

Sensitivity Evaluation and Optimization of Calibration Coefficients of AASHTOWare Pavement ME Design Jointed Plain Concrete Pavement Faulting Models

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Abstract

The AASHTOWare Pavement ME Design software uses faulting predictions as one of the performance measures for Jointed Plain Concrete Pavement (JPCP) structural designs. Faulting prediction is calculated as the sum of incremental change (monthly) in mean transverse joint faulting during each month in design service life. The faulting prediction computation requires eight input variables along with eight calibration coefficients (C_1 to C_8). It is obvious that these input variables and calibration coefficients are needed to calibrate JPCP faulting model. However, in the computation of the incremental change in mean transverse joint faulting, three interdependent equations are used, which makes this computation long and complicated. This study evaluates the sensitivity of calibration coefficients associated with the JPCP faulting model for optimization of calibration coefficients under local conditions and presents discussions on the feasibility of developing of a simplified faulting prediction equation having comparable accuracy to AASHTOWare Pavement ME Design faulting prediction equation.

Introduction

The AASHTOWare Pavement ME Design software, built upon the Mechanistic-Empirical Pavement Design Guide (MEPDG), uses nationally calibrated performance models to predict Jointed Plain Concrete Pavement (JPCP) performance measures (faulting, transverse cracking and smoothness). To improve the accuracy of nationally calibrated performance models for various local conditions, further calibration and validation studies in accordance with the local conditions are highly recommended.

Transverse joint faulting is defined as the elevation difference across the joint measured almost 30.5 cm. (1 ft.) from the slab edge for conventional lane width and from the rightmost lane paint stripe for widened slabs (AASHTO 2008). Faulting is an important parameter affecting ride quality on a pavement. Therefore, predicting faulting distress accurately throughout the pavement design service life is important for state highway agencies (SHAs) to design the pavement accordingly and take necessary actions to mitigate this distress in a timely manner. There are many factors playing an important role in the faulting mechanism such as repeated heavy axle loads, insufficient load transfer from joint to joint, free moisture beneath the PCC slab, disintegration of

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the supporting base/subbase, subgrade, or shoulder base material, and upward curling of the slab in the joint, etc. However, having a better understanding of which factors play the major roles in the propagation of faulting is of great interest. Therefore, many sensitivity studies have been conducted to assess sensitivity of each possible parameter in terms of their contribution to faulting (Buch et al. (2008), Haider et al. (2008), FHWA (2007), Haider et al. (2009), Kapmann (2008), Tanesi et al. (2007), Valesquez et al. (2009), and Ceylan et al (2013)).

In the AASHTOWare Pavement ME Design software, faulting prediction is calculated as the sum of incremental change (monthly) in mean transverse joint faulting during each month in the design service life (AASHTO 2008). The computation of incremental change (monthly) in mean transverse joint faulting requires eight input variables along with eight calibration coefficients (C_1 to C_8). The eight input variables required include an initial maximum mean transverse joint faulting, a maximum (monthly) mean transverse joint faulting, a base/subbase erodibility factor, differential deformation energy accumulated during the month, a maximum mean monthly slab corner upward deflection, an overburden pressure on subgrade, a percent subgrade soil material passing No. 200 sieve, and an average annual number of wet days. It is obvious that these inputs are needed to calibrate JPCP faulting model. To implement local calibration of faulting model effectively, the sensitivity of each calibration coefficients to the faulting change should be studied. Also, computation of incremental change (monthly) in mean transverse joint faulting is implemented using three interdependent equations, which makes it long and complicated procedure. It should be also noted that these 3 interdependent equations have some equation variables themselves and calibration coefficients to be known to calculate incremental change (monthly) in mean transverse joint faulting.

This study evaluates the sensitivity of equation variables and calibration coefficients associated with the JPCP faulting model for optimization of calibration coefficients under local conditions. A total of 35 Iowa JPCP pavement sections across the state were used in this study to provide required parameters data to the faulting equation (a base/subbase erodibility factor, an overburden pressure on subgrade, a percent subgrade soil material passing No. 200 sieve, and an average annual number of wet days) and to conduct sensitivity analysis study under local conditions. A detailed review of the JPCP faulting model is documented to better understand its internal numerical algorithm. The methodology and results of sensitivity evaluations are discussed in this paper highlighting the optimization of JPCP faulting model calibration coefficients to improve the prediction accuracy under local conditions. In addition, this study discusses the feasibility of developing a simplified faulting prediction equation having comparable accuracy to AASHTOWare Pavement ME Design faulting prediction equation.

Sensitivity Analysis of the Variables and Calibration Coefficients of Faulting Pavement Performance Model

AASHTOWare Pavement ME Design JPCP Faulting Prediction Model. The incremental faulting value in each month, starting from the traffic opening date is calculated and summed to predict the mean joint transverse faulting value at any time during the JPCP design service life. The JPCP transverse joint faulting predictions are calculated from a set of equations as follows (AASHTO 2008):

$$Fault_m = \sum_{i=1}^m \Delta Fault_i \quad (1)$$

$$\Delta Fault_i = C_{34} \times (FAULTMAX_{i-1} - Fault_{i-1})^2 \times DE_i \quad (2)$$

$$FAULTMAX_i = FAULTMAX_{i-1} + (C_7/10^6) \sum_{i=1}^m DE_i \times \log(1 + C_5 \times 5^{EROD})^{C_6} \quad (3)$$

$$FAULTMAX_0 = C_{12} \times \delta_{curling} \times [\log(1 + C_5 \times 5^{EROD}) \times \log(\frac{P_{200} \times Wet\ Days}{p_s})]^{C_6} \quad (4)$$

Where,

- $Fault_m$ = mean joint faulting at the end of month m (in.),
- $\Delta FAULT_i$ = incremental change (monthly) in mean transverse joint faulting during month i (in.),
- $FAULTMAX_i$ = maximum mean transverse joint faulting for month i (in.),
- $FAULTMAX_0$ = initial maximum mean transverse joint faulting (in.),
- $EROD$ = base/subbase erodibility factor,
- DE_i = differential density of energy of subgrade deformation accumulated during month i ,
- $\delta_{curling}$ = maximum mean monthly slab corner upward deflection PCC due to temperature curling and moisture warping,
- Ps = overburden on subgrade (lb),
- P_{200} = percent subgrade material passing #200 sieve,
- $WetDays$ = average annual number of wet days (greater than 2.5 mm. (0.1 in) rainfall),
- $C_{1, 2, 3, 4, 5, 6, 7, 12, 34}$ = calibration coefficients.

C_{12} and C_{34} among calibration coefficients are defined as the following equations:

$$C_{12} = C_1 + C_2 \times FR^{0.25} \quad (5)$$

$$C_{34} = C_3 + C_4 \times FR^{0.25} \quad (6)$$

Where,

- FR = base freezing index defined as the percentage of time when the top base temperature is below freezing 0 °C (32°F) temperature.

Note that the equations 2, 3 and 4 are interdependent. The incremental change (monthly) in mean transverse joint faulting during month i should be calculated in AASHTOWare Pavement ME Design as following steps:

Step 1: $FAULTMAX_0$, $EROD$, P_{200} , $Wet\ Days$ and Ps values for each pavement section are provided in the intermediate output files of AASHTOWare Pavement ME Design. Using these values, $\delta_{curling}$ values can be back calculated employing equation 4.

Step 2: Using the provided $FAULTMAX_0$ value, compute $FAULTMAX_1$ utilizing equation 3. Following the same pattern, calculate $FAULTMAX_{i-1}$ value, i being the month the incremental change (monthly) in mean transverse joint faulting during month would be calculated for.

Step 3: Using the calculated $FAULTMAX_{i-1}$ and other equation variables, compute incremental change (monthly) in mean transverse joint faulting during month i ($\Delta FAULT_i$) in inch.(Equation 2)

Combining the equations 2, 3, 4, 5 and 6, faulting increment between any i and $i-1$ months can be calculated as follows:

$$\Delta Fault_i = (C_3 + C_4 \times FR^{0.25}) \times [((C_1 + C_2 \times FR^{0.25}) \times \delta_{curling} \times [\log(1 + C_5 \times 5^{EROD}) \times \log(\frac{P_{200} \times Wet\ Days}{p_s})]^{C_6} + (C_7/10^6) \times \sum_{i=1}^m \sum_{i=1}^m DE_{i-1} \times \log(1 + C_5 \times 5^{EROD})^{C_6}) - Fault_{i-1}]^2 \times DE_i \quad (7)$$

Sensitivity analysis of all of the variables and calibration coefficients of equation 7 was conducted. Sensitivity analysis basically indicates the sensitivity (change) in an output (y) as a result of a change in the input (x). In this study, the sensitivity analysis of the equation variables and calibration coefficients were performed to understand which equation variables and calibration coefficients play a major role in faulting prediction.

One-at-a-time sensitivity analysis (OAT) was utilized to quantify the sensitivity of each equation variable and calibration coefficient in this study. OAT sensitivity study figures out the extent of change in the output as response to a change in only one input at a time. (Schwartz et al. 2011). Two numerical parameters, a coefficient sensitivity index (S_{ijk}) and a coefficient-normalized sensitivity index (S^n_{ijk}), were calculated for each equation variable and calibration coefficient to assess and compare the sensitivity level of variables and calibration coefficients quantitatively.

The coefficient sensitivity index S_{ijk} can be calculated as follows (Ceylan et al. 2013):

$$S_{ijk} = \left. \frac{\partial Y_j}{\partial X_k} \right|_i \cong \left. \frac{\Delta Y_j}{\Delta X_k} \right|_i \quad (8)$$

$$\left. \frac{\Delta Y_j}{\Delta X_k} \right|_i = \frac{Y_{j,i+1} - Y_{j,i}}{X_{k,i+1} - X_{k,i}} \quad \text{when } X_{j,i+1} > X_{j,i} \quad (9)$$

$$\left. \frac{\Delta Y_j}{\Delta X_k} \right|_i = \frac{Y_{j,i} - Y_{j,i-1}}{X_{k,i} - X_{k,i-1}} \quad \text{when } X_{j,i-1} < X_{j,i} \quad (10)$$

Where, Y_{ji} , X_{ki} are the values of the performance prediction j and calibration coefficient (or the value of equation variable) k evaluated at national calibrated condition i for the faulting model. The partial derivative in the coefficient of sensitivity index can be approximated into a standard central difference approximation (equation 8). The S_{ijk} implies the percentage change in performance prediction Y_j as a result of the percentage change in the calibration coefficient X_k (or the value of equation variable) at national calibrated condition i in the faulting model. To exemplify the interpretation of S_{ijk} , the value of 0.5 of S_{ijk} would imply that a 40% change in the calibration coefficient value of X_{ki} would cause a 20% change in performance prediction Y_{ji} (Ceylan et al. 2013).

For each calibration coefficient and equation variable X_k , two coefficient sensitivity indices (S_{ijk}) were calculated using the 20 % increased and decreased values of calibration coefficient and equation variable values, ($X_{j,1.2i} > X_{j,i}$ and $X_{j,0.8i} < X_{j,i}$). To compare the coefficient sensitivity indices amongst calibration coefficients and equation variables, the indices should be normalized. The normalization of S_{ijk} was performed using the associated national calibration coefficient (or the value of equation variable). A normalized sensitivity index (S^n_{ijk}) can be calculated as follows (Ceylan et al. 2013):

$$S_{ijk}^n = \frac{\partial Y_j}{\partial X_k} \bigg|_{\left(\frac{X_{ki}}{Y_{ji}}\right)} \cong \frac{\Delta Y_j}{\Delta X_k} \bigg|_{\left(\frac{X_{ki}}{Y_{ji}}\right)} \quad (11)$$

The normalized sensitivity index (NSI) can be defined as the relative predicted distress (faulting) change to its design limit (e.g., 1.3 cm. (0.5 in.) for faulting) because of a change in the equation variable (e.g., curling). To exemplify, NSI=0.5 for the sensitivity of faulting to curling means that, for example, 20 % increase in curling would cause 0.5*20=10 % increase in its design limit (0.10*0.5=0.05 in. (0.13 cm.) increase in faulting design limit).

It is important to mention that the sensitivity analysis of both calibration coefficients and equation variables were directly performed using equation 7 outside of the software rather than inputting the 20 % increased and decreased values of calibration coefficient and equation variable values and evaluate the outputted faulting predictions to figure out the sensitivity of each variable and calibration coefficient. That way, the interaction between the equation variables and calibration coefficients was easily observed and understood. In the sensitivity analysis of JPCP faulting model, a JPCP section representing typical Iowa JPCP pavements was determined. This pavement section is on I-29 highway with Mile-post (MP) numbers 76.54 to 90.72 in Harrison County, Iowa. The pavement section is composed of a 30.5 cm. (12 in.) PCC layer with 4 in. granular subbase layer. It has 2 lanes with 3,104 annual average daily truck traffic (AADTT).

Sensitivity Analysis Results

Table 1 and Table 2 present the sensitivity analysis results for equation variables and calibration coefficients of JPCP faulting model, respectively. The negative sign of coefficient sensitivity index implies that as equation variable or calibration coefficient increases, the faulting prediction decreases or vice versa. As can be seen in Table 1, curling deflection computed from concrete pavement response model as one of surrogate models in AASHTOWare Pavement ME Design is the major equation input variable affecting faulting predictions. Also note that, DE, EROD, Fault_{i-1}, Freezing Index, DE_{Accumulated}, PS, P₂₀₀ and Wet Days are the less sensitive variables respectively

Table 1. Summary of Equation Variable Sensitivity Indices for JPCP Faulting Model

Equation variables	Coefficient sensitivity index (S _{ijk})		Average normalized sensitivity index (S ⁿ _{ijk})	Rank
	X _{j,i+1} > X _{j,i}	X _{j,i-1} < X _{j,i}		
Curling	0.016490	0.013431	2.04	1
DE	0.000253	0.000254	1.00	2
EROD	0.000054	0.000055	0.54	3
Fault i-1	-0.003312	-0.003400	-0.26	4
Freezing Index	0.000467	0.000525	0.26	6
DE Accumulated	0.000000	0.000000	0.22	5
PS	0.000000	-0.000001	-0.18	7
P₂₀₀	0.000001	0.000001	0.18	8
Wet Days	0.000000	0.000000	0.17	9

According to Table 2, C_6 is the most sensitive coefficient while C_5 is the least sensitive one. C_6 relates the combination of P_{200} , Wet Days Ps and EROD into the incremental faulting while C_5 only relates EROD into the incremental faulting (See equation 7). Note that the sensitivity of a calibration coefficient implies whether there is a strong relationship between associated parameter and faulting predictions. Having high sensitivity of a calibration coefficient implies that the percentage change in the related equation variable causes high percentage change in the incremental faulting prediction. This information was taken into account in reducing the equation variables in the overall simpler incremental faulting equation as compared to original incremental faulting equation.

Table 2. Summary of Calibration Coefficient Sensitivity Indices for JPCP Faulting Model

Calibration factors	Coefficient sensitivity index (S_{ijk})		Average normalized sensitivity index (S^n_{ijk})	Rank
	$X_{j,i+1} > X_{j,i}$	$X_{j,i-1} < X_{j,i}$		
C6	0.00335	0.00223	2.22	1
C1	0.00065	0.00058	1.24	2
C2	0.00046	0.00042	0.80	3
C3	0.17882	0.17882	0.78	4
C4	0.12794	0.12794	0.22	5
C7	0.00006	0.00006	0.22	6
C5	0.00000	0.00000	0.07	7

Multivariate Linear Regression (MVLRL) for the Faulting Equation

Since the combined faulting equation (equation 7) is long and complicated, replacing this equation with a shorter one, requiring less variables to be known, with sufficient accuracy was necessary. Moreover, based on the sensitivity analysis results, it was realized that the sensitivity of some variables to the incremental faulting is minimal. Reducing the number of variables in the equation would save the sources allocated to collect data with related variables. To replace equation 7 with a shorter, simpler and less effort intensive linear equation with sufficient accuracy, multivariate linear regression (MVLRL) was employed. A total of 35 Iowa JPCP sections that Ceylan et al. (2013) used in their study was also included in this study to supply the faulting equation with required input parameters. The pavement structure (thickness of layers etc.), material (materials used, modulus of materials etc.) and traffic (AADTT, truck percentages uses the pavement etc.) related input parameters that 35 JPCP pavement sections had were inputted into the software and the software was run. The sub outputs required to be used in equation 7 was executed from the related intermediate output files. Note that, in running the software, nationally calibrated pavement performance models were employed. Then, the equation variables executed from intermediate output files in 60th, 120th, 180th and 240th months were used (140 data sets) as input in the multivariate linear regression model. The equation variables that have p value less than 0.05 (less significant) were taken out from the model and the model was rerun. At the end of the regression analysis, a shorter linear equation having significant accuracy was determined (equation 12).

$$\Delta Fault_i = -0.00011 + 0.00013 \times DE_i - 0.0000011 \times \sum_{i=1}^m \sum_{i=1}^m DE_{i-1} + 0.0025 \times \delta_{curling} + 0.005 \times Fault_{i-1} \quad (12)$$

Where,

- $Fault_{i-1}$ = mean joint faulting at the end of month $i-1$ (in.),
- $\Delta FAULT_i$ = incremental change (monthly) in mean transverse joint faulting during month i (in.),
- DE_i = differential density of energy of subgrade deformation accumulated during month i ,
- $\delta_{curling}$ = maximum mean monthly slab corner upward deflection PCC due to temperature curling and moisture warping,

Faulting increments using equation 12 was calculated and compared with the calculated faulting increments using equation 7 to ensure that these two equations have similar incremental faulting predictions. Table 3 summarizes the regression statistics for equation 12. As can be seen from the table, using equation 12, an accurate model was acquired with around 95 % R^2 . That means, using equation 12, with 95 % accuracy, similar faulting increment predictions would be attained only having 3 variables: DE , $\delta_{curling}$ and $Fault_{i-1}$.

Table 3. Regression Statistics of Equation 12

<i>Regression Statistics</i>	
Multiple R	0.939145
R Square	0.881992
Adjusted R Square	0.878496
Standard Error	5.25E-05
Observations	140

Figure 1 compares the faulting increments calculated using equation 7 and equation 12. As can be seen from the figure, there is a robust correlation between the faulting increments calculated using equation 7 and equation 12. In other words, using equation 12, similar incremental faulting predictions were attained as compared to the predictions using equation 7.

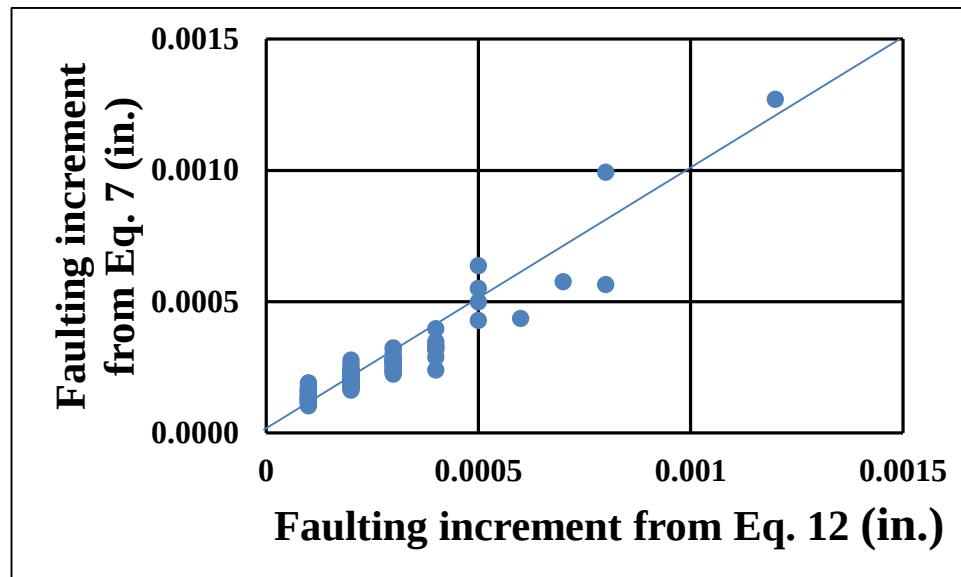


Figure 1. Comparison of the Faulting Increments Using Equation 7 and Equation 12

Discussions and Conclusions

Faulting is an important distress to evaluate ride quality. Predicting this value accurately throughout the projected pavement life is crucial in designing JPCP pavements. Predicting it accurately would save significant amount of funds since the pavement can be designed to resist this stress during the design life and if needed, timely maintenance strategies can be employed. The state-of-art pavement design software, AASHTOWare Pavement ME Design, calculates this distress based on incremental method. Faulting increment in each month is calculated and summed to predict total faulting at any time throughout the pavement design life.

In this study, the sensitivity analysis of equation variables and calibration coefficients utilized in the incremental faulting equations were conducted. The sensitivity analysis results were summarized in Table 1 and Table 2. As a result of sensitivity analysis, curling was found to be the most sensitive equation variable to incremental faulting. Note that, the sensitivity of a variable indicates the extent of contribution of a variable to the faulting increment. The least sensitive variables to the incremental faulting were found to be Wet Days, P_{200} and P_s . The least sensitive variables were determined to understand which variables would be eliminated in determining the simpler and shorter faulting equation. Also, in this study, the sensitivity analysis of calibration coefficients were conducted. The most sensitive coefficient was found to be C_6 . Note that, calibration coefficients relates the variables that they are multiplied by with the incremental faulting. Thus, they show the magnitude of relationship between accompanied variable and incremental faulting. The sensitivity analysis results of calibration coefficients are also widely used in the local calibration of faulting model too. Based on the local calibration results, by modifying the most sensitive coefficients accordingly, a faulting model producing similar faulting prediction to actual local faulting measures can be determined. Additionally, in this study, a shorter, simpler and less inputs demanding requiring linear equation for incremental faulting

calculation was determined applying multivariate linear regression (MVLR). It was found out that using this simpler faulting increment equation, comparably similar faulting prediction were acquired comparing to Pavement ME Design faulting model. This simpler equation would be recommended to be used in predicting faulting distress in conventional pavement design purposes for Iowa JPCP pavement systems as alternative to Pavement ME Design faulting model.

Any state highway agency (SHA) could follow the steps documented in this study to evaluate sensitivity of equation variables and calibration coefficients based on their own local conditions for JPCP faulting model. Also, they can determine their own shorter and simpler faulting equation following the steps detailed in this study. Note that, using more data points, more accurate faulting equation could be determined.

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