Building a Framework for Determining the Optimal Supplier Shipping Performance

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Summary: Most companies aim for perfect on-time delivery from suppliers, since late deliveries cause supply disruptions. But some companies incur direct costs in maintaining supplier delivery performance. Our empirical research looked at a company that invests in suppliers to help them achieve a desired performance level. We developed a framework that captured the costs of late deliveries and target attainment. Using regression analysis, we modeled cost behavior in order to determine a delivery target that minimizes total cost.

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KEY INSIGHTS

1. When investing in suppliers, the optimal internal supplier performance target lies below 100%.

2. A supplier development program yields less predictable results at high supplier performance levels. The risk of failure increases significantly.

3. Key Performance Indicators are not always aligned with business and decision making processes. An empirical study on cost sensitivity can reveal aspects of observed costs and their true drivers.

The Problem

When setting performance targets for suppliers, most companies aim for 100% on-time deliveries, since late deliveries can cause supply disruptions and associated costs. But this assumes that companies do not incur expenses in increasing or maintaining (nearly) perfect supplier deliveries. Some companies actually invest in their suppliers to help them achieve desired targets. In these cases, aiming for 100% delivery compliance may no longer yield the minimum cost over a delivery performance spectrum. Our research provides a framework that companies can use and compare costs at different levels of supplier performance in order to determine a target that minimizes their total cost.

Methodology

We pursued an empirical approach, using sales and order data from the service parts business of an industrial equipment manufacturer (MiCo\(^1\)). All metrics, decisions and policies reviewed were based on actual observations. Within the scope of MiCo’s existing performance management system, we determined the cost categories relevant to an optimization-oriented analysis and collected data for each category. We then created cost models projecting each category’s expected behavior. Finally, we combined all models into one system to determine its optimal (lowest) point.

\(^{1}\) Name has been changed for anonymity.
The Metric: Supplier Shipping Performance (SSP)

MiCo’s supplier delivery metric credits suppliers when they ship more than 90% of items ordered within a given time window. By measuring the shipment date instead of the delivery date, any variability in transport is excluded. SSP is a binary hit-or-miss metric that aggregates monthly deliveries at the line item level. Supplier decisions are based on a 3-month rolling SSP.

\[
SSP \text{ (line item)} = \frac{\text{# of timely shipments}}{\text{# of scheduled shipments}}
\]  

The 5-Step Framework

After identifying relevant cost categories, we modeled their cost sensitivity over five steps, applied iteratively.

1. **Collect available cost data** over multiple iterations. Each iteration increased the understanding of available data and decision drivers.

2. **Ensure data integrity** by cleansing for outliers and exceptions that may skew trends. We performed this step regularly during the data analysis, for entire samples as well as over aggregated ranges.

3. **Aggregate data entries** into sets and associate them with SSP values. Aggregating data into SSP ranges ensured that we had enough observations to work with summary statistics. It also reduced the impact of observed cost variability over the SSP spectrum.

4. **Convert the aggregated data** to a common SSP scale, in some cases by transforming conditional probabilities. Some of the collected data provided a distribution of SSP values, given a cost-driving event. Using Bayes' Theorem, we transformed these distributions into conditional probabilities of cost-driving events, given defined SSP ranges.

\[
P(A|B) = \frac{P(B|A) \times P(A)}{P(B)}
\]

We obtained the cost of SSP ranges by multiplying respective event probabilities with the average cost of an event and the total number of observations.

5. **Build regression model** from the cost distribution. We built each regression model using SSP as input and expected cost as output. After determining the best-fit curve, we compared its behavior with the anticipated shape. If these did not correspond, we revisited our analysis from step 1 or investigated for alternate assumptions on the cost-driving dynamic.

Application of Framework

At the onset, we classified performance maintenance and consequence management. The former category aims to improve supplier performance, while the latter does not. We identified four cost elements that might correlate to SSP and applied our framework to each.

1. **Lost Sales Due to Late Delivery**

This category consisted of foregone revenue from lost sales to customers. We focused on short-term lost sales, since the long-term loss of customers proved too complex to correlate exclusively with late suppliers. MiCo provided data on canceled customer orders tied to late shipments. We confirmed the correlation of lost sales and late supplier deliveries by matching all sales records with snapshots of incoming deliveries past due. The 5-step framework resulted in the model for lost sales shown in Figure 1, which illustrates the expected cost of lost sales per supplier over the SSP spectrum.

![Figure 1: Expected cost of lost sales at a given SSP](image)

2. **Inventory Increase to Compensate for Late Delivery**

We expected to find an increase in planned inventory buffers as SSP decreased. Our data analysis showed the exact opposite: inventories increased in line with SSP. We identified the reason for this discrepancy in MiCo’s inventory policy, whose budget limits forced selective inventory increases. MiCo’s decision rules preferred increasing more stable suppliers, resulting in smaller inventory boosts spread over a larger supplier base. The total budget remained constant, which meant that the investment decisions would adapt as supplier delivery patterns changed—a fact that kept us from dynamically modeling inventory increases.
Further, we learned that the decision rules did not consider SSP but average days late, a related but not identical measure. We therefore could not fully evaluate the correlation between SSP and inventory increases.

3. Expediting Shipments

This category comprised the cost of rushed deliveries into, within or out of MiCo’s network as a result of late shipping. Unfortunately, MiCo’s systems captured neither conclusive nor sufficient data on expediting. The few data points measured did not provide a reason for expediting, so that we could not establish the necessary relationship between late deliveries and transportation cost. More accurate future measurement on cost per order and reason codes will allow for the development of a cost model through the application of our framework.

4. Investment in Supplier Improvements

This category represented MiCo’s cost of performance maintenance, executed by a group of employees whose assignments to suppliers we compared with observed changes in supplier performance. We aggregated assignments by initial SSP positions and used salaries to quantify supplier investments cost over the SSP spectrum, as shown in Figure 2. Improvement efforts on suppliers above 80% SSP showed a lower success rate and on average yielded negative changes.

![Figure 2: Incremental Investment Required to Improve SSP](image)

**Combining the Models**

To determine the point of minimal total cost, we added the individually modeled cost curves. Our conversion to a common scale enabled this simple operation. While the total consequence management cost curve followed a pattern of exponential decay, the cost of performance maintenance grew exponentially. Added together, the curves formed a convex curve with a global minimum that represented the optimal SSP target. As fixed components of individual cost categories did not affect the shape of the individual curves, they also did not impact the position of the optimal SSP target.

Since we assumed a limited lifetime return for supplier investments, we added the total present value of discounted avoided consequence management costs \( F \) to the current cost of performance maintenance \( G \), as depicted in Equation 3 and Figure 3 below. Using the limited available data and a lifetime of 3 years per supplier investment yielded a minimum total cost SSP target of 67%. MiCo should therefore focus on improving suppliers performing below this level.

\[
H(SSP) = G(SSP) + \sum_{t=0}^{3}(1 + i)^{-t} \times F(SSP) 
\]

![Figure 3: Total Present Cost for SSP Target](image)

**Conclusions and Future Research**

1. **Our work represents a successful first attempt at empirically determining an optimal delivery target.**

2. **Because the outcome of this optimization is heavily dependent on the availability of input, collecting further data on cost categories will allow for a more accurate target calculation.**

3. **Diminishing returns and increasing uncertainty greatly constrain the expected yield of investing in supplier improvement at high performance levels.**

4. **Our framework is adaptable to other companies and performance metrics. It can help companies determine the value of investment decisions.**