the weight in each shipment. When the program runs, this function maximizes the weight of each truck, one-by-one, before filling the next truck. This objective function is interchangeable. One can maximize weight, volume, or floor position as one desires. We discovered that it is best to maximize weight based on the fact that Shipper’s products are, for the most part, volume heavy. Fortunately, in the process of maximizing weight, volume is also maximized as a by-product of maximized weight.

The constraints are the floor position, cube, and volume benchmarks set by Shipper. In our chosen example, Shipper originally ships four shipments to the customer. Linear programming helps better allocate those same SKUs to those same trucks, resulting in better utilization. Indeed, our model eliminates an entire shipment, as shown in Table 2.
SKU mixing

Based on our data analysis of product category and customer, it is easy to conclude that most shipments are not optimally mixed. To address this problem, we develop a model to mix SKUs through a comprehensive segmentation of weight and volume. We categorize each SKU based on pallet density, defined as pallet weight divided by pallet volume. The optimal density, then, is based on the maximum weight and volume permissible in a truck. The spread of SKUs for Shipper is shown in Figure 2.

Based on this categorization, we conduct a utilization calculation, as shown in Figure 3. The average truck utilization for different types of SKUs demonstrates a pattern. For cube-constrained categories, the SKUs meet the cube target. However, these same SKUs are unable to meet weight limit by a high margin. This trend is opposite for the weight-constrained SKUs, where weight is much better utilized than cube. For neutral categories, the SKUs fulfill both criteria simultaneously, making this category naturally optimal.

This utilization calculation was used as the premise for our SKU mixing algorithm. Obviously, the cube-constrained SKUs should be mixed with the weight-constrained SKUs in order to balance high weight utilization with low cube utilization. The neutral SKUs should be mixed with one another, as they are already helping Shipper to achieve their target utilization. We conduct calculations to support these findings and they have been shown in Table 3. The best solutions have been highlighted in blue for each category combination.

<table>
<thead>
<tr>
<th>Primary category ordered</th>
<th>Mixing category</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Category</strong></td>
<td><strong>Average Density</strong></td>
</tr>
<tr>
<td>Cube-constrained</td>
<td>4.85</td>
</tr>
<tr>
<td>Neutral</td>
<td>10.8</td>
</tr>
<tr>
<td>Neutral</td>
<td>10.8</td>
</tr>
<tr>
<td>Weight-constrained</td>
<td>24.85</td>
</tr>
<tr>
<td>Weight-constrained</td>
<td>24.85</td>
</tr>
</tbody>
</table>

Table 3: Mixing table for different SKU categories
Conclusion

Based on the aforementioned findings, we’ve arrived at three recommendations. First, Shipper should examine whether to use floor position as a criterion for declaring when to ship a truck, excepting anomalies. As shown in our analysis, there is evidence that the calculation of cube fill already encompasses floor positions for the majority of Shipper’s shipments. Eliminating the floor position metric as an operating heuristic may make the implementation of order guidelines easier.

Second, Shipper should implement linear programming to better mix their orders at a tactical level. As the number of decision variables becomes very large, it becomes impossible to use linear programming at a strategic level. As such, we propose that Shipper use linear programming only for mid-size customers. In order to implement this, tactical personnel at the operations level would have to be trained in the usage of this tool.

Shipper should also explore utilization opportunities by mixing SKUs that belong to different density categories. This would help Shipper to obtain much better truckload utilization rates. There are a few SKUs that are outliers, and would have to be treated on a case-by-case-basis, but they are part of a minority. For a more robust order-mixing model, Shipper should explore the ordering pattern of their high volume customers. Shipper can then use those customers as a jumping off point for extending cross-mixing opportunities to other customers in the same geographic vicinity. Overall, these steps should help Shipper to achieve significantly better truckload utilization rates, while also reducing their carbon footprint.

The applicability of these strategic methods extends beyond Shipper to other companies and other modes of freight transport. Strategic mixing of trucks and SKUs can be further explored for any firm’s most important customers, as it can help companies to achieve much better utilization. Finally, strategic mixing also provides greater value proposition to companies as it increases channel integration with supply chain partners.