Rail Fatigue Life Forecasting Using Big Data Analysis Techniques

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Overview

- US Railroads spend on the order of $11 Billion on Track and Property
- Rail Fatigue is one of the Primary causes of rail failure
- Weibull Analysis allows determination of the rate of failure
- Recent advances in “Big Data” present the option of refining the Weibull methodology
- Better prediction means less waste, saving money or allowing more to be repaired

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Data and Baseline Analysis

- 10 years of data from a Class 1 railroad
  - 11,000 miles of track
  - 98,000 defects, of which 41,000 are fatigue defects
  - Rail Grinding, Curvature and Location data included
- Traditional 2-parameter Weibull Analysis has been used by railroads to forecast rate of fatigue defect development
- Data does not always follow traditional Weibull expectations
  - Various reasons why: data collection methods, errors in recording
- Enhanced 3-Parameter Weibull Analysis applied
  - 3rd Parameter is an intercept/"failure free" period
  - Often results in better fits, but justification behind the use is still in debate

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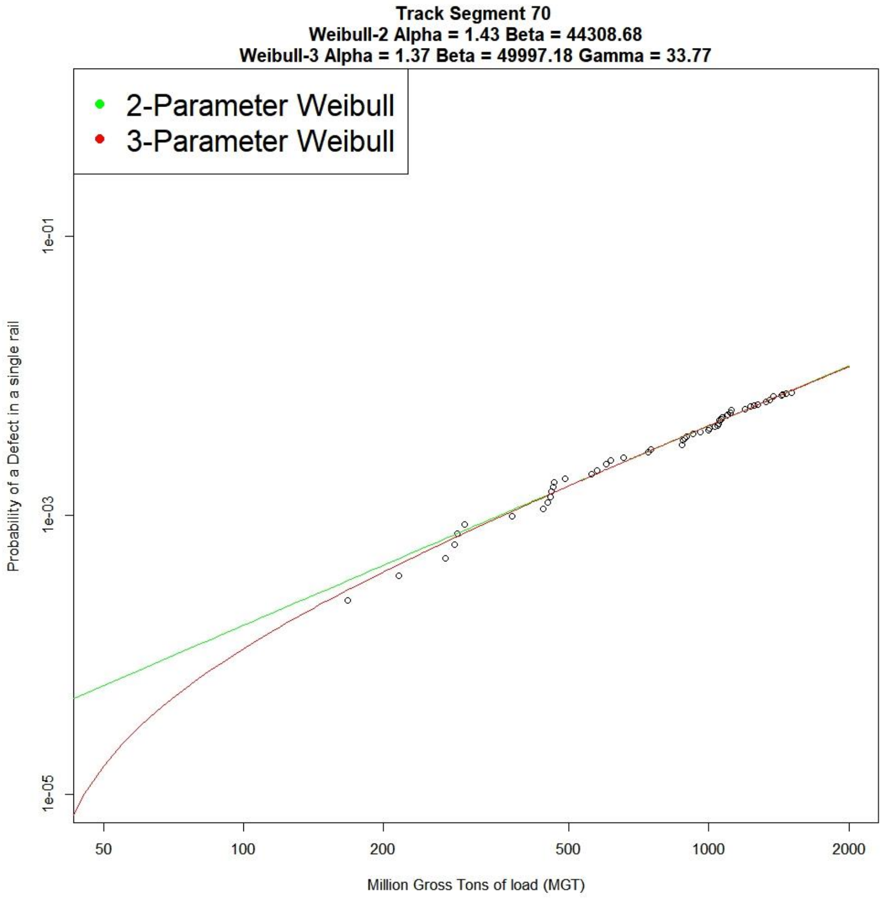
Track Segment A



- Shows a good relationship to the 2-parameter Weibull Function
- 3-parameter Weibull overlaid with similar results
- Several small “jumps” observed; corresponding to several defects occurring at the same time (tonnage level of MGT)

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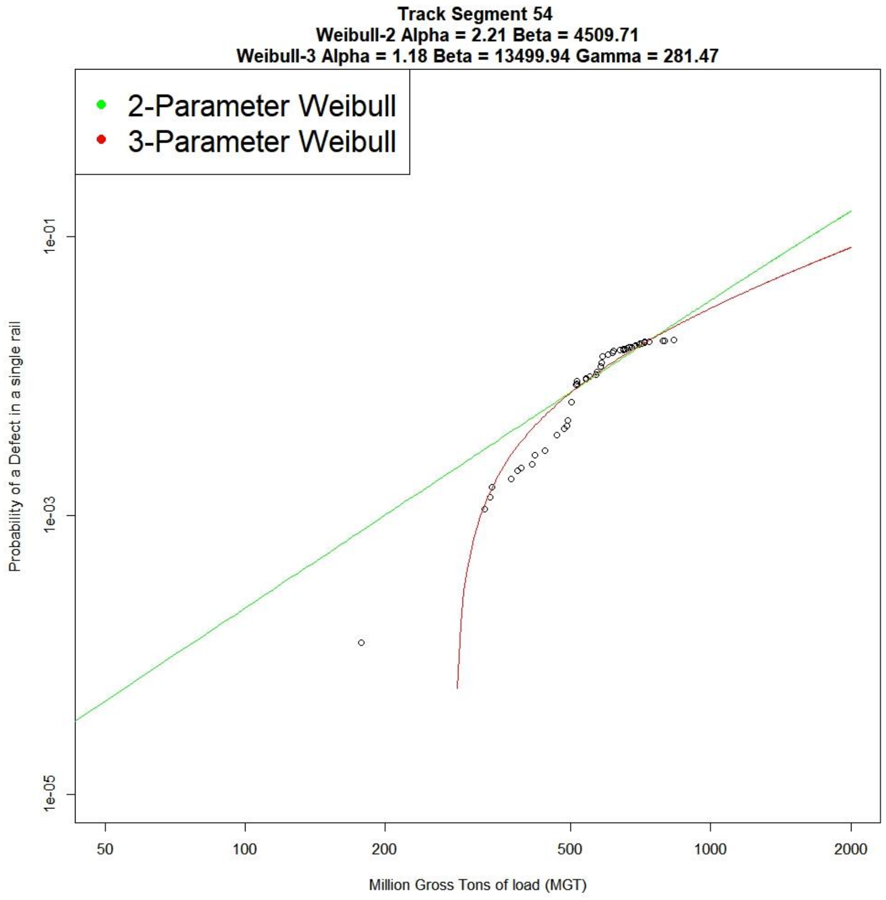
Track Segment B



- “Steps”/”Jumps” in data are more noticeable
- 3-Parameter Weibull fits better, but cannot be rationalized

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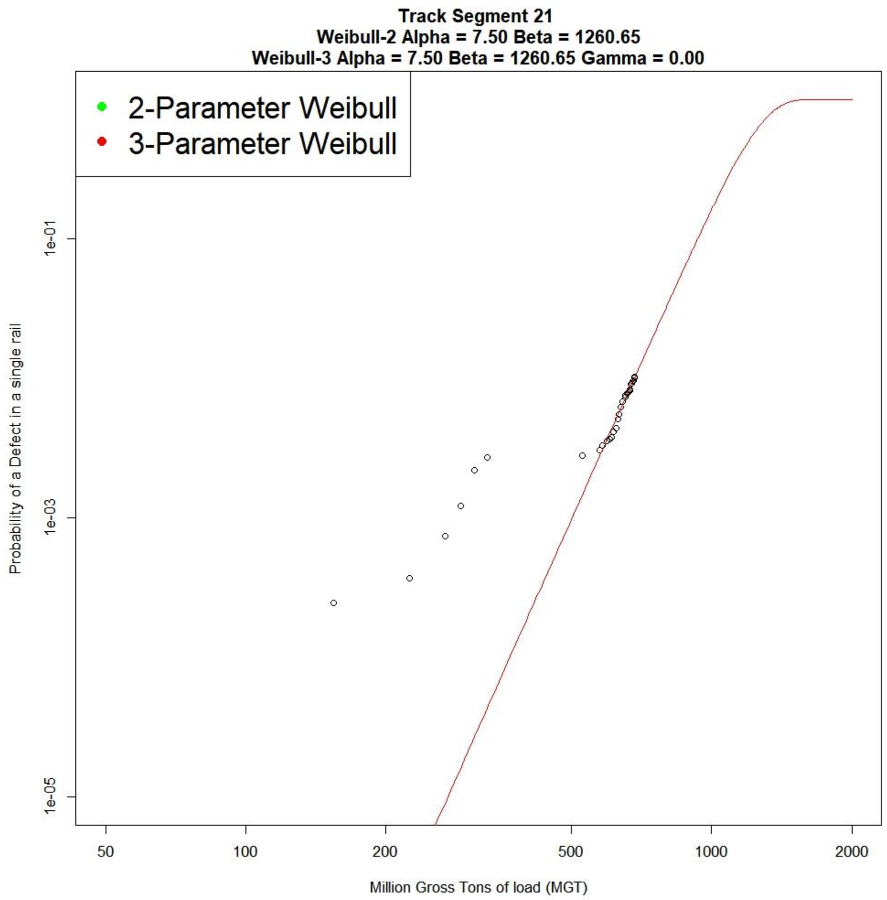
Track Segment C



- 2-parameter and 3-parameter Weibull curves are identical
- "Early"/Low MGT defects do not appear to follow Weibull
- "Late"/High MGT defects follow Weibull much better
- Possibly a result of two different defect types

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Literature Search

- To date, over 60 papers were reviewed
- One approach looked at the applications of hazard functions in the Weibull equation
  - Allows a better fit when two defect populations result in “jumps” or “steps” similar to Segments B and C.
- Rare-Event prediction with Big-Data may allow more precise pinpointing of future defects
  - Instead of track segments on the order of 30 miles, could reduce down to <1 mile
- Expanding the Weibull function to account for situational variations
  - Follows other work that generalized the Weibull function up to a 5-parameter method

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Early Machine Learning Tests

- K-Nearest Neighbors was applied to the data
  - Looked at predicting the state of individual track segments approx. 1 mile in length vs. Weibull's ~30 mile segments
  - Included tests to see if increasing years of historical data improved results
  - Due to majority of null-responses, accuracy was based on only positive predictions
  - Not an effective fit

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KNN Results Pt.1

Trial 1	Output 0	Output 1		Trial 2	Output 0	Output 1
Input 0	21739	93		Input 0	21832	0
Input 1	420	1		Input 1	421	0
False Positive Rate		0.426%		False Positive Rate		0.000%
False Negative Rate		99.762%		False Negative Rate		100.000 %

- Trial 1 was a basic KNN using a single year of historical data
  - Only one track segment was correctly determined
- Trial 2 expanded K to 6
  - Overabundance of null-responses resulted in everything being classed as Null

KNN Results Pt.2

Trial 3	Output 0	Output 1
Input 0	21751	261
Input 1	229	12
False Positive Rate		1.186%
False Negative Rate		95.021%

Trial 4	Output 0	Output 1
Input 0	21761	251
Input 1	225	16
False Positive Rate		1.140%
False Negative Rate		93.361%

- Trial 3 included Milepost as an additional location parameter
- Trial 4 dropped MGT as a parameter

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Future Work

- Apply methodologies found in Literature Search
- Expand Machine Learning tests to include other methodologies, such as Neural Networks
- Apply Big-Data methodologies to generate Weibull functions that are sensitive to key railroad variables
- Provide a detailed method of forecasting rail life due to fatigue and the improvements to maintenance efforts

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