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# Canadian Calibration on Mechanistic – Empirical Pavement Design Guide to Estimate International Roughness Index (IRI) using MTO Data

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**Abstract:** This paper presents flexible pavement performance models developed for the Ministry of Transportation of Ontario (MTO) by using data from the MTO's Pavement Management System (PMS2). The performance model coefficients have been developed for application in the Mechanistic – Empirical Pavement Design Guide (MEPDG) and were calibrated using statistical tools through a series of analyses on historical pavement condition data that was collected in the field. The statistical analysis involved collection of historical data and development of pavement model categories. It was then classified according to pavement type, equivalent total pavement thickness, traffic volume, soil type, and climatic zone. In the development of the performance curves, 75% of the data was used to calibrate the performance curves, which is described by the predicted Pavement Condition Index (PCI) as a function of pavement age in years. The remaining 25% of the data was used to validate the various performance models using various statistical tools. The procedure and analysis methodology used in the development of the performance models are presented in the paper.

The paper provides a practical framework for comparing existing PMS2 flexible performance curves to performance predictions obtained from the MEPDG. Example case studies for typical Ontario roads are presented in the paper in terms of statistical analysis method.

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**Key words**: *Calibration; Mechanistic – Empirical Pavement Design Guide (MEPDG); Pavement Condition Index; Pavement Performance Models.*

## Introduction

Pavements deteriorate throughout their life cycle. Traffic loading and environmental loading have a huge impact on the performance of pavement. As pavements deteriorate, they lose the ability to meet the needs of the users. Pavement performance models and associated Key Performance Indicators (KPIs) are not only important for monitoring the current Level of Service (LOS) but are also important for selecting the most effective pavement maintenance, preservation, and rehabilitation treatments throughout the life cycle. These KPIs and associated performance models also assist in determining the end of service life when rehabilitation or reconstruction is required. In addition, performance models provide engineers and managers with the ability to properly allocate resources through effective use of the Pavement Management Systems (PMS). The development of the new Mechanistic – Empirical Pavement Management Design Guide (MEPDG), may also be an opportunity to utilize existing PMS data to improve the prediction of pavement performance [1].

According to the American Association of State Highway and Transportation Officials (AASHTO), pavement performance is defined as the serviceability trend of the pavement over a designed period of time, where serviceability indicates the ability of the pavement to serve the demand of the traffic in the existing condition [1]. A PMS is divided into two main levels, project level and network level. The pavement performance models are calibrated and validated at the network level with project level data. Basic pavement performance models vary from simple linear regression models to complicated Markov Chain models by using empirical, mechanistic, or mechanistic-empirical approaches [2].

The newly developed MEPDG presents a new model for pavement design, analysis, and management. The MEPDG considers input parameters that influence pavement performance including traffic, climate, pavement structure, and material properties and applies the principles of engineering mechanics to predict critical pavement responses. It can be used for both flexible and rigid pavement. The MEPDG is divided into three main levels: Level One requires very detailed material, traffic, and climate information to conduct the pavement design; Level Two requires a moderate level of data inputs; and Level Three uses default values of data inputs. The MEPDG is advancing state- of-art-practice by enabling the inclusion of material characterization with both traffic and environmental data to better predict pavement performance [3]. In addition, it is not only predicting roughness but also predicting specific pavement distress performance based on traffic and environment. If this guide can be effectively implemented it will result in a vast advancement of pavement management as it will enable for a better prediction of deterioration and allow for the improvement of treatments. However, it should be noted the MEPDG was never designed to work with PMS, even though; there are many features in the MEPDG that could assist with PMS. Consequently, some adjustments may be required.

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## Objective and Scope

The objective of this paper is to evaluate the feasibility of using the MEPDG models to improve current pavement management systems. Furthermore, it is also necessary to determine the MEPDG coefficients for Ontario flexible pavements, which includes a wide range of pavements exposed to various traffic and environmental conditions.

## Background

### Pavement Management System (PMS)

A Pavement Management System (PMS) can be defined as a tool that assists decision makers in finding optimum strategies for providing and maintaining pavements in a serviceable condition over a given period of time. With the increase in the number of roads, the PMS was developed by Ministry of Transportation Ontario (MTO) in 1985 and in 1998 the MTO decided to develop a second generation PMS, which is PMS2 in this paper. PMS2 was developed to facilitate data management to enhance the analytical components for the network level funding needs and project priorities and to help monitor and evaluate the pavement condition by engineers and decision makers. It operates at two levels, the network level and the project [4]. The network level perspective uses the top-down approach, which takes into consideration the overall network performance goal and the available budget to address the question of what should be done for maintaining overall satisfactory condition of the network, while maximizing benefit and/or minimizing cost. The project level perspective uses the bottom-up approach, which considers each segment in the network and evaluates the point when it reaches a failure threshold to address the question of what should be done. It then recommends the application of rehabilitation actions to those projects and segments, to restore them to near new condition.

### Mechanistic Empirical Pavement Design Guide (MEPDG)

In North America, pavement design has traditionally relied on experience. In 1998, the Mechanistic–Empirical Pavement Design Guide (MEPDG) was initiated by the National Cooperative Highway Research Program (NCHRP) and adopted by AASHTO in 2008 to advance pavement engineering; many agencies in Canada are considering adopting this program. In fact, the Transportation Association of Canada (TAC) has established a working group composed of provincial departments of transportation to explore how feasible this is. MEPDG involved using state-of-the-art practice tools and methods to better predict pavement performance by including traffic loading, material characterization, climate, and construction procedures to estimate the overall pavement performance in terms of roughness but, also in terms of specific types of pavement distress over the design period. Originally the MEPDG was first evaluated in 2005 and a road map for implementation was developed [5]. This combined approach to predicting roughness and specific distress would not only improve design but would also potentially improve management, as specific treatments could be directed at mitigating specific distresses. It is also aimed at improving the pavement design process by allowing designers access to three levels of performance analysis based on available data and the type of road. Pavement performance for both types of pavement can be predicted by using MEPDG software. The prediction models are made in terms of pavement distresses and ride quality [6].

### PMS Key Performance Indicators (KPIs)

Key performance indicators are an important element in the pavement management system. They are quantifiable measurements that show the current pavement condition. To monitor the level of service for the pavement, two basic KPIs are suggested.

#### *International Roughness Index (IRI)*

Roughness is defined, according to the American Society for Testing and Materials (ASTM), as “the deviation of surface from a true planar surface with characteristic dimensions that effect vehicle dynamics and ride quality” [7]. IRI is known as a key indicator for pavement quality, and represents pavement roughness. It can be calculated by measuring a single longitudinal profile on the inside and outside wheel paths for each 0.1 km of the pavement section using a road profile. The average of these two IRIs is then known as the roughness of the pavement.

#### *Pavement Condition Index (PCI)*

PCI is a method to evaluate the condition of the road. It combines both a distress evaluation and roughness measure to determine the maintenance and rehabilitation needs. It is a subjective method that shows a numerical rating of the pavement surface condition and varies from (0) failure to (100) excellent [8]. Also it is not impossible for a PCI to reach zero, it may be rare. PCI is measured annually or biennially (every two years) for pavement distresses and its severity, and the smoothness and ride comfort of the road. Each distress has its own weighting based on its overall impact on performances. The calculation of PCI can be carried out manually or by using the pavement management program. In this paper, PCI is calculated based on the International Roughness Index (IRI) and Distress Magnification Index (DMI) based on MTO equations. In fact, the MTO has examined the usage of automated distress measurements to improve pavement management [9].

#### *Pertinent Studies on Local Calibration for MEPDG*

Local calibration for Ohio State was executed through collection of relevant input data for the MEPDG, followed by the development of time series data. Statistical analysis was developed to check for the adequacy of the predicted results from the MEPDG models [10]. Standard Error Estimate (SSE) was used to determine the model accuracy. Three statistical t-tests were executed for each model to determine if the model is biased or not. Models passing all three tests were considered unbiased. The biased models were considered unsatisfactory and a re-calibration was performed using modified Hot Mix Asphalt (HMA), base and subgrade coefficients based on

Long Term Pavement Performance (LTPP) data [10].

MnRoad was used to develop MEPDG local calibration in Minnesota. Rutting measurements were collected from 31 test sections constructed on Highway 94, which represents the mainline of MnRoad. MEPDG runs were executed to compare the simulated and measured rutting depths for these sections. Actual traffic inputs were used for MEPDG runs through traffic sensors installed on site [11]. The research findings proved that MEPDG over predicts the rutting depth. The analysis of collected data indicated the Asphalt Concrete (AC) rutting model is accurate in the prediction of actual AC rutting. However, the main source of error in the total rutting model was the granular base and subgrade rutting models [11].

The Washington State Department of Transportation (WSDOT) undertook the project of local calibration of MEPDG using a split sample approach and jackknife testing approach. The split-sample approach uses half the selected sections for calibration and another half for validation. The jackknife approach withholds each selected section as prediction measurements and other sections for calibration [12]. The reason to use the combination of the above both approaches is to provide stable and accurate predictions with limited sample size. Transverse cracking results of MEPDG matched those measured and documented in WSDOT database. Therefore, default calibration factors of the transverse cracking model resulted in sufficient accuracy. Various MEPDG models were subsequently calibrated such as fatigue model, longitudinal cracking and alligator cracking followed by the roughness model [12]. The final calibration factors were chosen based on the least Root Mean Square Error (RMSE) method. The local calibration process was finalized by model validation using an independent dataset that was not used in the calibration process.

## Data Description

The data was collected over a period of twenty years, from 1990 to 2010. There are two types of data: historical data and survey data. Historical data includes equivalent total thickness, subgrade type, climate zone, and pavement type. The survey data includes Average Annual Daily Traffic (AADT), Equivalent Single Axle Load (ESAL), International Roughness Index (IRI) measurement, Pavement Condition Index (PCI), and Distress Magnification Index (DMI). There are a total of 870 sections; however, when sections are broken down into treatment cycles (i.e. pavement preservation/ rehabilitation to next pavement preservation/rehabilitation), it results in 17,868 cycles. Each pavement section varies in terms of pavement type, equivalent total thickness, subgrade type, and climate zone are categorized and then evaluated [13]. The 870 sections were classified according to pavement type, equivalent total thickness, ESAL class, subgrade type, and climate zone, as summarized in Table 1. As noted, within each class, the total number of sections is 870, the majority of data that is available in PMS2 is for asphalt pavement. This is largely due to the fact that there are relatively few concrete roads and most of the concrete roads have been constructed in the last ten years. Thus, very few treatment cycles are available for analysis purposes. Although surface treated pavement type was included in the database, it was removed due to the lack of data in any of the categories. The thin pavement thickness is also the most prevalent with the sandy silt subgrade being the dominant subgrade in the available data set. The ESAL categories are more weighted on Class 1 and Class 2; although, there are still 108 sections in Class 3.

**Table 1.** Distributions of Influence Factors and Corresponding Levels.

| Influence Factors | Corresponding Levels | Total Sections |
|---|---|---|
| Pavement Type | (AC) Asphalt | 651 |
| | (PC) Portland Cement | 6 |
| | (CO) Composite | 26 |
| | (ST) Surface Treatment | 187 |
| Equivalent Total Thickness | TH (Thin) (<500 mm) | 846 |
| | M (Moderate) (≦500-750 mm) | 19 |
| | TK (Thick) (≧750 mm) | 5 |
| ESAL | (L) ( Class 1 (< 50,000) | 423 |
| | (M) Class 2 (50,000 - 500,000) | 339 |
| | (H) Class 3 (> 500,000) | 108 |
| Subgrade Type | (SM) Sandy Silt | 645 |
| | (GM) Granular Material | 114 |
| | (LC) Lacustrine Clay | 93 |
| | (VC) Varved Clay | 18 |
| Climate Zone | Southern | 496 |
| | Northern | 374 |

There are slightly more sections from southern Ontario; though, for the analysis purposes, Northern Ontario still has a good portion of the sample. This is important as pavement design and management for Southern and Northern Ontario can be obtained.

## Methodology and Results

Various methods have been used for determining pavement performance. In this paper, a multiple regression analysis with data obtained from PMS2 has been assessed. In addition, performance prediction using the PMS2 data has been used as inputs into the MEPDG method. The results were then compared with the Analysis of Variance (ANOVA) method. It is expected that MEPDG models should predict performance that is statistically the same as the existing pavement management performance models that were developed from multiple regression analysis. Fig. 1 shows the methodology flowchart. Research needs to be completed to evaluate whether MEPDG models can replace network-level models in the future, or whether there is a need to maintain these models separately. Furthermore, if they are able to replace these models they will likely require significant calibration and validation for Ontario.

### PMS2 Multiple Regression Analysis Method

A multiple regression analysis was carried out to assess performance of three typical treatments. The regression analysis was selected due to the large amount of data available from the PMS2.

As shown in the database analysis, the most dominant influence factors include: asphalt, thin pavement thickness, sandy silt subgrade, and ESAL Class 1 and Class 2. Therefore, these influence

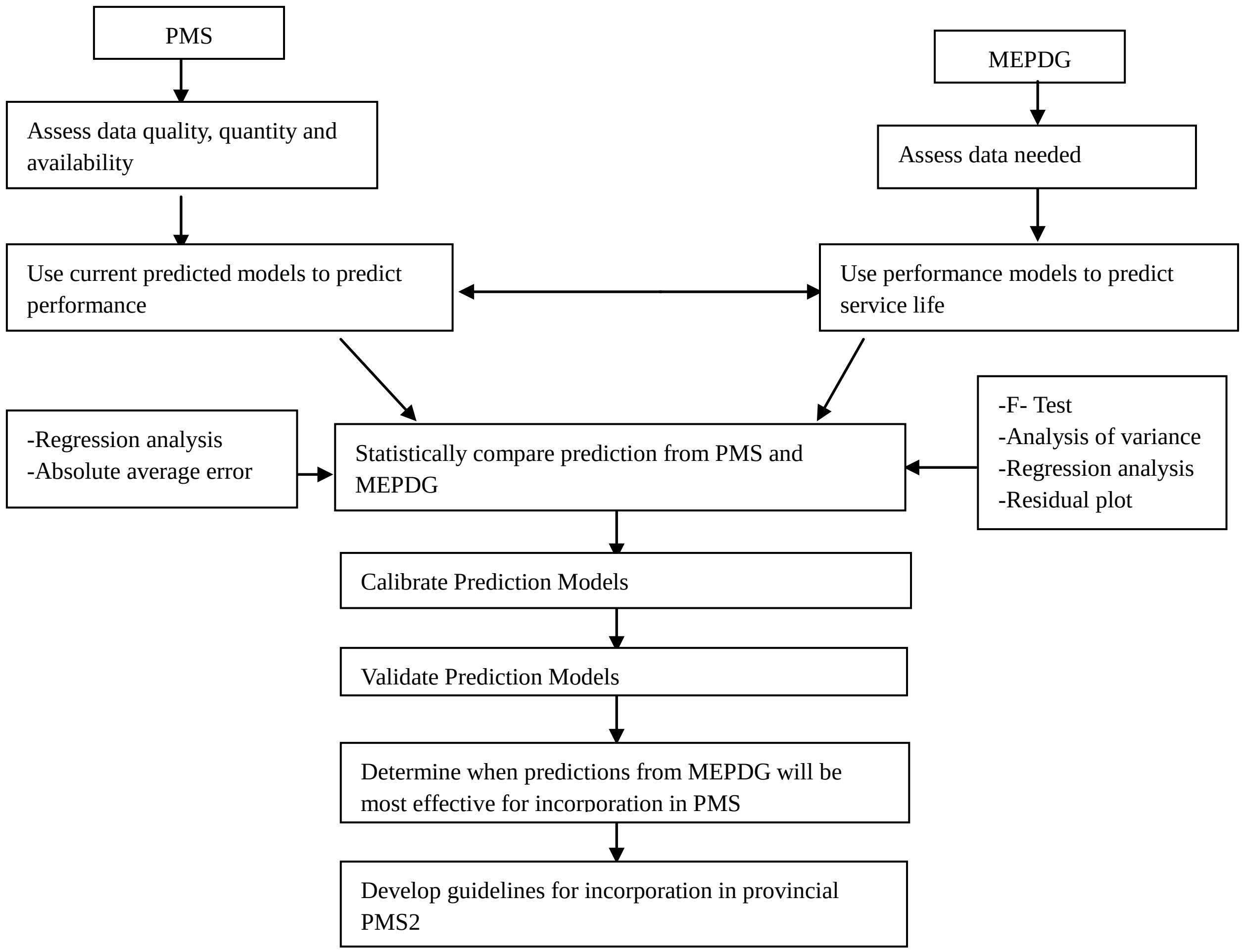


**Fig. 1.** Methodology Flowchart.

factors were considered in the preliminary analysis. Table 2 provides a summary of the various pavement treatments that were assessed for each pavement type. These treatments were selected for the analysis as they are the most frequently used treatments in Ontario.

The data was sorted and filtered according to the pavement type, equivalent total thickness (mm), soil type, ESAL, and climate zone. Approximately, 290 categories were found within the database. However, in order to develop models that were statistically valid, a minimum of 30 treatment cycles within each category was required to carry out the analysis. Thus, any category that had less than 30 data points was removed. For a given section, the PCI was supposed to be above 50 and/or have a minimum thickness of 30 mm. A 30 mm thickness was determined to be an error, as this was too thin for typical roads, these observations were discussed with MTO PMS2 experts, and it was agreed that they were errors [14]. Consequently, any section or treatment cycle that had a PCI value less than 50 and an equivalent total thickness less than 30 mm was removed. Overall, 10 models were developed as shown in Table 3 and pavement age was selected as the independent variable.

The models contain the number of sections as a function of soil type, pavement type, equivalent total thickness, climate zone, and ESAL. Each model is calibrated using 75% of the data. Models are fitted to a polynomial function, and the Coefficient of Determination ($R^2$) is determined for each model as a measure of error explained by the equation. For example, $R^2$ of 0.85 means that the model explains 85% of the error that is represented by the model. Thus, it is desirable to have a high $R^2$ value. The remaining 25% of the data in each respective category was used to validate the models by estimating the Average Absolute Error (AAE) according to Eq. (1). A small AAE represents that the model is valid. The AAE was then used to determine the validity of each of the developed models. If the AAE was less than 15%, the model was considered to be an acceptable model. Furthermore, the model slope was calculated based on the derivative of the first term in the polynomial equations. The slope assisted in comparing the two models to assess which model has a faster deterioration rate [15].

$$Average\ Absolute\ Error\ (AAE) = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{Oi - Pi}{Pi}\right| \quad (1)$$

where:
$Oi$ = Observed Value
$Pi$ = Predicted Value
$N$ = Number of Validating points

**Table 3.** Summary of Category Types Analyzed.

| Number | Activity | Pavement Type | Equivalent Total Thickness | ESAL | Subgrade Type | Climate Zone | Number of Treatment Cycles in Model | Number of Treatment Cycles for Calibration | Number of Treatment Cycles for Validation |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 101 | AC | Thin | CLASS 1 | SM | NO | 190 | 143 | 47 |
| 2 | | AC | Thin | CLASS 2 | SM | NO | 88 | 66 | 22 |
| 3 | 102 | AC | Thin | CLASS 1 | SM | NO | 57 | 43 | 14 |
| 4 | | AC | Thin | CLASS 2 | SM | NO | 128 | 96 | 32 |
| 5 | 107 | AC | Thin | CLASS 1 | SM | NO | 184 | 138 | 42 |
| 6 | | AC | Thin | CLASS2 | SM | NO | 54 | 40 | 14 |
| 7 | 101 | AC | Thin | CLASS1 | SM | SO | 94 | 71 | 23 |
| 8 | | AC | Thin | CLASS2 | SM | SO | 120 | 90 | 30 |
| 9 | 107 | AC | Thin | CLASS1 | SM | SO | 193 | 145 | 48 |
| 10 | | AC | Thin | CLASS2 | SM | SO | 330 | 248 | 82 |

**Table 4.** Summary of Performance Model Analysis.

| Category | Treatment | ESAL | Subgrade Type | Environment | Model | $R^2$ | AAE | Slope | Service Life (yrs) |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 101 | CLASS 1 | SM | NO | $PCI= 0.033*Age^2-2.688*Age+96.02$ | 0.77 | 0.13 | 0.07 | 25 |
| 2 | | CLASS 2 | SM | NO | $PCI=0.062* Age^2-3.39*Age+91.86$ | 0.81 | 0.05 | 0.12 | 19 |
| 3 | 102 | CLASS 1 | SM | NO | $PCI= 0.123* Age^2-3.465*Age+95.48$ | 0.51 | 0.01 | 0.25 | 14 |
| 4 | | CLASS 2 | SM | NO | $PCI= -0.032* Age^2-1.173*Age+83.35$ | 0.62 | 0.11 | -0.06 | 19 |
| 5 | 107 | CLASS 1 | SM | NO | $PCI= -0.035* Age^2-0.915*Age+92.96$ | 0.75 | 0.03 | -0.07 | 24 |
| 6 | | CLASS 2 | SM | NO | $PCI= -0.023* Age^2-1.686*Age+94.27$ | 0.72 | 0.03 | -0.46 | 21 |
| 7 | 101 | CLASS 1 | SM | SO | $PCI= 0.022* Age^2-2.463*Age+97.48$ | 0.78 | 0.06 | 0.04 | 24 |
| 8 | | CLASS 2 | SM | SO | $PCI= 0.017* Age^2-2.061*Age+93.6$ | 0.7 | 0.04 | 0.03 | 27 |
| 9 | 107 | CLASS 1 | SM | SO | $PCI= 0.04* Age^2-2.098*Age+93.13$ | 0.5 | 0.01 | 0.08 | 26 |
| 10 | | CLASS 2 | SM | SO | $PCI= -0.083* Age^2-0.275*Age+89.19$ | 0.51 | 0.08 | -0.17 | 20 |

where:
PCI = Pavement Condition Index (0-100)
Age = Age of Pavement (yrs)
Class1 = ESAL is < 50,000
Class2 = ESAL is 50,000 - 500,000
SO = Southern Ontario, NO = Northern Ontario
SM = sandy silt

**Table 2.** Summary of Treatments Types Analyzed.

| Activity Code | Activity Description |
|---|---|
| 101 | Hot Mix Overlay One Lift |
| 102 | Mill and Hot Mix Overlay One Lift |
| 107 | Full Depth Reclamation (FDR) and Hot Mix Overlay Two Lifts |

## Mechanistic Empirical Pavement Design Guide (MEPDG) Method

The MEPDG inputs were divided into two groups: design parameters, which are the parameters that depend on the project specification; and default values, which are the inputs that will be assumed or as a default value in the MEPDG. The following inputs are entered in MEPDG: design life, traffic data, climate data pavement layers thickness and asphalt binder to predict the IRI.

## PMS Results from Multiple Regressions

Table 4 presents the results for the predicted models as a function of pavement type, equivalent total thickness, ESAL, subgrade type, and treatment types. Figs. 2 and 3 show the performance curves for Category 2 and 10 based on maintenance activity. All pavement curves show deterioration over time [13].

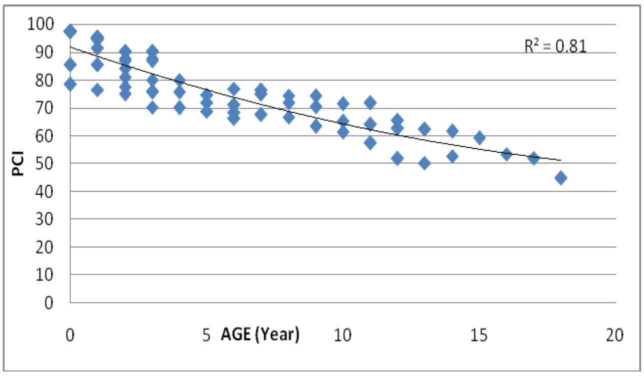


**Fig. 2.** Pavement Performance Prediction for Category 2.

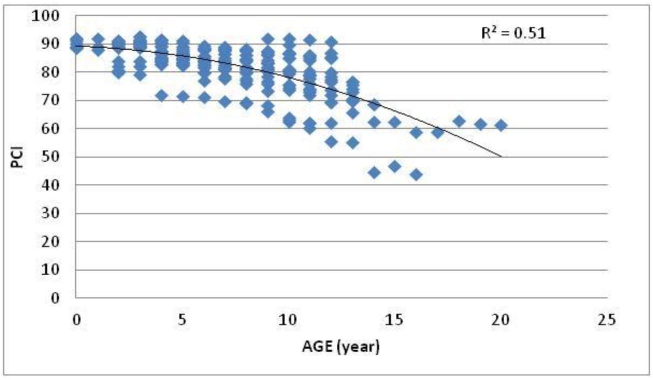


**Fig. 3.** Pavement Performance Prediction for Category 10.

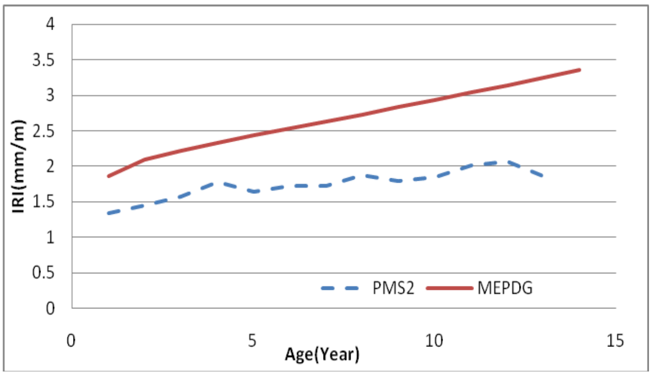


**Fig. 4.** Un-calibrated IRI form MEPDG and IRI Observed from PMS2 for One Section.

As noted Fig. 2, the performance curve for the pavement category of Northern Ontario, asphalt concrete, thin pavement thickness (less than 500mm) with Class 2 ESALs (50,000-500,000), and sandy silt subgrade that received activity 101(hot mix overlay one left). There is slightly faster pavement deterioration for the Class 2 traffic over the thin thickness that lean to a shorter pavement expected service life.

### Assessment MEPDG Results

Depending on the results of the MEPDG, the pavement performance models can be potentially incorporated into PMS. This is desirable as there are some deficiencies in the current models in the PMS2. Fig. 4 shows a comparison between the uncalibrated IRI from the MEPDG and the IRI observed from PMS2 for one section in Category 2. As noted, the MEPDG model may show the same trend but have higher values for IRI and that will result in an unallocated budget for preservation and maintenance.

Therefore, a model prediction calibration and validation process for the whole category has been tested using statistical tools to examine the accuracy of the models. Fig. 5 shows a plot of uncalibrated IRI from MEPDG and IRI observed from PMS2 for the whole category of Northern Ontario, asphalt concrete, thin pavement thickness (less than 500mm) with Class 2 ESALs (50,000-500,000) and sandy silt subgrade that received activity 101 (hot mix overlay one lift). As noted in the plot, an over prediction of MEPDG IRI is observed. Further research into other categories and variables will be assessed.

## Analysis

Based on the results from Fig. 5, further analysis scenarios were considered, including the evaluation of the maximum likelihood estimate of liner regression parameters. In addition, multiple linear regressions were used to further analyze the IRI data and the associated correlation with various parameters according to Eq. (2). Moreover, the IRI values from PMS2 has been compared with the IRI value from MEPDG by adjusting the coefficients in Eq. (2)

$$\begin{aligned} IRI\ \ PMS2 = \beta_0 + \beta_1 * (IRI\ \ MEPDG) + \beta_2 * (Age) + \beta_3 * (Thickness) \\ + \beta_4 * (AADT) + \varepsilon i \end{aligned} \quad (2)$$

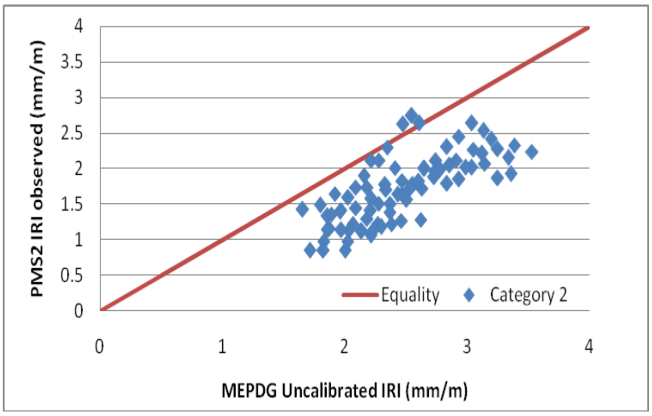


**Fig. 5.** Un-calibrated IRI form MEPDG versus IRI Observed from PMS2 for entire Category**.**

where:
*IRI PMS*2 = is a matrix including the IRI for a category from PMS2
*IRI MEPDG* = $X_{12}$ is uncalibrated IRI from MEPDG
*Age* = $X_2$ is pavement age corresponding to the IRI value
*Thickness* = $X_3$ is pavement equivalent total thickness for the pavement
*AADT* = $X_4$ is the traffic volume on the section represent by AADT
$\beta_0, \beta_1, \beta_2, \beta_3, and \beta_4$ = are matrices of the coefficients relating the dependent variables with the independent variables.
$\varepsilon_i$ = is the error or the discrepancy between the value calculated through the model and the actually measured value.

In multiple linear regression models, the independent variables can be of higher order such as second, or third degree order, or in logarithmic function. For example, the variable representing any of the independent variables can be $X_i^2$, $X_i^3$ or $\ln X_i$. The Y and X are matrices where, the solution of matrices can be executed using a statistical software package or Excel work sheets. The linear regression coefficients are calculated and determined in the $\beta$ matrix. Once the $\beta$ has been determined Analysis of Variance (ANOVA) is carried out to examine the overall significance of the regression. To perform an ANOVA the hypothesis test to evaluate the significance of the model:

$H_0$: $\beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$
$H_1$: $\beta_1 \neq 0$ at least one of the $\beta \neq 0$

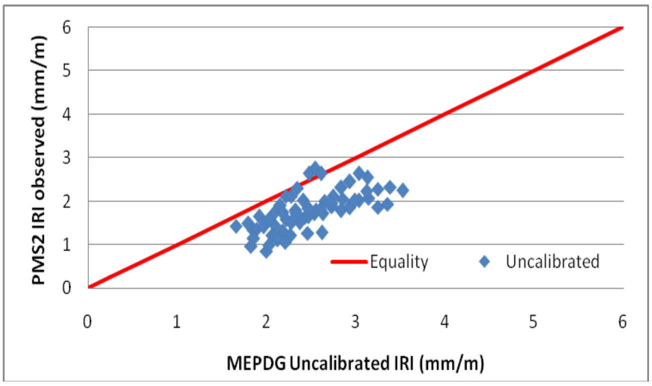


**Fig. 6.** Un-calibrated IRI from MEPDG versus IRI Observed from PMS2 SC1.

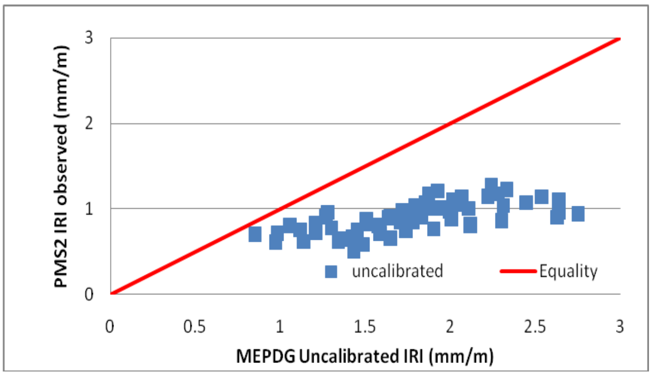


**Fig. 7.** Un-Calibrated IRI form MEPDG versus IRI Observed from PMS2 SC2.

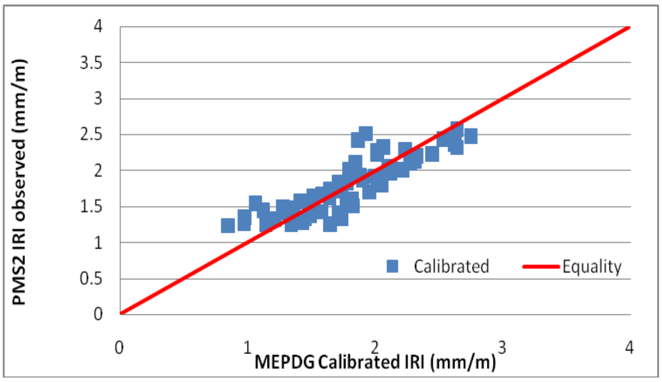


**Fig. 8.** Calibrated IRI form MEPDG versus IRI Observed from PMS2 SC2.

### Scenario One

Scenario one is proposed to calibrate the model taking into account the effect of the intercepted, IRI from the MEDPG, age, thickness and AADT.

Fig. 6 shows the un-calibrated IRI form the MEPDG versus the observed IRI from the PMS2 for Scenario One (SC1).

As noted, the MEPDG over-predicts the IRI value. Therefore, further calibration is needed. The results from the β matrix are (1.04.0.14, 0.08, 0, 0) for $\beta_0$, $\beta_1$, $\beta_2$, $\beta_3$, and $\beta_4$ respectively. The values of $\beta_3$ and $\beta_4$ are zero, which represents their irrelevancy for inclusion in the model. As noted these variables were not shown to be statistically significant.

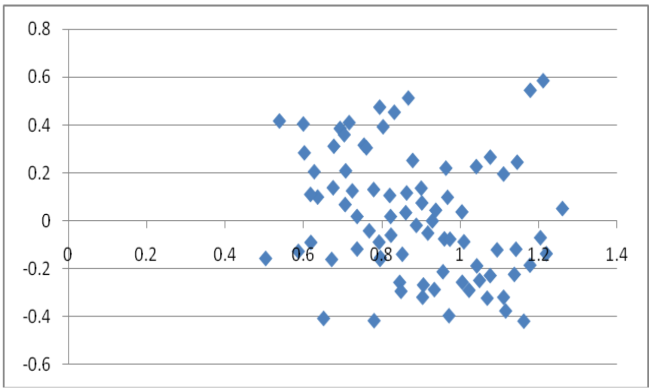

**Fig. 9.** Residual Un-Calibrated IRI form MEPDG versus error in PMS2 SC2.

### Scenario Two

For the reason above, Scenario Two has been proposed to find a better fit for the model. Scenario two is similar to Scenario One, with the exception of $X_2$; the un-calibrated MEPDG was changed to Natural logs ln ($X_2$), and Thickness ($X_3$), and AADT ($X_4$) and were excluded from the model. Fig. 7 shows un-calibrated IRI from MEPDG with IRI observed from the PMS2. As noted, the MEPDG over-estimated IRI indicating that a calibrated model is needed.

The same method of analysis in SC1 has been used herein to calibrate all other models. The results from the β matrix are (1.3, -0.2, and 0.11) for $\beta_1$, $\beta_1$ and $\beta_2$, respectively. The model is calibrated using 75% of the data by using β values and substituted in Eq. (2), to get the calibrated IRI value from MEPDG. Fig. 8 shows a plot for calibrated IRI values with IRI values from PMS.

The remaining 25% of the data has been used for validation by using Eqs. (1) and (2) the AAE is 2.3 %. Furthermore, the ANOVA table has been completed and showed F ratio > F critical which shows a significant difference in variance shown in Fig. 8. Moreover, a 91% coefficient of determination ($R^2$) shows a goodness of fit.

The results show this is a better model as compared to the first SC1 model. The same method will be followed to predict other performance models and for calibration and validation of models. We can reject the $H_0$.

As noted in Fig. 9, the residual plot shows that the there is no trend in the error, it is normally distributed, and the model is a good fit.

## Conclusions

This paper provides an analysis on the feasibility of using 870 sections and almost 18,000 treatment cycles from MTO PMS2 database to calibrate and validate flexible pavement models in the MEPDG for a 20 year period. The prediction variables affecting the PCI value include rutting, longitudinal cracking, transfers cracking, and roughness. All structural factors are affected by environmental impacts, traffic loads, and mechanical property of the pavement material. The developed performance models from the MEPDG can be used to improve the current PMS2 prediction of pavement models simulating deterioration from a certain category of: traffic, equivalent total thickness, traffic volume, subgrade type, and environmental that can be examined for a future design of an appropriate maintenance and rehabilitation program (M&R). The MTO PMS2 database should be updated as some gaps were identified in the process of calibrating MEPDG analysis at a higher level. The most dominant type of subgrade soil was sandy silt, while asphalt concrete was the most dominant pavement type in the available data.

Analytically, the size of the database will be essential for this paper so that PMS2 data can be calibrated and validated for use in MEPDG. The model developed for Category 2 shows a good fit. The analysis of performance models for the same group of Northern climate zone, sandy silt subgrade, and low thickness pavement with a variation of Class 2 ESALs to study the performance and expected service life of different treatments was conducted to predict IRI and from there PCI can be calculated based on IRI and DMI values. Finally, further study of other treatments and other pavement section groups will be done.

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## References

1. AASHTO (1993). Guide of Pavement Structures, American Association of State Highway and Transportation Officials, Washington, DC, USA.
2. Li, N. (1997). Development of A Probabilistic Based, Integrated Pavement Management System, PhD Thesis, Department of Civil Engineering, University of Waterloo, Waterloo, Ontario, Canada.
3. Ddamba, S. (2011). Evaluation of the Effect of Recycled Asphalt Shingles on Ontario Hot Mix Pavement, Master Thesis, Department of Civil Engineering, University of Waterloo, Waterloo, Ontario, Canada.
4. Transportation Association of Canada (TAC) (2012). Pavement Design and Management Guide, TAC, Ottawa, Ontario, Canada.
5. Dore, G., Tighe, S., and Hein, D. (2005). AASHTO 2002 MEPDG Canadian calibration Phase 1, Prepared for Transportation Association of Canada, Ottawa, Ontario, Canada.
6. Banerjee, A., Aguiar-Moya, J., Smit, A, and Prozzi, A. (2010). Development of a Flexible Pavements Database, Technical Report, FHWA, Austin, Texas, USA.
7. ASTM E1926-08 (2003). Standard Practice for Computing International Roughness Index of Roads from Longitudinal Profile Measurements, ASTM International, West Conshohocken, PA, USA, DOI: 10.1520/E1926-08
8. Ministry of Transportation Ontario (1990). Pavement Design and Rehabilitation Manual, Downsview, Ontario, Canada.
9. Chamorro, A, Tighe, S., Li, N. and Kazmierowski, T. (2009). Development of Distress Guidelines and Condition Rating to improve Network Management in the Province of Ontario, *Transportation Research Record*, No.2093, pp. 128-135.
10. Glover, L.T. and Mallela, J. (2009). Guidelines for Implementing NCHRP 137A M-E Design Procedures in Ohio: Volume 4-MEPDG Models Validation, and Recalibration. Applied Research Associated, Inc., Champaign, Illinois, USA.
11. Hoegh, K., Khazanovich, L., and Jensen, M. (2010). Local Calibration of MEPDG Rutting Model for MNROAD Test Sections. Transportation Research Board 89th Annual Meeting,Washington, DC, USA.
12. Li, J., Pierce, L.M., and Uhlmeyer, J. (2009). Calibration of Flexible Pavement in Mechanistic-Empirical Pavement Design Guide for Washington State. *Transportation Research Record,* No. 2095, pp. 73-83
13. Hamdi, A. (2012), Improving Ontario Pavement Management through Long Term Monitoring. Proceedings of Transportation Research Board – Poster Session, Washington DC, USA.
14. Li, N. (2006). Long-Term Monitoring of Low-Volume Road Performance in Ontario, Annual Conference of the Transportation Association of Canada Charlottetown, Prince Edward Island, Canada.
15. El-Assaly, A. (2002). Development of Deterioration Models For The Primary Highway Network in Alberta, Canada. Annual Conference of the Canadian Society for Civil Engineering, Montréal, Québec, Canada.