Construction and Building Materials 127 (2016) 546–555

Contents lists available at ScienceDirect

Construction and Building Materials

journal homepage: www.elsevier.com/locate/conbuildmat

Using multiple adaptive regression to address the impact of track geometry on development of rail defects

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HIGHLIGHTS

- This paper presents an application of multivariate regression splines (MARS) to a model looking at the railroad track defect behavior.
- As part of this study, it was determined that there is a reduction in rail life of approximately 30%, when track geometry defects are present.
- This paper has important ramifications in railroad track geometry maintenance and its economic importance.

ARTICLE INFO

Article history:
Received 22 February 2016
Received in revised form 8 September 2016
Accepted 6 October 2016

Keywords:
MARS
Track geometry defects
MGT
Railway

ABSTRACT

This paper presents an application of multivariate regression splines (MARS) to a model looking at the railroad track defect behavior. MARS is a non-parametric function estimation technique that shows great promise for fitting non-linear multivariate functions. The MARS approach was used here, together with traditional regression analysis techniques, to develop equations to predict the life (in Millions of Gross Tons or MGT) of a rail defect in the presence of track geometry defects. The MARS approach, using extensive input data, identified and accounted for the key variables contributing to a reduction in rail life. The MARS technique allows for easy interpretation of the relative importance of the different input parameters, to include defect type, and resulted in the development of rail defect life predictive equations as a function of these key parameters. As part of this study, it was determined that there is a reduction in rail life of approximately 30%, when track geometry defects are present.

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1. Introduction

A recent FRA[1] sponsored study looked at the relationship between the presence of one of more track geometry defects and the development of rail defects at that same location, after the occurrence of the geometry defects. This is a relationship, that basic track engineering theory has suggested, but which has never been proven or validated. Theoretical research has shown that the presence of geometry defects generates increases dynamic wheel/rail loads [1–3], which in turn can result in earlier development of rail fatigue defects and an associated reduction in fatigue rail life. That is because the defects result in a dynamic effect on every wheel that passes over the rail section, increasing the level of loading and the associated level of stress experienced by the rail [4–7]. This includes both bending stresses and contact stresses, both of which have an effect on the development of rail defects [8–11]. There have been some few papers on the application of curve fitting methods in rail track engineering including Paixao et al. [12] and Kouroussis et al. [13].

In order to examine this relationship, the study correlated multiple years of track geometry with a database of several years of rail defects obtained from a major US Class 1 railroad. The railroad system data represented more than 22,000 track miles (37,000 km), and included:

- Three years of rail defect data, representing approximately 50,000 defect records, which was subsequently narrowed to approximately 26,000 defects of “interest”.
- Five years of track geometry data representing approximately 335,000 defect records.
- Tonnage data (annual MGT).

This paper proposes the use of MARS as another tool in track degradation. The MARS technique is a data-driven procedure. It produces a model for the response that automatically selects the

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[1] INTEGRATION OF MULTIPLE INSPECTION SYSTEM DATA TO IDENTIFY POTENTIALLY UNSAFE TRACK RAIL CONDITIONS, FRA Contract DTFR53-13-C-00066, October 2015.

http://dx.doi.org/10.1016/j.conbuildmat.2016.10.012
0950-0618/Published by Elsevier Ltd.

variable appearing in the final equation. It also indicates whether a variable enters additively, or interacts with other variables. Finally, it selects the complexity of the relationship between the response and each variable. The main idea behind the MARS strategy is that different areas of sample space or different variables may have a greater or lesser contribution to the response surface. MARS can incorporate categorical variables, logit regression, and missing data.

2. MARS

Friedman [14] introduced the MARS approach as a method for fitting the relationship between a set of predictors and a dependent variable. MARS is fast and is based on a divide and conquer strategy, partitioning the training data sets into separate regions, each of which gets its own regression line. MARS is a data-driven procedure, compared with the more frequently used model-driven procedures. The MARS model is a regression model using basic functions as predictors in place of the original data. The basic problem facing railroad engineers in performance and deterioration modelling is how best to determine the fundamental relationship between the dependent variable (usually MGT), and a vector of predictors. The question is how best to specify f in the following equation:

$$MGT = f(G_1, G_2, \ldots, G_n) \tag{1}$$

The MARS algorithm searches over all possible knot locations, and across interactions among all variables. It does so through the use of combinations of variables.

The general form of a MARS predictor is as follows [15]:

$$y = \beta_0 + \sum_{j=1}^{P}\sum_{b=1}^{B}[\beta_{jb}(+)Max(0, x_j - H_{bj}) + \beta_{jb}(-)Max(0, H_{bj} - x_j)] \tag{2}$$

for P predictor variables and B basis function. The basis functions $Max(0, x - H)$ and $Max(0, H - x)$ are univariate and do not have to each be present if their β coefficients are 0. The H values are called hinges or knots. An example of MARS model is:

$$y = 28 - 0.5Max(0, x_1 - 6) + 2.5Max(0, 6 - x_1) + Max(0, x_2 - 7) + Max(0, 2 - x_3) - Max(0, x_3 - 13)$$

Since $Max(a, b) = -Min(-a, -b)$ and $a + Max(b, c) = Max(a + b, a + c)$, a MARS predictive model is always expressible as a sum of Max and Min operators on piecewise linear univariate expressions. The MARS algorithm proceeds as follows: a forward stepwise search for the basis function takes place with the constant basis function, the only one present initially. At each step, the split that minimized some "lack of fit" criterion from all the possible splits on each basis function is chosen. This continues until the model reaches some predetermined maximum number of basis functions, which should be about twice the number of expected in the model to aid the subsequent backward stepwise deletion of the basis function. The backward stepwise function involves removing basis functions one at a time until the "lack of fit" criterion is a minimum. In the backward stepwise deletion, the least important basis functions are eliminated one at a time. The lack of fit measure used is based on the generalized cross-validation (GCV) [16]:

$$GCV = A * \sum_i \left(y_i \hat{f}(x)\right) / N \tag{4}$$

with $A = [1 - C(M)/N]^{-2}$ and $C(M) = 1 + trace[\mathbf{B}(\mathbf{B}^{-}\mathbf{B})^{-1}\mathbf{B}']$ being the complexity function [14]. M represents the maximum number of linear basis functions (BFs). N is the number of observations. $\mathbf{B}$ denotes the matrix of BFs with dimension $M \times N$. The GCV criterion is the average residual error multiplied by a penalty to adjust for the variability associated with estimation of more parameters in the model [17].

3. Analysis approach

Correlation and statistical analyses were performed together with a series of analyses looking at the relationship between the life of a rail defect (in cumulative MGT) and the presence of geometry defect(s).

Table 1 presents a summary of the initial correlation between rail defects and geometry defects for the full system (22,000 miles) and for the high tonnage segments, defined here as having a minimum annual tonnage of 20 MGT. As can be seen from Table 1, for the full system, 11% of all rail defects were preceded by one or more track geometry defects. For track with greater than 20 MGT annual tonnage, this percentage increases to almost 12%. Likewise for the full system, 15% of all Traverse Detail Defect (TDD) rail defects were preceded by one or more track geometry defects and for track with greater than 20 MGT annual tonnage, this percentage increases to almost 17%.

In contrast, if the relationship between rail defects and geometry defects were purely random the probability of a match at a given location was calculated to be 1.4% for all defects and 0.6% for TTD. Thus the actual percentages of matches were of the order of 7–20 times that which would occur purely by random chance.

Analysis of the matches between the rail defects and preceding geometry defects, showed that a large percentage of these matches had in fact multiple two or more geometry defects preceding the rail defect, at the same location. These repeat matches were either the same type of geometry defect occurring at a different time (corresponding to a different geometry car run) or were a different type of geometry defect at the same location. These results, show that for the full system, 38% of the matches had multiple geometry defect matches (Repeats), while for TDD defects 41% of the matches had multiple geometry defect matches (Repeats). The higher density (>20 MGT) track showed a similar behavior.

On curves, the results were even more dramatic, with 21% of all rail defects were preceded by one or more geometry defects and approximately 10% of all rail defects were preceded by two or more track geometry defects (Table 2). For TDD defects only, over 30% of all rail defects were preceded by one or more geometry defects and 15% of all TDD rail defects were preceded by two or more track geometry defects.

3.1. Rail defect by type vs. geometry defect by type

As part of this correlation analysis, the Class 1 railroad system rail defect-geometry defect matches were correlated by specific defect type (as defined previously). This is shown for the geometry and rail defects in Table 3. Note, this is a consolidated matrix where various defects with few occurrences are eliminated and many of the geometry defect classes consolidated, particularly left and right rail geometry defects such as cant and alignment. As seen in Table 3, TDDs represent the largest class of matched defects with 51% of all rail defects. Other key rail defect types include Bolt Hole Breaks (BHB) representing approximately 8%, Electric Flash Butt Welds (EFBW) approximately 7%, Thermit Welds (TW) approximately 12%, Vertical Split Heads (VSH) around 5%, Head and Web separation (HW) around 8% and Shelly Spots (SD) around 9%. Table 4 presents a summary of the major matched track geometry defect categories to include Cant (31.6% of all defects and 39.4% of TDDs), Cross-level/Cross-Level Index Meter (CLIM) (18.0% of all defects and 13.8% of TDDs), Warp (25.0% of all defects and 21.2% of TDDs) and Gage/Track Strength (11.8% of all defects and 14.7%