Reservations, Forecasting, Yield Management and Railroads

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Presentation Outline

- Introductory thoughts and comments yield management and railroads
- Demand Forecast Project overview and considerations
- Statistical Forecast Methodologies and Assumptions
- Forecast results: Summary and Detailed
- Conclusions and Recommendations

Yield Management and Railroads

- What is yield management?
 - The process of allocating the right type of capacity to the right customer at the right price in order to maximize revenue or 'yield' (Kimes 1989)
- Do railroads "do" yield management?
- Examples of yield management-related activities in rail:
 - Market segmentation:
 - Differential pricing by commodity, customer, and service level
 - Train type and block space allocation, track allocation, locomotive allocation...
 - Car allocation priorities (and BNSF's car allocation pricing: COTs, LOGs)
 - Price bundling and unbundling
 - But, in general... no.

When does YM work?

- Yield Management suits industries where:
 - Demand is unstable or highly time-varied
 - The service/product is perishable
 - Market can be segmented



Inventory of capacity is homogenous

Do Railroads have these?

these

Railroads don't have

Railroads have these

- Selling of service to their customers occurs well in advance of consumption
 - In effect, price is determined well in advance of consumption, but volume is not determined until the point of consumption
 - (no reservations)
- Low marginal costs of service
 - Railroads have the blessing, and the curse, of flexible capacity, which creates significant marginal costs of service (extra sections, extra locomotives, etc.)
 - And makes pricing to maximize yield a challenge (due to a created cost focus)

Yield Management Ingredients

• Demand forecast –

- What is coming, at a detailed level, that is to be priced

• Capacity identification –

- What capacity is available, at a detailed level, that is to be sold

• Demand management –

 What component of demand that can be shifted to better match capacity; how can customers be differentiated

• Pricing –

- What price may drive the desired customer behavior (demand shifting);
- What price roughly equates known revenue with an order now against expected foregone revenue of future reservations

• Overbooking/Order acceptance –

 When do you accept a customer car order (reservation), not knowing what orders are yet to come, or even which train capacities the customer may use?

Railroads Fall Short on many of these critical ingredients:

Demand forecast –

Very little advanced knowledge of customer behavior

- Generally, no reservations to speak of (BNSF has tried with "RSVP", COTS, LOGS; CN may be an exception)
- <u>Many</u> different products (origin, destination, train types, service levels, equipment types, time of day, day of week) to predict statistically

• Capacity identification –

Rail capacity is complex, not well-known, and not fixed

- 5 different physical capacity constraints (car, yard, line, crew, loco);
- Train is the sixth capacity type that uses all of these physical capacities and ties them all together
- But, the train capacity changes daily with second sections, annulments and consolidations --- effectively negating the fixed capacity assumptions that are bedrock in most yield management applications.
- Contrary to airlines, hotels, etc., rail capacity is much more flexible than pricing, so supply adjusts to demand. Despite a growing "run the plan" philosophy, we still reroute 10% or so (or more?) of all traffic... well beyond airlines or hotels.

Railroads fall short on these ingredients – cont.

• Demand Management –

Shipping patterns are not easily swayed by price

- Not much of demand is easily ported between days of week or equipment type.
 Production and delivery schedules aren't flexible enough to be swayed by production costs.
- Demand management principally takes the form of pushing off accepted loads to nonpeak days, which often results in service failures.

• Pricing –

Systems and commercial relationships limit ability of railroads to use price

- Rail pricing isn't nimble enough to take advantage of perceived mismatch of demand and supply conditions.
- Rail pricing systems are not made for quickly changing prices, and the majority of historical customer relationships and longer-term contracts are not geared towards fluctuating prices.

Load Acceptance –

The load acceptance function is not executed in rail

- Typically, railroads accept all orders, then fail to provide a car or on time service
- Akin to overbooking; But the "cost" of failure is not as well-known as in airlines, where an explicit cost is paid to "volunteers"

MFG Consulting – BNSF Network Predictability Project

• Objective:

To evaluate <u>predictability</u> of network at various levels of <u>aggregation</u> to support <u>operational decision-making</u>.

(Conversely, the "unpredictability" the limits operational decision-making.)

- <u>Predictability:</u> the "signal" or explainable portion of shipper behavior relative to the "noise" or unexplained fluctuations
- <u>Levels of Aggregation:</u> level of detail of forecast; hub complex, hub, equipment type, equipment length, shipper, time interval, etc.
- <u>Operational decision-making:</u> asset deployment to better match shipper demand patterns
- Opportunity:

Better visibility into "what is coming" will allow better asset deployment, improving both asset utilization and availability

- Project Scope:
 - Three major intermodal ramps
 - Historical Data: Jan 1, 2003 March 31, 2005 In-gate data (821 days)
 - Trailer and Container Loads only (not empties)
 - Forecast at a level which may be used to improve flat car and double stack car positioning, lift forecasting, train planning (not aggregate financial forecasting)

Operational Forecast Requirements

- We evaluate the feasibility of forecasting shipper patterns as an alternative to shipper reservations for each shipment
 - "Reservation" level of detail:
 - Shipper, Date, Origin, Destination, Equipment, Length (and Service Level) (not time of day, but, would be nice)
- However, the desired level of detail for a forecast depends on its intended operational use
 - Very different from financial forecasting
- We can examine in gates at various levels of detail:
 - Ramp Management -- Total in-gates
 - Train Planning
 Total vans and containers by destination
 - Car management Total vans and containers (and lengths)
- If we can forecast accurately at these levels of detail, the value derived from customer reservations is reduced to some degree
 - If shipper-level forecast helps improve forecast accuracy, then forecasts can be made a more detailed level, then aggregated up

Pictorial of Forecasting Aggregation How far down the "pyramid" can we go and maintain accuracy?



We evaluate forecast accuracy at various levels of operational detail.

Forecasting Parameters, Measures, Methods and Assumptions Summary

- Forecasting Parameters:
 - One day ahead forecast horizon
 - Static forecast
 - In-sample forecast evaluation
- Measure of forecast quality:
 - Mean Absolute Error (MAE)
 - Mean Absolute Percent Error (MAPE)
- Methods Explored:
 - Exponential Smoothing
 - Holt-Winters (with daily/monthly smoothing)
 - Stepwise autoregressive (by Day of Week)

Forecast Evaluation Overview

- <u>Summary Forecast:</u>
 - Holt/Winters, Stepwise Autoregressive and Exponential Smoothing are evaluated
 - At the Hub level of aggregation
- Dive Down detailed forecast:
- One day ahead forecasts Holt-Winters Method Used
 - Holt/Winters Seasonal Multiplicative adjustment
- Various forecast levels of detail (Dive Downs)
 - Shipper Focused
 - Dive Down 1: Hub/Shipper
 - Dive Down 2: Hub/Shipper/Equipment Type
 - Dive Down 3: Hub/Shipper/Equipment Type/Equipment Length
 - Dive Down 4: Hub/Shipper/Equipment Type/Equipment Length Destination (reservation level of detail, excluding service level)
 - Operations Focus (Exclude shipper disaggregation)
 - Dive Down 1: Hub/Equipment Type
 - Dive Down 2: Hub/Destination
 - Dive Down 3: Hub/Destination/Equipment type

Pictorial of Forecasting Aggregation Summary Forecast: Hub Level, Day of Week



Stepwise Autoregressive vs. Holt-Winters

Winters with Weekly and Monthly Seas									
MAE									
	Winters-Seas	Winters	Stepar						
А	69.76	86.69	62.15						
В	46.20	53.06	40.24						
С	77.30	91.26	67.63						

Stepwise Autoregressive has lowest MAE, Holt-Winters with (daily) Seasonality performs comparably.

•Holt-Winters will be used for "dive-down" forecasts -

•Single equation with daily adjustment versus seven different day-of-week equations

•More economical for automation

•Leverages Uses "same time last year" information – more intuitive •Leverages More recent information - One day ahead forecast (uses last three days' information to better adjust to within-month variations)

Holt-Winters with Monthly/Daily Seasonality



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Confidence Interval on Forecast: Hub Level

	Hub-Level Forecast Method: Additive Holt/Winters							
		Lower 95%	Upper 95%					
		Confidence	Confidence					
		Interval	Interval					
	Origin Ramp	Boundary	Boundary					
Δ		704	1,177					
F	ξ.	588	890					
c		1,107	1,607					
~	/							

Even at the highest (Hub) level of aggregation, the 95% confidence interval around the forecasted value is 300-500 units.

Shipper Dive Down 4: (Reservation Level of Detail) Hub, Shipper, Equipment Type, Length and Destination



Illustrative Graphs Shipper-Hub Level Forecast Accuracy (all Equipment)



Illustrative Graphs Shipper-Hub-Equipment-Length Level of Detail



Comparison of Forecast Accuracy: Shipper-Specific Illustration Dive Down Levels 1-4

Level 1								
Ramp								
	CONSTANT	MAE	MAPE	Ν	Δ	Il units f	orecast	
	4.59	2.15	16.83				0100000	
	29.99	6.30	34.14	820.00				
	85.17	13.46	28.42	821.00				
_evel 2					-	-		
₹amp	Equipment							-
		CONSTANT	MAE	MAPE	N		Four Gr	oups not forecast
	К	3.60	5.27	26.99	800.00			•
	К	2.31	2.40	25.96	373.00			
	V	26.62	6.23	34.24	820.00			
	V	85.11	13.45	28.42	821.00			
.evel 3						-		
Ramp	Equipment	Length						
			CONSTANT	MAE	MAPE	N		Seven by groups (
	К	53	3.51	3.26	10.52			beenvetion:
	К	53	2.50	1.89	52.02	176	C	
	V	48	0.86	0.96	2.77	778	1	5 aroups
		53	26.44	6.21	34.27	820		
	V	48	(0.20)	1.62	10.91	818	ſ	Not forecast (22 to
		53	84.55	13.41	28.42	821		-
_evel 4								
Ramp	Dest	Equip	Length					
				CONSTANT	MAE	MAPE	N	
		К	53	3.33	13.78	19.58		
		V	53	10.76	3.66	45.62	820	
		V	53	2.39	1.02	22.64	817	60 aroups one
		12	E 2	0.54	4 70	40.70	176	
		n	53	2.54	1.76	49.79	1/0	
		r V	53	2.54	<u>1.76</u> 4.14	49.79	820	127 not foreca
		N V V	53 53	2.54 15.30 1.01	1.76 4.14 1.85	49.79 44.65 56.92	820 396	127 not foreca
		K V V V	53 53 53 53	2.54 15.30 1.01 0.76	1.76 4.14 1.85 1.09	49.79 44.65 56.92 3.44	820 396 733	127 not foreca (187 total)
		K V V V	53 53 53 53 53 53	2.54 15.30 1.01 0.76 10.23	1.76 4.14 1.85 1.09 2.99	49.79 44.65 56.92 3.44 51.69	820 396 733 821	127 not foreca (187 total)
		K V V V V V	53 53 53 53 53 53 53	2.54 15.30 1.01 0.76 10.23 3.21	1.76 4.14 1.85 1.09 2.99 1.68	49.79 44.65 56.92 3.44 51.69 66.84	820 396 733 821 819	127 not foreca (187 total)
		K V V V V V	53 53 53 53 53 53 53 53 53	2.54 15.30 1.01 0.76 10.23 3.21 5.10	1.76 4.14 1.85 1.09 2.99 1.68 2.39	49.79 44.65 56.92 3.44 51.69 66.84 64.07	820 396 733 821 819 820	127 not foreca (187 total)
		K V V V V V V	53 53 53 53 53 53 53 53 53 53	2.54 15.30 1.01 0.76 10.23 3.21 5.10 24.61	1.76 4.14 1.85 1.09 2.99 1.68 2.39 4.20	49.79 44.65 56.92 3.44 51.69 66.84 64.07 40.81	820 396 733 821 819 820 820	127 not foreca (187 total)
		K V V V V V V V	53 53 53 53 53 53 53 53 53 53 53	2.54 15.30 1.01 0.76 10.23 3.21 5.10 24.61 5.61	1.76 4.14 1.85 1.09 2.99 1.68 2.39 4.20 2.10	49.79 44.65 56.92 3.44 51.69 66.84 64.07 40.81 73.32	820 396 733 821 819 820 820 820	127 not foreca (187 total)
		K V V V V V V V V	53 53 53 53 53 53 53 53 53 53 53 53	2.54 15.30 1.01 0.76 10.23 3.21 5.10 24.61 5.61 34.29	1.76 4.14 1.85 1.09 2.99 1.68 2.39 4.20 2.10 8.21	49.79 44.65 56.92 3.44 51.69 66.84 64.07 40.81 73.32 28.01	820 396 733 821 819 820 820 820 820 821	127 not foreca (187 total)

Customer Forecast Dive Down:

only one otal)

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obs;

Operational Dive Down 1: Hub and Equipment Type



Operational Dive Down 1: Hub and Equipment Type Forecast Accuracy Summary

Sum of Value		Stat			
Ramp	Ramp Equip		MAE	MAPE	Ν
	K	710.73	69.30	42.07	821
V K		0.23	0.50	13.93	761
		259.86	28.47	32.69	821
	V		24.40	20.09	821
	K	63.79	11.42	28.71	821
	V	914.05	72.43	21.33	821

Sum of Va	alue		Stat			
Ramp	Equip Date		L95	U95	Fcst	95% Error Band
	K	1-Apr-05	703.90	1,177.01	940.45	25%
	V		(2.31)	2.46	0.07	3217%
	K	1-Apr-05	251.91	425.21	338.56	26%
	V		322.60	478.37	400.49	19%
	K	1-Apr-05	50.92	111.36	81.14	37%
	V	1-Apr-05	1,036.75	1,515.57	1,276.16	19%

Operational Dive Down 1: Hub and Equipment Type Illustrative Examples



Operational Dive Down Forecast Accuracy Comparison Hub, Destination, Equipment Type

Sum of Value		Stat			
Ramp	Equip	CONSTANT	MAE	MAPE	Ν
	K	710.73	69.30	42.07	821
	V		0.50	13.93	761
	K	259.86	28.47	32.69	821
	V	293.77	24.40	20.09	821
	K	63.79	11.42	28.71	821
	V	914.05	72.43	21.33	821

As operational forecast detail increases, forecast accuracy decreases at a slower rate than customer-specific forecasts. further, more "full" data sets are available for forecasting.

Sum of N	Ramp	Stat								
Dest	CONSTANT	MAE	MAPE	N	Sum of Value		Ramp	Stat		
	209.35	18.77	19.02	821						
	202.39	21.54	18.49	821	Dest	Equip	CONSTANT	MAE	MAPE I	7
	89.92	11.30	18.49	821		V	190.98	17.11	20.82	821.00
	89.17	8.73	22.56	821		K	18.37	5.75	43.94	821.00
	64 79	9 17	37 51	821		V K	160.20	19.54	70.00	821.00
	58 70	6.74	16.67	821		K V	82.88	10.04	20.82	820.00
	50.70	0.74	10.07	021		ĸ	7.05	2 40	67.69	820.00
	58.45	5.97	15.33	820		V	63.42	8 91	36.58	821.00
	32.39	4.04	27.79	820		ĸ	1 42	1.50	39.33	805.00
	27.26	4.42	23.99	821		V	11 47	3.83	27 43	821.00
	26.77	4.07	23.42	820		ĸ	15.80	1.85	41.08	821.00
	26.55	4.56	23.77	820		V	55.72	6.51	16.83	821.00
	26.52	4 24	23.29	820		К	2.98	1.56	49.43	815.00
	25.25	2 77	12 01	020		V	88.79	8.62	22.23	821.00
	25.55	3.77	43.01	017		K	0.61	0.94	28.08	806.00
	17.89	2.96	27.99	820		V	0.33	0.23	10.76	239.00
	13.65	2.20	36.07	820		V	8.69	2.82	56.07	820.00
	10.23	3.19	55.36	820	1	К	1.54	1.17	39.86	818.00
	5.78	1.13	19.12	488					2	4

General Statements Forecasting Accuracy and Feasibility

- Generally, the "finer" or more detailed the shipper-specific forecast, the less accurate it becomes
 - Noise begins to dominate trend
 - Small deviations and fluctuations in shipper behavior have larger impact on error level
 - Many forecast groups have miniscule expected values; making forecasting in any meaningful way a challenge
 - However, forecasting at a disaggregate level, and then aggregating, is often more accurate at the aggregate level than an aggregate forecast
 - There seem to be strong shipper-specific patterns that are somewhat more easily forecast than the more aggregate level
 - These patterns are lost when aggregated before forecasting
- As we dive down the pyramid, fewer and fewer observations per forecast group, which hampers forecasting
 - Many dates with zero units for small forecast groups
 - Fewer days over which to build forecast
 - Missing (zero) observations are "gapped"
 - MAPE is only calculated for non-zero observations
 - In many cases, not enough observations exist to generate any forecast equation
 - Hardest groups to forecast, but aren't included in our forecast error estimates
 - Many of the forecast groups (even for large customers) are too small to forecast at all would require "All Other Groups" aggregation to forecast them

Observations

- We might not need to forecast at a "Reservation" level of detail (Customer, origin, destination, equipment type, equipment length) in order to have more proactive operations
 - We just aggregate the reservation-level forecast into an operational level, for examples:
 - Origin In gate planning, hub management
 - Origin-Destination train planning
 - Origin-Equipment Type lift planning
 - (etc.)
 - Forecasting at this level generally has lower forecast error, and more detail does not significantly decrease forecast accuracy or ability
- Forecast is a second best to actual reservations
 - Accuracy is reasonable, but nothing close to a reservation
 - Anecdotal evidence of "regular, predictable" traffic is seemingly confirmed by graphical representation, but clearly contradicted by numerical summaries
 - Aggregate volumes are predictable; marginal loads are nearly impossible to forecast with any level of detail
 - Knowing what is coming (via forecast) has different management implications than a reservation
 - Operations makes adjustments due to forecasted volume
 - "Load Acceptance" (no such current function) can make a determination on whether a reservation should be accepted, or at what price and with what service level promise, as opposed to preparing for a forecasted volume