

PAVEMENT DETERIORATION MODELS FOR PAVEMENT MANAGEMENT

Final Report

Prepared By:

Applied Pavement Technology, Inc. 115 West Main Street, Suite 400 Urbana, IL 61801 217-398-3977 www.appliedpavement.com

July 2024

pr oviding engine ering solutions to improve pavement performance

PAVEMENT DETERIORTATION MODELS FOR PAVEMENT MANAGEMENT

Mark Woods, Katie Zimmerman, Shafkat Alam‐Khan Applied Pavement Technology, Inc.

Reid Kiniry Vermont AOT, Asset Management Bureau

July 2024

Research Project Reporting on Project PS1041 – VTRC023‐602

Final Report 2024‐03

You are free to copy, distribute, display, and perform the work; make derivative works; make commercial use of the work under the condition that you give the original author and sponsor(s) credit. For any reuse or distribution, you must make clear to others the license terms of this work. Any of these conditions can be waived if you get permission from the sponsor(s). Your fair use and other rights are in no way affected by the above.

The information contained in this report was compiled for the use of the Vermont Agency of Transportation. Conclusions and recommendations contained herein are based upon the research data obtained and the expertise of the researchers and are not necessarily to be construed as Agency policy. This report does not constitute a standard, specification, or regulation. The Vermont Agency of Transportation assumes no liability for its contents or the use thereof.

This material is based upon work supported by the Federal Highway Administration under SPR [PS1041]. Any opinions, findings and conclusions or recommendations expressed in this publication are those of the author(s) and do not necessarily reflect the views of the Federal Highway Administration.

TECHNICAL DOCUMENTATION PAGE

Table of Contents

List of Figures

List of Tables

Introduction

The Vermont Agency of Transportation (VTrans) oversees the ownership and maintenance of an extensive network comprising 3,100 centerline miles of paved public roads. In 2004, VTrans pioneered the development of pavement performance models, utilizing historical pavement performance data categorized by the underlying structure and paving surface treatment. Since that time, the agency introduced bonded wearing course and thin overlay paving treatments. However, there are currently no performance models in place to project conditions for these treatments. Additionally, Federal standards for National Performance Measures (NPMs) on National Highway System (NHS) pavements have since been established, including metrics such as rutting, cracking, and pavement smoothness. The existing VTrans Performance models already includes deterioration rates for smoothness and rutting, but a model is needed for cracking that is in alignment with NPM standards. This project aimed to fill this gap by conducting a comprehensive review of the most recent historical pavement condition and treatment history data. Existing performance models were updated, and new models were established for bonded wearing course and thin overlay treatments and the NPM cracking metric.

Data Receipt and Preparation

Datasets were furnished by VTrans via the Vermont SharePoint site. Datasets encompassed three distinct categories of information, including:

- 1. Pavement condition data, detailing the current state of road surfaces.
- 2. Pavement surface type data, describing the composition and characteristics of the road surfaces.
- 3. Pavement treatment history data, offering a comprehensive account of past maintenance and intervention measures applied to the road infrastructure.

The structured presentation of these datasets served as a foundation for analyses for development of new and revised performance models.

Pavement Condition Data

VTrans supplied a comprehensive dataset comprising eleven Microsoft Access databases, each cataloging annual pavement condition data from 2012 to 2022. The data were provided in five installments. Following a comprehensive review, a catalog of pertinent data attributes was identified:

- 1. **Length:** This parameter delineates the extent of the pavement segment in miles.
- 2. **AADT:** Average annual daily traffic is a key metric representing the average volume of daily traffic over the course of a year.
- 3. AVG IRI: The average international roughness index (IRI) is a measure denoting the pavement surface roughness, expressed in inches per mile.
- 4. AVG RUT: This measure indicates the average amount of rutting on the pavement, measured in inches.
- 5. **COMP_INDEX:** The average of the four indexes—RUT_INDEX, IRI_INDEX, STRC_INDEX, and TRAN_INDEX.
- 6. **IRI_AVG:** A metric unit representation of the roughness, indicating average IRI pavement surface roughness in meters per kilometer.
- 7. **IRI_INDEX:** An indexed value ranging from 0 to 100, based on IRI.
- 8. **LastWork_Year:** The calendar year when the most recent maintenance or construction work was performed on the pavement.
- 9. **RUT_AVG:** The average amount of rutting on the pavement surface measured in millimeters.
- 10. **RUT_INDEX:** A numerical index ranging from 0 to 100, providing an assessment of pavement rutting.
- 11. **STRC_INDEX:** An aggregate index representing pavement structural condition on a scale of 0 to 100. Transverse cracking is not included in the aggregate index.
- 12. **TRAN_INDEX:** A numerical representation, ranging from 0 to 100, indicating the extent of transverse cracking on the pavement.
- 13. **NRPM** WP CRK: An index ranging from 0 to 68, based on NPMs, assessing the level of cracking specifically in the pavement wheel path.
- 14. **Data_Date:** The date that condition data was collected.

An initial summary of pavement condition data is presented in table 1. Based on the initial assessment of these data, condition values appeared to be consistent and complete. For most data rows in each pavement condition table, condition values reflect a roadway segment one-tenth of a mile long. Some data segments that exist at the end of roadways occasionally were less than one-tenth of a mile. Pavement condition data sets for each reporting year include condition data for all rows, though collection of non-NHS routes occurred biennially. If data were not collected for a non-NHS segment in the reporting year, the most recent value is brought forward. So, all condition data tables included NHS condition data for the reporting year, approximately half the non-NHS data for the reporting year, and the remaining non-NHS data brought forward from the previous year. Data values that were collected the previous year were able to be identified in the "Data_Date" column.

Data Attributes	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Length	71,331										
AADT	31,442	12,475	31,325	23,362	31,549	19,132	30,668	13,997	39,809	23,545	31,279
AVG_IRI	31,198	12,381	31,240	23,469	31,278	22,406	30,668	14,845	31,171	21,320	31,213
AVG RUT	31,350	12,413	31,448	15,127	31,457	16,518	30,668	15,002	31,326	20,782	31,370
COMP INDEX	31,195	12,352	31,240	14,747	31,272	16,254	30,668	14,845	31,171	20,443	31,213
IRI_AVG	31,198	12,381	31,240	23,469	31,278	22,406	30,668	14,845	31,171	21,320	31,213
IRI INDEX	31,198	12,381	31,240	23,469	31,278	22,406	30,668	14,845	31,171	21,320	31,213
LastWork Year	31,370	12,439	31,608	12,181	31,303	12,160	30,629	11,456	31,442	11,094	31,084
RUT AVG	31,350	12,413	31,448	15,127	31,457	16,518	30,668	15,002	31,326	20,782	31,370
RUT INDEX	31,350	12,413	31,448	15,127	31,457	16,518	30,668	15,002	31,326	20,782	31,370
STRC INDEX	31,293	12,422	31,376	15,127	31,465	17,280	30,668	14,991	31,328	21,689	31,370
TRAN INDEX	31,293	12,393	31,376	15,127	31,460	17,280	30,668	14,991	31,328	21,689	31,370
NPRM WP CRK	25,455	10,922	27,752	15,081	31,396	17,280	30.668	14,991	31,328	21,689	31,370

Table 1. Pavement condition data summary (number of occurrences).

Pavement Surface Type Data

VTrans furnished a Microsoft Access database detailing pavement surface types along with their construction dates spanning from 1955 to 2014. This data set is essential to developing performance models since pavement surface type is one of two data items VTrans uses to group performance models. Based on discussions with VTrans, it was determined that the data attribute Pave Type contained the relevant information. Table 2 summarizes the Pave Type values by occurrence and mileage. Asphalt on concrete pavement types depicts a pavement with an asphalt surface over a pre-existing concrete pavement. Thick on strong pavement types describe pavements with a thick layer of asphalt over a strong base. No specific thickness threshold exists for defining a thick asphalt layer or base strength, but these classifications are established on a case-by-case basis. Thin on strong and thin on weak pavement types are similarly established for thin asphalt layers. All pavement type data values had a "CreatedOn" value of 1/12/2021, indicating the date that these values were recorded. If any change occurred to pavement type values for a particular segment before or after this date, it is not expected to be captured in the modeling data. Based on conversations with VTrans staff, the number of these change occurrences is expected to be small. Following a virtual data review meeting with VTrans staff, it was confirmed that models did not need to be developed for gravel or concrete surface pavements.

Pavement Treatment History

VTrans provided a dataset outlining pavement project histories and treatment dates spanning from 1955 to 2022. Discussions with VTrans verified that the data attributes "PHA_TreatmentFamily" from the project history application (PHA) and "Treatment_Year" encompass the pertinent information for the analysis. Table 3 summarizes the values identified in the Treatment_Year data column by occurrence and mileage. Following a data review update via virtual meeting with VTrans staff, it was confirmed that models did not need to be developed for values in the blank treatment families, which represents multiple miscellaneous scenarios that did not need to be modeled.

Data Consolidation and Master Database Development

The three datasets provided were combined into a master database including all necessary condition data, pavement surface type, and treatment history aligned in one data file. This master database organized the pavement condition data to allow analysis tools to separate data by pavement surface type or treatment family, allowing performance trends to be plotted. The integration of pavement condition, pavement type, and pavement project treatment history data is outlined as follows:

- 1. **Consolidation of Condition Data Tables:** All unique entries within the historical pavement condition data were consolidated into one single database using Microsoft Access default features.
- 2. **Elimination of Duplicate Entries:** This process ensures that the master condition data table remains free of redundant entries, maintaining data integrity. The most common duplicate entry encountered was condition data values for non-NHS routes. Condition data on these routes are collected biennially and included in condition data tables to provide comprehensive reporting of network condition in each reporting year. Condition data for these routes, which were collected in the previous year, were identified by the Data Date and removed.
- 3. **Removal of Non-NHS NPM Cracking Entries:** Values shown in condition data tables for NRPM_WP_CRK for NHS sections were part of Highway Performance Monitoring System (HPMS) submittal requirements and considered to be valid. For some non-NHS segments, entries were available. However, discussions with VTrans indicated data quality for the entries was questionable. Therefore, these non-NHS NPM cracking values were removed.
- 4. **Adjustment of Overlay Treatment History Data to Consider Bonded Wearing Courses and Thin Overlays:** The initial pavement treatment history dataset did not include bonded wearing course and thin overlay projects as a treatment family but rather subsets within the OVL-Overlay treatment family. These treatments were able to be identified within this group by reviewing the "Treatment_Type" column data for all OVL-Overlay records in the "PHA_treatment_family" column. The data identified within this data column in this model family are provided in table 4. Based on conversations with VTrans staff, all treatment types within the OVL-Overlay treatment family other than OVL-Overlay were considered thin overlays, including those identified as Novachip or paver-placed surface treatment. Due to the small number of occurrences, this adjustment was made by manually changing these entries to have a treatment family of "TNOL-Thin Overlay."

Table 4. Overlay data by treatment type.

- 5. **Incorporation of Pavement Treatment Project Histories:** Unlike pavement condition data that exist primarily in tenth-mile segments, pavement treatment data span larger distances and multiple years. To address this incongruity, longer pavement treatment project sections were subdivided into tenth-mile segments for compatibility with pavement condition data. Following this subdivision, treatment histories were merged into the master condition data file.
- 6. **Correlation with Pavement Type Data:** The product obtained from the step above was similarly correlated with variable-length pavement type data to associate appropriate pavement types with relevant treatment categories and condition.
- 7. **Removal of Non-Uniform Sections:** This combination of the three datasets resulted in a substantial volume of data. In many locations, tenth-mile condition data segments include a break in either treatment history or pavement type as shown in figure 1. This results in condition data values that are represented more than once in data sets and are less than one-tenth mile. To simplify the process of merging these tables of varied length and reduce bias from partially matched segment less than one-tenth of a mile at the end of project segments, segments less than one-tenth of a mile were excluded from the final merged data set. Additionally, condition data values less than one-tenth mile exist at the end of inventory lengths, such as State lines. These segments were also removed from the final data set so that all data values used in the modeling process were homogeneous and had equal bias towards the model.

This process of removing unnecessary data values and merging tables establishes homogeneous segments to support development of performance models. The remaining data values were organized for each grouping of pavement type, model family, and performance indicator to begin the regression process of developing initial proposed models.

Figure 1. Example overlap of variable length data.

Data Completeness Check

To understand the nature of the completed data set, data were summarized through techniques aimed at verifying completeness and reasonability. The distribution of performance indicators is shown in table 5. The distribution observed for each performance indicator fell within the range of expectations. For example, index values that are reported between 0 and 100 were confirmed to not have any values in the data set outside of that range. NPM cracking did not demonstrate any negative values or unreasonably high records.

Percentile	AVG IRI	AVG RUT	COMP INDEX	IRI INDEX	NPWM WP CRK	RUT INDEX	STRC INDEX	TRAN INDEX
10%	45	0.069	33.5	49.7	$0.0\,$	53.7	50.2	70.8
20%	54	0.108	52.8	66.8	0.0	64.5	70.2	85.6
30%	63	0.138	63.6	73.7	0.0	70.5	81.8	91.0
40%	74	0.177	70.6	77.7	0.5	74.4	89.0	94.2
50%	87	0.216	75.8	80.3	1.0	78.3	94.0	96.6
60%	103	0.256	80.1	82.3	3.0	82.3	97.4	98.5
70%	124	0.295	83.8	83.7	6.5	86.2	99.5	99.6
80%	154	0.354	87.3	84.8	13.5	89.2	100.0	100.0
90%	207	0.463	91.2	85.8	24.5	93.1	100.0	100.0

Table 5. Overview of VTrans pavement data.

Once data completeness was confirmed, the master database was organized into individual comma separated value (csv) files for each of the five performance indicators to be modeled. Those indicators include:

- International Roughness Index (IRI).
- Rut index (RUT).
- Transverse Cracking index (TRAN).
- Structural Cracking index (STRC).
- National Performance Cracking Metric (NPM).

During the analysis process, the data were further reduced for each combination of pavement type and treatment family as shown in table 6. No model is required for gravel surface and concrete – rigid pavement types.

Table 6. VTrans pavement types and treatment families.

Organized data were plotted to visualize each performance indicator versus age, which is the nature of the intended performance models. These organized data plots were established for each combination of pavement type, treatment family, and performance indicator. A total of 140 datasets were established for model building.

Assessing Data Variability and Preparing Datasets

Before performing regressions to establish initial recommended models, each dataset was evaluated for variability. As shown in figure 2, box plots demonstrate the distribution and variability of data in addition to identifying outliers in the data. These box plots were developed for each prepared combination of pavement type, treatment family, and performance indicator. The box plots were used to assess whether any data needed to be excluded from model building. When the data were observed to have a positive trajectory, it was presumed that this increase in performance resulted from either missing treatment data or undocumented maintenance activities. Time-series box plots, such as the one in figure 3, were used to identify these changes in trajectory. In figure 3, it can be observed that the median IRI index increases after year 10 and the range of IRI index values beyond that age is broader and includes segments with index values of 75. It is expected that these values reflect roadway segments that either received maintenance in these later years or were repaved with treatments not documented in the master database. This change in trajectory was commonly observed between years 12 and 25 when treatments tend to reach their end of service life and are repaved. Since treatment life varies by pavement type and treatment, this location of changing trajectory also varied accordingly. Since values beyond this age are considered not representative of historical performance, they were excluded from model building. This was done by identifying age values where the median performance indicator began to increase and excluding values beyond that age value prior to performing regressions.

Figure 2. Explanation of boxplots.

Figure 3. Boxplot of IRI index data for the Asphalt on Concrete (AONC) pavement type and Mill and Fill (MAF) treatment family.

To improve the reliability of data prior to developing regressions, an additional assessment of variability was performed, and datasets were reduced. For each organized data set, the standard deviation of the performance indicator was determined within each year. Values determined to be within the mean value plus or minus 0.674 standard deviations were declared to be within a "50 percent confidence interval." This process of filtering data prior to performing regressions is the same process that was originally used to develop VTrans' current performance models in 2003. The value 0.674 represents a common numerical assumption that normally distributed data typically has fifty percent of its values within range of the median. Eliminating values outside of this range reduces year-to-year variability, eliminates outliers, and improves the overall reliability of data performed to develop models. The example provided in figure 4 (and table 7) shows the same data from figure 3 with observations outside the allowable range shown as hollowed circles. The remaining values to be used for model building are shown as solid circles.

Figure 4. IRI index data for AONC MAF filtered based on standard deviation within each year.

Data Sampling

A common practice used to verify that models can reasonably predict conditions with minimal error involves setting aside a small sample of data for testing models. Typically, 5 percent of data will be randomly selected and set aside for model testing. The remaining 95 percent will be used to develop models. Once initial models are established, the sample data will be used to compare actual observations to model predictions. The differences between the model-predicted and actual values, known as residuals, are plotted against the control variable and visually checked for distribution. A reasonable model should produce sample residuals that are symmetrically distributed around a residual value of zero, indicating the prediction average is equivalent to the sample observations. Residual plots should also not demonstrate any visible trends along the horizontal axis, which may be an indication that the model does not adequately reflect the relationship between the two variables. Additional discussion on residual plots and related findings from this work are described later in this report.

Development of Recommended Models

Models were developed for the four VTrans index measures, plus NPM cracking. Since the nature of the index values and NPM cracking are different, slightly different approaches were used for establishing and evaluating models.

(1)

Developing Models for Index Measures with Fixed Endpoints

Once each individual dataset was organized and filtered, regressions were performed using a non-linear least squares regression based on the model forms currently used in the VTrans pavement management system (PMS). The two model forms considered are the power model form and the quadratic model form, shown as equations 1 and 2.

Quadratic Model Form:

$$
Y = a - b \times X - c \times X^2
$$

where:

 $Y =$ Performance indicator (e.g., IRI index, RUT index). $X = Age$. a, b, $c =$ Model coefficients.

Power Model Form:

$$
Y = a - b \times X^c \tag{2}
$$

where:

 $Y =$ Performance indicator (e.g., IRI index, RUT index). $X = Age$. a, b, $c =$ Model coefficients.

Fixed Model Intercepts

Prior to performing regressions to identify model coefficients, model forms for indices were also predefined to have a forced y-axis intercept according to VTrans procedures. For rutting, transverse cracking, and structural cracking indices, the y-axis intercept is set at 100 to reflect a brand-new pavement at year zero with no defects. For the IRI index, that value is set to 90. These forced y-axis intercepts or year-zero values, however, may not always match actual performance immediately after placement. For example, the average and median IRI index value for many base type and treatment family combinations is less than 80. The VTrans PMS accounts for this discrepancy using model fitting. Model fitting is an approach that accounts for available data by adjusting performance models either horizontally or vertically to match the most recent available condition value. An example of horizontal model fitting is shown in figures 5 and 6. This type of model fitting helps ensure performance models use available historical data to make improved performance predictions.

Figure 5. Historical performance data compared to a default model.

Figure 6. Performance model horizontally adjusted to fit historical data.

VTrans additionally restricts model forms to intersect the x-axis, commonly referred to as a fixed endpoint. This approach depicts a point when the projected performance reaches an index of 0. While it is unlikely that treatments will deteriorate to this point, the fixed endpoint is assumed to be representative of the deterioration that would occur if no repairs were made to the road. This "do nothing" condition is compared to a proposed treatment in the PMS network-wide analysis to calculate a benefit value associated with the application of the treatment. These benefit calculations for all possible treatment options in an analysis are compared to optimize treatment selections for the entire network. Forcing models to have these fixed endpoints ensures benefit area calculations are comparable between different treatments and base types.

Using models with fixed x- and y-intercepts is reasonable pavement management practice but can have a noticeable effect on the model-building process. Typically, when using historical performance data to develop prediction models, the data are prepared, and model forms are established as described above. Then, a least-squares regression is used to identify model coefficients that have the least amount of prediction error. In this context, "error" refers to the difference between an observed historical value and the model-predicted value at the same pavement age. Error calculations are often squared to account for model predictions that are both over- and under-predicting conditions, eliminating the effect of negative error values. When unrestricted by forced intercepts, least-squares regressions identify coefficients that define a model with the lowest possible total squared error. However, when performing regressions using model forms with fixed endpoints, the resulting errors can be much higher. As noted above, VTrans predefines a y-intercept of 90 for IRI models when actual values are closer to 80. Forcing a model form to this fixed y-intercept results in predictions at year zero that are 10 points higher than the average observation, where an unrestricted regression would result in predictions much closer to the mean value. Fixed endpoints forcing models to intercept the xaxis have a similar effect on model errors. A typical fixed endpoint value might be 15, reflecting an index value of zero at a pavement age of 15 years, while actual index observations can easily be 60 or higher as shown in figure 7.

Figure 7. Regression results for Mill and Fill, Thin on Strong IRI index with forced y-intercept = 90 and fixed endpoint = 19.

It can be observed in figure 7 that without model fitting, the resulting models consistently overpredict performance until approximately year 10. This can be further identified by observing the sample residuals identified shown in figure 8.

Figure 8. Quadratic residual plot for Mill and Fill, Thin on Strong IRI index with forced yintercept = 90 and fixed endpoint = 19.

As noted earlier, prediction errors occurring in earlier years are accounted for in the PMS model fitting process. Errors that occur in later years of prediction result from the fixed endpoints and are accepted based on the premise that fixed endpoints provide more value to the PMS optimization process. Plus, most roadways are anticipated to be repaved prior to the reaching the fixed endpoint age. So, the lower prediction accuracy for later years is not considered a high risk. These fixed intercepts do, however, limit the number of approaches available for establishing the best-fit models. For example, models from traditional linear regressions are commonly assessed using the coefficient of determination, also known as r-squared. This value ranges from 0 to 1 with values closer to 1 representing models that have a high goodness of fit. For a nonlinear regression performed on data with fixed x- and y-intercepts, this value is not a practical measure of fit for comparing models. Also, as shown above in figure 8, the common practice of reviewing residuals of sample data can become more difficult. Typically, the objective of that process is to verify that residuals are evenly distributed, which is unlikely in this situation.

To evaluate goodness of fit for the index measure models, the mean squared error (MSE) was calculated for each regressed model. The MSE is the mean value of the squared error for all observations in the regression set. A low MSE indicates a better model fit than a higher value. For most models, default predictions tend to underpredict in early years of prediction, reach a period where predictions are relatively accurate, and then eventually enter a stage of underpredicting. As fixed endpoints are increased, the second phase where prediction accuracy improves happens in increasingly later years of prediction. This causes the MSE to decrease with increasing fixed endpoints. For example, in figure 7, the existing agency model with a fixed endpoint of 15 has a narrow range of years where the model predicts near the mean observed value. Alternatively, the quadratic and power models for a higher fixed endpoint predict near the median of observed values for 5 or more years. This reduces the total amount of model error demonstrated by the MSE. A range of MSE values determined for TONS MAF IRI data using a quadratic form are shown in figure 9. Based on this visualization, the lowest MSE value occurs when using a fixed endpoint of 40. However, little improvement in the MSE is observed above 25. Selecting a model with the highest possible fixed endpoint results in a model that does not properly fit the shape of historical performance after fitting. This can affect the area calculation used in the PMS optimization process, causing bias towards treatments with higher benefit area calculations. It is better to select a fixed endpoint that reflects a more realistic "end of life" scenario for the treatment even if it is only theoretical and unlikely that the pavement section will ever deteriorate that far. To select the most appropriate model, fixed endpoints were selected that minimized the MSE without going so high that diminishing returns were observed. Typically, the first fixed endpoint that improved the MSE by less than 5 percent was selected.

Figure 9. Example quadratic MSE values for a range of fixed endpoints.

Based on these observations, the approach selected for developing preliminary recommended index models while accounting for fixed endpoints was as follows:

- 1. Fix model forms to the y-intercept established by VTrans.
- 2. Establish non-linear least square regression models for the power and quadratic forms at various fixed endpoints in increments of 5 years.
- 3. Review MSE values for the preliminary models.
- 4. If considered beneficial, establish models at smaller increments of 1 to identify the optimum fixed endpoint.
- 5. Determine the MSE of the preexisting agency model to verify the new models improve prediction.
- 6. Select the model with the lowest MSE without selecting a fixed endpoint that produces diminishing returns.

Least-squares regressions were performed for all organized combinations of index type, pavement type, and treatment family where enough data existed to perform one. Datasets that did not have enough observations to have 30 or more values within each year for at least 12 years were considered too small to form a model. For those scenarios, a surrogate model was recommended based upon available data, other preliminary models, and a general understanding of the treatment and pavement type.

Developing Models for NPM Cracking Measures

The NPM cracking measure differs from VTrans' index measures and required a slightly different approach for model development. Defined in the HPMS Field Manual¹ as cracking percent, this measure represents the percentage of the total pavement area with visible fatiguetype cracking in the wheelpath. For new pavements, values are expected to be zero. As pavements age, cracking percentages increase. Percentages are determined based on the amount of cracked wheelpath divided by the total pavement areas. For a 12-ft-wide asphalt pavement, the maximum value expected for fully cracked wheelpaths is 54 percent.

The approach for establishing preliminary models for NPM cracking considered quadratic and power forms with models fixed to the origin, forcing all models to start at year 0 with 0 percent cracking. Linear models were also considered and are described in the section on results. For NPM cracking models, r-squared was considered a reasonable measure of fit and was used as the primary measure of model fit.

¹ Federal Highway Administration (FHWA). 2016. *Highway Performance [Monitoring System Field](https://www.fhwa.dot.gov/policyinformation/hpms/fieldmanual/page06.cfm) [Manual.](https://www.fhwa.dot.gov/policyinformation/hpms/fieldmanual/page06.cfm)* Control No. 2125-0028. FHWA Office of Management & Budget (OMB), McLean, VA.

Findings and Model Recommendations

Model recommendations for all measures are provided below in tables 8 through 12. Boxplots and regression plots used to establish model recommendations are provided in appendix A and appendix B, respectively. Once initial model recommendations were established, each model recommendation was presented to VTrans staff in a virtual review meeting. Some models have been adjusted from their original recommended forms based on feedback received during those meetings. Those adjustments are described below.

Index Measures

Recommended models were established for the four index measures and each treatment family. General observations made during the model development include:

- Reconstruction models were not developed for the AONC base type.
- Little data existed for the CROL treatment family for all index measures and base types. Surrogate models are recommended based on other treatment families.
- Little to no data existed for TNOL and PAO in the AONC base type.
- Little to no data existed for TNOL, PAO, and REC in the TONS and TONW base types.
- Surrogate models are recommended for groupings that did not have sufficient data for establishing satisfactory models.

Table 10. STRC index preliminary models.

During the review of preliminary recommended models with VTrans staff, it was noted that two recommended AONC MAF and THCK TNOL RUT index models had an undesirable upward concave shape as shown in figure 10. VTrans staff requested that different models be developed that did not have this form.

Figure 10. Preliminary recommended AONC MAF RUT index models with upward concave shape.

To address the concave behavior of the two regressed models, a linear model was considered for the two base type and model family groupings. Recommended linear models are provided in figures 11 and 12 as well as table 12.

Figure 11. Proposed RUT index linear model for AONC MAF.

Figure 12. Proposed RUT index linear model for THCK TNOL.

L

National Performance Measure (NPM) Cracking

Due to lack of historical data until recently, VTrans did not previously have models for NPM cracking. So, when developing models, no comparison to pre-existing models was performed. Some initial regressions produced power and quadratic models that demonstrated an upward curvature that projected cracking values beyond what is considered reasonable, as shown in figure 13. Others projected values less than ten percent as far out as 15 years, as shown in figure 14. Models developed using the quadratic model form were found to have an eventually upward curvature that projected values well above what is reasonable.

Figure 13. NPM cracking power and regression models for THCK REC.

Figure 14. NPM cracking power and regression models for TONS MAF.

To establish models that are more consistent with expectations, linear models were developed for each grouping. To evaluate the relative predictive characteristics between each linear model, projected values at year 20 were compared between all model families and base types, shown in figure 15.

Figure 15. Linear projected NPM cracking values for year 20.

Some treatment families such as CROL did not have sufficient data to develop a linear model. Therefore, a surrogate model is required. For other groupings, sufficient data was available to build a model, but the resulting linear model did not produce a slope that was intuitive when compared to other groupings. For example, the projected NPM cracking at year 20 for THCK MAF is higher than for TONS MAF, implying that a mill and fill treatment on thin pavements outperforms thick pavements when placed on the same base type. Lastly, some regressed models projected unrealistically low cracking values for 20-year-old pavements. To account for this and establish models with realistic relative performance, the following surrogate recommendations are made:

- The THCK MAF linear model is recommended for predicting NPM cracking on THCK REC, THCK TNOL, THCK OVL, TONS REC, TONW REC, and AONC REC.
- The THCK PAO linear model is recommended for predicting NPM cracking on THCK CROL.
- The OVL linear model is recommended for predicting NPM cracking on TNOL, MAF, PAO, and CROL for the TONS, TONW, and AONC base types.

Linear projected year 20 values including surrogate and replacement recommendations are provided in figure 16.

NPM cracking values should generally not exceed 54 percent for 12-ft lane width, 59 percent for 11-ft lanes, or 65 percent for 10-ft lanes. These models are to be used for predicting overall NPMs and are not expected to be used in PMS analyses that extend beyond 20 years. The recommended models from this approach are provided in table 13 are considered the most reasonable NPM cracking predictions without extending beyond the typical maximum range during PMS analysis.

Pavement

Deterioration

Models

for PM

Pavement

Deterioration

Models

for PM

32

Conclusions and Recommendations

This project developed new and updated prediction models for VTrans' pavement condition indicators, including an IRI index, rutting index, transverse cracking index, structural cracking index, and the National performance measure for cracking. Historical pavement surface condition data were compiled for condition years ranging from 2012 to 2022 and merged into a master database, including four different base types and treatment history data for six treatment families. The data were organized into individual master datasets for each performance indicator to establish time-series plots for each combination of performance indicator, base type, and treatment family. Box plots were developed for 140 different family combinations. After reviewing boxplots for data variability and filtering datasets, nonlinear regressions were performed to establish models for all index family combinations using power and quadratic forms. Models were compared to previously existing models used by VTrans, and the model with the lowest MSE was selected. The MSE was reduced for all combinations that had preexisting models, reducing prediction error for all cases. For family combinations where insufficient data was available, surrogate models were recommended based on similar groupings where models were able to be established. Two index family combinations returned regressions with undesirable prediction characteristics and were replaced with linear models. For NPM cracking, initial models were considered using power and quadratic forms, but returned undesirable prediction characteristics and were replaced with linear models. A review of 20-year NPM predictions for all base types and treatment families was conducted. Surrogate and replacement models were recommended.

It is recommended that VTrans consider using these new and updated models in all PMS analyses. When using these new models for establishing work programs, it is advisable to consider parallel analyses with the new and current models to review work program differences. If work programs are considered reasonable or improved when using these new models, it is recommended the new models replace the previous models. A similar assessment may be performed when using the NPM cracking models to predict NPMs. An initial analysis can be performed to test the reasonableness of overall NPM predictions.

It is best practice to continuously evaluate PMS predictions and other outputs in conjunction with daily PMS work activities. If a prediction is observed that appears to be out of range, it may be reviewed to verify model predictions are still considered reasonable. Another recommended best practice is to routinely review treatment history data when reviewing historical and projected performance for individual segments. If incorrect, missing, or improperly dated work activities are identified for a segment, the segments should be corrected. Surface age is the most significant predictor of pavement condition, and high-quality treatment history is required to identify accurate age values for segments. Furthermore, including maintenance history in the PMS can identify segments that are no longer representative of the treatment family or pavement age.

These model recommendations are recommended for use in the VTrans PMS for no more than 10 years. After 10 or more years, an updated review is recommended. If desired, reviews may be conducted more frequently. If changes to design or construction practices may alter pavement performance, model reviews are recommended.