Forecasting Day of Week Volume Fluctuations
In the Intermodal Freight Transportation

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Abstract

Average daily volume fluctuates intensely based on the day of week in the intermodal freight transportation. Shippers tend to peak around Thursdays and receivers tend to peak around Mondays. These fluctuations bring challenges to the industry in terms of capacity management and getting reliable service from the railroad companies. The purpose of this study is to forecast J. B. Hunt Transport Services, Inc.’s load volume on railroads. Load is meant to be the number of containers that will arrive at a rail ramp during a 24hrs time window. The end in mind is to have better service from the railroad companies and to manage the company owned equipment better. The forecasting model applied to tackle this problem is a multiple linear regression model and is based on the historical in-gate numbers. It uses the previous two year’s data and day of week information as independent variables, and current year’s data as the response variable. The results indicate better accuracy levels for the model when compared to the two week moving average.

Keywords
Intermodal freight transportation, multiple linear regression, forecasting, day of week

1. Introduction

Intermodal transportation is defined as the type of transportation that involves multiple modes. Transfers between ocean to/from highway, railway to/from highway, and highway to/from airway are common in intermodal transportation. When compared to the single mode transportation, intermodal transportation brings challenges in terms of equipment, capacity management, and scheduling of resources [1]. In the single mode transportation, the processes and equipment types stay the same during the entire hauling of freight. On the other hand, intermodal transportation requires at least one transfer of the freight between transportation modes during the trip. This transfer operation can only be handled with well-trained operators and specifically designed equipment. The transfer of freight from a mode to a different mode is like a fresh start to the flow of freight for the successor mode. Similar to the demand forecasting at the beginning of a transportation operation, the load volume at this interchange should also be predicted accurately for good service. Forecasting models have been developed for single mode freight transportation [2, 3, 4], but the forecasting models in intermodal transportation still deserves attention [5, 6].

The aim of this study is to forecast the load volume of the freight transportation from highway to railway. The multiple linear regression model detailed here is effectively applied at J. B. Hunt Transport Services, Inc. (JBHT) with minimal software costs using an open source library. The volume fluctuations based on different days of week is specifically addressed in the forecasting model. The rest of the paper is designed as follows: In the second section, the real life problem is explained. In the third section, the forecasting model and implementation details are given. The fourth section gives the test cases and the accuracy of the multiple linear regression models for various lanes (i.e., origin city to destination city pair). Finally, the conclusion is provided in the fifth section.

2. Problem Description

The problem descriptions in intermodal transportation differ between full truckload (TL) transportation and less-than-truckload (LTL) transportation. In this study, TL transportation is the main focus and LTL transportation is left out of the scope. For a simple load in TL transportation, the interchange between highway and railway involves
management of a container, truck, and railcar among a shipper, a receiver, a transportation company, and a rail company. TL transportation process involves the following steps: (1) the transportation company picks up the loaded container from the shipper with a truck, (2) the container is hauled on the truck from the shipper to the rail ramp, (3) the truck in-gates at the rail ramp based on a cut-off time set by the rail company, (4) the rail company takes the container from the truck and stacks the container on a railcar, usually one top of another container (i.e., double stacking), (5) the train departs the origin ramp and arrives at the destination ramp after two to four days of transit on railways, (6) a truck of the transportation company expects the incoming container at the destination ramp to the receiver location. Each one of these steps can be formulated as an industrial engineering problem such as pick-up and delivery scheduling, driver and load assignment, vehicle routing, train scheduling, and railcar planning [1, 5, 6]. Here, the concentration is on the first, second and third steps of the TL transportation process.

In the third step, the term in-gate is used as a verb to define the action of the truck entrance from the gate of the rail ramp. In-gate time is critical in intermodal industry, because the responsibility for the container management is transferred to the rail company at that time. In-gate time is defined as the time when a truck enters from the gate of the rail ramp. The cut-off time is defined as the latest time to catch an outgoing train. In-gate time of a truck at the rail ramp is usually before the cut-off time set by the rail company. If in-gate time is later than the cut-off time, the rail company is not responsible from leaving the container behind to the next ongoing train. This might cause a service failure at the receiver. Rail companies can provide reliable service only if they plan ahead of time for the outgoing trains. The planning of a train involves decisions such as the length of the train, the order of the containers on railcars (i.e., which companies’ containers will be loaded first), the number of locomotives to use, train consolidation, and train annulment. Although rail companies are the decision makers of these business problems, they rely on the information transportation companies provide them. Most of these decisions depend on the number of trucks that will in-gate during a certain time frame at a rail ramp.

Average daily volume fluctuates strongly based on the day of week in the intermodal freight transportation. Shippers tend to peak around Thursdays and receivers tend to peak around Mondays in terms of shipping and receiving volume. The rationale behind this might be to make use of the weekends as much as it is possible for a non-value adding service like transportation. This tendency brings challenges to the industry in terms of capacity management and getting reliable service from the railroad companies. Figure 1 depicts the cyclic pattern of the shipper and receiver volume for different days of week for a three week period representing the network wide total volume.

![Figure 1: Shipper and receiver volume for different days of week (*)(* Actual volume is altered by a percentage to meet JBHT’s confidentiality rules.](image)
As a result of the cyclic pattern in the load volume in the intermodal network, there is a surplus in equipment supply in some days of week, and a shortage in some days of week. For example, it gets harder for a container to get on a train on a Thursday when compared to a Tuesday. Similarly, it is hard to find a truck to load the incoming container at the destination ramp on a Monday when compared to a Wednesday. The problem here is to account for different days of week while forecasting the number of trucks that will in-gate at a rail ramp in a day. The practice in the industry is to take a moving average of the past two weeks for the same day of week. Although this practice gives accurate results for lanes with stable volume, it might not work well for all lanes. We discuss our methodology to tackle this problem in the next section.

3. Forecasting Methodology

We use a multiple linear regression model which is based on the historical in-gate volume. It uses the previous two years’ data and the day of week information as independent variables, and the current year’s data as the response variable. Formally, the model is given in Equation (1) as:

\[ y = B_0 + B_1x_1 + B_2x_2 + B_3x_3 + B_4x_4 + B_5x_5 + B_6x_6 + B_7x_7 + B_8x_8 \]  

where,

- \( y \): In-Gate volume on day \( t \).
- \( x_1 \): 1 if day \( t \) is a Sunday, 0 otherwise.
- \( x_2 \): 1 if day \( t \) is a Monday, 0 otherwise.
- \( x_3 \): 1 if day \( t \) is a Tuesday, 0 otherwise.
- \( x_4 \): 1 if day \( t \) is a Wednesday, 0 otherwise.
- \( x_5 \): 1 if day \( t \) is a Thursday, 0 otherwise.
- \( x_6 \): 1 if day \( t \) is a Friday, 0 otherwise.
- \( x_7 \): Volume of 364 days ago from day \( t \).
- \( x_8 \): Volume of 728 (364x2) days ago from day \( t \).

\( B_0, \ldots, B_8 \) are coefficients of the model and determined with the input data specific to each lane.

The length of the time horizon that is used in the history matters a lot in terms of forecast accuracy; therefore, each lane uses a different optimal number of days in history. A multiple linear regression model with variables \( y, x_1, \ldots, x_6 \) (i.e., excluding \( x_7 \) and \( x_8 \)) is ran to find the optimal number of days in history in a range from 30 to 300 days with ten days increments. Although ten day increment might not give the global optimum number of days in history, it is seen in several test cases that ten day increment is covering enough solution space and is practically feasible.

The regression model is coded in Java. Open Forecast 0.4 [7] is used as the main forecasting library which is open-source. It is a general purpose forecasting model library written in Java. Figure 2 shows the Unified Modeling Language (UML) diagram for the main regression model and the dependencies with other classes.

![Figure 2: UML class dependency diagram for the regression model](image-url)
Best Accuracy class with current year’s data. Then, we run the regression for myOptimalDays number of days in history. Not every lane has two years of historical data, so there is a check method called isThereEnoughData(). This method checks if we have volume in 80% of the all days starting from today and going back in history for myOptimalDays. For example, if we have three years’ data, then forecastWithThreeYears() method is called. DateMatch class matches the dates of current year to the dates in previous years, because a date in current year does not usually fall to the same day of week in previous years. If any of the historical years or the current year is a leap year, then subtracting 52 weeks from the current date doesn’t work. Since the day of week fluctuation is an independent variable in the regression model, it is important to keep the same day of week in the historical data. Figure 3 shows how the data for the previous years are fed into the model.

<table>
<thead>
<tr>
<th>INPUT</th>
<th>OUTPUT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Today - myOptimalDays</td>
<td>Today</td>
</tr>
<tr>
<td>Current Year</td>
<td>Today + myNumForecastDays</td>
</tr>
<tr>
<td>myOptimalDays</td>
<td>myNumForecastDays</td>
</tr>
<tr>
<td>One Year Ago (-364 days)</td>
<td>Two Years Ago (-728 days)</td>
</tr>
</tbody>
</table>

Figure 3: Historical data for the Regression Model input and output

MovingAverage class is used when the Regression Model cannot be formulated and in the cases where loads are transferred among railroad companies. Four week weighted moving average is used with an emphasis in the last two weeks. Holidays class contains the dates for official holidays. DateMatch class uses Holidays class to overwrite the dates of the holidays. For example, Thanksgiving is observed on the fourth Thursday of November which doesn’t follow the 52 week pattern. Holidays class is also used to check if a date is a holiday to get an adjusted forecast for it with getHolidayForecast() method.

4. Experimental Results
The transportation company’s network consists of 356 lanes. Figure 4 shows the sorted cumulative shares of lanes in the total network volume. It is seen from Figure 4 that the bottom 200 lanes represent about 5% of the total network volume. The top 70 lanes correspond to 80% of the total network volume. Here, the accuracy of the multiple linear regression model is tested with 15 representative lanes from JBHT’s network in the U.S. The test lanes are selected to cover five high volume lanes, five medium volume lanes, and five low volume lanes. The date range for the lane volume is selected to be three months in 2010 from the start of June to the end of August. The total share of high, medium, and low volume lanes are calculated as 13.58%, 3.15%, and 1.27% of the whole network volume, respectively. San Bernardino to Chicago, Norfolk to Chicago, and Houston to Laredo can be given as examples for high, medium, and low volume lanes, respectively.
In the experimental study, the multiple linear regression model and the two week moving average is compared. Mean Absolute Percentage Error (MAPE) is selected as the accuracy measure. Equation (2) is used to calculate MAPE:

$$MAPE = \frac{1}{n} \sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right|$$

where \( t \) is a specific day, \( n \) is the sample size (i.e., 90 days), \( A_t \) is the actual volume, and \( F_t \) is the forecasted volume.

Table 1 gives the comparison of MAPE values between multiple linear regression model and two week moving average model for the same day forecast (i.e., the model is run on the same day to forecast the volume of that day). It is seen from this table that multiple linear regression model is better than the two week moving average. It should be noted that high volume lanes can be predicted using two week moving average with comparable accuracy levels. On the other hand, multiple linear regression model outperforms two week moving average significantly for the middle and low volume lanes.

<table>
<thead>
<tr>
<th>Lane(*)</th>
<th>High</th>
<th>Middle</th>
<th>Low</th>
<th>Volume</th>
<th>High</th>
<th>Middle</th>
<th>Low</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>20.7%</td>
<td>45.2%</td>
<td>52.7%</td>
<td></td>
<td>24.7%</td>
<td>59.7%</td>
<td>62.6%</td>
</tr>
<tr>
<td>2</td>
<td>28.5%</td>
<td>23.5%</td>
<td>44.5%</td>
<td></td>
<td>29.8%</td>
<td>24.1%</td>
<td>99.8%</td>
</tr>
<tr>
<td>3</td>
<td>16.4%</td>
<td>27.8%</td>
<td>54.2%</td>
<td></td>
<td>16.9%</td>
<td>35.7%</td>
<td>58.5%</td>
</tr>
<tr>
<td>4</td>
<td>19.9%</td>
<td>29.2%</td>
<td>64.0%</td>
<td></td>
<td>20.6%</td>
<td>53.3%</td>
<td>74.9%</td>
</tr>
<tr>
<td>5</td>
<td>24.4%</td>
<td>58.1%</td>
<td>71.9%</td>
<td></td>
<td>25.1%</td>
<td>75.9%</td>
<td>77.1%</td>
</tr>
<tr>
<td>Avg</td>
<td>22.0%</td>
<td>36.8%</td>
<td>57.5%</td>
<td></td>
<td>23.4%</td>
<td>49.7%</td>
<td>74.6%</td>
</tr>
</tbody>
</table>

(*) The city names for the selected lanes (i.e., origin city to destination city pair) were not disclosed because of the confidentiality rules of JBHT.
5. Conclusion
This study presented a multiple linear regression model to forecast the number of trucks that will in-gate at a rail ramp for specific destination ramps. This is a collaborative work between JBHT and its rail partners. The in-gate volume at the interchange ramp between the highway mode and the railway mode is analyzed. Developed model outperformed the common practice of two week moving average model.

The multiple linear regression model has been in use for the last two years at JBHT. Every morning a ten days out daily forecast is run for each lane to predict the number of trucks that will in-gate at a rail ramp on a 24hrs time window. This forecast is forwarded to the rail companies via FTP. Then, the rail companies feed this ten day predictions to their forecasting system to plan their capacity ahead of time. By using this forecast, they make decisions related to train schedules, capacity of trains, and train consolidations. JBHT uses the result of the in-gate forecast to balance its intermodal network better. By the use of this model, the disrupting effects of weekly peaks on the network are less visible to JBHT.

In the future, the multiple linear regression model should be modified to address the high MAPE values for some lanes. As an alternative, a traditional seasonal model with weekly seasonal adjustments might be compared with the current regression model. Forecasting models might be differentiated by clustering different volume levels. Consolidating multiple destinations from an origin ramp, thus calculating a ramp level forecast might be another extension for low volume lanes.

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References