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**MSBA5314-APPLIED ANALYTICS**

**University of Central Oklahoma**

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**Predicting Yield Scores per Load of Transportation Carrier**

**Katz, Sapper, Miller Transport Advisors (KSMTA).**

**LOG(X)**

**April 27th, 2020**

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# **Executive Summary**

This report presents the application of different predictive modeling tools such as decision tree, regression, neural networks and auto-neural networks to predict yield of future loads for Karts, Sapper Miller Transport Advisors’ carriers. The purpose of the research is to allow for transportation carriers to predict the yield of a load before the load occurs. This will allow for better load selection, resulting in high NPVs for the loads. By using different software programs, we will be able to create these models including, SAS Enterprise Miner, Python, Tableau, and Excel.

In the research there is two models. There is a full model including variables that will only be obtained after the load is completed, therefore our full model. The second model will only include variables that we will have before the load has started, thus being able to predict the yield before it has happened. After running both models, we will be able to compare the differences of the models. The first model will provide good insight for a company that is still in the diagnostic stage of the analytical process. They will be able to use the historical data to provide yield numbers. Although, the second model will allow companies that are farther along in the analytical process be able to predict future yield numbers. This will improve the companies load selection process and result in higher profits.

# **Introduction**

The purpose of this study is to predict our target variable, which is the yield of a truckload. Yield is a score or ranking given to a truckload to determine how profitable a truckload it was. For example, a load that has a yield of 500 is much more desirable than one that has a yield of 100. A yield is given to a load after the load has been completed and ran through proprietary software that a company pays for. The software looks at multiple variables for determining the yield; for example, Margin per Day, Linehaul revenue, total costs as well as geographic identifiers to determine how profitable and desirable that load was. This yield number is given to the carrier’s executives to have a quick insight into which type of loads they should take and not take in the future.

# Organization Description

KSM Transport Advisors, LLC (KSMTA) was founded in 2006 as a financial advisory services company exclusively serving the trucking and logistics segments of the transportation industry. Some of their services focus on profit improvement by enhancing margins, gaining efficiencies and driving down operating costs in the following areas:

* Freight network engineering
* Maintenance
* Transportation Management System (TMS) and related systems
* Risk
* Driver recruiting and retention
* Business planning

KSMTA is a part of Katz, Sapper & Miller Network, which includes Katz, Sapper & Miller, LLP, a top 100 independently owned and operated accounting firm. Through the firm’s 100-plus trucking and logistics clients located throughout the U.S., Katz, Sapper & Miller has become a leader in tax and business consulting for the transportation industry.

(source :<https://www.ksmta.com/about>)

## Business Problem

The problem topic in this research is how the yield number is calculated. The software calculates the yield after the load has been completed. Thus, there are no capabilities for predicting yields of future loads. This creates a problem when a carrier is deciding what load they should take over any other load. The current standard in the supply chain management and logistic industry does not have much for predictive analytics such as what we are creating. This could be due to the fact the quality of data being poor or the availability of data in the industry (Waller & Fawcett, 2013). By cleaning the data and having a proficient understanding of the data we can create a model to predict yields of future loads for carriers.

## Projections

The solution for the problem stated above is to use SAS enterprise miner, and other methods to create a model that predicts the yield of a load like the proprietary software that is being used KSMTA. In doing so, we can predict the yield of a future load given the model that is created. Therefore, creating a better load selection process for trucking carriers. The method that we will take is to use the historical load data with their yields and train a model to predict yields of loads that are being considered.

## Project Motivation

The company that the data was received from is Katz, Sapper, Miller Transport Advisors (KSMTA). KSMTA has been advising trucking companies for over 13 years. They serve as a financial advisory service that exclusively focuses on the trucking and logistics segments of the transportation industry. Some of the features they provide are freight network engineering, business planning, and transportation management systems.

This issue came to attention during a meeting at KSMTA when the president made a proposal that we investigate different options of ranking systems other than the current proprietary software we are using. This arose the issue with the current software is strictly a historical based model. The yield is given to the executives after the load has been completed, and the executive must make intuitive decisions for choosing future loads.

From a carrier’s perspective, the goal is to maximize profit on the deliveries made. Cost cutting is at the heart of load optimization. It is important that all trucking factors are evaluated and managed such that the fleet operates in the most efficient yet cheapest way possible. For instance, how trailers are loaded, the distance traveled to make deliveries, dead miles…all these are some of the factors that need to be studied when evaluating loads for profit optimization.

One of the past studies looks at the benefit of information for a truckload carrier. It evaluates all attributes of loads and trucks in order to help carriers make decisions on whether to accept or reject a load and the sequence in which the accepted loads are carried out. Advanced load information (ALI) which is a method that aims at minimizing the latency of costly load operations was the heart of this research. This is because communication of timely load information is perceived to be one of the least costly methods when transportation service clients and carriers collaborate to maximize profit. A flexible mixed integer mathematical model was used and implemented in a dynamic rolling horizon context. The research concluded that second and third-day ALI can improve profit (which in our context is represented by yield) by averages of 22% and 6% respectively. The radius of the carrier service and trip length were factors found to be statistically related to the impact of ALI (Zolfagharinia & Haughton, 2014)

Our solution is to create a model that will predict the yield of a future load so that a carrier company will have complete actionable insight into which load to choose. In doing this it will reduce the number of low yield loads and unprofitable loads. This will have a direct impact on the company’s NPV.

# **Literature Review**

The transportation industry is quite complex with multiple factors affecting the profitability of trucking companies and carriers. Factors such as, maintenance, repairs, varying fuel price, regulatory requirements, increase and decrease in production, competition, etc., directly or indirectly affect the profitability of trucking companies (Lingard, Turner, Charlesworth, 2015). One way to have better yields for increased productivity is by splitting loads with other carriers to reduce cost in most cases (Nowak and White, 2008). In addition, Barnham (2015) proposed that management should carry out more diagnostic testing to ensure the carries know exactly what yields are beneficial to them. The table below is a description of relevant literatures gathered for the completion of this project.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Sources (author) & Year)** | **Data Source**  **(Country of Origin)** | **# of Samples** | **Timeline of Data** | **Variables** | **Methods Used** | **Important findings** |
| Kaul, Hill, Walthall, (2005) | Historical Maryland corn and soybean yield data from the Maryland Cooperative Extension | 108 corn and 109 soybean samples | 1978–1998 | 20 | ANN (auto neural network) | ANN yield prediction models produced consistently higher r2 and lower RMSE values than multiple linear regression-based yield models. |
| Xu & Katchova (2018) | USA from ten different states | 12,027 | 2000-2016 | 10 | Flexible Fourier Transform Regression | The FFT model has potential to forecast crop yields by improving RMSE |
| Das& Nair & Reddy & Venkatesh (2018) | India Costal Districts | 33 Years of data | 1938-2015 | 5 Weather Variables | Neural Networks, Stepwise Regression, LASSO | The performance of ANN was good during calibration while it was the worst model during validation. LASSO was the best model during Validation |
| Mesa-Arango, R., & Ukkusuri, S. V. (2015) | USA | NA  (Linear programming on a mathematical model was used) | NA | Cost associated with each arc in the model, set of all lanes, set of lanes served by carrier, loading and unloading costs, fleet size, volume of shipments, shipment prices | Clustering  using Linear Programming | Lanes with lower strength may leave stronger elements (carriers) clustered or may agglomerate in new clusters with others. Some lanes operate better alone because they are distant with opposite directionalities from the rest or are not competitive with other clusters. |
| Dai, B., & Chen, H. (2011) | France | NA  (Linear programming on a mathematical model was used) | NA | Decision variable i.e. profit of carrier m after collaboration and real auxiliary variable representing the maximum difference between profit or allocation ratios of any 2 carriers | A centralized planning model | Profit increases of each carrier after collaboration generated by the 3 LPM may be different because the core of each instances contains multiple feasible allocations. Fairness of allocation each alliance can only be defined by the carriers included in the alliance. |
| Zolfagharinia, H., & Haughton, M. (2014) | Canada | --  (50 cities) | -- | Revenue, cost of moving loaded trucks, cost of moving empty trucks, dwelling cost, lateness cost, radius of service, trip length, fleet size, load density, advanced load information (ALI) | Linear Regression | Third-day ALI improved profit (which in our context is represented by yield) by averages of 22% and 6% respectively. The radius of the carrier service and trip length were factors found to be statistically related to the impact of ALI |
| (Santén, 2017) | “Wholesale Alpha and Freight Beta, Sweden.” | 34 | February 2010 and in February 2011 | “packaging efficiency, loading efficiency and booking efficiency,  (Load meters, height & volume)” | “Semi-structured interviews, archival sources and  observations of vehicles.” | Logistics actions that can increase load factor are identified and categorized according to  packaging efficiency, loading efficiency and booking efficiency.” |
| (Han & Murphy, 2011) | “Western Oregon trucking company and the  Oregon Department of Transportation (ODOT), USA.” | 21,945 journeys through 107 courses | May 2007 to May 2008 | “Purchase price, Machine life, Salvage value, Interest rate, Fuel cost, Fuel consumption,  Road user charges,  Truck and trailer maintenance,  Insurance, Tire cost, Tire life.” | Biomass Transportation Model (BIOTRANS). | “Labor (27%) and fuel (28%) were the two largest  components of total cost.” |
| (Töyli et al., 2013) | LPS, world | “over-all 150; 57 American, 27 European, 27 Asian Pacific and 39 companies from the rest of the  world.” | -- | “Sea freight, railway, trucking, courier-, express-,  parcel- service (CEP) LSPs, third-party (3PL) LSPs and fourth-party (4PL) LSPs.” | “Balance sheet analysis using contingency theory, complemented by a correlation analysis.” | “The asset and liquidity structure of LSPs show significant differences, while the capital structure is  mostly homogeneous.” |
| Haankuku, C., & Epplin, F. M. (2015) | American Society of Agronomy ( United States, Madison) | Yield data from randomized field experiments from 1994 - 2000 | 1994-2000 | Current and anticipated yields (defender), termination cost, cost of establish new variety, yield loss during transition, discount rate, price, life span, | Linear and log-linear regression models, Net Present Value (NPV), Capital budgeting. | With regards to having a better yield over time, the log-linear model had a better fit. This is important in deciding what replacements will benefit our project to get a better for our data set to our combined models. |
| Sudheer Kumar, S.D. Attri and K.K Singh (May 2019) | Journal of Agrometeorology, New Delhi-India | 2 years of data | 1984-2015 | 30 | Stepwise Regression, Lasso regression, ordinary Lease Square (OLS) | The lasso regression model offered the best fit model in predicting and forecasting yields as compared to Stepwise and OLS. In addition, the percent error by Lasso regression model was less than Stepwise. |
| Parviz, L., & Paymai, M. (2017) | Montenegro, Titograd | Wheat and oil seed yields from 40 farms | 1984 –  2013 | Air temperatur, wind speed, air pressure, vapor pressure, relative humidity, minimum and maximum relative humidity, precipitation, sunshine hours, number of cloudy days, dew point temperature | Fuzzy Linear Regression, Classical Regression, Sensitivity analysis, Artificial Neural Networks (ANN). | As per the methods used in the article, predicting yields with Artificial neural network produces an improved forecasted outcome as compared to classical and fuzzy regression methods, and sensitivity analysis. |

# **Synthesis of Articles**

### Methods

Efforts have been made to increase yield numbers through big data. To first have a better understanding of the methods that other researchers have conducted to find yields in other fields we looked at multiple articles. According to research carried out by Kaul, Hill and Walthall (2005), auto neural networks produced the highest R-squared number when they were evaluating yield numbers of corn and soybeans. This method is a model we would like to incorporate when we are evaluating the yield number of the transportation loads. On the other hand, Das& Nair & Reddy & Venkatesh (2018) reported that the neural networks had the highest calibrations, however it also reported some issues during the validation tests. Sudheer, Attri and Singh (2019) reported LASSO regression method to be the best during the validation testing. With this project, we intend to maintain the fact that neural networks have issues with validation as per Das & Nair & Reddy & Venkatesh (2018), while proceeding with our predictions of foreseeable yield increase.

### Important Variables

Predictive analytics is changing the game for shippers, carriers and overall logistics operators are relying on historical and real-time trucking and shipment patterns in order to predict different profitability metrics. As previously discussed, the goal of this project is to focus on profit optimization for carriers. We want to come up with a model that helps evaluate and identify the most profitable loads for carriers in the market by studying and finding freight combinations that will create the best profitability for the carriers. At the heart of the trucking franchise is a revenue model, the goal as it is for any business is to increase profitability. This paper presents a review of the related research.

From their research study, Dai & Chen, (2011), investigated carriers’ profitability by studying carriers’ collaboration in pickup and delivery services. This is done through forming alliances by sharing transportation requests and vehicle capacities in the goal of reducing empty back hauls as well increasing vehicle utilization rates (thus increasing carrier profitability). They used mathematical linear programming while focusing on two major variables: a decision variable i.e. profits of carrier after collaboration and a real auxiliary variable that represents the maximum difference between profit or allocation ratios of any two carriers. Different parameters included in variables are also used in order to carry out the research. The variable parameters are: a set that included all the carriers in the alliance, pre-collaboration profit of carrier before collaboration, post-collaborative total profit of carrier coalition, post-collaborative total cost of carrier coalition, post-collaborative cost of carrier m after collaboration and total revenue of the requests offered by carrier. This study contributes to the logistics and trucking disciplines and expands our knowledge regarding profit allocation and optimization in a trucking service where carriers collaborate.

Furthermore, Mesa-Arango, & Ukkusuri (2015), used an algorithmic approach to demand clustering based on sampling historical data and a series of network transformations. Samples of prices and volumes are collected, and a profit maximization linear program is solved to find the optimal distribution of trucks associated to each sample. This study focuses on truckload combinatorial auctions where carriers bundle lanes of demand and price them taking advantage of economies of scope. The importance of this study was to understand how carriers can incorporate new business to their networks in order to take advantage of economies of scope. Mesa-Arango, & Ukkusuri (2015) considered the following variables to be of importance: loading and unloading costs, fleet size, volume of shipments, shipment prices, cost associated with each arc in the model, set of all lanes and finally the set of lanes served by a carrier.

According to Zolfagharinia & Haughton (2014), they evaluated all attributes of loads and trucks in order to help carriers make decisions on whether to accept or reject a load and the sequence in which the accepted loads are carried out. Advanced load information (ALI) which is a method that aims at minimizing the latency of costly load operations is at the heart of this research. This study models and measures the profit improvement trucking companies can achieve by collaborating with their clients to obtain advance load information (ALI). The authors considered revenue, cost of moving loaded trucks, cost of moving empty trucks, dwelling cost, lateness cost, radius of service, trip length, fleet size, load density and finally, advanced load information (ALI) as their most significant variables.

Even though our further studies does not completely fall in line with our research as they use mathematical linear programming approaches to solve the profit optimization problem, they provided insights on the trucking industry and the profit optimization processes carriers can incorporate in their business.

Santén (2017) ran an investigation to discover in what way transporters could raise weight aspect in their highway transportation by recognizing chances for logistics act and effects on weight aspect output actions produced by these prospects. This effort examined a transporter’s outward stream of things. The drive was to discover prospects to raise the weight aspect from a transporter’s viewpoint.

Another examination was done by Han & Murphy, (2011) on trucking manufacturing and price model advancement to guess conveyance *output and price*. They argued that new features of this model comprised that the output module of it was founded on a great, actual statistics group and it permitted resolving of prices for multi-journey/multi-product conveyance by a variety of automobile outlines. The main objects of this examination were to make a processor model guess the conveyance output and price for improved timber left-over and besides to assess the influences of dissimilar automobile outlines, related physical kinds, and transportable road features on conveyance prices.

However, assuming other variable that influence carrier’s truckload and yield increase, Haankuku and Epplin (2015) proposed that the value of increased yields from new variety (i.e., loads, distance, location, weight, etc.) should be sufficient to the offset cost of yield lost during the time of establishment. This would depend on the tradeoff between the cost to establish the new variety to the net value of subsequent additional yield.

### Findings

Based on our study, there are multiple different models in which other fields use to predict yields. The consensus seems to be that the most popular approaches are ‘Neural Networks’ and ‘Regression Models’ to predict yields. These methods seem to be more accurate and easier to interpret than other methods such as decision trees. Their overall outcome produced better R-Squared as well as Root Mean Squared Error (RSME) numbers. Our goa is to incorporate these methods in our models for predicting yields for transportation loads. Some of the important variables that were found in previous studies for transportation profitability or yield, includes margin, geographical locations, length of haul, and empty miles. Therefore, by combining the previous research of different methods and important variables we can have a better understanding of our target variable yield.

### Summary

The objective of this present study is to create a model that predicts the yield of a load like the proprietary software that is being used by KSMTA. In doing so, we can predict the yield of a future load given the model that is created, and the sensitivity of the expected yield increment with respect to given loads. Therefore, creating a better load selection process for trucking carriers. The method that we will take is to use the historical load data with their yields and train a model to predict yields of loads that are being considered. However, the future of yields is unknown. Considering constant expected yields, declining yields, and previous yield structure, different data mining criterion will be applied to provide benchmarks required for carriers to stay profitable in the long run

# **Data Understanding**

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*Figure 1: Data Understanding flow diagram*

To understand the data properly one must understand how the transportation industry works. What is referred to as a load is when a truck takes some materials or merchandise from one point to another point. A load does not mean it is a truck, a truck can carry multiple loads. Once that load is completed the data is sent out for analysis using a software that will give that load a yield number. Our target variable in this research project is yield, which gives the carrier a better understanding of how profitable a load is/was. Yield is based on multiple factors such as, total revenue, margin, loaded miles and even uses the geographical aspects of the load as well.

There are three portions in the geography of a load. There is the projected time available (PTA), which is where the truck is at when the order is received. From the PTA, the truck will go to the required origin place. The distance between the PTA and the origin is what is referred to as empty miles, or deadhead miles, this is when the truck is carrying no materials. After the truck picks up the materials at the origin place the truck will then head to the destination. The distance between the origin and the destination is what is called loaded miles, miles when the truck is carrying materials. The loaded miles are also broken down into Length of Haul bands, which are calculated by the company. Each three parts of the load. PTA, origin, and destination, all have multiple fields in the data. The three parts will have a city, state, zip code, market, area and dates corresponding to each part.

To further understand the data structure, we explored the structure for Total revenue and its various components.

* ***Line Haul Revenue***: baseline pay for transporting the load.
* ***Fuel surcharge:*** an optional pay that is given if the shipper wants to pay for the carrier’s fuel.
* ***Accessorial revenue:*** an optional pay given if there are any special requirements that must be done with the load. This can include loading and unloading the truck, team drivers, or even transporting hazardous material.

In addition, we explored the various costs that a carrier will incur during the transporting of the load. These include:

* ***Empty cost***: cost when the truck is driving on empty miles when the truck is empty.
* ***Loaded cost***: cost that the carrier will incur when they are carrying material from the origin to the destination.
* ***Cost to load and unload:*** when the truck is loading for material at the origin and unloading the material when it arrives at the destination.
* ***Stop cost***: cost that the truck has when it makes any stops during the transit.
* ***Toll cost:*** payment of tolls on the highways.
* ***Other costs***: cost not already categorized are classified as other costs.

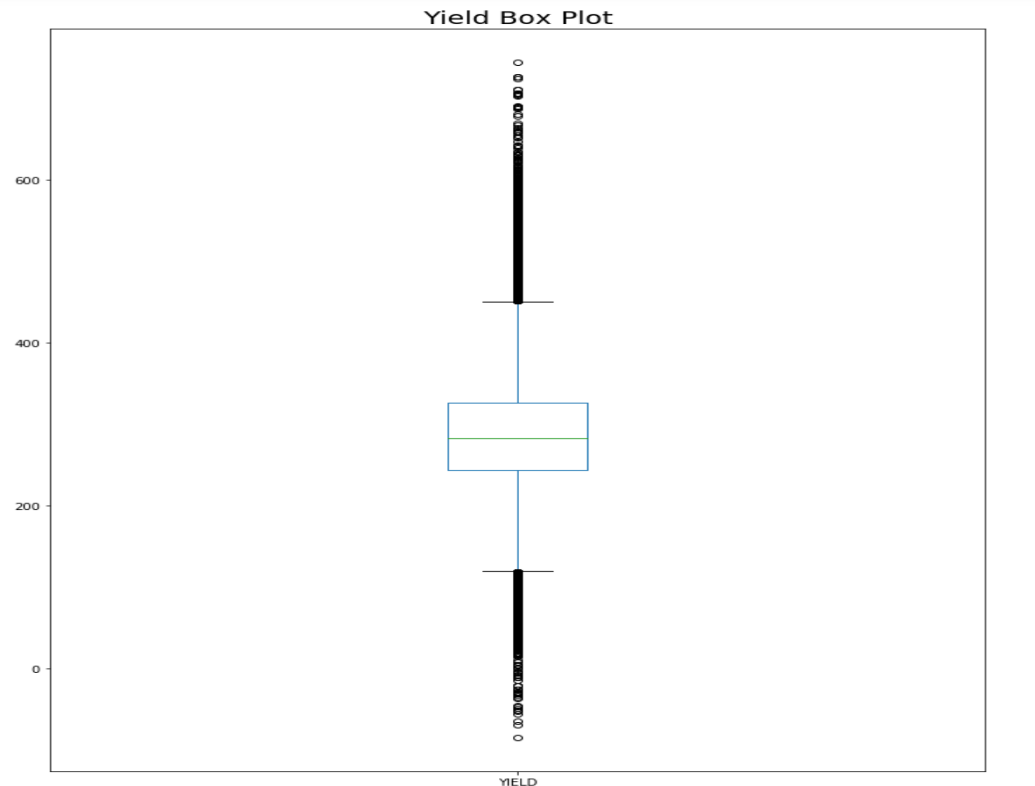
Now that the revenue and cost has been defined, we can explore the margins of the load.

* ***Margin:*** total margin of that load (Total revenue -Total Cost)
* ***MAR:*** Margin above replacement
* ***Margin per day (MPD):*** over the course of the load.
* **MPD in and MPD out**: The MPD in is calculated by the MPD when the truck is going to the origin area. The MPD out is the MPD when the truck is leaving the destination area. These two variables are used to analyze the movements of the load before and after the load is completed.

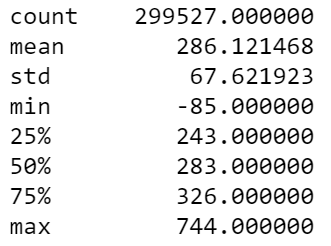
A very crucial understanding of a transportation network is not only getting from point A to point B. Nevertheless, it is how you get to point A and how you will leave point B, as a carrier’s transportation network is never ending. During the transportation of the load there are other variables that we have taken in consideration. Such as stops, how many times the truck stopped during the load. There is repowers or how many times maintenance had to be done on the truck. There is also delays and dwell. Delay is how long the tuck was late after the scheduled time and dwell is time spent not moving the truck.

Using Python, the initial stage of our data preparation began with cleaning of null values. We deleted all records that had null values or values of zero in the total revenue column. In situations that the total revenue is zero, means that the truck was just moved from its positions for better network management. We also made sure the data types were correct. The dates of the PTA, pick up, and delivery were not read as time-date data types. Therefore, we converted them to date-times to allow for analysis. There were null values in the place of the yield category column that we left as we were not going to use that column for analysis. The yield category is an ever-changing field by KSMTA that is not useful for predicting yield. There were many spaces in our column labels that SAS would not read. Therefore, we had to rename most of our columns with underscores in place of spaces so that SAS will read our data set. There were some outliers in our data set, that caused a high skewness to the right. We decided to fix the issue of outliers by removing 20 records that were extreme outliers in the data set, which dropped the skewness of yield below 0.5.

# **Exploratory Analysis**

Considering previously carried out research, we decided to explore our data and truly see how certain variables interacted with yield and with each other, to provide some insight into which the most important variables are in yield. To begins, we stated off with a box plot showing the distribution of Yield with the outliers removed for better analysis.

*Graph 1: Yield distribution*

Below is the summary statistics for Yield to have a better specific understanding of our target variable. The mean yield of all 299,527 records is 286.12, with a standard deviation of 67.62. The lowest yield in this data set was -85 and the max was 744, keeping in mind that we removed high outliers before this.

*Figure 2: Yield Summary Statistics*

The following graphs show the interactions between our dependent variable, yield, and other independent variables to find any relationships between the two. This will give us a better understanding of which variables are important for our model.

A close up of a map

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*Graph 2: Total Revenue by Yield*

Looking at *graph 2,* there is a slight positive relationship between total revenue and Yield, with a linear pattern As the Total revenue per load increases, so does that load’s yield. While this graph does not take in effect the amount of costs for that load there is reason to believe that the costs would have an impact on the yield as well. This is represented in the graph below showing the margin (revenue subtracted by all the costs for that certain load).

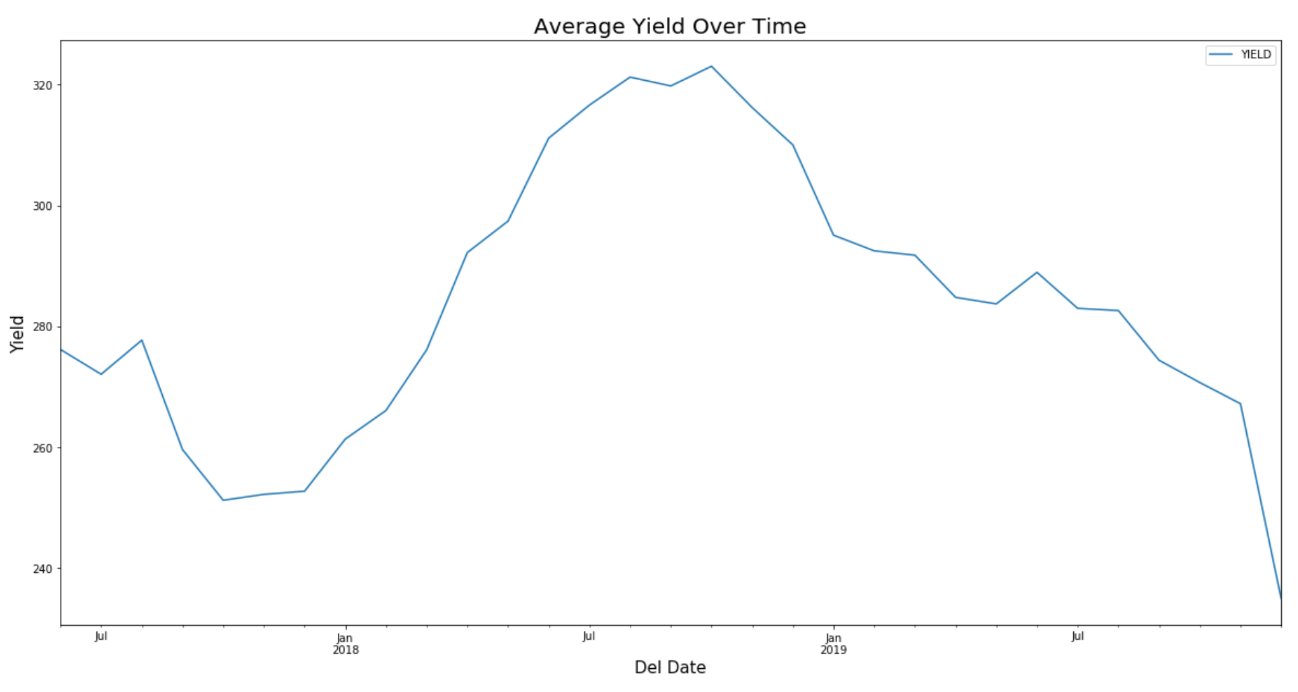
**A close up of a map

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*Graph 3: Margin by Yield*

Based on the graph above, it is evident there exist a stronger relationship with a liner patter between yield and margin than what there was with revenue and yield. This leads us to believe that there is importance in using margin in our yield predictions. Taking in account the costs for the yield seems to have more of an impact than just using total revenue.

## **Time Series Analysis**

We decided to look at how yield trends over time and see if there is any impact on yield over the course that the data was collected. Below is a graph of the average yield over time.

*Graph 4: Average Yield over time*

****The average yield tends to drop during the holiday seasons. In addition, we did an exploratory forecast over a 13 months period and realized that on average, there will be no change from December 2019 through December 2020. Forecasts were computed using exponential smoothing.

*Figure 3: Average Yield over time (Actual and Forecast)*

**A close up of a map

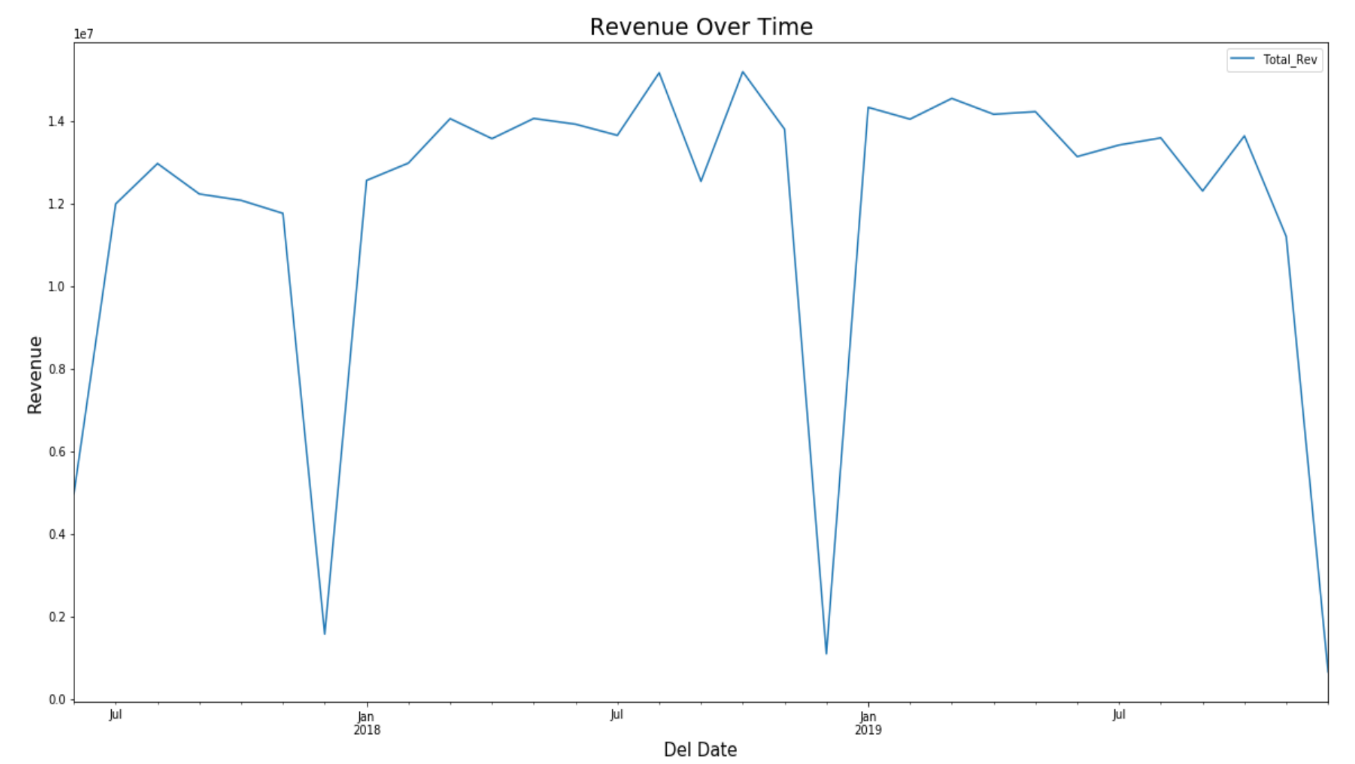
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*Graph 5: Average Yield over time (actual and predicted)*

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Model** | | |  | **Quality Metrics** | | | | |  | **Smoothing Coefficients** | | |
| **Level** | **Trend** | **Season** |  | **RMSE** | **MAE** | **MASE** | **MAPE** | **AIC** |  | **Alpha** | **Beta** | **Gamma** |
| Additive | None | Additive |  | $10 | $8 | 0.21 | 2.9% | 166 |  | 0.500 | 0.000 | 0.000 |

*Table 1: Average Yield over time forecast model statistics*

The consensus is that, business would increase during this time as people are doing their holiday shopping during these times. On the other hand, most trucking carriers allow their drivers to be home for the holidays or only have the drivers take short haul loads so they can be with their families during the holiday season. This ideology is backed by looking at the graph below of total revenue over time.



*Graph 5: Revenue over time*

*![A screenshot of a cell phone

Description automatically generated](data:image/jpeg;base64,/9j/4AAQSkZJRgABAQEAeAB4AAD/4RDoRXhpZgAATU0AKgAAAAgABAE7AAIAAAAKAAAISodpAAQAAAABAAAIVJydAAEAAAAUAAAQzOocAAcAAAgMAAAAPgAAAAAc6gAAAAgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAEFsb3RhIENoZQAABZADAAIAAAAUAAAQopAEAAIAAAAUAAAQtpKRAAIAAAADNzAAAJKSAAIAAAADNzAAAOocAAcAAAgMAAAIlgAAAAAc6gAAAAgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA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graph above shows a constant deep during the months right before January, which can be classified as the holiday season (seasonal effect). Although there are huge drops in the sum of the total revenue the average of the yield does not drop as significantly. This is caused by smarter load selection during this time frame. The carriers only select loads that are not high in costs because they want to keep their drivers close to home. The figure, graph and table below further explain the exponential forecast nature of Total revenue over time.

*Figure 4: Revenue over time (Actual and Predicted)*

**A close up of a map

Description automatically generated**

*Graph 6: Revenue over time (Actual and Predicted)*

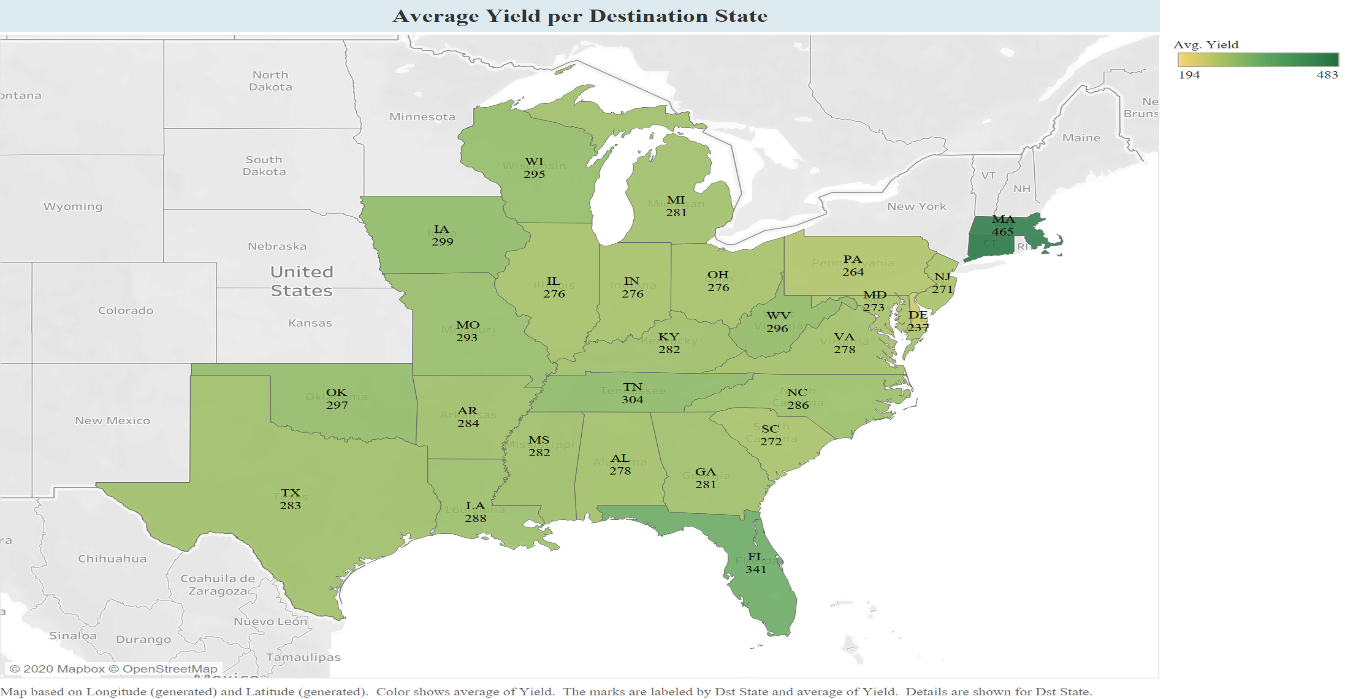
|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Model** | | |  | **Quality Metrics** | | | | |  | **Smoothing Coefficients** | | |
| **Level** | **Trend** | **Season** |  | **RMSE** | **MAE** | **MASE** | **MAPE** | **AIC** |  | **Alpha** | **Beta** | **Gamma** |
| Additive | None | Additive |  | $1.5M | $0.9M | 0.57 | 14.6% | 882 |  | 0.249 | 0.000 | 0.000 |

*Table 2: Revenue over time forecast model statistics*

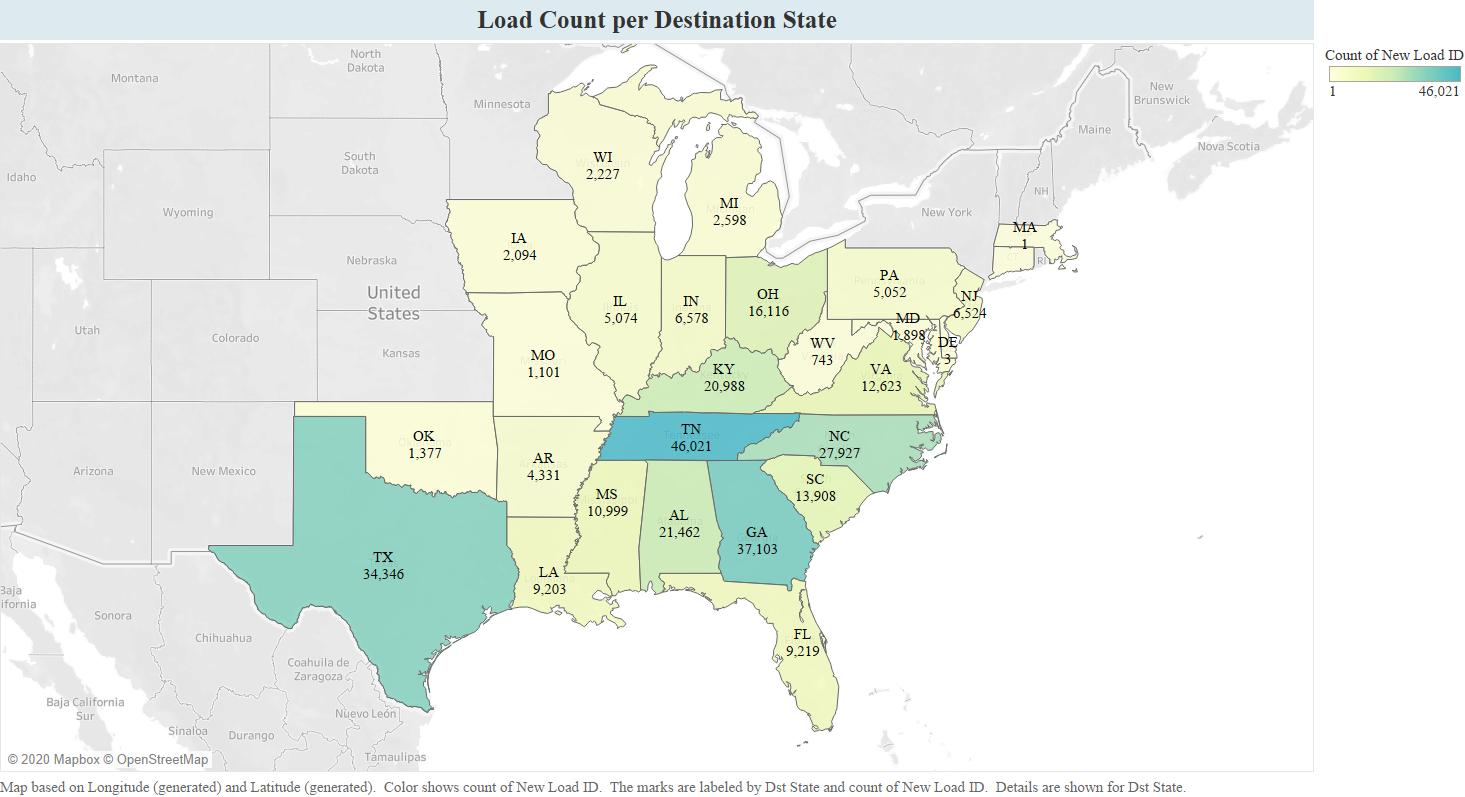
Based on the charts above, there is clear indication there is a seasonality effect on yield and total revenue. Thus, this leads to high drops in total revenue and drops in average yield.

## Mappings

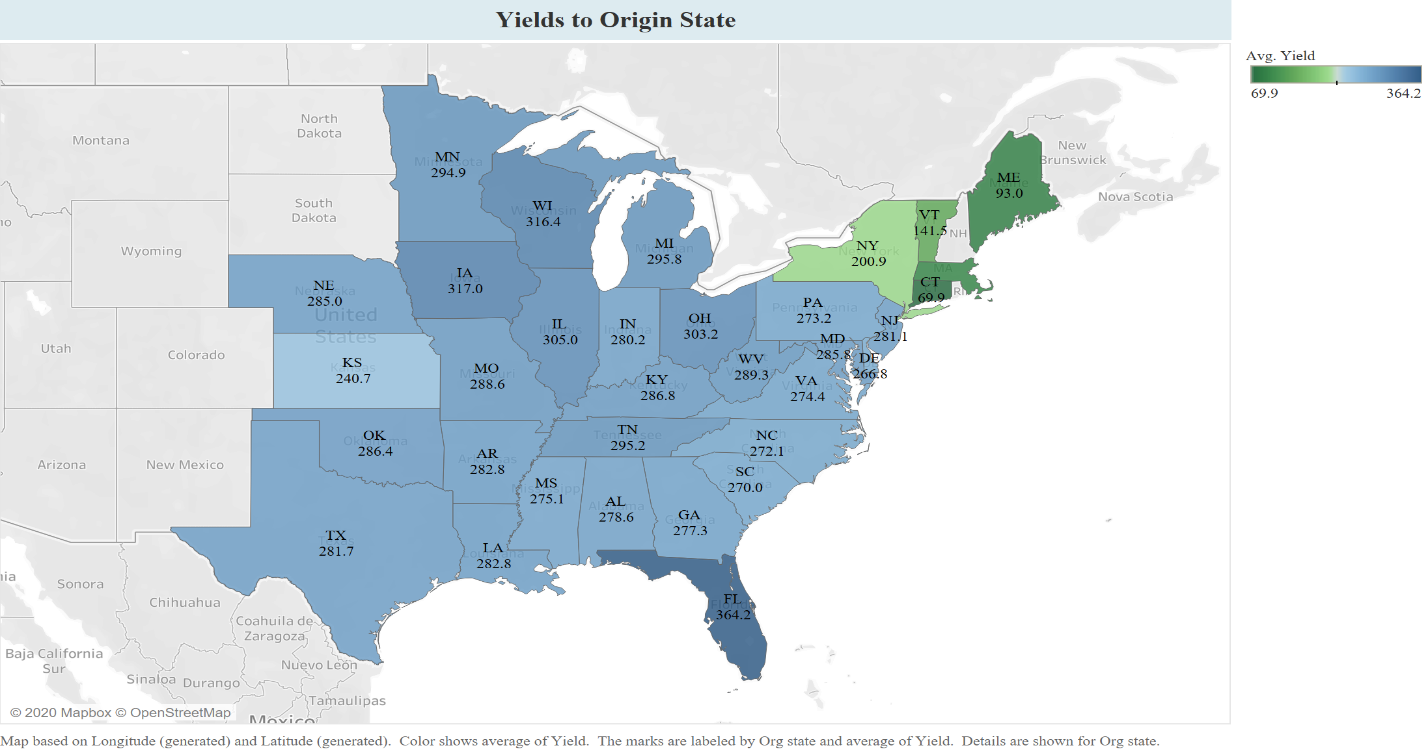
Considering the above understandings of yield and how margin and total revenue impacts it, we decided to look at how yield is allocated amongst the carrier’s transportation networks. Below is a geographical mapping of the carrier’s destination states in relation to that states average yield



*Map 1: Average Yields per Destination State*

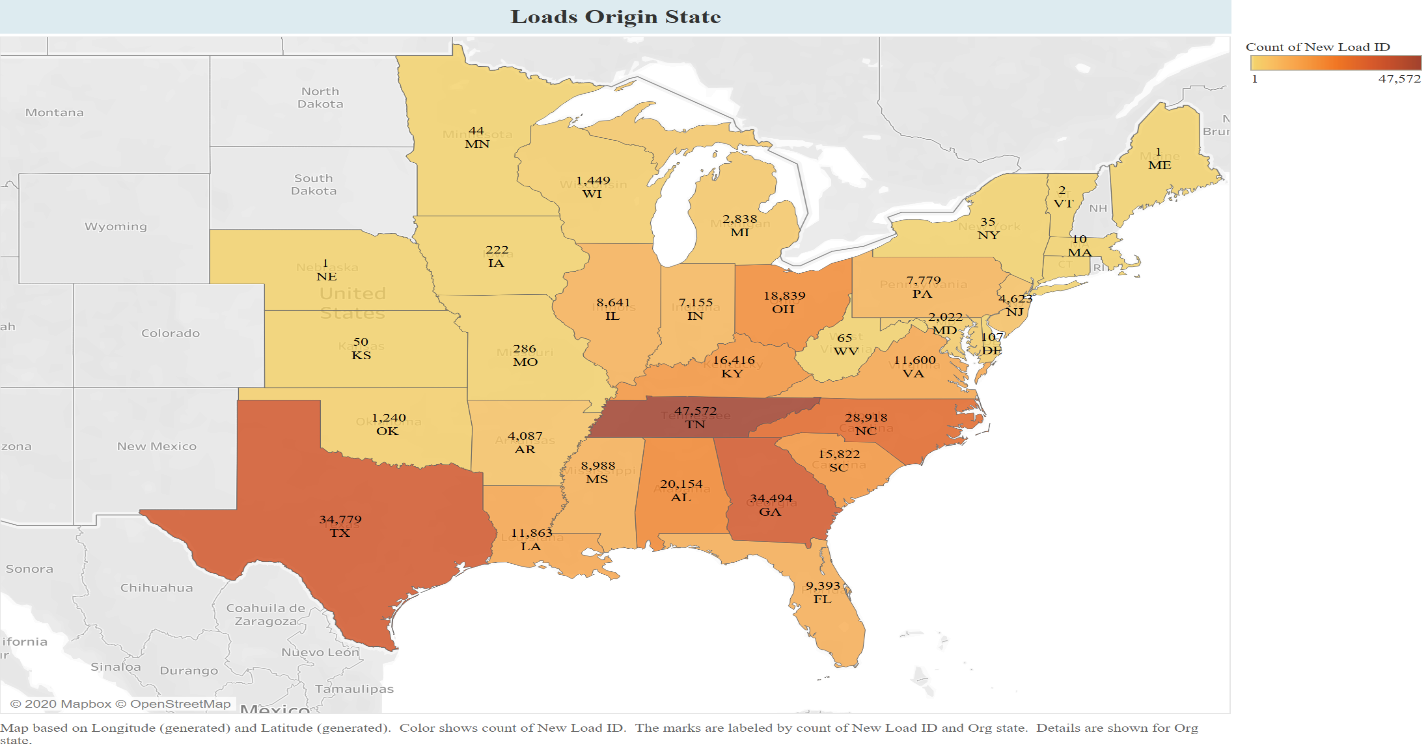
Most of the destination states yields are around the 300-yield mark. Although, there is MA, SL, and CT that have quite higher yields than the rest of the states. To drill down and see why these states were higher than the average of the rest of the states, we decided to look at the number of loads per state. Below is a graph that shows the load count per state and it reveals why those three states were higher than the rest of the states.

*Map 2: Load Count per Destination State*

The three states MA, SL, and CT all have load counts of 1. This means that these states were special occasions for this carrier, and some shippers paid a high amount for them to carry this load out of their normal transportation network. Thus, that is the reason why those 3 states are higher than the rest of their normal network. Although a transportation network is not only made up of the destination but also the origin. Therefore, the charts below are analyzing the origin areas. Looking at the average yield per Origin State and the number of loads per origin state.

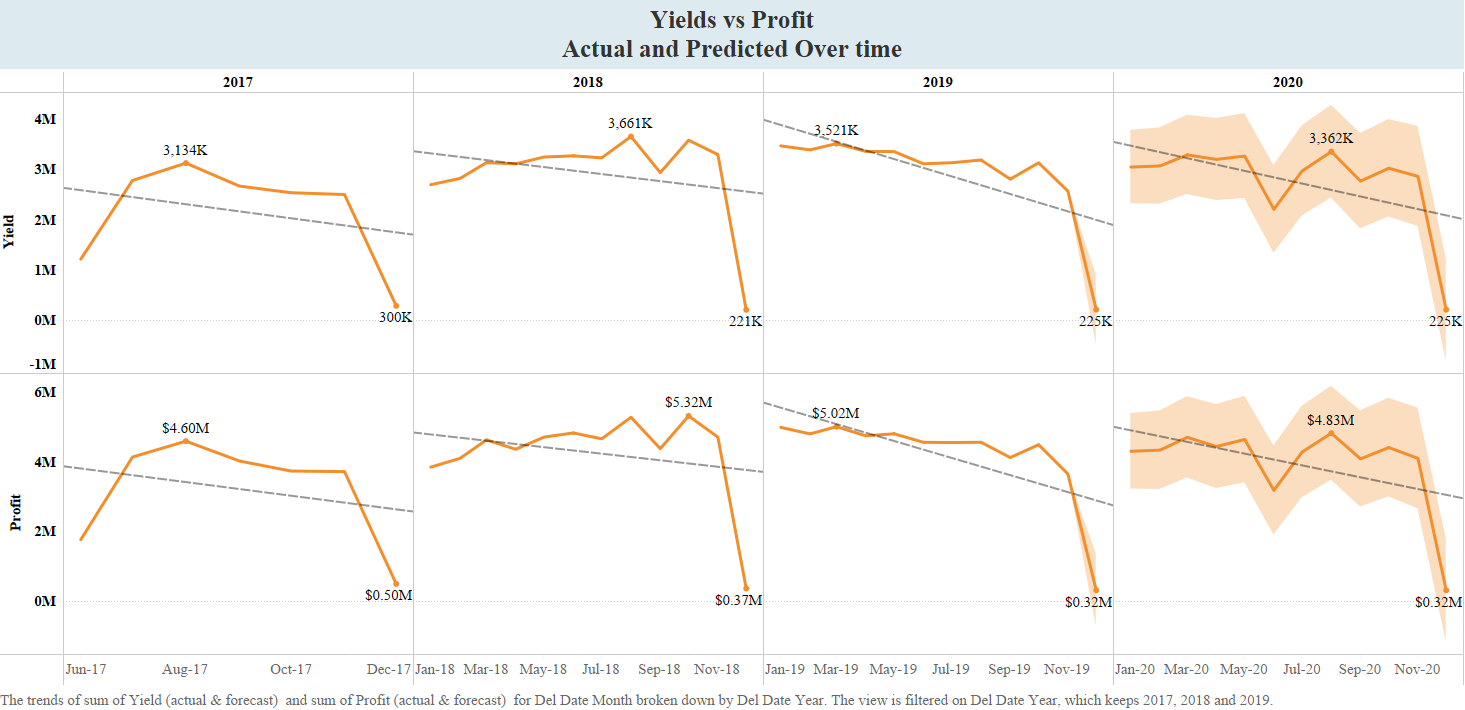
*Map 3: Yield to Origin State*

From *Map 3* above, loads that come out of the Northeast tend to have lower yields. One possible reason could be lack of manufactures in those locations. These areas should be avoided for origins, as they do not yield good results and are out of this carrier preferred network. The graph below shows that the carrier networks seem to be around the Tennessee and Georgia region. Transportation networks are built around certain relationships with shippers. These relationships need to be built inside the optimal network otherwise the yield of these out of network yields will start to decrease.



*Map 3: Yield to Origin State*

## Profit Distribution

Since our goal is predict the profitability of yield, we decided to compare actual yield and profit over time (Profit = Total Revenue -Total cost)

*Graph 7: Yield vs Profit*

Profit

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Model** | | |  | **Quality Metrics** | | | | |  | **Smoothing Coefficients** | | |
| **Level** | **Trend** | **Season** |  | **RMSE** | **MAE** | **MASE** | **MAPE** | **AIC** |  | **Alpha** | **Beta** | **Gamma** |
| Additive | None | Additive |  | $0.53M | $0.37M | 0.51 | 17.2% | 821 |  | 0.290 | 0.000 | 0.000 |

*Table 3: Profit forecast model statistics*

Yield

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Model** | | |  | **Quality Metrics** | | | | |  | **Smoothing Coefficients** | | |
| **Level** | **Trend** | **Season** |  | **RMSE** | **MAE** | **MASE** | **MAPE** | **AIC** |  | **Alpha** | **Beta** | **Gamma** |
| Additive | None | Additive |  | 355K | 247K | 0.48 | 18.5% | 797 |  | 0.307 | 0.000 | 0.000 |

*![A picture containing screenshot

Description automatically generated](data:image/jpeg;base64,/9j/4AAQSkZJRgABAQEAeAB4AAD/4RDoRXhpZgAATU0AKgAAAAgABAE7AAIAAAAKAAAISodpAAQAAAABAAAIVJydAAEAAAAUAAAQzOocAAcAAAgMAAAAPgAAAAAc6gAAAAgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAEFsb3RhIENoZQAABZADAAIAAAAUAAAQopAEAAIAAAAUAAAQtpKRAAIAAAADNDEAAJKSAAIAAAADNDEAAOocAAcAAAgMAAAIlgAAAAAc6gAAAAgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA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4: Yield forecast model statistics*

*Figure 5: Yield and Profit (Actual and Predicted model)*

Based on the charts and graphs above, it is evident that that the industry is highly affected by changing seasons, thus a change in yield cause a change in profits, i.e., an increase in yield will lead to an increase in profits. The scatter plot shows a positive and strong relationship between yield and profits.

A screenshot of a cell phone

Description automatically generated

*Graph 8: Yield to Profit distribution*

Now that we understand the relationship between yield and profit, its worth knowing the profit of each state given the project time available for each state (PTA State). The map below shows that ME, CT and NE are the least profitable, while NM, CA, SD and LA and a host of other stats seems to be more profitable

*A picture containing text, map

Description automatically generated*

*Map 4: Average profit per state*

## Loaded Miles

A close up of a map

Description automatically generatedWithin the transportation industry, there is movement from point A to point B. These movement could either be loaded miles or empty miles (see data understanding and section). Haankuku and Epplin (2015) reported that distance traveled is important is determining yield. We therefore sought to see the relationship that exist between yields and miles.

*Graph 9: Yield to Loaded Miles*

A screenshot of a social media post

Description automatically generated

*Graph 10: Yield to Empty Miles*

From the charts above, graph 10 shows that as carries moving from PTA to origin with no material are wasting resources and reducing their profit. This shows a strong negative relationship between both variables

## Summary

Give the large number of variables in the dataset, and considering the variable of other researchers, its worth stating the exploratory analysis carried above provided enough insights into the company and the dataset in question. Therefore, with the use of SAS enterprise miner we will further carry out predicting modelling to provide solutions to our problem.

# **Modeling**

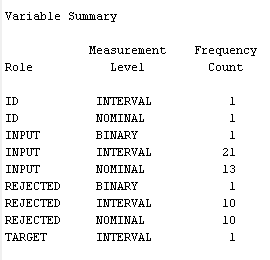
Two approaches have been taken regarding predicting our target variable. In this section, we will cover both:

1. Prediction with all non-redundant variables (covered in part 1)
2. Prediction using a dataset adjusted to exclude more outliers and less variables used in prediction process. (covered in Part 2)

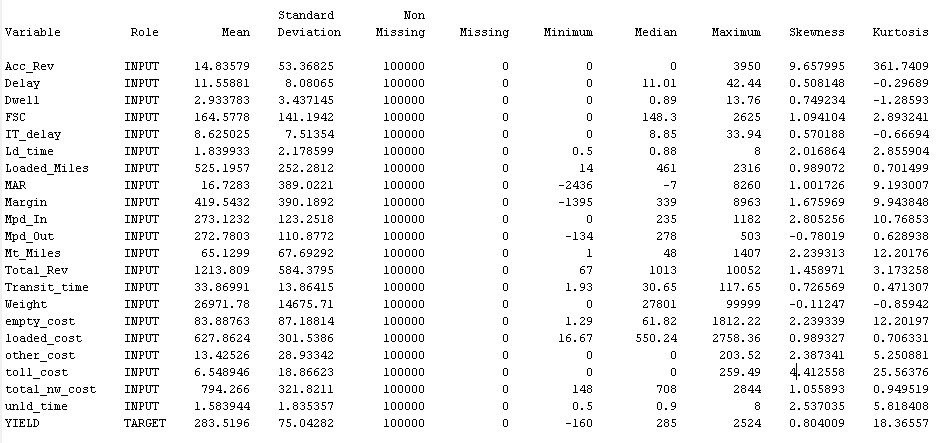
## Part 1: Prediction using all non-redundant variables.

### Data Adjustment:

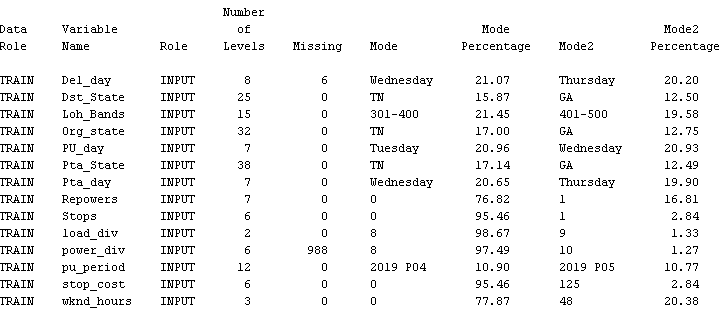
We started our modeling process by loading the data into SAS Studio then SAS Enterprise Miner. Our first goal was to get some understanding of the variables. Using the StatExplore node, got information such as variable means, deviation, skewness and kurtosis. With StatExplore we were able to also look at how many missing values for both the nominal and interval variables. The StatExplore results are presented below:



*Figure 6: Variable Summary*



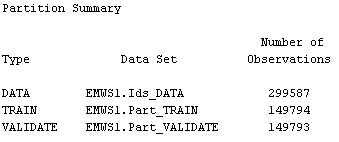
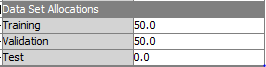
*Figure 7: Missing values for interval variables*



*Figure 8: Missing values for class variables*

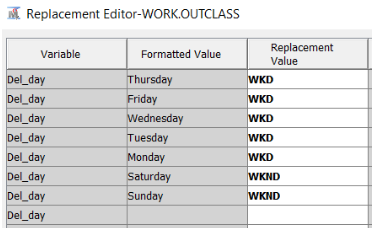
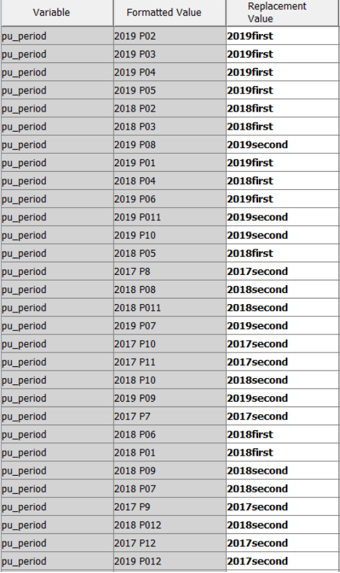
Notice that there are two class variables and no interval variables for which there are missing values. To fix this, we will later impute these values and replace the missing values, in order to run the regression model.

As part of the data adjustment process, we partitioned our data. We split the dataset allocation 50:50 meaning half of our dataset was used as our training data and the other half was used as validation data. The image below shows the partition summary.



*Figure 9: Data Partition Summary*

In addition to that we changed the levels in the categorical variables PU\_day, Del\_day, Loh\_Bands, PU\_period and Pta\_day. The days variables were changed such that weekdays are categorized as WKD and weekends as WKND. Loh\_Bands had periods which represent month; for instance P01 represends the January period. What we did was reduce the levels and just categorize the 12 periods into 2 periods where the Yearfirst would indicate the first six months and Yearsecond would indicate July through december. Here below are the captured images of the replacement editor.

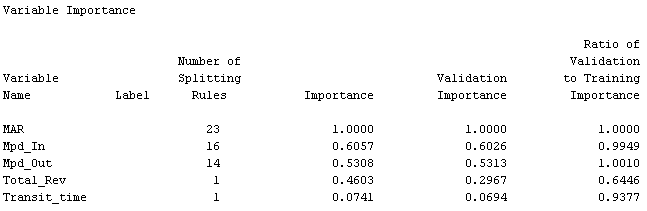
 

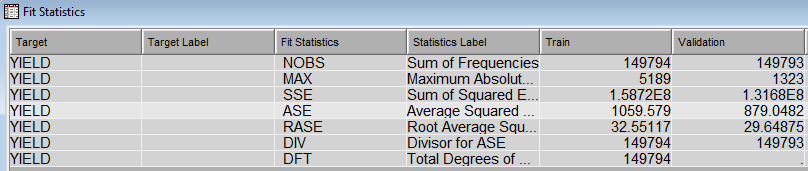
### Data Analysis and Modeling Methods.

In this project with the help of SAS Enterprise Miner, we used five primary predictive modeling techniques **Decision Trees**, **Regression**, **Neural Networks** and **Auto neural Networks**. Each of these techniques had different parameters to get the best predictive model. Two decision trees were made, four regression models and a variable selection model were imputed and used to make six neural network models as well as one Auto neural Network model. The variable were transformed to control for input skewness via a log transformation. Given that our goal is to optimize our interval target variable **Yield,** we evaluated the models based on the selection criterion average squared error. SAS Enterprise Miner suggests using average squared error as the selection criterion. Although mean squared error is another good criterion to use for interval target variables, it is not nearly as useful for neural networks as it is for linear models. Thus, this is the reason why we stuck to average squared error (ASE). Throughout the data analysis of our project, we had the goal to get the best predictive model by minimizing the ASE and thus maximizing accuracy between the outcomes and predictions.

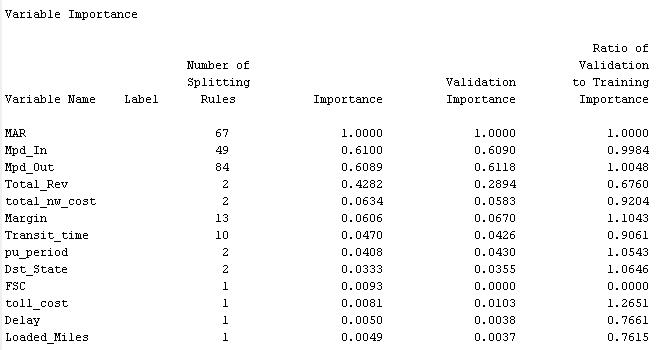
### Decision Trees.

We build two decision trees: two maximum trees except that for the second maximum tree we set the splitting rule in the properties panel to three so that the number of branches emanating from a node are exactly three branches. The first maximum tree used the SAS Enterprise Miner default number which is two branches. Below are some screenshots of both decision trees. The 3-branch decision tree performed better. In terms of variable importance, both trees showed that variable MAR, mpd\_in and mpd\_out were the trees’ most important variables, respectively. The next two most important variables for the maximum tree are total\_rev and transit\_time whereas the next two most import variables for the 3-branch decision tree are total\_rev and total\_nw\_cost. The maximum tree and 3-branch tree gave us validation average squared errors of 879.0482 and 389.59, respectively. The maximum decision tree has 56 leaves and on the other hand the 3-branch decision tree has 458 leaves.

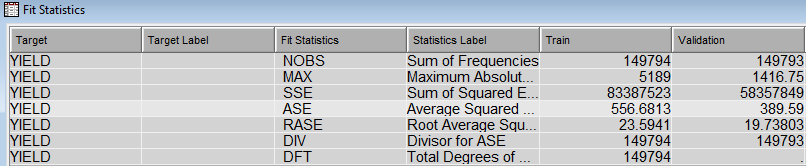


*Figure 10: Variable importance for Maximum Tree*

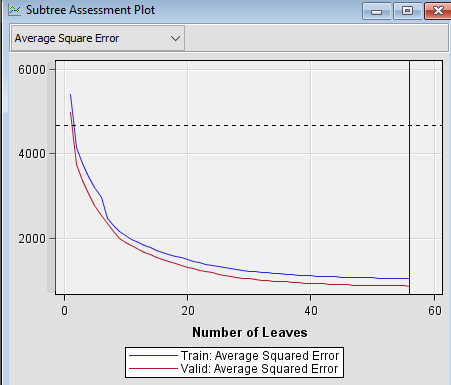
*Figure 11: Fits statistics for Maximum (MAX) Tree*

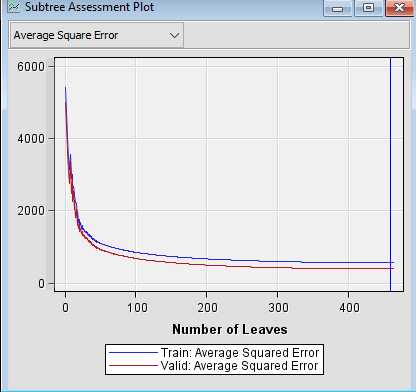


*Figure 12: Variable Importance Information for 3 branch decision Tree*

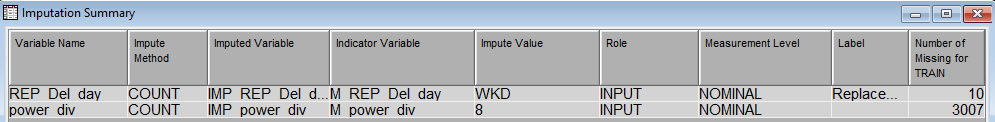


*Figure 13: Fits statistics for 3 Branch Tree*



*Figure 14: Subtree Assessment Plot for Maximum tree*

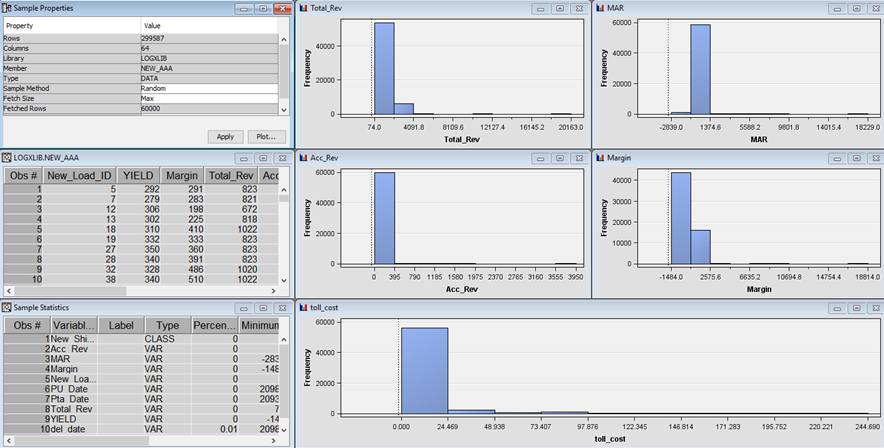
*Figure 15: Subtree Assessment plot for 3-branch Decision tree*

After the creating the decision tree models, we then wanted to look at how well a regression model would fit to data. In order to run the regression models and take care of the missing values problem mentioned previously, we imputed the data and the results are shown in the screenshot below.

*Figure 16: Imputation Results*

The imputation summary above shows that two variables: the replaced variable REP Del\_day and the variable power\_div were imputed. The two variables are nominal and so as such the imputation process replaced the missing values in those columns with the most common/mode of the non-missing values.

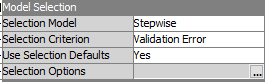
Regression is sensitive to extreme values in the input space. Inputs that have a high skewness can affect our prediction models and outcomes. To minimize this issue, we transformed variables that showed a high skewness i.e. a skewness of lower than -3 or higher than 3 via a log transformation. Those variables are Margin, total\_rev, acc\_rev, MAR and toll\_cost. The folowing figure describes the skewed variables’ distributions.



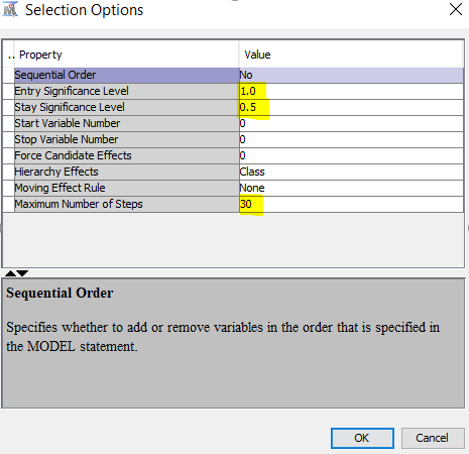
*Figure 17: Skewed variables’ distributions*

### Regression Models.

We ran regression models using the regression node in SAS enterprise miner. We ran two different types of regression models; regression model using selection defaults in the model criterion and a regression model that does not use selection defaults.

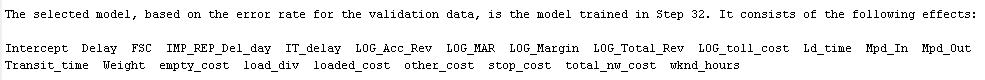


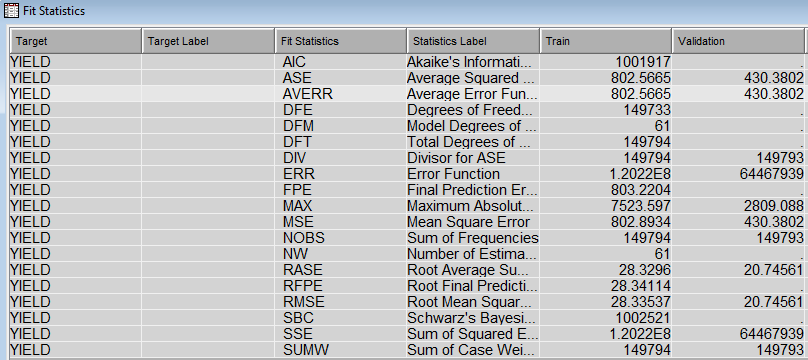
*Figure 18: Model Selection with selection defaults*



*Figure 19: Selection options for regression full model node*

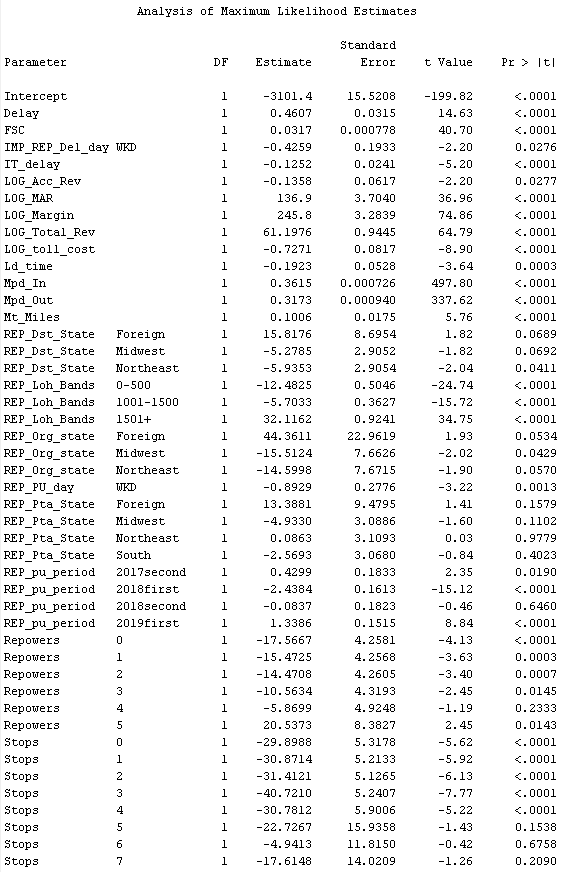
The first regression that used the defaults criterion gave us an average squared error of 430.3802. The summary shows the step in which the model was added and all variables that are statistically significant (P-value<0.05). The model is selected at step 32 as shown below in the summary stepwise selection. The iteration plot shows that the model with the smallest average squared error which also occurs at step 32. The following variables are included in the final model: Delay, FSC, IMP\_REP\_Del\_day, IT\_delay, LOG\_Acc\_Rec, LOG\_Margin, LOG\_Total\_Rev, LOG\_toll\_cost, Ld\_time, Mpd\_in, Mpd\_out, Mt\_Miles, REP\_Dst\_State , REP\_Loh\_Bands REP\_Org\_state, REP\_PU\_day, REP\_Pta\_State, REP\_pu\_period , Repowers, Stops, Transit\_time, Weight , empty\_cost, load\_div, loaded\_cost, other\_cost, stop\_cost , total\_nw\_cost and wknd\_hours0.



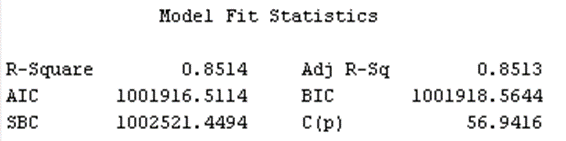


*Figure 20: Fit Statistics for Regression Node*

The above parameter estimates tells us that for every one unit increase in delay, yield of the load increases by 0.4670 . Everyone dollar increase in fuel surcharge leads to 0.0317 decrease in Yield. For North East destination states, the Yield is -5.9353 lower relative to the other destination states. Etc.

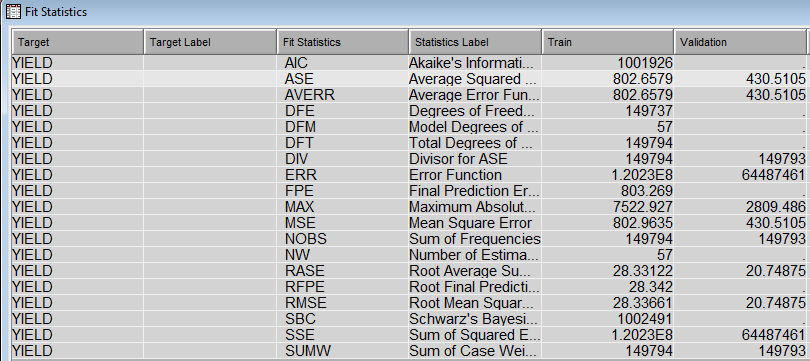


*Figure 21: Parameter estimates for Regression Node*

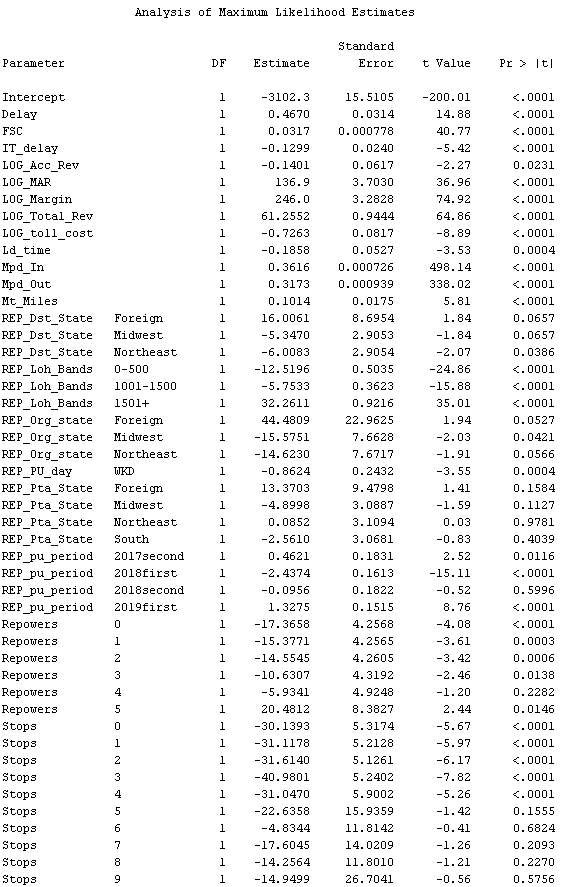
****It is worth noting that the adjusted R-Squared, as shown below, is 0.8513 which may be an indication that we are overfitting the model. Later in this report, we will introduce a new model that minimizes the overfitting problem.

*Figure 22 Model Fit Statistics*

The second regression gave us an average squared error of 430.5105 as shown in the fit statistics image below. The summary shows the step in which the model was added and all variables that are statistically significant (P-value<0.05). For this regression, the model is selected at step 30. The iteration plot shows that the model with the smallest average squared error occurs at step 29. The same variables included in the first regression model were also the ones included in this altered one.



*Figure 23: Fit Statistics for Altered Regression Node*

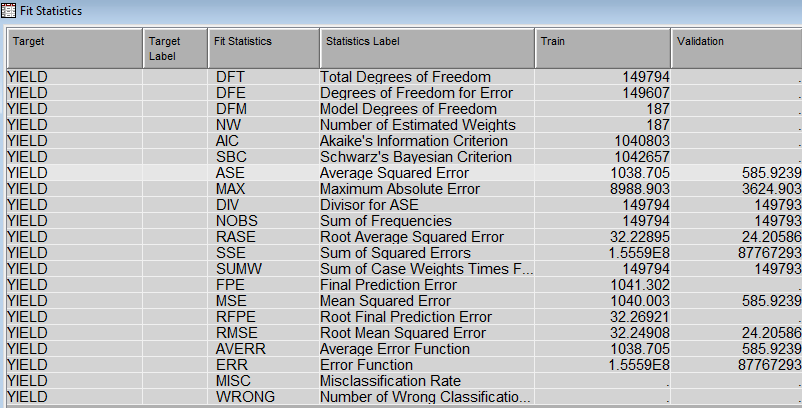


*Figure 23: A few of the parameter estimates for Altered Regression Node*

### Neural Networks.

Our final models are neural network models that go through the regression, variable selection and decision tree nodes.

#### **Neural Network using regression node:**

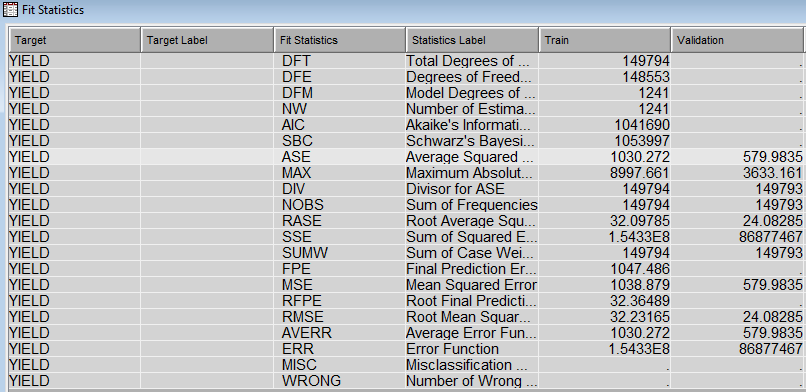
We connected a neural network node to the first regression node (regression defaults) node to help with input selection. The results below show that iteration 100 was selected with a validation average squared error of 585.92 which is only better than the first decision tree; the maximum tree. This neural network was not better than the other decision tree or either regressions.

*Figure 24: Neural Network fit statistics*



*Figure 25: Neural Network iteration plot*

#### **Auto neural networks using regression node:**

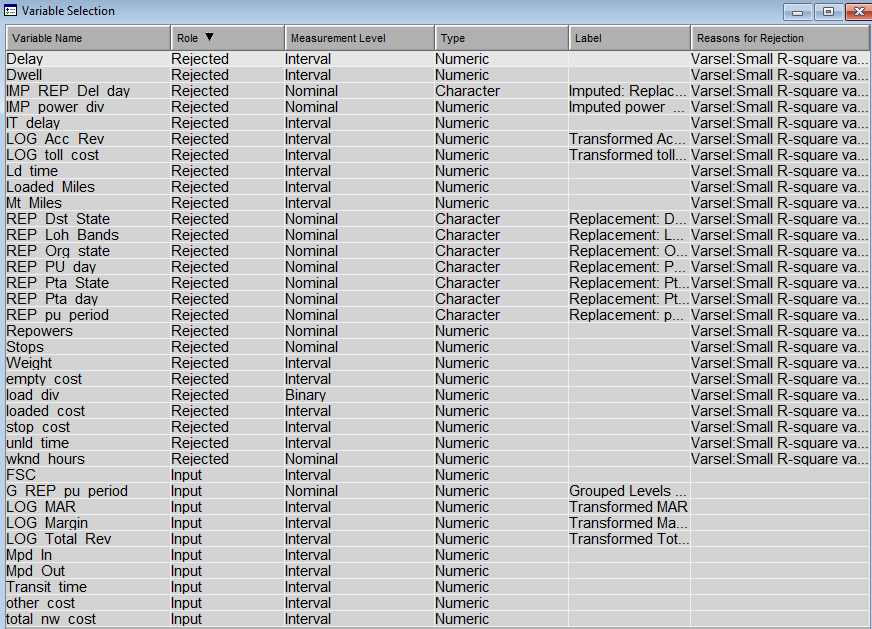
An auto neural network was used with the regression node to select inputs. Ten hidden units were selected, and the validation average squared error was 579.983.

*Figure 26: Auto Neural Network fit statistics*



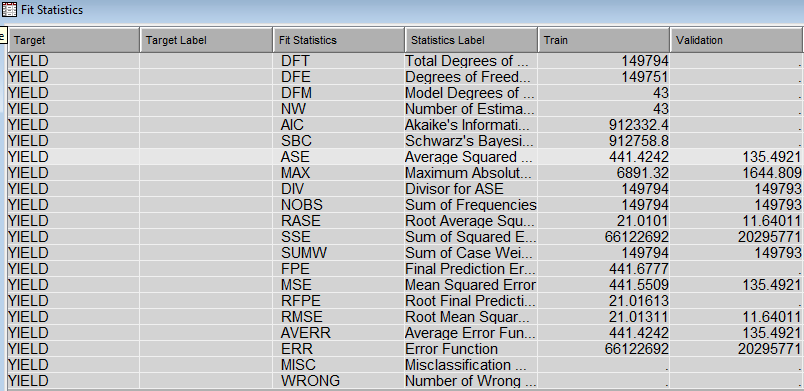
*Figure 27: Auto Neural Network iteration plot*

#### **Variable selection:**

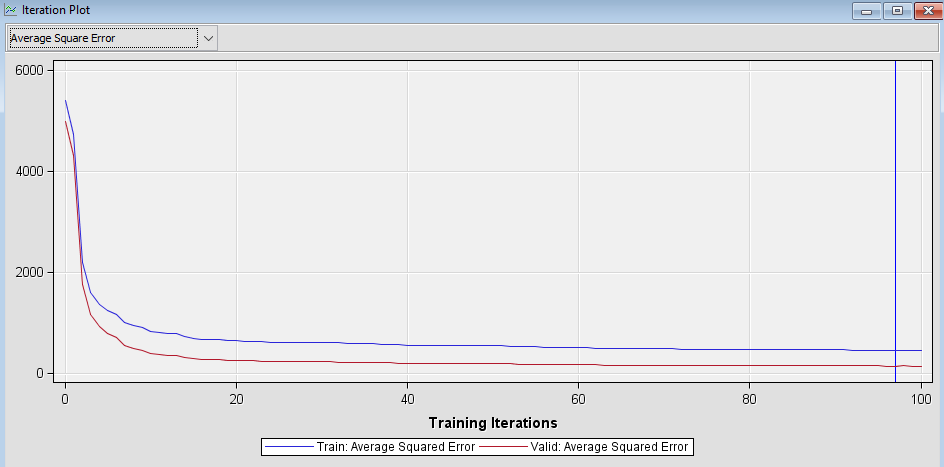
We used the variable selection tool to evaluate the importance of input variables in predicting our target variable Yield. To select the important inputs, we used the R-square selection criterion since we were working with an interval target variable. The variable selection process allowed for removal of variables that have large percentages of missing values and thus rejected those variables. Note that these rejected variables are not passed to subsequent tools in the process flow diagram; they are not used as model inputs by more detailed modeling tools such as neural networks. The image below of the variable selection window shows us the rejected variables and the reasons for rejection. This means that all the rejected variables have insufficient target correlation to justify keeping them. Note that 26 input variables were rejected.

*Figure 28: Variable selection Results*

A neural network was connected to our variable selection node. Iteration 98 was selected with an average squared error of 135.49 which is smaller than those of the previous models used.

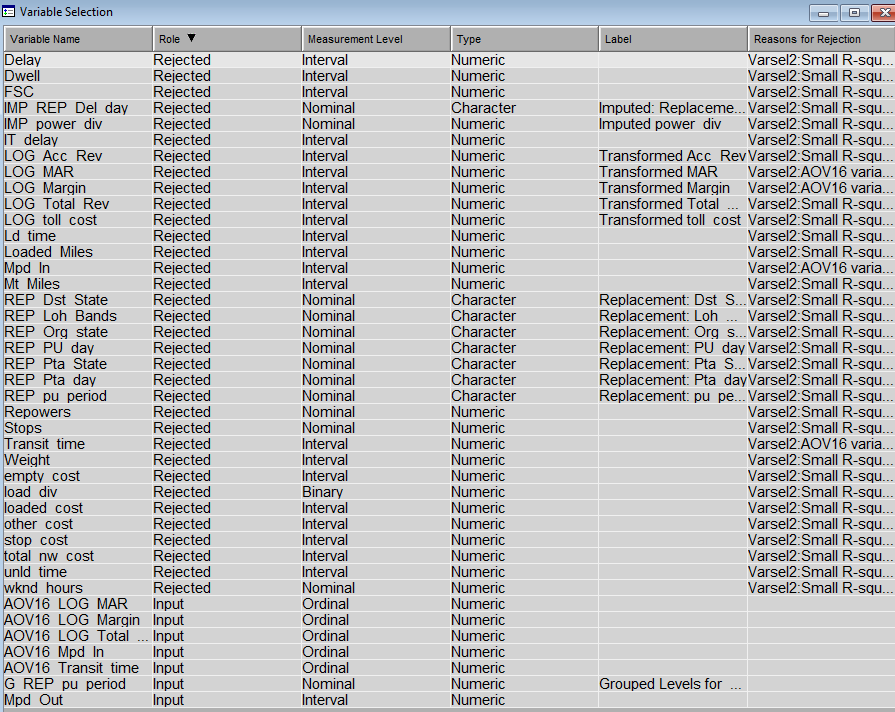


*Figure 29: Variable selection fit statistics*

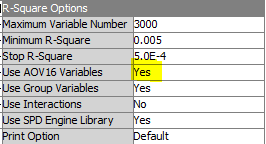


*Figure 30: Variable selection iteration plot*

#### **A0V16 Variable Selection:**

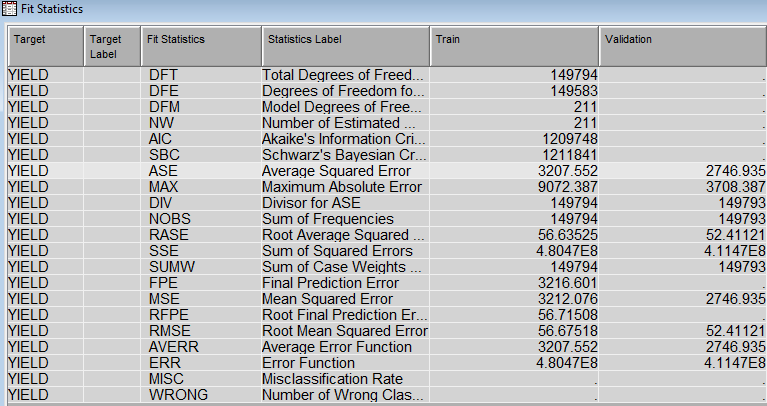
We also proceeded to use another variable selection node that uses A0V16 variables. These variables are created to help identify nonlinear relationships between the inputs and target. With this R-Square option, SAS Enterprise Miner bins interval variables into 16 equally spaced groups. From the variable selection window, we can see that 34 inputs were rejected

*Figure 31: AOV16 Variable selection rejected and input variables*

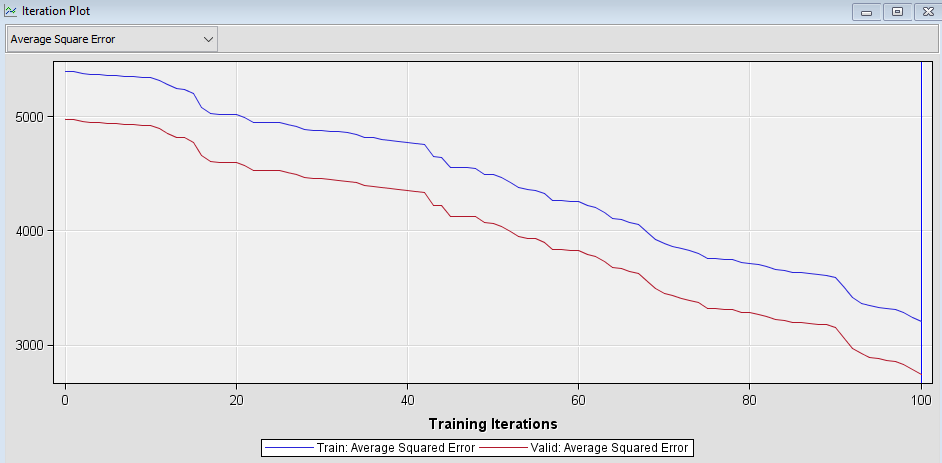


*Figure 32: AOV16 Variable*

A neural network was connected to our variable selection node. Iteration 100 was selected with an average squared error of 2746.93 which is a very high average squared error to have. The iteration plot also shows us that the train and validation iterations do not converge nor diverge.

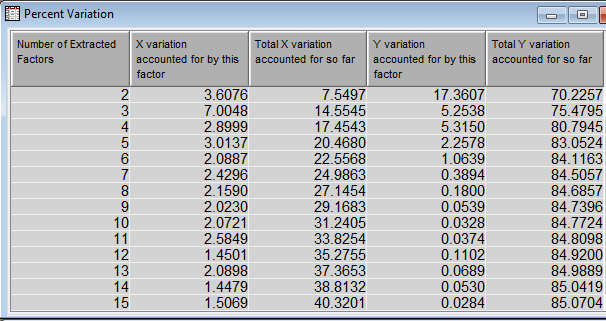


*Figure 33: AOV16 Variable selection fit statistics*

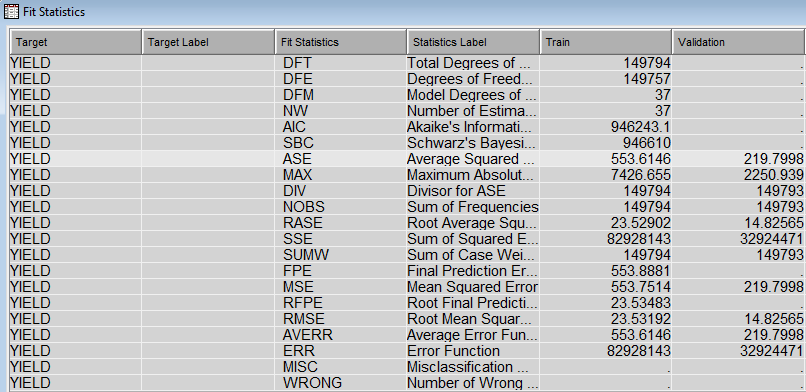


*Figure 34: AOV16 Variable selection iteration plot*

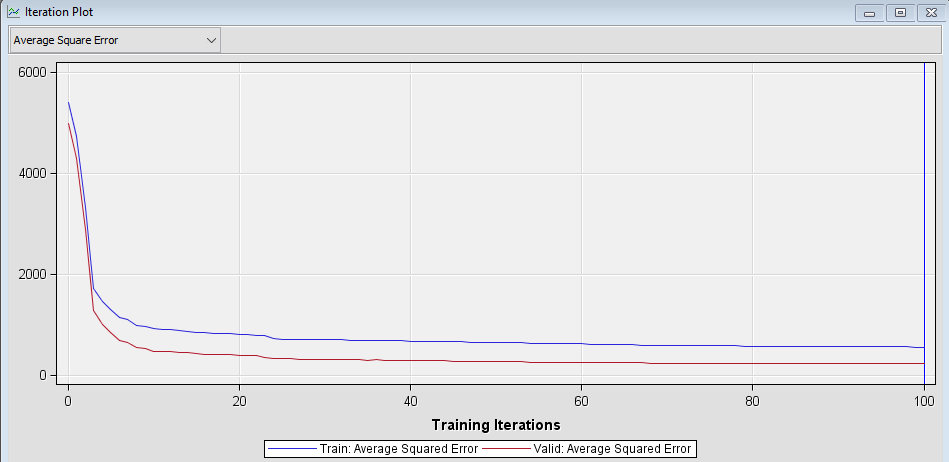
#### **Partial Least Squares (PLS) for Input Selection:**

By using PLS, the goal was to have linear combinations of the input variables that account for variation in both the inputs (or else referred to as latent vectors) and our target variable Yield. By default, the PLS tool extracted 15 latent vectors/factors from our training data set. These factors account for 40.32% and 85.07% of the variation in the inputs and target variable Yield, respectively. Similarly, to the neural network above, iteration 100 was selected for Neural Networks-Partial Least Square. (i.e. indicating 100 hidden units).

*Figure 35: Partial least Square percent variation*



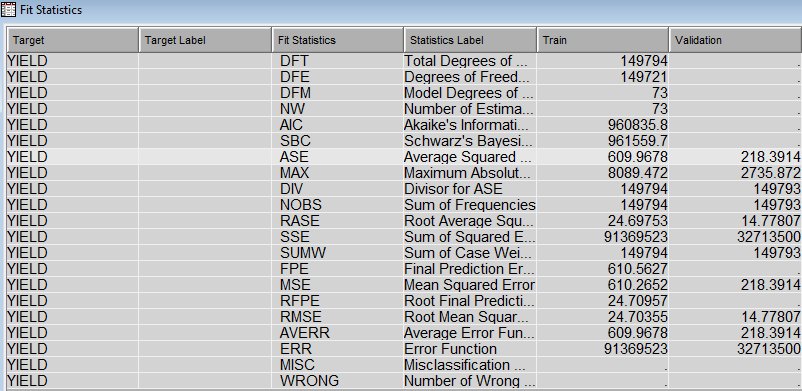
*Figure 36: Partial least Square fit statistics*



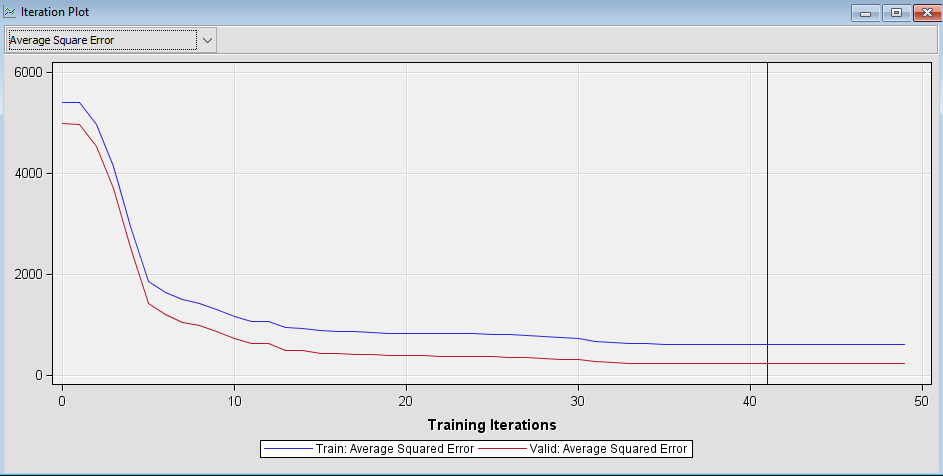
*Figure 37: Partial least Square iteration plot*

#### **Neural Network using Decision Tree variable selection (NN DT):**

The validation average squared error was 218.39 and 41 hidden units were selected.

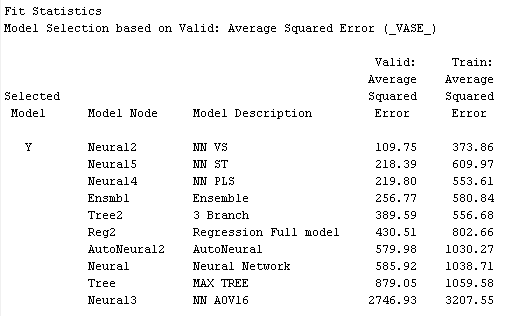


*Figure 38: Neural Networks using decision tree variable selection fit statistics*



*Figure 39: Neural Networks using decision tree variable selection iteration plot*

#### **Model Comparison:**

For estimates predictions, the model comparison tool rates the models’ performances based on average squared errors. After running all the different predictive models, the selected best model was the variable selection Neural Network (NN VS). The model comparison results are shown here below.

*Figure 40: Model selection fit statistics*

## Summary:

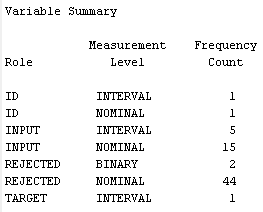
The first model we provided accurately represented the data set we were provided. With our best model being the Neural Network from our variable selection node with Average squared error of only 109.75 over nearly 300,000 records. This fits closely with ideas we have developed from our literature review showing that Neural Networks seem to have the best fit statistics out of other models. The model fits very well almost to the point of overfitting. Although, the goal of our research is to give C-Suite executives better understanding of loads before they happen. In doing so carriers can have a better load selection process. This model we provided is very useful for carrier’s that wish to have a diagnostic view on their analytics. Although, the goal of this paper is to provide an insight for carriers that wish to have a predictive view on analytics.

# **Part 2: Prediction using reduced version of dataset.**

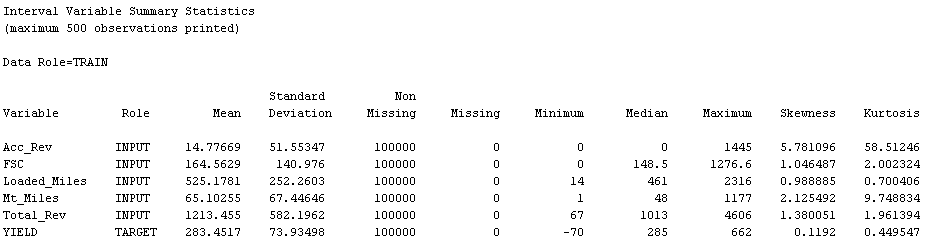
## Data Adjustment

After running our models with the previous version of the dataset, we noticed that there is an overfitting problem since the adjusted R-Squared was very high. We decided to remove more outliers from the dataset and use fewer variables in the constructed models. The reason for using fewer variables was that, based on all the variables included in the previous models in Part 1, the selected best model is not applicable for predicting future loads. Variables related to costs or time that were previously used are not useful for the purpose of our project. That is because such variables are only calculated/generated once the load is completed. The goal is to predict Yield before the load is carried out for delivery. Variables like transit-time can only be determined once the delivery of the load has been completed. For that reason, it does not serve useful to include the costs, times variables such as delay, transit\_time, ld\_time, and other variables such as repowers and stops. In addition to columns being deleted, six new variables were created in this version of the model. Since we had data for historical Margin per day in and margin per day out, we decided to use that to tie to our origin and destination regions. We grouped the average mpd-in and mpd-out for each region and assigned them to their respected reasons. We also took the average MAR of the destination and origin regions. In doing so our regions now have something meaningful connected to them. By created these new columns it increased the fit statistics of our model.

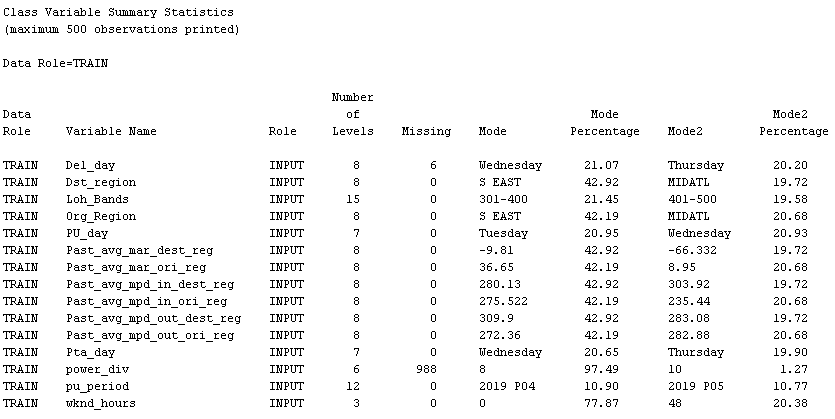
The new changes were made to be reflected in the new data set used. The figures below are the variable summary results. Notice that now only twenty inputs are used compared to thirty-five inputs previously used. Once categorical variable power\_div had missing values whereas no interval variable did. This reflected in the results shown here below:



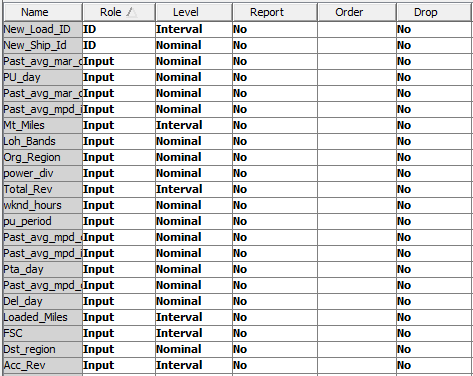
*Figure 41: Variable Summary*



*Figure 42: Missing values for interval variables*



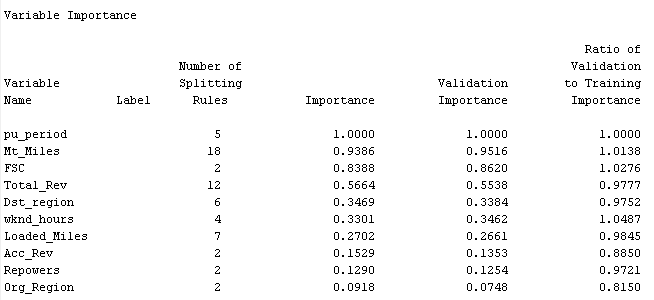
*Figure 42: Missing values for class variables*

The figure below shows the lists of inputs. The same diagram process flow from the previous section was duplicated, with minor changes when necessary, and was used to come up with good but more applicable predictive models.

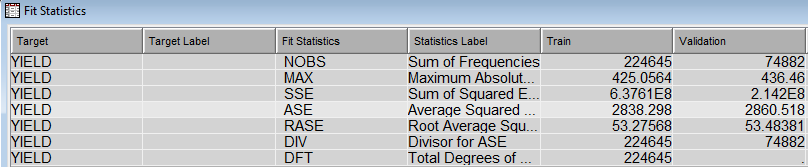
*Figure 43: Reduced Dataset input list*

## **Data Analysis and Modeling Methods**

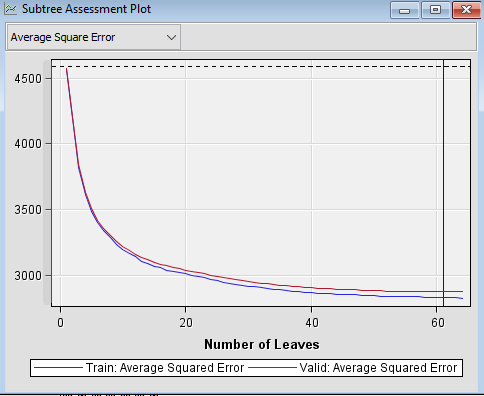
### **Decision Trees:**

The maximum tree was created using average squared error as the model assessment statistic gave us 62 leaves. The variable importance results are captured and inserted here below. Pu\_period which is the pickup period is the most important variable in the maximum tree.

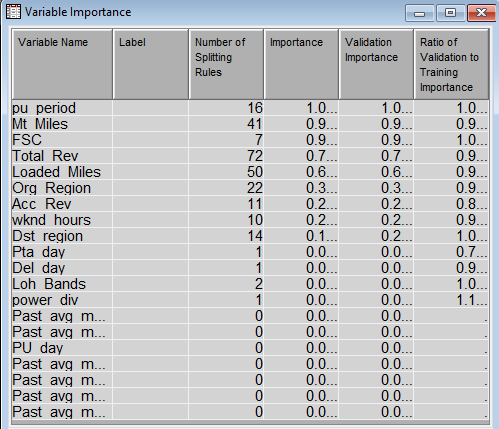
*Figure 44: Decision Tree Variable Importance*



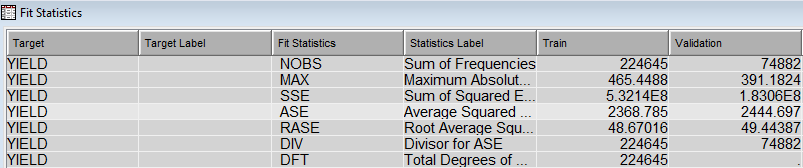
*Figure 45: Decision Tree Fit Statistics*



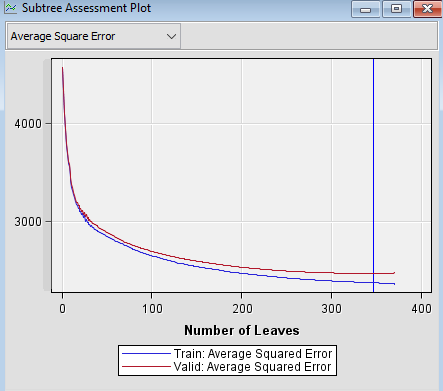
*Figure 46: Decision Tree subtree assessment plot*

The three-branch decision tree, on the other hand, gave a validation average squared error of exactly 2444.697 as show in fit statistics graph below. The subtree assessment plot shows us that this tree has 347 leaves.

*Figure 47: Decision Tree(3-Branch) Variable Importance*

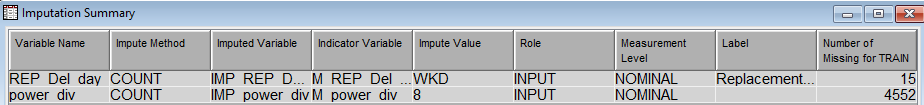


*Figure 48: Decision Tree(3-Branch) Fit Statistics*



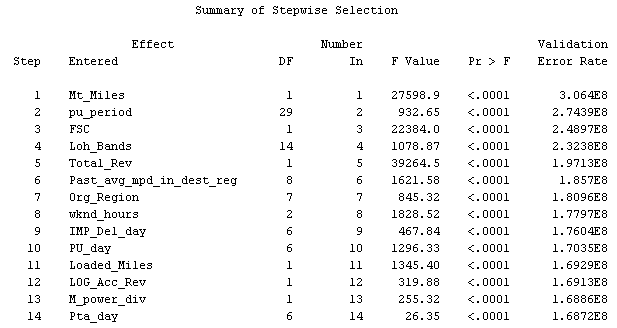
*Figure 49: Decision Tree (3-branch) subtree assessment plot*

The ProbF used which is the p-value of the F test that is associated with the node variance is sensitive to outliers. As we can see, the high number of outliers and variables in the model decreases the validation average squared error (or in other words, removing the outliers and rejecting more variables raise the average squared error).

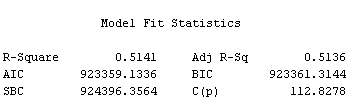
Before doing regression, we transformed, replaced and imputed variables. The transformations of the data were necessary, because the variable Acc\_rev and total\_rev had a high skewness. We split the data 50:50 between the validation and training nodes. The imputed variables are REP\_Del\_day and power\_div.

*Figure 50: Transformation imputation summary*

### **Regression models:**

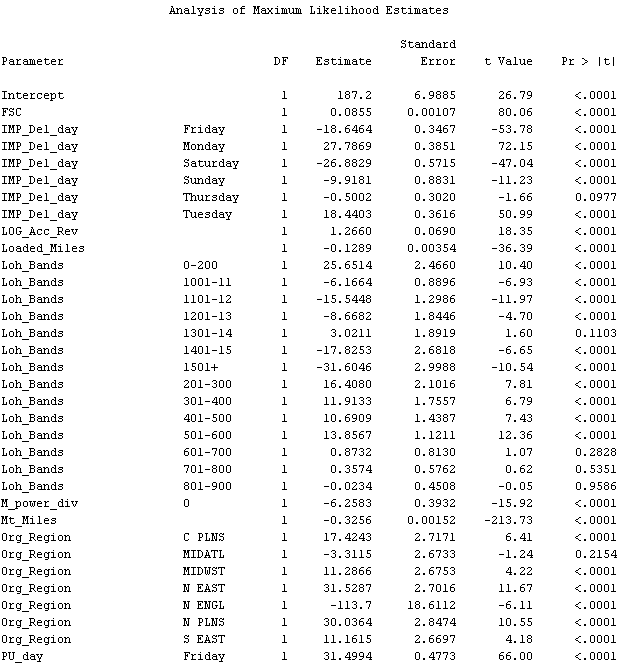
By using a similar diagram process flow, we ended up using the stepwise selection model and the average squared error as the selection criterion exactly as we had in secton1. This first regression model (which did not pass through the replacement node) was better than both decision trees; it has a validation average squared error of 2253.188 and an adjusted R-Squared of 0.5136.

*Figure 51: Summary of stepwise selection*



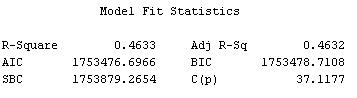
*Figure 52: Model fit Statistics*

Some of the parameters estimates of the non-reduced categorical variables are captured here below. All of them were not captured as there were many categorical variables and we believed a better model could be generated after reducing the number of levels.

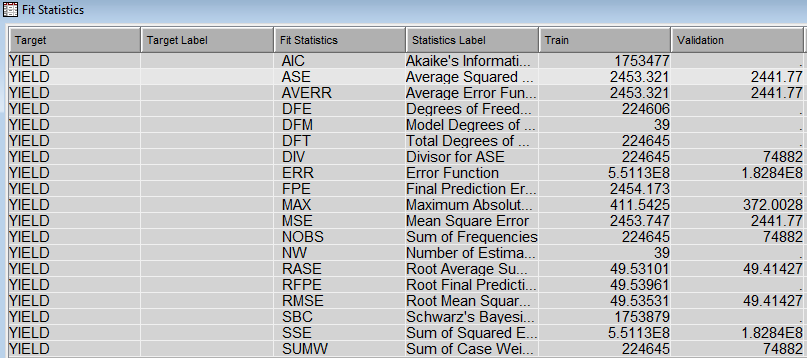


*Figure 53: Parameter estimates*

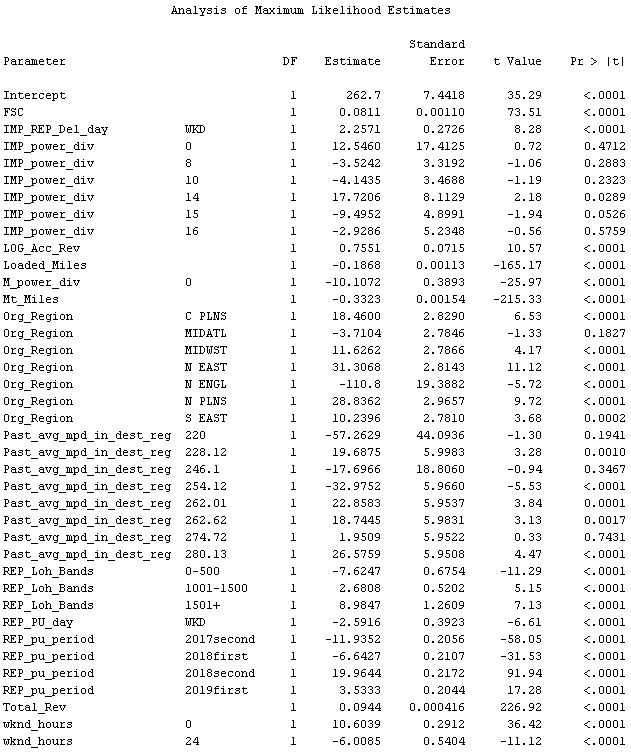
#### **Reduced Regression Model (Regression Full Model):**

The previous regression node was copy-pasted and placed after the replacement node to see whether reducing the number of levels of the categorical inputs would improve the regression model. The variables PU\_day, Del\_day, Loh\_Bands and PU\_period were good candidates for reduction. After the reduction, the validation average squared error increased from 2253.188 to 2441.77 and the adjusted R-Squared decreased from 0.5136 to 0.4632 as captured in the model fit statistics below. Therefore, reducing the number of levels in the categorical variables did not improve the model as it increased the validation average squared error.

*Figure 54: Reduced Regression Model fit statistics*



*Figure 55: Reduced Regression Model fit statistics*

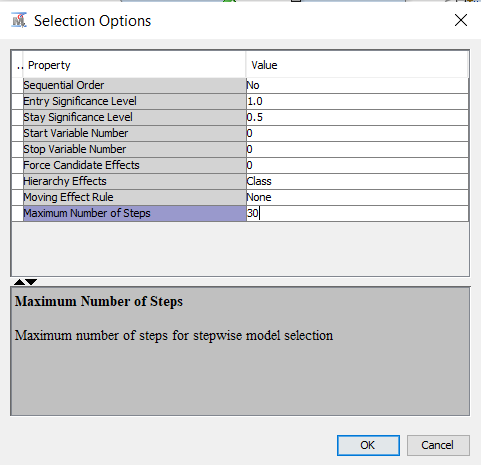


*Figure 56: Reduced Regression Model parameter estimates*

Of the twenty input variables, the following fourteen variables were included in the final mode: FSC, IMP\_REP\_Del\_day, IMP\_power\_div, LOG\_Acc\_Rev, Loaded\_Miles, M\_power\_div, Mt\_Miles, Org\_Region, Past\_avg\_mpd\_in\_dest\_reg, REP\_Loh\_Bands, REP\_PU\_day, REP\_pu\_period, Total\_Rev and wknd\_hours.

For weekday delivery days, yield of the load is 2.25 times higher than for weekend delivery days. Every one-mile increase in deadhead miles (which are miles where the truck is on the road, but no load is carried) decreases yield by 0.323 units. Similarly, for trucks that operate in sector division 8, yield of the load those trucks carry is -3.52 times less than relative to trucks that operate in other sector divisions.

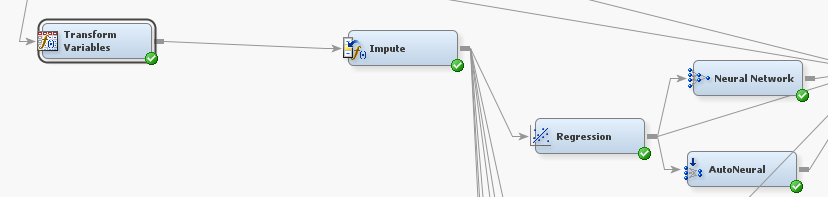
#### **Full Model Regression:**

Our full regression model contains selection criterion validation error because our prediction is an interval variable. Similarly, to the previous regression models, we used selection model stepwise.

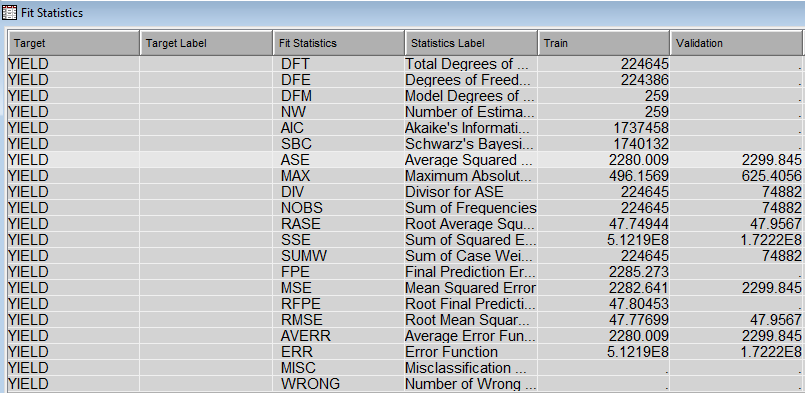
*Figure 56: Selection option*

#### **Neural Networks:**

1. **Neural Network Node using regression nodes:**

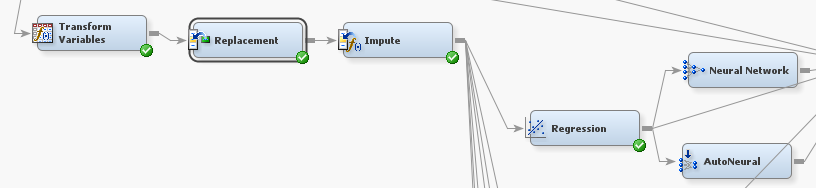
The first neural network used was passed through the non-reduced regression node (i.e. the diagram process flow did not have a replacement node). It gives us a validation average squared error of 2299.845. The second neural network is passed through the reduced regression node and gives us a validation average squared error of 2376.759.

*Figure 57: Neural Network Diagram*

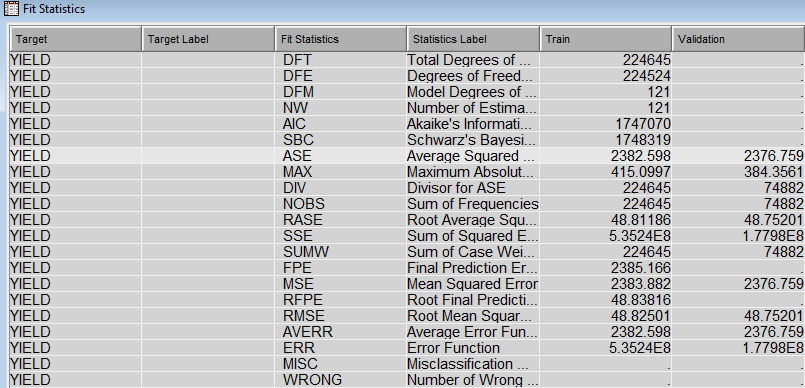


*Figure 58: Neural Network fit statistics with no replacement*

The second neural network used was passed through the reduced regression node (i.e. the diagram process flow did not have a replacement node).

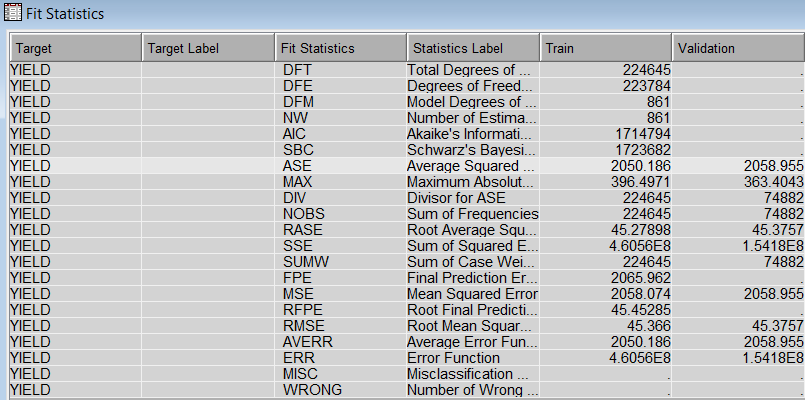


*Figure 59: Neural Network Diagram via replacement*

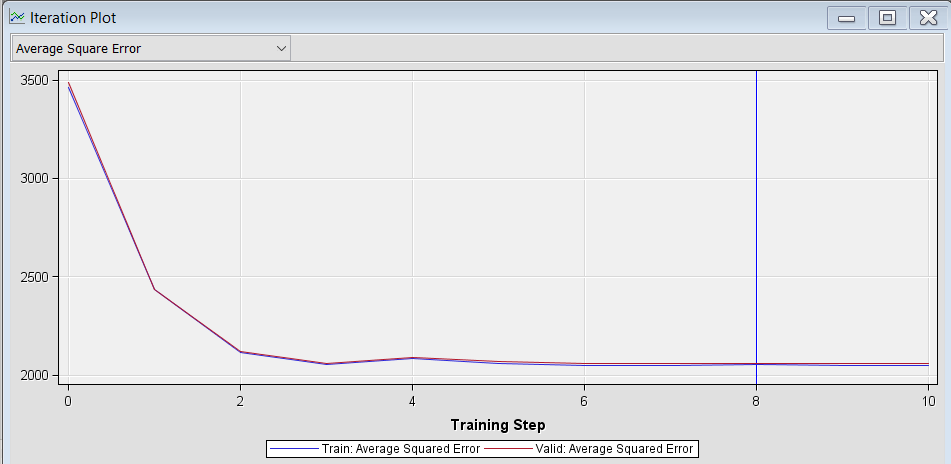


*Figure 60: Neural Network fit statistics via replacement*

1. **Auto Neural Network:**

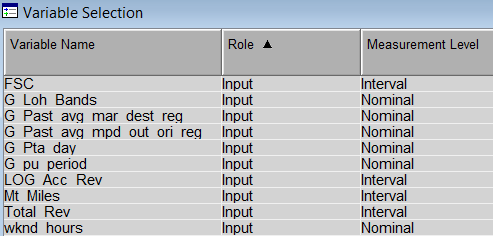
An auto neural network was used. The latter used regression model to select inputs. 8 hidden units were selected, and the validation average squared error was 2058.955 which is the lowest fit statistics so far in this section

*Figure 61: Auto Neural Network fit statistics*

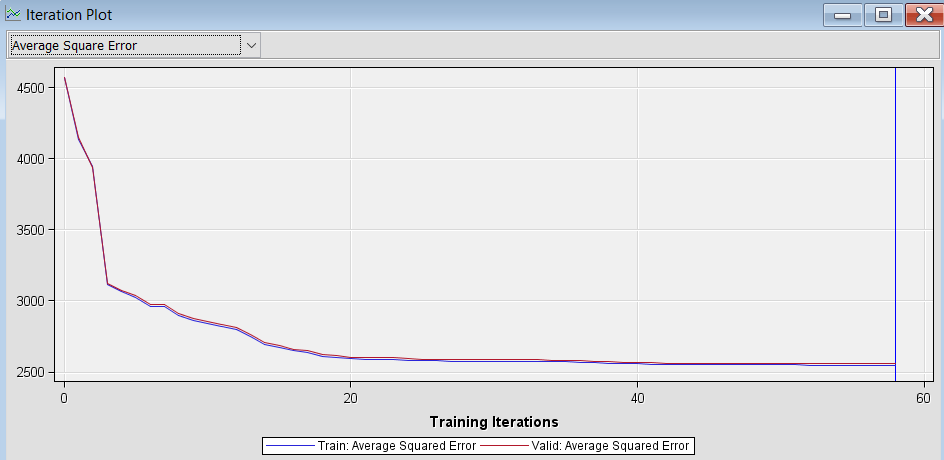


*Figure 62: Auto Neural Network iteration plot*

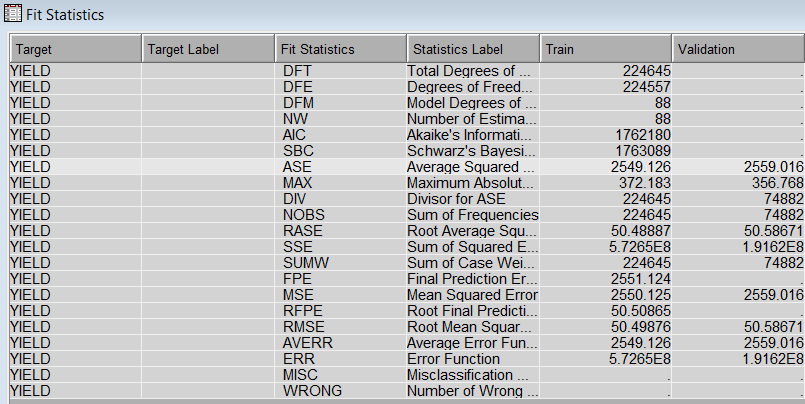
1. **Neural Network Variable Selection (NN VS) Node:**

Variable Selection tool was used into the diagram workspace. We selected Target Model R-Square and ran the node. The results from the variable selection window are captured here below. Thevariables FSC, G\_Loh\_Bands, G\_Past\_avg\_mar\_dest\_reg, G\_Past\_avg\_mpd\_out\_ori\_reg, G\_Pta\_day, G\_pu\_period, LOG\_Acc\_Rev, Mt\_Miles, Total\_Rev and wknd\_hours. Note that the G means it is a grouping of the original input variable.

*Figure 63: Neural Network variable selection*

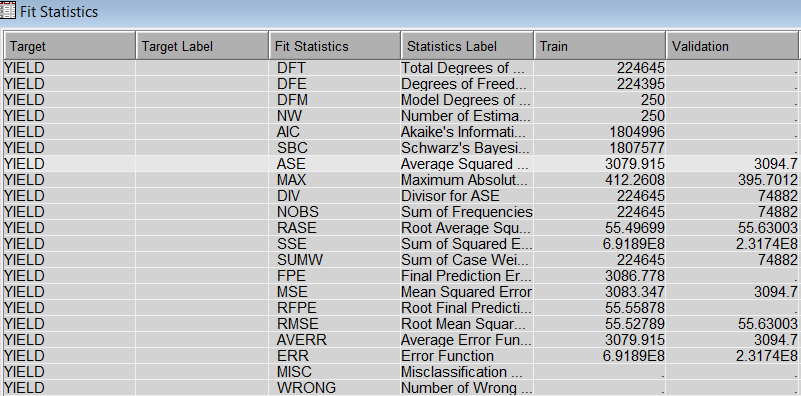
We proceeded to add another Neural Network tool (NN VS) to the diagram. We connected it to the Variable Selection node that created above. We set the model selection criterion to average error and ran it. Here below is the captured Iteration Plot of ASE for the NN VS. Iteration 58 was selected with a validation average square error of 2559.016.

*Figure 64: Neural Network variable selection iteration plot*

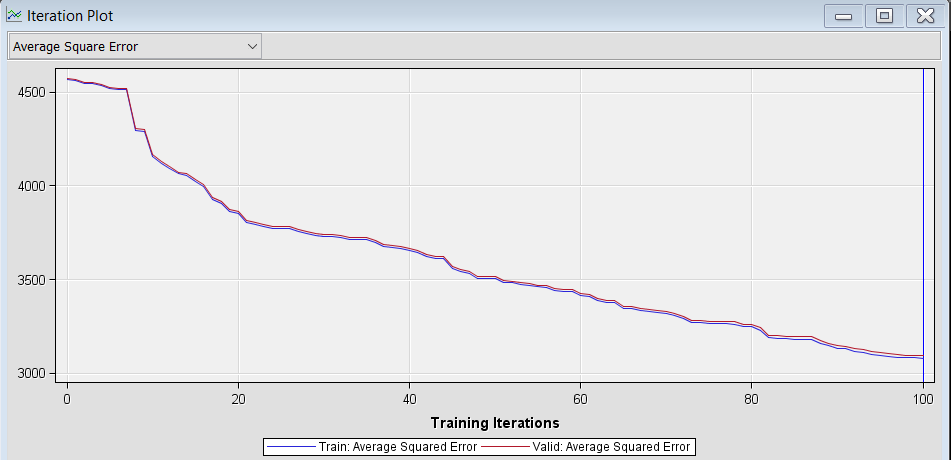


*Figure 65: Neural Network variable selection fit statistics*

1. **Neural Network with AOV16 (NN A0V16) Input Selection:**

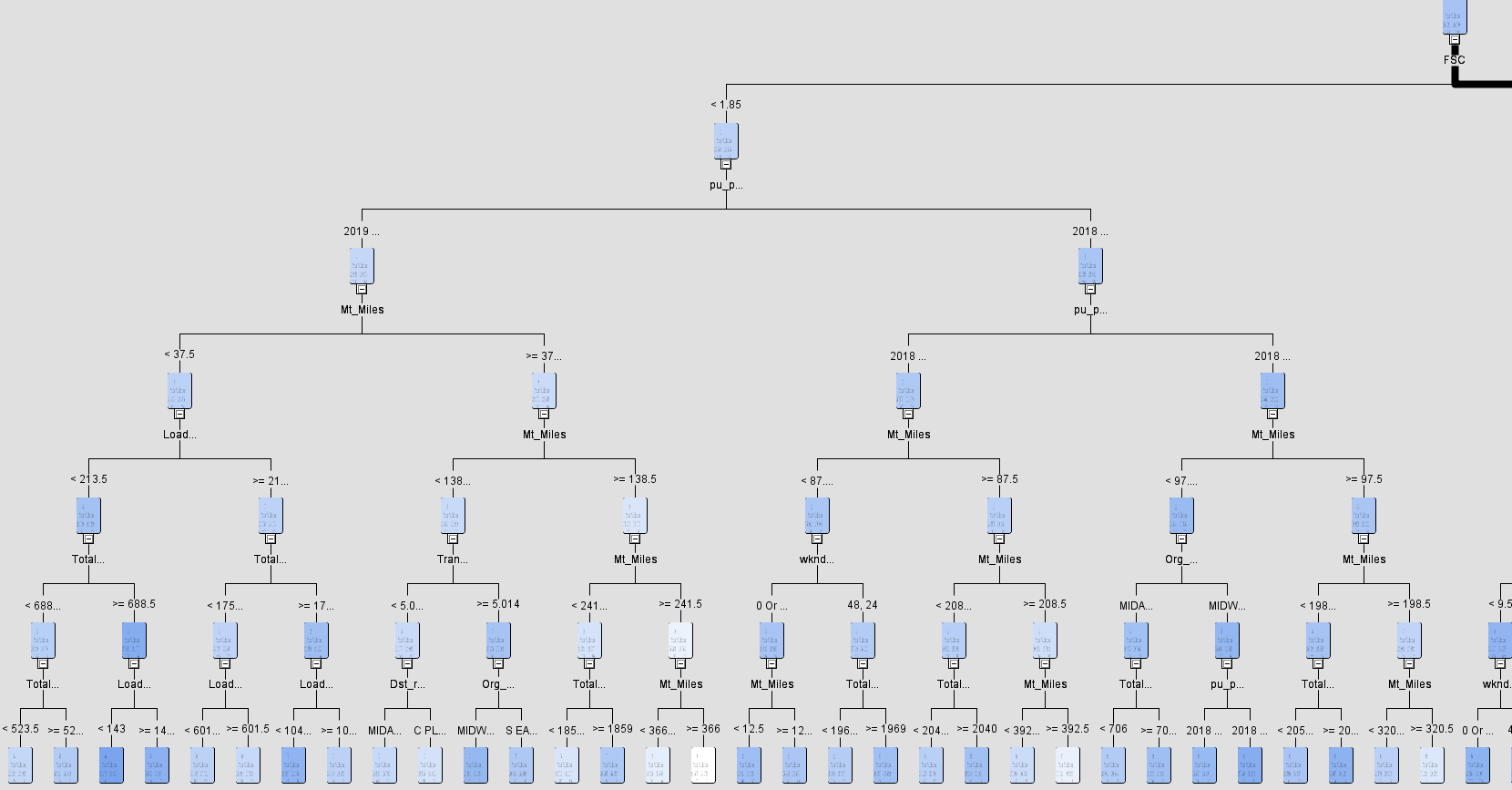
Like the AOV16 node conducted in Part A, we ran the neural network that was connected to AOV16 Variable selection node. Iteration 100 was selected with a validation average square error of 3094.7. This is the model that gave us the highest validation average square error which makes it the worst model so far in the project. The variable selection nodes did not improve the average square error of the neural networks.

*Figure 66: Neural Network with AOV16 fit statistics*

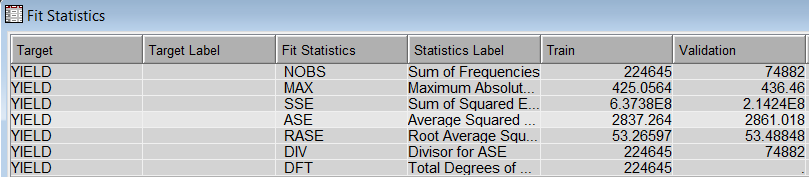


*Figure 66: Neural Network with AOV16 iteration plot*

1. **Neural Network using Decision Tree (NN DT) Input Selection:**

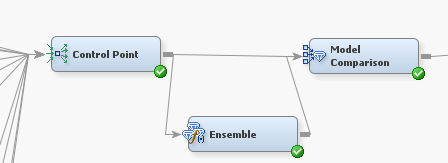
We used a decision tree (selection tree node) to once again help with input selection. A snapshot of the decision tree is captured here below but it does not show all the leaves generated. 64 leaves were generated, and the average square error was 2861.018. This did not improve the fit statistics of the Neural Network.

*Figure 67: Neural Network with decision tree*

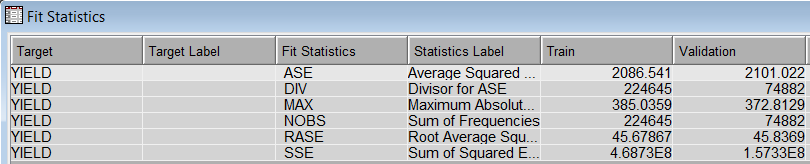


*Figure 68: Neural Network with decision tree fit statistics*

1. **Ensemble for Model Improvement:**

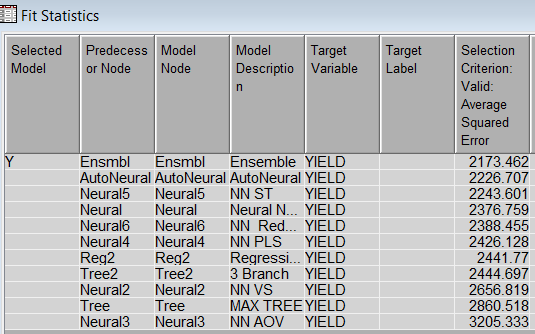
In the continued attempt to improve our models, dragged control point, model comparison and ensemble nodes in the diagram as such.

*Figure 69: Ensemble for model improvement diagram*

The ensemble gave us a validation average squared error (ASE) so far in this Part B of 2101.022.

*Figure 69: Ensemble fit statistics*

1. **Model Comparison Results:**

After all the models were created, they were all connected to the Model Comparison node. From the results, as shown here below, the Ensemble model was selected as the best model with a validation average squared error of 2173.46.

*Figure 70: Model Comparison fit statistics*

1. **Model Implementation (Scoring):**

The score data is the same as the original data except that it does not have the target variable, Yield. That is, you will predict the score data to calculate Yield prediction estimates. We used the score then saved score data as a csv file. And exported it.



*Figure 71: Scoring*

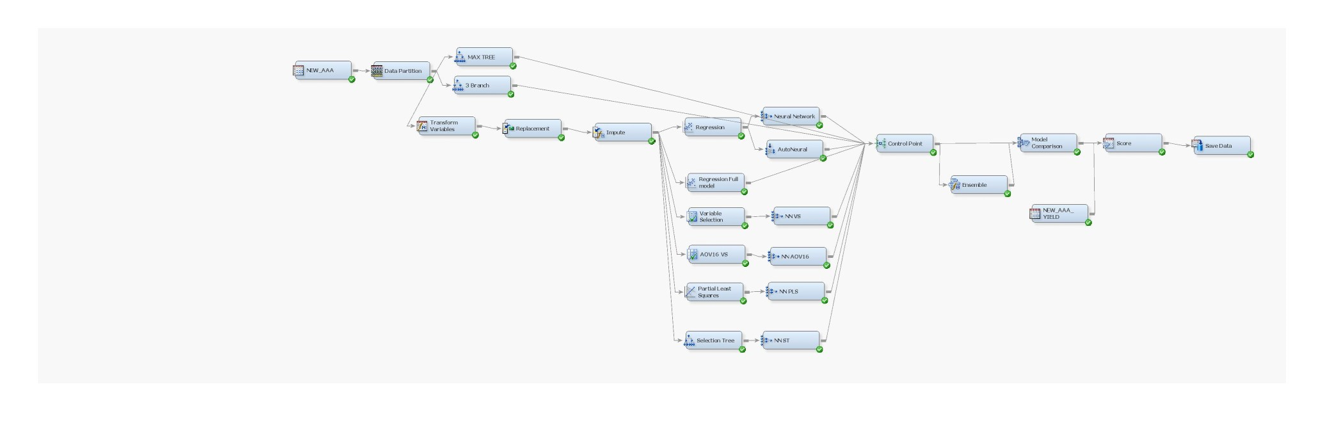
# **Conclusion**

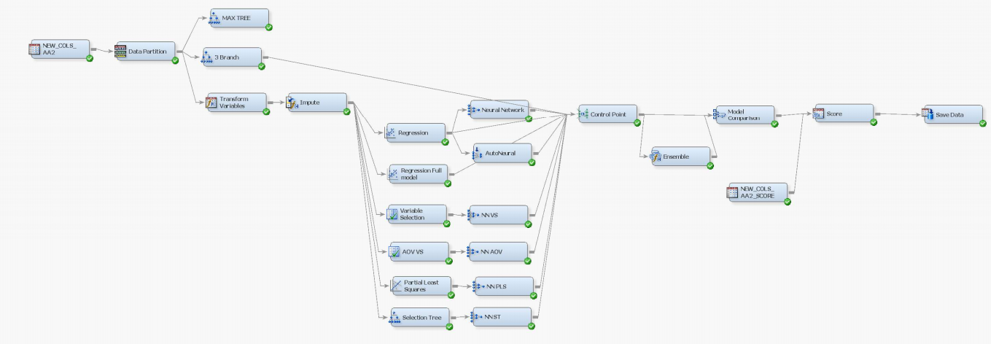
Although our second model’s average square error is quite lower than the first model, this is still a great way to predict future loads yields. The practicality of the second model is more reliable in real world situations when you do not have data that hasn’t happened yet. Giving a company the ability to have a better load selection process based on statistics rather than intuition. If a company is faced with a pool of loads, they must select from, this model will give better insight into which load will produce a higher yield.

Some actionable insight that carriers need to realize include important variables that they have before the load starts. Variables that are important in this model that companies should pay attention to include but are not limited to, the fuel surcharge, the length of haul, and the historical average mpd-in and out of the region that the load will be in. I still believe that there is room to improve this method if there is better quality and availability of data. Most of the transportation industry has not moved to using data for decisions. The companies that are incorporating data in their business practices are causing disruption in the industry and succeeding. This model will allow these companies to either further their analytic processes or start using analytics to increase profits. Ideas for further research include using more historical data to be able to predict yields of future yields. Also, having higher quality data will allow us to give better insight in how to predict yield.

# **Appendix**

*Project diagram using SAS Enterprise Miner*

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**Data Dictionary.**

* Yield - Ranking of how good the load is.(Target Variable)
* Margin per day, In and out - The margin per day going into the origin and margin per day out is when you leave the destination. There is a total margin described and the cumulative made from the margin made from revenue.
* MAR-Margin Above Replacement. Takes into account the average margin of that area and subtracts the margin of that load.
* Origin Market , city , area and PTA - Represents the origin of the trucks and load.
* Postal code for pickup, delivery and PTA - Shipping postal codes used for both picking up the load and delivering the load.
* City for pickup, delivery, and PTA- The city names in which the load was picked up and delivered.
* State for pickup, delivery, and PTA- The state in which the load was picked up and delivered.
* Dates and time for pickup, delivery, PTA- The day and the time in which the loads were picked up and delivered.
* Load id- The unique identifier of the load that is being carried.
* Load time and Unload time - Time taken for loading and unloading the shipment.
* Shipper id- The identifier of the shipper that has issued merchandise to be carried.
* Fuel surcharge- The amount of money given to a carrier by the shipper for the price of fuel.
* Line haul revenue- A cost that is given to carry a shipper’s load.
* Accessorial revenue- Any extra costs that the shipper might have for a carrier.
* Loaded miles- The number of miles the load was carried for.
* Deadhead miles/MT miles- The number of miles that no load was carried from point to point.
* Stops- Amount of times a truck was stopped in transit.
* ‘Total revenue- Total amount of money earned for a load. Linehaul revenue + Fuel surcharge + Accessorial revenue
* Time to load and unload- The amount of time that it took to load and unload a truck of its merchandise.
* Weight- The weight of the merchandise that was shipped.
* Pick up date and day - The dates and day where the load is picked up.
* Delivery date and day - The dates and days when the load is delivered.
* Dwell - The time in which the truck was Idle
* Delay - The time when the truck has material in it but was idle.
* In-Transit Delay - The time when the truck was moving without any material in it.
* Power division - Sectors of trucks which operate in the same group or division.
* Stop cost - The cost that incurs to make a stop by a truck.
* Toll cost - The cost that is paid at toll gates in total.
* Market rate index - Finding the average of the market profits.

*Project codes using Python*

**Python Code for graph 1:**

box\_plot=newdf[['YIELD']]

box\_plot.plot(figsize=(15,15),kind='box')

plt.title('Yield Box Plot',fontsize=20)

**Python Code for graph 2:**

plt.figure(figsize=(12,12))

sns.regplot(x='YIELD', y='Total\_Rev', data=newdf).set\_title('Total Revenue By Yield');

**PythonCode for graph 3:**

plt.figure(figsize=(12,12))

sns.regplot(x='YIELD', y='Margin', data=newdf).set\_title('Margin By Yield');

**Python Code for graph 4:**

newdf.resample('m').agg({'YIELD':'mean'}).plot(figsize=(20,10))

plt.title('Average Yield Over Time',fontsize=20)

plt.xlabel('Del Date',fontsize=15)

plt.ylabel('Yield',fontsize=15)

**Python Code for graph 5:**

newdf.resample('m').agg({'Total\_Rev':'sum'}).plot(figsize=(20,10))

plt.title('Revenue Over Time',fontsize=20)

plt.xlabel('Del Date',fontsize=15)

plt.ylabel('Revenue',fontsize=15)

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