Estimation of Run Times in a Freight Rail Transportation Network

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Summary: This research aims to improve the accuracy of individual freight train run time predictions. A regression model is proposed utilizing a broad selection of explanatory variables. The performance of the proposed regression model is compared against a baseline simple historical averaging technique. The proposed regression model offers substantial improvements in accuracy over the baseline technique: 36.79%, 28.74%, and 20.95% for low, medium, and high priority trains, respectively. The model justifies further exploration by the partner railroad to enable more accurate train schedules with subsequent improvements in railroad capacity, customer service, and asset utilization.

KEY INSIGHTS

1. Meet-pass conflicts are a leading contributor to train run times.

2. Substantial improvements in run time estimate accuracy are possible when predictable delay causing events are incorporated into the estimation methodology.

3. The proposed model accuracy varies inversely with variation in historical run times.

Introduction

Railroads are a critical element of transportation infrastructure and subject to growing demand. According to a recent Federal Highway Administration report, total freight movements on rail are projected to rise from an estimated 16.9 billion tons in 2010 to 27.1 billion tons in 2040 — almost a 61 percent increase (AAR, 2011a).

In terms of monetary impact, according to the U.S. Department of Commerce, freight railroads generate nearly $265 billion in total economic activity each year (AAR, 2011b) This includes direct and indirect effects. IBIS World forecasts, that the industry’s revenue will grow at an average annual rate of 3.4% reaching $90.0 billion by 2016. In 2012 alone, IBIS World projects revenue will increase 2.6% to $78.2 billion.

According to a market study conducted by Hertenstein and Kaplan in 1991 and cited in Hallowell and Harker (1998), a 1% improvement in the reliability of cargo delivery time could yield as much as a 5% revenue increase in several markets.

The main goal of this research is to develop a model to help the partner railroad, a major Class 1 U.S railroad, improve the accuracy of run time predictions. Increased accuracy when estimating run times allows the partner railroad to drive improvements in capacity utilization and punctuality/reliability of its operations.
Research Scope

The analysis conducted and regression model developed are specific to single tracked freight rail network segments. The partner railroad provided a dataset to support this research from a 141 mile, 97% single tracked network segment, running east to west in Missouri. This dataset consists of historical actual network operational data over a two year period from January 2010 to January 2012. This segment was selected out of the entire 31,000 mile network as a sample data set for the following reasons:

- Predominately single tracked, only 3% of the route is double tracked.
- Strong directional influence on run times.
- Broad cross-section of train priorities. Trains have a unique priority which captures their relative importance and unique operating characteristics. Having a broad mix of priorities captures the heterogeneous nature of freight rail networks.

Exhibit 1 shows the mean run times by direction and priority for trains transiting the Missouri track segment over the two year historical data period.


Methodology

Run time is defined as the time of departure from an origin station to the time of arrival at a destination station, with no yard time included. A variety of different methodologies such as simulation, queuing, probabilistic and regression modeling can be used to estimate train run times. In our research we used regression modeling to analyze the individual impact on train run times of the different explanatory variables identified.

A logarithm transformation was applied to the train run times, to compensate for the right-tailed nature of the run times distribution. In place of an untransformed run time, the logarithm of the run time was used both as the dependent variable in the regression model and to build a rolling run time average.

A correlation analysis was conducted to identify explanatory variables that capture predictable sources of delay and influence run times for use in a regression model. A regression model was proposed utilizing the following explanatory variables to predict train run times: rolling historical average, congestion window, meets, passes, overtakes, direction, arrival headway, and departure headway. The performance of the proposed regression model was compared against a baseline simple historical averaging technique for a two year period of actual train operational data.

It is useful to define the following terms utilized in this research:

Meets - the number of trains traveling in the opposite direction a particular train encounters during its transit.

Passes - the number of trains a particular train passes while traveling in the same direction during its transit.

Overtakes - the number of trains a particular train is overtaken by when traveling in the same direction.

Arrival headway - the difference in time between the arrival of the last train at the destination station and the train in question.

Departure headway - the difference in time between the departure of the last train at the origin station and the train in question.

Congestion window - the number of trains that have or will depart within some time period of the departure of the train in question.

Rolling historical average - the average of the logarithms of total run time for trains with the same direction and priority as the train in question from the previous thirty day period.
Model Proposed and Results

A simple thirty day historical average, by train priority and direction, was utilized as a baseline run time prediction estimate.

Exhibit 2 shows the performance of each of these priority specific regression models. The regression model explained a greater portion of the variability for the low priority trains. The greatest improvement over the simple average baseline occurs with low priority trains.

| Term                  | Coefficient | Std. Error | t Ratio | Prob>|t| |
|-----------------------|-------------|------------|---------|------|---|
| Intercept             | 0.5065      | 0.0383     | 13.23   | <0.0001* |
| Rolling Run Time Average | 0.3217  | 0.0474     | 6.79    | <0.0001* |
| Departure Congestion Window | -0.0049 | 0.0005     | -10.86  | <0.0001* |
| Meets                 | 0.0229      | 0.0008     | 29.1    | <0.0001* |
| Passes                | -0.0462     | 0.0080     | -5.78   | <0.0001* |
| Overtakes             | 0.0718      | 0.0037     | 19.54   | <0.0001* |
| Direction             | 0.0161      | 0.0044     | 3.69    | 0.002* |
| Arrival Headway       | 0.0128      | 0.0012     | 11.03   | <0.0001* |
| Departure Headway     | -0.0142     | 0.0012     | -11.81  | <0.0001* |

Exhibit 3 - Regression model coefficients for low priority trains on Missouri segment

We did not analyze the impact of removing one-off events from the historical data, such as flooding or specialized track maintenance, on the model’s explanatory power and accuracy. It may be worthwhile to investigate periods of relative calm with respect to unpredictable delay causing events to get an improved sense of the model’s true capabilities.

Similar improvements in accuracy were observed when the proposed model was applied to historical run data from two additional track segments, one in North Dakota, the other in Oregon. The regression model was re-created for each of the two track segments utilizing the same calculated explanatory variables to generate term coefficients specific to the low, medium, and high priority trains operating on each segment.

Limitations

The regression model utilizes explanatory variables that depend upon accurate operational data. With respect to the historical data, the variability is 0%. However, with forward-looking operational schedule data, there is significant variability present in the types and numbers of the trains departing other than the ones that are scheduled. This decreases the accuracy and negatively influences the predictability of the model.

Conclusion

Meets represent the highest statistical significance when predicting run times which intuitively mirrors the expected operational dynamics. Attention should be focused on train conflict resolution: meets, passes, and overtakes, as they weigh heavily on train run times. It is clear the proposed model shows strong promise in being able to improve the accuracy of freight train run time predictions.

References

AAR. (2011a). America needs more rail capacity. Association of American Railroads, (October)
