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**MODELS FOR THE RESIDUAL LIFE OF RAILROAD BEARING GREASE IN  
LABORATORY AND INDUSTRY APPLICATIONS**

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**ABSTRACT**

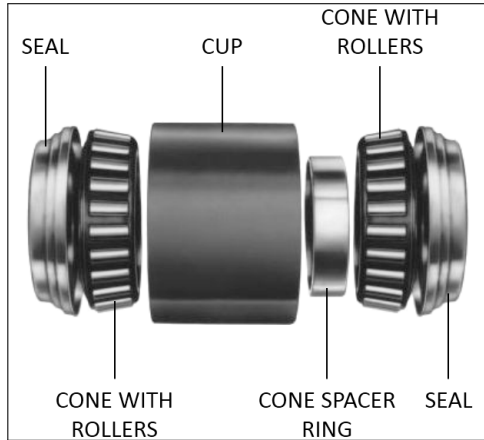
*Adequate lubrication in railroad bearings is crucial to the safe operation of these components. An investigation of the residual life of railroad bearing grease was conducted in a laboratory setting. The data was collected using a split-split-plot design of experiments. The Oxidation Induction Time (OIT), which is the time required for the remaining antioxidants in a sample of grease to be consumed in a test, is the response variable for this study. Low values of OIT indicate small remaining amounts of antioxidants in the grease and thus small remaining residual life in the grease. OIT measurements were made using differential scanning calorimetry. Laboratory testing was performed utilizing a specialized dynamic test rig that allowed four railroad bearings of the same class, mounted on a test axle, to be subjected to varying operating conditions. The independent factors manipulated in this study were total service mileage, miles at load, average speed, mounted lateral spacing, and average temperature at three locations within each bearing. Additional information was recorded for each axle tested that includes axle number, bearing location within the test axle, grease location within each bearing and the presence or absence of a small sprall on the bearing surface.. Regression analysis was employed to fit mixed effects models using JMP software. The first modeling effort was to develop the best possible model for laboratory usage. A second modeling effort was conducted to develop a model for industry usage without several variables available only in the laboratory setting. Web-based applications are provided for users to investigate the residual life of railroad bearing grease in*

*both laboratory and industry settings.*

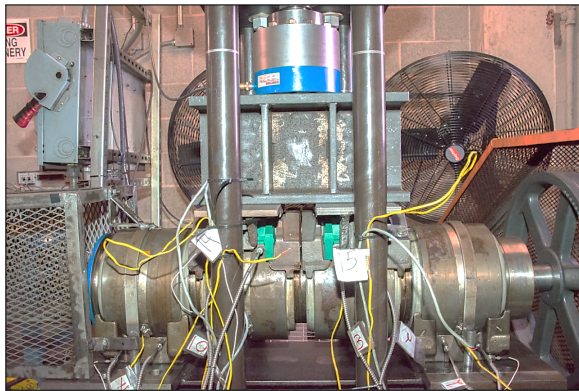
**INTRODUCTION**

Liu, Saat and Barkan [1] found that bearing failures in railway cars was the third most common cause of freight train derailments. Anterton [2] examined the common causes of bearing failures and observed that lubrication played a major role in bearing failures and that 20% of bearing failures were due to aged lubricant. Based upon this information the University Transportation Center for Railway Safety (UTCRS) at the University of Texas Rio Grande Valley decided to conduct a research study to investigate the residual life of bearings. The goal of this research is to develop mathematical models that can easily and accurately predict the remaining life of bearing grease for railway bearings based upon the operational history of the bearing.

A picture of a typical railway bearing shown in Figure 1 is provided by the Canadian Pacific Railway [3]. Each railway bearing is composed of two cone assemblies containing roller bearings, a spacer ring, a cup and two seals. Grease is applied to both cone assemblies and the spacer ring. In service operations, to differentiate between the two cone assemblies, the one closest to the wheel is referred to as the inboard cone assembly, and the one closest to the cap is referred to as the outboard cone assembly. In the laboratory, a similar terminology is utilized where the inboard cone assembly is the one closest to the pulley, which simulates the wheel, and the outboard cone assembly is the one closest to the end cap. The two cone assemblies are referred to



**FIGURE 1.** TAPERED ROLLER BEARING COMPONENTS



**FIGURE 2.** DYNAMIC BEARING TESTING RIG

as the inner and outer raceways. A testing machine was designed and built by the UTRGV UTCRS to investigate the life of the railway bearings. The testing machine is shown in Figure 2. The testing rig is designed to simultaneously test up to four bearings under identical speed and load settings. The properties of the grease used in this research are presented in Table 1.

The Oxidation Induction Time (OIT) is the response variable for this investigation. Grease has two primary constituents: lubricating molecules and antioxidants. The role of antioxidants is to inhibit free-radicals from reacting with the lubricating molecules. OIT is the time required for all of the remaining antioxidants in a sample of grease to be consumed in a test. Low values of OIT have very few antioxidants remaining and thus the residual life of the grease is very low. OIT is measured using Differential Scanning Calorimetry (DSC). A more detailed discussion of the process to measure OIT is provided by Martinez [4]. The following independent variables were either controlled or observable on the testing machine: total mileage, miles at load, average speed, bearing location, mounted lateral spacing, grease sampling location and average service temperature of the bearing at the grease

**TABLE 1.** GREASE PROPERTIES

NLGI Grade	15	
Thickener	Li/CA Soap	
Dropping Point, °C	180	ASTM D 566
Bomb Oxidation at 99° C kPA Drop at 500 hr.	48	ASTM D 942
Oil Separation % by mass, 24 hr. at 25° C	3.6	ASTM D 1742
Wear, 4-Ball, mm Scar. Dia.	0.5	ASTM D 2266

sampling location. The variables total mileage, miles at load, average speed, mounted lateral spacing and average temperature at each grease sampling location are continuous variables. The variables bearing location, grease location and presence of a spall are nominal variables. The bearing location represents the location on the axle of each bearing and the grease location represents the position within each bearing (inner raceway, outer raceway and spacer ring).

The goal of this paper is to develop mathematical models to accurately predict OIT in the laboratory and in the field and to provide a web-based tool to enable interested parties to predict the residual life of bearing grease based upon operational settings. The paper contains the following sections: background, statistical models, web application and conclusions.

## BACKGROUND

Previous efforts were made to develop empirical models to predict the residual life as measured by OIT [5], [4]. The first model attempted was a simple linear regression model. The simple linear regression model did not perform well due to the multi-variate nature of the dataset. Regression trees were utilized next and they too did not perform well. One of the important discoveries in analyzing the experimental data was recognizing the method that the data was collected. The railroad grease data set was not a completely randomized design and linear regression techniques are based upon the assumption that the data was collected using a completely randomized design. The data was collected using a split-split plot design. A split-plot design occurs when one or more factors cannot be changed as often as other factors [6]. For this study, each axle represents a whole plot. Each of the bearings on an axle represent the subplots. Each bearing is further divided into three regions: inner raceway, outer raceway and spacer ring. The three regions of the bearing are sub-subplots.

**TABLE 2. SUMMARY STATISTICS**

Variable	N	Mean	StDev	Minimum	Maximum
Mileage	206	48892	21118	19173	99033
%MilesLoaded	206	0.6283	0.2970	0.1534	1.0000
Avg Speed	206	68.00	15.61	47.62	85.73
Mounted Lateral	206	0.004602	0.003585	0.000000	0.012000
Lat. Spacing Avg	206	0.024015	0.001388	0.020000	0.027000
AvgTemp	206	74.77	18.19	40.84	113.27
OIT	206	7.014	5.590	0.000	25.970

**STATISTICAL MODELS**

Before models for split- split-plot data can be developed, it is important to understand how the data was collected. Twenty-four axles were placed on the testing machine. Each axle could hold up to four bearings. On each bearing, the grease was sampled in three locations. Thus there were a potential of  $24 \times 4 \times 3 = 288$  observations. The dataset collected for this analysis had a total of 206 observations that were observed because not every axle had four bearings for each test. Thus the dataset is unbalanced. The summary statistics of the variables used in predicting OIT are shown in Table 2.

Statistical models were developed using Jmp [7] software. The whole, sub- and sub-sub plots were treated as random effects and regression models with both quantitative and qualitative variables were developed. Models are developed for the laboratory and industrial settings.

**Laboratory Model**

A series of models were developed while searching for the best possible model to use in the laboratory setting. A list of the variables included in the final laboratory model is shown in Figure 3. The final laboratory model contains mileage, spall, grease location, average temperature and mileage by grease location interaction. All terms in the final model have extremely small  $p$ -values and all terms are statistically significant. The summary of the model fit is shown in Figure 4 and the model has a large  $R^2$  value. One of the nice features of Jmp is the development of a Prediction Expression. The Prediction Expression is an algebraic equation that describes how to predict OIT based upon the values of mileage, spall, grease location, and average temperature. The Prediction Expression for the final laboratory model is given in Figure5. Figure 6 provides the summary statistics for the quantitative variables used in the final laboratory model. In general when using the Laboratory model, the values of average temperature and mileage should be within their respective minimum and maximum values. If values are used outside of the minimum or maximum values, the regression model is being

Term	Estimate	Std Error	DFDen	t Ratio	Prob> t
Intercept	21.020165	3.258176	27.13	6.45	<.0001*
Mileage	-0.000108	3.619e-5	17.28	-2.97	0.0084*
Spall (1/0)[0]	-0.986293	0.452263	53.78	-2.18	0.0336*
Grease Location[1]	-1.086708	0.245537	137.2	-4.43	<.0001*
Grease Location[2]	-1.373585	0.248361	143.1	-5.53	<.0001*
AvgTemp	-0.110963	0.035231	37.95	-3.15	0.0032*
(Mileage-48892.4)*Grease Location[1]	2.2968e-5	1.149e-5	132.6	2.00	0.0476*
(Mileage-48892.4)*Grease Location[2]	3.1117e-5	1.148e-5	132.6	2.71	0.0076*

**FIGURE 3. LABORATORY MODEL PARAMETERS**

RSquare	0.862747
RSquare Adj	0.857895
Root Mean Square Error	2.454043
Mean of Response	7.014126
Observations (or Sum Wgts)	206

**FIGURE 4. LABORATORY MODEL SUMMARY**

Prediction Expression	
21.0201653556888	
+ -0.0001076732622 * Mileage	
+ Match { Spall (1/0) }	$\begin{cases} 0 \Rightarrow -0.9862931540807 \\ 1 \Rightarrow 0.98629315408066 \\ \text{else} \Rightarrow . \end{cases}$
+ Match { Grease Location }	$\begin{cases} 1 \Rightarrow -1.0867081665133 \\ 2 \Rightarrow -1.3735854278365 \\ 3 \Rightarrow 2.46029359434975 \\ \text{else} \Rightarrow . \end{cases}$
+ -0.1109633968862 * AvgTemp	
+ ( Mileage - 48892.3841259708 ) * Match { Grease Location }	$\begin{cases} 1 \Rightarrow 0.00002296772066 \\ 2 \Rightarrow 0.00003111685323 \\ 3 \Rightarrow -0.0000540845739 \\ \text{else} \Rightarrow . \end{cases}$

**FIGURE 5. LABORATORY MODEL PREDICTION EXPRESSION**

	N	Mean	Std Dev	Min	Max
OIT	206	7.0141262135728	5.5895273122202	0	25.97
AvgTemp	206	74.767757283689	18.190392241862	40.84455964	113.268765
Mileage	206	48892.384125971	21117.905949279	19173.2777	99032.65625

**FIGURE 6. LABORATORY MODEL VARIABLE STATISTICS**

used to extrapolate predictions. Caution should be used when statistical models are used to extrapolate results.

**Industrial Model**

When preparing a model for industrial use, it is important to recognize several limitations. First of all, information about spalls is not available. Identifying spalls would require the bear-

	N	Mean	Std Dev	Min	Max
OIT	100	5.3860833329	3.576638200506	0.46	14.21333333
AvgTemp	100	74.2016760057	17.888025485935	47.45389995	110.3274644
Mileage	100	49270.8745644	22156.380887788	19173.2777	99032.65625

FIGURE 7. INDUSTRIAL MODEL VARIABLE STATISTICS

ing to be removed and individual rollers to be examined. The spalls used in this study were minor cosmetic defects and were not severe enough to trigger a catastrophic failure in the bearing. When examining the Prediction Expression shown in Figure 5, bearings with spalls (value 1) have a larger value of OIT than bearings without spalls. Subject matter experts attribute this phenomenon to rollers with spalls having a small pocket of extra grease provides improved circulation and a reduction in lubricant temperature. For the industrial model, only bearings without spall will be used for model development. Since the slope coefficient for bearings with spalls is negative, this will result in a conservative model.

The grease location variable was also examined. Recall that within a bearing, there are three locations: inner raceway, outer raceway and spacer ring. The Prediction Expression for the Laboratory Model 5 utilizes a value of 1 for the inner raceway, a value of 2 for the outer raceway and a value of 3 for the spacer ring. The slope coefficient for the space ring grease location has a positive value and the slope coefficients for the inner and outer raceways have a negative value. The reason for the larger OIT values for the spacer ring location is due to the grease in the spacer ring being subject to minimal mechanical forces. Therefore, the grease in the spacer ring is not likely to cause a bearing failure and the spacer ring grease data will not be utilized in the industrial setting.

Finally when examining the summary statistics for the laboratory model provided in Figure 7, there are some cases in which the OIT has a value of zero. Recall that an OIT value of zero indicates that all antioxidants have already been removed the grease. For the Industrial Model, any observations with an OIT value of zero are removed. In summary, the following changes are made to the Industrial Model dataset:

- The variable spall is removed from the Industrial Model dataset,
- Observations from the spacer ring within each bearing are removed,
- Observations with OIT equal to zero are removed.

The summary statistics for the variables in the Industrial Model are shown in Figure 7. Notice that with the changes described above, the dataset for the Industrial model only contains 100 observations.

Once the contents of the Industrial Model dataset was estab-

Parameter Estimates					
Term	Estimate	Std Error	DFDen	t Ratio	Prob> t
Intercept	15.696953	2.696318	27.24	5.82	<.0001*
Mileage	-7.924e-5	2.912e-5	17.65	-2.72	0.0142*
AvgTemp	-0.084651	0.030283	35.11	-2.80	0.0083*

FIGURE 8. INDUSTRIAL MODEL PARAMETERS

Summary of Fit	
RSquare	0.937037
RSquare Adj	0.935739
Root Mean Square Error	1.150944
Mean of Response	5.386083
Observations (or Sum Wgts)	100

FIGURE 9. INDUSTRIAL MODEL SUMMARY

Prediction Expression
15.6969526534858 + -0.000079236044 * Mileage + -0.0846514243805 * AvgTemp

FIGURE 10. INDUSTRIAL MODEL PREDICTION EXPRESSION

lished, model construction was very straightforward. A sequence of models was investigated to find the best model for industrial setting. The best Industrial Model is a function of mileage and average temperature. The parameter estimates for the Industrial Model are shown in Figure 8. The  $p$ -values for all terms in the Industrial Model are small indicating that these terms are statistically significant. The Industrial Model summary is provided in Figure 9. The  $R^2$  value for the Industrial Model is larger than the  $R^2$  for the Laboratory Model indicating that the model explains a greater amount of the total variability. The root mean square error for the Industrial Model is approximately one-half the value of the root mean square error for the Laboratory Model. The prediction expression for the Industrial Model is provided in Figure 10 and only contains linear terms with negative slope coefficients for mileage and average temperature.

## WEB APPLICATION

One of the goals of this research effort is to widely disseminate the results in an accessible and easy to use format. Java Server Faces (JSF) was selected as the web-application technology. Java Server Faces is a server-side application for building JAVA technology-based web application [8]. Java Server Faces facilitates web application development by providing web pages that utilize Facelets with the power of the Java programming language and JavaBeans. The Java Server Faces application was developed using the NetBeans IDE. The NetBeans IDE is an open source application that facilitates JSF applications [9]. The JSF application is implemented on a GlassFish server. GlassFish is



FIGURE 11. WELCOME PAGE

also an open source program [10].

The URL for the JSF web application to predicate railway grease OIT is <http://quality.engr.utrgv.edu:8080/RailwayGreaseOIT-Predictor/>. The Welcome Screen for the Railway Grease OIT Predictor application is displayed in Figure 11. The Welcome Screen contains some of the information provided in Introduction section of this paper. Users must select to investigate either a Laboratory model or Industrial model through a drop down menu and click on submit.

The Laboratory Model section of the Railway Grease OIT Predictor application will be discussed first. If the Laboratory Model is selected from the Welcome Screen, the Laboratory Model Design Page (see Figure 12) is displayed. From the Laboratory Model Design Page, users enter the values of the variables used in the Laboratory Model. Two variables (mileage, and average temperature) are quantitative and values must be entered. The summary statistics for the quantitative variables and OIT are provided on the Laboratory Model Design Page. There are also two qualitative variables in the models and values for spall and grease location are entered via drop down menus. Once the values of the variables are set, click on the Submit button to predict

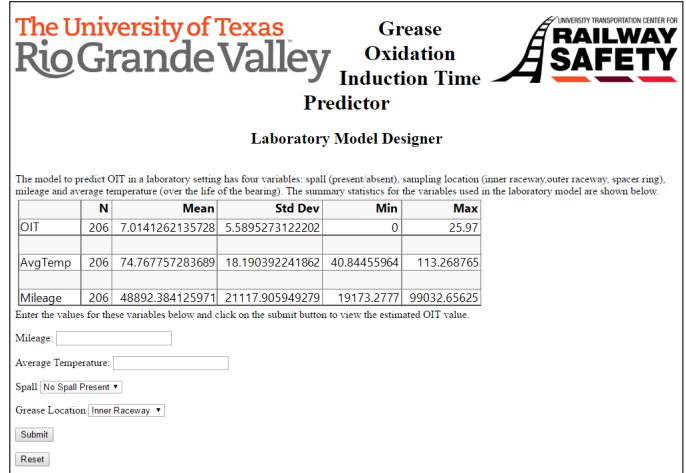


FIGURE 12. LABORATORY MODEL DESIGN PAGE

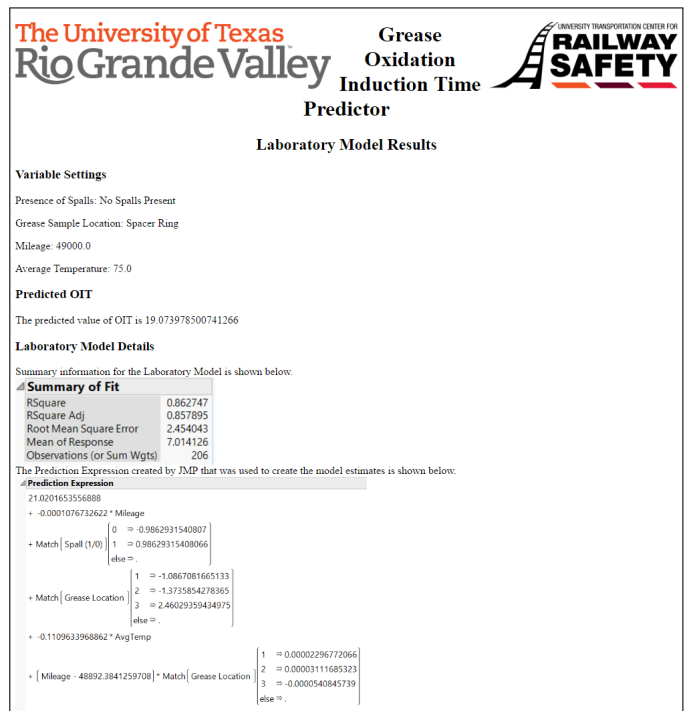


FIGURE 13. LABORATORY MODEL RESULTS PAGE

OIT values using the Laboratory Model. The predicted value of OIT is displayed on the Laboratory Model Results Page shown in Figure 13. The Laboratory Model Results Page displays the values that were entered on the Laboratory Model Design Page, the predicted value of OIT. Additional information about the Laboratory Model is provided including the Jmp Summary of Fit and Prediction Expression.

The Industrial Model section of the Railway Grease OIT

**The University of Texas Rio Grande Valley** Grease Oxidation Induction Time Predictor  
**INDUSTRIAL MODEL DESIGNER**

Changes were made in the dataset to more accurately reflect information available in an industrial setting. The variable spill was removed from the modeling dataset. The only method to determine if a spill is present is to disassemble the bearing and examine each roller bearing. The spills used in the laboratory setting had minor cosmetic defects and were not in danger of causing a catastrophic failure. Further, the OIT for bearings is slightly higher than for bearings without spills. Thus the removal of the data with spills will result in a more conservative estimate of OIT.

A second change was to eliminate the OIT readings for the spacer ring and no longer distinguish between inner and outer raceway. The OIT readings found in the laboratory for samples taken in the spacer ring were higher than the values observed in the inner and outer raceways. Thus, the failure of the grease in the spacer ring was less likely than the failure of the grease at the raceway locations.

Finally, observations with OIT equal to zero were removed from the model. An OIT value of zero indicates that all antioxidants were already removed from the grease when the bearing was tested. Thus, we do not know the exact mileage when the OIT value was equal to zero.

The model to predict OIT in an industrial setting has two variables: mileage and average temperature (over the life of the bearing). The summary statistics for the variables used in the industrial model are given below.

	N	Mean	Std Dev	Min	Max
OIT	100	5.38608333329	3.576638200506	0.46	14.21333333
AvgTemp	100	74.2016760057	17.888025485935	47.45389995	110.3274644
Mileage	100	49270.8745644	22156.380887788	19173.2777	99032.65625

Enter the values for these variables below and click on the submit button to view the estimated OIT value.

Mileage:

Average Temperature:

FIGURE 14. INDUSTRIAL MODEL DESIGN PAGE

**The University of Texas Rio Grande Valley** Grease Oxidation Induction Time Predictor  
**INDUSTRIAL MODEL RESULTS**

**Variable Settings**

Mileage: 50000.0  
Average Temperature: 75.0

**Predicted OIT**

The predicted value of OIT is 5.386293624948301

**Laboratory Model Details**

Summary information for the Industrial Model is shown below.

**Summary of Fit**

RSquare	0.937037
RSquare Adj	0.935739
Root Mean Square Error	1.150944
Mean of Response	5.386083
Observations (or Sum Wgts)	100

The Prediction Expression created by JMP that was used to create the model estimates is shown below.

**Prediction Expression**

15.6969526534858 + -0.000079236044 \* Mileage + -0.0846514243805 \* AvgTemp

FIGURE 15. INDUSTRIAL MODEL RESULTS PAGE

Predictor application is very similar to the Laboratory Model section. To start the Industrial Model Analysis select Industrial Model on the drop down menu in the Welcome Screen shown in Figure 11. The Industrial Model is simpler than the Laboratory Model and only contains two quantitative variables: mileage and average temperature. The Industrial Model Design Page is shown in Figure 14. The predicted value of OIT is displayed on the Industrial Model Results Page. The Industrial Model Results page is shown in Figure 15. The Industrial Model Results Pages displays the variable settings, the predicted value of OIT and model information including the Industrial Model Summary of Fit and Prediction Expression.

## CONCLUSIONS

Two models were developed to accurately prediction OIT values of railway bearing grease. Each model targets a specific operating environment; either a laboratory setting or a industrial setting. The Laboratory Model is based upon four variables and the Industrial Model is based upon two variables. Both models provide good predictions of OIT and have high  $R^2$  values found in Figures 4 and 9. Simple algebraic expressions to predict OIT values for both models are found in Figures 5 and 10. The information for both the Laboratory Model and Industrial Model are provided in an easy-to-use web application that allows interested users to predict OIT values for different situations.

## ACKNOWLEDGMENT

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