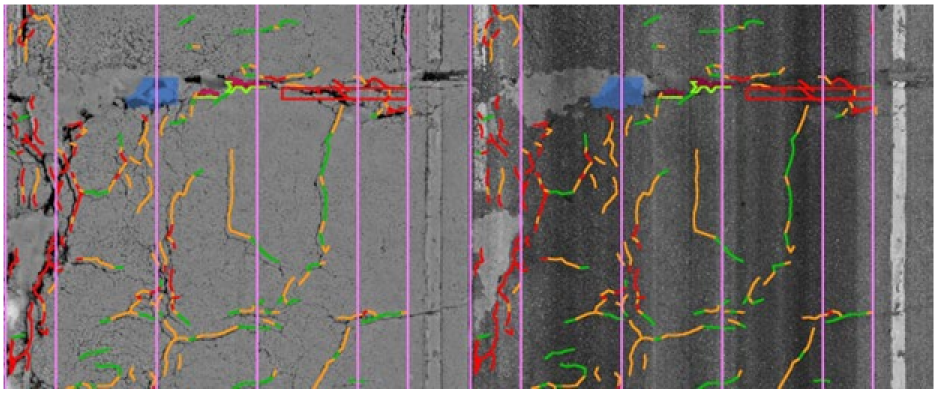
DEVELOPMENT OF AUTOMATED PAVEMENT CONDITION SCORE AND DECISION LOGIC



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16. Abstract

The Ohio Department of Transportation (ODOT) has been collecting 3D digital data on their pavement network since 2014. This data contains a variety of information derived from 3d laser scans of the pavement. While ODOT has been using the data to meet federal HPMS reporting requirements of pavement condition, the agency wished to leverage this wealth of data to aid their pavement management system and transition from a manual pavement condition survey to an automated one. This research aims to provide ODOT a means to interpret the data and use it to make the same decisions as the existing pavement management system. Topics include analysis and development of a new rating methodology for automated distress detection and classification as well as deterioration models and decision trees for the new rating methodology. The rating system was developed using comparisons with existing manual ratings and automated data collected from 2014 through 2018. Additionally, the report covers how to implement this methodology and how it impacts pavement management decisions.

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Problem Statement

A critical component of pavement management systems is a reliable, repeatable evaluation of the pavement condition. The Ohio Department of Transportation (ODOT) has been using Pavement Condition Rating (PCR) since the 1980’s to conduct field evaluations of condition to fulfill this need. According to the PCR manual, pavement raters would conduct both windshield survey of conditions as well as a survey of sample sections from the pavement shoulder.

In 2014, ODOT began collecting automated pavement condition data using a Pathway Services vehicle equipped with a 3d laser-based crack detection unit to satisfy federal reporting requirements. While both forward imagery and downward laser data available would allow engineers to conduct some evaluations digitally, not all distresses could be adequately rated from the data. The need was identified to build a new rating system that allowed ODOT to automatically generate ratings to leverage the data provided by the collection vehicle.

There are potential drawbacks to an automated rating system that should be considered. Limitations of data collection hardware or processing software make some distress types difficult or inconsistent to detect automatically. Inconsistencies in data collection, vehicle calibrations, or equipment between data collection cycles may cause wider differences in results using an automated system compared to manual ratings. Advancements in technology and processing software could also pose similar issues when comparing year-to-year data.

Another factor to consider is the institutional knowledge and historical data available through the existing rating methodology. An automated system would only have seven years of data available for analysis, even including all data collected during the timespan of this research. PCR has decades of data, including experienced raters. This means that any automated system needs to at least make some account of historical data.

While the raw data is collected as part of annual efforts to meet federal requirements, additional data processing is required to achieve automated distress classification and ratings. This processing presents additional costs for automation in terms of time, data storage, equipment, and necessary quality control. This is in stark contrast to manual ratings that are ready to use for pavement management nearly as soon as they are collected.

With these factors in mind, ODOT needed research to develop an automated pavement condition score (PCS). This research would need to include an evaluation of the data, both in terms of accuracy of rating and consistency. Additionally, comparisons would be needed between PCR and PCS ratings, deterioration, and the impact on pavement management decisions. The primary goal is a 90% minimum match of decision outcomes between the current manual rating practice and the automated rating methodology.

Research Background

Under the current PCR methodology, ODOT raters evaluate pavements with visual inspection based upon the combination of distress, severity, and extent (DSE) present in a pavement management section. Each DSE has a base deduct value for the distress type and a multiplier between 0 and 1 for each severity and extent. The sum of the distress deducts for a section is then subtracted from 100 to arrive at the PCR score. Distress deducts are designed such that a PCR score of zero requires the maximum extent and severity of all distress types to be present.

Additionally, a structural deduct score is computed. This score is the simple sum of all deduct values from distresses flagged as structural defects in the PCR manual. While the overall PCR score gives a general evaluation of pavement condition, the structural deduct total is useful for identifying more critical needs for repairs. As such, pavement management decisions may use this score to trigger specific activities, such as an overlay with repairs, even if the PCR score wouldn't.

Once PCR ratings have been assigned to sections, the information can be used in conjunction with decision trees to arrive at appropriate treatment options. The current decision trees are broken into three main network categories: urban, general, and priority. Each tree considers the pavement type, PCR score, structural deduct, annual average daily traffic, and the individual DSE ratings. The resulting decision bin includes one or more viable activities that could be considered by pavement management software for treatments, including some bins where "do nothing" is suggested.

Changes to the pavement management software were beyond the scope of this research, but an understanding of how the decisions are utilized was important. Currently, decision outcomes and the viable activities will be used by the pavement management software in computing the best projects to pursue based upon a cost/benefit analysis. Calculating the benefit area of a treatment is found by integral difference between the projected condition after a proposed treatment and the projected condition with no treatment, based upon a deterioration model for that pavement section.

Multiple deterioration model methodologies are used by ODOT to fill this need. The most robust was developed by Chou et al. (2008) and is based on transition probability matrices (TPMs), sometimes referred to as Markov models. This approach attempts to predict the likelihood a DSE changes state from year to year, such as increasing severity or extent. Predicting the shift in deduct value over time is computed by multiplying a vector that describes the deduct values of a given distress by a matrix of the transition probabilities for each year predicted forward. Using the base DSE deduct values in the vector results in an age-based prediction of the deduct value for each starting state. Using the section's current deduct value as the vector instead results in a prediction of that section's deduct value for a given distress in the prediction year.

Existing models were derived from a large set of historical PCR data for each distress type for a variety of pavement families. These families separate out pavement by type, traffic, and last surface treatment. Where these families lacked sufficient data, a regression model is used to extend the slope of previous deterioration within a family to predict future deterioration. In cases where neither the TPM nor regression model adequately describe the family's deterioration, the most similar family's model is substituted.

A research study completed in 2013 compared various data collection technologies available versus PCR evaluations conducted by ODOT raters (Vavrik et. al. 2013). Tests of the automated detection of pavement distress were conducted on a sample of pavements to compare the manual ratings with different equipment vendor automated results. The results revealed a high success rate of detecting the existence of several PCR distress types, but poor identification of severity and extent. Following the study, ODOT initiated the process of collecting the data required for automated distress identification.

Additional literature review may be found in Appendix 1. Topics cover a wide range of other research into utilizing automated data for pavement management purposes, various collection systems, and reporting requirements. Of note is the mix of both success and failure reported by other research in matching automated data with manual ratings. These inconclusive results may point to the need for further development of automated systems, both in terms of hardware and software, before fully-automated pavement ratings are feasible for widespread adoption for pavement management systems.

Starting in 2014, image data were collected statewide on a two-year cycle. Along with imagery, the collection vehicle provides the necessary data to meet federal reporting requirements established by The Moving Ahead for Progress in the 21st Century Act (MAP-21). However, the methodology to translate from automated distress data to pavement management decisions was unavailable, leaving the ODOT unable to compare the results of the automated distress identification to PCR-based decisions. Having this comparison allows the continuity of pavement performance prediction and forecasting which serves as the foundation of a pavement management system.

To gauge industry trends, a questionnaire was sent to state-level transportation officials. Of the 25 agencies that responded, 64 percent use fully-automated data collection to meet MAP-21 requirements, with the remainder using a semi-automated approach. For pavement management decisions, 52 percent use fully-automated while 36 percent use a semi-auto and the remaining 12 percent still use a manual process.

While the overall responses indicate widespread use of automation, the practical application of a 100% automated system is far less common than those numbers may indicate. Even within the group of agencies reporting a fully-automated processes, the systems used and what agencies consider to be a fully-automated system varies widely. Many agencies that reported fully-automated distress classification for PMS purposes still included manual ratings on concrete pavements and manual corrections on other pavement types for some distresses. This manual effort often includes a quality control/assurance process that must be conducted on the data before it is used for pavement management decisions.

Further, not all agencies use the same level of detail for their pavement management ratings as ODOT. This follows the same pattern as the inconsistent results shown in the literature review. Different software, hardware, and existing rating systems have seen varying degrees of success with various drawbacks. More detailed responses and a sample of the questionnaire may be found in Appendix 6.

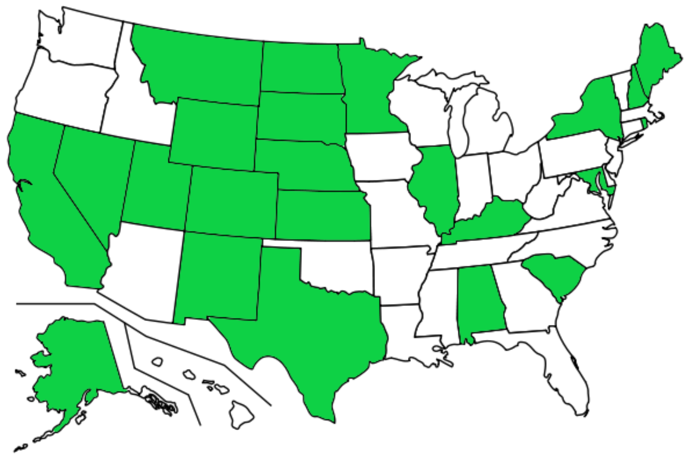

Figure 1: A map of state transportation agencies responding to questionnaire.

This study establishes a pavement condition score (PCS) using the automated distress data, analyses the relationship between PCR and PCS, and provides a methodology to transition to an automated data collection and analysis-based pavement management system. Goals for the project were broken down into four main categories: development of PCS methodology, adjustments to decision tree logic, development of a PCS manual, and creation of this final report.

Development of PCS encompassed several subtasks. The three primary tasks to arrive at a rating system were distress classification, extent, and severity calculations, and to weight the contribution of individual distresses. After having a rating system in place, a methodology to compare between PCS and PCR needed to be developed. Finally, new deterioration models for each distress would need to be considered as available data allowed.

The goals pertaining to the decision tree logic included understanding the existing activity codes and decision tree logic, developing new logic to account for PCS, and validation of the changes. Validation would include a statistical analysis of the PCS decisions compared to the equivalent PCR decisions, field visits to compare PCS decisions with engineering practices, and analysis of additional data not used for the development of PCS. This additional data would come from a 10% sample of 2017 and 2018 data that was collected during the research project duration.

A manual for calculating PCS was developed and covers the complete process of arriving at a score, starting with required processing in the equipment vendor's software. A breakdown of calculations used to compute the score from reports generated from that software is included. Additionally, instruction for using the Excel worksheet macros developed by the research team for calculating PCS and computing the decision trees is included for reference.

Research Approach

Data received from ODOT initially included all data from 2014, 2015, and 2016 data collections. The full set of data was compiled onto a network attached storage device provided as part of this research effort. Throughout the course of the research, ODOT delivered additional data from 2017 and 2018 data collections as they became available. Due to the size of the data, only 2017 data was added to the storage system, with 2018 data being stored and processed externally.

Initial data received were previously processed through Pathview's AutoCrack software, which detects the presence of various distresses from 3d laser scan data. This process only detects presence and does not classify the distress into type, severity, or extent. Processing the annually collected data, representing half the network, may take several months to complete distress detection using the AutoCrack software.

Data had also been processed using Pathview's AutoClass tool prior to the research team receiving it. This tool attempts to classify each distress identified by the AutoCrack tool into a distress type and severity. Processing the annually collected data through this tool can take several weeks. This led to significant delays later in the research when the data needed to be reprocessed using an updated version of the software.

Initial review of the data by the research team identified several distress types utilized by PCR that were not reported or detected by the Pathview software. A series of meetings between researchers, ODOT, and the software developer were held to attempt to increase the available distress types. This was a lengthy process that included development time for the software updates required, reprocessing the data through a revised tool, and analysis/reporting of the results. Several iterations of these steps were conducted to arrive at the final list of distresses available to develop the PCS methodology.

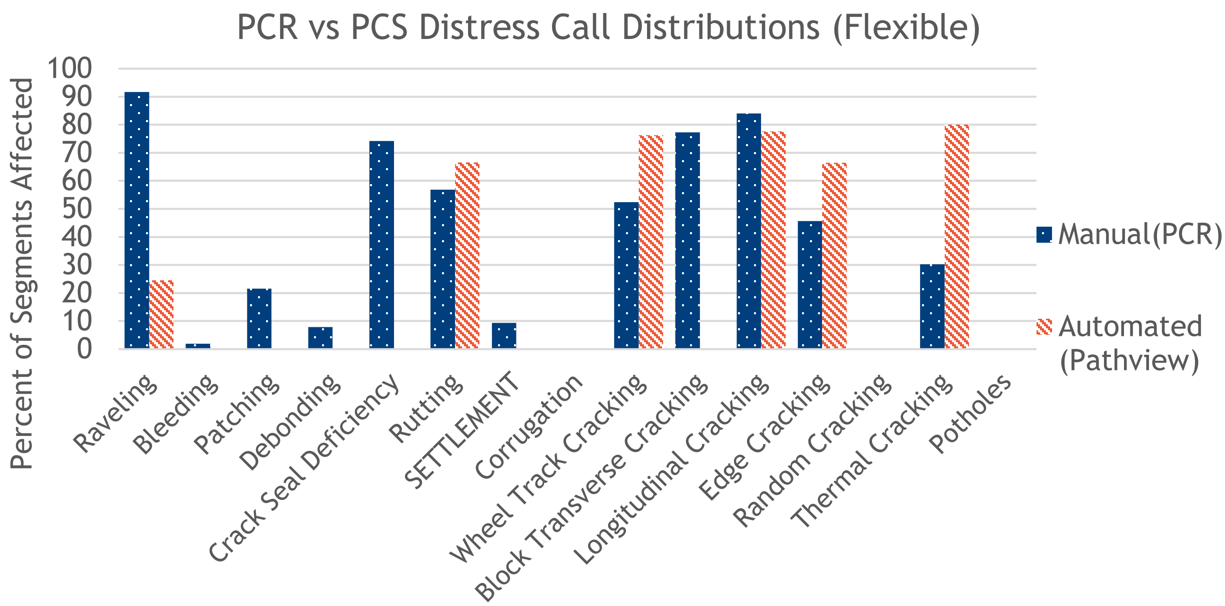

Figure 2: An example of charts used to identify distresses detected by automated distress detection compared to manual ratings.

For a given distress to be considered for the final list of PCS distresses, it needed to be adequately reported by the software. Pathview software provides a reporting feature that can aggregate distress quantities by a set interval along with section identification information. For a majority of distresses reported, quantity for each severity is reported for each distress. Quantities can be reported in units specified by the user, such as length, width, or area. In all cases, distress quantities were output in units that matched their PCR definitions.

Consideration was given to the reporting interval to use for research purposes. Overall section totals limited analysis of distresses such as rutting, which would only be reported as the section average. Researchers decided to use a tenth-mile reporting frequency in Pathview software to allow more flexibility in evaluating such distresses. Additionally, this smaller interval allows ratings to eliminate intervals with invalid data, rather than having them influence the section average.

For a distress to appear in the interval report, it must be defined in a configuration file (*.C11) and be supported by Pathview software. Researchers worked with Pathway Services to obtain a new configuration file and software updates to support as many distresses as Pathway Services could manage to implement.

Several rounds of updates to the configuration and software were conducted. Each round required sample data to be reprocessed with the new version of Pathview software and configuration file. Data from 2016 covering district 1 was used to gauge the impact of the changes. Once the final software version and configuration were set, the full data set (2015 and 2016 data collection cycles) was reprocessed with the updates. The processing required several months to complete, with additional time required to extract reports necessary for PCS calculations.

However, after these updates, a variety of distresses failed to report quantities for any sections in the research data despite being present in the report header and in manual PCR evaluations. These distresses are noted in the final distress list but were not used in the development of PCS. Additional PCR distresses are noted in the following tables that were not used directly in PCS but were included in other distress types.

Table 1: Final distress list for flexible pavement.

Description	PathwayCode	PCR Code	Notes
Raveling	Ravel	1	
Bleeding	Bleeding	2	Header present, but no quantity in data. Not used in PCS calculations.
Patching	Patching	3	Header present, but no quantity in data. Not used in PCS calculations.
Debonding	N/A	4	Debonding reported as Potholes by Pathview
Rutting	Rut	6	
Wheel Track Cracking	WheelT	9	
Block Transverse Cracking	N/A	10	All transverse cracking reported together by Pathview, PCS reports all as code 14.
Longitudinal Cracking	Long	11	
Edge Cracking	Edge	12	
Thermal Cracking	Trans	14	
Potholes	PotHoles	15	

Table 2: Final distress list for composite pavement.

Description	PathwayCode	PCR Code	Notes
Raveling	Ravel	1	
Bleeding	Bleeding	2	Header present, but no quantity in data. Not used in PCS calculations.
Patching	Patching	3	Header present, but no quantity in data. Not used in PCS calculations.
Rutting	Rut	5	
Shattered slab	Slab	7	
Tvs. Cracking – unjointed	Trans	9	
Tvs. Cracking – joint reflection	N/A	10	No distinction between composite base type, all transverse reported as code 9.
Tvs. Cracking – intermediate	N/A	11	No distinction between composite base type, all transverse reported as code 9.
Longitudinal cracking	Long	12	

Table 3: Final distress list for concrete pavement.

Description	PathwayCode	PCR Code	Notes
Patching	Patching	3	Header present, but no quantity in data. Not used in PCS calculations.
Faulting	FAUA	5	
Transverse Joint Spalling	TSpall	7	
Transverse Crack - Reinforced Concrete	N/A	10	No distinction between types, all transverse reported as code 14
Longitudinal Cracking	Long	11	
Corner breaks	Corner	12	
Longitudinal Spalling	LSpall	13	
Transverse Crack - Plain Concrete	Trans	14	

In parallel to supporting the adjustments to the software, the research team began the quality control process. Review of imagery provided within Pathview allowed engineers and technicians to compare the distresses identified and classified by the software against the PCR methodology. While initial review identified several misclassifications or missed distress ratings, a few more widespread issues were noted that needed additional review.

One issue was the appearance of duplicate distress calls in the distress features database for the same physical distress. Quality control efforts here focused on identifying how widespread the issue is within the research data and attempting to identify the source. Tools within Pathview allowed the team to review the distress features database while viewing related imagery and location data.

A second vein of quality control was related to distresses that were marked as "unassigned" in the distress features database. The research team wished to establish if these distresses were not being classified correctly or were correctly discarded. A sample set of 2016 data was prepared for analysis of the distress features database, covering district 1. The review would attempt to identify common causes of a distress being unassigned and give an estimate of how often this issue appeared in the data.

Additional results from quality control identified several potential issues in the automated data. In several instances, the pavement type was mis-identified by the automated system or within the collection system database. This led to distress calls being made for the wrong pavement type, creating further disparity between automated and manual data. Such differences lead to incorrect classification of distress that is inconsistent with the rating methodology. This has a negative impact on matching decisions between automated and manual rating systems. Further details on this and other issues noted are reviewed in Appendix 2.

To identify data that was invalid for the development process, an additional check was conducted to remove outliers in the data. Because the automated data is not collected at the same time as manual ratings are completed, some discrepancies between the two can be found when maintenance or road closures occur in between the two data sets.

Developing a rating system

To facilitate calculation and iteration of PCS, a macro was developed using Visual Basic for Applications within Microsoft Excel. This macro pulls data from Pathview's sensor reports as well as a segmentation file derived from ODOT's PCR history. Settings within the spreadsheet for the macro include defining which headers from Pathview's output correspond to each distress. Each distress defined also has options to set the base deduct value, the multipliers used for each severity and extent combination, as well as a flag to mark a distress as structural. Thresholds between each extent are also defined on the sheet. More details on the PCS calculation tool are presented in the PCS Manual included in Appendix 5.

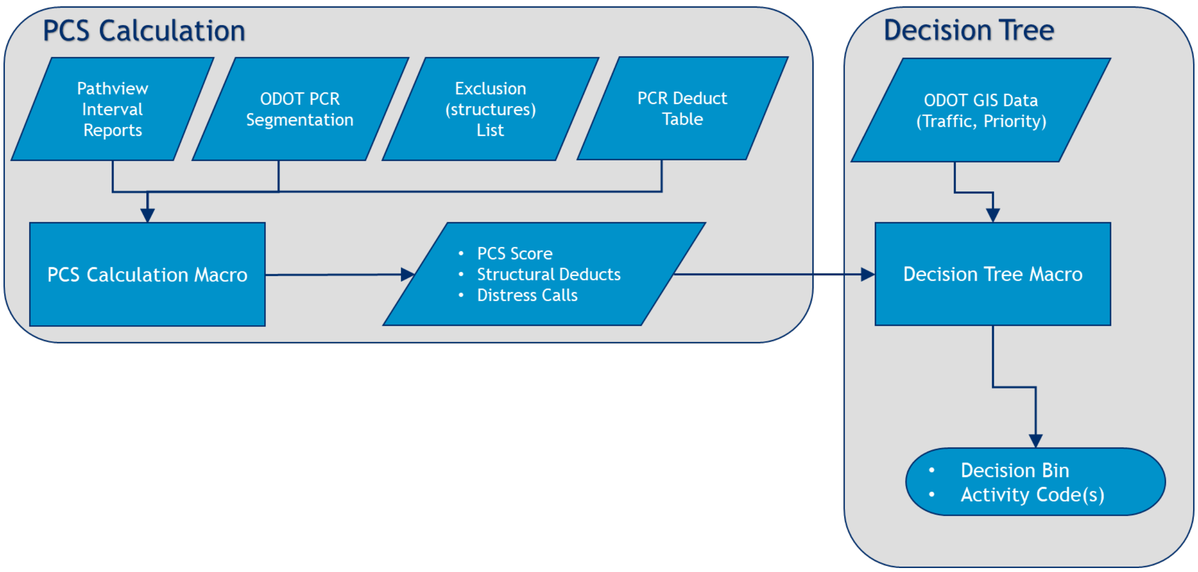

Figure 3: A flowchart showing the process of generating a PCS rating and pavement management decision from Pathview data.

The sensor report output from Pathview has an optional reporting interval. Using an overall section total of distress would be possible, but the additional detail using a tenth-mile reporting interval allowed for additional granularity in the research. For example, an overall section average for rut depth could be used to generate a section score, but evaluating the smaller intervals allowed individual extents to be calculated for each severity. As such, all research data used the tenth-mile interval for sensor reports generated by the Pathview software as input to the PCS calculation tool.

Data from Pathview is reported in total quantity per distress type and severity combination. The PCS calculation tool generates a deduct value for each severity for an extent derived from the amount of distress and the section area or length (as appropriate). To arrive at a section's overall rating for each distress, the deducts for each severity are compared, with the highest deduct rating being the final section distress rating. In the event of a tie for highest deduct, the higher severity is used as the final rating.

Output from the PCS calculation includes a rating sheet with the section's identifying information, overall PCS score, the corresponding manual PCR score, structural deduct total, and a breakdown of individual distress ratings and deducts. Included on one of the output worksheets is a copy of the deduct worksheet from the tool. This allows both a record of the deducts used for the calculation to be captured as well as allowing adjustments after the rating for the purposes of calibrating the models. The total score and distress deducts are formulas that update with changes to this deduct sheet.

Consideration was given to allow for exceptions in the data that would normally not be included as part of a pavement management section's rating. The primary source of these exceptions is bridges. Using structure location information provided by ODOT, researchers compiled a list of exclusions that would have a potential impact on PCS calculations. The PCS calculation tool was modified to read this list of exemptions and skip any interval that included a bridge of a length greater than 25% of the interval length (132ft/40.23m for a 0.1 mile/160.93m interval).

A small study was conducted to gauge the impact of these exclusions on the score calculation, which showed the effect was minimal. The impact on decisions was insignificant, as most sections with scores changing were already calling for no treatment, which continued after the slight improvement to score from removing the exclusions. Sections with PCS under 80 saw less change in score, as the distresses throughout the section made up a larger portion of reported distresses.

To establish a baseline for development of PCS, a direct calculation using the PCR methodology was used. All fields available from Pathview's sensor report were mapped within the PCS calculation tool to their appropriate PCR distress. All deduct values, severity/extent multipliers, extent thresholds, and structural definitions were retained from PCR. The resulting PCS ratings were then compared to the manual PCR ratings provided from ODOT's PCR history. Initial data utilized was from 2016 and collected in District 1, representing the full district's collected data for that year. The single district was chosen due to data availability, given the reprocessing requirements mentioned previously.

The baseline data would later be compared to other possible approaches the researchers analyzed. Four possibilities were given consideration, as summarized in the table below. Each of these would be used to generate a PCS rating, which would be compared to the manual ratings. Each method would be evaluated by researchers and compared in correlation as well as practicality of implementation.

Table 4: A list describing various methodologies considered for development of Pavement Condition Score.

Method	Description
PCR Baseline	Direct translation of PCR deduct values, multipliers, and definitions
PCI	Based on Pavement Condition Index (ASTM D6433 - 11), mapping automated to PCI distress definitions and using PCI deduct curves
PCR Sliding Scale	Direct translation of PCR with modification of the extent deduct multiplier on a linear interpolation between thresholds
PCR Percentile	Composite scoring based upon the percentile a section falls into within the sample data using PCR distress definitions
PCR Regression	Direct translation of PCR distress definitions, but using linear regression to adjust deduct values

The Pavement Condition Index (PCI) is a widely used standard for rating pavements, originally created by the Army Corps of Engineers for the purposes of rating airport runways. It has since been adopted by agencies for the purposes of pavement ratings for roadways. In order to use Pathview data to calculate PCI, an optional feature was added to the PCS calculation tool to report distress quantities for each section in PCI distress types.

Decision trees used by ODOT contain distress checks that look for individual distress severity-extent combinations that exist in PCR. To accommodate these checks in the initial analysis of PCI methodology, the base model PCR distress ratings were used. PCI score was calculated in accordance with the ASTM specification, using the PCI distress quantities generated by the PCS calculation tool. Additionally, structural deduct was calculated from the original PCR distress deducts.

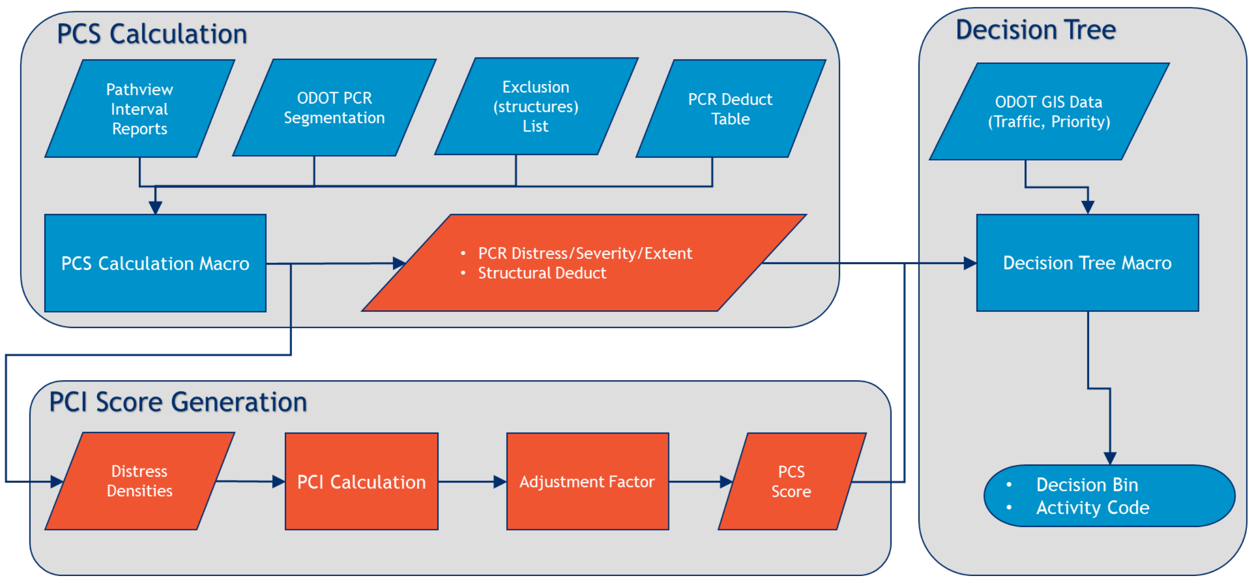

Figure 4: A flowchart showing how a calculation of Pavement Condition Index could be incorporated into the Pavement Condition Score rating to generate pavement management decisions.

Due to the limited nature of distresses available to calculate PCS in the baseline model, one method was considered for allowing the system a little more flexibility to achieve closer correlation with PCR. Normally in PCR, each extent bracket is fixed deduct multiplier that covers the whole range with the same score multiplier regardless of relative extent. In the PCR sliding scale method, the extent deducts were adjusted along a linear interpolation between the minimum deduct and maximum deduct for the bracket, using the relative extent within the bracket.

For example, if the Frequent extent call has 20% and 50% as the respective lower and upper bound with a section that has 35% of that distress, then the overall deduct multiplier would be calculated as halfway between the Occasional deduct multiplier and the Frequent multiplier. This means each bracket would consider the normal PCR multiplier as its maximum deduct multiplier.

Another approach considered was to generate a score based upon how a section ranked compared to other sections in the data set via a percentile rank. Each section was given a percentile rank for each distress type and severity combination, based upon the percent of pavement length or area exhibiting that distress as reported by Pathview. Under this approach, an overall PCS score would be assigned based upon some aggregation of the individual percentile of distresses reported, taking the PCR score at that percentile as a predicted score.

The difficulty of this method is finding an aggregation of percentiles that presented reasonable correlation with a section's actual ratings. No single distress would reliably predict overall score. A direct average of percentile ranks would fail to account for the different possible combinations of distress that may arrive at the same score, as distresses with zero quantity would skew score towards a higher percentile. There may be a possibility to utilize coefficients to weight the contribution of individual distresses to the overall percentile rank, however this approach would further complicate the model and make it further removed from actual data. These factors make the application of such method a less attractive option.

The final method tested for generating a PCS rating was using a regression model to set the deduct values, using the distress definitions from PCR. This is the same as the baseline model, but with the weight of each distress being adjusted to minimize the sum of squared error between PCS and PCR scores. To support regression modeling, the PCS calculation tool was adjusted to output ratings as formulas that calculate deduct values from the deduct sheet. As regression modeling is conducted, the resulting changes to the PCS are automatically updated on the sheet.

Regressed values would be generated using the Solver add-in for Microsoft Excel. A basic regression only constrained variables to be greater than or equal to zero. Initial results were reviewed and highlighted a few potential issues that needed addressed in the methodology. Several distresses were minimized to zero deduct value, whereas others trended toward rather high values. While this did improve the correlation between PCS and PCR, it was inconsistent with engineering practices to have additional distress not contribute to score deterioration.

Because of these inconsistencies, an additional trial for each pavement type was conducted with different constraints placed upon the regression model. Constraints were chosen to cap distresses which trended towards extremely high deduct coefficients and to prevent other distresses from trending to zero deduct.

In each case, distresses which were not reported by Pathview were removed from consideration. The resulting deduct values from each trial generated PCS scores within the PCS calculation tool output that was used for regression modeling. Scores and ratings from the PCS tool were then used as inputs for the decision tree calculation tool. All regression model scores and resulting decisions were then compared for both correlation with PCR scores and PCR-based decisions. The final regression model for each pavement type was selected based upon overall correlation of decisions.

Based upon the overall results from all possible PCS methodologies, and with the approval of the technical advisory committee, researchers selected the regression model as the final PCS model for the purposes of this project.

Deterioration model development

Once the PCS model was finalized, work could begin on developing deterioration models. Several options for predicting pavement deterioration exist. Within ODOT's existing pavement management, two primary methods are used. Markov transition probability matrix (TPMs) models are used where sufficient historical data is available. Where data is lacking, a regression model is used.

Markov models predict the probability a given pavement will transition between the various possible distress severities and extents each year. This TPM is then multiplied by an array containing the deduct value of each severity and extent combination. The result describes the next year's predicted rating. Further multiplication by the TPM deteriorates that result another year. As such, multiplying the deduct array by the TPM to the n^{th} power results in a n^{th} year prediction.

Provided by ODOT was a workbook that contains a complete list of TPMs available for each pavement family as defined by pavement type, last surface treatment, and district. Each distress has a 10 by 10 matrix that describes the deterioration of that distress type. All distresses are deteriorated within this sheet out to 40 years, for each starting state.

The main drawback of the TPM method is the requirement for a significant amount of data to build reliable transition probabilities spanning the range of distress states and pavement families. Estimates from previous research estimates the need for around ten years of data from annual collections to build reliable models for most pavement families. This need is exacerbated by some pavement families being less common due to construction and maintenance practices. (Chou, 2008)

Regression models are used to give a general deterioration when the source data was insufficient to generate a TPM with adequate combinations of distress. Under this approach, the prediction for a future score is calculated from a fit curve between previous years projected forward. Because this model is used when insufficient data is present, development of a consistent model may not always be feasible, particularly for each distress. At a minimum, a regression model requires three data points to generate a curve and subsequent prediction.

Under the original proposal, researchers had planned to use 2014 and 2016 data collections as a source for development of deterioration models. Initial quality control checks revealed a couple of issues. In PCS rating, the overall network trend was an increase in score. This is at odds with maintenance data provided by ODOT as well as the changes in manual PCR ratings in those years of data. Additionally, reported rutting was trending lower in 2016 than 2014, again inconsistent with PCR and maintenance records.

To verify whether this was an inconsistency in source data or an error in the PCS methodology, 2018 data available was compared against 2016 data. The resulting trends compared well with the PCR deteriorations. This led researchers to conclude that the 2014 data may not be consistent enough to use reliably for deterioration modeling purposes. Further evaluation of the 2014 data by ODOT and Pathway would be necessary to determine the root cause of the issues. Without an identified and corrected cause, the data should be removed from consideration for future research.

Instead of using 2014 data, a smaller set of data from 2018 data was used to create a basic deterioration model. The data was taken from District 11 in both 2016 and 2018 data sets. This data set is not necessarily representative of the whole state and was chosen only due to data availability. Data from 2018 had already been processed through Pathview's AutoClass with the original intent to be only used as a verification data set. The time required to process additional data to cover a wider portion of the state was too much to include in the project schedule.

Given the rather small source data available to develop a model, generating new TPMs for all pavement families was deemed to be infeasible. Linear regression models were developed, but these suffer from the limited data as well. Instead, researchers pursued the possibility of using the existing PCR TPMs for distresses reported by PCS. Because TPMs describe the likelihood of distresses changing from one state to another, distresses reported by automated should follow similar trends in increasing quantity and severity over time. However, some variance is expected from the model given the differences between PCS and PCR distresses available.

A generic model was used for initial investigation to determine the viability of using these PCR TPMs with PCS data. The PCR deterioration model selected for this initial effort represents data from asphalt pavements from all districts with most recent activity as an overlay without repairs on the priority network. It was selected based upon the quantity of data used to develop the original TPM.

To build a deterioration model curve from existing TPMs, the “null” deterioration from each distress was combined into a total deduct, then subtracted from 100. This presented a 40-year deterioration from a new pavement with zero distress based upon an existing PCR model. While other severity and extent combinations provide similar deterioration curves, the “null” level was chosen because it covered the range of possible deduct values while also matching similar slopes to TPM curves generated using higher deduct distresses.

To arrive at a PCS curve, distresses not reported by Pathview were removed and the PCS regressed coefficients replaced the baseline PCR coefficients. For comparison purposes, an additional curve was generated using the PCR TPM with only PCS distresses, but retaining the PCR deduct values. This curve would help gauge the impact of the change in distress deducts between PCS and PCR on deterioration. All curves were plotted to compare the 40-year trend.

To gauge the accuracy of the deterioration models, PCS scores were taken from 2015 and 2016 data and plotted at the section’s age measured from when the last activity was reported in ODOT’s maintenance records to the rating year. Segments were selected to match the PCS model definition used, flexible pavement having a last activity listed as code 50 (overlay without repairs).

As shown in Figure 5, this set of PCS data did not trend well with either the regression model derived from 2016/2018 PCS scores or the TPM model derived from a PCR model. Pavements within the first few years of deterioration after an overlay displayed notably lower PCS scores than any of the models would predict. However, the later years of data follow a similar slope to the simple TPM model using PCS distresses and coefficients, just shifted along the age axis.

The overall result is that age itself may not be a reliable predictor of PCS. Calculating an apparent age from the model, however, may allow reasonable deterioration along the slope, even if the calculated apparent age and actual age differ. It must be noted, though, that all the models diverge from the data most on newer pavements. This should have a minimal impact on pavement management decisions due to the PCS scores being above 80 for these sections, where no treatment would be suggested by the decision trees.

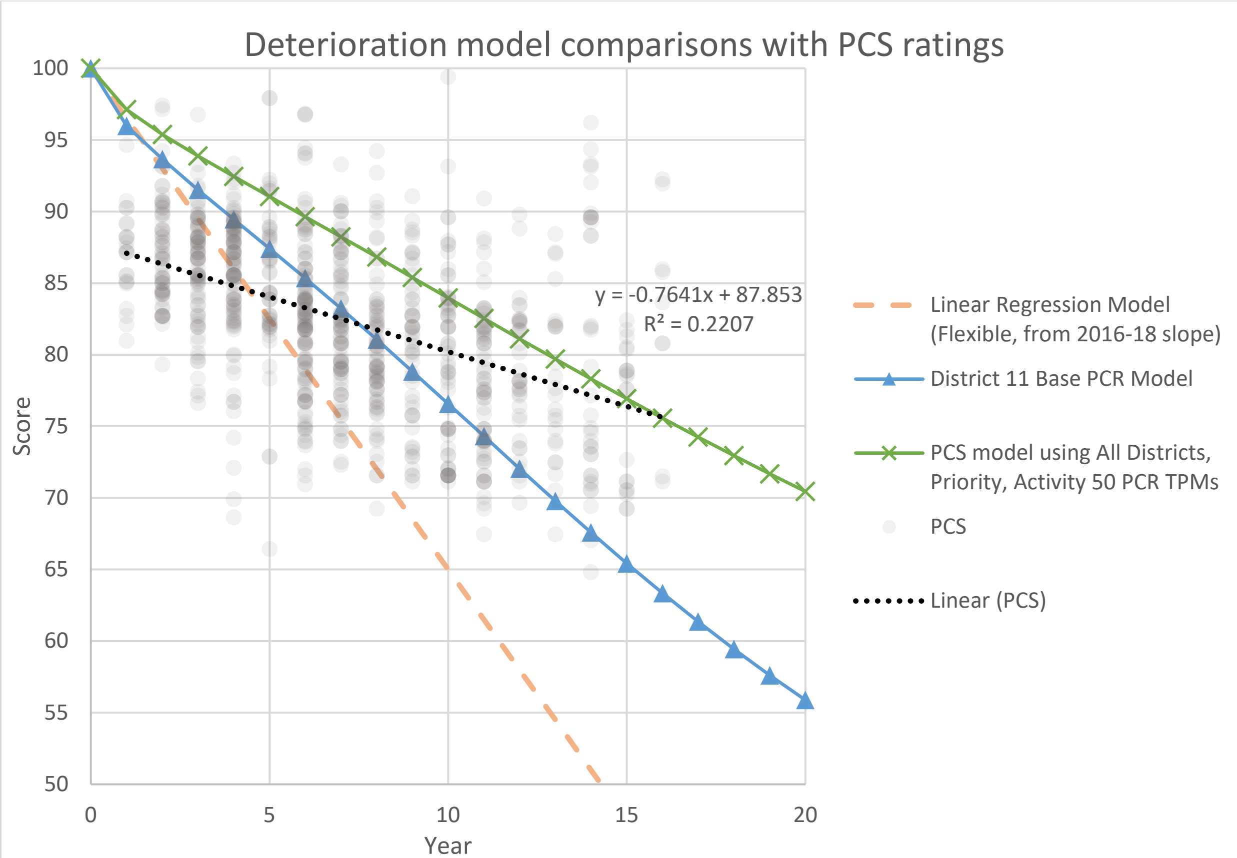

Figure 5: Chart comparing the 20-year score predictions of three different deterioration models and 2015/2016 PCS scores for sections with last activity 50.

As an additional check of the performance of this generic curve, PCS scores calculated from 2016 District 11 data were deteriorated two years forward using the model, then compared to corresponding 2018 District 11 calculated PCS scores. All pavement types were considered for this initial test, despite using a model derived from asphalt pavement, as a proof of concept. Only segments that showed a decrease in PCR between actual 2016 and 2018 data were considered.

The tested simple model showed a reasonable prediction trend from 2016 PCS data, typically falling within 5 points of the actual 2018 PCS rating once projected forward. Considering the model chosen did not necessarily reflect the pavement type or family of sample data, the results are promising for applying more specific models to the data.

The actual PCS scores trended lower than the prediction. This would have an impact on pavement management decisions relying on projected scores to plan future work activity. Less sections would be assigned a treatment from the decision tree in later years than would necessarily be warranted.

While the data in figure 5 would seem to be at odds with the higher r-squared shown in the predicted vs actual data in figure 6, this is due to the predictions using apparent age instead of actual age. The score is computed by finding the year in the model that corresponds to the 2016 score (the apparent age). Then, shifting the model forward 2 years results in the 2018 prediction. This highlights that the slope of the model is closer to the rate of change seen in PCS, even though the age-based score is far less accurate.

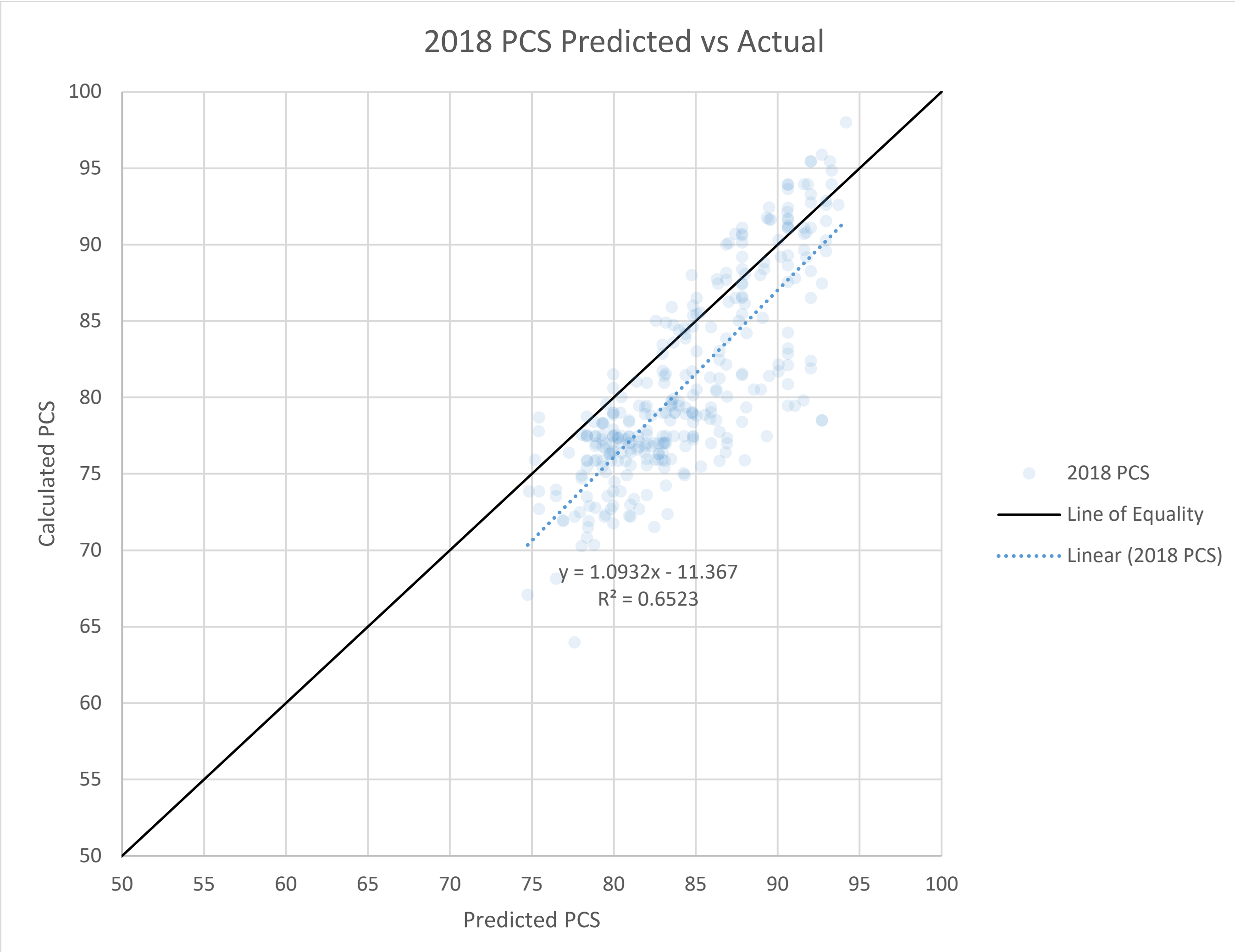

Figure 6: Chart displaying predicted versus actual 2018 PCS scores compared to predicted 2018 PCS scores derived from 2016 data using the generic TPM model.

Decision Tree Development

Determining which treatment or treatments are viable for a given section is handled by decision tree logic in the current PCR methodology. These decision trees are broken into three main pavement management categories: Urban, General, and Priority. Factors such as pavement type, PCR score, structural deduct total, traffic, and individual distress presence are used to arrive at a decision bin. These bins have one or more activity codes, including a "do nothing" result.

Because of the need to evaluate many sections and potentially iterate on new decision logic, a macro was developed in Visual Basic for Applications for Microsoft Excel. This macro takes a variety of inputs from a sheet that combines a section's identifying information with traffic data and PCR (or PCS) ratings. As output, additional columns are populated on the input sheet with the resulting decision bin, activity code(s), and a path code for each section. The path code is a string where each character represents a result of a node on the tree. Typically, each character is either the pavement type code or a number representing yes or no (one or zero, respectively). Further output describes any distress check that was performed, as well as a list of any distresses that matched the check.

Basic analysis of the PCR decision trees was conducted to evaluate which nodes were primary drivers of the final decision. For this analysis, the decision tree calculation macro was used on 2016 data. The resulting path codes were used to summarize the frequency individual nodes were checked across the set of sections. These would later be compared with results from the same sections using the final PCS methodology.

Because the stated goal of the project was to attempt to match PCR decisions with the PCS methodology, updates to the decision trees focused on smaller adjustments to account for differences rather than building new trees from scratch. Analysis of the existing decision trees highlighted a strong connection between score and decision outcome. Checks in the trees looking for individual distress type/severity/extent combinations (distress checks) impacted a significantly smaller portion of sections.

By choosing a PCS model that derives from PCR and using regression to minimize the sum of squared error between the systems, it follows naturally that decision tree changes should be minimal. While the error is targeted to be minimized, some adjustments to score thresholds are reasonable since error is not reduced to zero.

To arrive at adjusted score thresholds, the equation from a best fit regression line was used to back calculate a PCS score, using the existing PCR score as an input. Similarly, thresholds for structural deduct would be set using a best fit line of the correlation of PCR and PCS structural deduct scores. This method does require that a reasonable correlation between PCS and PCR exists.

Other than these two types of score-based checks, decision tree logic is the same. Distress checks could remove distresses from consideration that are undetected or unreported by Pathview software, but they will already be removed by omission in the data and would not impact the decision outcome.

Findings and Conclusions

Data presented in this report shows a relationship between automated and manual pavement ratings exists but good correlation is difficult to achieve. It also supports previous research showing automated data currently available to ODOT struggles to achieve parity with a manual process, particularly for the purposes of pavement management decisions targeted by this research. This resulted in the researchers being unable to achieve the stated goal of a 90% correlation between PCS-based pavement management decisions and the existing PCR-based decisions.

Efforts to process the automated data into a score as part of this research also highlight the additional effort that would be required to implement automated ratings from the raw data already being collected. Quality control checks suggested that more stringent controls on data collection and a robust quality control plan would also be required. The net result is that implementing fully-automated distress ratings does not remove the need for manual efforts in the process.

Final PCS models selected based upon their correlations with PCR-based decisions were only able to achieve 58% match of decision bins and 63% match of activity selected for asphalt and composite pavements. PCS performed far worse on concrete pavements, only reaching a 30% and 35% match for bin and activity, respectively.

Data Quality

Review of the automated data revealed several issues that had an impact on the results. Starting at the data collection step, automated data was not always collected in the same lane or direction as manual raters would have evaluated. In the case of automated data, it appears to have generally been collected in the outside lane of traffic. With manual ratings, PCR procedure would be to rate the heaviest traveled lane, which may not always be the outside lane. This difference was observed in at least one field visit section. The overall impact of such collection differences may be small within the data set but would be a contributing factor to lower correlation.

While some false-positive or false-negative results on crack detection and classification were expected, these were difficult to quantify in terms of impact because they didn’t occur in a consistent manner. During previous research, Pathview showed a strong ability to detect the existence of a distress but had much lower ability to correctly identify severity and extent (Vavrik et al. 2013). In the smaller sample size of that study, Pathview showed a 94 percent success rate at identifying PCR distress types. However, the reports generated by Pathview in that research were created using a semi-automated methodology. Fully-automated processing for the current research did not report all distress types previously reported.

As noted during quality control review of the data, there were several inconsistencies between data presented in Pathview and PCR evaluations conducted by ODOT. Differences in pavement type reported by the two systems reduced the accuracy of the PCS regression model. Discrepancies in lane and direction of travel rated by the two systems would further add inaccuracy to the PCS model.

Researchers noted that in some cases, the data contained duplicate distress ratings, where a single distress in the pavement might be reported several times in the distress features database. This duplication wasn't present in the whole dataset but appeared intermittently. The exact cause of this phenomenon was not able to be ascertained by the research team. This duplicated data may be present in some sections that were used in the development of PCS and/or the deterioration models.

It is possible that the duplicated distress issue could be related to processing the data with varied versions of Pathview software or an error in the crack detection step that occurred before the data was delivered to the research team. Should ODOT adopt an automated rating system, additional quality control would need to be in place to verify the results in Pathview from AutoCrack and AutoClass. Given how inconsistently the problem existed in the data, initial quality control efforts may need to cover a significant portion of collected data to ascertain the root cause or verify the issue is not impacting new data. Manual editing of the distress features database in Pathview would be required to remediate duplicate distresses, which may be a time consuming process.

Crack sealing also presented issues in the Pathview software as clusters of crack sealant were commonly mistaken for patching, and over band crack sealing that deviates from a straight line or followed a curved path (possibly errant sealant from the wand) often triggered an unassigned distress. A large percentage of unassigned distresses (4.52% of all distresses identified), in which the software identified an anomaly but did not assign a distress type or severity were identified in District 1, 2016 data. Pavement markings, railroad tracks, end dams, and expansion joints were also found to occasionally be identified as an unassigned distress.

The pavement type assigned in Pathview software does not always reflect the road inventory. When they do not match, generally Pathview mistakenly identifies a composite pavement as an asphalt pavement. This results in a large percentage of distresses on a segment that are not consistent with the pavement type. While mistakenly identify the pavement type largely impacts composite pavements, distresses such as edge cracking, shattered slab, and wheel track cracking were also rated on jointed concrete pavements which is not consistent with the pavement type. Also, edge cracking was found to be rated on pavements with paved shoulders or curbs which is contrary to typical pavement management practice.

Additional concerns were raised when attempting to use 2014 data for development of deterioration models. Comparison between 2014 and 2016 showed overall network score would increase, rather than deteriorate. This is inconsistent with the PCR and maintenance activity data available for these years. Researchers also noted that rutting saw a reduction on average between these data sets, despite a lack of maintenance that would cause such an improvement. Researchers believe this may have been caused due to differences between data collection vehicles, their calibrations, or the crack detection software between data collection years.

In-depth analysis to identify the exact cause was beyond the scope of this project. However, it is worth noting that such issues will require additional quality control effort to catch and correct should ODOT implement a fully-automated rating system. Discrepancies in vehicles and their calibrations would need to be found and corrected before data collection begins, otherwise data may need to be recollected after the correction. Changes to processing software would need evaluated on sample data before processing the full collection cycle. Given the lengthy processing time encountered during this research, issues requiring reprocessing of the full data set would lead to considerable delays—possibly months if the AutoCrack tool must be reran.

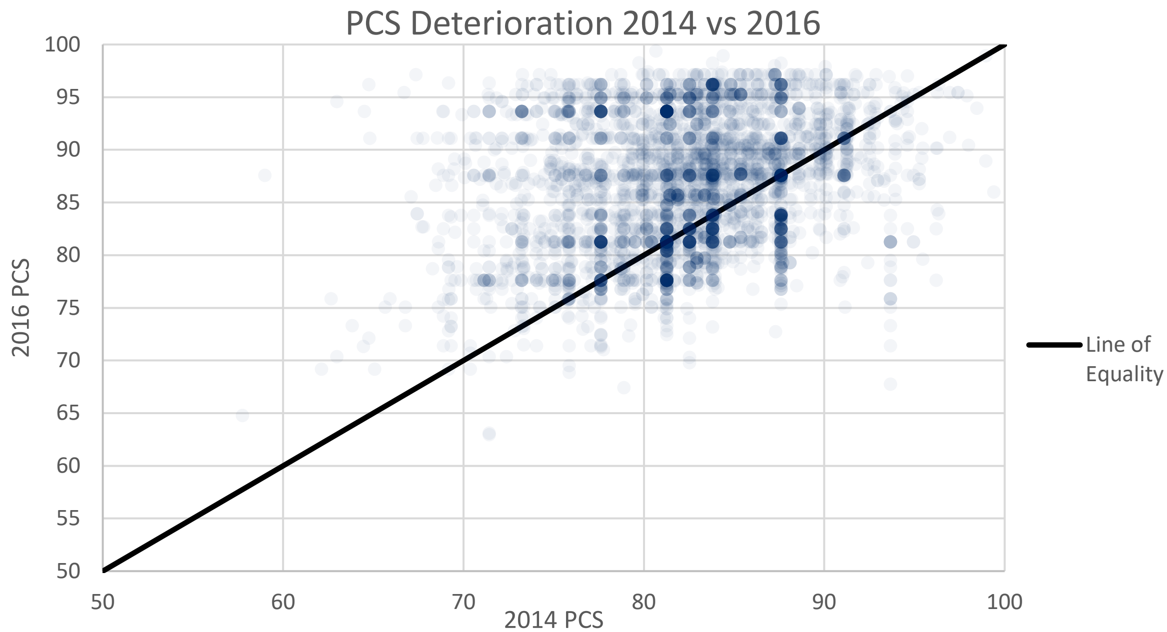

Figure 7: A scatter plot showing the comparison of 2014 and 2016 automated scores showing that 2016 data had a general trend of being higher than 2014 data.

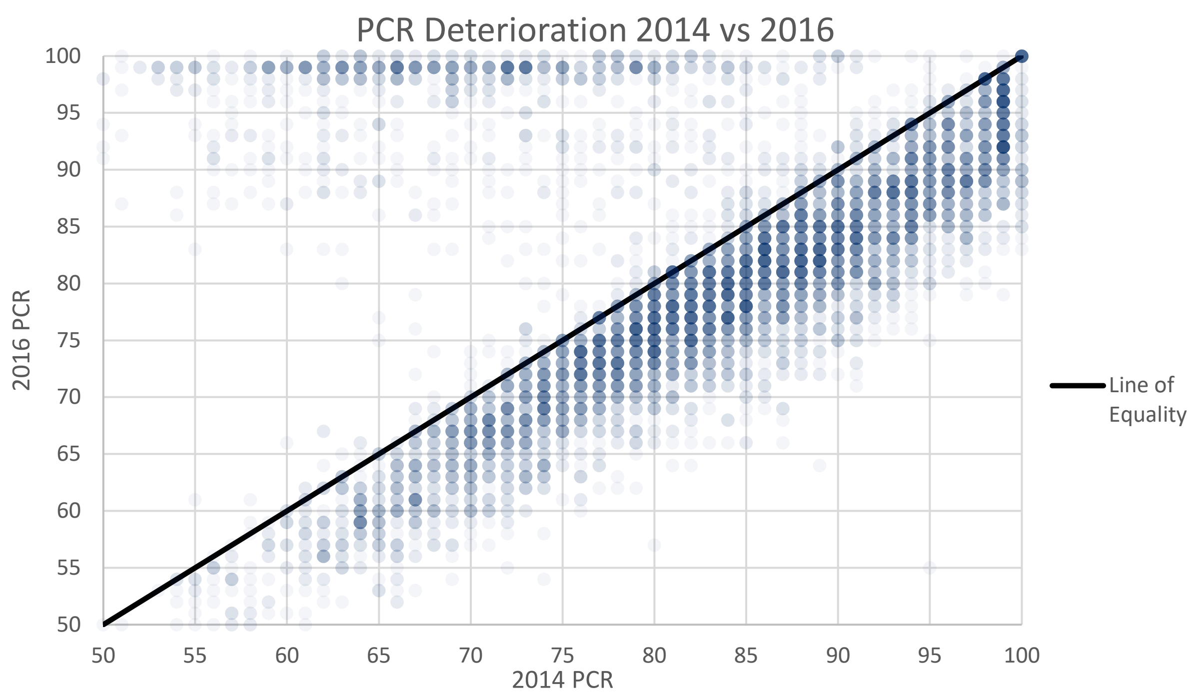

Figure 8: A scatter plot showing the comparison of 2014 and 2016 manual PCR ratings displaying the expected decrease in score for the majority of sections over the two-year span while other sections improved scores with maintenance activities.

Selection of Rating Methodology

Investigations into the current decision outcomes generated by manual PCR ratings indicated a strong reliance on overall score. Critical checks in the decision tree were found to be score-based cutoff thresholds. For example, a score greater than or equal to 80 PCR for asphalt pavements would typically trigger a no treatment result and scores below 65 would often trigger an overlay with repairs. Given the strong correlation between score and decisions, researchers evaluated the various methods considered for their correlation with PCR scores. Strong correlation in score would result in better correlation of decision outcomes.

The sliding scale method did have a marginal improvement on initial correlation between PCS and PCR compared to the baseline. However, researchers felt this method was of minimal improvement for the additional effort that would need to be considered. One of the practical considerations for implementation is manual quality control. This method adds additional complexity to manual ratings, increasing the difficulty of manual review of the automated process for minimal gain.

The Pavement Condition Index (PCI) methodology produced scores from the automated data that followed a similar trend to the PCR scores, but with additional shifts in the data due to the differences in score calculations between the systems. PCI scores covered a wider range of values between 0 and 100 than PCR. A linear correction factor could be used to account for this and shift the thresholds of the decision tree to match the PCI methodology, but overall correlation was not better than the PCR-based regression model.

However, the overall process at ODOT from data collection to pavement management is designed around a different methodology and different distress classifications. Switching to a PCI-based method would require changes to the data processing software developed by the data collection vendor to report distresses in the correct classification. Additionally, ODOT's pavement management software would need considerable updates to allow for the new distress types and their individual deterioration curves. Given the differences in rating systems, the PCI-based deterioration models, once developed, would be inconsistent with existing score deterioration models. Developing entirely new models for this system would take several years of data collection with processing software designed to report the correct data.

For those reasons, researchers elected to choose a system more closely related to PCR. Taking the PCR distresses available from Pathview software's detection and classification directly into the rating system eliminated the need for considerable change to that end of the process. However, given the limited number of distresses available, a regression model was chosen to help fill the gap between the automated and manual data. Several iterations of the regression model were compared not just for overall correlation with the manual data score, but also with the correlation of decision outcomes. The final deducts represent what the researchers believe to be the best result in terms of decision outcomes with the available data and methodology.

Of specific note is the extreme lack of distress types reported for concrete pavement. While all pavement types have less distress types than PCR available, this lack in concrete pavement leads to a considerable deficiency in correlation of score and pavement management decisions. Despite reporting seven distress types, only five reported by Pathview report values within the research data. Of those distress types, several appear to be difficult for Pathview to classify correctly. Creation of a higher accuracy rating would need additional data to be reported by the distress detection and classification system.

After establishing the methodology for PCS, including the presented deduct values, researchers compared both score and decision results.

Table 5: Regressed coefficients for flexible pavements.

Pathway Code	Code	Description	Original	Regressed	Regressed (constrained)
Ravel	1	Raveling	10	12.0	12.0
Bleeding	2	Bleeding	5	5	5
Patching	3	Patching	5	5	5
Rut	6	Rutting	10	15.8	15.8
WheelT	9	Wheel Track Cracking	15	10.3	7.7
Long	11	Longitudinal Cracking	5	0.0	3.0
Edge	12	Edge Cracking	10	0.0	3.0
Trans	14	Thermal Cracking	10	18.1	16.1
PotHoles	15	Potholes	10	10	10
Recommended Final					✓
Total Sections			**5172**	**5172**	**5172**
Percent Same Bin			**34.3**	**57.5**	**58.3**
Percent Same Activity			**55.6**	**63.2**	**63.3**

Table 6: Regressed coefficients for composite pavements.

Pathway Code	Code	Description	Original	Regressed	Regressed (constrained)
Ravel	1	Raveling	10	1.7	15
Patching	3	Patching	5	5	5
Rut	5	Rutting	10	21.1	21.1
Slab	7	Shattered slab	10	2.1	2.1
Trans	9	Tvs. Cracking – unjointed	20	21.9	21.9
Long	12	Longitudinal cracking	5	15.2	5
Recommended Final				✓	
Total Sections			**4701**	**4701**	**4701**
Percent Same Bin			**52.3**	**58.3**	**51.0**
Percent Same Activity			**55.6**	**63.3**	**59.5**

Table 7: Regressed coefficients for concrete pavements.

Pathway Code	Code	Description	Original	Regressed	Regressed (constrained)
Patching	3	Patching	10	10	10
FAUA	5	Faulting	10	24.7	22.0
TSpall	7	Transverse Joint Spalling	10	7.1	5.0
Long	11	Longitudinal Cracking	10	12.3	8.0
Corner	12	Corner breaks	10	10	10
LSpall	13	Longitudinal Spalling	5	0.0	3.0
Trans	14	Transverse Crack - Plain Concrete	15	0.0	3.0
Recommended Final					✓
Total Sections			**467**	**467**	**467**
Percent Same Bin			**21.4**	**29.1**	**29.6**
Percent Same Activity			**26.8**	**36.6**	**35.1**

Decision Outcomes

Additional output from the decision tree processing tool allowed researchers to analyze the frequency decision nodes were considered in the final decision outcomes. In both PCR and PCS analysis showed that the key drivers of decision outcomes, outside values such as pavement type and general traffic volume, were score and total structural deduct value. Distress checks only accounted for 14 percent of nodes tested before decisions were reached. A majority of sections (64%) that failed to achieve the same decision in PCS as PCR failed to do so at a score-based check. This highlights the importance of high correlation between automated and manual scores to arrive at the same decisions.

Adjustments to the score-based decision nodes were considered to aid in correlation of decisions. These adjustments were calculated from the best fit line of the correlation plot between PCR and PCS data. To test the impact of these adjustments, researchers analyzed a data set comprised of all flexible pavement from the full 2015/2016 data set.

Because the data had already been regressed to a best fit, these adjustments were minimal. The smallest adjustments were required at the “do nothing” cutoff score (PCR score of 80). The calculated adjustment to this increased the threshold by 0.25 points. The most significant change was to the lower end threshold that typically triggers overlay with repairs (PCR score of 55), increasing by just over 1 point for the PCS.

While this adjustment moved the threshold to be along the best fit line, changes in decision correlation were minimal. Less than a tenth of a percent shift in the number of decision bin and activity matches between PCS and PCR were noted with the threshold adjustments applied to flexible pavements in the research data. That small shift in the total resulted in a negligible decrease in the model’s percent match PCR decisions, rather than an expected improvement. This led researchers to conclude that changing these values is unnecessary because the regression model causes the best fit line to be at/near the existing threshold. In other words, the regression has succeeded in minimizing error around this threshold, leaving the remaining difference in decision outcomes to be driven primarily by variance in the data.

Review of the structural deduct differences between PCS and PCR showed a lack of correlation due to the regressed coefficients targeting to reduce error in score, not to reduce error in structural deduct. The correlation was also impacted by the smaller number of structural distresses reported. This lack of correlation prevented researchers from applying a correction factor to the decision tree thresholds based upon the line of best fit in the correlation plot.

In the case of flexible pavements, which displayed the strongest correlation, the results showed an r-squared value of only 0.19 with a slight decrease in average deduct. Composite and concrete pavements fared far worse, with r-squared values of 0.08 and 0.04, respectively. Heavy banding in the data suggests that distresses unreported by Pathview, particularly for composite and concrete, are a significant portion of the structural deducts reported by PCR raters.

Poor correlation in structural values reported did not support any conclusive changes to the decision tree. In the case of flexible pavements, there is some potential to pick a new threshold from the data but the impact on overall correlation of decision is minimal. Only a small percentage (<1%) of flexible sections would be impacted by the change.

For composite and concrete pavements, little justification exists to pick a new threshold. It appears that PCR decisions on when structural deducts should trigger more extensive treatments are largely dictated by distresses not detected/reported by Pathview. This prevents an automated system from providing the same decision outcomes when the treatment would have normally been decided based on structural defects in these pavement types.

Deterioration Modeling

For deterioration modeling, the original proposal of using 2014 and 2016 data to create the models was determined to be infeasible due to the inconsistencies in 2014 data. Because of the lengthy processing time required to process the data with Pathview's AutoClass tool, only a single district of 2018 data was available to fill in for deterioration modeling purposes. This data exhibited deterioration much more in line with the corresponding PCR data.

To generate accurate transition probability matrices (TPMs) requires a significant amount of data to cover all the possible combinations of pavement families, distress types/severities/extents, and overall score distribution. Due to the limited nature of PCS data available for this study, generating new TPMs proved to not be a feasible solution.

However, researchers did find that existing TPMs taken from PCR may still be used with PCS data to a degree. For Markov models, there are two components: the TPM which describes the probability of change between distress states, and the array of deduct values for each given state. This allows PCS to use the rate of change derived from the TPM, but with the deduct values from the regression model.

Rather than compute the result via distress deteriorations using individual TPMs, researchers elected to generate a model derived from the TPM where PCS is a function of apparent age. This model was generated from the "null" state for each distress, where a pavement starts at zero distress for all types. The worksheet provided by ODOT for deterioration models already contained the correct equations to compute individual distress deterioration as a function of age. The sum of these deducts each year would result in the predicted total deduct for that age of pavement.

Two changes were made to the model to account for the differences between ratings systems. First, distresses that cannot be detected or are not reported by Pathview software were eliminated from the total. Additionally, the regressed deduct values from PCS were used. The slope of the deterioration curve was minimally impacted, but these changes did cause a divergence in overall deterioration over the 40-year span to predict higher scores than the PCR model. A large portion of this divergence appears to be created by removing the distress types, with a much smaller portion being caused by the change to use regressed deduct values.

The variance of the deterioration from the PCR deterioration is expected for a generic model derived from a small sample of data. Currently, PCR deterioration uses models for each pavement family that were developed using a large amount of historical data. The generic model used in this research may be taken as a proof of concept for developing similarly focused models using a blend of automated deduct values and existing TPMs as a stopgap until sufficient PCS data is available to generate quality TPMs purely from automated data.

These blended models produced slopes similar to the actual data but are not sufficient to predict score based solely on age. Calculating apparent age along the model by finding the age value where the model produces the same score resulted in a better prediction in the 2-year projection used with 2016 and 2018 data comparisons than using the section's actual age would. This at least shows the model is feasible for short term predictions, but more data would be needed to verify longer-term performance or build more accurate models.

Validation

For field verification, a single, generic model was developed using a PCR TPM from one pavement family with significant source data and the regressed deduct values. The model selected is from the priority network and covers sections from all districts with the last activity being an overlay without repairs. This model was then used to project the 2021 PCS score and resulting decisions from 2015 PCS data. Field locations were selected where differences were noted between the 2021 projected PCR decisions and 2021 PCS decisions.

Researchers noted that in both PCR and PCS, deterioration trended towards recommending an overlay with repairs (activity 60) frequently. This is apparent when looking at the decision trees. There are several ways to trigger this activity related to score, depending on which decision tree is used. In most cases, a score below 65 or a structural deduct score above 15 would trigger this result independent of contributing distress. Because PCS deducts are largely flagged as structural and have increased weight in the regression model, PCS tends to trigger the treatment on structural deduct value at a rate higher than PCR when using the TPM to project structural deducts. However, PCR's overall score deteriorates at a faster rate, resulting in triggering the same treatment for a different reason.

This resulted in a shift in the planned field validation process. Because both systems trended towards the same activity, too few sections met the original criteria for selection for field visits. These criteria were focused on sections where the two systems had differing decision outcomes and formed a representative mix of pavement type and general condition.

Instead, researchers selected only the small set of sites that displayed differences between PCS and PCR for field visits. Details on the site selection can be found in Appendix 4, along with more detailed analysis of the comparison between projected and actual conditions.

The field verification highlighted a considerable discrepancy between the projected structural deducts and the field conditions. While normal PCS calculations appear to report lower structural deducts in general due to less distresses contributing, the projection used for field comparison tended to over-report structural distress. More extensive repairs were recommended by the PCS model than field conditions warranted due to this over-reporting. Because the model used for projecting PCS forward to present was generic, and taken from only one pavement type, some portion of the over-reporting may be attributed to model selection.

In attempts to modify the decision tree's structural deduct checks, it was noted that the structural scores generated by PCS did not correlate well with decision outcomes from manual ratings. The issues noted here with deterioration model over-reporting structural deduct are likely attributed to shortcomings with the data available for structural distresses.

Recommendations

Implementing an automated rating system must be an ongoing process, rather than a turn-key operation. The sensitivity of an automated system to changes in data collection and processing necessitates a robust procedures and quality control plan that covers all steps of the process. Poor performance of automation at rating concrete pavements necessitates that a semi-automated approach to supplement automated data with manual ratings. Annual data collection by all collection vehicles on well-known, manually-rated field validation sections as part of a robust quality control/assurance plan should be considered for both continuous improvement of the automated rating system and for verifying the consistency of data collection from year to year.

Automated crack detection and classification is still a relatively new and constantly developing technology. Previous research to compare technology between competing systems was conducted in 2013 (Vavrik et al. 2013). Similar research may be worthwhile to analyze new technologies if they become available.

Improvements or changes in both hardware and software will require updates to automated models to account for shifts in data. Some manual ratings will be required to verify these shifts and to inform adjustments to the automated distress and deterioration models. Using field verification sites that are rated by both manual and automated methods, this process could be conducted in parallel to the quality control plan. Some discrepancies between manual and automated ratings are expected, so a margin of error should be established that would trigger changes to the system.

Higher quality deterioration models will require additional automated data be incorporated over time. During this research, a lack of data prevented the development of new transition probability matrices. Over time, enough data should become available to develop these directly from PCS data, rather than borrowing from PCR deterioration models. Any new deterioration models implemented should be compared to the existing models to gauge the impact of the change on cost/benefit analysis used by pavement management software as shifts in these curves would change the benefit area calculation.

During this project, researchers noted several instances where simple human error could have considerable impact in terms of time lost or data reliability. Pathview software has many processes and options that must be done to facilitate PCS calculation accuracy. When processes take hours or days to complete before verification can be done, small mistakes can compound into significant delays. A procedures plan with specific details and order of operations would help reduce this risk from year to year or in the case of change in processing staff.

While the PCS manual is tailored specifically to the goals of this research, it may serve as a basis for a portion of a procedures plan. The manual covers the portion of the processing starting from running AutoClass all the way through to generating decisions with the decision calculation spreadsheet. Additions would be needed to cover data collection, quality control, processing with AutoCrack, and utilizing the PCS data in pavement management software. The process for updating the regression models for PCS is also included in the manual. Generation of deterioration models using transition probability matrices has already been covered in previous research (Chou, 2008) but should be added to a procedures plan in a simplified form.

As observed from 2014 data comparisons, PCS will only be as reliable as the data used as an input. Quality control must begin at data collection and continue through the process. Data collection staff should be maintaining equipment calibrations in line with manufacturer recommendations. In the case data collection is conducted by a contractor, the contractor should provide ODOT with records of these calibrations. The annual collection of field validation sites with both manual and automated PCS ratings would allow ODOT to verify the vehicle calibrations meet expectations.

Field validation sites also offer an opportunity for manual surveys to regularly be compared with PCS data, even after switching statewide collection to a semi or fully automated rating system. This allows the ongoing development of PCS as additional distress types or new technologies become available. These comparisons also offer an opportunity to provide data collection vendors feedback on their crack detection and classification algorithms, which may help improve future automated distress ratings.

Ideally, these sites would have a mix of representative pavements that reflect the most common pavement designs in the network of varied age and condition. Considering the practical requirements, site selection may be skewed towards picking areas that are more easily collected as part of routine, annual collection efforts. Manual rating of the selected sites would be conducted and then compared to data pulled from the annual collection of automated data. Selected test sections should be 528 feet (160.93 meters) in length, at the minimum. The maximum length of a section should be limited by the length of consistent construction and age of pavement, as well as limitations of manually rating the section.

Thorough field ratings of these sections should be conducted initially, with annual ratings thereafter. Continued annual monitoring may be via field visits or from manual review collected imagery and sensor data delivered by the collection vehicle. The intention of manual review is to ensure the field conditions are well established as a baseline to compare against the automated data. Existing test sections constructed as part of other research and federal programs such as long-term pavement performance (LTPP) research sites may be considered but may not adequately represent typical construction practices throughout the network.

Catching deficiencies in equipment calibration or condition early is essential to maintain a timely, accurate data collection. At least one field validation site should be utilized to verify vehicles before data collection begins in earnest. Any sites chosen for this preliminary verification should contain a mix of various distresses. Precise field measurements of distresses such as rutting and faulting must be available for comparison to the automated results for sections used for this verification. A measurement of the section's roughness may be appropriate to allow verification of the vehicle for federal reporting purposes in addition to the checks for automated distress reporting.

Data collected on these verification sites should be processed through the full process to arrive at PCS rating. Reported distress classification and quantities from Pathview's AutoCrack and AutoClass processing can be reviewed by quality control staff and compared to both manual ratings and historical automated data for the same site. The PCS calculation tool also offers a raw quantity output per section, which may be similarly compared to manual and historical automated data. As part of the procedures plan, a maximum tolerance for the difference between reported and actual values should be established to trigger additional scrutiny of the collection vehicle and its calibration.

Once data has been verified and processed through Pathview software to generate distress reports at tenth-mile intervals, it should be processed through the PCS calculation tool. The output of the tool will give a score, structural deduct value, and individual distress severity-extent ratings. These ratings should be compared with manual ratings of the section as well as any historical PCS ratings available. Quality control should ensure that conditions and distresses did not improve year over year without maintenance activities. Conditions such as rutting, roughness, and faulting should be within a tolerance factor of historical data and/or field measurements.

The tools for calculating PCS and decision outcomes provided by the research team were developed for research purposes and may not meet the future needs of ODOT. Consideration should be given to how to integrate proper software into ODOT's existing practices to address these needs. The implementation in Visual Basic for Applications has limits that lead to longer processing times and less flexibility than would be present were it to be implemented using more robust programming languages such as C#.

Future development of such robust software could integrate the PCS and decision tree calculations with other software and submit data directly to pavement management software. Potential exists to automate development of transition probability matrices using PCS data stored as part of such software. Tools may be included to aid in tracking field validation sections and other quality control tasks.

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Appendix 1: Literature Review

Pavement condition data is one of the prime elements of a pavement management system. Currently, most parts of the pavement condition data are collected by examining pavement surface images either through foot-on-ground manual surveys or with the help of computer programs. Pavement data collection normally includes gathering data on surface cracking and other distresses for both asphalt and concrete surfaced pavements, as well as rutting for asphalt pavements, and faulting for concrete pavements. Distress Identification Manual for the Long-Term Pavement Performance (LTPP) (FHWA, 2003) provides instructions and procedures for pavement condition surveys. National Cooperative Highway Research Program (NCHRP) published Synthesis 334 (McGhee, 2004) which describes the techniques available for automated pavement data collection.

The Moving Ahead for Progress in the 21st Century Act (MAP-21) which became law on July 2012 includes a Declaration of Policy: "Performance management will transform the Federal-aid highway program and provide a means to the most efficient investment of Federal transportation funds (FHWA, 2017)" The main objectives that led to the MAP-21 law include increasing the transparency and accountability of states for their investment of federal taxpayer dollars into transportation infrastructure and services nationwide, and ensuring that states invest money in transportation projects that collectively make progress towards achieving the national goals. The final rule, effective since May 20, 2017, requires State DOTs to submit the Interstate System's pavement condition data annually and non-Interstate National Highway System's data biennially.

There are three approaches to collecting pavement condition data: manual, semi-automated, and automated pavement data collection methods. Although manual data collection methods have unique characteristics that agencies depend on, currently most states are leaning towards automated data collection systems. Comparisons of automated and manual pavement data collection methods are provided in Table 1.. These methods can be compared based on time, safety, objectivity of measurements, cost, data size, data handling, and agency's point of view.

Table 1.1: Comparison of automated and manual pavement data collection methods (Attoh-Okine, N. and Adarkwa, O., 2013).

Category	Automated Data Collection	Manual Data Collection
Time	Reduces data collection times	Longer data collection times
Safety	Much safer means of collecting data	Personnel at risk collecting data
Objectivity	Objective measurements	Usually subjective since it depends on experience of personnel
Cost	Very expensive equipment costs	Relatively less expensive
Data Size	Vast amounts of data collected & stored depending on capacity of equipment	Agencies may only be able to collect smaller amounts of data at a time
Data Handling	Not subject to transcription errors	Subject to transcription errors
Employers	Suitable in agencies seeking to downsize number of employees	Source of employment for rating staff

Category	Automated Data Collection	Manual Data Collection
Coverage	May cover footprint of data collection vehicle. Multiple runs sometimes needed to cover entire road width	Inspectors can cover entire width of road section relatively easier

Manual Data Collection

Visual assessment of pavements began with the original American Association of State Highway Officials tests performed in 1920 and the development of the present serviceability index (PSI). This index is based on some objective quantity including roughness, rutting, cracking, and patching. A panel provided a qualitative score based on their ride experience (Hallin et al., 2007). Many indices including pavement condition index (PCI) were developed after the PSI; however, those were mainly based on the manual survey of pavements.

The visual and manual pavement data collection can be categorized into the following techniques:

- Windshield assessment – Surveyors travel the roadway section by car, traveling at a lower speed. This allows the surveyors to perform 100% assessment and take notes on observed distresses. Survey forms are filled out for every pavement section of pavement management system.
- Walk-over assessment – Surveyors walk over a surveyed length of pavement section and record all surface distresses on a survey form. The survey length can vary from agency to agency depending on the location of the pavement section, policy of the agency, and budget available for the survey. An agency can survey 100% of their network or it can choose a sample section.

Semi-Automated Data Collection

In a semi-automated survey, windshield survey is replaced by an automated pavement imagery collection. Pavement imagery is collected using high-resolution camera(s) mounted on the data collection vehicle, and the collected images are surveyed manually. Semi-automated data collection not only provides increased safety but also results in more accurate and efficient assessment of pavement condition compared to the windshield survey. In semi-automated methods, pavement condition data are collected in two phases. In the first phase, pavement imagery and sensor data such as roughness, rutting, and faulting data are collected. The second phase involves the manual rating of the images, and identifying surface distresses from the imagery.

Image viewing requirements depend on whether the images are captured on film, tape, or digital media. The manual element of distress data reduction from images typically involves the use of multiple image monitors and at least one computer monitor for data display. There may be a substantial loss of resolution compared with what is visible to the human eye from the same source. Almost all image collection procedures now require that the images be a date, time, and location stamped. The location stamp is typically coordinates derived from GPS instrumentation on the survey vehicle. The identification of various distress types, as well as their severities and extents from images, requires observers or raters who have been well trained in both pavement distress evaluation and in the use of the workstation hardware and software. Such surveyors require extensive training in at least some aspects of the process.

Sometimes agencies collect imagery and sensor data in one lane, and this data is applied to all lanes while performing the manual survey. However, pavement maintenance and rehabilitation strategies are becoming increasingly more localized and lane-based; therefore, the necessity of collecting data from all lanes is increasing. As the semi-automated method is time-consuming and requires significant manual surveys, it has given way in recent years to the digitizing of images for better data handling and processing.

Automated Data Collection

In a fully automated pavement condition survey, surface distresses are identified and quantified through analysis with very little or no manual work. Typically, automated distress detection is performed by software capable of identifying and quantifying the crack length, depth and width, as well as the depth and extent of surface roughness, raveling, faulting, and rutting. Most crack detection system rely on 3d laser scans of the pavement providing both range and intensity information in a grid pattern as a vehicle drives at highway speed.

Over the past decade, a significant amount of research and development work has occurred in the field of fully automated pavement distress detection and measurement. This emphasizes the difficulties involved in manual reduction of pavement data and resources required to accomplish the associated manual tasks. Table shows distress data requirements by the various standards/agencies.

Table 1.2: Pavement Condition Data Requirements by Various Standards/Agencies

Standard/Agency	Distress Data Requirements
Ohio Department Transportation Requirements (Chou et al. 2008)	• Automated collection of pavement smoothness, rutting, and faulting measurements on the interstate highway system and the highway segments required for HPMS reporting • ODOT's current system also offers inventory collection capabilities, which ODOT has expanded to refine their geographic information system (GIS) pavement site location inventory and their statewide guardrail inventory • Future expansions available to ODOT include inventories of guardrails, signs, pavement markings, traffic controls, medians, curb and gutter, drop inlets, bridges, and overpasses • Video images from this system may also provide traffic litigation assistance

Standard/Agency	Distress Data Requirements
Federal Highway Pavement Management System (HPMS) Requirements (FHWA 2012)	• The HPMS, developed in 1978, supports the 23 U.S.C. 502(h) requirements for collecting "a biennial condition and performance estimate of the future highway investment needs of the nation" • Each State is required to prepare an annual submittal of HPMS data in accordance with the procedures, formats, and codes specified in HPMS Field Manual 2016 • Actual values are to be reported for the various roadway attributes (i.e., section data) that are collected in HPMS • Each State needs to submit their Linear Reference System (LRS), which enables the attribute data to be represented in a geospatial format • Pavement condition-related data include section data for functional system, urban code, facility type, structure type, through lanes, IRI or PSR for roads on the NHS with a posted speed limit < 40 mph, surface type, rutting, faulting, cracking percent, NHS (national highway system) and a dual-carriageway, LRS-enabled, and geospatial routes dataset
AASHTOWare Pavement M-E Design Software Implementation Requirements (AASHTO, 2008)	• Pavement performance measures in Pavement ME Design include slab cracking, faulting, and IRI for PCC pavements; IRI and punchouts for continuously reinforced concrete pavements; and rutting, bottom-up fatigue cracking (alligator cracking), load-related top-down cracking (longitudinal cracking in the wheelpath), thermal cracking (transverse cracking), and IRI for AC pavements. The performance data is typically used for calibrating the performance models for pavements, traffic and climate. • Pavement layer thicknesses and properties also play a critical role in the analysis
MAP-21 Requirements (FHWA 2017)	• Based on MAP-21 final rule, the data requirements for the Interstate and non-Interstate National Highway Systems are IRI, cracking percent, rutting, and faulting in one direction with missing, invalid, unresolved data no more than 5.0 percent • MAP-21 final rule also requires HPMS data collection and submittal annually for the Interstate System and biennially for the non-Interstate National Highway System

Evaluation of Technologies

Four major vendors in the United States provide 3D line-scan automated distress rating systems:

- Dynatest Consulting, Inc.
- Fugro-Roadware Inc.
- Mandli Communications, Inc., and
- Pathway Services, Inc.

These vendors also offer a range of 2D systems; however, because of reported limitations of the 2D line-scan systems, only their 3D line-scan systems are described below. WayLink, Inc. has also been included in these descriptions due to the advanced nature of their technology. Dynatest, Fugro, and Mandli incorporate Pavemetrics Laser Crack Measurement System (LCMS) 3D sensors, while Pathway and WayLink have developed unique 3D sensors in addition to offering LCMS sensors. Because Dynatest uses the same LCMS sensors as Fugro and Mandli, their system is not discussed below.

Fugro-Roadware Pave3D System

Fugro began offering the Pave3D System in 2010, incorporating the Pavemetrics INO LCMS sensors. Currently, the system can include 2D and 3D downward pavement imagery, combined with Fugro's forward cameras, global positioning sensors, an inertial measurement suite, ground penetrating radar, and LIDAR equipment (Figure 1.1).

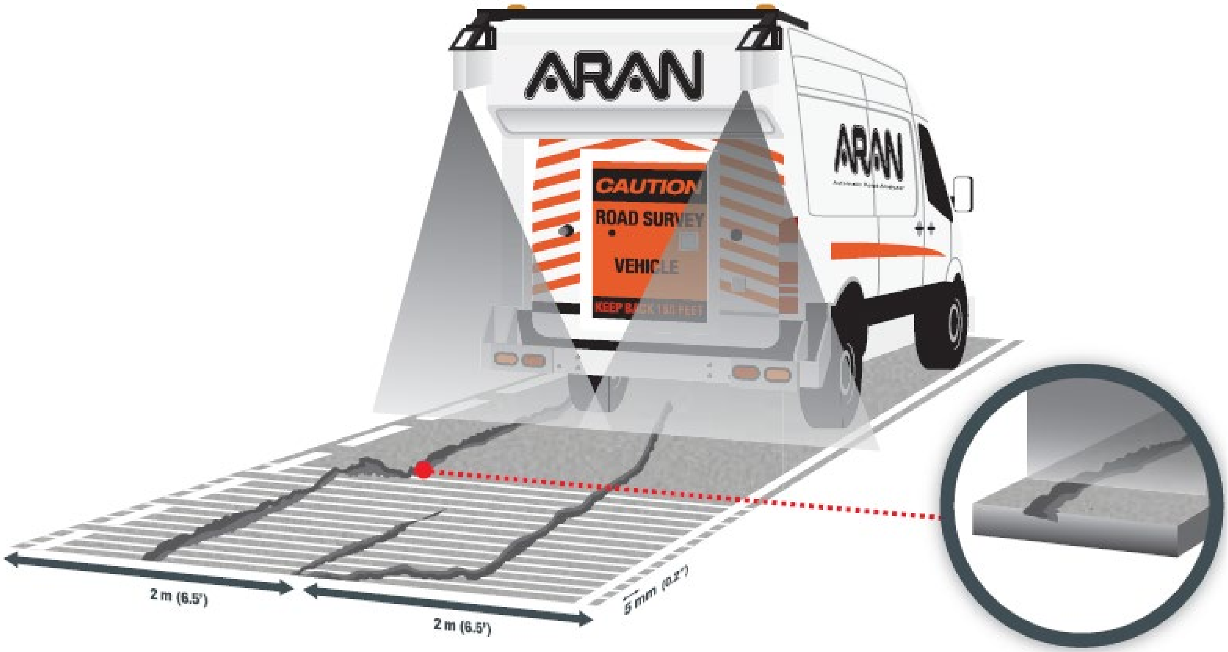


Figure 1.1: Fugro Pave3D sensor working principle (Adopted from Fugro Roadware, 2017).

The ARAN 9000 survey vehicle can be configured with a maximum of six right-of-way (ROW) Sony high-definition cameras using charge-coupled device (CCD) broadcast-quality image sensors. Each camera is housed in a weatherproof housing that includes an extended visor to shield the lens from the direct sun above. Furthermore, forward-facing cameras are mounted on a platform located in the front of the vehicle (thus reducing the risk of images being obstructed by the vehicle). Three HD charged coupled device (CCD) broadcast-quality cameras provide extremely high-quality images over a range of lighting conditions, as the 60 frames per second (fps) free-running frame rate is able to adapt to the local environmental lighting conditions better than trigger-based cameras. Additionally, these ROW images are calibrated and can be used to determine the offset and dimensions of roadway assets. Image capture is linked to the ARAN distance measuring instrument (DMI), with images typically captured at a rate of 200 frames per mile.

The system can be configured to collect global positioning system (GPS) coordinates with a stand-alone accuracy of 16 feet or better. The inertial reference system also employs gyroscopes, accelerometers, software, and algorithms to measure pavement cross fall, transverse profile, vertical alignment (grade), and horizontal alignment (curve radius) of the roadway. To assist operators with routing, Fugro provides GPS coordinates and pre-established routing information loaded into the Fugro's ARAN data collection software.

Distress rating software is available and is continuing to be expanded by Fugro and Pavemetrics to develop and incorporate the 3D capabilities of the LCMS sensors. Currently, they report the ability to automatically detect crack type (transverse, longitudinal, and alligator) and severity, raveling, potholes, rutting, and faulting. Their semi-automated approach reportedly identifies corner cracks and block cracking. Distresses such as debonding, pumping, bleeding, patching, crack sealant distress, and punchouts require manual identification.

Mandli Communications LCMS

Mandli offers a 3D distress collection and identification system that includes the Pavemetrics LCMS and associated subsystems. Typically, these subsystems are mounted on a full-sized van, selected by the purchasing agency (Figure 1.2).

They typically provide up to three (3,296 x 2,472 pixels) industrial ROW cameras, mounted above the rearview mirror. This camera requires little operator adjustment. Image capture is linked to Mandli's DMI, and collection intervals can be controlled by the operator. ROW camera images are stored digitally in JPEG format and typically stored at a 5:1 to 15:1 compression ratio.

Figure 1.2: Mandli LCMS distress collection system (Adopted from http://mandli.com).

The Mandli Applanix POS LV 220 collects real-time differential GPS coordinates using satellite positions and ground station or satellite-based augmentation systems to provide sub-meter X-Y-Z accuracy. If post-processing is employed, the reported X-Y accuracy is about 0.8 ft. To maintain precision when satellite lock is lost, Mandli's DMI and POS LV inertial measurement unit are employed. These same instruments can provide pavement crossfall, vertical alignment (grade), and horizontal alignment (curve radius).

Mandli provides pavement profiles at 0.07-inch intervals (60 mph) using Dynatest's rear-mounted Mark IV Portable Road Surface Profiler (RSP). Two Selcom 16-kHz laser sensors and high-quality accelerometers are mounted in this system and positioned in selected wheelpath locations. The RSP system reportedly meets ASTM E 950-09 Class 1 specifications, providing a vertical displacement resolution of 0.002 inches. It is rated with an ASTM E1556-11 Code of L111.

Mandli employs the Pavemetrics LCMS 2D and 3D pavement imaging system, sampling at 5,600 (alternately 11,200) transverse profiles per second. This subsystem reportedly meets the requirements of ASTM E 1656-11 C 2321. Distresses automatically reported by this system include block/transverse, longitudinal, and wheel track cracking, rutting, faulting, crack sealing deficiency, and potholes.

Two separate software applications are utilized to analyze the collected data and automatically detect pavement distresses. The data is first run through RoadAnalyser, which automatically detects cracks and assigns crack width by analyzing the intensity and range data. RoadAnalyser outputs four sets of viewable images: range, intensity, and both range and intensity with detected distress overlay. The data is then run through Mandli's internally developed classifier application which analyzes the marked cracks and classifies them according to the client specifications. Rutting and transverse profile information are also processed and reported.

Pathway Systems 3D Data Acquisition System

The Pathway, out of Tulsa, Oklahoma, offers the PathRunner XP collection vehicle, shown in Figure 1.3, with an expanded top to allow for higher ROW camera angles while protecting cameras from the elements. This system includes high-resolution forward cameras, supplemented with GPS capabilities and pavement roughness and texture measurement. They offer a wide range of pavement 3D imaging subsystems based on industry standards and their proprietary Pathway 3D Data Acquisition System. Supplemental collections systems such as LIDAR and ground penetrating radar are also available.

The Pathway offers both forward ROW and 360-degree imaging. Up to three industrial forward cameras (3,296 x 2,472 pixels) can be mounted in the high-top extension, with optional side and rear view cameras as well. Wide-angle lenses can be used to collect more panoramic images. These images can also be used to determine offset and dimensions of roadway assets, including guardrail, signs, and edge of a roadway.

The PathRunner XP typically includes an enhanced GPS that uses real-time differential corrections from base stations, satellites, or transmitters to achieve true sub-meter accuracy. Post-processing using auxiliary input and onboard inertial measurement unit (IMU) data is also available to further improve the accuracy. Pathway uses an inertial measurement unit (including military grade or optical gyroscopes) and its DMI to retain accuracy when satellite lock is limited or lost. This system is also capable of accurately providing pavement crossfall, curve radius, and roadway grade.

Figure 1.3: PathRunner XP collection vehicle.

Pathway's longitudinal profiling system typically collects pavement profiles at 0.067-, 0.031-, and 0.16-inch intervals at 60 mph using Selcom 16-, 32-, or 64-kHz spot lasers. They can also provide Selcom Roline lasers for agencies with significant longitudinal texturing or grooving. All spot sensors meet the ASTM E-950-11 Class 1 measurement sampling and resolution requirements and achieve an ASTM 1656-11 rating of L122, reporting such roughness indices as IRI (quarter- and half-car), Ride Quality Index (RQI), and Ride Number. Additionally, Pathway can collect 0.016-inch samples and report mean profile depth at highway speeds, with one or more 64 kHz spot lasers. Their ground-penetrating radar option includes both high- and lower-frequency antennas to collect pavement layer information at a range of depths.

Pathway offers 2D and 3D downward pavement image collection systems. Their advanced system collects up to 6,000 transverse profile points at more than 9,000 cycles per second, recording longitudinal elevations at 0.125-inch intervals while traveling at 60 mph. Pathway reports their ASTM E 1656-11 crack measurement capabilities as C3331. Sensors draw minimal power and can be supplied from the vehicle electrical generation system.

Pathway continues to expand and refine their pavement distress identification software to incorporate the 3D capabilities of their new sensors. With an 80 percent accuracy level, they anticipate the ability to automatically detect cracking (wheel track, longitudinal, edge, thermal, and intermediate transverse cracking), rutting, potholes, crack sealing deficiencies, punchouts, shattered slabs, and joint spalls. Reportedly, minimal quality control (QC) is required to identify raveling, bleeding, patching, reflective cracks, surface deterioration, and patching. Identification of debonding requires both manual and automated processing, as pressure damage cannot be easily discerned using automated data collection.

WayLink PaveVision3D System

WayLink has developed the PaveVision3D System for identifying pavement distresses and other measurements, mounting it on a standard full-sized digital highway data vehicle (DHDV), as shown in Figure 1.4. This system reportedly offers the highest 2D and 3D imaging resolution on the market. Currently, WayLink is developing algorithms for semi-automated and automated identification of pavement surface distress, severity and extent (DSE).

Figure 1.4: WayLink PaveVision3D DHDV.

WayLink's ROW camera is mounted in the vehicle cabin, collecting images through the windshield. This camera provides 1,920 x 1,080 pixel images, recording them either continuously or using triggered intervals, and storing JPEG files (or other standard formats) with a typical compression ratio of 10:1.

To ensure accurate positioning, the WayLink system includes a standard 10 Hz industrial GPS that provides 3.3-ft (1-m) accuracy. When combined in real time with augmented satellite or ground station positioning input, the accuracy can be within 4 inches. Additional post-processing of the data can further improve their locational accuracy. Presently, WayLink offers crossfall, grade, and curve radius collection services using IMU output.

WayLink is in the process of confirming the precision and accuracy of longitudinal profiles collected by their Ultra 3D image height sensors and their correlation to the industry standard Selcom spot laser road profiling systems. They report that the PaveVision3D Ultra sensors exhibit substantially less electronic "noise" than the standard spot lasers, making them a viable option for longitudinal profiling and even for texture measurements typically collected with 64 kHz spot lasers, as the Ultra 3D sensors operate at 30 KHz data rate for the entire pavement surface.

WayLink, in their PaveVision3D Ultra System, has two sensor cases mounted in the back of their DHDV van. Each sensor case has two subsystems for data acquisition: 2D and 3D. The 2D subsystem reportedly provides laser imaging at 0.04-inch (1-mm) resolution in both the X and Y directions using one 2D camera, one laser assembly, and required optics. WayLink's 3D subsystem reportedly includes laser imaging at 0.04-inch resolution in the X and Y directions (0.01-inch resolution in the vertical direction), employing four 3D cameras, one laser assembly, and required optics. The use of multiple 3D cameras in a single PaveVision3D Ultra 3D sensor allows the four cameras to collect synchronously, operating at 30 KHz collection rate over the entire pavement surface. In other words, when 3D line profile data from the four cameras are stitched transversely and combined longitudinally, the longitudinal sampling interval reportedly falls below 0.04 inch, with a system collection rate of about 4,160 transverse profile points recorded at 30,000 samples each second. Combined, ten 2D and 3D cameras are included in a pair of PaveVision3D Ultra sensors. This configuration reportedly meets ASTM E 1656-11 Code C1111.

Recent Research on Automated Distress Detection

Crack Detection

Pavement surface cracking is one of the most important distresses monitored on asphalt pavements. Surface cracking is an indication of layer failure since cracking is one of the design parameters of asphalt surfaces (Austroads 2012). Significant funding is allocated by transportation agencies to assess pavement condition through manual and automated surveys. Historically, condition data was exclusively used for maintenance and rehabilitation (M&R) decisions. Lately, cracking information has been utilized in performance monitoring of different asphalt mixes and performance modeling to select proper mix design (Tapper et al. 2013). As MAP-21 requires transportation agencies to report the amount of surface cracks annually, the need for more accurate and quicker data collection systems is imperative.

Table 1. summarizes some of the testing and research for the robustness of LCMS crack detection. Note that the effectiveness of the digital technologies was not investigated further as they were proven to be less effective on chip seals, thus questioning their suitability for local roads with chip seals (Wix and Leschinski, 2012).

Table 1.3: Research into the robustness of LCMS crack identification and quantification

Research	Reference	Research Background	Conclusions from the Study
Delaware Dept. of Transportation – Implementation and Calibration of LCMS for the DelDOT	Gerber, A., Miller, T., and Richardson, M. (2018)	• Determination of overall pavement condition (OPC) using LCMS detected pavement surface distresses • Identified and minimized differences between field-based distress measurements (windshield), LCMS-based distress measurements, and the resulting treatment recommendations originating from the DelDOT's pavement management system	• The researchers adopted 39 in. wheel path width in order to detect fatigue cracking • To rate block cracking, the LTPP requirement of minimum 50 ft. extent was also removed • It was reported that LCMS-based survey was not adequately recording raveling presented on flexible pavements, which significantly lowered the distress deduction in overall pavement condition calculation • They also revealed that LCMS imagery data processing follows a sequence, and once one distress is detected, it gets removed from the imagery and further processing continues. • It was mentioned that the distress detection order is transverse cracks first, followed by alligator cracking, and then block cracking.
Univ. of Cambridge, UK – Automated Detection of Multiple Pavement Defects	Radopoulou, S. and Brilakis, I. (2016)	• Development of low-cost method that automatically detects pavement distress such transverse and longitudinal cracks, patches, and potholes • Used the semantic texton forests (STFs) algorithm as a supervised classifier on a calibrated region of interests	• The overall accuracy of the method is above 82%, with a precision of more than 91% for longitudinal cracks, more than 81% for transverse cracks, more than 88% for patches, and more than 76% for potholes • It developed a method for calculating the region of interest within a video frame considering pavement manual guidelines
TRL, UK - Use of high-resolution 3D surface data to monitor change over time on pavement surfaces	McRobbie et al. (2015)	• The development of improved and accurate methods for aligning data from successive surveys • The use of high-resolution 3-D parameters for identifying the onset of surface disintegration	• The application of GPS combined with longitudinal profile and the use of transverse profile improved the automated alignment of data across the surveyed lane • This research demonstrated that there is a strong potential for the use of change in profile (longitudinal and transverse) to detect the progression of surface disintegration

Research	Reference	Research Background	Conclusions from the Study
FHWA (USA) – Field evaluation of automated distress measuring equipment	Serigos et al. (2014)	• 20 pavement sections were selected for field testing • Pavement surface cracks, texture, roughness, and digital crack maps were collected • Four different automated survey vehicles collected pavement surface distresses, texture, and cross slopes at highway speeds: TxDOT, WayLink-OSU, Fugro-Roadware, and Dynatest • Survey results of automated and manual assessment were compared and accuracy of transition from manual to automated survey was evaluated	• No clear pattern was found in manual raters surveys • In both flexible and rigid pavement, TxDOT and WayLink-OSU (Oklahoma State University) appeared to miss cracks more than reporting false positives, whereas Dynatest and Fugro-Roadware offered maps with cases of both missed cracks and false positives. Therefore, TxDOT and WayLink-OSU system's algorithms inclined to underestimate the crack lengths • Although WayLink-OSU outclassed the other vendors at detecting cracks on many flexible pavements, it inclined to overestimate the crack width • Manual correction provided significant improvement in Dynatest and Fugro-Roadware produced distress measurements • For texture, Dynatest and Fugro-Roadware showed similar results compared to the reference measurements taken by the research team using a circular texture meter (CTM), whereas WayLink-OSU and TxDOT's estimated average reading were usually higher in magnitude; WayLink-OSU shadowed a similar trend in shape as the reference measurement • For cross slope, Dynatest measurements showed a similar trend to the reference in the graph-line shape and slope magnitude. Fugro-Roadware and WayLink sometimes followed the reference graph-line shape, though they display variations above and below the reference slope magnitude

Research	Reference	Research Background	Conclusions from the Study
New Zealand - Did we get what we wanted? Getting rid of manual condition surveys	Henning and Mia (2013)	• The main objective of this research was to establish whether laser scanning crack detection methods could effectively identify cracking on chip seal surfaces. The further objective was to determine the effectiveness of crack detection on a larger scale compared with a visual rating that typically looked at either a 10% or 20% sample size.	• There was a strong correlation between the LCMS and the LTPP cracking data • The comparison with Road Asset Maintenance Management (RAMM) network survey data suggested more than 60% of crack lengths were missed according to the 10% sampling length used for the RAMM surveys • It was recommended that authorities in New Zealand should give strong consideration of using the automated crack detection
ARRB - Cracking - a tale of four systems	Wix and Leschinski (2012)	• Comparative performance among different automated crack measurement systems • Testing on asphalt and sprayed seals pavements	• Both automated crack measurement systems showed excellent repeatability on asphalt pavement surfaces as well as the good similarity between their cracking intensity results. However, there was a distinguishable difference on sprayed seal surfaces. Although the repeatability of the LCMS on sprayed seal surfaces was promising, it overestimated the crack intensity and showed a very poor overall correlation with RoadCrack.
Canada, Pavemetrics - Using 3D laser profiling sensors for the automated measurement of road surface conditions (ruts, macro-texture, raveling, cracks)	Laurent et al. (2011)	• General introduction to a specific LCMS is presented along with some robustness testing was undertaken in Québec (MTO), Canada	• The LCMS system was tested at the network level (6,225 miles) to evaluate its performance at automatic detection and classification of cracks; The system was evaluated to be over 95% correct in the general classification of cracks

Detection of Patching and Raveling

Serigos et al. (2014) concluded in FHWA Report 0-6663-2 that detection of patching and raveling can be improved with manual corrections. They observed that WayLink-OSU and Fugro-Roadware semi-automated distress survey reported fewer numbers and smaller patch sizes, while the Fugro-Roadware automated system and Dynatest's automated and semi-automated systems failed to report patching.

Van Aalst et al. (2015) reported they developed a system that can identify asphalt pavement raveling from high-resolution 3D measurements of road surfaces by means of high-speed laser triangulation. This system is capable of determining the pavement type, the extent of raveling, and remaining service life on porous asphalt in the Netherlands. They have trained a quadratic classifier based on the eleven texture features on about 1,685 mile pavement sections.

Sensor-Measured Data

Automated methods were developed with the objective of performing more accurate, repetitive, and fast collection of transverse profiles. Automated rut measurement systems are usually grouped into four categories according to the technology applied: ultrasonic, point laser, scanning lasers, and optical camera and laser systems. Ultrasonic and point laser-based system generally collect 3 to approximately 30 data points and are, therefore, considered point-based systems. However, the last two systems are able to collect up to approximately 4,160 data points per profile and are, therefore, considered continuous profile-based systems.

Vendors such as Mandli Communications Inc., Dynatest, Fugro-Roadware, and Applus RTD use the LCMS system in order to collect pavement surface roughness, rutting, and faulting data. LCMS system collects up to 4,160 points per transverse profile at highways speeds.

In automated pavement data collection systems, sensor-measured data are collected and processed almost in real-time and results comply with sensor data collection protocols set by the transportation agencies. Sensor data processing involves the analysis of longitudinal and transverse profiles. The parameters that come out of the sensor data analysis are the IRI, rutting of asphalt pavements, and joint faulting of jointed concrete pavements.

2012 ODOT Pavement Condition Ratings Evaluation Project

A previous study to investigate the current technology for automated and semi-automated collection and processing of pavement condition ratings (PCR) data was completed for ODOT in 2013 (Vavrik et al. 2013). The primary objective of that study was to determine if the systems and rating methods were a suitable replacement for ODOT's manual data collection and processing methods. Primarily, this included identifying the quality of vendor-collected data and its consistency with ODOT PCR practices and results. An additional goal was to determine the relative benefits of each option—monetary, safety, speed, etc. Finally, should ODOT pursue transitioning to the automated image collection and automated, semi-automated, or manual distress data identification from the images, this research was designed to provide recommendations for PCR data collection and processing that meets ODOT's needs.

Pathway showed good ability to identify the existence of ODOT-rated distresses on AC pavements, but low success at matching ODOT's severity and extent (42.2% distress/severity match and 23.3% DSE match). Pathway matched 94 percent of ODOT distresses. The best AC pavement distress correlations occurred with standard crack types (block, transverse, and longitudinal). Figure 1.5 illustrates Pathway's abilities to match the DSEs noted by the ODOT raters. Numbers in parenthesis indicate the number of sites in which ODOT identified the distress. Table 1.4 quantifies and summarizes these AC pavement correlation ratings.

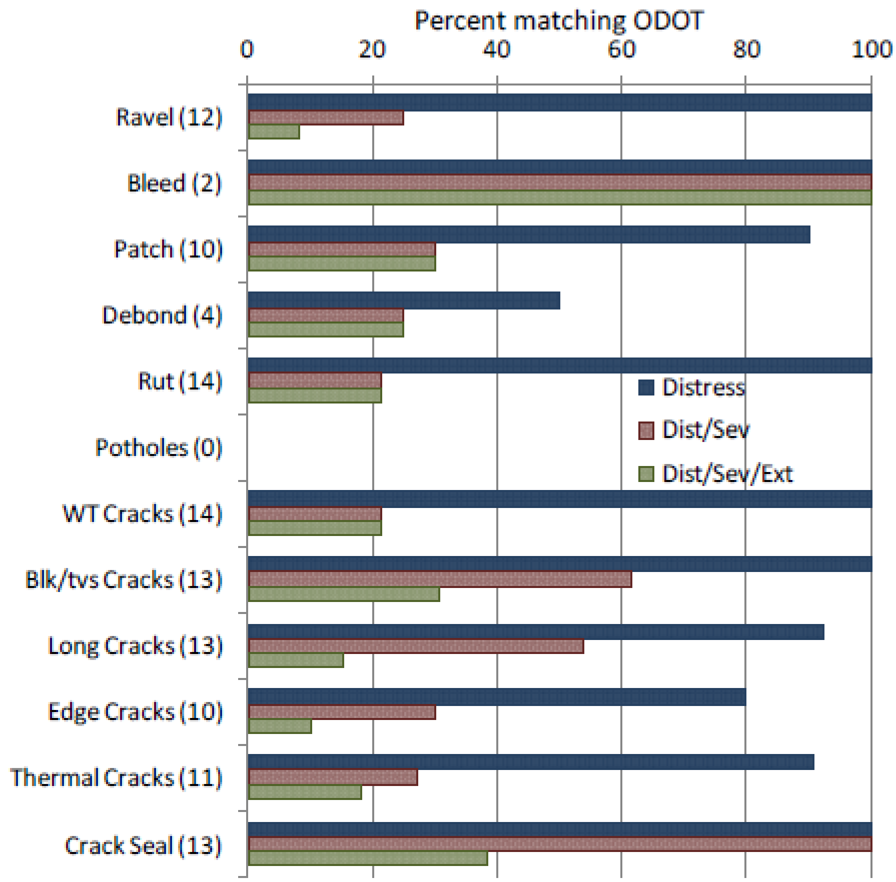


Figure 1.5: Pathway DSE rating match with ODOT for AC pavements (Vavrik et.al. 2013).

Table 1.4: Summary of Pathway match with ODOT DSE ratings for AC pavements (Vavrik et.al. 2013).

Distress	Sites	Distress/severity match, %	DSE match, %
Ravel	12	25	8
Bleed	2	100	100
Patch	10	30	30
Debonding	4	25	25
Rut	14	21	21
Pothole	0	N/A	N/A
Wheeltrack cracks	14	21	21
Block/trans cracks	13	62	31
Long cracks	13	54	15
Edge cracks	10	30	10
Thermal cracks	11	27	18
Crack seal damage	13	-	38
Weighted Avg:		42.2	23.3

Comparisons for AC/PCC overlay pavements reveal some reduction in Pathway's ability to identify DSEs, compared to their ability to identify AC pavement DSEs. Pathway matched ODOT distress identification on 58 percent. Table 1.5 summarizes the Pathway's correlations with ODOT ratings for AC/PCC test sites. Figure 1.6 provides summaries of the Pathway matches for DSE.

Table 1.5: Summary of Pathway matches with ODOT DSE ratings for AC/PCC pavements (Vavrik et.al. 2013).

Distress	Sites	Distress/severity match, %	DSE match, %
Ravel	20	55	20
Bleed	1	0	0
Patch	19	37	21
Debonding	9	11	0
Rutting	19	16	5
Pumping	6	0	0
Pressure	7	0	0
Corner Break	6	0	0
Long Cracks	20	60	15
T Cracks - unj	8	25	13
T Cracks - joint	12	58	17
T Cracks - int	12	8	0
Crack Seal	20	n/a	30
Punchout	5	0	0
Shat Slab	1	0	0
Weighted Avg:		26.7	9.1

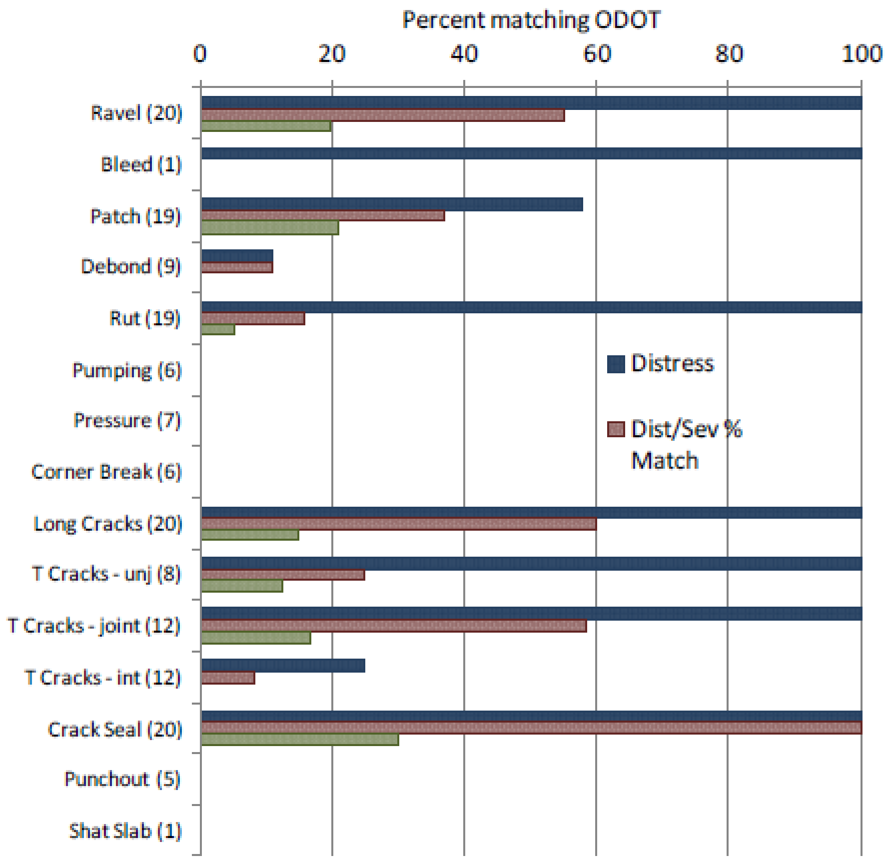


Figure 1.6: Pathway DSE rating match with ODOT for AC/PCC pavements (Vavrik et.al. 2013).

Pathway was able to identify 69 percent of the PCC distresses noted by ODOT raters. Primarily, Pathway encountered difficulties matching ODOT surface deterioration, pumping, and pressure damage. Severity matches with ODOT raters were 33 percent. Figure 1.7 shows Pathway's DSE rating match with ODOT for PCC pavements. Table 1. shows a summary of Pathway's match with ODOT DSE ratings for PCC pavements.

Table 1.6: Summary of Pathway's match with ODOT DSE ratings for PCC pavements (Vavrik et.al. 2013).

Distress	Sites	Distress/severity match, %	DSE match, %
Surface	11	0	0
Longitudinal spall	9	22	0
Patch	11	64	36
Fault	8	63	0
Transverse spall	11	18	0
Pumping	1	0	0
Pressure	8	0	0
Corner break	2	0	0
Longitudinal cracks	6	50	17
Tvs. cracks <20'	3	100	33
Tvs. cracks >20'	8	50	25
Weighted Avg:		33.3	10.3

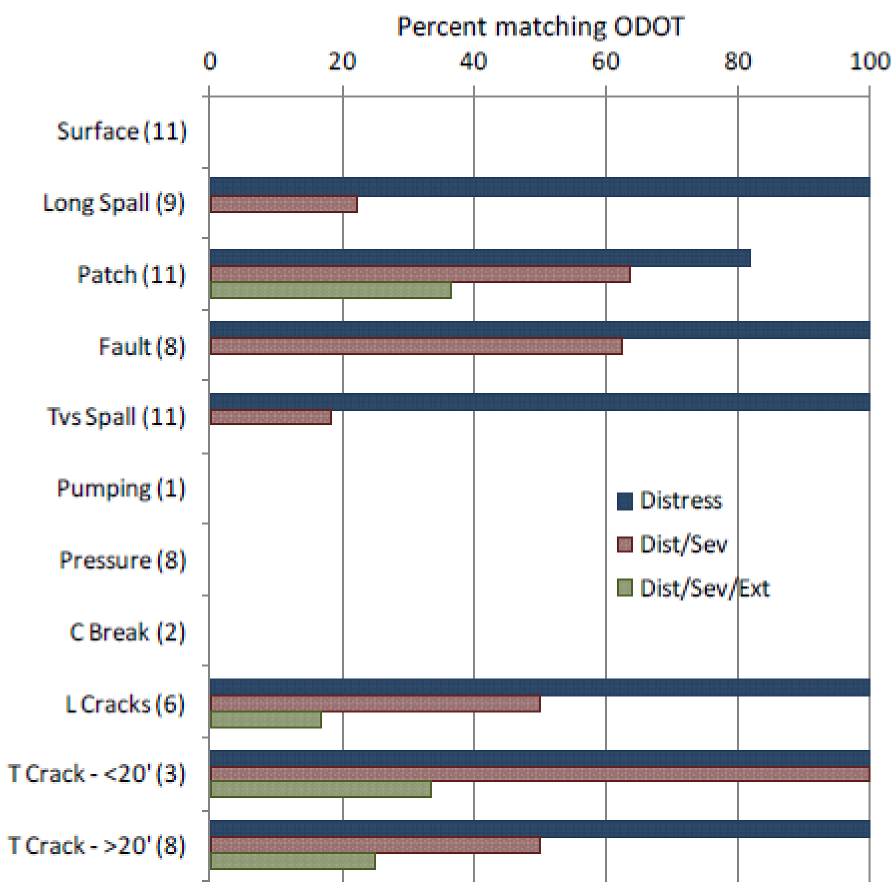


Figure 1.7: Pathway's DSE rating match with ODOT for PCC pavements (Vavrik et.al. 2013).

The ability of Pathway to repeatedly collect DSE information leading to the same PCR values was evaluated using repeat runs on sites representing each pavement type. Pathway was asked to collect a second set of distress videos and to evaluate them independently. As Table 1. indicates, very little difference was noted between repeated vendor evaluations of all pavement types.

Table 1.7: Variability of Pathway's PCR results.

Site	PCR 1	PCR 2	Std. dev
AC (site 20)	57.6	57.3	0.2
AC/PCC (site 35)	71.0	71	0
PCC (site 19)	77.0	77	0

Figure 1.8 illustrates the ODOT and Pathway's PCR ratings and trends for all sites, plotted by increasing PCR. Similar trends can be noted between Pathway's and ODOT PCR values.

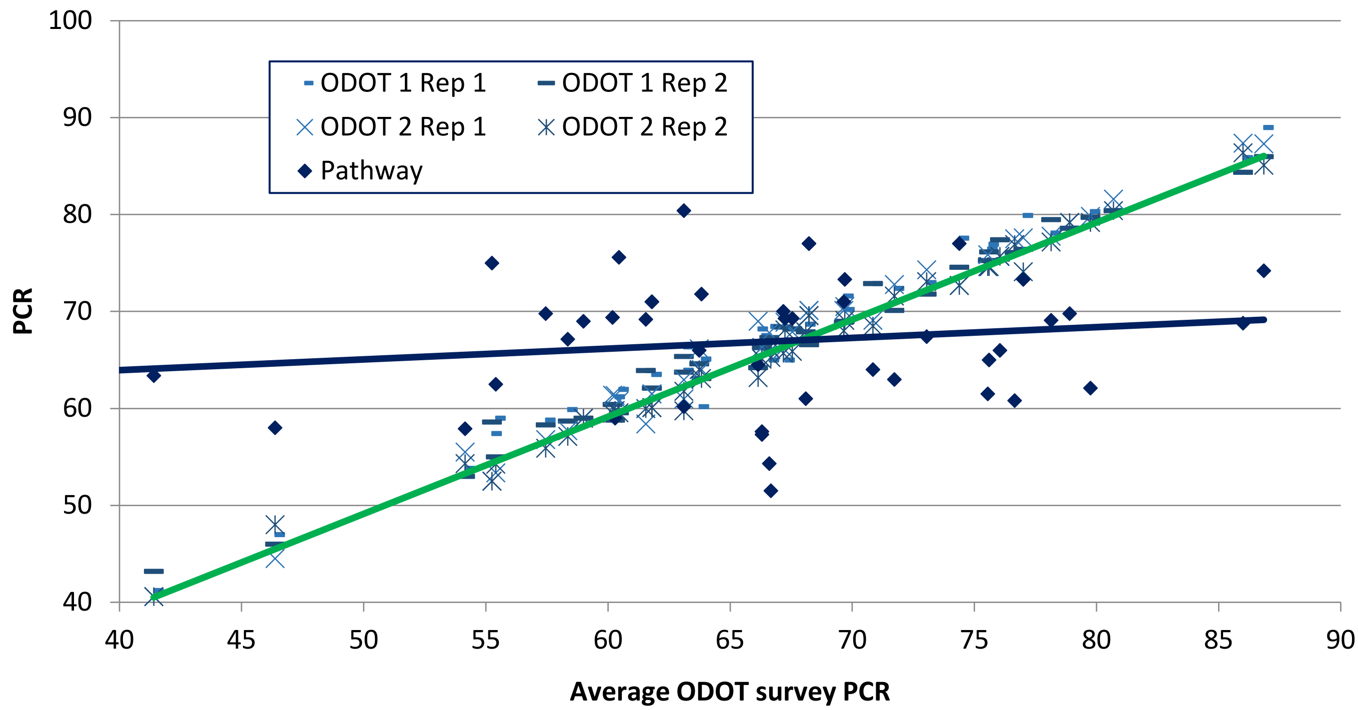


Figure 1.8: Comparison of Pathway's PCR with average ODOT PCR for all sites.

The information gained in this research had contributed greatly to achieving the ODOT objective of determining if the state-of-the-practice systems and rating methods were a suitable replacement for ODOT's current manual data collection method. This was primarily achieved through a detailed review of the quality and consistency of vendor-collected pavement distress, severity, and extent data. Additionally, factors associated with transitioning to semi-automated distress data collection and reporting, including productivity, cost, benefits, and risks, were identified and evaluated. Finally, the research team developed an understanding of differences in current vendor processes, capabilities, and plans.

Transition from Manual to Automated Data Collection Methods

Vavrik et al. (2013) stated that currently over 35 agencies in the US collect network level pavement surface image and sensor data for semi-automated and manual surface distress data identification. They conducted a survey of 18 state agencies to identify their pavement distress collection and processing methods, distresses identified, privatization criteria, and quality management process. The results of the data collection methods survey is shown in Figure 1.9. As observed from the data, a majority of the state agencies in the survey utilized automated pavement data collection methods.

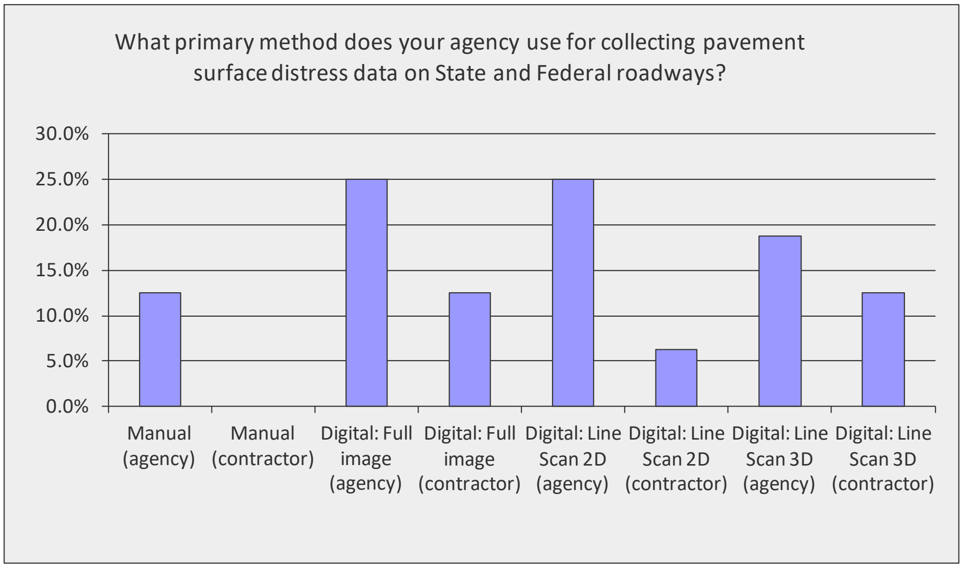


Figure 1.9: Agency data collection methods (adopted from Vavrik et al. 2013)

Texas Department of Transportation (TxDOT) conducted a pilot study to collect network-wide automated pavement condition and distress data in Bryan and Houston districts (Serigos et al. 2015). Once the data were collected and converted to TxDOT PMIS ratings, the research team evaluated the differences between the results produced by the automated methods, and methods currently employed by TxDOT. Results indicated the semi-automated visual distress ratings captured more distresses than collected with TxDOT visual ratings. This pilot study is expected to provide TxDOT with valuable information on implementing automated or semi-automated visual distress surveys in place of the TxDOT PMIS manual survey to improve safety and provide more accurate measurements of visual distress data.

Alabama Department of Transportation (ALDOT) conducted a research study to develop a methodology for updating the ALDOT pavement condition ratings using automated data collection (Timm and Turochy, 2014). The two methods evaluated for this project included use of Artificial Neural Networks (ANN), and recalibrating the existing ALDOT PCR model through regression analysis using automated data collected in 2009 and 2010. An independent validation of the revised model was conducted using automated and manual data collected from 10 quality control segments in 2011. Results from the study indicated that ANN modeling proved unreliable, and is not recommended for PCR prediction. Recalibration of the original model using regression analysis provided acceptable results, with 86% of the vendor computed condition ratings within 10 points of the ALDOT manual surveys.

Nebraska Department of Roads (NDOR) evaluated the use of automated data collection to calculate the pavement condition ratings, and its implementation into the Nebraska Pavement Management System (Rami and Kim, 2015). No change to the existing decision making process was expected as part of this study. A user friendly program was developed to convert the automated distress ratings to manual distress rating format, and data for over 7,000 miles was compared to assess the correlation between manual and automated methods. Results indicated that the Nebraska Serviceability Rating (NSR) calculated from automated methods was within 10% of the manual ratings, and automated distresses were rated with higher sensitivity levels.

The Ministry of Transportation Ontario (MTO) conducted a research study to develop and validate interim performance models using various combinations of manual and automated distress sets (Chan et al. 2016). The study uses data from 934 pavement sections surveyed using manual and automated methods. Pavement condition using manual distress ratings, and automated data was available, while a new hybrid condition assessment methodology was developed in this study. The hybrid assessment incorporates distress types identified by LCMS, and manual data collection methods. The results of this study were expected to facilitate the Ministry's transition from a manual to an automated pavement management system by 2017.

A research study conducted by North Carolina Department of Transportation (NCDOT) focused on developing new performance models for the automated pavement distress data, and update of the NCDOT pavement management system (Hildreth and Nicholas, 2016). Performance models for asphalt and concrete pavements were developed using automated data collected from three years (2013, 2014 and 2015). The study evaluated the impact of the new performance models on the trigger points and benefit weight factors by studying a composite performance index developed using Analytical Hierarchy Process (AHP), and determine benefit weight factors through performing Cost-Benefit Analysis (CBA) and sensitivity analyses.

Gerber et al. (2018) conducted a study for the Delaware Department of Transportation (DelDOT) to perform distress calibrations to transition from manual to LCMS-based pavement condition assessment. The study involved comparing the manual and LCMS based distress surveys from 30 test sites, and adjusting data processes to improve M&R treatment selection and index calculations in the PMS. Though the process did not result in complete agreement between manual and LCMS based surveys, the project was successful in minimizing the gaps between automated and manual surveys for the test sites.

Researchers from International Cybernetics Co. (2020) developed the Pavement Surface Cracking Metric (PSCM) and converted this metric into a Pavement Surface Cracking Index (PSCI). The PSCM is calculated based on the amount of cracking detected on the surface area and utilizes the actual crack width and length. The PSCM was converted into an index from a 0-100 scale by plotting the PSCM and the Pavement Condition Index and deriving the best fit exponential function. Data collected on multiple runs on three asphalt sections showed good repeatability of the PSCM metric. The index values calculated from the PSCM were found to be repeatable with low standard deviation and coefficient of variation.

Summary

Although the automated collection and processing of pavement distress data have progressed greatly in the last decade, there still are barriers to overcome before the technologies involved can come to completion as real-time, reliable, and generally applicable tools. First is the need for the development of systems capable of consistently producing high-quality digital images under most data collection conditions (lighting, the angle of the sun, shadowing, etc.). Although there is evidence that the technologies have progressed to the needed capability, they are not generally applied within the industry. Once good images are consistently produced, greater progress can be made in the second major problem area: that of improving the quality of data automatically reduced from those images and the speed with which data can be acquired. Again, there is strong evidence that the necessary technologies exist, but they seem to need further maturing to address both quality and speed. There may be a need for a focused effort to bring about that maturity.

Appendix 2: Data Quality Control

Overview

The segments rated by Pathview relative to the pavement segments rated through ODOT's PCR method were compared for data collected from District 1 in 2016. Pathview data are collected by ODOT's Office of Technical Services, and segments are generally delineated by major points of interest on the pavement network (e.g. county line, intersections with state routes). In comparing Pathview segments as they are collected and without any post-processing, Pathview segments tend to be longer than PCR segments. Therefore, generally there are fewer Pathview segments than PCR segments on a route. Shown in Table 2.1 are the individual segments rated by Pathview and PCR in 2016 for State Route 81 in Allen (ALL) County, where begin and end log points are listed as the county true log. The length and begin/end points of the segments rated via Pathview were not always consistent with the segments rated via PCR. For example, the second segment collected by Pathview in the up direction on ALL-81 is 12.4 miles long and encompasses 6 flexible PCR segments and 3 composite PCR segments. Pathview segment lengths can be edited after collection. The difference in segment lengths is attributed to the manner in which data are collected. Currently data are collected for HPMS reporting of surface distress, IRI and rutting, and reported based on surface type (asphalt or concrete). Pathview enables HPMS reporting in 1/10th mile segments by post-processing the data. According to ODOT's Office of Technical Services, post-processing of the data could be performed to aggregate data for PCR segments, although, it would require quite a bit of effort initially. ODOT should consider developing the files necessary for Pathview to report data by PCR segments.

Additionally, the segments rated by Pathview may not be in the same direction as the segment rated by PCR. As shown in Table 2.1, 3 segments in the up direction and 6 in the down direction were rated by Pathview, while 18 segments in the up direction and no segments in the down direction were rated on the same route by PCR in 2016.

Table 2.1: Example of Difference in Segments Rated by Pathview and PCR in 2016

County-Route	Direction	PCR			Pathview	
		Begin	**End**	**Pavement Type**	**Begin**	**End**
ALL-81	Up	0	3.07	FLEXIBLE	0	3.066
		3.31	9.27	FLEXIBLE	3.306	15.718
		9.27	11.35	FLEXIBLE	15.718	16.65
		11.35	13.47	FLEXIBLE		
		13.47	14.25	FLEXIBLE		
		14.25	14.47	FLEXIBLE		
		14.47	14.59	COMPOSITE		
		14.59	15.54	COMPOSITE		
		15.54	15.72	COMPOSITE		
		15.72	16.13	FLEXIBLE		
		16.13	16.65	COMPOSITE		
		16.85	17.01	COMPOSITE		
		17.01	17.53	COMPOSITE		
		17.53	18.15	COMPOSITE		

County-Route	Direction	PCR			Pathview	
		Begin	End	Pavement Type	Begin	End
		18.15	18.47	FLEXIBLE		
		18.47	19.08	JOINTED CONCRETE		
		19.08	19.67	FLEXIBLE		
		19.67	29.4	FLEXIBLE		
	Down				13.465	15.718
					15.718	16.65
					16.842	18.47
					18.47	18.873
					18.873	19.08
					19.08	29.404

ODOT Office of Technical Services indicated the pavement type is entered prior to data collection and is based on ODOT's roadway inventory. The pavement types for which PCR segments were rated on ALL-81 in 2016 are listed in Table 2.1. The Pathview software lists pavement type twice, once for the segment and then also when a distress is identified. However, these pavement types may not match each other. For instance, the segment, ALL-81 16.842 – 18.47 which was rated by Pathview, has a pavement type of "A" for asphalt listed in the road condition information system. However, an "O," presumably for overlay indicating a composite pavement, is listed in the distress features database for each distress identified between log points 16.881 and 18.139. As shown in Table 2.1, the pavement type for the up direction between 16.85 and 18.15 was reported for PCR as composite. Pathview data on this segment were not collected in the up direction, only in the down direction. The straight-line diagram for this segment, shown in Figure 2.1, shows a composite pavement between 17.102 and 18.133. This indicates the pavement type, "P" listed in the Pathview software in the distress features database where a distress is identified, appears to be more in-line with the road inventory.

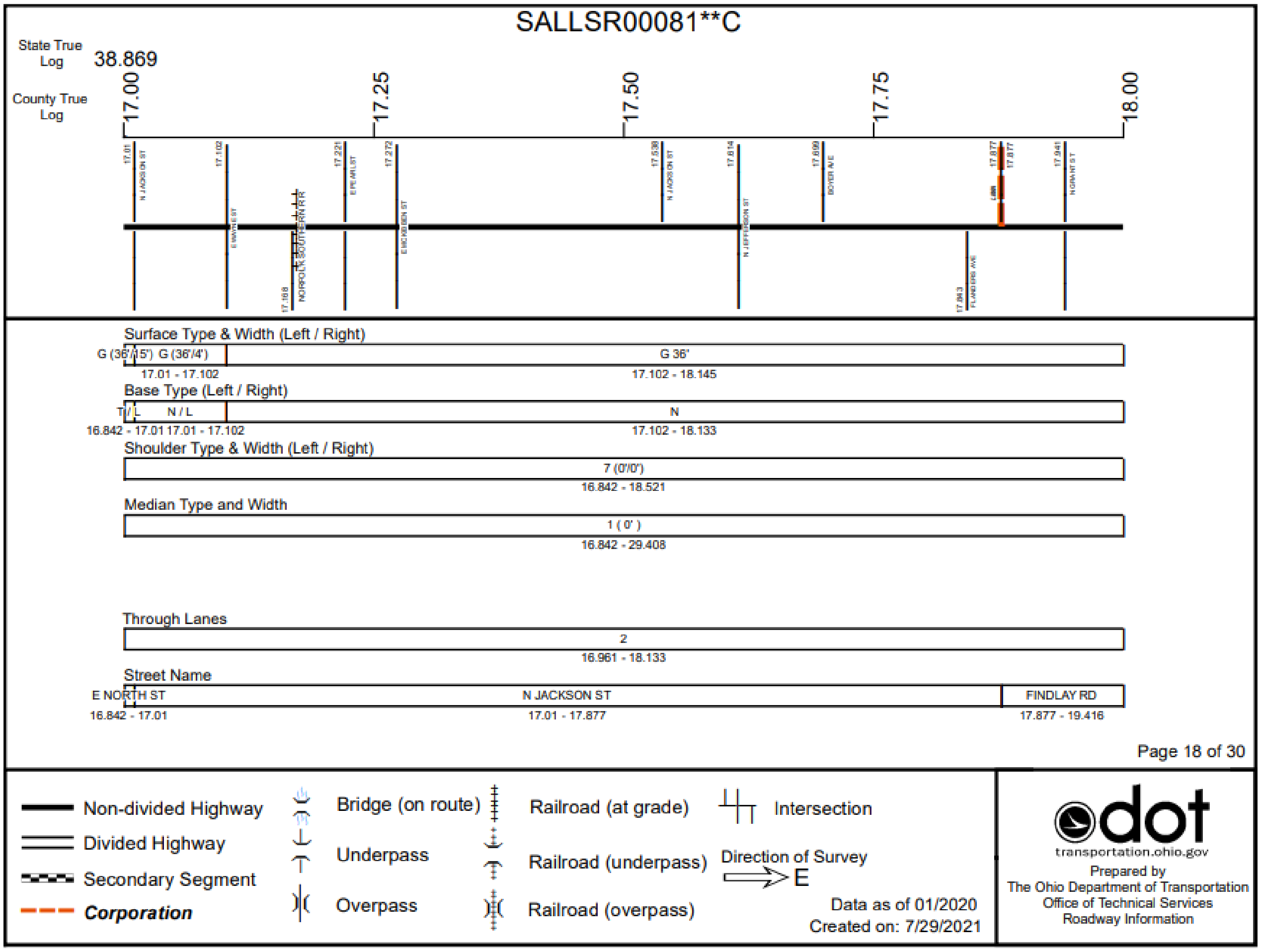


Figure 2.1: Straight-line Diagram of ALL-81 17.00-18.00 (Surface type "G" = Bituminous Concrete; Base type "L" = Bituminous Concrete or Penetration Macadam, type "N" = Plain Concrete)

The review of available data indicated the pavement type listed in Pathview for each distress was not always reflective of the inventory. As an example, District 6 PCR data from 2015 show log points 0.00 to 3.16 were rated in both directions on I-71 in Pickaway County as composite pavement and ODOT straight-line diagrams confirm this pavement type. However, in the Pathview data, the same segment on I-71 in both directions was listed as an asphalt pavement (listed as "A"). It is unclear whether this error is related to the entry of the pavement type prior to collection, the roadway inventory, or the Pathview software. However, as noted below, differentiating between asphalt and composite pavements is important to ensure the appropriate distresses are rated. Prior to collecting data, the road inventory file should be reviewed to ensure the pavement type entered prior to the data collection process is accurate.

The pavement type is important as it dictates the distresses rated. Misidentifying the pavement type presents issues when comparing Pathview distresses to PCR distresses. For the PCR method, distresses rated for each pavement type are listed in Table 2.2.

Table 2.2 Lists of Distresses Rated by Pavement Type for PCR Method (after ODOT, 2006)

Distresses Rated		
Flexible	**Composite**	**Jointed Concrete**
Raveling	Raveling	Surface Deterioration
Bleeding	Bleeding	Longitudinal Joint Spalling
Patching	Patching	Patching
Debonding	Surface Disintegration/ Debonding	Pumping
Crack Sealing Deficiency	Rutting	Faulting (Joints and Cracks)
Rutting	Pumping	Settlements
Settlements	Shattered Slab (Jointed Base)	Transverse Joint Spalling
Potholes	Settlements	Transverse Cracking (Plain Concrete)
Wheel Track Cracking	Transverse Cracks (Unjointed Base)	Pressure Damage
Block and Transverse Cracking	Joint Reflection Cracks (Jointed Base)	Transverse Cracking (Reinforced Concrete)
Longitudinal Cracking	Intermediate Transverse Cracks (Jointed Base)	Longitudinal Cracking
Edge Cracking	Longitudinal Cracking	Corner Breaks
Thermal Cracking	Pressure Damage/ Upheaval	
	Crack Seal Deficiency	
	Corner Breaks (Jointed Base)	
	Punchouts (Unjointed Base)	

Pathview is not capable of identifying all the composite pavement distresses listed for the PCR method. As shown in Table 2.2, the biggest differences in the PCR method between asphalt and composite pavements are as follows:

- Potholes, wheel tracking cracking, block and transverse cracking, thermal cracking and edge cracking are rated on asphalt pavements only.
- Transverse cracks and joint reflection cracks on composite pavements are categorized based on the presence of joints in the underlying concrete.
- Composite pavements include additional distresses: pumping, shattered slab, pressure damage/upheaval, corner breaks (jointed base), and punchouts (unjointed base).

Because the base type (jointed or unjointed concrete) on a composite pavement is not included in the Pathview software, transverse cracks are not defined in the same manner as the PCR method. Furthermore, Pathview cannot identify settlements, crack seal deficiency, pumping, pressure damage/upheaval, corner breaks or punchouts. Therefore, when a composite pavement is misidentified as an asphalt pavement, some of the differences between distresses on asphalt and composite pavements are not of concern. However, Pathview may assign distresses specific to asphalt pavements including potholes, edge cracking and wheel track cracking to composite pavements. This was the case for I-71 in Pickaway County, of the 4,241 distresses identified in both directions, 439 were wheel track cracking, 1,228 were edge cracking, and 39 were potholes. Thus, 40% of all identified distresses on this composite segment were rated by Pathview as distresses specific to asphalt pavements in the PCR method. Additionally, 1,239 instances of transverse cracking (29% of all distresses on this segment in both directions) were identified by Pathview, which may not depict transverse cracking on a composite pavement, as defined by the PCR method. While this does not appear to be the case for this segment of road, as ratings from the PCR method do not show any shattered slab, misidentifying a composite pavement as an asphalt pavement would prevent shattered slab distresses from being identified in Pathview.

The types of distresses assigned by Pathview for each pavement type were further evaluated. The distresses identified by the Pathview software and current Autoclass and Autocrack (Ohio _Updated_011919.C11) algorithms were evaluated for District 1 data collected in 2016. First, the distresses were summarized for each pavement type, and are listed in Tables 2.3 – 2.5. The pavement types listed below are defined by Pathview. For the 2016 data provided to the research team, a total of 525,144 distresses were identified in District 1. It should be noted one set, 485, was not provided to the research team, although Pathview indicated some District 1 data were stored in set 485. Although rutting and IRI are not listed in the tables, they were identified by the software. However, they were excluded from the quality control check of the software, as they are not easily identifiable from forward facing and downward facing images.

Table 2.3 Distresses Identified on Asphalt Pavements, District 1, 2016 Data

Asphalt Distresses	No.	% of Total	% of Total (Excluding Unassigned)
Edge Cracking	25,007	5.59%	5.86%
Longitudinal Cracking	115,603	25.85%	27.10%
Patching	13,569	3.03%	3.18%
Pot Holes	0	0.0%	0.00%
Raveling	458	0.10%	0.11%
Transverse Cracking	204,367	45.71%	47.90%
Wheel Track Cracking	67,654	15.13%	15.86%
Unassigned	20,467	4.58%	
Total	447,125	100.00%	100.00%

Table 2.4 Distresses Identified on Composite Pavements, District 1, 2016 Data

Composite Distresses	No.	% of Total	% of Total (Excluding Unassigned)
Longitudinal Cracking	10,665	22.88%	24.60%
Patching	1,696	3.64%	3.91%
Raveling	61	0.13%	0.14%
Transverse Cracking	22,542	48.35%	52.00%
Slab	499	1.07%	1.15%
Wheel Track Cracking	7,884	16.91%	18.19%
Unassigned	3,271	7.02%	
Total	46,618	100.00%	100.00%

Table 2.5 Distresses Identified on Jointed Concrete Pavements, District 1, 2016 Data

JCP Distresses	No.	% of Total	% of Total (Excluding Joint)
Longitudinal Cracking	301	0.96%	6.67%
Longitudinal Spalling	557	1.78%	12.34%
Patching	45	0.14%	1.00%
Transverse Cracking	1,165	3.71%	25.82%
Transverse Spalling	1,118	3.56%	24.78%
Edge Cracking	278	0.89%	6.16%
Joint	26,856	85.62%	
Slab	907	2.89%	20.10%
Wheel Track Cracking	141	0.45%	3.13%
Total	31,368	100.00%	100.00%

In reviewing the distresses identified by Pathview in District 1, Pathview found approximately 25,000 occurrences of edge cracking on asphalt pavements. While edge cracking is a distress for asphalt pavements in the PCR method, it is only rated if the asphalt pavement is not bordered by a shoulder or curb. During a field visit to District 6 (PIC-22 18.42 – 18.58) as part of this study, it was confirmed edge cracking was identified by Pathview software on a pavement which is bordered by a curb. As noted previously, Pathview software identified edge cracking on PIC-71 0.00 – 3.16, the interstate where a composite pavement was mistakenly identified as an asphalt pavement. Regardless of the misclassification of pavement type, PIC-71 0.00 – 3.16 is an interstate segment with a paved shoulder and therefore should not have been rated for edge cracking. Along with interstate routes, four-lane divided routes also have paved shoulders and should not have edge cracking rated according to the PCR manual. Conducting either pre- or post-processing of the data should be considered to exclude edge cracking on pavements with curb or paved shoulders.

Additionally, a substantial number of distresses were identified on asphalt pavements that were unassigned (4.6%), meaning an anomaly on the pavement surface was identified by Pathview, but not assigned a distress or severity.

As noted previously, Pathview is not able to identify the underlying concrete as jointed or unjointed, as a result transverse cracking as defined by Pathview differs from the various transverse cracks in the PCR method (transverse cracks unjointed base, joint reflection cracks, and intermediate transverse cracks). Overall, transverse cracking makes up a significant portion (approximately 50%) of all distresses identified by Pathview on composite pavements in District 1 in 2016. Approximately 7% of the total distresses identified were unassigned.

Edge cracking, as well as slab (shattered slab) and wheel track cracking were identified on jointed concrete pavements, as listed in Table 2.5. However, all three distresses are not rated on jointed concrete pavements by the PCR method. Edge and wheel track cracking are specific to asphalt pavements and shattered slab is specific to composite pavement. Another distress, "joint" was also identified on jointed concrete pavements. However, it is understood this distress is simply the identification of the presence of a joint, which explains the large percentage (85%) of this distress relative to all distresses identified on concrete pavements in District 1 in 2016. Therefore, percentages of each distress are also shown when “joint” is excluded from the count. When “joint” is excluded, distresses which are not specific to concrete pavements (edge cracking, shattered slab, and wheel track cracking) make up more than a quarter (29.4%) of all distresses on concrete pavements in District 1 in 2016.

Of those distresses identified by Pathview for District 1 in 2016 data, 23,738 were not assigned a distress type or severity. These distresses were further evaluated. As discussed in the next section, unassigned distresses were evaluated to determine if any trends or patterns were observed. Unassigned distresses were also reviewed to check the assigned location, quality of the image, and the assigned distress matches the pavement type. Additionally, instances were observed in which the location for a distress was not provided. The source for the error could not be determined. The research team attempted to locate them however, they could not be found in the software. Overall, the number of occurrences were low compared to the total number of distresses on each pavement type.

Quality Control Check of Images

Due to the large number of unassigned distresses identified in District 1, 2016 data, all images could not be reviewed. Rather, approximately 1% of the unassigned distresses were randomly selected for further review. Data are stored by set which are generally collected by segment. To ensure a range of routes and locations within District 1, distresses to be reviewed were selected based on set. Approximately 1% of the unassigned distresses in each set were randomly selected for review. The number of unassigned distresses reviewed from each set are listed in Table 2.6. In the course of reviewing the selected unassigned distresses, any additional observations of note were also recorded.

Table 2.6 Number of Unassigned Distresses Reviewed by Set Number, District 1, 2016 Data

Set	1% of each set
486	5
487	32
488	1
489	5
490	22
491	1
492	4
493	3
494	2
495	7
496	17
497	29
498	3
499	4
500	37
501	19
502	12
503	5
504	9
505	9
506	6
507	8
Total	240

A quality control (QC) check of the images was performed by viewing the forward facing and downward facing images relative to the distresses identified by the software. The goal of the QC check was to note any issues with the software related to distress location, image quality, and to determine if any patterns were observed for the unassigned distresses.

As part of the QC check, the GPS location of the identified distress was entered into Google Maps to confirm the location was on the same roadway and portion of the segment as was listed by the software. A visual confirmation was also conducted by comparing Google Maps street view with the forward facing image. There were a few instances in which the GPS coordinates in the software were slightly offset from the pavement in Google Maps. On segment WYA-30-18-24.561, Pathview identified a "SlabLow" (shattered slab of low severity) distress at image starting at 1:07:11:16. The starting latitude and longitude however are for an entirely different pavement segment on DEF-18, although the end latitude and longitude coordinates are correctly assigned for the pavement segment. It should be noted the pavement segment is concrete and should not be rated for shattered slab following ODOT PCR method. Aside from these observations, no other issues regarding the location of the unassigned distress or pavement segment were observed.

The quality of the downward facing images were also noted. The image quality of the downward facing images were rated as good, fair, or poor. Overall, images were good with occasional fair quality reported. Very few images of poor quality were noted. An example of a very poor image quality is shown in Figure 2.2 for a small portion collected on segment HAR-68-0.000-9.245. Each downward image shown below captures 26.4 feet of pavement length at one lane wide. The image on the left is the pavement surface intensity, while the image on the right is the 3D elevation. These images were not one of the 240 unassigned distresses. The reason for such low quality could not be determined from the images shown in the Pathview software.

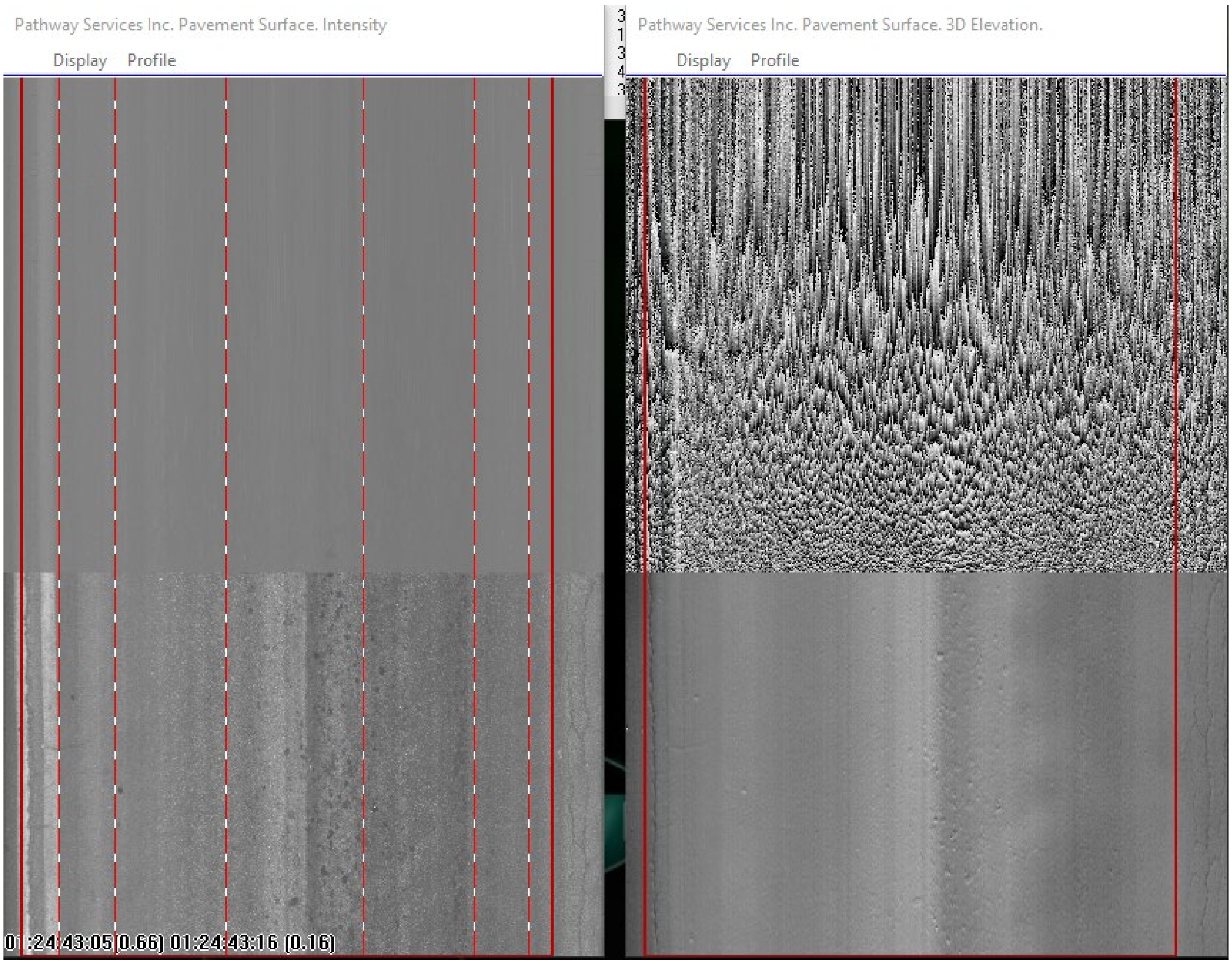


Figure 2.2 Example of Very Poor Image Quality

An unassigned distress is where the Pathview software has detected an anomaly on the pavement surface but cannot identify it as one of the defined distresses. In Pathview, an unassigned distress is highlighted by a lavender box on the downward facing images, which can be difficult to see, therefore in the example in the figure below it is shown with a yellow circle for both the intensity and 3D elevation images.

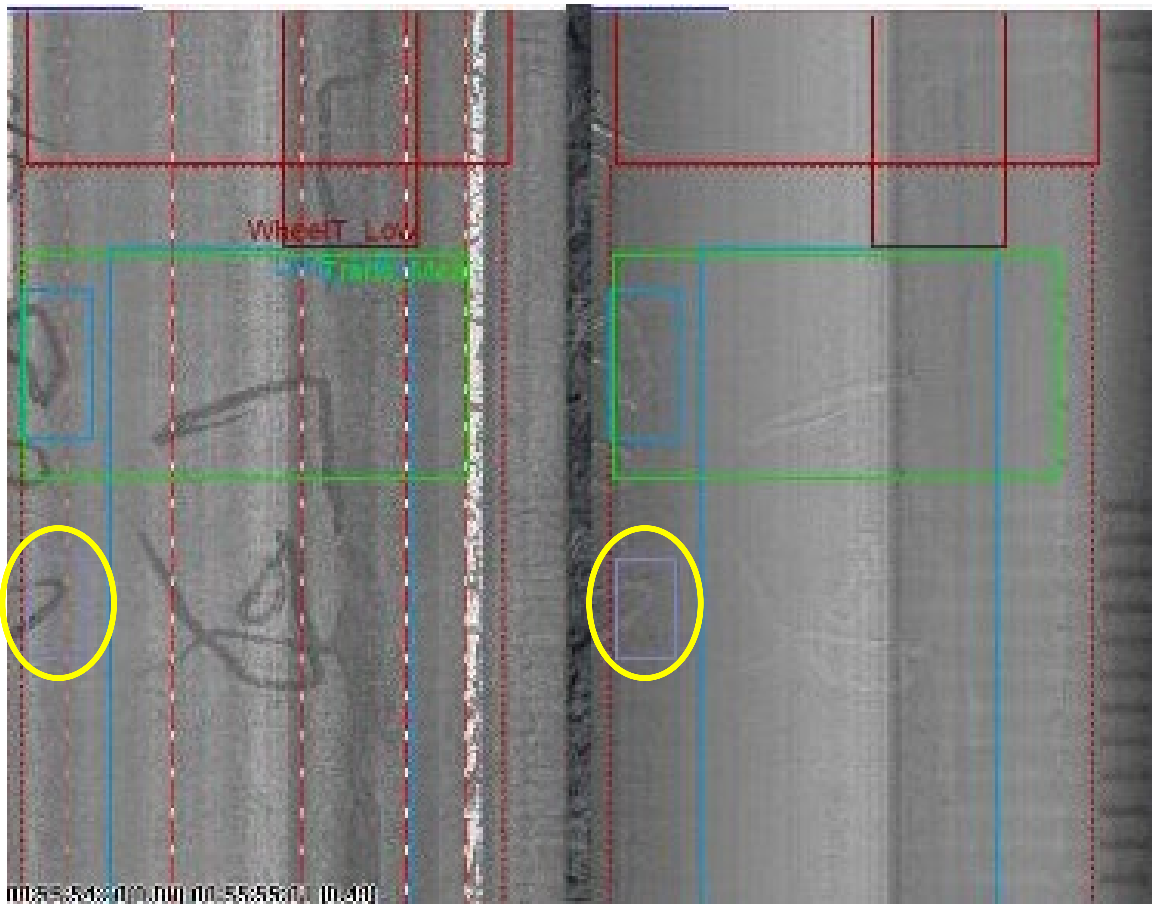


Figure 2.3 Example of an unassigned distress in Pathview, intensity, left and 3D elevation, right

In reviewing the unassigned distresses several observations were made. First, several instances were found in which replicates of an individual distresses were identified. An example of this is shown in Figure 2.4 in which one instance of transverse cracking is identified multiple times resulting in 2 or 3 boxes highlighting the same distress. Duplicate or triplicate assignments of a distress are not specific to any one distress. However, there are at least 6 boxes for unassigned distresses in the image shown, and none of them are replicates of the same distress. Several occurrences of replicate distresses were reviewed, although the source of the error could not be identified.

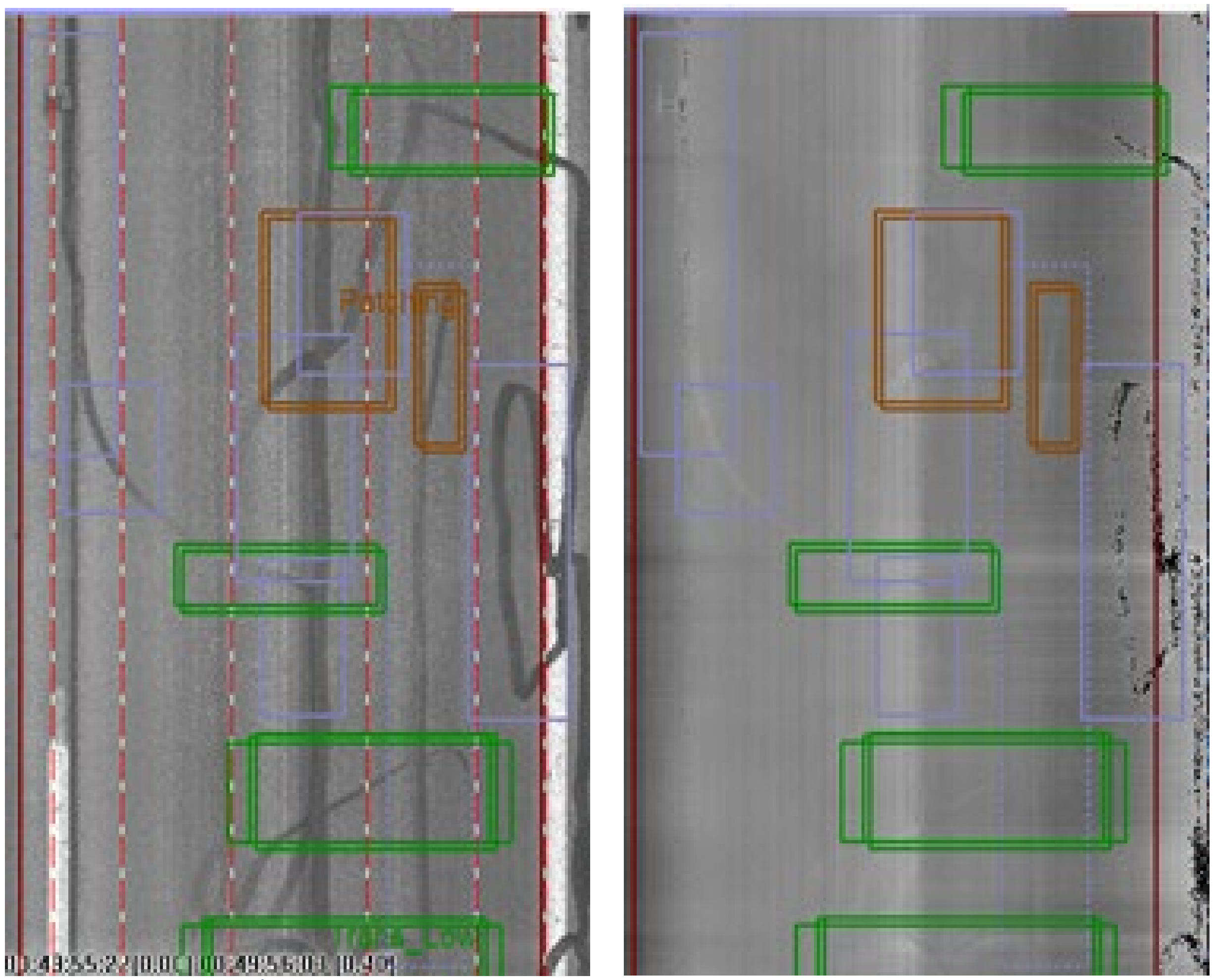


Figure 2.4 HAR-30-12.000 – 2.949, Image 00:49:55:21

In Figure 2.4, patching was identified in two locations on the image. However, the areas identified do not appear to show patching, nor does the forward facing image at this location; rather, the images show crack sealing. Pathview appears to have difficulty with crack sealing. Crack sealing deficiency is not rated by the Pathview software, however, crack sealing may erroneously be rated in the software as the crack type (transverse, longitudinal, or edge cracking), patching when closely spaced, or unassigned. Many of the unassigned distresses that were reviewed were crack sealing. Interestingly, it appears the software picks up only a portion of the crack seal in these cases. In particular over band crack sealing that deviates from a straight path or has sharp (nearly 90 degrees) spurs from a straight path or where the seal is in a curved path tended to trigger the unassigned distresses. Further examples of this are provided in the following figure in which two unassigned distresses (yellow circles) are identified that are curved paths of over band crack sealing. Additionally, Figure 2.5 shows a cluster of crack sealing mistakenly identified as a patch.

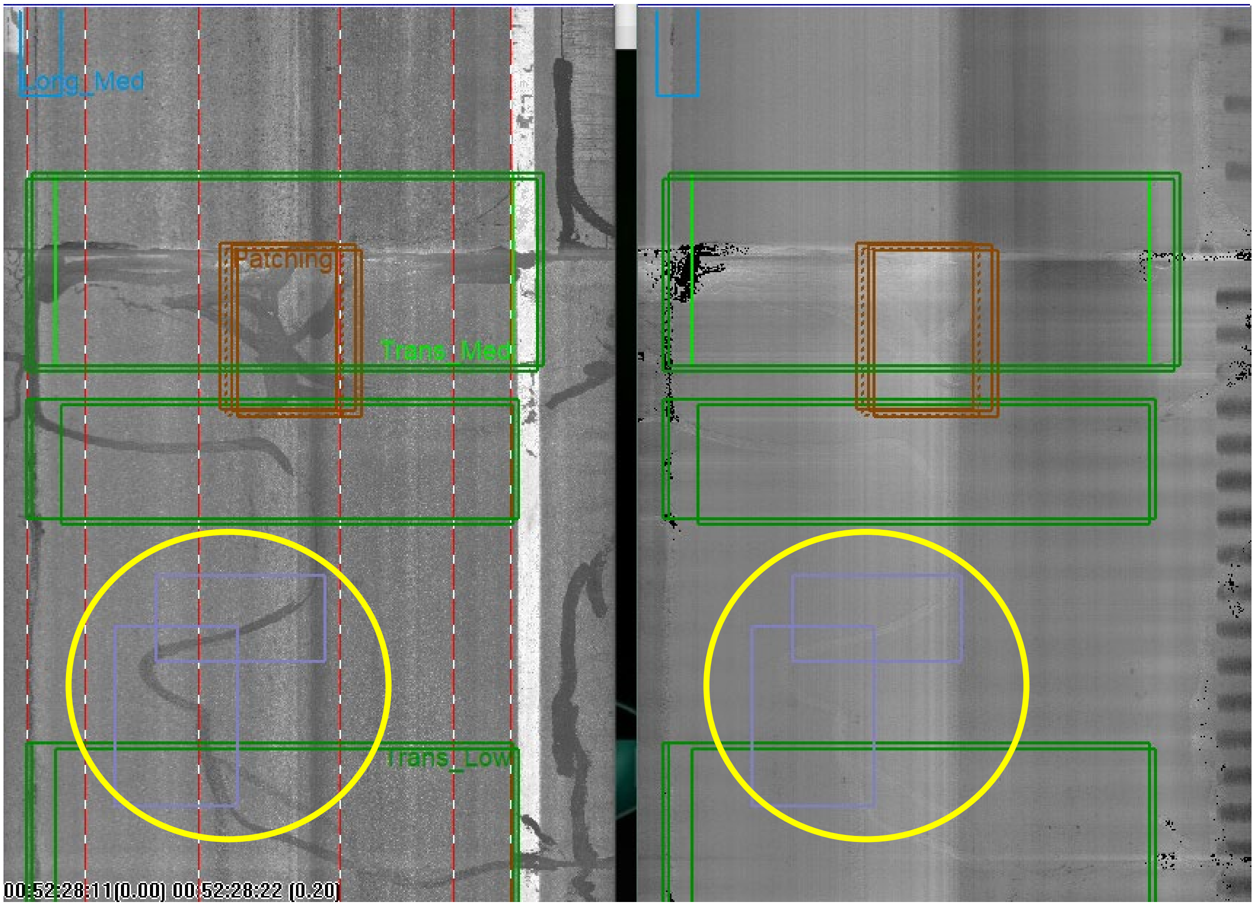


Figure 2.5 Examples of crack sealing as unassigned distresses and patching, HAN-30 12.000-2.949, Image 00:52:28:11

While in many cases it is evident the unassigned distress is due to crack sealing, there were occurrences observed in which the area of the unassigned distress included the entire lane width in the image. An example of this is shown in Figure 2.6 where the box for the unassigned distress is the entire lane width and is shown as a red dashed line. The forward facing image, also shown in the figure below, shows a wet pavement surface. This may have contributed to the poor image quality and the triggering of the unassigned distress. While this image shows the pavement surface is wet, other instances were observed in which unassigned distress boxes encompass the entire lane width and the surface did not appear wet.

There were also many occurrences in which the unassigned distress box could not be located within the image, this may be due to the color of the box which is difficult to see, or the box may be the entire width and not easy to see, or it simply does not exist.

Other observations that were noted are listed below:

- Pavement markings may be identified as unassigned distress, or mistakenly as a type of crack.
- Railroad tracks, expansion joints and end dams on bridges may trigger an unassigned distress.

Figure 2.6 Example of wet pavement surface and entire lane width identified as unassigned distress

Appendix 3: Field Validation

As discussed previously, a model was developed to project the 2021 PCS and decisions from the 2015 PCS data. In the same manner, decisions were generated for projected PCR data. Sections with a "do nothing" decision for both PCS and PCR were deleted from the data. The remaining sections are shown in Table 3.1.

Table 3.1 List of potential field visit sites

County	Route	Direction	Begin	End	Length	Priority System	Pavement Type	2021 PCR (Projected)	StrD	PCR Activity	2021 PCS (Projected)	StrD	PCS Activity
FRA	40	UP	15.99	16.84	0.85	Primary	COMPOSITE	63	16	60	69	25	60
MAH	7	UP	3.58	8.72	5.14	General	COMPOSITE	59	16	60	70	24	60
MAH	7	UP	8.72	11.26	2.54	General	COMPOSITE	59	19	60	70	24	60
FRA	317	DOWN	12.02	12.12	0.10	General	COMPOSITE	60	6	60	66	28	60
GRE	444	UP	6.56	7.91	1.35	Primary	COMPOSITE	63	8	60	72	23	60
HIG	134	UP	12.28	13.99	1.71	General	FLEXIBLE	63	18	60	71	23	60
MOE	260	UP	4.33	5.52	1.19	General	FLEXIBLE	35	27	60	72	23	60
CLA	54	UP	4.88	6.01	1.13	General	FLEXIBLE	58	14	60	66	28	60
LOG	235	UP	1.17	2.24	1.07	General	FLEXIBLE	57	16	60	70	25	60
LOG	235	UP	5.41	6.19	0.78	General	FLEXIBLE	55	19	60	70	25	60
HOC	664	UP	15.20	15.90	0.70	General	FLEXIBLE	53	17	60	68	26	60
CLI	729	UP	12.16	12.72	0.56	General	FLEXIBLE	60	14	60	67	27	60
CLI	729	UP	13.06	13.53	0.47	General	FLEXIBLE	63	14	60	67	27	60
FAI	674	UP	0.00	0.40	0.40	General	FLEXIBLE	57	20	60	69	25	60
HOC	180	UP	0.05	0.39	0.34	General	FLEXIBLE	61	11	60	70	24	60
MAH	625	UP	0.00	0.22	0.22	General	FLEXIBLE	63	13	60	69	25	60
KNO	308	UP	0.00	0.20	0.20	General	FLEXIBLE	47	21	60	71	23	60
MAR	309	UP	0.00	15.35	15.35	General	FLEXIBLE	49	24	60	67	27	60
FAI	204	UP	0.40	5.92	5.52	General	FLEXIBLE	62	19	60	65	29	60
HOC	678	UP	0.00	4.00	4.00	General	FLEXIBLE	47	23	60	66	28	60
HOC	56	UP	0.53	4.37	3.84	General	FLEXIBLE	58	17	60	69	26	60
HOC	328	UP	1.75	4.35	2.60	General	FLEXIBLE	52	20	60	66	28	60

County	Route	Direction	Begin	End	Length	Priority System	Pavement Type	2021 PCR (Projected)	StrD	PCR Activity	2021 PCS (Projected)	StrD	PCS Activity
CLI	133	UP	3.55	5.86	2.31	General	FLEXIBLE	55	20	60	68	26	60
HOC	328	UP	4.35	6.30	1.95	General	FLEXIBLE	48	21	60	66	28	60
HAM	264	UP	0.05	0.45	0.40	General	FLEXIBLE	71	14	30, 31, 38,or 50	65	29	60
FRA	317	DOWN	16.96	17.30	0.34	General	FLEXIBLE	59	15	60	69	25	60
CLI	73	UP	0.00	6.24	6.24	Primary	FLEXIBLE	59	19	60	68	26	60
PIC	674	UP	1.22	10.93	9.71	General	FLEXIBLE	61	17	60	67	27	60
FAI	256	UP	5.99	12.13	6.14	General	FLEXIBLE	46	23	60	65	29	60
MOE	537	UP	0.00	4.98	4.98	General	FLEXIBLE	47	22	60	71	23	60
UNI	37	UP	6.95	9.14	2.19	General	FLEXIBLE	58	22	60	68	26	60
PIC	56	UP	19.57	20.66	1.09	General	FLEXIBLE	58	19	60	67	27	60
FAY	***62***	***UP***	***13.65***	***14.60***	***0.95***	***General***	***FLEXIBLE***	***69***	***13***	***38 or 50***	***65***	***29***	***60***
FAY	753	DOWN	10.44	11.05	0.61	General	FLEXIBLE	54	11	60	66	28	60
KNO	3	UP	32.55	33.03	0.48	General	FLEXIBLE	46	25	60	68	26	60
KNO	3	UP	27.71	28.12	0.41	General	FLEXIBLE	51	19	60	66	28	60
FRA	***317***	***UP***	***18.54***	***18.89***	***0.35***	***General***	***FLEXIBLE***	***84***	***10***	***0***	***65***	***28***	***60***
LIC	13	UP	9.31	9.59	0.28	General	FLEXIBLE	50	15	60	70	24	60
PIC	***22***	***UP***	***18.42***	***18.58***	***0.16***	***General***	***FLEXIBLE***	***72***	***10***	***38 or 50***	***65***	***29***	***60***
KNO	229	UP	15.08	19.27	4.19	General	FLEXIBLE	54	26	60	72	23	60
WYA	30	UP	17.50	24.56	7.06	Primary	JOINTED CONCRETE	79	14	40	74	21	70, 77, 90, 100, or 110
MAH	76	DOWN	6.95	8.65	1.70	Primary	JOINTED CONCRETE	78	11	40	74	21	70, 77, 90, 100, or 110
MAH	711	UP	0.37	2.05	1.68	Primary	JOINTED CONCRETE	84	10	40	71	24	70, 77, 90, 100, or 110
HAM	***275***	***UP***	***36.58***	***37.51***	***0.93***	***Primary***	***JOINTED CONCRETE***	***86***	***9***	***40***	***74***	***21***	***70, 77, 90, 100, or 110***
GRE	***35***	***DOWN***	***0.00***	***1.12***	***1.12***	***Primary***	***JOINTED CONCRETE***	***70***	***24***	***60***	***71***	***24***	***70, 77, 90, 100, or 110***
MAH	422	DOWN	2.31	3.29	0.98	Primary	JOINTED CONCRETE	61	9	60	71	24	70, 77, 90, 100, or 110
GRE	***444***	***UP***	***7.91***	***8.16***	***0.25***	***Primary***	***JOINTED CONCRETE***	***88***	***1***	***0***	***72***	***23***	***70, 77, 90, 100, or 110***

Activity 60, overlay with repair, was the activity selected for a large majority of the projects. A significantly different activity for PCR and PCS was selected for 11 of the 47 sections. After considering section length, location, and travel time, the research team limited the site visit to six locations, shown in Table 3.1 in bold, italic font. Site visits were conducted over two days; September 30 and October 1, 2021. The results of the field trip are summarized below:

FAY-62-13.65. This flexible section is a curbed, 5 lane undivided road with two lanes in each direction and a turn lane in the middle located in the city of Washington Court House. The projected PCR was 69 with a structural deduct of 13. The projected PCS was 65 with a structural deduct of 29. Projected distresses are shown in Table 3.2.

Table 3.2 FAY-62-13.65 Distresses

Distress	PCR	PCS
Raveling	HO	HO
Patching	MO	
Debonding	LO	
Crack Sealing Deficiency	E	
Rutting	MF	LE
Wheel Track Cracking	MO	HO
Block & Transverse Cracking	HO	
Longitudinal Cracking	HO	MO
Edge Cracking		HO
Thermal Cracking		ME

Figure 3.1 is a typical view of the pavement. The wheel track cracking rated from the Pathview images is likely the block cracking. The inner lane was more distressed than the outer lane, with a longitudinal cracking, and accordance with ODOT procedures, likely the inner lane was rated by the PCR raters whereas the outer lane was rated by the Pathview. Thermal cracking was not observed on the section and the rutting and base failure typically associated with high severity wheel track cracking was not observed.

Figure 3.1 Typical Distresses on FAY-62-13.65

As shown in Table 3.1, the recommended activity based on PCR was activity 38, a fine graded polymer asphalt overlay or activity 50, asphalt overlay without repair. The recommended activity based on PCS was activity 60, asphalt overlay with repair. The OU research team did not observe areas needing structural repair.

FRA-317-18.54. This flexible section is a curbed, 5 lane undivided road with two lanes in each direction and a turn lane in the middle located in the city of Gahanna. The projected PCR was 84 with a structural deduct of 10. The projected PCS was 65 with a structural deduct of 28. Projected distresses are shown in Table 3.3.

Table 3.3 FRA-317-18.54 Distresses

Distress	PCR	PCS
Rutting	MO	ME
Wheel Track Cracking	LO	MO
Block & Transverse Cracking	LF	
Longitudinal Cracking	HO	MO
Edge Cracking		HO
Thermal Cracking	MO	ME

Figure 3.2 is a typical view of the pavement. Cracks were sealed. Debonding and patching were observed at the manhole locations. Thermal cracking were also observed however, the rutting and base failure typically associated with high severity wheel track cracking was not observed.

Figure 3.2 Typical Distresses on FRA-317-18.54

As shown in Table 3.1, the recommended activity based on PCR was activity 0, do nothing. The recommended activity based on PCS was activity 60, asphalt overlay with repair. The research team did not observe any areas needing structural repair.

PIC-22-18.42. This section is a 38' wide roadway with one lane in each direction and a turn lane in the middle located in the city of Circleville. The ODOT straight line diagram for this section indicates 28' of the width is flexible pavement and 10' of the width is composite. The section was rated as a flexible pavement. The projected PCR was 72 with a structural deduct of 10. The projected PCS was 65 with a structural deduct of 29. Projected distresses are shown in Table 3.4.

Table 3.4 PIC-22-18.42 Distresses

Distress	PCR	PCS
Raveling	HO	HO
Crack Sealing Deficiency	F	
Rutting	LE	LE
Wheel Track Cracking	LO	MF
Block & Transverse Cracking	LF	
Longitudinal Cracking	HF	MO
Edge Cracking		HO
Thermal Cracking	ME	ME

Figure 3.3 is a typical view of the pavement. There was fairly good agreement between the PCR and PCS ratings. The medium severity wheel track cracking rated by the PCS is likely what appears to be a widening crack in Figure 3.3

Figure 3.3 Typical Distresses on PIC-22-18.42

As shown in Table 3.1, the recommended activity based on PCR was activity 38, a fine graded polymer asphalt overlay or activity 50, asphalt overlay without repair. The recommended activity based on PCS was activity 60, asphalt overlay with repair. The OU research team did not observe areas needing structural repair.

GRE-35-0.00. This jointed reinforced concrete section is the westbound two lanes of a divided four lane limited access freeway east of Dayton Ohio. The projected PCR was 70 with a structural deduct of 24. The projected PCS was 71 with a structural deduct of 24. Projected distresses are shown in Table 3.5.

Table 3.5 GRE-35-0.00 Distresses

Distress	PCR	PCS
Longitudinal Joint Spalling	MO	MO
Patching	HO	
Faulting	HO	LE
Transverse Joint Spalling	LO	HO
Transverse Cracking (Plain Concrete)		HE
Pressure Damage	O	
Transverse Cracking (Reinforced Concrete)	ME	
Longitudinal Cracking		ME
Corner Breaks	LO	

The typical slab on this section had one or two failed transverse cracks as shown in Figure 3.4. The section also had cracking at the joint, shown in Figure 3.5, which is typical of the bottom up deterioration commonly called “tenting”. Longitudinal cracking was observed but extensive extent was not.

Figure 3.4 Typical Failed Transverse Crack on GRE-35-0.00

Figure 3.5 Failing Joint on GRE-35-0.00

As shown in Table 3.1, the recommended activity based on PCR was activity 60, asphalt overlay with repair. The recommended activity based on PCS was activity 70, crack and seat; activity 77 rubblize and roll; activity 90, unbonded overlay; activity 100, new flexible pavement; or activity 111, new rigid pavement. Based on the number of failed transverse cracks and failing joints, a major rehabilitation may be more economical than the repair and overlay activity.

HAM-275-36.58. This jointed reinforced concrete section is the southbound lanes of a divided six lane interstate on the east portion of the Cincinnati outerbelt. The projected PCR was 86 with a structural deduct of 9. The projected PCS was 74 with a structural deduct of 21. Projected distresses are shown in Table 3.6.

Table 3.6 HAM-275-36.58 Distresses

Distress	PCR	PCS
Longitudinal Joint Spalling	LO	LO
Patching	LO	
Faulting	LO	MO
Transverse Joint Spalling	LO	HO
Transverse Cracking (Plain Concrete)		HE
Transverse Cracking (Reinforced Concrete)	MO	
Longitudinal Cracking		LF
Corner Breaks	LO	

Figure 3.6 is a corner break in the middle lane and Figure 3.7 are spalled joints in the middle and outer lanes. Corner breaks were not observed in the outer lane. As with FAY-62-13.65, the ODOT raters likely rated the middle lane in accordance with ODOT procedure of rating the lane with more distress, and the outer lane was rated by the Pathview equipment.

Figure 3.6 Corner Break on HAM-275-36.58

Figure 3.7 Joint Spalling and Repairs on HAM-275-36.58

As shown in Table 3.1, the recommended activity based on PCR was activity 40, concrete pavement restoration (CPR). The recommended activity based on PCS was activity 70, crack and seat; activity 77, rubblize and roll; activity 90, unbonded overlay; activity 100, new flexible pavement; or activity 111, new rigid pavement. The OU research team did not observe any distresses which would warrant a major rehabilitation on this section.

GRE-444-7.91. This jointed reinforced concrete section is a 5 lane undivided road with two lanes in each direction and a turn lane in the middle at the interchange with I-675 just northeast of the city of Fairborn. The projected PCR was 88 with a structural deduct of 1. The projected PCS was 72 with a structural deduct of 23. Projected distresses are shown in Table 3.7.

Table 3.7 GRE-444-7.91 Distresses

Distress	PCR	PCS
Longitudinal Joint Spalling	MO	LO
Patching	LF	
Faulting		LE
Transverse Joint Spalling	LO	MO
Transverse Cracking (Plain Concrete)		HE
Pressure Damage	O	
Transverse Cracking (Reinforced Concrete)	LO	
Longitudinal Cracking		ME

Figures 3-7 through 3-9 show distresses observed during the field visit. The pavement transitions from two lanes to five lanes at the beginning of this section. The longitudinal cracking rated by PCS is likely the longitudinal joints in the transition area, shown in the Google image in Figure 3.10.

Figure 3.7 Patched Longitudinal Spalling, GRE-444-7.91


Figure 3.8 Joint Spalling, GRE-44-7.91

Figure 3.9 Patching, GRE-444-7.91

Figure 3.10 Longitudinal Joints within the travelled lanes (Google Maps, 2021)

As shown in Table 3.1, the recommended activity based on PCR was activity 0, do nothing. The recommended activity based on PCS was activity 70, crack and seat; activity 77, rubblize and roll; activity 90, unbonded overlay; activity 100, new flexible pavement; or activity 111, new rigid pavement. The OU research team did not observe any distresses which would warrant a major rehabilitation on this section. However, most of the repair were asphalt, which are temporary. Should funds be available, replacing the asphalt repair with concrete would help preserve the pavement and provide a better ride to the public.

In summary,

- On flexible pavements, PCS procedure will rate edge cracking on pavement with a pavement shoulder or curb, which is not rated when using the PCR procedure
- The decision trees for PCS recommend major rehabilitation for most jointed concrete pavements. The field survey showed many of these sections can be rehabilitated using a lesser treatment.
- The Pathway van collects the images from the outer lane on the four lane and Interstate system. The PCR raters rate the lane with the higher distress, which could be a lane other the outer lane. When the inner lanes are more distressed due to construction sequence, widening, mill and fill rehabilitation, there can be a significant difference in the distresses rated.

Appendix 4: Models and Data

Identifying Outliers

Table 4.1: Outlier selection criteria and impacted data.

Possible Cause of Outlier	Criteria	Percent of Sections
Not Collected, Pathview error, maintenance, or reconstruction	No distresses in automated data, but PCR < 100	9.9%
Maintenance or reconstruction between automated collection and PCR rating	PCR > 95, PCS < 80, flexible or composite*	3.6%
Maintenance or reconstruction between PCR rating and automated collection	PCR < 90, PCS >95, flexible or composite*	14.8%
	Total	**28.3%**

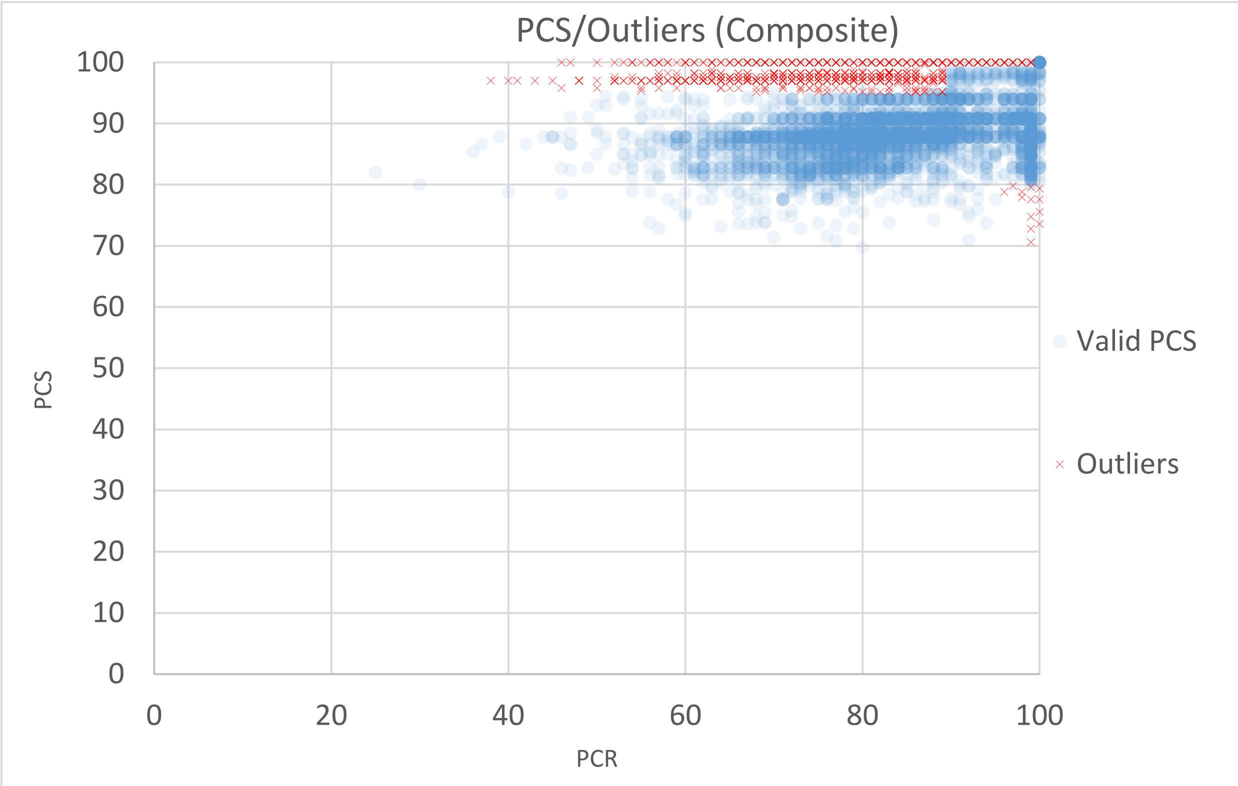


Figure 4.1: Scatter plot comparing PCS and PCR with outliers matching criteria marked for composite pavement.

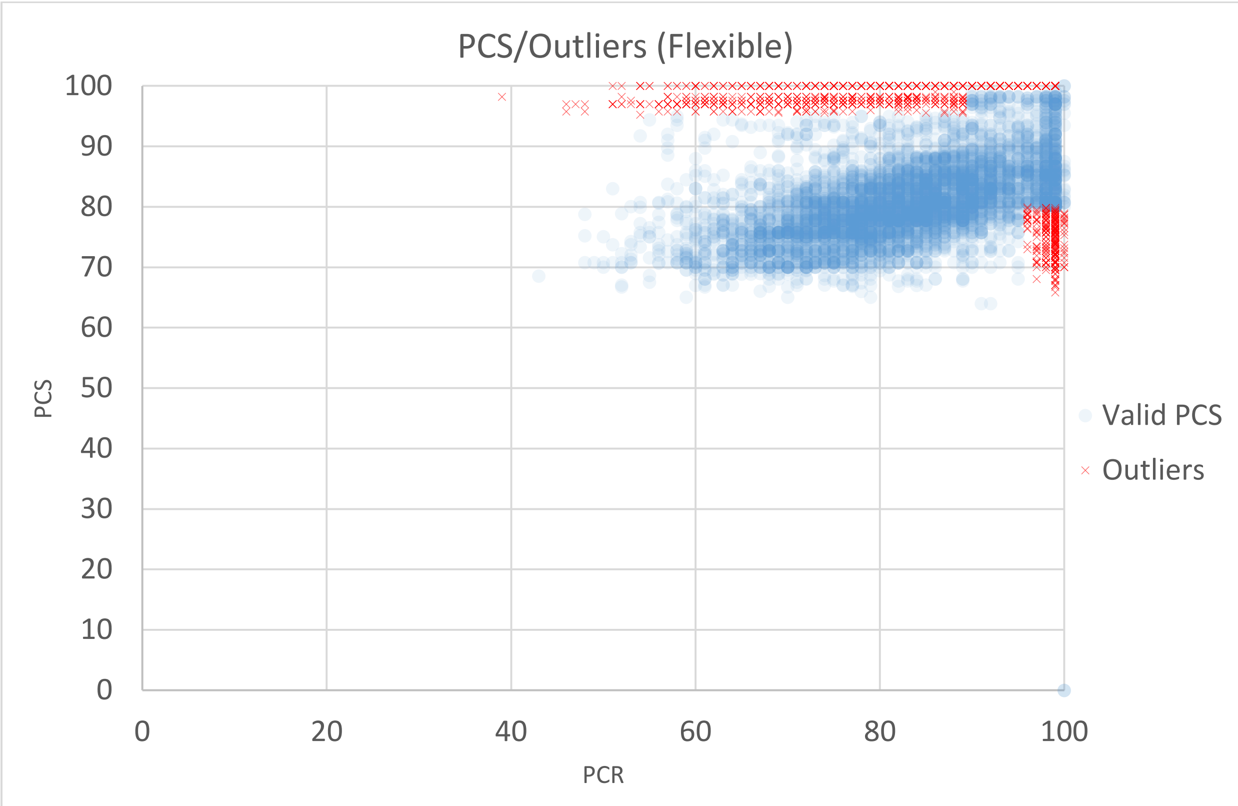


Figure 4.2: Scatter plot comparing PCS and PCR with outliers matching criteria marked for flexible pavement.

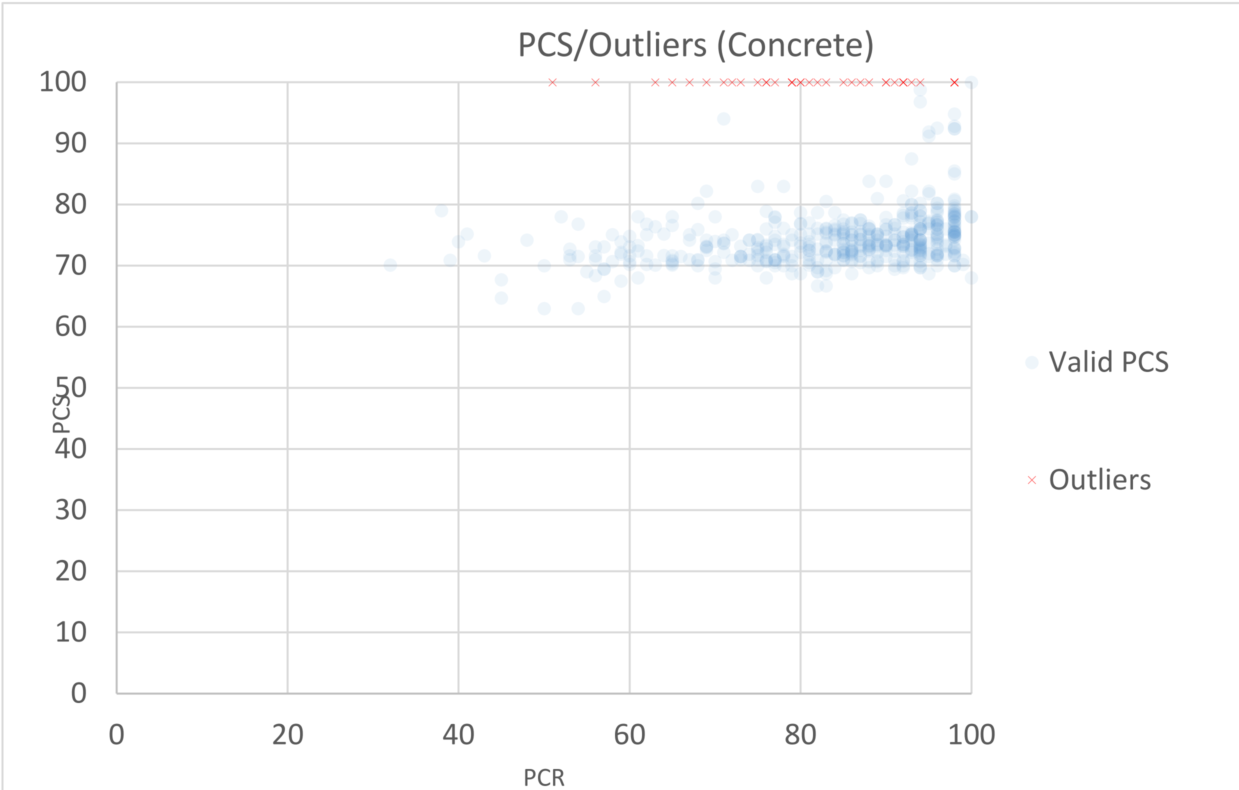


Figure 4.3: Scatter plot comparing PCS and PCR with outliers matching criteria marked for concrete pavement.

PCI Comparisons

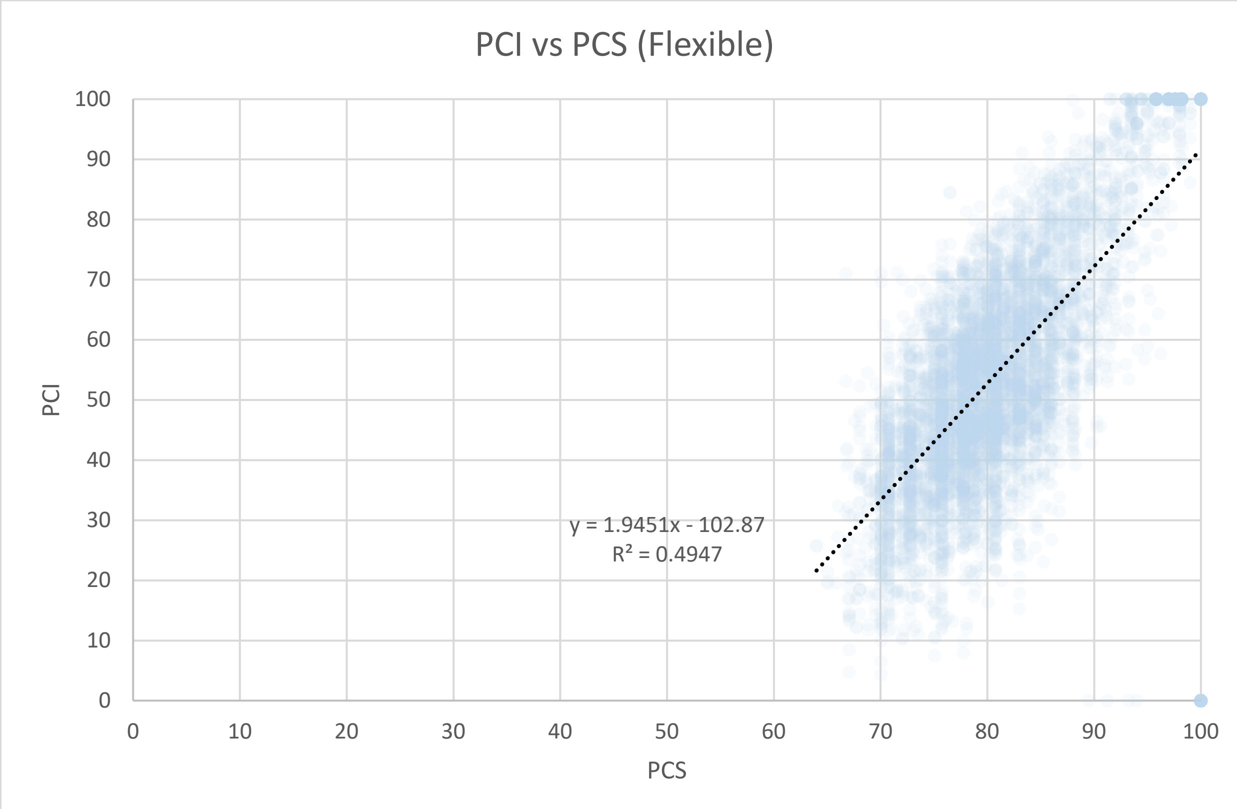


Figure 4.4: Scatter plot comparing automated PCS and automated PCI scores for flexible pavements.

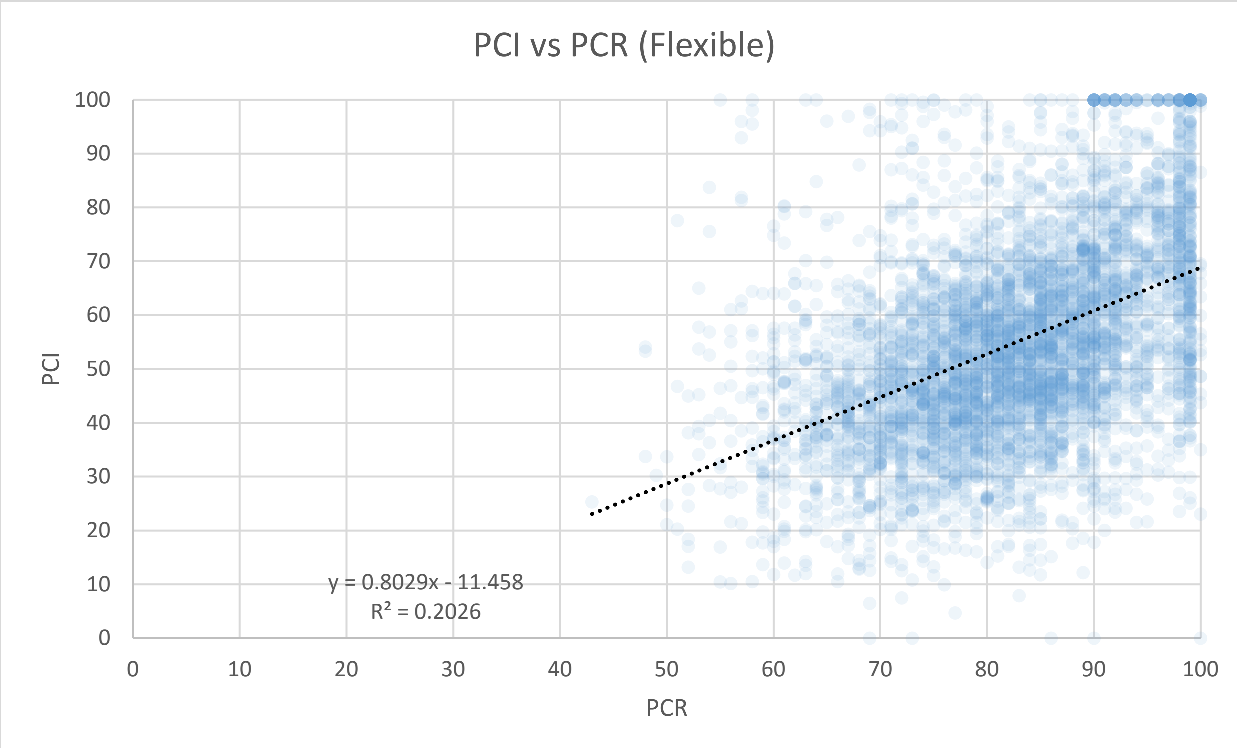


Figure 4.5: Scatter plot comparing manual PCR and automated PCI scores for flexible pavements

Regression Models

Table 4.2: Baseline PCS decision outcomes

Flexible	Sections	Percent
Total	5166	100%
Same Bin	2803	54%
Same Activity	3116	60%

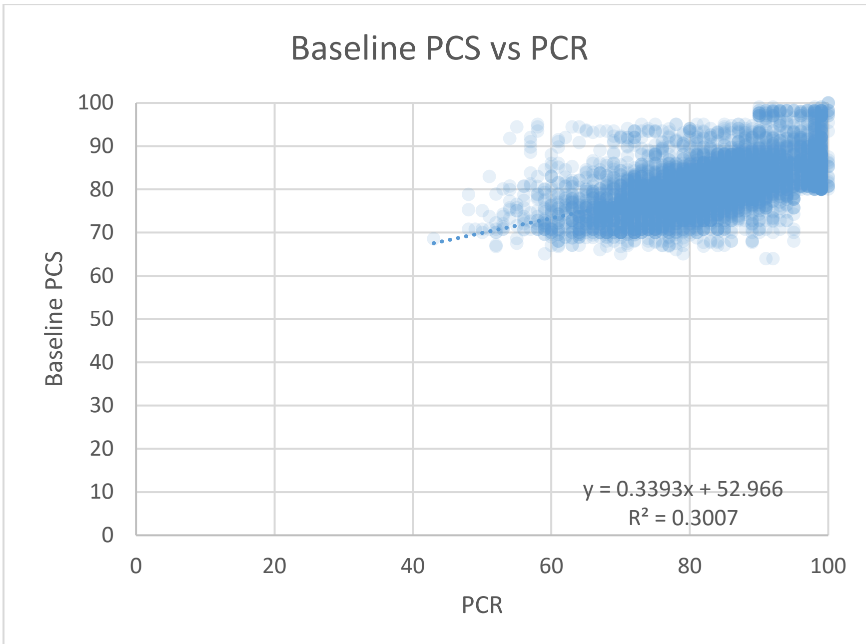


Figure 4.6: Scatter plot comparing manual PCR and automated PCS scores using the baseline PCS model.

Table 4.3: Regressed PCS decision outcomes

Flexible	Sections	Percent
Total	5166	100%
Same Bin	3082	59%
Same Activity	3383	65%

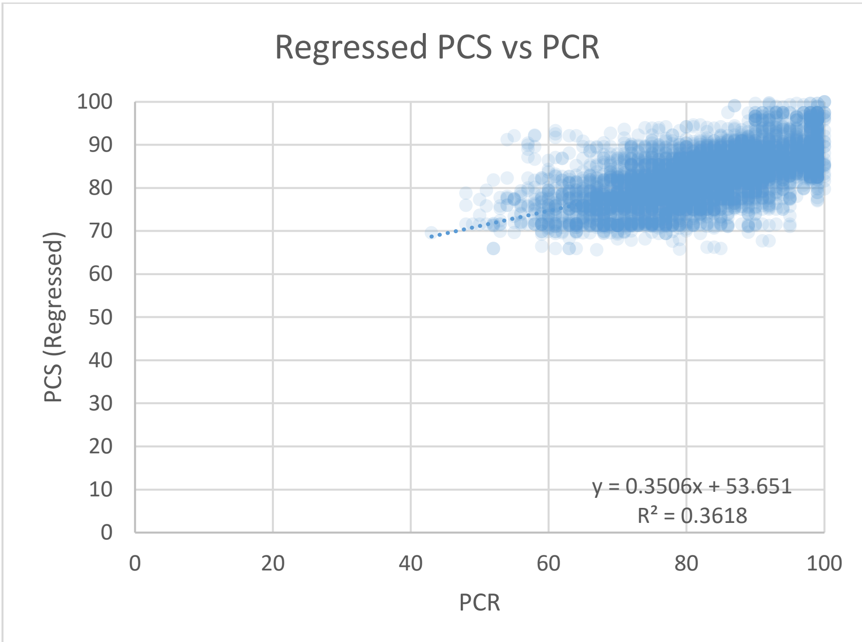


Figure 4.7: Scatter plot comparing manual PCR and automated PCS scores using the regressed PCS model.

$$PCS = .3506 * 80 + 53.651$$
$$PCS = 81.699$$

Equation 4.1: Calculation of new PCS threshold from best fit line

Table 4.4: Regressed PCS decision outcomes with modified thresholds

Flexible	Sections	Percent
Total	5166	100%
Same Bin	3077	59%
Same Activity	3381	65%

Bridge/Structure Exclusions

Table 4.5: PCS comparison between bridges included and excluded

	Baseline	Bridges Removed
Average	88.04	88.05
Median	87.8	87.8
Std. Dev.	8.73	8.73

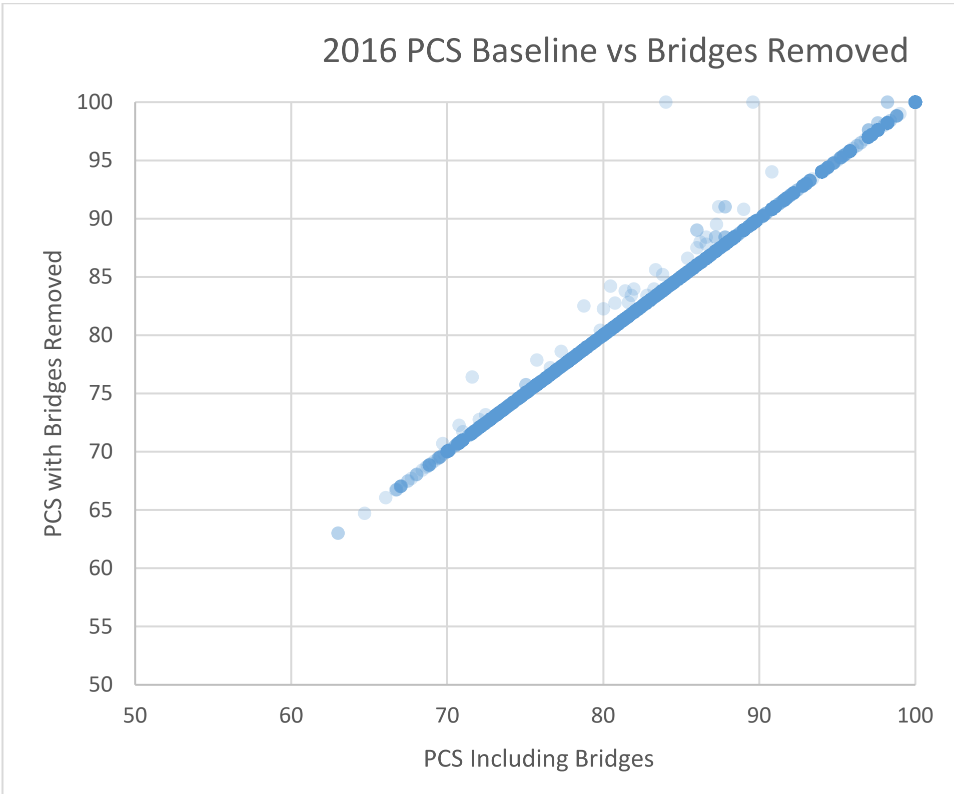


Figure 4.8: Scatter plot comparing PCS including bridges and other structures to PCS without them.

Faulting 2D vs 3D

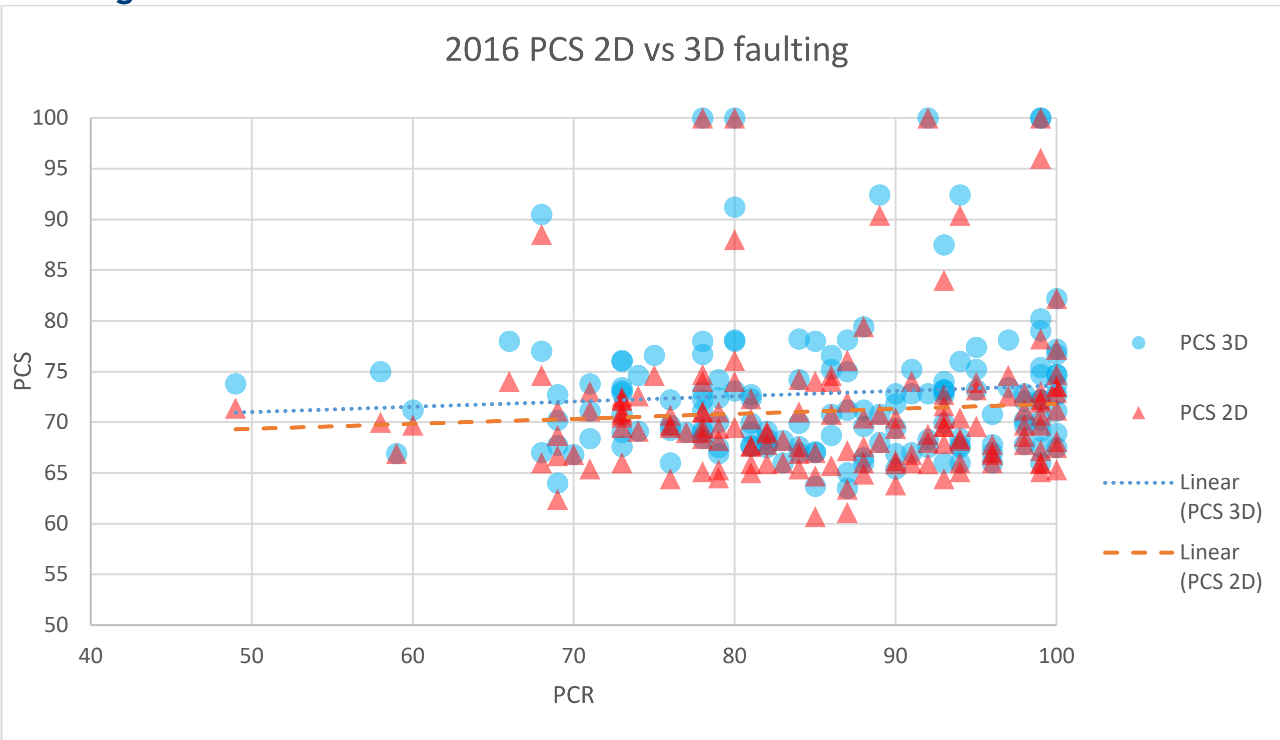


Figure 4.9: Combination plot comparing the correlation between PCS and PCR using 2D vs 3D faulting calculations for a sample set of data.

Appendix 5: Pavement Condition Score Manual

Process Overview

Pavement Condition Score (PCS) is a rating system that evaluates pavement using automated data while maintaining some level of parity to the Pavement Condition Rating (PCR) historically used by the Ohio Department of Transportation (ODOT). These evaluations are the middle ground between data collection and overall pavement management. This document covers the process of generating and extracting the necessary data from the data collection vendor's software, Pathview, as well as the steps needed to generate a rating, potential treatments, and deterioration models.

As part of the development of PCS, two macros were developed to aid calculations. One macro calculated the PCS rating, including score and distress calls, while the other generates decisions from this information. While PCS can be calculated manually, this manual also includes instructions to use these macros.

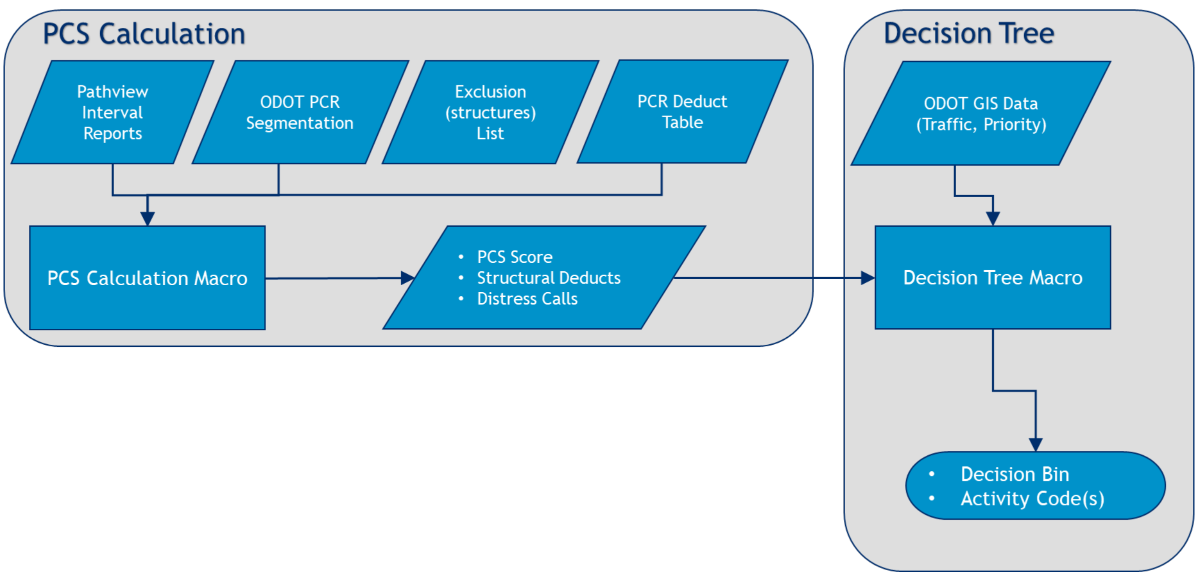


Figure 5.1: Flowchart of PCS calculation process.

Pathview Software Overview

Pathview II Road Condition Information System (Pathview) is a software package created by Pathways Services, Inc. to incorporate all data collected by their Pathrunner vehicles with pavement management segmentation. Images, 3d laser data, and various other measured data are all available and tied to the corresponding sections. Users can also process data with various tools and generate a variety of reports.

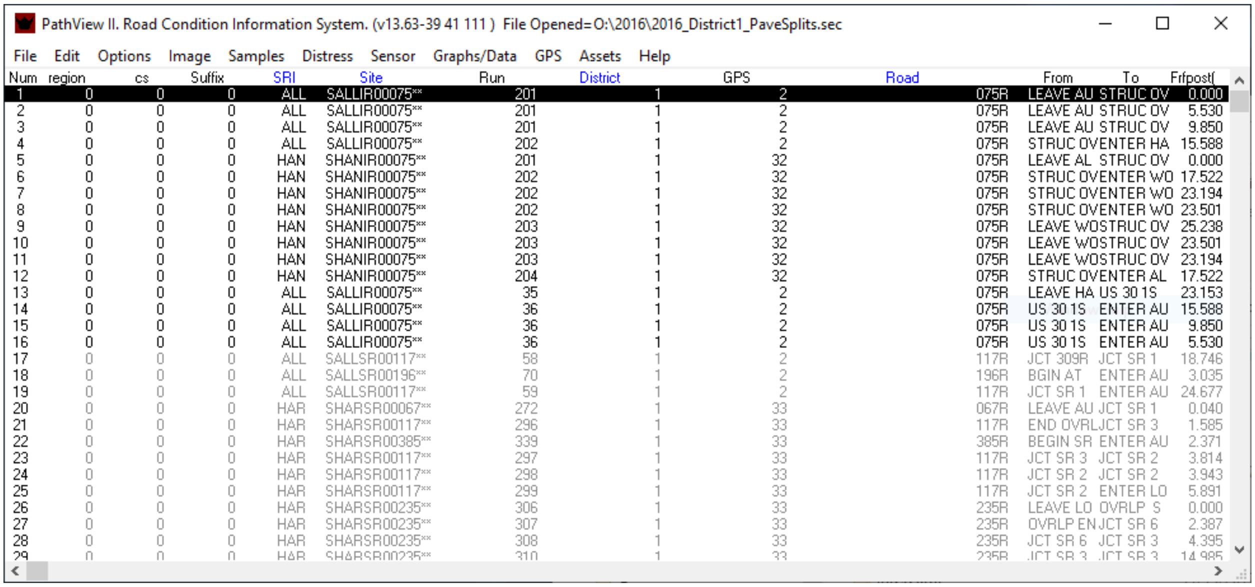


Figure 5.2: Main screen of Pathview software.

AutoCrack

Pathrunner vehicles equipped with 3d laser scan equipment produce raw data that must be further refined to detect cracking. The AutoCrack tool within Pathview analyzes this raw data to populate a distress features database with distresses. These distresses are not classified and are only marked as the presence of a distress with some measured characteristics.

This process must be done on all data that will be used for PCS ratings. Processing the whole data collection year can take months.

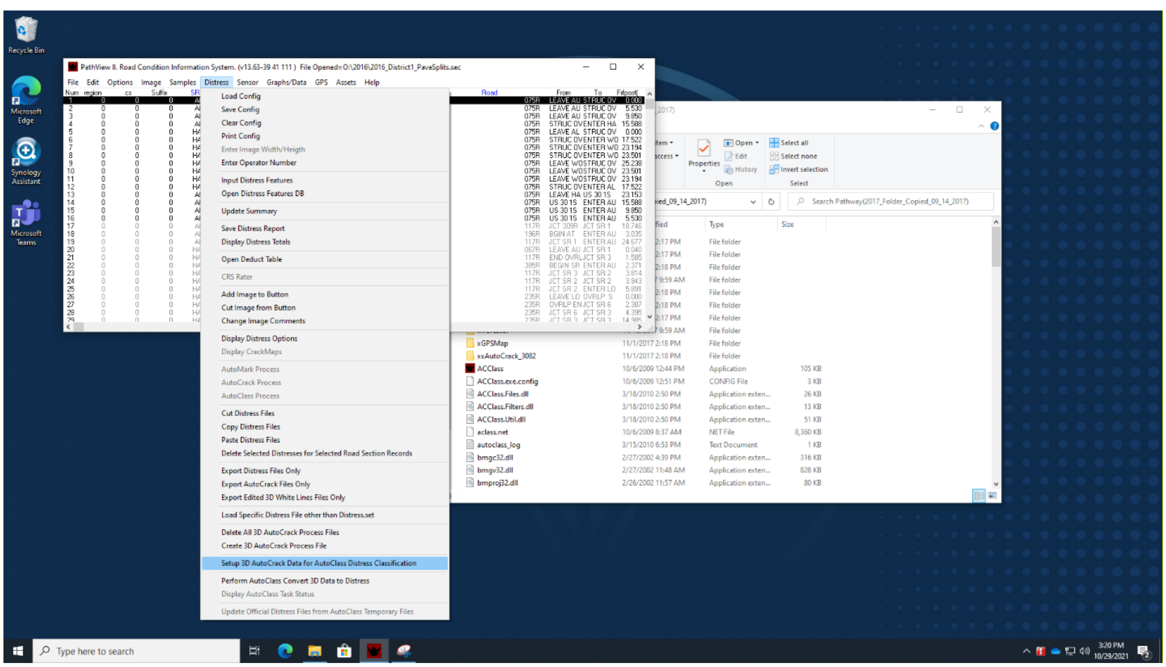
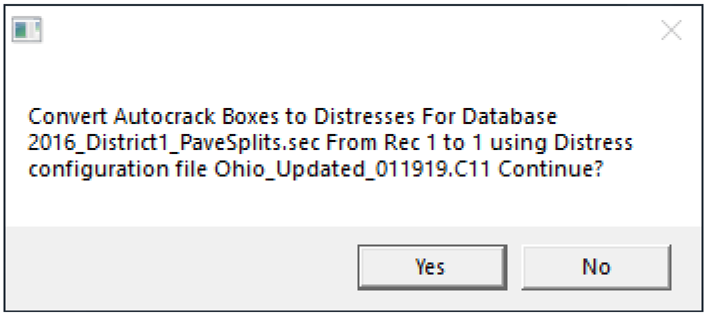
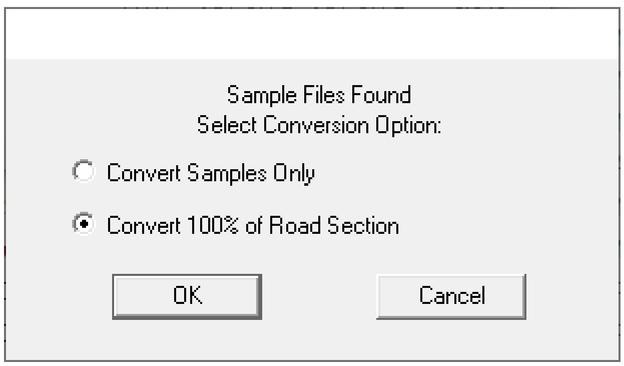


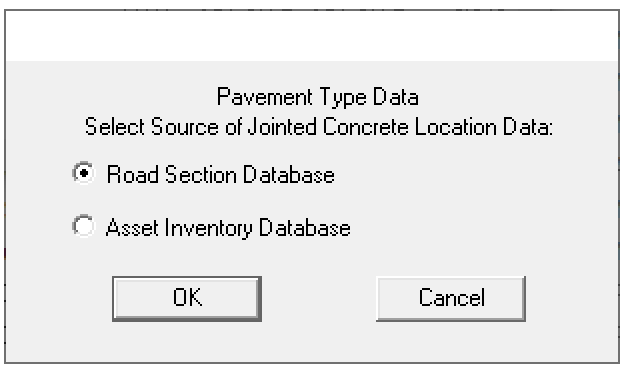
Figure 5.3: Screenshot showing the location of AutoCrack processing

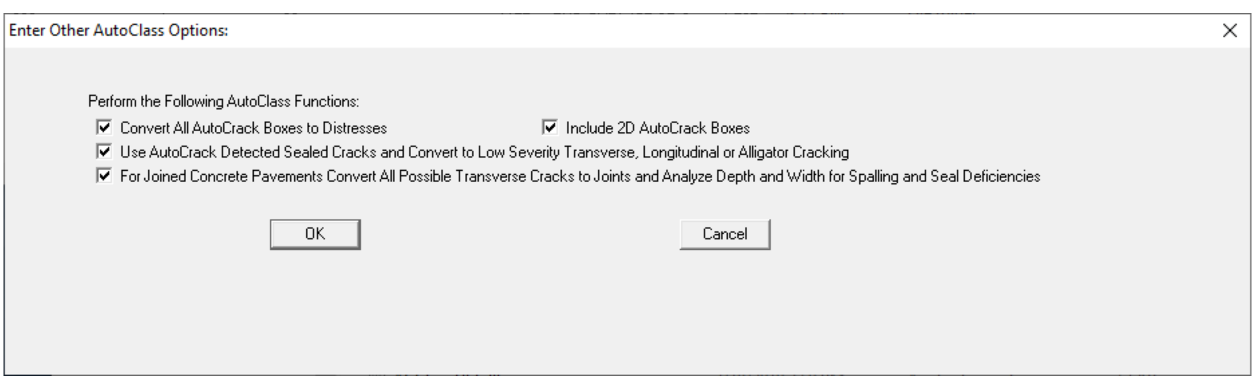
AutoClass

Once the distress features database is populated by AutoCrack, the AutoClass tool is ran to classify the identified distresses into type and severity. The classifications are done in accordance with settings defined by a .c11 file developed for ODOT by Pathway Services, Inc. This process can take several weeks to classify all distresses identified in a data collection year and must be completed for all data used for PCS rating.





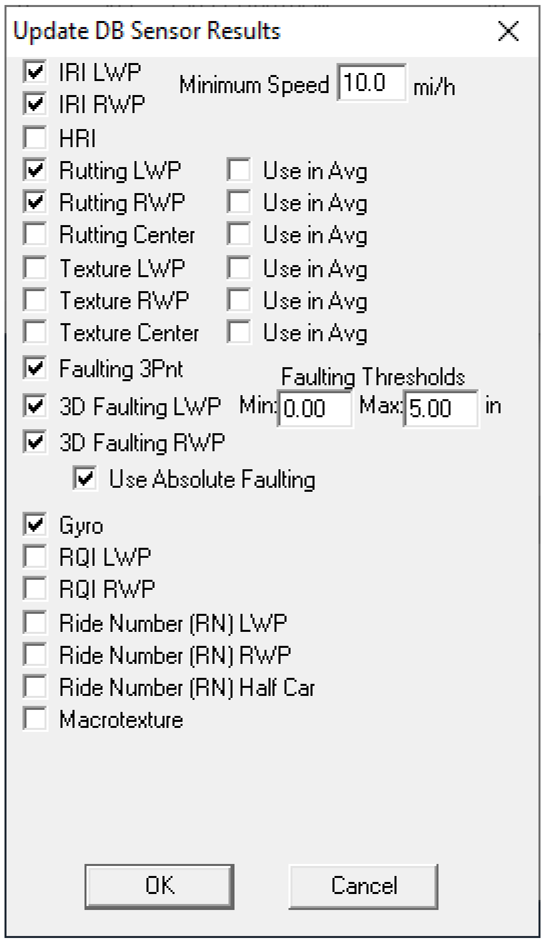




Updating Summary

Additional steps must be taken after distresses have been classified by AutoClass. First, a process to calculate faulting on all identified joints must be completed. While this process will calculate faulting, it will not automatically update the totals for each segment.

After all other tasks are complete in the software, a final step is required to update the totals for faulting, rutting, and IRI. This simple process just pulls all the data to the segments to prepare them for generating reports.



Generating Reports

The main source of data for PCS calculations is a distress report from Pathview. These reports are generated using an interval of 528 feet (0.1 miles/160.9344 meters) for the purposes of PCS calculation.

Required Headers

Before generating a report, several fields must be selected in Pathview by control-clicking the corresponding header. Selected headers are highlighted with blue text. Each of these is essential to the PCS calculation tool to properly identify intervals reported and match them to segmentation and exclusions.

Table 5.1: List of required headers that must be selected in Pathview for reports.

Required Header
SRI
Site
District
Road
Begin(mi)
End(mi)
Len(ft)
Set
Start-Image

Distress Quantities

When generating a report, Pathview will prompt the user to mark which properties of each distress type to report, such and length, width, an area. The PCS calculation macro will require specific properties of each distress type to be able to compute PCS.

Calculating PCS

Distress Definitions

Keeping compatibility with historical data, PCS uses the same definitions for distress types, severities, and extents as Pavement Condition Rating with a few exceptions to account for how data is reported by Pathview software.

Assumptions

To convert Pathway's distress data into a PCS rating, the following assumptions are considered:

1. Severity evaluations done by the Pathview software are correct and in line with existing practices.
2. Segmentation divides the pavement into sections with consistent pavement types and general condition.
3. Transverse cracks are full lane width.
4. The overall average spacing of transverse cracks is used to determine extent.
5. Twelve feet was used as the default lane width.
6. All transverse cracking is treated equally.
7. Segments containing multiple severities of the same distress have extent assigned to each severity level. Only the highest total deduct from the combination of extent and severity is reported.
8. When two severity/extent combinations have the same deduct value, the higher severity combination is reported. For example, if a segment has both ME and HO and both have a deduct value of 3, HO will be reported on the sheet.

9. “UP” on the PCR segmentation sheet is considered as Ascending Milepost, and “DOWN” is considered as Descending Milepost when differentiating between segments collected in both directions.
10. Patching and Pothole distresses are assigned deduct values based only on extent. Note: Pathview’s output contains columns for Patching and Potholes but does not detect them reliably.
11. Intervals from the interval report are only considered part of a PCR segment if their starting milepost is within the segment.
12. Intervals with more than 25% of the interval excluded due to structures and other exclusions are discarded entirely.

Extent Assignment

Because the severity was considered correct from the Pathview software, a simple conversion was used to map each distress output into a severity rating used by the PCR manual (L, M, or H). To reach a final rating for each distress, and subsequent deduct value, the extent had to be determined. Given that Pathview outputs values for each severity level, each must be evaluated for extent and given a deduct value. Only the highest deduct value is considered for each distress type for each segment.

The extent rating (O, F, or E) is determined by comparing criteria to the bounds presented on the “Deducts” sheet. The MedLowerBound and MedUpperBound are the inclusive limits of extent used for “Frequent” rating. Each type of distress has slightly different units for these bounds, as noted below. However, all extent ratings are calculated by converting the data into the same units as these bounds, and then comparing them. For example, if the lower and upper bounds for raveling are 20 and 50 percent of pavement with distress, then the raveling area will be converted into a percent of the segment area and compared to the limits.

$$Value < LowerBound = Occasional$$
$$LowerBound \leq Value \leq Upperbound = Frequent$$
$$UpperBound < Value = Extensive$$

For each type of distress presented by Pathway’s process, the extent was calculated using one of the following methods:

Length-Based Distress (Longitudinal Cracking):

According to the ODOT 2006 PCR manual, extent for longitudinal cracking was based on the feet of cracking present per 100’ of the sample unit. This can be expressed as the length of longitudinal cracking as a percent of the segment length.

$$\frac{TotalCracking}{SegmentLength} x\, 100 = ExtentPercent$$

Average Spacing Distress (Transverse Cracking):

Given the total width of transverse cracking, dividing by the lane width yields an estimated count of cracks (see Assumption 3). Dividing the total segment length by the estimated crack count results in an estimated average crack spacing (see Assumption 4). If the actual crack spacing is available, it should be used instead of the estimate.

$$\frac{TotalCracking}{LaneWidth} = EstimatedCount$$

$$\frac{SegmentLength}{EstimatedCount} = EstimatedAverageSpacing$$

Area-Based Distress:

The extent of an area-based distress, such as raveling, is determined by the percent of the segment's total area that is impacted by the distress. Given a total area of distress from Pathview's output, dividing by the total area and multiplying by 100 gives the percent of total area. The total area of the segment is based on the segment length from the PCR segmentation and the lane width (which is assumed to be 12' if no other data is available).

$$\frac{TotalDistressedArea}{SegmentLength\ x\ LaneWidth}\ x\ 100 = PercentDistressed$$

Wheel Path Length Distress:

Wheel track cracking and other distresses related to the length of the wheel path have their extent calculated based on the percent of total wheel path length in the segment (twice the total segment length). It is a simple calculation of the total distress length divided by twice the segment length times 100.

$$\frac{TotalCracking}{2\ x\ SegmentLength}\ x\ 100 = PercentOfWheelpath$$

Count per Mile Distress:

Distresses such as potholes are given extent based upon the total count per mile of the segment. Because SegmentLength is already converted into feet within the code, the value in count per feet must be converted by multiplying by 5280 feet per mile.

$$\frac{TotalCount}{SegmentLength}\ x\ 5280 = CountPerMile$$

Count per mile type distresses don't have a severity assigned by Pathview software. Only the Extent is used to assign a deduct value. To arrive at the deduct value, the extent's deduct multiplier is multiplied by the full deduct weight.

Note that when using the PCS calculation tool, MedLowerBound is the minimum spacing, even though lower spacing is a higher deduct. This is intentional to allow for logic to be reused and is accounted for in the tool. The lower and upper bounds should be set to the minimum and maximum limits of the "Frequent" extent values, respectively.

Rutting:

Rutting is not divided into severities by Pathview software, only the average rutting measurement is reported in the sensor report output for the interval specified. Using the tenth-mile interval report, a severity is determined for each interval and added to a total, in miles affected, for each severity. After totaling all of the intervals within the segment, the extent for each severity is assigned based on the percent of the total segment length affected by that severity of rutting.

For example, if a 2.31 mile PCS segment had 1.2, 1.01, and 0.1 miles of low, medium, and high severity rutting, respectively, the software would determine the three combinations of severity and extent as LE, MF, and HO. If this segment was a flexible pavement, HO would be assigned as it has the highest deduct value for rutting.

$$\frac{DistanceRutted}{SegmentLength}\ x\ 100 = PercentRutted$$

Note, that per the 2006 ODOT PCR Manual, rutting with a depth of less than 1/8” is not considered as a distress. Any interval with less than 1/8” rutting will not be counted/rated by the PCS conversion.

The manual also doesn’t specify whether the 3/8” bound between low and medium severity is inclusive/exclusive. Keeping consistent with the bounds used for extent calculations, the bounds for medium severity are considered as inclusive for the software, meaning 3/8” rutting is specifically a medium severity.

IRI & Rutting Summary:
Interval reports from Pathview’s software contain average IRI and Rutting for each interval. While the intervals are generally 0.1 miles, sections often have a remainder that is shorter than that interval. To properly account for this when averaging IRI and Rutting, segment length is used to create a weighted average.

$$\frac{\sum_{1}^{n} IRI_n * Interval_n}{TotalLength} = AverageIRI$$

Using the PCS Calculation Tool

Upon opening the PCS calculation workbook, a user interface will open that can be used to process reports from Pathview into PCS results. Should any calibrations to the deducts or exemptions be required, the user form must be closed first. To reopen the user form, save any changes and close then reopen the tool or use the “show user form” macro from the ribbon.

Inputs

The user form takes two main types of input and several that are optional. If any required inputs are not available, the tool will crash and require a restart.

A segmentation source workbook is required that defines the pavement sections to be rated. This workbook should be in the same format as the PCR history workbook, with each year of data on its own worksheet. Clicking the ellipsis next to this field will open a prompt that allows the user to select a source. Once a source is selected, an additional field will appear to prompt the user to select which sheet on the segmentation workbook to use. Data from this sheet, such as manual PCR ratings, will be copied to the resulting output workbook for reference.

Output path is optional and will automatically save the output workbook to the selected location and filename. The ellipsis button next to the field will open a Window's prompt for the user to select a save location and filename. Should the field be omitted, the output workbook will simply open and be unsaved once processing is complete.

One or more interval reports from Pathview software are required. Clicking the "Add Interval Reports" button will open a Windows form that allows the user to select one or more text files to process. Interval reports should only be processed if they match the segmentation source collection year. Only intervals within these reports that fit within the segmentation will be processed.

Given the nature of how Excel handles macro processing, once processing begins Excel will be locked into processing and may not respond properly to user input. A prompt will appear when processing is complete.

Deducts Sheet

The deducts sheet is the main calibration table for the tool. For convenience, all PCR distresses are listed so any not currently reported by Pathview be added quickly if the software beings reporting them in the future. Rows for distresses not used for PCS may be omitted if the user wishes to remove them.

Distresses are grouped by pavement types by defined ranges. Any future additions to the PCS distress list must be included in these defined ranges to be processed by the tool. Each row contains information described in the following table.

Table 5.2: List of fields in the deducts sheet and their descriptions.

Header	Definition
Pavetype	Pavement type must be one of the following: FLEXIBLE, COMPOSITE, or JCP.
PathwayCode	This is the main portion of the header Pathview reports in an interval report. Also referenced on HeaderNames worksheet.
Code	The PCR code related to the distress
Description	Distress name as given in PCR, for user reference
Weight	Maximum PCS deduct value assigned to the distress
Sev L	Deduct multiplier for low severity distress
Sev M	Deduct multiplier for medium severity distress
Sev H	Deduct multiplier for high severity distress
Ext O	Deduct multiplier for occasional extent of distress
Ext F	Deduct multiplier for frequent extent of distress
Ext E	Deduct multiplier for extensive extent of distress
LO	Calculated field for DSE deduct
LF	Calculated field for DSE deduct
LE	Calculated field for DSE deduct
MO	Calculated field for DSE deduct
MF	Calculated field for DSE deduct
ME	Calculated field for DSE deduct

Header	Definition
HO	Calculated field for DSE deduct
HF	Calculated field for DSE deduct
HE	Calculated field for DSE deduct
Type	Calculation method, as described above.
MedLowerBound	Minimum percent extent required for the distress to be rated as frequent
MedUpperBound	Maximum percent extent the distress can be before being called extensive
Structural	Marks a distress to be included in structural deduct. A “1” is included, blanks are not.

This sheet will also be copied to the resulting output workbook for reference.

HeaderNames
This sheet defines the exact header names to use from the Pathview interval reports for each distress and severity. The first column must match the PathviewCode column on the deducts sheet. Column B must be either “Low”, “Med”, “High”, “Count”, “Area”, or “Average”. These describe what type of data the PCS tool should be looking for in the defined column. The final column is the exact name used in the Pathview report for the distress.

This table serves as a lookup table for the tool and should only need edited if changes are made to Pathview software report. Any distresses added to the deducts sheet must be added to this sheet for the software to include them in the PCS calculation.

Exclusions
The “BridgeLookupTable” sheet is used to mark any exclusions required, mostly for bridges and other structures. An exclusion is defined by the route’s unique identifier (NLFID), the beginning centerline milepost, direction, and length. When processing intervals, the exclusions will be considered and any interval with 25% or more of the interval excluded will not be included in the final PCS calculation.

Outputs
The output of the PCS calculation tool is an Excel workbook with several worksheets. The primary worksheet is the PCS Evaluation, with the segmentation data as well the score computation, deduct values for each matching PCR distress code, average IRI, average rutting, and text versions of the distress calls. The Deducts sheet is copied from the PCS calculation tool with the settings used to process the data and may be modified in the output workbook to adjust distress deducts used in calculations on the PCS Evaluation sheet. The PCR data for the sections processed is included in an additional sheet. If the user selected raw outputs on the user form, it will also be included as a worksheet.

Adjusting the Regression Model
Because the PCS score result on the output sheet is a formula referencing the deducts sheet, a regression adjustment can be conducted using this sheet. An additional field must be added on the PCS result sheet to compute the squared error of each section compared to the corresponding PCR score. On the deducts sheet, a cell must contain the sum of the created column.

An Excel add-in, such as Solver, can be targeted to perform regression analysis with the goal of minimizing the sum of squared error via adjusting the maximum deduct value of the distresses. Care should be given to the minimum and maximum values set in the add-in. With unconstrained variables, some values may trend to zero or exceptionally high numbers. In these cases, it is up to engineering judgement to apply some restriction on the variables to keep in line with current practices.

Once a satisfactory solution is generated by regression, the deducts sheet may be copied to the PCS calculation workbook to generate further PCS results with the regressed coefficients.

Using the Decision Tree Macro

The decision tree macro workbook includes several worksheets as information sources as well as the main input sheet which will require data copied from the PCS calculation output.

Table 5.3: List of worksheets in the decision tree macro and their descriptions.

Worksheet	Description
Input	Contains the input PCR data, AADT, and segment data for ODOT roads. Column J through M are formulas.
AADT_Lookup	A lookup table that contains data from ODOT GIS, must be updated if changes in general traffic volume have occurred since 2016.
Distress Checks	Defines the distress checks for the macro to use. Copied from the ODOT decision trees. Changes here will be reflected the next time data is processed.
Activity Codes	For reference, the ODOT activity codes for individual repairs/maintenance activities.
Distress Codes	For reference, the ODOT PCR distress codes by pavement type. Copied from ODOT PCR manual.

Inputs

Data copied from the PCS calculation spreadsheet is the primary input required for the decision tree macro. The column names are identical to the PCS calculation sheet and follow a similar layout. The columns are detailed in the table below.

Table 5.4: List of fields in the input worksheet of the decision tree macro workbook and their descriptions.

Column Name	Column	Description
Dist	A	District number
Cou	B	County Abbreviation
Rt	C	Route number
Direction	D	Direction (UP or DOWN)
Begin	E	Starting Milepost
End	F	Ending Milepost
Length	G	Length in Miles
PCR	H	PCS or PCR Score
StrD	I	PCS or PCS Structural Deduct Total

Column Name	Column	Description
Date	N	(Optional) Data Collection Date/Year
Divided	O	D for divided road, U for undivided road
Pavement Type	P	Pavement type must be: COMPOSITE, JOINTED CONCRETE, or FLEXIBLE
Code_#	Q-AG	Distress rating for corresponding PCR code number. (LF, HO, etc.)
Nlf_Id	AH	Unique identifier for the route

Outputs

Once the required inputs are in the input sheet, running the ComputeAll macro (from View->Macros on the ribbon) will process all rows of data through the decision tree. Output will be populated in columns AI through AN and overwrite any existing data there. As with most Excel macros, Excel may be non-responsive until the macro has completed processing the full data set.

Output columns contain both the resulting decision bin and activity as well as additional information that was used analysis during development of the PCS methodology. The following table describes the output columns.

Table 5.5: List of output fields from the decision tree macro and their descriptions.

Column Name	Column	Description
DecisionTree	AI	Name of the decision tree used for this section (General, Priority, or Urban)
DecisionPath	AJ	A string of characters describing the path taken through the tree (0 for no, 1 for yes, etc)—used for development.
DecisionInputs	AK	A comma-separated list of inputs given to each node in the tree—used for development.
BinID	AL	The ID of the decision bin result.
Activity	AM	A list of activity codes within the bin (0 for Do Nothing)
Distress Check Triggers	AN	A list of distress checks performed and list of checked distresses that were present in the section.

Primary results are described by the BinID and Activity columns. However, the distress check column provides useful information that may be relevant to those making pavement management decisions. When data is present in this column, the macro evaluated a distress check as defined on the decision tree and Distress Checks sheet. In the case that no distress matched the check's criterion, only the name of the check will be present. When a distress check encounters one or more distresses the check is looking for, they will be listed after the check name in the format Code:Rating, such as 14:HE.

Because distress checks often trigger more extensive repairs, distresses called out in the distress check column are prime candidates for quality control review—especially if the section's result doesn't meet expectations.

Procedure Checklist

Step	Description	Completed
1. Quality Control: collected data	• Verify segmentation • Review pavement type • Check collection direction vs segmentation • Field verification section review	
2. AutoCrack	• Process all sections through Pathview's AutoCrack tool (long process) • <additional details needed from ODOT staff>	
3. AutoClass	• Ensure .C11 file is loaded in Pathview • Mark all records • Distress->Perform AutoClass • Ensure all required checkboxes are checked in accordance with the PCS manual • Finish prompt and begin processing (long process)	
4. Quality Control: distress features database	• Verify distresses were classified by AutoClass • Review field verification section(s) for correct classifications • Ensure joints were identified for jointed pavement	
5. Process Joints for Faulting	• Use Pathview's tool for evaluating joints for faulting. • This process will only work correctly if AutoClass identified joints.	
6. Update Section Summary	• Mark all records • Distress->Update Summary • If this process isn't completed, IRI, Rutting, and Faulting data will not be reported correctly.	
7. Generate Sensor Report	• Ensure required fields are selected (ctrl+click to select, highlighted with blue text) • Mark all records • Distress->Save Report • Ensure all checkboxes are checked according to the PCS Manual	
8. PCS Calculation Tool	• Select segmentation workbook • Select sheet within workbook with correct segmentation • Add interval report(s)	
9. Quality Control: compare with historical and maintenance records	• Identify sections that saw improvement in PCS year over year and compare with maintenance records • Compare all sections with historical PCS data and identify sections with drastic shifts in score for manual review	
10. Decision Calculation Tool	• Copy data from the PCS result sheet into the required columns • Run ComputeAll Macro from the ribbon	

Appendix 6: Questionnaire

To evaluate common industry practices, researchers sent a questionnaire out to several transportation agencies. Notes from various responses highlight mixed success in implementing automated systems, with several agencies either correcting or manually rating some distress. Several agencies noted that automated collection had some shortcomings, but felt they were achieving higher consistency between collection years than manual ratings.

Much like results discussed in this report, other agencies reported issues with composite and concrete pavement requiring additional manual effort than flexible pavements. Additionally, some agencies reported the need to manually rate some specific distresses that were not adequately reported by automation.

All agencies responding use semi- or fully-automated methodologies for HPMS reporting, which covers distresses automated detection methods seem to reliably detect. However, for pavement management purposes agencies were more inclined to add manual adjustment or ratings.

The impact of transitioning to more automation in pavement management has had mixed results among the agencies responding. Because of the variance in rating systems employed by the various agencies, it is difficult to discern how much an impact this change had on overall network average rating and whether such impacts are caused by the automation or by the differences with the original methodology. In most cases, verification is done during/after the transition by manual review of collected imagery and sensor data.

For the impact on pavement management decisions, agencies often reported the need to revisit or monitor the decision methodology as new automated data is collected. Some agencies noted that extra care was taken in selection of rehabilitation projects as the automated system may be causing a bias towards selecting more extensive maintenance activities. This same phenomenon was noted in this research.

An overall theme of responses often included ongoing efforts and continued research to bridge between the previous, manual methodologies and more automated methodologies. Several agencies are still in a transition phase where historical data from automated methods is being accumulated and analyzed to build better deterioration and decision models.

The questionnaire is included at the end of this section. Below are tables summarizing the responses.

Table 6.1: List of agencies responding to the questionnaire.

Agency	Responding	Agency	Responding
Alabama	Yes	Montana	Yes
Alaska	Yes	Nebraska	Yes
Arizona	No	Nevada	Yes
Arkansas	No	New Hampshire	Yes
California	Yes	New Jersey	No
Colorado	Yes	New Mexico	Yes
Connecticut	No	New York	Yes
Delaware	No	North Carolina	No
District of Columbia	Yes	North Dakota	Yes
Florida	No	Ohio	N/A
Georgia	No	Oklahoma	No
Hawaii	No	Oregon	No
Idaho	No	Pennsylvania	No
Illinois	Yes	Puerto Rico	Yes
Indiana	No	Rhode Island	Yes
Iowa	No	South Carolina	Yes
Kansas	Yes	South Dakota	Yes
Kentucky	Yes	Tennessee	No
Louisiana	No	Texas	Yes
Maine	Yes	Utah	Yes
Maryland	Yes	Vermont	No
Massachusetts	No	Virginia	No
Michigan	No	Washington	No
Minnesota	Yes	West Virginia	No
Mississippi	No	Wisconsin	No
Missouri	No	Wyoming	Yes

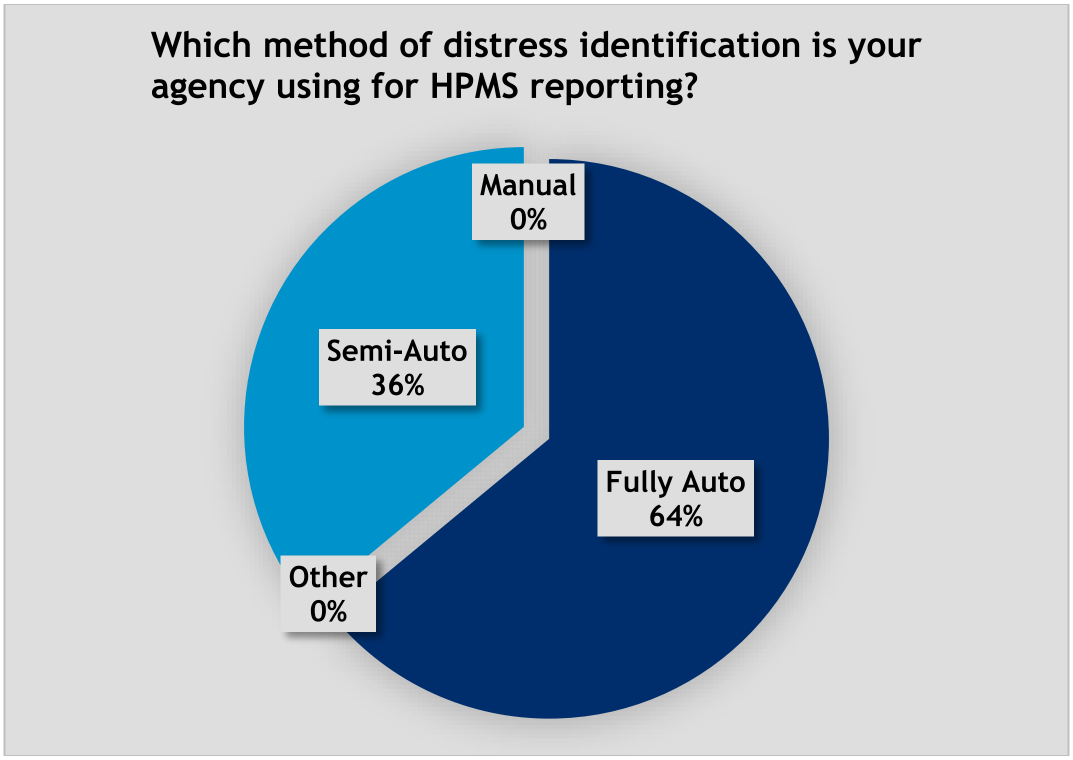


Figure 6.1: Responses to question 1 related to HPMS

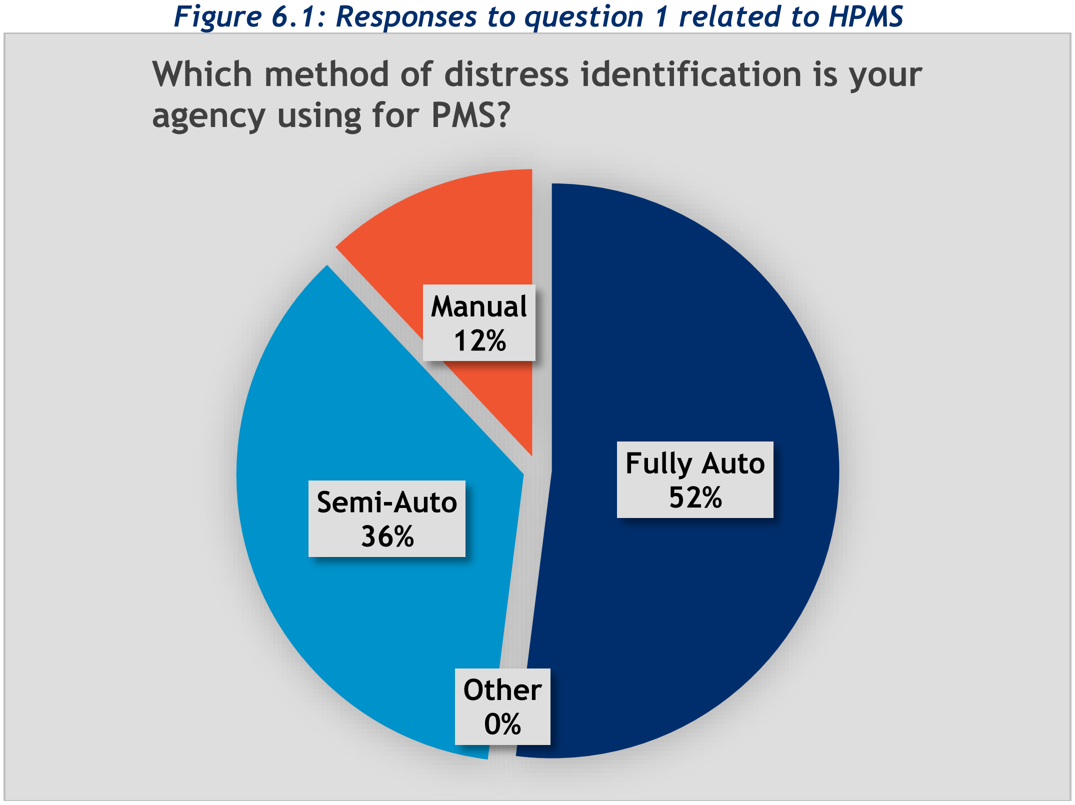


Figure 6.2: Responses to question 1 related to PMS

Table 6.2: Responses to question 2 of the questionnaire

If pavement distresses are combined to form an overall pavement condition rating/index/score, did fully- or semi-automated distress identification result in a higher or lower overall rating/index/score when compared with the manual ratings?		
Answer Options	Response Percent	Response Count
Higher	16	4
Lower	20	5
NA	56	14
Depends	8	2
Agency Response	**100**	**25**

Table 6.3: responses to question 3 of the questionnaire

What specific changes (removal, modification, addition) have you made to the distresses you rate because of the transition to automated pavement condition rating?		
Answer Options	Response Percent	Response Count
Added Distress	43	10
Removed Distress	35	8
Modified	43	10
Other	26	6
Agency Response	**100**	**25**

Table 6.4: Responses to question 4 of the questionnaire

What effect did the transition to fully- or semi-automated distress identification have on your Maintenance and Rehabilitation decision methods? How did you adjust for the differences?		
Answer Options	Response Percent	Response Count
Modifications to Decision Methods	43	10
New Decision Methods	4	1
No Changes	39	9
Other	13	3
Agency Response	**100**	**23**

Pavement Data Collection and Condition Rating Methods Questionnaire

Ohio Department of Transportation (ODOT) contracted ARA Inc. to develop a methodology to transition from a manual data collection based pavement management system (PMS), to an automated data collection based pavement management system. The project objectives include analyzing the automated roadway image data (Laser Crack Measurement System), developing a pavement condition score based on the automated distress data, and updating the pavement performance models and decision tree logic.

ARA has developed this questionnaire to gather relevant/available information to identify the current pavement data collection methodologies used by various states in the U.S., and the use of automated pavement data in the pavement management system.

For this survey the following definitions are used:

- **Fully-automated** pavement distress identification: All pavement distresses are identified and recorded through computer algorithms using images, lasers, sensors, etc., with little to no human intervention after configuration.
- **Semi-automated** distress identification: Some or all pavement distresses are identified and recorded by personnel viewing images in the office. Some distresses may be fully automated.
- **Manual** pavement distress identification: All pavement distresses are identified and recorded by foot-on-ground, windshield surveys, or similar methods.

Agency:
Contact:
Address:
Email:
Telephone:
Date:

1. Which method of distress identification is your agency using for the following? Please check all that apply. If “Other”, please describe below.

	Fully	Semi	Manual	Other
HPMS	☐	☐	☐	☐
Supplement to Manual Survey	☐	☐	☐	☐
Used in PMS	☐	☐	☐	☐
Other	☐	☐	☐	☐

____

____

2. If pavement distresses are combined to form an overall pavement condition rating/index/score, did fully- or semi-automated distress identification result in a higher or lower overall rating/index/score when compared with the manual ratings?

Higher ☐ Lower ☐ NA ☐

____

____

3. What specific changes (removal, modification, addition) have you made to the distresses you rate because of the transition to automated pavement condition rating? Please describe.

   Added Distresses: ______________________

   Removed Distresses: ______________________

   Modified Distress Definition: ______________________

   Other: ______________________

4. What effect did the transition to fully- or semi-automated distress identification have on your Maintenance and Rehabilitation decision methods? How did you adjust for the differences?

   Modifications to decision methods ☐ Completely new decision methods ☐ No changes ☐ Other ☐

   ____

   ____