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MODELING TRACK GEOMETRY DEGRADATION USING SUPPORT VECTOR MACHINE TECHNIQUE

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ABSTRACT

Analyzing track geometry defects is of crucial importance for railway safety. Understanding when a defect will need to be repaired can help in both planning a preventive maintenance schedule and reducing the probability of track failures. This paper discusses the data cleaning and analysis processes for modeling track geometry degradation. An analytical data model named the Support Vector Machine (SVM) was developed to model the deterioration of track geometry defects. This paper mainly focuses on the following three defect types - surface, cross level and dip. The model accounts for traffic volume, defect amplitude, track class, speed and other potential factors. Results demonstrate that the proposed analytical data model can have a prediction accuracy above 70%.

INTRODUCTION

Infrastructure safety is the top priority of the railroad industry. Track geometry defects are a common cause of train accidents and service disruptions in the United States. There are various track geometry defects, such as surface, cross level and dip. According to the Railway Applications Section (RAS) of the Institute of Operations Research and the Management Sciences (INFORMS), surface is uniformity of the rail surface, which is measured in short distances along the top of the rail, measured over a 62-foot chord. Cross level is the difference in elevation between the top surfaces of the rails at a single point along a straight segment of track. Dip is the largest change in elevation of the centerline of the track within a 31 foot moving window. These defects are identified periodically by track geometry cars. Track geometry defects can be classified into two severity levels, i.e. red tags and yellow tags. The U.S. Federal Railroad Administration (FRA) requires severe defects (aka. red tags), to be fixed immediately, while the less severe defects (aka. yellow tags), shall be fixed within a planned period. Nevertheless, the yellow tags could become red tags if left unfixed. In order to facilitate risk-based track maintenance planning, it is important to accurately predict when a yellow-tag defect may grow to a red-tag defect.

LITERATURE REVIEW

There have been several track condition prediction methods developed by researchers. Ferreira and Murray (1997) provided an early overview of several important track deterioration models up to the late 1990’s and summarized three major categories of predictors frequently used, namely, dynamic forces, train speeds and axle loads [1]. Alfelor et al. (2001) built a track degradation database that recorded information from insert preposition (i.e. “the,” “a”) Gauge Restraint Measurement System (GRMS), which included gauge restraints, track geometry parameters, traffic loads and environmental factors [2]. Using this database, the relationship between track degradation and a specified influencing factor can be estimated using regression techniques. In China, Chen et al. (2006) developed an Integrated Factor Method (IFM) to predict track geometry parameters in the next month, based on the assumption that the monthly track geometrical conditions are correlated [3]. Veit and Marschnig (2010) used an exponential model to predict track condition over five-meter-long track sections between two successive maintenance activities of the same kind (e.g., ballast temping) [4]. Recently, Liu et al. (2010) developed a short-range prediction model which employs linear regression and repeated substitution to predict track irregularity over short track sections of a unit length [5]. Xu et al. (2012) proposed a multistage linear method to describe track condition deterioration processes [6]. Later, Xu et al. (2013) estimated the historical deterioration rate by aggregating historical values of track geometrical parameters and then predicted future track failure using a linear formulation that is updated dynamically [7]. He et al. (2014) proposed a log-transformed linear regression model to characterize degradation processes of different types of yellow tag geometry defects [8].

In addition to using regression modeling, some researchers also used stochastic modeling to characterize track geometry degradation processes. Mercier (2009) estimated track deterioration through a bivariate Gamma process constructed by a trivariate reduction [9]. Their model was applied to fitting the empirical data from the Paris-Lyon high speed line. Andrade et al. (2012) found that longitudinal leveling track defects can be characterized by a simple linear equation where the parameters follow a correlated bivariate lognormal distribution and can be estimated by a corresponding random field [10]. Costello et al. (2012) presented a stochastic rail wear model in which future track deterioration can be predicted using a stationary Markov process where the transition probability matrix is obtained by historical data [11]. Alemazkoor et al. (2015) conducted a survival analysis with a Weibull distribution assumption to model the probability of track failure [12].

Data mining techniques have emerged as a new research tool. Andrade and Teixeira (2012) proposed a Bayesian model to assess the linear relationship between the standard deviation of longitudinal leveling defects and the accumulated tonnage [10]. Sinha et al. (2015) introduced a hybrid predictive framework which includes logistic regression, decision trees and clustering to analyze track geometry degradation data [13]. Cárdenas et al. (2015) created an ensemble classifier based on Gamma process approximation, logistic regression and SVM, in order to improve the prediction accuracy of track geometry defects [14]. Elleuch et al. (2015) adopted the Variable Neighborhood Search (VNP) algorithm to look for the optimal solution set by minimizing mean absolute errors [15].

PROBLEM STATEMENT

The primary objective of this paper is to build an analytical data model that allows railroads to predict when a yellow-tag defect will evolve into a red-tag defect that requires immediate repair. That is to say, the ultimate response variable is the binary Yellow/Red tag. There are two major challenges in the track geometry data provided by the INFORMS RAS. First, within the study period, one specific type of defect at the same location may occur only once or twice, making it imperative to somehow group some records so as to create repetitive data points. Second, the raw data contains a large amount of records that are either missing or suspicious, thus making it inevitable to either aggregate the information or exclude the problematic observations. The following section explains a data cleaning process for modeling data.

DATA CLEANING

Data investigation and cleaning is an important step prior to conducting any statistical analysis. The following sections explain how the raw data were treated and the assumptions made given data limitations.

The dataset used in this paper was provided by the RAS Problem Solving Competition 2015. The original dataset contains four line segments for all three defect types as mentioned before. For simplicity, only data on the 2nd line is used in the following analysis. There are 921 inspection records of dip, 2,039 inspection records of surface, and 4,437 inspection records of cross level. Each inspection record has several potential predictor variables (Table 1.). RAS contends that the Yellow/Red tags are deterministically decided by both defect amplitude (field name is DEF_AMPLTD) and class of tracks. Therefore, instead of modeling the binary outcome Yellow/Red directly, modeling the continuous DEF_AMPLTD over time is also a reasonable choice. In the following analysis, the variable DEF_AMPLTD and track class are of importance in aggregating the dataset.

Table 1. Variables in the Track Geometry Dataset

Variable Name	Description
MILEPOST	Point on the track
TRACK_SDTK_NBR	Track type
TEST_DT	Inspection date
DEF_NBR	Defect sequence number
GEO_CAR_NME	Track geometry car name
DEF_PRTY	Severity of the defect: Yellow or Red
DEF_LGTH	Length of defect in feet
DEF_AMPLTD	Defect Amplitude - Maximum size of defect in inches
TSC_CD	Track type (tangent, spiral and curve)
CLASS	Class of Track
TEST_FSPD	Operating speed of freight train
TEST_PSPD	Operating speed of passenger train

DFCT_TYPE	Defect type (Cross Level, Surface, Dip)
TOT_CAR_EAST	Total number of cars traveling east
TOT_CAR_WEST	Total number of cars traveling west
TOT_TRN_EAST	Total number of trains traveling east
TOT_TRN_WEST	Total number of trains traveling west
TOT_DFLT_MGT	Sum of total gross tons

Step 1: Segmentation

In order to create repetitive data points, the raw dataset is restructured into a number of 100-foot-long sections, a benchmark adopted in the literature [8] and also in the information provided by RAS. For each defect type, the minimum MILEPOST is set as the initial value for the first 100-foot section. The segmentation is conducted until the last section covers the maximum MILEPOST. Finally, the data is sorted first by section number, then by TEST_DT, and lastly by MILEPOST.

To illustrate this procedure, examine the data of defect type "dip" as an example. In this case, the minimum MILEPOST is 2.1392 (in miles), therefore, the first section (referred to as "section 1") covers all the track geometry defects whose milepost locations are between 2.1392 and 2.1581 (the segment length is 100 feet). Similarly, section 2 covers all defects whose milepost locations are between 2.1581 and 2.1771. Based on this procedure, the last section starts at milepost 281.9309 and ends at milepost 281.9498, with the maximum MILEPOST of 281.93326 included.

Using this segmentation procedure, the same track section can be assumed to be "spatially homogeneous." In other words, they are close enough in location to be considered as the same record.

Step 2: Aggregation

Within each section, some of the records were from the same test date, but had different values for variables such as track class, defect length and defect amplitude. The following is an example from data of defect type "dip." Note that INFORMS RAS did not clarify the source for track class. In this paper, we assume that the track class is delineated based on the maximum operating speed.

Table 2. Example of Data Aggregation

MILEPOST	TEST_DT	DEF_PRTY	DEF_AMPLTD	CLASS
5	18-Aug-13	YEL	1.69	4
5	18-Aug-13	YEL	1.82	3
5	21-May-13	YEL	1.33	5
5	21-May-13	YEL	1.45	5

The following assumptions were made in this paper to account for this and other data challenges.

Assumption 1: For the records with the same test date but different values for other variables, if they are of the same track class and the same severity of defect (i.e. Yellow or Red), then they are combined. The resulting values for differing variables are simply the corresponding average values from the original records. Otherwise, such contradictory information is excluded from the analysis.

As mentioned before, Yellow/Red is largely defined by both DEF_AMPLTD and class, suggesting records from different defects should never be aggregated since different classes may have different paths for deterioration of defects. Therefore, records from Class 3 and 4 were dropped from the analysis since they are from different classes. Thus records in Table 2. can be aggregated into the following new observation.

Table 3. Example of Data Aggregation (continued)

MILEPOST	TEST_DT	DEF_PRTY	DEF_AMPLTD	CLASS
5	21-May-13	YEL	1.39	5

Step 3: Filtration

A close scrutiny of the segmented and aggregated data shows that within each section, the DEF_AMPLTD- our potential response variable- can experience a complex increase/decrease pattern. Here is an example from the data of defect type "dip."

Table 4. Example of Data Filtration

MILEPOST	TEST_DT	DEF_PRTY	DEF_AMPLTD	CLASS
105.4569	7-May-09	YEL	**1.41**	5
105.4597	1-Jun-11	YEL	**1.30**	5
105.4674	26-Apr-12	YEL	**1.47**	5
105.4563	17-Sep-12	YEL	**1.48**	5

Assumption 2: Any decrease in DEF_AMPLTD suggests a maintenance action.

The INFORMS RAS did not provide information on maintenance records; hence, it is difficult to validate this assumption. However, the amplitude of a defect may not reduce as traffic accumulates unless a maintenance action was executed. Another possibility is that the track geometry measurement might be erroneous. But such a problem is beyond the scope of this paper.

This analysis only includes the sections with increasing values of DEF_AMPLTD only. In summary, for each section, only inspection records that form the longest complete path of defect evolution without disruption from maintenance are retained in the new dataset. For the example in Table 4., the final sub-section is kept as follows.

Table 5. Example of Data Filtration (continued)

MILEPOST	TEST_DT	DEF_PRTY	DEF_AMPLTD	CLASS
105.4597	1-Jun-11	YEL	1.30	5
105.4674	26-Apr-12	YEL	1.47	5
105.4563	17-Sep-12	YEL	1.48	5

Time intervals between two consecutive inspection records within the same section are calculated. Some time intervals are very large. Here is an example from data of defect type "dip."

Table 6. Example of Data Filtration (continued)

MILEPOST	TEST_DT	DEF_PRTY	DEF_AMPLTD	CLASS	Time Interval
279.1637	8-May-09	YEL	1.54	4	NA
279.1653	17-Jun-09	YEL	1.58	4	40
279.1611	6-Oct-09	YEL	1.73	4	111
279.1641	15-Apr-11	RED	1.85	4	556

The example shows that the 4^{th} and 3^{rd} records are almost one year and a half apart in time.

Assumption 3: Inspection is conducted at least once a year.

This assumption eliminates the inspection records that are too temporally distant from the last inspection record. In Table 6, it is reasonable to imagine that there must be some missing inspection records between 6-Oct-09 and 15-Apr-11, thus making the last inspection record less consistent with its predecessors than it should be. As a result, the final record was dropped from the analysis.

After the above three-step cleaning procedure, there are 281 inspection records left for the defect type "dip," 443 inspection records for "surface," and 805 inspection records for "cross level."

TRAFFIC ACCUMULATION

Traffic volume is an important factor for track degradation [16]. The traffic volume (number of trains, number of cars, total gross tons) between any two consecutive inspections along the same section was estimated. INFORMS RAS also provided monthly traffic volumes on different sections of the selected line segment. The following assumption is made to allow for estimating accumulated traffic volume between inspections.

Assumption 4: Due to a lack of daily traffic information, it is assumed that traffic is uniformly distributed within any month.

For instance, if the total tonnage of January is 31 million gross tons, the daily tonnage in January is assumed to be 1 million gross tons. This assumption makes it easier to extrapolate the traffic volumes between any two specific dates. Note that such calculations are conducted only for inspection records that are within the same section. Also, the first record in any section is set to be the starting point for traffic accumulation (Table 7.).

Table 7. Example of Traffic Accumulation

TEST_DT	TOT_CAR_EAST	TOT_CAR_WEST	TOT_TRN_EAST	TOT_TRN_WEST	TOT_DFLT_MGT
8-May-09	NA	NA	NA	NA	NA
17-Jun-09	13210.32	13210.32	1070.258	838.5763	12.56534

Again the first record is the starting point of the section; hence, no calculation is carried out. The traffic volume between the two defect records is the accumulated number of total cars and trains, and total gross tons running within the studied section from May 9th, 2009 to June 9th, 2009. Note that although the total number of trains and the total number of cars are computed in the above example, they are actually omitted in the analysis that will be introduced in the next section. This is because a significantly large portion of train and car information was missing in the RAS dataset. Hence, only TOT_DFLT_MGT is retained for future analysis.

Besides traffic volume, changes in DEF_AMPLTD are also obtained between consecutive inspection records within the same section. DEF_AMPLTD in the "cross level" defect type can be positive or negative. For cross level data, absolute values of DEF_AMPLTD are used instead of the original values. The next section will introduce a two-stage approach which will model DEF_AMPLTD first and then predict whether a defect will be classified into a Yellow or Red tag based on the predicted track geometry defect amplitude.

TWO-STAGE PROCEDURE

The objective of this paper is to predict when Yellow tags will become Red tags. Recall that the Yellow/Red tags are actually determined by DEF_AMPLTD and track class. In this case, the underlying variable that should be modeled first is the main determinant of the deterioration, i.e. DEF_AMPLTD.

A two-stage procedure is formulated as below:

Stage 1: Model the changes in DEF_AMPLTD (denoted as “diff” hereafter) for each defect type. Then add the predicted diff and the DEF_AMPLTD of the last inspection to obtain the DEF_AMPLTD for the next inspection.

Stage 2: Classify a defect as a Yellow or Red tag based on the predicted DEF_AMPLTD. The classification thresholds for Yellow and Red tag defects were provided by the RAS of INFORMS.

Note that only DEF_AMPLTD and track class should be inputs for Stage 2 analysis because all other variables are irrelevant in the determination of Yellow/Red tag as mentioned before.

SUPPORT VECTOR MACHINE DATA MINING TECHNIQUE

The Support Vector Machine (SVM) is applied to the two-stage procedure above. SVM is one of the most popular machine learning methods that can be used for both classification and regression analysis [17]. Given training data, SVM categorizes new data through optimal separation of hyperplanes that maximize the margin of the training data. In the field of data mining, the SVM represents one type of supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis. Given a set of training examples, each belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into either one category or the other. Like classical techniques, SVMs also classify the category of each observation.

In this paper, all numerical analyses were conducted on the platform of R 3.1.1 with package e1071. For each defect type, 60% of the cleaned RAS data are used as the training data and the other 40% were used for blind prediction. To reduce sampling errors, the SVM analysis was repeated 50 times. For Stage 1 analysis, the input variables are track class, traffic volume and time intervals. For Stage 2 analysis, the input variables are track class and the predicted DEF_AMPLTD. The average prediction accuracy for dip is 76.18%, the average prediction accuracy for surface is 82.81%, and the average prediction accuracy for cross level is 72.93%.

In order to investigate the effects of other variables not included in the Stage 1 analysis, they were added to the model in succession. Additional variables can be retained in the model only if this variable can significantly improve the model fit. Table 8. demonstrates the highest prediction accuracy with the variables retained in the final model.

Table 8. Prediction Accuracy of the Overall Procedure

Defect Type	Highest Average Prediction Accuracy	Predictors
DIP	76.82%	Traffic, Class, Time Interval, TRACK_SDTK_NBR, TSC_CD, TEST_PSPD
SURFACE	84.42%	Traffic, Class, Time Interval, DEF_NBR
CROSS LEVEL	73.10%	Traffic, Class, Time Interval, DEF_LGTH, TSC_CD, TEST_FSPD,TEST_PSPD

CONCLUSION

This paper applies data mining techniques to analyzing track geometry degradation. A Support Vector Machine (SVM) model was used to predict the change in track geometry defect amplitude and when a yellow tag defect may grow large and become a red tag defect. The model accounts for traffic volume, track class, inspection interval and other potential factors. The analysis shows that the SVM model can achieve an overall prediction accuracy above 70% for all three selected track geometry defect types.

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