Improving Forecasting Accuracy of Intermodal Pickup Demand by Integrating Statistical Forecasting Methods

Problem

J. B. Hunt Transport Services, Inc. is a Fortune 500 company providing supply chain solutions across North America. The company is broken down into four divisions: Intermodal, Dedicated Contract Services, Integrated Capacity Services, and Truckload. From the pie chart below, it can be noted J.B. Hunt Intermodal accounts for 58% of the company's total revenue.



Our project falls within the Network Planning division with J. B. Hunt Intermodal. The main goals of the Network Planning team are to predict pick-up demand for the 65 existing ramp groups across North America. A ramp group is collection of rail stations where containers are sent to and from. Our task was to determine a proactive predictive approach for projecting pickup volumes. Since 21% of JB Hunt Intermodal's (JBI) loads are requested to be picked up from the customer on the same day that the order is booked. This provides them very little time to react and plan their operations efficiently. Our hope is to reduce uncertainty by integrating mathematical forecasting methods to better identify pickup demand for specific ramp groups.

Current System

The process of network planning begins with the capacity managers using historical data, intuition and information from the employees at specific rail stations to determine the number of containers needed for each ramp group. Their goal is to predict container volumes for each ramp two weeks out. The forecast is presented by Capacity Managers. Their role is to communicate with their assigned ramp groups and predict pickup volumes for those ramp groups. The colored regions below designate each capacity manager's market they serve.

There are two directors who share responsibility across North America, each oversee three markets outlined in the map above. Every Thursday, all six capacity managers meet with the directors, and the vice president for the empty plan meeting. In this meeting, they go through the network and integrate each capacity managers predictions



to ensure the resources within the network are balanced. Once the capacity managers and directors have gone through the forecasted resource demand, they determine the Empty Maintenance Plan. This plan is for routing containers from their starting location to their destination location to meet demand for the upcoming week based off their expected demand.

Within the network planning team their only current key performance indicator is the Forecast Balance Report. This interface is used to view the results of pickups, deliveries and the difference between them by weekday. During the process of forecasting the capacity managers will use this tool to help them create the number of containers needed per week day.

Forecast Balance Report	Balance Report	Forecast
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Ramp Group	IMM	Pickups									Deliveries									Balance									
	ALL 🔽	Mon	Tue	Wed	Thu	Fri	Sat	Sun	Total	Mon	Tue	Wed	Thu	Fri	Sat	Sun	Total	Mon	Tue	Wed	Thu	Fri	Sat	Sun	Tota				
ALBANY	SMITH	40 +8	51	49	58	51	26	25	300 +8	51 +8	60	47	48	40	23	23	292 +8	-11	9	-2	-10	-11	-3	-2	-8				
ALBUQUERQUE	MODI	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
ATLANTA	WALKER	571 -97	582	581	578	554	311	223	3400 -97	527 +179	596	552	503	461	296	197	3132 +179	-44	14	-29	-75	-93	-15	-26	-268				
AYER	SMITH	69 -2	63	68	65	70	10	5	350 -2	71 +21	69	60	56	55	24	20	355 +21	2	6	-8	-9	-15	14	15	+5				
BALTIMORE	SMITH	10 +4	9	11	15	15	2	3	65 +4	28 -2	22	18	16	19	6	6	115	18	13	7	1	4	4	3	+50				
BETHLEHEM	SMITH	36 +11	48	49	48	57	26	16	280 +11	79 +29	75	62	57	51	40	36	400 +29	43	27	13	9	-6	14	20	+120				
BIRMINGHAM	WALKER	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
BUFFALO	SMITH	70 -21	61	66	73	64	8	3	345	41 +16	42	38	32	35	12	3	203 +16	-29	-19	-28	-41	-29	4	0	-142				
CALGARY	LOWE	2 -2	3	2	2	3	0	3	15 -2	5 +11	9	7	6	8	0	3	38 +11	3	6	5	4	5	0	0	+23				
CHAMBERSBURG	SMITH	18 +1	18	20	19	17	6	12	110 +1	65 +1	68	57	44	37	18	26	315 +1	47	50	37	25	20	12	14	+205				
CHARLOTTE	WALKER	149 -1	181	177	171	145	68	59	950 - 1	108 +64	122	106	102	90	61	48	637 +64	-41	-59	-71	-69	-55	-7	-11	-313				
CHICAGO	FRANCIS	1196	1346	1434	1436	1196	511	331	7450	856	897	823	719	690	351	549	4885	-340	-449	-611	117	-506	-160	218	-256				



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Solution Design

We considered a variety of factors when designing the forecasting method. We considered factors to be any variation of the system having a potential impact on the pick-up demand. After statistical analysis on the data available, we were able to narrow down the significant factors to day of the week, seasonality, and location.

Since we are forecasting pick-up demand on a daily basis, time-series forecasting methods are appropriate to evaluate. Our desire to produce an accurate and robust forecast initially lead us to assess three mathematical forecasting methods. The three selected were Holt-Winters, Auto-Regressive-Integrated Moving Average (ARIMA), and a Tukey Pairwise Day of the Week Comparison.

The mathematical forecasting accuracy measures we used to evaluate the system were mean absolute percent error and **Forecast** mean absolute deviation. Mean absolute percent error (MAPE) is a percentage-based error averaging the quotients of the absolute difference between the actual data and forecasted data divided by the actual.

$$MAPE = \frac{100\%}{n} \sum \frac{|Actu|}{n}$$

Mean absolute deviation (MAD) is a value-based error averaging the absolute difference between the actual and the forecast.

 $MAD = \frac{1}{n} \sum |Actual - Forecast|$

Additionally we sought out alternative forecasting methods such as socio-economic factors and using orders placed in advance to make assumptions about final demand.



Lead Time (Days) There are strengths and weaknesses of all forecasting methods, based on research written in Forecasting: The Key to Managerial Decision Making. Waddell explains the choice of the best forecasting method can sometimes be unclear, in which she gives a solution: "using more than one forecasting method or forecaster and then combining their predictions...has proved to be an extremely effective way of increasing forecasting accuracy and decreasing the variance in errors." (Waddell, 1994)

Interpolation of Forecasting Methods

In order to utilize these strengths, our final forecast will be comprised of all the methods as mentioned earlier. Each method will have a different weight on the final forecast.

We developed an optimization methodology to assign the weights of each forecast. The objective function for our optimization is to minimize mean absolute deviation.

$$\min \sum_{i=1}^{n} (A_{i} - (w_{1}ARIMA_{i} + w_{2}HW_{i} + w_{3}W))$$

The model compares the deviation of the fitted values of each method. The method incrementally tests each possible weight to the hundredths place to determine the which combination of weights minimizes the deviation. The only constraint to the model is the sum of the weights must equal one (representing 100%).

$$w_1 + w_2 + w_3 + w_4 + w_5 = 1$$

Our team provided J. B. Hunt with a forecasting tool built with R. In our R script, we used a combination of packages to make our script more optimized and run faster. The most significant benefit of an R-script is its ability to be implemented on the backend of numerous other software packages and coding languages. Our tool gives them the advantage of implementing the software in a variety of ways.

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- ıal–Forecast|
- Actual

$(MA_i + w_4SER_i + w_5LTO_i))^2$



To gather results, we tested the forecasting method for different weeks of the year and compared our forecast to the J. B. Hunt forecast. Our forecast will be represented as the Ark forecast and the capacity manager's forecast as the JBH forecast. The JBH forecasts are the values entered into the forecast balance report the Thursday before the actual week; they keep an update key in their database, allowing us to roll it back to the exact date easily. We tested multiple weeks that vary with historical demand.

The week of July 4th poses to be a difficult week due to variability among the demand. Since the day of the week July 4th falls on changes each year, it can be difficult to forecast demand on July 4th and the days surrounding it. Additionally, we looked into the **Deviation over Four Test Weeks** week of October 14th because this is the early 10000 stages of peak season. Demand begins increasing around this time in the year, so we wanted to 8000 forecast and compare the results to J. B. Hunt's. 6000 The following weeks represent the middle of 4000 peak season and the end of peak season. We felt these weeks were also interesting to 2000 compare our forecast to J. B. Hunt's since the demand can be unknown and widespread. 13-Jan



An issue we ran into when testing our model is that predicting volumes for smaller ramp groups is a challenge; therefore, we decided to forgo forecasting for small ramp groups because they are non-asset locations. The map on the right includes the 13 ramps, which translates to about 20% of the total ramp groups fo J. B. Hunt Intermodal. Due to the difficulty of producing valuable forecast we decided to forgo formulating forecasts for these groups. Fortunately, SILAO these ramp groups are non-asset locations, which TOLUCA means the importance of forming a forecast is unnecessary in J. B. Hunt's eyes because demand volumes are low.

Further testing was done with our forecasting model, J. B. Hunt's forecast, and the actual pickup demand for the week of January 13th. These tests were run in real time to see how our forecast performed compared to J. B. Hunt's. Overall, our forecast was more accurate by 1700 containers.



Along with providing J. B. Hunt with a robust forecasting mathematical solution we wanted to include a confidence interval to supplement the point forecast. Creating confidence intervals is common practice among forecasting due to the uncertainty associated with planning for unknown demand. When developing our forecasting model, we knew having a user interface for our forecast would be useful and valuable for a capacity manager, so we built a proof of concept for the dashboard in Tableau. Our purpose for creating an example dashboard was to aid in building exactly what the capacity managers need when the J. B. Hunt developers create it on their systems. This includes the point forecast, the confidence intervals, rollovers from previous days and a side by side comparison of the last weeks pickup demand and the upcoming weeks forecast.



Results



J.B. Hunt Intermodal and Capacity Planning

J.B. Hunt Intermodal

What is J.B. Hunt?

J.B. Hunt is a transportation and logistics company that was incorporated in 1961 Johnnie Bryan Hunt out of the city Springdale, AR. Today, J.B. Hunt is Fortune 500 company providing supply chain solutions across North America.





What does J.B. Hunt do?

The company is broken down into four divisions: Intermodal, Dedicated Contract Services, Integrated Capacity Services, and Truckload. These four divisions are all different forms of how J.B. Hunt accomplishes the task of receiving freight from a customer in an origin location and then transporting that freight to a desired final destination.

Freight being loaded onto a chassis

What is Intermodal?

Out of the four divisions, Intermodal accounts for the most revenue at nearly 60% of the company's total revenue. Intermodal can be summarized in 6 simplified steps: (1) Customer's freight is picked up via truck, (2) the freight is transported via truck to a local "ramp" or rail transferring station, (3) At the ramp the freight is transferred to rail transportation, (4) It is then transported across the U.S. via rail to a destination ramp (5) At the destination ramp, the freight is transferred back to a truck,

(6) Finally the truck takes the freight to its customer's desired final destination.



Container at a ramp being taken off of a truck chassis for placement onto a rail



Network Planning

How is Intermodal Planned?

In order to execute the tens of thousands of orders processed each week efficiently, a Network Planning team is entrusted with ensuring the Intermodal network feasibility and efficiency of equipment used. This team is composed of six Capacity Managers, two Directors of Network Planning, and one Vice President of Network Planning. Simply put, the Network Planning team is concerned with ensuring that every ramp location has the equipment necessary to carry out new orders. This needs to be planned out because equipment is constantly being sent and received at different ramp locations across the country resulting in a natural inclination toward imbalance of equipment in the network.



Illustration of cause of Network Planning disequilibrium

Importance of Network Planning:

As an Intermodal order is carried out there are many moving parts involved to achieve this. There needs to be a truck available to pick up a customer's freight initially, this truck needs a container for the chassis to carry the incoming freight, the initial and final destination ramps need to be aware of how many containers they are receiving in a day that they will need to place onto either rails or trucks. All of these aspects require adequate planning so they can have equipment in place and ready to go. The Network Planning team is responsible for ensuring the components of the network are working together to execute the process.

Forecasting & Equipment

How does the team forecast?

To adequately plan out where equipment is needed to satisfy upcoming orders within the network, the Network Planning team generates forecasts of customer demand on a daily basis. Every Thursday, at their Capacity Planning meeting, the team solidifies the forecasts and implements the forecast into the plan for how equipment will be moved around the country to ensure the network is feasible in the upcoming week of operations.

Edit 🖊	Week B	eginning: 11/26/	2018		×																				Expo	ort 差
Ramp C	Group	IMM				Pick	ups							Deliv	reries			Balance								
ALL.	~	ALL 🗸	Mon	Tue	Wed	Thu	Fri	Sat	Sun	Total	Mon	Tue	Wed	Thu	Fri	Sat	Sun	Total	Mon	Tue	Wed	Thu	Fri	Sat	Sun	Total
ALBA	NY	SMITH	40 +8	51	49	58	51	26	25	300 +8	51 +8	60	47	48	40	23	23	292 +8	11	9	-2	-10	-11	-3	-2	-8
ALBUQU	ERQUE	MODI	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ATLA	NTA	WALKER	571 -97	582	581	578	554	311	223	3400 -97	527 +179	596	552	503	461	296	197	3132 +179	-44	14	-29	-75	-93	-15	-26	-268
AYE	R	SMITH	69 -2	63	68	65	70	10	5	350 -2	71 +21	69	60	56	55	24	20	355 +21	2	6	-8	-9	-15	14	15	+5
BALTIN	IORE	SMITH	10 +4	9	11	15	15	2	3	65 +4	28 -2	22	18	16	19	6	6	115	18	13	7	1	4	4	3	+50
BETHLE	EHEM	SMITH	36 +11	48	49	48	57	26	16	280 +11	79 +29	75	62	57	51	40	36	400 +29	43	27	13	9	-6	14	20	+120
BIRMIN	GHAM	WALKER	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
BUFF	ALO	SMITH	70 -21	61	66	73	64	8	3	345	41 +16	42	38	32	35	12	3	203 +16	-29	-19	-28	-41	-29	4	0	-142
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CHAMBER	RSBURG	SMITH	18 +1	18	20	19	17	6	12	110 +1	65 +1	68	57	44	37	18	26	315 +1	47	50	37	25	20	12	14	+205
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EDMON	NTON	LOWE	1 +2	1	1	2	1	0	2	8 +2	1 +2	2	1	1	1	0	3	9 +2	0	1	0	-1	0	0	1	*1
EL PA	NSO	MODI	7 -2	8	9	9	11	3	3	50 -2	6 +3	6	4	3	1	0	2	22 +3	-1	-2	-5	-6	-10	-3	-1	-28
ELIZAR	RETH	SMITH	258	281	207	302	250	103	75	1575	287	202	240	225	214	88	80	1454	20	11	-48	-67	.45	-15	14	121

Weekly forecasts produced by team members are entered into the Forecast Balance Report

What resources need to be balanced in the system?

 Trucks & Personnel Chassis Containers (Or Boxes)



Truck and Personnel

Chassis

Containers