An Innovative Approach for the Development of Pavement Performance Prediction Models with Limited Historical Data

Amr Ayed, M.Sc., P.Eng. Stantec Consulting 49 Frederick St., Kitchener, ON N2H 6M7 Phone: (519) 585-7464 Fax: (519) 579-7945 Email: amr.ayed@stantec.com

E J (Ed) Clark, P.Eng., Roads and Drainage Engineer City of Burnaby Engineering Operations

Leanne Whiteley-Lagace, M.A.Sc., P.Eng., Pavement Engineer Stantec Consulting

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ABSTRACT

Prediction models are one of the vital components in pavement management systems. Along with decision trees, the prediction models are ultimately used to set the priorities for maintenance planning and budget allocations at the network level. Within a pavement management system, raw performance data is often converted to aggregated performance indices, such as a riding comfort index to quantify the road roughness and a surface distress index to quantify the extent and severity of surface distresses. A historical database with pavement performance indices can be used as a source for the development of prediction models. However, in some cases the database may suffer from incomplete data. In addition to the historical performance data, the age of the pavement or the date of the last major rehabilitation is required to develop a relationship between the performance data and the age of the pavement.

This paper provides a methodology to develop performance prediction models with the absence of the construction or rehabilitation dates. The models developed use the limited historical data and accounts for different parameters such as pavement thickness, traffic, and subgrade classes. The pavement construction dates, or age of the pavement, were incorporated into the proposed model and were constrained based on local experience and engineering judgment. A linear programming technique was employed to develop the performance prediction models. The approach presented in this paper can be expanded to additional parameters and can easily be adapted to different agencies based on their local experience.

INTRODUCTION

Pavement management systems have been extensively used by municipalities across Canada for the last two decades. As a result, many of these municipalities have multiple years of performance data from condition surveys. The three most common performance data recorded for municipalities are roughness, distress, and deflection. The raw data is often converted to a performance indicator (PI) which is used to qualify the pavement performance. It is expected that the pavement will deteriorate over time and that this deterioration can be modeled through the performance indicators. This paper presents a methodology to use the historical roughness and distress performance indicators to develop prediction models for asphalt pavements the City of Burnaby, British Columbia.

Riding Comfort index (RCI)

One of the primary operating characteristics of a road, from the user's perspective, is the roughness, which represents the traveling public's opinion of the smoothness and hence, the quality of service provided by a pavement. The negative consequences associated with pavements with poor ride characteristics include increased:

- vehicle maintenance costs
- decreased vehicle life
- increased fuel consumption
- increased travel time
- vehicle operator discomfort
- safety hazards (in extreme cases)

For years, the City of Burnaby, along with many other municipalities across Canada, have undertaken data collection surveys to record roughness and distress data across their road network.

The ride characteristics of a pavement can be objectively measured by commercially available equipment, which measures the longitudinal profile of the pavement surface. The profile data is then used to calculate an International Roughness Index (IRI) reported at 30-metre intervals. Roughness measurements are correlated to an assessment of ride quality as determined by the ratings of a group of representative users of the pavements. This ride quality indicator is the Riding Comfort Index (RCI). The IRI, and ultimately the RCI, for the pavement section is then based on the RCI for all 30-metre stations included in the section. Theoretically, the RCI can vary from 0.0 to 100, where 0.0 is considered an extremely rough surface and 100 is an extremely smooth surface.

Surface distress index (SDI):

The Surface Distress Index (SDI) is a measure of physical pavement cracking, deformations and surface defects, collectively referred to as distresses. This provides an excellent indicator of material deficiency, rate of deterioration, structural adequacy, environmental and soil type problems. The SDI is, therefore, a key indicator of pavement performance, which may be used to monitor the condition of the network.

For the City of Burnaby, 13 types of distresses are rated in terms of their severity and extent. Similar to the roughness data, the distress data is recorded at each 30-metre stations within each section of the network. The distress ratings are transformed from a 0.0 to 100 scale for

each of the thirteen distresses, which are further combined using distress-specific weighting factors to general an overall SDI for each station. A sectional SDI score is then computed based on these stational SDI scores. The distresses surveyed include:

- Patching
- Rippling & Shoving
- Raveling/Streaking
- Flushing & Bleeding
- Distortion
- Excessive Crown
- Progressive Edge Cracking

- Alligator Cracking
- Potholes
- Block/Map Cracking
- Longitudinal Cracking
- Transverse Cracking
- Wheel Track Rutting

The SDI can vary between 0.0 and 100.0. A value of 100.0 indicates that the pavement surface is free of surface distress defects. Normally, an SDI of 60 to 70 is viewed as the critical range. Scores above this range generally indicate that any distresses that might exist are not severe or extensive in nature, while a score below this range generally indicate that significant distresses exist on the section. A section with an SDI below this range may experience an accelerated deterioration of performance due to rapid ingress of moisture, rapid propagation of cracking, increased susceptibility to freeze / thaw cycles or other factors.

MODELING APPROACH

Several mathematical models have been used in the past to describe pavement performance (1, 2). These models varied from mechanistic-empirical, where a response parameter is related to structural or functional deterioration through regression, to subjective models where experience may be captured through transition matrix such the one used for Markovian models(3). This study combines the two approaches historically used in development of the deterioration models to establish new evolved models that are developed mainly based on mathematical regression and adopted through the use of local historical data and engineering experience.

A sigmoidal (i.e. S-shaped) form is adopted in this study to describe the pavement performance over the age. This model form has a greater degree of flexibility in describing the deterioration of pavement performance as it allows the models produced to be concave, convex, S-shaped, or almost linear. The following is the standard sigmoidal model form used in this study:

$$PI = O - e^{\left(A - B \cdot C^{\ln\left(\frac{1}{Age}\right)}\right)}$$

In this model,

- O represents the initial condition of the pavement, immediately after rehabilitation (at age zero)
- PI is the performance index and could be the RCI or SDI parameter
- Age is the number of years since the last major rehabilitation or construction activity
- Coefficients A, B, and C are the model parameters to be calibrated

Although it is expected that there may be some differences in the initial PI of the rehabilitated pavement section based on the type and thickness of the rehabilitation activity, the initial condition (performance at age 0) for all rehabilitation activities was assumed to have the same value, which is the maximum possible PI value of 100.0 since a new surface is initially expected to be free of distress and have the highest ride comfort level. It should be noted the RCI model, which converts IRI to RCI, has been locally calibrated such that a score of 100 represents an optimal or acceptable roughness level.

DATA AGGREGATION

The data used in this study was extracted from the pavement management system for the City of Burnaby. This pavement management database contains historical data collected over a span of 18 years. Not all sections were surveyed during each data collection survey and surveys were not collected on an annual basis. It is recommended that condition surveys for roughness and distress be collected every 3 years, with either one-third of the network being collected every year or on a recurring 3-year basis for the entire network.

As previously indicated, roughness and distress measurements are collected using automated data collection and then converted into RCI and SDI scores. Table 1 shows the total number of sections that have been extracted from the system with observations. The table also indicates how many sections have records for each performance index, as well as, the number of observations per section. For example, there are 4,176 sections that have RCI performance data, of which, 74 sections have 4 years of RCI performance data.

PI	No. Sections with Observations	No. of Observations per Section					
		1	2	3	4	5	
RCI	4,176	111	1,355	2,630	74	6	
SDI	4,174	109	1,348	2,636	76	5	

Table 1: Number of Sections with Observations by PI

In order to prepare a dataset that can be used for the models development, several steps are needed to filter the data and remove outliers and unrealistic records. The first step is to remove sections that have only one observation since they can not be used to formulate a performance trend. Since it is rare to have sections for long periods without any treatment or rehabilitation activity, sections with two or more observations were further investigated and filtered out if the span between consecutive observations is too long. In addition with the absence of any construction historical records, sections that do not have a deteriorating trend were removed from the dataset that was used for model development, as sections are expected to deteriorate over time. It is assumed that any increase in performance is a result of a rehabilitation-type activity.

MODEL DEVELOPMENT

Design of Experiment

In order to estimate the future rehabilitation requirements of a pavement network, it is necessary to formulate a series of performance curves that model RCI and SDI. The rate of deterioration depends on many factors, including, but not limited to:

- Environment/climate
- Pavement type
- Traffic volume
- Quality of materials used
- Construction quality
- Type of treatment strategy (overlay vs. reconstruction)
- Subgrade strength

However, it can be demonstrated that the principal factors are traffic loadings, properties and thickness of pavement structure layers, and subgrade strength. Therefore, there is a need develop deterioration models specific for each condition and class combination. For this study, three parameters were selected to classify the pavement condition:

- Thickness 3 levels (thin, medium, thick) based on equivalent granular thickness (EGT)
- Traffic 3 levels (low, medium, high) based on average annual daily traffic (AADT)
- Subgrade 2 levels (weak, strong) based on local knowledge of soil properties

Table 2 shows the number of sections that have been used in the model development for each combination of the three performance classes after data aggregation and filtering. These sections shown in Table 2 are for the flexible pavement type only as these represent the vast majority of the road network.

		Thickness	Subgrade	Traffic			
				Low	Medium	High	
Performance Indicator	RCI	Thin	Weak	49	32	292	
			Strong	72	152	111	
		Medium	Weak	21	14	63	
			Strong	30	68	132	
		Thick	Weak	7	6	54	
			Strong	15	27	123	
	SDI	Thin	Weak	45	23	321	
			Strong	84	161	141	
		Medium	Weak	22	21	64	
			Strong	47	67	124	
		Thick	Weak	7	6	58	
			Strong	18	17	95	

Table 2: Number of Sections with Records for Model Performance Classes

Expected Service Life

The service life is defined as the number of years between the implementation of the rehabilitation activity and the age at which the pavement condition reaches its rehabilitation trigger level, which, in this case, is defined to be PI of 60%. That is to say, once a PI reaches 60, it is expected to undergo some form of major rehabilitation, such as a mill and overlay.

In order to develop prediction models for each class combination shown in Table 2, an expected range of service life needs to be established in advance. This expected service life represents the incorporation of experience and engineering judgment into the prediction models. For this study it was assumed that the expected service life for asphalt sections with thick pavement, low traffic volume and a strong subgrade condition would be approximately 20-30 years (model 13 as shown in Table 3) representing the best case condition for a pavement. That is to say, that it will be 20 to 30 years before a pavement with these characteristics will require a major rehabilitation, which is reasonable in a municipal environment especially on local (i.e., low volume) roads. At the other extreme, an asphalt section with a thin pavement structure, high traffic volume and weak subgrade may require major rehabilitation as early as 7 to 10 years given that it has been under-designed based on traffic loading and subgrade strength. As compared to a typical design, this would essentially be considered a premature failure.

It should be noted that the majority of section falls in the "medium" range as would be expected. However, service lives are developed for all cases, including the over-designed (best case) and under-designed (worst case) scenarios.

Accordingly, different service lives for model combinations were estimated and referenced to the best condition as shown in Table 3. It should be noted that these values for maximum and minimum expected service life are flexible and can be tailored to each agency practice and needs.

				Expected Service Life to Reach Trigger Level of 60	
Model ID	Thickness	Traffic	Subgrade	Min	Max
1	Thin	Low	Strong	14	21
2	Thin	Medium	Strong	12	18
3	Thin	High	Strong	10	15
4	Thin	Low	Weak	10	15
5	Thin	Medium	Weak	8	12
6	Thin	High	Weak	7	10
7	Medium	Low	Strong	17	26
8	Medium	Medium	Strong	14	22
9	Medium	High	Strong	12	18
10	Medium	Low	Weak	12	18
11	Medium	Medium	Weak	10	15
12	Medium	High	Weak	8	12
13	Thick	Low	Strong	20	30
14	Thick	Medium	Strong	17	26
15	Thick	High	Strong	14	21
16	Thick	Low	Weak	14	21
17	Thick	Medium	Weak	12	18
18	Thick	High	Weak	10	15

 Table 3: Expected Service Life for Each Model Class Combination

Model Implementation and Optimization

Initial seeds for the coefficients A, B and C were used to produce a preliminary deterioration model, which were based on engineering judgment related to the initial performance of the

pavement. For example, roughness may initially stay at a high level for a couple of years before it starts to deteriorate. On the other hand, it is expected that surface distress will start to develop within the first couple of years after rehabilitation.

This step was performed for each section in the database. As previously indicated, the trigger level for major rehabilitation was assumed to be 60% for all performance indices. Accordingly it is expected that each of the 18 prediction models shown in Table 3 will reach the rehabilitation trigger level within its anticipated range of service life.

The next step was to calculate the error between the measured observations and predicted conditions using the initial prediction model coefficients as shown in Figure 1. The least square error was calculated for each observation and summed for each section as shown in the following equation:

$$\sum (x_i - y_i)^2$$

where x_i is the measured value and y_i is the predicted value at the same age. The least squares fitting is a mathematical procedure for finding the best-fitting curve to a given set of points by minimizing the sum of the squares of the offsets, or residuals, of the points from the curve (4).

Excel solver which employs linear programming optimization technique was used to minimize the error between measured and predicted performance index for each section. The optimization process was constrained so that expected service life for each section should fall within the expected range as shown in Table 3. Figure 2 shows the final RCI model for one selected section from the database after running optimization procedure.



Figure 1: Prediction Models before Optimization



Figure 2: Prediction Models after Optimization

Deterioration Model Results

Optimization to minimize the error in prediction was applied for each section and accordingly a value for A, B and C coefficients were obtained which represent the most representative prediction model that characterize the change in performance over the pavement life. The coefficients were grouped and averaged for each model class combination. The previous steps were applied to both performance indices presented in this study: RCI and SDI.

Due to the lack of data near the end of the pavement life, the models resulted in performance classes not reaching the terminal value of 20 - a point at which total reconstruction is expected. As such the models were modified after the trigger level such that their rate of deterioration remained constant after the expected rehabilitation trigger level. A tangent was drawn once the performance curve reached the trigger level. Figure 3 and Figure 4 show the final developed RCI and SDI models, respectively, for the City of Burnaby



Figure 3: Final RCI Models for each Class Combination



Figure 4: Final SDI Models for each Class Combination

FUTURE ENHANCEMENTS

The predictions models are based on the assumption that the current performance classification is applicable to all historical records. In reality, there may be cases where traffic volumes have increased such that a particular section has moved from one performance class level to another. However, filtering these sections from the analysis would further reduce the number of sections being used for modeling. Moreover, these cases are most likely to represent the lower end of the service life range, that is to say if a section has seen a significant increase in traffic volume, it will likely have a higher rate of deterioration, thereby representing the lower end of the service life range.

It's important to note that prediction models are intended to represent the "average" or "typical" conditions. Prediction models are not representative of the super-achievers (pavements that far exceed their expected service life) or the premature failures, which are often due to construction or material quality issues.

Due to the sections being classified into different performance classes, these prediction models can easily be expanded to include other factors, such as climate or environmental zones. They can also be expanded to include other performance indicators or other performance data stored within the pavement management system.

The key to model development such as this is the pavement management system itself: how well it is maintained and how often the data is collected and/or updated. Any data not captured in the database, can then not be captured in the modeling.

CONCLUSIONS

This paper has provided an approach to prediction model development using data from an existing pavement management system.

- Through data aggregation and filtering of the pavement management system data, observations were grouped into 18 performance classes
- Performance classes represent various levels of pavement thickness, traffic, and subgrade condition
- Based on engineering judgment and local experience, expected ranges of service were developed for each performance class
- A sigmoidal model was used due to its flexibility in terms of describing the deterioration of pavement performance
- Initial sigmoidal model coefficients were developed based on engineering judgment and local experience
- Model coefficients were developed for each section in the database and the least squares error was calculate and summed for each section
- A linear programming optimization technique was employed to minimize the error for each section
- The optimization included a constraint to limit the service life to the pre-defined expected service lives for each performance class
- The various coefficients were evaluated to determine the most representative coefficients for each performance class

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