Carrier Choice Optimization with Tier Based Rebate for a National Retailer

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Abstract

In this study, we develop a decision-support system to help a high-end national retailer optimize their shipping costs. Our first meeting with the retailer introduced us to the type of shipping agreements that usually exist between the retailer and their delivery service provider within this industry. This retailer has a tier-based rebate system with their usual delivery service provider which incentivizes them to accrue higher shipping. Besides, some of the retailer's transactions qualify for the rebate total while others don't. But, the raw dataset wasn't organized in a way where we could easily isolate the rebatable transactions. Hence, we had to do data preparation based on the business rules. Our goal here was to ensure the net total of all rebatable transactions in the retailer's dataset equaled the total provided by the delivery service provider. Once we identified the right records, we aggregated sales by week and built time series models to predict future sales. Beginning with Simple Moving Average (SMA), we built Exponential Weighted Moving Average, and Auto Regressive Moving Average (ARIMA) to forecast weekly sales going forward. Then, we developed an optimization model that would simulate various transportation scenarios and identifies the scenario that minimizes their overall annual transportation costs.

Introduction

As of September 2017, retailers and wholesalers account for more than half of the global demand for package and courier services. According to a study by SAP, most businesses use the major, well-known parcel delivery services and call it done for shipping services to the end customer. But, SAP shows that doing so would cost them more than it should, and businesses should consider other options for at least some of their packages. But, picking a shipper is not an easy choice to make, since most package delivery services try to distinguish themselves along the dimensions of security, speed of delivery, special requests, price, customer experience, professional appearance. And the delivery service companies try to keep their customers loyal with volume-based contracts that make the retailers eligible for special discounts, services, privileges by accruing shipments with the same delivery service firm.

One such arrangement is the tier-based rebate percentage which has the delivery service provider refund a percentage of net value of the transactions back to the retailer in appreciation of their loyalty to the delivery service provider. This percentage increases as the net volume of transactions increases giving the retailer a greater incentive to ship more packages using the same shipper to maximize their rebate.

But, the usual delivery service provider might not always be the cheapest transportation vendor in the marketplace and with every shipment the retailer makes, he/she is making a trade-off choice between increasing the total sales with the regular carrier (that can be used in achieving a higher tiered discount) and choosing an alternative cheaper carrier. It is important for the retailer to find the right balance between the two to minimize their shipping costs (28% of shoppers abandon their carts/rethink their purchase if shipment costs are too high). We intend to build a model that optimizes the amount of current and future deliveries that the retailer should direct towards each carrier to reduce their overall shipping costs.

The rest of the paper follows this plan. We performed a literature review to understand what studies have been done in the past about shipper optimization and what models/algorithms work best/are currently being used in solving this problem. We give a brief introduction into the data we used in our study. Next, we discuss the models built and their respective results. An optimization model that finds the best choice of delivery service provider was built to identify the best shipment mixture between the regular carrier and the alternate carrier. Then, we discuss our conclusions and give insights into areas of future research.

Literature Review

For the purpose of this paper, we first focused on research that would provide actual solutions for business that do not have a developed distribution network and, thus, rely on third party carriers to deliver products for the final customer. However, since this concern is as recent as the e-commerce boom, there is no specific published paper with a straightforward solution or framework to assess this issue. Companies may desire to optimize their shipment expenses, but the optimal approach is likely still being tested empirically in the market.

Because of the unavailability of published work focusing on comparable problems, our research shifted to benchmarking similar solutions for a broader optimization problem in the transportation industry aligned with practical solutions that could be applied such as financial models and rebatable refund models. The models that were found vary in focus and complexity, ranging from a focus on transportation cost minimization to elaborate network problems requiring an optimal solution to several variables such as location and modality.

Many scholarly works can be found that address the issue of rebate promotional activities, but these works largely focus from the side of the offeror of the rebates, rather than determining the maximum utility of such a program to the offeree. Additionally, many publications in this area (Ali, 1994) focus on such promotional activities for consumer products to an end-consumer. While some factors discussed in these papers have parallels in a supply chain setting (purchase acceleration could translate to intentionally increasing business with a specific carrier to redeem a higher rebate), many factors that are developed in these models do not apply with the exogenous environment of the business-to-business supply chain (rebuys, redemption rate, etc.).

A common area of modeling within the supply chain industry is known simply as the “Transportation Problem” (“TP”), in which a product must be moved from many factories to many warehouses at the lowest possible cost. Recently, a new mathematical framework for solving such problems was published which results in what the authors deem as a better initial basic feasible solution that other algorithms previously published (Ahmed, 2014). A variant of the Transportation Problem is the Fixed Cost Transportation Problem, which can be solved with uncertainty theory mathematical methods (Yuhong, 2012). However, both of these methods are highly mathematical and theoretical, and lack ease of applicability in a real-world setting. Real-world solutions have been developed using linear programming methods in Excel with premium solver packages, but less documented work is available regarding these methods, and the applicability of such methods seems to be limited to specific corporate-consulting situations (LeBlank, 2014).

Models of increasing complexity are also available. One such model for solving a intermodal, service and finance constrained transportation optimization problem focused on a table search metaheuristic model, comparing neighboring solutions until an ideal solution is achieved. Ishfaq and Sox provided the framework for such a model including different types of shipments, modes of transport, and economies of scale (Ishfaq, 2010).

When it comes to focusing on predicting and optimizing cost of transportation alone, less recent published work is available. Hall and Galbreth recognize the fact that often in optimization problems, transportation costs are assumed to be linear, when in reality this is often not the case due to bulk or specialized discounts (or "rebates"). Hill and Galbreth model transportation costs as a piecewise function and deploy a heuristic model to determine an optimal solution for situations involving one factory shipping to multiple warehouses (Hill, 2008). While this work begins to address the complexity of transportation costs, it still does not accurately model or forecast costs based on a varying-rebate contract structure.

Additional work can be found that analyzes the empirical relation between the price of goods sold, the price charged to consumers of shipping the good, and the quality of shipping service (Dinlersoz, 2004). This work also discusses the impact of economic searching costs on consumer willingness to absorb shipping costs. However, these correlations all assume the shipping costs are fixed or known by the company making such decisions. Such work cannot be effectively deployed by a company unless accurate costing forecasts can be created from which to base these decisions.

A review of recent work in the area of freight transportation reveals an interesting "anomaly" in field, specifically that there seems to be a general lack of relationship between transportation optimization models and transportation cost functions (Bravo, 2013). Additionally, this review determined that limitations exist in current transportation cost functions, such as "the role of time and distance in transportation cost analysis". This review, in junction with the fact that fewer publications seem to exist focused on transportation-cost predictive modeling, provide a strong justification for our particular research problem and solutions.

Data

The data provided by the retailer included two main tables and an auxiliary table. One of the main tables consists of the retailer's record of transactions detailed to the individual transaction level while the other has transactions and summary from the delivery service company. The retailer's record had all of their shipments while only a subset of these shipments was eligible for rebate total. Some of the columns in the dataset were Shipping Country, Shipping State, Tracking Number, Type of Shipment, Code for the Type.

In the shipper's record of transactions, we had data summarized into different tiers records included tracking number, shipment type, shipment group etc., The auxiliary table had different type of shipment types and their respective eligibility for rebate status. This table had to be joined with the retailer's record of transactions to identify a shipment's eligibility for a rebate. Some of the shipment type had to be imputed based on the appropriate business rule (For example, tracking number has information about the type of shipment).

Once we matched the rebatable amount that the retailer's transactions indicate to the rebatable amount that the delivery service provider reported, we were certain that we had the right subset of the data to build models on. we aggregated the net weekly charge invoiced by the delivery service to retailer. This net payable to delivery service was used for time series modeling.

Figure 1 Actual Shipping Cost aggregated by Week

Exploratory Data Analysis (EDA)

During the Exploratory Data Analysis, we first plotted the payables graph to understand the peaks and troughs through the year. The retailer seems to experience high volume of shipments in the first quarter followed by a slower 2nd and 3rd quarter before the sales increase again in the 4th quarter. Based on our discussion with the retailer, this could be a result of the typical cycle of Spring cleaning and holiday shopping that increases the number of new units ordered/shipped on either end of the calendar year.

Figure 2 Decomposition of the Weekly Invoices

Then, we used seasonality decomposition function to determine how different elements of the demand are affecting sales. This helps us understand the determinants of sales and build the proper models to account for them. Figure 2 shows different components of the demand and it shows that most sales are due to the generic trend. We also see that there appears to be a weekly seasonality. This could be due to that most shipments go out towards the latter part of the week and hence the invoices generated by the delivery service provider increase then. However, we do notice high residuals in the early part of the year that decrease towards the 2nd and 3rd quarter before increasing for the holiday season. Since we only have data for 1 calendar year, we cannot quantify the amount of holiday seasonality and any models built with uneven residuals would perform worse once applied to following calendar year since the holiday seasonality/ spring cleaning would not be explained by the model.

Methodology

Considering the values of payables are in millions, we decided to take log of the values for the purpose of modelling. This didn't alter the distribution of the payable values as shown in the visuals below.

Figure 3 Log Shipping Costs with Moving Average

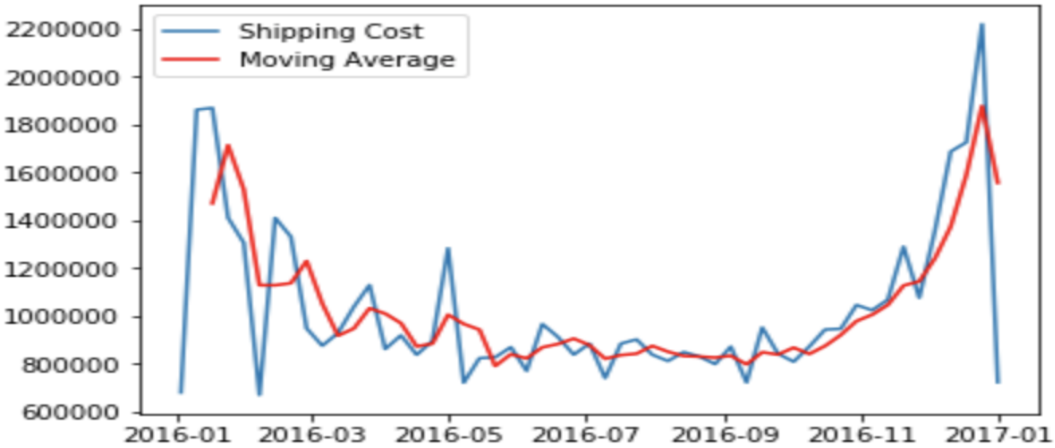
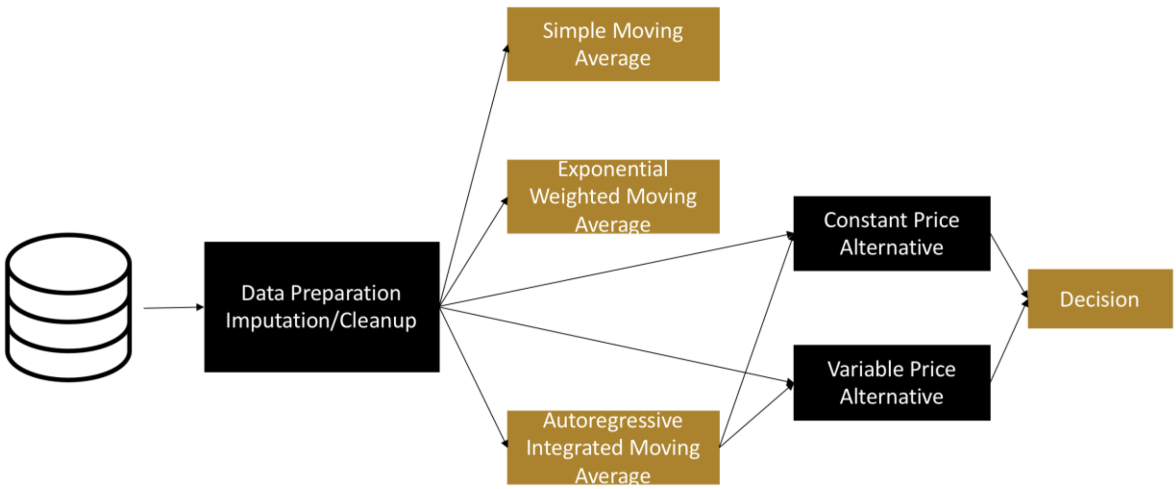


Figure 4 Shipping Costs with Moving Average

Our data analysis process was as follows:



We used a planning window of 3 periods for the Simple Moving Average and a half-life of 3 periods for the Exponential Weighted Moving Average. These parameters along with the parameters for ARIMA are explained in detail in the methods. We used Dickey Fuller Test for evaluating SMA and

EWMA and used Residual Sum of Squares for the ARIMA model. Our optimization problem was designed as follows:

Objective Function
Min {TC} = TCORC – {TCORC * RP} + TCOCC

Constraints
POSTCC >= 0
POSTCC <= 1
POSTCC + POSTRC = 1

Parameters
TC = Total Annual Cost of Shipping
TCORC = Total Cost of Regular Carrier
RP = Rebate Percentage
TCOCC = Total Cost of Cheaper Carrier
POSTCC = Percentage of the shipments to Cheaper Carrier
POSTRC = Percentage of Shipments to Regular Carrier
PC = The factor by which the cheaper carrier is cheaper.

Our decision variable was the PostCC which ought to be optimized to find the value that minimizes the overall shipping costs for the retailer.

Models

Simple Moving Average

A simple moving average is an arithmetic moving average calculated by adding the values for a number of time periods and then dividing this total by the number of time periods. One of the advantages of this model is that it is customizable for different number of time periods easily and hence fits into any planning window. Further, it smoothens out volatility making it easier to view the trend in a series. Increasing the time period increases its the level of smoothing and shorter time frame attempts to fit the source data much closely. As with any model, an optimum planning window ought to be taken to avoid overfitting and/or high volatility.

Moving Average are important analytical tools since they identify trends in current and potential change in an established trend. Comparing two moving averages, each covering different time windows, gives us a slightly more complex analytical tool to predict trend. A shorter term SMA that is higher than longer term SMA would imply an uptrend in future and vice versa.

Exponential Weighted Moving Average

The weakness of a simple moving average is that all prior values being used in the window have the same weight. The most recent observation has no more influence on the variance than that of an observation few periods back. This would imply that our calculation of the future costs is diluted by distant (less relevant) data. This problem is fixed using the exponentially weighted moving average in which values are weighed by recency.

Exponential Weighted Moving Average function takes a decay factor and weighs preceding observations based on an exponential function of the decay factor to forecast the future value. In our model, we built the EWMA with half-life of 3 periods which implies a given observation loses half of its influence in 3 periods following its occurrence. Other ways of mentioning decay factor include span, for how many observations after its occurrence will a given observation exert its influence, alpha, smoothing parameter and com, center of mass.

Auto Regressive Integrated Moving Average

Autoregressive Integrated Moving Average is a form of regression analysis that seeks to predict future values by examining differences between values in the series instead of using the actual data values. Lags in differed series are referred to as autoregressive and lags within the forecasted data are referred to as "moving average"

ARIMA includes parameters p,d,q for the Auto regressive part, integrated and moving average parts of the dataset respectively and it can take into account trends, seasonality, cycles, errors and other non-stationary aspects of a dataset when making forecasts.

Results

Simple Moving Average

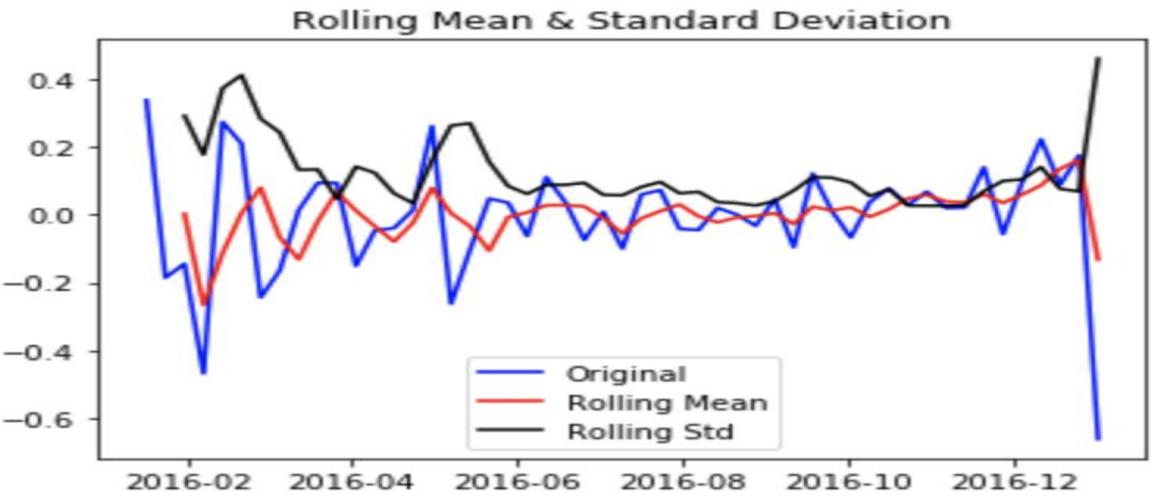


Figure 5 Moving Average and Standard Deviation

A Dickey Fuller Test on this gave us the following statistics

Metric	Value
Test Statistic	-7.188414
P - Value	2.540907 * 10-7

Table 1 Dickey Fuller Test of SMA model

Exponential Weighted Moving Average

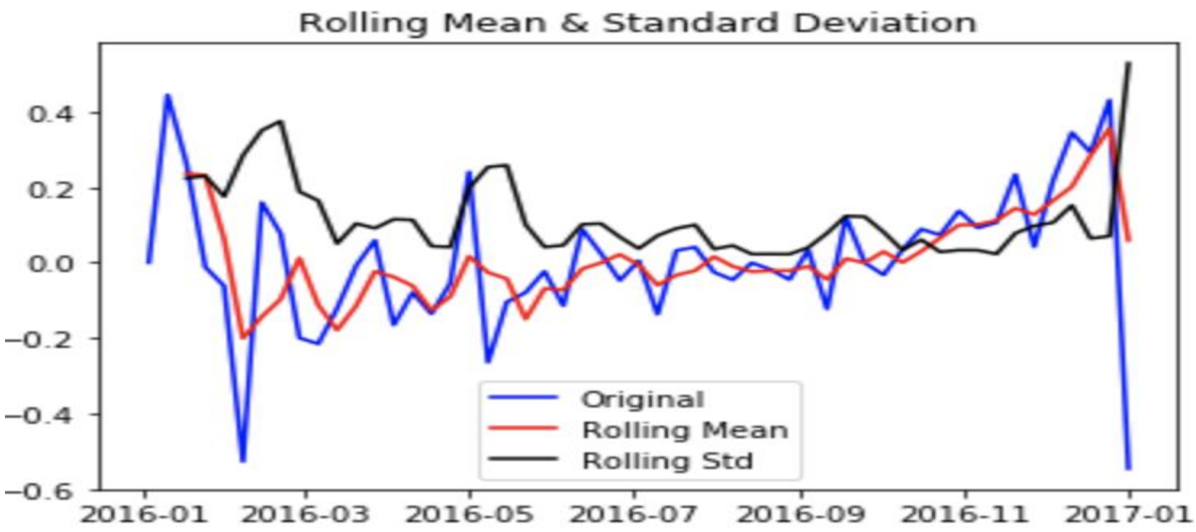


Figure 6 Exponential Moving Average (Half Life = 3, Min_Periods = 1)

A Dickey Fuller Test on this gave us the following statistics:

Metric	Value
Test Statistic	-1.745780
p - value	0.407693

Table 2 Dickey Fuller Test for EWMA model

The magnitude of the Test Statistic and the p-value indicate that we fail to reject the null hypothesis acknowledge that the forecasted series could be non-stationary. Since EWMA predictions are non-stationary, it is wiser to move to an alternative model.

Autoregressive Integrated Moving Average

We built three autoregressive models with p,d,q values as follows and used the Residual Sum of Squares as the criterion of determination.

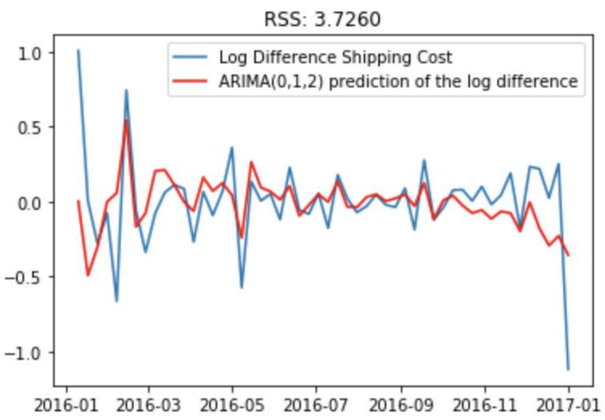


Figure 7 ARIMA (2,1,0)

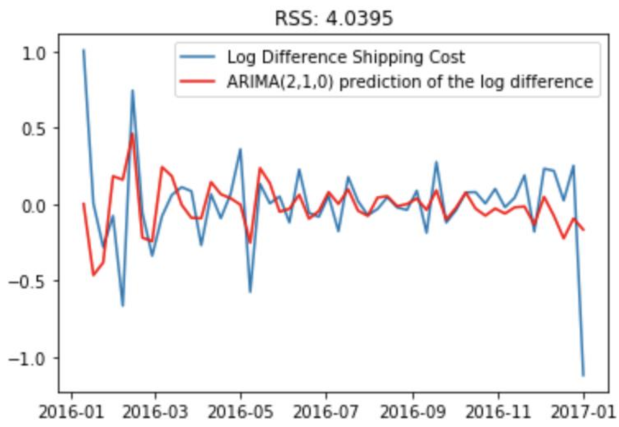


Figure 8 ARIMA (0,1,2)

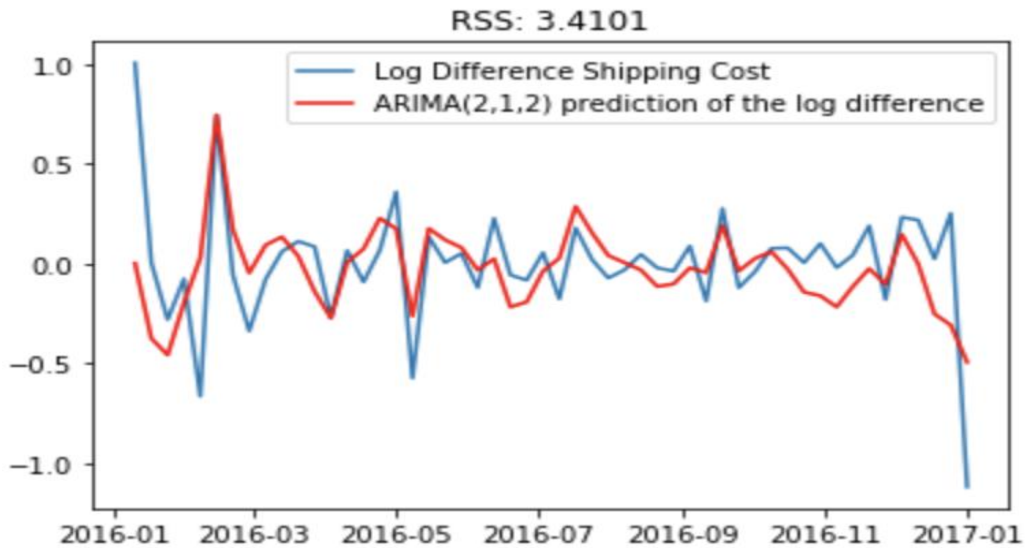


Figure 9 ARIMA (2,1,2)

The residual sum of squares is shown on top of each graph and as the hybrid model of the first two with (p,d,q) parameters (2,1,2) had the best outcome with RSS = 3.4101. Now that we found a ARIMA model with good results, we attempt to scale it back to the units of the sales figures to see how well our model performed in predicting the sales figures.

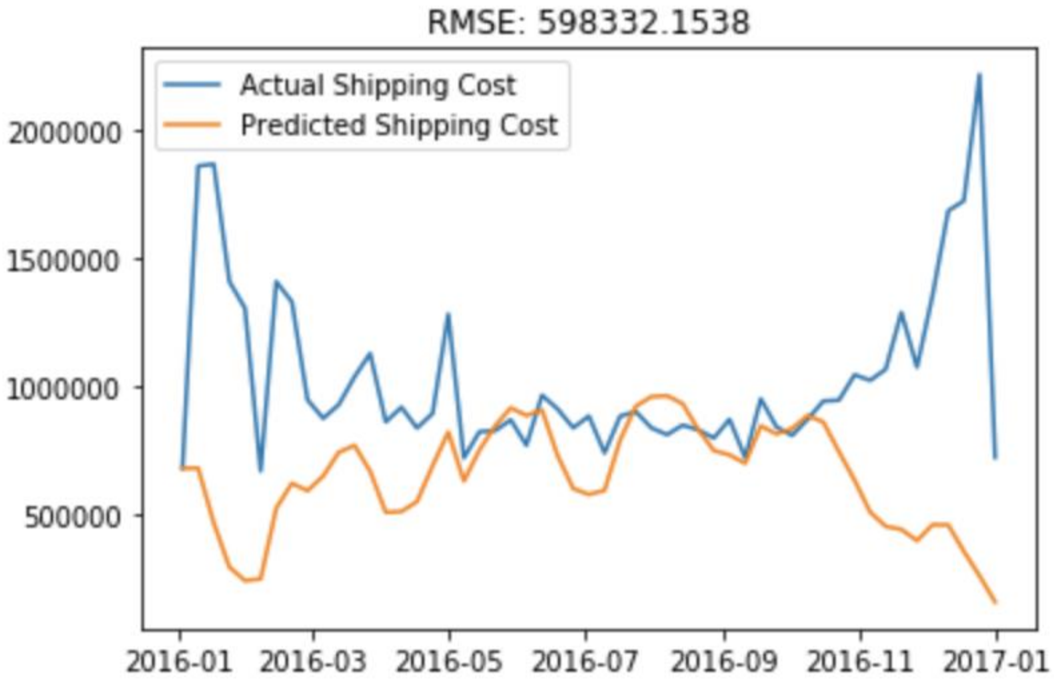


Figure 10 Predictions scaled back

As expected, our model was efficient at forecasting the shipping costs during the second and third quarters but failed to predict the shipping costs on either end of year where there was a lot of residual due to unexplained seasonality. However, the model seems to have integrated the general trend of the shipping costs in both first quarter and fourth quarter accurately even though the magnitude of this trend seems to have been underestimated.

Optimization

Since we realized that we cannot accurately predict the demand for the beginning and ending quarters accurately without factoring in the seasonality, we decided to place ourselves in the beginning of the calendar year 2016 and attempt to optimize for the delivery service provider choice for the calendar year of 2016.We built two optimization models:

- **Constant Cheaper Alternative**: There always exists a delivery service provider that is x% cheaper than the retailer's current delivery service provider.
- **Random variable Cheaper Alternative**: There is a possibility of a cheaper alternative if searched. But, the rate by which it is cheaper changes for each week.

Constant Cheaper Alternative

A constant cheaper alternative model is one which expects the presence of an x% cheaper alternative always. The value of x was selected in series from 0 to 100% in steps of 10. However, the effective rebate rate that the retailer is enjoying with their current delivery service provider (say y) presented a hurdle to this model. Every time a decision on the delivery service provider had to be made, the decision maker had two choices, “Pick their usual delivery service provider and get y cents for every dollar or pick the cheaper carrier and get x cents for every dollar spent”. This is rather easy decision to make based on the values of x and y i.e.,

- Pick the usual delivery service provider if y > x or
- Pick the alternate carrier if x > y

This caused the model to direct all the shipments one way based on the values of x and y i.e., ship using the regular carrier always if y>x and ship using the alternate carrier if x > y which isn’t an optimization in true sense of the word.

Random Variable Cheaper Alternative

Expecting an x% cheaper carrier to exist always is bit unrealistic and considering the peculiar challenge we faced in our model, we decided make the model more realistic by randomizing the %cheaper variable each week and the random number is between 0% to 15% i.e., in any given week, the retailer can expect the presence of an alternate delivery service provider that quote the same price as their current delivery service provider or quote a price that is upto 15% cheaper.

This model adds a unique twist to the earlier problem in that in the earlier case, since a x% cheaper alternative is guaranteed, the retailer could simply pick the carrier by comparing x and y. But, given that finding a cheaper carrier in a given week wouldn’t always guarantee a similar deal the following week. Diverting all of a large shipment in a given week to the cheaper carrier could potentially bring the retailer down a tier with their usual delivery service provider and the retailer has to balance these priorities to minimize the overall cost.

Optimization Results

Based on the above model, we used Palisade @Risk software to find the optimal proportion of shipments that can be diverted to a cheaper carrier and ran this simulation for 30 minutes. @Risk stochastically generates values for the PC parameter and finds the value of POSTCC that minimizes the Total Shipping Cost for the retailer. We see that a policy of diverting about 9.82% of the shipments on average always is the most optimal method of bringing down costs.

The distribution of shipping costs are as follows:

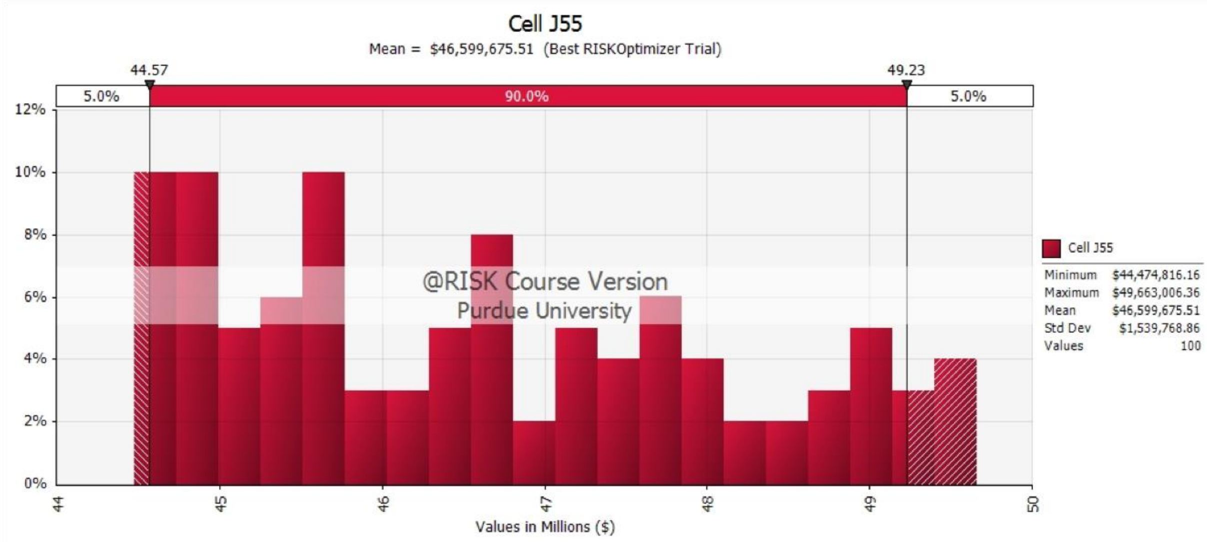


Figure 11 Distribution of Shipping Costs

By applying our model, the retailer can have higher autonomy in their delivery options while retaining rebate benefits from the delivery service provider. The retailer can opt to divert their shipments based on the above model and expect to pay anywhere between 46.610 million and 47.383 million in annual shipping costs. This would mean a savings of about $3 million dollars had they stuck with the same carrier. However, knowing the proportion of transactions to divert is a reasonable academic exercise but in the corporate world, a retailer would want to know which transactions to divert to save on the costs. When these results were communicated to the retailer, we were asked to try to identify the shipments that ought to be diverted along category/package weight/geographic information. This analysis opens the possibility of new avenues of cost saving for the retail industry.

Conclusion

We first used business rules to clean the data and impute the transactions to ensure we have the right data to begin with. Once we aggregated the shipments by week, we were able to build models that were able to forecast for the future in 2nd and 3rd quarters but failed to show similar success in the first and fourth quarters which were mixed with seasonality. Our request for more data was honored with the retailer giving us access to another calendar year of data that can be used to calculate the seasonality index for the first and fourth quarters and build models on those. Then, we built an optimization model that can identify how much of the shipment can be routed to alternate cheaper carriers. Further research can be along the dimensions of what shipments to route to the alternate carrier.

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