Quality Improvement and Application of TDOT Pavement Management Systems (PMS) Data

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16. Abstract

Tennessee Department of Transportation (TDOT) established Pavement Management System (PMS) since 1980's. TDOT started to systematically collect roughness data since 1993 and distress data since 1998 and started using videotaping from 2002. Similar to many other agencies in the United States, TDOT utilized PMS to perform maintenance demand analysis based on which the budget allocation is determined. Furthermore, cost-effectiveness analysis of maintenance activities or preventative maintenance, prediction analysis of long-term pavement performance, and calibration of pavement design equations are conducted based on the content and accuracy of PMS data. The purpose of this research is to identify the current quality issues of PMS data and to establish the data quality management guideline by which a standard data production procedure can be followed.

The summary of results are as follows. Findings from the questionnaire indicated field validation/calibration of testing equipment is considered as the most selected steps before data collection. The survey also indicated that although some state DOTs have already implemented or have been developing data quality control procedure, there is no consensus on how to perform data quality control and assurance. The research team also systematically evaluated the data variability and its consequence on maintenance planning. The influence of data quality on maintenance planning varies in terms of current pavement conditions, how the pavement condition indices are defined, and how the maintenance and rehabilitation analyses are performed.

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EXECUTIVE SUMMARY

Tennessee Department of Transportation (TDOT) established Pavement Management System (PMS) since 1980's. TDOT started to systematically collect roughness data since1993 and distress data since 1998 and started using videotaping from 2002. Similar to many other agencies in the United States, TDOT utilized PMS to perform maintenance demand analysis based on which the budget allocation is determined. Furthermore, cost- effectiveness analysis of maintenance activities or preventative maintenance, prediction analysis of long-term pavement performance, and calibration of pavement design equations are conducted based on the content and accuracy of PMS data. The purpose of this research is to identify the current quality issues of PMS data and to establish the dataquality management guideline by which a standard data production procedure can be followed. Main research activities were summarized as follows,

1. The research team conducted a nationwide online survey to investigate the current practices on PMS data quality management. By reviewing the survey, the researchteam identified the general quality issues on PMS data.
2. The research team systematically investigated the current PMS data, including roughness data and distress data and established a framework of data quality management.
3. Variability analyses were performed to quantitatively evaluate the influence of data variability on pavement maintenance planning at network level. The data considered in these analyses included International Roughness Index, Rutting depth, distress extent and severity level.
4. The influence of maintenance activities on abnormal change of pavement condition data was investigated. The changes of pavement condition data due to the influence of maintenance activities are then identified. A Java based code was developed to construct the performance curve and determined analytical quality ofpavement condition data.
5. The difference of roughness data collected from different collection devices werecompared and evaluated. Field verification tests were also performed to evaluate the accuracy and reliability of roughness data collected by agency's devices and data provider's device through statistical analyses.
6. A practical procedure for quality management of PMS data was developed to improve the quality control and quality assurance in data collection in the future.

The following conclusions are summarized.

1. The results from questionnaire indicated field validation/calibration of testing equipment is considered as the most selected steps before data collection. Individual distresses are recognized as the most common way in evaluating the confidence of data collection. The completeness of collected data is considered as the content of basic quality evaluation. The engineer ranked the following factors in order of the amount impact on quality of pavement condition data: device calibration; personnel training; sensor accuracy; accuracy of internal measurement;system that is used to process the raw data; weather and testing conditions; and speed of testing vehicles.
2. The survey also indicated that although some state DOTs have already implemented or have been developing data quality control procedure, there is no consensus on how to perform data quality control and assurance. The indicators and criteria used by different state DOTs on evaluation of data quality are different.
3. The data quality was classified into basic and analytical quality. By extensively investigating current practices from other state agencies and reviewing current PMS data, the measurers and criteria for different quality level are determined.
4. Data variability estimated the accuracy and preciseness of a value to a reference value. It is considered as the most significant factor that influences the overall data quality. The research team systematically evaluated the data variability and its consequence on maintenance planning. The analyses indicated that:
    1) The roughness data collected from two wheel path were not statistically identical. IRI value from two wheel paths correlated well with each otherwith high R-square, whereas rut depths from two wheel paths were not linearly correlated. IRI for state routes exhibited larger variation than thatfor Interstates.
    2) For the three levels of distress severity, the accuracy of distress extent at low severity level had little influence on the calculation of PDI while the accuracy distress extent at moderate and high severity levels significantlyinfluenced the accuracy of PDI. Transition matrices analyses showed thatthe accuracy of distresses severity at moderate level influenced the accuracy of PDI significantly.
    3) The influence of data quality on maintenance planning varies in terms of current pavement conditions, how the pavement condition indices are defined, and how the maintenance and rehabilitation analyses are performed. For the current PMS used in Tennessee, the variability of IRI and distress severity level was the dominant influence factors for maintenance planning. The variability of distress extent had slight

influence on maintenance planning. There is no significant influence of variability of rut depth on the maintenance planning.

5. Results indicated that there is a significant decrease of IRI and increased of PDI after the maintenance activities. Meanwhile, there is a slight decrease of rut depth after maintenance activities. This is because the rut depth for interstates and state routes were generally low at the time of maintenance. Maintenance activities weregenerally applied to correct distress such as cracking. Therefore, the influence of maintenance on improvement of rut depth seems limited.
6. Field validation tests were conducted to compare the difference of IRI collected between agency's devices and contractor's device. Results indicated there might be significant difference between different test devices in terms of IRI collecting.Periodically lateral comparisons are necessary to validate the test results from different devices.

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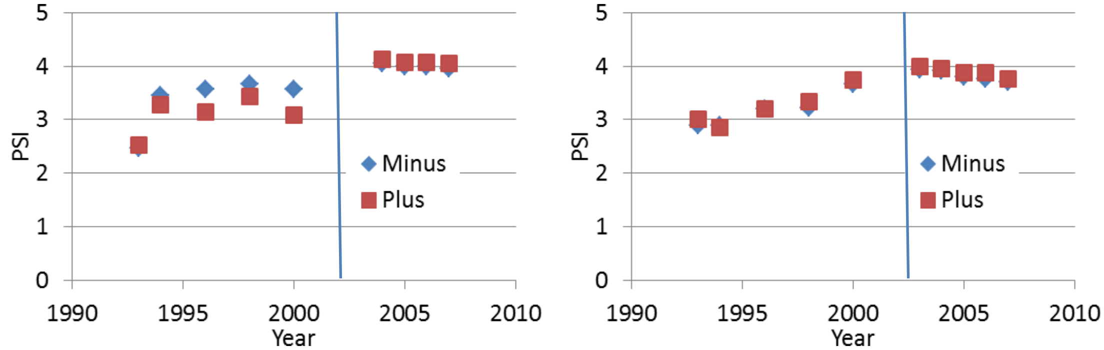
1. Introduction

1.1 Problem statement

The Pavement Management System (PMS) of the Tennessee Department of Transportation (TDOT) has provided an immense amount of data on pavement surface conditions at the network level. Since instituted in 1980s, the system covers the 1,104 miles interstate and 14,359 state routes (1). The pavement condition data for interstates were collected every year, whereas those for state routes were measured once every two years. TDOT has systematically collected pavement roughness data since 1993 and pavement distresses data since 1998 and started using videotaping from 2002.

Because of the enormous information and convenience for access, more and more users have started to use the PMS data for pavement maintenance strategy analysis. From 2007to 2011, TDOT conducted a pavement preventive maintenance research project to investigate the cost-effectiveness of different pavement maintenance treatments and to develop a guideline on pavement maintenance strategy analysis. The measured pavementperformance data were exported from PMS to build treatment performance models and acertain amount of abnormal pavement performance data was identified. The researchers collected 553 HMA resurfacing maintenance records applied in the Region 2 of Tennessee from 1999 to 2005 to build the post-treatment performance curves. However, only 380 (69%) of the 553 road sections show a clear trend that Present Serviceability Index (PSI) values decrease with the increase of overlay age. Figure 1 shows the PSI on the two interstate sections on both plus and minus direction. It can be seen that the PSI after 2000 decrease with the increase of pavement age while the PSI before 2000 led an abnormal trend. Although TDOT has calibrated the treatment performance models for PMS and developed a practical pavement strategy analysis guide, the existence of those incorrect data will cause misleading pavement maintenance decisions, especially at project levels. Thus, it is of great importance to assure the accuracy of the PMS data so that more confidence and credentials can be established with the PMS data.



(a) I-75 Campbell County (18.5-24.5) (b) I-40 Madison County (1.1-7.5)

Figure 1- 1 Samples of abnormal PSI trends

Another issue with the current TDOT PMS is the lack of pavement distress data. In the preventive maintenance project (2007 to 2011), the researchers investigated 2742 road sections identified in Tennessee. However, only 215 of them (7%) have Pavement Distress Index (PDI) curves and 176 (82%) of the 215 road sections show that PDI decrease with the increase of overlay age. The lack of pavement distress data is mainly due to the pavement videotaping methods. TDOT collects pavement distress data by manually reading the videotapes of pavement. From 2002 to 2009, TDOT used the forward facing images (photo log) which make the pavement surface distress difficult toidentify due to the splashing of sunlight in the image. Although TDOT has the images ofall their highways, it does not have distress data for all the highways. In order to collect distress data, TDOT has already switched to downward images since 2010. Pavement distress condition is an important indicator for triggering pavement maintenance and selecting specific maintenance treatments, especially at project levels. Thus, it is meaningful to investigate the quality of TDOT's new pavement distress data collection system.

Utilizing PMS data for pavement preservation analysis at both network and project levelsis of great importance. At the network level, department policies and guidelines developed based on PMS data have vital and extensive impacts on TDOT's operation, functions, and performance. At project level, pavement maintenance engineers rely on more specific data such as friction and structural capacity to determine specific maintenance methods and budget requirements for individual pavement segments. Clearly, a guideline is needed to assess and improve the quality of TDOT current PMS data, which will help PMS managers improve their quality control and quality assurancein data collection and management. Furthermore, a guideline of utilizing PMS data for maintenance strategy analysis including the limitation of current PMS data in those applications will be presented with examples. This will be very helpful to help pavementmaintenance engineers make maintenance strategy at both network and project levels.

1.2 Objective

The main objective of this project is to develop guidelines on quality management of pavement data collection and the application of PMS data in pavement strategy analysis on both network and project levels. This objective will be accomplished by a comprehensive assessment of the data provided by the current PMS.

To investigate the current status of TDOT PMS data and to determine the featureof abnormal datasets.

7. To evaluate the accuracy and reliability of the PMS data through field survey andstatistical analyses.
8. To develop a practical procedure for quality management of PMS data to improvethe quality control and quality assurance in data collection in the future.

2. Pavement condition data

The pavement condition data are used to evaluate the condition of pavement. The data arecrucial to the decision support system which is used to make maintenance decisions of transportation infrastructure. The pavement condition data can also be used to evaluate the cost-effectiveness of different maintenance strategies. The current pavement design system also utilizes pavement condition data to calibrate the performance models.
Therefore, the precise and accuracy of the pavement condition data is crucial to not onlyto the pavement management activities but also to other related works as well.

The pavement condition data consists of four aspects: riding comfort, surface deterioration, riding safety, and structural capacity. These data are utilized to support decision making process in terms of different levels. At network level, riding comfort andsurface deterioration are usually used for evaluating the current pavement condition and making maintenance decisions.

2.1 International roughness index (IRI)

The International Roughness Index (IRI) is used to evaluate the pavement performance associated with riding comfort. It is a combination reaction of the subjective feeling of individual passengers, vehicles vibrations (1), and surface profile of pavement. The subjective feeling of passengers differs from individuals. The vibrations of each vehicle are different depending on the design and installation of damping system and cruising speed. The profile of pavement surface is the root of vehicle vibrations and determines the surface roughness.

The pavement profile related to the ride quality can be characterized by pavement roughness index, one of the pavement condition indicators. The roughness index describes the mathematical property of a two-dimensional road profile obtained from measured longitudinal direction of the roadway. It can be calculated using a quarter-car vehicle math model, whose response is accumulated to yield a roughness index with unitsof slope (in/mi, m/km, etc.)(2). Introduced in 1986 (3), the International Roughness Index (IRI) has become the most commonly used worldwide in the process of construction and management of roadway facilities.

The National Cooperative Highway Research Program (NCHRP) initiated a research project in 1980's to help state agencies improve their use of roughness measuring equipment (4). Consequently, The World Bank conducted a project aiming to compare orconvert data obtained from different countries and built a bridge between the IRI and other roughness indices from different countries (5). The methods for measurement of

IRI can be rod and level surveying equipments, dipsticks (6), and laser profilometer systems which is a common nationwide used method in pavement condition data collection(7).

The international roughness index (IRI) has been proven to be a very useful tool to evaluate rideability. In pavement management system, IRI is employed to establish indices that reflect pavement serviceability. (26) The IRI is also a transferable reference scale that can be used as a suitable calibration standard for all response-type and profilometric instruments. (27)

The IRI was defined as the cumulative relative displacement of the axle with respect to the frame of this reference quarter-car per unit distance travelled over the pavement profile at a speed of 80km/h. It is expressed in m/km or in/mi at selected interval, (e.g., every 100m or 0.1mi.) (28) The traditional way of measuring IRI is to use response-type pavement roughness measuring devices (29) which were equipped with a mechanical integrator of the relative displacement of the axle with respect to the frame of the trailer. A significant drawbacks of these device is that the results are influenced by vehicle mechanic system and measuring speed. And in those days, the mechanical systems were not advanced enough to provide the correct damping shocks or to calibrate the unit correctly. (30)(31) The application of signal processing theory into the measure road profiles give the birth to the high-speed road profiling which is firstly developed by Spangler and Kelly in the 1960s. (32) Nowadays, with the application of non-contact technique in obtaining road profile, the measurement of IRI has been changed. IRI is nowcalculated from a measured longitudinal road profile by accumulating the output from a quarter-car model and dividing by the profile length to yield a summary roughness index with units of slope. (2) (33)

The IRI is influenced by changes of longitudinal elevation in wheel paths which is associated with the characteristics of pavement surface. The pavement roughness profile can be divided into a large variety of wavelength ranging from several centimeters to tensof meters, with varying amplitudes. These wavelengths affect the excitation of the various vehicles traveling the road in different ways, depending on their traveling speed and dynamic characteristics such as suspension configuration, wheel and frame inertial properties, and so on. (28)

In the calculation of IRI, not all the wavelength needs to be involved since some of the wavelength has little effects on the ride quality of traversing vehicles, such as wavelengths shorter than the dimensions of pavement macrotexture and longer than roadway geometric features perceived as longitudinal slope or curvature. (28) The moving average smoothing filter is usually used to obtain a profile of IRI. (34) This filter consists of a low-pass filter to remove short wavelengths from the profile and a high-passfilter to remove long wavelengths from the profile. The base length used for the IRI averaging must be considered. Specifying the base length becomes particularly importantwhen specifications for road quality are formulated, or when profiling accuracy is prescribed. That the variation in IRI found over the length of a road is more extreme when the base length is short should be taken into account when reporting instrument accuracy or writing roughness specifications. Specifically, the accuracy of high-speed profiling systems should be specified according to base length. (28) To date, there are no established standards for pavement profile filtering; rather, the selection of filters dependson the application at hand. (28)

Some factors influenced the precision of IRI are summarized as follows. (35)

- The procedures used in making the longitudinal profile measurement.
- The interval between adjacent profile elevation measures. The precision of IRI can be improved by applying shorter interval.
- IRI precision is roughly equivalent to the precision of the slope obtained from thelongitudinal profile measurements, fro distance ranging from the approximately 1.5m (5ft) to about 25m (80ft).
- Errors in locating the wheel track longitudinally and laterally can influence the IRI values significantly.

NCHRP Project 10-47 recommended guidelines for measuring a longitudinal pavement profile to use in computing that pavement's International Roughness Index (IRI) and/or Ride Number (RN). The investigators investigated the factors that affect roughness measurements, quantified the effect of these factors on repeatability and accuracy, and determined how and when these factors can be controlled. (36)

The report summarized the factors that affect profiler accuracy and repeatability.

- The utilization of improper filter may result in errors in IRI of 2 to 10 percent anderrors in RN of 10 to 50 percent on typical roads.
- A sample interval of 167 mm or less is required for accurate measurement of IRI.A sample interval of 50 mm or less is required for accurate measurement of RN.
- Pavements exhibit significant transverse, seasonal, and daily variations in roughness. Thus, a single roughness measurement, no matter how accurate, mustbe considered only as a statistical sampling of the roughness.
- Typical variations in lateral positioning may cause repeat measurements of IRI tovary up to 20 percent on a section 300 m long.
- Profilers should, at a minimum, measure roughness in two wheel tracks. Height

sensor footprint has a strong influence on the way a profiler measures cracks and open joints. Proper use of anti-aliasing filters improves the accuracy of profilerson pavements with these features, as well as the agreement between measurements obtained with different types of height sensors.

- Moderate acceleration and deceleration of less than 0.15 g can be tolerated in network-level measurements of profile, but should be avoided in project-level measurements.
- Ultrasonic sensors should be replaced due to the unreliable measurements of IRI or RN.

Theoretically, an actual pavement profile can be simulated by an infinite number of sinusoidal of various wavelengths and amplitudes. The pavement profile can be translatedinto its constituent sinusoidal to form profile spectral content. By using the Fourier analysis, the relationship of elevations of longitudinal profile and distance can be transformed to the form of powers spectral density (PSD) in which amplitude is the function of wave number. (28)

The PSD is primarily used to evaluate vehicle response, suspension optimization and control, dynamic pavement loading and energy consumption. (37) As a direct statistic ofroughness, PSD roughness is different from the IRI in that the former has been routinelyadopted by vehicle manufactures for automobile design purpose for many years.
However, the IRI is the most commonly used statistic for evaluating roughness in highway transportation agencies. It is believed that if a relationship can be found betweenthe IRI and the PSD roughness, it will be much easier and produce more benefits for bothhighway and vehicle industries to compare their criteria and further to improve their production designs. (38)

To correlate IRI with PSD, Sun simulated the IRI using PSD of pavement surface fluctuation. Quarter-car models recommended by the World Bank for measuring pavement roughness are adopted to simulate vehicle response. Surface roughness in timedomain is generated based on 36 known PSDs of roughness. Results showed that the IRIis linearly correlated with the standard deviation of relative vertical velocity between theaxle and sprung mass. It was found that if PSD roughness is expressed as a polynomial function, the IRI can be simply calculated by means of the square root of the sum of the weighted regression coefficients of PSD roughness. (39)

Correlation of IRI and PSD becomes possible based on their PSD-based expression which made transportation agencies possible to use PSD-based models to precisely convert IRI to PSI given that PSD roughness of a pavement is known. (39) Sun et al. also proved that the average of the absolute response of the quarter-car model was directly proportional to the standard deviation of that response quantity which correlated the indirect statistics with PSD roughness. They also found that a linear correlation exists between the IRI and the standard deviation of roughness.(40)

Some new pavement roughness indices were presented based on the PSD concept such asRIDE, which is based on the sprung mass acceleration response of a reference vehicle to the pavement profile. It is calculated in the frequency domain by multiplying the power spectral density (PSD) of the pavement profile by the square of the transfer function of the sprung mass acceleration of the reference vehicle. The resulting sprung mass acceleration PSD is integrated over frequency to yield the root-mean-square of the sprungmass acceleration per unit length of pavement traveled. The sprung mass acceleration is shown to be the main contributor of dynamic axle loads in heavy trucks, which relate to vehicle and cargo damage and also to pavement damage. (41)

Wei et al attempted to integrate pavement surface roughness into a roughness index. By using different wavelet transformation and analysis technique, the useful information for pavement maintenance management will be extracted. The characteristics of a pavement roughness profile are identified in both the frequency and distance domains. It was demonstrated that using appropriately selected analysis methods and wavelet parameters,detailed roughness features of interest to pavement engineers not currently available fromsummary roughness statistics can be obtained together with summary roughness statisticsas part of the roughness survey report for highway agencies. (42) Wei et al. also pointed out that the use of wavelet transform to overcome can correlate various convenient numerical indices with one another. In his study, comparisons were made with four common roughness indices, namely, the international roughness index (IRI), root mean- square vertical acceleration (RMSVA), mean absolute vertical acceleration (MAVA), andslope variance (SV). They found that IRI, RMSVA, MAVA, and SV had pair wise coefficients of multiple determination (R^2) ranging from 0.18 to 0.75. But wavelet energystatistics had an R^2 of at least 0.857 with each of the roughness indices. (43)

2.2 Surface distress

The pavement condition data of surface deterioration are especial important to those whoare in charge of making decisions on maintenance strategies. The determination of maintenance tools for a specific project mainly depends on the types of distress that the surfaces are suffering. Owing to the large quantity of required data, collection methods typically involve windshield surveys and automated methods (8).

Since the surface deteriorations are highly definition- depended, the determination of distress can be either subjective (9).In order to standardize the types of distress and quantify the distress in the same way so that deteriorations at different road sections are comparable, pavement distress library are developed which is used to identify the distresses (10). Overall distress indices are developed to quantify the severe degree of surface deterioration.

Long-Term Pavement Performance (LTPP) proposed a manual to identify the distress ofpavement. Three types of pavement are involved: asphalt concrete surfaces, Joint Portland Cement Concrete surfaces, and continuously reinforced concrete surface. The distresses of each type are classified as shown in Table 2-1 to Table 2-3. (10)

Table 2- 1 Distress of pavement for asphalt concrete surfaces

Category	**Type**
Cracking	Fatigue cracking
	Block cracking
	Edge cracking
	Longitudinal cracking
	Reflection cracking at joints
	Transverse cracking
Patching and Potholes	Patching deterioration
	Potholes
Surface Deformation	Rutting
	Shoving
Surface Defects	Bleeding
	Polished aggregate
	Raveling
Miscellaneous Distress	Lane-to-shoulder dropoff
	Water Bleeding and Pumping

Table 2- 2 Distress of pavement for joint Portland Cement Concrete surfaces

Category	**Type**
Cracking	Corner breaks
	Durability cracking(“D” Cracking)
	Longitudinal cracking
	Transverse cracking
Joint Deficiencies	Joints seal damage
	Spalling of longitudinal joints
	Spalling of transverse joints
Surface Defects	Map cracking
	Scaling
	Polished aggregate
	Popouts
Miscellaneous distress	Blowups
	Faulting of transverse joints and cracks
	Land-to-shoulder dropoff
	Land-to-shoulder separation
	Patch/patch deterioration
	Water bleeding and pumping

Table 2- 3 Distress of pavement for continuously reinforced concrete surfaces

Category	**Type**
Cracking	Durability cracking(“D” Cracking)
	Longitudinal cracking
	Transverse cracking

Surface Defects	Map cracking
	Scaling
	Polished aggregate
	Popouts
Miscellaneous distress	Blowups
	Transverse construction joint deterioration
	Land-to-shoulder dropoff
	Land-to-shoulder separation
	Patch/patch deterioration
	Punchouts
	Spalling of longitudinal joints
	Water bleeding and pumping
	Longitudinal joint seal damage

The distress indices listed above are employed by many transportation agencies to assessthe pavement condition. A national wide survey on the distresses collected by various transportation agencies indicated that rutting was the universally collected distress followed by transverse cracking and fatigue cracking which indicate pavement deformation and fatigue failure *(8)*. Other commonly collected asphalt pavement distresses data include longitudinal cracking, bleeding and flushing.

Tennessee DOT collects seven types of distress for asphalt pavement. Table 2-4 listed thetype of each distress and their extents and percentage conversion.

Table 2- 4 Types of distress collected in Tennessee for asphalt pavement

Distress	Extents (Each severity)	Percentage conversion (Each severity)
Fatigue cracking	Affected areas	The percentage of affected

		area
Longitudinal wheel pathcracking	Cracking length	The percentage of length ofcracking to length of wheelpath
Patching and Pothole	Affected areas	The percentage of affected area
Block cracking	Affected areas	The percentage of affected area
Transverse cracking	Number of transverse cracks	Number of transverse cracks
Longitudinal Non-wheel path cracking	Cracking length	The percentage of length ofcracking to length of non- wheel path
Lane Joints	Joint length	The percentage of length tothe total section

Since, the pavement management system uses these indices for evaluating the transportation facilities, it is important to make a good knowledge of pavement distress data before dealing with the pavement condition data.

The digital image-processing concepts was presented and applied to collect the pavementcondition data more safety, consistence and cost-effectively. Digital imaging technology which plays a significant role in the process of pavement data collection consists of distress-data acquisition and interpretation. (44)

The digital imaging technology is integrated with other advanced technique such as an illumination assembly to illuminate the region from which the pavement deterioration is recorded; and a processor in the computer to process and interpret the image to form an automation inspection system. (45) The utilization of automation inspection system is beneficial to the collection of pavement condition data at high-speed condition, but to themonitoring and inspection of bridge management system as well. (46)

Some studies have already proved the effectiveness of using automatic distress detectingmethod in collecting the pavement condition data. Raman et al. *(47)* compared the severity and extent of the transverse crack by statisticalanalysis. The researchers used analysis of variance for normally distributed data and nonparametric test (Kruskar–Wallis) in the remaining cases. Statistical comparison of sample and full-section image data showed that a 5% sampling rate was enough to evaluate transverse cracks with the precision desired for network-level pavement management in Kansas.

Wang et al. *(48)* compared the use of an automated cracking survey system with manual evaluations. The evaluators reviewed and analyzed 5% of the images for each comparison section. Differences were found between the manual and automated process;however, it was suggested that these discrepancies may be caused by the low repeatability of the manual surveys.

The Ontario Ministry of Transportation compared automated and semi-automated pavement distress collection techniques from three service providers with in-house manual surveys *(49)*. The study investigated various pavements including surface-treated,hot-mix asphalt, composite, and PCC pavement. The distress manifestation index was used for the comparisons. The study found that automated results are comparable with manual surveys.

The image capturing subsystems included conventional analog-based area-scan, analog and digital line-scan, laser scanning, and shadow Moire method. Newer implementationsof image processing include artificial neural net and parallel processing. (50) Nowadays,the automation inspection system based on image technology is well developed to identify most of the typical distress on roadway surface such as cracking (51)(52) (53) and pothole. (54)

However, there are still some unsolved problems in the automation inspection system. Some environmental factors may have influence on the image capturing of pavement deterioration, as a result the interpretation of digital pictures will be a difficult job. An investigation conducted by Florida Department of Transportation (FDOT) indicated that the HID lighting system introduces a significant level of noise into the images in both asphalt and concrete pavements, leading to an inability to accurately distinguish pavement cracks from their background. (55) To date, a large variety of algorithm is developed and under developing to facilitate the automation inspection system to identifythe pavement distress more precise and efficiency.

Cheng et al proposed a novel pavement cracking detection algorithm based on fuzzy logic. The main idea of the proposed method is based on the fact that the crack pixels in pavement images are “darker than their surroundings and continuous.” First, the proposed method determines how much darker the pixels are than the surroundings by deciding thebrightness membership function for gray levels in the difference image. Second, they mapped the fuzzified image into the crack domain by finding the crack membership values of the pixels. Third, they checked the connectivity of the darker pixels to eliminatethe pixels lacking in connectivity. (54)

Mohamed et al. compared traditional and neural classifiers for pavement crack detection.Results showed the neural network classifier performed slightly better than the traditionalclassifier on the test data set. However, the parameters needed to be carefully selected and extensive empirical training performed to achieve good results in neural classifiers.(55)

Koch et al presented a method for automated pothole detection in asphalt pavement images based on MATLAB prototype. Based on the geometric properties of a defect region the potential pothole shape is approximated utilizing morphological thinning and elliptic regression. Subsequently, the texture inside a potential defect shape is extracted and compared with the texture of the surrounding non-defect pavement in order to determine if the region of interest represents an actual pothole. (57)

The image-processing methods often mistakenly treat oil spillages, shadows, and road markings as distresses because their features are similar to those of distresses. Therefore, Su et al proposed a dual-light inspection (DLI) method to reduce false alarms. A field testwas conducted to verify the DLI method. A total of 212 pairs of images were captured during nighttime, including images of alligator cracks (42 pairs), manholes (42 pairs), longitudinal cracks (58 pairs), spillages (34 pairs), and road markings (52 pairs). Twenty percent of the images (i.e.,45 pairs) were used as training sets to train the classification model. The remaining images were then used to test the accuracy of the classification model. The accuracy of the DLI method, which uses dual-light image pairs, was compared with that of the traditional method, which uses individual images. The DLI cansignificantly improve the accuracy in determining spillage (traditional: 18%, DLI: 82%) and road markings (traditional: 8%, DLI: 96%). The DLI is also reasonably accurate in determining other distresses including alligator cracks (traditional: 95%, DLI: 90%), manholes (traditional: 97%, DLI: 100%), and longitudinal cracks (traditional: 62%, DLI: 69%).(56)

3. Summary of the DOT survey

3.1 Overview of survey

A questionnaire was created through the Website of office of information technology in the University of Tennessee, in January 2014. It was normally distributed in March 2014,through the link below:

https://utk.co1.qualtrics.com/SE/?SID=SV_9sheS6lSoMh3TOR

In the first round, we sent the invitation to state DOT's Maintenance agency of 41 states and received twenty-four (24) responses, as shown in Table 3. Among all the respondents,Pennsylvania Department of Transportation is currently conducting a project through which a pavement asset management system (PAMS) will be developed. Therefore, they left several questions blank that pertained to how the PAMS works.

Table 3- 1 List of invited States DOT and response to the Survey

No.	STATE	Invited	Response	No.	STATE	Invited	Response
1	Alabama	Y	Y	28	Nevada	Y	
2	Alaska	Y		29	New Hampshire	Y	Y
3	Arizona	Y		30	New Jersey	Null	
4	Arkansas	Y	Y	31	New Mexico	Y	Y
5	California	Y		32	New York	Y	Y
6	Colorado	Y		33	North Carolina	Y	
7	Connecticut	Y	Y	34	North Dakota	Y	
8	Delaware	Y	Y	35	Ohio	Y	
9	Florida	Y	Y	36	Oklahoma	Y	
10	Georgia	Y		37	Oregon	Y	Y
11	Idaho	Y		38	Pennsylvania	Y	Y
12	Hawaii	Nul		39	Rhode Island	Y	Y

		1					
13	Illinois	Y	Y	40	South Carolina	Y	Y
14	Indiana	Y		41	South Dakota	Y	Y

15	Iowa	Null		42	Tennessee	Null	
16	Kansas	Y		43	Texas	Y	Y
17	Kentucky	Y	Y	44	Utah	Y	Y
18	Louisiana	Y	Y	45	Vermont	Y	
19	Maine	Y	Y	46	Virginia	Y	
20	Maryland	Y		47	Washington	Y	Y
21	Massachusetts	Null		48	West Virginia	Y	
22	Michigan	Y		49	Wisconsin	Y	
23	Minnesota	Y	Y	50	Wyoming	Null	
24	Mississippi	Y	Y				
25	Missouri	Y	Y				
26	Montana	Y	Y				
27	Nebraska	Null					

3.2 Responses of DOTs

The main information gained in this round is summarized below.

Question 1:What types of management systems are used in your agency?

All the respond states own pavement management system. Three of them have their ownasset management system. DTIMS system is the most popular software that used to support pavement management activities, followed by Agile Assets. Some states also useHighway Pavement Management Application (HPMA) developed by Stantec. It is also found that a few states developed their own system in supporting pavement managementactivities such as Washington State which has Washington State Pavement Management System (WSPMS).

Table 3- 2 Summary of the software that used in supporting PMS

Name	Number of State Agency used
Agile Assets	6
dTIMS	7
HPMA	2
Others	2
Total responses	17

Question 2: How does your agency conduct quality assurance for the collected data?

Eight response agencies (44%) have the standalone system to conduct quality assurance for collected data; two (11%) are developing the standalone system; two (11%) are conducting quality assurance through a third-party; and the rest six (33%) are not specified. This means the state agencies begin to emphasize data quality assurance for PMS, as a result, more than half of the response states conduct the quality assurance through a specific system.

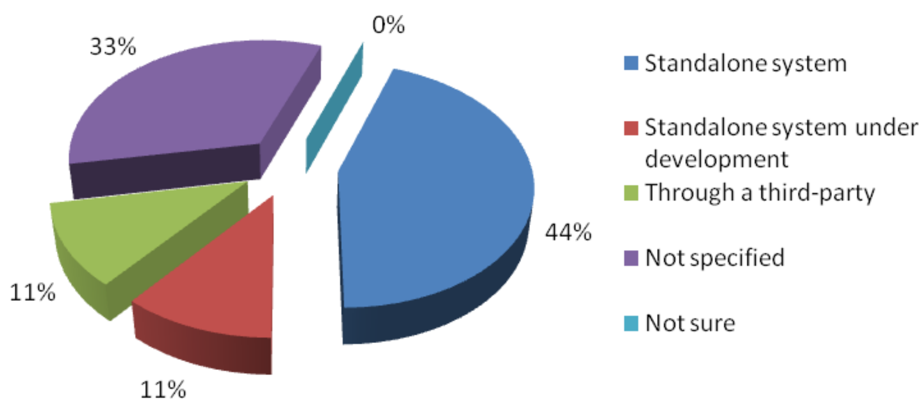


Figure 3- 1Results from Question 2

Question 3: On what cycle is the pavement data collected?

Figure 3-2 to Figure 3-4 illustrated the results of the answers. For interstate, all the response states collect the roughness data (smooth) at least biannually. 89% of the states collect roughness data annually and 78% of them collect distress data annually. For stateroute, 44% states collect roughness data annually, 33% biannually, and the rest states areeither in more than once every two years or in irregular cycles. As for the distress data ofstate route, 33% states collect roughness data biannually while 33% annually. 7 out of 18states collect roughness and/or distress data for non-state routes while 5 of them collect these data either once every two years or less. From this questions, we can find that the states highway administration make their efforts mainly on monitoring interstates at high frequency. As for state routes, there seems a tendency that the monitor frequencies forroughness data are higher than distresses.

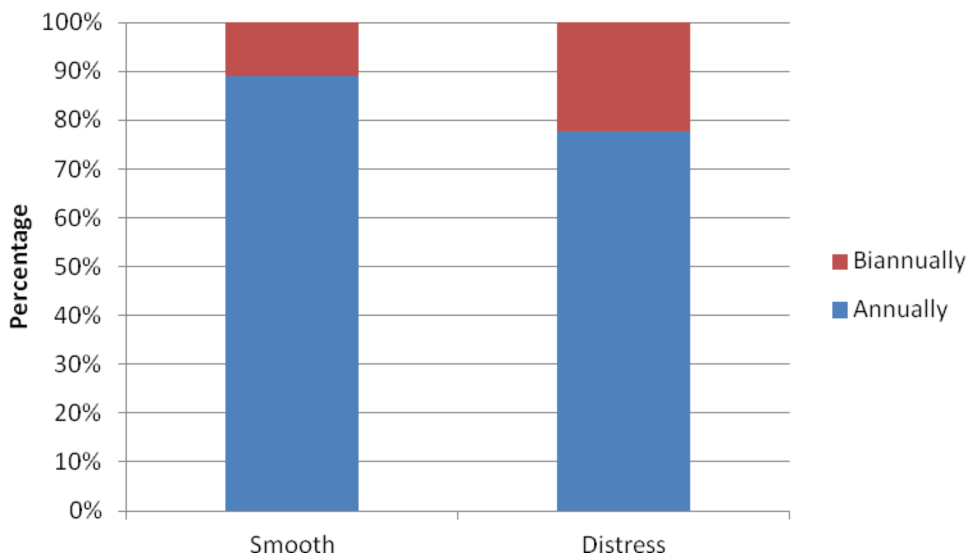


Figure 3- 2 Collecting frequency of interstate

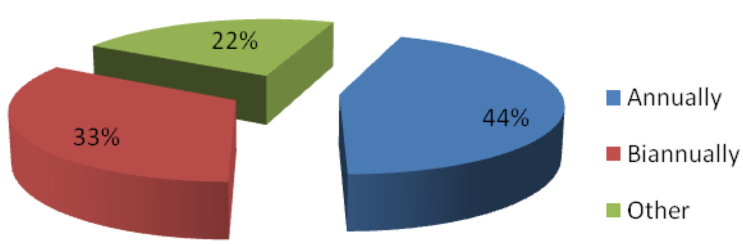


Figure 3- 3 Collecting frequency of state route (Smooth)

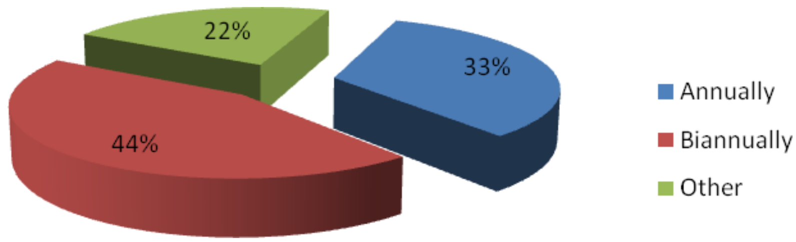


Figure 3- 4 Collecting frequency of state route (Distress)

Question 4: How many centerline miles of roadway does your agency collect each cycle?

This question illustrated the scales of centerline miles managed by each highway administration. It can be seen that most of the state highway agencies monitor centerlinemiles of interstates less than 3000 miles. Meanwhile, the centerline miles of state route vary different ranging from less than 500 miles to greater than 6000 miles.

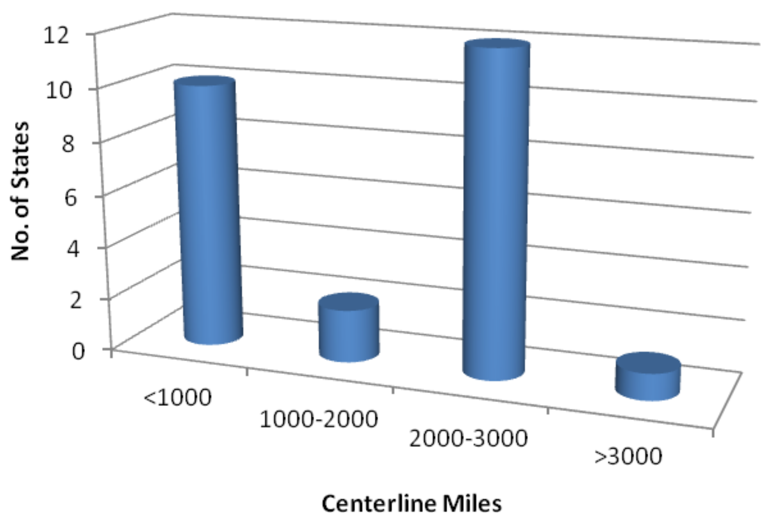


Figure 3- 5 Centerline miles of interstates managed by highway administration

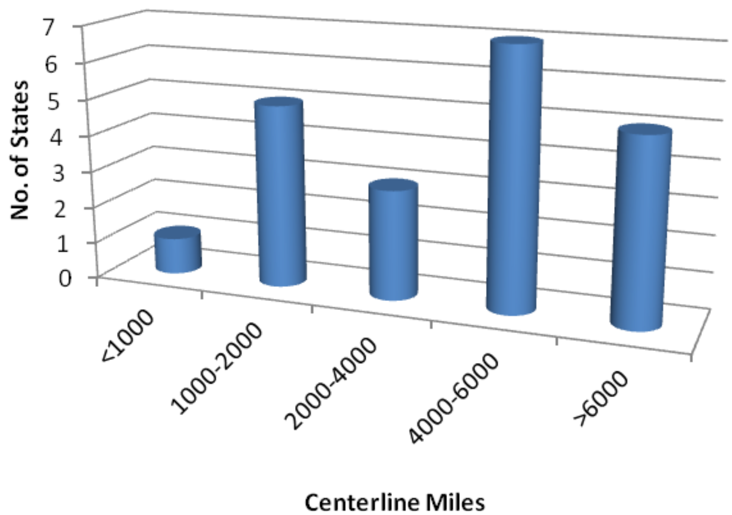


Figure 3- 6 Centerline miles of state routes managed by highway administration

Question 5: What type of pavement condition data does your agency collect?

It can be seen that all the response states collect pavement condition data of surface distress and smooth at network level while 56% of the response states collect frictional properties of pavement surface. Only 13% of the states collect structural capacity at network level. At project level, roughness data (smooth) are most popular, followed by structural capacity (64%), surface distress (55%), and frictional properties (50%). All theabove information is used to determine the specific treatment strategies.

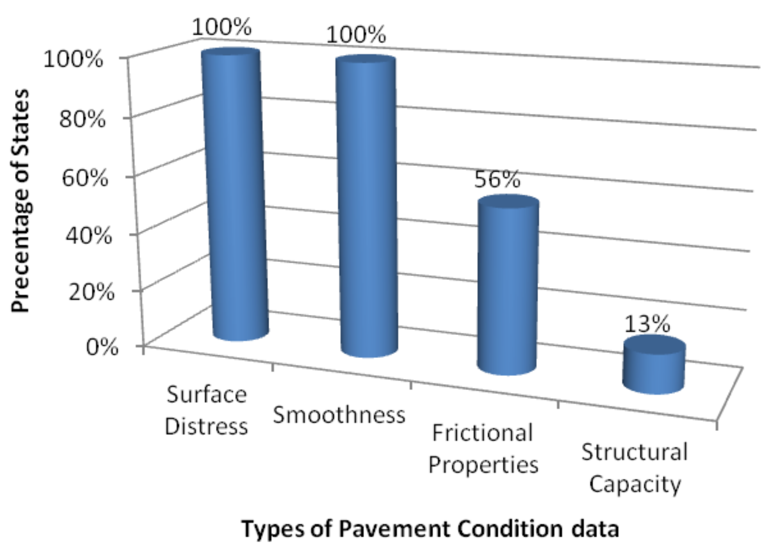


Figure 3- 7 Types of pavement condition data collected by highway administration (Network level)

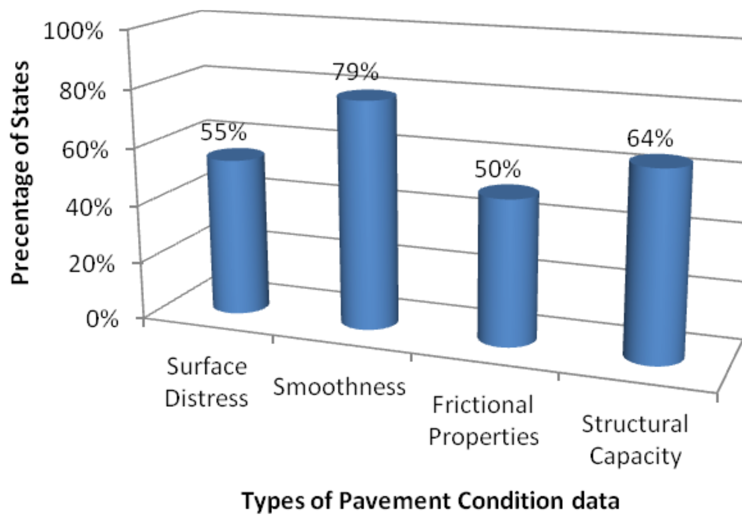


Figure 3- 8 Types of pavement condition data collected by highway administration (Project level)

Question 6: Does your agency employ an overall pavement condition index to describe the following distress?

The overall pavement condition index is employed to describe surface distresses since thedifferent distresses are summarized and calculated separately. Therefore, the total index associated with surface distress is needed to reflect the distress level of current pavement condition. The indices used to describe the distress including Surface Condition Index (SCI), Performance Index (PI), Surface Rating (SR), Pavement Condition Rating (PCR), Cracking Index (CI), Overall Pavement Condition (OPC), and etc. Although the ways of calculation of each index are quite different from each other, the principles of each index are similar. The finalized index is calculated by weighing and summarizing each distress type based on the expertise's experience. The roughness data was usually quantified by international roughness index (IRI). Some states also employ a model to transfer IRI into other index such as Ride Quality Index (RQI), Ride Comfort Index (RCI), Ride Index (RI), etc. Since IRI may vary different. The selection of these indices may decrease the variability of roughness data in the finalized roughness index which may be able to reduce errors and improve data quality.

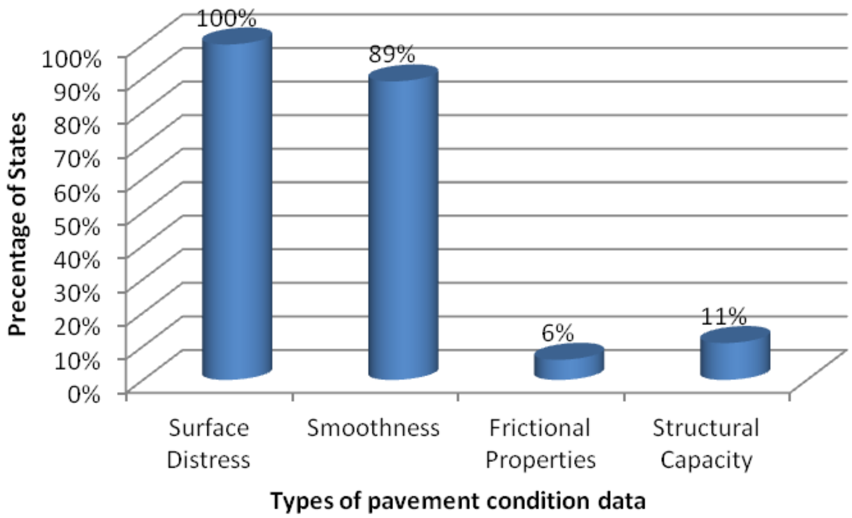


Figure 3- 9 Use of overall index to describe the pavement condition

Question 7: Is your pavement management system used for support in determiningmaintenance strategies? What kinds of pavement data do you use for determining strategies of pavement maintenance?

17 states agencies response this question. 76% of the response states use PMS in determining maintenance strategies. The other 24% states may determine the maintenance plans or strategies based on information from specified projects and PMS don't play an important role in the final decision of maintenance plans. For those who employ PMS to make the maintenance plans or strategies. The overall pavement condition indices of surface distress and smoothness are mostly adopted to describe the pavement condition at network level. At project level, the individual distress especially surface distress data is used to determine the specified maintenance treatments. Normally,the decisions are made based on the experience of pavement management engineers.
Based on the response of this question, the importance of pavement condition data in decision-making process of maintenance strategies can be ranked as surface distress the most important, followed by smoothness, frictional properties, and structural capacity.

Table 3- 3 Use of pavement condition data to determining maintenance strategies

Is your pavement management system used for support in determining maintenance strategies?
Yes,76%; No, 24%
What kinds of pavement data do you use for determining strategies of pavementmaintenance?

Items	Total pavement condition index		Individual distress	
	Project level	Network level	Project level	Network level
Surface Distress	5	**11**	**8**	5
Smoothness	6	**10**	3	4
Frictional Properties	4	3	5	0
Structural Capacity	3	1	5	0

Question 8: Do you keep the record of pavement maintenance activities? Do you integrate the maintenance history into the current pavement management system? Do you include cost information in your maintenance history?

The maintenance histories are important when one conducts cost-benefit analysis or costeffectiveness analysis on pavement maintenance activities. From the respective of data quality control, it can be used to identify the abnormal changes in spatial-temporal seriesof pavement condition data by correlating maintenance history with pavement conditiondata when some improvements in pavement condition are caused by the maintenance interference. The answers obtained from these questions indicated that about three quarters of the response states keep the maintenance record and most of them are included in PMS. For those who keep the maintenance record, 67% of them contain costinformation regarding to the maintenance history. The purpose of introducing cost information in PMS is mainly to conduct cost benefit analysis.

Table 3- 4 Collection of maintenance information in PMS

Do you keep the record of pavement maintenance activities?
Yes 76%; No 18%; Not sure, 6%

Do you integrate the maintenance history into the current pavement managementsystem?
Yes 92%; No 8%; Not sure, 0%
Do you include cost information in your maintenance history?
Yes 67%; No 33%; Not sure, 0%

Questions 9: What distress data does your agency collect? Where?

This question was used to obtain the general distress data that state agencies collect. For asphalt pavement, rutting and cracking are the most common collected distresses. Other surface deterioration such as pothole/patching, raveling, bleeding/flushing may also be included in some states. For concrete pavement, faulting and spalling are most common collected distresses. Shattered slab, cracking, and punch-outs are also collected by some states. A few states also evaluate joint damage; patching/potholes; and failures; etc. Mostdistresses are collected in single lane where the measuring vehicle ran. A few states collected distress in multiple lanes. The multiple-lane distress can reflect the pavement condition data completely and is useful at project level which specified maintenance treatments and plan are needed. As for network level, the distresses are collected in the lane or lanes where truck traffic is usually applied.

Table 3- 5 Distresses data collected by state agencies

Asphalt Pavement		
Distress	Single Lane	Multiple Lanes
Rutting	14	4
Fatigue cracking	13	4
Longitudinal Cracking	14	2
Transverse Cracking	14	3
Map/Block Cracking	8	2
Bleeding/Flushing	6	1
List of others that some states indicated: raveling, patching/potholes, etc. International roughness index is not included here since it is classified as roughness data.		
Concrete Pavement		

Distress	Single Lane	Multiple Lanes
Raveling	2	2
Shattered Slab	7	1
Faulting	11	4
Durability Cracking	6	1
Spalling	10	4
Edge Cracking	6	1
Pumping	1	1
Punch-outs	5	2
List of others that some states indicated: general cracking; traverse cracking; Joint SealDamage; Longitudinal cracking; Patching/potholes; Joint Deterioration; Mid-slab cracking; failures; etc. International roughness index is not included here since it is classified as roughness data.		

Question 10: How is the distress data collected?

44% response state highway administration contract with data provider to distress collection. 39% states perform the data collection by themselves. There are also some states collected the distress data in both ways. It seems the number of states who prefer tocontract with a data provider or vendor is close to those prefer in-house collection (44% versus 39%) Due to the limitation of question, no more information was obtained for the reason for those states adopting both in-house and contractor collection. The reasons might be associated with issues such as expenses, devices, etc.

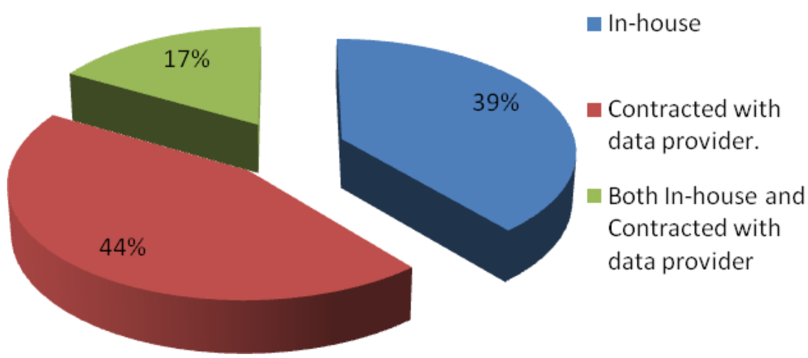


Figure 3- 10 Way of distress data being collected

Question 11: How is the pavement distress being analyzed?

The semi-automatic image process is the commonly used method to analyze pavement distresses. In semi-automatic distress identification method, the distresses are manually identified. Then an automatic process summarizing the individual distresses and calculating the distress index is employed to obtain the total distress index. Since the identification of distresses is subjective, the total distress index obtained by different person may be different. That is the main source of error. The automatic distress identification method seems to be more objective since no human errors is introduced through the entire process. However, the algorithms of distress identification method arestill under development. The errors from algorithms in recognizing and classifying the distresses may be the main error of the total distress index.

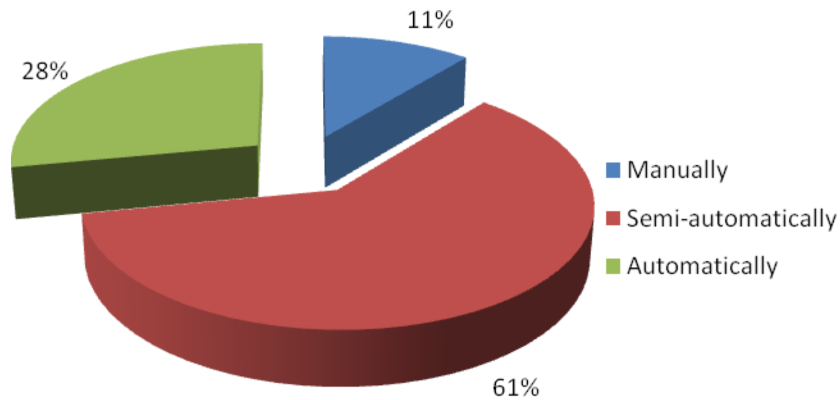


Figure 3- 11 Ways of distress being analyzed

Question 12: Which of the following activities are utilized by your agency to check data?

In this question, all the listed procedures were selected by state highway administrators. This means all these measurements are often adopted by these administrators in assuring the pavement condition data quality. Meanwhile, it can be found that some states listed other activities that they adopted during data collecting procedure. These activities can also be utilized in the procedure of data quality control and assurance for Tennessee DOT.

Before data collection, it noted that the field calibration of testing equipment was selectedby all the response states. The field calibration will be performed to assure the consistence of pavement condition data. This step will eliminate the error introduced by devices. It is recommended that the testing equipment be calibrated in a specified section which refers to as calibration section. This section is used to calibrate the measurement of roughness data such as longitudinal elevation for IRI and transverse elevation for ruttingdepth. The purpose of calibration section is to evaluate the accuracy and repeatability oftesting equipment. By the calibration result, the state highway administrators can decidewhether the testing equipment is suitable for the continuous collecting the pavement condition data.

During the data collection, equipment and data monitoring should be required. This will directly affect the data quality. The monitoring of equipment includes whether the equipment is operating normally, whether the data is recorded normally or there is a missing data during collection.

After data collection, data proving is the most important part since it will determine the validation of data and affect the follow-up activities in PMS. All the response states checked completeness of data after collection. The completeness of data indicated that how the testing sections cover the total specified sections. Other options after data collection can also be verification of collected data by statistical analysis; determination of confidence of collected data; detection of abnormal data by data mining technology. The data assurance procedures after data collection aim to determine the reliability of collected data. This is used to estimate how much confidence can be put on the pavementcondition data. It is also based on this confidence that the payment be made which is similar to the pay factor in the QC/QA of pavement construction.

Before data collection	
Activities	Numbers of States used
Equipment adjustment	17
Staff training	15
Testing of known segments for verificationof equipment	18
Others: Statistical Tests; Annual certification; Field verification, internal data sampling on photolog viewer; shadow collections; comparison with previous years; Certify profilerat TTI	
During data collection	
Activities	Numbers of States used
Requirements for equipment operation	17
Data monitoring	18
Others: Blind ratings of same sections by a rater; Audits by 3rd party	

After data collection	
Activities	Numbers of States used
Verification of collected data by statisticalanalysis	6
Verification of collected data by a third-party	3
Determination of confidence of collecteddata	10
Check for abnormal data	16
Check for missing data	18
Comparison with time-history data	12

Question 13: Which of the following parameters do you use for evaluating the acceptance or confidence of data collection?

Individual distresses are recognized as the most common way to evaluating the confidence of data collection. Since the individual distresses are measured through images captured from the pavement surface, the severity and extents can be re-evaluated by the highway administrations before they accepted these data. Those roughness data, however, is not the desirable parameters that can be used for evaluating the data confidence. These roughness data are highly dependent of the longitudinal and transverseprofiles on which the pavement roughness indices and rutting depth were determined.

Some states prefer to use synthesized index when determining the acceptance or confidence of data collection. These indices contain information that users will be interested in including roughness data; distress data, etc. However, there are still some drawbacks when these indices are used. Since the synthesized indices are calculated fromeach individual distress, the errors from the individual distresses may be eliminated whenthe calculations are perform. In another word, the bias of synthesized indices is determined not only by errors from the individual distress but by the ways of how those synthesized indices are calculated as well.

Answers	Number of States used
Synthesized index	7
Individual distress classifications (severity and extents)	12
Other methods listed are: digital images; verification by video; passing the audits	

Question 14: What percentage of collected data is typically considered invalid and required correction?

It can be seen that about 61% of the response states thought their invalid data are less than 5%. Other 17% ranges from 5% to 10%. The rest 22% states were not sure the exactpercentage of invalid data in their PMS. The invalid data are those data with obvious mistakes, such as incomplete data, missing data, abnormal data, etc. In the previous quarterly report, the research team evaluated the completeness of pavement condition data. The results indicated that the percentages of missing data and invalid data are usually less than 5%. This means that the data quality of PMS in Tennessee state may represent the most states in U.S.

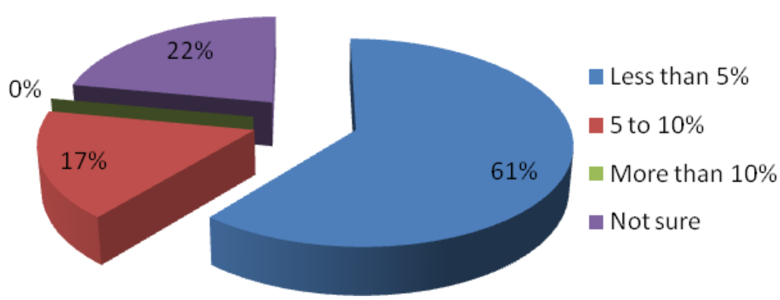


Figure 3- 12 Percentage of invalid data

Question 15: Based on your experience, please rate the following factors in order ofthe amount impact each has on data quality.

Based on the response of this question, the engineers rank the device calibration as the most importance factors that impact the data quality, followed by personnel training, sensor accuracy, accuracy of internal measurement, system that is used to process the rawdata, weather and testing conditions, and speed of testing vehicles. The guideline of data quality control and assurance will reflect these points.

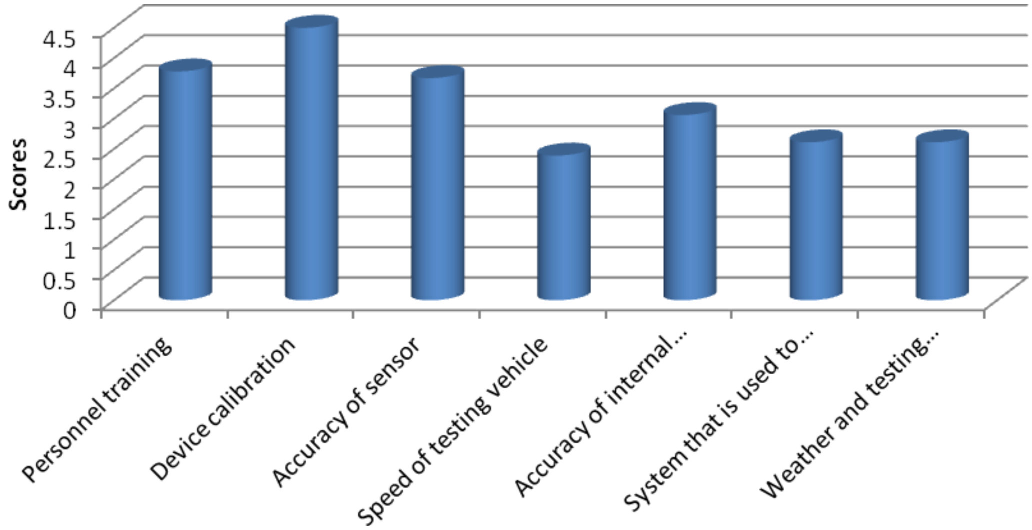


Figure 3- 13 Scores of different influence factors on data quality

3.3 Summary and Conclusions

From the current response of this survey the team has found out that:

- The state agencies are aware of the data quality issues during the data collecting. Many states agencies have already performed data quality control procedure either in-house or through third-party
- The interstates were monitored at high frequency and the roughness data had a highermonitoring frequency than distress data for state routes.
- Some states collected distress data in-house while others prefers to contract with dataprovider. There are also a few states adopt both methods to collect data. Furthermore,the common used way to interpret distress image is to use semi-automatic image process.
- To assure the data quality, the field calibration of testing equipment is the most selected steps before data collection. During the collection, monitoring of equipmentis selected by all the states. After the data collection, all the response states checked completeness of data.
- Individual distresses are recognized as the most common way to evaluating the confidence of data collection.
- The engineers rank the device calibration as the most importance factors that impact the data quality, followed by personnel training, sensor accuracy, accuracy of internalmeasurement, system that is used to process the raw data, weather and testing conditions, and speed of testing vehicles.

It was found that many states had already realized the importance of data quality control and some of them already adopted or are developing a standalone system to perform data quality control. However, there is no consensus on how to perform data quality control and assurance. The states have different ideas on evaluating the acceptance or confidence of pavement condition data. Since the participants of questionnaire are from pavement management division of each state DOTs, the information that provided will reflect the current state-of-practice in data quality control and assurance in PMS.

4. Data quality management framework

4.1 Quality management components

The data quality management consists of quality assessment, quality design, and quality monitoring.

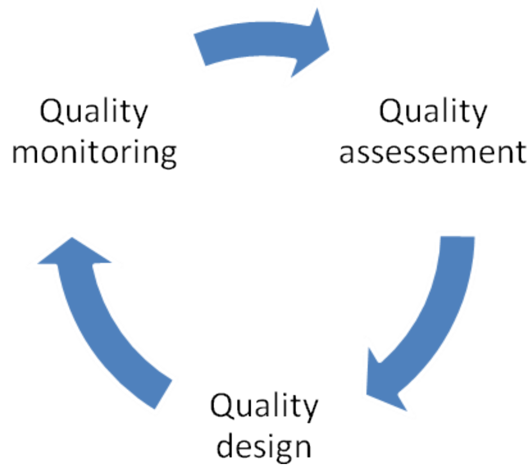


Figure 4- 1 Phase involved in providing quality information

(1) Quality design

The data rules are designed to perform data assessment. The data rules specify the criteriaof acceptance. Some principles of data rules need to be followed.

Variability

The criteria for variability consist of two parts: 1) The collected data are repeatable. This means the data collected from the same testing equipment are repeatable under the same testing condition, whereas the data collected from the different testing equipment are repeatable under the same testing condition; 2) The difference of collected data from bothsides are low. The roughness data (IRI and rut depth) are collected from left and right wheel path, respectively. The difference of collected data should be within the allowable tolerance difference.

Validity

The criteria for validity are to specify the reasonable ranges of collected data. Any data out of the reasonable ranges is considered as the abnormal data. They should be re-checked by the data provider and re-processed or re-collected based on request.

Consistency

The requirement for consistency means the change of collected data from one wheel pathshould be consistent with that from another. The trend line which illustrates the change ofindices over time should follow the normal direction. The abnormal change of trend line may be the indication of abnormal data or other interference such as maintenance actions.

Logicality

The change of different types of data should be consistent with each other. There are interrelationships between different types of indices. These should also be considered when the quality of data is designed,

(2) Quality assessment

In quality assessment process, the overall quality of data provided by the vendor should be estimated. The content of quality assessment includes: the data content, data formationand structure. The checklist of pavement condition data may include:

1) Completeness;
2) Correctness;
3) Tolerance of the invalid data;
4) Variability; and
5) Consistency.

(3) Quality Monitoring

During the production, the data collecting process should be monitored from the beginning of equipment verification till the end of the data delivery. The collected data should be checked periodically to ensure that:

1) The operation of testing equipment is normal;
2) Data production is conducted in accordance with the expectation;
3) Collected data are within the expected range of value;

The results of quality monitoring should be reported as a part of quality management report.

4.2 Quality classification of pavement condition data

The purpose of data quality management is to ensure high-quality data which can be usedto correctly perform maintenance and rehabilitation (M&R) analyses. Therefore, the dataquality is classified in terms of different purposes. In this study, the data quality is classified into basic quality and analytical quality.

The purpose of basic quality is to estimate whether the collected data are within the expected ranges. When the basic quality of data is estimated, those sections in which the collected data were obvious abnormal or out of the range will be double checked. Thedate within those sections may either be re-collected or re-processed.

The purpose of analytical quality is to evaluate the suitability of data which can be used to perform M&R analyses. The analytical quality is conducted based on the result of basic quality. The indicators which are used to evaluate basis quality and analytical quality are listed in Table 4-1.

Table 4- 1 Data used for quality classification

Data used for basis quality	Data used for analytical quality
IRI_{LT}; IRI_{RT}; $\lvert IRI_{LT} - IRI_{RT} \rvert$;$RUT_{LT}$; RUT_{RT}; $\lvert RUT_{LT} - RUT_{RT} \rvert$; PDI.	Number of data record; Latest maintenance record; R square of the fitting model.Performance curve

4.2.1 Basic quality

Data used for estimating basis quality include: IRI from both side, rut depth from both sides, the difference of IRI and rut depth from both sides and pavement distress index (PDI). The definition of basic quality of data is listed in Table 4-2. The collected data of high-quality should be in accordance with the range specified in Table 4-3, Table 4-4 andTable 4-5.

IRI and rut depth are collected in both wheel paths. The pavement serviceability index (PSI) is calculated from IRI. The representative value of PSI and rut depth for a section isthe average of value from both wheel paths. Therefore, the variability of PSI and rut depth can be represented by the difference of both paths. With the increase of difference of IRI and rut depth from both paths, the variability of PSI and rut depth increases. The
representativeness of the average value of PSI and rut depth for a section is compromised.Sections with differences of IRI and rut depth out of range are classified as medium for quality level.

The pavement condition data are classified as low quality if either the value of IRI, rut depth or the difference between both sides is out of range.

Table 4- 2 Definition of basic quality

Quality level	Requirements
High	• Rut depth and IRI are within the range in Table4-3. • Difference of IRI and rut depth between twowheel paths is within the limit in Table 4-5. • Distress data are within the limit in Table 4-4. All requirements above are met
Medium	• Rut depth and IRI are within the range in Table4-3. • Differences of IRI and rut depth between twowheel paths are out of the limit in Table 4-5. • Distress data are within the limit in Table 4-4. All requirements above are met
Low	• Rut depth and IRI are out of the range in Table 4-3. • Differences of IRI and rut depth between twowheel paths are out of the limit in Table 4-5. Distress data are out of the limit in Table 4-4.

Table 4- 3 Expected value of roughness data

Items	Expected Values	Percent within limits
IRI	20.0-400.0 in/mi	100
Rut depth	0-1.00 in	100

Table 4- 4 Expected value of distress data

Items	Expected Values (Sum of each severity)	Percent within limits
Pattern cracks*	0-100	100
Patch	0-100	100

Pattern cracks are the sum of each severity of fatigue cracks and block cracks.

Table 4- 5 Expected value of difference between two wheel paths

Items		Criteria	Percent within limits
Difference of IRI between two sides, in./mi.	interstates	Less than 10.0	95%
	Others	Less than 30.0	
Difference of Rut between two sides, in.		Less than 0.20	95%

The purpose of basic quality analysis is to evaluate whether the collected data can represent the pavement condition. Data with high quality can accurately and precisely represent the current pavement condition. Due to the possible bias between two wheel paths, data with medium data quality overestimate one wheel path and underestimate theother.

Table 4-5 lists the tolerance of difference of roughness data between two wheel paths. It indicates that the difference of value between two wheel paths is allowed. The criteria of difference were determined by analyzing the historical data value. The large difference ofvalue between two wheel paths may be the result of surface distresses on one wheel-path and no distresses on the other. The average value may not accurately or precisely represent real pavement condition. Note that the difference of value (IRI and rut depth) between two paths is allowed. However, if the percentage of out-of-range sections increases, the representativeness of average value is compromised. Therefore, if the differences of value between two wheel paths are larger than the limit in Table 4-5, the data quality is classified as medium.

4.2.2 Analytical quality

Data used for estimating analytical quality include: the number of data records for curving fitting; latest maintenance records; R square of the fitting model; trend of performance curve. The definition of analytical quality of data was listed in Table 4-6.

The number of data record depends on the collection frequency of data. Normally, the roughness data were collected once a year on interstates and once every two years on state routes. The distress data were normally collected once every two years. Note that the more data used for fitting the curve, the higher reliability of the performance curve will be. The analytical quality of data is classified as “High-”, if the number of data was lower.

The performance curve indicated the performance change over time. The normal changeof performance curve shows the performance decreased over time. However, due to pavement maintenance actions, the trend of performance curve might be different. Withthe latest maintenance actions, the data before the latest maintenance action can be excluded in the M&R analysis by assuming that these data have little influence on thetrend of performance curve after latest maintenance action.

R square of the fitting model is an indicator to evaluate the goodness-of-fit. The higher R square is, the better the performance curve will be and the more reliable the M&R resultswill be. The data quality is determined by R square.

Table 4- 6 Definition of analytical quality

Quality level	Requirements
High	• Collecting frequency: (Roughness data: 1 times/year for interstates; 2times/year for state routes; Distress data: 2 times/year for all roads.) • R square of the fitting model is greater than 0.6. • Latest maintenance actions are recorded. • Trend of performance curve is normal • All requirements above are met

High-	• Collecting frequency: (Roughness data: 1-1.5 times/year for interstates;2-2.5 times/year for state routes; Distress data: 2- 2.5 times/year for all roads.) • R square of the fitting model is greater than 0.6. • No latest maintenance records • Trend of performance curve is normal • All requirements above are met
Medium	• R square of the fitting model is 0.2-0.6. • Trend of performance curve is normal • No latest maintenance records • All requirements above are met
Low	• R square of the fitting model is less than 0.2. • Trend of performance curve is abnormal • One of the above requirement is met
Incomplete	• Collecting frequency: (The number of data is less than 30% of the number of years for all roads.) • No latest maintenance records • All requirements above are met

5. Evaluation of current pavement condition data

In this part, the completeness and validity of current PMS data were evaluated. Both completeness and validity are considered as the basic quality of pavement condition data.

The completeness check was conducted to estimate the percentage of missing data. It provided a general estimation of the total amount of data that can be used for representingcurrent pavement condition. The total segments occurred in the HPMA are listed in Table5-1. The road segment was identified in accordance with the following items, including, HR_ROUTCOD, HR_COUNTY, HR_CNTYSQ, HR_ROUTTYP, HR_ROUTNUM, HR_ROUTAUX, and HR_DIRECTN. Other types of highway include functional route and local routes which is not classified as state route and is managed by TDOT. Since the majority of highways are Interstates or State routes, the rest was not included in this study.

Table 5- 1 Number of segments for each type in HPMA (roughness data)

Type of highway	ID in HPMA	Total collected mileage	Percen tage,%
Interstate	I	3708	16.1
State route	SR	19022	82.5
Others	0A,0E,0F,0 h,T,0	330.7	1.4

5.1 Completeness of pavement condition data

The total coverage of pavement condition data is defined as,

$$\textbf{Tot. Coverage} = \frac{M_{\mathrm{a}} - M_{\mathrm{overlay}}}{M_{\mathrm{p}}} \qquad \text{(Eq. 5-1)}$$

Where, M_a is the actual collected length; $M_{overlay}$ is the overlaid length; M_p is the total length of the collected segments.

In HPMA, each segment was generally reported at one-tenth of a mile. The length of the last sub-segment of each segment is usually less than 0.1 mile. The actual collected length is calculated by summing up the length of each sub-segment as listed in Eq. 2. Thelength of each sub-segment (d_i) is the difference of “Beg_mil” and “End_mil”.

$$\mathbf{M_a} = \sum \mathbf{d_i} \qquad \text{(Eq. 5-2)}$$

Where, $d_i = (End\_mil) - (Beg\_mil)$.

The total length of the collected segments, M_P is calculated by summing up the lengths ofeach segment (L_i), as listed in Eq. 3.

$$\mathbf{M_P} = \sum \mathbf{L_i} \qquad \text{(Eq. 5-3)}$$

The overlaid length (Δ_i) is determined by the difference of actual collected length of segment d_i and length L_i of each segment. If Δ_i >0, there is overlaid within one segment; If Δ_i <0, it means there are gaps within the segment; If Δ_i =0, it means the collected lengthfully covers the segment.

$$\mathbf{\Delta_i} = \sum \mathbf{d_i} - \mathbf{L_i} \qquad \text{(Eq. 5-4)}$$

Figure 5-1 and Figure 5-2 illustrate the coverage and total collected length of roughness and rutting. The coverage after 2002 were generally greater than 90%. Before 2002, the total coverage ranged from 20% to 90%. In 1995, the actual collected length was only 80.52 miles. Comparing with other years, it can be inferred that there was something disturbed the data production in 1995. It can also be seen that the total collected length ofroughness and rutting data tended to increase after 2002.

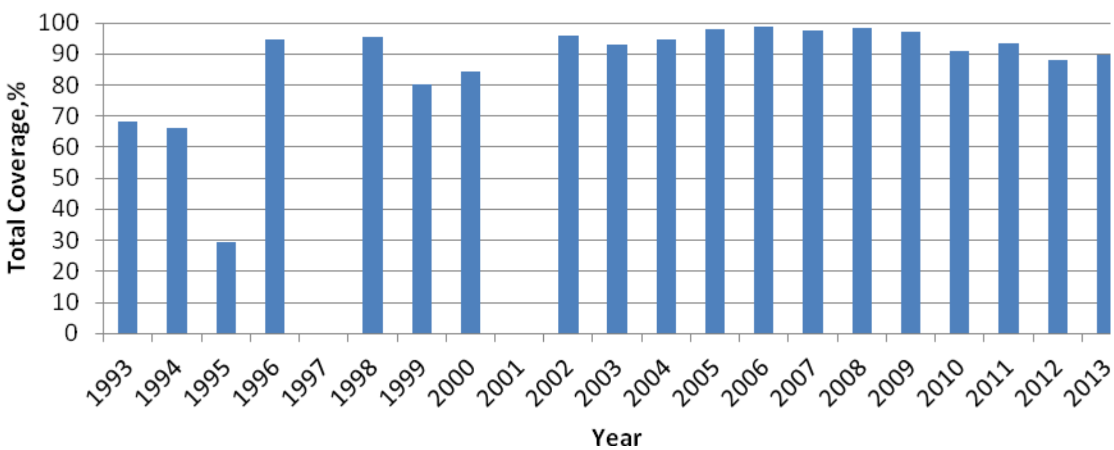


Figure 5- 1 Total coverage of pavement condition data (Roughness/Rutting)

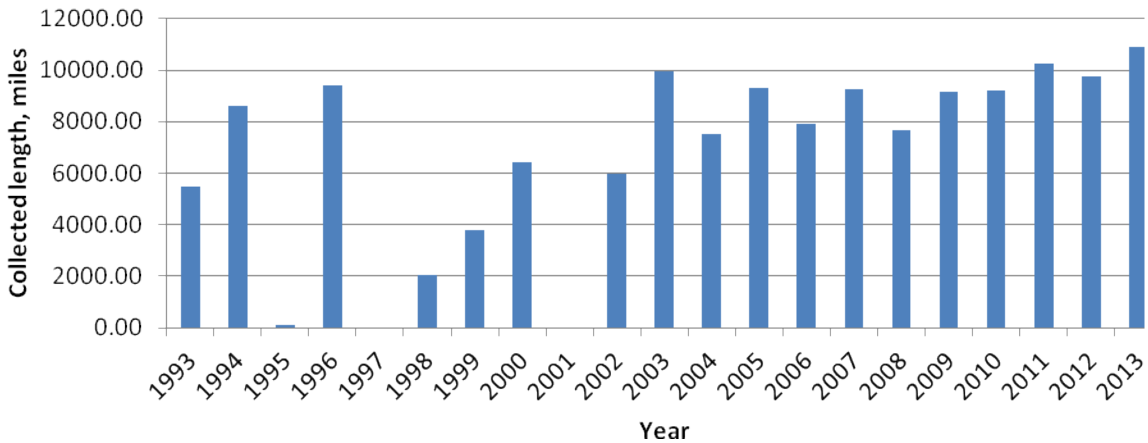


Figure 5- 2 Collected lengths (Roughness/Rutting)

Figure 5-3 and Figure 5-4 illustrate the coverage and total collected length of distress data.The collection of distress data started from 1998. The coverage of distress data was generally greater than 80%. The total collected length of distress data were from 7000 miles to 8000 mile annually.

$$|IRI_{lt} - IRI_{rt}| < \varepsilon$$

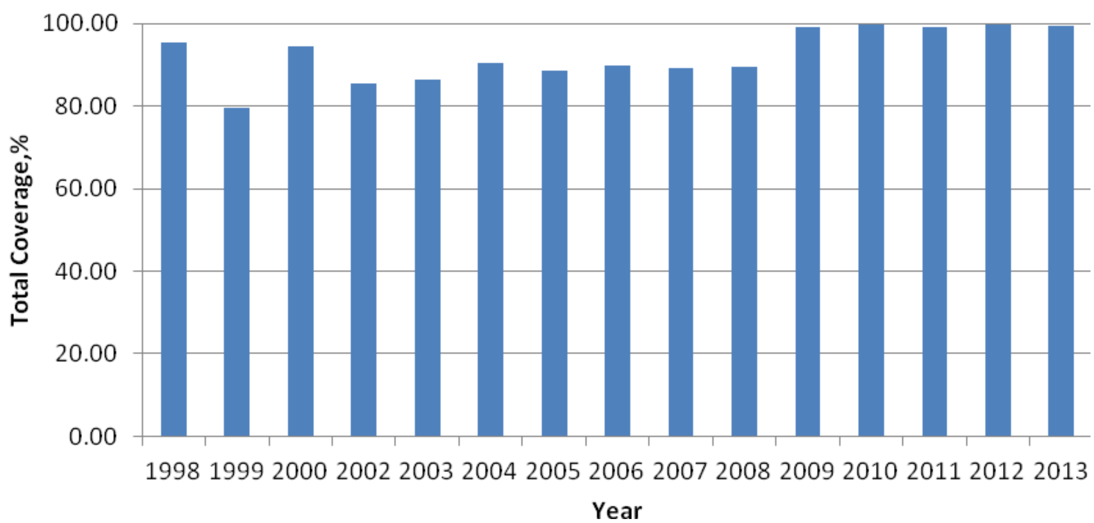


Figure 5- 3 Total coverage of pavement condition data (Pavement distress data)

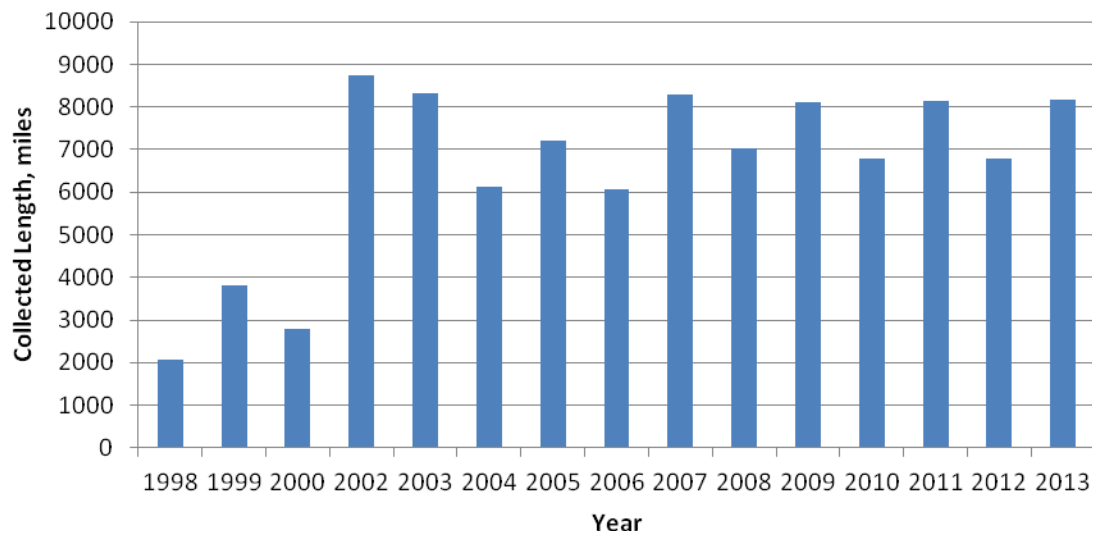


Figure 5- 4 Collected lengths (Pavement distress data)

5.2 Evaluation of abnormal data

The process of validity check is to identify those data out of the reasonable ranges. Table5-2 listed the expected values for distress for some state agencies. According to the historical data from HPMA, the expected values for distress for TDOT were listed in Table 4-3.

Table 5- 2 Agency expected values for distress

Distress	Colorado[1]	Nebraska[2]	Oklahoma[3]
IRI	800 in./mi.	+190 in./mi.	20-600 in./mi.
Rut Depth	1.5 in	+0.2 in.	0-1.25 in.
Faulting	-	+0.04 in.	0-0.8 in.

Note: 1) the maximum expected values for each one-tenth of a mile; 2) maximum increase of expected value from previous year's survey; 3) the maximum expected valuesfor each 0.01-mile.

The length of road sections with abnormal data is illustrated in Figure 5-5 and Figure 5-6.Figure 5-5 indicates that the length of sections with IRI out of range was less than 10 miles except for 2002 (15.785 mile). Comparing with the total collected length, the ratio of abnormal data was less than 1%. Figure 5-6 illustrates the length of sections with abnormal rut data. In 2002, the length of sections with rut depth greater than 1.25 in. was 5718 miles for the left side and 552 miles for the right side. This means over

90% collected segments had abnormal data in the left side while about 10% collected segments in the right side. There might be something wrong with either the data collection equipment or data post-processing. The length of abnormal data seemed reasonable on other years.

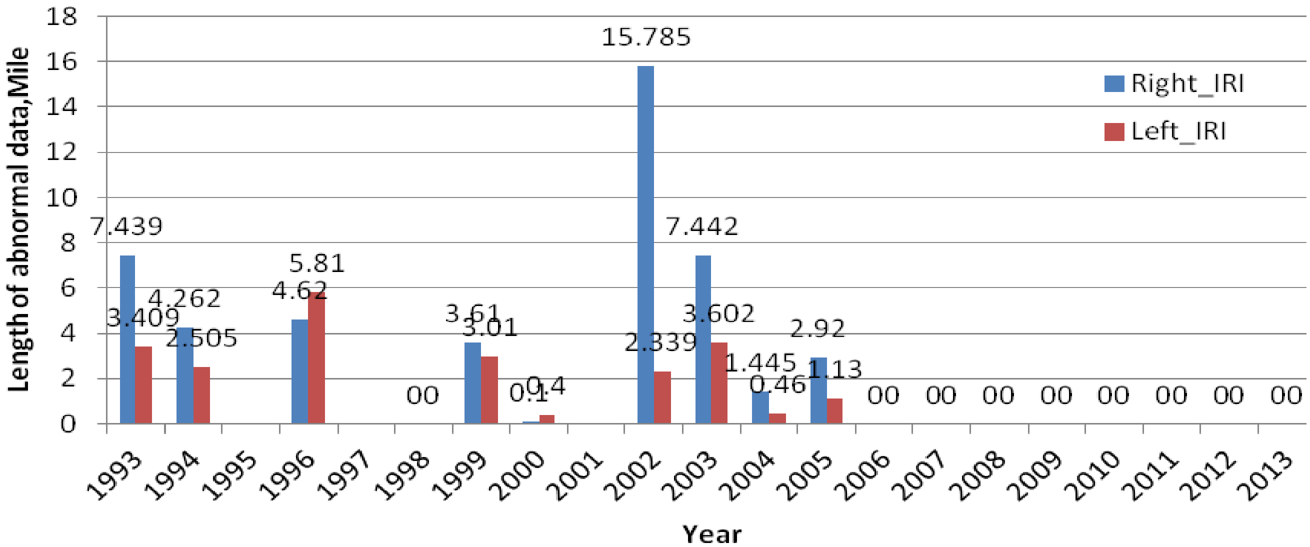


Figure 5- 5 Length of sections with abnormal data (IRI out of range)

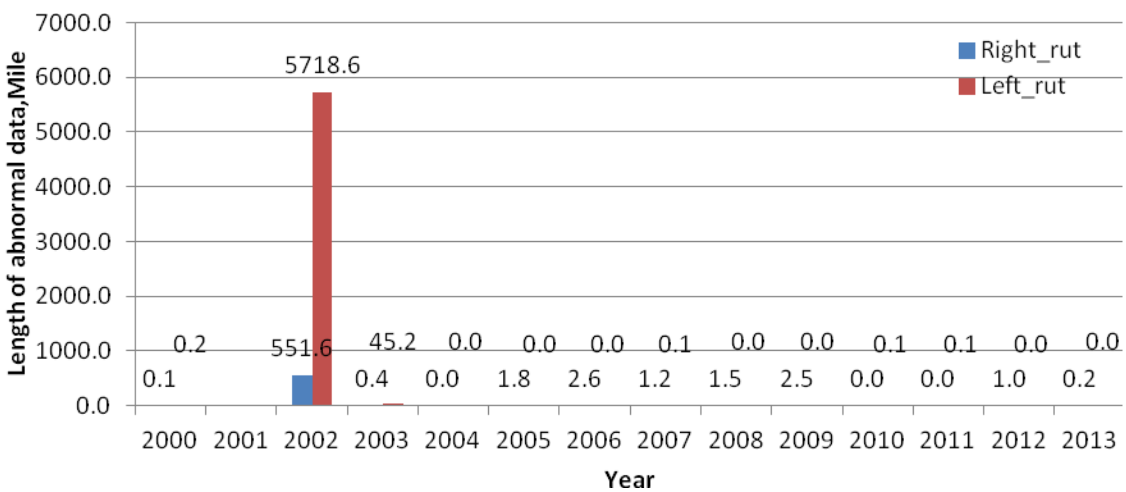


Figure 5- 6 Length of sections with abnormal data (rut depth out of range, since 2000)

Generally speaking, the criteria for expected value in Table 4-3 seem reasonable. Comparing with other states in Table 5-2, the recommended ranges are covered by the ranges specified by other states. By applying these criteria, the agency can assess the basic quality of data production and determine whether some sections with out-of-range data needs to be re-collected or re-processed before accepted.

According to the expected value in Table 4-4, the length of road sections in which the distresses were out of range was listed in Table 5-5. The abnormal distress data were observed before 2008, whereas no section was found to have abnormal distress data after2008.

Table 5- 3 Length of section containing out-of-range distress data

Year	Length of out-of-range sections
1998	13.8
1999	147.31
2000	0
2002	38.69
2003	45.02
2004	2.3
2005	21.24
2006	11.42
2007	49
2008	129.37
2009	0
2010	0
2011	0
2012	0
2013	0

5.3 Explore the function of completeness check in HPMA

The highway data check function in HPMA could be found from “Data Update” menu. Itcan check for completeness, pavement type and width, condition, and work history.

In the completeness part, the following types were activated to be checked by users.(SeeFigure 5-7)

- **Landmarks/Events**, which is reported in total counts of Landmarks/Events or noLandmark/Event data;
- **Administrative,** which is reported in length of highway gaps, length of no data occurrence;
- **Jurisdictions,** which is reported in length of highway gaps, length of no data occurrence;
- **Environment,** which is reported in length of highway gaps, length of no data occurrence;
- **Geometric,** which is reported in length of highway gaps, length of no data occurrence;
- **Shoulders,** which is reported in length of highway gaps, length of no data occurrence;
- **Traffic history**, which is reported in length of highway gaps, length of no data occurrence;
- **Roughness/Rut,** which is reported in length of highway gaps, length of no data occurren**ce;**
- **Distress,** which is reported in length of highway gaps, length of no data occurrence.

The some of these above data have seldom changed since they were put into the HPMA, such as landmarks/events, administrative, jurisdictions, environment, etc. Others may change accompanied with the pavement maintenance or rehabilitation, such as geometric,shoulders. The traffic history, roughness/rut and distress will change every year when new recorded data are added.

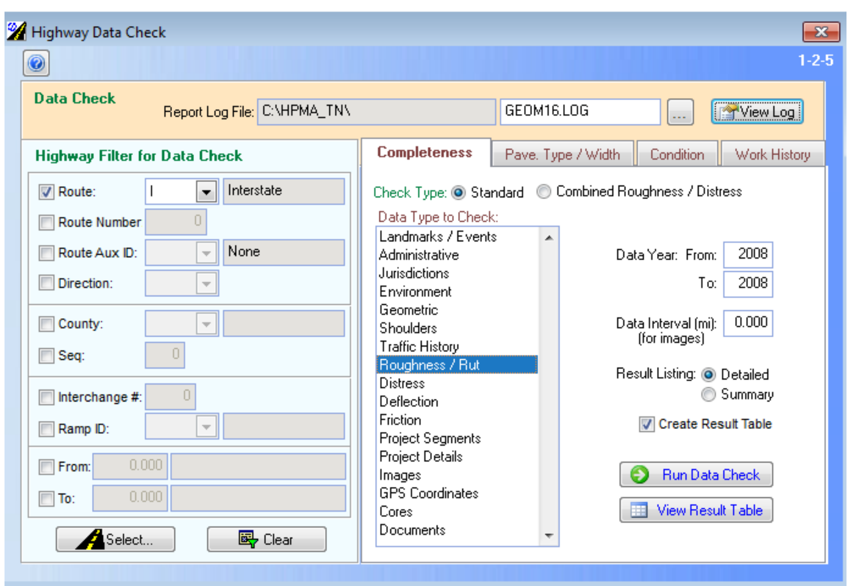


Figure 5- 7 Interface of data completeness check in HPMA

In the “pavement type/width” part, the user can check with the roadway geometric data such as pavement width, numbers of lanes, etc (see Figure 5-8). It consists of three mainoptions.

- The pavement type with project segment and/or distress data reported the record conflicts on pavement type and pavement distress type (see Figure 5-9);
- Pavement width with project segment reported the inconsistency of pavement width in project and geometry (see Figure 5-10);
- Pavement width/No. of Lanes reported the segments less than selected lane width(Standard land width-Check difference) and other pavement width information about the total length of selected segment (see Figure 5-11).

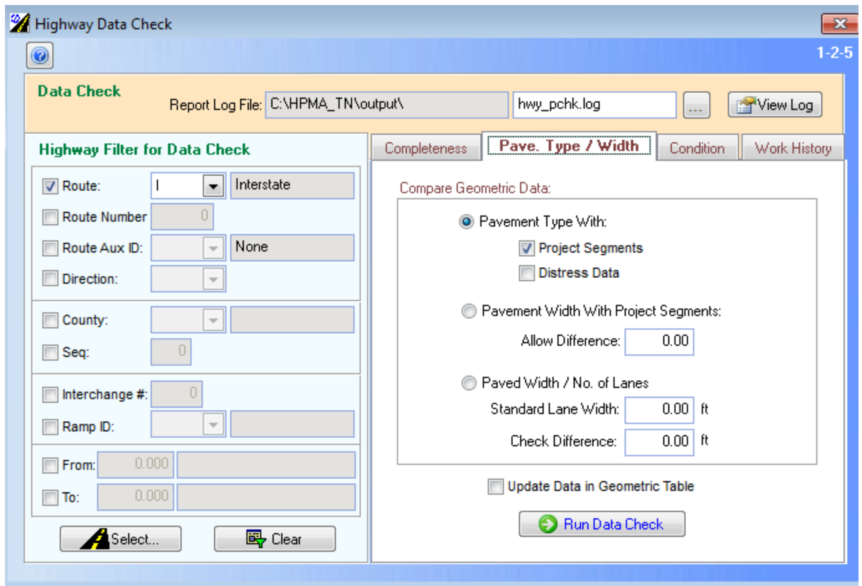


Figure 5- 8 Interface of checking pavement type and width in HPMA

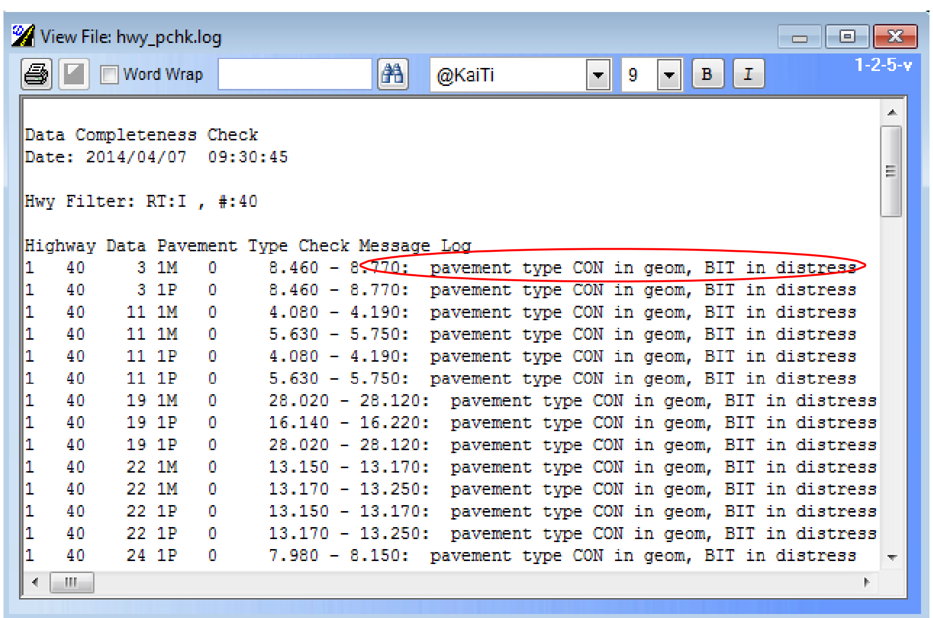


Figure 5- 9 Report of record conflicts on pavement type and pavement distress

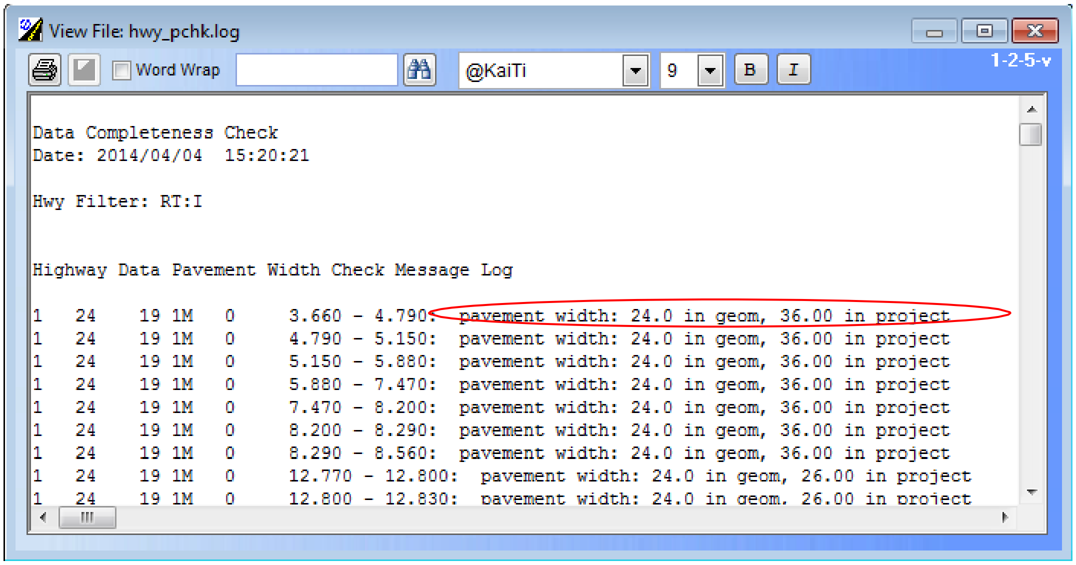


Figure 5- 10 Report of record conflicts on pavement width in project and geometrics

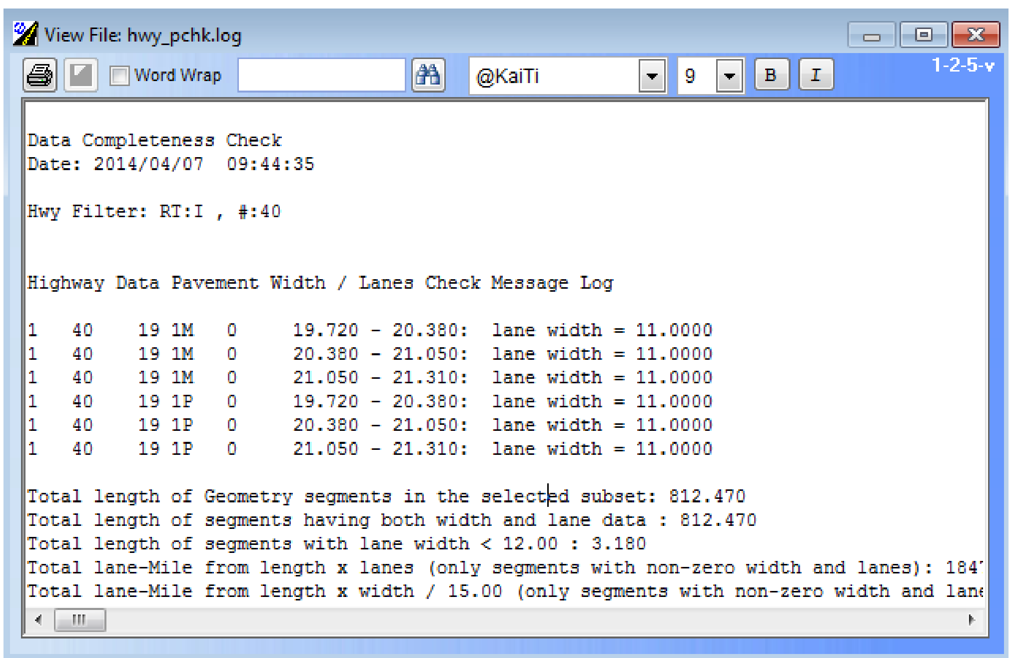


Figure 5- 11 Report of lane width information of the selected segments

In the “condition” part, the user can check with the completeness of pavement conditiondata. (See Figure 5-12) After selecting the interested segments and clicking “View Results”, a table showed the record of roughness data and distress data will pop out. It will reveal details of the missing data of pavement roughness and/or distress in each segments involved in this selection, including:

- Highway ID information;
- “R length” and “D length” length of segments that don’t have roughness data (IRIand RUT);

- “Gap length” length of segments that have data gaps.

An example of report of completeness of roughness and distress was illustrated in Figure5-13.

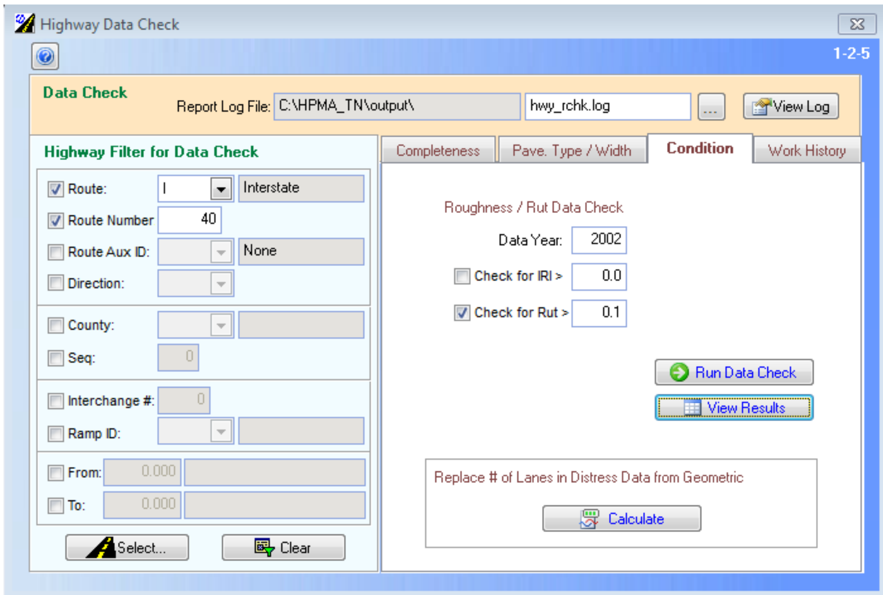


Figure 5- 12Interface of checking pavement condition data in HPMA

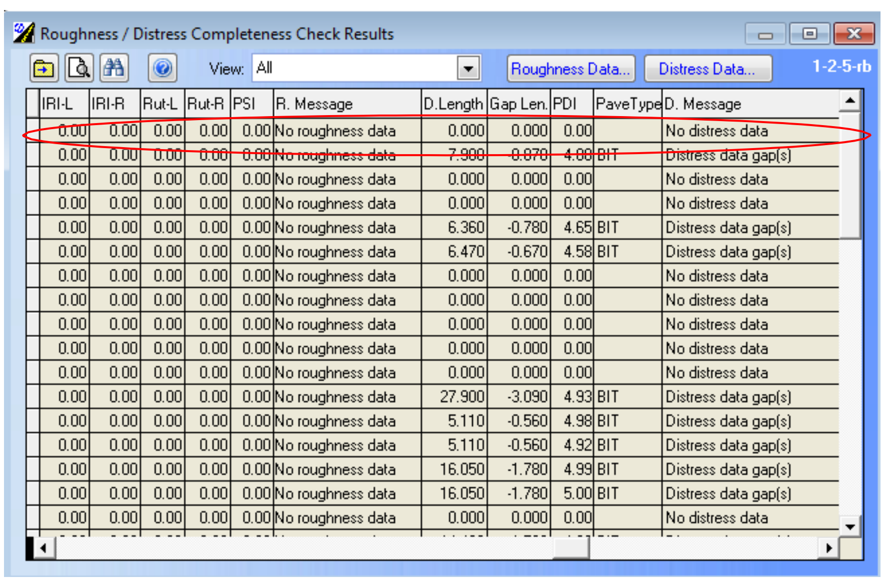


Figure 5- 13 Report of roughness and distress completeness of selected segments

In the “Work history” part, the user can check with the maintenance record of selected pavement segments. (See Figure 5-14) The detailed information will be reported in the table by clicking the “View results”. (See Figure 5-15) It would illustrate the length of segments with no construction and/or maintenance.

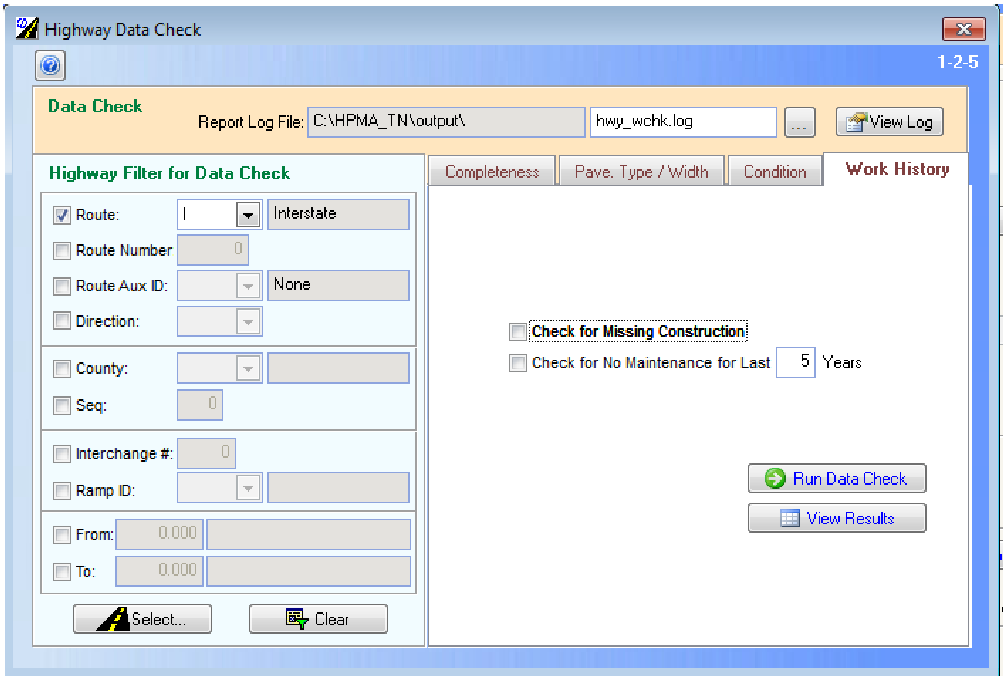


Figure 5- 14 Interface of checking work history in HPMA

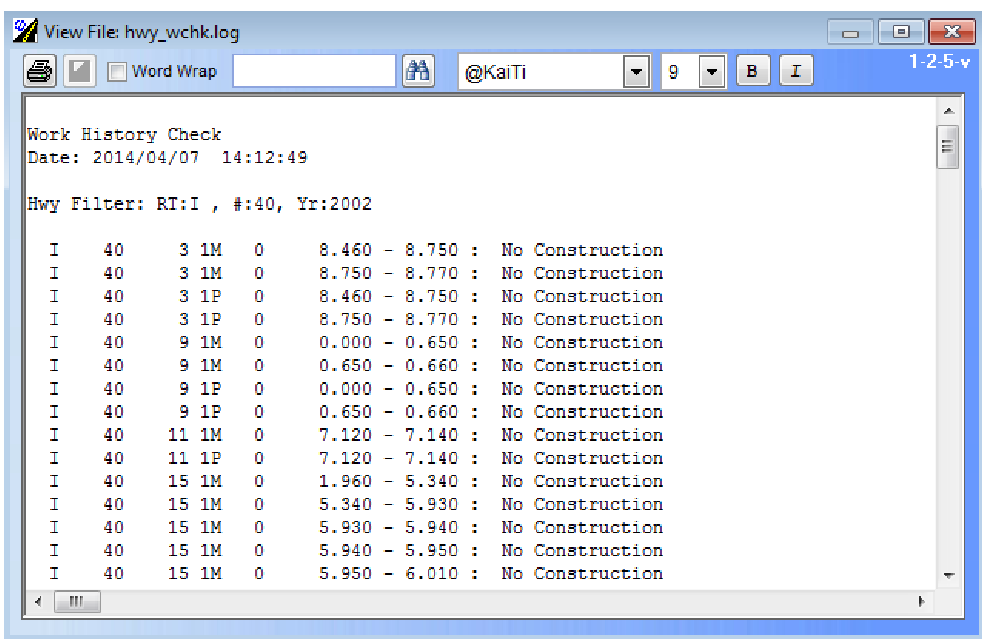


Figure 5- 15 Interface of checking work history in HPMA

6. Evaluation of variability of roughness data

Variability describes the bias and dispersion of series of measurements to a true value ora reference value. It consists of accuracy and precision. Accuracy can be considered as systematic errors, whereas precision can be considered as random errors. These errors generate data variability and cause uncertainty on pavement evaluation and maintenancedecision. To better understanding the data variability, a systematic evaluation of variability of roughness data was conducted.

6.1 Methodology

The variability of roughness data was evaluated in terms of different pavement condition.The pavement conditions were classified based on pavement distress index (PDI). Figure6-1 illustrates the analysis scheme. The roughness data were first grouped into "Interstates" and "State routes". For each route type, the data were grouped based on the PDI value. There were three scenarios considered: PDI=5, 2.5<PDI<5, and PDI≤2.5.

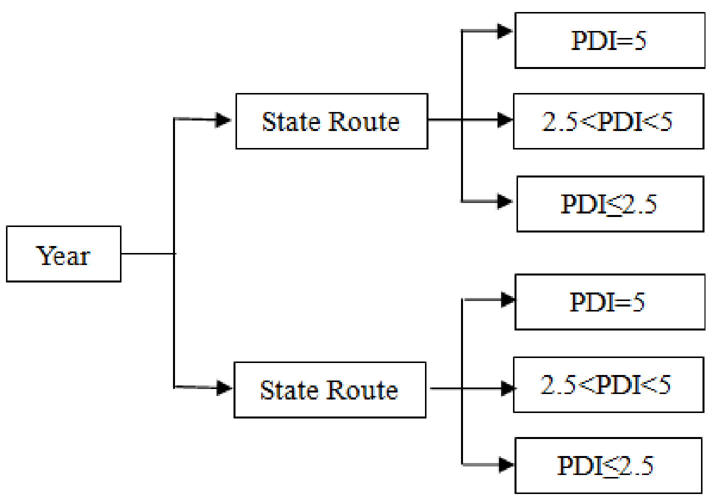


Figure 6- 1 Analysis scheme for roughness data

To evaluate the data variability, the following statistics parameters were used.

- Sum of squares due to error, *SSE*;
- Mean squared error, *MSE*;
- Root means squared error, *RMSE*;

Assume that $X(x_1,x_2,\ldots,x_n)$ and $Y(y_1,y_2,\ldots,y_n)$ represent the pavement roughness data collected from each side. *SSE* is the sum of square difference (d^2) from the measured point to equity line as shown in Eq. 6-1.

$$SSE = \sum_{i=1}^{n}(x_i - y_i)^2 \qquad \text{(Eq. 6-1)}$$

The *MSE* is the mean of square difference is calculated as Eq. 6-2,

$$MSE = \frac{SSE}{n} = \frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2 \qquad \text{(Eq. 5-2)}$$

The RMSE is determined by Eq. 6-3.

$$\boldsymbol{RMSE} = \sqrt{\frac{\boldsymbol{SSE}}{\boldsymbol{n}}} = \sqrt{\frac{\mathbf{1}}{\boldsymbol{n}}\sum_{\boldsymbol{i}=\mathbf{1}}^{\boldsymbol{n}}(\boldsymbol{x}_{\boldsymbol{i}} - \boldsymbol{y}_{\boldsymbol{i}})^{\mathbf{2}}} \qquad \text{(Eq. 6-3)}$$

The RMSE indicated the overall difference of roughness data between two sides. The higher the RMSE is, the higher difference of IRI value (or rutting depth) between two sides will be.

Matched pairs tests were used to study the mean difference of data from both sides. The matched pairs tests were conducted by assuming the two population distributions are normal with unequal variances and the two random samples are independent. In this study, the hypothesis was:

$$H_0: \overline{\mu_{left}} - \overline{\mu_{right}} = 0$$

$$H_1: \overline{\mu_{left}} - \overline{\mu_{right}} \neq 0$$

$$T.S.: t = \frac{\overline{\mu_{left}} - \overline{\mu_{right}} - 0}{\sqrt{\frac{{s_1}^2}{n_1} + \frac{{s_2}^2}{n_2}}}$$

For a level α, Type I error rate,

Reject H_0 if $|t| > t_{\alpha/2}$

For a specified level α, the approximate confidence interval for $\overline{\mu_{lt}} - \overline{\mu_{rt}}$ is

$$\overline{\mu_{lt}} - \overline{\mu_{rt}} \pm t_{\alpha/2}\sqrt{\frac{s_1{}^2}{n_1} + \frac{s_2{}^2}{n_2}}$$

Where, the t percentile has

$$d_f = \frac{(n_1-1)(n_2-1)}{(1-c)^2(n_1-1)+c^2(n_2-1)}, \text{ with } \quad c = \frac{s_1^2/n_1}{\frac{s_1^2}{n_1}+\frac{s_2^2}{n_2}}$$

6.2 Variability of International roughness index

The results of RMSEs for Interstate and State route at different PDI levels were illustrated in Figure 6-2 and Figure 6-3. The RMSEs indicates the bias of measured points towards the equity line. The lower the RMSE is, the closer the measured value from both sides will be.

Both Figure 6-2 and Figure 6-3 indicate that the RMSEs increased with the decreasing ofPDI for interstates in 6 out of 12 years while that for state routes in 10 out of 12 years. This means the pavement distresses do affect riding of the test vehicle. Data variability increased as the pavement performance decreased. There was a more significant influence of PDI on IRI for state routes than for interstates. RMSE values for interstate were lower than that for state routes. The lowest RMSEs were round 20.0 in./mi. for stateroutes, whereas the largest RMSEs were round from 10.0 to 25.0 in./mi for interstates. This means the variability of IRI for interstates were significantly lower than state routes.Based on RMSEs result, it seemed that IRI results for interstates were generally less affected by the pavement distress and exhibited a lower variability.

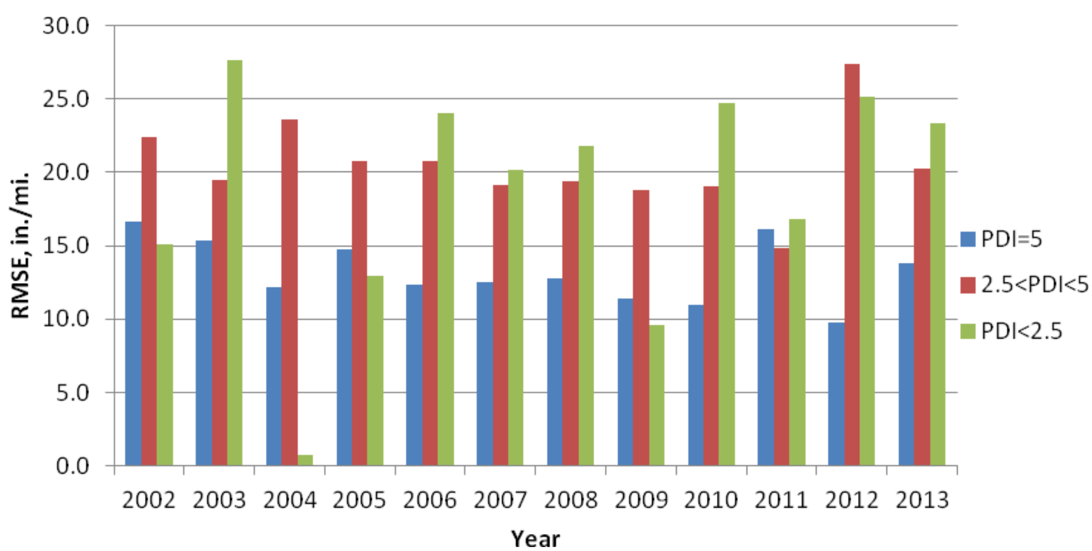


Figure 6- 2 RMSE of IRI (Interstates)

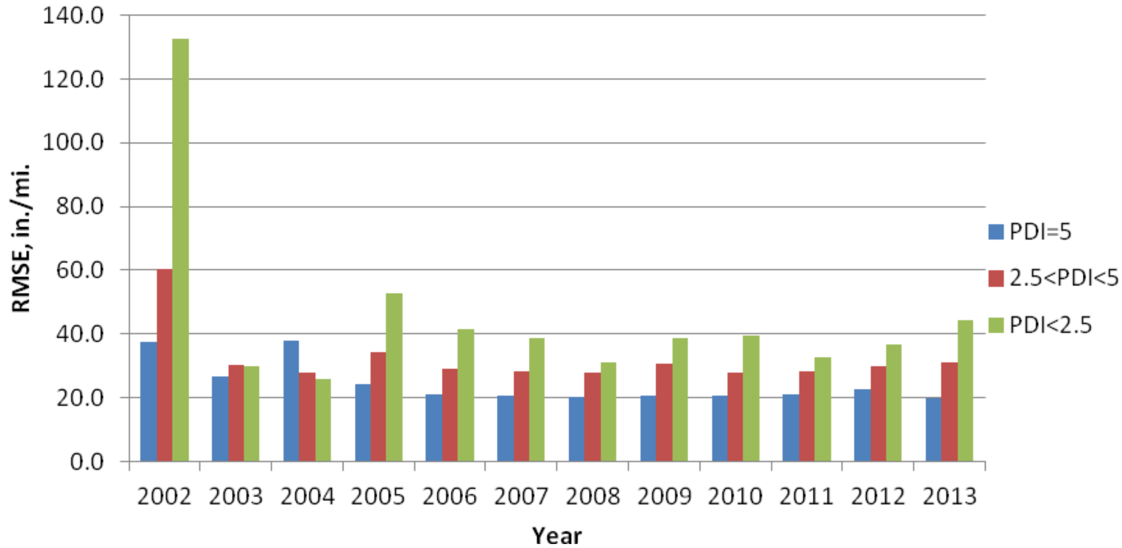
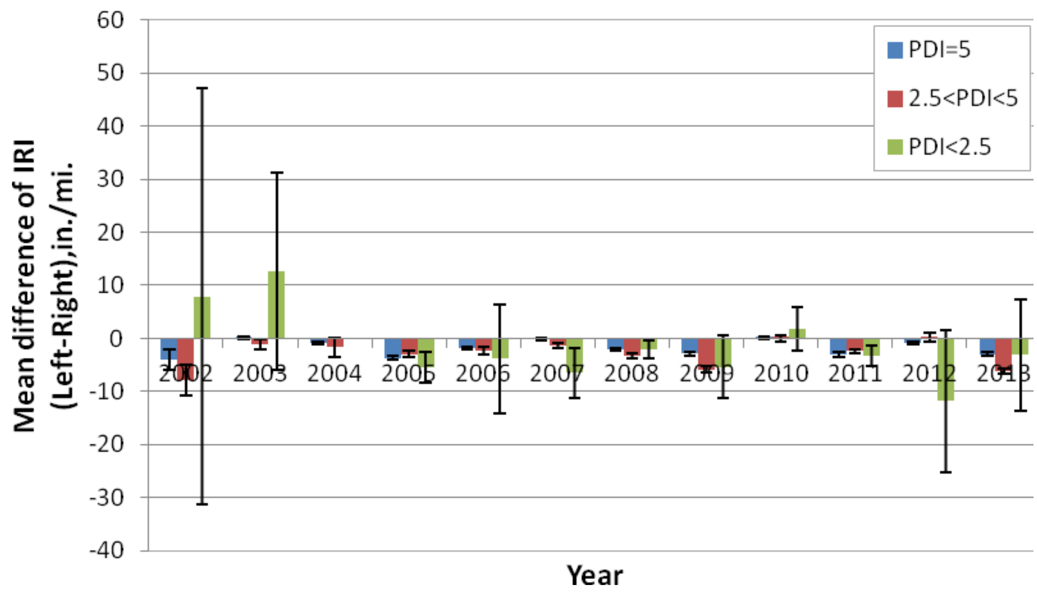


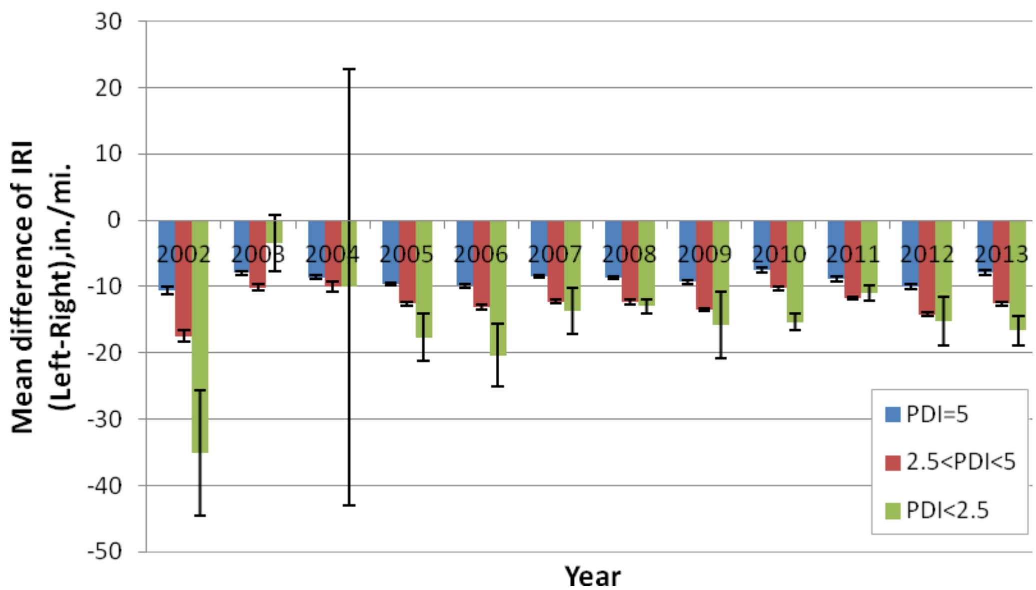
Figure 6- 3 RMSE of IRI (State Routes)

Figure 6-4 illustrates the results for matched pairs test. The error bar on each column indicates the 95% confidence interval. If zero falls down within the range of confidence interval, the mean value for IRI from both sides were statistically identical. It can be seenthat:

- The mean difference of IRI was generally less than zero for both interstate and state route, indicating the mean IRI from left side was lower than right side. Notethat results in 2002 and 2003 should be excluded since the samples population inthese years was small.
- With the decreasing of PDI, the mean difference of IRI seems to be increasing which indicated that pavement distress may increase the variability of IRI.
- The mean difference of IRI for state route was lower than that for interstate whichindicated the variability of IRI for interstate was lower than state route. Since the pavement performance of interstate is generally better than state route, it can be concluded a lower mean difference of IRI may be an indication of the better pavement condition.
- Lower mean difference of IRI and larger confidence interval may be the indication of good quality for pavement condition data. For example, quality of pavement condition data in 2007, 2010 and 2012 seems better than that in 2002 and 2003 for interstate.
- The mean of IRI from left side was generally lower than right side. This indicatedthat the pavement surface seems smoother on the left side than on right.



(a) Interstates



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b) State Routes

Figure 6- 4 Difference of IRI from both wheels

6.3 Variability of rut depth

The results of RMSEs for Interstate and State route at different PDI levels were illustrated in Figure 6-5 to Figure 6-6. One may not find:

- It illustrated that 6 out of 12 years showed a trend of increasing of RMSEs with the decreasing of PDI for state routes. This means the PDI seemed to affect the rutting depth in some degree for state routes.
- It was also found that RMSEs for interstates seemed a slight lower than state routes which means the variability of rutting depth from both sides for state routeswas larger.
- It indicated that in calendar year 2002, the variability of rutting depth is greatest among all the 12 years according to the value of RMSEs in each year. The variability of rutting depth for interstate showed a more stable trend than state routes.

Based on RMSEs result, it seemed that results of rutting depth for interstates were generally less affected by the pavement distress and exhibited a lower variability given that the fact that pavement conditions for interstates were better than state routes.

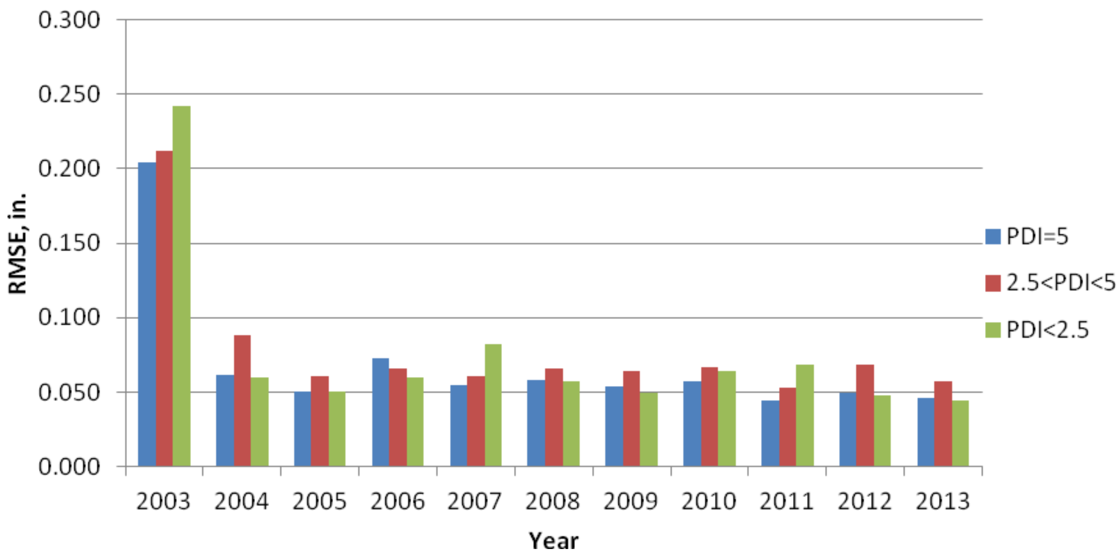


Figure 6- 5 RMSE of rutting depth (Interstates)

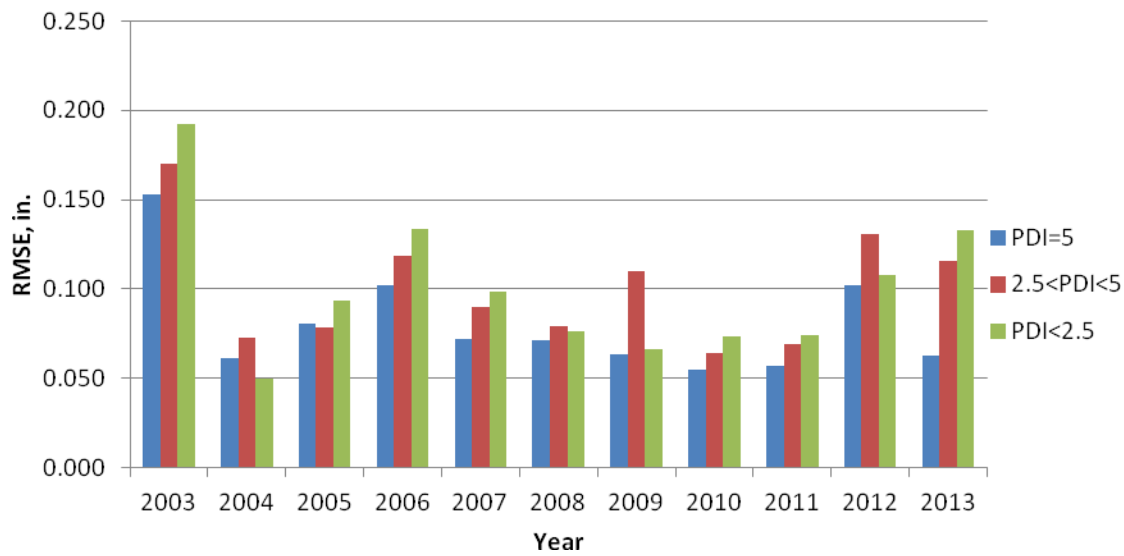
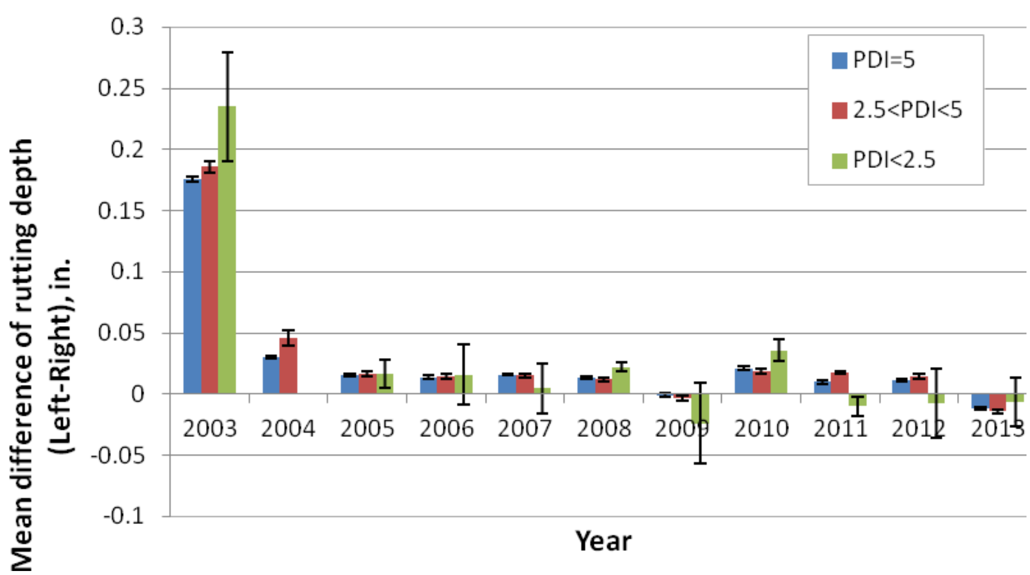


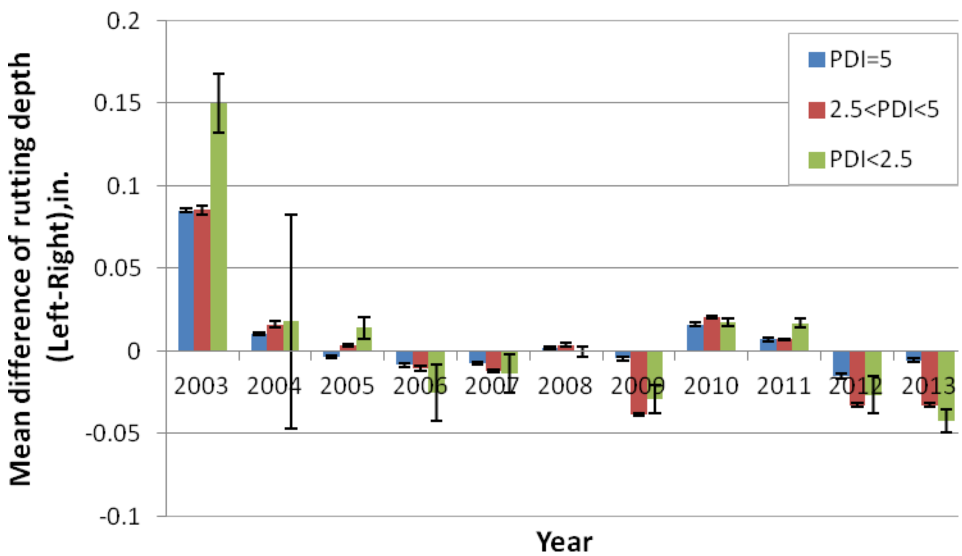
Figure 6- 6 RMSE of rutting depth (State Routes)

Figure 6-7 illustrated the results for matched pairs test. It can be seen that:

- The mean differences of rutting depth were generally greater than zero with PDI>2.5 for interstates except 2009 and 2013. This indicated the rutting depth inthe left side is larger than the right for interstates.
- It seemed that the data quality became stable after 2003. And the changes of rutting depth from both sides were less than 0.05 in.
- The results indicated that rutting depth from both sides were not statistical identical. However, it can be concluded that the rutting depth from both sides were very close since the 95% confidence interval were within $\pm$0.05 in.



(a) Interstates



(b) State Routes

Figure 6- 7 Difference of rutting depth from both wheels

6.4 Determination of allowable variation of roughness data between two sides

The pavement serviceability index (PSI) is a function of IRI. It is also a synthesized indexfor making pavement maintenance strategies. The errors of IRI will influence the variation of PSI.

Given the series $\{X_i\}$, the mean absolute error ΔX can be defined as

$$\Delta X = \frac{1}{n}\sum_{i=1}^{n}\left|X_i - \overline{X}\right| \quad \text{or,} \quad \Delta X = \frac{1}{n}\sum_{i=1}^{n}\Delta X_i \qquad \text{(Eq. 6-4)}$$

Where, n is the sample number.

The relative error, E_r, is the ratio of mean absolute error to mean value is defined as

$$E_r = \frac{\Delta X}{\overline{X}} \times 100\% \qquad \text{(Eq. 6-5)}$$

The standard deviation σ_x can be written as

$$\sigma_x = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(X_i - \overline{X}\right)^2} \qquad \text{(Eq.6-6)}$$

The above equation represents the standard deviation when the sample number n→∞.

For the limit number of samples, the unbiased estimation of standard deviation S_x is written as

$$S_x = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(X_i - \overline{X}\right)^2} \qquad \text{(Eq. 6-7)}$$

For dependent valuable, assume that the relationship between indirect measurement f and direct measurements, x, can be written as

$$f = f\left(x_1, x_2, \ldots, x_n\right) \qquad \text{(Eq. 6-8)}$$

The mean value and absolute error for the measurements can be written as,

$$\begin{cases} x_1 = \hat{x}_1 + \varepsilon_1 \\ x_2 = \hat{x}_2 + \varepsilon_2 \\ \quad \ldots \\ x_n = \hat{x}_n + \varepsilon_n \end{cases}$$

$$f = f\left(\hat{x}_1, \hat{x}_2, \ldots, \hat{x}_n\right) + \mathrm{E}\left(\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_n\right) \qquad \text{(Eq. 6-9)}$$

f can be represented by Taylor's series at $\left(\hat{x}_1, \hat{x}_2, \ldots, \hat{x}_n\right)$ as Eq. 6-10.

$$f\left(x_1, x_2, \ldots, x_n\right) = f\left(\hat{x}_1, \hat{x}_2, \ldots, \hat{x}_n\right) + \sum_{i=1}^{n} \left.\frac{\partial f}{\partial x_i}\right|_{x_i = \hat{x}_i} \left(x - \hat{x}_i\right) + R\left(x_1, x_2, \ldots, x_n\right) \qquad \text{(Eq. 6-10)}$$

Where: $R\left(x_1, x_2, \ldots, x_n\right)$ is the infinitely small part.

Comparing Eq.6-9 with Eq. 6-10, the absolute error can be written as by omitting $R_2(x)$
,

The relative error can be
written as,

(Eq. 6-12)

The standard deviation of *f* can be written as

(Eq. 6-13)

The relative standard deviation of *f* can be written as

(Eq. 6-14)

According to the HPMS, the PSI model is
written as

$$PSI = 5 * e^{(-0.0055 \times IRI)}$$ (Eq. 6-15)

The absolute error can be written as,

$$E_{PSI} = 0.0275 * e^{(-0.0055 \times IRI)} \bullet \varepsilon_{IRI}$$ (Eq. 6-16)

The relative error can be written as,

(Eq. 6-17)

The absolute standard deviation of *PSI* is determined as,

$$\sigma_{PSI} = 0.0275 * e^{(-0.0055 \times IRI)} \sigma_{IR}$$ (Eq. 6-18)

The relative standard deviation of *PSI* is determined as,

q (Eq. 6-19)

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E 6

Eq. 6-19 indicated that the absolute error of *PSI* is determined by *IRI* value and its error. The relationships between absolute error of *PSI* and *IRI* error were illustrated in Figure 6-

7. It can be seen that the absolute error of *PSI* will increase with the increase of *IRI* error and decrease of *IRI* value. In general, IRI value is no less than 20 in./mi. Therefore, the curve with IRI of 20 determines the upper limit. Eq. 6-19 represents that the relative errorof *PSI* is dependant of *IRI* error. The curve in Figure 6-8 can be used to estimate the relative variance of *PSI* based on *IRI* error.

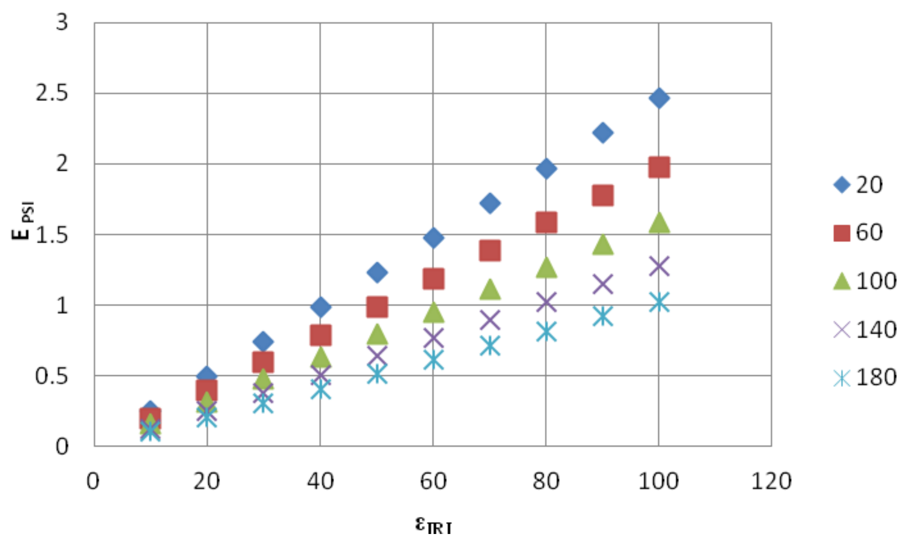


Figure 6- 8 Relationship of EPSI and εIRI

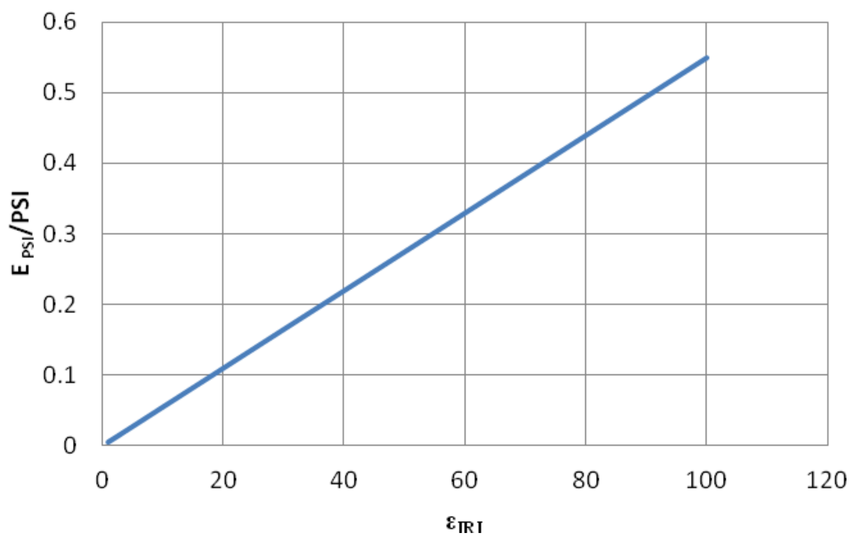


Figure 6- 9 Relationship of relative error of PSI and ε IRI

Table 4-5 lists the suggested tolerance of variability of roughness data (IRI and rutting depth) by analyzing the historical data. The tolerance of variability of roughness data is determined in terms of the route types. For interstates, the percentage of sections with IRIdifference less than 10.0 in./mi. should be at least 95%. For state route, the tolerance of IRI difference is wider comparing with the interstates. The percentage of sections that have higher variations (difference of IRI greater than 30.0 in./mi) in IRI between two paths should be less than 10%.

Table 6-1 lists the influence of IRI difference on *PSI* difference. A difference of IRI with 10.0 in./mi. may generate *PSI* difference less than 0.1, whereas, a difference of IRI with 30.0 in./mi can generate *PSI* difference up to 0.2. This means by applying the requirement in Table 4-5, the expected *PSI* difference could be less than 0.1 for interstates and less than 0.2 for state routes.

Table 6- 1 Influence of IRI difference on PSI difference

PSI	IRI, inch/mile	Difference of IRI between twosides, inches/mile	
		10	30
2.70	112.0	+0.07	+0.22
2.50	126.0	+0.07	+0.21
2.20	149.3	**+0.06**	**+0.18**
2.00	166.6	**±0.06**	**±0.17**
1.80	185.8	±0.05	±0.15

Figure 6-10 and Figure 6-11 illustrate the percentage of sections with the difference of IRI over the limit for interstates and state routes. The length of sections over limit before2000 was generally greater than that after 2000. TDOT contracted with two different service providers at that time. Therefore, the later contractor might utilize new technology or implement new procedure during collection production which resulted in less variability of IRI. The percentage over the limits ranged from 5.0% to 7.5% during 2002 to 2013, which was slightly higher than the value in Table 4-6. Therefore, re-checkor re-collection may be needed based on request from the pavement management engineers. It is recommended that those sections with PSI value less than 2.70 be re-checked.

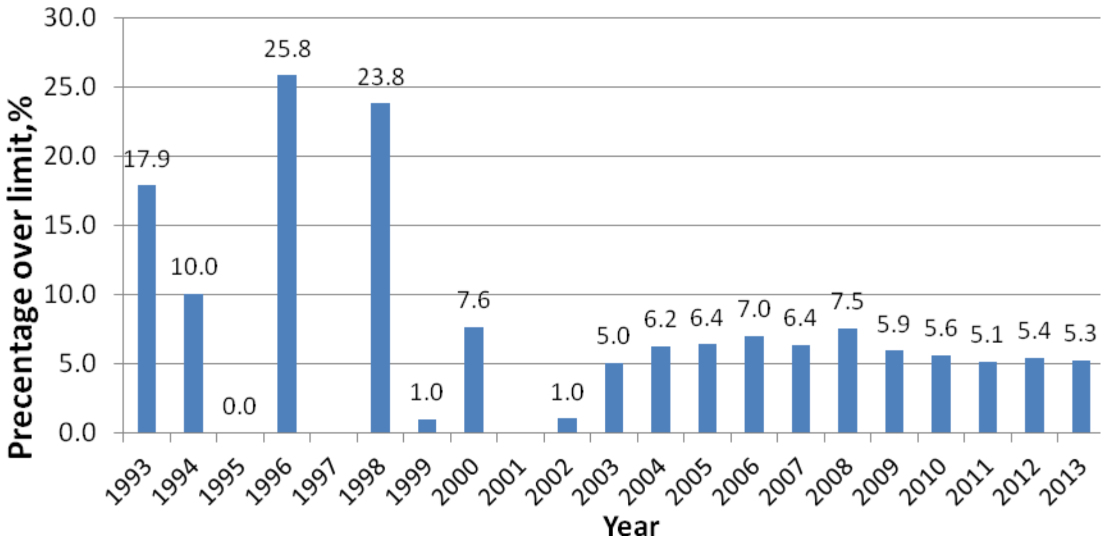


Figure 6- 10 Percentage over the variation limit-IRI (Interstates)

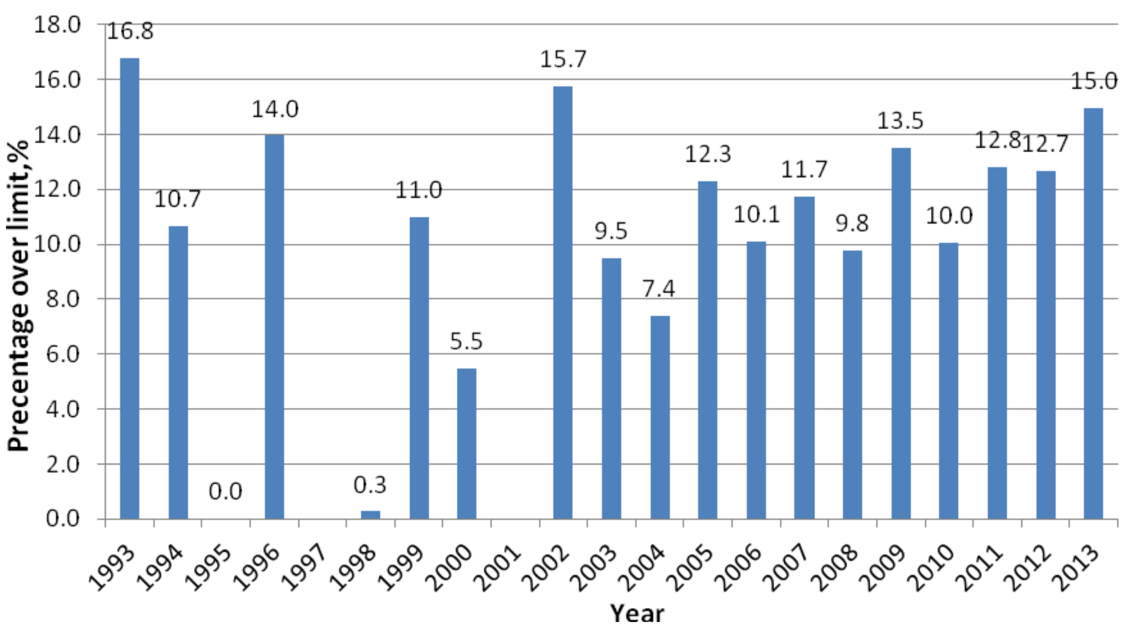


Figure 6- 11 Percentage over the variation limit -IRI(State routes)

Figure 6-12 illustrates the percentage over the limit of rut depth difference. The percentages over limit were less than 5% after 2004. Therefore, the requirement for rutting depth in Table 4-5 seems reasonable. The percentages over limit were higher than95% in 2002 and 2003. This means there might be some collection errors in these two years. Therefore, the rutting data in these years were questionable.

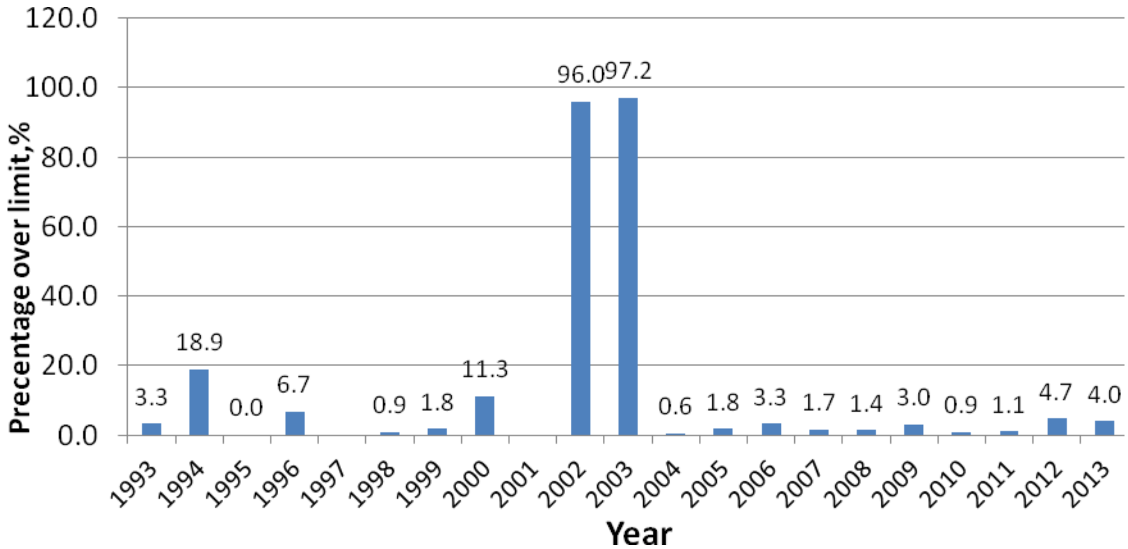


Figure 6- 12 Percentage over the variation limit –rut depth

7. Evaluation of variability of distress data

The major source of errors for distress data usually comes from the misinterpretation of distressimages. As most state DOTs, TDOT utilizes full-automated approach to interpret pavement surface distress images. The accuracy of distress data are directly associated with the quality ofdistress images and distress identification system (or algorithm). AASHTO PP68-10 also specifies the minimum requirements for an applicable Image and Distress Identification System(IDIS).

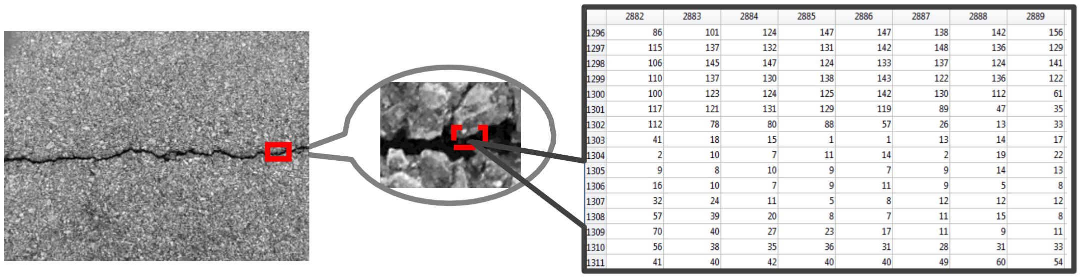
7.1 Source of errors for distress data

The online survey indicated most state agencies are using automatic image and distress identification system to determine and calculate the extent and severity level of surface distress. For the automatic distress recognizing system, the quality of image will have significant influence on the interpretation of distresses. To eliminate the errors of distress data caused by theimage quality, distress image will be picked up to ensure that only high-quality images are used for calculating distress extent in the post-processing procedures.

The core of IDIS is to split an image into the areas of interests and the area of background. Theinterested areas are those areas with distresses and used to calculate the distress extent and severity level. Due to the complexity of surface features and difference of lighting conditions when the distresses are imaged, the background noise may affect the determination of areas of interests. Therefore, many software systems have been or are being developed to decrease the background noise of the original image so that the distresses could be easily identified.

Below is an example of a procedure to process an image. Figure 7-1 illustrated the original image of a crack. The original image is firstly converted into grey-scale images as illustrated inFigure 7-2. The grey-scale image has the image matrix with values ranging from 0 to 255, with‘0’ representing the darkest area and ‘255’ representing the lightest area.

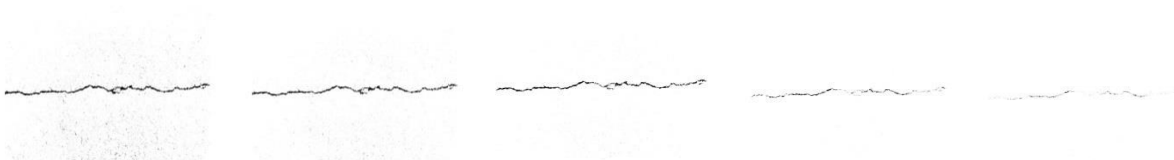
Figure 7- 1 Original image of a crack



	2882	2883	2884	2885	2886	2887	2888	2889
1296	86	101	124	147	147	138	142	156
1297	115	137	132	131	142	148	136	129
1298	106	145	147	124	133	137	124	141
1299	110	137	130	138	143	122	136	122
1300	100	123	124	125	142	130	112	61
1301	117	121	131	129	119	89	47	35
1302	112	78	80	88	57	26	13	33
1303	41	18	15	1	1	13	14	17
1304	2	10	7	11	14	2	19	22
1305	9	8	10	9	7	9	14	13
1306	16	10	7	9	11	9	5	8
1307	32	24	11	5	8	12	12	12
1308	57	39	20	8	7	11	15	8
1309	70	40	27	23	17	11	9	11
1310	56	38	35	36	31	28	31	33
1311	41	40	42	40	40	49	60	54

Figure 7- 2 Gray-scale image and image matrix

The boundary of a crack can be determined by defining a threshold through which the gray-scaleimage can be converted into binary image with only two values in the matrix. Figure 7-3 illustrated the binary image of different splitting threshold of gray-scale image. It can be seen that the threshold of a gray-scale image affect the results of crack boundary significantly. Figure7-4 illustrated the change of distress areas at different splitting threshold. It was found that the distress area is sensitive to the threshold. As the threshold increased from 5 to 32, the distress areas increased 250%. With the increase of the threshold, both distress extent and severity level will increase. Therefore, a threshold through which a gray scale image is converted to binary image is an important factor that influences the precision and accuracy of distress data.



(a) 32 (b) 18 (c) 13 (d) 8 (e) 5

Figure 7- 3 Binary images at different thresholds

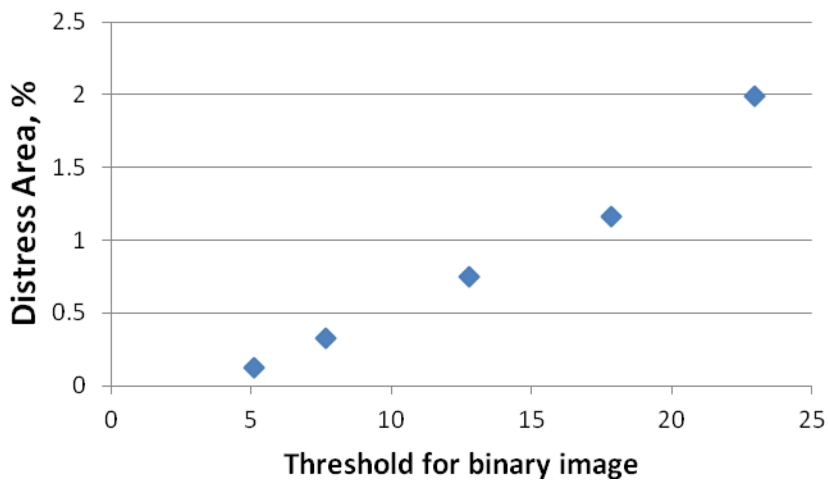


Figure 7- 4 Change of distress areas at different splitting threshold

To date, there are numerous of algorithm for splitting an objective from a background. The core of these algorithms is to find a reasonable threshold that can determine the areas of interest within an image. Unfortunately, due to high variations in image quality and interference of surface features, it is difficult to find a certain threshold that can be used for identifying all the distress images. Some factors that influence the threshold for an image are summarized as below.

1) Surface features

Surface features include pavement marks, surface tire tracks, surface contaminations, etc. These features significantly influence the interpretation of distress. It is hard to detect these surface features and eliminate them from the image by automatic distress identification methods. Imageswith these features may either be moved manually or be excluded in calculating the distress value. There are also algorithms to detect these surface features. However, most of them are stillunder development and far from implementation.

2) Background noise

Background noise may be recognized as the objective of interest if the pixel values for background noise were within the range of objective pixel value. It occurs when the lighting conditions for the image is weak. For newly constructed asphalt pavement, it may be more different to recognize a distress since the distress image may have low contrast. In response tothis issue, contrast enhancement is applied prior to differentiate the background noise from anobjective. There are also other algorithms, such as smoothing average, to eliminate the background noise.

From the respective of state highway agencies, one of the most concerns is that how to quantitatively evaluate the errors of distress data and the consequence of data errors on maintenance decision. To achieve this goal, the state agencies need to determine the reference value based on which the errors of distress data can be estimated. The sample images with known extent and severity level of distresses will be selected to construct a standard distress database. The difference between the distress value (extent and severity level) obtained from an Image and Distress Identification System and the reference value (extent and severity level) can be used to determine the errors of distress data. It should be note that images at different quality level may also be included in the standard distress database so that the influence of image qualityon the identification of distress can be estimated.

7.2 Influence of Variability of Distress Extents on PDI

The cause of variability of distress in extent comes from those distresses that are not identifiedby the IDIS. Therefore, the measured PDI may be higher than the true value which results in overestimating the current pavement condition. Eq. 7-1 can be used to calculate the probabilitythat the distress can be identified.

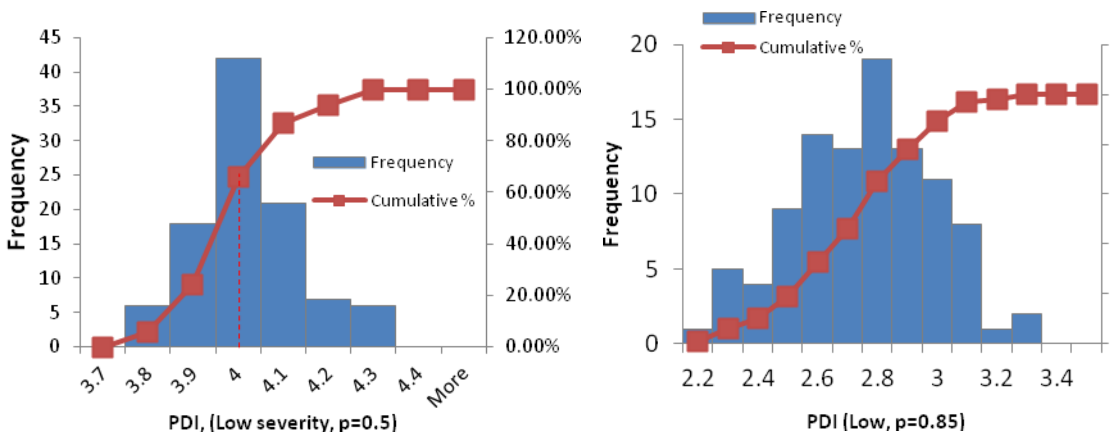
$$P(E < E_t) = \int_0^{E_t} g(x)dx = p$$
(Eq. 7-1)

Where, E represents for the distress extent; E_t is the true value of distress extent at a specific severity level; *g(x)* represents for the distribution function; *p* is the probability that the specifieddistress can be identified. The distribution function can be determined through field verificationtest.

Figure 7-5, 7-6 and Figure 7-7 illustrate the distribution of PDI at each severity level by Monte Carlo simulation. The true value of percentage of fatigue crack (Et) was assumed to be 50%. It is also assumed that the distribution function *g(x)* satisfy normal distribution with mean value of μ, and standard deviation of σ. Therefore, the normalized distribution of measured value satisfiesstandard normal distribution as Eq. 7-2. The distribution parameters for each scenario can be determined based on E_t and P.

$$\frac{X-\mu}{\sigma} \sim N(0,1) \qquad \text{(Eq. 7-2)}$$

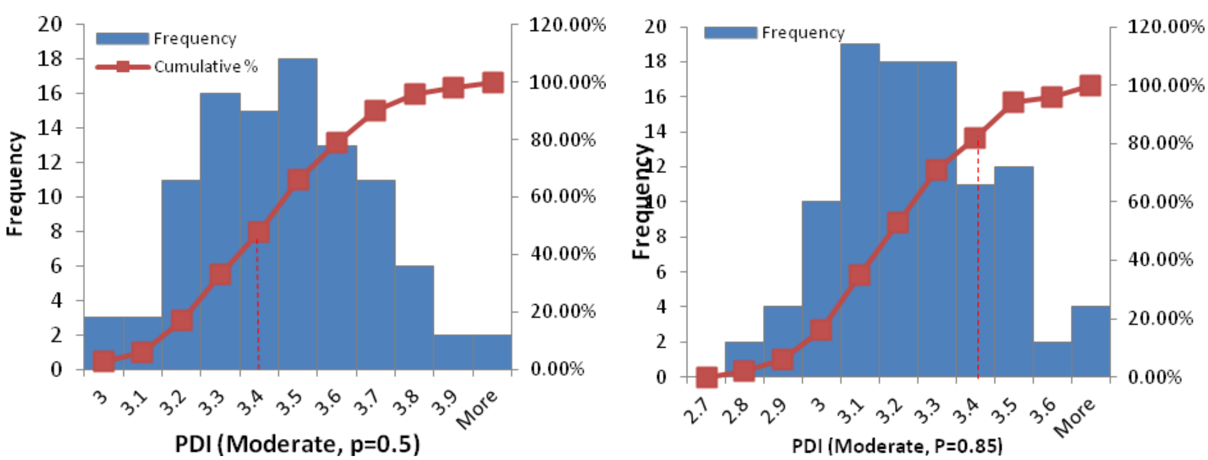
Figure 7-5 (a) and 7-1(b) illustrate the distribution of measured PDI at low severity level. The cumulative distribution for PDI<3.96 was about 70% when P=0.5. PDI=3.96 was calculated by assuming distress extent of fatigue cracks was 50% at low severity level while no fatigue crackswas observed at moderate and high level. This means if all the present fatigue cracks was at lowseverity level and the probability of all the cracks being identified was 0.5, the probability that measured PDI equals to or less than the true value was 0.7. This means the probability that the current pavement condition was overestimated would be less than 0.3. It is also found that if the probability of all the cracks being identified was 0.85, there was less likely that the measuredPDI was greater than the true PDI.



(a) Low severity (p=0.5) (b) Low severity (p=0.85)

Figure 7- 5 Distribution of measured PDI at low severity level

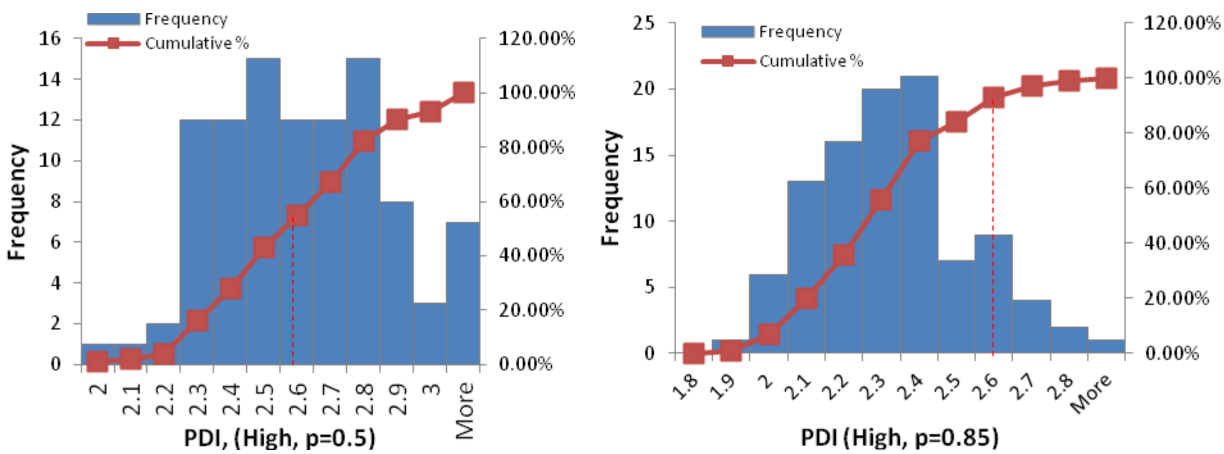
Figure 7-6 (a) and (b) illustrate the distribution of PDI at moderate severity level. The true PDIvalue was 3.41. It is found that the cumulative distribution were 50% and 80% for P=0.5 and P=0.85, respectively. This means if the probability of cracks that can be identified were 0.5 and 0.85 at moderate severity level, the probability that PDI greater than the true value would be 0.5and 0.8. This is significantly lower than the scenarios at low severity level. This indicated there was limited improvement on measured PDI by increasing the accuracy of extent of fatigue cracking at moderate level Compared to that at low level.



(a) Moderate severity (p=0.5) (b) Moderate severity (p=0.85)

Figure 7- 6 Distribution of PDI at moderate severity level

Figure 7-7 (a) and (b) illustrate the distribution of PDI calculated from the measured PDI at high severity level. It can be seen that if the accuracy of data was low at high severity level, the accuracy of measured PDI would be compromised. The probability of PDI less than the true value was only less than 0.6 (cumulative distribution was 60%) with the P=0.5. With the increaseof accuracy (P from 0.5 to 0.85), the cumulative distribution of PDI<2.6 (the true value at this severity) was more than 90%. This means there seems less likely that the measured PDI was greater than the true value.



(e) High severity (p=0.5) (f) High severity (p=0.85)

Figure 7- 7 Distribution of PDI calculated from the measured PDI at high severity level

FIGURE 7-1 to Figure 7-2 presented the results from simulation by assuming the true value, measured mean value, and measured standard deviation. These parameters can be evaluated anddetermined by field verification test through which the results from manual distress survey can be compared with that from automated survey. The results from manual survey may be considered as true value. By running multiple automated tests, the measured mean value and measured standard deviation of automated survey can be determined. Then, the two parameters,Et and *p*, at difference scenarios from Equation 6 can be calculated and the influence of variability of distress data on pavement distress indices can be evaluated.

The accuracy of extents of distress data has influence on PDI, depending on the distress severitylevel. At low severity level, when P=0.85, the measured PDI is close to the true value. At moderated and high severity levels, there is a difference between the measured PDI and the truePDI, indicating the accuracy of distress increased at higher severity levels.

7.3 Influence of Variability of Distress on PDI

The severity levels of crack-related distresses are defined by the crack width. Figure 7-8 illustrates the general framework of determining crack-related distress content based on each severity level. The extent of distress at each crack width was firstly calculated. Then, the extentsof distress at each severity level are summed up in terms of crack width. It can be seen that theremight be a transition zone in which a crack may be classified into a wrong severity level. It is evident that the existing of transition zone may potentially generate bias on PDI calculation. To quantify the influence of transition zone on the calculation of distress value, the transition ratio curve is established.

Crack width, mm	Extents, units	Severity	Sum of Extent
0.1	L_1	Low	Σ Li
0.2	L_2		
...	...		
...	...		
5.8	L_{n-1}		
5.9	L_n		
6.0	M_1	Moderate	Σ Mi
6.1	M_2		
...	...		
18.8	M_{m-1}		
18.9	M_m		
19.0	H_1	High	Σ Hi
19.1	H_2		
...	...		
...	...		

Transition zone

Figure 7- 8 General framework to calculate extent of distress based on severity level

Figure 7-5 illustrates a typical transition ratio curve. The transition ratio ranges from 0 to 1. Transition ratio of "0" indicates that there is less likely that a crack may be classified into this level while "1" means there is most likely that a crack may be classified into this level. $f_i(w), i = 1,2,3$ is the transition function at each severity level. w_{1-2} is the boundary of low and moderate level, while w_{2-3} is the boundary of moderate and high level. It can be seen that cracks whose widths are far away from the transition zone are less likely to be classified into a wrong level. The sum of transition function at each severity level for an identified crack with a width $w_i$equals to 1. Eq. 7-3 provides the attribution of the transition function.

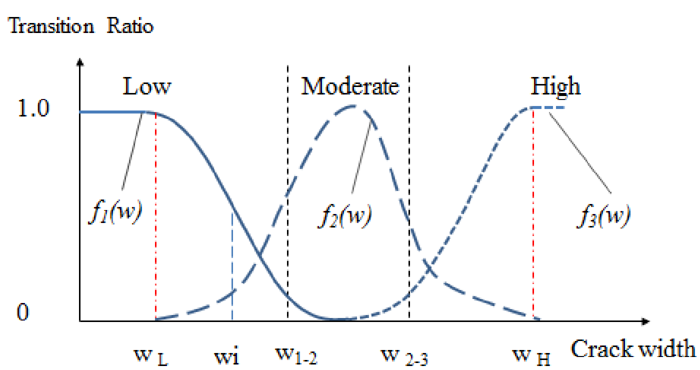


Figure 7- 9 Transition Ratio Curve

$$\begin{cases} f_1(w) = 1, if\ w < w_L \\ f_3(w) = 1, if\ w > w_H \\ \quad \sum_{i=1}^{3} f_i(w) = 1 \end{cases} \qquad \text{(Eq. 7-3)}$$

The transition function seems a reasonable way to quantify the influence of variability of severitylevel on PDI. However, the establishment of a transition function is time-consuming and varies from different distress identification techniques and algorithms. Therefore, the transition matrix was presented to quantify the influence of variability of severity level on PDI. The transition matrix is proposed based on the conception shown in Figure 7-6. It describes the transition ratio between different severity levels. The parameters in transition matrix are easily to be determined through field verification tests by comparing the results from automated survey with those from manual survey. The transition matrix is expressed as Eq.7-4.

$$P = \begin{bmatrix} p_{11} & p_{12} & p_{13} \\ p_{21} & p_{22} & p_{23} \\ p_{31} & p_{32} & p_{33} \end{bmatrix} \qquad \text{(Eq. 7-4)}$$

Where, $P(\cdot)$ is the transition matrix for each type of distress;p_{ij} is the ratio that an individual

distress at severity level i may be changed into severity level j. (i,j=1,2,3 represent for Low, Moderate, and High severity). The sum of each row in transition matrix P should be equal to 1,which is expressed as Eq. 7-5.

$$p_{\cdot j} = \sum_{i=1}^{3} p_{ij} = 1 \qquad \text{(Eq. 7-5)}$$

The original distress vector for individual distress k, $D(k)$ is expressed as Eq. 7-6.

$$D(k) = \begin{bmatrix} d_{k-L} \\ d_{k-M} \\ d_{k-H} \end{bmatrix} \qquad \text{(Eq. 7-6)}$$

The adjusted distress value D'(i) can be determined by transition matrix, which is expressed asEq. 7-7.

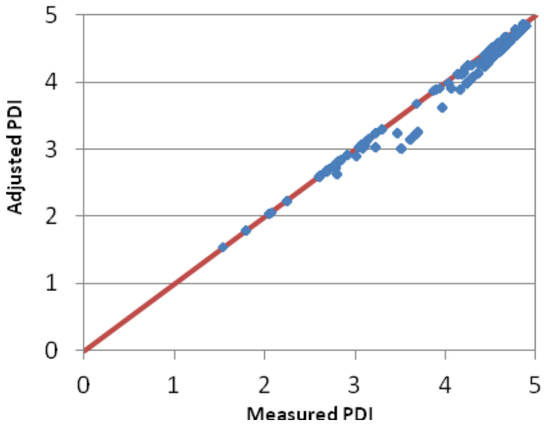
$$D'(k) = D(k)^T \cdot P \qquad \text{(Eq. 7-7)}$$

The adjusted distress value includes the influence of variability of severity level. It can be usedas a benchmark to evaluate the impact of variability on distress severity on PDI. Pavement sections with only block cracks in 2013 were extracted from the database. Four transition matrices P_L, P_M, P_H and P_{mix} were considered as listed in Equation 13. Note that the values in thetransition matrices were assumed based on experience. The transition matrix can be determined by comparing the difference between the distress data from automated survey and manual survey. P_L, P_M, and P_H only considered the influence of single severity level, while P_{mix} considered the interaction between severity levels.

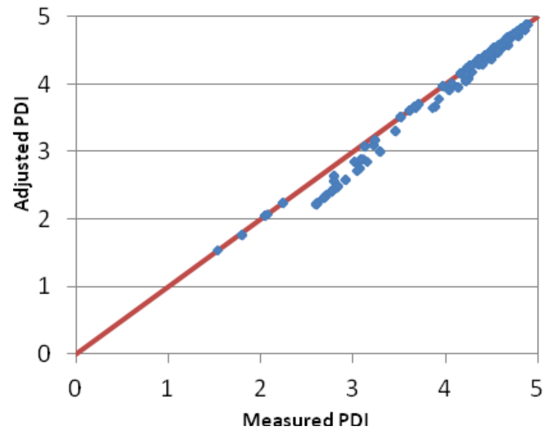
$$\left.\begin{aligned} P_L &= \begin{bmatrix} 0.75 & 0.2 & 0.05 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \\ P_M &= \begin{bmatrix} 1 & 0 & 0 \\ 0.15 & 0.7 & 0.15 \\ 0 & 0 & 1 \end{bmatrix} \\ P_H &= \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0.05 & 0.2 & 0.75 \end{bmatrix} \\ P_{mix} &= \begin{bmatrix} 0.75 & 0.2 & 0.05 \\ 0.15 & 0.7 & 0.15 \\ 0.05 & 0.2 & 0.75 \end{bmatrix} \end{aligned}\right\} \qquad \text{(Eq. 7-8)}$$

Figure 7-6 illustrates the comparison between measured PDI and adjusted PDI. The measured PDI were collected from sections with only wheel path cracks in 2013. The measured PDI werecalculated by raw distress value while the adjusted PDI were calculated by the equation above. It can be seen that the adjusted PDI were generally higher than measured PDI. This means the variability of distress severity may generally overestimate the current pavement condition.

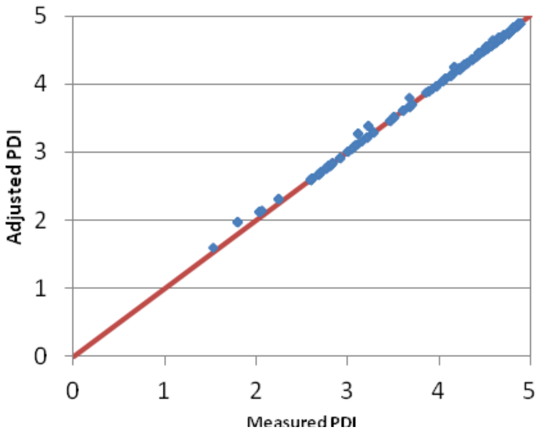
Figure 7-6 (a) indicates that the variability at low severity level may only influence the sections with measured PDI greater than 3.5. If the measured PDI is less than 3.5, there is only slight difference between the measured PDI and adjusted PDI. Figure 7-6 (b) indicates that there is a significant difference between measured PDI and adjusted PDI with measured PDI above 2.5. This means the variability at moderate severity level may be considered as a significant influence factor for the accuracy of PDI. Figure 7-6 (c) illustrates an opposite tendency Compared to other scenarios. The measured PDI seems less than adjusted PDI, which means variability at high severity level may underestimate the current pavement condition. This is because some distresses at high severity level were treated as moderate or low level as shown inthe transition matrix, resulting in an increased adjusted PDI value. Figure 7-6 (d) illustrated an interaction of variability of distress at different severity level. It is found that there was a significant difference between measured PDI and adjusted PDI with measured PDI ranging from 2.5 to 4.0. With the increase of measured PDI, the difference between two indices decreased. Since PDI of 3.0 is the trigger value in the decision tree used by TDOT, the variability of distress at moderate severity level may influence the maintenance decisions significantly.



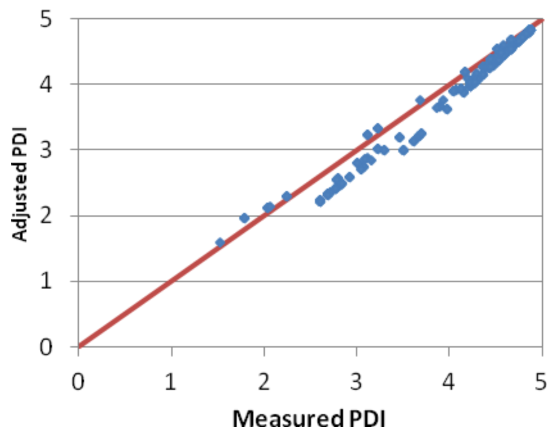
(a) P_L



(b) P_M



(c) P_H



(d) P_{mix}

Figure 7- 10 Comparison between measured PDI and adjusted PDI

8. Evaluation of data variability on pavement maintenance planning

8.1 Framework of Quality Analysis at Network-level

Figure 8-1 illustrates the loop of data quality analysis. Field tests are performed before data production to verify the test equipment and continue during data production process. The test results from the field verification tests can be used to evaluate the accuracy and repeatability of test equipment and estimate the errors between the collected data and the reference value. By Compared to the data quality requirements, pavement managers can evaluate the data quality anddecide the acceptance and confidence of the collected data. The quality analysis can be performed on a specified road network to quantitatively evaluate the influence of data variabilityon maintenance planning. Based on the results from quality analysis, suggestions on data quality requirements on next collection period can be made. Figure 8-1 provides a method through which the requirements for data quality can be determined. This means the data quality requirements depend on the current pavement condition and maintenance decision approaches.

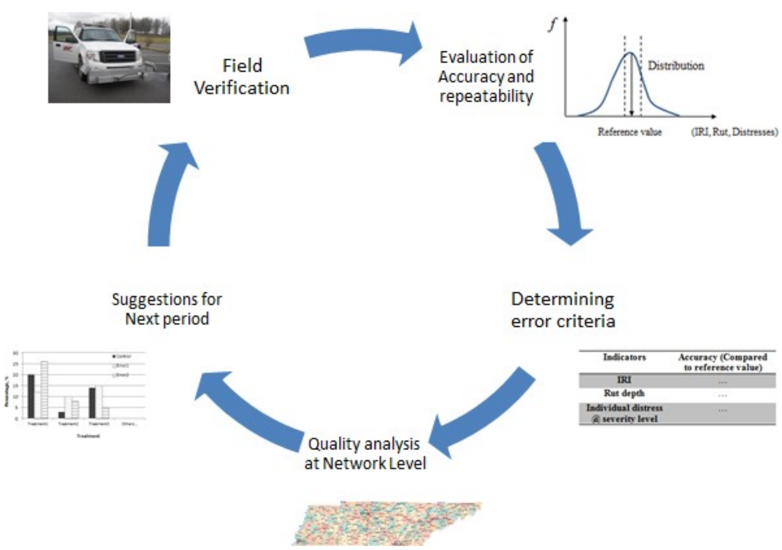
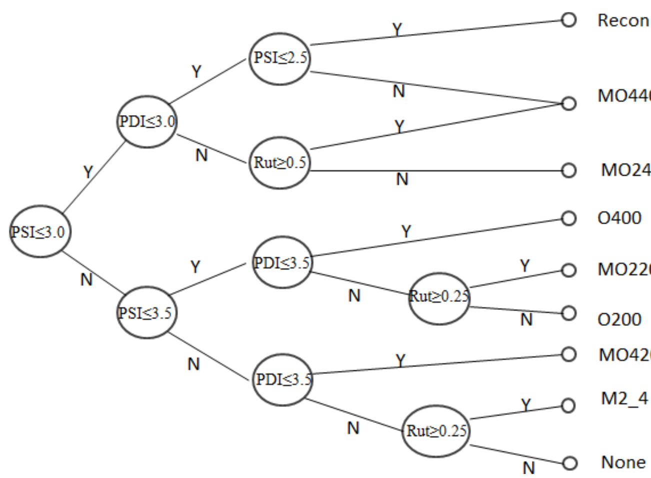


Figure 8- 1 Loop of data quality analysis

8.2 Influence of Data Variability on Maintenance Planning

In order to evaluate the influence of data variability on maintenance planning, the pavement condition data in 2013 were extracted from PMS which covered 8,093.8 centerline miles of highways. The decision tree in the PMS of TDOT used for this case is shown in Figure 8-2.



Code	Description
Recon	Reconstruction
MO4400	Mill & Replace 2-4"+ overlay of 400 pound per square yard
MO4200	Mill & Replace 2-4" + overlay of 200 pound per square yard
MO2400	Mill & Replace 1-2" + overlay of 400 pound per square yard
MO2200	Mill & Replace 1-2" + overlay of 200 pound per square yard
O200	overlay of less than 200 pound per square yard
O400	overlay of 200-400 pound per square yard
M2_4	Mill & Replace 2"-4"
None	Do nothing

Figure 8- 2 Decision Tree for Maintenance and Rehabilitation analysis

FIGURE 8-3 illustrates the influence of the accuracy of IRI on maintenance planning. Four morescenarios were analyzed by assuming there are ±5% and ±10% errors of IRI value. It can be seenthat the maintenance planning changes as inclusion of IRI errors. Compared to the control group,an error of ±5% IRI may generate ±3.1% errors of percentage of sections that need to be treated with Code MO2400 and ±2.7% errors of percentage of do-nothing sections. There were slight changes on sections with other code as well. As the IRI error increased, the difference between the control group and error groups increased. With ±10% IRI error, the errors of percentage of sections with Code MO2400 could be as high as ±6.3%.

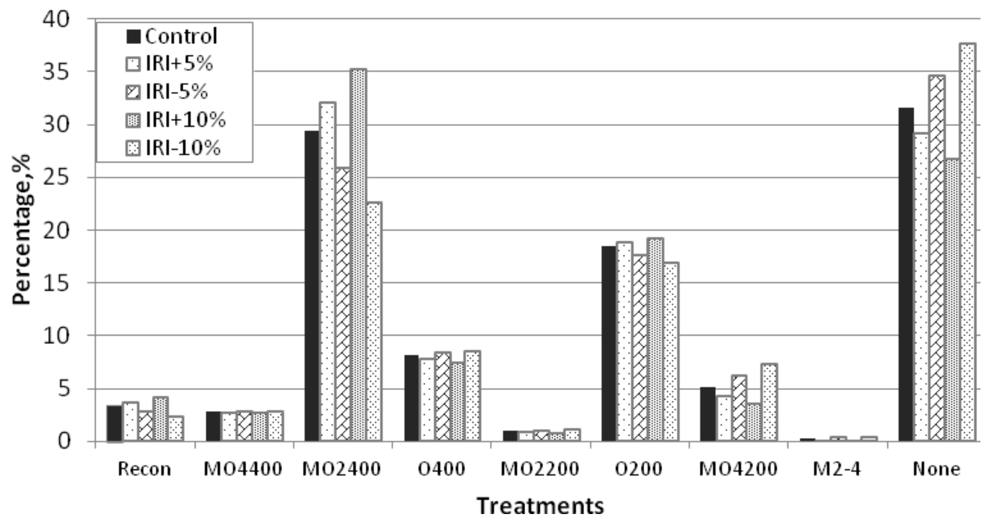


Figure 8- 3 Influence of accuracy of IRI on maintenance planning

FIGURE 8-4 illustrates the influence of accuracy of rut depth on maintenance planning. It can beseen that the difference between the control group and error group were less than 2% with the inclusion of ±20% rut depth error. This means that there was almost no influence of rut depth error on maintenance planning. This is because rut depth are generally low and +20% may still well under the trigger value. It was also found that there was no difference between control group and error groups for sections with code Recon, O400, and MO4200. This is because these maintenance codes are independent of the rut depth in the decision tree.

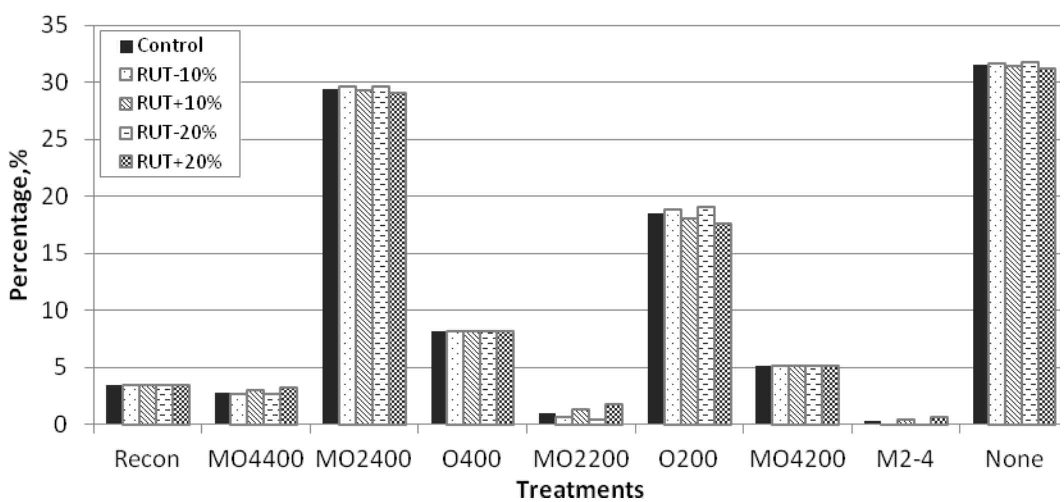


Figure 8- 4 Influence of accuracy of rut depth on maintenance planning

FIGURE 8-5 illustrates influence of errors of distress extent on maintenance planning. The distress extent in the error group was 85% to the original distress extent. In another word, the missing distress extent in error group was 15%. FIGURE 13 indicated that the total length of sections that need to be maintained decreased if there were missing distress extent in error group.The percentage of sections with code MO2400 and O200 increased while others decreased. In general, with the inclusion of errors in distress extents, there were slight changes on maintenanceplanning Compared to the control group. Therefore, it can be concluded that a maximum error ofdistress extents of 85% is sufficient for the purpose of maintenance and rehabilitation analysis and may not significantly influence the results of maintenance planning in Tennessee.

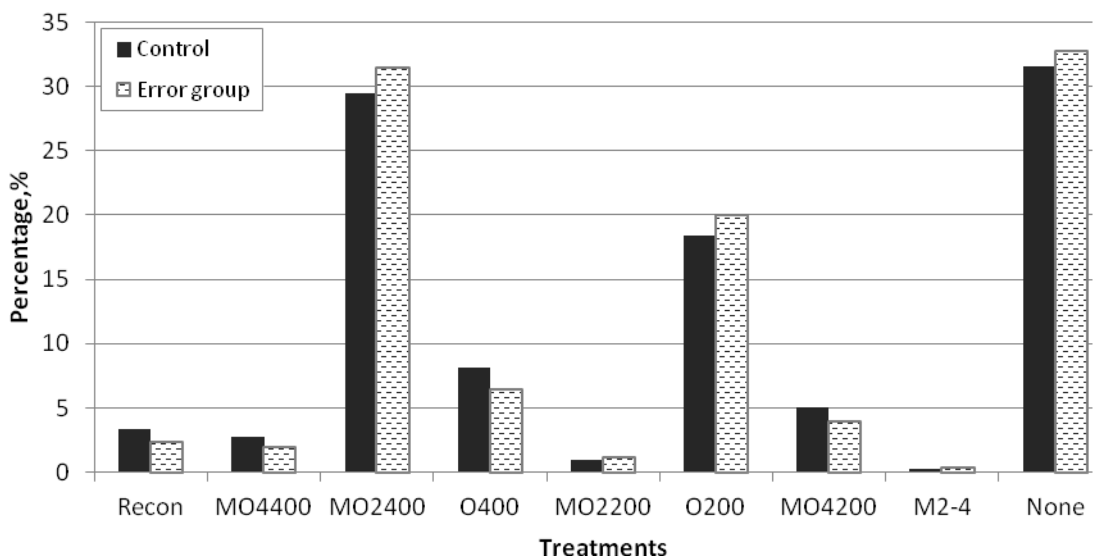


Figure 8- 5 Influence of errors of distress extent on maintenance planning

FIGURE 8-6 illustrates the influence of error of distress severity level on maintenance planning. Three transition matrices (P_{mix-1}, P_{mix-2} and P_{mix-3}), which represent different accuracy of distress identification from high to low, were considered as listed in Equation 14.

$$\left.\begin{aligned} P_{mix-1} &= \begin{bmatrix} 0.9 & 0.1 & 0 \\ 0.05 & 0.9 & 0.05 \\ 0 & 0.1 & 0.9 \end{bmatrix} \\ P_{mix-2} &= \begin{bmatrix} 0.75 & 0.2 & 0.05 \\ 0.15 & 0.7 & 0.15 \\ 0.05 & 0.2 & 0.75 \end{bmatrix} \\ P_{mix-3} &= \begin{bmatrix} 0.65 & 0.25 & 0.1 \\ 0.20 & 0.65 & 0.15 \\ 0.1 & 0.25 & 0.65 \end{bmatrix} \end{aligned}\right\} \quad \text{(Eq. 8-1)}$$

The percentage of sections that need maintenance increased if there were errors in distress severity level. It was also found that the percentage of sections with code MO2400 and O200decreased while that of sections with code Recon, MO400, O400, and MO4200 increased. It should be noted that the sum of extent for individual distress of the control group was the same as the error group. Therefore, the errors of distress severity level significantly affect the planningresults although all the distresses were correctly identified and quantified.

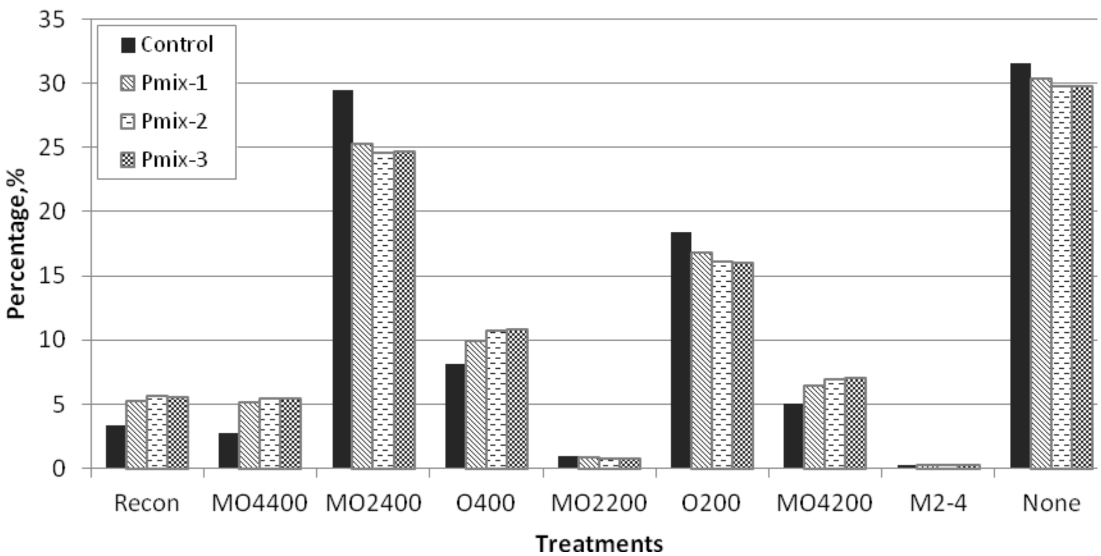


Figure 8- 6 Influence of errors of distress severity level on maintenance planning

9. Evaluation of the influence of maintenance actions on condition data

The maintenance actions may change the general trend of the performance curve. However, due to some missing maintenance records, it is impossible to identify all the maintenance actions. Byanalyzing the change of performance indices, it is possible to identify the maintenance actions through which the performance curve can be modified.

In this part, the influence of maintenance actions on performance indicators was evaluated. Themaintenance records were selected from the database since 2002.

9.1 Data preparation

The maintenance records were collected from construction record provided by TDOT. The maintenance record consists of segment information and construction information. The inventory was listed in Table 9-1. The segment information can be used to identify those sections containing a maintenance action between two adjacent collecting years.

Table 9- 1 Inventory in maintenance record

Segment information	Route Type; Route number; County; Start MPand End MP; Year; Length
Construction information	Contract No. ; State ID; Federal ID; Let date;Cost; Treatment Activities

The pavement condition data consists of roughness data and distress data. The inventory of roughness data and distress data are listed in Table 9-2. The segment information include county number (HR_COUNTY); route type (HR_ROUTTYP); route number (HR_ROUTNUM); direction (HR_DIRECTN); beginning and ending milestone of a section (HR_BEGMILE; HR_ENDMILE); collecting year (HR_DATYEAR); and other information on the road segment. The information can be used to recognize the sections that had maintenance actions.

Table 9- 2 Inventory in pavement condition data

Segment information	HR_ROUTCOD; HR_COUNTY; HR_CNTYSQ; HR_ROUTTYP; HR_ROUTNUM; HR_ROUTAUX; HR_DIRECTN; HR_DATYEAR; HR_BEGMILE; HR_ENDMILE
Roughness data	HR_IRI_RT; HR_IRI_LT; HR_RUT_RT; HR_RUT_LT; HR_PSI
Distress data	PDI-overall index; content and severity of individual distresses

Table 9-3 lists the counties in Tennessee and their available records in the HPMA since 2002.

Table 9- 3 Summary of individual tables for pavement condition data

Number ID	County	Available Records	Number ID	County	Available Records
1	ANDERSON	9202	51	LEWIS	4554
2	BEDFORD	9846	52	LINCOLN	11137
3	BENTON	9093	53	LOUDON	11350
4	BLEDSOE	4344	56	MACON	13834
5	BLOUNT	11411	57	MADISON	11031
6	BRADLEY	11644	58	MARION	6166
7	CAMPBELL	11521	59	MARSHALL	18773
8	CANNON	4994	60	MAURY	16378
9	CARROLL	16404	54	MCMINN	11326
10	CARTER	8284	55	MCNAIRY	17740
11	CHEATHAM	8417	61	MEIGS	4551
12	CHESTER	5674	62	MONROE	11417
13	CLAIBORNE	6390	63	MONTGOMERY	15098
14	CLAY	4371	64	MOORE	2663
15	COCKE	11926	65	MORGAN	7196
16	COFFEE	13750	66	OBION	12124
17	CROCKETT	7290	67	OVERTON	9009
18	CUMBERLAND	17319	68	PERRY	6053
19	DAVIDSON	38380	69	PICKETT	2994
20	DECATUR	8900	70	POLK	7386
21	DEKALB	6260	71	PUTNAM	17207
22	DICKSON	13710	72	RHEA	5441
23	DYER	15145	73	ROANE	13485
24	FAYETTE	17219	74	ROBERTSON	15482
25	FENTRES	7065	75	RUTHERFORD	21993
26	FRANKLIN	11385	76	SCOTT	4459
27	GIBSON	15830	77	SEQUATCHIE	4611
28	GILES	14440	78	SEVIER	11537
29	GRAINGER	6503	79	SHELBY	42713
30	GREENE	19091	80	SMITH	9862
31	GRUNDY	7456	81	STEWART	6635
32	HAMBLEN	7920	82	SULLIVAN	20037
33	HAMILTON	23738	83	SUMNER	16483

34	HANCOCK	4143	84	TIPTON	7964
35	HARDEMAN	10632	85	TROUSDALE	2766
36	HARDIN	11875	86	UNICOI	7359
37	HAWKINS	10351	87	UNION	4213
38	HAYWOOD	15007	88	VAN BUREN	5040
39	HENDERSON	16587	89	WARREN	10598
40	HENRY	12194	90	WASHINGTON	12971
41	HICKMAN	11735	91	WAYNE	9171
42	HOUSTON	3720	92	WEAKLEY	13551
43	HUMPHREYS	7732	93	WHITE	6371
44	JACKSON	7459	94	WILLIAMSON	18743
45	JEFFERSON	13307	95	WILSON	17366
46	JOHNSON	5782			
47	KNOX	28994			
48	LAKE	3249			
49	LAUDERDALE	8562			
50	LAWRENCE	9765			

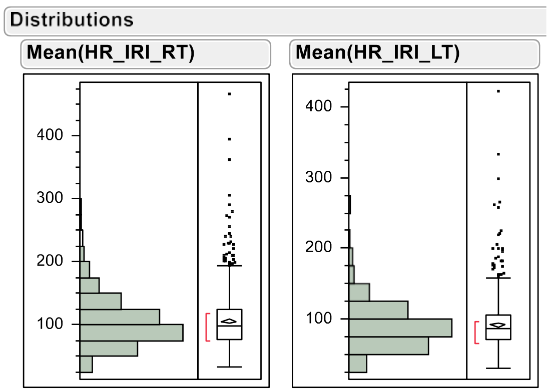
2364 maintenance records out of total 6320 were identified. The pavement condition data including IRI, rutting depth, and Pavement Distress Index (PDI) of pre and post maintenance action were extracted from the database. The difference of the indicators of pre and post maintenance action was calculated. The influence of maintenance actions on change of pavementindicators were listed as follows.

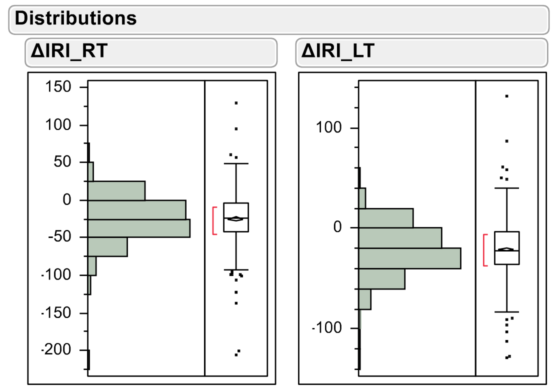
9.2 Evaluation of maintenance actions on pavement indices

9.2.1 Influence of maintenance actions on change of IRI and PSI

Figure 9-1 illustrated the distribution of initial IRI and change of IRI between two adjacent collecting years for state routes. Figure 9-1 (a) illustrated the distribution of initial IRI before maintenance actions. It was found that the mean value of IRI before maintenance was 105.9 and 91.7 in./mi for right and left side, respectively. The median quantiles for each side were 98.8 and 86.2 for right and left side, which were close to their mean value. Figure 9-1 (b) illustrated thedistribution of change of IRI due to the maintenance actions. The average changes of IRI were 24.8 and 21.1 in./mi for right and left side, respectively. Similarly, the median quantiles right and left side were close to their mean value. This means the maintenance actions would decreasethe IRI by 20 in./mi. in average for state routes.

Meanwhile, it can be seen that the maintenance actions may also increase the initial IRI (see change of IRI greater than zero). This means the maintenance actions in those sections would have little effect on the change of IRI comparing with others without the maintenance actions. It seems that the increase of IRI was limited. Figure 9-1 (b) indicated that there were less than 10%sections whose increase of IRI were greater than 10 in./mi.





Quantiles

		Mean(HR_IRI_RT)	Mean(HR_IRI_LT)	ΔIRI_RT	ΔIRI_LT
100.0%	maximum	467.1	421.5	128.1	131.1
99.5%		298.886	263.518	51.5336	53.752
97.5%		210.428	172.988	23.223	21.0357
90.0%		157.937	128.884	6.76054	7.01673
75.0%	quartile	124.278	106.064	-4.0418	-2.7875
50.0%	median	98.7634	86.2044	-24.412	-22.461
25.0%	quartile	77.4154	70.4667	-41.13	-35.814
10.0%		62.54	57.5391	-58.454	-48.87
2.5%		46.1383	43.8313	-83.458	-71.334
0.5%		38.6275	36.4675	-123.39	-100.46
0.0%	minimum	33.5745	31.4814	-206.3	-129.85

Moments

	Mean(HR_IRI_RT)	Mean(HR_IRI_LT)	ΔIRI_RT	ΔIRI_LT
Mean	105.94639	91.738853	-24.83697	-21.12701
Std Dev	43.441895	34.495622	28.528693	24.541949
Std Err Mean	1.4521024	1.1530615	0.953609	0.8203469
Upper 95% Mean	108.79632	94.001876	-22.96539	-19.51698
Lower 95% Mean	103.09647	89.475831	-26.70854	-22.73704
N	895	895	895	895

(a) Distribution of initial IRI (b) Distribution of change of IRI (ΔIRI)

Figure 9- 1 Distribution of initial IRI and change of IRI (State routes)

Actually, the change of IRI (ΔIRI) is related to the initial IRI before maintenance action. As the initial IRI increased, ΔIRI increased. However, ΔIRI will decrease with lower initial IRI value. Figure 9-2 illustrated the lower limit ΔIRI. The red dot-line indicated the lower limit of ΔIRI. It can be seen that with lower initial IRI, ΔIRI decrease. In Figure 9-2, IRI_2 is greater than IRI_1.

Therefore, the probability of $\Delta IRI_1 > 0$ is greater than $\Delta IRI_2 > 0$. This indicated that with the lower initial IRI, the probability that the post-maintenance IRI greater than initial IRI may increase. In another word, there is no effect of maintenance actions on the trend line of IRI.

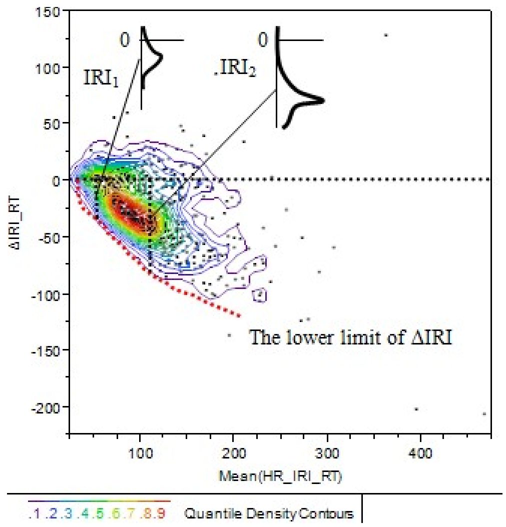
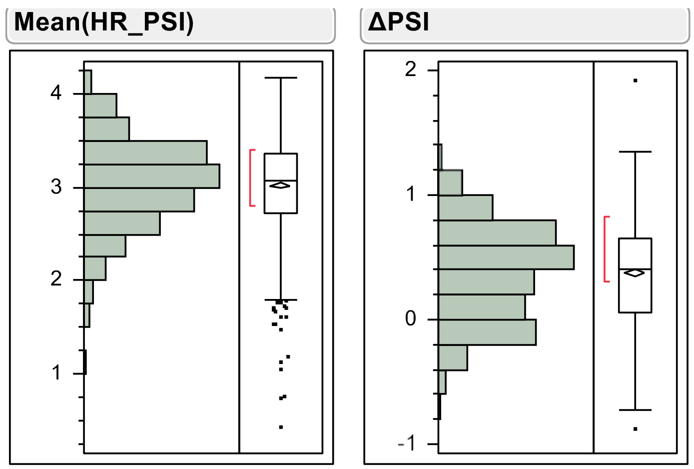


Figure 9- 2 Quantile density contours (state routes-right side)

Figure 9-3 illustrated the distribution of initial PSI and change of PSI (ΔPSI). It can be seen that the average initial PSI for state routes was 3.02 with the standard deviation of 0.51. There were only a few sections in which the PSIs were over 4.0 or less than 2.0. This means most of the maintenance actions were triggered at PSI between 2.0 to 4.0. The distribution of ΔPSI indicatedthat maintenance action increased the PSI by 0.38 in average with the standard deviation of 0.38.The distribution also indicated that maintenance action would generally increase PSI by less than 1.0. It was also found that in some sections, the maintenance action may not significantly increase PSI. In contrast, the PSI was slightly lower than the initial value which resulted in ΔPSIless than 0. Figure 6-4 illustrated the distribution of initial PSI when ΔPSI<0. It can be seen thatinitial PSI in these sections were 3.27 in average which is higher than the average value for the population (3.02).As the initial PSI increased, the change of PSI will decrease. Therefore, in some sections with higher initial PSI, the improvement of PSI after maintenance actions was insignificant.



Quantiles (Mean(HR_PSI))

100.0%	maximum	4.16364
99.5%		4.0796
97.5%		3.92714
90.0%		3.61323
75.0%	quartile	3.36302
50.0%	median	3.06674
25.0%	quartile	2.73133
10.0%		2.39042
2.5%		1.84254
0.5%		1.07592
0.0%	minimum	0.43

Moments (Mean(HR_PSI))

Mean	3.0187175
Std Dev	0.5102076
Std Err Mean	0.0171991
Upper 95% Mean	3.0524736
Lower 95% Mean	2.9849614
N	880

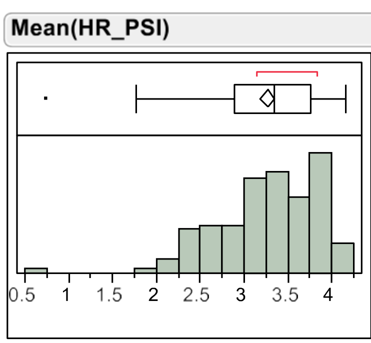
Quantiles (ΔPSI)

100.0%	maximum	1.91674
99.5%		1.26019
97.5%		1.09444
90.0%		0.83092
75.0%	quartile	0.65571
50.0%	median	0.41184
25.0%	quartile	0.05086
10.0%		-0.1238
2.5%		-0.3259
0.5%		-0.5617
0.0%	minimum	-0.89

Moments (ΔPSI)

Mean	0.3754779
Std Dev	0.3813466
Std Err Mean	0.0128552
Upper 95% Mean	0.4007083
Lower 95% Mean	0.3502474
N	880

Figure 9- 3 Distribution of initial PSI and change of PSI (State routes)



Quantiles

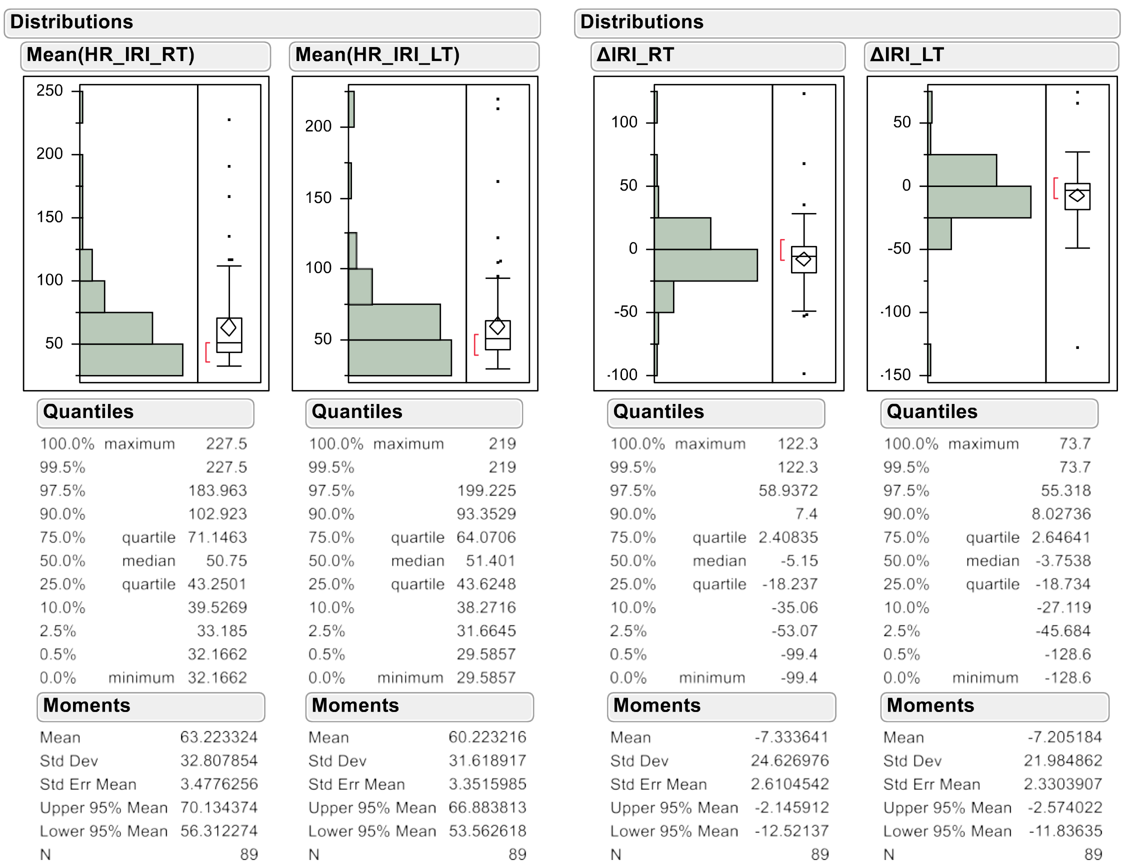
100.0%	maximum	4.16364
99.5%		4.16364
97.5%		4.07917
90.0%		3.9249
75.0%	quartile	3.75308
50.0%	median	3.34
25.0%	quartile	2.88806
10.0%		2.45486
2.5%		2.16583
0.5%		0.74
0.0%	minimum	0.74

Moments

Mean	3.269061
Std Dev	0.5629031
Std Err Mean	0.041611
Upper 95% Mean	3.351163
Lower 95% Mean	3.186959
N	183
Sum Wgt	183
Sum	598.23817
Variance	0.3168599
Skewness	-0.8663
Kurtosis	1.190188
CV	17.219107
N Missing	0

Figure 9- 4 Distribution of initial PSI (ΔPSI<0)

Figure 9-5 illustrates the distribution of initial IRI and change of IRI between two adjacent collecting years for interstates. Figure 9-5 (a) illustrated the distribution of initial IRI before maintenance actions. It was found that the mean values of initial IRI were higher than the medianvalue. The IRI from both sides were close to each other. Comparing with Figure 6-1, both the mean value and median value of initial IRI of interstates were lower than state routes. Generally, the maintenance actions were triggered with IRI of 60 in./mi. Figure 9-5 (b) illustrated the distribution of change of IRI. It seemed that the maintenance actions would only decrease the IRIby 7 in./mi. in average. Since the pavement condition of interstates were generally better than state routes, the decrease of IRI for interstates caused by maintenance action was less significant than for state routes.



(a) Distribution of initial IRI (b) Distribution of change of IRIFigure

9- 5 Distribution of initial IRI and change of IRI (Interstates)

Figure 9-6 illustrated the quantile density contours for interstates. It was found that the change of IRI (ΔIRI) tend to be close to the zero line (dash line). This indicated the influence of maintenance action on IRI decreased. Figure 9-5 (b) also indicated that the median value of ΔIRIwere close to zero (only -5.2 and -3.7 in./mi. for right and left side), while the 75% quantiles of ΔIRI for both sides were greater than 0. This means there were at least 75% of the sections of which the IRI increased after maintenance actions were completed. Meanwhile, it can be inferredthat there were less than 10% of the maintained sections of which the IRI values were increased by 10 in/mi. IRI value of interstates would be generally decreased by the maintenance actions. If not, the increase of IRI should be less than 10 in./mi.

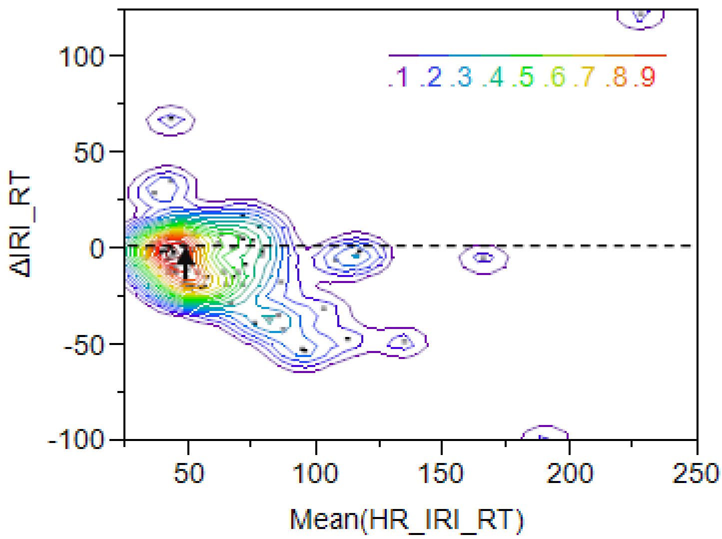
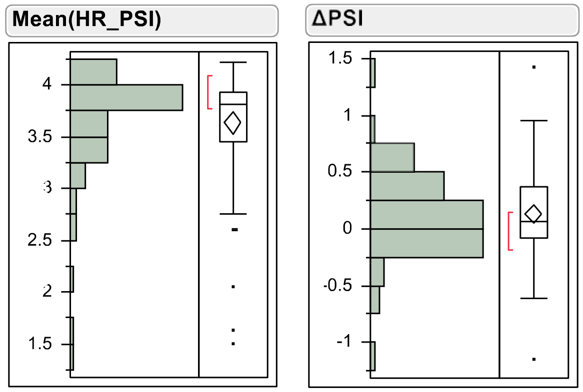


Figure 9- 6 Quantile density contours (IRI in right side for interstates)

Figure 9-7 illustrated the distribution of initial PSI and change of PSI (ΔPSI). It was found that the initial PSI was 3.64 in average with the standard deviation of 0.51. The distribution of ΔPSIindicated that the maintenance action on interstate may generally increase PSI by only 0.13 in average. Comparing with the state routes, the improvements of PSI on interstates seem limited. This is because the initial PSI for interstates (3.64) was generally higher than state routes (3.02).Therefore, the increase of PSI for interstates was limited.

Figure 9-8 illustrated the quantile density contours of initial PSI and ΔPSI for interstates. It can be seen that there were two areas with 90% quantile. One was close to zero line (dash line) whileanother was greater than zero. The one close to zero line had initial PSI around 4.0 which was higher than the other. This indicated as the initial PSI increased, there was no significant difference in PSI between pre- and post-maintenance.



Quantiles (Mean(HR_PSI))

100.0%	maximum	4.22393
99.5%		4.22393
97.5%		4.19173
90.0%		4.06793
75.0%	quartile	3.93231
50.0%	median	3.818
25.0%	quartile	3.455
10.0%		3.04078
2.5%		1.706
0.5%		1.49
0.0%	minimum	1.49

Moments (Mean(HR_PSI))

Mean	3.6375443
Std Dev	0.5093317
Std Err Mean	0.0546061
Upper 95% Mean	3.7460977
Lower 95% Mean	3.528991
N	87

Quantiles (ΔPSI)

100.0%	maximum	1.42
99.5%		1.42
97.5%		0.90688
90.0%		0.52361
75.0%	quartile	0.36724
50.0%	median	0.07
25.0%	quartile	-0.0852
10.0%		-0.1805
2.5%		-0.5994
0.5%		-1.157
0.0%	minimum	-1.157

Moments (ΔPSI)

Mean	0.1329366
Std Dev	0.3525852
Std Err Mean	0.0378011
Upper 95% Mean	0.2080826
Lower 95% Mean	0.0577905
N	87

Figure 9- 7 Distribution of initial IRI and change of IRI (Interstates)

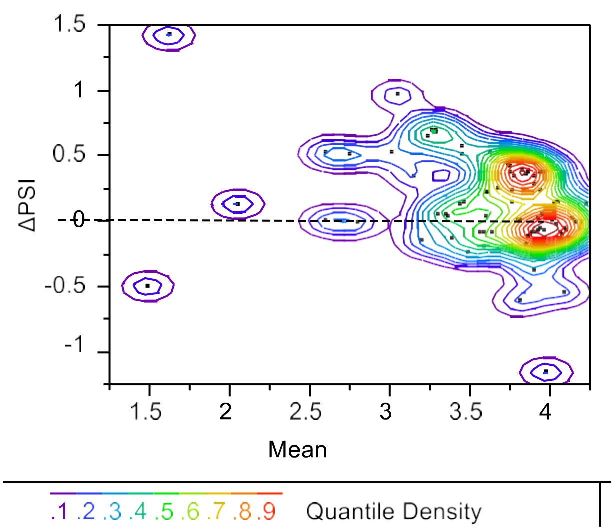
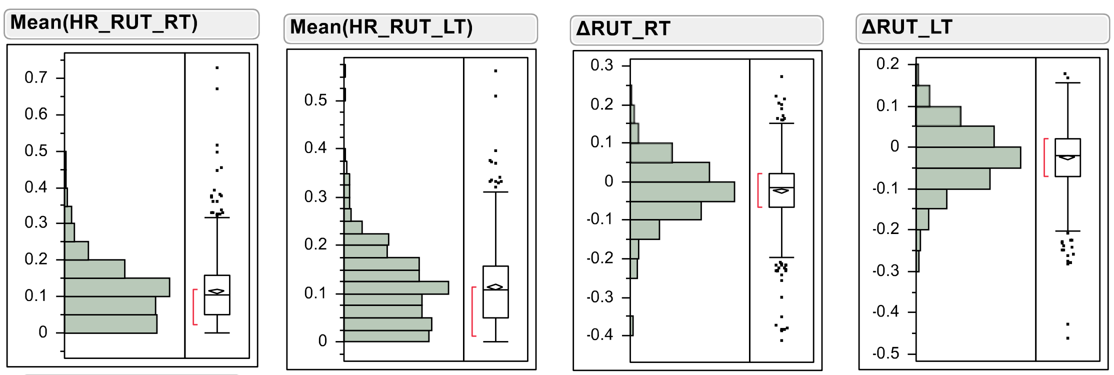


Figure 9- 8 Quantile density contours (Interstates)

9.2.2 Evaluation of the influence of maintenance actions on rut depth

Figure 9-5 illustrated the distribution of initial rut depth and change of rut depth between two adjacent collecting years for state routes. Figure 9-5 (a) illustrated the distribution of initial rut depth before maintenance actions. It can be seen that the average rut depth before maintenance were around 0.11 in. with the standard deviation around 0.08 in. Meanwhile, it can be seen that rutting was partially corrected after maintenance actions. The rut depth was reduced by 0.02 in. in average. It seems that most of the maintenance actions occurred with the low severity level ofrutting. This is because rutting is not a major issue for asphalt pavement in Tennessee. Most of the maintenance actions were applied to correct other distresses or improve the longitudinal roughness.

Figure 9-6 illustrated the quantile density contours for initial rut depth and change of rut depth. Itcan be seen that the zero line (ΔRUT=0) across through the high density area (red area) which means the initial rut depth was slightly decreased by the maintenance actions. In another word, the change of rut depth seems insensitive to the maintenance actions.



Quantiles

		Mean(HR_RUT_RT)	Mean(HR_RUT_LT)	ΔRUT_RT	ΔRUT_LT
100.0%	maximum	0.7275	0.56043	0.27187	0.17738
99.5%		0.48443	0.37386	0.20265	0.15334
97.5%		0.31918	0.28709	0.11098	0.11358
90.0%		0.21456	0.21197	0.06974	0.07318
75.0%	quartile	0.15821	0.15801	0.02167	0.02234
50.0%	median	0.10547	0.10692	-0.017	-0.0202
25.0%	quartile	0.05223	0.05155	-0.0668	-0.0701
10.0%		0.02543	0.02159	-0.1142	-0.119
2.5%		0.00742	0.00535	-0.2171	-0.1915
0.5%		0.00032	0	-0.3835	-0.279
0.0%	minimum	0	0	-0.415	-0.4613

Moments

	Mean(HR_RUT_RT)	Mean(HR_RUT_LT)	ΔRUT_RT	ΔRUT_LT
Mean	0.115725	0.1134265	-0.024094	-0.024835
Std Dev	0.0841621	0.0759989	0.080461	0.0776992
Std Err Mean	0.0028936	0.0026129	0.0027663	0.0026714
Upper 95% Mean	0.1214044	0.118555	-0.018664	-0.019592
Lower 95% Mean	0.1100456	0.108298	-0.029524	-0.030079
N	846	846	846	846

(a) Distribution of initial IRI (b) Distribution of change of IRIFigure

9- 9 Distribution of initial IRI and change of IRI (State routes)

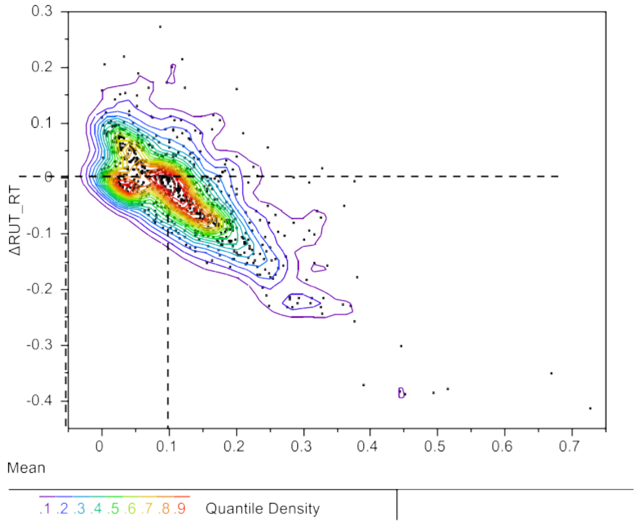
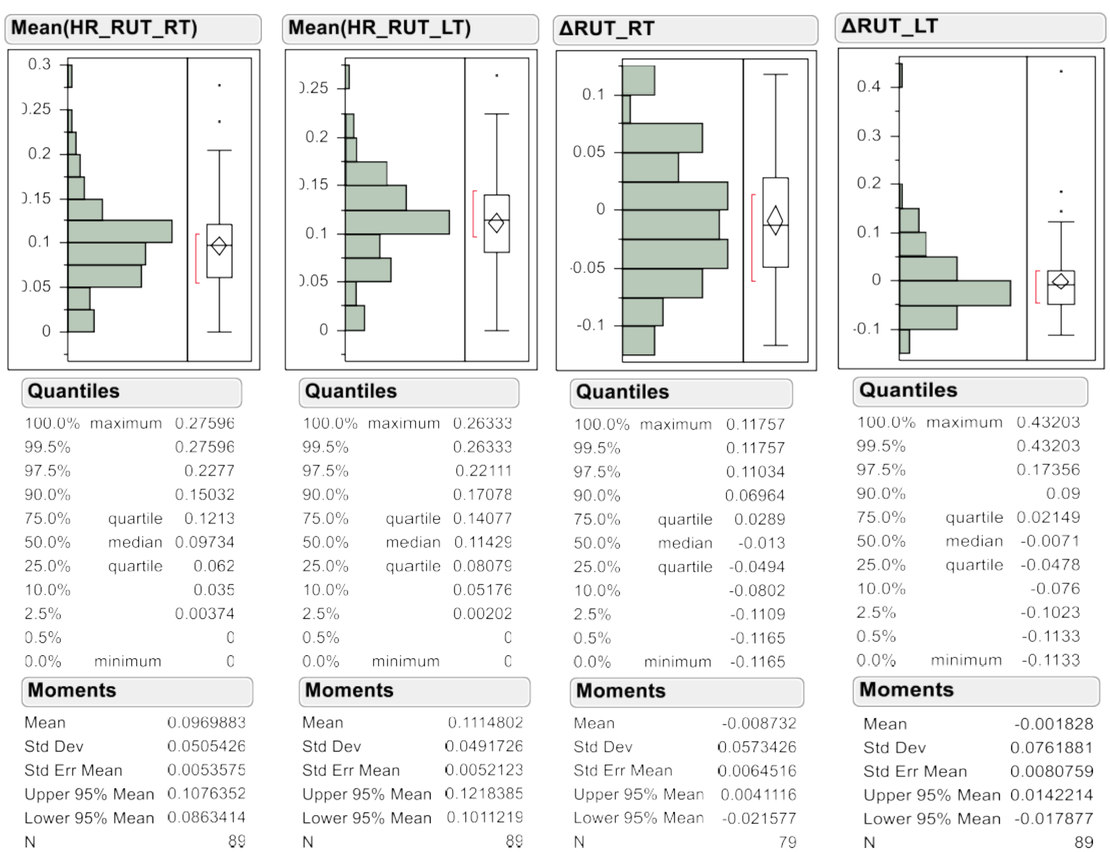


Figure 9- 10 Quantile density contours (rut depth in right side for state routes)

Figure 9-7 illustrated the distribution of initial rut depth and change of rut depth between two adjacent collecting years for interstates. Figure 9-7 (a) indicated that the maintenance actions occurred with the rut depth around 0.11 to 0.15 in. which was similar to state routes. Meanwhile,Figure 9-7 (b) indicated that there was a slightly decrease of rut depth due to the maintenance action. Comparing with state routes, the change of rut depth for interstates seems less sensitive.



(a) Distribution of initial rut depth (b) Distribution of change of rut depth

Figure 9- 11 Distribution of initial rut depth and change of rut depth (Interstates)

Figure 9-8 illustrated the quantile density contours for initial rut depth and change of rut depth for interstates. Generally, the density contours for interstates was similar to that for state routes.

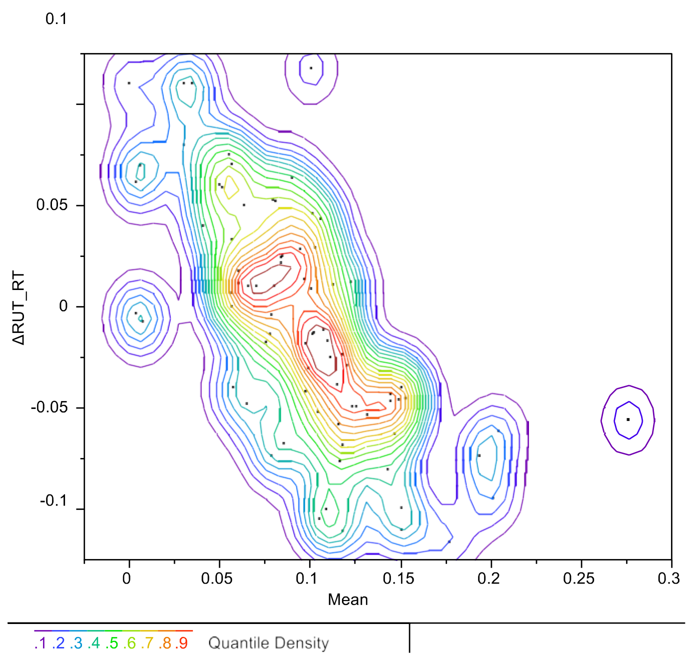


Figure 9- 12 Quantile density contours (rut depth in right side for interstates)

9.2.3 Influence of different maintenance actions on pavement distress data

Figure 9-9 illustrates the distribution of initial PDI and change of PDI. The 75% quantiles for initial PDI was 5, which means there were about 25% of the sections free from distresses at thetime of maintenance actions. The distribution of change of PDI indicated that the maintenance may result in an increase of PDI by 0.8 in average. It was also found that there were 25% maintained section whose performance become worse. The reasons could be: 1) there is little influence of maintenance actions on pavement deterioration; and/or 2) there might be errors in interpreting the image.

Figure 9-10 illustrated the relationship between initial PDI and ΔPDI. The linear relationship wasfound between initial PDI and ΔPDI. The results of fitting model were listed in Table 9-6.

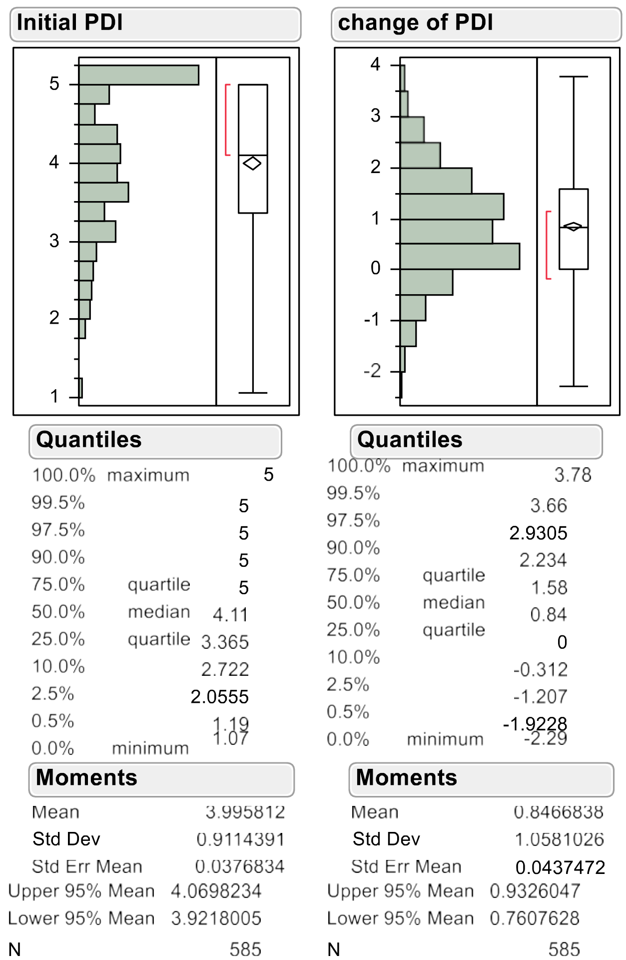


Figure 9- 13 Distribution of initial and change of PDI (ΔPDI)

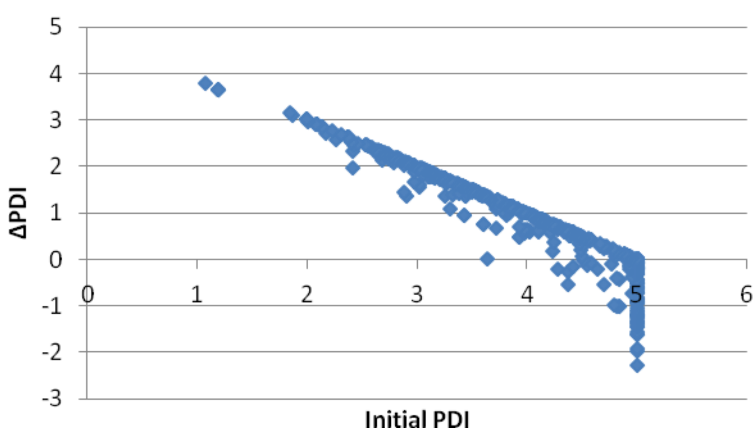


Figure 9- 14 Change of PDI by the influence of maintenance actions

Table 9- 4 Fitting results of linear model

Summary of Fit		Results
R-Square		0.976
R-Square Adj		0.976
Root Mean Square Error		0.134
Mean of Response		1.157
Observations		481
Parameters Estimates		
Intercept	Estimate	4.882
	Standard Error	0.027
	Lower 95%	4.829
	Upper 95%	4.936
Slope	Estimate	-0.983
	Standard Error	0.00698
	Lower 95%	-0.996
	Upper 95%	-0.969

9.3 Establishment of performance curve

9.3.1 Determination of the initial year for performance model

To establish a performance model to predict the performance change over time, the historical data will be employed. Before it can be used to construct performance model, the initial yearafter the latest maintenance action should be identified.

In HPMA, most maintenance and rehabilitation actions with biding documents were recorded insystem. However, routine maintenance actions were not included since they were performed by the TDOT maintenance staffs and without biding document. The routine maintenance contains pothole repairs, crack sealing, and patching. These actions may have significant influence on the change of pavement performance at the minimum road unit (Note the minimum road unit is one-tenth of a mile, by which the pavement condition data are recorded). It was also found that a fewmaintenance and rehabilitation actions were excluded in the system out of some reasons. Therefore, a threshold should be setup to identify the latest maintenance action.

The indicators which can be used to identify the maintenance action include roughness index: IRI, rutting depth; individual distress; and the Pavement performance index (Pavement Serviceability Index, Pavement Distress Index and Pavement Quality Index). The analyses fromthe previous quarterly reports indicated that the influence of maintenance action on different indicators were different, depending on the types of routes.

Table 9-5 listed the statistic characteristics of indicators in the presence of maintenance actions. It was found that the PDI is most sensitive indicator to the maintenance action, followed by IRI and PSI. The rut depth seems the most insensitive indicator. As the most collected data (annuallyfor interstates, and biannually for state routes), in this report, IRI was employed to identify the maintenance action.

Table 9- 5 Statistic characteristics of indicators in the presence of maintenance actions

Indicators	Means (Interstates, State routes)	Standard Deviation (Interstates, State routes)	Median (Interstates, State routes)
ΔIRI_LT	-7.205,-21.127	21.985,24.542	-3.754,-22.461
ΔIRI_RT	-7.334,-24.837	24.627,28.529	-5.15,-24.412
ΔRut_LT	-0.002,-0.025	0.076,0.078	-0.0071, -0.0202
ΔRut_RT	-0.009,-0.024	0.057,0.080	-0.013,-0.017
ΔPSI	0.133,0.375	0.353,0.381	0.07,0.412
ΔPDI	0.85	1.06	0.84

Figure 9-11 illustrated the change of IRI over time from county 3 (SR 191 County 3 from 21.6mile to 21.7mile, P direction). There is a jump of IRI in 2009 from 168 in./mi. in average to 57 in./mi.. This change probably caused by the maintenance action. Therefore, the IRI before 2009 will be excluded when the performance curve is constructed. If the performance curve is determined by including the data before 2009, the general trend of performance curve will be considered as abnormal.

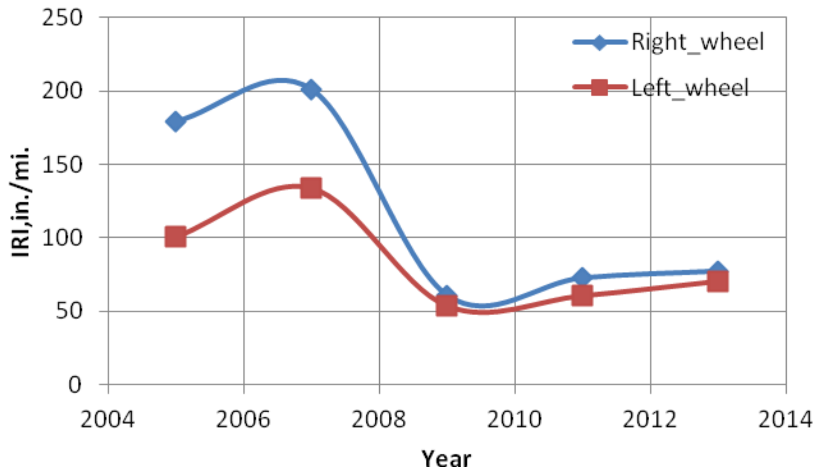


Figure 9- 15 Change of IRI over time

Figure 9-12 illustrated two performance curves with and without data before 2009. It can be seenthat with data before 2009, the general trend of performance curve seems abnormal. The slope ofthe linear equation is positive, which means PSI increases with time. However, if the data before2009 were excluded, the general trend of performance curve illustrated a normal change of PSI with R^2 (greater than 0.9) higher than the form linear equation (less than 0.6).

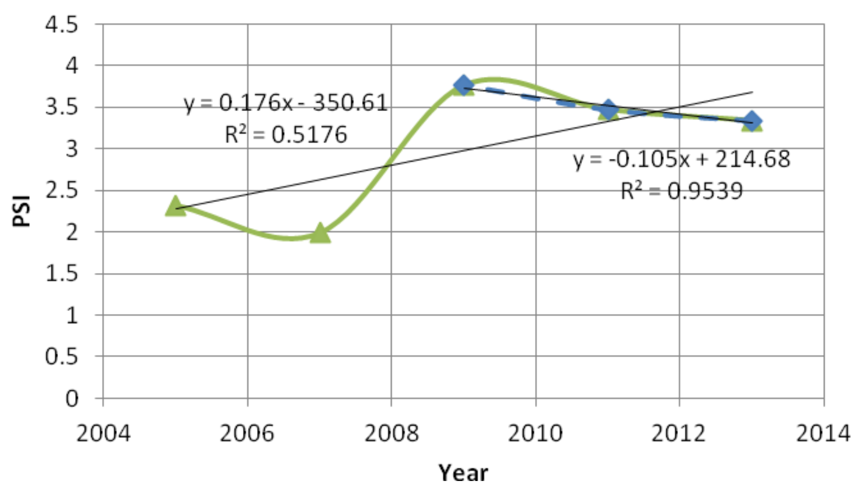


Figure 9- 16 Performance curve (with and without data before 2009)

Figure 9-13 illustrated a typical change of IRI over time with IRI slightly drop in 2009. Since nomaintenance records was found within this segment from 2008 to 2010. It cannot conclude that the maintenance action is responsible for drop in IRI. The reason could be either maintenance action or measurement error.

Figure 9-14 illustrated the performance curves with and without data before 2009. It can be seenthat the general trend of two performance curves are similar. The slope of one with three years isslightly higher than that with five years, which means the deterioration rate of former is slightly higher than the later. Therefore, the predicated PSI value determined by the former equation willhigher than the later. This means the performance curve with five years' data leads to a conservative result.

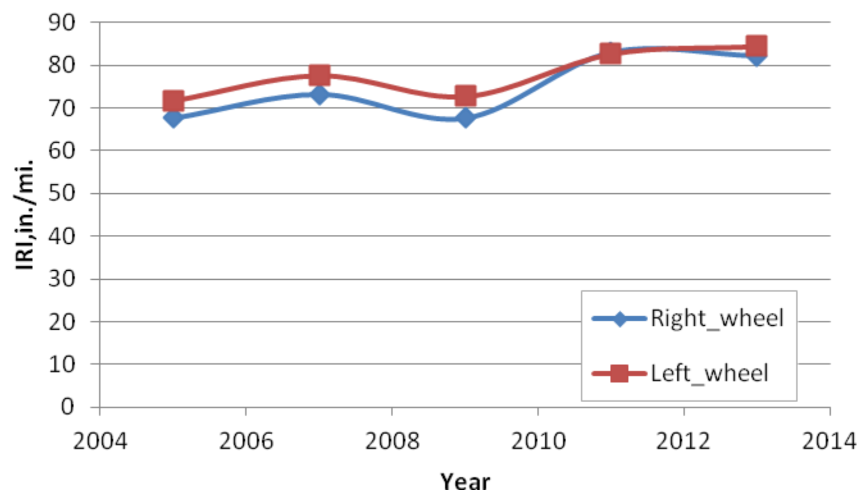


Figure 9- 17 Change of IRI over time (slightly drop in IRI in 2009)

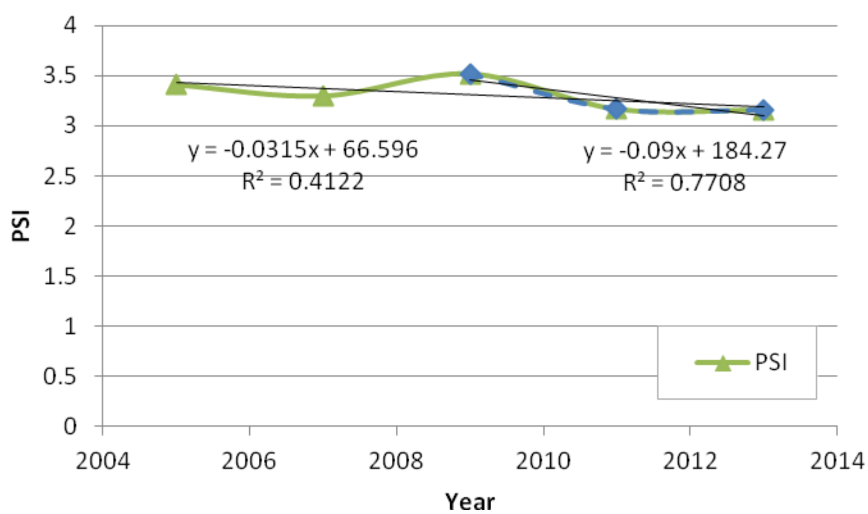


Figure 9- 18 Performance curve (slightly drop in IRI in 2009)

Figure 9-15 illustrated the change of IRI over time. It can be seen from Figure 6 that there seemsto be an abnormal change of IRI in 2010 on the left side. Figure 9-16 illustrated the performancecurves. Results from linear equation indicated that the general trend of performance curves seemnormal. Although the R-square of performance curve with less data is higher than that with moredata, the performance curve determined by five years' data seems more appropriate since more data were included.

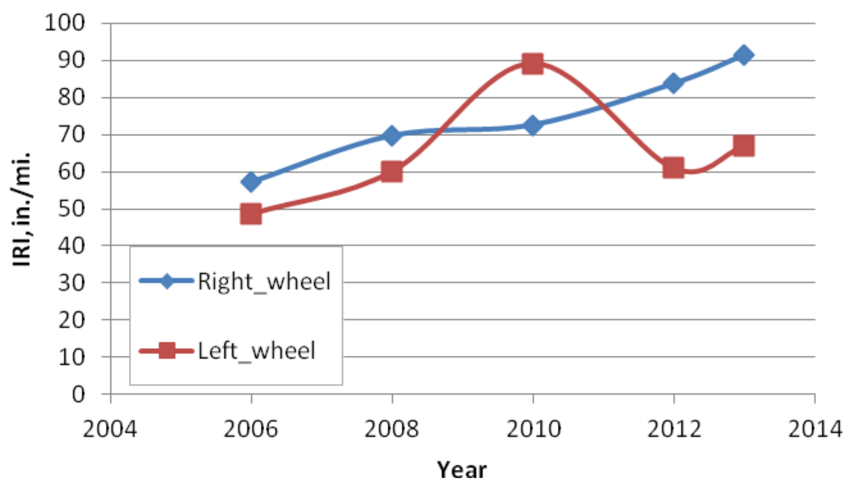


Figure 9- 19 Change of IRI over time (with abnormal change of IRI on one side)

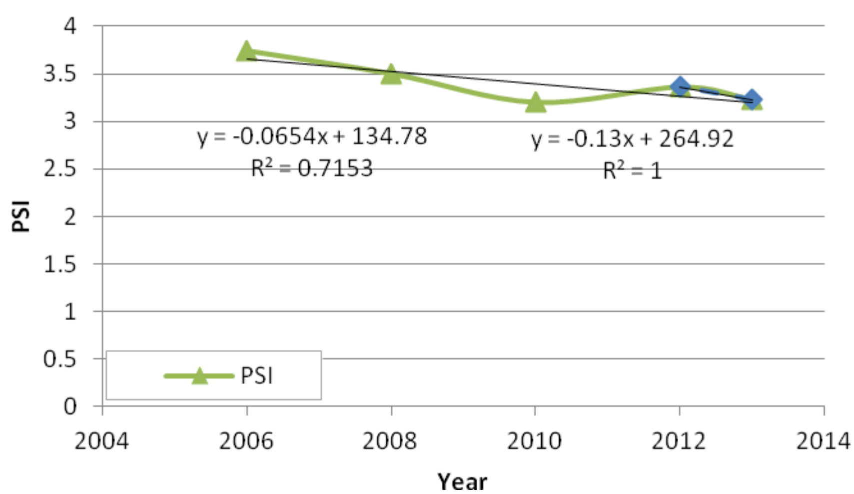


Figure 9- 20 Performance curve (with abnormal change of IRI on one side)

9.3.2 Determination of the performance curve

Linear equation is employed to describe the performance curve. There are many other models can be used to describe the change of pavement performance over time. In this report, the linearmodel was employed due to the following reasons:

1) The form of linear model is relative simple. The equations of determining the parameters of linear model by Least-square method are simple and can be programedeasily.
2) The slope of linear model can be used to indicate the general trend of performancechange. Therefore, the abnormal changes in performance can be easily identified.
3) The linear model is capable of predicating the short-term change of performance curve. There is no significant difference in short-term prediction of performance between linear model and other models.

Pavement Serviceability Index, PSI, was used to construct the performance model. PSI is calculated from IRI, which is calculated from the longitudinal profile. As exponential function isemployed, the variability of PSI significantly decreases. As an index to describe the riding comfort, PSI is used for M&R analysis by decision tree.

9.3.3 Framework of determining performance curve

The performance curve is determined in accordance with the following steps.

1) Determining the road unit and route ID for each unit.

The road unit is the minimum analysis section based on which the performance curve was established. The road unit is determined based on the analysis demand. With larger road unit, thereliability will decrease. However, it is hard to make maintenance plan if the road unit is too small. In HPMA, the road unit is one-tenth of a mile, which is the minimum unit for analysis.
Obviously, the lower road unit may lead to better prediction results comparing with the larger ones. In this report, the road unit to be analyzed is one-tenth of a mile. Lager road unit can alsobe used depending on the analysis demand.

To identify each road unit, the following ID codes were employed: HR_ROUTCOD; HR_COUNTY; HR_CNTYSQ; HR_ROUTTYP; HR_ROUTNUM; HR_ROUTAUX; HR_DIRECTN; HR_BEGMILE.

2) Time series of collected performance data.

The performance matrixes were established in terms of the following pavement condition indices:IRI, rut depth, and PSI by collecting year.

Table 9- 6 Matrix of PSI

ID code	Y ea r1	Y ea r2	…	Y ea ri	…	Y ea rn
131I40M0						
131I40M0.1						
131I40M0.2						
131I40M0.3						
…						

In Table 9-6, the ID code for each road unit represents the minimum road segment within the route. The ID code is named as follows. The ID number is the unique code for identifying theroad unit.

HR_ROUTCOD	131I40 *M*0.1
HR_COUNTY	
HR_CNTYSQ	
HR_ROUTTYP	
HR_ROUTNUM	
HR_ROUTAUX	
HR_DIRECTN	
HR_BEGMILE	

3) Identify the maintenance action and modify the PSI matrix.

The maintenance actions are identified by change of IRI between two adjacent years. The changes of IRI over year from each side and the average changes of IRI over year are determinedas the follows

$$\Delta HR\_IRI\_RT = (HR\_IRI\_RT)_i - (HR\_IRI\_RT)_{i-1}$$
$$\Delta HR\_IRI\_LT = (HR\_IRI\_LT)_i - (HR\_IRI\_LT)_{i-1}$$
$$\Delta HR\_IRI = (\Delta HR\_IRI\_RT + \Delta HR\_IRI\_LT)/2$$

The matrix of ΔIRI is constructed as shown in Table 9-7. The latest $\Delta HR\_IRI_{i-1,i}$ with values lessthan -15 in./mi. is first identified. The initial year which is used to construct performance model is the later year of $\Delta HR\_IRI_{i-1,i}$. If no value of ΔHR_IRI is found to be less than -15 in./mi., all data will be included to construct performance model.

Table 9- 7 Matrix of ΔIRI

ID	ΔHR_IRI$_{1-2}$	ΔHR_IRI$_{2-3}$	…	ΔHR_IRI$_{n-1-n}$
1				
2				
3				
4				

4) Determining the parameters for the performance model utilizing least-square method.

After pavement condition data and the initial year being screened out, the least-squared methodis employed to estimate the parameters of performance model.

The formation of performance model is written as Eq. 9-1.

$$PSI=A*Year+B \qquad \text{(Eq. 9-1)}$$

Where, A, B is the coefficient of performance model, indicating the slope (A) and intercept (B). Independent variable (Year) starts with the initial year in the order of Year=1, 2,…,n. PSI startswith the initial PSI value from the initial year.

In the program, the coefficient of A and B is determined as the following equations:

$$A = \frac{\sum Y}{n} - \frac{B\sum X}{n}$$

$$B = \frac{n\sum XY - \sum X \sum Y}{n\sum X^2 - (\sum X)^2}$$

Where: X represents for Year; Y represents for PSI; n represents for the number of samples usedin constructing the model.

R square is used to indicate the Goodness-of-fitting. It can be calculated by the following equation.

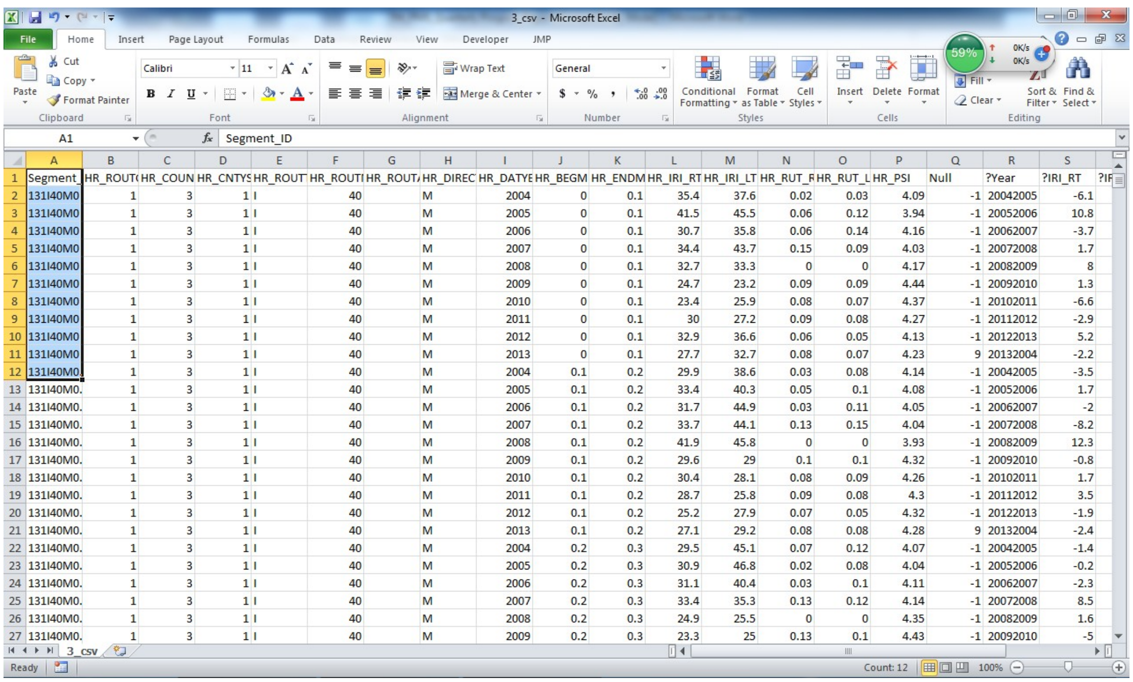
$$R^2 = \frac{A\sum Y + B\sum XY - n\sum \bar{Y}^2}{\sum Y^2 - n\bar{Y}^2}$$

Where: X, Y,n are the same as above.;

The flowchart of determining the performance curve was illustrated as below and Java based code was also developed. The program is developed on the platform of Java. It consists of .exe file (gawk.exe) and AWK file (PSI.awk). The program runs under cmd.exe. The command forthe program is:

Gawk –F, –f PSI.awk *filename*.csv

The file containing original data should first transfer to the .CSV file format as illustrated inFigure 9-17. The output interface of results is illustrated in Figure 9-19.



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	
1	Segment_	HR_ROUT(	HR_COUN	HR_CNTYS	HR_ROUT	HR_ROUTI	HR_ROUT/	HR_DIREC	HR_DATYE	HR_BEGM	HR_ENDM	HR_IRI_RT	HR_IRI_LT	HR_RUT_R	HR_RUT_L	HR_PSI	Null	?Year	?IRI_RT	?IF
2	131I40M0	1	3	1	I	40		M	2004	0	0.1	35.4	37.6	0.02	0.03	4.09	-1	20042005	-6.1	
3	131I40M0	1	3	1	I	40		M	2005	0	0.1	41.5	45.5	0.06	0.12	3.94	-1	20052006	10.8	
4	131I40M0	1	3	1	I	40		M	2006	0	0.1	30.7	35.8	0.06	0.14	4.16	-1	20062007	-3.7	
5	131I40M0	1	3	1	I	40		M	2007	0	0.1	34.4	43.7	0.15	0.09	4.03	-1	20072008	1.7	
6	131I40M0	1	3	1	I	40		M	2008	0	0.1	32.7	33.3	0	0	4.17	-1	20082009	8	
7	131I40M0	1	3	1	I	40		M	2009	0	0.1	24.7	23.2	0.09	0.09	4.44	-1	20092010	1.3	
8	131I40M0	1	3	1	I	40		M	2010	0	0.1	23.4	25.9	0.08	0.07	4.37	-1	20102011	-6.6	
9	131I40M0	1	3	1	I	40		M	2011	0	0.1	30	27.2	0.09	0.08	4.27	-1	20112012	-2.9	
10	131I40M0	1	3	1	I	40		M	2012	0	0.1	32.9	36.6	0.06	0.05	4.13	-1	20122013	5.2	
11	131I40M0	1	3	1	I	40		M	2013	0	0.1	27.7	32.7	0.08	0.07	4.23	9	20132004	-2.2	
12	131I40M0	1	3	1	I	40		M	2004	0.1	0.2	29.9	38.6	0.03	0.08	4.14	-1	20042005	-3.5	
13	131I40M0.	1	3	1	I	40		M	2005	0.1	0.2	33.4	40.3	0.05	0.1	4.08	-1	20052006	1.7	
14	131I40M0.	1	3	1	I	40		M	2006	0.1	0.2	31.7	44.9	0.03	0.11	4.05	-1	20062007	-2	
15	131I40M0.	1	3	1	I	40		M	2007	0.1	0.2	33.7	44.1	0.13	0.15	4.04	-1	20072008	-8.2	
16	131I40M0.	1	3	1	I	40		M	2008	0.1	0.2	41.9	45.8	0	0	3.93	-1	20082009	12.3	
17	131I40M0.	1	3	1	I	40		M	2009	0.1	0.2	29.6	29	0.1	0.1	4.32	-1	20092010	-0.8	
18	131I40M0.	1	3	1	I	40		M	2010	0.1	0.2	30.4	28.1	0.08	0.09	4.26	-1	20102011	1.7	
19	131I40M0.	1	3	1	I	40		M	2011	0.1	0.2	28.7	25.8	0.09	0.08	4.3	-1	20112012	3.5	
20	131I40M0.	1	3	1	I	40		M	2012	0.1	0.2	25.2	27.9	0.07	0.05	4.32	-1	20122013	-1.9	
21	131I40M0.	1	3	1	I	40		M	2013	0.1	0.2	27.1	29.2	0.08	0.08	4.28	9	20132004	-2.4	
22	131I40M0.	1	3	1	I	40		M	2004	0.2	0.3	29.5	45.1	0.07	0.12	4.07	-1	20042005	-1.4	
23	131I40M0.	1	3	1	I	40		M	2005	0.2	0.3	30.9	46.8	0.02	0.08	4.04	-1	20052006	-0.2	
24	131I40M0.	1	3	1	I	40		M	2006	0.2	0.3	31.1	40.4	0.03	0.1	4.11	-1	20062007	-2.3	
25	131I40M0.	1	3	1	I	40		M	2007	0.2	0.3	33.4	35.3	0.13	0.12	4.14	-1	20072008	8.5	
26	131I40M0.	1	3	1	I	40		M	2008	0.2	0.3	24.9	25.5	0	0	4.35	-1	20082009	1.6	
27	131I40M0.	1	3	1	I	40		M	2009	0.2	0.3	23.3	25	0.13	0.1	4.43	-1	20092010	-5	

Figure 9- 21 Original pavement condition dataThe input interface of cmd command is illustrated in Figure 9-18.

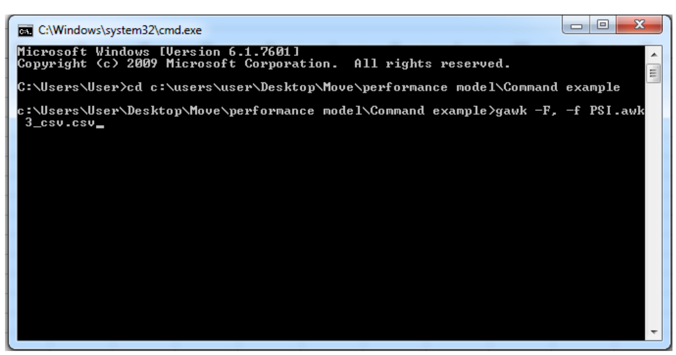
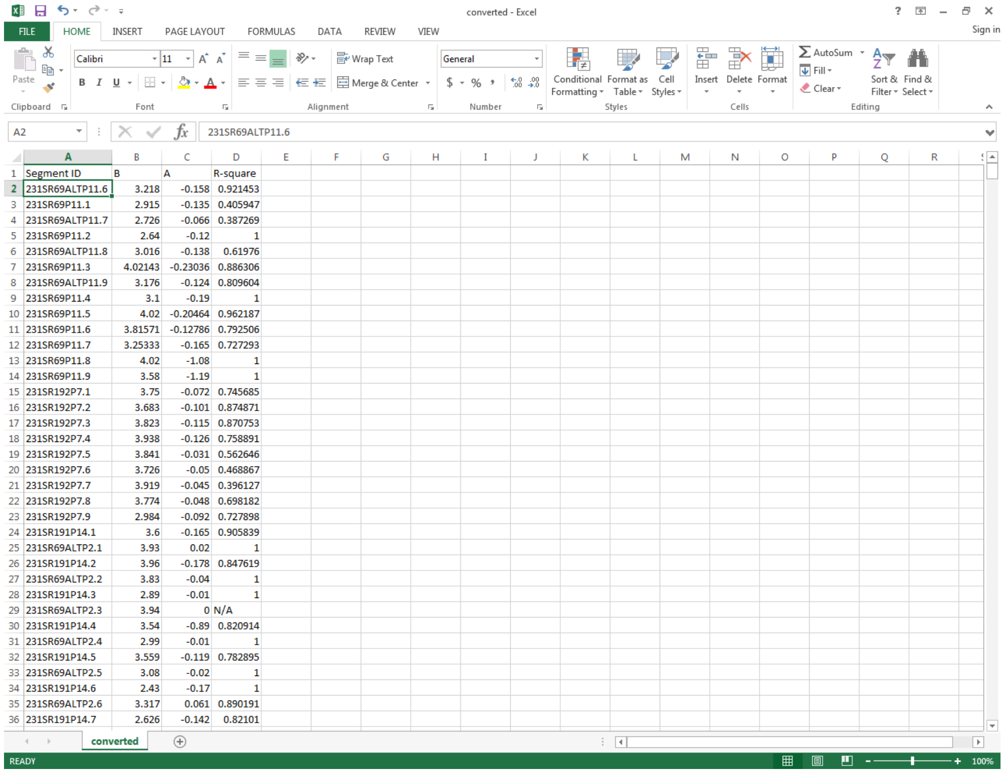
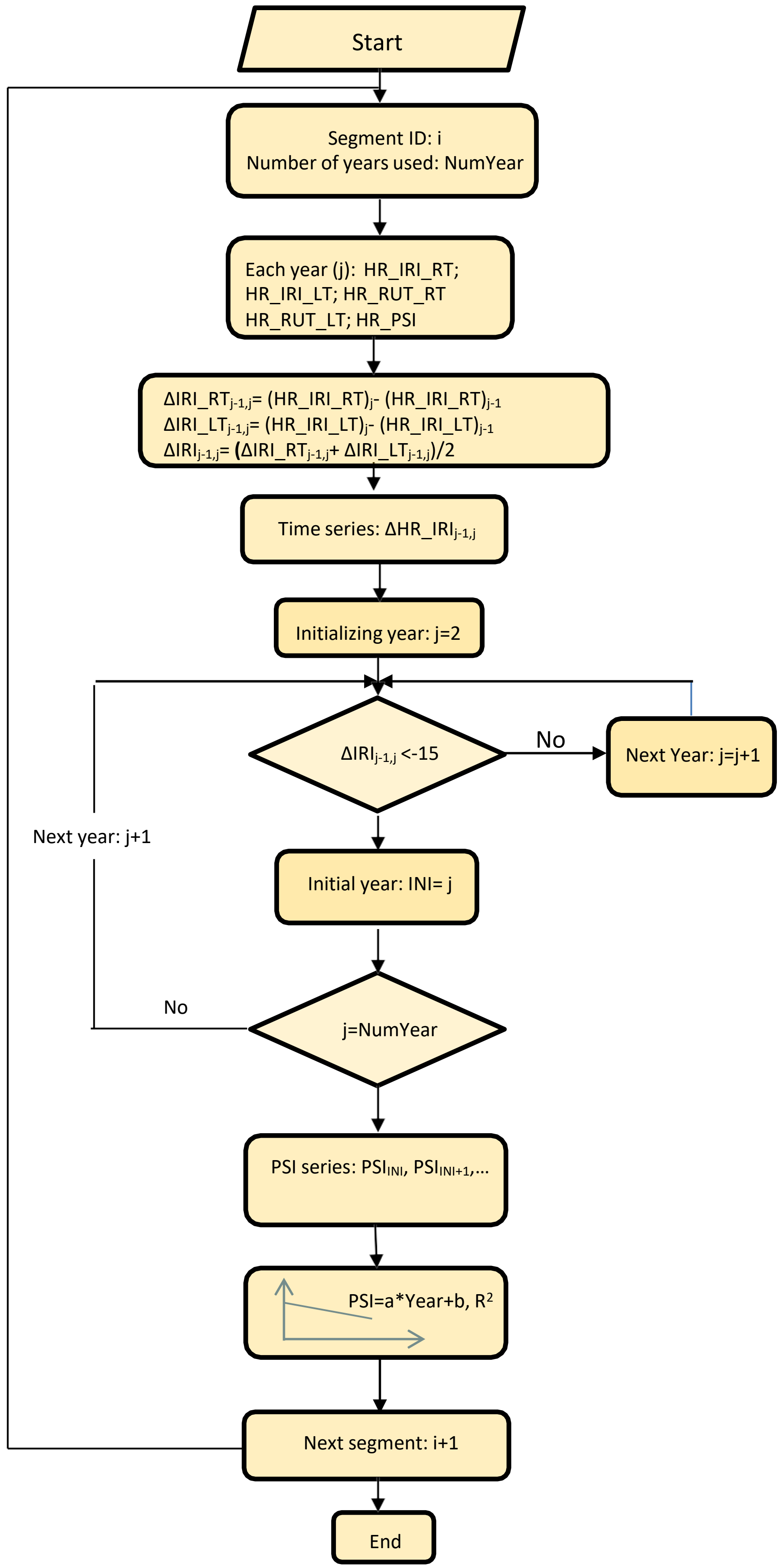


Figure 9- 22 Interface of input command (cmd.exe)



	Segment ID	B	A	R-square
2	231SR69ALTP11.6	3.218	-0.158	0.921453
3	231SR69P11.1	2.915	-0.135	0.405947
4	231SR69ALTP11.7	2.726	-0.066	0.387269
5	231SR69P11.2	2.64	-0.12	1
6	231SR69ALTP11.8	3.016	-0.138	0.61976
7	231SR69P11.3	4.02143	-0.23036	0.886306
8	231SR69ALTP11.9	3.176	-0.124	0.809604
9	231SR69P11.4	3.1	-0.19	1
10	231SR69P11.5	4.02	-0.20464	0.962187
11	231SR69P11.6	3.81571	-0.12786	0.792506
12	231SR69P11.7	3.25333	-0.165	0.727293
13	231SR69P11.8	4.02	-1.08	1
14	231SR69P11.9	3.58	-1.19	1
15	231SR192P7.1	3.75	-0.072	0.745685
16	231SR192P7.2	3.683	-0.101	0.874871
17	231SR192P7.3	3.823	-0.115	0.870753
18	231SR192P7.4	3.938	-0.126	0.758891
19	231SR192P7.5	3.841	-0.031	0.562646
20	231SR192P7.6	3.726	-0.05	0.468867
21	231SR192P7.7	3.919	-0.045	0.396127
22	231SR192P7.8	3.774	-0.048	0.698182
23	231SR192P7.9	2.984	-0.092	0.727898
24	231SR191P14.1	3.6	-0.165	0.905839
25	231SR69ALTP2.1	3.93	0.02	1
26	231SR191P14.2	3.96	-0.178	0.847619
27	231SR69ALTP2.2	3.83	-0.04	1
28	231SR191P14.3	2.89	-0.01	1
29	231SR69ALTP2.3	3.94	0	N/A
30	231SR191P14.4	3.54	-0.89	0.820914
31	231SR69ALTP2.4	2.99	-0.01	1
32	231SR191P14.5	3.559	-0.119	0.782895
33	231SR69ALTP2.5	3.08	-0.02	1
34	231SR191P14.6	2.43	-0.17	1
35	231SR69ALTP2.6	3.317	0.061	0.890191
36	231SR191P14.7	2.626	-0.142	0.82101

Figure 9- 23 Output interface


Start
Segment ID: i
Number of years used: NumYear
Each year (j): HR_IRI_RT; HR_IRI_LT; HR_RUT_RT HR_RUT_LT; HR_PSI
$\Delta IRI\_RT_{j-1,j}= (HR\_IRI\_RT)_{j}- (HR\_IRI\_RT)_{j-1}$
$\Delta IRI\_LT_{j-1,j}= (HR\_IRI\_LT)_{j}- (HR\_IRI\_LT)_{j-1}$
$\Delta IRI_{j-1,j}= (\Delta IRI\_RT_{j-1,j}+ \Delta IRI\_LT_{j-1,j})/2$
Time series: $\Delta HR\_IRI_{j-1,j}$
Initializing year: j=2
$\Delta IRI_{j-1,j} <-15$
No
Next Year: j=j+1
Initial year: INI= j
Next year: j+1
No
j=NumYear
PSI series: PSI_{INI}, PSI_{INI+1},…
PSI=a*Year+b, R^2
Next segment: i+1
End

10. Equipment verification on control site

10.1 Test verification site

The test equipment should be validated before data production and needs to be periodically checked during the data collection. Control sites are used to perform equipment verification. In Tennessee, there are 16 control sites for the purpose of equipment validation. Details were listedin Table 10-1. Most of the control sites are 1 mile length. The sections are free of intersections and are relative flat. The traffic is low at these sites. Therefore, the test vehicle can easily keep the cursing speed. The influence of change of speed on repeatability of collected data can be decreased.

10.2 Comparison of historical data

Historical data in different test sites over Tennessee were collected to make comparisons of IRI from different testing equipment. The test sites were listed in Table 2. The length of test sites was 1 mile except for site 1-5 with 0.5 mile-length. Each site was divided into 10 sub-segments with 0.1 mile length. Site 1-5 was divided into 5 sub-segments. The IRI for each sub-segment was calculated. The mean value, standard deviation, and coefficient of variance for each site were calculated and listed in Table 3. The IRI data provided by the contractor were collected from the HPMA. Since the data form TDOT and contractor were collected at different time, there might be some errors on the results due to the change of weather or pavement surface characteristics. Comparisons were made herein to estimate the possible bias of two datasets. It isassumed that there is no significant change of IRI over time within a year.

Table 10- 1 Test sites for evaluating the data repeatability

Site No.	County	Route No.	Direction	Begin	End	Length	Test Date (TDOT)	Test Date (contractor)
1-1	Jefferson	34	M	8.155	7.155	1	9/18/2014	11/6/2014
1-2	Sullivan	34	P	0.29	1.29	1	09/16/2014	10/7/2014
1-4	Roane	58	P	14.95	15.95	1	09/18/2014	11/15/2014
1-5	Knox	1	P	35.09	35.59	0.5	9/17/2014	11/18/2014
2-1	Hamilton	29	P	13.69	14.69	1	7/11/2014	10/26/2014
2-2	Rhea	29	M	25.55	24.55	1	07/11/2014	11/10/2014
2-4	Putnam	111	M	6.69	5.69	1	08/20/2014	11/3/2014
3-3	Rutherford	10	P	3.67	4.67	1	08/27/2014	10/18/2014
3-4	Montgomery	76	P	1	2	1	10/16/2014	10/19/2014
4-1	Madison	20	M	4	3	1	4/24/2014	9/24/2014
4-2	Henderson	20	P	18.6	19.6	1	12/9/2014	9/25/2014
4-3	Obion	3	M	29	28	1	11/10/2014	9/20/2014

According to Table 10-2, the mean value of IRI ranged from 25.8 to 97.0 with the highest standard deviation of 5.3, which means all the test sites were in good or fair condition. Note thatIRI of 90 equals to the PSI of 3.0. In another word, these test sites are suitable to perform tests for equipment verification.

Table 10- 2 Statistic results of IRI

Site No.	IRI- left			IRI-right		
	Mean value, in/mi	Standard deviation,in/mi	Coefficient of variance,%	Meanvalue, in/mi	Standard deviation,in/mi	Coefficient of variance,%
1-1	49.0	0.7	1.43	49.4	1.3	2.63
1-2	65.2	0.4	0.61	73.6	1.8	2.45
1-4	40.8	0.4	0.98	51.6	1.7	3.29
1-5	73.2	3.6	4.92	73.6	3.2	4.35
2-1	38.0	0.7	1.84	39.4	0.9	2.28
2-2	71.2	0.4	0.56	76.2	0.4	0.52
2-4	25.8	0.4	1.55	32.0	0.0	0.00
3-2	48.7	2.5	5.13	47.6	5.3	11.13
3-3	51.8	1.6	3.09	52.2	0.4	0.77
3-4	52.0	0.0	0.00	50.4	0.5	0.99
4-1	41.8	0.8	1.91	53.2	0.8	1.50
4-2	95.4	0.5	0.52	97.0	0.7	0.72
4-3	39.0	1.2	3.08	40.8	0.4	0.98
4-4	44.2	0.8	1.81	53.4	0.5	0.94

Figure 10-1 illustrated the comparison of two datasets (IRI) obtained from two different testingequipment (TDOT and contractor) in 2014. The closer the points were to the equity line, the better agreement would be on the two datasets. Although the data were not collected at the samedate, the scatters were close to the equity line. This means the results from two different testing equipment are inconsistent with each other.

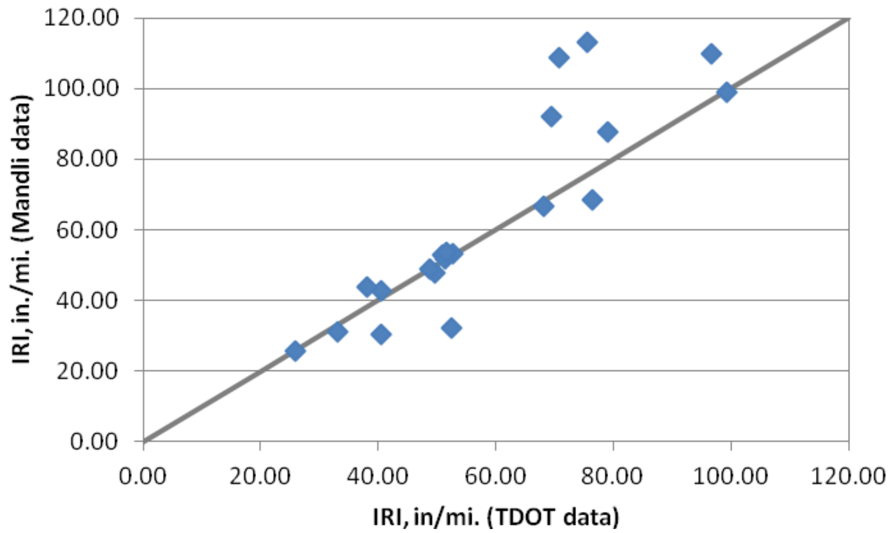


Figure 10- 1 Relationship of IRI between collection devices (segment)

Figure 10-2 illustrated the comparisons of IRI value at each one-tenth of a mile. Generally, the scatters were close to the equity line. It can also be seen that with higher IRI value, the scatters tend to be away from the equity line. The results in Figure 8 indicated that the contractor seemedto overestimate IRI value comparing with TDOT at higher IRI value. It should be noted that the test date for the contractor was generally later than TDOT. The deterioration of surface may alsocontribute to this result. Although the IRI of TDOT and contractor were not collected at same date, fair good consistency was observed by comparing the two datasets.

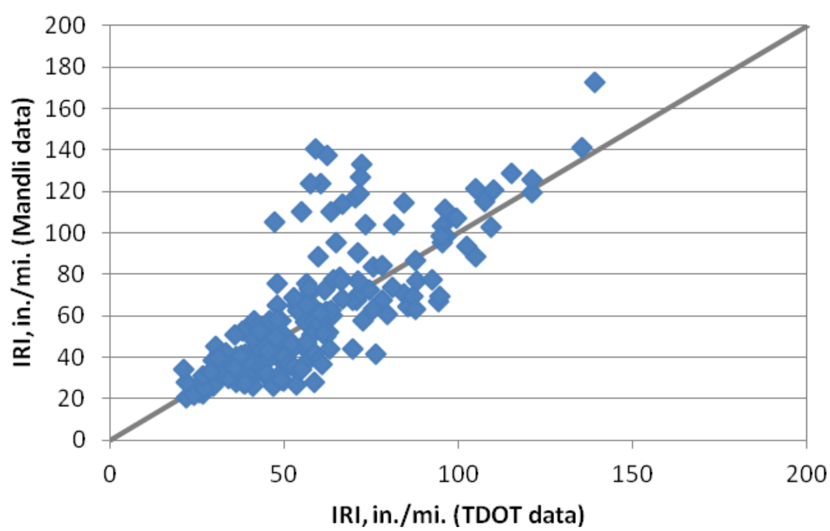
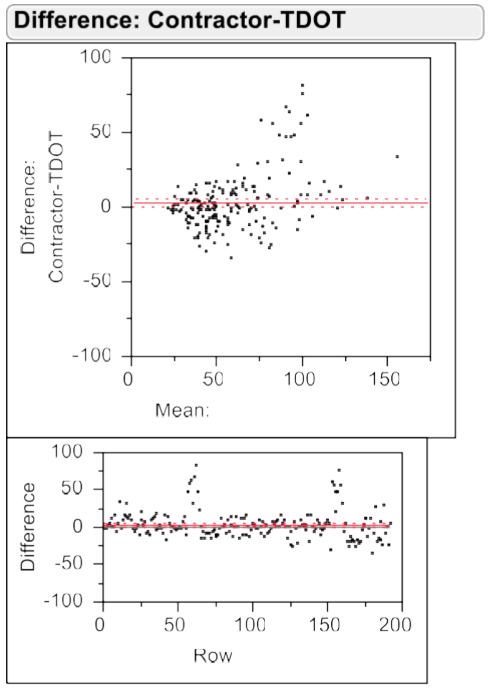


Figure 10- 2 Relationship of IRI between collection devices (0.1 mile sub-segment)

Matched pairs test was performed to evaluate whether the two datasets were from the same population. Figure 9 illustrated the test results. It can be seen that the upper and lower 95%

ranges from 0.09 to 5.51. This means contractor overestimated the IRI data comparing with theTDOT. Meanwhile, the two datasets were not from the same population statistically.



Contractor	60.2406	t-Ratio	2.037295
TDOT	57.4405	DF	191
Mean Difference	2.80012	Prob > |t|	0.0430 *
Std Error	1.37443	Prob > t	0.0215 *
Upper 95%	5.51113	Prob < t	0.9785
Lower 95%	0.08911		
N	192		
Correlation	0.78147		

Figure 10- 3 Results of matched pairs test

10.3 Field verification test

The two validation tests were conducted. One was at control site 3-3 in Rutherford County on March 27th, 2015, the other was at control site 1-1 in Knox County on September 30th, 2015. The weather was sunny. Figure 10-1 illustrated the test equipment that TDOT and the contractor used.

10.3.1 Control site 3-3

In control site 3-3, each test vehicles ran the test section 10 times. The longitudinal profile of pavement surface was collected by laser profiler. The contractor ran the first 0.1 mile to evaluatethe repeatability of IRI. The rest of section was used to check the accuracy of DMI.

Table 10-2 and Table 10-3 listed the result of T-test with the assumption that the samples have equal variance and unequal variance. T-test is performed by assuming that the two samples havethe same means value. With p=0.05, the Ho hypothesis is rejected which means the mean value of two samples were different.

(a) TDOT test equipment

(b) Contractor Equipment

Figure 10- 4 Test Equipment

Table 10- 3 T-Test: Two-Sample Assuming Equal Variances

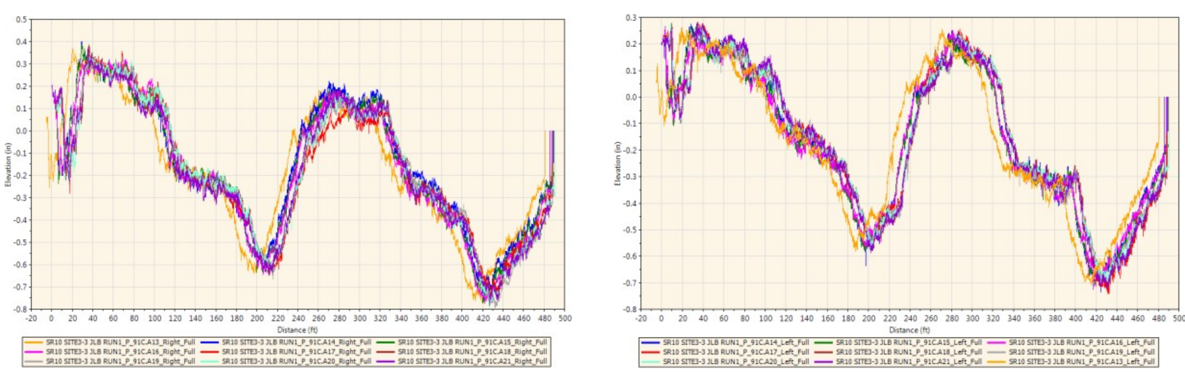
	Contractor left	*TDOT Left*	*Contractor Right*	*TDOT Right*
Mean	69.38	72.74	55.97	58.92
Variance	1.08	79.01	7.62	14.39
Observations	10.00	10.00	10.00	10.00
Pooled Variance	40.04		11.00	
Hypothesized Mean Difference	0.00		0.00	
df	18.00		18.00	
t Stat	-1.19		-1.99	
P(T<=t) one-tail	0.13		0.03	
t Critical one-tail	1.73		1.73	
P(T<=t) two-tail	0.25		0.06	
t Critical two-tail	2.10		2.10	

Table 10- 4 T-Test: Two-Sample Assuming Unequal Variances

	Contractor left	*TDOT Left*	*Contractor Right*	*TDOT Right*
Mean	69.38	72.74	55.969	58.922
Variance	1.08	79.01	7.622	14.387
Observations	10.00	10.00	10.000	10.000
Hypothesized Mean Difference	0.00		0.000	
Df	9.00		16.000	
t Stat	-1.19		-1.991	
P(T<=t) one-tail	0.13		0.032	
t Critical one-tail	1.83		1.746	
P(T<=t) two-tail	0.27		0.064	
t Critical two-tail	2.26		2.120	

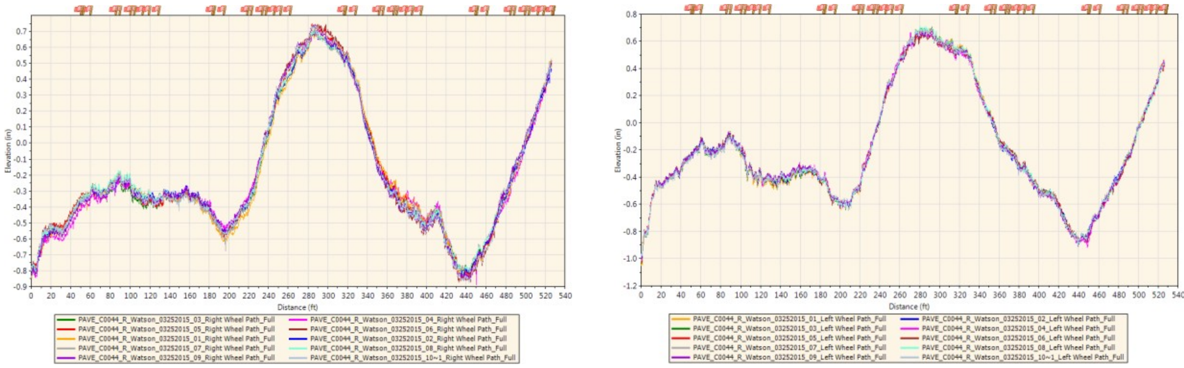
The results from Table 10-2 and Table 10-3indicated there seems no significant difference of IRIbetween two test devices, statistically. It should be noted that p-value in right wheel path (0.06) was slightly higher than the threshold (0.05). This means the difference of IRI in right path between two devices may be potentially significant.

Figure 10-5 and Figure 10-6 illustrate the longitudinal profile collected by two devices. It wasfound that there is no exact the same elevation curve between two runs for the same collectiondevice. However, the general change of elevation curve appeared similar. As for different collection device, the change of elevation curve appeared different.



(a)-Right wheel path (b)-Left wheel path

Figure 10-5 Longitudinal Profile-TDOT's equipment



(a)-Right wheel path (b)-Left wheel path

Figure 10- 6 Longitudinal Profile-Contractor's equipment

Figure 10-7 and Figure 10-8 indicated that after processed by High-pass Butterworth filter and offsetting a certain distance, the adjusted elevation curves matched well with each other. Table 10-7 compared the difference of IRI with and without Butterworth high pass filter. There was almost no change in IRI if Butterworth high pass filter was applied with long cutoff wavelengthgreater than 120 foot.

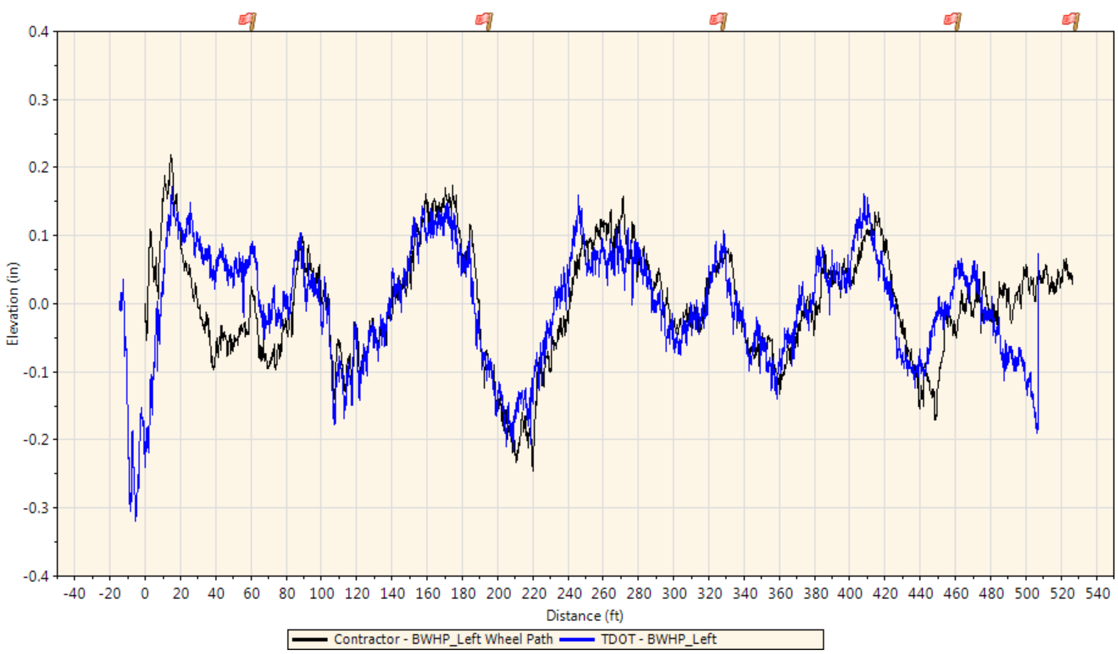


Figure 10- 7 Comparison of processed elevation on left wheel path with Butterworth High-pass filter applied (long cutoff wavelength120 ft.) and maximum offset 18 ft.

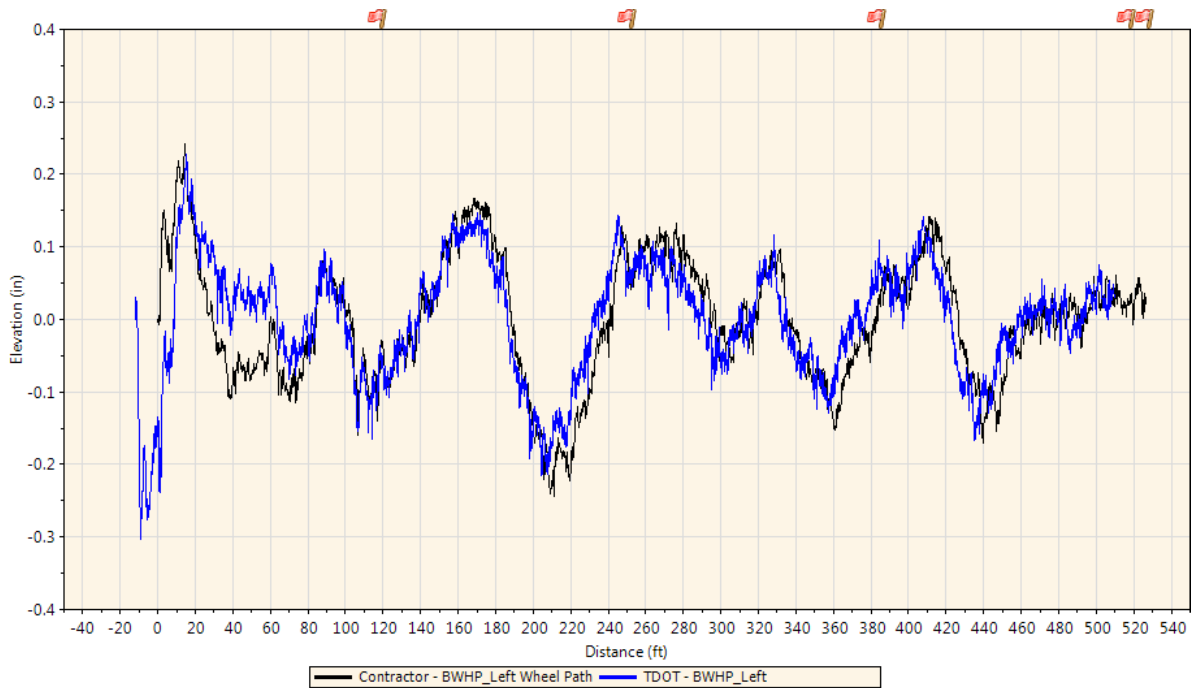
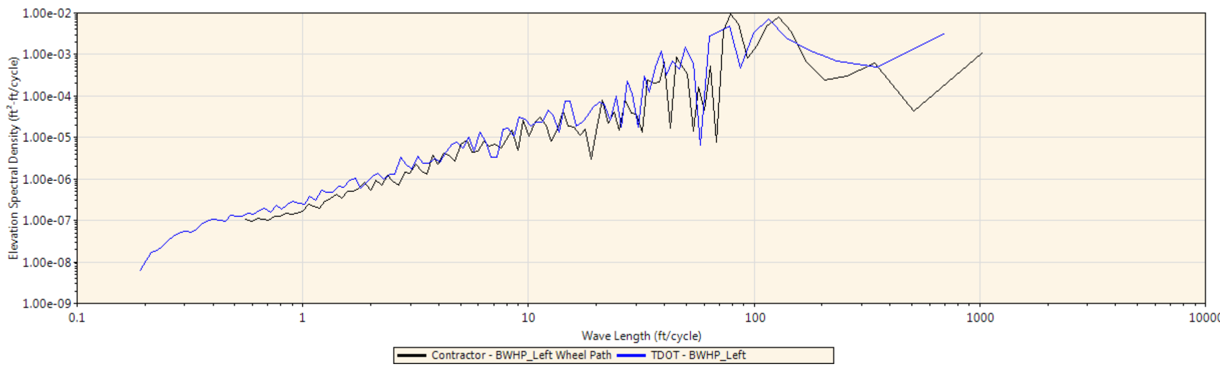


Figure 10- 8 Comparison of processed elevation on right wheel path with Butterworth High-passfilter applied (long cutoff wavelength 120 ft.) and maximum offset 18 ft.

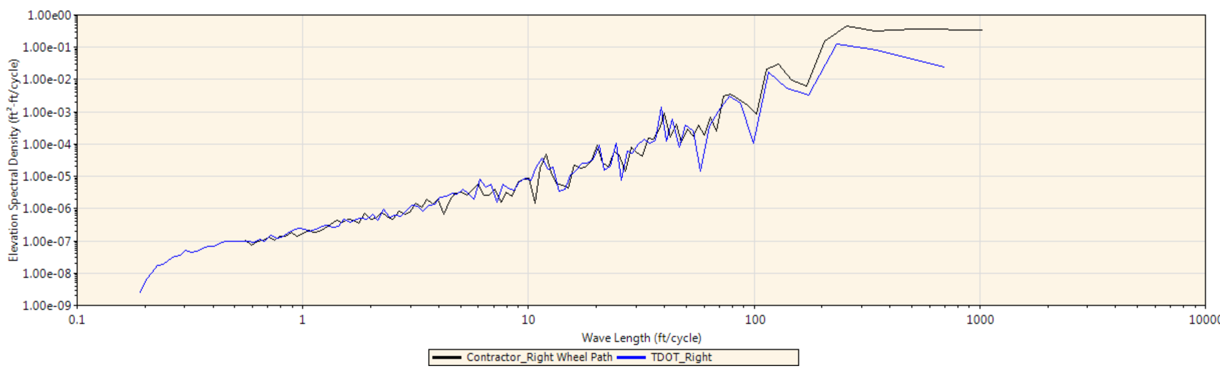
Table 10- 5 Influence of filter technique on IRI calculation

Position	IRI from original elevation inch/mile	IRI from processed elevation inch/mile
TDOT left	74.39	74.07
Contractor left	69.58	68.98
TDOT Right	59.44	59.27
Contractor Right	55.65	55.38

Figure 10-6 compared elevation PSD of two representative elevation data. It was found that although the elevation data were quite different from two collection devices, the elevation PSD curves were close. Previous studies indicated there is fairly good relationship between IRI valueand PSD. Therefore, the closeness of PSD curves supported the conclusion that there was no significant difference between two collection devices.



(a) Left



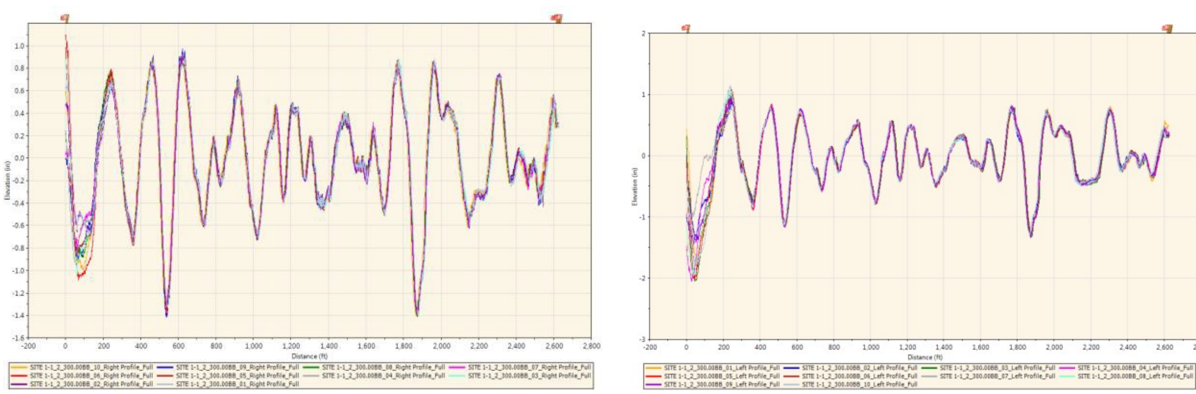
(b) Right

Figure 10- 9 Comparison of Elevation PSD from two profile data

10.3.2 Control site 1-1

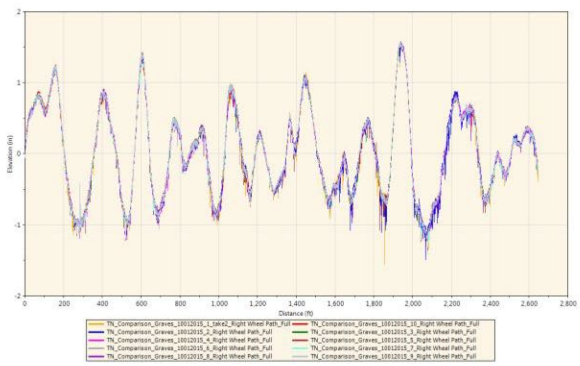
Control site 1-1 is located on Rutledge Pike, Knox County. The total length of the section is 0.5mile. The two reflective tapes are embedded permanently in the pavement structure indicating the start point and end point of the test site. The validation test was performed by each test vehicles running 10 times.

Figure 10- 10 Map of Control site 1-1

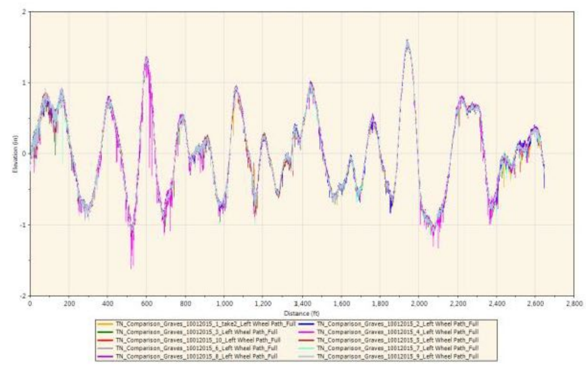


(a)-Right wheel path (b)-Left wheel path

Figure 10- 11 Longitudinal Profile-TDOT's equipment



(a)-Right wheel path



(b)-Left wheel path

Figure 10- 12 Longitudinal Profile-contractor's equipment

T-test was also employed to estimate whether there is a statistic difference between two datasets.Table 10-4 and Table 10-5 listed the result of T-test with the assumption that the samples have equal variance and unequal variance.

Table 10- 6 T-Test: Two-Sample Assuming Equal Variances

	Left Contractor	*Left TDOT*	*Right Contractor*	*Right TDOT*
Mean	77.01	58.93	76.95	64.75
Variance	97.28	2.71	73.17	22.17
Observations	10.00	10.00	10.00	10.00
Pooled Variance	49.99		47.67	
Hypothesized Mean Difference	0.00		0.00	
df	18.00		18.00	
t Stat	-5.72		-3.95	
P(T<=t) one-tail	0.00		0.00	
t Critical one-tail	1.73		1.73	
P(T<=t) two-tail	0.00		0.00	
t Critical two-tail	2.10		2.10	

Table 10- 7 T-Test: Two-Sample Assuming Unequal Variances

	Left Contractor	*Left TDOT*	*Right Contractor*	*Right TDOT*
Mean	77.01	58.93	76.95	64.75
Variance	97.28	2.71	73.17	22.17
Observations	10.00	10.00	10.00	10.00
Hypothesized Mean Difference	0.00		0.00	
Df	10.00		14.00	
t Stat	-5.72		-3.95	
P(T<=t) one-tail	0.00		0.00	
t Critical one-tail	1.81		1.76	
P(T<=t) two-tail	0.00		0.00	
t Critical two-tail	2.23		2.14	

As listed in Table 10-3 and Table 10-4, with p value less than 0.05, the Ho hypothesis is rejectedwhich indicates the mean value of two samples were significantly different.

The relative error can be expressed as Equation 10-1.

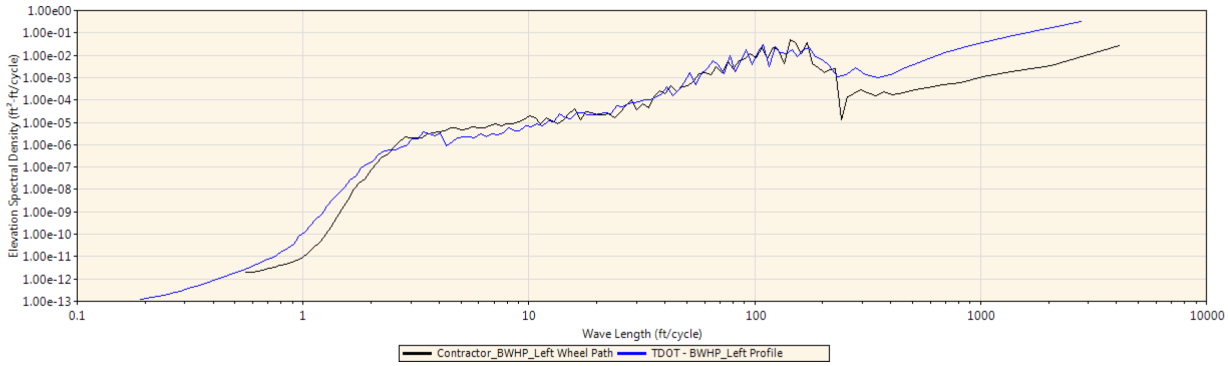
$$Error = \frac{|IRI_C - IRI_{AG}|}{IRI_{AG}} \quad \text{(Eq. 10-1)}$$

Where, IRI_c is the mean value of IRI from contractor's equipment; IRI_{AG} is the mean value of IRI from agency's equipment. Table 10-4 lists the comparison of two collection systems. Table 10-4 indicates there is a significant difference between the two collection devices. For each one-tenth of a mile, evident difference in IRI was found. The lowest relative error was 5.70%, whereas the highest relative error was greater than 50%.

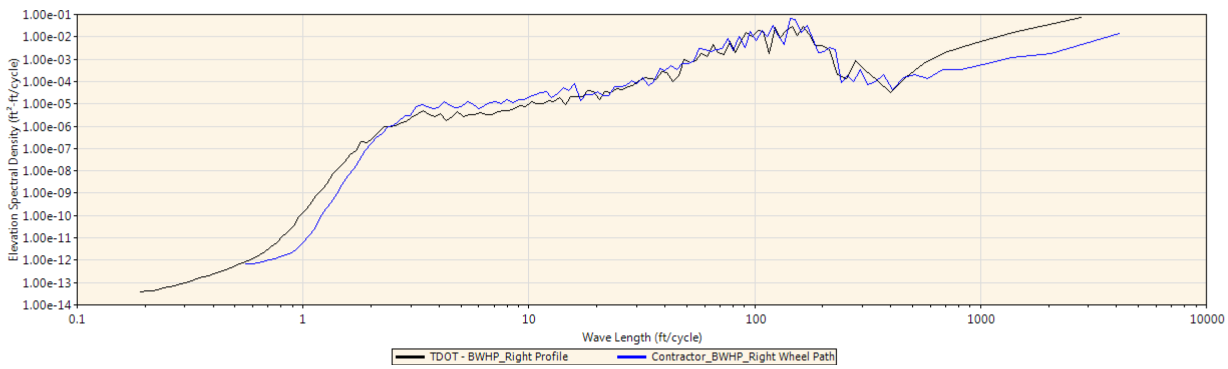
Table 10- 8 Comparison of two collection systems

Section ID	Site 1-1					
Milestone	Left			Right		
	TDOT in./mi.	Contractor in./mi.	Error %	TDOT in./mi.	Contractor in./mi.	Error %
0-0.1	63.61	85.52	34.44	58.00	69.36	19.58
0.1-0.2	56.05	83.47	48.92	66.72	82.00	22.91
0.2-0.3	64.95	77.81	19.80	74.37	79.55	6.97
0.3-0.4	61.09	64.57	5.70	68.38	84.98	24.28
0.4-0.5	48.55	73.72	51.84	56.01	69.21	23.58
Total	58.93	77.01	30.68	64.75	76.95	18.84

Figure 10-13 illustrated the comparison of elevation PSD from two collection devices. Note thatthe raw elevation was filtered by low pass Butterworth filter to excluded wavelength length thatless than 3 foot and greater than 120 foot. It was found that there was significant difference of PSD curves at wavelength from 3 foot to 10 foot in both sides. Therefore, the source of errors inIRI could be due to the measurement errors within this range.



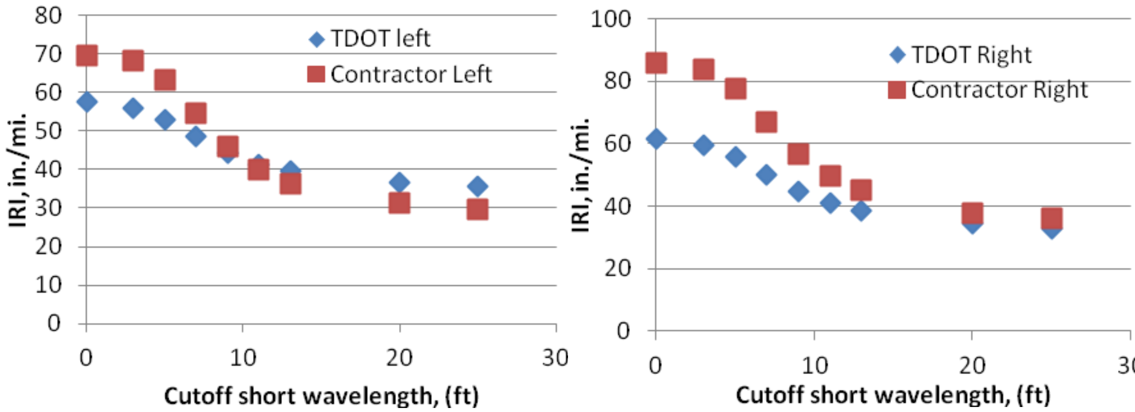
(a) Left



(b) Right

Figure 10- 13 Comparison of PSD from two collection devices

Figure 10-14 illustrates the influence of short cutoff wavelength on the difference of IRI between two collection devices. The IRI values were calculated by excluding the wave features that were less than cutoff wavelength. Butterworth filter was employed to filter out the short waves. As the cutoff short wavelength increased, the difference of IRI between two collection devices decreased. This indicated the errors of IRI between two collection devices decreased. With short waves less than 10 foot excluded, the IRI values were fair close. The results from Figure 10-14 were in agreement with the findings from Figure10-14.



(a) Left (b) Right

Figure 10- 14 Comparison of influence of cutoff short wavelength on IRI

10.4 Influence of error factors on time series

There are two basic change of IRI over time: 1) The IRI along both paths increased with time orthe IRI along one wheel paths increased with time while the IRI on the other path remain stable; 2) Change of IRI over time generally remains stable. The above two scenarios are considered asnormal tendency of IRI over time when prediction analyses are conducted. There are some abnormal IRI trends that were identified as below in accordance with LTPP data.

- The IRI of both wheel paths, or one of the wheel path, for a given date was considerablyhigher or lower than the IRI obtained before and after the date.
- The variations of IRI for both wheel paths at different dates were high.

The factors that caused the above abnormal IRI trends can be summarized as below.

10.4.1 Variation in wheel track

Figure 10-15 illustrated that the value of IRI in right wheel path at pavement age of 20 years wasconsiderably higher than other profile dates, whereas the change of IRI in left wheel path remained stable. The elevations for the first three visit at section 19-1044 were illustrated in Figure 10-16. Butterworth filter was applied to filter the long wavelength greater than 125.0 foot.Field distress survey indicated that transverse cracks were observed. The location of transverse cracks were identified as spikes on elevation curves. One may find that there were some difference in elevation data near the spikes in terms of wavelength and amplitude. This means there were some errors when the transverse cracks were being collected.

Figure 10-17 illustrated the elevation PSD on right wheel path for the first three profile dates. Results indicated that main difference of PSD in frequency domain between the second profile date and other profile dates were at wavelength less below 10 foot. The variation in wheel trackmay be responsible for the abnormal change of IRI over time. One of the reasons pointed by LTPP report was that the driver appeared to have followed a wheel path closer to the shoulder during that year. And in this wheel track, the cracks of transverse cracks tended to be wider.

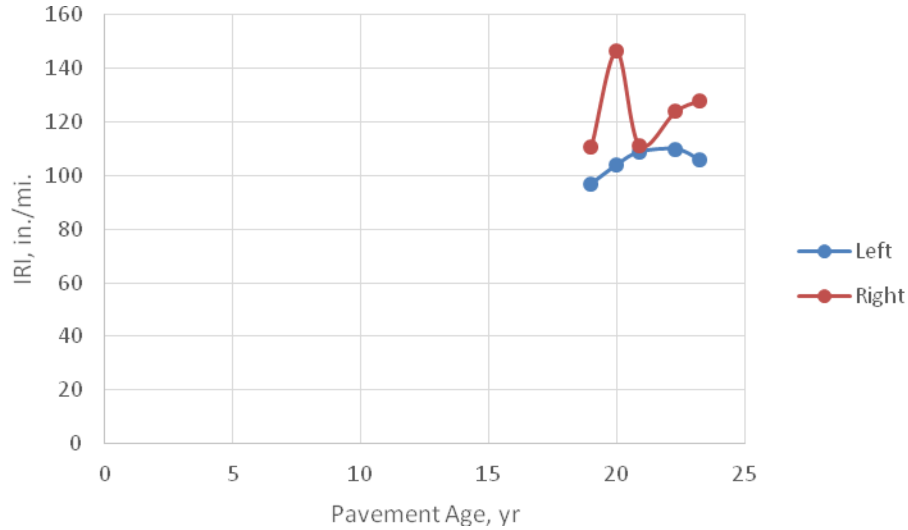


Figure 10- 15 Inconsistent IRI in one wheel path at section 19-1044

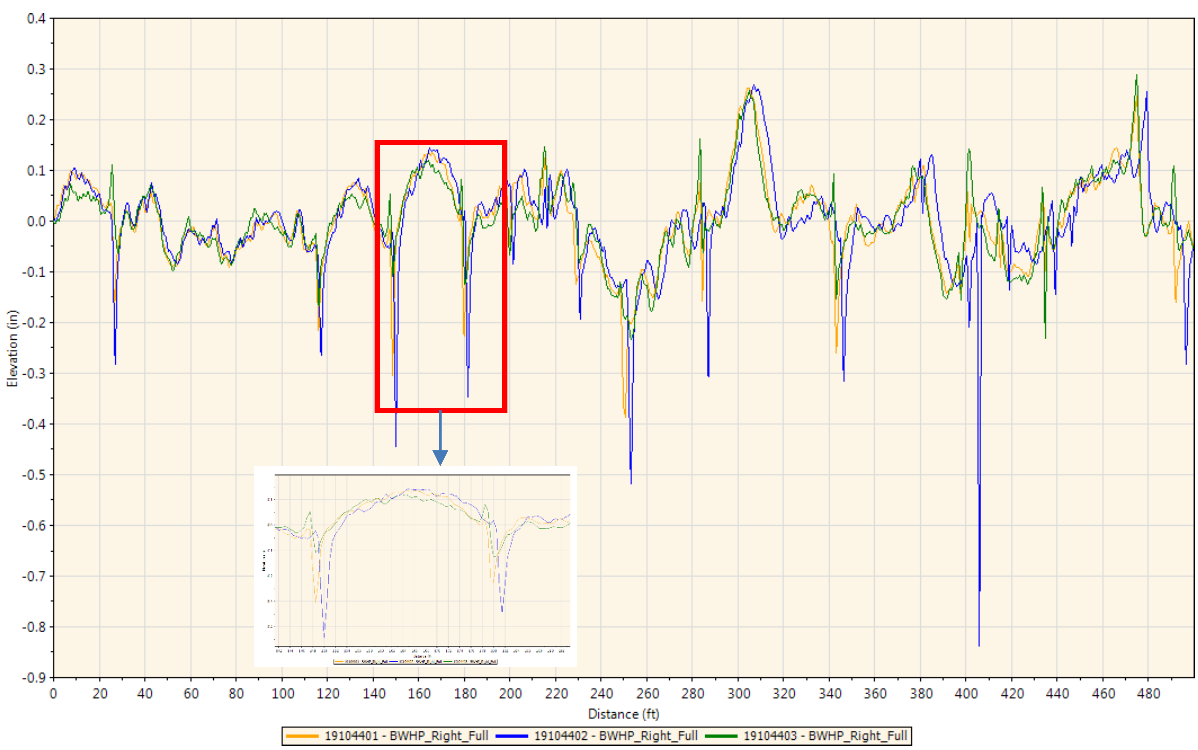


Figure 10- 16 Elevation for right wheel path for the first three profile dates (Section 191044)

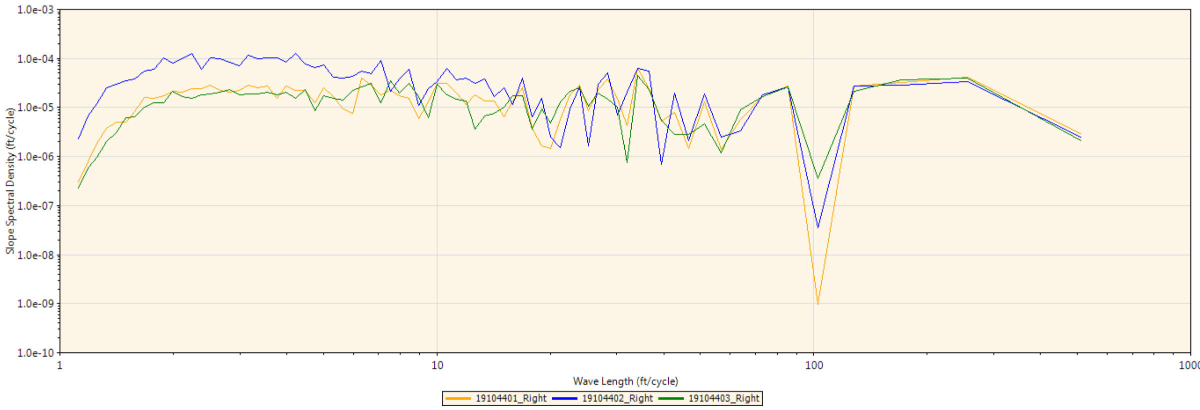
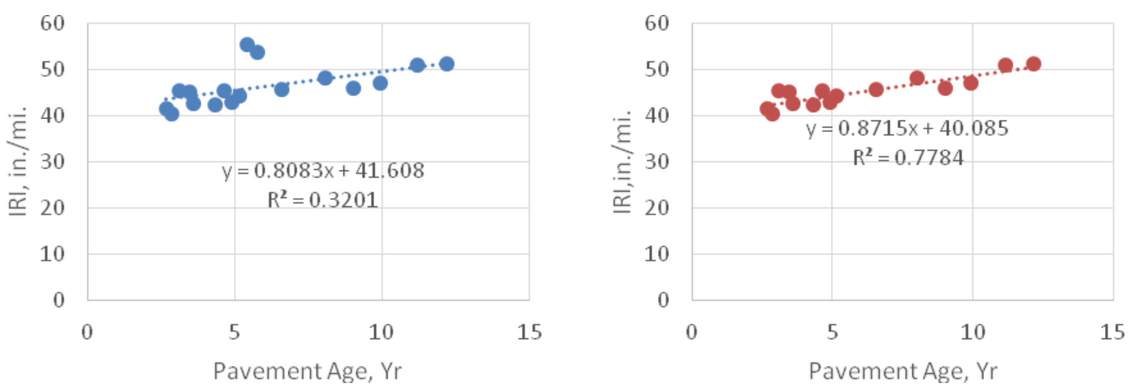


Figure 10- 17 Elevation PSD curve (Section 191044)

Figure 10-18 illustrated the change of IRI over time for section 1-0101. It seems that the IRI obtained from the 10th and the 11th visit deviated from the trend of IRI over time. By the IRI from the two profile dates being excluded, the R-square of regression curve increased from 0.32to 0.78. Note that this section was used as control section in LTPP and there is no maintenance records found in the section for the entire monitoring period.



(a) Original data (b) Abnormal data excluded

Figure 10- 18 Change of IRI on right wheel path over time (Section 01-0101)

Figure 10-19 illustrated the elevations at four visits (the 9th to 12th visit) by applying Butterworthfilter to filter the long wavelength greater than 125.0 foot. It was found that the general trend of pavement profiles from each profile dates were similar. There were also some spikes in the elevation data for the 10th and 11th visit, which might be the indication of crack or other surface features. The elevation PSD curve illustrated in Figure 10-20 indicated that there were some difference in wavelength ranging from the minimum value to 60 foot between each visit. This means the abnormal change of IRI over time may be caused by the elevation profile with wavelength range less than 60 foot. One of the possible reason is that the operators profiled the elevation at different wheel tracks for each visit. The spikes in the elevation also indicated that the surface distresses may also be responsible for this abnormal change. As indicated by the distress data, there were wheelpath cracks on the profile section.

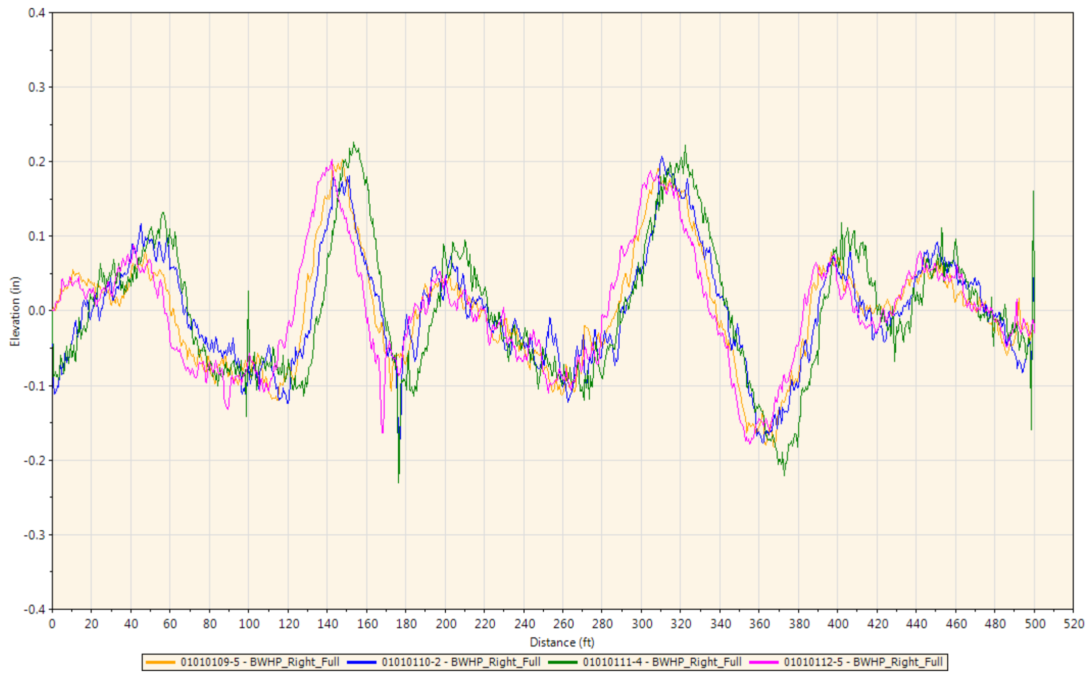


Figure 10- 19 Elevations for the right wheel path on the 9th to the 12th visits (Section 1-0101)

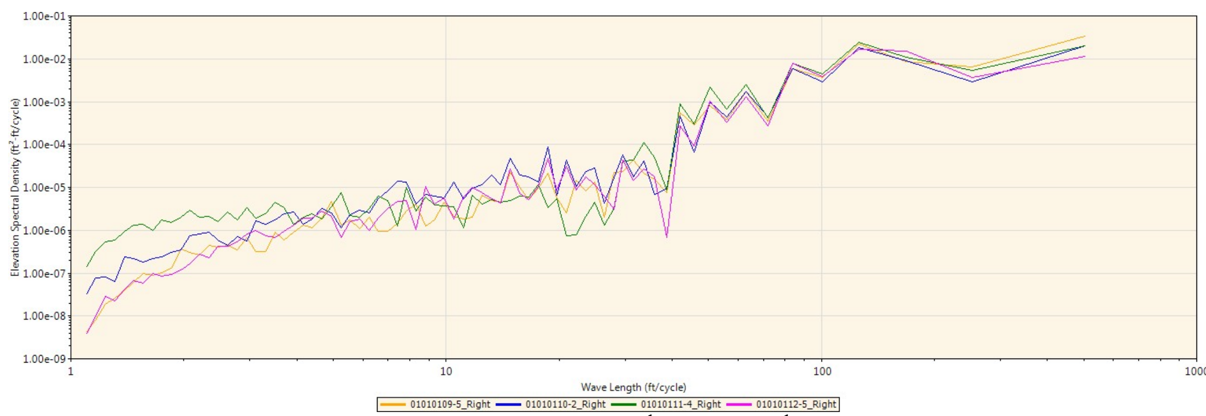


Figure 10- 20 PSD for right wheel path on the 9th to the 12th visits (Section 1-0101)

10.4.2 Equipment-related problem

Figure 10-21 illustrated the typical abnormal change of IRI over time. The IRI were collected from LTPP section GPS-261010. It was found that IRI on both wheel paths for the second profiledate were significant higher comparing with the other dates. Figure 10-16 illustrated the elevation PSD for three visits. In the figure, the abnormal change of IRI was found at 26101003. Evident difference was found between the second visit (26101003) and other two visits. The main difference in wavelength ranged from 2.6 ft./cycle to 10.2 ft./cycle. Figure 10-19 illustratedthe elevation after applying Butterworth filter with wavelength greater than 125.0 foot excluded. By reviewing the elevation data in Figure 10-22, one can find that the changes of elevation for three profile dates were almost identical at long wavelength ranges. However, at short wavelength ranges, the amplitudes of elevation for the second visit were different from other visits. This error was attributed to the improperly working condition of the accelerometer of thedevice according to LTPP report.

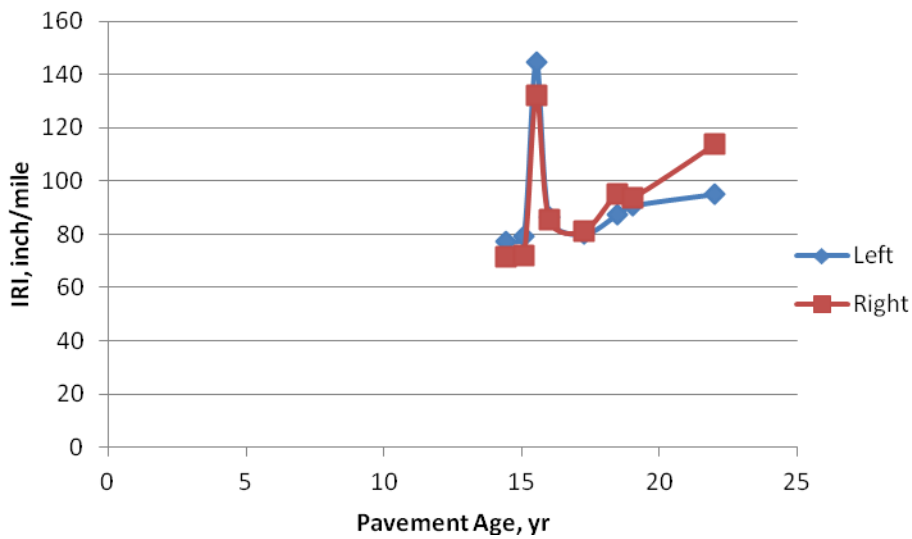


Figure 10- 21 Inconsistent IRI trends in both wheel paths at section 26-1010

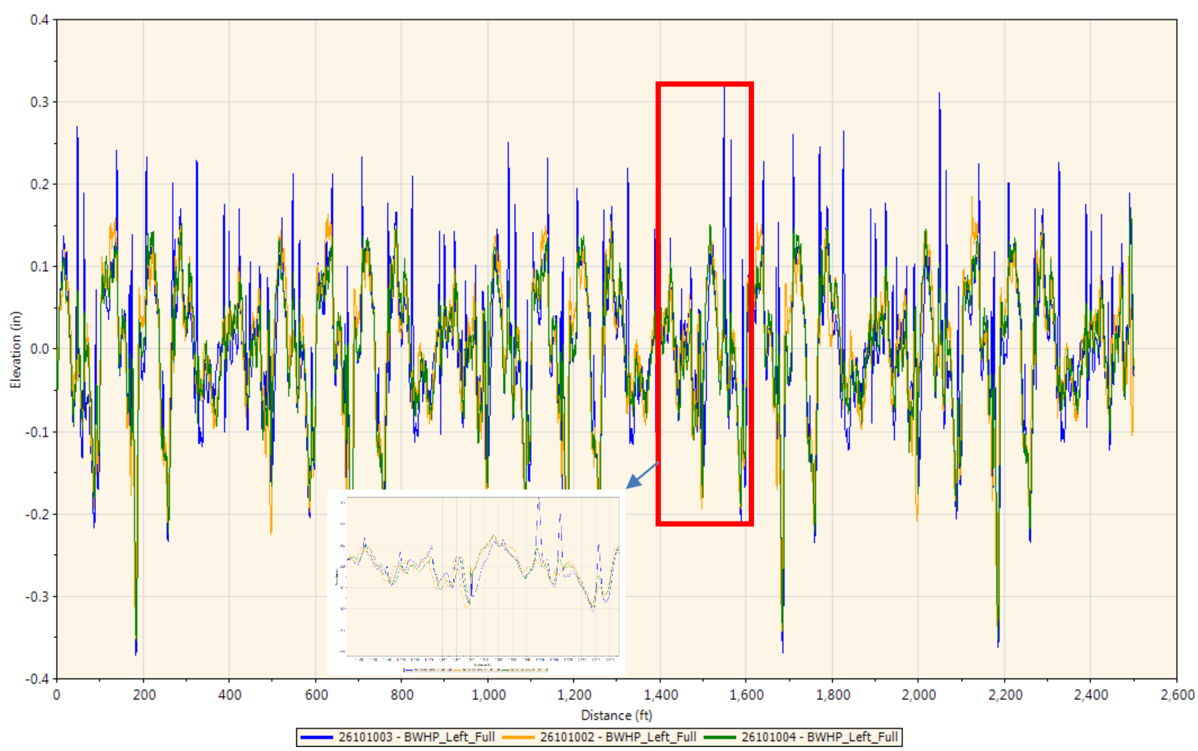


Figure 10- 22 Elevation for left wheel path for the first three profile dates (Section 261010)

Figure 10-23 illustrated the elevation PSD for the three profile dates. The main difference ofPSD was at wavelength range below 10 foot. PSD curves for three profile dates were almostoverlapped at the wavelength ranges from 20 foot and above. Since the errors in profile datawere attributed to accelerometer, the PSD curve may indicate that the errors in PSD at shortwavelengths below 10 foot may be associated with the improper working condition of accelerometer.

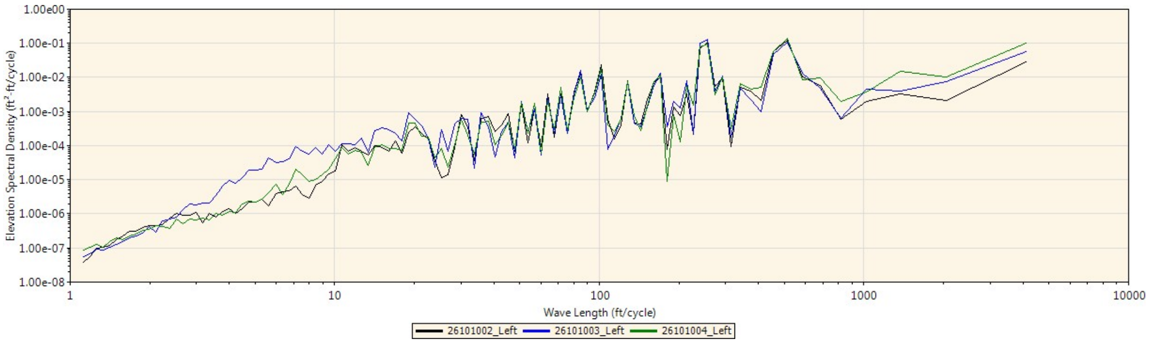
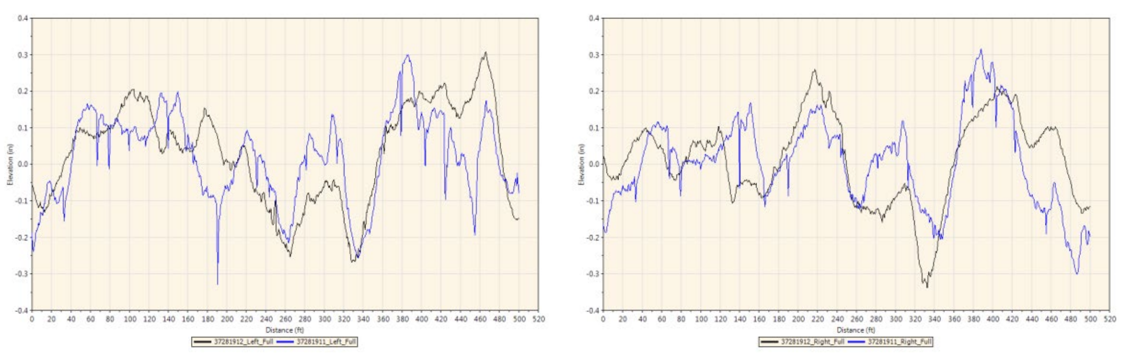


Figure 10- 23 Comparison of elevation PSD (Section 261010)

10.4.3 Pavement resurfacing

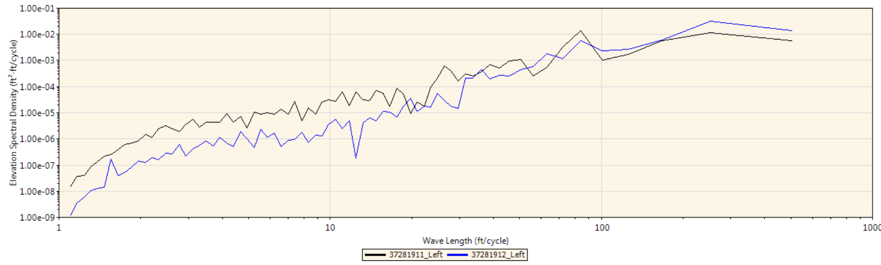
The surface profile will be significantly changed after the maintenance activities are applied. Theinvestigated LTPP section was resurfaced between the two profile dates. Figure 10-24 illustrated the comparison of elevation before and after the maintenance activities were applied. The surfaceprofile appeared to be smooth after maintenance activities. Figure 10-25 illustrated the comparison of PSD. Comparing with PSD curves above (Figure 10-17, Figure 10-20 and Figure 10-23), one may find that the PSD curves were quite different at all wavelength ranges. This means pavement resurfacing will completely change the pavement characteristics rather than partially change surface characteristics at some wavelengths or wavenumbers.



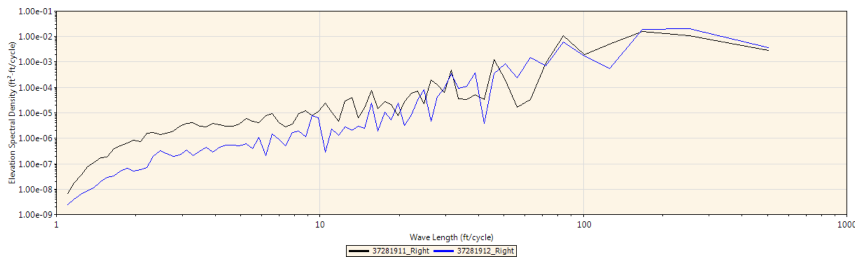
(a) Left wheel path

(b) Right wheel path

Figure 10- 24 Comparison of pavement profile after maintenance action being applied (Section37-2819)



(a) Left wheel path



(b) Right wheel path

Figure 10- 25 Comparison of PSD after maintenance action being applied (Section 37-2819)

11. Summary and Conclusion

This study investigated the quality of pavement condition data in current PMS in Tennessee. A nationwide survey was conducted to collect the current practices on quality management on pavement condition data. The general data quality over year in Highway Pavement ManagementAdministration (HPMA) system in Tennessee was evaluated. Factors influencing data quality areidentified by reviewing and analyzing PMS data. As International Roughness Index (IRI) is the most important indicator to PMS, field validation tests between different collection devices wereconducted to evaluate the potential variability of IRI. Based on the result and findings above, a guideline to implement data quality management was established. Based on the analyses, following conclusions are drawn:

1. A nationwide online survey was conducted to collect the current practices on data quality management of state DOTs. The results from questionnaire indicated field validation/calibration of testing equipment is considered as the most selected stepsbefore data collection. Individual distresses are recognized as the most common way in evaluating the confidence of data collection. The engineer ranked the following factors in order of the amount impact on quality of pavement condition data: device calibration; personnel training; sensor accuracy; accuracy of internal measurement; system that is used to process the raw data; weather and testing conditions; and speed of testing vehicles.
2. The quality of pavement condition data are classified into basic quality and analytical quality. By evaluating the current PMS data, the measurers and criteriaof data quality were determined. The overall quality of pavement condition data over years were evaluated based on these measurers and criteria.
3. Data variability and its influence on maintenance planning were investigated. Theanalyses indicated that:
    1) The roughness data, including International Roughness Index and Rut depth, collected from two wheel path were not statistically identical. For IRI value, there is a linear relationship between two wheel paths with highR-square, whereas rut depths from two wheel paths were not linearly correlated.
    2) For distress data, the accuracy of distress extent at low severity level had little influence on the calculation of PDI while the accuracy distress extentat moderate and high severity levels significantly influenced the accuracy of PDI. The accuracy of distresses severity at moderate level influenced the accuracy of PDI significantly.
4. The analyses of influence of data variability on maintenance planning indicated that the variability of IRI and distress severity level was the dominant influence

factors for maintenance planning. The variability of distress extent had slight influence on maintenance planning. There is no significant influence of variabilityof rut depth on the maintenance planning.

5. The analysis of data variability also indicated that the influence of data variabilityon maintenance planning may vary in terms of current pavement conditions, howthe pavement condition indices are defined, and how the maintenance and rehabilitation analyses are performed. In response to this issue, a dynamic framework towards data quality analysis at network level was established.
6. By investigating pre- and post-maintenance pavement condition data, the changesof pavement condition data due to maintenance activities are identified. The linearmodel was used to construct the performance curve and determine the analytical quality of pavement condition data. A Java based program was also developed to construct the performance curve.
7. Field validation tests were performed to evaluate the difference of IRI from agency's devices and contractor's device. Statistical analyses indicated there is a possibility that the IRI obtained from different devices could be significant different. Further analyses were also performed to identify the revolution pattern of IRI over time. It is recommended that lateral comparisons between tests devices be performed to improve the reliability of collected data.
8. The results and findings were summarized to establish a practical procedure for quality management of PMS data which aims to assist TDOT to improve the quality control and quality assurance in data collection.

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Appendix

Guidelines on quality management ofpavement condition data

(Draft edition)

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