Impact of Upgrading the Distresses Measurement System on Assessed Pavement Network Condition

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Pavement management systems rely on accurate distress data (such as rutting and cracking data) for supporting managerial decision. Therefore, it is important to understand how the measurement errors propagate into the processes of the management system and to quantify the associated consequences, such as the misallocation of funds. This study proposes a methodology for evaluating the impact of changes in the pavement distresses measurement system that influence the assessment of the pavement network condition. The proposed methodology was applied to a case study that estimated the impact of migrating from a 5-sensor discrete automated rut measurement system to a continuous system on the assessed condition of the pavement network in Texas. The condition of the pavement network was determined using the models and indices defined in the Texas Department of Transportation Pavement Management Information System. The impact of the measurement errors and associated uncertainties on the pavement management system outputs was quantified simulating the processes involving measured data using Monte Carlo Simulation. The findings from the case study showed that transition from a 5-sensor discrete automated rut measurement system to a continuous one, would result in a significant drop in the network condition score. The quantified change in the assessed pavement network condition provides key information that can be utilized to design strategies that mitigate the apparent increase in deterioration of the highway network. The proposed methodology is general enough to be applied to the analysis of other types of measurement systems, pavement distresses, or infrastructure management systems.
INTRODUCTION
The collection of accurate pavement distress data (such as rutting and cracking data) is a key factor for the success of Pavement Management Systems (PMS). Distress data is used in PMSs for assessing the condition of the pavements in the network, which is used for prioritizing candidate projects at network-level as well as selecting the best maintenance and rehabilitation (M&R) treatment at project-level (Zhang, et al. 1999). Also, historical and current condition data is used to calibrate and monitor the performance models used to forecast the deterioration of pavement and schedule M&R activities. Therefore, it is important to understand how the measurement errors propagate into the processes of the management system and to quantify the associated consequences, such as the misallocation of funds.

Pavement surface distress data has been traditionally collected manually. Manual methods are considered a reliable and low budget option. However, they involve time-consuming processes and require the use of traffic control which makes them inefficient for network-level data collection (Wang, 2005). The subjectivity associated with manual measurements and the small percentage of the network that can be sampled due to practical limitations, has led to the development of systems for the automated measurement of distress data at high-speeds. These automated systems have improved over time, increasing sampling rates and improving the quality of measurements. For example, the first systems for the automated measurement of rutting used acoustic sensors to measure a few coordinates per transverse profile (discrete systems) whereas nowadays it is possible to scan more than a thousand points (continuous systems) using more accurate and reliable technologies, such as high-resolution 3-D camera and laser (Li et al., 2009).

The development of new technologies and the increasing demand for more accurate and effective systems to collect pavement condition data at network level create the need for transportation agencies to update their measurement systems. A change in accuracy and precision of pavement condition data will affect the PMS outputs possibly resulting in misleading information about the performance of the pavement network. For instance, the larger number of distresses captured by transitioning to a more precise measurement system will cause an apparent increase in the deterioration of the pavement network. Therefore, it is necessary to quantify the impact of upgrading the distresses measurement system on the PMS outputs in order to assess for the actual pavement network condition.

This study proposes a methodology for evaluating the impact of a change in the pavement distresses measurement system on the assessment of the pavement network condition. The proposed methodology was applied on a case study consisting of estimating the impact of migrating from a 5-sensor discrete Automated Rut Measurement System (ARMS) to a continuous one, on the assessed Texas’ pavement network condition. The condition of the pavement network was determined using the models and indices defined in the Texas Department of Transportation’s (TxDOT) Pavement Management Information System (PMIS).

Literature Review
Several studies have been conducted to evaluate the precision and accuracy of automated systems for different technologies and type of measured data. Different authors showed
that 5-sensor rut measurement systems tend to underestimate the Rut Depth (RD) because of several issues like lateral wander of the survey vehicle and unconventional forms of rut configuration among others (Ksaibati, 1996; Bennett et al. 2002; Simpson, 2001). Simpson (2001) evaluated discrete system for the automated data collection of rutting and recommended the minimum number of sensors as nine. Tsai et al. (2011) quantified the error of a continuous rut measuring system conducting both laboratory and field tests and observed that the automated system tended to underestimate the values manually measured. Serigos (2012a) reported the accuracy and precision of five different state-of-the-art continuous automated rut measuring systems from the analysis of more than 5,000 field measurements. Examples of studies found in the literature for the evaluation of automated crack measuring systems are Wix et al. (2012) and Pierce et al. (2012). The former assessed the accuracy and repeatability of both 2-D and 3-D systems, and indicated a worse quality of measurements for coarser surface textures. The latter reported high discrepancies between the cracks measured manually and by two different state-of-the-art automated distress measuring systems. Also, Pierce, et al. (2012) showed that the amount of missed cracks and false positives increased as the crack width decreased.

Buchheit et al (2005) manifested that errors in pavement condition data are unavoidable. The magnitude of impact of pavement condition data errors on PMS depends on the severity, amount and type of errors themselves. Manzella and McNeil (2006) concluded that such errors could directly lead to incorrect project prioritization by making wrong assessment of current pavement conditions. Previously, Garza et al. (1998) reported that PMS with incorrect pavement condition data is also prone to predicting the future pavement conditions incorrectly (24). Ng et al. (2011) introduced the price of uncertainty to capture the impact of uncertainty and showed that uncertainty can significantly increase maintenance costs. Most recently, Saliminejad and Gharaiabeh (2012) investigated the effect of pavement condition data errors on PMS outputs and reported that accumulated errors in current pavement condition data disorient the maintenance and rehabilitation policies by falsely predicting future pavement conditions.

THEORETICAL BACKGROUND

This project studies the propagation of measurement errors throughout the models contained in PMSs. This section defines the types of error in measurements of pavement distresses data and describes the terminologies and deterioration models used by the TxDOT PMIS to assess for the pavement network condition.

Definition of Error in Pavement Distresses Data

Measured data error can be divided into systematic error (or bias) and random error (or precision). ASTM E177 defines the former as “…a consistent or systematic difference between a set of test results from the process and an accepted reference value of the property being measured”; and the latter as “…the closeness of agreement between test results obtained under prescribed like conditions from the measurement process being evaluated”. In other words, the bias refers to the degree of closeness between a measured values and the true value whereas the precision refers to the closeness between consecutives measurements. The higher the accuracy of an instrument, the lower the systematic error; and the more precise the instrument is, the lower the random error.
Regarding the effect of error type in pavement condition data on the assessed pavement network condition, Saliminejad and Gharaihe (2012) suggested that systematic errors have a higher impact on the PMSs outputs than random errors.

**Description of TxDOT PMIS**

Budget allocations for the different TxDOT districts are made on the basis of the PMIS condition scores and ratings. This study uses the TxDOT PMIS distresses data and rating system for determining the condition of the pavement sections in the network. The condition score (CS) represents the average person’s perception about the road network (Stampley et al., 1995). A CS greater than, or equal to, 70 is considered as “Good/Better” pavement condition. Equation 2 presents the expression to calculate the CS for a given PMIS pavement section; where CS is the Condition Score, DS is the Distress Score and $U_{Ride}$ is the utility value for ride quality.

$$CS = 100 * DS * U_{Ride}$$  \hspace{1cm} (1)

TxDOT PMIS uses Ride Score (RS) and Distress Score (DS) for defining the level of severity of the pavement based on how comfortable and safe it is to drive in a particular pavement section (Stampley et al. 1995). Utility curves are basically empirically drawn trend lines of distress or loss of ride quality and are used for determining usefulness of pavements and depend on factors such as the type of pavement and traffic volume. The utility value for ride quality is based on the Average Daily Traffic (ADT), the design speed for the particular road facility and the ride score of the pavement. The distress score is determined by multiplying the utility values corresponding to each of the surface distresses corresponding to the type of pavement under consideration. As an example, the expression to calculate the DS for flexible pavements is presented in Equation 2, where $U_i$ is the utility value for each type of distress (e.g., Rutting, Patching, Alligator Cracking, Longitudinal Cracking, Transverse Cracking, and Failures). The definition and complete list of surface distresses defined for each type of pavement in Texas can be found in the PMIS Rater’s Manual (TxDOT, 2010).

$$DS = 100 * U_{Rut} * U_{Patch} * U_{AligCrack} * U_{LCrack} * U_{TCrack} * ... * U_{Failures}$$  \hspace{1cm} (2)

The utility function for each of the different distress types allows the system to weigh in the effect of different distresses according to the effect that they have on the overall condition of the pavement. For example, the effect of shallow rutting will not be as pronounced as deep rutting. The general expression of the PMIS utility curves is presented in Equation 3; where: $L_i$ the amount of distress measured on section “i”, and $\alpha$, $\beta$ and $\rho$ are shape parameters controlling for the maximum amount of usefulness, the rate of utility lost in the middle of the curve, and the length of the curve above a certain utility value.

$$U_i = 1 - \alpha e^{-\left(\frac{L_i}{\rho}\right)^\beta}$$  \hspace{1cm} (3)
The values for $\alpha$, $\beta$ and $\rho$ are tabulated as a function of factors such as the type of distress and the type of pavement. For example, the $\alpha$, $\beta$ and $\rho$ values corresponding to an asphalt concrete pavement with less than 6.40 mm thickness of asphalt concrete layer are: $0.31$, $1.00$ and $19.72$ for shallow rutting, $0.69$, $1.00$ and $16.27$ for deep rutting and $1.00$, $1.00$ and $45.7$ for failures, respectively (Stampley, 1995).

**METHODOLOGY**

Condition is defined as the description of the distresses and ride quality of the pavement. In PMSs, the condition of pavement sections is used to design and decide different maintenance and rehabilitation or reconstruction strategies and fund them accordingly. Therefore, when upgrading the pavement distresses measurement system, it is imperative to assess for the possible impact on the PMS outputs. The methodology described in this section was developed to quantify the difference in overall network condition due to a change in the measurement system.

Figure 1 presents a schematic representation of the proposed methodology for our case study. Two types of data will be used in our approach:

- Experimental Distress Measurements, to be obtained from an experiment designed to estimate the difference in measured value due to upgrading the system; and
- IMS Distress Data, which consist of the last measurements taken with the current measurement system used to populate the IMS distress databases.

The experiment to collect the first type of data will be designed with the objective of comparing the difference in measured distress value, $\Delta Distress$, between the current and the proposed measurement system. This data will allow for modeling the distribution of the change in distress value. The modeled distributions will account for the uncertainties of each measurement system and will be used to perturb the current IMS Distress Data. The current and past distress measurements data will be extracted from the IMS attribute databases.

As presented in Figure 1, the next analysis will consist of estimating the IMS outputs simulating the use of the proposed new measurement system. This analysis will be carried out in two steps. The first step consists of perturbing each value in the current database by the modeled $\Delta Distress$. The new perturbed distress database would represent the distress values that would be obtained if the proposed measurement system is adopted. The second step consists of computing the IMS outputs using the estimated distress data perturbed by the modeled $\Delta Distress$.

Since the difference in distress value between the current and proposed measurement system has an associated uncertainty, the IMS outputs will be treated as random variables. In order to capture this variability, a Monte Carlo Simulation will be conducted to estimate the distribution of the IMS outputs and make inferences about the impact on the pavement network condition.
Case Study
The case study carried out consisted on estimating the change in CS, as defined on the TxDOT PMIS, due to using two different methodologies for the automated measurement of rutting. The two different ARMS considered in our case study were a 5-sensor and a continuous system. The former has been used by TxDOT for the last 15 years to measure rutting data at network level and populate the PMIS condition database. The continuous system has been recently developed by TxDOT with the objective of replacing the 5-sensor systems.

According to the literature, 5-sensor systems tend to underestimate the RD values whereas the continuous systems are expected to produce more accurate and precise results. Therefore, the continuous system is expected to produce higher RD values and consequently lower CS. This section describes how the presented methodology was applied in order to quantify the drop in TxDOT’s PMIS CS that would occur when transitioning from the current 5-sensor discrete system to a continuous one.

Rutting Measurements
The rutting data used in our case study is divided into two main types: experimental field measurements of rutting and PMIS Rutting data. The former comprise detailed rutting data obtained from a controlled experiment and it is used in our case study to model the difference in RD value between the two ARMS. The latter consist of the rutting data stored in the TxDOT PMIS Condition Database for their entire highway network. The following paragraphs describe in detail these two types of rutting data and the processing applied to them.

Figure 1 Schematic Representation of Proposed Methodology
Experimental Field Measurements of Rutting

The experimental field measurements consists of RD values measured in the field at the same locations by three different methodologies: manual measurements using a 6-ft straight-edge, RD\textsubscript{manual}; measurements calculated simulating the use of a discrete 5-point automated system, RD\textsubscript{5p}; and measurements using a continuous automated system, RD\textsubscript{c}. Both the manual and the automated measurements were obtained from an experiment conducted for the TxDOT research project: “0-6663: Field Evaluation of Automated Rutting Measuring Equipment” (Serigos et al, 2012b). The rutting data was collected at 24 different 550-ft test sections selected to cover representative conditions of pavements encountered in Texas’ highways and challenging conditions for the ARMS. The manual measurements were performed statically at each wheel-path using a 6-ft straight edge and a metallic gauge following the procedures indicated in the ASTM E1703 standard. The automated measurements were performed at highway speeds by an optical 3-D system that scanned the pavement surface coordinates of contiguous transverse profiles along the travelled direction. Figure 2 shows the ARMS used to collect automated rutting data. The red and yellow shaded areas in Figure 2 indicate the projection planes of the ARMS’s laser and 3-D camera respectively. The dashed blue line indicates the location of the scanned transverse profile.

The RD\textsubscript{c} values for both wheel-paths were calculated every 25 feet on the entire scanned transverse profile (more than 1,000 coordinates) using an algorithm developed by the authors that simulates the criteria and processes carried out during the manual data collection. Therefore, the set of calculated RD\textsubscript{c} comprised a total of 1,104 values (= 24 sections * 23 profiles per section * 2 RD values per profile). The RD values produced by the calibrated algorithm were evaluated using the set of RD\textsubscript{manual} values as the benchmark reference, obtaining an accuracy of -0.51 16th in and a precision of 1.79 16th in. Therefore, the RD\textsubscript{c} values tended to underestimate the manual measurements, in average, for less than one 16\textsuperscript{th} of an inch.

Figure 2 TxDOT 3D system for the automated measurement of rutting (Serigos et al, 2012b)
The RD\textsubscript{5p} values were calculated using the same transverse profiles used for the calculation of the RD\textsubscript{c} values, but selecting only 5 coordinates of each profile, in order to simulate the use of a 5-sensor automated system. Figure 3 shows an example of a continuous transverse profile scanned by the ARMS in green, and the sensors location of the simulated discrete system with yellow circles. The locations at which the five coordinates were sampled replicated the sensors location of TxDOT’s discrete system; i.e. -4 in, -2.5 in, 0 in, 2.5 in and 4 in, zero being the center of the survey vehicle’s front. The algorithm developed to calculate the RD\textsubscript{5pts} values simulated 300 runs of the discrete system at each transverse profile varying the lateral placement of the survey vehicle in order to account for the effect of lateral wandering on the measurement error. The lateral placement of the sensors at each run was randomly generated using a normal distribution with mean and standard deviation equal to -2.36 in and 4.92 in respectively, zero being the middle point of the transverse profile.

Figure 3 Sensor Location of simulated 5-sensor system (Huang et al, 2009)

PMIS Rutting Data
The PMIS Rutting data was obtained from the “Condition Summary” table of the TxDOT PMIS Database. This table contains historical information necessary to assess the pavement condition at each year of the entire TxDOT’s highway network. Some of the information contained in the table includes summarized pavement surface distresses and ride data, as well as the calculated CS, DS and RS for each TxDOT pavement section. The information used in our case study comprised the CS (Equation 3), RS, and rutting data of the entire network for the Fiscal Year 2011.

The rutting data stored at the PMIS database consist of the distribution of measured RD values falling into each of the five rut severity levels for each pavement section; i.e. percentage of No Rut, Shallow, Deep, Severe and Failure Rutting. The RD measurements were collected at highway speeds by the TxDOT’s float of 5-sensor discrete systems. The “Condition Summary” table was processed in order to eliminate the PMIS sections not presenting valid values or missing rutting measurements. The final dataset used in our case study comprised FY2011 CS, RS and rutting data of 202,718 PMIS sections covering the 25 TxDOT Districts.

Estimation of Difference in RD value Distribution
Once the RD values for both the discrete and continuous ARMS were obtained, the next step in our case study consisted on estimating the distribution of the difference in RD value, ΔRD, defined as:

\[
\Delta RD = RD_c - RD_{5p}
\]
The difference in measured RD was computed for each profile and run, obtaining a total of 331,200 \( \Delta RD \) values (= 1,104 RD values \(*\) 300 runs). Since the available rutting data covered a wide range of RD values, the distribution of \( \Delta RD \) was estimated for each of the four PMIS Rut Severity Levels separately. The histograms of \( \Delta RD \) categorized into the four rutting categories are presented in Figure 4. The \( \Delta RD \) summary statistics for each of the categories are presented in Table 1.

![Histograms of \( \Delta RD \) categorized into the four PMIS Rut Severity Levels](image)

<table>
<thead>
<tr>
<th>PMIS Rut severity level</th>
<th>No Rut</th>
<th>Shallow</th>
<th>Deep</th>
<th>Severe</th>
<th>Failure</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>count</strong></td>
<td>129000</td>
<td>123900</td>
<td>44400</td>
<td>28800</td>
<td>5100</td>
</tr>
<tr>
<td><strong>median</strong></td>
<td>2.17</td>
<td>4.43</td>
<td>8.21</td>
<td>12.26</td>
<td>15.38</td>
</tr>
<tr>
<td><strong>mean</strong></td>
<td>2.04</td>
<td>4.45</td>
<td>8.06</td>
<td>13.16</td>
<td>17.18</td>
</tr>
<tr>
<td><strong>std</strong></td>
<td>1.20</td>
<td>1.64</td>
<td>3.23</td>
<td>6.63</td>
<td>8.02</td>
</tr>
<tr>
<td><strong>COV</strong></td>
<td>0.59</td>
<td>0.37</td>
<td>0.40</td>
<td>0.50</td>
<td>0.47</td>
</tr>
</tbody>
</table>
As presented in the proposed methodology, the next analysis consisted of estimating the PMIS outputs simulating the use of continuous ARMS. This analysis was carried out in two steps. The first step consisted of estimating the PMIS Rutting data as if it were measured using continuous instead of discrete ARMS. The second step consisted of computing the TxDOT PMIS outputs using the estimated rutting data at network level.

Perturbation of PMIS Rutting Database

The PMIS Rutting data simulating the use of continuous ARMS, referred to as PMIS_RUT_cont, was estimated by perturbing the actual FY2011 PMIS Rutting data, referred to as PMIS_RUT_5pts, using the modeled ∆RD distribution. Since the table PMIS_RUT_5pts does not contain the measured RD values but instead the percentages of rutting into each rut category, an auxiliary table, referred to as PMIS_RD_5pts, was created to convert each percentage into RD values. For simplicity, the RD value adopted to represent each rut severity level was the middle value of each category’s range; i.e. RD_NO_RUT = 1/8 in, RD_SHALLOW = 3/8 in, RD_DEEP = 3/4 in, RD_SEVERE = 1.5 in, and RD_FAILURE = 3 in.

The auxiliary table PMIS_RD_5pts was formed by 202,718 columns (one per PMIS section) and 100 rows, reproducing the distribution of rutting into the five severity levels. Thus, if the PMIS_RUT_5pts table indicated that a particular section presented 30% shallow rutting, then the RDSHALLOW value was inputted into 30 elements of the corresponding column of the PMIS_RD_5pts table, resulting in 100 rows. The table containing the perturbation of the RD values, referred to as DELTA_RD, was similarly formed inputting perturbing values randomly generated using the modeled ∆RD distributions for each rut severity level. Therefore, the DELTA_RD table was also formed by 202,718 columns and 100 rows, containing the corresponding ∆RD to perturb each RDCAT value. The auxiliary table PMIS_RD_cont was computed using Equation 5.

\[
PMIS\_RD\_cont = PMIS\_RD\_5pts + DELTA\_RD
\]  

(5)

The elements of table PMIS_RD_cont represent estimates of the RD values simulating the use of a continuous system. These values were then categorized into the five rutting severity levels for each PMIS sections to obtain the PMIS_RUT_cont table, necessary to estimate the condition of the network using the proposed measurement system.

Calculation of TxDOT PMIS Outputs

For the second step of the analysis, the PMIS outputs simulating the use of continuous ARMS were calculated using the estimated PMIS Rutting data. The calculated PMIS outputs were: the Rutting Utility Value, URUT_cont and the Condition Score CS_cont. The former was computed using equation 6 and the latter was computed using Equation 7.

\[
URUT\_cont = U_{Shallow\_cont} * U_{Deep\_cont} * U_{Failure\_cont}
\]  

(6)
Where: “s” is the PMIS section analyzed; and the Rutting Utility Factors for Shallow, Deep and Failure Rut were calculated using Equation 1, obtaining the $L_i$ values from PMIS_RUT_cont and adopting the $\alpha$, $\beta$ and $\rho$ parameters corresponding to a pavement type 06 (Stampley, 1995).

$$CS_{cont_s} = 100 \times DS \times RS = U_{RUT\_cont_s} \times \left(\frac{CS_{5pts}}{U_{RUT\_5pts}}\right)$$ (7)

Where: “s” is the PMIS section analyzed; the $U_{RUT\_5pts}$ were calculated using Equation 1, obtaining the $L_i$ values from PMIS_RUT_5pts; and the $CS_{5pts}$ were obtained from the TxDOT FY2011 PMIS Condition Database.

**Results from Monte Carlo Simulation**

Since the difference in RD value between the discrete and continuous measurement system has an associated uncertainty, the PMIS outputs should be treated as a random variable. In order to capture this variability, a Monte Carlo Simulation was conducted to estimate the distribution of the PMIS outputs and make inferences.

The analyses carried out to estimate the TxDOT network condition simulating the use of a continuous ARMS were repeated a large number of times, changing the values of the perturbing table DELTA_RD. The elements of DELTA_RD in each iteration were determined using a random generator function following a Normal distribution with the mean and standard deviation for the corresponding rut severity level (Table 1). The PMIS outputs calculated in each iteration consisted of the change in Rutting Utility value (Equation 8) and the change in Condition Score (Equation 9).

$$\Delta U_{RUT\_i} = U_{RUT\_5pts_s} - U_{RUT\_cont\_i}$$ (8)

Where: $U_{RUT\_5pts_s}$ and $U_{RUT\_cont\_i}$ are the Rutting Utility values using the discrete and the continuous ARMS respectively calculated for section “s” at iteration “i”. Note that the Utility value for the case of the 5-sensor system is fixed throughout the iterations.

$$\Delta CS_{i} = CS_{5pts_s} - CS_{cont\_i} = \Delta U_{RUT\_i} \times \prod_{i \neq RUT} U_{i} = \Delta U_{RUT\_i} \times \left(\frac{CS_{5pts}}{U_{RUT\_5pts}}\right)$$ (9)

Where: $CS_{5pts_s}$ and $CS_{cont\_i}$ are the Condition Score using the discrete and the continuous ARMS respectively calculated for section “s” at iteration “i”. Note that the Condition Score for the case of the 5-sensor system is fixed throughout the iterations.

Figure 6a and 6b present the histograms of the change in Rutting Utility value, $\Delta U_{RUT}$, and Condition Score, $\Delta CS$, respectively considering all sections and iterations. From Figure 6b it is observed that the $\Delta CS$ distribution presents a fatter tail towards the positive side. This observation can be explained by analyzing Equation 9, in which the change in CS is expressed as the multiplication between the change in Rutting Utility value and the Utility values for all other distresses. The second term can vary from a value close to zero, when the analyzed section presents a large number of distresses, and close to or equal to 1, when the section does not present distresses. Therefore, the set of
ΔCS comprise scaled values of ΔU₄₅, where the scaling factor varies for each particular section. The summary statistics for the distribution of both ΔU₄₅ and ΔCS are presented in Table 2. From the table it can be observed that both confidence intervals have negative values, indicating that the transition from a 5-sensor to a continuous ARMS causes a drop in the condition score with more than 97.5% confidence.

Figure 5 Histograms of (a) ΔU₄₅ and (b) ΔCS from Monte Carlo simulation.

Table 2 Summary Statistics of the Impact of Upgrading ARMS on PMIS Outputs

<table>
<thead>
<tr>
<th>Impact of upgrading ARMS on</th>
<th>median</th>
<th>mean</th>
<th>std</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rutting Utility ΔU₄₅</td>
<td>-21.22</td>
<td>-21.35</td>
<td>2.01</td>
<td>-26.00, -19.16</td>
</tr>
<tr>
<td>Condition Score ΔCS</td>
<td>-20.56</td>
<td>-19.23</td>
<td>4.14</td>
<td>-24.35, -8.02</td>
</tr>
</tbody>
</table>

SUMMARY AND CONCLUSIONS

This study investigated the impact of distress measurement errors on PMSs outputs related to the assessment of the network condition. A methodology was proposed for analyzing the propagation of inaccuracies of measurement systems throughout PMS models. The case study consisted of estimating the impact of upgrading the rut measurement system from a 5-sensor discrete ARMS to a continuous 3D optical one, on the condition assessment of TxDOT’s highway network. The quantified change in the assessed pavement network condition provides key information for designing strategies to mitigate the sudden apparent increase in the deterioration of the highway network caused by upgrading the measurement system.

The main observations and conclusion from the study are:

- The proposed methodology was effective to estimate the impact of rutting measurement inaccuracies on the assessed condition of the pavement network.
- The methodology is general enough to be applied for the analysis of other types of measurement systems, type of pavement distresses or IMSs.
Transition from a 5-sensor discrete ARMS to a continuous ARMS resulted in:

- a drop in the Utility Value and in the Condition Score with more than 97.5% confidence;
- the drop in Utility Value was, in average, 21.35 points and the 95% confidence interval ranged between 26.00 and 19.16; and
- the drop in Condition Score was, in average, 19.23 points and it ranged from 24.35 and 8.02 with 95% confidence level.

REFERENCES


