Effect of Frequency of Pavement Condition Data Collection on Performance Prediction

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Monitoring pavement surface conditions over time is essential for pavement management and performance models. Time series distress data can be used to determine the remaining service life at the project level, which can then be used for all projects to assess the overall health of the pavement network. Observed field performance is also crucial for calibrating performance prediction models for pavement design purposes. Therefore, highway agencies collect pavement condition data to accomplish both policy and engineering objectives. However, differences exist among agencies between the monitoring frequency used for pavement surface distress (imaging) and that used for sensor-measured features. These differences pertain primarily to the relative difficulties in collecting and processing imaging data. Many agencies collect sensor data more frequently than images. Most highway agencies monitor pavement condition at 1-, 2-, or 3-year frequencies. Discrepancies between performance model predictions and observed field performance are conventionally attributed solely to errors in predicted pavement distresses. In fact, inherent uncertainty may also be present in measured pavement distresses due to spatial variability, sampling, and measurement errors. The frequency of distress data collection adds further uncertainty in performance prediction. This paper explores the effect of pavement condition monitoring frequency on pavement performance prediction. Analyses of observed pavement performance show that condition data collection frequency can significantly affect performance prediction. Therefore, more frequent data collection for image-based methods can reduce the associated risk in performance prediction and thus be more effective for better decision making for pavement management.

Monitoring pavement surface conditions over time is essential for pavement management and performance modeling at both the project and network levels. At the network level, time series condition data can be used to determine the remaining service life (RSL) to assess the overall health of assets, but observed field performance is also crucial for calibrating performance prediction models for pavement design purposes. Therefore, highway agencies collect pavement condition data to accomplish both policy and engineering objectives. However, differences exist among agencies between the monitoring frequency used for pavement surface distress (imaging) and that used for sensor-measured features (roughness, rut depth, and joint faulting). These differences are mainly related to the relative difficulties (cost, resources, and technology) in collecting and processing imaging data. Many agencies collect sensor data more frequently than images. Most highway agencies monitor pavement condition at 1-, 2-, or 3-year frequencies (*1*).

Discrepancies between performance model predictions and observed field performance are conventionally attributed solely to errors in the predicted pavement distresses (*2*). In fact, there may also be significant inherent uncertainty in the measured pavement distresses due to spatial variability, sampling, and measurement errors (*3–5*). The frequency of distress data collection further adds to the uncertainty in performance prediction. The uncertainty associated with the method (manual, semiautomated, and automated) of condition data collection has been well documented in the literature (*6–17*). However, there is a need to investigate the effects of condition monitoring frequency on pavement management decision making. Determining the effects of data collection frequency will assist highway agencies in bridging the information gap for pavement management purposes and their support for the evaluation and calibration of the performance models. It is also anticipated that monitoring equipment (method of data collection and technology) may have an important role in studying the effect of monitoring frequency because of their inherent associated measurement variabilities. Also, several pavement surface condition indicators are collected at the same frequency, although the optimum frequency could be different from one parameter to another depending on the progression with time.

This paper explores the effect of pavement condition monitoring frequency on pavement performance prediction, which can be subsequently used to investigate its impact on pavement management decision making. A statistical approach is described for quantifying the effect of condition data collection frequency on performance prediction using typical model forms for different condition indicators [e.g., cracking and international roughness index (IRI)]. This statistical formulation can quantify the risk in performance predictions associated with the use of different data monitoring frequencies. An optimal data collection frequency can then be recommended on the basis of the investigation of measured condition indicators.

FACTORS INFLUENCING PERFORMANCE PREDICTION

In this paper, a methodology is developed to investigate the effects of monitoring frequency on performance prediction. The pavement surface condition data monitored in the field were used to formulate the analysis approach. The analyses include alligator cracking and pavement surface roughness according to the IRI for flexible and rigid pavements in the specific pavement study (SPS) experiments (SPS-1 and SPS-2) of the Long-Term Pavement Performance (LTPP) database. First, a general approach for a condition indicator is presented.

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Then, examples from observed condition data are documented to validate the methodology. Typically, the following factors need to be considered for performance prediction using an empirical model:

- Variability of measured distress,
- Frequency of data collection with time,
- Age of the pavement section, and
- Form of the model.

It can be shown that all these factors can interact with each other. As an example, Figure 1 shows a schematic of a power model form fitted to rut depth data. It can be seen that if the variability of the data with time is low, the monitoring frequency may not have a significant effect on performance prediction in terms of RSL. However, if the variability in the observed data is high, the monitoring frequency may have a significant effect on the predicted RSL, as shown in Figure 2.

Another source of variability in the predicted RSL (which depends on predicted performance) is the age of pavement sections. At the network level, the pavement sections may have a distribution of age. This age distribution is an outcome of the pavement maintenance, rehabilitation, and reconstruction activities at the network level over time. It is anticipated that the performance prediction will be more uncertain for pavement sections having only a few monitoring cycles (newer pavements) compared with those having a higher number of monitoring cycles (older pavements). Figure 3 shows the effect of age on the RSL for newer and older pavement sections. Although variability in the monitored data is low, the number of monitoring cycles may have a significant effect on the predicted RSLs of the two sections.

The error in the performance predictions has several components, including model, measurement, and sampling errors. Also, each error type may be random, systematic, or both. The random model error can be reduced by improving the performance models to capture a phenomenon (i.e., model form and input variables), whereas a systematic model error can be reduced by model calibration (i.e., minimization of bias). The random measurement error can be reduced by improving the accuracy of measurements (i.e., new, improved technologies), whereas systematic measurement error can be eliminated by appropriate equipment calibration. The random sampling error can be reduced by increasing the sample size, whereas unbiased sampling procedures should be adopted to eliminate any systematic error.

In pavement management and design, performance models are typically empirical in nature; therefore, monitoring of field data for

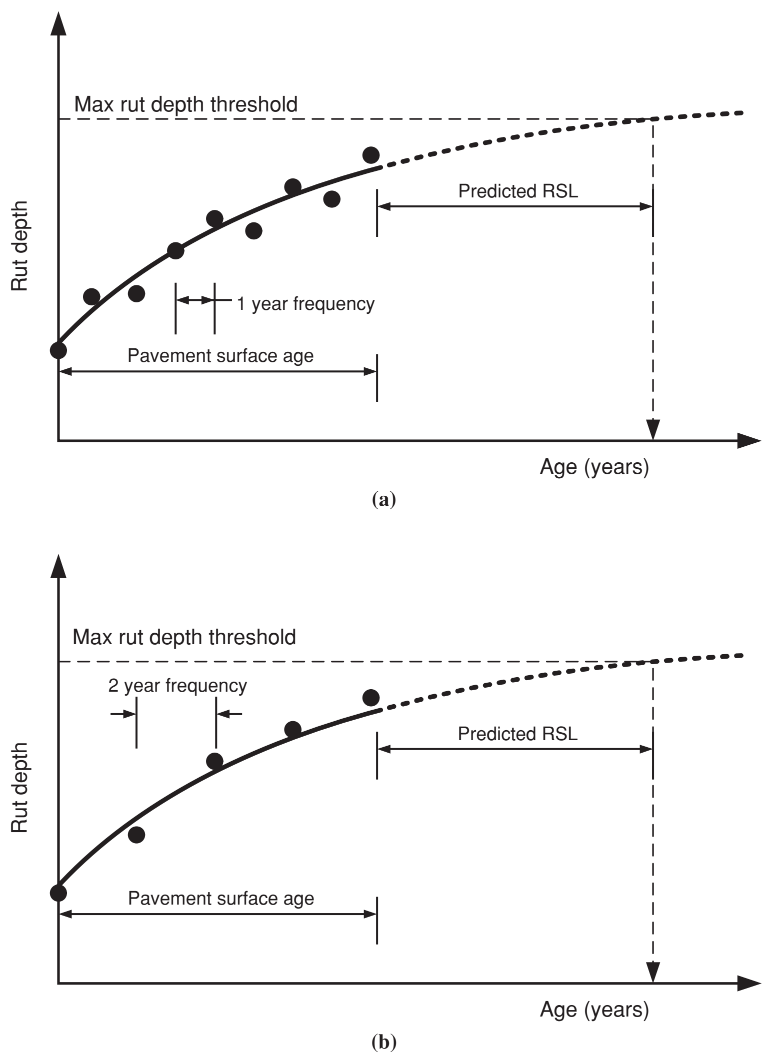

FIGURE 1 Effect of monitoring frequency on prediction for data with low variability: rut depth data at (*a*) 1-year interval and (*b*) 2-year interval.

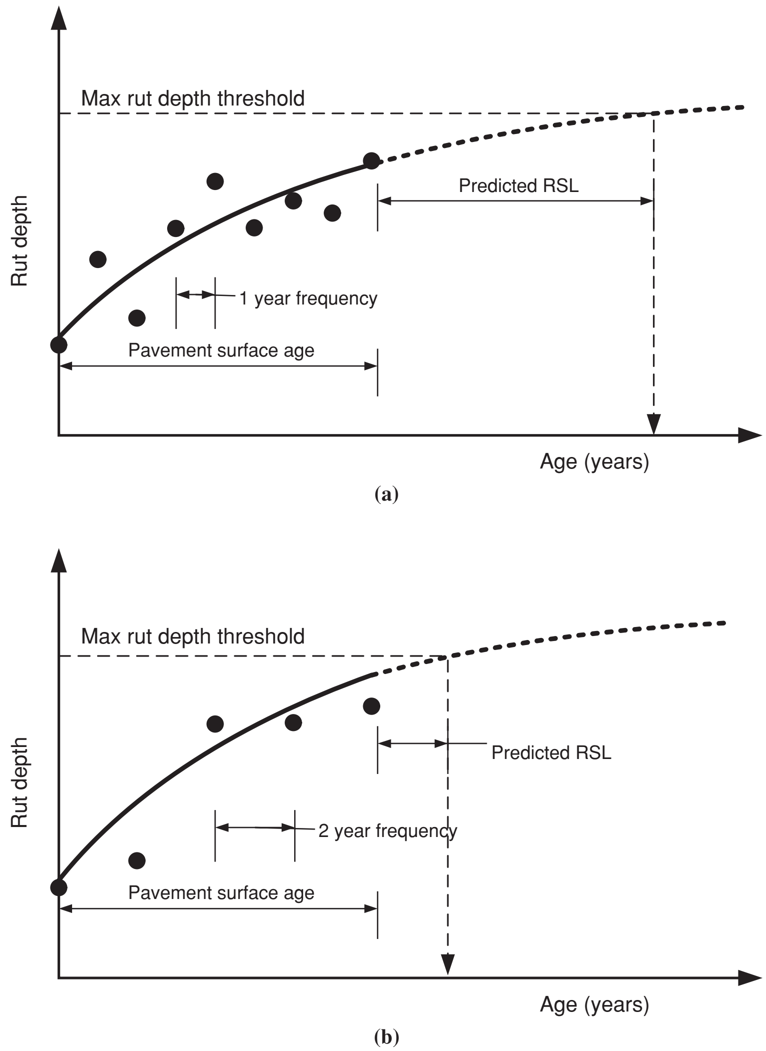

FIGURE 2 Effect of monitoring frequency on prediction for data with high variability: rut depth data at (*a*) 1-year interval and (*b*) 2-year interval.

any distress or condition indicator is essential for the development and calibration of these models. Although performance model prediction accuracy is dependent on all sources of errors in the data, the frequency of monitoring cycles can also have an important impact. The schematic in Figure 4 shows the effects of data variability on a performance prediction model. The model error variance (σ^2) can be determined by the unbiased estimate of the variance (s^2):

$$s^2 = \sum_{i=1}^{n} \frac{\left(y_i - \hat{y}_i\right)^2}{\left(n-2\right)} \tag{1}$$

where

y_i = measured distress at monitoring cycle i,
$\hat{y}_i$ = predicted distress at monitoring cycle i, and
n = number of monitoring cycles.

The standard error (SE) of a regression model can be estimated by using Equation 2.

$$\text{SE} = \sqrt{\sum_{i=1}^{n} \frac{\left(y_i - \hat{y}_i\right)^2}{\left(n-2\right)}} \tag{2}$$

As an example, the SE for a power model can be estimated by using Equation 3.

$$\text{SE} = \sqrt{\sum_{i=1}^{n} \frac{\left(y_i - \left(at^b\right)_i\right)^2}{\left(n-2\right)}} \tag{3}$$

where

$\hat{y} = at^b$,
a, b = regression constants,
t = time,
y_i = measured distress, and
$\hat{y}$ = predicted distress.

Higher SE in the model will add more uncertainty in the model prediction, as shown in Figure 4. The most important reason for developing a performance model is to predict distress (e.g., rut depth, IRI, and cracking) growth with time or traffic. It is also anticipated that there would be an associated error with prediction. The error of prediction will be higher in the case of a single predicted value than in the case of the mean being predicted (*18*), which would affect the width of intervals for the values to be predicted (see Figure 4*c*). For

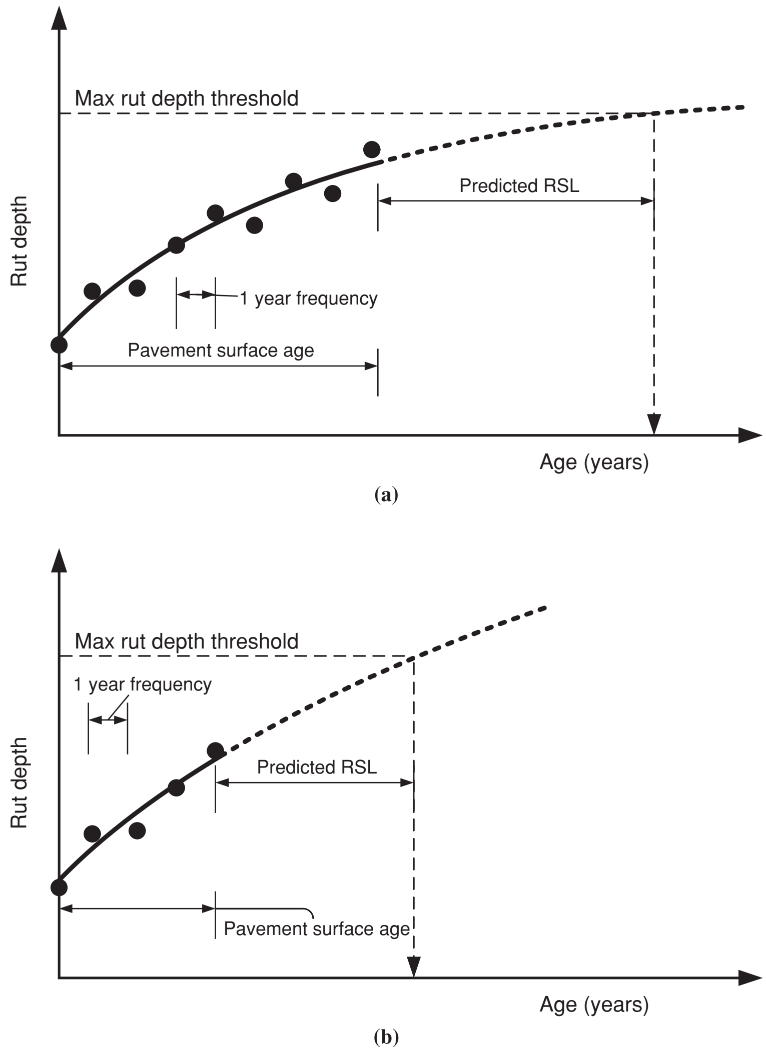

FIGURE 3 Effect of pavement surface age on prediction: (*a*) older pavement and (*b*) newer pavement.

a linear regression model, a 100 $(1 - \alpha)$% confidence interval for the mean is given by Equation 4.

$$\hat{y}_o - t_{a/2} s\sqrt{\frac{1}{n} + \frac{(x_o - \bar{x})}{S_{xx}}} < \mu_{y|x_o} < \hat{y}_o + t_{a/2} s\sqrt{\frac{1}{n} + \frac{(x_o - \bar{x})}{S_{xx}}} \tag{4}$$

where

$t_{a/2}$ = value of t distribution with 2 degrees of freedom,
$\hat{y}_o$ = predicted value,
s = standard deviation,
n = number of monitoring cycles,
x_o = initial distress value,
$\bar{x}$ = mean distress,
$S_{xx} = \sum_{i=1}^{n} (x_i - \bar{x})^2$, and
$\mu_y|x_o$ = mean of y response (time) given the value x_o (distress).

Conversely, a 100 $(1 - \alpha)$% confidence interval for a single response (y_o) is given by Equation 5:

$$\hat{y}_o - t_{a/2} s\sqrt{1 + \frac{1}{n} + \frac{(x_o - \bar{x})}{S_{xx}}} < y_o < \hat{y}_o + t_{a/2} s\sqrt{1 + \frac{1}{n} + \frac{(x_o - \bar{x})}{S_{xx}}} \tag{5}$$

Both types of confidence intervals are shown in Figure 4*c.* The higher the variability (SE), the more uncertainty in the prediction. A statistical approach needs to be developed on the basis of this discussion for various model forms to capture several common pavement condition indicators. For example, power, exponential, and logistic model forms will be used to predict rut depth, IRI, and cracking in pavements, respectively. The objective of the methodology is to quantify the effect of monitoring frequencies on the pavement performance prediction. The approach will also address the determination of the uncertainty (risk) in the pavement performance prediction. To validate the approach, samples of pavement sections from both flexible and rigid pavements were selected, and the effect of monitoring frequency on the observed performance was investigated.

PAVEMENT PERFORMANCE DATA ANALYSIS

SPS-1 and SPS-2 in the LTPP program were designed to study the effects of design and construction features and new flexible and rigid pavement performance, respectively (*19*). The two experiments were selected to investigate the impact of condition data

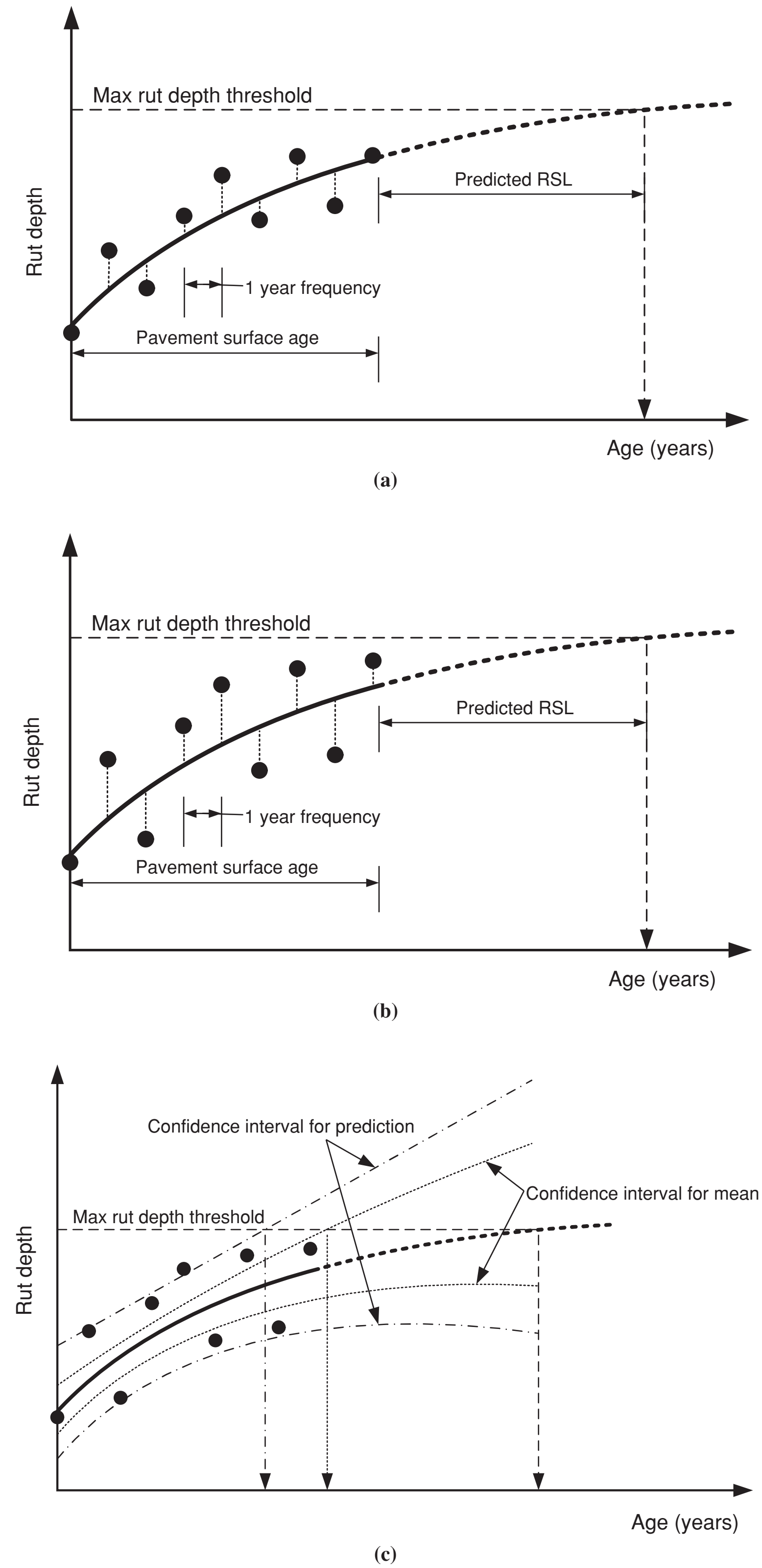

FIGURE 4 Effect of data variability on prediction: (*a*) low variability, (*b*) high variability, and (*c*) confidence interval.

collection frequency on pavement performance prediction because of the following reasons:

1. The pavement sections represent new pavements (i.e., no maintenance or rehabilitation actions were taken on these pavement sections).
2. The pavement sections were monitored for more than 10 years (i.e., adequate time series data for several distresses or condition indicators are available).
3. Several condition indicators (structural and functional distresses) are available for the same sections.
4. The distresses are available in the original units for all severity levels (i.e., not in the form of distress indices).
5. The performance data from these pavement sections were a part of the calibrations of the *Mechanistic–Empirical Pavement Design Guide* performance models.

In this paper, two performance measures, one representing structural (cracking) and the other representing functional (roughness) distress, were investigated for flexible and rigid pavements. Within each experiment (SPS-1 and SPS-2), five pavement sections were sampled on the basis of the monitoring frequency (years of data) and magnitude of the distress. An S-shaped curve of the form shown by Equation 6 was considered reasonable to fit the observed cracking, whereas Equation 7 was used to fit the observed IRI in both types of pavements.

$$\text{crack} = \frac{\max}{1 + e^{a \times t + b}} \tag{6}$$

where

crack = cracking area or length,
max = maximum cracking area or length,
t = time (years), and
a and b = regression constants.

$$\text{IRI} = a \times e^{b \times t} \tag{7}$$

where IRI is measured in meters per kilometer.

Time series data for cracking (alligator cracking area in the case of flexible pavements and transverse cracking length in the case of rigid pavements) and roughness (IRI) for both pavement types were plotted. The highest data collection frequency was considered for the full case (i.e., all time series data points); an average frequency of data collection was determined by dividing the full age with the number of monitoring cycles. For example, if the age of a pavement section at the latest data collection is 13.63 years and distress is monitored 17 times on the section, the average frequency will be one observation per 0.8 year (i.e., interval = 13.63/17 = 0.8 years). The average frequency was adopted in the analysis because the interval between monitoring cycles is not discrete for all pavement sections within the SPS-1 and SPS-2 experiments. Subsequently, the monitoring cycles were deleted between adjacent cycles to decrease the monitoring frequency. The respective model forms were fitted to data at full and decreased monitoring frequencies to investigate the impact of the monitoring frequency on performance prediction. The examples for each pavement type are presented next.

Flexible Pavements

The pavement sections in Figures 5 and 6 show the effect of frequency on the predicted performance through the use of time series alligator cracking data. The time series data show different amounts of variability in the pavement sections. The data for Section 01-101 have higher

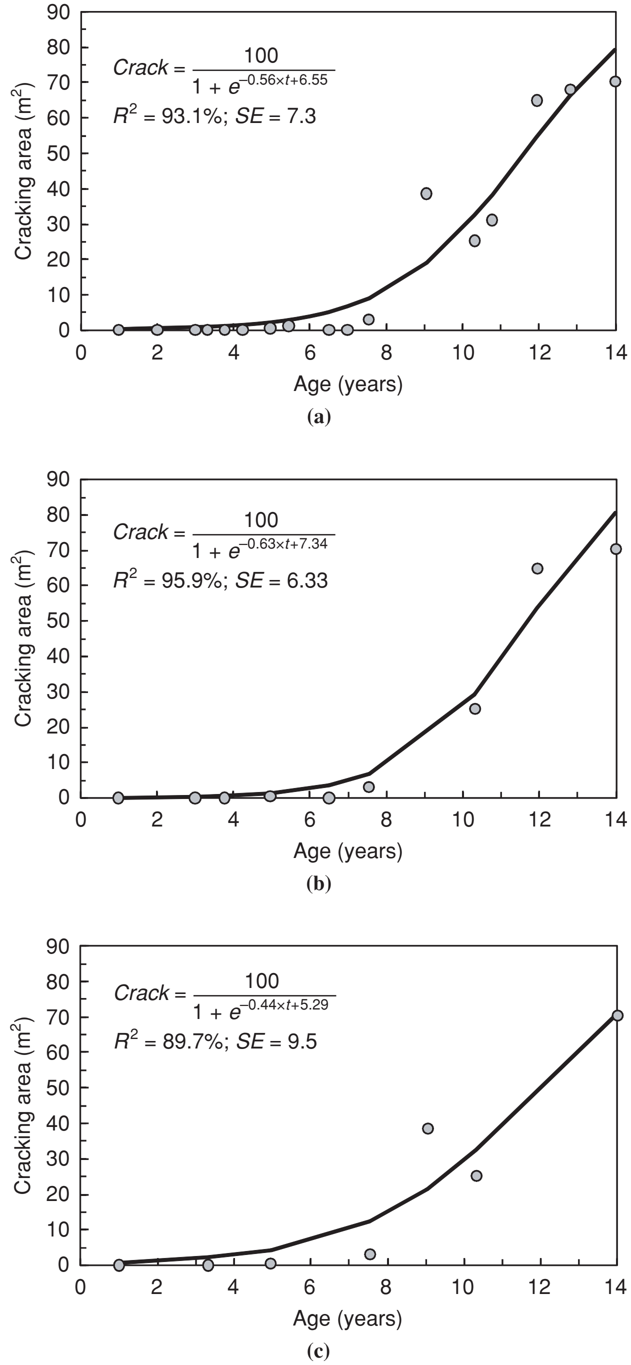

FIGURE 5 Effect of cracking data frequency on performance model, Section 01-101: average monitoring interval of (*a*) 0.82 year, (*b*) 1.55 years, and (*c*) 2.0 years.

variations compared with data for Section 05-114. It can also be seen that the monitoring frequency can have a significant impact on capturing the time series cracking data. The effect of frequency is more pronounced in the case of higher variability in the time series data.

In the case of cracking, the point in time when cracks just appear on the surface is critical for preventive actions on the pavement. However, at a lower monitoring frequency (interval of 2 years), time series data, and subsequently the model, may not capture this phenomenon. Conversely, the performance prediction may not be accurate because higher SEs for the model fit could be the result of lower monitoring fre-

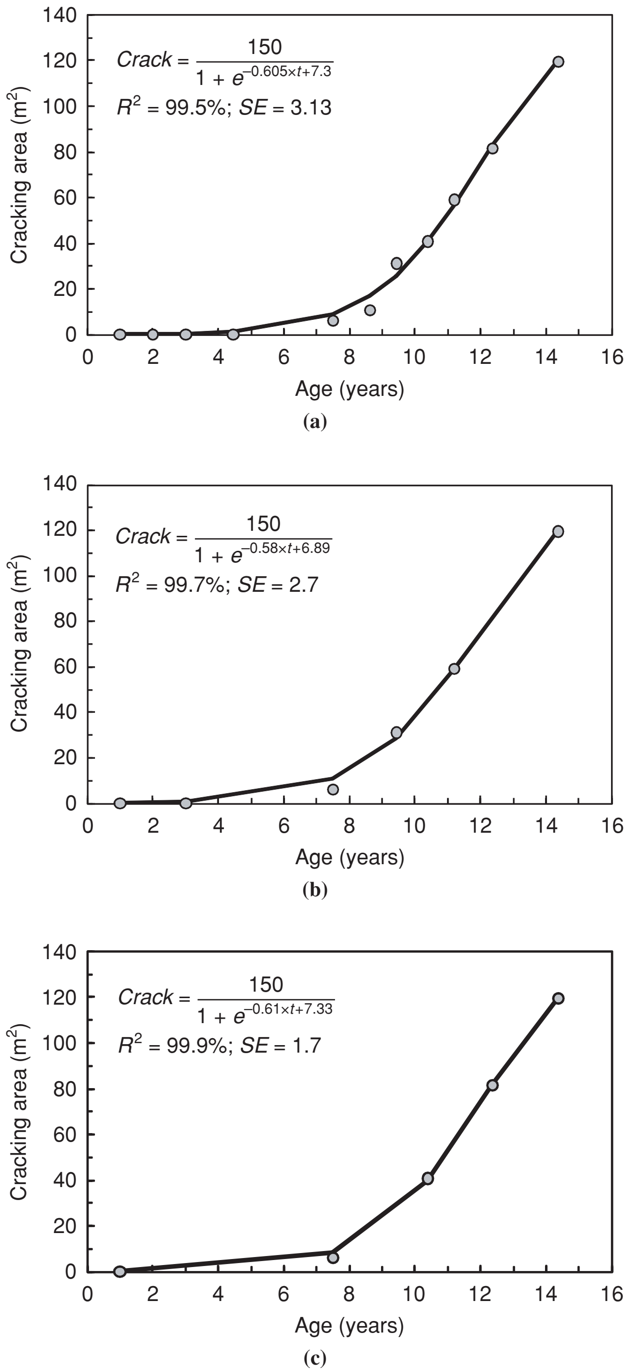

FIGURE 6 Effect of cracking data frequency on performance model, Section 05-114: average monitoring interval of (*a*) 1.31 years, (*b*) 2.4 years, and (*c*) 2.88 years.

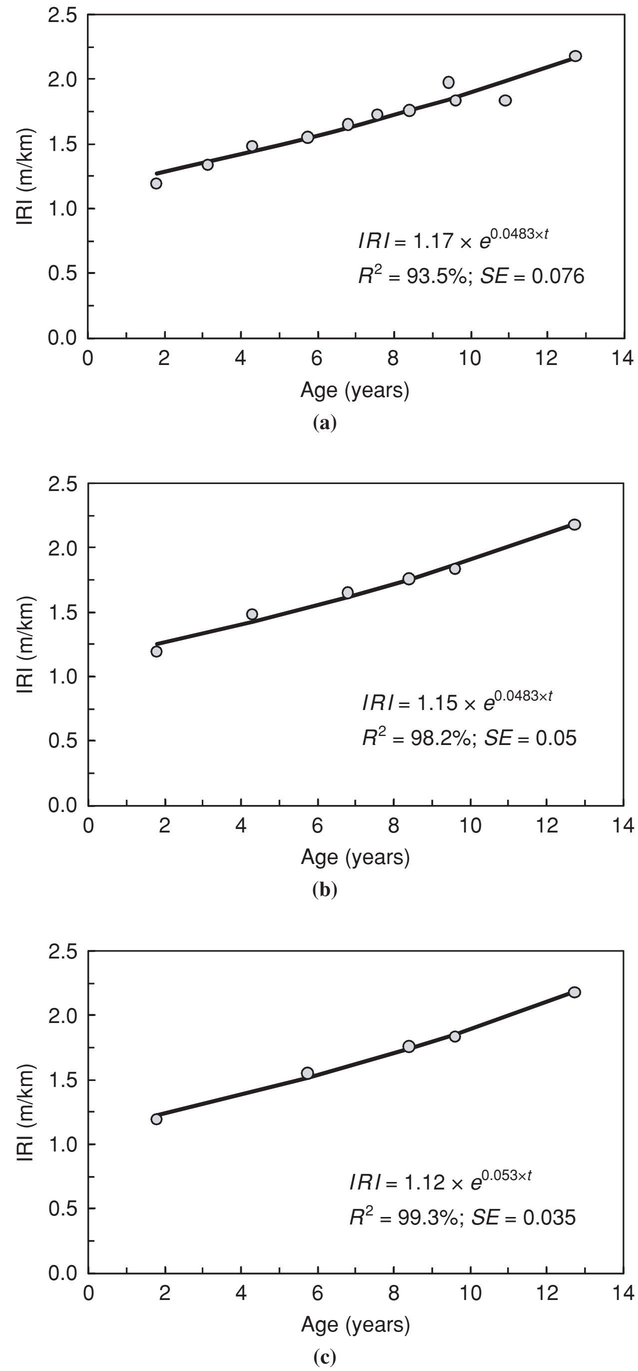

FIGURE 7 Effect of IRI data frequency on performance model, Section 19-101: average monitoring interval of (*a*) 1.16 years, (*b*) 2.12 years, and (*c*) 2.55 years.

quency. Figures 7 and 8 show examples of the IRI time series data for the two SPS-1 pavement sections. The time series data for Section 19-101 have lower variability, leading to a lower SE in the fitted model, whereas data for Section 19-102 show a higher variability and a higher SE for the fitted model.

The effect of the monitoring frequency on the predicted IRI seems minimal in the case of lower data variability. However, the predicted IRI will be significantly affected by a lower monitoring frequency, especially when the variability in the data is high. Also, higher R^2 for the fitted model with increasing monitoring frequency may not guarantee a better performance prediction.

Rigid Pavements

The pavement sections in Figures 9 and 10 show the effect of frequency on the predicted performance through the use of time series transverse cracking data.

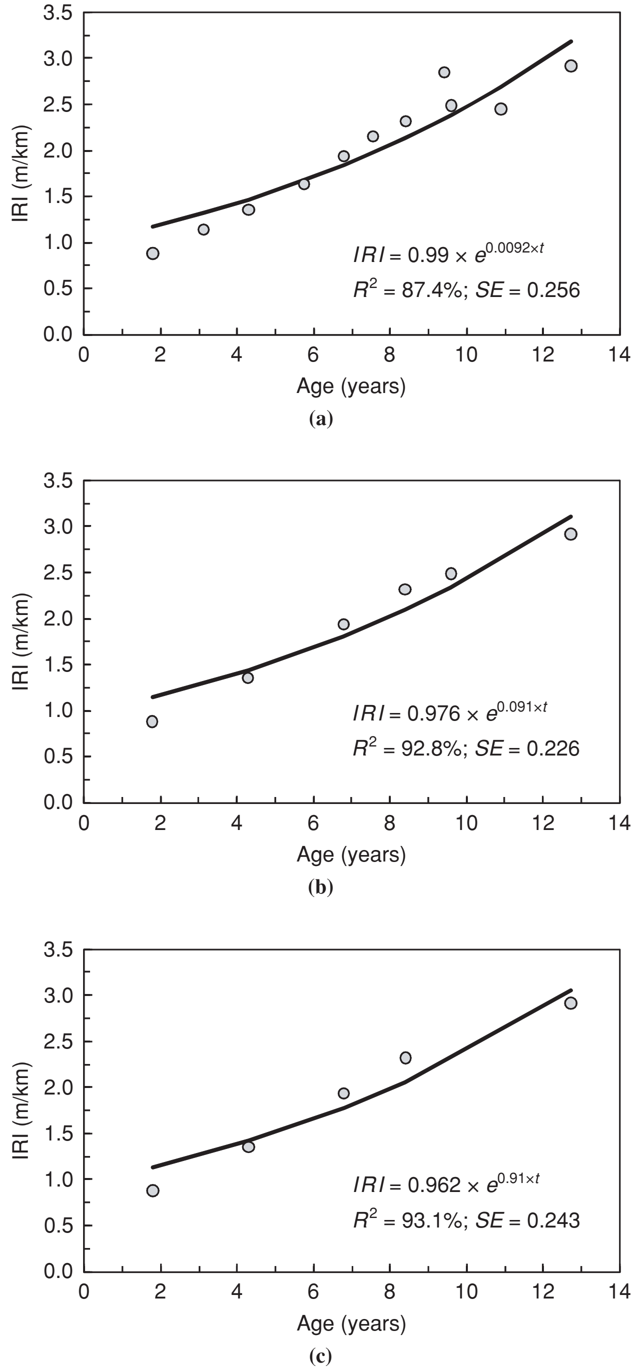

FIGURE 8 Effect of IRI data frequency on performance model, Section 19-102: average monitoring interval of (*a*) 1.16 years, (*b*) 2.12 years, and (*c*) 2.55 years.

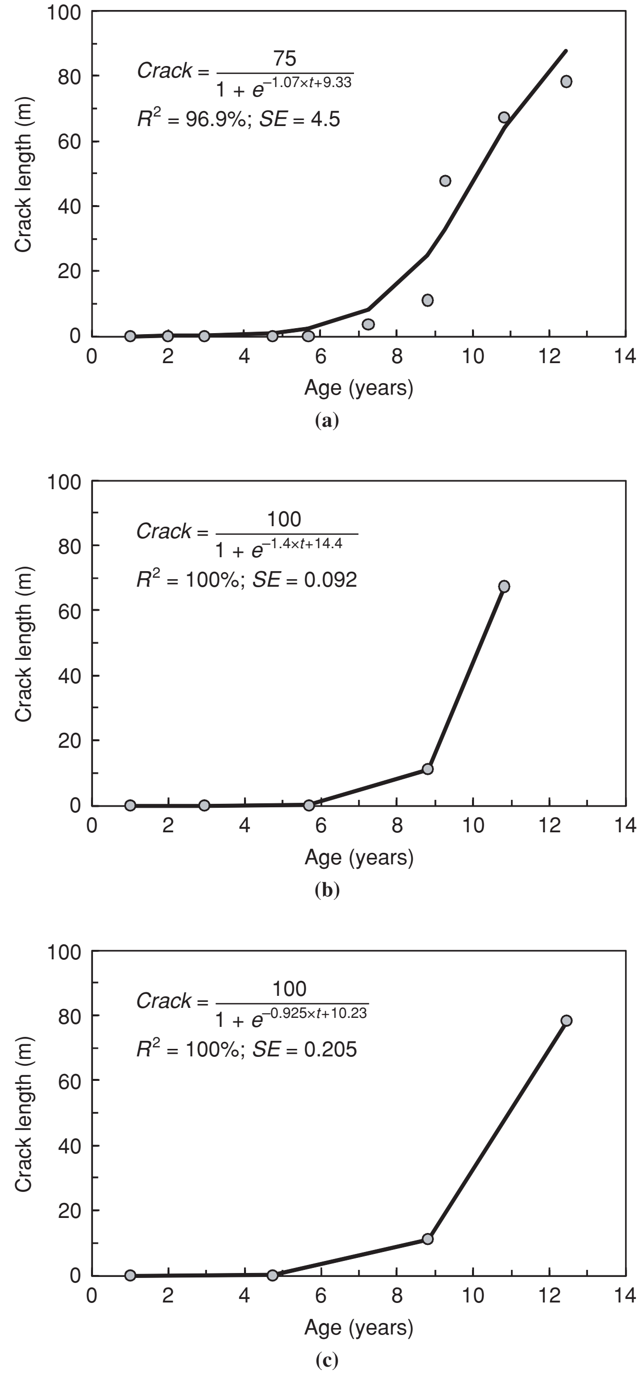

FIGURE 9 Effect of cracking data frequency on performance model, Section 39-204: average monitoring interval of (*a*) 1.24 years, (*b*) 2.16 years, and (*c*) 3.11 years.

The time series data show different variability in the pavement sections. The data for Section 39-204 have higher variations compared with the data for Section 32-207. It can also be seen that the monitoring frequency can have a significant impact on capturing the time series cracking data. Figures 11 and 12 show examples of the IRI time series data for the two SPS-2 pavement sections. The time series data for Section 26-214 have higher variability, whereas data for Section 26-219 show a lower variability. Again, the predicted IRI will be significantly affected by a lower monitoring frequency, especially when the variability in the data is high.

EFFECT OF DATA COLLECTION FREQUENCY ON PAVEMENT PERFORMANCE PREDICTION

Pavement sections from the SPS-1 (new flexible) and the SPS-2 (new rigid) experiments were analyzed in this paper. For each section, time series distress data were considered to examine the effect of monitoring frequency on the performance prediction. For the performance prediction, a logistic (S-shaped) model form was fitted to the cracking data, whereas an exponential model form was used to fit the IRI data. In the case of cracking, for each pavement section, the model was

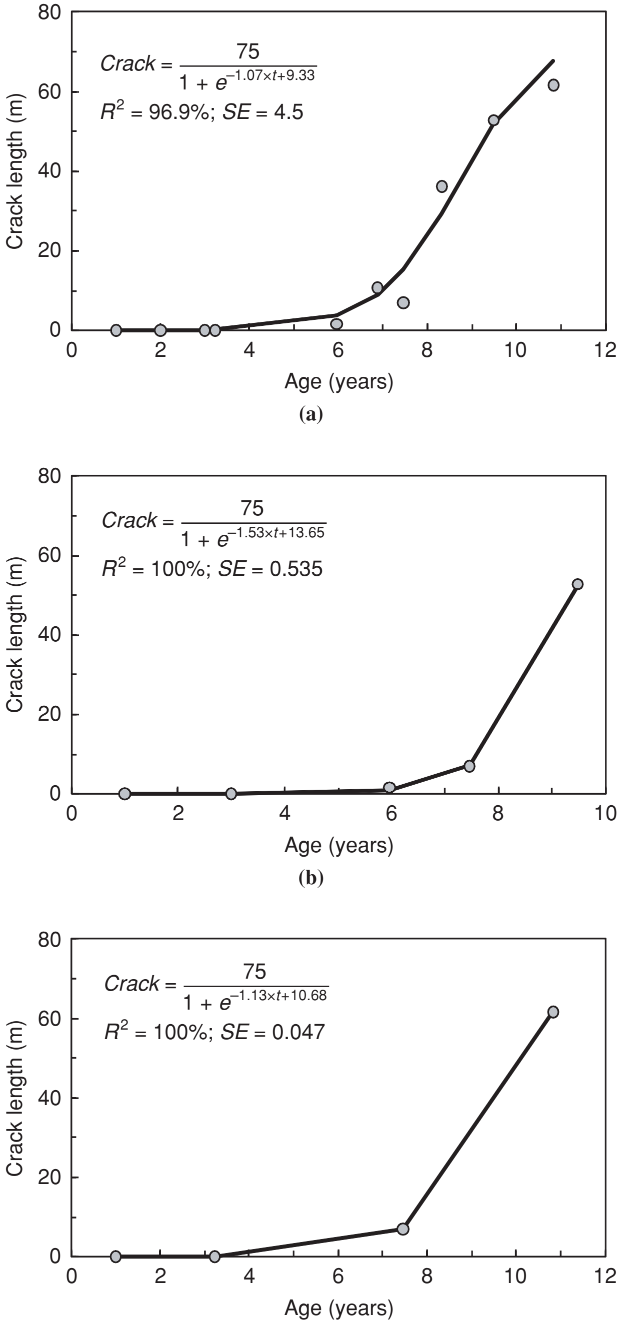

FIGURE 10 Effect of cracking data frequency on performance model, Section 32-207: average monitoring interval of (*a*) 1.08 years, (*b*) 1.9 years, and (*c*) 2.71 years.

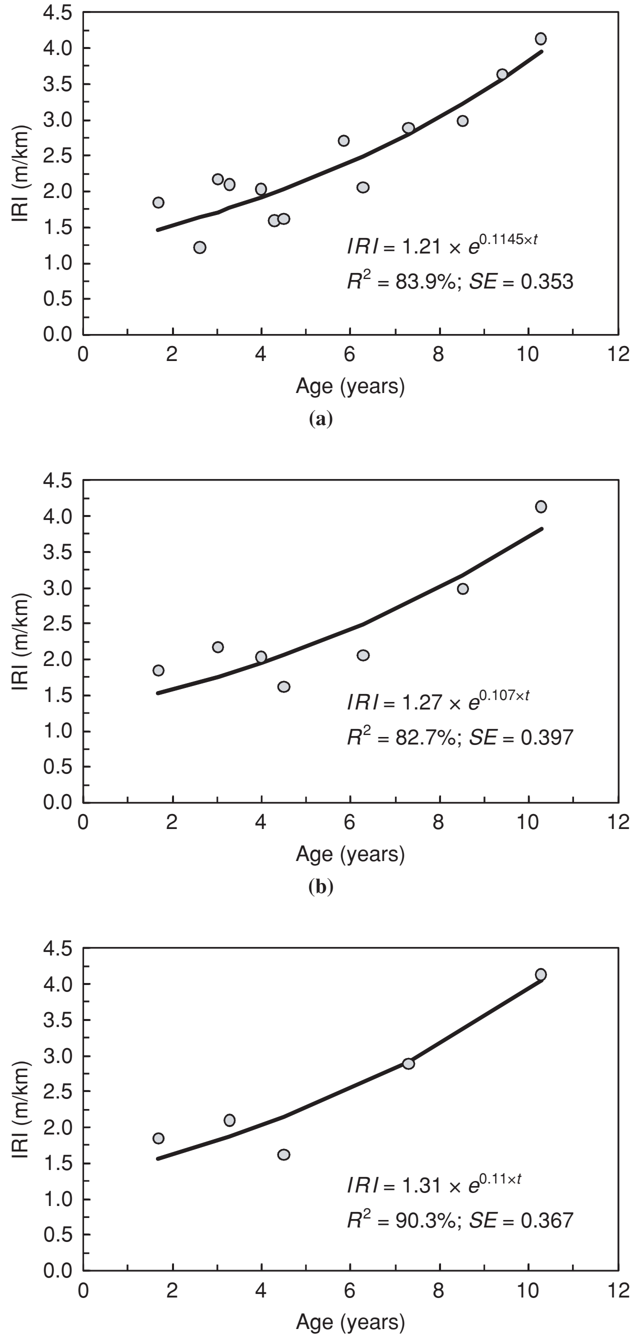

FIGURE 11 Effect of IRI data frequency on performance model, Section 26-214: average monitoring interval of (*a*) 0.79 year, (*b*) 1.47 years, and (*c*) 2.05 years.

used to predict the maximum amount of cracking and the time (years) required to reach it. The maximum threshold for IRI was assumed on the basis of present serviceability index = 2.0 (i.e., IRI = 3.0 m/km) by using existing relationships between the present serviceability rating (PSR) and IRI (*20, 21*), as shown by Equation 8.

$$\mathrm{PSR} = 5'e^{-0.24'\mathrm{IRI}} \qquad (8)$$

The predicted life to reach a given distress threshold (both for cracking and IRI) was estimated for each pavement section for different monitoring frequencies. The RSL was estimated by subtracting the age of the pavement section from the predicted life. At each monitoring frequency, the respective models were refitted to the reduced data within each pavement section. The results of the analysis by pavement type are discussed next.

Flexible Pavements

Tables 1 and 2 present the summary results for all the pavement sections considered in the analysis of alligator cracking and IRI within

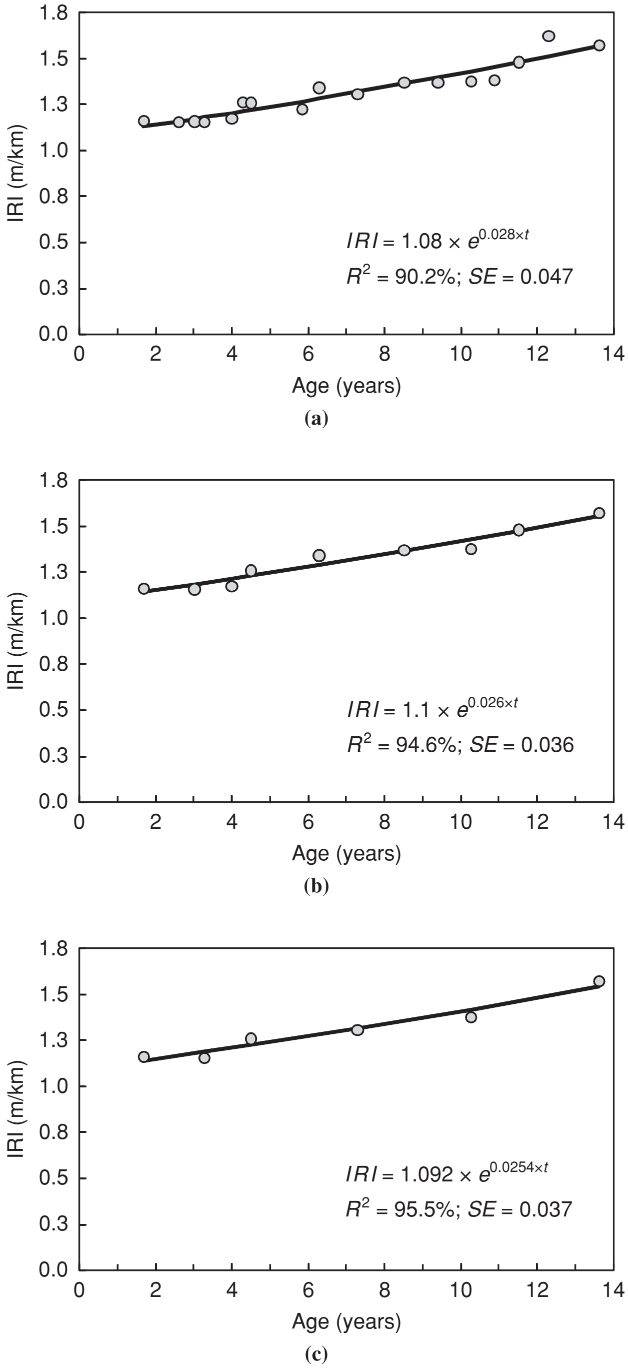

FIGURE 12 Effect of IRI data frequency on performance model, Section 26-219: average monitoring interval of (*a*) 0.8 year, (*b*) 1.51 years, and (*c*) 2.27 years.

the SPS-1 experiment. The monitoring cycles are the number of times the distress data were collected for a particular pavement section until the latest age. The average monitoring interval is determined by dividing the age of a section by the number of monitoring cycles. The SE was determined for each fitted model by using Equation 2. Using the fitted model, the time required to reach a distress threshold was predicted for each pavement section. After the predicted life was estimated, the RSL was determined by subtracting the pavement age from the predicted life. A normalized RSL was also calculated by dividing each RSL with the RSL determined for maximum monitoring cycles within each pavement section. The normalized RSL shows the variation of RSL with the referenced monitoring frequency within each pavement section. The higher the variation in normalized RSL within a pavement section, the more significant is the effect of monitoring frequency on predicted performance. The mean and standard deviation of the predicted RSL are also presented within each pavement section to quantify the uncertainty in the predicted performance caused by variations in the monitoring frequencies. Figure 13 presents the variations in the normalized RSL with monitoring frequency for cracking and IRI of flexible pavement sections. The results show that monitoring frequency of the distresses has a significant effect on the RSL prediction for both types of distresses considered in this study. However, the impact of monitoring frequency will depend on the variability in the actual distress measurements. The results of this limited analysis show that in general if the SE of the fitted model is higher, reducing the monitoring frequency will induce more uncertainty in the performance prediction. As an example, for transverse cracking, Section 51-113, which has a high SE, results in overprediction of RSL by 40% if the monitoring is reduced from 16 to six cycles. However, Sections 5-113 and 5-114, which have a low SE, don't show a change in predicted RSL when monitoring is reduced from 11 to four cycles per year. However, exceptions do exist. For example, Section 1-101, which has a relatively low SE, leads to doubling the predicted RSL when the monitoring cycles are reduced from 17 to seven per year. In contrast, Section 1-102, which has a very high SE, does not lead to much different RSL when monitoring is reduced from 17 to 7. The reason for these two discrepancies is that the data variability in Section 1-101 is highly nonuniform, whereas that in Section 1-102 is quite uniform. For IRI, however, higher SE (Sections 20-105 and 19-102) leads to significantly different RSL predictions, depending on monitoring frequency, whereas lower SE (Sections 26-219, 19-101, and 19-110) leads to essentially identical RSL predictions irrespective of monitoring frequency.

Rigid Pavements

Tables 3 and 4 present the summary of results for all the pavement sections considered in the analysis of transverse cracking and IRI within the SPS-2 experiment. Figure 14 shows the variations in the normalized RSL with monitoring frequency for cracking and IRI of rigid pavement sections. Again, the results show that monitoring frequency of the distresses has a significant effect on the RSL prediction for both types of distress considered in this study. However, the impact of monitoring frequency will depend on the variability in the actual distress measurements. This limited analysis shows that in general if the SE of the fitted model is higher, reducing the monitoring frequency will induce more uncertainty in the performance prediction. For example, this result is seen in the case of cracking for Sections 39-202, 39-204, and 5-218 and in the case of IRI for Section 26-220. In addition, higher variations in the predicted performance are expected for cracking if the monitoring frequency is reduced.

STATISTICAL APPROACH

To quantify the risk of using various data collection frequencies on pavement management decisions, a statistical approach was formulated for image-based (cracking) and sensor-based (roughness) con-

TABLE 1 Effect of Frequency of Flexible Pavement Alligator Cracking Data on Prediction

Number	Section	Monitoring Cycles	Average Interval (years)	SE[a]	Predicted Life (years)	Age (years)	RSL (years)	Normalized RSL	Mean[b]	SD[c]
1	1-101	17	0.82	7.30	33.2	14.0	19.2	1.0	20.33	4.51
	1-101	9	1.55	6.33	30.5	14.0	16.5	0.9		
	1-101	7	2.00	9.50	39.3	14.0	25.3	1.3		
2	1-102	17	0.82	20.73	33.1	14.0	19.1	1.0	18.62	3.08
	1-102	9	1.56	23.40	29.3	14.0	15.3	0.8		
	1-102	7	2.00	13.40	35.4	14.0	21.4	1.1		
3	5-113	11	1.31	4.24	48.1	14.4	33.7	1.0	34.38	1.18
	5-113	6	2.40	4.15	48.1	14.4	33.7	1.0		
	5-113	4	3.09	0.79	48.1	12.4	35.7	1.1		
4	5-114	11	1.31	3.13	31.9	14.4	17.5	1.0	18.14	1.10
	5-114	6	2.40	2.70	33.8	14.4	19.4	1.1		
	5-114	5	2.88	1.70	31.9	14.4	17.5	1.0		
5	51-113	16	0.62	20.00	14.6	9.9	4.7	1.0	5.53	1.03
	51-113	8	1.17	7.80	14.6	9.4	5.2	1.1		
	51-113	6	1.65	10.04	16.6	9.9	6.7	1.4		

[a]Standard error of the fitted model.
[b]Average RSL within a section.
[c]Standard deviation of RSL within a section.

dition data. The same model forms (logistic and exponential, Equations 6 and 7) after linearization were used to fit time series cracking and IRI data. Several simulations were performed by assuming an SE similar to that observed in the field. Based on the SE, an error was introduced in the expected performance curve, assuming a normal distribution at each monitoring interval (e.g., 1, 2, or 3 years) for capturing the variability in the predicted life to reach a given threshold (2.5 in./mi and 20% for IRI and cracking, respectively). Various statistics (SE of fitted model, confidence intervals for mean and predicted distress) were estimated using Equations 3 through 5 for increasing monitoring intervals. The example results for cracking and IRI are presented in Figure 15.

Figure 15*a* shows the expected pavement life and associated 95th confidence band with monitoring interval for 500 simulated performance cracking curves. The results show that expected cracking is somewhat similar for all monitoring intervals, whereas the uncertainty in predicted life increases with low monitoring frequency. Similarly, results for IRI indicate that as the condition monitoring frequency for pavement roughness is decreased, the predicted time to reach a given threshold will become more uncertain (i.e., wider confidence intervals). Figure 15*b* presents the expected pavement life and associated 95th confidence interval for various condition monitoring intervals. Assuming that the smallest monitoring interval represents the "true" expected roughness, Figure 15*b* indicates that lower condition monitoring frequency may lead to overprediction of expected roughness.

In general, most decision making in pavement management systems (PMSs) is based on pavement performance prediction by using the observed or measured pavement performance. However, if the performance prediction (or RSL) is uncertain, or over- or underpredicted, the PMS will be much less effective. One way of quantifying the consequence is to integrate the discussed statistical approach

TABLE 2 Effect of Frequency of Flexible Pavement IRI Data on Prediction

Number	Section	Monitoring Cycles	Average Interval (years)	SE[a]	Predicted Life (years)	Age (years)	RSL (years)	Normalized RSL	Mean[b]	SD[c]
1	20-105	8	1.17	0.20	9.7	9.4	0.3	1.0	0.86	0.73
	20-105	4	2.05	0.19	9.9	8.2	1.7	4.7		
	20-105	3	3.12	0.05	9.9	9.4	0.5	1.6		
2	26-219	8	1.17	0.04	21.6	9.4	12.2	1.0	12.32	0.33
	26-219	4	2.05	0.05	20.9	8.2	12.7	1.0		
	26-219	3	3.12	0.03	21.4	9.4	12.0	1.0		
3	19-101	11	1.16	0.08	19.5	12.7	6.8	1.0	6.34	0.40
	19-101	6	2.12	0.05	19.0	12.7	6.3	0.9		
	19-101	5	2.55	0.04	18.7	12.7	6.0	0.9		
4	19-102	11	1.16	0.26	12.1	12.7	–0.6	1.0	–0.43	0.20
	19-102	6	2.12	0.23	12.3	12.7	–0.4	0.6		
	19-102	5	2.55	0.24	12.5	12.7	–0.2	0.3		
5	19-110	10	1.27	0.10	23.6	12.7	10.9	1.0	10.92	0.27
	19-110	5	2.18	0.12	22.1	10.9	11.2	1.0		
	19-110	4	3.18	0.12	23.4	12.7	10.7	1.0		

[a]Standard error of the fitted model.
[b]Average RSL within a section.
[c]Standard deviation of RSL within a section.

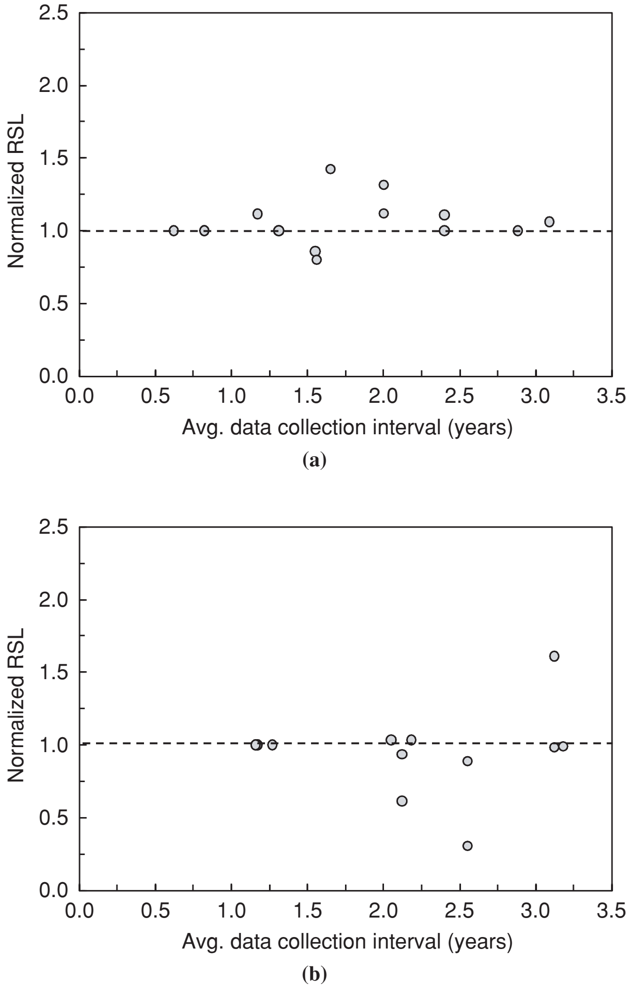

FIGURE 13 Variation of predicted RSL with monitoring frequency, flexible pavements: (*a*) alligator cracking and (*b*) IRI.

with the cost associated with making the wrong decision on the basis of pavement performance prediction.

SUMMARY AND CONCLUSIONS

Time series pavement surface condition data are an essential part of any PMS and pavement performance modeling. Highway agencies collect pavement condition data on a regular basis. However, the frequencies of pavement condition data collection vary among highway agencies. Some agencies collect the data every year. Others do so every 2 years. Still others do it every 3 years. Generally, pavement condition data are collected at two different frequencies according to the method of data collection within an agency: one frequency for pavement surface distress (cracking, patching, etc.) using imaging (videotaping) or manual observation, and the other for sensor-based data (roughness, rut depth, and faulting). The discrepancies between the predicted pavement performance and the observed field performance are functions of the prediction model and the inherent uncertainty in the measured pavement distresses caused by spatial variability such as sampling, measurement errors, and frequency of data collection.

This paper explores the effect of the frequency of pavement condition data monitoring on pavement performance prediction. Samples of pavement sections were analyzed for flexible and rigid pavements. The analyses are based on pavement condition data from several pavement sections in the SPS-1 and SPS-2 experiments of the LTPP. Two types of pavement surface condition data were considered in the analyses: (*a*) structural distress—alligator cracking (flexible pavements) and transverse cracking (rigid pavements) and (*b*) functional distress—roughness (IRI) for both pavement types. Subsequently, two model forms (logistic and exponential) were considered to fit the observed time series distress data. The condition data monitoring frequency was reduced by randomly eliminating adjacent data points within each pavement section. The resulting reduced time series distress data were refitted to the respective model forms.

TABLE 3 Effect of Frequency of Rigid Pavement Transverse Cracking Data on Prediction

Number	Section	Monitoring Cycles	Average Interval (years)	SE[a]	Predicted Life (years)	Age (years)	RSL (years)	Normalized RSL	Mean[b]	SD[c]
1	39-202	9	1.38	10.30	28.1	12.5	15.7	1.0	13.55	2.26
	39-202	5	2.49	8.24	23.6	12.5	11.2	0.7		
	39-202	4	3.10	7.07	26.3	12.5	13.9	0.9		
2	39-204	10	1.24	8.18	24.3	12.5	11.8	1.0	10.46	2.24
	39-204	5	2.16	0.09	18.7	10.8	7.9	0.7		
	39-204	4	3.11	0.21	24.1	12.5	11.6	1.0		
3	37-205	10	1.14	2.08	18.9	11.4	7.5	1.0	8.58	2.90
	37-205	5	2.05	0.14	22.1	10.2	11.9	1.6		
	37-205	4	2.85	0.02	17.8	11.4	6.4	0.9		
4	5-218	10	1.37	9.73	26.5	13.7	12.8	1.0	12.43	2.81
	5-218	5	2.21	8.20	26.1	11.0	15.1	1.2		
	5-218	4	3.43	8.84	23.2	13.7	9.5	0.7		
5	32-207	10	1.08	4.49	19.6	10.8	8.8	1.0	8.15	1.16
	32-207	5	1.90	0.54	16.3	9.5	6.8	0.8		
	32-207	4	2.71	0.05	19.7	10.8	8.9	1.0		
6	4-217	10	1.20	4.42	36.1	11.95	24.1	1.0	22.25	3.83
	4-217	5	2.19	4.92	28.8	10.96	17.8	0.7		
	4-217	4	2.99	6.43	36.7	11.95	24.7	1.0		

[a]Standard error of the fitted model.
[b]Average RSL within a section.
[c]Standard deviation of RSL within a section.

TABLE 4 Effect of Frequency of Rigid Pavement IRI Data on Prediction

Number	Section	Monitoring Cycles	Average Interval (years)	SE[a]	Predicted Life (years)	Age (years)	RSL (years)	Normalized RSL	Mean[b]	SD[c]
1	26-214	13	0.79	0.35	7.9	10.3	−2.4	1.0	−2.46	0.24
	26-214	7	1.47	0.40	8.0	10.3	−2.3	0.9		
	26-214	5	2.05	0.37	7.6	10.3	−2.7	1.1		
2	26-219	17	0.80	0.05	37.2	13.6	23.5	1.0	25.00	1.31
	26-219	9	1.51	0.04	39.0	13.6	25.4	1.1		
	26-219	6	2.27	0.04	39.7	13.6	26.1	1.1		
3	26-220	16	0.85	0.28	22.5	13.6	8.9	1.0	9.14	1.99
	26-220	8	1.54	0.27	23.5	12.3	11.2	1.3		
	26-220	6	2.27	0.28	20.9	13.6	7.3	0.8		
4	26-222	17	0.80	0.12	30.5	13.6	16.9	1.0	15.32	2.28
	26-222	9	1.51	0.13	30.0	13.6	16.4	1.0		
	26-222	6	2.27	0.09	26.3	13.6	12.7	0.8		
5	39-205	12	1.05	0.08	36.4	12.6	23.8	1.0	35.92	23.77
	39-205	6	1.89	0.10	32.0	11.3	20.7	0.9		
	39-205	4	2.52	0.06	73.4	10.1	63.3	2.7		
6	53-208	11	1.22	0.10	23.6	13.4	10.1	1.0	10.68	0.79
	53-208	6	2.24	0.13	23.8	13.4	10.3	1.0		
	53-208	5	2.69	0.08	25.0	13.4	11.6	1.1		

[a]Standard error of the fitted model.
[b]Average RSL within a section.
[c]Standard deviation of RSL within a section.

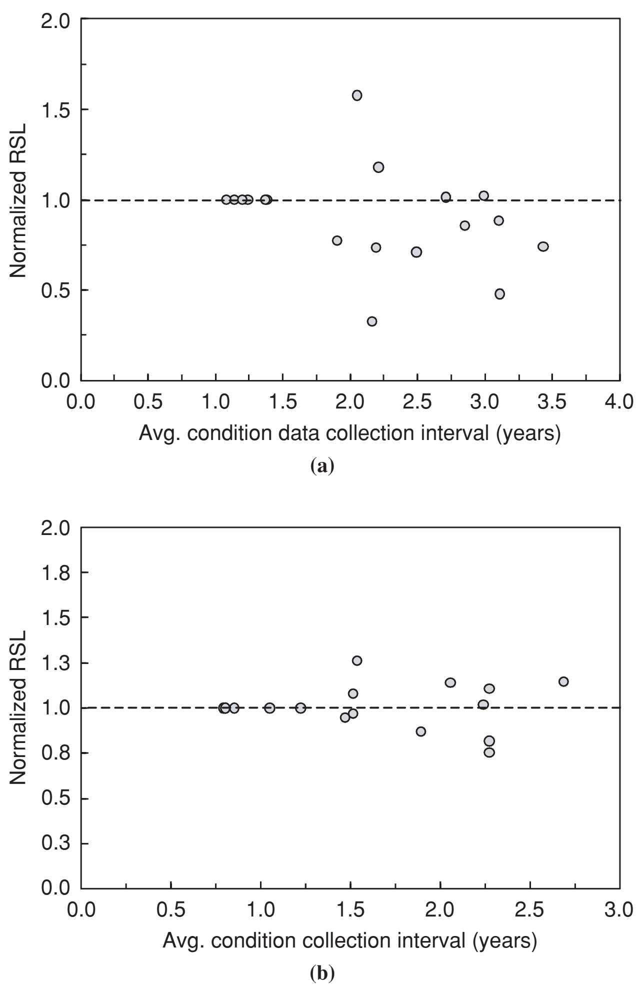

FIGURE 14 Variation of predicted RSL with monitoring frequency, rigid pavements: (*a*) transverse cracking and (*b*) IRI.

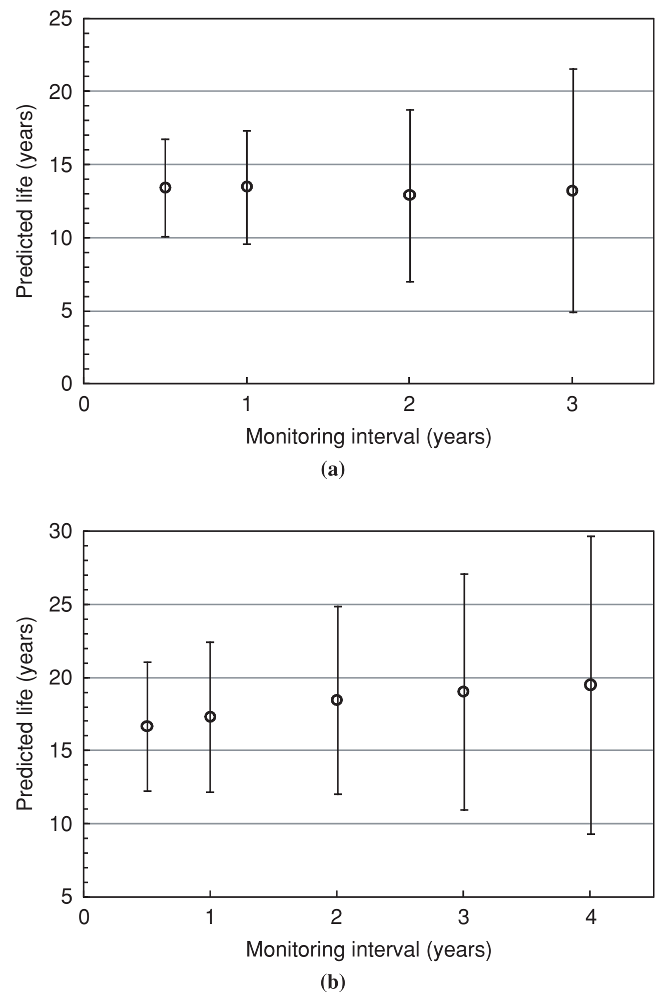

FIGURE 15 Effect of condition monitoring interval on expected life: (*a*) cracking—logistics model form and (*b*) roughness (IRI)—exponential model form.

The distresses were predicted to a fixed distress threshold value within each pavement section. The variations in the predicted performance were analyzed to investigate the effects of monitoring frequency on predictions. On the basis of the analyses, the following preliminary conclusions can be made:

- The frequency of condition data collection has a significant effect on the performance prediction. Lower data collection frequency (i.e., data collection after every 2 or more years) will induce higher uncertainty in the predicted performance. This interaction between the variability in the distress data and monitoring frequency was more clearly seen in the rigid pavement sections; it was less clear in the flexible pavement sections.
- The effect of data collection frequency is more pronounced when the time series distress data have higher variability. Higher variability in the data will introduce higher SE in the fitted model.
- If the condition data can be collected with high accuracy (i.e., low variability), the data collection frequency can be decreased (i.e., every 2 years or so), especially for IRI. This was more clearly seen in the rigid pavement sections.
- The distress predictions also depend on the fitted model form. Higher data collection frequency for structural distresses (cracking in the rigid pavement sections) will reduce the uncertainty in the prediction. The true time series behavior for cracking can be captured only if the pavement is monitored every year.
- The preliminary results of the analyses presented in the paper indicate that there may be a need for more frequent condition data collection for image-based technologies, whereas a lower frequency of condition data collection can be adopted for sensor-based methods.

These conclusions are based only on the performance prediction associated with the frequency of condition data. However, a more realistic approach should include a statistical formulation to quantify the risk in pavement management decisions based on the uncertainty in performance predictions by using different data monitoring frequencies.

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