Maintenance Model for Railway Substructure

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ABSTRACT: A maintenance model for railway substructure is proposed by combining a ballast deformation model presented in this study and a previously developed railway track subgrade model. This model is used to predict the deformation of railway track and to estimate a schedule for ballast maintenance and tamping. The prediction of the permanent deformation of fouled railway ballast is based on an empirical ballast deformation model and a statistical technique called "Support Vector Regression – SVR". Both approaches are based on data obtained from a large-scale cyclic triaxial (LSCT) apparatus for the fouled ballast. The empirical deformation model of railway ballast incorporates the strong correlation between the plastic strain rate of ballast under cyclic loading with fouling and stress conditions (overall prediction R^2=0.89). The concept of statistical learning regression (i.e., Support Vector Regression, SVR) was implemented to compare the predictions from the statistically based model with those from the empirical deformation model. The results show a strong correlation (R^2=0.98) between the predicted and calculated rate of plastic strain of ballast by SVR. The maintenance planning model in this study was developed based on the empirical deformation model of ballast and predicts the intervals between corrective maintenance activities (e.g., tamping) and necessity for preventive maintenance activities (e.g., undercutting or drainage systems, etc.) in the railway track.

KEYWORDS: Railway Track, Maintenance, Ballast, Fouling, Statistical Method

1. INTRODUCTION

Maintenance of railway substructure is one of the main concerns facing the freight rail industry. Increasing demand for higher freight capacity (heavier loads and greater traffic volume) can shorten the intervals between maintenance operations and increases costs. Among components of the track structure, railway ballast plays a significant role in the railway track maintenance. Typically, the ballast layer distributes load to the subgrade and, therefore, track deformation is closely related to the quality of ballast. The frequency of railway maintenance is linked to the quality of ballast, which changes continually due to the generation of fine particles (i.e., 'fouling'). The maintenance cost for ballast tamping and surface alignment is about $500M annually for the 150,000 km of Class 1 track in the USA ($3,800/km/yr, Christmer and Davis 2000). The fouling process is initiated by several mechanisms including fracture and abrasion of ballast particles (i.e., 'mineral fouling'), infiltration from underlying layers (e.g., subgrade fouling), and spillage from surface sources (e.g., coal fouling) (Selig and Waters 1994; Darell 2003; Su et al. 2010, Huang et al. 2009). Fouling causes accumulation of fines between ballast particles and consequently increases the permanent deformation within the ballast layer and results in increased surface deviation of railway track. Increasingly heavier freight loads in the US would likely increase the surface deviation of railway track and related maintenance costs (Lee 2009). Larsson and Gunnarsson (2001) stated that a 20% increase in axle load results in 24% extra maintenance cost.

Timely maintenance of railway substructure is essential to provide a continuous service at a reasonable cost for railway industry. Maintenance decisions within the railway industry depend on available information from inspections, standards, and individual and institutional experience (Andersson 2002). Typically, inspection tends to detect the rate of track deterioration. Within the rail industry, there are limited standard procedures or protocol to schedule preventive maintenance activities or, and possibly more importantly, to evaluate their potential effects (Andersson 2002). Typically, there are two approaches to develop a maintenance planning program for rail track: (i) performance-based and (ii) mechanistic-based.

Significant historical data (e.g., traffic, maintenance activities, substructure conditions, and climate data) are required in the performance-based approach to create a comprehensive maintenance model. However, sufficient historical data are unlikely to be archived or accessible in many cases (Andersson 2002; Stirling et al. 1999). The key aspect of a mechanistic empirical model is to integrate the performance of various components of the railway track as developed on the basis of mechanical principles. Use of a mechanistic empirical model can explain and predict the rate of track deterioration in various conditions and decreases the uncertainties of rate of deterioration during the service life of track. A comprehensive track deterioration model should combine both performance and mechanistic empirical models to determine the track quality (Fazio and Prybella 1980; Zarembski 1998). A ballast deterioration model was proposed by Chrismer and Selig (1994) to predict ballast-related maintenance timing and costs based on field data; however, the change of fouling conditions, moisture contents, and state of stress on the deformation of ballast and rail track was not accounted in the study by Chrismer and Selig (1994).

The objective of this study was to develop a deformation model for railway ballast to account for various fouling conditions, moisture (i.e., climate), traffic, freight capacity (i.e., level of stress), and ballast quality (e.g., rate of fouling generation). The previously developed subgrade model by Li and Selig (1994) was also incorporated into the deformation model to account for the entire railway substructure deformation. A statistical model for fouled ballast deformation was used based on the concept of support vector regression (SVR) to compare with the empirical deformation model and to evaluate the effectiveness and limits of each method. A substructure maintenance planning software incorporated the mechanistic empirical deformation model of track substructure to predict surface deviation of the railway track. This software is a tool for determining the intervals between corrective maintenance activities (e.g., tamping) and necessity for preventive maintenance activities (e.g., undercutting).

2. BACKGROUND

2.1 Fouling Index

Selig and Waters (1994) defined a fouling index (FI) that has been widely used in the USA as,

$$FI = P4 + P200 \tag{1}$$

where P4 fraction is % mass of particles < 4.75 mm, and P200 fraction is % mass of particles < 0.075 mm. In this study, fouled ballast was tested at the FI ranging between 5 and 30%.

2.2 Maintenance Model for Railway Ballast

The framework of track maintenance planning for railway track is shown in Figure 1. The main parts of this model are track inspection, a time-dependent track deterioration model, and standards for maintenance planning. This concept can be adopted for railway ballast. Prior to using the maintenance model, ballast quality is determined by inspection techniques. From the deterioration model (or deformation model of substructures), the surface deviation of the track due to the subgrade and ballast deformation can be predicted under traffic loading. Maintenance criteria are assigned with respect to rail class (i.e., passenger or freight rail and operating speed) to estimate the timing for corrective (e.g., tamping) or preventive (e.g., ballast cleaning) maintenance activities. This concept is further used to develop the maintenance model in this study.

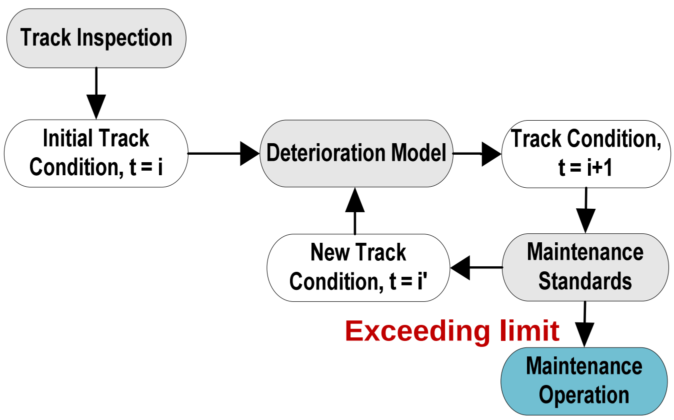

Figure 1 Components of Railway Maintenance Model

3. STATISTICAL APPROACH

3.1 Support Vector Regression for Geotechnical Applications

Support vector machines (SVMs) are valuable tools for data classification. Application of SVMs in geotechnical engineering is an emerging area. Dibike et al. (2001), Maalouf et al. (2010), and Pal (2006) used the SVM for infrastructure applications. Dibike et al. (2001) used SVMs in rainfall and run-off problems. Maalouf (2008) used this method to predict asphalt mix performance for highways. Pal (2006) examined the potential of SVMs for assessing liquefaction potential from field data.

Support vector machines are based on statistical learning theory as proposed by Vanpik (1995) to find an optimal hyper-plane as a decision function in high dimensional space. SVM produces a model based on the training data and predicts the target values of the test data (given data attributes or independent variables). In statistical learning theory (Vapnik 1995), the problem of learning an input-output relationship from a data set is generally viewed as the problem of choosing from the given set of functions $f(x, \alpha)$, α is scalar and $\alpha \in R$, where $x \in Rn$ is the vector of independent variable (e.g., fouling index, water content, stress, etc) with fixed but unknown probability distribution function P(x). The conditional distribution function P(y|x) that best approximates the output value y (e.g., plastic strain of ballast) to every input vector x is fixed but unknown. The selection of the desired P and f function is based on a training set of independent and identically distributed observations $(x_1, y_1),\dots,(x_l, y_l)$ according to P(x, y) = P(x) P(y|x). The expected loss (or discrepancy) due to classification or estimation errors, is given by the risk function

$$R(\alpha) = \int L(y, f(x,\alpha))\ dP(x,y) \tag{2}$$

where $L(y, f(x, \alpha))$ is the discrepancy between the measured y and the predicted $f(x, \alpha)$ by the SVM. The goal is to find the function $f(x, \alpha)$ that minimizes this risk function, $R(\alpha)$, where the only available information is the training set (e.g., plastic strain of ballast obtained from experiments). The risk function is unknown since P(x, y) is unknown; therefore, a risk minimization is necessary. One method is called the empirical risk minimization (ERM) inductive principle. This straightforward approach is to minimize the empirical risk:

$$R_{emp}(\alpha) = \frac{1}{l}\sum_{i=1}^{l}\frac{1}{2}\left|f_\alpha(x_i) - y_i\right| \tag{3}$$

To minimize the actual risk of the model with a limited number of training samples (e.g., limited measured data), Vanpik (1995) developed a statistical technique that incorporated structural risk minimization. Details of this solution are presented in Vanpik (1995).

3.2 Support vector regression

Support vector machines can be applied to regression problems by the introduction of an alternative loss function that is modified to include a distance measure (Smola and Scholkopf 2004). Let the observed variable y (e.g., plastic strain of ballast) have real value, and let $f(x, \alpha)$, $\alpha \in R$, be a set of real functions that contains the regression function $f(x, \alpha_0)$. Given a training set of instance label pairs (x_i, y_i), i = 1, 2, 3, … , l, where $x_i \in Rn$ and $y_i \in R$ with a linear function, $f(x,\alpha) = (w.x) + b$. The training pattern is linearly separable if there exists a vector w and a scalar b. The optimal function is given by minimizing the empirical risk

$$R_{emp}(w,b) = \frac{1}{l}\sum_{i=1}^{l}\left|f_\alpha(x_i,\alpha) - y_i\right|_\varepsilon \tag{4}$$

with the most general loss function with ε-insensitive zone described as

$$\begin{aligned} &\left|f(x,\alpha) - y\right|_\varepsilon = \varepsilon && \text{if} \quad \left|f(x,\alpha) - y\right| \le \varepsilon; \\ &\left|f(x,\alpha) - y\right|_\varepsilon = \left|f(x,\alpha) - y\right| && \text{otherwise} \end{aligned} \tag{5}$$

The objective is now to find a function $f(x, \alpha)$ that has at most a deviation of ε from the actual observed targets y_i for all the training data and, at the same time, is as flat as possible. This is equivalent to minimizing the functional

$$\Phi(w, \xi^*, \xi) = \|w\|^2/2 + C\left(\sum \xi^* + \sum \xi\right) \tag{6}$$

where C is a pre-specified value; and ξ^*, ξ are positive slack variables representing upper and lower constraints on the outputs of the system (Figure 2). Using a Lagrange function (Vanpik 1995), the partial derivatives of this function with respect to the primary variables (w, ξ, ξ^*) have to vanish for optimality (i.e., the saddle point condition). The desired vectors can be found as:

$$w_0 = \sum_{\text{sup port Vector}} (\alpha_i^* - \alpha_i) x_i \quad (7)$$

where $0 \leq \alpha i^*$ and $\alpha i \leq C$ and therefore:

$$f(x) = \sum_{\text{sup port Vector}} (\alpha_i^* - \alpha_i)(x_i . x) + b_0 \quad (7a)$$

When linear regression is not appropriate, as in the case of many engineering applications, a nonlinear mapping kernel K is used to map the data into a higher-dimensional feature space. In this model, the kernel K function replaces the dot operation between x in Eq. 7a. The kernel function is defined as

$$K(x_i, x_j) = \exp(-\gamma \left\| x_i - x_j \right\|^2) \quad (8)$$

that creates a reasonable mapping function for typical engineering data. γ is a multiplier in the kernel function.

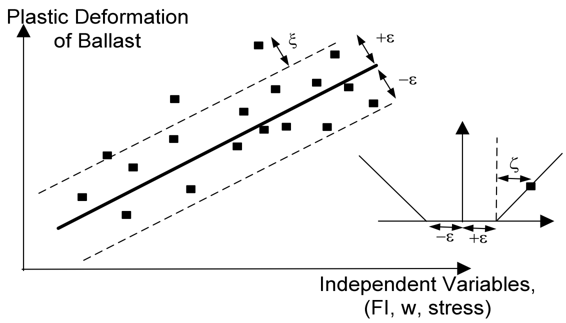

Figure 2 Pre-specified Accuracy ε and Slack Variable (ζ) in Support Vector Regression (after Scholkopf et al. 1997)

4. MATERIALS AND METHODS

The ballast deformation model was based on experiments performed on a granitic ballast sample that was provided from a quarry in Wyoming by BNSF Rail Company. Particle size of the ballast is 25 to 63 mm. Fouling from ballast breakage (i.e., mineral fouling) was considered in this study. The mineral fouling was non-plastic based on the Atterberg test.. The details of tested materials are given in Ebrahimi (2011).

A prototype large-scale cyclic triaxial (LSCT) apparatus was developed to test a specimen with 305-mm diameter and 610-mm length (Ebrahimi et al. 2012). Plastic deformation of ballast in various fouling, moisture, and stress condition was determined to 2×10^5 traffic cycles, with few cases up to 1×10^6 cycles. The ballast specimens were tested at a reference stress state consisting of a confining stress ($\sigma_{3\ ref}$) of 90 kPa and a cyclic stress ($\sigma_{d\ ref}$) of 300 kPa (as established by Ebrahimi et al. 2012) to study the effect of fouling conditions. The ballast specimens were also tested in various states of stress to determine the deformational behavior of ballast under heavier freight loads. Ballast specimens were prepared by rodding and tamping compaction to the maximum dry unit weight of ballast γ_d = 15.8 ± 0.3 kN/m^3. Additional details on specimen preparation are given in Ebrahimi (2011).

5. SUMMARY BEHAVIOR OF FOULED BALLAST

Plastic strain (ε_p) of fouled ballast was measured as a function of loading cycles (N) for a wide range of FI and water contents (w). The rate of ε_p in semi-logarithmic scale, $r_p = \dfrac{d\varepsilon_p}{d(\ln N)}$, was calculated. The number of load repetitions (N) was also converted into million gross tons (a unit commonly used in the USA) for rail cars with axle load of 27.2 Mg (30 short tons) ($MGT = \dfrac{N \times 30}{10^6}$).

The ε_p of ballast increases linearly up to N=10^4 (0.3 MGT) in a semi-log scale as shown in Figure 3. This part of the deformation model is called the "initial compaction phase (ICP)". The r_p of ballast is fairly constant in the ICP. When the ICP is passed, increase in ε_p is pronounced and the r_p increases approximately linearly. This part of the deformational behavior of ballast is called the 'fouling impact phase - FIP'. Therefore, a deformation model was proposed as shown in Fig. 3 to account for ICP and FIP parts of the plastic strain of fouled ballast. Parameters 'a' and 'b' in Fig. 3 represent the ICP and FIP in the deformation model of ballast.

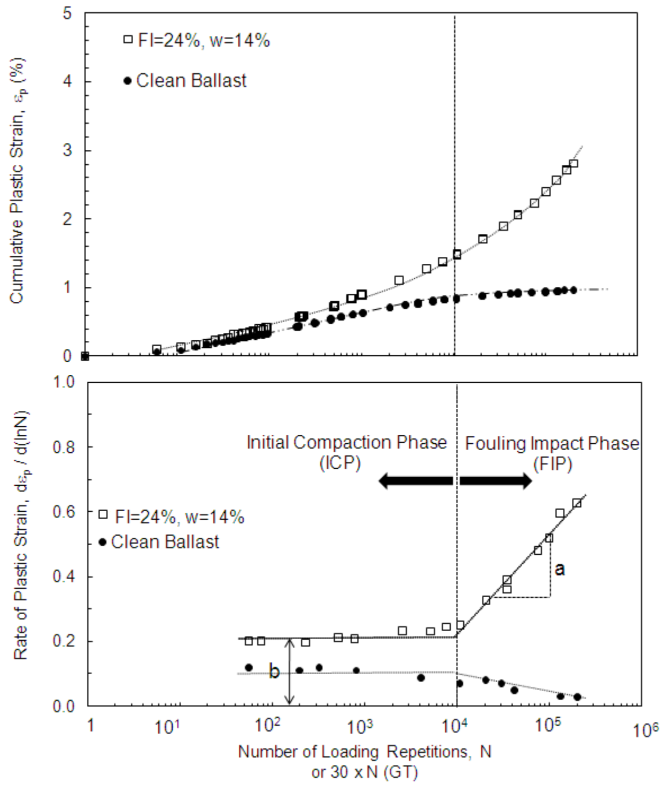

Figure 3 Deformation Model for Clean and Fouled Railway Ballast (Fouled Ballast with FI=24% and w=14%)

6. DEFORMATION MODEL OF RAILWAY BALLAST

Ballast is typically placed in a railway track in a clean or slightly fouled condition. However, generation of fouling continues during the service life of the track. To predict the deformation of ballast during the service life of rail track, three steps were taken: (i) ballast deformation at various fouling conditions (combination of w and FI) was studied; (ii) ballast deformation at different states of stress was assessed; and (iii) an incremental analysis (integrating the change of FI, w, and traffic loading during the service life of track) was performed.

6.1 Effect of Fouling and Water content on Ballast Deformation

The mechanistic empirical deformation model of ballast at given FI and w at the reference confining stress ($\sigma_{3\ ref}$) of 90 kPa and cyclic stress ($\sigma_{d\ ref}$) of 300 kPa was studied. Change in the FI during the LSCT tests is assumed negligible (less than 0.5%). This assumption is in good agreement with the typical rate of fouling generation in ballast approximately 0.1%/MGT (Selig and Waters 1994). As shown in Figure 3, the rate of plastic strain (r_p) of ballast is defined by:

$$r_p = \frac{d\varepsilon_p}{d\ln N} = b \qquad N < 10^4 \text{ (0.3 MGT)} \qquad (9a)$$

$$r_p = \frac{d\varepsilon_p}{d\ln N} = b + a\log(N - 10^4) \qquad N > 104 \qquad (9b)$$

The effect of fouling and moisture on parameters 'a' and 'b' at the representative state of stress is shown in Figures 4a and 4b. The parameters a_{ref} and b_{ref} can be defined as:

$$a_{ref} = S_a\, FI\,(w-3) \qquad (w > 3\%) \qquad R^2=0.91 \quad (10a)$$

$$b_{ref} = S_b\, FI\,(w-3) + b_o \qquad (w > 3\%) \qquad R^2=0.87 \quad (10b)$$

when $w \leq 3\%$, the r_p of ballast is constant (b_o= 0.08) and r_p diminishes toward zero (Figure 3) at FIP. Empirical constants S_a and S_b are 0.0012 and 0.0005, respectively, for fresh ballast conditions. S_a and S_b may change for different types of ballast (recycled or clean ballast) and fouling materials. Increasing FI and w accelerates the r_p of ballast both at the ICP and FIP, with corresponding parameters 'a' and 'b'. At a given w, the r_p of ballast at the ICP (i.e., parameter a) increases 2.5 times more than the r_p of ballast in the FIP (compare S_b). The parameters a and b increase relatively linearly with FI and w for the series of tests conducted on fouled railway ballast in the present study.

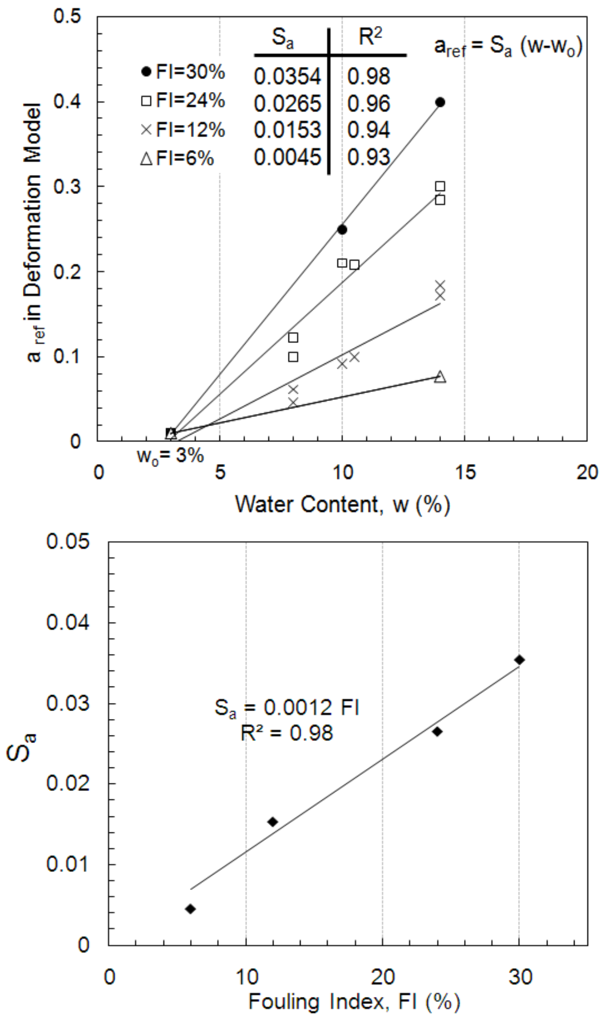

Figure 4a Parameter 'a' in Mechanistic-Based Deformation Model of Railway Ballast as a Function of FI and w

6.2 Effect of State of Stress on Fouled Ballast Deformation

To include the state of stress in the mechanistic empirical deformation model of railway ballast, parameters 'a' and 'b' at various states of stress were calculated relative to those with the reference state of stress (i.e., a_{ref} and b_{ref}). The ratio of principal stresses (σ_1/σ_3) is used to determine the deformational behavior of ballast in various states of stress, where $\sigma_1 = \sigma_d + \sigma_3$. The reference confining stress ($\sigma_{3\,ref}$) of 90 kPa and cyclic stress ($\sigma_{d\,ref}$) of 300 kPa results in σ_1/σ_3 = 4.3. The range of σ_1/σ_3 from 3 to 10 was considered in the series of LSCT tests to account for the range of stresses that ballast can experience in railway track, as described by Ebrahimi et al. (2012).

The parameters of the deformation model (i.e., 'a' and 'b') at various states of stress are summarized in Table 1. The normalized parameters $\frac{a}{a_{ref}}$ and $\frac{b}{b_{ref}}$ are shown in Figure 5 as a function of σ_1/σ_3 and expressed as:

$$\frac{a}{a_{ref}} = 0.20\,(\frac{\sigma_1}{\sigma_3}) \qquad R^2=0.94 \qquad (11a)$$

$$\frac{b}{b_{ref}} = 0.26(\frac{\sigma_1}{\sigma_3}) - 0.26 \qquad R^2=0.95 \qquad (11b)$$

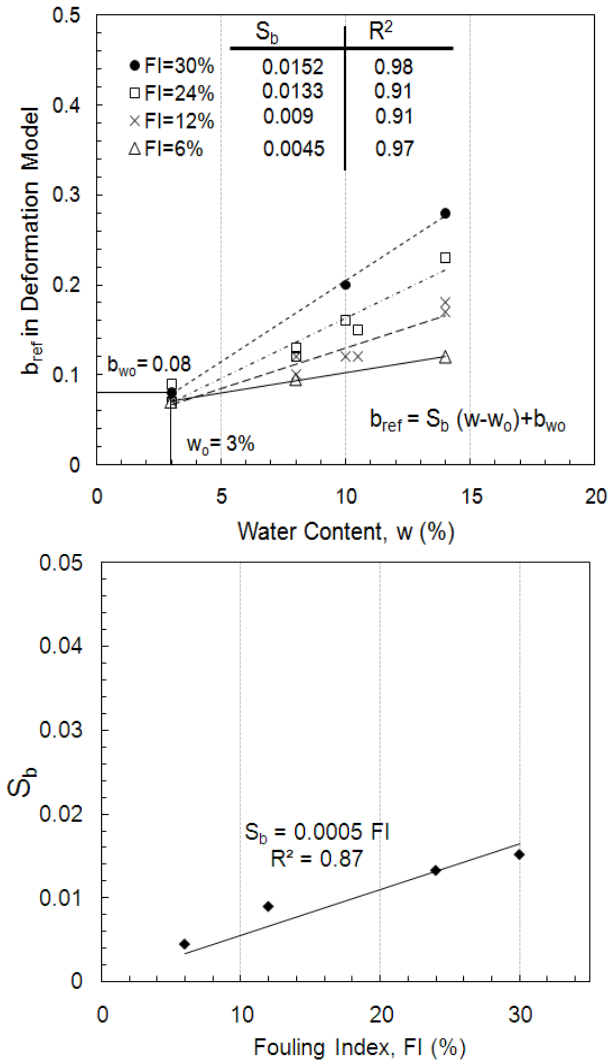

Figure 4b Parameter 'b' in Mechanistic-Based Deformation Model of Railway Ballast as a Function of FI and w

Parameter 'a' increases linearly by a factor of 0.20 and parameter 'b' increases linearly by a factor of 0.26 with the ratio of principal stresses. The r_p in initial compaction phase (i.e., 'b' parameter) approaches zero when σ_1/σ_3 reaches to 1; i.e., isotropic stress condition for the ballast.

Table 1 Deformation Model Parameters for Fouled Railway Ballast

FI	w[2]	σ_3	σ_d	b	a	$\frac{\sigma_1}{\sigma_3}$	$\frac{b}{b_{ref}}$	$\frac{a}{a_{ref}}$
20	13	35	300	0.45	0.3	9.5	2.36	1.87
		35	200	0.35	0.23	6.7	1.84	1.43
		90	300	0.19	0.16	4.3	1	1
		90	200	0.1	0.1	3.2	0.52	0.62
	8	90	200	0.1	0.01	3.2	0.52	0.5
		90	300	0.19	0.02	4.3	1	1
		35	300	0.4	0.05	9.5	2.10	2.5
	3	90	200	0.02	-0.031	3.2	0.4	- [1]
		35	200	0.07	0.1346	6.7	1.4	- [1]
		90	300	0.05	-0.003	4.3	1	1
10	12	35	201	0.2	0.22	6.7	0.5	1.29
		90	205	0.12	0.1	3.27	0.48	0.59
		92	304	0.25	0.17	4.3	1	1
		35	300	0.5	0.33	9.5	2	1.94
0	0	33	301	0.12	-0.05	10.1	2.4	- [1]
		88	303	0.05	0	4.4	1	1
		96	198	0.02	0	3.1	0.4	- [1]

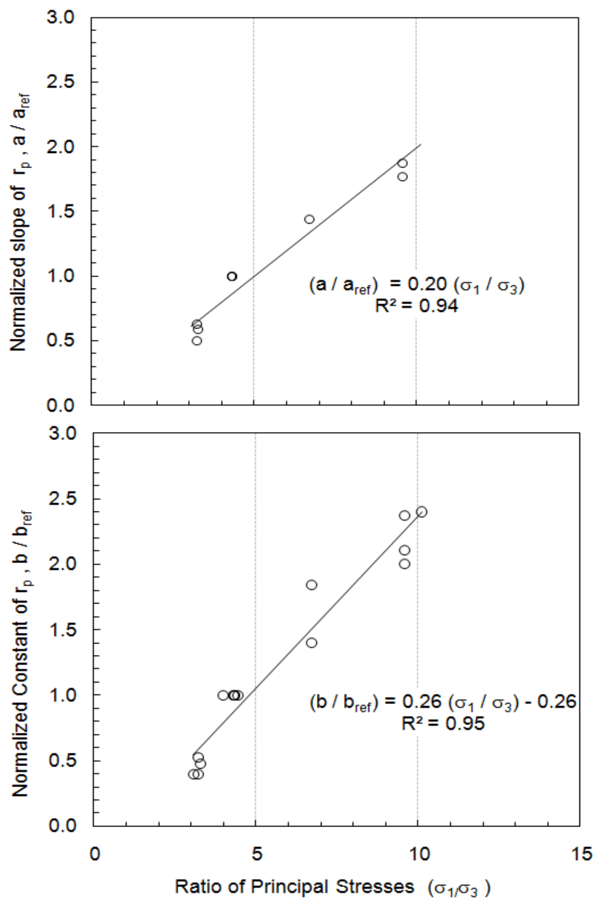

Figure 5 Normalized Deformation Parameters (i.e., a and b) of Railway Ballast as a Function of Principal Stress Ratios

6.3 Incremental Analysis to Develop Maintenance Model

The continual change of fouling (i.e., due to generation of fouling), moisture (i.e., effect of climate), and stress (due to heavier freight load or higher speed) should be incorporated into the deformation model of railway ballast to predict the surface deviation of a railway track during traffic loading. To account for changes in fouling, moisture, and stress, the ε_p of ballast should be calculated in increments of traffic (i.e., δN or δMGT). Figure 6 demonstrates how changes in fouling, water content, and state of stress are captured in an integrated deformation model for railway ballast.

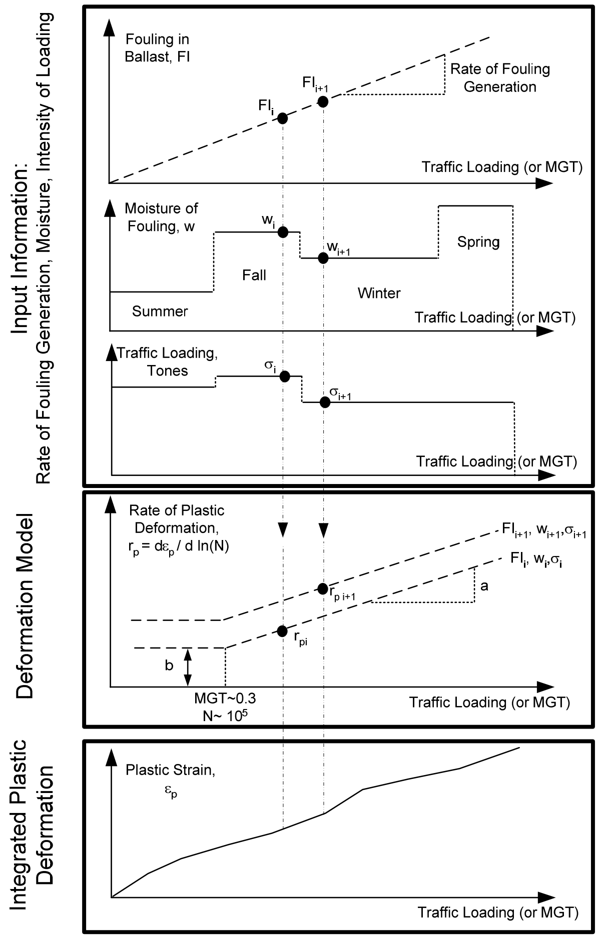

Figure 6 Incremental Calculation of Ballast Deformation Using the Developed Deformation Model at Various Fouling, Moisture, and Traffic Conditions

Based on this approach, FI is determined from the rate of fouling generation from the field data (or currently available information in literatures) which depends on the quality of ballast, subgrade conditions, and traffic loading, while moisture and state of stress are from the climate and traffic data. Accumulation of εp of ballast (δεpi) in a period of N_i to N_{i+1} traffic loading is calculated by integrating the r_p of ballast

$$\delta\varepsilon_{pi} = \int_{N_i}^{N_{i+1}} \frac{d\varepsilon_p}{d(\ln N)} d(\ln N) \tag{12}$$

where N_i is the i^{th} increment of integration for the plastic strain. Accumulation of ε_p of ballast in different fouling conditions is calculated by summing the $\delta\varepsilon_{pi}$ in increments of traffic, as

$$\varepsilon_P(N) = \sum_{i=1}^{N} \left(\int_{Ni}^{N_{i+1}} \left(\frac{d\varepsilon_p}{d(\ln N)} \right)_i d(\ln N) \right) \tag{13}$$

In Eq.13, the r_p of ballast $\left(\frac{d\varepsilon_p}{d(\ln N)}\right)_i$ in i^{th} increment of traffic is a function of FI, w, and stress level at the beginning of each traffic (or time) increment and is calculated from the developed deformation model of railway ballast in this study.

7. DEFORMATION MODEL OF RAILWAY SUBGRADE

To determine the surface deviation of railway track due to accumulation of deformation in the rail substructure, deformational behaviour of both the ballast and the subgrade layers are required. The deformation of subgrade can be predicted using the model proposed by Li and Selig (1994),

$$\varepsilon_{ps}(N) = c\left(\frac{\sigma_{ds}}{\sigma_s}\right)^m N^d \tag{14}$$

[1] The rate of plastic deformation decreases (i.e., fouling impact phase (FIP) was not observed) at water w < 3%.
[2] Moisture content (%)

where ε_{ps} (%) is the plastic strain of railway subgrade, σ_{ds} is the deviator stress on the subgrade, and σ_s is the unconfined subgrade strength described by Li and Selig (1994). Parameters 'c', 'd', and 'm' are related to the type of subgrade materials as proposed by L_i and Selig (1994) and summarized in Table 2. The incremental accumulation of plastic strain within the subgrade is also calculated with similar approach to the railway ballast to incorporate the strength of subgrade (i.e., σ_s) and the state of stress (i.e., σ_{sd}).

Table 1 Deformation Model Parameters for Railway Subgrade (from Li and Selig 1994)

Model Parameters	Subgrade Classification (USCS)			
	ML	MH	CL	CH
d	0.1	0.13	0.16	0.18
c	0.64	0.84	1.1	1.2
m	1.7	2.0	2.0	2.4

Equation proposed by Talbot (1985) was used to find the cyclic stress on subgrade (σ_{sd}). The stress beneath the centerline of the tie at depth h (mm) below the tie, σ_{sd}, (kPa) is a function of stress over the bearing area of the tie (σ_t, kPa). Therefore, for a given thickness of ballast equal to h, stress on the subgrade is

$$\sigma_{sd} = 957\,\frac{\sigma_t}{h^{1.25}} \tag{15}$$

8. RAIL TRACK SURFACE DEVIATION

Chrismer and Selig (1994) showed that the change in surface deviation of the railway track (δv) is a function of initial surface deviation (δ_{v0}), and the deformation of the track (d_L) under traffic loading and is given as:

$$\delta_v = \delta_{vo} + 0.15\, d_L \tag{16}$$

where δ_{v0} = 2.5 mm was recommended if input data is lacking. d_L is the track deformation (from fouled ballast and subgrade), which is calculated from the deformation model presented in this study. This approach is adopted here.

9. MECHANISTIC EMPIRICAL MAINTENANCE MODEL FOR RAILWAY SUBSTRUCTURE (WiscRail^{TM})

A computer software program was developed using MATLAB^{TM} to predict the surface deviation of the railway track due to deformation of railway substructure. This program incorporates the mechanistic-based deformation model of railway ballast and subgrade as described above. The graphical user interface of the mechanistic-based maintenance planning model for railway substructure, called 'WiscRail^{TM}', is shown in Figure 7. This program is capable of predicting the surface deviation of railway track for different fouling condition, weather conditions, subgrade materials, and traffic loads. As shown in Figure 7, the program includes traffic data, change in axle load (indication of heavier freight load), moisture in fouled ballast, ballast condition (i.e., initial fouling condition), subgrade materials, initial track condition, rate of fouling generation (due to particle breakage, subgrade infiltration, and external fouling from droppings), and depth of tamping. The depth of tamping in ballast is also assigned. These inputs were implemented in the program to predict the surface deviation of the track by using the concept described in Figure 6. It was assumed that the rate of plastic deformation of ballast deeper than the depth of tamping follows the previous traffic loading (i.e., smaller rate of plastic deformation due to a denser condition) since the structure of ballast below tamping depth does not change during tamping; however the rate of plastic deformation within the tamped layer starts over (i.e., fouled ballast is rearranged to a looser condition after tamping). When surface deviation of railway track due to deformation of substructure exceeds the assigned limit (based on various classes of railway systems and operation speeds), the maintenance is required. An example of required track alignments (i.e., tamping) with specified 10-mm limit for surface deviation is shown in Figure 7. As predicted, for the given traffic and track conditions, five tamping maintenances are required in seven years of track operation, while the fouling index of ballast increases from 5 to 29%.

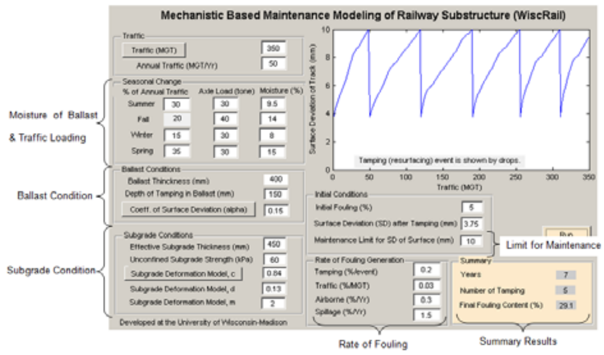

Figure 7 Graphical User Interface Software of Mechanistic-Based Maintenance Model of Railway Substructure (called, 'WiscRail^{TM}')

10. STATISTICAL SUPPORT VECTOR REGRESSION

In addition to the mechanistic-based deformation model discussed in this study, the concept of statistical learning (i.e., SVR) was used to predict the permanent deformation of ballast for comparison. Hsu et al. (2010) proposed the consideration of the radial base function (RBF) kernel $K(x_i, x_j) = \exp(-\gamma \left\| x_i - x_j \right\|^2)$ that creates a reasonable mapping function for typical engineering data. There are two parameters for SVR method with an RBF kernel: C and γ. Parameters C and γ are unknown beforehand, and model selection (parameter search) must be done. The parameter search is done to identify C and γ so that the statistical deformation model can strongly predict unknown testing data (i.e., plastic strains).

A common method is to separate the data set into two parts, of which one is considered unknown. An improved version of this procedure is known as cross-validation. Five-fold cross-validation was done in this study where the training set was first divided into 5 subsets of equal size. Sequentially one subset is tested using the regression model trained with the remaining 4 subsets. Each instance (i.e., rate of plastic strain) of the entire training set is predicted. The cross-validation accuracy is the percentage of data which are correctly predicted.

Various pairs of (C, γ) values were tried by exponentially growing sequences of C and γ to identify good parameters. The set of C and γ with the best cross-validation accuracy was selected. All of the experimental calculations for SVR were conducted using the LIBSVM toolbox for MATLAB (Chang and Lin 2001). C = 1000 and γ = 0.6 resulted in the best statistical model with a coefficient of deterioration (R^2) of 0.96. The comparison between the predicted rate of plastic strain (r_p) of railway ballast from the developed mechanistic-based deformation model in this study and the statistical-based SVR is shown in Figure 8. The SVR can predict the r_p of railway ballast with R^2= 0.98, whereas the R^2 is 0.89 for the developed mechanistic-based deformation model. Even though the SVR more accurately predicts the r_p of railway ballast, the lack of data in N > 1 million significantly limits the application of this method for prediction of the railway maintenance in long-term service life. Whereas mechanistic empirical deformation model of railway ballast has a continuous correlation for long-term service life of railway track as presented in Eq. 9.

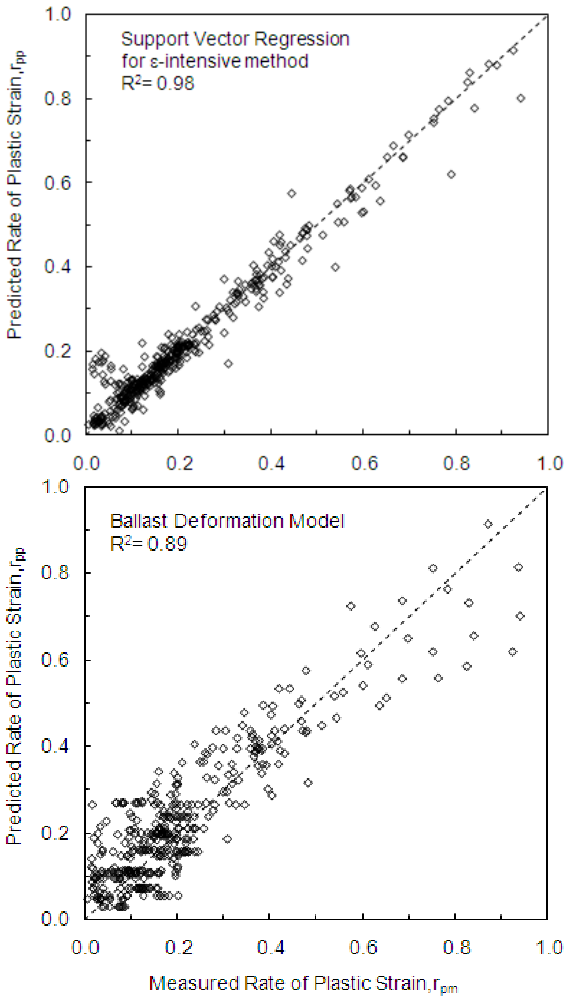

Figure 8 Comparison of Predicted Data from Ballast Deformation Model and Statistical Regression Method (SVR with ε-insensitive of 0.1)

11. SUMMARY AND CONCLUSIONS

A maintenance planning program was presented based on a deformation model of railway substructure. For predicting the permanent deformation of ballast, two approaches were taken. The first approach was based on a mechanistic empirical ballast deformation model, and the second approach was based on a statistically based technique called "Support Vector Regression – SVR". Both approaches were based on the data obtained using a large-scale cyclic triaxial apparatus. Two main phases were distinguished in the deformation model: (1) an initial compaction phase, where the semi-logarithmic rate of plastic strain of ballast (r_p) remains constant for loading cycles, N up to 10 000 and (2) a fouling impact phase, where r_p increases linearly in a semi-log scale due to the presence of fouling materials. Parameters 'a' and 'b' were used to characterize the FIP and ICP in the deformation model. A correlation between 'a' and 'b' parameters and fouling index, moisture content, and state of stress are presented. An incremental integration of plastic deformation of railway ballast in different fouling, moisture, and traffic loading conditions is used, along with an existing subgrade deformation model, to predict the surface deviation of the railway track. Similarly, SVR was applied to the data to develop a predictive model. The SVR method predicts the r_p of railway ballast more accurately (R^2=0.98) than mechanistic-based model (R^2=0.89); it should be noted that the SVR method is developed over the range of N for which the data was collected in the laboratory and for the results of limited laboratory tests in this study.

Finally, a mechanistic-based maintenance planning software program was developed by incorporating the mechanistic empirical deformation model for railway substructure. The model presented in this paper was developed based on the laboratory tests on one source of ballast in different fouling conditions and moisture contents. Field-scale verification of the model is recommended. Further verification of this model for different sources of ballast is warranted.

12. ACKNOWLEDGEMENT

This research was funded by the National Center for Freight and Infrastructure Research and Education. The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. The U.S. Government assumes no liability for the contents or use thereof. The contents do not necessarily reflect the official views of the National Center for Freight and Infrastructure Research and Education, the University of Wisconsin, the Wisconsin Department of Transportation, or the USDOT's RITA at the time of publication.
Assistance from the BNSF Railway and Wisconsin and Southern Railroad Company for providing the ballast is appreciated.

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