The Impact of Product Portfolio Complexity on Fleet Size

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Summary: The assortment of products that a company offers is one aspect that affects the complexity of their supply chain: the greater number of products, the greater the complexity. This project aims to measure how reducing the number of products affect the multi-compartment fleet size in a chemical company. The reduction of products, called replacement, was done by aggregating the demand of products that have similar characteristics, without affecting the revenue. The analysis was performed by running 8 scenarios of a Monte Carlo simulation for each of the plants the company operates: one scenario for each quarter, with and without product replacement. Following a fitted demand pattern distribution for each product, the simulation generated random product demand for each scenario. The simulation also generated random distance traveled per trip following a normal distribution with an empirical average and standard deviation. The results showed that reducing the number of products can reduce the fleet size in 7%. Other factors like reducing the average distance per trip or decreasing the time per customer stop can also reduce the fleet size.

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KEY INSIGHTS

1. The reduction of the number of products can reduce the fleet size in 7%
2. Replacing products with similar characteristics but high density and concentration can reduce the number of trucks used in the operation
3. Other factors like reducing the distance per trip and decreasing the time per customer have a significant impact

Introduction

The construction chemical industry in the US is facing a series of challenges that are affecting the way in which the business is handled. Price is each day becoming more important: once thought of as high-value-added products, construction chemicals are slowly coming to be considered as commodities as new competitors offer similar products at reduced prices.

For this industry, transportation accounts for approximately 60% of total supply chain costs. The shift from high-value-added products, the tight trucking industry, new competitors in the market, and the high dependence on transportation costs all challenge the companies in the construction chemical industry to optimize their supply chains to minimize costs.

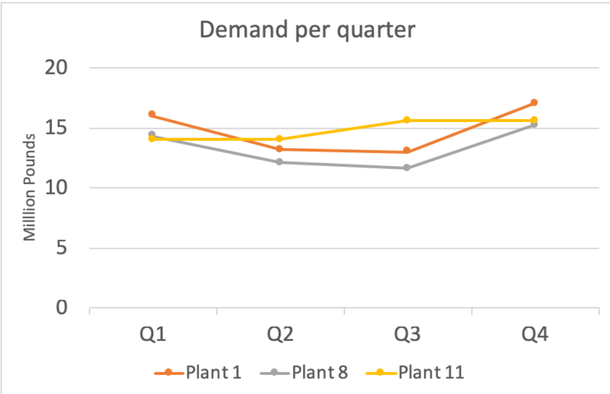
In order to be able to differentiate in a commodity business, companies need to offer more products or reduce selling price, affecting profit. The company sponsoring this capstone project, ChemicalCO, wants to understand how it can reduce costs. This project will focus on how the product portfolio complexity, represented by the number of SKUs, impact the sponsor's fleet cost. Assuming that fleet costs are directly affected by the quantity of trucks ChemicalCO needs for its regular operation, this project will analyze the impact different scenarios have on the fleet size.

Methodology

Data Analysis

The data provided included shipments from 11 plants that delivered between 11 and 33 products each. As construction chemicals are used to give certain properties to construction materials in specific weather conditions, a seasonality demand was expected for most of the products and plants. It is interesting to note, though, that the aggregate demand for each plant also showed seasonality.

Examples of plants 1, 8, and 11 can be seen in Figure 1 below. This fact was very important for determining how to generate the random demands for the Monte Carlo simulation.



Assumptions

The next step was to develop a model to understand the problem. Several assumptions were agreed with ChemicalCO in order to move forward with the initial approach:

- Normally distributed average miles per delivery.
- Truck capacity is measured in weight, not volume.
- All trucks have the same characteristics: 38,000 lbs. capacity and four equally sized compartments.

Prototype Model

We built a simplified model over only one plant to explain why the transportation fixed costs differ as more products are introduced. This prototype included simplified assumptions with tailored data so as to test the different variables that could affect the costs. In agreement with the sponsor, the following assumptions were included:

- All product demands followed a normal distribution for simplification purposes.
- Each truck has 4 equal compartments, each with a 10,000 lbs. capacity

A simulation in R was created, in which the algorithm compared the total demand of compartments to the total available compartments each week and its output, which we called Demand Served, consisted of the percentage of weeks ChemicalCO would be able to deliver all the orders. A flow diagram of the algorithm is shown below.

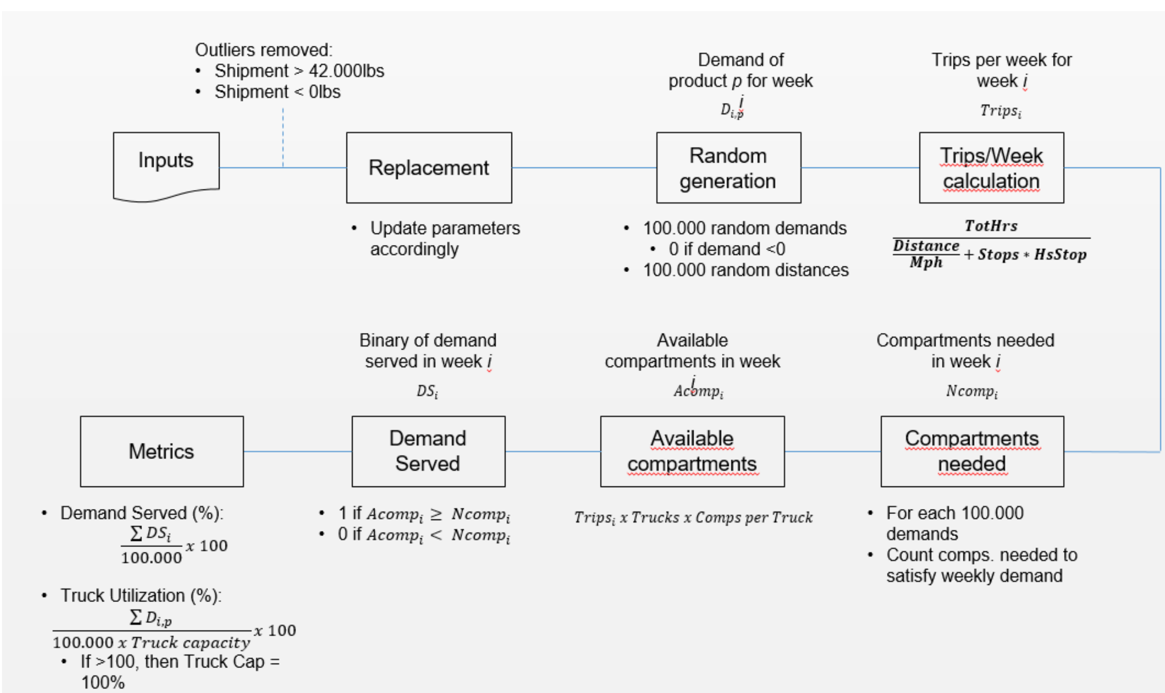
Simulation Definition

Once the Toy Model was able to explain how different variables affected the system, a more complex model was designed. The most important factors to be considered were discussed with the sponsor, and the following concepts were included in the simulation in R:

- Demand distribution fit: The model checks the weekly demand for each product on each plant and provides the best fit from the Normal, Lognormal and Weibull probability distributions.
- Seasonality: As Monte Carlo simulations repeat one scenario enough times to obtain an expected value, it was agreed to run 4 simulations per plant to detect the impact of seasonality; these would be divided by quarter.

Replacement definition

Two factors were considered to do the replacement of the products: Concentration and Density. Concentration” is the volume of a specific product



that is needed to obtain the same results as other products from the same group. “Density” is the kilograms that 1 cubic meter of a specific product weights. In order to make the replacement of a product B for product A correctly without affecting the revenue, we used the following formula:

$$Dem._{AFinal} = Dem._{A} + Dem._{B} * \frac{Con_A x Den_A}{Con_B x Den_B}$$

Simulation Outputs

ChemicalCO was particularly interested in the truck numbers, and how different combinations of delivery commitments would affect the utilization. A set of three outputs was designed to allow this analysis. The outputs are shown in the figure below.

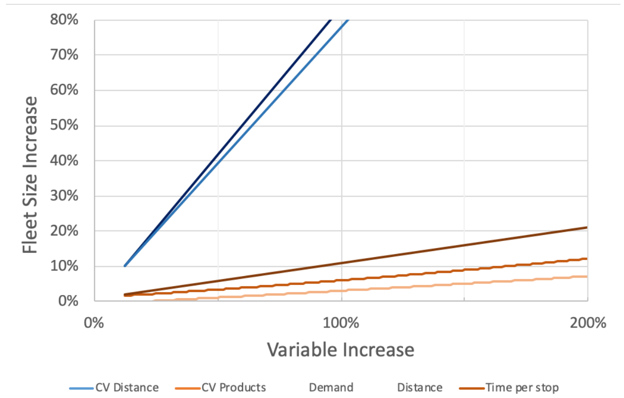
100% delivery commitment:
Distribution of number of trucks needed in order to deliver 100% of the demand, including average and standard deviation.
90% delivery commitment:
Distribution of number of trucks needed in order to deliver 90% of the demand, including average and standard deviation.

Results

From the analysis we can deduce, on one hand, that the replacement of redundant products can reduce the fleet size by approximately 10%. Even though most of the reduction is given by the selection of denser products, in this analysis around 1%-2% of the reduction is explained by the reduction in the number of products. It should be noted that this number is not precise though the simulation results do not measure this specific metric.

On the other hand, the results show how the different variables affect how many trucks ChemicalCO needs. We can clearly see that even though average demand is the stronger variable, other variables may also affect the outputs significantly. Particularly plants that have high product and/or distance coefficient of variations are most likely to need more trucks than expected to be able to fulfill with 100/90%.

Even though the objective of this project was to evaluate the cost of product portfolio complexity in relation to the cost of the fleet size, the results produced additional information regarding how different variables affect the fleet. Interpreting this information and running additional scenarios will allow ChemicalCO to understand what action is preferred for different plants and quarters. Also, the simulation will help the sponsor company understand how different strategic decisions would affect the number of trucks needed.



Conclusions

This capstone project was able to address the issue ChemicalCO had in terms of understanding what is the impact of changing the product portfolio to the number of trucks needed in the fleet. Even though the results show that the most important variables are not intimately related to the complexity of dealing with more products, understanding the impact of each variable separately provides a framework for ChemicalCO to make decisions regarding the removal or addition of products.

The research also provided evidence of other factors that the sponsor company should analyze in detail. For example, the fact that reducing the time per stop to 30 minutes would reduce the number of trucks needed by around 10% should definitely be considered

Finally, the results of the sensitivity analysis can be used as a guide to understand what should ChemicalCO research next. Although Inventory Routing (IRP) has been studied for several years, the routing for ChemicalCO has its complexities and should definitely be the next step to further understand the impacts of a complex product portfolio. Hopefully, applying IRP and using the simulation described in this project will conclude in a detailed characterization of ChemicalCO’s operation with a specified product portfolio.

					Serve 90% of demand		Serve 100% of demand	
Scenario	Quarter	Products	Average Demand	Average Distance	Mean	90% of the runs	Mean	90% of the runs
Baseline	Q1	61	8,655,765	700	107.1	128.3	117.2	140.3
Replaced	Q1	45	8,126,155	699	98.4	118.8	107.9	130.3
Baseline	Q2	59	8,554,123	753	115.2	138.6	126.3	151.8
Replaced	Q2	44	7,979,280	752	105.0	127.7	115.1	140.1
Baseline	Q3	59	8,807,100	756	119.5	144.0	130.8	157.9
Replaced	Q3	44	8,206,579	756	109.1	132.8	119.6	145.9
Baseline	Q4	59	9,736,646	734	125.3	158.7	137.5	174.2
Replaced	Q4	44	9,185,746	733	115.9	148.5	127.2	163.4