Prioritizing Inbound Transportation

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ABSTRACT

Retailers must coordinate inbound shipments from a large number of vendors. In order to manage capacity, retailers need to have a system to prioritize inbound loads with capacitated carriers. This practice creates a constraint when the number of loads exceeds the capacity of committed carriers due to seasonality and consumer shopping behaviors. A prioritization mechanism needed to be developed to support decision making for the selection of loads when capacity is constrained. This research applied the Analytic Hierarchy Process to define prioritization logic for each inbound load and solved a Knapsack model to optimize the assignment. This decision-making model allows the retailer to properly assign load priority based on company objectives. Further, opportunities were found to optimize load priority by up to 8.3 percent as compared to the current assignment. Similar retailers can leverage this research not only to prioritize inbound loads but also to prioritize other decisions such as which initiatives to pursue.

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# 1 Introduction

Retailers often face demand uncertainty due to seasonality and consumer shopping behaviors, so supply chain robustness is critical to ensure sufficient product availability. A common strategy to combat demand uncertainty is the use of safety stock, but this also increases the risk of excess stock, increased obsolescence, and higher carrying costs. We propose an alternative solution that does not increase inventory levels. Our research focused on restructuring the inbound transportation to ensure that the right inventory is moved at the right time as opposed to ordering more.

A retailer, ShopCo, places weekly orders for various types of merchandise throughout the United States, but its ordering can exceed the capacity of committed carriers. Historically, ShopCo relied on its suppliers and carriers to determine which loads were picked up – each load may consist of one or more purchase orders (PO's). Unfortunately, these suppliers and carriers would use logic to determine order of pickup that may not match the needs of ShopCo. ShopCo is striving to improve product availability at the store level and wishes to ensure the supply chain is prioritized around this goal. Currently, it uses an internally developed load allocation tool to assign PO's to loads, but this tool's objective function is largely based on reducing costs rather than improving product availability.

To address this shortfall, we developed a method based on the Analytic Hierarchy Process (AHP) to assign priority scores to each PO, thus resulting in a final priority score for each load awaiting shipment. Then, we extended this research by optimizing load priority scores through a Knapsack optimization model. Our sample results showed an improvement in load priority score by up to 8.3 percent as compared to the current assignment.

In the next chapter (Chapter 2), we discuss the literature review of prioritization methods, focusing on the AHP and Knapsack. Subsequent chapters cover the AHP methodology and results (Chapter 3), Knapsack methodology and results (Chapter 4), and discussion (Chapter 5). We conclude (Chapter 6) with a summary and next steps.

# 2 Literature Review

Our thesis topic is prioritizing inbound transportation for a retailer. Specifically, we are helping define how to prioritize loads from different supplier locations shipping to a central point, given carrier capacity constraints. We did not find research that directly addressed this problem. Most of the current literature on transportation was conducted on outbound logistics, and there was limited research on inbound logistics in general (Natarajarathinam et al., 2012). However, we gained significant insights from order prioritization and capacity rationing in the manufacturing industry, where companies need to make decisions to prioritize orders under capacity constraints.

Our literature review begins with case studies in the manufacturing industry to shed light on how companies may make prioritization decisions and how it relates to our thesis problem. Then, we will explore a few of the major methodologies for multi-criteria decision making (MCDM) methods and dive deep into the AHP, one of the most widely used MCDM methods that fits well with our research problem. We will discuss its background, methodology, and application to our research problem. Finally, we will conclude with the gaps and our expected contributions to the research literature.

## 2.1 Case Studies

### 2.1.1 Why Prioritization?

Customer order prioritization is very important for manufacturing companies given their limited production capacities (Akyildiz et al., 2015), especially in Make-to-order (MTO) environments. Under MTO, companies start manufacturing an order only when the customer order is received (Mestry et al., 2011). The key challenge is that customer orders arrive stochastically (Hemmati et al., 2012), but manufacturing capacity is usually fixed in the short-term. When incoming orders exceed the firm's available capacity, the firm has to make short-term capacity allocation decisions to determine which orders receive higher priorities and utilize the resources (Balakrishnan et al., 1996). It is crucial for firms to have efficient methods to prioritize orders to compete in the market (Akyildiz et al., 2015).

This setting is similar to the research problem we are confronting. Inbound loads needing to be picked up may exceed the available transportation capacity, so ShopCo needs to prioritize the loads so that it can better allocate the existing transportation capacity to meet company requirements and expectations in a competitive environment.

### 2.1.2 Order Prioritization

To tackle the order prioritization problem in the MTO environment, Balakrishnan et al. (1996) proposed a capacity allocation policy to enable firms to make better decisions. They recommended that firms group their products into priority classes based on profit contribution per unit of capacity. Firms would accept orders with higher profit contribution and reject the others. Balakrishnan et al. (1996) contributed a model to allocate capacity when demand exceeded available capacity. However, they mainly focused on profit maximization. In many cases, decision criteria are not single dimensioned. In our research problem, we needed to find ways to account for multiple criteria.

Akyildiz et al. (2015) developed such a framework for MCDM through studying order prioritization in the steel industry. They found that the decision process is usually very difficult, as there are multiple team members involved with differing opinions; thus, it is important to develop a model that accounts for everyone's input. They determined related criteria based on literature review as well as confirmation with decision makers and then evaluated customer orders against the criteria.

The complication of decision-making studied by Akyildiz et al. (2015) is similar to our research with ShopCo. Multiple stakeholders are involved in inbound transportation, each with differing goals. For example, a replenishment team may focus on in-stock availability while the transportation team tries to minimize shipment cost. However, Akyildiz et al. (2015)'s model has only one layer of decision criteria. In our research, each dimension of decision criteria may include multiple sub-criteria, which may call for a more robust method that works with multiple layers of decision criteria.

## 2.2 Multi-criteria Decision Making (MCDM)

MCDM problems can be solved in several ways. The AHP is the method we used in our research, which we will discuss in depth throughout this paper, but there were also other MCDM methods considered. For example, Akyildiz et al. (2015) used the Analytic Network Process (ANP) and Hemmati et al. (2012) proposed prioritizing incoming orders by similarity to ideal solution using the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). Other methods include the Simple Multi-Attribute Rating Technique (SMART), the Simple Additive Weighting (SAW) method, and the Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) (Velasquez & Hester, 2013; Barfod & Leleur, 2014). However, we did not select these methods as they either did not fit well with our research problem or suffered some drawbacks.

ANP is a generalization of the AHP. While it does not require independence among factors, it structures a problem as a network rather than a hierarchy (Saaty, 2008). TOPSIS is "an approach to identify an alternative which is closest to the ideal solution and farthest to the negative ideal solution in a multi-dimensional computing space" (Qin et al., 2008). While it is easy to use, it is difficult to weight factors and keep consistency of judgment. As we will discuss, AHP allowed for consistency checking, which was important in our research problem.

With SMART, ratings of alternatives are assigned directly in the natural scales of the criteria and then the different scales of criteria are converted to a common internal scale by means of a "Value Function", which is complicated to define (Konidari & Mavrakis, 2007). With SAW method, "a value function is established based on a simple addition of scores that represent the goal achievement under each criterion multiplied by the particular weight" (Qin et al., 2008). While the calculation is simple, it could yield distorted evaluation data (Podvezko, 2011). PROMETHEE is an outranking method based on concordance analysis. However, it assumes that the decision maker is able to weight the criteria and does not provide guidelines for determining the weight of the criteria (Velasquez & Hester, 2013).

## 2.3 Analytic Hierarchy Process (AHP)

An effective technique to prioritize multiple factors in a decision-making process is the AHP. Saaty (1980) introduced this technique by generating priorities for a decision's factors through a mathematical process: defining the problem (or goal), structuring the decision hierarchy, performing pairwise comparison matrices, and weighting the priorities (Saaty, 2008).

When applying the AHP, there are different techniques to assigning priority factors to each factor in a decision. Saaty (1980) described two approaches for defining each priority factor: the relative model method and the ratings method. The former rates each specific criterion against the alternatives, whereas the latter rates each criterion against a set of standards (Saaty, 1980). An advantage of the ratings method is that a large number of alternatives can be quickly rated, but the relative model method is more accurate (Saaty, 1980). When the number of alternatives exceeds seven, the ratings method is recommended (Bahurmoz, 2006).

### 2.3.1 AHP Application

The AHP has many applications and has been applied across many industries and decision-making processes, demonstrating its flexibility.

Karlsson and Ryan (1997) developed a cost-value approach to prioritizing software requirements by utilizing the AHP. They had the end user perform pairwise comparisons to define the priorities of each requirement. It is critical to involve the end user in the process, as he or she has the knowledge and experience to ensure appropriate priority factors are set and accurate pairwise comparisons are made.

To demonstrate AHP's capability across many industries, Saaty (2008) described various applications of the AHP, with the following closely resembling the scope of our research:

- The Department of Defense uses it to allocate resources;
- Xerox Corporation uses it to allocate funding across research projects;
- The General Services Administration uses it to prioritize its information technology initiatives;
- The Federal Financial Institutions Examination Council used it to prioritize its objectives;

- The state of North Carolina used it to develop criterion to rate and select vendors.

Each of these applications was conducted in a limited resource environment, which mirrored our study, since we were prioritizing loads to determine the optimal allocation of loads to a limited number of carriers.

### 2.3.2 AHP Integration

Recent research has focused on the integration of the AHP with other tools. Ho (2008) conducted a review of these integrations and found that five tools were commonly combined with the AHP: mathematical programming; quality function deployment; meta-heuristics; strengths, weaknesses, opportunities, and threats (SWOT) analysis; and data envelopment analysis (DEA). Of these tools, the mathematical programming technique using mixed integer linear programming (MILP) was the most relevant to our research, because it is a tool that can optimize AHP inputs against assigned constraints such as capacitated carriers.

In similar research, Korpela and Lehmusvaara (1999) utilized the AHP-MILP method to provide a holistic approach in a warehouse network design. The AHP prioritized the likelihood that a warehouse operator would satisfy a customer's needs (Korpela & Lehmusvaara, 1999). The AHP weightings were then inputted into an MILP to maximize customer satisfaction (Korpela & Lehmusvaara, 1999).

Further, Stannard et al. (2006) used the AHP-MILP method to allocate a limited number of aircrafts to airlift users. The AHP was used to prioritize the airlift users, and then these weightings were inputted into an MILP to maximize the total worth of aircraft use at each priority level (Stannard et al., 2006). Similar to Korpela and Lehmusvaara

(1999), Stannard et al. (2006) conducted the AHP first before running the MILP. The reversed process is also used, but it does not apply to our research. For our research, we used a Knapsack optimization model to distribute PO's to loads, maximizing the total load priority scores shipped given the carrier constraint. This is similar to Bennett and Saaty (1993)'s research of maximizing the benefits of choosing Air Force missions with the forces available.

### 2.3.3 Gaps

Although much research had been completed on standalone and integrated AHP methods, none of the research found addressed the prioritization of loads for capacitated carriers, so we filled this gap. Lessons learned from order prioritization in the manufacturing industry, especially within MTO environments, could help shed light on how companies may make multi-criteria decisions. We expect that our research will add additional research to inbound transportation/logistics, and, to our best knowledge, we are the first to apply the AHP to inbound load prioritization under constrained carrier capacity.

## 2.4 Summary

Our research introduces a new variant of the AHP-MILP method that (1) assigns priority scores to inbound loads to facilitate better decision making under carrier capacity constraints and (2) optimizes load priorities through a Knapsack optimization model. Our findings and recommendations will enable ShopCo to make informed decisions on load prioritization.

# 3 AHP Methodology and Results

The main purpose of this research was to develop priority weights for a list of factors and sub-factors impacting a load's characteristics using the AHP and to develop a model to assign those weights to each load. This chapter begins by describing the development process for the AHP as well as providing justification for its use. Subsequent sections describe the findings from the application of the AHP weight outputs to ShopCo's inbound loads.

## 3.1 AHP Steps

The AHP was the prioritization technique chosen, because it had been found to perform the best when compared against alternative prioritization techniques (Khan et al., 2015). This method provides results on a ratio scale and provides a consistency check to ensure the transitive property (i.e., if A>B and B>C, then A>C) is met, thus avoiding random results. Further, this process is reliable, because the use of pairwise comparisons adds redundancy to avoid judgment errors (Khan et al., 2015). Conversely, the AHP becomes more difficult to use as the number of factors increases (Khan et al., 2015).

The ratings method, as opposed to the relative method, was the technique utilized to define the priority weights. Although the relative method is more accurate, the ratings method should be used when there is a high number of alternatives (i.e., loads) and the decisions are standardized (Saaty, 2008; Bahurmoz, 2006). ShopCo will be assigning these priority weights to specific characteristics of 1,000's of loads each day, so the ratings method provides the needed flexibility.

The AHP is a comprehensive process that can be broken down into the 9 steps described in Figure 1 (Ariff et al., 2008).

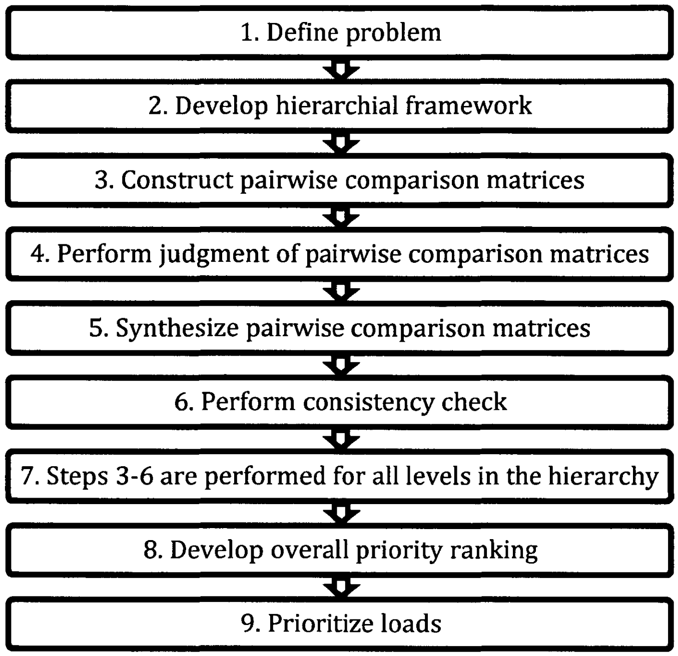



**Figure 1 – AHP Steps**
**Source:** (Adapted from Ariff et al., 2008, 5)

### 3.1.1 Defining the Problem

Historically, ShopCo deferred the prioritization of inbound loads to its suppliers and carriers. Recently, ShopCo has taken over this role but has had difficulty in prioritizing loads against company objectives. When interviewing subject matter experts across multiple departments, we discovered that priorities differed across departments, as will be discussed in section 3.1.4. The challenge was to obtain universal agreement of the weights across multiple departments. ShopCo emphasized that a ratio-scaled output was desired, as some loads may have the same level of priority, confirming our choice of the AHP.

### 3.1.2 Developing Hierarchical Framework

To develop the hierarchical framework, we conducted multiple interviews with ShopCo's transportation strategy team to determine key factors. From these interviews, a 3-level hierarchical framework, illustrated in Figure 2, was created to break down the key factors that determined a PO's priority. These factors were identified through discussions with ShopCo of each characteristic attached to a PO being tracked in ShopCo's database. Each factor had to be mutually exclusive across all levels to ensure each factor was fairly weighted. From here on, the Level 2 factors will be referred to as factors, and the Level 3 factors will be referred to as sub-factors.

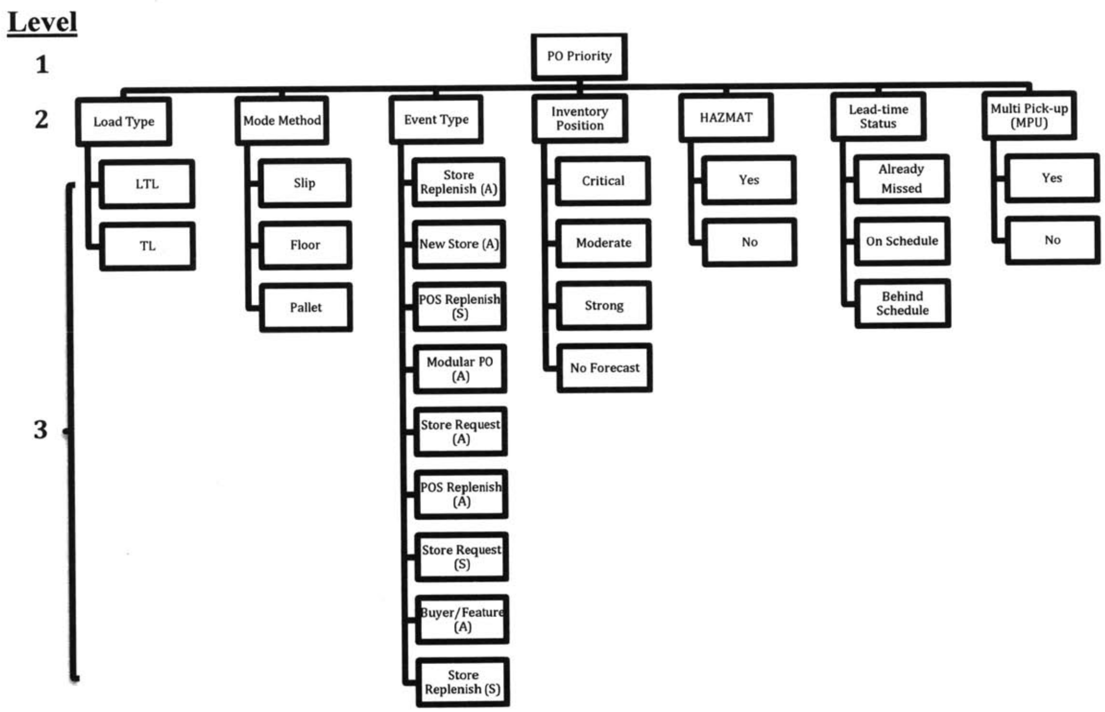



**Figure 2 – ShopCo's 3-Level Hierarchical Framework**

Level I

The objective of the AHP is identified at the top level of the hierarchy. Specifically, it was to define a priority weight for each PO that could be rolled up into a load priority score, since some loads had more than one PO. This will be further discussed in section 3.1.9.

Level II

The second level identified the main criteria affecting a PO's priority. These criteria were classified into 7 factors as described in Table 1 and were the dimensions used to calculate a PO's priority.

**Table 1 – AHP Factors and Descriptions**

| Factor | Description | Sub-factors |
|---|---|---|
| Load Type | Identifies whether a PO is a Truckload (TL) or Less-than-Truckload (LTL). | TL, LTL |
| Mode Method | Identifies how a PO is loaded onto the carrier. E.g., is the PO palletized or loaded by hand? | Slip, Floor, Pallet |
| Event Type | Identifies the purpose of the PO. E.g., is the load for a short-term promotion? | Store Replenish (A), New Store (A), PO Replenish (A), Modular PO (A), Store Request (A), POS Replenish (A), Store Request (S), Buyer/Feature (A), Store Replenish (S) |
| Inventory Position | Identifies the current pipeline inventory position of the PO's contents. | Critical, Moderate, Strong, No Forecast |
| HAZMAT | Identifies whether the PO contains hazardous materials, thus requiring special handling. | Yes, No |
| Lead-time Status | Identifies the current status of the PO's movement against established timelines. | Already Missed, On Schedule, Behind Schedule |
| Multi Pick-up | Identifies whether a PO has multiple stops before arriving at the distribution center. | Yes, No |

Level III

The third level identified the sub-factors attributable to each of the factors.

**Load Type Sub-factors**

A PO's Load Type was either Truckload (TL) or Less-than-Truckload (LTL). The former identified a PO that consumed the full capacity of a truck, whereas the latter identified a PO that shared the capacity of a truck with other PO's. LTL PO's were a greater concern to ShopCo, because the delay of those PO's impacted the movement of other PO's as determined by ShopCo's load allocation tool.

**Mode Method Sub-factors**

The Mode Method determined how a PO was loaded into a truck. Palletized PO's are the easiest to load but take up the most space because of the size of the pallets. Slips are thin, palletized sheets and take up less space but require specialized equipment to unload. Floor-loaded PO's are loaded by hand and are the hardest to load and unload but take up the least space. ShopCo placed higher priority on PO's that were more difficult to load and unload.

**Event Type Sub-factors**

Individuals cannot compare more than 7 +/- 2 factors without becoming confused, so the number of Event Type sub-factors reached that maximum (Bahurmoz, 2006). We initially had another factor identifying Assembly (A) and Staple (S) sub-factors but found dependence between that factor and Event Type, so we merged the 2 factors. Staple items are those that have inventory stored at the distribution center, whereas Assembly items flow through the distribution center, similar to cross-docking. Event Type descriptions can be found in Table 2. ShopCo considered Assembly Event Types to have greater importance, since safety stock was not stored at the distribution centers to cover demand fluctuations.

**Table 2 – Event Type Descriptions**

| Event Type | Description |
|---|---|
| Store Replenish (A) | System generated replenishment orders. |
| Store Replenish (S) | System generated replenishment orders. |
| POS Replenish (A) | Manually (non-system) generated replenishment orders. |
| POS Replenish (S) | Manually (non-system) generated replenishment orders. |
| Store Request (A) | Orders generated to provide inventory to stores at the request of the store. |
| Store Request (S) | Orders generated to provide inventory to stores at the request of the store. |
| Buyer/Feature (A) | Orders generated to provide additional inventory or items to stores for features (endcaps, clipstrips, etc.). |
| New Store (A) | Orders generated to stock new stores. |
| Modular PO (A) | Orders genereated to provide inventory to stores to set a new modular. |

### Inventory Position Sub-factors

A PO's Inventory Position was determined using Equation 1. The 4-Week Forecast was used as the denominator to identify the percentage of the forecast that was covered by the current pipeline inventory, since this was the forecast duration currently tracked in the PO dataset.

$$\frac{\text{Currrent Warehouse On Hand + Current Store On Hand + Current Store In Transit}}{\text{4-Week Forecast}} \quad \textbf{Eqn 1}$$

To identify the Inventory Position sub-factor thresholds, we plotted the Inventory Position distribution across the PO's, as shown in Figure 3, and found that most of the Inventory Positions were greater than 1. Using this distribution, we consulted with ShopCo to determine a threshold for each Inventory Position sub-factor.

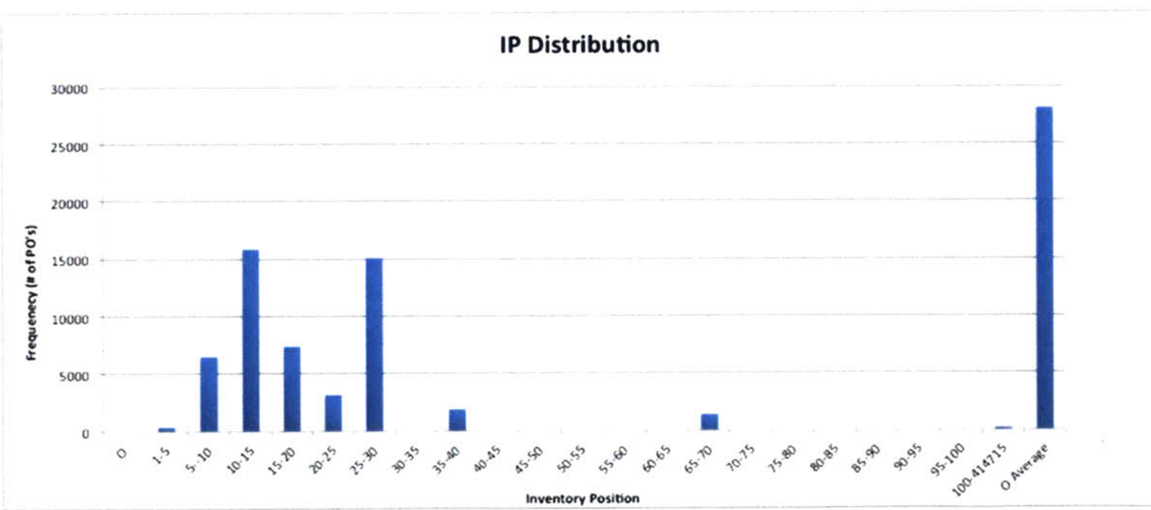



**Figure 3 – Inventory Position Factor Distribution**

The final thresholds are listed in Table 3. Inventory Positions greater than 1 were considered Strong, because the pipeline inventory covered the 4-week forecast. Inventory Positions between 0 and 1 were considered Moderate, and Inventory Positions that equaled 0 were considered Critical. Since Inventory Positions greater than 1 had pipeline inventory that could cover the 4-week forecast, these PO's were not as critical as Inventory Positions less than 1. Further, PO's that did not have an inventory forecast resulted in an Inventory Position of 0 and are labeled in Figure 3 as "0 Average". Per ShopCo, PO's with no forecasts were typically for limited release or obsolete items.

**Table 3 – Inventory Position Sub-factor Thresholds**

| Inventory Position Sub-factor | Eqn 1 Value | Comment |
|---|---|---|
| Strong | $x \geq 1$ | Current pipeline inventory covers 4-week forecast. |
| Moderate | $0 < x < 1$ | Current pipeline inventory cannot cover full 4-week forecast, but there is inventory to meet part of the forecast. |
| Critical | $x = 0$ | There is no inventory to cover 4-week forecast. |
| No Forecast | Undefined | There is no forecast data. |

**HAZMAT Sub-factors**

The HAZMAT sub-factors determined whether a PO contained hazardous materials, thus requiring special handling. ShopCo preferred PO's with HAZMAT to have higher priority, because it is more difficult to arrange carriers with the proper clearances to ship HAZMAT.

**Lead-time Status Sub-factors**

Lead-time Status had three sub-factors: On Schedule, Behind Schedule, and Already Missed. On Schedule PO's were those that were on schedule in accordance with the established timelines. ShopCo inputs a 2-day buffer in its timeline to account for transportation delays, so On Schedule PO's were those that had not used any of the 2-day buffer. Behind Schedule PO's were those that could still make the required delivery date but had fallen behind and were using the 2-day buffer to catch up. Already Missed PO's were those that had not been shipped and were past the required delivery dates.

**Multi Pick-up Sub-factors**

The Multi Pick-up sub-factor determined whether a PO had to be picked up from multiple supplier destinations. PO's that had multiple stops received higher priority, because those are more difficult to coordinate than PO's located at one location.

### 3.1.3 Constructing Pairwise Comparison Matrices

Pairwise comparison matrices were constructed for each set of factors and sub-factors. These matrices were used by ShopCo to rank each factor and sub-factor's alternatives by comparing two alternatives at a time to develop relative values of importance that could be converted into weights using the following terms:

C: factor or sub-factor criteria

$n$: number of factors/sub-factors

$i$: first factor or sub-factor being compared

$j$: second factor or sub-factor being compared

$a_{ij}$: pairwise comparison score for factor/sub-factor $i$ and $j$

$w$: Fundamental Scale for Pairwise Comparisons weight

Letting $C_1, C_2, \dots, C_n$ be the set of criteria, the pairwise comparison of activities $C_i, C_j$ were represented by an $n$-by-$n$ matrix, $a$, where

$$a_{ij} = w_i/w_j\,, (i,j = 1, 2, \dots, n).$$

Saaty (1980) identified 2 rules that $a_{ij}$ must follow:

- Rule 1: If $a_{ij} = w_i/w_j$, then $a_{ji} = w_j/w_i$, $w_i/w_j \neq 0$.
- Rule 2: If $C_i$ and $C_j$ are of equal importance, then $a_{ij} = 1$ and $a_{ji} = 1$.

This results in the following matrix:

$$a = \begin{bmatrix} 1 & a_{12} & \dots & a_{1n} \\ 1/a_{12} & 1 & \dots & a_{2n} \\ \vdots & \vdots & \dots & \vdots \\ 1/a_{1n} & 1/a_{2n} & \dots & 1 \end{bmatrix} = \begin{bmatrix} w_1 / w_1 & w_1 / w_2 & \dots & w_1 / w_n \\ w_2 / w_1 & w_2 / w_2 & \dots & w_2 / w_n \\ \vdots & \vdots & \dots & \vdots \\ w_n / w_1 & w_n / w_2 & \dots & w_n / w_n \end{bmatrix}$$

The weights, $w$, to determine the relative importance of one factor/sub-factor over another were based on The Fundamental Scale for Pairwise Comparisons, as shown in Table 4 (Saaty, 2008). For example, ShopCo determined that the Mode Method sub-factor Slip, $a_i$, was between equally and moderately more important than Mode Method sub-factor Pallet, $a_j$, so $a_{ij} = w_i/w_j = 2/1 = 2$ (Table 5). Conversely, if factor/sub-factor Pallet, $a_j$, was between equally and moderately more important than factor/sub-factor Slip, $a_i$, then $a_{ij} = w_i/w_j = 1/2$. The Mode Method results are further discussed in the next section.

**Table 4 – The Fundamental Scale for Pairwise Comparisons**

| The Fundamental Scale for Pairwise Comparisons | | |
|---|---|---|
| **Intensity of Importance** | **Definition** | **Explanation** |
| 1 | Equal importance | Two elements contribute equally to the objective |
| 3 | Moderate importance | Experience and judgment slightly favor one element over another |
| 5 | Strong importance | Experience and judgment strongly favor one element over another |
| 7 | Very strong importance | One element is favored very strongly over another, its dominance is demonstrated in practice |
| 9 | Extreme importance | The evidence favoring one element over another is of the highest possible order of affirmation |
| Intensities of 2, 4, 6, and 8 can be used to express intermediate values. Intensities 1.1, 1.2, 1.3, etc. can be used for elements that are very close in importance | | |

**Source:** (Saaty, 2008)

The levels of the scale could have been labeled with numbers (the numerical mode) or preference phrases (the verbal mode). Huizingh and Vrolijk (1997) found that the numerical mode resulted in a significantly higher degree of consistency, so that was the mode we chose.

### 3.1.4 Performing Judgment of Pairwise Comparison Matrices

To conduct the pairwise comparisons, we held a meeting with 5 key stakeholders, each with differing roles within the inbound transportation process: transportation strategy, transportation operations, replenishment strategy, supply chain strategy, and data visibility strategy. Preceding the meeting, definitions of the factors and sub-factors were introduced to all parties to avoid controversial arguments, as recommended by Saaty (1980). Each matrix had $\frac{n \times (n-1)}{2}$ judgments. Table 5 shows the Mode Method results, which were determined by the 3 pairwise comparisons highlighted in yellow. Whole numbers were used when the $i$ sub-factor was considered more important than the $j$ sub-factor, and fractional numbers were used for the reverse, so Floor was considered moderately more important than Slip, Slip was considered between equally and moderately more important than Pallet, and Floor was between moderately and strongly more important than Pallet. The full factor and sub-factor results are listed in Appendix A.

**Table 5 – Mode Method Pairwise Comparison Results**

| i \ j | Slip | Floor | Pallet |
|---|---|---|---|
| Slip | 1.000 | 0.333 | 2.000 |
| Floor | 3.000 | 1.000 | 4.000 |
| Pallet | 0.500 | 0.250 | 1.000 |

**Behavioral Dimension**

Although there was consensus from the group of subject matter experts on most of the pairwise comparison rankings, there were disagreements on a few of the comparisons: Load Type vs. Event Type, Event Time vs. Lead-time Status, and LTL vs.

TL. Under these circumstances, either the majority or average ranking determined the final ranking. In the former scenario, the ranking that had the highest consensus was used. For example, two of the three subject matter experts ranked the sub-factor LTL as more important than TL, so LTL was ranked higher. In the latter scenario, if the rankings were evenly split, the group tended to use the average as the final ranking for the pairwise comparison. For example, the group evenly ranked factors Event Type and Lead-time Status (i.e., one more, one less, and one even), so these factors were ranked as equally important.

There was a human element to the AHP model, since subject matter experts completed the pairwise comparisons, so conflict during the pairwise comparison rankings was a concern. To minimize these conflicts, we ensured having the key subject matter experts in attendance for each factor and sub-factor so that consensus could be reached. Although each attendee had knowledge of the importance of each factor and sub-factor, it was interesting that the discussion often entailed the subject matter expert enlightening the group on the underlying importance of that factor, thus swaying the group to his ranking.

### 3.1.5 Synthesizing Pairwise Comparison Matrices

Each pairwise comparison matrix was synthesized to convert the relative values into priority values (PV). There are different methods to perform the synthesis, but we chose the row geometric mean method (RGMM), as it is insensitive to an inversion of the scale (Ishizaka & Lusti, 2006). An inversion of the scale occurs when the reciprocal of each pairwise comparison is taken. Logically, the ranking of an inverted scale should be the exact reverse of a non-inverted scale, but ranking differences have been found when using Saaty's popular right eigenvector method. Further, Crawford (1987) found that as the matrix dimension or pairwise comparison consistency variance of errors increase, the RGMM outperformed the right eigenvector method by all measures, to include rank preservation.

Aguarón and Moreno-Jiménez (2003) defined the RGMM as

$$x_i = \frac{(\prod_{j=1}^{n} a_{ij})^{\frac{1}{n}}}{\sum_{i=1}^{n}\left(\prod_{j=1}^{n} a_{ij}\right)^{\frac{1}{n}}}, i = 1, \ldots, n,$$

where $x_1, x_2, \ldots, x_n$ is the PV.

For example, the Slip sub-factor's PV in Table 6 equals

$$\frac{(1.000 \times 0.333 \times 2.000)^{1/3}}{(1.000 \times 0.333 \times 2.000)^{1/3}+(3.000 \times 1.000 \times 4.000)^{1/3}+(0.500 \times 0.250 \times 1.000)^{1/3}} = 0.238.$$

The numerator is the Slip sub-factor's geometric mean (GM), and the denominator is the sum of each sub-factor's GM to include Slip's. The other sub-factors' PV's were found by replacing the numerator with that respective sub-factor's GM. Table 6 shows the PV for the Mode Method sub-factors. The Floor sub-factor had the highest PV and was considered the most important, followed by the Slip and Pallet sub-factors.

**Table 6 – Mode Method Priority Value Results**

| | | j | | | |
|---|---|---|---|---|---|
| | Slip | Floor | Pallet | GM | PV |
| Slip | 1.000 | 0.333 | 2.000 | 0.874 | 0.238 |
| i Floor | 3.000 | 1.000 | 4.000 | 2.289 | 0.625 |
| Pallet | 0.500 | 0.250 | 1.000 | 0.500 | 0.136 |
| | | | | 3.663 | |

### 3.1.6 Performing Consistency Check

A key advantage of the AHP is that it allows the user to measure the consistency of the pairwise comparison judgments (Aguarón & Moreno-Jiménez, 2003). Aguarón and Moreno-Jiménez (2003) formalized the Geometric Consistency Index (GCI) as the inconsistency measure for the RGMM and defined it as

$$\frac{2}{(n-1)(n-2)} \sum_{i<j} log^2 e_{ij},$$

where the consistency error, $e_{ij} = a_{ij} \times w_j/w_i$.

For a matrix to be considered consistent, the GCI had to be less than the thresholds defined by Aguarón and Moreno-Jiménez (2003), as listed in Table 7.

**Table 7 – GCI Maximum Thresholds**

| n | GCI Max |
|---|---|
| 3 | 0.3147 |
| 4 | 0.3526 |
| >4 | 0.3700 |

If the GCI exceeded the threshold, the most inconsistent judgments (those with large $e_{ij}$) had to be reconsidered (Aguarón & Moreno-Jiménez, 2003). Table 8 shows the consistency for the Mode Method sub-factors. Since the GCI of .0548 was less than the threshold of 0.3147, this matrix was consistent. The GCI was used for each pairwise comparison matrix to ensure consistency was met, and the full results are listed in Appendix A.

**Table 8 – Mode Method Consistency Results**

| | | j | | | | | |
|---|---|---|---|---|---|---|---|
| | Slip | Floor | Pallet | GM | PV | GCI | 0.0548 |
| Slip | 1.000 | 0.333 | 2.000 | 0.874 | 0.238 | Threshold | 0.3147 |
| i Floor | 3.000 | 1.000 | 4.000 | 2.289 | 0.625 | | |
| Pallet | 0.500 | 0.250 | 1.000 | 0.500 | 0.136 | Consistent? | YES |
| | | | | 3.663 | | | |

### 3.1.7 Steps (3.1.3-3.1.6) are performed for All Levels in the Hierarchy

Each factor and sub-factor matrix had steps 3.1.3-3.1.6 performed. The full results are listed in Appendix A.

### 3.1.8 Developing Overall Priority Ranking

After each matrix was consistent, the final PO priority weights were determined by multiplying the factor and respective sub-factor weights. The PO priority weights are yellow-highlighted in Table 9. The higher the weight, the greater the importance of that factor/sub-factor combination. For example, all else being equal, a PO with a Critical Inventory Position (weight = 0.240) was more important than a PO with a Strong Inventory Position (weight = 0.017).

# Table 9 – AHP PO Priority Weights

**Load Priority**

| Inventory Position | 0.370 | |
|---|---|---|
| Critical | 0.649 | 0.240 |
| Moderate | 0.190 | 0.070 |
| No Forecast | 0.113 | 0.042 |
| Strong | 0.047 | 0.017 |

| Event Type | 0.209 | |
|---|---|---|
| Modular PO (A) | 0.298 | 0.062 |
| New Store (A) | 0.217 | 0.045 |
| POS Replenish (A) | 0.175 | 0.037 |
| Store Replenish (A) | 0.082 | 0.017 |
| Buyer/Feature (A) | 0.082 | 0.017 |
| Store Request (A) | 0.057 | 0.012 |
| POS Replenish (S) | 0.044 | 0.009 |
| Store Request (S) | 0.024 | 0.005 |
| Store Replenish (S) | 0.020 | 0.004 |

| Lead-time Status | 0.205 | |
|---|---|---|
| Already Missed | 0.649 | 0.133 |
| Behind Schedule | 0.279 | 0.057 |
| On Schedule | 0.072 | 0.015 |

| Load Type | 0.120 | |
|---|---|---|
| LTL | 0.750 | 0.090 |
| TL | 0.250 | 0.030 |

| Multi Pick-up | 0.047 | |
|---|---|---|
| Yes | 0.875 | 0.041 |
| No | 0.125 | 0.006 |

| HAZMAT | 0.031 | |
|---|---|---|
| Yes | 0.833 | 0.026 |
| No | 0.167 | 0.005 |

| Mode Method | 0.019 | |
|---|---|---|
| Floor | 0.625 | 0.012 |
| Slip | 0.238 | 0.005 |
| Pallet | 0.136 | 0.003 |

**Factor & Sub-factor Priority Weights**

The key motivation behind this project was to establish load prioritization logic to improve inventory position at the retail level, so, not surprisingly, Inventory Position was the highest weighted factor at 0.370. Its weight was 77 percent greater than that of the second highest factor, Event Type, as depicted in Table 10. The next two biggest drivers of priority, Event Type and Lead-time Status, were the second and third highest factors at .209 and .205, respectively. The largest difference between factors occurred between Load Type and Multi Pick-up where Load Type had a priority weight 155 percent higher than that of Multi Pick-up.

**Table 10 – AHP Factor Weight Comparison**

| Factor | Ranking | % Increase |
|---|---|---|
| Inventory Position | 0.370 | 0.77 |
| Event Type | 0.209 | 0.02 |
| Lead-time Status | 0.205 | 0.71 |
| Load Type | 0.120 | 1.55 |
| Multi Pick-up | 0.047 | 0.53 |
| HAZMAT | 0.031 | 0.60 |
| Mode Method | 0.019 | N/A |

At the sub-factor level, the Critical Inventory Position, Already Missed Lead-time Status, and LTL Load Type sub-factors had the three highest weights, accounting for 46.3 percent of the total priority points. Further, these sub-factors were part of the most impactful factors, as measured by the score range of the sub-factors within each factor (Table 11). The larger the range, the more impactful that factor could have on the final PO priority score. For example, the range between the highest and lowest Inventory Position sub-factor weights was 0.223, making the Inventory Position factor the most impactful factor on the PO priority score.

**Table 11 – AHP Sub-factor Ranges**

| Factor | Sub-factor | Priority | Sub-factor Range |
|---|---|---|---|
| Inventory Position | Critical | 0.240 | 0.223 |
| Lead-time Status | Already Missed | 0.133 | 0.118 |
| Load Type | LTL | 0.090 | 0.060 |
| Inventory Position | Moderate | 0.070 | 0.223 |
| Event Type | Modular PO (A) | 0.062 | 0.058 |
| Lead-time Status | Behind Schedule | 0.057 | 0.118 |
| Event Type | New Store (A) | 0.045 | 0.058 |
| Inventory Position | No Forecast | 0.042 | 0.223 |
| Multi Pick-up | Yes | 0.041 | 0.035 |
| Event Type | POS Replenish (A) | 0.037 | 0.058 |
| Load Type | TL | 0.030 | 0.060 |
| HAZMAT | Yes | 0.026 | 0.020 |
| Inventory Position | Strong | 0.017 | 0.223 |
| Event Type | Store Replenish (A) | 0.017 | 0.058 |
| Event Type | Buyer/Feature (A) | 0.017 | 0.058 |
| Lead-time Status | On Schedule | 0.015 | 0.118 |
| Mode Method | Floor | 0.012 | 0.009 |
| Event Type | Store Request (A) | 0.012 | 0.058 |
| Event Type | POS Replenish (S) | 0.009 | 0.058 |
| Multi Pick-up | No | 0.006 | 0.035 |
| HAZMAT | No | 0.005 | 0.020 |
| Event Type | Store Request (S) | 0.005 | 0.058 |
| Mode Method | Slip | 0.005 | 0.009 |
| Event Type | Store Replenish (S) | 0.004 | 0.058 |
| Mode Method | Pallet | 0.003 | 0.009 |

| Factor | Sub-factor Range |
|---|---|
| Inventory Position | 0.223 |
| Lead-time Status | 0.118 |
| Load Type | 0.060 |
| Event Type | 0.058 |
| Multi Pick-up | 0.035 |
| HAZMAT | 0.020 |
| Mode Method | 0.009 |

### 3.1.9 Prioritizing Loads

We developed a prioritization tool to calculate a priority score for each load based on the output of the AHP. First, we converted raw transactional data to normalized, categorical data for each PO so that the categories matched the AHP sub-factors. Then, we fetched the priority weights for each sub-factor the respective PO had. We used the Microsoft Excel VLOOKUP function to locate the respective weight in the AHP output for each categorical value to populate the respective columns in the prioritization tool. Lastly, the summation of the PO sub-factor weights determined the final load priority score for loads with only one PO. For loads with more than one PO, each PO's priority score was weighted by its case quantity – the summation of the case-weighted PO priority scores was then divided by the total case quantity for all of the PO's in the load, resulting in a case-weighted, final load priority score.

**Calculating Load Priority Score Formulation:**

**Variables:**

$i$: PO number

$P_i$: Priority score for $PO_i$

$Q_i$: Case quantity for $PO_i$

$n$: Number of PO's within the load

**Load Priority** =

$$(\sum_{i=1}^{n} P_i * Q_i) \,/\, \sum_{i=1}^{n} Q_i$$

In the next section, we discuss the findings when the AHP outputs were applied to ShopCo's inbound load dataset.

## 3.2 AHP Priority Score Findings

In this section, we describe our findings from when the AHP output was applied to the dataset, specifically the PO and load priority distributions.

### 3.2.1 PO Priority Score Distribution

The PO priority score distribution is depicted in Figure 4. There is a higher slope once the PO exceeds the $90^{th}$ percentile, so we deep dived into this sample of PO's to determine the key differentiators that could push a PO from the $90^{th}$ to the $99^{th}$ percentile. The key differences were due to the Event Type and Inventory Position. As the percentile increased from the $90^{th}$, the difference between the new percentile and the $99^{th}$ percentile was mostly due to the Event Type. This difference was favorable, because if two PO's had Critical Inventory Positions but one of the PO's was for a promotion, as indicated by its Event Type, ShopCo preferred that the promotional PO have priority.

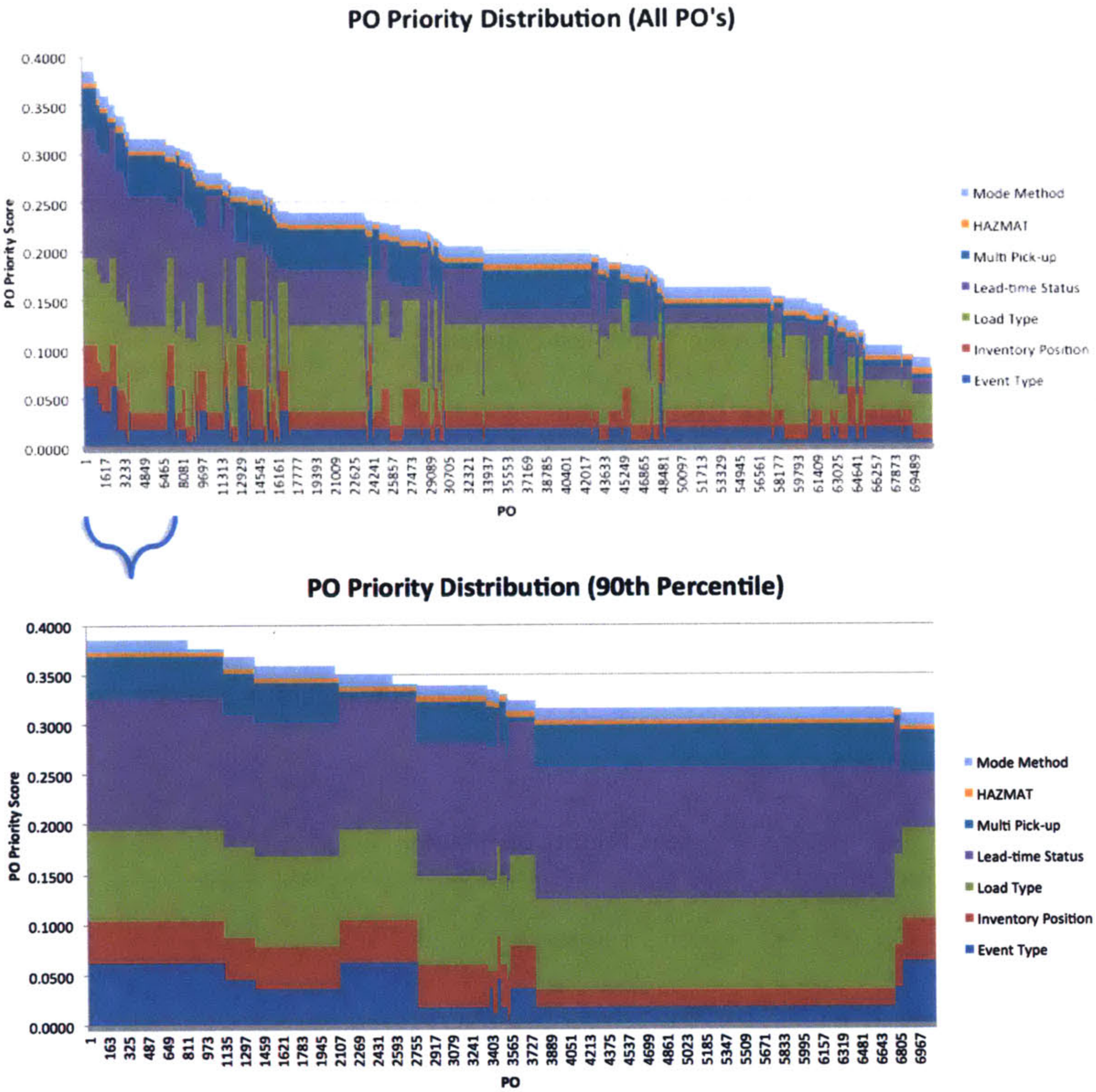



**Figure 4 – PO Priority Distribution (All PO's & 90th Percentile)**

Although the Inventory Position factor was the most impactful based on its sub-factor range (Table 11), it did not have the highest correlation with the PO priority score. Using the PO priority score as the dependent variable and the factors as the independent variables, the correlation between a PO's factor weights and priority score for each factor was found. Excluding the HAZMAT factor since all of the PO's did not contain HAZMAT, each factor had a positive correlation, as shown in Table 12.

Table 12 – AHP Factor Weight and PO Score Correlation

| Event Type | Inventory Position | Load Type | Lead-time Status | MPU | HAZMAT | Mode Method |
|---|---|---|---|---|---|---|
| 0.49 | 0.41 | 0.54 | 0.78 | 0.51 | - | 0.08 |

This finding is not surprising, since each factor's weight summed to the final PO priority score. The Lead-time Status had the highest correlation of 0.78. Interestingly, although the Inventory Position factor had the most impact on the PO priority score based on its sub-factor range, it had the 5th highest correlation.

### 3.2.2 Load Priority Score Distribution

As discussed in section 3.1.9, the case-weighted PO priority scores were summed to calculate the load priority score for loads that had more than one PO; otherwise, the PO priority score was the same as the load priority score. The load priority score distribution showed that load priority score 0.10206 had the highest frequency with 1,219 occurrences (Figure 5).

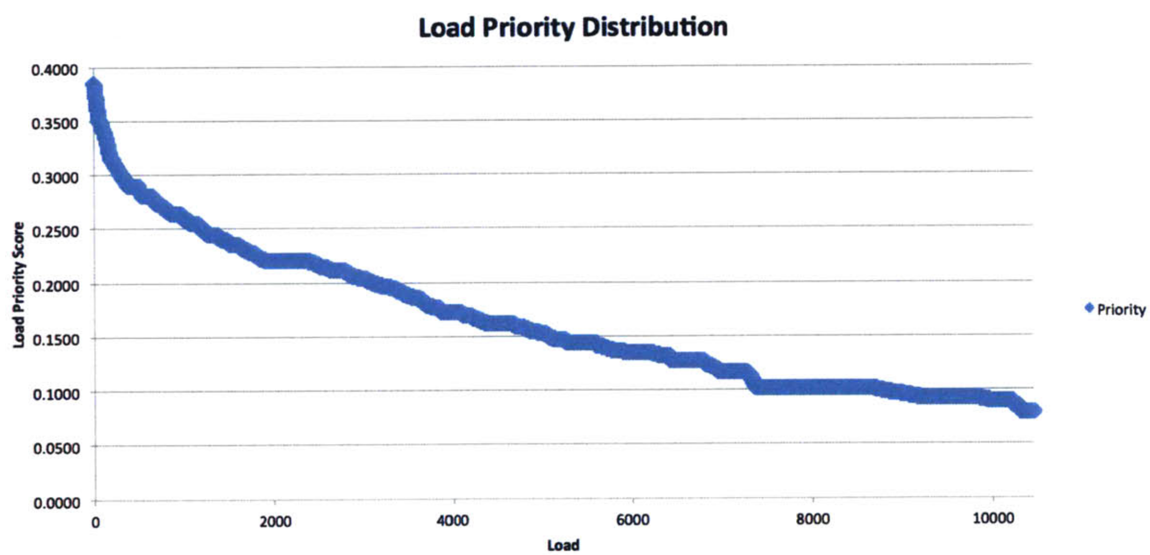



Figure 5 – Load Priority Distribution

Upon further investigation, it was found that 90.7 percent of these loads had a single PO and that each off these loads had almost identical characteristics, the only differences being the Event Type in which 99 percent of these loads were for Store Replenishments and 1 percent were for Buyers/Features (Table 13).

**Table 13 – Load Characteristics of Load Priority 0.10206**

| Factor | Sub-factor Characteristics |
|---|---|
| Event Type | Store Replen (A) (99%), Buyer/Feature (A) (1%) |
| Inventory Position | Strong (100%) |
| Load Type | TL (100%) |
| Lead-time Status | On Schedule (100%) |
| Multi Pick-up | No (100%) |
| HAZMAT | No (100%) |
| Mode Method | Floor (100%) |

Further, the correlation of the case-weighted factor priority scores showed that Lead-time Status had the highest correlation with the final load priority score (Table 14). We also tested the correlation between total load case quantity and the final load priority score and found that it had an inferior correlation of 0.17 compared to that of the Lead-time Status. These findings suggested that the Lead-time Status against established timelines of PO's in a load was the best predictor of a load's priority score, thus alleviating ShopCo's concern of loads continually being surpassed by higher priority loads, because a load's priority would increase if it was continually skipped in the rotation for inbound movement.

**Table 14 – AHP Factor Weight (Case-weighted) and Load Score Correlation**

| Event Type | Inventory Position | Load Type | Lead-time Status | MPU | HAZMAT | Mode Method | Case Qty |
|---|---|---|---|---|---|---|---|
| 0.49 | 0.40 | 0.58 | 0.73 | 0.48 | - | 0.07 | 0.17 |

**Impact of Holding a Load**

The impact of holding a load on a load's priority was a key concern for ShopCo, because ShopCo wanted to ensure that the AHP model added additional priority to a load not being shipped. Theoretically, a load's priority would increase if that load was continually skipped for shipment, because its (1) Lead-time Status would deteriorate and

(2) Inventory Position would decrease, thus increasing the priority weight for each of those factors. Further, a load with the highest possible Lead-time Status and Inventory Position weights would have a load score $\geq 0.3908$, which was greater than all of the load scores from the sample data.

To test the impact of holding a load for 1 and 2 days, we took a random sample of 5 loads and adjusted the Lead-time Status priority weights accordingly, assuming that all else remained equal (Table 15). Except for the Load 4, which already had a load priority score above the 98 percentile, the rest of the sample loads increased in percentile by at least 21.8 percentage points within 1 to 2 days. It is important to note that these improvements in percentile are conservative, because this test shows the effect on only the Lead-time Status but not Inventory Position. The Inventory Position impact could not be determined without dynamic demand and/or forecast data, but as a load is held, the Inventory Position would deteriorate, resulting in a higher Inventory Position weight for that load. Thus, the loads in Table 15 may increase to an even greater priority percentile with dynamic data. For example, if Load 5's Inventory Position went from "Strong" to "Moderate" after a 2-day hold, its priority would increase from 0.1444 to 0.1970, resulting in a new rank of 3,224 and percentile of 69.17%. If the Inventory Position deteriorated even more drastically from "Strong" to "Critical" after a 2-day hold, the load's priority would increase to 0.3670, resulting in a new rank of 33 and percentile of 99.68%.

Table 15 – Impact of Holding a Load

| | Initial | | | 1-Day Hold | | | 2-Day Hold | | |
|---|---|---|---|---|---|---|---|---|---|
| Load | Priority | Rank | Percentile | Priority | Rank | Percentile | Priority | Rank | Percentile |
| 1 | 0.1172 | 6,992 | 33.14% | 0.1596 | 4,712 | 54.94% | No Change | | |
| 2 | 0.1948 | 3,332 | 68.14% | No Change | | | 0.2706 | 754 | 92.79% |
| 3 | 0.1172 | 7,072 | 32.38% | 0.1596 | 4,712 | 54.94% | No Change | | |
| 4 | 0.3160 | 181 | 98.27% | 0.3337 | 135 | 98.71% | No Change | | |
| 5 | 0.1021 | 8,107 | 22.48% | 0.1444 | 5,272 | 49.59% | No Change | | |

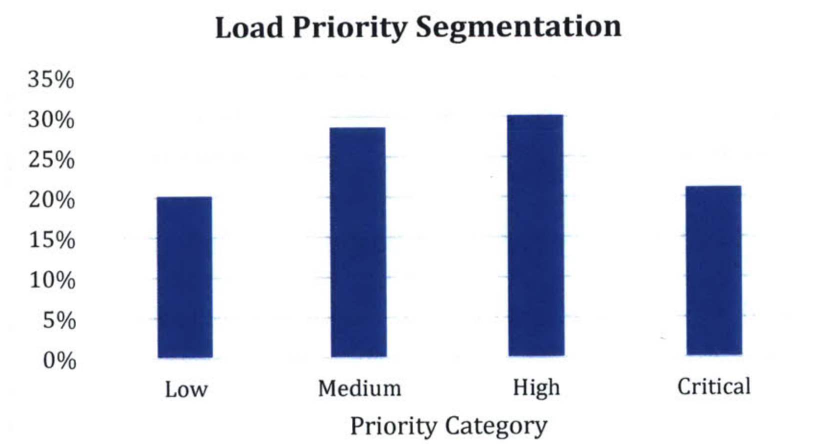
**Segmenting Load Priority Scores**

Since each load priority score has multiple decimal points, it may be difficult for humans to register and make sense of the number and to communicate it among stakeholders. For example, if a load has a priority score of 0.2678, what does it mean and how should ShopCo interpret the result? If we compare it to a load score of 0.0992, we know that the load with the higher priority score has the higher priority, but how much more important is it? We may need to place the scores among the rest of the loads to fully understand their relative rankings. In fact, when we looked at the rankings of these two scores within the sample data of 10,458 loads, we realized that the load with the score of 0.2678 ranked higher than 93% of the loads, while the load with the score of 0.0992 ranked within the bottom 20%, meaning that 0.2678 was a much higher priority than 0.0992.

In order to help ShopCo interpret and manage the results and to make it easier for ShopCo to communicate among stakeholders, we segmented the priority scores into four categories: critical, high, medium, and low based on the distribution of the load priority scores (Table 16). We followed a 20/60/20 split to segment the scores. The top 20% were assigned a critical priority while the bottom 20% received a low priority. For the middle 60%, we divided them up roughly equally between high and medium priorities.

**Table 16 – PO Segmentation Categories and Distribution**

| Category | Priority Score Range | Proportion within Sample Data |
|---|---|---|
| Critical | 0.22 – 0.4 | 21% |
| High | 0.14 – 0.22 | 30% |
| Medium | 0.10 – 0.14 | 29% |
| Low | 0 – 0.10 | 20% |
| | Total | 100% |




This segmentation equipped ShopCo with thresholds to more efficiently manage the loads. For example, loads deemed critical could be required to ship that day, so if there was not enough trucking capacity to move all of the critical loads, more capacity would need to be purchased.

# 4 Load Optimization and Results

ShopCo uses an internal load allocation tool that optimizes transportation costs; however, we extended our research to explore optimizing the loads to maximize the total load priority scores shipped given the capacitated carrier constraint. This could be beneficial to ShopCo, assuming it is possible to reshuffle currently allotted PO's into different loads.

Based on our literature review, MILP is often used in combination with AHP to optimize the results; therefore, we developed an MILP model using the Knapsack algorithm to optimize each load's priority score.

## 4.1 Knapsack Optimization Model

Since our objective was to maximize the total load priority scores being shipped as well as to minimize the number of trucks utilized, we set a large penalty point for each utilized truck so that the optimizer would minimize the number of trucks while maximizing the total load priority scores.

The Knapsack model had four key constraints:

1) Volume constraint: the total volume of all the PO's within a load needed to be less than or equal to the maximum volume capacity of a truck;
2) Weight constraint: the total weight of all the PO's within a load needed to be less than or equal to the maximum weight capacity of a truck;
3) Each PO needed to be allocated to only one load, to include the dummy truck*;
4) The total number of loads needed to be less than or equal to the number of trucks available.

* In our model, we created a dummy truck that was not subject to the volume and weight constraints so that we could track the PO's that were not assigned to the available trucks; therefore, it forced all the PO's that were not loaded into a truck to go to the dummy truck.

The formulation of the model is shown below:

**Variables:**

$$X_{i,j} = \begin{cases} 0 & (if\ PO\ i\ is\ not\ in\ Truck\ j) \\ 1 & (if\ PO\ i\ is\ in\ truck\ j) \end{cases} \qquad (i = 1, 2, \ldots, n;\ j = 1, 2, \ldots, m)$$

$$T_i = \begin{cases} 0 & (if\ truck\ i\ is\ not\ in\ use) \\ 1 & (if\ truck\ i\ is\ in\ use) \end{cases} \qquad (i = 1, 2, \ldots, m)$$

$V_i$: Volume of $PO_i$ $(i = 1, 2, \ldots, n)$

$W_i$: Weight of $PO_i$ $(i = 1, 2, \ldots, n)$

$P_i$: PO priority points $(i = 1, 2, \ldots, n)$

$c$: Penalty priority points per truck (We used the average load priority score as the penalty cost per truck so that a truck is used only when it's able to capture priority scores above at least the average)

$k$: Number of trucks available

$M$: A very big number

$n$: Number of PO's

$m$: Number of trucks

$Vmax_j$: Maximum volume capacity for truck j

(j = 1, …, m. We used 3,300 cube ft. for all the trucks in our model, except for the dummy truck, which had unlimited capacity)

$Wmax_j$: Maximum weight capacity for truck j

(j = 1, …, m. We used 42,000 lbs. for all the trucks in our model, except for the dummy truck, which had unlimited capacity)

All variables are non-negative

**Objective Function (Maximize):**

$$\sum_{j=2}^{m}(\sum_{i=1}^{n}(X_{i,j} * P_i)) - c * \sum_{j=2}^{m} T_j \qquad (Total\ Priority\ Points)$$

**Subject to:**

$$\sum_{i=1}^{n} X_{i,j} * V_i \leq Vmax_j \quad \forall j = 2, \ldots, m \qquad (Volume\ constraint)$$

$$\sum_{i=1}^{n} X_{i,j} * W_i \leq Wmax_j \quad \forall j = 2, \ldots, m \qquad (Weight\ constraint)$$

$$\sum_{j=1}^{m} X_{i,j} = 1 \quad \forall i = 1, 2, \ldots, n \qquad (A\ PO\ loaded\ in\ one\ and\ only\ one\ truck)$$

$$\sum_{j=2}^{m} T_j \leq k \qquad (Number\ of\ trucks\ used\ not\ exceed\ trucks\ available)$$

$$\sum_{i=1}^{n} X_{i,j} \leq M * T_j \quad \forall j = 1, 2, \ldots., m \qquad (Truck\ is\ in\ use\ if\ there\ is\ PO\ loaded)$$

## 4.2 Knapsack Dataset Selection

We were interested in selecting a sample of load data that would allow us to compare the optimized results against the original load priority scores. For example, assuming that we had four loads to be picked up and only three trucks available, we would pick up the three loads that had the highest priority scores, but if we ran the Knapsack model and were able to reshuffle the PO's among the trucks, we should be able to improve the total priority scores within the three trucks.

However, it was not easy to identify the appropriate sample from the dataset to conduct the comparison. Most of the loads created by the existing load allocation tool ShopCo was using were already sub-optimal and optimized with a different set of criteria, thus making any optimization capable of significantly improving the results, potentially leading to a bias. We observed that over 85% of the loads used only half of the weight capacity (i.e. the weight loaded was less than half of the capacity of 42,000 lbs.) and 60% of the loads used only half of the space (i.e. the volume loaded was less than half of the capacity of 3,300 cubic feet). One of the key reasons for the underutilized capacity was that ShopCo allowed no more than two stops when picking up a load, so any capacity remaining after the second stop was lost.

We narrowed our sample data scope to only include those loads that could be reshuffled without adding additional transportation complexity (e.g. adding more stops, mixing PO's from or to different locations, etc.).

The main criteria we used to select our sample to perform the optimization included:

- Load Creation Date was the same for all loads to ensure that the PO's were within the same data batch that the load allocation tool used to initially create the loads.
- Load Ready Date was the same for all loads to ensure that each load had the same arrival time requirement.
- PO Origin Zip Code and PO Destination Zip Code were the same so that we were not mixing PO's to or from different locations.
- PO Suppliers were the same so that we could avoid multiple stops when

optimizing the priority score, thereby avoiding adding additional transportation costs.

- There were multiple PO's within each load so that it was possible to reshuffle the PO's among multiple trucks.

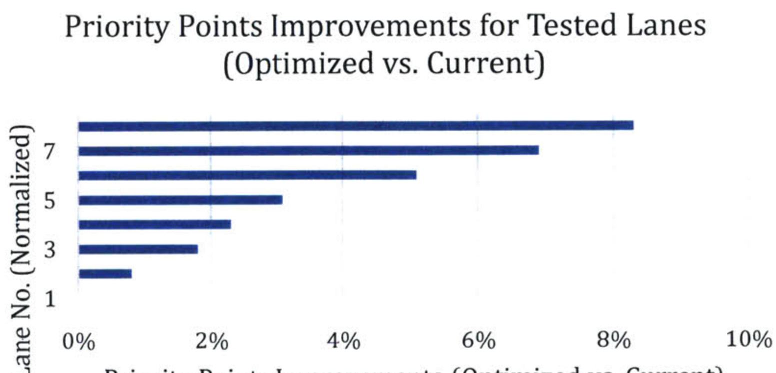
In the end, we were able to find one supplier with loads that satisfied all of the above criteria, so we used that sample to perform our optimization.

## 4.3 Optimization Test Runs

Table 17 lists the results from multiple optimization runs on the sample's lanes (lane numbers were normalized).

**Table 17 – Knapsack Model Optimization Test Run Results**

| Lane No. | # of Loads | # of Trucks | Total Priority Points Shipped | Total Priority Points Shipped w/ Knapsack | % Improvement with Knapsack |
|---|---|---|---|---|---|
| 1 | 4 | 3 | 637.9 | 637.9 | 0% |
| 2 | 5 | 3 | 727 | 733.1 | 0.80% |
| 3 | 4 | 3 | 602.5 | 613.5 | 1.80% |
| 4 | 4 | 3 | 660.6 | 676 | 2.30% |
| 5 | 5 | 3 | 693.5 | 715.2 | 3.10% |
| 6 | 4 | 3 | 643.4 | 676.2 | 5.10% |
| 7 | 4 | 3 | 641.4 | 685.5 | 6.90% |
| 8 | 5 | 3 | 687.8 | 743.7 | 8.30% |



From these results, we observed that there were pockets of opportunities (see column "% Improvement with Knapsack") to improve load priority scores by up to 8.3 percent when there was a carrier capacity constraint. However, the potential to ShopCo may be limited. A key assumption of the optimization was that we could reshuffle the PO's within the loads, but this may not be realistic to ShopCo. As mentioned previously, ShopCo uses a load allocation tool to assign PO's to loads. Once the PO allocation is completed, a load is determined and difficult to change.

Fortunately, this may not pose a big loss to ShopCo as we found that the load priority results were very close between the Knapsack optimization results and current load assignments. The existing load allocation tool ShopCo is using appears to be sufficiently optimizing the loads; therefore, although the key objective of the existing load allocation tool is to minimize total transportation costs, it may also consider service level factors as well, producing close-to-optimal results.

# 5 Discussion

In this chapter, we discuss the implications of our findings. First, we compare the AHP weights to ShopCo's expectations. In the subsequent sections, we discuss managerial insights, extensions, external applications, and limitations.

## 5.1 AHP Weight Expectations

We found that the AHP weights for the factors were consistent with expectations, increasing confidence in the AHP. Before the pairwise comparisons were conducted, we had ShopCo manually weight the factors for comparison – these are listed as the "Initial" scores in Table 18. Overall, there was no rank reversal between the "Initial" and "Actual" weights, so the pairwise comparison results were consistent with ShopCo's expectations.

**Table 18 – Comparison of Initial and Actual AHP Factor Weights**

| Factor | Initial | Actual |
|---|---|---|
| Inventory Position | 0.273 | 0.370 |
| Event Type | 0.273 | 0.209 |
| Lead-time Status | 0.273 | 0.205 |
| Load Type | 0.121 | 0.120 |
| Multi Pick-up | 0.020 | 0.047 |
| HAZMAT | 0.020 | 0.031 |
| Mode Method | 0.020 | 0.019 |

## 5.2 Managerial Insights

Since the objective of this research was to prioritize inbound loads to improve inventory position at the retail level, it was not surprising that Inventory Position had the highest AHP weight among the factors. Interestingly, the Event Type had the highest correlation with the PO and load priority scores, as indicated in Tables 12 and 14 – we anticipated the Inventory Position would have the highest correlation based on its factor weight (Table 9) and sub-factor range (Table 11).

This finding could be due to ShopCo's recommendation on how to calculate each PO's Inventory Position. To simplify the calculation, we calculated each PO's current pipeline inventory over its 4-week forecast, but ShopCo indicated that these forecasts were not very accurate. The resulting Inventory Positions supported this indication, because every PO had either a "Strong" or "No Forecast" Inventory Position, resulting in the use of only the two lowest Inventory Position sub-factor weights. Realistically, there would also be PO's that have "Critical" or "Moderate" Inventory Positions. Since the "Critical" or "Moderate" Inventory Positions have the first and fourth highest sub-factor weights, we suggest that more accurate Inventory Positions would make this factor the highest correlated with the PO and load priority scores. Also, our analysis showed that ShopCo's current load allocation tool was an acceptable method, since the Knapsack optimization model increased the sample loads' priority score by only 0-8.3 percent.

The key value of this research to ShopCo was the prioritization logic, allowing ShopCo to prioritize inbound loads in alignment with ShopCo's objectives. However, the behavioral dimension of the AHP had to be considered when implementing this system. As mentioned in 3.1.4, conflicts during the pairwise comparisons were amicably resolved among the parties involved, but it would be rather optimistic to assume all stakeholders of the inbound transportation process would fully agree with the AHP output weights.

## 5.3 AHP Extensions

### Kicker Extension

To extend the current AHP model, ShopCo requested a kicker be added to inflate the scores of certain PO's. We contemplated adding the kicker to the current AHP model, but it would require ShopCo to perform seven pairwise comparisons each time the kicker was used, since the kicker's importance would likely change for each situation. Further, it could cause a rank reversal of the current factors. We found a specific example of rank reversal in Table 19. The Event Type factor was ranked higher than the Lead-time Status factor, but after the addition of one factor, the kicker, the Lead-time Status factor was ranked higher than the Event Type factor. Thus, rank reversal had occurred after the addition of another factor, the kicker.

In discussion with ShopCo, it was initially proposed that the kicker be a predetermined value added to each applicable PO, as determined by ShopCo. The issue was how to transfer the kicker impact from the PO to the load level when there were multiple PO's in a load. Recall that a load's priority score was the sum of the case-weighted PO's within that load. If a PO influenced by the kicker had a lower case quantity relative to the total load case quantity, the impact of the kicker would be minimal, so we decided to apply the kicker directly to the load priority score. For example, if a load has a PO with the characteristics that the kicker is to be applied to, then the kicker would be applied to the load priority score.

## Table 19 – Rank Reversal Example

| i \ j | Load Type | Mode Method | Event Type | Inventory Position | HAZMAT | Lead-time Status | Multi Pick-up | Kicker | GM | PV | Old Rank | New Rank | Difference |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Load Type | 1.000 | 8.000 | 0.333 | 0.250 | 6.000 | 0.333 | 5.000 | 0.333 | 1.105 | 0.093 | 4 | 5 | -1 |
| Mode Method | 0.125 | 1.000 | 0.125 | 0.111 | 0.333 | 0.125 | 0.250 | 0.143 | 0.200 | 0.017 | 7 | 8 | -1 |
| Event Type | 3.000 | 8.000 | 1.000 | 0.333 | 7.000 | 1.000 | 6.000 | 0.200 | 1.692 | 0.143 | 2 | 4 | -2 |
| Inventory Position | 4.000 | 9.000 | 3.000 | 1.000 | 8.000 | 3.000 | 7.000 | 1.000 | 3.407 | 0.287 | 1 | 1 | 0 |
| HAZMAT | 0.167 | 3.000 | 0.143 | 0.125 | 1.000 | 0.167 | 0.333 | 0.250 | 0.325 | 0.027 | 6 | 7 | -1 |
| Lead-time Status | 3.000 | 8.000 | 1.000 | 0.333 | 6.000 | 1.000 | 6.000 | 0.333 | 1.769 | 0.149 | 3 | 3 | 0 |
| Multi Pick-up | 0.200 | 4.000 | 0.167 | 0.143 | 3.000 | 0.167 | 1.000 | 0.250 | 0.470 | 0.040 | 5 | 6 | -1 |
| Kicker | 3.000 | 7.000 | 5.000 | 1.000 | 4.000 | 3.000 | 4.000 | 1.000 | 2.903 | 0.245 | | 2 | |
| | | | | | | | | | 11.871 | | | | |

| | |
|---|---|
| GCI | 0.3562 |
| Threshold | 0.3700 |
| Consistent? | YES |

| Kicker |
|---|
| Yes |

**Profitability/Value Extension**

Due to the sensitivity of financial information and the limited availability of such data, we did not explicitly include financial measures such as PO dollar value or profitability into our AHP and Knapsack models; however, given that any activity a for-profit company performs aims to impact the bottom-line, ShopCo not an exception, we could further improve the practical value of the model by explicitly tying the output of the model with dollar value or profitability. There are multiple ways we could use PO value or profitability to determine the final load priority score.

For example, profitability could be used as the weighting factor to calculate the final load priority score for loads that have multiple PO's. For this research, we used the case quantity as the PO weighting factor to determine the final load priority score, but if PO profitability data was available, we could have used it to weight the PO priority score so that the more profitable PO's had a higher impact on the final load priority score, thus connecting load priority with bottom-line impacts.

Also, PO dollar value could be used as one of the AHP factors, making it a key input into the AHP model. By performing pairwise comparisons with other factors, we could determine the relative importance of a PO's dollar value/priority vis-à-vis other factors. The final priority score would thus have PO financials as a component. We assume that the higher the profitability or dollar value of a PO, the higher the priority of the PO. Additionally, the Knapsack optimization model aimed to optimize the total priority score for each load. If profitability data is available, maximizing total profitability could be used as the objective function.

## 5.4 External Application

While our research was focused on prioritizing inbound loads for a retailer, its methodology and results could also be applied to a broader range of companies and industries, especially those wishing to prioritize inbound transportation, conduct multi-criteria decision-making, and optimize load allocation under constraints.

### 5.4.1 Prioritizing Inbound Transportation

Companies managing their inbound transportation with capacitated carriers could leverage this research by applying the AHP to develop a decision-making framework. Although companies differ in practices and perspectives, thus having different priority factors, the factors we used could serve as a starting point for them to build their own factors around. We believe that the factors we used are relevant to most companies such as Inventory Position, Lead-time Status, Mode Method, and Load Type, though other factors could be used by the respective company/industry. As previously discussed, companies may want to include profitability as a factor if the data is available. However, the pairwise comparisons that we detailed in this paper would follow the same process.

### 5.4.2 Multi-criteria Decision Making

Companies that need to make a decision involving multiple alternatives could benefit from our MCDM framework, specifically the AHP. As the number of factors increases, decision makers may struggle to properly weight these factors to determine a cohesive score for each alternative being considered. The AHP could be utilized to develop weights for each factor that would effectively score all the relevant factors for each alternative.

Additionally, the AHP could be a tool to align the interests and perspectives of different stakeholders in a decision, because each stakeholder's position would be considered and debated during the pairwise comparisons. The pairwise comparisons open the discussion and differing perspectives could be aligned during these discussions, as occurred during ShopCo's pairwise comparisons.

### 5.4.3 Load Allocation Optimization

The Knapsack model found potential opportunities to improve the total priority of loads when the carrier capacity was constrained. For ShopCo, the optimization may not be especially useful, since the flexibility to reconstruct the load allocation was limited; however, companies that do not have a sophisticated tool to create load allocation could leverage the Knapsack optimization model to optimize their load allocation. It would enable them to create loads that have optimized load priority scores while meeting various constraints (e.g., volume, weight, and number of trucks).

## 5.5 Limitations

This section describes the limitations of using static data as well as using the AHP.

### 5.5.1 Data Cleansing

We performed data cleansing to ensure that the results were accurate and not skewed. To build upon our research, the use of real-time data would further improve accuracy. After we collected data from ShopCo, the first step was to cleanse and normalize the data. Some of the columns in the PO data were coded and did not match the values of the AHP sub-factors, so we converted the raw transactional data to categorical data. For example, the data had only the PO Type numerical code, so we needed to convert each code to either "Assembly" or "Staple", as specified in the AHP decision tree. This was done through ShopCo-provided conversion tables for each factor, thus converting raw data to normalized categorical data.

Another issue was that some records had missing values. We tried to fill in those missing values based on other fields for those respective records and through discussions with ShopCo. For example, some of the PO's did not have an Event Type listed, but the "Buyer Name" column stated "Store Replenish", so we assumed that the Event Type was "Store Replenish".

Additionally, data updating may be an issue, especially with dynamic fields. In the data provided, all fields were static, but in ShopCo's database, there are two types of fields: static and dynamic. For static fields, the values do not change (e.g., PO Number, PO Type, and Load Type). For dynamic fields, the values change over time. For example, a PO's Inventory Position will change constantly based on changes in the pipeline inventory continuously being consumed and the forecast. Lead-time Status is another dynamic field – if a load does not ship, it may miss established millstones, thus resulting in a change in its Lead-time Status. In our sensitivity analysis, delaying a load could lead to a higher priority; however, this change would be captured only if the dynamic fields were timely updated. Unfortunately, all fields remained static in the dataset provided.

### 5.5.2 AHP Limitations

Although the AHP is a mechanism to assign priority scores to each inbound load, it has several limitations. First, each pairwise comparison matrix should have fewer than 10 factors/sub-factors, because individuals cannot compare more than 7 +/- 2 factors/sub-factors without becoming confused. This limitation could require the user to further branch out the factor/sub-factors, thus resulting in additional effort creating the model and conducting the pairwise comparisons. Second, it is difficult to add and/or remove factors and sub-factors after the initial AHP is developed. This limitation not only requires the user to perform additional pairwise comparisons but also could cause rank reversal of the current factors/sub-factors, as shown in Table 19. Third, the pairwise comparisons are subjective and may not align with company objectives. For example, a user conducting the pairwise comparisons may make decisions that benefit his or her role rather than the overall company.

Before using the AHP, the user(s) need to understand each limitation to ensure the priority weights align with the objectives; therefore, the user(s) should properly categorize factors in buckets fewer than 10 alternatives and assign key personnel to perform the pairwise comparisons.

# 6 Conclusion

In this thesis, we discussed how to prioritize inbound transportation for ShopCo. More specifically, we defined the logic to prioritize inbound loads with multiple-criteria using the AHP. We also extended the AHP model by incorporating a Knapsack optimization model to maximize total priority scores for each load under various constraints.

The AHP was the MCDM used to develop the prioritization logic. We first identified key decision criteria in inbound transportation and developed a hierarchical framework. Then, we had ShopCo perform pairwise comparisons to rate the relative importance of each factor and sub-factor. Finally, we synthesized the pairwise comparison results and calculated priority scores for each load based on the AHP weight outputs.

The AHP model provided ShopCo a tool to prioritize inbound loads awaiting shipment by assigning a score to each load based on factors and sub-factors defined by ShopCo. ShopCo will be able to identify the relative priority of the loads and determine which loads should receive priority when carrier capacity is constrained, facilitating improved service levels with minimal additional logistics costs. Further, the Knapsack optimization model found opportunities to improve load priority by up to 8.3 percent as compared to the assignment of the current load allocation tool.

We believe this research will benefit not only ShopCo but also other companies and industries managing their own inbound transportation with carrier capacity constraints by applying this framework. Although the factors and sub-factors used may differ, this underlying framework would align load priority with company objectives.

Further, there are opportunities for future studies. First, the influence of the prioritization model on company metrics needs to be tracked. It would be interesting to track the implementation of the model and compare the service level (e.g. metrics related to on-stock availability) before and after to gauge the outcome and to adjust the factors and sub-factors accordingly, if needed.

Second, the scope of this research could be expanded. We focused on a specific region and time period, but it would be interesting to rollout this research across the nation. We suspect the distribution of the priority scores could be different, requiring an update to the segmentation method currently being used.

Third, additional factors could be included. As discussed in section 5.3, we did not explicitly include financial measures in our model. To further improve the model, PO profitability or dollar value could be added to align load priority score with the bottom-line. Also, we did not discuss the cost of expediting critical priority loads (e.g. cost of buying additional capacity at a spot rate) or how to tradeoff cost and priority.

Finally, this research could be integrated with other tools. Currently, ShopCo uses a sophisticated load allocation tool, but the Knapsack optimization model could serve as a starting point for further studies to improve the current tool by taking into account the load priority score.

# Appendix A

This appendix lists the results from the AHP. The first diagram shows the yellow-highlighted final weights. The subsequent diagrams show the pairwise comparison results as well as the consistency.

<u>Priority Weight Results</u>

**Load Priority**

| Inventory Position | 0.370 | |
|---|---|---|
| Critical | 0.649 | 0.240 |
| Moderate | 0.190 | 0.070 |
| No Forecast | 0.113 | 0.042 |
| Strong | 0.047 | 0.017 |

| Event Type | 0.209 | |
|---|---|---|
| Modular PO (A) | 0.298 | 0.062 |
| New Store (A) | 0.217 | 0.045 |
| POS Replenish (A) | 0.175 | 0.037 |
| Store Replenish (A) | 0.082 | 0.017 |
| Buyer/Feature (A) | 0.082 | 0.017 |
| Store Request (A) | 0.057 | 0.012 |
| POS Replenish (S) | 0.044 | 0.009 |
| Store Request (S) | 0.024 | 0.005 |
| Store Replenish (S) | 0.020 | 0.004 |

| Lead-time Status | 0.205 | |
|---|---|---|
| Already Missed | 0.649 | 0.133 |
| Behind Schedule | 0.279 | 0.057 |
| On Schedule | 0.072 | 0.015 |

| Load Type | 0.120 | |
|---|---|---|
| LTL | 0.750 | 0.090 |
| TL | 0.250 | 0.030 |

| Multi Pick-up | 0.047 | |
|---|---|---|
| Yes | 0.875 | 0.041 |
| No | 0.125 | 0.006 |

| HAZMAT | 0.031 | |
|---|---|---|
| Yes | 0.833 | 0.026 |
| No | 0.167 | 0.005 |

| Mode Method | 0.019 | |
|---|---|---|
| Floor | 0.625 | 0.012 |
| Slip | 0.238 | 0.005 |
| Pallet | 0.136 | 0.003 |

## Factor Results

| i \ j | Load Type | Mode Method | Event Type | Inventory Position | HAZMAT | Lead-time Status | Multi Pick-up | GM | NP |
|---|---|---|---|---|---|---|---|---|---|
| Load Type | 1.000 | 8.000 | 0.333 | 0.250 | 6.000 | 0.333 | 5.000 | 1.311 | 0.120 |
| Mode Method | 0.125 | 1.000 | 0.125 | 0.111 | 0.333 | 0.125 | 0.250 | 0.210 | 0.019 |
| Event Type | 3.000 | 8.000 | 1.000 | 0.333 | 7.000 | 1.000 | 6.000 | 2.296 | 0.209 |
| Inventory Position | 4.000 | 9.000 | 3.000 | 1.000 | 8.000 | 3.000 | 7.000 | 4.059 | 0.370 |
| HAZMAT | 0.167 | 3.000 | 0.143 | 0.125 | 1.000 | 0.167 | 0.333 | 0.337 | 0.031 |
| Lead-time Status | 3.000 | 8.000 | 1.000 | 0.333 | 6.000 | 1.000 | 6.000 | 2.246 | 0.205 |
| Multi Pick-up | 0.200 | 4.000 | 0.167 | 0.143 | 3.000 | 0.167 | 1.000 | 0.514 | 0.047 |
| | | | | | | | | 10.973 | |

| | |
|---|---|
| GCI | 0.2764 |
| Threshold | 0.3700 |
| Consistent? | YES |

Consistency Error

| | | | | | | |
|---|---|---|---|---|---|---|
| 1.000 | 1.282 | 0.584 | 0.774 | 1.543 | 0.571 | 1.961 |
| 0.780 | 1.000 | 1.366 | 2.146 | 0.535 | 1.336 | 0.612 |
| 1.714 | 0.732 | 1.000 | 0.589 | 1.028 | 0.978 | 1.344 |
| 1.292 | 0.466 | 1.697 | 1.000 | 0.665 | 1.660 | 0.887 |
| 0.648 | 1.869 | 0.972 | 1.504 | 1.000 | 1.110 | 0.508 |
| 1.752 | 0.749 | 1.022 | 0.602 | 0.901 | 1.000 | 1.374 |
| 0.510 | 1.634 | 0.744 | 1.127 | 1.967 | 0.728 | 1.000 |

## Load Type Results

| i \ j | LTL | TL | GM | NP |
|---|---|---|---|---|
| LTL | 1.000 | 3.000 | 1.732 | 0.750 |
| TL | 0.333 | 1.000 | 0.577 | 0.250 |
| | | | 2.309 | |

| | |
|---|---|
| GCI | N/A |
| Threshold | N/A |
| Consistent? | YES |

Consistency Error

| | |
|---|---|
| 1.000 | 1.000 |
| 1.000 | 1.000 |

## Mode Method Results

| i \ j | Slip | Floor | Pallet | GM | NP |
|---|---|---|---|---|---|
| Slip | 1.000 | 0.333 | 2.000 | 0.874 | 0.238 |
| Floor | 3.000 | 1.000 | 4.000 | 2.289 | 0.625 |
| Pallet | 0.500 | 0.250 | 1.000 | 0.500 | 0.136 |
| | | | | 3.663 | |

| | |
|---|---|
| GCI | 0.0548 |
| Threshold | 0.3147 |
| Consistent? | YES |

Consistency Error

| | | |
|---|---|---|
| 1.000 | 0.874 | 1.145 |
| 1.145 | 1.000 | 0.874 |
| 0.874 | 1.145 | 1.000 |

## Event Type Results

| i \ j | Store Replenish (A) | New Store (A) | POS Replenish (S) | Modular PO (A) | Store Request (A) | POS Replenish (A) | Store Request (S) | Buyer/Feature (A) | Store Replenish (S) | GM | NP |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Store Replenish (A) | 1.000 | 0.333 | 4.000 | 0.200 | 2.000 | 0.167 | 4.000 | 1.000 | 5.000 | 1.066 | 0.082 |
| New Store (A) | 3.000 | 1.000 | 5.000 | 0.250 | 6.000 | 3.000 | 8.000 | 3.000 | 7.000 | 2.822 | 0.217 |
| POS Replenish (S) | 0.250 | 0.200 | 1.000 | 0.143 | 0.500 | 0.200 | 4.000 | 0.500 | 5.000 | 0.577 | 0.044 |
| Modular PO (A) | 5.000 | 4.000 | 7.000 | 1.000 | 4.000 | 3.000 | 5.000 | 4.000 | 6.000 | 3.885 | 0.298 |
| Store Request (A) | 0.500 | 0.167 | 2.000 | 0.250 | 1.000 | 0.333 | 5.000 | 0.500 | 2.000 | 0.744 | 0.057 |
| POS Replenish (A) | 6.000 | 0.333 | 5.000 | 0.333 | 3.000 | 1.000 | 8.000 | 3.000 | 7.000 | 2.282 | 0.175 |
| Store Request (S) | 0.250 | 0.125 | 0.250 | 0.200 | 0.200 | 0.125 | 1.000 | 0.250 | 3.000 | 0.314 | 0.024 |
| Buyer/Feature (A) | 1.000 | 0.333 | 2.000 | 0.250 | 2.000 | 0.333 | 4.000 | 1.000 | 4.000 | 1.066 | 0.082 |
| Store Replenish (S) | 0.200 | 0.143 | 0.200 | 0.167 | 0.500 | 0.143 | 0.333 | 0.250 | 1.000 | 0.261 | 0.020 |
| | | | | | | | | | | 13.017 | |

| | |
|---|---|
| GCI | 0.3468 |
| Threshold | 0.3700 |
| Consistent? | YES |

Consistency Error

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 1.000 | 0.882 | 2.167 | 0.729 | 1.395 | 0.357 | 1.177 | 1.000 | 1.225 |
| 1.133 | 1.000 | 1.023 | 0.344 | 1.581 | 2.426 | 0.889 | 1.133 | 0.648 |
| 0.461 | 0.977 | 1.000 | 0.961 | 0.644 | 0.790 | 2.172 | 0.923 | 2.262 |
| 1.372 | 2.905 | 1.041 | 1.000 | 0.766 | 1.762 | 0.404 | 1.098 | 0.403 |
| 0.717 | 0.633 | 1.553 | 1.306 | 1.000 | 1.023 | 2.109 | 0.717 | 0.703 |
| 2.803 | 0.412 | 1.265 | 0.567 | 0.977 | 1.000 | 1.099 | 1.401 | 0.801 |
| 0.850 | 1.125 | 0.460 | 2.478 | 0.474 | 0.910 | 1.000 | 0.850 | 2.500 |
| 1.000 | 0.882 | 1.083 | 0.911 | 1.395 | 0.714 | 1.177 | 1.000 | 0.980 |
| 0.816 | 1.543 | 0.442 | 2.478 | 1.423 | 1.248 | 0.400 | 1.020 | 1.000 |

Inventory Position Results

| i \ j | Critical | Moderate | Strong | No Forecast | GM | NP |
|---|---|---|---|---|---|---|
| Critical | 1.000 | 5.000 | 9.000 | 6.000 | 4.054 | 0.649 |
| Moderate | 0.200 | 1.000 | 5.000 | 2.000 | 1.189 | 0.190 |
| Strong | 0.111 | 0.200 | 1.000 | 0.333 | 0.293 | 0.047 |
| No Forecast | 0.167 | 0.500 | 3.000 | 1.000 | 0.707 | 0.113 |
| | | | | | 6.243 | |

| | |
|---|---|
| GCI | 0.1515 |
| Threshold | 0.3526 |
| Consistent? | YES |

Consistency Error

| | | | |
|---|---|---|---|
| 1.000 | 1.467 | 0.651 | 1.047 |
| 0.682 | 1.000 | 1.233 | 1.189 |
| 1.535 | 0.811 | 1.000 | 0.803 |
| 0.955 | 0.841 | 1.245 | 1.000 |

HAZMAT Results

| i \ j | Yes | No | GM | NP |
|---|---|---|---|---|
| Yes | 1.000 | 5.000 | 2.236 | 0.833 |
| No | 0.200 | 1.000 | 0.447 | 0.167 |
| | | | 2.683 | |

| | |
|---|---|
| GCI | N/A |
| Threshold | N/A |
| Consistent? | YES |

Consistency Error

| | |
|---|---|
| 1.000 | 1.000 |
| 1.000 | 1.000 |

Lead-time Status Results

| i \ j | Already Missed | On Schedule | Behind Schedule | GM | NP |
|---|---|---|---|---|---|
| Already Missed | 1.000 | 7.000 | 3.000 | 2.759 | 0.649 |
| On Schedule | 0.143 | 1.000 | 0.200 | 0.306 | 0.072 |
| Behind Schedule | 0.333 | 5.000 | 1.000 | 1.186 | 0.279 |
| | | | | 4.250 | |

| | |
|---|---|
| GCI | 0.1936 |
| Threshold | 0.3147 |
| Consistent? | YES |

Consistency Error

| | | |
|---|---|---|
| 1.000 | 0.776 | 1.289 |
| 1.289 | 1.000 | 0.776 |
| 0.776 | 1.289 | 1.000 |

Multi Pick-up Results

| i \ j | Yes | No | GM | NP | NV |
|---|---|---|---|---|---|
| Yes | 1.000 | 7.000 | 2.646 | 0.875 | 2.000 |
| No | 0.143 | 1.000 | 0.378 | 0.125 | 0.286 |
| | | | 3.024 | | |

| | |
|---|---|
| GCI | N/A |
| Threshold | N/A |
| Consistent? | YES |

Consistency Error

| | |
|---|---|
| 1.000 | 1.000 |
| 1.000 | 1.000 |

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