Predicting Pervious Concrete Pavement Performance for Usage in Cold Climates

by

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AUTHOR'S DECLARATION

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Abstract

Pervious Concrete Pavement (PCP) has the potential to provide significant benefits. To better understand the technical, economical, and environmental impacts of PCP, the performance must be comprehensively evaluated and quantified. Because PCP is a new material, there is no mechanism for properly quantifying its performance. In addition, the application of this technology in cold climates is limited and therefore limited in-service performance data is available.

A comprehensive engineering based performance model quantifies the deterioration rate and predicts future performance. Pavement performance models are developed using a pavement condition index and extensive pavement condition databases. A pavement condition index is a value which expresses the overall condition of pavement by considering various factors such as surface distresses, structural defects, and ride quality. This research will assist pavement engineers and managers in the design, construction, and management of PCP.

The review of published literature reveals that there is currently a large gap in the performance evaluation of PCP in cold climates. Neither extensive condition indices nor comprehensive performance models have been developed for PCP. This research involves development of comprehensive performance models for PCP in cold climates using laboratory and field experiments and existing available data in order to predict functionality (permeability rate) and surface distresses of PCP. This study is, furthermore, aimed at developing an extensive condition index for better management of PCP by predicting and quantifying the various types of distresses and the associated functionality of PCP with particular emphasis on cold climate usage and performance.

The scope of this research is to design a comprehensive tool which is simple and cost-effective. The tool involves first defining the typical types of distresses that are occurring on PCP. This is facilitated through laboratory and field design, construction, and evaluation of two test sites located in Ontario. It also involves continuous evaluation of these sites and evaluation of several other sites in the United States. The main sources of data in this research are panel rating data and field investigations data. A panel rates the condition of PCP in terms of surface distresses and permeability rates. In addition to this, field measurements of distresses and permeability rates are obtained manually. As a result, the Pervious Concrete Condition Index (PCCI) is developed through incorporation of field measurements and panel ratings. By using regression analysis, performance models are developed between PCCI and pavement age. The performance models are validated using the data splitting technique.

Ultimately, the performance models are calibrated using field data by applying the Markov Chain process (acquiring expert knowledge by distributing questionnaires) and the Bayesian technique.

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Finally, I would like to express my deepest gratitude to my wife and my son for their understanding and sharing many hours rightfully theirs. Without their encouragement and love this work could not have been completed. I would also thank my kind-hearted mother for her patience during my studies in Canada.

Dedication

This thesis is dedicated to my lovely wife, Zahra Golrounia, and my brilliant son, Amirtaha Golroo.

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Chapter 1
Introduction

1.1 BACKGROUND

Pervious concrete has the potential to provide many beneficial environmental impacts in cold climates. It has several features that serve environmental demands, such as reducing the volume of stormwater runoff, reducing noise, minimizing heat, protecting native ecosystems, recharging ground water, and protecting tree growth. The use of pervious concrete is thus a best management practice recommended by the Environmental Protection Agency (EPA) (Tennis et al. 2004). Pervious Concrete Pavement (PCP), moreover, improves traffic safety since it increases skid resistance (Water Environment Research Foundation 2005). Adequate pervious pavement infiltration can also reduce the need for sewer facilities. PCP may reduce the potential for legal problems for an owner or developer by reducing the need for stormwater ponds and subsequent safety i.e., drowning, etc. However, there are some key functional considerations, such as a high void ratio, low strength, and possible susceptibility to freeze-thaw damage in cold climates.

Several experimental research studies preliminary for use in warm climates have been conducted on pervious concrete properties. Various mix designs have been tested to develop pervious concrete that not only has adequate porosity for infiltration of stormwater but that also has the desirable strength and freeze-thaw durability (Schaefer et al. 2006). In terms of water quality, the water purification properties of pervious concrete have been evaluated by the removal amount of total phosphorus and total nitrogen (Xu et al. 2006). Pervious concrete made with smaller sized aggregate and higher void ratio is recognized to have a better capability to remove the aforementioned materials (Xu et al. 2006). Several researchers have studied the specifications of pervious concrete. For instance, Tennis et al. (2004) determined that the void ratio of pervious concrete should be between 15% and 25%, with a permeability rate of approximately 0.34 cm/s. Pervious concrete can achieve strengths in excess of 20 MPa and flexural strength of more than 3.5 MPa. On the other hand, using smaller sized aggregate, silica fume (SF), and superplasticizer (SP) can considerably improve the strength of pervious concrete and result in higher values. The compressive and flexural strength of the pervious concrete may reach 50 MPa and 6 MPa, respectively (Yang and Jiang 2003). In the preliminary laboratory research done as a part of this study, 24.7 MPa and 5.7 MPa have been achieved for compressive and flexural strength, respectively (Golroo and Tighe 2007).

Although PCP has been widely acknowledged in terms of laboratory performance and field performance in non freeze environments, it appears that few research studies have evaluated the performance of PCP in cold climates. In particular, PCP performance has not been investigated in a systematic way that incorporates the impact of winter maintenance and performance in cold climates with identification of typical distresses and progression over time. To assess pavement performance in such conditions, long term pavement monitoring and data collection are required. Since PCP use is relatively novel in cold climates, laboratory and field data and research are required.

Once PCP performance has been investigated, an appropriate condition index needs to be determined. Only a few PCP condition indices have been proposed by researchers. These indices, however, are not comprehensive. For example, pavement strength (Eller and Izevbekhai 2007), its permeability rate (Haselbach et al. 2006), and the quality of stormwater treatment (Briggs et al. 2006) are some of the proposed indices. However, these indices are not able to extensively describe condition of PCP over time.

In order to overcome the lack of data and knowledge on PCP performance, various distresses that are associated with PCP should be indicated. For this purpose and ultimately to obtain a performance model for PCP, different pervious concrete sites should be observed and evaluated through incorporation of an appropriate condition index throughout their service life on a regular basis. The ACI Committee 522 (2006), for instance, proposed clogging, structural stresses, and freeze thaw damage as appropriate PCP characteristics for evaluation.

In this research, performance models for PCP are developed that use field experiments and available PCP performance data from existing research studies. In addition, the development of a comprehensive condition index is proposed for PCP, along with the corresponding methodology.

1.2 PROBLEM STATEMENT AND RESEARCH NEED

The assessment of pavement performance includes a study of the functional behavior of a section or length of pavement. For functional or performance analyses, extensive information is required on the riding quality, structural adequacy, and surface distress of the pavement over a specific time period. Periodic pavement observations and measurements should be performed to gather this data. This data history demonstrates the deterioration of serviceability of the pavement during its service life. The serviceability-performance concept has been acknowledged as an important part of pavement technology since the 1960s. In fact, development of an appropriate model for predicting pavement performance in terms of the Pavement Serviceability Index (PSI), the Riding Comfort Index (RCI), or other applicable condition indices versus age or accumulated axle load application has been a major challenge for technologists, engineers, and transportation managers.

A review of existing literature has demonstrated some advancement in the development of various pavement performance prediction models and different condition indices for various types of pavement.

However, PCP has not been fully investigated in terms of performance models and pavement condition indices. While, several research studies have evaluated the characteristics of pervious concrete with respect to mix design, stormwater management, and compressive strength, very limited research has been carried out to address the long-term performance of PCP in cold climates with particular emphasis on freeze thaw performance. A comprehensive study is required to investigate an appropriate PCP index and to develop performance models that are appropriate for the cold climates (e.g., Canadian climate). The research study presented herein is an initiative toward that goal.

The deficiencies in the available research and studies on PCP performance are as follows:

I) Most studies focused only on permeability rate as an indicator for evaluating PCP performance.

II) A few studies have investigated other characteristics of PCP such as surface distresses (e.g., ravelling and polishing) and structural adequacy (e.g., cracking). However, these parameters were seldom evaluated in the same context.

III) A PCP distress evaluation guideline is not available, yet is fundamental for managing PCP.

IV) No study has attempted to develop an extensive pavement condition index for PCP.

V) There is no adequate understanding of how these structures will perform under cold climates and typical freeze thaw conditions.

VI) No performance models have been developed for PCP and understanding of PCP performance is vital to the development of such models.

1.3 RESEARCH OBJECTIVES

The proposed research will investigate PCP performance with the following objectives in mind:

1) Integrating available PCP performance data and field testing capabilities to study PCP performance,

2) Developing pavement segmentations for PCP with respect to its attributes (e.g., pavement age, traffic load, environment condition, and pervious concrete thickness),

3) Monitoring PCP distresses and developing a pavement evaluation guideline for PCP for related agencies to aid in pavement distress assessment,

4) Evaluating various pavement condition indices and associated methodologies and developing an appropriate pavement condition index for PCP that allows consideration of associated distresses,

5) Assessing various types of pavement performance models and developing PCP performance models

1.4 SCOPE OF RESEARCH

As mentioned, studies on PCP performance from the Canadian perspective are scarce and inadequate in quantifying a condition index for PCP and predicting its performance. The proposed research study will include extensive field experiments of PCP performance with particular emphasis on better understanding the way PCP performs in cold climates. The limited field data available from various agencies working on PCP performance will be evaluated and incorporated into this study. The scope of this research is as follows:

1) Review the relevant literature and summarize the achievements to date, including methodologies and models.

2) Periodically test performance of available PCP parking lots, which were constructed as a part of this study and measure their performance in terms of permeability rates and pavement distresses.

3) Conduct surveys by organizing rating panels that will determine the pavement condition ratings of various PCP parking lots.

4) Distribute questionnaires to experts in order to study the performance of PCP incorporating the Markov Chain technique. Develop appropriate pavement categories for PCP according to its traffic loads, pavement age, and pervious concrete thickness.

5) Develop Transition Probability Matrices (TPM) in accordance with expert knowledge for the various PCP categories.

6) Develop adequate pavement condition indices for PCP incorporating suitable methodologies (i.e., an adjusted MTO protocol and a proposed methodology).

7) Develop defendable performance models for PCP based on the field investigations conducted in this program and supplement with any available literature.

1.5 THESIS ORGANIZATION

An introduction has been presented in this chapter, with relevant background and presentation of the problem statement and research needs, research objectives, and research scope. Chapter 2 provides an overview of major topics associated with pavement performance modeling. A summary of relevant research studies with models and methodologies is provided in Chapter 3. Chapter 4 presents the research approach, data collection and preparation. Chapter 5 provides a detailed data analysis and results. The developed PCP performance models are presented in Chapter 6. Finally, Chapter 7 provides conclusion and recommendation for future work. This thesis ends by providing a list of references.

Chapter 2
Overview of Pavement Performance Modeling

This chapter presents an overview of the major factors associated with Pervious Concrete Pavement (PCP) performance. It encompasses an overview of pervious concrete and its characteristics, pavement condition indices, pavement performance models, and issues related to these concepts.

2.1 PERVIOUS CONCRETE

"Pervious concrete" is a term that is applied to zero-slump material that allows water to infiltrate through it and be recharged as ground-water. This open-graded cast-in-place material consists of portland cement, coarse aggregate, little or no fine aggregate, water, and admixtures. These ingredients produce hardened concrete with connected voids (American Concrete Institute 2006).

The void ratio ranges between 15% and 25%; its permeability rate is approximately 0.34 cm/s. Properly placed pervious concrete can achieve compressive strengths in excess of 20 MPa and flexural strength of more than 3.5 MPa (Tennis et al. 2004).

Pervious concrete is of significant importance in stormwater management and water quality control. Engineers have realized that runoff has potential impacts on surface and groundwater supplies. As land is developed, impervious areas increase, which results in increasing runoff volume leading to downsream flooding and bank erosion. Not only does PCP reduce the effect of land development by decreasing the runoff, it also protects water supplies (American Concrete Institute 2006). The use of pervious concrete is one of the Best Management Practices (BMP) recommended by the Environmental Protection Agency (EPA) (Tennis et al. 2004). Most importantly from a pavement engineers' perspective, having a reduced amount of runoff may improve the level of road safety. In addition, pervious concrete has several other beneficial specifications such as reducing noise, minimizing heat, protecting native ecosystems, recharging ground water, and protecting tree growth.

2.2 PERVIOUS CONCRETE CHARACTERIZATIONS

2.2.1 Compressive Strength

Several parameters affect the compressive strength of pervious concrete which include the void ratio, amounts of fine aggregate, admixtures, and the compaction level of pavement during installation. Generally, a high void ratio leads to lower compressive strength. Therefore, pervious concrete applications have been limited mostly to low volume roads, parking lots, driveways, and walkways. In addition, its performance in cold climates is a concern as open structures may be susceptible to freeze thaw damage.

However, further research is required to enhance the strength and durability of pervious concrete. The ability of pervious concrete to withstand heavy traffic (highways traffic) will result in its wide application. It is desirable to use PCP for applications such as highways (cover large areas in each city) since these highways significantly decrease impervious areas resulting in reducing runoff. In laboratory studies, Yang and Jiang (2003) reported that a composite consisting of pervious concrete for both a surface layer and a base layer with different gradations obtained a compressive strength of 50 MPa and a flexural strength of 6 MPa.

2.2.2 Freeze Thaw Durability

There is a difference between the void structure of pervious concrete and the entrained air in regular portland cement concrete. The entranced air is the air voids intentionally incorporated into concrete while, the void structure includes both entrained air and entrapped air (naturally entrapped in the concrete during mixing). If PCP is installed and maintained, water should not stay in the void structure; it drains through the pervious concrete to an underlying drainage layer and soil, as shown in Figure 2-1. If the pervious layer is saturated and subjected to freezing, water will not drain through. Consequently, if water freeze in this layer, it causes expansion, leading to deterioration of PCP. Thus, fully saturated non-air-entrained PCP performs poorly during the freezing and thawing cycles typically observed in Canada (American Concrete Institute 2006).

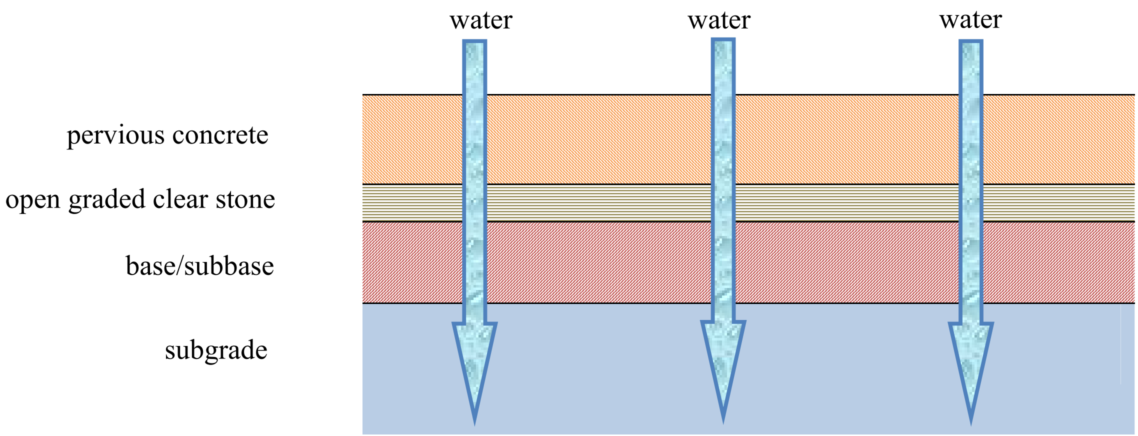


Figure 2-1 PCP Cross Section.

Some researchers claim that the laboratory freeze thaw testing protocol, ASTM C 666 (2007) is not an appropriate or relevant method for assessing the durability of pervious concrete to freezing and thawing regarding the fact that it cannot simulate the PCP performance in the field (American Concrete Institute 2006).

2.2.3 Hydrological Property

Another benefit of PCP is that the pavement structure reduces runoff volume, and reduces the impervious area on the site (American Concrete Institute 2006). The runoff can be stored in the pavement structure as opposed to requiring large stormwater ponds. However, the water will still require treatment to minimize its contaminations. Treatment volume is the quantity of stormwater that should be treated before leaving a property. Buildings, sidewalks, and conventional pavements are common examples of impervious areas that do not allow infiltration of rainfall at the start of a rainfall event (American Concrete Institute 2006).

2.3 PAVEMENT CONDITION DATA

The condition of pavement can generally be defined in terms of pavement roughness, pavement structural adequacy, pavement surface condition, and pavement safety (Haas 1997).

2.3.1 Pavement Roughness

The serviceability of a pavement section is described as its ability to accommodate road users at a reasonable level of comfort (Carey and Irick 1960). At any point in the life cycle of a pavement section, serviceability is a function of a set of factors: parameter accounting for construction quality, thickness and types of the individual pavement layers, stiffness of the pavement layers, subgrade type and moisture conditions, environmental conditions, types and effectiveness of maintenance activities, and traffic composition and loading. Roughness of a pavement surface describes user comfort level. Roughness is defined as " a distortion of the pavement surface that contributes to an undesirable or uncomfortable ride" (Hudson 1978). The distortion may be due to defects in the construction or deterioration because of traffic and environmental conditions.

The impact of the roughness level on vehicles depends on specific factors, such as the severity of pavement distortion, vehicle suspension characteristics, and speed of vehicles. The impact on users (serviceability) is difficult to measure due to differences in the dynamic response of each vehicle traversing the pavement. However, several attempts have been made to quantify pavement roughness. Three main methods and devices have been developed to do so: a profile measuring device, a response measuring device, and subjective rating (Haas 1997).

2.3.2 Pavement Structural Adequacy

Another important criterion at both the project and network levels of pavement management is to collect pavement condition data and to determine pavement structural adequacy. The evaluation of structural adequacy can be carried out either by an evaluation of pavement materials and subgrade or through direct field measurements. Structural adequacy of a pavement section has a significant correlation with its ability to withstand its traffic load at a reasonable level of service. Thus, structural adequacy can assist in the development of pavement performance and its remaining service life.

Structural adequacy can be measured by two major methods: destructive and nondestructive. Destructive methods involve probe holes, and coring and sampling for laboratory material characteristics. Nondestructive methods involve surface deflection distress testing (Falling Weight Deflectometer (FWD), Heavy Weight Deflectometer (HWD), Dynaflect, Road Rater, Benkelman Beam, and Plate Road) and Spectral Analysis of Surface Wave (SASW) techniques (Haas et al. 1994). Although deflection measurement may not normally be measured throughout a transport network, some agencies responsible for small networks can afford to collect continuous deflection measurements on major roads using rapid bearing capacity measuring instruments such as the Belgian Curviameter, which can collect continuous deflection measurements at 18 kph (Gorski 1999).

2.3.3 Pavement Surface Condition

An important factor of pavement condition evaluation is surface assessment, which provides authorities with the ability to maintain required levels of service and to plan for maintenance actions. One adequate technique involves a surface distress survey. Most agencies conduct surveys through visual inspection and rate of all irregularities, defects, and flaws contained within specific areas of pavement. Most agencies have developed their own pavement distress survey manual e.g., the Ministry of Transportation of Ontario manual (Chong and Wrong 1995) and Long-Term Pavement Performance manual (SHRP 2003; SHRP 2003; SHRP 2003). This manual extensively explains the procedures for detecting various distress types. Automated and semi-automated methods of performing distress surveys have also been developed (e.g., ARAN, ARIA, and VIV) (Tighe et al. 2008).

Pavement surface distress is affected by principal factors such as material deficiency, construction deficiency, environmental and climatic conditions, and traffic loadings. Distress surveys should encompass a reasonable level of detail to address pavement surface conditions properly. Some methods indicate the location of the distress recorded. Most survey methods express the following factors: type of distress, severity of distress (various levels), density of distress (different levels or percentage of the associated area).

The type and severity of distresses may provide information about their cause. For instance, structural defects represent themselves as visible load-related distresses such as cracking. The results of distress evaluation together with the cause of each distress may suggest an appropriate maintenance action. A single numerical value generally summarizes the information from a distress survey such as PCI (i.e., the Pavement Condition Index) which can be applied alone for assessment of a pavement section or with other measures of pavement condition such as functionality or ride quality.

2.4 MANUAL PAVEMENT CONDITION DATA COLLECTION STRATEGIES

Data collection is the foundation of all management systems and help with both network and project-level activities and decisions. For example, detailed project-level data for design, construction, and maintenance could simply be made available for subsequent network level use.

2.4.1 Pavement Condition Evaluation by a Panel Rating

A panel of raters can be useful for collecting data when comprehensive data inventory is not readily available as is often the case with new materials and products. In this method, a rating panel is conducted and brought to sites. The raters then rate rideability or surface distresses of pavement either from vehicle running at lower speed or by walking on the pavement. The raters are asked to rate the pavement based on a defined scale (e.g., from very good to very poor or from 10 (perfect) to 0 (failure)). This method has been widely applied in the development of a condition index for a new type of pavement but has not been extensively investigated (Karan 1977). Namely, a panel rating is not typically used to collect condition data at the network level, but it assists to convert the data collected into indices.

2.4.2 Pavement Condition Evaluation by Sampling

The visual assessment of pavement distresses is still common practice for project level management with many transportation agencies. However, it is impracticable to collect detailed visual data for every section in a network using the manual data collection method. The process for visual data collection is to record distresses observed on the pavement together with their severity and density levels. Each agency has its own protocol for collecting data. These protocols are different according to the types of distresses to be detected for each type of pavements and levels of severity and density (Ningyuan et al. 2004).

Both mentioned methods are applied to collect pavement condition data. The first method provides an overall condition index such as roughness or appearance while, the second method can provide detailed information about pavement distresses.

2.5 PAVEMENT CONDITION INDICES

Functional performance of a pavement section is generally evaluated from the user perspective with measures or indicators such as quality or level of service, system effectiveness, productivity and efficiency, and resource utilization and cost-effectiveness (Goodwin and Peterson 1984). Alternatively, the technical evaluation of pavement performance is of significance to engineers. It includes a measure of mechanistic behavior and physical deterioration and results in correct selection of maintenance, rehabilitation, and replacement alternatives. Thus, it is important to include users, engineering, and management assessments to obtain a comprehensive pavement condition index. A condition index measures how well a pavement serves the users. This index may be aggregated to support the network level decisions. However, at the project level, a major drawback of using an aggregated condition index is the combination of all distress ratings into a single measure. In other words, the aggregated index is not able to determine which type of distress is critical and should be treated. Therefore, this type of index is not applicable at the project level. Several pavement condition indices have been developed worldwide. The most commonly applied methodologies are the Pavement Condition Index (PCI) and the Distress Manifestation Index (DMI) (Ningyuan et al. 2004; Shahin 2005).

2.5.1 Pavement Condition Index (PCI)

The Pavement Condition Index (PCI) was initially developed by the U.S. Army Corps of Engineers in 1984. The PCI represents pavement condition assessed under repeatable and reliable methodology (Shahin 2005) and is a numerical value that ranges from 0 to 100, where 0 represents a pavement section in a failure condition and 100 shows a pavement section in an excellent condition. A description of pavement conditions or condition ratings is presented as a function of PCI, as it is provided in Figure 2-2. The value of PCI decreases regarding various distresses observed on pavement.

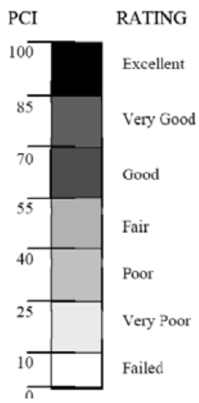


Figure 2-2 Pavement Condition Index and Rating Scale (ASTM D 6433 2007).

The distresses considered by PCI are those described in detail by the ASTM Standard Practice D 6433-03(2007). The calculation procedure can be summarized in the four steps: 1) Indicate the density and severity of each distress type 2) Indicate the Deduct Value (DV), considering the distress type and severity level by using the appropriate curves presented in the ASTM Standard Practice 3) Determine the maximum Corrected Deduct Value (CDV) by using the iterative procedure described in detail in ASTM Standard Practice (2007) once DVs are calculated for all distress types 4) Calculate the estimation of PCI by subtracting CDV from 100.

2.5.2 MTO Distress Manifestation Index (DMI)

The Ministry of Transportation of Ontario (MTO) has developed the MTO Pavement Condition Index (PCIMTO) and Distress Manifestation Index (DMI). DMI, typically, represents overall pavement surface conditions using various distresses observed on a pavement section. DMI is estimated by computing a weighted summation of distresses indicated in the MTO condition rating manual. The relative weighting figures dedicated to each distress for concrete pavement are represented in Table 2-1. These weights are presented by experienced engineers and simply elaborate on the effect of various distresses on the overall pavement surface condition.

The DMI varies between 0 and 10, and 0 shows the poorest condition of a pavement section, while 10 presents a newly installed or rehabilitated pavement section. DMI is estimated applying Equation 2-1 (Ningyuan et al. 2004):

$$DMI = 10 \times \frac{DMI_{max} - \sum_{i=1}^{n} W_i \, (s_i + d_i)}{DMI_{max}} \tag{2-1}$$

Where,

DMI = distress manifestation index

i = distress type

W_i = weighting factor ranging from 0.5 to 3.0

s_i = severity of distress presented in a 5 point scale ranging from 0.5 to 4.0

d_i = density of distress occurrence represented in a 5 point scale ranging from 0.5 to 4.0

DMI_{max} = the maximum theoretical value dedicated to an individual pavement distress (196 for Portland cement concrete)

Table 2-1 Weighting Factors (Ningyuan et al. 2004)

Distress	Weight
Ravelling	0.5
Polishing	1.5
Scaling	1.5
Potholing	1
Joint Crack/Spalling	2
Faulting	2.5
Distortion	1
Joint-Failure	3
Longitudinal Meander Failure	2
Transverse Cracking	2
Sealant Loss	0.5
Diagonal Corner/Edge Cracking	2.5

2.6 DEVELOPMENT OF SINGLE SURFACE CONDITION INDICES

Pavement distresses may be combined to derive a single value representing pavement condition in order to facilitate the comparison of pavement sections. Such condition indices may also be applied to monitor pavement sections over time. Hence, the information can then be used to determine maintenance, rehabilitation, and replacement operations. Condition indices are equally important in communication between engineers and decision makers (government) when budget requests are involved. Such indices should be repeatable, reproducible, and cost-effective at the same time. Moreover, condition indices may be used in predicting pavement conditions, i.e., developing performance models.

Several methods have been applied to obtain a single value of pavement condition using pavement distresses, among which the following have been employed with some success: weighted summation, deduct value, fuzzy set, and artificial neural network (Tsoukalas and Uhrig 1997).

2.6.1 Weighted Summation

A condition index can be calculated by assigning weighting factors to each distress based on its impact on the condition index. Generally, severity and density levels of each distress are also determined. The weighting factors are applied to these severity and density levels to obtain the condition index. There are several methods to indicate the weighting factors. As mentioned earlier, the MTO protocol developed DMI which is a weighted summation of distress severity and density levels. The weighting factors associated with various distresses are defined by the MTO protocol. Note that the weighting factors have been developed for the conventional pavement types (asphalt, concrete, and composite). These factors provide an excellent basis for a new type of pavement.

2.6.2 Deduct Value

A condition index can be calculated by subtracting points known as deduct values from the score that corresponds to a pavement in a perfect condition (generally 100) due to presence of distress on pavement. The deduct values are determined based on type, severity, and density of distresses. The first approach is to apply the existing protocols (e.g., ASTM). Several curves were provided by ASTM expressing the deduct values for various pavement types, distresses, severity, and density (ASTM D 6433 2007). The second approach is to develop a set of curves representing deduct values for desirable pavement using expert knowledge (Wang and Han 2002).

2.6.3 Fuzzy Sets

The weighting factor of each distress can be represented using fuzzy sets (Bandara and Gunaratne 2001; Wang and Liu 1997). For example, adequate fuzzy sets can be assigned to the importance factor of alligator cracking ("very important") and rutting ("important") in the flexible pavement. Also, evaluation of each distress in terms of its severity and density can be expressed by applying fuzzy sets. For instance, the presence of cracking on a section of pavement can be deemed "slight" or "severe". Dedication of a single numerical value to each of these subjective terms is difficult. To assign objective values to subjective terms, fuzzy sets are applied. Fuzzy set is a set of numbers that express subjective descriptions in terms of their degree of belonging along the scale. For example, assume that severity of distress is defined on the scale of 0 to 10. The subjective term, "very important", could be represented by the fuzzy numbers: 8, 9, and 10 (0/8, 0.5/9, 1/10). Thus, the degree of belonging of "very important" to value 10 is fully representative (i.e., 1), 9 is partially representative (i.e., 0.5), and 8 and less than that are not representative (i.e., 0). Therefore, through incorporation of the weighting factor of each distress together with its fuzzy severity and density, the condition index can be presented in fuzzy sets, yet may be translated back (defuzzified) into a subjective description of pavement conditions.

Functions are applied in fuzzy sets to indicate a value that would be a member of the set to a number between 0 and 1, representing its real degree of membership. Accordingly, a degree of 0 means that the associated value is not in the set, while value 1 expresses the corresponding value is completely representative of the set. The fuzzy system is an efficient tool for representing multiple cooperating, collaborating, and even conflicting experts' opinions. That is, it can combine various even conflicting ideas of experts in a fuzzy membership function. This is the privilege of fuzzy numbers in comparison with crisp values (Tsoukalas and Uhrig 1997).

A fuzzy system consists of three graphical components: a horizontal axis of increasing real numbers that comprise the population of a fuzzy set; a vertical membership axis between 0 and 1 determining the degree of membership in the fuzzy set; and the curve of the fuzzy set that connects each value in the domain with the degree of membership in the set.

A linear membership function, namely, Triangular Fuzzy Numbers (TFNs), is a simple and adequate approach for pavement evaluation. TFNs are identified by only three parameters (left domain, full representative value, right domain) which can be easily determined by experts. Figure 2-3 illustrates the concept of TFNs. Where μ(x) is a membership function and "l" and "u" are lower and upper domains, respectively. That is, if "x" is lower than "l" or more than "u", the membership function is equal to zero, i.e., the associated values are not in the set. "m" is the value which the corresponding membership measure is equal to one, i.e., the associated value is completely representative of the set. Figure 2-3 and Equations 2-2, 2-3, 2-4, 2-5, and 2-6 present membership formulas corresponded to various domains. For instance, in the second domain [l, m] suppose that $\mathrm{x} = \frac{\mathrm{m+l}}{2}$, the membership function is calculated using $\mu(\mathrm{x}) = \frac{\mathrm{x-l}}{\mathrm{m-l}}$ which is equal to 0.5. Likewise, in the third domain [m, u] suppose that $\mathrm{x} = \frac{\mathrm{m+u}}{2}$, the membership function is equal to 0.5, which is computed by utilizing $\mu(\mathrm{x}) = \frac{\mathrm{u-x}}{\mathrm{u-m}}$.

$$\mu(x) = 0\,; \quad x < l \tag{2-2}$$

$$\mu(x) = \frac{x-l}{m-l}\,; \quad l < x < m \tag{2-3}$$

$$\mu(x) = 1\,; \quad x = m \tag{2-4}$$

$$\mu(x) = \frac{u-x}{u-m}\,; \quad m < x < u \tag{2-5}$$

$$\mu(x) = 0\,; \quad x > u \tag{2-6}$$

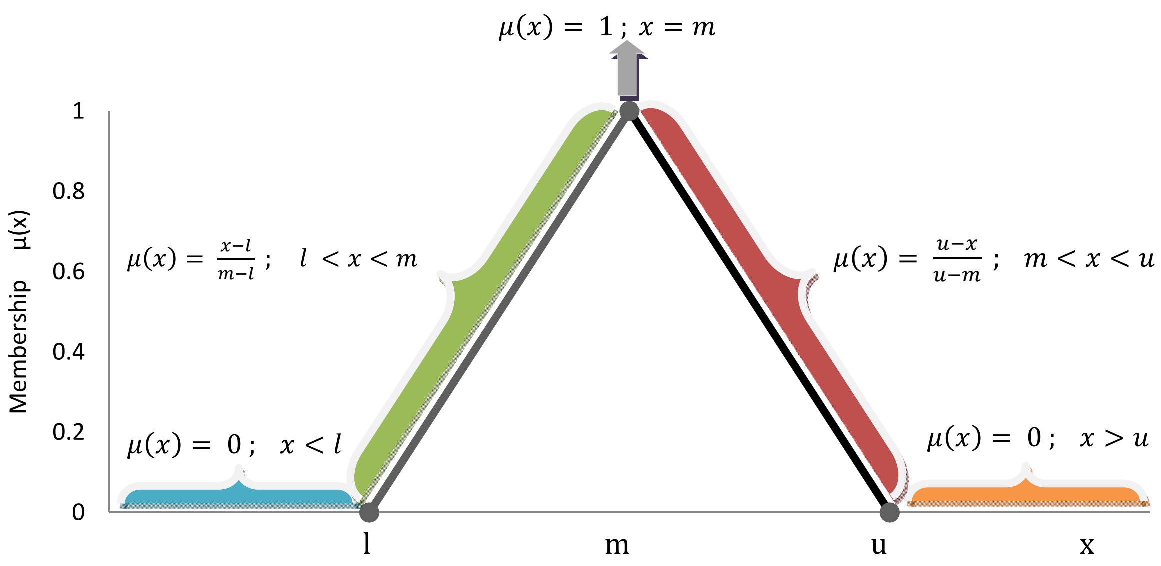


Figure 2-3 Membership Function Equation Related to Each Domain.

2.6.4 Artificial Neural Network

Artificial Neural Network (ANN) has been addressed as a "black box" data processing system that obtains inputs and provides outputs (Simpson 2007). ANN includes a number of interconnected units which involve inputs, implement a local calculation and produce outputs (Schalkoff 1997). ANN has a learning capability. This is accomplished by providing both data (input) and decision (output) to ANN and it learns the correspondence between a set of inputs and outputs. The most important advantage of ANN in developing a condition index is that engineers no longer have to decide on the weighting factors for various distresses. However, pavement condition data is required for a large number of sections as inputs and the corresponding condition ratings are needed as outputs which can be obtained by a panel of raters.

2.6.5 Fractional Factorial

Another method to derive a condition index is the fractional factorial technique (Delphi method) (Haas 1997). This technique is an alternative to having a panel out in the field. It may also be possible to quantify the knowledge of experts through a series of questions. These questions are to indicate a number as a condition index for an individual scenario. Each scenario describes a pavement section with various distresses at different severity and density levels (Fernando and Hudson 1983). Finally, a condition index is produced with incorporation of experts' ratings and various distresses through application of the regression analysis method.

2.7 DEVELOPMENT OF OVERALL COMBINED CONDITION INDICES

Roughness, deflection, and surface distress measurements can be aggregated or transformed into indices such as Riding Comfort Index (RCI), Structural Adequacy Index (SAI), and Surface Distress Index (SDI), respectively. Another level of combination can be performed by aggregating all these indices to a single combined overall condition index. In fact, each level of aggregation would cause loss of information so that the combined condition index would provide a quick picture of a pavement section at the network level which would be desirable for senior administrators (Haas 1997). The most important task to develop a combined condition index is to indicate the weighting factors of various parameters which are aggregated. Several methods have been used for indication of weighting factors among which the following have been applied with some success.

2.7.1 Engineering Judgment

The weighting factors for combining condition indices can be indicated based on personal experience and engineering judgment. The simplest way is to assign a single pair of values to weighting factors (Amador and Mrawira 2008). For instance, if there are two parameters that should be combined in a model, a single pair of weighting factors can be presented as α= 0.8 and β =0.2 which means that the importance of the parameter corresponded to α is four times more than that of second parameter in the overall condition index. This approach is easy to use, yet it cannot address complicated situations such as a case in which the weighting factors vary with variation in one of condition indices (parameters).

An alternative and more rigorous approach is to apply a various pairs of weighting factors (Karan et al. 1981). These weighting factors vary based on the most influential parameter. Assume that there are two parameters such as Surface Distresses Index (SDI) and Structural Adequacy Index (SAI) that should be combined. Also, assume that SDI is more influential on the overall condition index rather than SAI. Hence, a pair of weighting factors is assigned to each parameter based on the different levels of SDI. Table 2-2 is an example presenting various pairs of weighting factors for SDI and SAI based on SDI levels. For instance, in a case of poor SDI (SDI < 4.0), a higher weighting factor is dedicated to SDI to magnify the effect of poor SDI on the overall pavement condition index, while in a case of good SDI (SDI > 8.0), a lower weighting factor is assigned to SDI.

Table 2-2 Variable Weighting Factors

SDI level	Weighting Factors	
	β (for SDI)	γ (for SAI)
< 4.0	0.85	0.15
4.0 – 6.0	0.60	0.40
6.0 – 8.0	0.45	0.55
> 8.0	0.30	0.70

2.7.2 Panel of Experts

Weighting factors can be determined by asking a panel of experts to indicate weighting factors of various parameters. Assume that three condition indices are included in developing an overall condition index: Structural Adequacy Index (SAI), Surface Distresses Index (SDI), and Functional Performance Index (FPI). Hence, the experts should be asked to indicate the effects of these parameters on the overall condition index. They should indicate a relative weight (α, β, and γ) for each index between 0 and 1. A value of 1 indicates the most influential and 0 expresses not influential. The overall condition index can be represented as follows.

$$OCI = f\,(FPI, SAI, SDI) = \alpha \times (FPI) + \beta \times (SAI) + \gamma \times (SDI) \qquad (2\text{-}7)$$

Where OCI is the Overall Condition Index, FPI is the Functional Performance Index, SAI is the Structural Adequacy Index, SDI is the Surface Distresses Index, and α, β, and γ (α + β + γ = 1) are the weighting factors corresponding to FPI, SAI, and DSI, respectively. Consequently, once the data is processed, the average of their responses for α, β, and γ will be assigned to each weighting factor.

2.7.3 Panel of Raters

The last approach for developing weighting factors is to employ a panel of raters. In this case, a panel of raters either drives or walks on various pavement sections and rate the overall condition of the pavement sections. The mean of panel ratings is assigned to the overall condition index (e.g., OCI in Equation 2-7). Other parameters (e.g., FPI, SAI, and SDI in Equation 2-7) are measured for the same pavement sections. Ultimately, through conducting regression analysis, regression coefficients (weighting factors: α, β, and γ) can be obtained.

2.8 PAVEMENT PERFORMANCE MODELS

The change in the level of pavement condition with time is called pavement performance and is expressed as a function of pavement age or cumulative traffic loads. Since the 1960's, the serviceability-performance concept has been widely acknowledged (Haas 1997). Development of appropriate performance models is based on an adequate condition index (e.g., PCI, PSI, and IRI). This has been a major challenge for engineers and managers of pavement networks. Although performance has been well-defined since Carey-Irick development of the serviceability-performance concept (Carey and Irick 1960), the term "performance" has been used in a loose way by people in the pavement field because it has a common use and general meaning in the everyday life. Thus, engineers and researchers have been applied alternative terms such as deterioration or damage (Haas 1997).

In fact, a performance model plays significant role in pavement management. Common methods of maintenance assessment involve condition surveys. These surveys are performed in a particular year and used as the basis of maintenance treatments in the following year. Incorporation of performance models would enhance the quality of decision making so that decision on treatments can be based on expected pavement conditions at the treatment time instead of those at the time of assessment. In addition, performance models are employed either implicitly or explicitly by all second and third generation techniques of prioritization since knowledge is required to predict pavement condition for developing maintenance plans (Robinson et al. 1998).

The deterioration rate is of significance to determine the needs year for a pavement section. It might be, moreover, desirable to predict the changing rate of some distresses such as cracking in order to estimate the corresponding maintenance requirement. The schematic elaboration of the future deterioration prediction of pavement is shown in Figure 2-4. The deterioration rate is applied to an existing pavement section to estimate the future deterioration rate and the needs year.

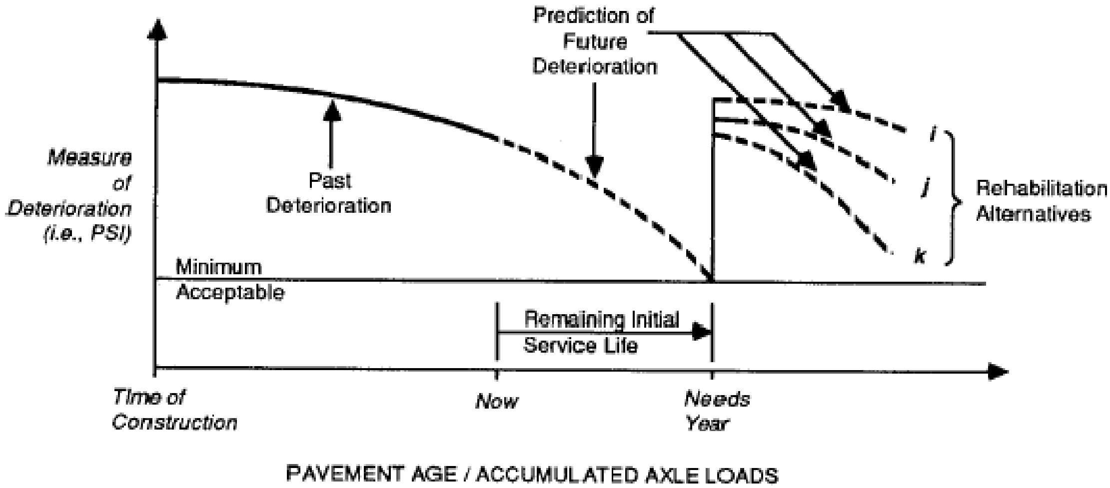


Figure 2-4 Illustration of Deterioration Model and Rehabilitation Alternatives (Haas 1997).

Furthermore, this figure demonstrates the application of deterioration models to rehabilitation alternatives applied in the needs year. Darter (1980) described the fundamental requirements for any prediction models as follows:

1) An adequate data base should be used to develop the models.
2) All significant variables affecting deterioration should be included.
3) The fundamental form of the model should represent a physical real-world situation.
4) Criteria to assess the accuracy of the model should be employed.

Mahoney (1990) suggested a classification of prediction models based on the earlier work conducted by Lytton (1987) as summarized in Table 2-3. This figure provides two levels of management, namely, project and network level management and two major types of performance models: deterministic and probabilistic. Deterministic models are subdivided into the primary response, structural, functional, and damage models, whereas probabilistic models are often described by survivor curves and transition process models.

Table 2-3 Classification of Prediction Models (Mahoney 1990).

	Types of Models						
	Deterministic				Probabilistic		
Levels of Pavement Management	Primary Response • Deflection • Stress • Strain • etc.	Structural • Distress • Pavement • Condition	Functional • PSI • Safety • etc.	Damage • Load Equiv.	Survivor Curves	Transition Process Models: Markov	Transition Process Models: Semi-Markov
National Network				•	•	•	•
State Network		•	•	•	•	•	•
District Network		•	•	•	•	•	•
Project	•	•	•	•			

Haas (1997) suggested a convenient way of aggregating the breakdown of Table 2-3 into four basic types for operational purposes as follows:

1) Mechanistic

Where a primary response or behavior parameters such as stress, strain or deflection describes performance.

2) Mechanistic-Empirical

Where a response parameter is related to measured structural or functional deterioration such as distresses or roughness through regression equations.

3) Empirical

Where the dependent variable of observed or measured structural or functional deterioration is related to one or more independent variables like subgrade strength, axle load applications, pavement layer thicknesses and properties, environmental factors, and their interactions.

4) Experience

Where experience is captured in a formulized or structured way using transition process models, for instance, to develop prediction deterioration models.

As mentioned earlier, the performance models can be broadly categorized into two major classes: deterministic and probabilistic.

2.8.1 Deterministic Models

Deterministic models present a future condition of pavements using a single point value (i.e., a condition index, e.g., DMI) based on an independent variable or variables which are assumed to be constant during prediction time. For instance, traffic volume or Equivalent Single Axle Load (ESAL) as an independent variable has commonly been assumed to be a single value over the pavement performance period. Often an annual growth rate will be applied but variability is not formally considered. Therefore, the performance model outcomes will also be presented as a single point value. Markov Chain, Regression, and Bayesian models can also be used for deterministic modeling, and these are described later.

2.8.2 Probabilistic Models

Probabilistic performance models present a future condition of pavement using a mean, standard deviation, and appropriate probability distribution functions. There are four common types of probabilistic models commonly applied in developing pavement performance models which use probabilistic tools (Lytton 1987): these probabilistic principles are combined with Markov models, Bayesian regression (Hajek and Bradbury 1996; Molzer et al. 2001), survivor curves, and semi-Markov models (Golroo and Tighe 2009). The main advantage of using a probabilistic approach combined with the other tools is to incorporate uncertainty in pavement performance. This better describes reality as compared to the deterministic approach. The other advantage of probabilistic models, particularly the Markov Chain, is the ability to handle an incomplete, low quality, and imprecise database by incorporating expert knowledge (Amador and Mrawira 2008). The Markov Chain method and the Bayesian technique (used in this research for performance model development) are described in the following sections.

2.8.2.1 Markov Chain

The Markov models employ Transition Probability Matrices (TPMs) that describe the probability that a pavement section in a given condition at a given time will shift to another (or remain in the same) condition in the next time period. Various pavement condition levels which is defined based on a pavement condition index called a "state" (e.g., very good, good, …) and a stage is defined as one year of traffic and environmental degradation. A series of time periods and condition states should be presented in TPMs. The Markov prediction model is exposed to three restrictions (Ortiz-García et al. 2006). The Markov process should be discrete in time, have a countable or finite state space, and satisfy the Markovian property. The Markovian property is to state that the conditional probability of any future events, given any past events and the present state, is independent of the past events and depends only on a present state (Hillier and Lieberman 1990). The conditional probability for the process to shift from one state (i) in stage (t) to another state (j) in stage (t+1) is called the transition probability (p_{ij}) given by Equation 2-8:

$$p_{ij} = prob[\,X(t+1) = j / X(t) = i] \tag{2-8}$$

The transition is, also, termed a step. Therefore, the one-step transition probability p_{ij} is described as the conditional probability that the random variable X starting from state i will be in state j after one step. p_{ij} should meet the following constraints (Wang et al. 1994).

$$0 \le p_{ij} \le 1, \quad for\ all\ i\ and\ j, \quad and\ i, j = 0, 1, 2, \ldots, M \tag{2-9}$$

$$\textstyle\sum_{j=0}^{M} p_{ij} = 1, \quad for\ all\ i, \quad and\ i = 0, 1, 2, \ldots, M \tag{2-10}$$

Where i and j are defined within the M-state space. M is the total number of states. These transition probabilities can be arranged in one-step TPM as follows.

$$TPM_I = \begin{array}{c} \\ \text{Present} \\ \text{Condition} \end{array} \begin{array}{c c} & \text{Future Condition} \\ & \begin{array}{cccc} \text{Best} & & & \text{Worst} \end{array} \\ \begin{array}{c} \text{Best} \\ \\ \\ \text{Worst} \end{array} & \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1M} \\ 0 & p_{22} & \cdots & p_{2M} \\ \vdots & \vdots & & \vdots \\ 0 & 0 & \cdots & 1 \end{bmatrix} \end{array}$$

TPM_I is the case that considers only asset deterioration (no improvement/maintenance). In this type of TPM, P_{ij} is equal to zero for each i that is greater than j. Also, p_{MM} is equal to one according to Equation 2-10.

The Markov Chain process starts with the condition probability vector P(0) addressing the initial or current condition of a given pavement section. This vector presents the condition of a pavement section and incorporates probabilistic principles. For example, assume that the condition levels range is between 0 and10, and it is divided into 10 states: 10-9, 9-8, …, and 2-1. Suppose that the current condition index of a pavement section would lie in the interval of 8-7 and 7-6 with probability of 60% and 40%, respectively. Therefore, the P(0) can be presented as (0, 0, 0.6, 0.4, 0, 0, 0, 0, 0).

The condition of a pavement section in the next stage can be described using the current condition and TPMs:

$$P(t) = P(t-1) \times TPM_t \tag{2-11}$$

Where,

P(t) = probability condition vector of a pavement section at time t
P(t-1) = probability condition vector of a pavement section at time t-1
TPM_t = transition probability matrix corresponding to transition from stage t-1 to t

Therefore, the condition vector of a pavement section at any time (t) can be readily specified based on an initial condition vector of a pavement section and TPMs associated with stages 1 to t.

$$P(t) = P(0) \times TPM_1 \times TPM_2 \times \cdots \times TPM_t = P(0) \times \prod_{i=1}^{t} TPM_i \tag{2-12}$$

Where,

P(0) = probability condition vector of a pavement section at time 0
TPM_i = transition probability matrix corresponding to transition from stage i-1 to i (i=1, 2, …, t)

The Markov Chain process is broadly divided into two categories: homogenous and non-homogeneous. The homogeneous Markov Chain process assumes that all TPMs are identical. In other words, a series of probability of transferring from one state to another is time-independent. Chapman-Kolmogorov relations provide a simplified method for computing the condition of an asset after n-step transition for the homogeneous Markov Chain (Hillier and Lieberman 1990).

$$\begin{aligned} P(t) &= P(0) \times TPM_1 \times TPM_2 \times \cdots \times TPM_t \\ &= P(0) \times TPM \times TPM \times \cdots \times TPM \\ &= P(0) \times TPM^t \end{aligned} \tag{2-13}$$

Where,

P(0) = probability condition vector of a pavement at time t=0

TPM_i = transition probability matrix corresponding to transition from stage i-1 to i (i=1, 2, …, t)

TPM = individual transition probability matrix corresponding to transition from each stage to the next stage

According to this approach, the state vector for any stage t can be obtained by product of the current condition vector P(0) and the t-step TPM. However, the non-homogeneous Markov Chain process is more realistic but also more complex computationally. In this case, TPMs are time dependent and would change throughout the service life of a pavement section with respect to changing in traffic volumes, subgrade strength, and environmental conditions. An ideal approach is to develop individual TPMs for each stage. However, this approach significantly increases the uncertainty and decreases the reliability of data presented in TPMs. Besides, it is hardly feasible to build non-homogeneous TPMs for all stages over the planning horizon in the case of pavement that suffers from long term performance data limitation. The combination of non-homogeneous and homogeneous Markov Chain might be an efficient approach to develop a performance model to reflect changes that may occur in terms of deterioration rate.

2.8.2.2 Bayesian Regression

The Bayesian method provides a systematic approach for incorporation of new information (such as results of a new series of tests or experiments or expert knowledge) with previous or prior data to derive new or posterior values for current results. The main concept is to apply both sets of information including observations and expert knowledge to estimate the posterior probabilities. The Bayes' theorem defines the transformation from prior probability (based on observations) to posterior probability (based on expert knowledge) (Winkler 2003).

The main purpose of applying the Bayesian method is to estimate the parameters' regression coefficient of performance models. The classical regression analysis is carried out on prior data (expert knowledge) to obtain coefficients of parameters. The prior data is reinforced with experimental data (observations).

Essentially, as more data (observations) is added to the data base, the posterior will become more definitive (Schmitt 1969). Namely, the reliability of the posterior estimates is more than prior expert knowledge data. The ultimate goal is to determine the posterior estimate of the coefficients.

The difference between the classical regression and the Bayesian regression is that the classical regression does not apply the prior data in making the estimate of the coefficients. Bayesian regression is useful where a database is of low quality, or insufficient data is available, or the data is noisy. Bayesian approach can be employed to tackle some of these problems (Winkler 2003).

The classical regression method has widely been applied by analysts (Hajek and Bradbury 1996; Molzer et al. 2001). This wide application provides a good frame used in the Bayesian regression. The classical regression in matrix form will be presented in this section. Linear regression assumes a linear relationship (in terms of coefficients) between a dependent variable and independent variables. The standard linear regression equation is presented in Equation 2-14 (Press 2003):

$$Y = b_0 + b_1X_1 + b_2X_2 + \cdots + b_kX_k + e \tag{2-14}$$

Where k is the number of independent variables, b_i is the regression coefficient of variable X_i (the unknown factor), X_i is the regression variable i, Y is the dependent variable, and e is a random error term.

The prior data (expert knowledge) is applied to determine the coefficients (unknown factors). The prior data can be represented in Table 2-4.

Table 2-4 Prior Data

Observation	Dependent variable	Independent variables			
	Y	X_1	X_2	…	X_k
1	Y_1	X_{11}	X_{21}	…	X_{k1}
2	Y_2	X_{12}	X_{22}	…	X_{k2}
3	Y_3	X_{13}	X_{23}	…	X_{k3}
⋮	⋮	⋮	⋮	⋮	⋮
n	Y_n	X_{1n}	X_{2n}	…	X_{kn}

The prior data is applied to build up the matrix X and vector Y. X is the matrix of independent variables. A column of "ones" (for constant, b_0) was added to the matrix X in order to calculate a constant factor for the regression.

$$X = \begin{bmatrix} 1 & X_{11} & X_{12} & \cdots & X_{1k} \\ 1 & X_{21} & X_{22} & \cdots & X_{2k} \\ 1 & \vdots & \vdots & \vdots & \vdots \\ 1 & X_{n1} & X_{n2} & \cdots & X_{nk} \end{bmatrix}$$

Y is a vector of the dependent variable.

$$Y = \begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{bmatrix}$$

Once the prior data (expert knowledge) is obtained, the Ordinary Least Squared (OLS) regression process is applied to estimate the mean of the coefficients. Equation 2-15 is used to calculate the mean of the coefficients.

$$b = (X^t X)^{-1} X^t Y \tag{2-15}$$

Where X^t indicates the transpose of matrix X. The inverse of matrix X is shown by X^{-1}. By using Equation 2-15, the vector of regression coefficient means is obtained, b:

$$b = \begin{bmatrix} b_0 \\ b_1 \\ \vdots \\ b_k \end{bmatrix}$$

The Bayesian regression procedure is organized into three major parts as follows:

1) Specify prior data (expert knowledge)
2) Analyze experimental data (observation)
3) Calculate posterior results

2.8.2.3 Specify Prior Data

The initial step in performing the Bayesian regression is to provide prior information. The prior equation has the same form as the classical regression equation, given by Equation 2-16:

$$Y = b_{pr0} + b_{pr1} X_1 + b_{pr2} X_2 + \cdots + b_{prk} X_k + e_{pr} \tag{2-16}$$

Where k is the number of independent variables, b_{pri} is the regression coefficient associated with variable I for the prior, X_i is the regression variable i, Y is the dependent variable, and e_{pr} is the random error term for the prior.

Two types of priors are commonly used: N-prior and G-prior. The N-prior and G-prior differ only in the way the prior precision matrix is indicated. The N-prior requires a variance-covariance matrix to indicate the prior precision matrix while the G-prior applies a set of independent data to calculate the prior precision matrix. The G-prior (selected for sake of simplicity) is described as follows.

The G-prior applies independent variable observations to compute the prior precision matrix. To build up the prior precision matrix, G-prior independent variables data and G-prior factors are required. The G-prior independent variable data is a set of independent variable (expert knowledge), similar to the data used to carry out the classical regression, as follows:

$$X_G = \begin{bmatrix} 1 & X_{11G} & X_{12G} & \cdots & X_{1kG} \\ 1 & X_{21G} & X_{22G} & \cdots & X_{2kG} \\ 1 & \vdots & \vdots & \vdots & \vdots \\ 1 & X_{n1G} & X_{n2G} & \cdots & X_{nkG} \end{bmatrix}$$

The G-prior factor is a positive real number deployed as a weight in the computation of the prior precision matrix. The G-prior factor is applied to increase or decrease the influence of the prior in the calculation of the posterior. The G-prior factor is called “g”. A typical value of “g” is 1. The prior precision matrix is calculated using Equation 2-17:

$$A = g({X_G}^t X_G) \tag{2-17}$$

Where A is the prior precision matrix, g is the G-prior factor, X_G is the G-prior independent variable matrix, and ${X_G}^t$ is the transpose of X_G. Then, the regression coefficients, b_{pr}, are computed using Equation 2-18:

$$b_{pr} = A^{-1}(X^t Y) \tag{2-18}$$

Where b_{pr} is the prior regression coefficients, A is the prior precision matrix, X^t is the transpose of independent variables, and Y is the dependent variable.

2.8.2.4 Analyze Experimental Data (Observation)

The second step, analyzing experimental data, is similar to classical regression except the calculation of the precision matrix. The precision matrix for the experimental data, H, is calculated using Equation 2-19:

$$H = (X^t X) \tag{2-19}$$

Then, the regression coefficients, b, are computed using Equation 2-20:

$$b = H^{-1}(X^t Y) \tag{2-20}$$

Where b is the regression coefficients, H is the precision matrix of experimental data, X^t is the transpose of independent variables, and Y is the dependent variable.

2.8.2.5 Calculate Posterior Results

The final step is to estimate the posterior results by combining the prior with experimental data. The posterior precision matrix is calculated by adding the prior precision matrix (A) to the experimental data precision matrix (H).

$$M = A + H \tag{2-21}$$

Where M is the posterior precision matrix, A is the prior precision matrix, and H is the experimental data precision matrix.

The posterior regression coefficient is the weighted summation of prior regression coefficients and experimental data regression coefficients. The weighting factors are the corresponding precision matrices. The posterior precision matrix is applied to normalize the results:

$$b_{pos} = M^{-1}(Ab_{pr} + \ Hb) \tag{2-22}$$

Where b_{pos} is the posterior regression coefficients, b_{pr} is the prior regression coefficients, b is the experimental data regression coefficients, A is the prior precision matrix, and H is the experimental data precision matrix

2.9 SUMMARY

This chapter provided an overview of PCP performance and associated models. The definition of PCP structures along with the pervious concrete characteristics such as the compressive strength, freeze thaw durability, and hydraulic conductivity were explained. Moreover, various types of condition indices such as the Pavement Condition Index (PCI), the Present Serviceability Index (PSI), and the Pavement Quality Index (PQI) were explained. Pavement performance models were categorized as: mechanistic, mechanistic-empirical, empirical, and experience based. Overall, performance models were broadly subdivided into deterministic and probabilistic models. Finally, the Markov Chain and the Bayesian regression modeling approaches were described. Information in this chapter provides a good basis for subsequent analysis.

Chapter 3
Literature Review

This chapter provides a brief summary of past research studies, associated available data, and methodologies related to pervious pavement performance, pavement condition indices, and pavement performance models. The contributions of these studies are also discussed.

3.1 PERVIOUS PAVEMENT PERFORMANCE

Murata (2005) studied durability and serviceability of Pervious Concrete Pavement (PCP) as well as their behavior in cold regions. The major parameters investigated consisted of pavement smoothness, skid resistance, rutting, and difference in elevation at the joints. Permeability and noise level tests were carried out on PCP. Two 40-metre sections of PCP were monitored. The thickness of pervious concrete was 200 mm over 50 mm of asphalt cushion course on the top of 250 mm base. Several tests were conducted on PCP including evenness, skid resistance, permeability, rutting, crack, and noise reduction.

The study found that the smoothness of PCP generally remained relatively unchanged after the commencement of service. Namely, neither winter tires nor snow plows damaged the road surface in the first three years. It was also observed that permeability rates sharply reduced due to passage of agricultural vehicles. The study indicated that pores might have been filled with soil since there was borrow pit in the vicinity. The permeability rate was restored applying jet high pressure water by 40%. In addition, rutting was only 0.7 to 3.1 mm after three years that caused no problems. This study, also, indicated that noise level increased after three years of service since permeability rate decreased and pores were filled with soils. Finally, cracking was observed at two points between vertical and horizontal joints early after construction due to poor curing. A crack transversely crossed the pavement to the other end after three years performance that meant design joint spacing should be revised. It was concluded that although deterioration was observed in a few sections, PCP is fully applicable to cold regions.

Eller (2007) measured the first year performance of a PCP section in a parking lot. The first performance measure was the stress-strain response through loading from the 80 kip (355 KN) MnROAD truck and Falling Weight Deflectometer (FWD). The vibrating wire strain gauge sensor response was applied as a second performance measure. The modulus values were estimated from the sensor data. Additionally, macroscopic and microscopic characteristics of PCP were measured using petrographic analysis of cores taken from the pavement. This study incorporated the use and development of surface ratings of PCP in order to corroborate petrographic and freeze-thaw data to determine the cause of any structural deficiencies within the PCP structure.

FWD results of PCP were larger (2 to 5 times) than that of conventional concrete (Eller and Izevbekhai 2007). Moreover, the study found that the modulus value estimated for one section was more than the other due to lower porosity. This might occur due to overworking during placement. The research reported that PCP would have tolerated opening time criteria as conventional concrete based on modulus of rupture (Burnham and Load 2004). In addition, distress observation determined that the poor finishing techniques led to ravelling and spalling of PCP surface used in a driveway. Overall, this research concluded that the mixture consisting of crushed aggregates performed better than a mixture with a combination of rounded and crushed aggregates.

Briggs (2006) presented a study on water quality and hydrologic performance of porous asphalt pavement parking lots in cold climate conditions. The pavement included a 100 mm (4-inch) thick open-graded friction course layer on the top of a high porosity sand and gravel reservoir. Surface infiltrations were measured on a monthly basis as a pavement performance indicator. The research revealed that there was no recognizable sign of change in the surface infiltration rates of different points although heavy sand and salt applications were carried out during winter. Moreover, the porous pavement demonstrated no patterns of distresses except two issues. Firstly, sharp edge of snow plows abraded few shallow strips of pavements. Secondly, the porous pavement located next to two closely spaced wells had failed. None of them, however, were expected to limit the performance.

Haselbach (2006) studied permeability predictions of PCP parking lots in coastal areas. This study measured the permeability of a pervious concrete block fully covered with extra fine sand in a flume applying simulated rainfall. Rainfall rates were simulated for both direct rainfall (passive runoff) and additional stormwater runoff from adjacent areas (active runoff). This study concentrated on many coastal areas where PCP might be placed over sand. Pervious concrete voids were clogged or covered with blowing sand.

Consequently, this research resulted in a new system for permeability measurements. It suggested that the permeability rate would be reduced by the extreme condition to a fraction of the permeability of the sand. This fraction could be described by the porosity of the pervious concrete surface as indicated in Equation 3-1:

$$K_{eff} = \left(\frac{P_{top}}{100}\right) \times K_{sand} \tag{3-1}$$

Where,

K_{eff} = theoretical effective permeability of sand-clogged or covered pervious concrete block systems (cm/s)

P_{top} = average porosity of the top quarter of the block as determined by an equation developed from laboratory analyses of other blocks taken from the same slab and given in percent

K_{sand} = permeability of sand (cm/s)

There was a significant vertical porosity distribution rate within the pervious concrete block. The porosity in the top quarter can be presented by Equation 3-2:

$$P_{top} = 1.07 \times P - 7 \quad (3\text{-}2)$$

Where,

P_{top} = average porosity of the top quarter of the block as determined by an equation developed from laboratory analyses of other blocks taken from the same slab and given in percent

P = average porosity of the block is the ratio of the volume of the voids to the total volume of the block given in percent

Moreover, the permeability of the clogged pervious concrete block (K_{clog}) with various layers of sand and rainfall intensities can be calculated using Equation 3-3:

$$K_{clog} = \frac{(Rainfall\ rate - Runoff\ rate)}{Area\ of\ the\ block} \quad (3\text{-}3)$$

Finally, this study proposed a theoretical relation between permeability of a cast in place sand-clogged pervious concrete block, the porosity of the block near the surface, and permeability of sand in the flume experiments for the conditions tested with the high rainfall intensities. The research demonstrated that the real permeability rate should be between the lower limit (theoretically calculated) and the expected permeability rate of the unclogged system affected by the permeability of the subbase or subgrade of PCP.

The ACI committee 522 (2006) published a document focused on PCP characteristics. The eighth chapter is dedicated to the PCP performance. This report is based on limited information from selected controlled studies dealing with long-term performance of PCP in mostly southern climates which do not experience freeze thaw cycles. This study added that two major areas of concern would be degradation in permeability rates due to clogging and structural distresses because of wear; however, PCP with more than 20 years of age might be still in service in southern climates.

Firstly, this document described that clogging happens when foreign materials limited the ability of water to seep through PCP. The authors added that these foreign materials could be either fines (e.g., water-borne, wind-borne, or tracked onto PCP by a vehicle) or vegetative matters (which would come from trees or plants adjacent to PCP). It suggested that a geometric design of PCP should not allow stormwater to carry fines onto PCP. For instance, PCP should not be placed at the same elevation with the adjacent landscaping. The landscaping sloping should be away from the pavement.

Secondly, this research summarized PCP structural distresses into two forms: cracking or subsidence due to loss of subgrade support and surface ravelling. It described heavy loads (more than structural capacity of the pavement), weak subgrade materials, or horizontal water flowing through PCP washing away subgrade material might be the causes of structural distresses. It was also claimed that surface ravelling would be caused by high surface contact pressures or a weak PCP surface.

Finally, this study described freezing and thawing damage as PCP distress. It explained that if PCP was properly implemented, water should not retain in the void structure. When PCP is completely saturated due to saturation of underlying layers and subjected to freezing; however, water is frozen and would result in pressure on the cement paste coating the aggregates. It suggested that adding air-entraining admixture to the pervious concrete mixture might protect the coating paste. Moreover, this document reported that adequate pores for movement of water led to suitable freezing and thawing resistance. ASTM C 666 (2007) is not recommended by this report to evaluate freeze thaw resistance of PCP due to the fact that it does not simulate the performance of the product in the field.

Wingerter and Paine (1989) conducted extensive field performance investigations on various PCP sites in the southern climate. In essence, the following was presented:

1. Development of a field test procedure
2. Pavement long-term durability, significant signs of distresses, and effect of materials or placing methods on performance
3. Subgrade conditions relative to permeability and density after years of water intrusion
4. Degree of infiltration of PCP
5. Field permeability relationships of pavement, subgrade and subbase, and grass sod
6. Unit weight determination of pavement samples
7. Cylinder modeling and testing relationships

The study concluded that the small amount of clogging after many years of service observed if a PCP section was properly designed, constructed, and maintained. This study also involved evaluation of permeability rates of clogged pavements, which was still equal to adjacent landscape (grass). This evaluation strongly revealed that potential clogging of PCP was not a significant consideration in the long term performance of the pavement permeability. The authors claimed that inadequate water/cement ratio and/or inadequate compaction would result in surface ravelling of PCP. PCP sections were functioning well after many years of service without significant patterns of structural distresses. Infiltration of foreign materials did not reduce its permeability. They proposed that the application of reinforcement in PCP might offer little value to the pavement performance. The investigators, moreover, reported that PCP in actual field service conditions demonstrated the ability to perform as a stormwater system while also provided an appropriate pavement structure to accommodate traffic loadings. This study, besides, investigated subgrade conditions. It claimed that subgrade conditions after many years of service did not significantly change. The major concern about the subgrade was its permeability rate. It was revealed that no considerable reduction could be observed during the PCP service life. As well, there was no pavement failure reported due to lack of subgrade support.

Delatte (2007) conducted a thorough investigation plan including an extensive visual inspection for signs of distresses (cracking, surface ravelling, and clogging), two types of surface infiltration measurements, and ultrasonic pulse velocity (UPV) testing at PCP sites in Ohio, Kentucky, and Indiana. Moreover, some laboratory tests were carried out on extracted cores including void ratio, hydraulic conductivity, and direct transmission UPV. Afterwards, some of the specimens were tested for compressive or splitting tensile strength. In addition, properties of pervious concrete through the pavement thickness were investigated by cutting samples into two top and bottom specimens. The investigators evaluated the performance of PCP sites through the density of clogging, ravelling, and cracking. A part of results are presented in Table 3-1 for illustration. They described distress density using three major linguistic terms: minimal, moderate, and severe. They determined whether or not PCP sites required maintenance due to clogging using equations developed by Youngs (2006) as presented in Equations 3-4 and 3-5:

$$IR = \frac{19{,}958{,}400}{(a)(T)} \sim \frac{20{,}000{,}000}{(a)(T)} \tag{3-4}$$

$$MR = (DS)(SF)(FC) \tag{3-5}$$

Where,

a= area of wet spot in square inches

T= time to empty one gallon of water onto PCP in seconds

FC= flow concentration (area drained/ area of pervious concrete)

DS= design storm in inches (usually the 100 year, 24 hour storm event)

SF= safety factor (usually 2 or 3)

IR= infiltration rate in inches of rain per day

MR= maintenance rate in inches per day

If *IR*>*MR*, no maintenance is required; otherwise, cleaning is required

Table 3-1 Summary of Field Performance Investigation Characteristics (Delatte 2007)

Project	Clogging	Ravelling	Cracked
Charter School	Moderate	Minimal	Yes
Keystone Concrete	Severe	Minimal	No
Kuert Concrete	Minimal	Minimal	Yes
Merry Lea College	Severe	Minimal	Yes
Patterson Dental	Moderate	Minimal	Yes
Boone Cty. Market	Moderate	Minimal	Yes
Sanitation Dist. #1	Moderate	Moderate	No
Ball Brothers Contract.	Severe	Minimal	Yes
Bettman NRC	Moderate	Moderate	No
Cleveland State	Severe	Minimal	No
Collinwood Concrete	Severe	Minimal	No
Fred Fuller Park	Severe	Minimal	No
Harrison Concrete	Minimal	Minimal	No
Indian Run Falls	Minimal	Moderate	No
John Ernst Patio	Minimal	Minimal	No
Kettering Hospital	Severe	Minimal	No

This study concluded that all PCP sites performed well in freeze-thaw environments with little maintenance required. None of the installations demonstrated patterns of freeze-thaw damage. However, it is notable that PCP sites were mostly two or three years in service and had not encountered severe winter conditions. They expected to observe widespread ravelling progressing through the thickness of the pavement as a result of freeze-thaw damage. The investigated damage was due to either early age ravelling or structural overload (e.g., passage of heavy vehicle). Approximately all PCP sites showed a fair to good infiltration capability based on drain time measurements although some pore structures were sealed during construction due to improper mix design or over compaction. Pressure washing and vacuuming were proposed as suitable maintenance methods to restore infiltration rates. However, aggressive pressure washing might damage the surface of PCP. Additional findings included:

I) The void ratio at the top of the pavement structure and at the bottom of a PCP structure was considerably different. Generally, the top was much better compacted.

II) Gravels provided higher strength than crushed limestone.

Losa (2003) conducted a thorough investigation in order to describe the degradation of porous pavements in terms of both physical parameters and acoustical properties within a climatic region in the centre of Italy. Two experimental pavement sections (a single layer and a double layer porous asphalt pavement) were built and monitored for a period of three years. The experimental measurements were performed every six months by carrying out tests in situ and in a laboratory on the pavement specimens.

The study concluded that the percentage of connected air voids and air permeability decreased for the double layer pavement. Consequently, the peak value of acoustical absorption factor decreased. For the single layer, once the pavement began to ravel, there was both an increase of air permeability and peak values of an acoustical absorption factor, while the fraction of communication air voids decreased as the number of passing vehicle increased.

Miradi and Molenaar (2006) developed Artificial Neural Network (ANN) models for a porous asphalt lifespan defined by the combination of mixture properties, historical damage, construction conditions, and environmental factors. This study applied 102 porous asphalt road sections obtained from the Strategic Highway Research Program Netherlands (SHRP-NL) database containing ten years data (1991-2000). In order to develop a model, they proposed a novel condition index for porous asphalt which was depended on porous asphalt damage. The prevalent distress of porous asphalt was observed as ravelling which might have originated from improper mix designs, traffic load, and environmental influences like rain, pollution, aging of the bitumen in the mixture, and deviations in composition during the construction. The study proposed three levels of severity for ravelling: light, moderate, and severe (Table 3-2). In order to estimate a single measure, three severity levels of ravelling were combined using weighting factors given by Equation 3-6:

$$Meq = 0.25\,L + M + 5\,Se \tag{3-6}$$

Where,

L = amount of light ravelling [% of total area]

M = amount of moderate ravelling [% of total area]

Se = amount of severe ravelling [% of total area]

Table 3-2 Three Severities of Ravelling (Miradi 2006)

Severity of ravelling	Percentage of stone loss per m^2 (%)
Low	6-10
Moderate	11-20
Severe	>20

The investigators developed ANN model FMeq5 and FMeq8 which would predict the total amount of ravelling five and eight years after construction, respectively. They proposed that FMeq5 or FMeq8 allowed engineers to determine the mixture composition required to prevent ravelling over the first five or eight years of its lifespan. FMeq5 received density, bitumen, void content (VC), coefficient of variation of void content (CVVC), type of stone, %fine, %coarse, warm days, cold days, and cumulative volume of traffic five years after construction as input parameters. During initial model development, the parameters

Cu (coefficient of uniformity = d_{60} / d_{10}) and d50 (sieve size through which 50% of the coarse material passes) did not contribute to training of ANN. Thus, these two parameters were not applied in the model. The same initial inputs were utilized for FMeq8. The outcome of the ANN analysis indicated that the relative importance of various mixtures in a general way (Figure 3-1). They claimed that the amount of overall ravelling five years after construction depended 10% on the amount of traffic, 23% on climatic condition, and 67% on the mixture composition in which stone type had a significant influence. The study reported the following findings:

1) Ravelling increased approximately 10% faster on roads with a heavy traffic during the first five years.
2) Extreme temperatures in the first five years could decrease its lifespan up to 23%.
3) Greywacke provided the best performance from the four stone types involved.
4) Crushed siliceous river gravel should not be used.

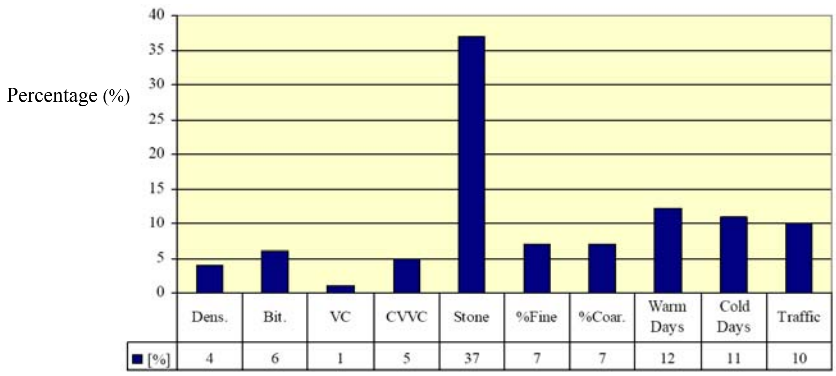


Figure 3-1 The Relative Importance of Input Parameters for Model FMeq5 (Miradi and Molenaar 2006).

Miradi (2004) employed ANN to predict ravelling using time-series ravelling, climate, construction, and traffic factors. The required data was obtained from the SHRP-NL data base. The study developed various ANN models. Firstly, Model I predicted the severity of ravelling: low, moderate, and high. Secondly, Model II involved a sensitivity analysis determining the relative contribution of factors related to climate conditions, traffic factors, thickness, roughness, and age. Finally, Model III analyzed the relation between material properties and ravelling.

They concluded that Model I with a correlation coefficient of 0.9995 during the learning stage and 0.986 during the validation stage was the most appropriate. These values would be improved by providing more data. Model II allowed quantifying the relative contributions of input factors with ravelling as output. It credited most of low ravelling to the climate factors (about 58%), followed by traffic factor (14%), thickness (6%), roughness (12%), and age (10%). Model III was developed for producing relationships between materials and ravelling and could indicate which combination of material properties would cause ravelling to avoid applying it in road construction and design.

3.2 PAVEMENT CONDITION INDEX

Ningyuan (2004) proposed the pavement performance prediction models applied in the second generation Ministry of Transportation of Ontario (MTO) pavement management system (PMS-II). The study suggested that three indices were used to characterize pavement conditions:

1) Riding Comfort Index (RCI) to express pavement roughness
2) Distress Manifestation Index (DMI) to measure severity and extent of several categorized pavement surface distresses which affect riding safety of pavement
3) Pavement Condition Index (PCI) to measure an overall pavement serviceability which is a function of combined components of RCI and DMI.

The investigators suggested an overall condition index for conventional pavement based on roughness and distresses using Equation 3-7:

$$PCI = 10 \times (0.1RCI)^{1/2} \times DMI \times C_i \quad (3\text{-}7)$$

Where the PCI value changes from 0 to 100, and the values defined for RCI and DMI vary from 0 to 10. C_i is a coefficient calibrated for each pavement type applying the regression analysis technique to build a relationship between the calculated PCI and PCR (Pavement Condition Rating) which is visually observed and ranked by road condition raters.

Ultimately, the authors expressed a procedure employed by PMS II for predicting PCI:

I. Predict RCI and DMI separately applying their default prediction models.

II. Calculate PCI for individual pavement sections using Equation 3-8 relating PCI with RCI and DMI by inputting predicted RCI and DMI measures.

$$P = P_0 - 2 \times e^{(a - b \times c^t)} \quad (3\text{-}8)$$

Where,

P = condition index, RCI or DMI
P_0 = P at the age 0
t = $\log_e$ (1 / age)
a,b, and c = model coefficients

Amador and Mrawira (2008) built a locally calibrated pavement condition index from the available FWD and International Roughness Index (IRI) data, and subsequently applied it to network-level modeling. The study claimed that the conventional Pavement Condition Index (PCI) was derived from summing up pavement surface distresses by employing, for example, the deduct value concept in the US Corps of Engineers' PAVER system (Shahin 2005). They proposed a methodology for formulating PCI as a linear combination of measured values of the pavement roughness index (PRI), the structure adequacy index (SAI), and the surface distress index (SDI) using adequate weighting factors. The study stated that the planning process should be more sensitive to structural needs of the network, such as pavement strengthening. Therefore, it was decided to dedicate a higher weight of 60% to the structural adequacy index and a smaller weight of 40% to the surface roughness index. They presented Equation 3-9 as a pavement condition index:

$$PCI = \alpha_1(SAI) + \alpha_2(PRI) \tag{3-9}$$

Where,

SAI = structural adequacy index derived from FWD data
PRI = pavement roughness index derived from IRI data
α_1, α_2 = 0.6, 0.4, respectively

The investigators presented PRI in terms of IRI data measured using high speed laser profilers. They applied a normalization function to reduce each IRI value into a 0 – 100 scale index using Equation 3-10:

$$PRI_j = 100\,\left(\frac{IRI_{max} - IRI_j}{IRI_{max} - IRI_{min}}\right) \tag{3-10}$$

Where PRI_j is the pavement roughness index of section j, IRI_{max} and IRI_{min} are maximum and minimum IRI values in the network data, and IRI_j is the pavement roughness index of section j.

SAI was computed by obtaining the strength of pavement described by the deflection basin parameter "AREA" normalized by the deflection at the centre of the load, D_0 and then scaled into a 0 – 100 scale index given by Equation 3-11:

$$AREA = 6\left[1 + 2\left(\frac{D_1}{D_0}\right) + 2\left(\frac{D_2}{D_0}\right) + \left(\frac{D_3}{D_0}\right)\right] \tag{3-11}$$

Where D_0, D_1, D_2, and D_3 are FWD deflection readings at zero offset, first, second, and third geophones, respectively. Finally, the study modified the SAI index to consist of 70% weight by a 0 – 100 scale index from the deflection basin AREA parameter and 30% weight by a 0 – 100 scale index derived from D_0 using Equation 3-12:

$$SAI_j = 70\left(\frac{AREA_j - AREA_{min}}{AREA_{max} - AREA_{min}}\right) + 30\left(\frac{D_{0,max} - D_0}{D_{0,max} - D_{0,min}}\right) \quad (3\text{-}12)$$

Where,

SAI_j = structural adequacy index of the j_{th} section

$AREA$ = as defined in Equation 3-11

$AREA_{\max}$ and $AREA_{\min}$ = maximum and minimum $AREA$ values in the network data

D_0 = the FWD deflection at the centre of the load

$D_{0,max}$ and $D_{0,min}$ = maximum and minimum values of D_0 in the network data

Silva et al. (2000) applied a pavement condition index called PASER (Pavement Surface Evaluation and Rating) which was based on visual conditions of pavement. They declared that the procedure to obtain PASER was simpler than rigorous distress data collection methods such as the Pavement Condition Index (PCI) procedure. PASER made data collection easier but it was less accurate. The investigators suggested that the accuracy of data was found adequate for local agency applications. The applied PASER assessed asphalt pavement surfaces using a scale that ranged between "1" (very poor condition) and "10" (excellent condition) in the whole number increments. The method did not involve the quantification of distresses. However, the ratings were assigned based on photographs of roads in various conditions presented in the PASER manual. The data was either collected on paper forms or entered directly into the RoadSoft Laptop Data Entry Program.

The logistic growth model was in combination with the PASER/RoadSoft data (Equation 3-13). The starting distress index was assumed to be a distress free pavement section (like new after reconstructed or resurfaced). The logistic growth model reflected the non-linear deterioration rate of the segments. The study proposed that this model was an appropriate deterministic model to be used by local agencies.

$$\text{Rating} = 10 - \left[\frac{\alpha + \beta}{\alpha} + \beta\, e^{-\gamma t} - 1\right] \times \alpha \quad (3\text{-}13)$$

Where,

α = 1.1 (potential initial distress index)

β = 10 (limiting distress index)

$\gamma = -\,(1/\text{DSL})\ \text{LOG}\{[((\alpha + \beta)/(\alpha + \text{cDP})) - 1]\ \alpha/\beta\}$

DSL = the last rating the selected pavement received

cDP = Duration of time for pavement to receive DSL rating

Tack and Chou (2001) proposed a Pavement Condition Rating (PCR) which is based on a visual inspection of condition of pavement by trained raters to analyze possible differences among various pavement districts in the state of Ohio. The study reported that PCR would have values between 0 and 100 representing poor and perfect pavement sections, respectively. The failure rate was assumed to be near 40. The investigators employed four types of pavement (flexible, composite, continuously reinforced concrete, and jointed reinforced concrete) for indication of PCR. They expressed various distresses and weighting factors for each classification. Every distress had a distress weight between 5 and 20. For each distress, they presented severity levels including High, Medium, and Low. Distress extent levels consisted of Occasional, Frequent, and Extensive. Each severity and extent level corresponded to a weighting factor between 0 and 1. In order to obtain a deduct value for a given distress, the distress weight was multiplied by the distress severity and extent factors. Ultimately, to calculate PCR for a pavement section, the sum of all distress deducts was subtracted from 100.

The study presented each year query of the relational database to count the mileage of each district in a certain PCR range. The PCR ranges which were applied included 100-95; 95-90; 90-85; 85-80; 80-75; 75-70; 70-60; 60-50; 50-40; and 40-0. Consequently, they developed a statewide Probability Transition Matrix (TPM) on the bases of these queries. Another meaningful result obtained from the data was the average PCR value of each district. The weighted average PCR value was estimated employing Equation 3-14:

$$PCR_{avg} = \frac{\sum_{i=1}^{n} L_i \times PCR_i}{\sum_{i=1}^{n} L_i} \tag{3-14}$$

Where,

PCR_{ave} = weighted average of PCR

i = current pavement section

n = number of all pavement sections currently in consideration

L_i = length of section i

PCR_i = PCR of section i

Karan (1977) developed an urban pavement serviceability index. The model incorporated serviceability of pavement defined as the magnitude of human responses to physical characteristics of pavement that created inconvenience on the user while driving on pavement. The urban pavement condition index would be defined as a combination of riding comfort and appearance presented in Equation 3-15:

$$USI = f(RI, AI) \tag{3-15}$$

Where,

USI = urban serviceability index which is an overall measure of serviceability of an urban pavement section at any specific time.

RI = riding index that is a measure of ride quality of pavement. It is described in a scale of 0 to 10 (RI = 10 is a perfect ride quality condition, while RI=0 is a completely intolerable ride quality condition.)

AI = appearance index which is a measure of visual distress or deterioration of an urban pavement section. It is also presented on a scale of 0 to 10.

However, regarding the high correlation between three aforementioned variables (Table 3-3), the suggested variables could not be separated from each other. Therefore, there would be no need to use all these three variables to model the serviceability of urban pavement.

Table 3-3 Correlation Coefficient (Karan 1977)

Variables	Simple correlation coefficient
USI vs AI	0.97
USI vs RI	0.98
AI vs RI	0.95

Besides, the tested regression models for relating serviceability to either roughness or the percent damage area are summarized in Equations 3-16 and 3-17, respectively:

$$USI = 8.608 - 0.019 \times x_1 \tag{3-16}$$

$$USI = 7.425 - 0.035 \times x_2 - 0.604 \times lnx_2 \tag{3-17}$$

Where,

USI = urban serviceability index

X_1 = roughness of the pavement as measured by BPR Roughometer

X_2 = percent damage area

3.3 PAVEMENT PERFORMANCE MODELS

3.3.1 Mechanistic Pavement Performance Model

Mechanistic deterioration models had not been developed since pavement engineers did not measure basic response factors in the field (e.g., stress and strain) (Haas 1997). Instead, pavement distresses are measured directly and then related to performance parameters.

Lytton (1987) reported that mechanistic models might forecast future changes in some fundamental mechanistic responses of pavement such as strain, stress, or deflection as a function of some understood factors that would cause changes in those responses such as the level of load and support.

AASHTO (2001) declared that since mechanistic evaluation of materials exposed to different types of loading had provided valuable insights into pavements performance, no pure mechanistic condition prediction models had been available. The study added that each applied condition measure was affected by several factors. Some of these factors could be described in purely mechanistic items, while it is impossible to forecast performance based on basic mechanics equations.

3.3.2 Mechanistic-Empirical Pavement Performance Model

Queiroz (1983) applied linear elasticity as a basic constitutive relationship for pavement materials in thorough research of 63 flexible pavement test sections. The study investigated surface deflection, horizontal tensile stress, strain and strain energy at the bottom of the asphalt layer, and vertical compressive stress and strain at the top of the subgrade. The regression analysis technique was employed to define an adequate relationship between a response and observed roughness and cracking. For instance, the investigator presented the following predictive equation (Equation 3-18) which its correlation coefficient was 0.52 and the standard error for residuals was 0.11:

$$Log(QI) = 1.297 + 9.22 \times 10^{3}\, AGE + 9.08 \times 10^{-2}\, ST - 7.03 \times 10^{-2}\, RH + 5.57 \times 10^{-4} SEN1\, Log\, N \quad (3\text{-}18)$$

Where,

QI = roughness (quarter- car index, in count/km)
AGE = pavement age in years
ST = surface type dummy variable (0 for constructed and 1 for overlayed)
RH = state of rehabilitation indicator (0 for constructed and 1 for overlayed)
$SEN1$ = strain energy at the bottom of the asphalt layer (10^{-4} kgf cm)
N = cumulative Equivalent Single Axle Loads (ESAL)

The study, moreover, proposed the other predictive equation include cracking (Equation 3-19) which its correlation coefficient and standard error for residuals were 0.54 and 15.40, respectively:

$$CR = -8.70 + 0.258\, HST \times Log\, N + 1.006 \times 10^{-7}\, HST \times N \quad (3\text{-}19)$$

Where,

CR = percent of pavement area cracked
HST = horizontal tensile stress at the bottom of the asphalt layer (kgf/sq cm)

N = cumulative ESAL

The new Mechanistic-Empirical Pavement Design Guide (MEPDG) provides significant potential benefits in achieving cost-effective pavement designs and rehabilitation strategies (NCHRP 2007). The Mechanistic-Empirical (M-E) approach is based on the limited use of structural analysis to estimate the critical stress and strain within the structure. The MEPDG has user-oriented computational software which implements an integrated analysis approach to predict pavement condition over time that accounts for the interaction of traffic, climate, and pavement structure. The software can also serve as an effective tool for analyzing the condition of available pavements and indicating deficiencies in past designs. The MEPDG allows consideration of particular traffic load with multiple tires and axles; and provides a means for evaluating design variability and reliability. Moreover, MEPDG allows pavement designers to make better decisions and take the cost-effective advantage of new materials and features. In short, MEPDG provides more appropriate designs, better performance predictions, better material related research, and a powerful forensic tool (Ceylan et al. 2006).

3.3.3 Empirical Pavement Performance Model

Karan et al. (1983) developed an empirical performance model for granular base pavements by applying up to 25 years of data on roughness, surface distress, traffic, and deflection in Alberta (Equation 3-20). The equation correlation coefficient and standard error of estimate were 0.84 and 0.38, respectively:

$$RCI = -5.998 + 6.870 \times Ln\,(RCI_B) - 0.162 \times Ln\,(AGE^2 + 1) + 0.185 \times AGE - 0.084 \times AGE \times Ln\,(RCI_B) + 0.093 \times \Delta\,AGE. \tag{3-20}$$

Where,

RCI = riding comfort index (scale of 0 to 10) at any AGE

RCI_B = previous RCI

AGE = age in year

ΔAGE = four years

Jackson (1993) employed a long-term pavement performance data base to develop a set of regression equations for the state of Washington (Equation 3-21):

$$PCR = C - mA^P \tag{3-21}$$

Where,

PCR = pavement condition rating, scale of 0 to 100

C = 100

m = slope coefficient

A = age of the pavement, years

P = constant which controls the shape of the curve

A set of performance models were presented for different pavement designs or types for Western Washington using Equation 3-21 (Table 3-4).

Table 3-4 Standard Performance Models of Equation 3-21 for the State of Washington (Haas 1997)

Location	Type of Construction/ Pavement Surfacing	Number of Analysis Units	Performance Equation	Age to PCR = 40
Western Washington	New or Reconstructed/ Bituminous Surface Treatment	2	$PCR = 100 - 0.086\ (AGE)^{2.50}$	13.7
	New or Reconstructed/Asphalt Concrete	26	$PCR = 100 - 0.22\ (AGE)^{2.00}$	16.5
	New or Reconstructed/Portland Cement Concrete	19	$PCR = 100 - 0.85\ (AGE)^{1.25}$	30.1
	Resurfacing/BST over AC	5	$PCR = 100 - 8.50\ (AGE)^{1.25}$	4.8
	Resurfacing/BST over BST	6	$PCR = 100 - 3.42\ (AGE)^{1.50}$	6.8
	Resurfacing/AC Overlay (under 1.2 inches)	75	$PCR = 100 - 0.58\ (AGE)^{2.00}$	10.2
	Resurfacing/AC Overlay (1.2 inches to 2.4 inches)	126	$PCR = 100 - 0.76\ (AGE)^{1.75}$	12.1
	Resurfacing/AC Overlay (over 2.4 inches)	19	$PCR = 100 - 0.54\ (AGE)^{1.75}$	14.8

Shekharan (1998) employed ANN to develop an empirical performance model. The investigator trained ANN to predict the Present Serviceability Rating (PSR) of pavement with structural number, age, and cumulative ESAL as input variables. The study generated a synthetic data base employing the Highway Performance Monitoring System model for flexible pavements. Equation 3-22 was proposed by Lee (Lee et al. 1993):

$$Log\ (4.5 - PSR) = 1.1550 - 1.8720 \times Log\ SN + 0.3499 \times Log\ AGE + 0.3385 \times Log\ CESAL \qquad (3\text{-}22)$$

Where,

SN = structural number

AGE = age of pavement since construction or major rehabilitation (years)

$CESAL$ = cumulative 80-KN (18-kip) ESALs applied to pavement in the heaviest traffic lane (millions)

The study trained ANN under four different alternatives as follows:

1) Predicting PSR with structural number, age, and traffic
2) Predicting PSR with structural number, age, and traffic with pruned connection weights
3) Predicting PSR with structural number, age, traffic, and RAN (random number)

4) Predicting PSR with structural number, age, traffic, and RAN (random number) with pruned connection weights

The study concluded that ANN had been successful in predicting PSR with reasonable accuracy for the entire aforementioned alternatives. This success was evaluated by indicating root mean square error (about 0.1). The investigator, ultimately, determined the percentage effect of each input variable on the PSR for various ANN configurations. An additional input variable of random numbers, RAN, was defined to assess its effects on the PSR. It was concluded that its contribution to the PSR was minimal.

Shekharan (2000) employed Genetic Algorithm (GA) to develop a complex nonlinear prediction model. For this purpose, the study applied a few pavement deterioration models to develop synthetic databases as follows:

1) Present Serviceability Rating (PSR) model
2) Distress Maintenance Rating (DMR) model
3) Pavement Condition Rating (PCR) model
4) Punchouts and Patches model

For instance, in terms of PSR, the author deployed the combination of input variables, namely, structural number, age, and cumulative ESALs in order to create the database using Equation 3-23.

$$Log\,(4.5 - PSR) = 1.1550 - 1.8720 \times Log\,SN + 0.3499 \times Log\,AGE + 0.3385 \times Log\,CESAL \qquad (3\text{-}23)$$

Where,

SN = structural number
AGE = age of pavement since construction or major rehabilitation (years)
$CESAL$ = cumulative 80-KN (18-kip) ESALs applied to pavement in the heaviest traffic lane (millions)

The GA technique was applied to indicate solutions based on the synthetic database. Equation 3-23 could be represented in a new form given by Equation 3-24:

$$Log\,(4.5 - PSR) = a - b \times Log\,SN + c \times Log\,AGE + d \times Log\,CESAL \qquad (3\text{-}24)$$

Where,

PSR = present serviceability rating
SN = structural number
AGE = age of pavement since construction or major rehabilitation (years)

CESAL = cumulative 80-KN (18-kip) ESALs applied to pavement in the heaviest traffic lane (millions)

The study proposed the GA technique as a powerful tool to estimate four parameters of the model: a, b, c, and d. The objective function was to minimize the error sum of squares (SSE), namely, to minimize the differences between the predicted value using GA and the actual value using the model. The author concluded that the solution provided by GA produced a model such as that presented in Equation 3-25:

$$Log\ (4.5 - PSR) = 1.1578 - 1.8749 \times Log\ SN + 0.3493 \times Log\ AGE + 0.3384 \times Log\ CESAL \tag{3-25}$$

$$RMSE = 9.604 \times 10^{-3}, N = 80$$

Where,

PSR = present serviceability rating
SN = structural number
AGE = age of pavement since construction or major rehabilitation (years)
CESAL = cumulative 80-KN (18-kip) ESALs applied to pavement in the heaviest traffic lane (millions)
RMSE = root mean square error
N = number of data sets

Bandara and Gunaratne (2001) applied fuzzy sets to deal with the subjectivity associated with human judgments of distress severity and extent for rapid, cost-effective, and reliable evaluation of pavement. They proposed a subjective pavement evaluation methodology. Three linguistic severity levels were considered in this methodology as low, medium, and high for each distress type. Four conventional observed distresses were considered: alligator cracking, pothole, edge failure, and ravelling.

The study suggested a linear membership function called triangular fuzzy members (TFNs) to represent severity, extent, and distress weight or its relative importance in the scale of [0,10]. The authors proposed four linguistic terms (associated with TFNs) for expressing distress weights or its relative importance: important, moderately important, very important, and extremely important. Finally, the investigators applied α – level operation in order to compute a combined distress index considering the fact that severity, extent, and relative importance were represented as TFNs. The efficient fuzzy weighted average (EFWA) method was applied to calculate the weighted fuzzy condition index (FCI) using Equation 3-26:

$$\mathrm{FCI} = \frac{\sum_{i=1}^{3}\sum_{k=1}^{n} w_{ki}A_{ki}S_i}{\sum_{i=1}^{3}\sum_{k=1}^{n} w_{ki}A_{ki}} \tag{3-26}$$

Where,

FCI = weighted fuzzy condition index

w_{ki} = subjective weight of distress k at severity level i

A_{ki} = subjectively assessed extent of distress k at severity level i

S_i = subjective assessment of severity level i

Ultimately, 11 α – values from 0.0 to 1.0 at 0.1 intervals were applied to perform calculations. These results could be utilized to build membership functions of fuzzy condition indices.

Wang (Wang et al. 2007) employed fuzzy set representations for introducing different pavement factors to indicate pavement performance ratings for various pavement condition states. The performance-based model applied pavement condition factors as follows:

1) Level of roughness (low, medium, and high)
2) Level of cracking (low, medium, and high)
3) Index to first crack (1, 2, 3, 4, and 5)

Thus, a total number of 45 (3 × 3 × 5) pavement condition states existed. The authors proposed a two-step approach to estimate performance ratings (f_i). Firstly, they collected experts' opinions about relative importance of three abovementioned factors with regards to performance rating. Secondly, they calculated f_i for all 45 condition states by multiplying importance weights by performance ratings.

$$f_i = P_R \times I_R + P_C \times I_C + P_I \times I_I \tag{3-27}$$

Where,

f_i = performance rating for pavement condition state i

P_R, P_C, P_I = performance rating for roughness, cracking, and index to the first crack, respectively

I_R, I_C, I_I = importance weights for roughness, cracking, and index to the first crack, respectively

The investigators used Fuzzy Weighted Average (FWA) applying α-cut algorithm to estimate the performance rating.

$$y = \frac{w_1 \times x_1 + w_2 \times x_2}{w_2 + w_1} \tag{3-28}$$

Where,

x_1, x_2 = fuzzy variables

w_1, w_2 = fuzzy weighting coefficients

The study applied modified Gaussian curves as the membership functions of the linguistic variables. These curves were proposed since they were suitable to produce the commonly used "AROUND" fuzzy sets. Experts and engineers may usually refer to "AROUND" as an average value for a certain factor.

The authors concluded that pavement performance ratings for each condition state could be calculated using two following steps:

1) Compute the fuzzy set membership function for each condition state

2) Indicate the final value of performance ratings for each pavement condition state

Ultimately, they proposed Equation 3-29 to estimate the conventional numeric value (ranking index) for final performance ratings:

$$IND = \frac{A_L - A_R + C}{2C} \tag{3-29}$$

Where,

IND = index measurement

A_L = area to left of a membership function that characterized a final fuzzy set

A_R = area to right of a membership function that characterized a final fuzzy set

C = a constant, equal to area enclosed by universe (usually C = 1 × 1 = 1)

3.3.4 Probabilistic Pavement Performance Model

Butt et al. (1987) proposed pavement performance and prediction models based on the pavement condition index (PCI) and age of pavement. A combination of homogenous and non-homogeneous Markov Chain was applied to develop prediction models. The authors built up Transition Probability Matrices (TPM) by employing a non-linear programming method. The difference between the actual PCI and expected (predicted) PCI produced by Markov Chain was minimized. The objective function applied had a following form:

$$MIN = \sum_{t=1}^{N} \sum_{j=1}^{M(t)} |Y(t,j) - E[X(t,p)]| \tag{3-30}$$

Where,

N = total number of duty cycles (age) for which PCI versus age data are available within each family

$M(t)$ = total number of data points recorded at duty cycle (age) t

Y (t, j) = PCI rating for each sample taken at the duty cycle (age) t

E[X (t, p)] = expected value in PCI at the duty cycle (age) t, as predicted by the current Markov model

The investigators suggested that homogeneous Markov Chain and individual TPM were developed for each zone (6-year period) since the duty cycle within the zone was assumed to be constant. Because the duty cycle varied from one zone to another, non-homogeneous Markov Chain was applied for transition from one zone to another.

Ortiz-Garcia et al. (2006) proposed three novel methods for deriving TPMs for pavement deterioration modeling rather than applying current conventional methods: using historical data and applying a panel of experienced engineers. The first method assumed that the historical condition data for the entire sites in a transportation network was available. The second method deployed the regression curve obtained from the original data. The third one supposed that the yearly distributions of condition were available to assist in the process. In each method, an objective function aimed to minimize the difference between the original data and the corresponding functions obtained from the transition probabilities. For instance, the authors proposed Equation 3-31 for estimation of transition probabilities from historical data grouped into distributions:

$$Z = \min \sum_t \sum_i [\, a_t\,(i) - a'_t\,(i)]^2 \tag{3-31}$$

Where,

$a_t\,(i)$ = the *i*th element of the distribution of condition applying TPM and the distribution of condition at time 0

$a'_t\,(i)$ = the *i*th element of the original data distributions at time *t*

The findings can be summarized as follows:

1) The transition matrix fitted curves and the regression curves were similar.

2) The standard deviation of the original data and the standard deviation of the transition matrix fitted data were similar.

3) The original condition distributions a'_t and the transition matrix fitted distributions a_t were similar.

Li et al. (1996) developed a non-homogeneous Markov Chain probabilistic modeling program to predict the pavement deterioration rate in different stages. TPMs were developed as a time-related transition process. Each element of TPM was indicated on the basis of a reliability analysis and the Monte Carlo simulation technique. The researchers declared that the process avoided using conventional methods which require subjective opinions of pavement engineers or a large number of multi-year pavement performance data. They assumed that both the predicted actual traffic in terms of ESALs at each stage and the maximum traffic that the pavement could withstand at each defined condition state interval were considered to be random variables. Ultimately, this study presented TPMs of the pavement deterioration at different stages (one, five, and ten years) on pavement section on Highway 402, Ontario, Canada. The study, moreover, reported tests of sensitivity of TPMs to traffic volume, subgrade strength, and pavement thickness.

Wang et al. (1994) proposed two approaches applied to assess TPMs. Firstly, an available pavement performance data base was utilized to develop new TPMs. Secondly, the Chapman-Kolmogorov method was employed to examine the logical extension of TPMs from a single step to long-term pavement behavior. As a result, the concept of pavement probabilistic curve (PBC) was established. TPMs were also modified with accessibility rules to improve the prediction of pavement performance. The investigators concluded that the fit of actual pavement behavior with Markovian prediction was satisfactory.

Madanat et al. (1995) reported that the available approaches applied to estimate TPMs from inspection data were mostly ad hoc and suffer from important methodological limitations. The authors proposed an econometric method to estimate infrastructure deterioration models and associated TPMs from condition rating data. They applied the expected-value method to estimate TPMs as follows:

1) Classify sections into groups with similar attributes
2) Develop condition ratings for each group
3) Develop TPMs for each group by minimizing a measure of distance between an expected value of a section condition rating and a theoretical expected value derived from the structure of Markov Chain.

The study concluded that the proposed method was more realistic than the state-of-the-art method since it recognized the latent nature of infrastructure performance and explicitly linked the deterioration rate to the relevant explanatory variables.

Hedfi and Stephanos (2001) applied both probabilistic and deterministic models as pavement prediction tools. Probabilistic models were applied to corroborate the predicting and planning analysis required at the network level while, deterministic models were used to perform complement analysis conducted at the project level. To incorporate both types of models, one type of processing technique was employed. This technique was used to interpret and transform data into probabilistic models with an included algorithm to convert the models into their equivalent deterministic curve. Expert knowledge was used in order to corroborate pavement data which was rarely perfect. First, a process of acquiring and transforming data from experts in a format to which they related was developed. Second, an algorithm was executed to ensure that performance data and expert knowledge were simultaneously applied during model generations.

The investigators expressed pavement groups in terms of pavement types (flexible, rigid, and composite), traffic levels (low and high), and environmental regions (mountain, piedmont, and coastal). They also proposed five states for measuring the pavement conditions using a performance scale of 0 to 100: very good (90 to 100), good (80 to 89), fair (70 to 79), mediocre (50 to 69), and poor (0 to 49). They employed experts' knowledge to obtain both an estimate of the life duration expected from a maintenance action and determination of life distribution among the condition states. They implemented a two-step process to generate TPMs. First, a series of equations which relate probability distributions to life frequency data was generated. Second, an optimum solution to the probability equations was searched. GA was applied to search for probability values. The authors conducted a goal-driven search to compute the probability distributions that would match the life frequency data. Ultimately, they proposed a new way of assembling and interpreting pavement performance using the concept of life frequencies with modeling techniques by applying both field of Operation Research (OR) and Artificial Intelligence (AI).

Karan (1977) proposed the homogeneous Markov Chain method for developing pavement performance models. He applied a subjective approach to obtain TPMs. Four criteria were expressed as important factors in developing performance models: pavement type and thickness, traffic volume and composition, subgrade type, and environment. The investigator developed TPMs based on the average ratings of six experienced engineers who filled the questionnaires. The author presented TPMs for various rehabilitation options: do nothing, single-lift overlay, double-lift overlay, and re-mixed and re-constructed. Finally, the study presented TPMs based on Urban Serviceability Index (USI) for various categories ($18 = 3 \times 3 \times 2$ groups) regarding the pavement thickness (thin, medium, and thick), traffic (low, medium, and high), and subgrade strength (strong and weak).

3.4 SUMMARY

A review of relevant research studies has been conducted on pervious concrete pavement performance, pavement condition indices, and pavement performance models in this chapter. The literature review has revealed that there are neither condition indices nor performance models have been developed for pervious concrete pavement. However, a significant number of studies have been devoted to development of pavement condition indices and pavement performance models for other types of pavements. The lessons learned from the development of other models for conventional pavements will be valuable in this research. For instance, in terms of pavement condition index development for PCP, the panel rating method is a good approach since no pavement condition index has been developed for PCP to date. In terms of pavement performance models, empirical models and Markov Chain models are good options. Empirical models can be developed through incorporation of short-term performance data collected from the available PCP sites and Markov Chain models can be developed using expert knowledge. In the next chapters, attempts will be made to develop condition indices and performance models for pervious concrete pavement.

Chapter 4
Research Approach, Data Collection, and Processing

An extensive study including Pervious Concrete Pavement (PCP), pavement condition indices, pavement performance models, and thorough literature review have been presented in Chapters 2 and 3. It has been realized that a significant gap still exists in evaluating PCP condition and predicting its performance over its service life. This research focuses on developing a condition index for PCP and producing performance models based on the proposed condition index. This chapter presents the research approach, data sources, and statistical evaluation of the data.

4.1 RESEARCH APPROACH

This research focuses on predicting performance of PCP during its service life. The first step is to develop a condition index for PCP by incorporating a panel of raters and conducting field investigations. The condition index is subsequently used to develop performance models using pavement condition data of several PCP sections visited in Canada and the United States. As a part of this research, two full scale test sections in Ontario were constructed.

This research includes an extensive field investigation study with major concentration on the performance of PCP. This study consists of monitoring of both functional (i.e., permeability rate) and structural (i.e., distresses) characteristics of PCP.

Two PCP parking lots were constructed and monitored during this research in partnership with the Centre for Pavement and Transportation Technology (CPATT), the Cement Association of Canada, Dufferin Construction, and the Ministry of Transportation of Ontario (MTO). Both of these sites were constructed in 2007. The first site is located in Georgetown, Ontario, in a concrete plant parking lot and the second site (called the Guelph Line parking lot) is in a MTO carpool parking lot adjacent to Highway 401 close to Milton, Ontario. These test sites have undergone extensive testing in terms of permeability rate and surface distress evaluation. The surface distress evaluation of these parking lots has been performed applying a pavement condition evaluation guideline to indicate severity and density of observed distresses (e.g., ravelling, spalling, polishing, cracking, stepping, and potholing).

After a detail literature review, it was concluded that several research studies have attempted to address the material characterization of pervious concrete such as strength (Yang and Jiang 2003), freeze thaw durability (American Concrete Institute 2006), and hydraulic conductivity (Haselbach et al. 2006). However, pervious concrete has not been widely investigated in terms of its long term field performance. Few research studies have attempted to assess permeability rates of PCP (Haselbach et al. 2006) and its distress evaluation (American Concrete Institute 2006; Delatte et al. 2007; Eller and Izevbekhai 2007; Murata et al. 2005). Most of the distress evaluation has been carried out subjectively and not necessarily by pavement engineering specialists. In addition, a condition index which is essential for future pavement design, maintenance, and management has not been developed for PCP.

This research approach includes three modules. The first module focuses on a pilot study to develop a Pervious Concrete Condition Index (PCCI) based on panel rating and field investigations. Essentially, to develop an index, a pilot study is required. Based on experiences gained during the pilot study, a second panel rating has been conducted. The second module concentrates on developing PCCI incorporating an experienced panel of raters and field investigations. The second module was different from the first module in terms of field investigation and panel rating approaches. The final module focuses on developing PCP performance models appropriate for cold climates. The detail of each module is described in the following sections. The methodology of the study is presented in Figure 4-1.

4.1.1 Module 1: Pilot Study

The first step for developing any index is to conduct a pilot study. Module 1 was to conduct a pilot study including field investigations and panel rating. Field investigations involved applying an appropriate protocol to measure distresses and combine them to obtain an index for PCP. The MTO protocol was used since it is well developed and provides an index for pavement condition. Few adjustments had been carried out prior to employing the MTO protocol which will be discussed later in this Chapter. Eight PCP sections were selected to be evaluated through field investigations and panel rating. The field investigations encompassed surface distress assessment (based on the MTO protocol) and permeability rate measurements. A guideline for panel rating was designed to evaluate surface distress and permeability of PCP (Appendix A). A survey was conducted incorporating 20 experienced pavement engineers to rate the same PCP sections using sections photos.

4.1.2 Module 2: Pervious Concrete Condition Index Development

The second module followed the first module except some modifications which are described in this section. The first step was to apply a protocol to measure distresses of PCP. According to experience achieved in the pilot study, a few more adjustments were carried out on the MTO protocol which will be discussed in Chapter 5. In addition, the ASTM protocol was applied to measure the surface distresses. The ASTM protocol was also used in this module since it has been widely used in all over the world. Various PCP sections (10 sections) were evaluated. The evaluation tasks included surface distress investigations and permeability measurements. The second step was to conduct panel rating to evaluate surface distresses.

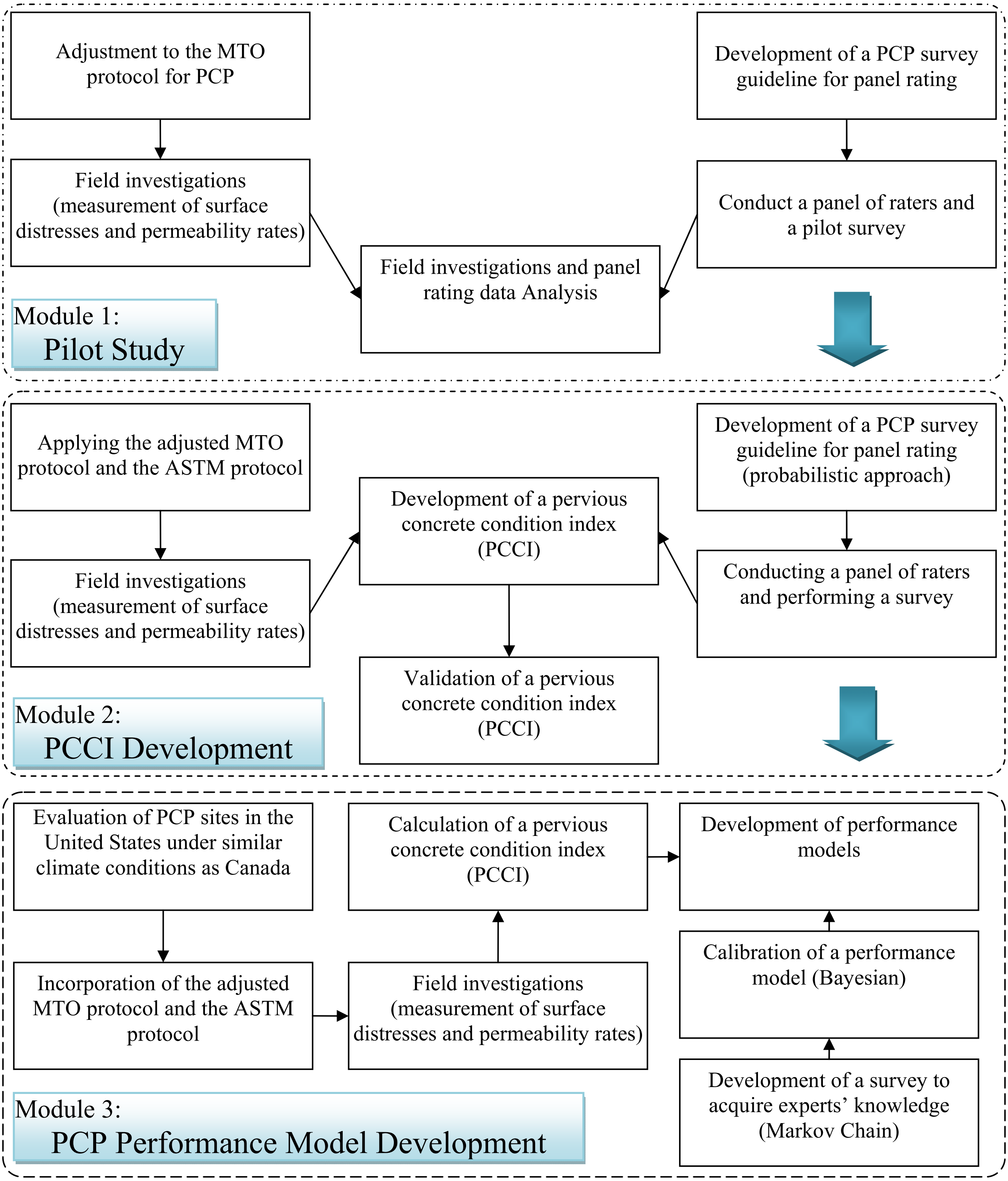


Figure 4-1 Framework of Research.

Applying field measurements and panel ratings, regression analysis was performed and PCCI was developed. The validation procedure was carried out by employing a set of data (25% of the total data) which had not been used in the regression analysis.

4.1.3 Module 3: PCP Performance Model Development

The third module focused on development of PCP performance models. The first step was to identify and contact the owners of several sites in the United States under climate conditions similar to Canada. After that, these sites were visited and evaluated. The surface distress investigations were conducted through incorporation of the MTO and ASTM protocols. Permeability testing was also performed. Through application of surface distress measures and permeability results, PCCI was calculated for the sites and performance models were built and validated for PCP. To calibrate the model, a calibration approach was applied which included integrated Markov Chain and Bayesian methods. A survey was conducted to build up Transition Probability Matrices (TPMs) for developing a Markov Chain model. In total, fourteen experts participated in this survey. Additional questionnaires were distributed to highly experienced engineers and their responses were used to validate the calculated TPMs. Then, the Bayesian approach was applied to provide a posterior model by incorporating both the prior data (expert knowledge: Markov Chain) and experimental data (field investigations).

4.2 DATA COLLECTION

4.2.1 Surface Distress Rating, Permeability Rating, and Field Investigations (Module 1)

4.2.1.1 Experimental Design: Panel Rating

Some preliminary steps should be taken to ensure that sufficient data is available for a successful experimental design before conducting panel rating. These initial steps are as follows:

1) Designing a guide for rating of PCP.

2) Selecting sample PCP sections.

3) Selecting a panel of raters.

4) Designing a rating form.

5) Conducting surface distress and permeability ratings.

4.2.1.2 Designing a Guide for Rating of PCP

First, a guideline was designed for rating surface distress and permeability rate of PCP by incorporating expert knowledge and available relevant research studies (Appendix A). The guideline applied five condition states for surface distress and permeability rate: very good, good, fair, poor, and very poor. Each of the condition states were verbally described together with a picture representing the associated condition state. Raters used this guideline for rating PCP sections in terms of surface distress and permeability rate.

4.2.1.3 Selecting Sample PCP Sections

This study focused on PCP applied in parking lots, while the other applications of PCP include driveways, walkways, bike paths, and low volume roads. Preliminary evaluation of PCP sections was carried out to select a set of PCP sections with a broad range of surface distresses and permeability rates. After screening, eight parking lot sections (in the Georgetown parking lot and Guelph line parking lot) were selected for further investigations.

4.2.1.4 Selecting a Panel of Raters

The raters were selected in an unbiased manner to be able to conduct an adequate rating experiment. Several researchers investigated the impact of age and gender on the judgment of raters (Chou and Wu 1997; Garg et al. 1988; Janoff 1986; Moore et al. 1987; Nair and Hudson 1986; Nick and Janoff 1983; Riverson et al. 1987). Fwa and Gan (1989) showed that the more the raters were involved in rating, the more accurate the results. A group of 20 raters was used in this research. According to research conducted by Nakamura and Michael (1963), the average of the 20 rates was less than 0.4 units away from the true rating at the 5% significance level. In this study, the group of raters provided a good distribution of age, gender, and pavement evaluation experience. The raters' age varied between 21 to 55 years. The rating group included seven females and thirteen males. They were able to observe, detect, and evaluate the pavement distresses. However, for rating of ride quality, non-technical experts might be employed since no related experience is required. Half of the raters were highly experienced pavement engineers (more than 10 years of experience) and the other half were experienced pavement engineers (less than 10 years of experience).

4.2.1.5 Designing a Rating Form

Various rating scales have been acknowledged (Chou and Wu 1997; Fwa and Gan 1989; Garg et al. 1988; Moore et al. 1987). The five-state scale was found more common and easier to use: very good, good, fair, poor, and very poor (Appendix A). The scale ranges from 0 to 10 at 2 intervals. A score of 0 indicates very poor condition, while 10 describes very good condition in terms of both surface distress and permeability rate. The raters were asked to individually indicate a score for surface distress and permeability rate for each section between 0 and 10.

4.2.1.6 Conducting Surface Distress and Permeability Ratings

Pavement distress and permeability rating were carried out by the rating panel. High resolution pictures of each section were provided to the raters for evaluating the PCP sections. The high resolution pictures were taken four metres above the ground covering the whole surface of each section. This approach was deemed to be technical and cost effective (in terms of transportation, time, and labour) especially in the case of incorporating a large group of raters and investigating remote sites. Moreover, this approach eliminated the need to take each evaluator to the site during this phase of the research. The raters also may not be influenced by the other raters. The panel of 20 rated the sections in terms of surface distress and permeability rate.

The panel rating experiment was conducted in one week. The package of data including the rating guideline, the section pictures, and the survey form was sent to the raters via email (due to providing softcopies of section pictures to raters, saving time and cost, and being environmentally friendly). The purpose of this study was explained, the PCCI was described, and the influential factors on PCP performance were expressed to the raters. They were given one week to complete the survey and return the completed survey via email. The panel rated the sections individually and the whole survey was accomplished in one week in a cost-effective way. Table 4-1 and Table 4-2 present results of the surface distress rating and permeability rating, respectively.

4.2.1.7 Field Investigations (Surface Distress Evaluation and Permeability Test)

Surface distresses were evaluated incorporating the adjusted MTO protocol. Adjustments involved in the pavement evaluation and weighting factors are further discussed in this chapter. Distress types detected on PCP surfaces were assessed describing distress severity and density using a developed PCP evaluation form (Appendix B).

Table 4-1 Surface Distress Ratings Data

		Rater number																			
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Section number	1	9	3	7	3	4	7	6	7	6	5.2	7	7	5	7	5.5	5	3	5	8	8
	2	6	9	8	7	5	5	8	8	5	7	8.5	8	7	9	8	7	7	8	8	9
	3	2	3	3	1	1	7	1	5	6	2.5	6.5	3	3	5	1	4	3	4.5	4	7
	4	2	1	2	3	1	7	4	4	3	3.5	6	2	3	3	3	5	3	4	4	6
	5	5	5	4	3	2	5	5	7	4	6	8.2	5	3	5	6.5	4	3	6	4	6
	6	6	3	2	1	1	1	2	2	3	2.5	4	3	3	3	3	5	1	6.5	3	5
	7	4	3	1	1	1	1	1	2	3	1.6	5	0	3	3	2	4	1	7	3	6
	8	7	3	5	5	0	1	2	3	5	5	9.2	3	3	1	4	7	5	7.5	3	5

Table 4-2 Permeability Ratings Data

		Rater number																			
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Section number	1	9.5	5	8	3	4	5	7	8	9	7	7.5	9	5	7	5	7	3	7	9	8
	2	9	7	10	7	5	5	9	8	6	8	8.5	9	7	7	9	8	7	9	10	8
	3	5	3	1	1	0	3	2	4	3	2	5	5	1	3	1	4	3	6	3	5
	4	2	3	4	3	1	3	3	3	3	2.5	7	3	3	1	3	4	5	5	4	5
	5	8	1	3	3	1	3	6	8	5	7	7.5	5	3	5	3	7	5	6.5	6	6
	6	7	3	3	1	0	1	2	3	3	3	4.8	4	5	1	1.5	5	1	7	4	6
	7	4	3	1	1	0	1	1	2	2	1.5	3	0	3	1	0.5	6	1	6	3	6
	8	8.5	1	7	3	0	1	3	3	4	4	9	4	5	1	3	8	3	8	2	6

Distress types which have been mostly observed on PCP were considered in pavement surface evaluation including polishing, cracking, ravelling, spalling, potholing, and stepping. Five types of severity (very slight, slight, moderate, severe, and very severe) and five types of density (few, intermittent, frequent, extensive, and throughout) were considered by the MTO protocol and a series of weighting factors were dedicated to these severity and density levels from low to high: 0.5, 1, 2, ,3, and 4, respectively (Ningyuan et al. 2004). All sections were evaluated and results are summarized in Table 4-3.

Table 4-3 PCP Surface Distresses

Section	Ravelling		Polishing		Potholing		Spalling		Cracking		Stepping	
	Severity Weights	Density Weights	Severity Weights	Density Weights	Severity Weights	Density Weights	Severity Weights	Density Weights	Severity Weights	Density Weights	Severity Weights	Density Weights
1	2	2	2	0.5	1	2	2	1	0	0	0	0
2	1	1	0	0	0.5	1	0.5	1	0	0	0	0
3	2	3	2	3	2	3	1	4	0	0	0	0
4	3	4	1	0.5	2	2	1	4	0	0	0	0
5	1	2	2	2	1	2	1	3	0	0	0	0
6	2	3	2	2	2	2	1	4	0	0	0	0
7	3	3	2	3	2	3	1	4	0	0	0	0
8	2	3	1	1	0.5	2	1	4	0	0	0	0

The permeability rate of PCP sections was measured using a Gilson Permeameter (Figure 4-2). The permeability test is based on the falling-head test which is usually applied to soil permeability measurements. The standpipe was placed on a pavement surface and the edges of the pipe were covered and sealed in order to direct water vertically through the pavement and minimize the horizontal flow of water. Then, water was poured in the standpipe and allowed to seep through the pavement. The time for water to drain and the drop in the height of water were recorded to calculate permeability rates. Equation 4-1 was applied to calculate permeability rates (Gilson Company Inc. 2006).

$$K = \frac{a\,L}{A\,t}\,ln\,(\frac{h_1}{h_2}) \qquad (4\text{-}1)$$

Where,

K= coefficient of permeability (cm/s)

a = inside cross sectional area of the standpipe (cm^2)

L= the length of the sample (cm)

A= cross sectional area of the sample (cm^2)

t= elapsed time between h_1 and h_2 (s)

h_1= initial height of water above a pavement surface (cm)

h_2= final height of water above a pavement surface (cm)

Figure 4-2 Apparatus Set-Up for Permeability Test on PCPs.

The permeability test was repeated three times on each PCP section, and the averages of the results are presented in Table 4-4.

Table 4-4 Permeability Rates

Section	h1 cm	h2 cm	Standpipe cm	t1 sec	t2 sec	t3 sec	K 1 cm/s	K 2 cm/s	K 3 cm/s	K Avg. cm/s	K Std. cm/s
1	24.0	21.0	38.3	2.5	2.8	3.0	0.184	0.169	0.157	0.171	0.013
2	10.0	5.0	167.5	6.5	6.7	6.5	1.661	1.617	1.654	1.645	0.023
3	23.0	22.0	38.3	6.1	6.6	7.0	0.025	0.024	0.022	0.024	0.001
4	27.5	27.0	38.3	4.0	5.2	4.5	0.016	0.012	0.014	0.014	0.002
5	32.0	31.5	38.3	15.9	23.7	29.9	0.005	0.003	0.003	0.001	0.001
6	25.0	22.0	38.3	22.2	24.8	25.4	0.025	0.017	0.016	0.020	0.002
7	30.0	25.0	38.3	12.7	16.9	19.9	0.066	0.047	0.042	0.050	0.014
8	25.0	20.0	38.3	15.4	18.2	18.6	0.077	0.065	0.064	0.069	0.007

4.2.2 Surface Distress Rating and Field Investigation (Module 2)

4.2.2.1 Experimental Design: Panel Rating

Similar to Module 1, preliminary steps should be taken to ensure that sufficient data is available for an experimental design prior to conducting panel rating. These steps are described below.

1) Provide a guide for surface distress ratings of PCP.

2) Select PCP parking lot sections to be surveyed.

3) Select a panel of raters.

4) Design a rating form.

5) Perform surface distress ratings.

4.2.2.2 Provide a Guide for Surface Distress Ratings of PCP

The guide that was designed and applied for rating of surface distresses in the pilot study was employed herein for panel rating. As mentioned earlier, the guide applied five condition states for surface distress and permeability rate: very good, good, fair, poor, and very poor. Each of the condition states was verbally described together with a picture representing the associated condition state (Appendix A). Raters incorporated this guide for rating the PCP sections in terms of surface distresses (not permeability) since in the pilot study the permeability rating could not provide statistically significant results which will be discussed later in this chapter.

4.2.2.3 Select PCP Parking Lot Sections to be Surveyed

Ten PCP sections were selected to cover the entire surface characteristics of two parking lots (Georgetown and Guelph Line parking lots). Each section includes several slabs. Every other slab was selected to be assessed in each section. Namely, in total half of the entire slabs (51 slabs) were evaluated. The evaluation involved surface distress measurements, permeability tests, and panel ratings.

4.2.2.4 Select a Panel of Raters

Raters should not be selected in a biased manner in order to conduct an adequate rating experiment. A group of five raters was employed in this research. According to the study conducted by Nakamura and Michael (1963), the average of the five ratings was less than 0.75 units away from the true rating at the 95% confidence level. In this study, the group of raters provided a good representation of age, gender, and pavement evaluation experience. The raters were between 21 and 32 years of age. The rating group included three females and two males. The panel consisted of experienced pavement engineers since the rating should be performed based on the understanding of various PCP distresses.

4.2.2.5 Design a Rating Form

The same scale was applied herein as used in the pilot study, that is, the five-state scale was found more common and easier to use (very good, good, fair, poor, and very poor). The scale ranges from 0 to 10 whereby a score of 10 expresses a very good condition, while a score of 0 indicates a very poor condition or failed state in terms of surface distress. As oppose to the normal (deterministic) rating form used in the pilot test, in this section, a probabilistic rating form was applied due to the fact that the previous PCP evaluation form has some discrepancies. For instance, a section would match with more than a single scale. Namely, a section can represent various scales at the different level of probability. For example, a section may match with the "good" scale with the probability of 70%, while at the same time it represents the "fair" scale with the probability of 30%. In other words, 70% of the section is similar to the "good" condition, while 30% of that is similar to the "fair" condition. The raters were asked to individually indicate five scores for surface distress of each slab between 0 and 100. Each score presents the similarity or goodness of fit of each scale to the evaluated slab (Appendix C).

4.2.2.6 Perform Surface Distress Ratings

Each survey participant attended a training session whereby the purpose of the study, the PCP condition, and the influential factors on PCP where explained. Most importantly, a few sample sections were exhibited, discussed, and rated for illustration. The training session had a significant impact on obtaining consistent results. The package of data including the rating guideline and the probabilistic rating form was given to the raters. The guideline for PCP surface distress rating was similar to the one used in the pilot study. Then, the rating panel including five pavement engineers was taken to the PCP sites to conduct the survey. It was not cost effective (in terms of transportation, time, and labour) especially for remote sites to include a large group of raters at the sites, as compared with a rating based on the digital visual evaluations (pilot study). The raters rated the sections individually and their ratings were not influenced by the other raters. A sample probabilistic rating of the first slab conducted by the raters is presented in Table 4-5. More details are provided in the following sections.

Table 4-5 Probabilistic Rating of Slab 1 Conducted by Five Raters

Condition level	Rater 1	Rater 2	Rater 3	Rater 4	Rater 5
Very Good	30	40	20	20	0
Good	50	20	50	20	70
Fair	20	30	30	40	30
Poor	0	10	0	15	0
Very Poor	0	0	0	5	0

4.2.2.7 Field Investigations (Surface Distress Evaluation and Permeability Test)

Surface distresses were assessed incorporating the adjusted MTO protocol and the ASTM protocol. A new pavement condition evaluation form (Appendix D) was designed for surface evaluation incorporating the adjusted MTO protocol. Distress types which were detected on the PCP surface were assessed (distress severity and density). In terms of the MTO protocol, according to experience gained in the pilot study, an adjustment was performed to evaluate the PCP sections. The adjustment was to express each distress severity by its observed percentage in a section. While, with the MTO protocol, only one type of distress severity together with its associated density can be reported. Namely, in a case where two levels of distress severity are present, the more prevalent severity is reported. In terms of the ASTM protocol, nine distress types were frequently observed and recorded on the PCP sections: popout, corner spalling, joint spalling, linear cracking, polishing, faulting, large patch, small patch, and shrinkage cracks. According to the ASTM and adjusted MTO protocols, 15 slabs in the Georgetown parking lot and 36 slabs in the Guelph line parking lot were evaluated. Pavement evaluation results for the Georgetown parking lot based on the adjusted MTO protocol and the ASTM protocol are presented in Appendix E. Similarly, pavement evaluation records for the Guelph line parking lot based on the adjusted MTO protocol and the ASTM protocol are exhibited in Appendix E. In addition, the permeability rates of the slabs were measured applying the Gilson permeameter as described earlier. The test was conducted three times for each slab and the results are exhibited in Appendix E for the Georgetown parking lot and the Guelph line parking lot.

4.2.3 Conducting a Survey and Field Investigation (Module 3)

4.2.3.1 Markov Chain Survey

A Markov Chain questionnaire included a series of Transition Probability Matrices (TPMs) for various PCP groups which were completed according to the survey participants experience on PCP performance. After extensive discussions with experts, several questionnaires were designed and pilot tests were carried out. Based on the feedback of participants, the questionnaire was adjusted and the final version of the questionnaire was developed. Appendix F shows the questionnaire applied in this study. The questionnaire was designed for calibrating a PCP performance model incorporating the Markov Chain method and the Bayesian technique (discussed in Chapter 6). The Markov Chain method was employed due to the lack of long term performance data for PCP. The obtained data, however, should represent the reality. In fact, several research studies have shown that this process has worked reasonably well for different type of pavements (Karan 1977; Li et al. 1996; Ortiz-García et al. 2006). The questionnaire briefly discussed a concept of PCCI. Then, it categorized PCP into groups based on the PCP characteristics (age, pervious concrete thickness, and traffic load). PCP characteristics are summarized in Table 4-6.

Table 4-6 PCP Group Characteristics

Pervious concrete thickness	Vehicle Traffic	Pavement Age	Environment Condition
Thin $100^{mm} < H \leq 150^{mm}$ (4 in < H ≤ 6 in)	Light	Primary Interval ($1^{year} < T \leq 2^{year}$)	Hard Wet Freeze
Thick $150^{mm} < H < 250^{mm}$ (6 in < H < 10 in)	Heavy	Secondary Interval ($2^{year} < T < 5^{year}$)	

Note that the “Light” traffic was assigned to a pavement section which is generally exposed to ordinary cars, vans, and trucks. The heavy vehicle is limited to trucks with at least six wheels excluding panel and pickup trucks. The “Heavy” traffic was dedicated to a pavement section that is essentially exposed to heavy vehicles (such as a plant which is frequently exposed to heavy vehicles with more than 25 average daily truck traffic). The “Hard Wet Freeze” climate condition was explained as certain wet freeze areas that undergo a number of freeze-thaw cycles annually (15+) and there is precipitation during the winter where the ground maintains frozen as a result of a long continuous period of average daily temperatures below freezing. These areas would have situations where the pervious concrete becomes fully saturated.

Two levels of pavement thickness, two levels of pavement age, and two traffic load patterns were used resulting in 8 ($2 \times 2 \times 2$) possible combinations, and 8 possible pavement groups. One type of environmental condition was assumed in this study: hard wet freeze climate such as the North Ontario, Canada climate. Since a typical design has been used for PCP, groups which have thin pervious concrete thickness and heavy traffic are rarely feasible. Therefore, these groups were eliminated and at a total of six groups were analyzed (Table 4-7).

Table 4-7 Different Pavement Groups

Group	Pervious concrete thickness	Vehicle Traffic	Pavement Age	Environment Condition
1	Thin	Light	Primary Interval	Hard Wet freeze
2	Thin	Light	Secondary Interval	Hard Wet freeze
3	Thick	Light	Primary Interval	Hard Wet freeze
4	Thick	Light	Secondary Interval	Hard Wet freeze
5	Thick	Heavy	Primary Interval	Hard Wet freeze
6	Thick	Heavy	Secondary Interval	Hard Wet freeze

Before distributing the questionnaire, respondents were trained. The Markov Chain process was explained and the method of completing TPMs was discussed. Several photos were provided showing the condition state of Pervious Concrete Distress Index (PCDI) of several sections during their service life (this index will be described in Chapter 5). Having trained the respondents, the questionnaire was distributed to 14 pavement engineers and they completed and returned the survey. A sample TPM is shown in Table 4-8.

Table 4-8 Sample Transition Probability Matrix

PCDI			Future Condition				
			State 5	State 4	State 3	State 2	State 1
			80-100	60-80	40-60	20-40	0-20
Present Condition	State 5	80-100	**50**	**50**	---	---	---
	State 4	60-80	---	**60**	**40**	---	---
	State 3	40-60	---	---	**65**	**35**	---
	State 2	20-40	---	---	---	**70**	**30**

4.2.3.2 Field Investigations (Surface Distress Evaluation and Permeability Test)

The PCP parking lots investigated in this section are located in the state of Ohio in the United States. Eleven parking lots were carefully selected and evaluated considering the fact that they are all located in the hard wet freeze condition. Project names and various relevant characteristics of the PCP parking lots are provided in Table 4-9.

Some sites were five years in service, while a few of them were practically brand new. These sites were visited and evaluated in terms of surface distresses (according to the adjusted MTO and ASTM protocols) and permeability rates in the same way as described in Module 2.

Table 4-9 Ohio PCP Parking Lot Characteristics

Project name	Traffic Load	Pervious concrete thickness	Date Constructed	Application	Location
Collinwood Concrete Saranac Plant	heavy	225 mm (9 in)	Apr 2005	concrete plant	Cleveland
Lake County Fairground	light	150 mm (6 in)	Jun 2008	parking lot	Painesville
Roush Honda Inventory Lot	light	150 mm (6 in)	Nov 2008	parking lot	Westerville
Cleveland State University Parking Lot D	light	150 mm (6 in)	Aug 2005	parking lot	Cleveland
Cleveland State University Admin. Building	light	150 mm (6 in)	Jul 2007	parking lot	Cleveland
Indian Run Falls Park	light	150 mm (6 in)	Mar 2006	parking lot	Dublin
Audubon Center	light	150 mm (6 in)	Aug 2008	parking lot	Columbus
Anderson Concrete Plant	light	150 mm (6 in)	Aug 2008	parking lot	Columbus
Bettman Natural Resource Center	light	150 mm (6 in)	Oct 2006	parking lot	Cincinnati
Ball Brother Foundations	heavy	150 mm (6 in)	Jan 2004	storage yard	Monroe
Philips Concrete	light	175 mm (7 in)	Jun 2006	parking lot	Beavercreek

4.2.3.3 Collinwood Concrete Saranac Plant

The PCP site located at the Collinwood Concrete Saranac plant in Cleveland, Ohio, (as shown in Figure 4-3) is heavily loaded by trucks. The concrete trucks pass across a strip multiple times daily. This strip was divided into three slabs for evaluation.

a) An overall view b) Sign of ravelling and spalling

Figure 4-3 A Strip of PCP in the Collinwood Concrete Saranac Plant.

The test strip at the Collinwood Concrete Saranac plant has degraded due to exposure to heavy loads. The overall pavement condition of the PCP site at the Collinwood Concrete Saranac plant was fair. The layout of the test strip and surface distress evaluation results are presented in Appendix G according to the MTO and ASTM protocols.

Clogging has become an issue for this test strip. The strip has clogged to the point where standing water collects on the pavement. Permeability was tested on each slab at a total of three in-situ points on the PCP strip. The test was conducted three times on each slab and results are shown Appendix G.

4.2.3.4 Lake County Fairground

The parking lot placed in the Lake County Space Fairground in Painesville, Ohio, (as shown in Figure 4-4) is used primarily by light vehicles. There are three strips of PCP which are separated by conventional concrete strips. Each strip was divided into five slabs (totally 15 slabs). The parking spaces are located within the PCP strips.

a) An overall view b) Shrinkage Crack

Figure 4-4 Lake County Fairground Parking Lot.

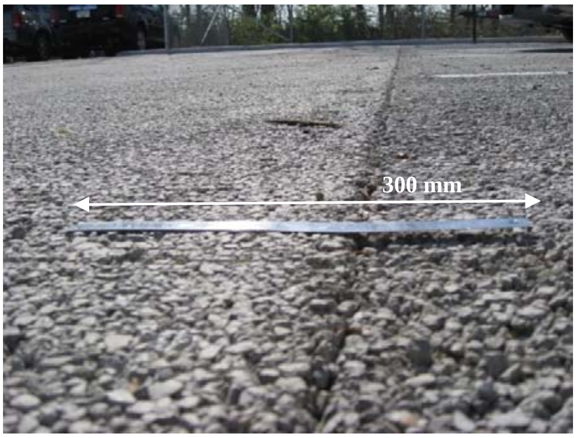
The test strips at the Lake County Fairground parking lot have performed adequately, while not being exposed to heavy loads. The overall pavement condition of the PCP site at the Lake County parking lot was good to very good. The layout of the test strips and surface distress evaluation results are presented in Appendix G according to the MTO and ASTM protocols.

Clogging has not become an issue for these test strips. The strips have performed adequately with respect to permeability. Permeability was tested at a total of 15 in-situ points on the pervious concrete strips. The test was completed three times on each slab and results are shown in Appendix G.

4.2.3.5 Roush Honda Inventory Lot

The PCP placed in the Roush Honda Inventory Lot in Westerville, Ohio, (as shown in Figure 4-5) is used primarily by light vehicles. The parking lot was observed to be heavily occupied. Four strips not within parking spaces were selected and evaluated. Each strip included six slabs. Every other slab was tested at this location (totally 12 slabs).

a) An overall view



b) Stepping

Figure 4-5 Roush Honda Inventory Lot.

The test site located at the Roush Honda Inventory Lot has performed well, while not being exposed to heavy loads. The overall pavement condition of the PCP site at the Roush Honda Inventory Lot was determined to be good to very good. The layout of the test strips and surface distress evaluation results are presented in Appendix G according to the MTO and ASTM protocols.

Clogging was not observed at this test site. The strip has performed adequately with respect to permeability. Permeability was tested on each slab at a total of 12 in-situ points on the pervious concrete strips. The test was completed three times on each slab. The results are shown in Appendix G.

4.2.3.6 Cleveland State University Parking Lot D

The PCP located at the Cleveland State University Parking Lot D in Cleveland, Ohio, (as shown in Figure 4-6) is exposed to light traffic as it is used to park cars for faculty and staff. There is only one pervious pavement strip in this parking lot which is subdivided into five slabs. All slabs are located within the parking spaces. Every slab at this location was tested (totally 5 slabs).

a) An overall view

b) Corner spalling

Figure 4-6 Strip of Pervious in Cleveland State University Parking Lot D.

The test strip at the Cleveland State University Parking Lot D has performed well, while not being exposed to heavy loads. The overall pavement condition of the PCP site at the Cleveland State University Parking Lot D was fair to good. The layout of the test strip and surface distress evaluation results are presented in Appendix G according to the MTO and ASTM protocols.

Clogging has become an issue for this test strip. Water has infiltrated slowly in the strip. Water applied to the surface tended to move horizontally (across the strip) rather than moving vertically through the pavement. Permeability was tested on each slab at a total of five in-situ points on the pervious concrete strip. The test was conducted three times on each slab and the results are shown in Appendix G.

4.2.3.7 Cleveland State University Administration Building Parking Lot

The PCP located at the Cleveland State University in Cleveland, Ohio, (as shown in Figure 4-7) is located in front of the Administration Building and is used for visitor vehicle parking. The parking lot was heavily loaded at the time of evaluation. There are three PCP strips in this parking lot. Each strip includes seven slabs. Two strips are located within the parking spaces. Five slabs in each strip were evaluated (totally 15 slabs).

a) An overall view b) Ravelling

Figure 4-7 Cleveland State University Administration Building Parking Lot.

The test strips at the Cleveland State University Administration Building have performed well, while not being exposed to heavy loads. The overall pavement condition of the PCP site at the Cleveland State University Administration Building parking lot was fair. The layout of the test strips and surface distress evaluation results are presented in Appendix G according to the MTO and ASTM protocols.

Permeability was tested on some slabs at a total of 15 in-situ points on the pervious concrete strips. The test was completed three times on each slab and the results are shown in Appendix G. Clogging has not become an issue for these strips. Water has infiltrated adequately although in few spots (slabs 1 and 12) the permeability rates were significantly reduced.

4.2.3.8 Indian Run Falls Park

The PCP parking lot located at the Indian Run Falls in Dublin, Ohio, (as shown in Figure 4-8) is used to park passenger vehicles. The parking lot was heavily loaded at the time of evaluation. There are three PCP strips in this parking lot. Each strip includes five slabs. Two strips (near the edges) are located within the parking spaces and no parking spaces are located within the middle strip. All slabs in each strip were tested (totally 15 slabs).

a) An overall view b) Potholing

Figure 4-8 PCP Parking Lot at the Indian Run Falls Park.

The overall pavement condition of the PCP site at the Indian Run Falls Park parking lot was deemed to be fair to poor. The layout of the test strips and surface distress evaluation results are presented in Appendix G according to the MTO and ASTM protocols.

Clogging was not observed on these test strips. Water has infiltrated adequately through the strips although in few locations, slabs 9 and 3, the permeability rates were low in comparison to others. Permeability was tested on all slabs at a total of 15 in-situ points on the pervious concrete strips. The test was completed three times on each slab and the results are shown in Appendix G.

4.2.3.9 Audubon Parking Lot

The PCP placed in the Audubon Parking Lot in Columbus, Ohio, (as shown in Figure 4-9) is used by passenger vehicles. The parking lot was slightly loaded at the time of evaluation. There are four pervious concrete strips in this parking lot. Each strip includes twelve slabs. All strips are located within the parking spaces. Two strips which were used by the visitors were evaluated. Every other slab in each strip was tested in this location (totally 12 slabs).

a) An overall view b) Polishing (polished aggregate)

Figure 4-9 PCP in the Audubon Parking Lot.

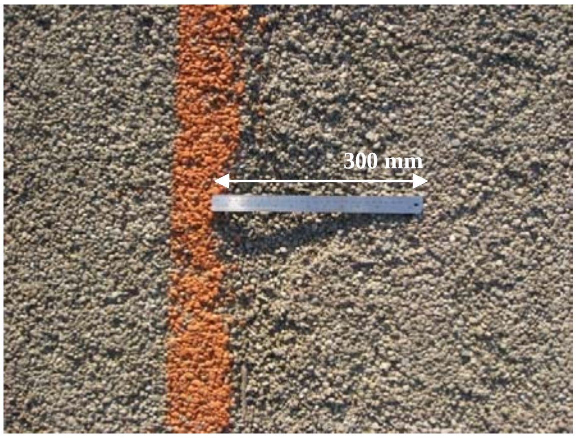
The test site located at the Audubon Parking Lot has performed well, while not being exposed to heavy loads. The overall pavement condition of the PCP site at the Audubon parking lot was good. The layout of the test strips and surface distress evaluation results are presented in Appendix G according to the MTO and ASTM protocols.

Clogging has not become an issue for these test strips. Water has infiltrated through these strips adequately. The permeability rate was high. Permeability was tested on some slabs at a total of 10 in-situ points on the pervious concrete strips. The test was conducted three times on each slab and the results are shown in Appendix G.

4.2.3.10 Anderson Concrete Plant

The PCP parking lot located at the Anderson Concrete Plant in Columbus, Ohio, (as shown in Figure 4-10) is occupied by passenger vehicles. The parking lot was heavily loaded at the time of evaluation. There are four pervious concrete strips in this parking lot. Each strip is divided into four slabs. All PCP strips are located within the parking spaces. The rest of the parking lot is made of conventional concrete. Two strips which were mostly used by the visitors were evaluated. Every other slab in each strip was tested in this location (totally 8 slabs).

a) An overall view



b) Potholing

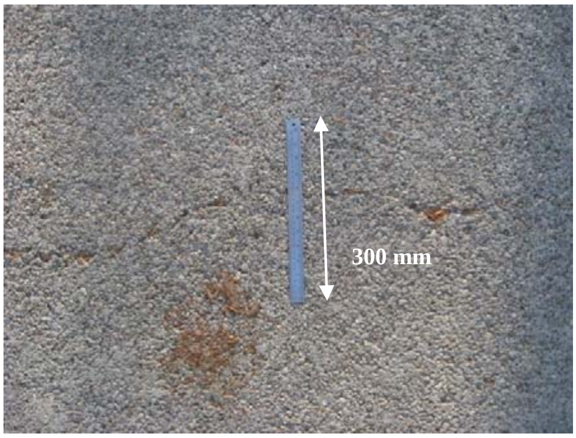
Figure 4-10 Anderson Concrete Plant Parking Lot.

The test strips at the Anderson Concrete Plant have performed well, while not being exposed to heavy loads. The overall pavement condition of the PCP site at the Anderson Concrete Plant parking lot was fair to good. The layout of the test strips and surface distress evaluation results are presented in Appendix G according to the MTO and ASTM protocols.

Clogging has not become an issue for these test strips. In these strips, water has infiltrated adequately through the pavement. The permeability rate was high. Permeability was tested on some slabs at a total of 8 in-situ points on the pervious concrete strips. The test was completed three times on each slab and the results are shown in Appendix G.

4.2.3.11 Bettman Natural Resource Center

The PCP placed in the Bettman Natural Resource Center parking lot in Cincinnati, Ohio, (as shown in Figure 4-11) is occupied by passenger cars. The parking lot was moderately loaded at the time of evaluation. There are four pervious concrete strips in this parking lot. Three strips are divided into six slabs and the remaining strip is divided into three slabs (which were not evaluated). Two strips are only located within the parking spaces. Every slab within the strips was tested in this location (totally 18 slabs).



a) An overall view b) Cracking

Figure 4-11 Bettman Natural Resource Center Parking Lot.

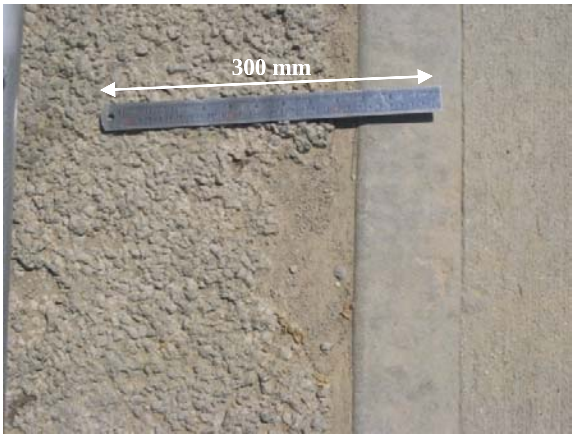
The test strips at the Bettman Natural Resource Center parking lot have performed fairly well, while not being exposed to heavy loads. The overall pavement condition of the PCP site at the Bettman Natural Resource Center parking lot was fair. The layout of the test strips and surface distress evaluation results are presented in Appendix G according to the MTO and ASTM protocols.

Clogging has not become an issue for these test strips. Water has seeped through the pavement adequately even though in few spots the permeability rate decreased, such as slab 6. Permeability was tested on some slabs at a total of 9 in-situ points on the pervious concrete strips. The test was conducted three times on each slab and results are shown in Appendix G.

4.2.3.12 Ball Brother Foundation

The PCP located at the Ball Brother Foundation in Monroe, Ohio, (as shown in Figure 4-12) is a plant storage yard. The parking lot has been loaded by the heavy vehicles. The entire storage area was made from pervious concrete except a single strip of conventional concrete pavement. Half of the storage surface was covered by the molds and instruments so that only four pervious concrete strips at the storage yard could be observed and evaluated. In total, 19 slabs were selected and tested at this location.

a) An overall view



b) Spalling

Figure 4-12 Ball Brother Foundation Storage Yard.

The test strips at the Ball Brother Foundation are experiencing distresses related to heavy loads. The overall pavement condition of the PCP site at the Ball Brother Foundation storage yard is fair to poor. The layout of the test strips and surface distress evaluation results are presented in Appendix G according to the MTO and ASTM protocols.

Clogging was observed during the permeability testing. In these strips, water has not infiltrated adequately. Permeability was tested on several slabs at a total of 19 in-situ points on the pervious concrete strips. The test was conducted once on most of the slabs and the results are shown in Appendix G. Note that due to the low permeability rate of these strips, permeability test was carried out once on the most of slabs.

4.2.3.13 Phillips Concrete Parking Lot

The PCP placed in the Philips Concrete Parking Lot is located in Beavercreek, Ohio, (as shown in Figure 4-13). The parking lot has been loaded by light vehicles. The whole parking lot was made from pervious concrete. The parking lot contains six strips. Four strips that have been used as parking spaces were selected and evaluated. Totally, 28 slabs were tested in this location.

a) An overall view b) Spalling

Figure 4-13 Philips Concrete Parking Lot.

The test strips at the Philips Concrete Parking Lot have performed well, while not being exposed to heavy loads. The overall pavement condition of the PCP site at the Philips Concrete parking ot was fair to poor. The layout of the test strips and surface distress evaluation results are presented in Appendix G according to the MTO and ASTM protocols.

Permeability was tested on some slabs at a total of 21 in-situ points on the pervious concrete strips. The test was completed three times on each slab and the results are shown in Appendix G. Note some spots were tested once or twice due to the low permeability rate. Permeability has become an issue in a few slabs such as slab 16.

4.3 DATA PROCESSING AND DESCRIPTIVE STATISTICS

4.3.1 Surface Distress and Permeability Ratings (Module 1)

Prior to developing PCCI, it is necessary to investigate the reliability of the data. Several processing approaches were applied to identify the reliability of the panel rating data. The data represented in Table 4-1 and Table 4-2 was analyzed and is discussed in the following sections. Figure 4-14 and Figure 4-15 show the probability mass function of surface distress rating and permeability rating of PCP sections, respectively. These figures address the probability of presence of each condition state for the entire sections with respect to surface distress and permeability rating. Both figures illustrate that the probability of occurrence of poor condition is more than the other condition states for all PCP sections. Namely, raters used poor condition in their rating more than the other condition states (e.g., very poor, fair, etc.) in both surface distress rating and permeability rating.

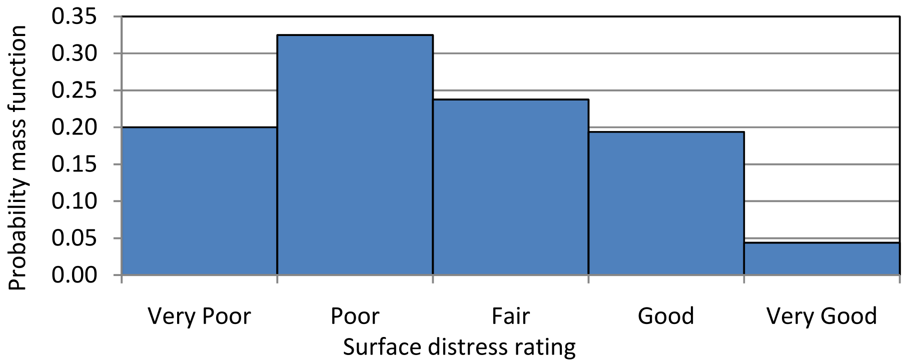


Figure 4-14 Distribution of Surface Condition Rating for the Entire Sections.

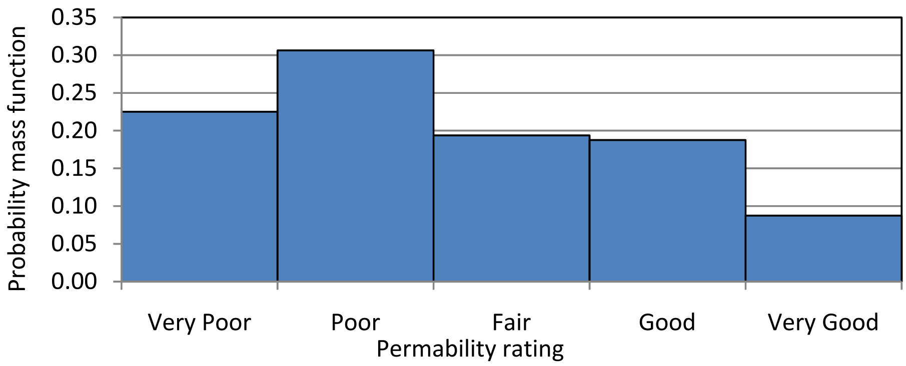


Figure 4-15 Distribution of Permeability Rating for the Entire Sections.

4.3.1.1 Systematic Errors in the Surface Distress and Permeability Ratings

Panel rating data was analyzed to examine whether any systematic errors were present in the rating procedures. The leniency error, halo effects, and central tendency effects were investigated as follows (Haas et al. 1994).

4.3.1.2 Leniency Error

The leniency error is defined as the average rating deviation of each rater from the grand mean. The grand mean is the average of all raters' average rating. The average rating for each pavement evaluator is calculated for all sections. This error (Delta R) was computed for each rater as shown in Table 4-10 for surface distress and permeability ratings.

Table 4-10 Deviation from the Mean of Surface Distress Ratings and Permeability Ratings

Rater	Surface Distress Rating				Permeability Rating			
	Mean	Std	Delta R	Rank	Mean	Std	Delta R	Rank
1	5.13	2.42	0.75	8	6.63	2.68	2.18	3
2	3.75	2.38	-0.63	10	3.25	1.98	-1.19	9
3	4.00	2.51	-0.38	13	4.63	3.34	0.18	18
4	3.00	2.14	-1.38	5	2.75	1.98	-1.69	6
5	1.88	1.73	-2.50	1	1.38	2.00	-3.07	1
6	4.25	2.82	-0.13	18	2.75	1.67	-1.69	6
7	3.63	2.56	-0.75	7	4.13	2.85	-0.32	17
8	4.75	2.38	0.37	14	4.88	2.64	0.43	15
9	4.38	1.30	0.00	20	4.38	2.26	-0.07	19
10	4.16	1.92	-0.21	17	4.38	2.57	-0.07	19
11	6.80	1.79	2.42	2	6.54	2.07	2.10	4
12	3.88	2.64	-0.50	12	4.88	3.00	0.43	15
13	3.75	1.49	-0.63	10	4.00	1.85	-0.44	14
14	4.50	2.56	0.12	19	3.25	2.71	-1.19	9
15	4.13	2.37	-0.25	15	3.25	2.73	-1.19	9
16	5.13	1.25	0.75	8	6.13	1.64	1.68	8
17	3.25	1.98	-1.13	6	3.50	2.07	-0.94	12
18	6.06	1.45	1.69	4	6.81	1.25	2.37	2
19	4.63	2.13	0.25	16	5.13	2.95	0.68	13
20	6.50	1.41	2.12	3	6.25	1.16	1.81	5
Mean	4.38	2.06	0	---	4.45	2.27	0	---

Table 4-10 clearly shows that leniency errors exist in the survey. Rater 11, for instance, rated the sections too high, while rater 5 rated them too low (Figure 4-16) compared to the mean. These leniency errors can be removed by transforming the raters' ratings to a distribution with mean and standard deviation equal to the grand mean rating and the mean standard deviation, respectively. These transformations were carried out in surface distress ratings and permeability ratings and no significant difference in resulting mean measures for PCP sections was observed. It was concluded that the magnitude of leniency errors did not affect the mean ratings. Therefore, the leniency errors were neglected and raw data was used in further analysis.

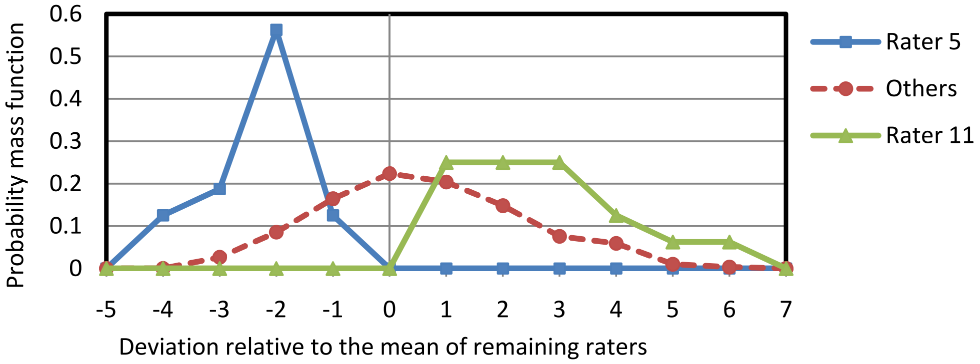


Figure 4-16 Distribution of Deviation for Raters 5 and 11.

4.3.1.3 Halo Error

The halo error occurs when two sections which have the same characteristics (surface distress) are rated differently. Surface distress of PCP could be evaluated using two protocols: the MTO protocol and the ASTM protocol. These well established and organized protocols were selected since they provide a single index describing pavement condition. Primarily, the MTO protocol was chosen for simplicity and compatibility with PCP. The MTO protocol proposes pavement distress evaluation by incorporating subjective descriptions for severity and density (e.g., slight and intermittent). To derive a single value for pavement condition, a series of weighting factors was provided by the MTO protocol associated with each severity and density level presented in Table 4-11 (Ningyuan et al. 2004).

Table 4-11 Severity and Density Weight Descriptions

Severity of Distress, S		Density of Distress, D		
Description	Weight	Description	Density	Weight
None	0	None	---	0
Very Slight	0.5	Few	<10	0.5
Slight	1	Intermittent	10-20	1
Moderate	2	Frequent	20-50	2
Severe	3	Extensive	50-80	3
Very Severe	4	Throughout	80-100	4

Since this methodology was conducted for conventional pavements, a few adjustments were required. First, only those distress types which have been frequently observed on PCP were incorporated in this pavement surface evaluation including ravelling, spalling, polishing, cracking, potholing, and stepping. However, the MTO protocol considers 15 distress types. Reducing distress types had a significant effect on the Distress Manifestation Index (DMI) as reducing number of distresses significantly affected DMI_{max} defined in Equation 4-2.

Secondly, a new set of distress weighting factors were established by a group of experienced engineers for PCP. The weighting factors represent the relative impact of each distress on DMI. In fact, the PCP weighting factors are different from weighting factors provided for conventional concrete pavements as shown in Table 4-12. Since the most important distress of PCP is ravelling, the highest weight was dedicated to this distress of 3.0. For instance, cracking, stepping, and polishing which have not been observed very frequently on PCP obtained the lowest weighting factors of 0.5.

Table 4-12 Weighting Factors

Distress #	Distress type	Weight
1	Cracking	0.5
2	Polishing	0.5
3	Stepping	0.5
4	Potholing	1.0
5	Joint and Crack Spalling	2.0
6	Ravelling and Coarse Aggregate Loss	3.0

The DMI was calculated using Equation 4-2, Table 4-11 and Table 4-12 for all PCP sections.

$$DMI = 10 \times \frac{DMI_{max} - \sum_{i=1}^{5} W_i\ (S_i + D_i\ )}{DMI_{max}} \tag{4-2}$$

Where,

DMI = Distress Manifestation Index

DMI_{max} = the maximum theoretical value dedicated to an individual PCP section (i.e., 60)

i = distress number identified in Table 4-12

W_i = weighting factor of distress i ranging from 0.5 to 3.0 (Table 4-12)

S_i = severity of distress i measured on a scale of 0.5 to 4 (Table 4-11)

D_i = density of distress i measured on a scale of 0.5 to 4 (Table 4-11)

Table 4-13 illustrates DMI of eight PCP sections together with the severity and density of various distress types observed on the associated sections.

Table 4-13 Surface Distresses Evaluation of PCP Sections

Section	Ravelling		Polishing		Potholing		Spalling		Cracking		Faulting		DMI
	Severity Weights	Density Weights	Severity Weights	Density Weights	Severity Weights	Density Weights	Severity Weights	Density Weights	Severity Weights	Density Weights	Severity Weights	Density Weights	
1	2	2	2	0.5	1	2	2	1	0	0	0	0	6.3
2	1	1	0	0	0.5	1	0.5	1	0	0	0	0	8.3
3	2	3	2	3	2	3	1	4	0	0	0	0	4.6
4	3	4	1	0.5	2	2	1	4	0	0	0	0	4.0
5	1	2	2	2	1	2	1	3	0	0	0	0	6.3
6	2	3	2	2	2	2	1	4	0	0	0	0	4.8
7	3	3	2	3	2	3	1	4	0	0	0	0	4.1
8	2	3	1	1	0.5	2	1	4	0	0	0	0	5.3

The halo error may exist in the data. For instance, Table 4-14 illustrates that although DMI of sections 1 and 5 were the same, they were rated differently (5.9 and 4.8, respectively). This difference might be the result of the fact that raters tended to rate sections based not only on surface distresses but also on their overall impression. Errors involved in assessment of pavement surface distresses (field investigation) could be, also, the reason.

Table 4-14 Different between Mean Panel Ratings and Field Investigations (Surface Distresses)

Section	Field investigation	Mean panel ratings			
	DMI	Mean	Delta R	Standard deviation	Range difference
1	6.3	5.88	1.51	1.742	6.0
2	8.3	7.37	3.00	1.286	4.0
3	4.6	3.62	-0.75	1.986	6.0
4	4.0	3.47	-0.90	1.602	6.0
5	6.3	4.83	0.46	1.521	6.2
6	4.8	3.00	-1.38	1.614	5.5
7	4.1	2.63	-1.75	1.853	7.0
8	5.3	4.18	-0.19	2.358	9.2

The statistical analysis was performed to examine whether significance difference existed between sections 1 and 5 (Table 4-15). T-tests (two cases: $\sigma_1 = \sigma_2$ and unknown, $\sigma_1 \neq \sigma_2$ and unknown) and

F-test were applied for this purpose (Table 4-16). The null hypothesis (H_0) was that the mean panel rating of section 1 was equal to that of section 5 at the 95% confidence level which was accepted. It was concluded that there was no significant difference between the two distributions (sections 1 and 5). Similar calculations could be performed to show that there is no significant difference between rater characteristics such as levels of experience: experienced pavement engineers (less than 10 years of experience) versus highly experienced pavement engineers (more than 10 years of experience) (Table 4-17). The results of t-test and F-test showed that there was no significant difference in the mean and variation between ratings of experienced raters and highly experienced raters (Table 4-18). This fact addressed that experience of pavement evaluators did not significantly affect the results of the panel rating.

Table 4-15 Descriptive Statistics for Section Number 1 and 5

Section number	Mean	Variance	n
1	5.88	2.97	20
5	4.83	2.31	20

Table 4-16 T-Test and F-test Of Section Number 1 and 5

t-test (σ1=σ2 and unknown)		t-test (σ1≠σ2 and unknown)		F-test	
S^2p	3.87	ν	30	$F_{observed}$	0.54
$t_{\alpha/2}$	2.66	$t_{\alpha/2}$	2.75	$F_{\alpha/2}$	2.03
d_{upper}	2.83	d_{upper}	3.04	H_0	Accepted
d_{lower}	-0.03	d_{lower}	-0.24	NA	NA
H_0	Accepted	H_0	Accepted	NA	NA

Table 4-17 Descriptive Statistics for Highly Experience and Experience Raters

Raters	Mean	Variance
Highly experienced raters	4.25	2.82
Experienced raters	4.53	2.41

Table 4-18 T-Test and F-test of Highly Experience and Experience Raters

t-test (σ1=σ2 and unknown)		t-test (σ1≠σ2 and unknown)		F-test	
S^2p	2.62	ν	14	$F_{observed}$	1.17
$t_{\alpha/2}$	2.14	$t_{\alpha/2}$	2.14	$F_{\alpha/2}$	3.79
d_{upper}	1.46	d_{upper}	1.46	H_0	Accepted
d_{lower}	-2.00	d_{lower}	-2.01	NA	NA
H_0	Accepted	H_0	Accepted	NA	NA

4.3.1.4 Central Tendency Effect

The range of difference of rating of each rater shows the central tendency effect. Namely, the central tendency effect of a rater is equal to his/her maximum rate minus minimum rate. The lowest rating for surface distress and permeability rate was 0 used by rater 5, whereas 9.2 (rater 11) and 10 (rater 2) were the highest values for surface distress rating and permeability rating, respectively. This means that, in total, the range of 0-9.2 and 0-10 was applied by raters for surface distress rating and permeability rating, respectively. These ranges were calculated for each rater and presented in Table 4-19 for surface distress ratings and permeability ratings.

Table 4-19 Range Difference Used by Each Rater

Rater	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Surface Distress ratings	7	8	7	6	5	6	7	6	3	5	5	8	4	8	7	3	6	4	5	4
Permeability ratings	7.5	6	9	6	5	4	8	6	7	7	6	9	6	6	9	4	6	4	8	3

The range varies from 8 to 3 in surface distress ratings and from 9 to 4 in permeability ratings. However, it is not possible to calculate the magnitude of the central tendency effect. The problem was to determine whether raters hesitated to use extreme values or the narrow range of pavement condition existed. That is, the true sections surface distress and permeability rate did not actually lie within the extremes of the rating scale. In this study, raters 9 and 16 (in surface distress rating) and rater 20 (in permeability rating) had the lowest range difference. As shown in Tables 4-1 and 4-2, raters 9, 16, and 20 did not hesitate to use extreme values. Therefore, it is concluded that the rater performance was reasonable and no correction was necessary.

In summary, ratings were analyzed to determine whether any systematic errors were present in the rating process. It was concluded that there were no significant systematic errors in the data. The summary of characteristics of raters in terms of surface distress rating and permeability rating is presented in Appendix H. This summary illustrates that rater 11 gained the first rank in rating of surface distress of sections far from the mean and rater 10 rated sections in the most consistent manner. Likewise, the summary demonstrates that rater 5 gained the first rank in rating of permeability of sections far from the mean and rater 10 rated sections in the most consistent manner.

4.3.1.5 ANOVA Test

The panel rating data, surface distress rating and permeability rating, was analyzed to detect whether or not there was any significant difference among raters and among PCP sections. Both sources of variations, that of among raters and among PCP sections, were examined to be significant at the 5% level of significance (Roberts and Hudson 1971). The difference between conditions of PCP sections is desirable herein since the main goal of selection of PCP sections was to cover a wide range of pavement conditions to be able to develop comprehensive PCCI. However, significant differences between ratings of various raters are not acceptable since the raters should evaluate the sections within the 5% level of significance. Table 4-20 shows that this requirement was violated (i.e., $F_{Observed} > F_{\alpha/2}$), namely, the difference in ratings (in both cases: surface distress ratings and permeability ratings) among various raters was significant. It is notable that this is likely caused by inexperience with the PCP structures. However, for the purpose of the research, it was further examined.

Table 4-20 ANOVA Test for Surface Distress Ratings and Permeability Ratings

Source	Surface Distress Ratings					Permeability Ratings				
	SS	df	MS	$F_{Observed}$	$F_{\alpha/2}$	SS	df	MS	$F_{Observed}$	$F_{\alpha/2}$
Between raters	207	19	10.9	5.3	1.9	339	19	17.8	9.4	1.9
Between sections	357	7	51.0	25.1	3.3	517	7	73.8	38.9	3.3
Error	270	133	2.0	NA	NA	252	133	1.9	NA	NA
Total	834	159	NA	NA	NA	1108	159	NA	NA	NA

Note SS stands for sum of square, df stands for degree of freedom, and MS stands for mean of square.

In order to tackle the problem of eliminating the source of variation among raters, outliers that have the most value of difference from the others' mean should be removed from the database. For this purpose, the "Box plot" method which addresses outliers was applied. The Box plot illustrates centre, spread, departure from symmetry, and identification of observations that lies unusually far from the bulk of the data (called outliers) (Montgomery 1994). The box encloses interquartile range with the lower edge at the 1st quartile and the upper edge at the 3rd quartile. Observations that are between 1.5 and 3 times of interquartile range from the edge of the box are called outliers. Observations that are beyond three times of the interquartile range from the edge of the box are called extreme outliers (Montgomery 1994). As shown in Figure 4-17, the outliers are indicated by circles while there are no extreme outliers. However, it should be noted that outliers provide information which other data cannot since it arises from the combination of certain circumstances which may be of vital interest and needs further investigation rather than simple rejection (Draper and Smith 1981). However, the reason of occurrence of outliers might be the respondents' error (Lindsey 1997), or inexperience with the PCP structures in this study. It appears that few respondents could not understand and reasonably respond to the survey. The main reasons for this would be the lack of related experience for PCP evaluation.

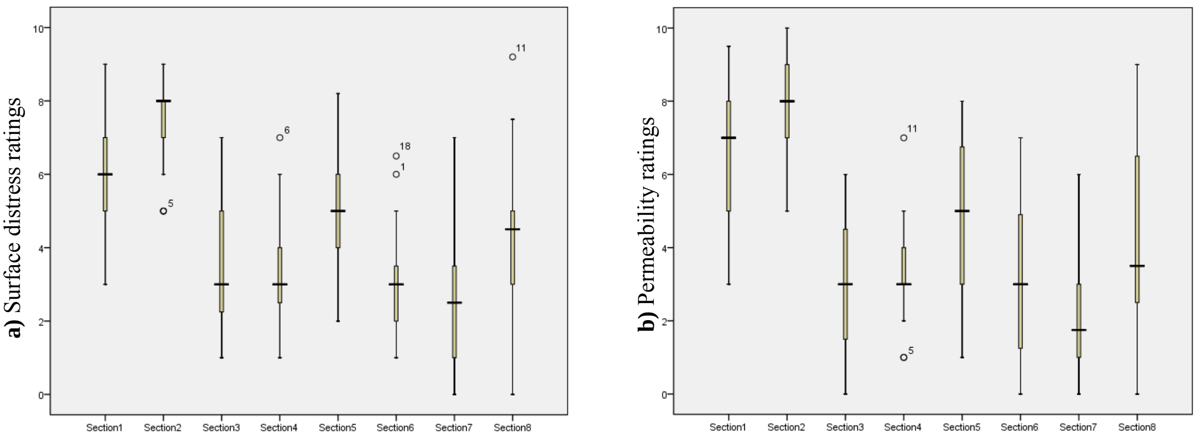


Figure 4-17 Box Plot for Surface Distress Ratings and Permeability Ratings.

In the case of surface distress ratings, Figure 4-17a illustrates that raters 1, 5, 6, 11, and 18 had the most deviated rates on sections 6, 2, 4, 8, and 6, respectively. When the data was reviewed and it was deemed certain that these values were either an error or misunderstanding, these points were removed and the ANOVA test was carried out again. The results (Table 4-21) clearly showed that there was no significant difference among the raters at the 5% level of significance for surface distress ratings after adjustments (i.e., $F_{Observed} < F_{\alpha/2}$).

Again, to ensure the data was of good quality, the sources of variation of the permeability ratings were examined. It was determined that these values were related to misunderstanding. Outliers are represented in Figure 4-17b incorporating the box plot method. Raters 5 and 11 had the most deviated ratings on section 4 which were discarded. Although the outliers were eliminated and the ANOVA test was adjusted, the results (Table 4-21) showed that there was still significant difference among the raters (i.e., $F_{Observed} > F_{\alpha/2}$), that is, the raters performed significantly different in conducting permeability rating. The permeability ratings were not statistically significant due to complexity of determination of PCP permeability rates based on a visual inspection (i.e., observing visible surface pores or clogged areas filled with debris and then determine a scale for the permeability of PCP). Consequently, the permeability ratings were replaced with measurements of permeability in developing PCCI.

Table 4-21 ANOVA Test for Surface Distress Ratings and Permeability Ratings (Adjusted)

Source	Surface Distress Ratings					Permeability Ratings				
	SS	df	MS	$F_{Observed}$	$F_{\alpha/2}$	SS	df	MS	$F_{Observed}$	$F_{\alpha/2}$
Between raters	91	19	4.79	1.50	1.93	282	19	14.86	6.29	1.93
Between sections	296	7	42.34	13.29	3.26	498	7	71.09	30.09	3.26
Error	408	128	3.19	NA	NA	310	131	2.36	NA	NA
Total	795	154	NA	NA	NA	1089	157	NA	NA	NA

Note SS stands for sum of square, df stands for degree of freedom, and MS stands for mean of square.

It was concluded that the data collected in the pilot study was of a low quality and high uncertainty (variation) from the engineering perspective although the data was statistically sound at least in terms of surface distress ratings. The high uncertainty and wide variation in the data might happen due to the lack of experience and training in PCP evaluation. Several adjustments have been performed to overcome this problem in the next module.

4.3.2 Surface Distress Rating and Field Investigation (Module 2)

As mentioned earlier, each rater rated the condition of surface distress of various sections using a total percentage (i.e., 30% “very good”, 70% “good” versus “good” as it represents the majority of the section). Consequently, a probability mass function that represented surface distress condition was established for each section instead of a single value. For instance, Figure 4-18 shows a sample rating on a scale of 0 to 10. In this function, interval [0, 2] represents very poor condition, interval [2, 4] represents poor condition, interval [4, 6] represents fair condition, interval [6, 8] represents good condition, and interval [8, 10] represents very good condition. This figure shows a section that is 0% similar to very poor condition (mean scale x=1), 15% similar to poor condition (mean scale x=3), 65% similar to fair condition (mean scale x=5), 20% similar to good condition (mean scale x=7), and 0% similar to very good condition (mean scale x=9). These percentages were normalized, namely, divided by the interval length (equal to 2) to obtain the probability mass function (Figure 4-18).

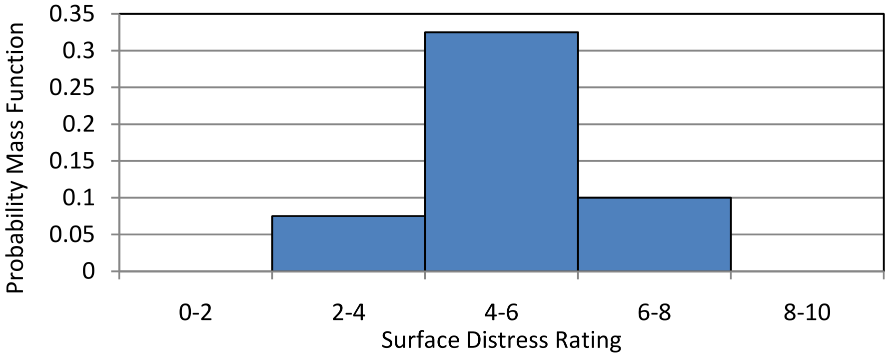


Figure 4-18 Sample Probabilistic Surface Distress Rating.

It is desirable to have a numerical rating score rather than a probability mass function for further calculations. For this purpose, the concept of the Expected Value (EV) for a probability mass function was applied as an overall output. The EV for a probability mass function of surface distress rating is given by Equation 4-3.

$$EV = \frac{\Sigma p_i \times x_i}{\Sigma p_i} \tag{4-3}$$

Where p_i is the probability associated with the interval i, x_i is the mean scale of interval i, and i is the interval number and it ranges between 1 and 5. The interval numbers 1, 2, 3, 4, and 5 correspond to very poor, poor, fair, good, and very good conditions, respectively. Prior to conducting any analyses, EV of the whole rating was computed. Further calculations will be performed using EV of each probability mass function of surface distress ratings. For instance, EV of probability mass functions shown in Figure 4-18 can be calculated as follows.

$$EV = \frac{1\times0+3\times0.075+5\times0.325+7\times0.100+9\times0}{0+0.075+0.325+0.100+0} = 5.10 \tag{4-4}$$

Similarly, EV of each probabilistic surface distress rating was calculated. The average of these EVs of the entire raters is equal to the mean surface distress rating of each section. The probabilistic ratings, EV, and the grand mean of raters for slab 1 is summarized in Table 4-22 for illustration.

Table 4-22 Probabilistic Rating, EV, and Grand Mean of all Raters for Slab 1

Condition level	Rater 1	Rater 2	Rater 3	Rater 4	Rater 5
Very Good	30	40	20	20	0
Good	50	20	50	20	70
Fair	20	30	30	40	30
Poor	0	10	0	15	0
Very Poor	0	0	0	5	0
EV	7.2	6.8	6.8	5.7	6.4
Grand Mean	6.58				

The EVs of probabilistic rating of each rater with the mean of panel ratings for the entire slabs together with the sites' plan are represented in Appendix I for the Georgetown parking lot and the Guelph Line parking lot.

All slabs evaluated were accumulated into ten sections. Sections included a number of slabs. Sections 1 to 4 are located within the Georgetown parking lot (section 1: slab 1-3, section 2: slab 4-8, section 3: slab 9-12, section 4: slab 13-15) and sections 5 to 10 are located within the Guelph Line parking lot (section 5: slab 1-6, section 6: slab 7-12, section 7: slab 13-18, section 8: slab 19-24, section 9: slab 25-30, section 10: slab 31-36) (Appendix I). Figure 4-19 shows the probability mass function of surface distress ratings for various sections. This figure addresses the probability of being in each condition state in terms of surface distress ratings. Figure 4-19 illustrates that probability condition state 3 (Fair) occurred more than the other condition states for the entire sections.

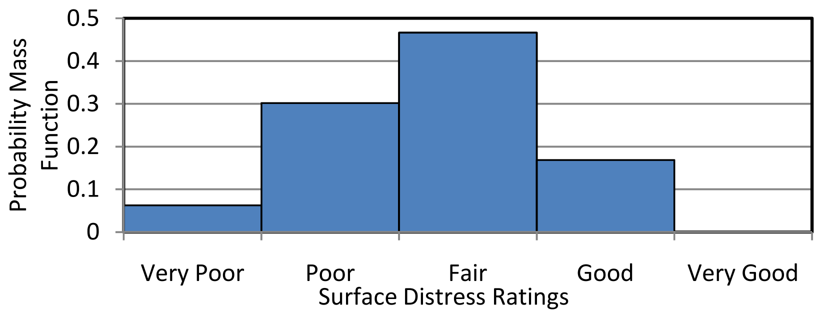


Figure 4-19 Distribution of Surface Condition Ratings for all Sections.

Table 4-23 summarizes surface distress ratings of various sections (average of EV of associated slabs in each section). The data represented in this table will be analyzed in the following sections.

Table 4-23 Surface Distress Ratings Data

Section Number	Rater Number					Average
	1	2	3	4	5	
1	6.87	6.53	6.13	5.17	5.43	6.03
2	5.16	4.44	5.36	2.24	4.56	4.88
3	5.85	4.28	5.10	2.43	5.25	5.12
4	7.27	3.43	6.57	5.53	6.00	5.76
5	6.00	2.77	4.75	4.80	3.17	4.30
6	4.95	4.48	4.23	4.48	2.40	4.11
7	6.60	4.12	4.73	4.83	3.43	4.74
8	6.33	4.90	4.63	5.30	3.60	4.95
9	5.60	4.80	4.50	4.17	2.93	4.40
10	4.97	4.72	4.47	2.97	3.33	4.09

4.3.2.1 Systematic Errors in the Surface Distress and Permeability Ratings

Before developing PCCI, it is important to investigate how reliable the data is. For this purpose, the panel rating data was analyzed to examine if any systematic errors were present in the rating procedures. The leniency error, halo effects, and central tendency effects were investigated as follows (Haas et al. 1994):

4.3.2.2 Leniency Error

The leniency error, which is defined as the deviation of each raters' average rating for all sections from the grand mean rating, was computed for each rater as shown in Table 4-24 for surface distress ratings. Also, the deviation of the ratings from the grand mean was computed for each rater and is represented in this table together with standard deviation and ranking (based on their deviation from the grand mean) of various raters.

Table 4-24 indicates that leniency errors may exist in the data. Rater 1, for instance, rated the sections high, while rater 5 had the lowest mean of ratings. These leniency errors can be removed by transforming the raters’ ratings to a distribution with mean and standard deviation equal to the grand mean rating and the mean standard deviation. These transformations were carried out in surface distress ratings and no significant differences in resulting mean indices for sections were found. It was concluded that the magnitude of leniency errors do not affect the mean ratings. Therefore, the leniency errors were not significant so that raw data was used in further analysis.

Table 4-24 Deviation from the Mean of Surface Distress Ratings

Rater	Mean	Delta R	Std.	Rank
1	5.96	1.23	0.81	1
2	4.45	-0.28	0.99	5
3	5.05	0.32	0.76	4
4	4.19	-0.54	1.21	3
5	4.01	-0.72	1.21	2
Grand Mean	4.73			

4.3.2.3 Halo Error

The halo error occurs when two sections which have the same characteristics are rated differently. The halo error does not exist in the data. Namely, if two sections had a similar PCDI, they would be rated approximately the same. Note that PCDI presented in Table 4-25 have been computed based on surface distress evaluation and will be discussed in Chapter 5.

Table 4-25 Different between Ratings and Field Investigation Assessment (Surface Distresses)

Section Number	Field Investigation (PCDI)	Panel Ratings			
		Mean	DeltaR	Std	Range difference
1	8.01	6.03	1.30	0.72	1.70
2	6.50	4.88	-0.38	1.24	3.12
3	6.96	5.12	-0.15	1.33	3.43
4	7.79	5.76	1.03	1.45	3.83
5	5.19	4.30	-0.43	1.32	3.23
6	4.59	4.11	-0.62	0.99	2.55
7	5.26	4.74	0.01	1.18	3.17
8	5.54	4.95	0.22	1.00	2.73
9	4.66	4.40	-0.33	0.98	2.67
10	4.61	4.09	-0.64	0.89	2.00

4.3.2.4 Central Tendency Effect

The range of difference in ratings of each rater shows the central tendency effect. The lowest rating for surface distress is 1.4 which was used by rater 5, whereas 7.9 is the highest values assigned to surface distress ratings by rater 4. This means that the range of 6.5 has been used by raters for surface distress rates. These ranges were calculated and presented in Table 4-26 for surface distress ratings.

Table 4-26 Range Difference Used by Each Rater

Rater	Range difference	Rank
1	3.80	5
2	5.20	3
3	3.80	4
4	6.30	1
5	5.80	2

The range varies from 6.3 to 3.8 in surface distress ratings. However, it is not possible to calculate the magnitude of the central tendency effect. The problem is to determine whether either the narrow range happened because the true surface distresses rates did not lay within the extremes of the rating scale or raters hesitated to use extreme values. Given the data, the raters did not hesitate to use extreme values so that it is concluded the rater performance was reasonable and no correction was necessary to perform.

4.3.2.5 ANOVA Test

The data collected from the surface distress ratings should be analyzed to detect whether or not there is any significant difference between raters (using F-test). Significant difference between raters is not acceptable since the ratings should be used interchangeably. The data exhibited in Table 4-27 shows that this requirement is violated (i.e., $F_{Observed} > F_{\alpha/2}$), that is, the difference in ratings between raters is significant at the 95% confidence level.

Table 4-27 ANOVA Test for Surface Distress Ratings

Source	SS	df	MS	$F_{Observed}$	$F_{\alpha/2}$
Between Raters	25	4	6.25	8.60	5.73
Between Sections	20	9	2.25	3.10	2.84
Error	26	36	0.73	NA	NA
Total	71	49	NA	NA	NA

Note SS stands for sum of square, df stands for degree of freedom, and MS stands for mean of square.

In order to eliminate the source of variation in ratings, the outliers should be discarded which have the most value of difference from the others' mean. For this purpose, the Box plot method was applied herein as mentioned earlier. Figure 4-20 illustrates that rater 2 had the most deviated rates on sections 1 and 5. It was identified and confirmed that there were errors with one of the evaluators. The particular ratings were eliminated. Having eliminated the outliers and carried out the ANOVA test, it was found that the constraint was met (i.e., $F_{Observed} < F_{\alpha/2}$). Table 4-28 shows that there is no significant difference between the raters at the 5% level of significance for surface distress ratings.

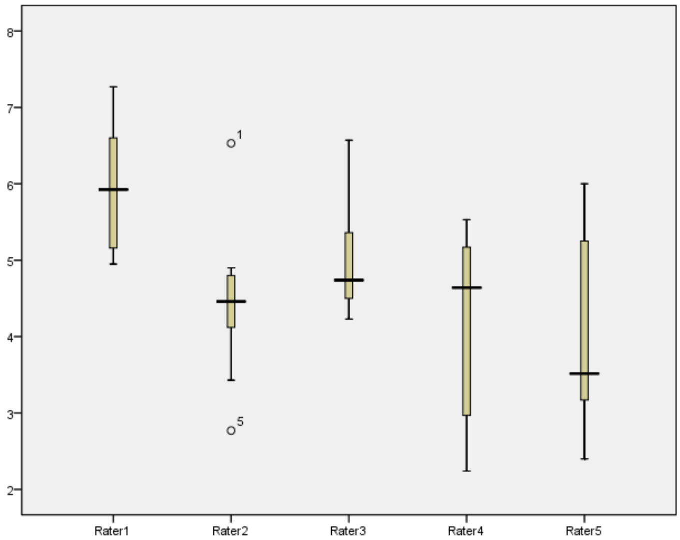


Figure 4-20 Box Plot for Surface Distress Ratings

Table 4-28 ANOVA Test for Surface Distress Ratings (Adjusted)

Source	SS	df	MS	F(obs.)	F
Between Raters	5	4	1.22	0.70	5.73
Between Slabs	2	9	0.19	0.11	2.84
Error	61	34	1.74	NA	NA
Total	67	47	NA	NA	NA

Note SS stands for sum of square, df stands for degree of freedom, and MS stands for mean of square.

4.3.3 Conducting a Survey and Field Investigations (Module 3)

A survey was conducted as mentioned earlier to set up Transition Probability Matrices (TPMs). In this survey, a panel of 14 experts was asked to complete TPMs for various PCP groups (totally six groups). Each cell of the final TPM is the adjusted average response of the panel of experts. A theoretical constraint applied to each row of TPM is that the sum of its cells should be equal to 1.0. However, the sum of average values of each row would not necessarily equal to 1.0. Therefore, the sum of average values of each row was applied to adjust each average value so that sum of each row became 1.0. The adjustments were very small. The final six TPMs and their standard deviations are presented in Appendix J.

The TPMs should be validated. For this purpose, 75% of data was applied as a data base for modeling and 25% of data was used for validation. The statistical analysis was performed to examine whether significant difference existed between these two sets of data. T-tests (two cases: $\sigma_1 = \sigma_2$ and unknown, $\sigma_1 \neq \sigma_2$ and unknown) and F-test were applied for this purpose (Table 4-29). The null hypothesis (H_0) was that the mean of modeling data was equal to that of validation data at the 95% confidence level which was accepted. It was concluded that there was no significant difference between two distributions. Consequently, the TPMs' results were successfully validated.

Table 4-29 T-Test and F-test for Validation of Markov Chain Model

t-test (σ1=σ2 and unknown)		t-test (σ1≠σ2 and unknown)		F-test	
S^2p	218	ν	90	$F_{observed}$	1.50
$t_{\alpha/2}$	2.63	$t_{\alpha/2}$	2.63	$F_{\alpha/2}$	1.62
d_{upper}	7.91	d_{upper}	7.92	H_0	Accepted
d_{lower}	-7.95	d_{lower}	-7.96	NA	NA
H_0	Accepted	H_0	Accepted	NA	NA

4.4 SUMMARY

This chapter has presented the research approach, data sources, data collection methods, and data evaluation. The research approach consists of three modules: pilot study, pervious concrete condition index development, and PCP performance model development. The PCP performance data has been collected in this research with incorporation of rating panels, field investigations, and survey distributions. The pilot panel rating has been successfully conducted in terms of surface distress and permeability rating. The experience gained in the pilot study has been used in Module 2. A probabilistic pavement evaluation form has been developed and used in the panel rating (in Module 2). Field investigations have included surface distress evaluation and permeability testing. The field investigations have been conducted on several PCP sites located in Canada and the United States. An extensive questionnaire (i.e., transition probability matrices) has been distributed to experts to predict performance of various PCP groups. The mean of expert responses to transition probability matrices have been applied to obtain the Markov models.

Chapter 5
Pervious Concrete Condition Index

This chapter presents several condition indices based on two major approaches: crisp values (i.e., single point values) and fuzzy sets. A set of data collected through a panel of raters together with field investigations (i.e., surface distress evaluation and permeability testing) were applied in this chapter to develop the Pervious Concrete Condition Index (PCCI).

5.1 DEVELOPMENT OF THE PERVIUOS CONCRETE CONDITION INDEX USING CRISP VALUES

The main objective of this section is to adjust the methodology proposed in pilot study based on conclusions made in order to develop PCCI. The adjustments were related to the PCP surface evaluation guideline, the panel rating technique, and surface distress evaluation calculations.

The scope of this section is to apply an adjusted guideline which is simple to follow and cost effective to evaluate PCP. This procedure applies a rating panel which was brought to the sites for PCP surface evaluation. The panel had to rate the surface condition of various PCP sections using a new guideline (including a probabilistic rating form). Field investigations were also conducted which involved surface distress evaluation and permeability testing of the PCP sections. As a result, the relative effect of the field investigations and the panel rating on PCCI was obtained using data provided in Module 2.

5.1.1 Develop PCCI: Hypothesized Model

To develop an extensive pavement condition index, pavement roughness, pavement structural adequacy, and pavement surface condition should be considered (Haas 1997). Due to the low speed application of PCP, pavement roughness (ride quality) does not have a significant impact on PCP condition evaluation. Since applications of PCP are limited, typical pavement design is applied. Therefore, unusual circumstances (excessive loading) rarely occur which results in structural capacity issues; i.e., structural adequacy therefore is not a typical problem. Consequently, the pavement roughness index and the structural adequacy index were not considered in the development of PCCI. However, the Surface Distress Index (SDI) was considered in the modeling. In addition to this, the permeability rate was measured and considered as an influential factor in PCCI which is generally called the Functional Performance Index (FPI). FPI is a novel index and was incorporated in this research to develop PCCI. Figure 5-1 illustrates the methodology of developing PCCI in this research.

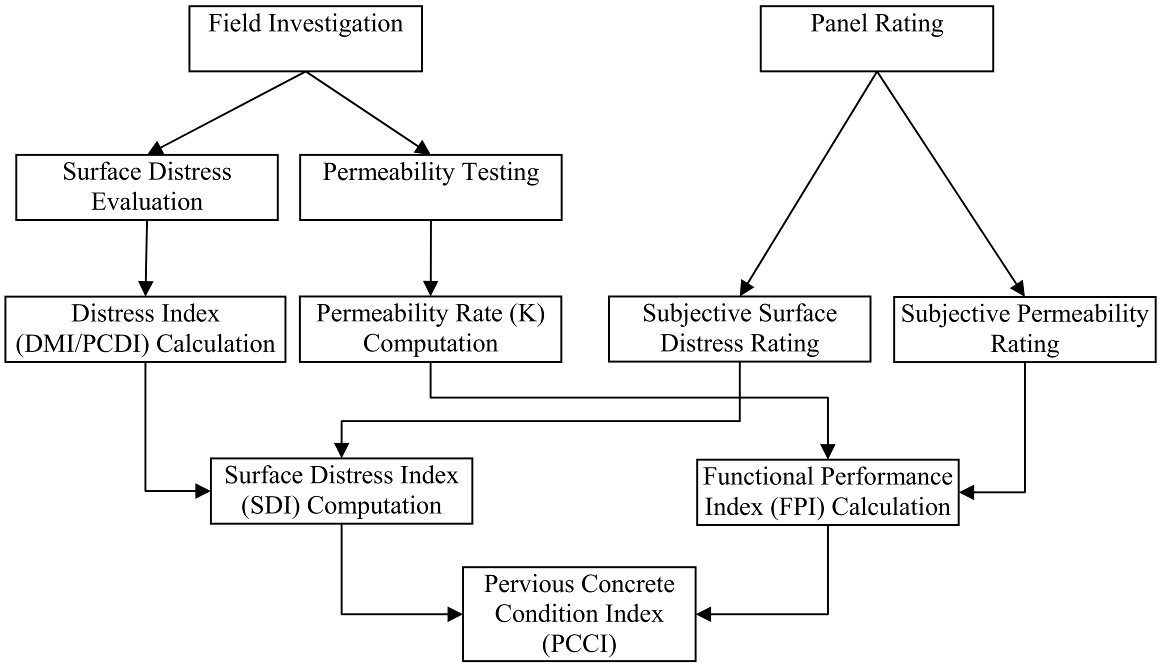


Figure 5-1 Framework for Developing PCCI.

The PCCI at any particular time was addressed as a combination of SDI and FPI. The following general model was hypothesized:

$$PCCI = f\ (SDI, FPI) \tag{5-1}$$

Where,

PCCI = Pervious Concrete Condition Index, which is an overall measure of PCP condition at any specific time.

SDI = Surface Distress Index, which is a measure of distress of PCP. It is defined in a scale of 0 to 10 (SDI = 10 is a very good surface condition, while SDI = 0 is a very poor condition).

FPI = Functional Performance Index, which is a measure of the permeability rate of PCP. It is also described on a scale of 0 to 10 (FPI = 10 is a very good permeability condition, while SDI = 0 is a very poor condition).

SDI is a mean of responses to surface distress condition of PCP. Since it is not practical (in terms of time and cost) to conduct panel rating for assessment (obtaining PCCI) of each PCP, various relationships were developed to relate SDI to the Pervious Concrete Distress Index (PCDI) and PCI (proposed by ASTM). PCDI and PCI can be simply calculated using field investigations data (severity and density of surface distresses). Similarly, FPI is an index showing permeability (between 0 and 10) of PCP which can be calculated by incorporating a relationship which relates FPI to permeability rate (measured in the field). All these relationships will be described in the following sections.

5.1.2 Surface Distress Assessment

The entire PCP sections were evaluated based on a proposed PCDI and PCI (proposed by ASTM). In this research, a percentage of density was applied to the various severity levels as opposed to assignment of 100% in only one level which is commonly done in practice. Namely, in a case where two levels of distress severity are present on a section, only one of them is recorded in the MTO protocol. Thus, in this research the more specific percentages were recorded. The PCDI was calculated applying Equation 5-2. The PCDI of PCP sections together with the percentage of various severity levels of different distress types at the Georgetown and Guelph Line parking lots were presented in Appendix L.

$$PCDI = 10 \times \frac{PCDI_{max} - \sum_{i=1}^{6} W_i \sum_{j=1}^{5} (S_{ij} \times D_{ij})}{PCDI_{max}} \tag{5-2}$$

Where,

PCDI= Pervious Concrete Distress Index

$PCDI_{max}$= the maximum theoretical value dedicated to an individual pavement distress (i.e., 30)

i= distress number

j= severity levels

W_i= weighting factor of distress i ranging from 0.5 to 3.0

S_{ij} = severity level j of distress i measured on a scale of 0.5 to 4

D_{ij} = density level j of distress i measured on a scale of 0 to 100 (percentage)

According to PCI, Micro PAVER (U.S. Army Corps of Engineers 2004) has been used to compute the overall pavement condition of all sections with regard to the ASTM protocol. Pavement evaluation records were entered as inputs into the software and PCIs were obtained as outputs.

All slabs, as discussed before, were categorized into ten sections. The PCDI of all sections (average of PCDI of associated slabs in each section) together with PCI and associated SDI are presented in Table 5-1.

Table 5-1 Field Investigation and Mean Panel Rating of PCP Surface Distress Condition

Section #	PCDI (field investigation)	PCI (field investigation)	SDI (mean panel ratings)
1	8.01	77	6.03
2	6.50	63	4.88
3	6.96	62	5.12
4	7.79	78	5.76
5	5.19	59	4.30
6	4.59	53	4.11
7	5.26	53	4.74
8	5.54	59	4.95
9	4.66	57	4.40
10	4.61	60	4.09

5.1.3 Data Analysis

5.1.3.1 Relationship between PCDI and SDI

Several regression models were tested to correlate SDI and PCDI. The dependent variable is SDI and the independent variable is PCDI. Figure 5-2 shows that SDI and PCDI are highly related. The linear model presented the best results in terms of the coefficient of determination, logical sense, and power of predictability. Consequently, the model presented in Equation 5-3 expresses the relationship between SDI and PCDI.

$$\mathrm{SDI} = 0.482 \times \mathrm{PCDI} + 1.992 \quad (5\text{-}3)$$

Where,

SDI= Surface Distress Index i.e., mean panel ratings of surface distress condition

PCDI = Pervious Concrete Distress Index i.e., surface distress measurements through field investigations

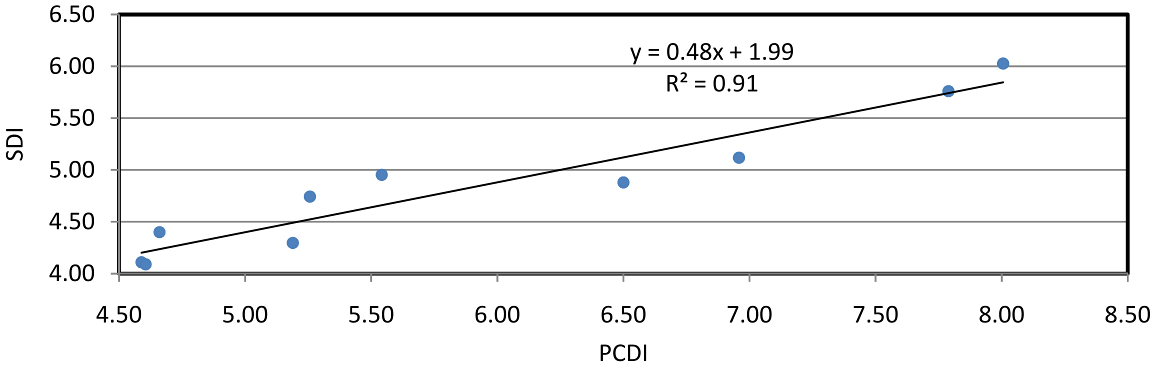


Figure 5-2 Relationship between PCDI and SDI

Regression statistics were determined encompassing the coefficient of determination (R^2 = 0.91) and typical errors (standard error of estimate 0.221). Also, the analysis of variance (ANOVA) was performed to check the overall significance of the regression. The two-tailed t-test was carried out to check the significance of the independent variable (Table 5-2). Ultimately, an analysis of residuals was carried out to determine any outliers. This included three methods: normal percentile plot, residual versus fitted values plot, and cook's distance. According to the various abovementioned methods, it was concluded that no outliers have been existed in the data and this information is provided in Appendix M.

Table 5-2 Coefficient of the Regression Model

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
	B	Std. Error	Beta			Lower Bound	Upper Bound
(Constant)	1.99	.325	NA	6.12	.000	1.24	2.74
PCDI	.48	.054	.95	8.94	.000	.36	.61

In order to evaluate the power of predictability of the model relating SDI to PCDI, the actual SDI (mean panel ratings) and calculated SDI (using Equation 5-3) have been compared in Table 5-3. This table clearly shows that the model has the high power of predictability and the difference between calculated SDI and actual SDI is negligible.

Table 5-3 Difference between Rated SDI and Calculated SDI using PCDI

Section #	SDI (calculated)	SDI (mean panel ratings)	Difference (%)
1	5.85	6.03	2.92
2	5.13	4.88	5.02
3	5.35	5.12	4.44
4	5.75	5.76	0.24
5	4.49	4.30	4.57
6	4.20	4.11	2.28
7	4.53	4.74	4.59
8	4.65	4.95	6.08
9	4.24	4.40	3.67
10	4.21	4.09	2.98
Mean	4.84	4.84	3.68

5.1.3.2 Relationship between PCI and SDI

Several regression models were attempted to relate SDI and PCI. The dependent variable is SDI and the independent variable is PCI. The linear model presented the best results in terms of the coefficient of determination, logical sense, and power of predictability as shown in Figure 5-3 and given by Equation 5-4:

$$\mathrm{SDI} = 0.065 \times \mathrm{PCI} + 0.787 \tag{5-4}$$

Where,

SDI = Surface Distress Index i.e., mean panel ratings of surface distress condition

PCI = Pavement Condition Index i.e., surface distress measurements through field investigations

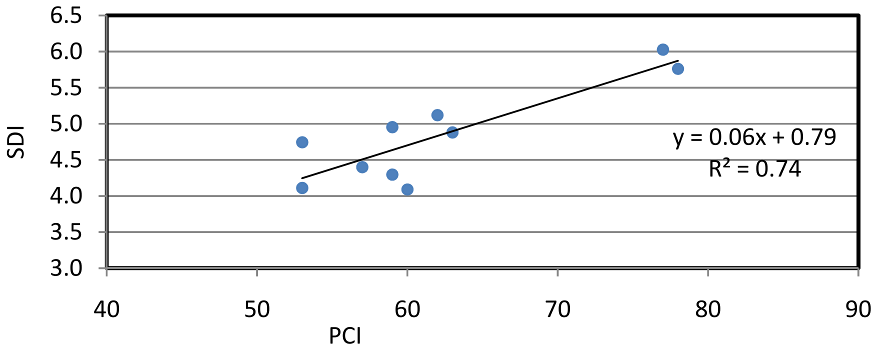


Figure 5-3 Relationship between PCI and SDI

Regression statistics were estimated including the coefficient of determination ($R^2 = 0.75$) and typical errors (standard error of estimate 0.235). Also, the analysis of variance (ANOVA) was carried out to control the overall significance of the regression. The two-tailed t-test was conducted to check the significance of the independent variable (Table 5-4).

Finally, an analysis of residuals was performed to determine the outliers. Diagnostic tests were conducted including three methods: normal percentile plot, residual versus fitted values plot, and cook's distance. According to the various discussed methods, it was concluded that no outliers have been existed in the data and this information is provided in Appendix N.

Table 5-4 Coefficient of the Regression Model

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95% Confidence Interval for B	
	B	Std. Error	Beta			Lower Bound	Upper Bound
(Constant)	.79	.845	NA	.93	.379	-1.16	2.73
PCI	.06	.013	.86	4.84	.001	.03	.10

The power of predictability of the model relating SDI to PCI was evaluated through comparison of the actual SDI (mean panel ratings) and calculated SDI (using Equation 5-4) in Table 5-5. This table shows that the model presented in Equation 5-4 has the high power of predictability and the difference between calculated SDI and actual SDI is negligible. It should be noted that the power of predictability of SDI in terms of PCDI (Equation 5-3) is more than that of SDI in terms of PCI (Equation 5-4). This result shows that SDI has a better relationship with proposed PCDI than PCI.

Table 5-5 Difference between Rated SDI and Calculated SDI using PCI

Section #	SDI (calculated)	SDI (mean panel ratings)	Difference (%)
1	5.79	6.03	3.89
2	4.88	4.88	0.04
3	4.82	5.12	5.89
4	5.86	5.76	1.68
5	4.62	4.30	7.57
6	4.23	4.11	2.97
7	4.23	4.74	10.78
8	4.62	4.95	6.69
9	4.49	4.40	2.09
10	4.69	4.09	14.60
Mean	4.82	4.84	5.62

5.1.4 Validation of Surface Distress Ratings

The validation process is similar to the method used in the pilot study. 75% of data was used for modeling and 25% of data, experts' ratings, was applied for validation. For this purpose, the two tailed t-test method was used to compare the sample mean of experts' rating and others' rating at the 5% significance level. The null hypothesis (H_0) was that the mean of experts' ratings was equal to the mean of the remaining at the 95% confidence level. According to the results as shown in Table 5-6, the interval between d_{upper} and d_{lower} contained 0 so that the null hypothesis was accepted and the regression was successfully validated.

Table 5-6 T-Test for Panel Ratings Validation

t-test (σ1=σ2 and unknown)		t-test (σ1≠σ2 and unknown)	
S^2p	0.54	ν	9.00
$t_{\alpha/2}$	3.17	$t_{\alpha/2}$	3.25
d_{upper}	0.23	d_{upper}	0.27
d_{lower}	-2.45	d_{lower}	-2.49
H_0	Accepted	H_0	Accepted

5.1.5 Permeability Rate and Scales

To incorporate the permeability rate in PCCI, it should be scaled into 0 to 10 (FPI) similar to SDI. Table 5-7 presents the different ranges of permeability rates which correspond to a value between 0 and 10. According to the results of the field experiments (more than 400 permeability tests completed on different PCP sites) 0.0004 cm/sec was selected as a lower bound in Table 5-7. Water could not adequately infiltrate through PCP sites with a permeability rate less than 0.0004 cm/sec. It is anticipated that PCP should have at least this permeability rate, otherwise water stands on PCP and this is referred to as clogging. The other intervals (bins) in this table were determined in the way that they included a significant number of observations (permeability measurements). Also, a mass distribution function of the permeability measurements should follow the Normal distribution.

Table 5-7 Permeability Rates and Scales

Permeability rate, K (cm/sec)	Permeability Scales (FPI)
$0 < K \leq 0.0004$	0
$0.0004 < K \leq 0.004$	2
$0.004 < K \leq 0.04$	4
$0.04 < K \leq 0.4$	6
$0.4 < K \leq 4.0$	8
$4.0 \leq K$	10

In order to scale the permeability rates into 0 to 10, the regression analysis method has been used. The independent variable was the mean of the range of permeability rates (K) and the dependent variable was the associated scale (FPI). Several attempts have been made to derive the best model. As shown in Figure 5-4, the Logarithmic model present the best relationship ($R^2 = 0.99$) between the parameters given by Equation 5-5:

$$FPI = 0.907 \times Log(K) + 7.558 \tag{5-5}$$

Where,

FPI = Functional Performance Index i.e., permeability scale

K = permeability rate (cm/s)

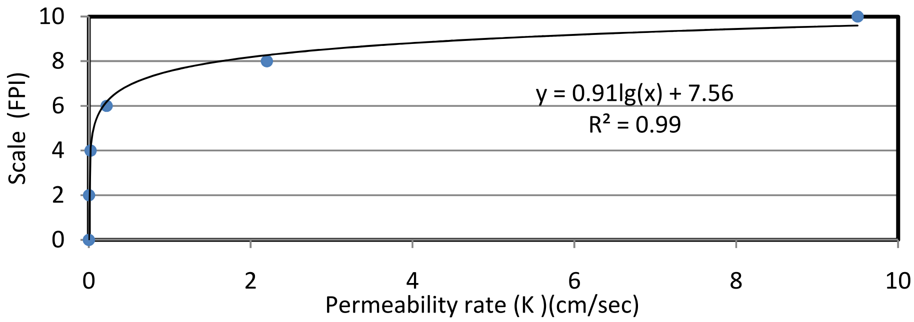


Figure 5-4 Relationship between Permeability Rates and Permeability Scales.

Also, the descriptive statistics of the model are represented in Table 5-8.

Table 5-8 Model Summary and Parameter Estimates

Equation	Model Summary						Parameter Estimates	
	R Square	F	df1	df2	Sig.	Std. Error of the Estimate	Constant	b1
Logarithmic	.99	911.03	1	4	.996	0.277	7.56	.91

The permeability was tested on every other PCP slab in both parking lots. The permeability rates of various sections were obtained by computing the mean of permeability rates of associated slabs. The permeability rate of each section with its permeability scale using Equation 5-5 is shown in Table 5-9.

Table 5-9 Permeability Rates and Scales

Section #	Permeability rate (cm/sec)	Permeability Scale (FPI)
1	0.057	4.96
2	0.047	4.79
3	0.119	5.63
4	0.391	6.71
5	0.205	6.12
6	0.011	3.47
7	0.026	4.25
8	0.073	5.18
9	0.090	5.37
10	0.024	4.18

5.1.6 Weighted Factors

PCCI is the weighted summation of SDI and FPI. In order to estimate the weighting factors corresponding to SDI and FPI, their respective impact on PCCI should be examined. FPI has the most significant effect on PCCI. That is, the main purpose of using PCP is to have a sufficient permeability rate that water can readily infiltrate towards the underground water. A single pair of weighting factors could be assigned to each parameter. However, a more sophisticated approach was applied herein. A series of weighting factors were developed by a group of experienced pavement engineers for FPI (α) and SDI (β) based on the magnitude of permeability rates (Table 5-10). Namely, weighting factors of both parameters change with respect to the magnitude of FPI since the first concern is to have permeable PCP (and the second concern is to have PCP with good surface condition). Essentially, if FPI of a PCP section is low, a larger weight is dedicated to FPI and a lower weight to SDI, whereas if

FPI of a PCP section is high, a lower weight is assigned to FPI and a larger weight to SDI. Sensitivity analysis was done to check results difference through application of a series of weighting factors versus a constant pair of weighting factor (with a higher weight assigned to FPI). It was concluded that in the case of high FPI and low SDI, there was a significant difference between results (PCCI). In this case a constant pair of weighting factor wrongly produced a high value for PCCI, while a series of weighting factors correctly provided a lower value due to low SDI. This approach significantly increases the impact of FPI on PCCI. PCCI of the entire sections were computed using Equation 5-6:

$$PCCI = \alpha \times FPI + \beta \times SDI \qquad (5\text{-}6)$$

Where,

$PCCI$ =Pervious Concrete Condition Index

FPI = Functional Performance Index

SDI = Surface Distress Index

α = weighting factor of FPI

β = weighting factor of SDI

Table 5-10 Weighting Factors of SDI and FPI

Permeability scale	α (weighting factor of FPI)	β (weighting factor of SDI)
0≤FPI≤2	0.9	0.1
2<FPI≤4	0.7	0.3
4<FPI≤6	0.5	0.5
6<FPI≤8	0.4	0.6
8<FPI≤10	0.3	0.7

The PCCI of each section was computed and shown in Table 5-11. Also, FPI and SDI have been summarized in this table. It is finally concluded that PCCI was significantly sensitive to the permeability rate of individual PCP sections (as anticipated) i.e., PCP with low permeability rates such as section 6, obtains the lowest value of PCCI, while the highest value is assigned to section 1 which has both a good permeability rate and a good surface condition.

Table 5-11 Pervious Concrete Condition Index of all Sections

Section #	FPI	SDI (mean panel ratings)	PCCI
1	4.96	6.03	5.49
2	4.79	4.88	4.83
3	5.63	5.12	5.37
4	6.71	5.76	6.14
5	6.12	4.30	5.03
6	3.47	4.11	3.66
7	4.25	4.74	4.49
8	5.18	4.95	5.06
9	5.37	4.40	4.88
10	4.18	4.09	4.13

5.2 DEVELOPMENT OF THE PERVIOUS CONCRETE CONDITION INDEX USING FUZZY SETS

5.2.1 Fuzzy Pavement Condition Data

Pavement condition data (distress severity and density) obtained from various PCP sites was affected by the human uncertainty with regards to each observer's judgment. The experienced engineers' opinions about weighting factors of distresses were, moreover, rarely consistent. However, these uncertainties and inconsistencies associated with pavement evaluation could be dealt with representing fuzzy sets.

Severity levels (very slight, slight, moderate, severe, and very severe) were modeled as Triangular Fuzzy Numbers (TFNs) on a [0.5, 4] scale based on the MTO protocol considering possible magnitude of uncertainty. Moreover, the weighting factors of various distresses occurring on PCP (ravelling, spalling, polishing, cracking, potholing, and stepping) were represented using fuzzy sets. The TFNs of severity and weighting factors are illustrated in Figure 5-5.

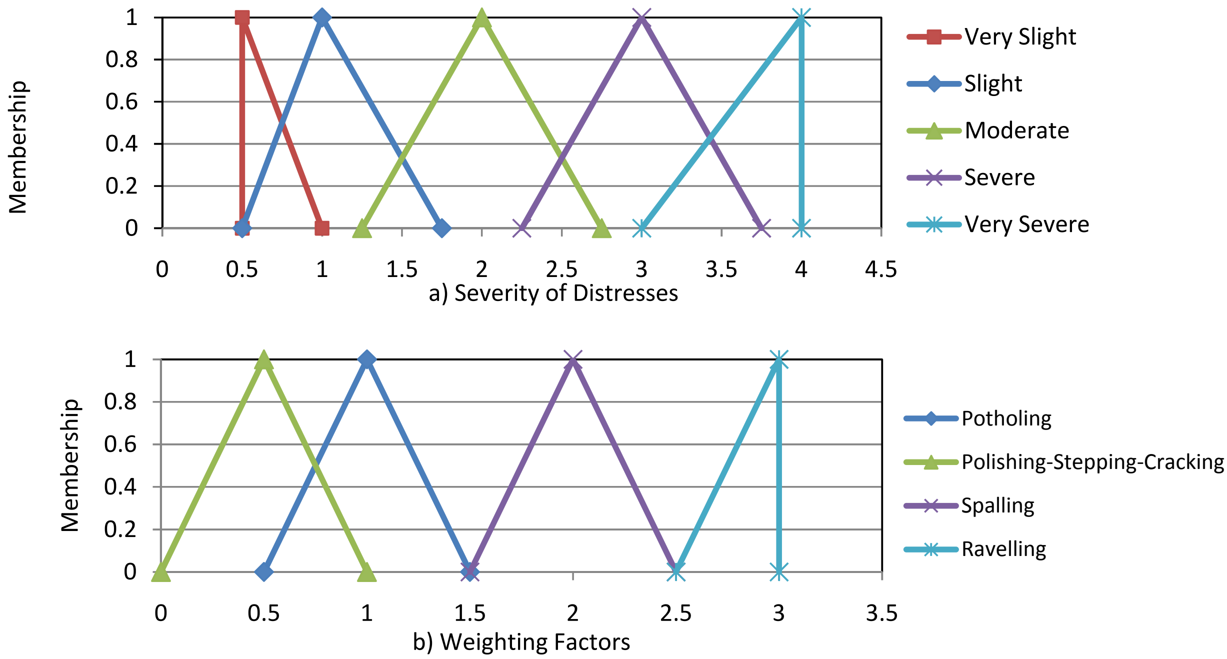


Figure 5-5 TFNs for Various Density, Severity, and Weighting Factors Levels

In order to compute PCDI, Equation 5-2 was applied. All associated computations were executed on both the lower and upper domains of each TFNs at the different α-level. For instance, as shown in Figure 5-5b, at the α-level of [0.0], the weighting factor of spalling is restricted to the domains of 1.5 and 2.5 and the most probable value is 2.0. Likewise, other domains of each TFNs can be computed at various α-levels.

In this study, in order to compute the PCDI (Equation 5-2), two major criteria (severity and weighting factors) should be estimated for six distress types (spalling, ravelling, cracking, stepping, potholing, and polishing). Therefore, in total, there are 12 variables ($12 = 2 \times 6$) which lead to 2^{12} ($2^{12} = 4096$) permutations of array (spalling severity, spalling weighting factor, ravelling severity, ravelling weighting factor, cracking severity, cracking weighting factor, polishing severity, polishing weighting factor, stepping severity, stepping weighting factor, potholing severity, potholing weighting factor).

5.2.2 Fuzzy Representation of PCDI

The computational procedure for calculating PCDI can be readily executed by applying various TFNs of each fuzzy variable. For this purpose, six α-values from 0.0 to 1.0 at 0.2 intervals were used. Accordingly, in order to calculate $PCDI_{fuzzy}$ 24,576 (24,576 = 6 × 4096) permutations were required to accurately perform for each PCP section (totally 245,760 = 10 × 24,576). Robust codes were written in Microsoft Excel by using the Macro feature to execute the fuzzy computational process in an efficient and accurate manner.

The surface distress severity and weighting factors represented in TFNs (Figure 5-5) were used to compute $PCDI_{fuzzy}$. Table 5-12 and Table 5-13 show the analysis intervals of various slabs for each parking lot. These tables can be applied to build the membership functions of fuzzy PCDI for the associated slabs. The PCDI membership functions of the Georgetown parking lot slabs are shown in Figure 5-6 for illustration.

Finally following the calculation of $PCDI_{fuzzy}$, a numerical rating score was calculated. For this purpose, the concept of Center Of Gravity (COG) for a membership function was applied as an overall output. The COG for a sample membership function is given by Equation 5-7:

$$COG = \frac{\sum \mu_i \times x_i}{\sum \mu_i} \qquad (5\text{-}7)$$

Where,

COG = Center Of Gravity,

μ_i = level of membership at α-level i

x_i = horizontal distance to the vertical axis at α-level i

Prior to conducting any further analyses, COG of $PCDI_{fuzzy}$ of the entire sections was computed. This rating score is then further analyzed in the next step using the regression analysis. Table 5-12 and Table 5-13 also show the COGs of various slabs of Georgetown and Guelph Line parking lot, respectively.

Table 5-12 α-Level Cut Representation of Fuzzy PCDI for the Georgetown Parking Lot

α Level	PCP slab number														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0	9.37	9.38	8.09	7.84	8.59	7.90	7.73	8.90	8.62	8.94	8.16	8.11	8.84	8.94	9.00
0.2	9.27	9.28	7.79	7.50	8.32	7.56	7.37	8.73	8.37	8.72	7.87	7.83	8.63	8.74	8.81
0.4	9.17	9.17	7.47	7.14	8.04	7.20	6.98	8.54	8.10	8.48	7.55	7.54	8.40	8.53	8.61
0.6	9.06	9.05	7.13	6.75	7.74	6.82	6.57	8.33	7.81	8.23	7.21	7.22	8.15	8.31	8.40
0.8	8.95	8.93	6.77	6.34	7.41	6.40	6.13	8.12	7.50	7.95	6.85	6.89	7.89	8.07	8.17
1	8.83	8.80	6.38	5.90	7.07	5.97	5.67	7.90	7.17	7.67	6.47	6.53	7.62	7.82	7.93
0.8	8.61	8.57	6.02	5.54	6.69	5.58	5.27	7.59	6.81	7.32	6.10	6.21	7.28	7.49	7.61
0.6	8.37	8.33	5.64	5.16	6.30	5.17	4.84	7.27	6.43	6.96	5.72	5.86	6.93	7.15	7.28
0.4	8.12	8.08	5.25	4.77	5.89	4.75	4.40	6.93	6.03	6.58	5.31	5.50	6.56	6.80	6.93
0.2	7.87	7.83	4.83	4.35	5.46	4.30	3.94	6.58	5.62	6.18	4.89	5.12	6.17	6.43	6.56
0	7.60	7.56	4.40	3.92	5.02	3.84	3.46	6.22	5.19	5.76	4.45	4.73	5.77	6.04	6.18
COG	**8.74**	8.71	6.38	5.94	7.02	5.98	**5.69**	7.82	7.12	7.60	6.46	6.53	7.55	7.74	7.85

Table 5-13 α-Level Cut Representation of Fuzzy PCDI for Guelph Line Parking Lot

α Level	PCP slab number																	
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
0	7.6	7.3	7.3	7.2	7.2	7.9	8.4	6.9	6.9	6.7	6.9	6.6	7.0	7.2	7.3	8.1	7.5	7.6
0.2	7.3	6.9	6.9	6.7	6.7	7.5	8.1	6.4	6.4	6.2	6.4	6.1	6.6	6.8	6.9	7.8	7.1	7.2
0.4	6.9	6.5	6.5	6.3	6.3	7.2	7.7	6.0	5.9	5.7	6.0	5.6	6.1	6.4	6.4	7.5	6.7	6.9
0.6	6.5	6.0	6.0	5.8	5.8	6.8	7.4	5.4	5.4	5.2	5.4	5.1	5.6	5.9	6.0	7.1	6.3	6.4
0.8	6.1	5.5	5.5	5.3	5.3	6.4	7.0	4.9	4.9	4.7	4.9	4.5	5.0	5.5	5.5	6.7	5.9	6.0
1	5.6	5.0	5.0	4.8	4.8	5.9	6.6	4.3	4.3	4.1	4.3	3.9	4.4	4.9	5.0	6.3	5.4	5.5
0.8	5.2	4.6	4.6	4.4	4.4	5.5	6.2	4.0	4.0	3.7	4.0	3.5	4.0	4.5	4.6	5.9	5.0	5.1
0.6	4.8	4.2	4.2	4.1	4.1	5.1	5.8	3.7	3.7	3.4	3.7	3.2	3.6	4.1	4.2	5.4	4.6	4.7
0.4	4.4	3.8	3.8	3.7	3.7	4.7	5.4	3.3	3.3	3.0	3.3	2.8	3.1	3.6	3.7	5.0	4.1	4.2
0.2	4.0	3.4	3.4	3.2	3.2	4.2	4.9	3.0	2.9	2.6	3.0	2.4	2.7	3.2	3.3	4.5	3.7	3.7
0	3.5	3.0	3.0	2.8	2.8	3.7	4.5	2.6	2.5	2.2	2.6	2.0	2.2	2.7	2.8	4.1	3.2	3.2
COG	5.6	5.1	5.1	4.9	4.9	5.9	**6.6**	4.5	4.5	4.2	4.5	4.1	4.5	5.0	5.1	6.3	5.4	5.5

α Level	PCP slab number																	
	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36
0	8.2	7.0	8.0	7.0	8.0	7.8	6.5	7.0	6.8	7.1	7.2	8.0	6.8	6.9	6.8	6.7	7.5	7.5
0.2	7.9	6.5	7.6	6.6	7.6	7.5	6.0	6.6	6.3	6.7	6.7	7.7	6.4	6.4	6.4	6.2	7.1	7.1
0.4	7.5	6.1	7.3	6.1	7.3	7.1	5.5	6.1	5.8	6.2	6.3	7.4	6.0	6.0	5.9	5.7	6.7	6.7
0.6	7.2	5.6	6.9	5.6	6.9	6.7	4.9	5.6	5.3	5.7	5.8	7.0	5.5	5.5	5.3	5.2	6.3	6.3
0.8	6.8	5.0	6.4	5.1	6.4	6.3	4.3	5.1	4.7	5.2	5.3	6.6	5.0	4.9	4.8	4.6	5.8	5.8
1	6.4	4.5	6.0	4.5	6.0	5.9	3.7	4.5	4.1	4.7	4.8	6.1	4.4	4.3	4.2	4.0	5.3	5.3
0.8	6.0	4.1	5.6	4.2	5.6	5.5	3.4	4.2	3.8	4.3	4.4	5.7	4.1	4.0	3.8	3.6	4.9	4.9
0.6	5.6	3.8	5.2	3.8	5.2	5.1	3.0	3.8	3.4	3.9	4.1	5.3	3.8	3.6	3.5	3.3	4.5	4.5
0.4	5.2	3.4	4.8	3.4	4.7	4.7	2.6	3.4	3.1	3.5	3.7	4.9	3.5	3.2	3.1	2.9	4.1	4.1
0.2	4.7	3.1	4.4	3.0	4.3	4.2	2.2	3.0	2.7	3.1	3.2	4.4	3.1	2.7	2.7	2.5	3.7	3.7
0	4.3	2.7	3.9	2.6	3.8	3.8	1.8	2.6	2.2	2.6	2.8	3.9	2.7	2.3	2.2	2.0	3.2	3.2
COG	6.4	4.6	6.0	4.7	6.0	5.9	**3.9**	4.7	4.3	4.8	4.9	6.1	4.6	4.5	4.4	4.2	5.4	5.4

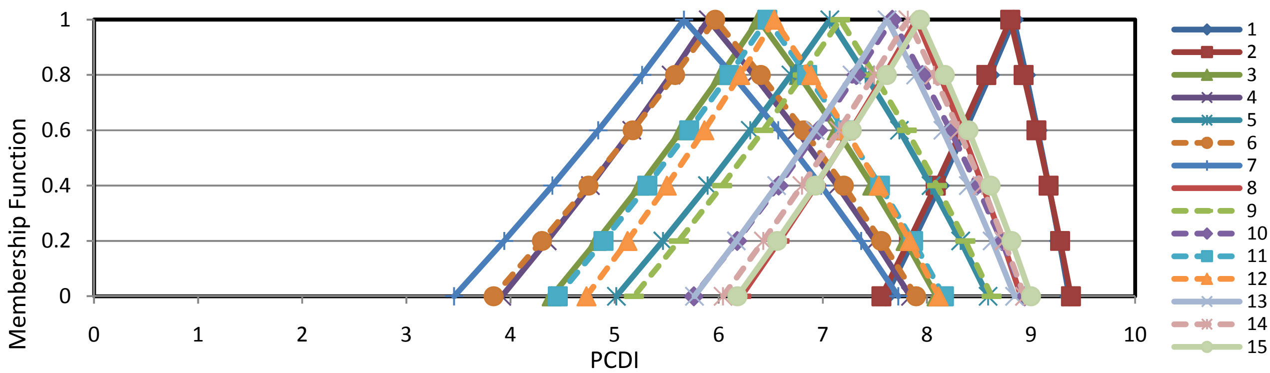


Figure 5-6 Fuzzy PCDI Membership Functions of the Georgetown Parking Lot Slabs.

Table 5-12 indicates that in the Georgetown parking lot, slab 1 performs better than the others, while PCDI of slab 7 is the worst (see the last row, COG). Likewise, Table 5-13 shows that in the Guelph line parking lot, slab 7 performs better than the others, while PCDI of slab 25 is the worst (see the last row, COG). Moreover from Figure 5-6, it can be observed that the uncertainty of PCDI of slab 1 in the Georgetown parking lot is the lowest, whereas that of slab 7 is the highest. In other words, Table 5-12 (at level α=0) demonstrates that PCDI of slab 1 is restricted to the domain of 7.60 to 9.37 (narrower range: 1.77, less uncertainty), while that of slab 7 is restricted to the domain of 3.46 to 7.73 (wider range: 4.27, more uncertainty).

In total, 15 slabs in the Georgetown parking lot and 36 slabs in the Guelph Line parking lot were evaluated in this research. These slabs were categorized into 10 sections as described earlier. The same calculations were executed for the whole sections and the fuzzy numbers of PCDI together with the associated GOCs were obtained. Table 5-14 presents fuzzy numbers of PCDI of various sections. The associated fuzzy membership functions were exhibited in Figure 5-7. Table 5-14 demonstrates that Section 1 performs better than the rest of sections and it has the lowest result uncertainty, while Section 10 has the worst pavement condition and the highest result uncertainty. It would be noted that fuzzy membership function of sections 6, 9, and 10 are approximately coincident.

Table 5-14 α-Level Cut Representation of Fuzzy PCDI for the entire Sections

α Level	PCP Sections Number									
	1	2	3	4	5	6	7	8	9	10
0	8.95	8.19	8.46	8.93	7.74	7.05	7.46	7.65	7.09	7.03
0.2	8.78	7.90	8.20	8.73	7.40	6.62	7.08	7.28	6.67	6.60
0.4	8.60	7.58	7.92	8.51	7.03	6.15	6.67	6.89	6.21	6.15
0.6	8.42	7.24	7.62	8.29	6.65	5.66	6.23	6.47	5.72	5.66
0.8	8.22	6.88	7.30	8.04	6.23	5.14	5.76	6.02	5.21	5.15
1	8.01	6.50	6.96	7.79	5.80	4.59	5.26	5.54	4.66	4.61
0.8	7.73	6.13	6.61	7.46	5.47	4.25	4.85	5.17	4.30	4.24
0.6	7.45	5.75	6.24	7.12	5.13	3.90	4.42	4.78	3.91	3.86
0.4	7.15	5.35	5.86	6.76	4.77	3.52	3.97	4.37	3.51	3.46
0.2	6.84	4.93	5.45	6.39	4.40	3.12	3.51	3.94	3.09	3.04
0	6.52	4.49	5.03	6.00	4.00	2.70	3.02	3.50	2.65	2.60
COG	7.94	6.49	6.93	7.71	5.86	4.73	5.30	5.60	4.78	4.72

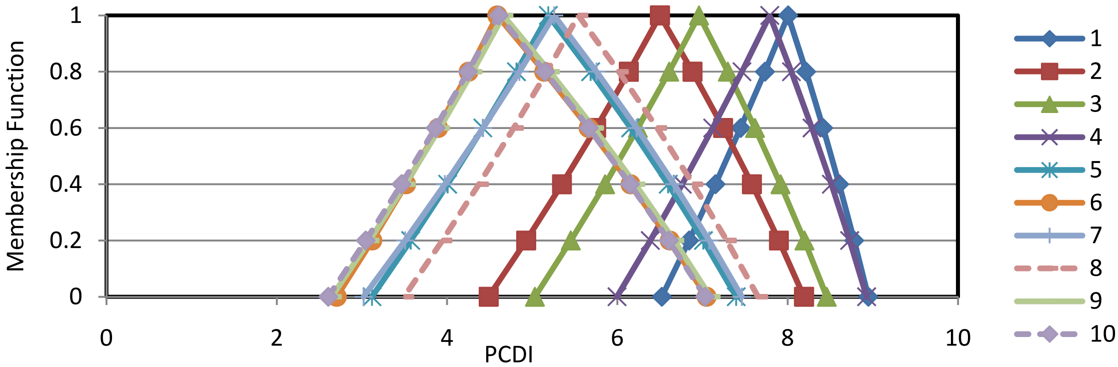


Figure 5-7 Fuzzy PCDI Membership Functions of all PCP Sections.

The next step was to correlate $PCDI_{fuzzy}$ to SDI (mean panel ratings) through the application of the regression analysis technique. The numerical rating scores of $PCDI_{fuzzy}$ (COG of $PCDI_{fuzzy}$) together with mean of panel ratings (SDI) of various sections are presented in Table 5-15. These parameters were applied to develop a regression model.

Table 5-15 Comparison of $PCDI_{fuzzy}$ and SDI of all PCP Sections

Section #	$PCDI_{fuzzy}$ (field investigation)	SDI (mean panel ratings)
1	7.94	6.03
2	6.49	4.88
3	6.93	5.12
4	7.71	5.76
5	5.86	4.30
6	4.73	4.11
7	5.30	4.74
8	5.60	4.95
9	4.78	4.40
10	4.72	4.09

5.2.3 Data Analysis

Several attempts have been made to derive a regression model to relate $PCDI_{fuzzy}$ to SDI (linear, quadratic, and exponential models). The dependent variable is SDI and the independent variable is $PCDI_{fuzzy}$. As it is shown in Figure 5-8, they are highly related. The linear model was selected herein due to the high coefficient of correlation and prediction power. The model presented in Equation 5-8 expresses the relationship between SDI and $PCDI_{fuzzy}$:

$$\mathrm{SDI} = 0.511 \times \mathrm{PCDI_{fuzzy}} + 1.797 \tag{5-8}$$

Where,

SDI = Surface Distress Index i.e., mean panel ratings of surface distress condition;

$PCDI_{fuzzy}$ = Fuzzy Pervious Concrete Distress Index.

Regression statistics were estimated encompassing the coefficient of determination (R^2 = 0.91) and the standard error of the estimate (0.211). Also, the analysis of variance (ANOVA) was performed to control the overall significance of the regression. The two-tailed t-test was done to check the significance of the independent variable (Table 5-16).

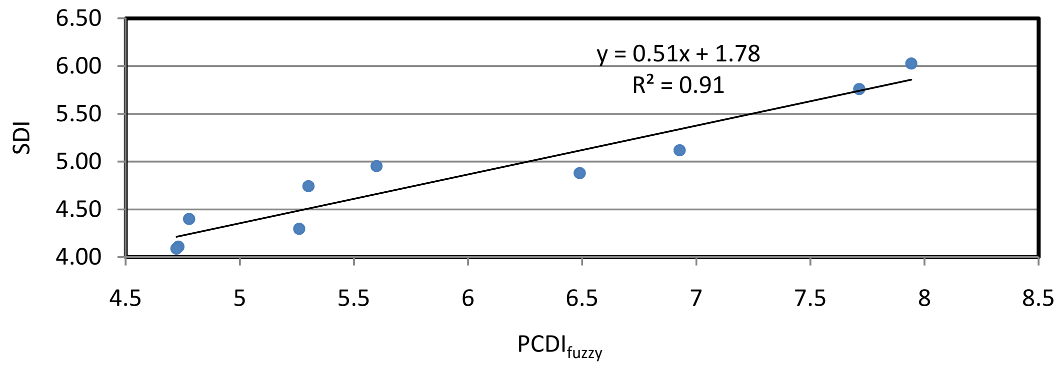


Figure 5-8 Relationship between $\mathbf{PCDI_{fuzzy}}$ and SDI.

Table 5-16 Coefficient of the Regression Model

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
	B	Std. Error	Beta			Lower Bound	Upper Bound
(Constant)	1.80	.346	NA	5.19	.001	1.00	2.59
PCDI	.51	.057	.95	8.95	.000	.38	.64

The next step was to convert $PCDI_{fuzzy}$ into SDI using Equation 5-8. For this purpose, the fuzzy calculations were performed. The SDI was calculated for various sections incorporating the α-cut concept at 0.2 intervals. The fuzzy membership functions representing SDI of different PCP sections were built up based on the SDI fuzzy numbers and are illustrated in Figure 5-9.

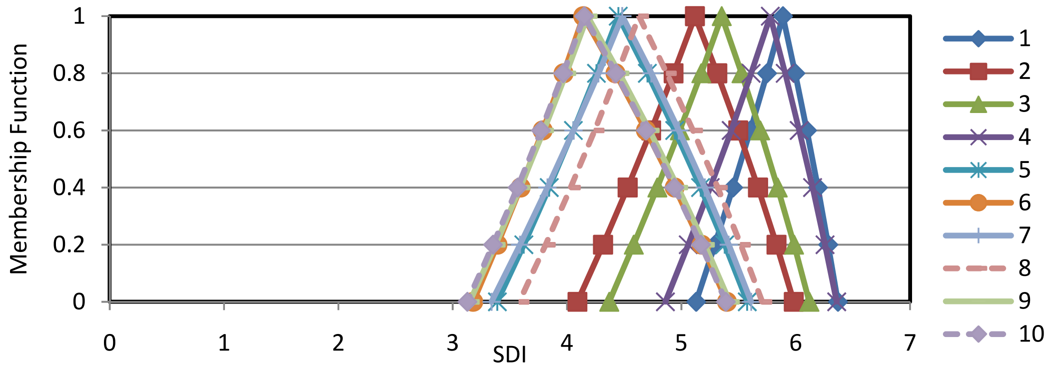


Figure 5-9 SDI Fuzzy Membership Functions of PCP Sections.

After calculating the fuzzy SDI, the next parameter that should be measured for developing the PCCI is the permeability rate. Since each scale covers a wide range of permeability rates, it is not accurate to assign a crisp value (scale) to each range. Accordingly, single scale values were replaced with fuzzy numbers (Table 5-17). These fuzzy numbers are plotted in Figure 5-10.

Table 5-17 Permeability Rates, Scales, and Associated Fuzzy Numbers

No.	Permeability rate, K (cm/sec)	Permeability condition	FPI (scale)	Fuzzy numbers
1	$0 < K \leq 0.0004$	Clogged	0	[0,0,1]
2	$0.0004 < K \leq 0.004$	Very poor	2	[1,2,3]
3	$0.004 < K \leq 0.04$	Poor	4	[3,4,5]
4	$0.04 < K \leq 0.4$	Fair	6	[5,6,7]
5	$0.4 < K \leq 4.0$	Good	8	[7,8,9]
6	$4.0 \leq K$	Very good	10	[9,10,10]

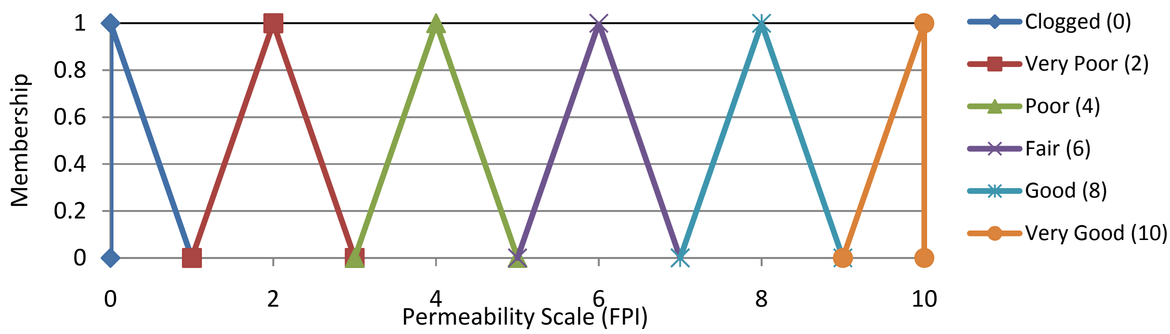


Figure 5-10 TFNs for Various Permeability Scales.

Finally, to develop PCCI, fuzzy Mathematics was employed. SDI_{fuzzy} and FPI were combined by applying Equation 5-6 and the weighting factors shown in Table 5-10. Note that fuzzy permeability scales (Figure 5-10) were used for computation of PCCI. Figure 5-11 represents the fuzzy membership function of PCCI of all sections. Figure 5-11 demonstrates that section 1 performs considerably well while section 10 has the worst PCCI.

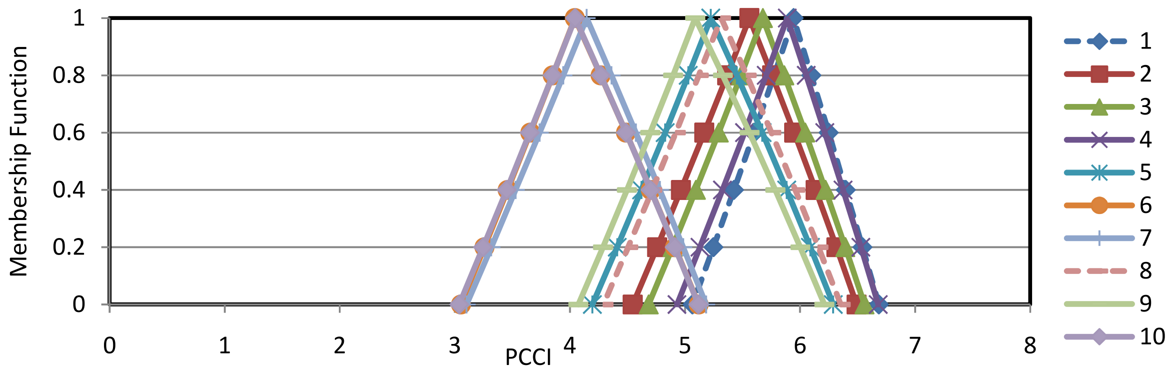


Figure 5-11 PCCI of Various PCP Sections.

The COG concept was employed herein to obtain a single value for a PCCI membership function for each section. The single value for PCCI of each section is shown in Table 5-18. It was finally concluded that PCP with the best SDI and FPI such as section 1, obtained the highest value of PCCI, while the worst PCCI was assigned to section 10 which has the lowest SDI. Since FPI of various sections are approximately in the similar range, it can be observed SDI had the most influence on the PCCI values. Table 5-18 also shows PCCI which had been computed in section 5.1.6 using crisp values. Table 5-18 presents that there is a negligible difference (average 3.7 %) between the final results obtained from various approaches. However, the fuzzy approach provides a domain (i.e., lower bound, most probable value, and upper bound) associated with PCCI in the form of a membership function (i.e., provide more detailed information). Moreover, the fuzzy approach is more compatible with uncertainties inherent in the PCP performance evaluation rather than the crisp approach.

Table 5-18 Comparison of PCCI Calculated Using Different Methods

Section #	PCCI based on crisp values	PCCI based on fuzzy numbers	Difference (%)
1	5.49	5.93	7.3
2	4.83	5.56	13.0
3	5.37	5.67	5.2
4	6.14	5.87	4.6
5	5.03	5.24	4.0
6	3.66	4.06	9.8
7	4.49	4.15	8.3
8	5.06	5.33	5.0
9	4.88	5.12	4.6
10	4.13	4.06	1.8
Average	4.91	5.10	3.7

5.3 SUMMARY

The PCCI has been described as a function of the Surface Distress Index (SDI) and the Functional Performance Index (FPI). Several relationships between the field investigation data (i.e., PCDI and PCI) and mean panel ratings of surface distresses (i.e., SDI) have been developed by incorporation of two major approaches: crisp (or single point) values and fuzzy sets. These approaches have approximately led to the similar results in terms of PCCI of various sections. However, the fuzzy approach enables for more detailed results (a membership function) than the crisp approach. Moreover, it is more compatible with uncertainties inherent in the PCP condition evaluation rather than the crisp approach. Two sources of data have been incorporated in this chapter including panel rating and detailed field investigations (surface distress evaluation and permeability testing) which has been successfully translated into PCCI. An appropriate model has also been developed to relate the permeability rate (measure in the field) to FPI (which ranges from 0 to 10).

Chapter 6
Pavement Performance Model

This chapter presents the development of performance models for Pervious Concrete Pavement (PCP), using regression analysis and the Markov Chain process based on the Pervious Concrete Condition Index (PCCI) proposed in Chapter 5. Several performance models are developed using different sets of parameters as independent variables. The models are compared and the most appropriate model is selected.

6.1 EMPIRICAL MODEL FOR PREDICTING PCP PERFORMANCE: REGRESSION METHOD

6.1.1 Regression Model Procedure

All multiple regression analyses and model development presented have been conducted using statistical analysis software SPSS Statistics Version 17.0 (2009). The relevant independent variables were entered into the models and statistically significant variables at the 5% level of significance with both high predictability and of engineering significance were selected to build the final models.

The best correlation of each independent variable with a dependent variable was determined using the curve estimation module in SPSS. Linear, quadratic, inverse, logarithm, exponential, and power were all evaluated. The trend that has shown the highest correlation coefficient (R^2) with the dependent variables and that made the most "engineering" sense was chosen. The normality was checked based on the distribution of standardized residual. Data which had standardized residual absolute values more than 2.0 was discarded as an outlier (Montgomery and Runger 2007). The multicollinearity was checked based on the variance inflation factor (VIF) which should not be less than 4 to 5 (Montgomery and Runger 2007).

To develop a performance model, PCCI should be predicted over time. As mentioned, PCCI is a function of the Functional Performance Index (FPI) and the Surface Distress Index (SDI). Therefore, prediction models should be developed for both FPI and SDI to be able to derive a model for PCCI in terms time. In other words, SDI and FPI should be predicted over time.

Three approaches were applied to predict SDI using regression methods. The first approach involved prediction of SDI by developing a model for the Pervious Concrete Distress Index (PCDI) incorporating pervious concrete thickness, traffic load, and pavement age. Note that having predicted PCDI, SDI could be calculated using equations presented in Chapter 5 (e.g., Equation 5-3). The second approach involved prediction of SDI by incorporating surface distresses (ravelling, spalling, potholing, cracking, stepping, and polishing). The last approach predicted SDI by developing a prediction model for PCI.

The FPI was also predicted by developing a prediction model for permeability rates (K). The regression analysis technique was applied to relate K to time. Having predicted K, FPI could be readily computed using Equation 5-5.

The data base utilized in this portion of the research included eleven PCP sites visited in the United States (in hard wet freeze climate condition), the two sites monitored in Canada (Georgetown and Guelph Line parking lots), and the sites from the United States which were constructed and evaluated by Delatte et al. (2007) (which were located within hard wet freeze climate). These sites were evaluated using the same protocols as the two sites at the Georgetown and Guelph Line parking lots. The PCDI was calculated for the PCP sites using Equation 5-2. In addition, PCI was computed for the PCP sites visited in the United States applying Micro PAVER (U.S. Army Corps of Engineers 2004). The whole PCP sites characteristics and associated condition indices (i.e., PCDI and PCI) are summarized in Table 6-1.

Since PCP has been investigated recently in cold climates, a limited range of pavement ages have been available and covered in this study (less than 6 years of age). In fact, models which will be developed in the following sections have this limitation and they can be adjusted in future using in-service data.

6.1.2 Model for Prediction of PCDI

6.1.2.1 Model Development for PCDI and Pavement Characteristics

The PCDI is a function of pervious concrete thickness, traffic load, and pavement age. The dependent variable is PCDI of various PCP sites. Pavement age, pervious concrete thickness, and traffic load were entered as independent variables.

Table 6-1 the United States PCP Sites Characteristics and Condition Indices

Site	Age (Year)	Pervious concrete thickness (mm)	Traffic Load [1]	PCDI	PCI [2]
Anderson Concrete plan	1.73	152	1	7.66	81
Audobon	0.73	152	1	8.35	87
Ball Brother Concrete	5.32	152	2	7.07	66
Ball Brother Concrete	3.43	152	2	7.54	NA
Bettman NRC	2.57	152	1	7.77	78
Bettman NRC	0.67	152	1	8.21	NA
Boone County	1.42	152	1	8.66	NA
Charter School Gary	1.04	203	1	8.21	NA
Cleveland State University Admin Build	1.81	152	1	8.03	78
Cleveland State University Admin Build	0.14	152	1	9.3	NA
Cleveland State University Parking Lot D	3.73	152	1	7.6	75
Cleveland State University Parking Lot D	1.99	152	1	7.87	NA
Cleveland State University Parking Lot D	1.12	152	1	8.25	NA
Collinwood Concrete	4.06	229	2	7.28	71
Collinwood Concrete	2.22	229	2	7.47	NA
Fred Fuller Park	3.55	152	1	7.28	NA
Harrison Concrete	0.76	152	1	8.82	NA
Indian Run Falls	3.15	152	1	7.38	78
Indian Run Falls	1.60	152	1	7.73	NA
Indian Run Falls	1.27	152	1	8.02	NA
Kentucky Sanitary	3.42	178	1	7.76	NA
Kuert concrete	2.04	152	1	7.99	NA
Lake County Space Fair Ground	0.89	152	1	9.04	79
Philips Company	2.90	178	1	8.01	80
Philips Company	1.01	178	1	8.78	NA
Roush Honda Inventory Lot	0.47	152	1	8.91	80

[1] Note 1 represents light traffic and 2 shows heavy traffic.
[2] Note PCI was only provided for sites that were visited.

Several combinations of independent variables were examined and their descriptive statistics data are presented in Table 6-2. The best model which has a high power of predictability, statistical significance, and that makes engineering sense was selected. Scenario 18 proposes a model which has a good coefficient of determination (R^2) of 0.72 with statistically significant variable at the 5% level of significance (p-value of 0 for the variable and intercept). This model shows a relationship between PCDI, age, and pervious concrete thickness.

Table 6-2 Scenarios with Descriptive Characteristics for Developing a Prediction Model for PCDI

Scenario	Independent Variable	B	Std. Error	t	p-value	R^2	Std. Error of Estimate
1	Constant	9.139	0.482	18.951	0.000	0.724	0.333
	Load	0.005	0.254	0.021	0.983		
	Age	-0.378	0.062	-6.092	0.000		
	Thickness	-0.002	0.003	-0.595	0.558		
2	Constant	8.853	0.769	11.507	0.000	0.509	0.533
	Thickness	0.026	0.138	0.185	0.855		
	Load	-0.853	0.339	-2.515	0.019		
3	Constant	9.138	0.468	19.538	0.000	0.724	0.325
	Thickness	-0.051	0.073	-0.693	0.495		
	Age	-0.377	0.051	-7.469	0.000		
4	Constant	8.884	0.216	41.131	0.000	0.720	0.328
	Age	-0.373	0.061	-6.157	0.000		
	Thickness	-0.071	0.216	-0.331	0.744		
5	Constant	8.825	0.119	74.087	0.000	0.718	0.322
	Age	-0.384	0.049	-7.826	0.000		
6	Constant	9.029	0.847	10.660	0.000	0.055	0.589
	Thickness	-0.006	0.005	-1.186	0.247		
7	Constant	8.980	0.343	26.168	0.000	0.258	0.522
	Load	-0.820	0.284	-2.889	0.008		
8	Constant	8.754	0.121	72.130	0.000	0.679	0.343
	Age*Thick	-0.002	0.000	-7.132	0.000		
9	Constant	8.629	0.257	33.548	0.000	0.212	0.538
	Load*Thick	-0.003	0.001	-2.538	0.018		
10	Constant	8.498	0.117	72.788	0.000	0.552	0.406
	Load*Age	-0.176	0.032	-5.438	0.000		
11	Constant	8.444	0.118	71.738	0.000	0.505	0.426
	Load*Age*Thickness	-0.023	0.005	-4.953	0.000		
12	Constant	8.805	0.118	74.321	0.000	0.713	0.325
	Age*Sqrt(Thickness)	-0.029	0.004	-7.722	0.000		
13	Constant	8.821	0.118	74.468	0.000	0.719	0.321
	Age*Lg(Thickness)	-0.173	0.022	-7.844	0.000		
14	Constant	8.821	0.118	74.468	0.000	0.719	0.321
	Age*Ln(Thickness)	-0.075	0.010	-7.844	0.000		
15	Constant	8.493	0.117	72.831	0.000	0.549	0.407
	Load*Age*Ln(Thickness)	-0.034	0.006	-5.403	0.000		
16	Constant	8.788	0.128	68.523	0.000	0.668	0.3491
	Age*Inv(Thickness)	-59.604	8.572	-6.953	0.000		
17	Constant	8.386	0.142	58.769	0.000	0.323	0.498
	Age*Exp(-Thickness)	-3.622	0.142	-3.391	0.002		
18	**Constant**	**8.824**	**0.120**	**73.376**	**0.000**	**0.714**	**0.324**
	Age*Inv(Lg(Thickness))	**-0.849**	**0.109**	**-7.741**	**0.000**		
19	Constant	8.818	0.122	72.092	0.000	0.703	0.329
	Age*Exp(-Lg(Thickness))	-3.485	0.461	-7.554	0.000		

The traffic load variable was eliminated from the model, and this is probably due to the limited variability in traffic load at the sites. The regression coefficient associated with age and pervious concrete thickness, as shown in Equation 6-1, indicates that PCP surface condition degrades with an increase in age and improves with increased pervious concrete thickness of PCP. All these variations are consistent with observed field performance.

$$PCDI = 8.824 - 0.849 \times \frac{T}{Lg\ (H)} \tag{6-1}$$

Where,

PCDI = Pervious Concrete Distress Index

T = age of a PCP section (year)

H = thickness of pervious concrete layer (mm)

The validation process has been carried out for the performance model. For this purpose, 25% of data has been used for validation and the rest (75% of data) has been applied for modeling. The validation data has been selected at random. Having applied Equation 6-1, the predicted PCDI was computed. A statistical tool should be employed to determine whether there is a significant difference between predicted PCDI and actual PCDI of validation data. For this purpose, the two tailed t-test method was used to compare the sample mean of predicted PCDI and actual PCDI at the 5% significance level. The null hypothesis (H_0) was that the mean of predicted PCDI was equal to the mean of the actual PCDI at the 95% confidence level which was accepted. According to the results shown in Table 6-3, the domain between d_{upper} and d_{lower} included 0 so that the null hypothesis was accepted and the regression was successfully validated.

Table 6-3 T-Test for Performance Model Validation

t-test (σ1=σ2 and unknown)		t-test (σ1≠σ2 and unknown)	
S^2p	0.07	ν	11
$t_{\alpha/2}$	3.01	$t_{\alpha/2}$	3.10
d_{upper}	0.12	d_{upper}	0.14
d_{lower}	-0.72	d_{lower}	-0.73
H_0	Accepted	H_0	Accepted

6.1.2.2 Model Development for PCDI and Pavement Age

Attempts were made to develop a model to relate PCDI to pavement age. Pavement age was entered as an independent variable to obtain a performance curve (PCDI versus time) and the dependent variable is PCDI. Several trends have been examined to derive the most appropriate relationship between PCDI and pavement age such as linear, inverse, logarithmic, quadratic, cubic, power, exponential, and logistic. Some of these curves are presented in Figure 6-1. The best fitted curve was a logarithmic trend. The linear model also presented a good correlation between the independent and dependent variables. Although the coefficient of determination for the linear model is lower than that of the logarithmic model, the linear model can describe the relation between parameters simpler than the logarithmic model. The linear model will also be applied in the model calibration procedure. The summary of the resulting models is presented in Table 6-4 and given by Equations 6-2 and 6-3:

$$PCDI = 8.336 - 0.644 \times Ln\,(T) \quad (6\text{-}2)$$

$$PCDI = 8.825 - 0.384 \times T \quad (6\text{-}3)$$

Where,

PCDI = Pervious Concrete Distress Index

T = age of a PCP section (year)

Table 6-4 Model Summary and Parameter Estimates

Equation	Model Summary						Parameter Estimates	
	R Square	F	df1	df2	Sig.	Std. Error of the Estimate	Constant	b1
Linear	.72	60.80	1	24	.000	0.32	8.83	-.38
Logarithmic	.77	81.27	1	24	.000	0.28	8.34	-.64

df stands for degree of freedom.

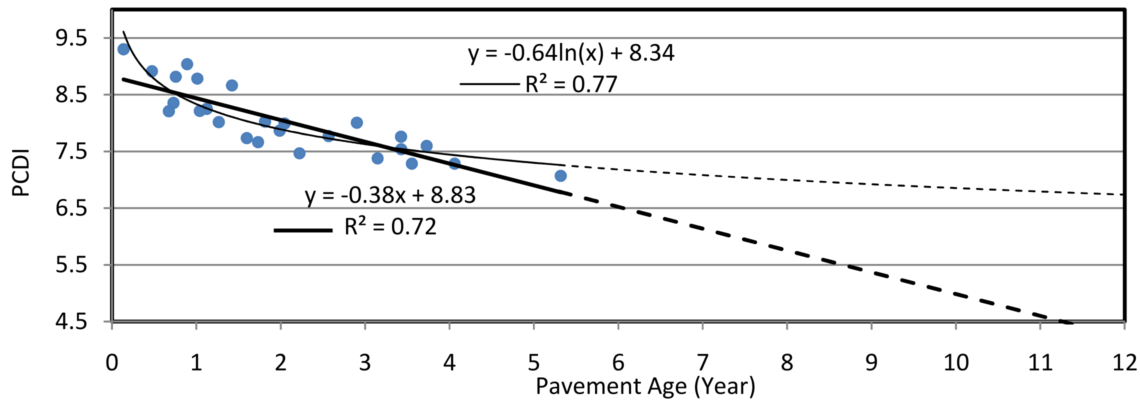


Figure 6-1 Performance Curve for PCP.

The models developed have good coefficients of determination (R^2) with a statistically significant independent variable at the 5% level of significance. The regression coefficient associated with age (in both cases) shows that PCP surface condition degrades with an increase in age which makes practical sense. The logarithmic trend demonstrates a higher deterioration rate in the first few months as compared to later months and this would be consistent with field performance. Based on the field investigations conducted to date and the available related literature, PCP degrades faster in the initial months after installation rather than during the later months over the pavement service life.

In order to determine the service life of PCP, the PCDI minimum acceptable level should be estimated. This level was assumed to be 4.5 in this research since PCP is commonly used on low volume roads and parking lots. The service life of PCP (in general) using Equation 6-3 was estimated to be approximately 12 years. Alternatively, a range of 8 to 16 years can be estimated to be the expected service life of PCP at the 95% confidence level. It should be noted that this service life is only an estimate (regression extrapolation cannot provide an accurate prediction) and should be validated in the future using in-service data. However, the estimate of 12 years does seem reasonable given current performance levels. It should be noted that the linear model was applied to predict the service life of PCP since the linear model provided more reasonable results in terms of extrapolation than the logarithmic model. Namely, the logarithmic model reaches the minimum acceptable level at large (unreasonable) pavement age.

The validation process has been conducted for the PCP model developed in this research. For this purpose, 25% of data has been used for validation and the remaining, 75% of data, has been used to develop the model. The validation data has been chosen at random. Having applied Equations 6-2 and 6-3, the predicted PCDI was calculated. Two tailed t-test was applied to indicate whether there is a significant difference between the sample mean of the predicted PCDI and the calculated PCDI using the remaining validation data at the 5% significance level. The null hypothesis (H_0) was tested for the mean of predicted PCDI to be equal to the mean of the actual PCDI at the 95% confidence level. According to the results shown in Table 6-5 and Table 6-6, the domain between d_{upper} and d_{lower} included 0 so that the null hypothesis was accepted and the regression models (Equations 6-2 and 6-3) were successfully validated.

Table 6-5 T-Test for Performance Model Validation for Equation 6-2

t-test ($\sigma1=\sigma2$ and unknown)		t-test ($\sigma1\neq\sigma2$ and unknown)	
S^2p	0.05	ν	8
$t_{\alpha/2}$	3.01	$t_{\alpha/2}$	3.35
d_{upper}	0.08	d_{upper}	0.12
d_{lower}	-0.64	d_{lower}	-0.68
H_0	Accepted	H_0	Accepted

Table 6-6 T-Test for Performance Model Validation for Equation 6-3

t-test ($\sigma1=\sigma2$ and unknown)		t-test ($\sigma1\neq\sigma2$ and unknown)	
S^2p	0.60	ν	11.00
$t_{\alpha/2}$	3.05	$t_{\alpha/2}$	3.11
d_{upper}	1.42	d_{upper}	1.44
d_{lower}	-1.12	d_{lower}	-1.14
H_0	Accepted	H_0	Accepted

6.1.3 Model for SDI and Surface Distresses

Several variables were examined during the development of a model relating SDI (mean of panel ratings) to pavement distresses including ravelling, spalling, potholing, cracking, stepping, and polishing. The dependent variable of this model is SDI (mean of surface ratings) of 10 sections within two PCP sites located in Canada. The summation of severity multiplied by density of all severity levels ($\sum_{j=1}^{5}(S_{ij} \times D_{ij}$) refer to Equation 5-2) was defined as an index for each distress type and entered as independent variables. This index ranges from 0 (i.e., no distress) to 4 (i.e., very severe throughout distress). Several scenarios have been evaluated including different combinations of independent variables represented in Table 6-7. The best model which has predictability power, high correlation, and one that makes engineering sense is the one which includes only "Ravelling" as an independent variable given by Equation 6-4:

$$SDI = 6.897 - 0.764 \times RI \qquad (6\text{-}4)$$

Where,

SDI = Surface Distress Index (mean panel ratings)

RI = Ravelling Index

This model has a good coefficient of determination value (R^2) with a statistically significant independent variable at the 5% level of significance. The regression coefficient associated with

"Ravelling" shows that SDI degrades with an increase in severity and density of ravelling which makes practical sense.

Table 6-7 Scenarios with Descriptive Characteristics for Developing a Prediction Model for SDI

Scenario	Independent Variable	B	Std. Error	t	p-value	R^2	Std. Error of estimate
1	(Constant)	7.580	0.865	8.761	0.000	0.953	0.176
	Ravelling	-2.262	1.516	-1.492	0.186		
	Spalling	0.655	0.417	1.570	0.167		
	Potholing	1.439	1.675	0.859	0.423		
2	(Constant)	6.857	0.196	34.991	0.000	0.947	0.173
	Ravelling	-0.968	0.166	-5.832	0.001		
	Spalling	0.492	0.364	1.350	0.219		
3	(Constant)	7.021	0.867	8.096	0.000	0.933	0.194
	Ravelling	-0.969	1.400	-0.692	0.511		
	Potholing	0.240	1.640	0.146	0.888		
4	(Constant)	6.323	0.215	29.435	0.000	0.935	0.191
	Potholing	-1.045	0.203	-5.156	0.001		
	Spalling	0.317	0.380	0.835	0.432		
5	(Constant)	6.433	0.167	38.506	0.000	0.929	0.187
	Potholing	-0.893	0.087	-10.210	0.000		
6	(Constant)	6.568	0.429	15.301	0.000	0.689	0.392
	Spalling	-1.442	0.343	-4.210	0.003		
7	**(Constant)**	**6.898**	**0.203**	**33.928**	**0.000**	**0.933**	**0.182**
	Ravelling	**-0.764**	**0.072**	**-10.562**	**0.000**		
8	Constant	5.975	0.219	27.285	0.000	0.808	0.308
	Ravelling*Spalling	-0.325	0.056	-5.797	0.000		
9	Constant	5.888	0.144	40.854	0.000	0.898	0.225
	Ravelling*Potholing	-0.196	0.023	-8.372	0.000		
10	Constant	5.869	0.193	30.359	0.000	0.823	0.296
	Spalling*Potholing	-0.436	0.072	-6.092	0.000		
11	Constant	5.674	0.168	33.795	0.000	0.819	0.299
	Spalling*Potholing*Ravelling	-0.113	0.019	-6.020	0.000		
12	Constant	5.900	0.317	18.591	0.000	0.898	0.240
	Ravelling*Potholing	-0.194	0.051	-3.776	0.007		
	Spalling	-0.019	0.431	-0.044	0.966		
13	Constant	7.506	0.377	19.925	0.000	0.955	0.160
	Spalling*Potholing	0.311	0.170	1.834	0.109		
	Ravelling	-1.263	0.279	-4.523	0.003		
14	Constant	6.594	0.195	33.768	0.000	0.944	0.177
	Spalling*Ravelling	0.176	0.125	1.404	0.203		
	Potholing	-1.328	0.320	-4.148	0.004		

Ravelling, spalling, and potholing are the most common distresses which have been observed on PCP. Therefore, the other distresses (cracking, polishing, and stepping) were not statistically significant to be included in the model. Ravelling, spalling, and potholing are highly correlated (Table 6-8) which is consistent with field observations. Therefore, ravelling, spalling, and potholing as independent variables could not be applied in a single model simultaneously. Only, one of these independent variables could be applied in the model. According to the models relating SDI to ravelling, spalling, and potholing individually (scenario 5, 6, and 7 in Table 6-7), model which related SDI to ravelling had the best model characteristics. Ravelling was, therefore, selected and the remaining were discarded. In short, ravelling was the most influential independent variable associated with SDI. It is a dominant distress occurring on PCP, and it has a power of predictability and high R^2.

Table 6-8 Correlation between Independent Variables

Variables	Panel Rating	Ravelling	Spalling	Potholing
Panel Rating	1.000	-.966	-.830	-.964
Ravelling	-.966	1.000	.910	.998
Spalling	-.830	.910	1.000	.898
Potholing	-.964	.998	.898	1.000

The validation process was performed for the SDI model. For this purpose, 25% of the data was employed for validation which was not used in the initial model development. The validation data has been chosen at random. Predicted SDI was calculated incorporating Equation 6-4. The two tailed t-test was applied to determine whether there is a significant difference between sample mean of predicted SDI and actual SDI of validation data at the 5% significance level. The null hypothesis (H_0) was that the mean of predicted SDI was equal to the mean of the actual SDI at the 95% confidence level. According to the results shown in Table 6-9, the domain between d_{upper} and d_{lower} included 0 so that the null hypothesis was accepted and the regression model was successfully validated.

Table 6-9 T-Test for Performance Model Validation

t-test ($\sigma1=\sigma2$ and unknown)		t-test ($\sigma1\neq\sigma2$ and unknown)	
S^2p	0.39	ν	4
$t_{\alpha/2}$	4.03	$t_{\alpha/2}$	4.60
d_{upper}	2.11	d_{upper}	2.40
d_{lower}	-2.03	d_{lower}	-2.33
H_0	Accepted	H_0	Accepted

In order to derive a model for SDI and surface distresses based on pavement age, an additional model is required to relate the ravelling index to pavement age. For this purpose, several attempts have been used to develop an adequate model incorporating linear, logarithmic, quadratic, power, and exponential trends. The best fitted model was determined to be logarithmic as shown in Figure 6-2 and given by Equation 6-5:

$$RI = 1.155 + 0.315 \times Ln\ (T) \tag{6-5}$$

Where,

RI = Ravelling Index

T = age of a PCP section (year)

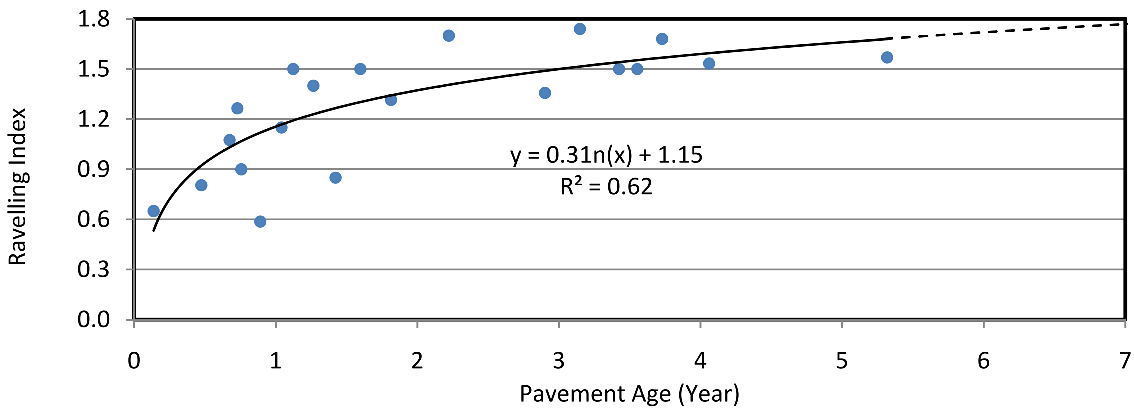


Figure 6-2 Ravelling Prediction Model.

Regression statistics were estimated including the coefficient of determination (R^2 = 0.62) and typical errors (standard error of estimate 0.224). Also, the analysis of variance (ANOVA) was conducted to control the overall significance of the regression. The two-tailed t-test was carried out to check the significance of the independent variable (Table 6-10).

Table 6-10 Coefficient of Regression Model

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
ln(Age)	.31	.058	.790	5.47	.000
(Constant)	1.15	.055	NA	21.02	.000

Figure 6-2 can be applied to develop a maintenance plan for PCP. For this purpose, a maximum acceptable level for RI was determined to be 1.8. This rate is consistent with the PCDI minimum acceptable level. Using Equation 6-5, if ravelling was observed, it would be expected that it would progress to the point where a major maintenance treatment is required approximately 7 years later which seems reasonable. It should be noted that this prediction for the maintenance action is only an estimate since a regression model cannot provide an exact prediction via extrapolation. This prediction can be adjusted in future using in-service data.

The validation process has been conducted for the model. For this purpose, 25% of data has been used for validation and the remaining (75% of data) has been used to develop the performance models. The validation data has been chosen at random. Having applied Equation 6-5, the predicted RI was calculated. The two tailed t-test was applied to indicate whether there is a significant difference between the sample mean of predicted RI and actual RI of validation data at the 5% significance level. The null hypothesis (H_0) evaluated whether the mean of predicted RI was equal to the mean of the actual RI at the 95% confidence level. According to the results shown in Table 6-11, the domain between d_{upper} and d_{lower} included 0 so the null hypothesis was accepted and the regression analysis was successfully validated.

Table 6-11 T-Test for Performance Model Validation

t-test (σ1=σ2 and unknown)		t-test (σ1≠σ2 and unknown)	
S^2p	0.20	ν	9.00
$t_{\alpha/2}$	3.17	$t_{\alpha/2}$	3.25
d_{upper}	0.77	d_{upper}	0.79
d_{lower}	-0.86	d_{lower}	-0.88
H_0	Accepted	H_0	Accepted

6.1.4 Model for PCI and Pavement Age

As shown in Table 6-1, PCI was calculated for the PCP sites visited in the United States using the Micro PAVER program. Attempts were made to develop a model using PCI as a dependent variable and pavement age as an independent variable. Several trends (linear, logarithmic, quadratic, power, and exponential) were investigated to develop an adequate model. The best fitted model was linear as shown in Figure 6-3 and given by Equation 6-6:

$$PCI = 84.94 - 2.92 \times T \tag{6-6}$$

Where,

PCI= Pavement Condition Index

T = pavement age (year)

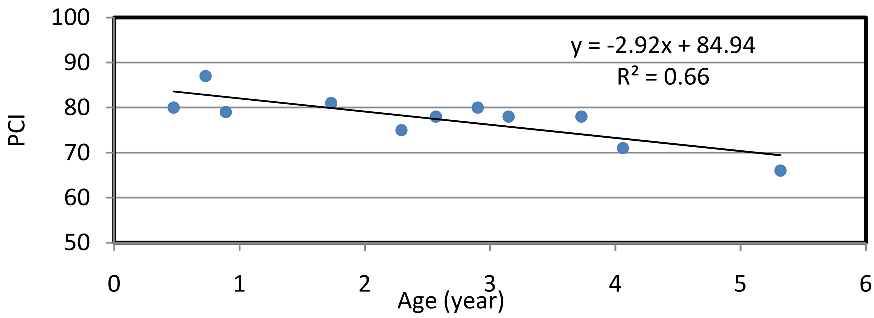


Figure 6-3 PCP Performance Model based on PCI

Regression statistics were estimated encompassing the coefficient of determination (R^2 = 0.66) and typical errors (standard error of estimate 3.38). Also, the analysis of variance (ANOVA) was performed to control the overall significance of the regression. The two-tailed t-test was carried out to check the significance of the independent variable (Table 6-12). The Regression diagnostic shows that errors were normally distributed. Data points are located around the straight line in the normal percentile plot and scatter plot of errors does not demonstrate any specific pattern further proving the adequacy of the SDI model (Appendix O). Finally, it is concluded that Equation 6-6 provided an appropriate model.

Table 6-12 Coefficient of Regression Model

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	84.94	2.055	NA	41.34	.000
Age	-2.92	.705	-.810	-4.14	.003

The validation process was performed for the model related PCI versus pavement age. For this purpose, 25% of data was used for validation and 75% of data was used for modeling. The validation data has been randomly selected. Predicted SDI was calculated incorporating Equation 6-6. The two tailed t-test was used to indicate whether there is a significant difference between sample mean of predicted PCI and actual PCI at the 5% significance level. The null hypothesis (H_0) tested the mean of predicted PCI was equal to the mean of the actual PCI at the 95% confidence level. According to the results shown in Table 6-13, the domain between d_{upper} and d_{lower} contained 0 so that the null hypothesis was accepted and the regression model was successfully validated.

Table 6-13 T-Test for Performance Model Validation

t-test (σ1=σ2 and unknown)		t-test (σ1≠σ2 and unknown)	
S^2p	47.61	ν	4.00
$t_{\alpha/2}$	4.03	$t_{\alpha/2}$	4.60
d_{upper}	21.43	d_{upper}	24.65
d_{lower}	-24.00	d_{lower}	-27.22
H_0	Accepted	H_0	Accepted

6.1.5 Model for Permeability Rate (K) and Pavement Age

In order to develop a model for FPI which is a function of pavement age, permeability rate should be related to pavement age (because FPI is a function of permeability rate). Modeling attempts were shown that a model could sufficiently relate permeability rates (K) to pavement age. The dependent variable is the permeability rate of various PCP sites located in the United States and Canada. Pavement age was considered as an independent variable to obtain a permeability prediction model. Several models were investigated to derive an adequate relationship between K and pavement age such as linear, logarithmic, quadratic, power, and exponential. The best fitted curve was an exponential model as shown in Figure 6-4 and given by Equation 6-7:

$$K = 5.633 \times Exp\,(-1.632 \times T) \qquad (6\text{-}7)$$

Where,

K = permeability rate (cm/sec)
T = age of a PCP section (year)

Regression statistics were estimated including the coefficient of determination (R^2 = 0.81) and typical errors (standard error of estimate 1.158). Also, the analysis of variance (ANOVA) was carried out to control the overall significance of the regression. The two-tailed t-test was performed to check the significance of the independent variable (Table 6-14). The model developed has a good coefficient of determination with a statistically significant independent variable at the 5% level of significance. The regression coefficient associated with age shows that the PCP permeability rate decreases with an increase in pavement age which would be expected based on field performance.

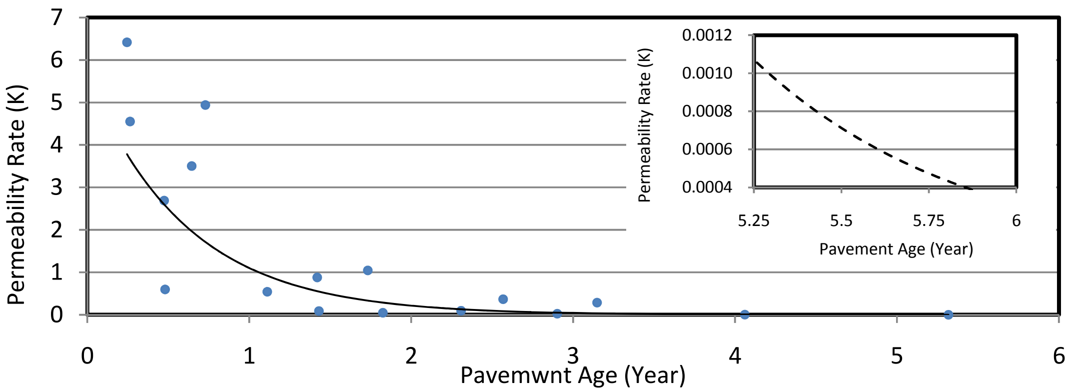


Figure 6-4 Permeability Prediction Model.

Table 6-14 Coefficient of Regression Model

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
Age	-1.63	.202	-.902	-8.08	.000
(Constant)	5.63	2.591	NA	2.17	.046

Figure 6-4 can be used to develop a maintenance plan for addressing clogging that would occur over time. As mentioned earlier, the minimum acceptable level for the permeability rate is equal to 0.0004 (cm/sec). Through application of Equation 6-7, it is estimated that PCP should be maintained (e.g., pressure washing and/or vacuuming) at least every six years.

The validation process has been conducted for the model. For this purpose, 25% of data has been used for validation and the remaining (75% of data) has been applied for modeling. The validation data has been chosen at random. Having applied Equation 6-7, the predicted K was calculated. The two tailed t-test was applied to indicate whether there is a significant difference between sample mean of predicted K and actual K of validation data at the 5% significance level. The null hypothesis (H_0) was that the mean of predicted K was equal to the mean of the actual K at the 95% confidence level. According to the results shown in Table 6-15, the domain between d_{upper} and d_{lower} included 0 so that the null hypothesis was accepted and the regression was successfully validated.

Table 6-15 T-Test for Performance Model Validation

t-test ($\sigma1=\sigma2$ and unknown)		t-test ($\sigma1\neq\sigma2$ and unknown)	
S^2p	0.78	ν	8
$t_{\alpha/2}$	3.35	$t_{\alpha/2}$	3.35
d_{upper}	2.06	d_{upper}	2.06
d_{lower}	-1.69	d_{lower}	-1.69
H_0	Accepted	H_0	Accepted

6.1.6 Model for PCCI and Pavement Age

Having predicted the parameters involved in the PCCI model (SDI and FPI) with regard to pavement age, various prediction models for PCCI can be presented by incorporating different approaches expressed earlier in this chapter and Chapter 5. To develop prediction models for PCCI, models for SDI and FPI should be applied. These models are summarized in Table 6-16.

Table 6-16 Summary of the Models required for PCCI Development

Dependent Variable	Independent Variable(s)	Model	R^2	SEE
Pervious Concrete Distress Index (PCDI)	Pavement Age (T) and Pervious concrete thickness (H)	$PCDI = 8.824 - 0.849 \times \frac{T}{Lg\ (H)}$	0.714	0.324
	Pavement Age (T)	$PCDI = 8.336 - 0.644 \times Ln\ (T)$	0.772	0.289
		$PCDI = 8.825 - 0.384 \times T$	0.717	0.322
Pavement Condition Index (PCI)	Pavement Age (T)	$PCI = 84.94 - 2.92 \times T$	0.656	3.378
Permeability Rate (K)	Pavement Age (T)	$K = 5.633 \times Exp\ (-1.632 \times T)$	0.813	1.158
Functional Performance Index (FPI)	Permeability Rate (K)	$FPI = 0.907 \times Ln(K) + 7.558$	0.996	0.277
Ravellig Index (RI)	Pavement Age (T)	$RI = 1.155 + 0.315 \times Ln\ (T)$	0.624	0.224
Surface Distress Index (SDI)	Ravellig Index (RI)	$SDI = 6.897 - 0.764 \times RI$	0.933	0.182
	PCDI	$\mathrm{SDI} = 0.482 \times \mathrm{PCDI} + 1.992$	0.909	0.212
	$PCDI_{Fuzzy}$	$\mathrm{SDI} = 0.511 \times \mathrm{PCDI_{Fuzzy}} + 1.797$	0.909	0.211
	PCI	$\mathrm{SDI} = 0.065 \times \mathrm{PCI} + 0.787$	0.745	0.354

SEE stands for Standard Error of Estimate

As presented in Chapter 5, PCCI is the weighted summation of SDI and FPI given by Equation 6-8:

$$PCCI = \alpha \times FPI + \beta \times SDI \quad (6\text{-}8)$$

Where,

$PCCI$ = Pervious Concrete Condition Index

FPI = Functional Performance Index

SDI = Surface Distress Index

α = weighting factor of FPI

β = weighting factor of SDI

In the PCCI model, FPI and SDI were replaced with the equations presented in Table 6-16 and given by Equations 6-9 to 6-11. In these equations, SDI was presented as a function of RI, PCDI, and PCI. FPI was presented as a function of K. Among the models presented for SDI and PCDI, $PCDI_{fuzzy}$ was employed since it was more compatible with this research and had better model characteristics:

$$PCCI = f(K, RI) = \alpha \times [0.907 \times Ln(K) + 7.558] + \beta \times [6.897 - 0.764 \times RI] \quad (6\text{-}9)$$

$$PCCI = f(K, PCDI) = \alpha \times [0.907 \times Ln(K) + 7.558] + \beta \times [0.511 \times \text{PCDI} + 1.797] \quad (6\text{-}10)$$

$$PCCI = f(K, PCI) = \alpha \times [0.907 \times Ln(K)] + 7.558 + \beta \times [0.065 \times \text{PCI} + 0.787] \quad (6\text{-}11)$$

Where,

$PCCI$ = Pervious Concrete Condition Index

K = permeability rate (cm/sec)

RI = Ravelling Index

$PCDI$ = Pervious Concrete Distress Index

PCI = Pavement Condition Index

α = weighting factor of FPI

β = weighting factor of SDI

The next step was to substitute K, RI, PCDI, and PCI for the associated models (which are function of pavement age) from Table 6-16. This step was taken to arrive at the performance models which were only functions of pavement age. Ultimately, the performance models given by Equations 6-12 to 6-15 adequately predict PCCI based on its characteristics (pavement age and pervious concrete thickness).

$$PCCI = f(T) = \alpha \times \{0.907 \times Ln[5.633 \times Exp(-1.632 \times T)] + 7.558\} + \beta \times \{6.897 - 0.764 \times [1.155 + 0.315 \times Ln(T)]\} \tag{6-12}$$

$$PCCI = f(T,H) = \alpha \times \{0.907 \times Ln[5.633 \times Exp(-1.632 \times T)] + 7.558\} + \beta \times \{0.511 \times [8.824 - 0.849 \times \frac{T}{Lg(H)}] + 1.797\} \tag{6-13}$$

$$PCCI = f(T) = \alpha \times \{0.907 \times Ln[5.633 \times Exp(-1.632 \times T)] + 7.558\} + \beta \times \{0.511 \times [8.336 - 0.644 \times Ln(T)] + 1.797\} \tag{6-14}$$

$$PCCI = f(T) = \alpha \times \{0.907 \times Ln[5.633 \times Exp(-1.632 \times T)] + 7.558\} + \beta \times \{0.065 \times (84.94 - 2.92 \times T) + 0.787\} \tag{6-15}$$

Where,

PCCI = Pervious Concrete Condition Index

T = pavement age (year)

H = pervious concrete thickness (mm)

α = weighting factor of FPI

β = weighting factor of SDI

The models presented in Equations 6-12 to 6-15 were simplified and represented as follows:

$$PCCI = f(T) = \alpha \times [9.126 - 1.480 \times T] + \beta \times [6.015 - 0.241 \times Ln(T)] \tag{6-16}$$

$$PCCI = f(T,H) = \alpha \times [9.126 - 1.480 \times T] + \beta \times [6.306 - 0.434 \times \frac{T}{Lg(H)}] \tag{6-17}$$

$$PCCI = f(T) = \alpha \times [9.126 - 1.480 \times T] + \beta \times [6.057 - 0.329 \times Ln(T)] \tag{6-18}$$

$$PCCI = f(T) = \alpha \times [9.126 - 1.480 \times T] + \beta \times [6.308 - 0.190 \times T] \tag{6-19}$$

Where,

PCCI = Pervious Concrete Condition Index

T = pavement age (year)

H = pervious concrete thickness (mm)

α = weighting factor of FPI

β = weighting factor of SDI

It is desirable to compare the presented models for PCCI in terms of their statistical characteristics to be able to determine which model would be the most appropriate. For this purpose, the actual PCCI values were compared to predicted PCCI values obtained by incorporating various models presented in Equations 6-16 to 6-19. Statistic descriptive measures used to determine which model would be the most adequate one are shown in Table 6-17.

Table 6-17 Comparison of Various Models for PCCI

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
Equation 6-16	.918	.842	.825	.691	1.676
Equation 6-17	.920	.846	.829	.688	1.601
Equation 6-18	.916	.839	.822	.702	1.631
Equation 6-19	.917	.840	.822	.698	1.286

According to Table 6-17, Equation 6-17 presents the best PCCI model among the others. However, the difference between the models is negligible and all models adequately predict the PCP condition over its service life. The models provide approximately identical results with regard to their statistic descriptive measures. Note that Durbin-Watson test tests the correlation between errors (Montgomery and Runger 2007). Namely, it tests whether adjacent residuals are correlated or not. In short, this test is important for checking the independence of errors. Values between 1 and 3 show that there is no significant correlation between errors.

6.2 PROBABILISTIC MODEL FOR PREDICTING PCP PERFORMANCE: MARKOVIAN APPROACH

The second performance model development in the research incorporates the Markov Chain methodology. In order to develop a Markov model, a condition index (condition states), an initial condition probability vector, stages (duty cycles), and Transition Probability Matrices (TPMs) should be defined.

6.2.1 PCDI and Condition States

As mentioned in Chapter 4, PCDI was applied herein as an index to develop TPMs. PCDI ranges from 0 to 10. In order to define condition states, PCDI was divided into five intervals as shown in Table 6-18. The average of each interval (E_{PCDI}) is also presented in this table.

Table 6-18 Definition of Condition States

i	Condition State	PCDI Boundaries		E_{PCDI}
		Lower limit	Upper limit	
1	Very Good	8	10	9
2	Good	6	8	7
3	Fair	4	6	5
4	Poor	2	4	3
5	Very Poor	0	2	1

Although more condition states provide more detailed TPMs, they simultaneously increase the uncertainty of TPMs elements. Namely, the probabilistic process suffers from increases of uncertainty of data with increases of condition states. That is, the more the number of states, the more uncertain and inconsistent data would be collected from experts to build the TPMs. Hence, this research suggests only five condition states to overcome this problem.

Moreover, it is assumed that a PCP section can shift only from one state to a consecutive lower state. This assumption, also, reduces the level of uncertainty and inconsistency since in each row of TPMs only two elements will be present. Namely, the experts were asked to indicate the probability of staying in a single condition state e.g., "Very Good" condition (p_{11}) presented by Equation 6-20. Likewise, the experts could determine the probability of transiting from one condition state to the lower condition one e.g., from condition state "Very Good" to "Good": p_{12} presented by Equation 6-21. Since the summation of elements in each row should be equal to 1, having one element in an individual row, the other element can be readily calculated using Equation 6-22. Therefore, there is only one variable in an individual row which significantly reduces the uncertainty of TPMs.

$$p_{ii} = prob[\,X(t+1) = i/X(t) = i] \tag{6-20}$$

$$p_{ii-1} = prob[\,X(t+1) = i-1/X(t) = i] \tag{6-21}$$

$$p_{ii} = 1 - p_{ii-1} \tag{6-22}$$

Where,

p_{ii} = probability of staying at state i over stage t

p_{ii-1} = probability of shifting from state i to state i-1 over stage t

Consequently, TPMs can be represented as follows:

$$
\text{TPM} = \begin{array}{c} \\ \text{Very Good} \\ \text{Good} \\ \text{Fair} \\ \text{Poor} \end{array}
\begin{array}{c}
\begin{array}{ccccc} \text{Very Good} & \text{Good} & \text{Fair} & \text{Poor} & \text{Very Poor} \end{array} \\
\begin{pmatrix}
P_{11} & P_{12} & 0 & 0 & 0 \\
0 & P_{22} & P_{23} & 0 & 0 \\
0 & 0 & P_{33} & P_{34} & 0 \\
0 & 0 & 0 & P_{44} & P_{45}
\end{pmatrix}
\end{array}
$$

Where p_{11} is the probability that a PCP section in state "Very Good" would stay in the same state over one stage (i.e., one year), p_{12} is the probability that a PCP section in state "Very Good" would deteriorate to the lower state (i.e., "Good") over one stage. Likewise, the other cells of TPM can be defined.

6.2.2 Initial PCDI Probability Vector

The Markov Chain model starts with a PCDI probability vector reflecting the initial condition of a given pavement section. An estimated initial condition probability vector of new PCP would not be in complete agreement with reality. The initial PCDI probability vector of a new PCP section was assumed PCDI(0) = (0.9, 0.1, 0, 0, 0) based on the observation, experience, and the relevant literature. In this case, there are 90 percent and 10 percent chance that a new PCP section immediately after installation will be in "Very Good" condition and "Good" condition, respectively.

6.2.3 Pavement Groups

The PCP is categorized into six groups with respect to its characteristics including pervious concrete thickness, environment condition, pavement age, and traffic load. Two levels of pavement thickness, one type of environment condition (i.e., hard wet freeze climate such as the North Ontario, Canada climate), two levels of pavement age, and two traffic load patterns were determined to be most appropriate for the PCP as discussed earlier in Chapter 4.

6.2.4 Transition Probability Matrices (TPMs)

Two main methods have been used in the literature to develop TPMs. These methods include applying subjective data and utilizing long term condition performance data (Karan 1977; Li et al. 1996; Ortiz-García et al. 2006). The later approach is not applicable to this study due to limited knowledge of long term performance of PCP. Consequently, the subjective approach was selected to build different TPMs for various groups based on a panel of experienced engineers including 14 experts. Six TPMs, for different pavement groups, were completed by the panel and the mean of the panel responses was applied as final TPMs.

Note that a limited number of experts have participated in this survey due to the lack of expertise in the field of PCP performance evaluation. However, the performance model can be readily updated incorporating field pavement condition data or expert knowledge because of the flexibility and compatibility of the Markov Chain process.

6.2.5 Markov Model for PCDI

In order to estimate the future probability vector of PCDI, the initial PCDI probability vector and TPMs were used by applying Equation 6-23.

$$PCDI\ (t) = PCDI(0) \times \prod_{t=1}^{T} TPM_{\ t} \qquad t = 1, 2, .., 5 \tag{6-23}$$

Where,

PCDI(t) = probability vector of PCDI at the end of stage t

PCDI(0) = initial probability vector of PCDI

TPM_t = transition probability matrix associated with year t

T = planning horizon which is equal to five years.

The PCDI probability vector of groups 1 and 2 over the planning horizon (PCDI(0), PCDI(1), PCDI(2), PCDI(3), PCDI(4), and PCDI(5)) are shown in Figure 6-5 for illustration.

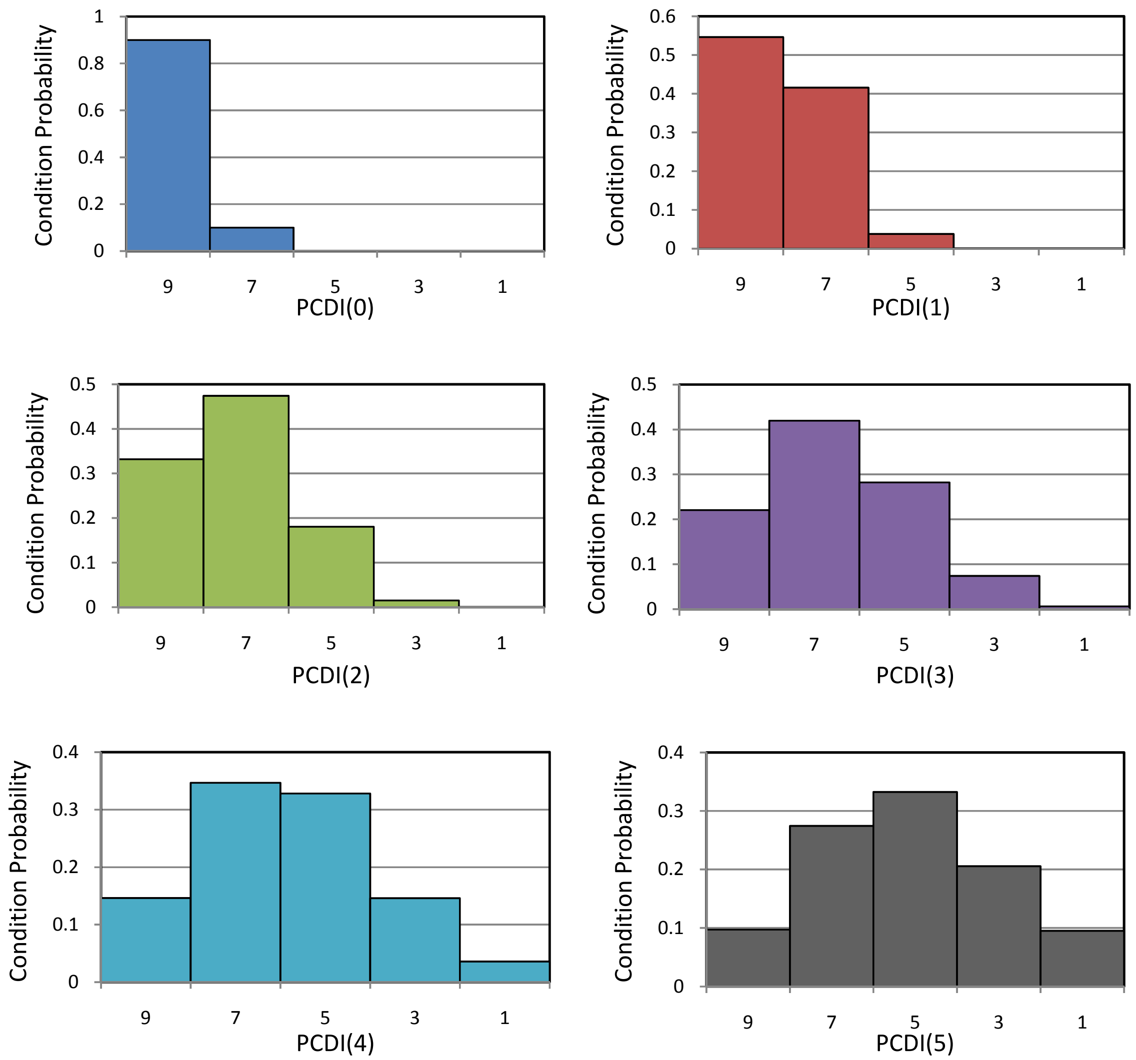


Figure 6-5 Histogram of the PCDI Probability Vector over the Planning Horizon.

It is desirable to have a single value for PCDI rather than a vector for further calculations. For this purpose, an Expected Value (EV) of PCDI can be computed incorporating its probability vector given by Equation 6-24.

$$EV_{PCDI}\,(t) = E_{PCDI} \times PCDI\,(t) \qquad (6\text{-}24)$$

Where,

$EV_{PCDI}\ (t)$ = expected value of the PCDI probability vector after stage t.

E_{PCDI} = vector of average of various state boundaries. According to Table 6-24, E_{PCDI} is equal to (9, 7, 5, 3, 1).

PCDI(t) = PCDI probability vector at the end of stage t.

For instance, the condition vector of a new PCP section is (0.9, 0.1, 0, 0, 0) so that the expected value of its condition vector is equal to 8.8 ($EV_{PCDI}\ (t) = 9 \times 0.9 + 7 \times 0.1 + 5 \times 0.0 + 3 \times 0.0 + 1 \times 0.0$ = 8.8).

It should be noted that the Markov chain process has been widely assumed to be homogenous over time (Karan 1977; Ortiz-García et al. 2006). That is, the same TPM is applied for all stages. However, it is more realistic to assign different TPMs to an individual year (non-homogeneous Markov Chain), but his approach increases the uncertainty and inconsistency in results. A combination of these methods has been used in this study, namely, two intervals have been assumed: primary (first and second year) and secondary intervals (third, fourth, and fifth year). In each interval, TPMs are homogeneous, while TPMs associated with primary interval are different from that of the secondary interval. Hence, non-homogeneous Markov Chain has been defined by shifting from one interval to another. This shift was restricted to a case where the deterioration pattern is likely to change significantly. Since short-term performance data of PCP is available, short-term prediction period has been selected for developing TPMs. Namely, experts cannot sufficiently predict the performance of PCP on a long-term period (more than 5 years) according to available data.

Having applied Equation 6-24, the expected value of PCDI was computed for each group within a five-year period. Performance models (according to the Markov Chain process) for different PCP groups are plotted in Figure 6-6. Performance models characteristics have been compared in Table 6-19. It should be noted that the uncertainty of expected values of PCDI increases with an increase in pavement age. This fact could not be shown in Figure 6-6 since the performance model presented in this figure is deterministic and only shows the mean values. However, the distribution of the PCDI mean values (point estimate) can indicate the increasing uncertainty (Figure 6-5). Figure 6-6 shows that Groups 3 and 4 (thick pervious concrete thickness and light traffic) performs better than the others while, Groups 5 and 6 (thick pervious concrete thickness and heavy traffic) has the worst performance. It is deemed that heavy traffic has more significant impact on PCDI rather than pervious concrete thickness. It should be noted that two modeling methods (empirical and Markov Chain) provide approximately the same results through comparison of Figure 6-6 and Figure 6-1. Namely, the mean of PCP groups' performance models in Figure 6-6 should be compared with the linear model in Figure 6-1. In general, the Markov Chain model provides more conservative results than the empirical models.

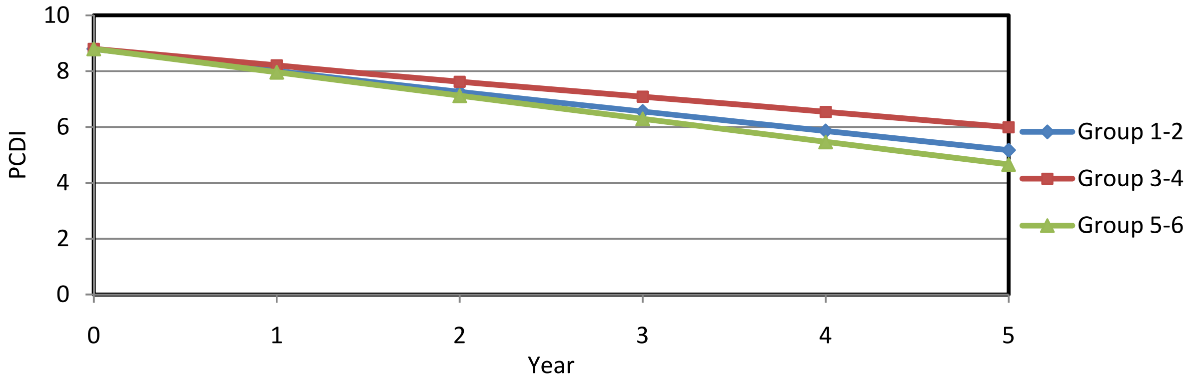


Figure 6-6 PCP Performance Models Using Markov Chain.

Table 6-19 Performance Models for PCP

Model	Independent Variable	B	Std. Error	t	*p*-value	R^2
Groups 1 and 2	(Constant)	8.75	0.030	296	.000	0.99
	Age	-0.72	0.010	-74	.000	
Groups 3 and 4	(Constant)	8.77	0.017	513	.000	0.99
	Age	-0.56	0.006	-99	.000	
Groups 5 and 6	(Constant)	8.79	0.009	947	.000	0.99
	Age	-0.83	0.003	-720	.000	

It should be also noted that the Markov Chain has been applied in this study in both deterministic and stochastic ways, while it has been commonly used in a deterministic way (Karan 1977; Tighe 1997). The deterministic approach provides the mean of panel ratings as elements of TPMs. However, a more detailed approach is to fit a Probability Distribution Function (PDF) to each TPM element to express a real distribution of the experts' responses. For this purpose, several attempts have been made to fit various PDFs (Normal, Exponential, Gamma, and Lognormal) to sets of responses data associated with each cell of TPMs. The PDF which had the best goodness of fit to the data (mean panel ratings) for the associated cells of all TPMs has been selected using various methods (Chi Square, Anderson Darling, and Kolmogorov Smirnov) through incorporation of @Risk software

(Palisade Corporation 2005). Ultimately, adequate PDFs were assigned to associated TPM cells for all groups. All PDFs and mean value of each PDF associated with various TPM are presented in Appendix P. For instance, the Gauss distribution function (Figure 6-7) had the best goodness of fit to the response values of p_{43} (probability of transition from state "Good" to state "Fair") of Group 5.

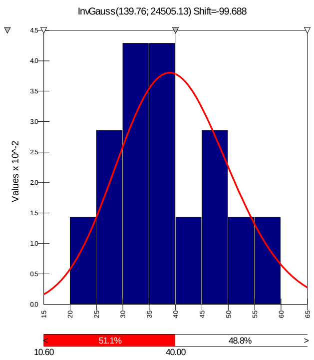


Figure 6-7 The Best PDF Fitted to Experts' Responses Associated with p_{43} of Group 5.

In the case of applying the stochastic Markov Chain process, the stochastic variables i.e., TPM_t (which have probability distribution functions) should be used in the calculation of the PCDI probability vector (Equation 6-23). For this purpose, a simulation technique was applied. The simulation was performed 1000 times using the Latin Hyper Simulation (LHS) technique (applying @Risk software). Equation 6-24 was used to compute expected values for PCDI(t) of all groups over the planning horizon. The outcome of Equation 6-24 was a histogram of results (not a crisp value). Several attempts have been made to fit adequate PDF to the histogram of results (PCDI(t)). For instance, the best fitted PDF to the histogram of results of PCDI(3) associated with Group 2 is shown in Figure 6-8 for illustration.

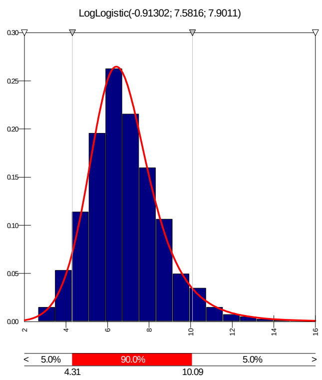


Figure 6-8 The Best PDF fitted to the Histogram of Results of PCDI(3) of Group 2.

Table 6-20 The Best Fitted PDFs to PCDI(t) for all Groups

Group	Age (Year)	PCDI(t)	PDF Fitted to PCDI(t)	Mean	Std	Mean +Std	Mean -Std
1	1	PCDI(1)	Loglogistic(-8.4777, 16.545, 26.772)	8.1	1.1	9.2	7
1	2	PCDI (2)	Loglogistic(-1.5738, 8.9144, 9.222)	7.5	1.8	9.3	5.7
2	3	PCDI (3)	Loglogistic(-0.91302, 7.5816, 7.9011)	6.9	1.8	8.7	5
2	4	PCDI (4)	Pearson5(26.644, 242.34, RiskShift(-3.1739))	6.3	1.9	8.2	4.4
2	5	PCDI (5)	Pearson5(17.686, 138.23, RiskShift(-2.5326))	5.8	2.1	7.8	3.7
3	1	PCDI(1)	Loglogistic(0.86295, 7.2802, 9.8461)	8.3	1.4	9.7	6.9
3	2	PCDI (2)	Loglogistic(-1.0026, 8.5557, 6.9203)	7.9	2.4	10	5.4
4	3	PCDI (3)	Pearson5(27.256, 304.08, RiskShift(-4.2098))	7.4	2.3	9.7	5.1
4	4	PCDI (4)	Loglogistic(-0.1417, 6.7153, 5.1137)	7.0	2.8	9.8	4.3
4	5	PCDI (5)	Loglogistic(0.31894, 5.7881, 3.9414)	6.8	3.4	10	3.3
5	1	PCDI(1)	Logistic(7.9645, 0.93792)	8.0	1.7	9.7	6.3
5	2	PCDI (2)	Pearson5(31.756, 438.42, RiskShift(-6.8819))	7.4	2.5	9.9	4.9
6	3	PCDI (3)	Loglogistic(-7.4777, 13.85, 10.568)	6.6	2.5	9	4.1
6	4	PCDI (4)	Loglogistic(-3.5749, 9.1491, 7.1635)	5.9	2.5	8.4	3.4
6	5	PCDI (5)	Loglogistic(-1.7682, 6.5969, 5.2705)	5.2	2.6	7.8	2.6

Note Std stands for standard deviation.

It is desirable to plot a stochastic performance model to illustrate the performance trends of PCP groups over time. For this purpose, the mean value of PDF associated with each PCDI(t) was selected together with the mean values plus and minus standard deviation (approximately 70% of true mean is restricted to this domain). The stochastic performance curves for various PCP groups are illustrated in Figure 6-9. This figure exhibits that the uncertainty of results in the first interval (first and second years) is less than the remaining years which has a practical sense. Moreover, the wider the prediction period, the more uncertain the results are. That is, the range presented for PCDI(5) is wider (more uncertain) than PCDI(4). This may not be distinguished in Figure 6-9, however, it can be corroborated by values presented in Table 6-20. Approximately in all cases, standard deviation of results increased by increasing the pavement age (prediction period). As it was anticipated, the overall performance of groups 3 and 4 (light traffic and thick pervious concrete thickness) was the best, while that of groups 5 and 6 (heavy traffic load and thick pervious concrete thickness) was the worst. In addition, the most consistent results (less uncertainty i.e., standard deviation) were related to groups 1 and 2 which is reasonable since groups 1 and 2 have been widely used (the most common PCP design) and the experts are more familiar with their performance as oppose to the other PCP groups which have been moderately utilized in the real world. Ultimately, it should be noted that the results achieved through incorporation of both Markov Chain approaches (deterministic and stochastic) were approximately the same (compare Figure 6-6 and Figure 6-9). However, the stochastic Markov model provides more detailed results than the deterministic one.

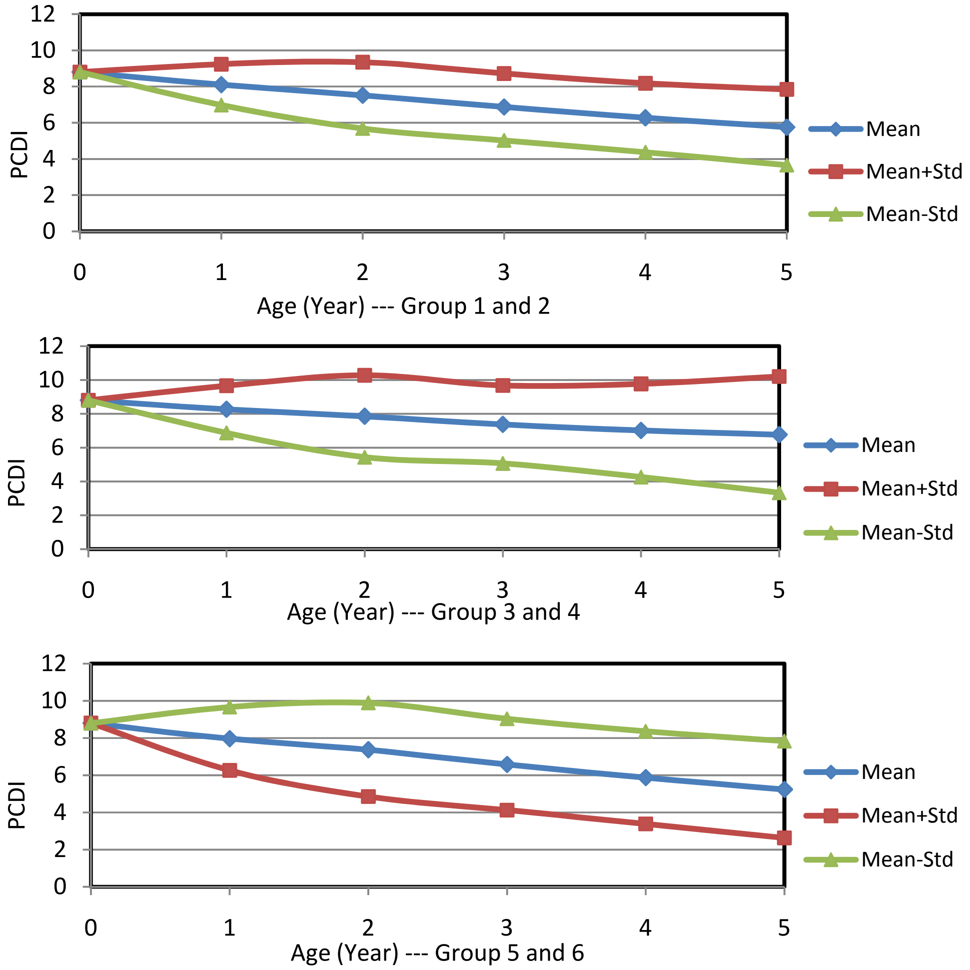


Figure 6-9 Stochastic Performance Curves of Various PCP Groups.

6.3 CALIBRATION PROCESS USING THE BAYESIAN METHOD

The Bayesian regression technique recasts classical regression into a more general form that includes both prior information and experimental data. The equations used in Bayesian regression closely parallel to those for classical regression and the resulting linear regression equation is in the same form as the classical result. In fact, results identical to the classical regression results can be obtained by making the prior information sufficiently diffuse or vague.

The main purpose of this section is to calibrate the performance model developed based on the expert data (Markov Chain) with experimental data (PCP field investigations). In other words, a performance model is developed incorporating both prior data (expert knowledge) and experimental data. The independent variables are PCP characteristics (pavement age, pervious concrete thickness, and traffic load) and the dependent variable is PCDI.

6.3.1 Specify Prior Data (Expert Knowledge)

The first step in performing Bayesian regression technique is to specify the required prior information. The prior data was collected from the experts by conducting a survey as mentioned earlier. The survey was to predict PCDI(t) of various PCP groups by setting up TPMs for developing Markov Chain models. The expert knowledge (PCDI(t) of various PCP groups summarized in Table 6-21) was applied as prior data.

Table 6-21 shows the groups characteristics and associated PCDI(t). Note that 152 mm (6 inches) was dedicated to thin pervious concrete thickness and 203 mm (8 inches) was assigned to thick pervious concrete thickness according to the PCP inventory data base collected in this research.

Incorporating both PCP sections' characteristics and their PCDI, the regression analysis was performed and regression coefficients were estimated using Equation 2-18.

$$b_{pr} = \begin{bmatrix} 8.737 \\ -0.690 \end{bmatrix}$$

Regression statistics were estimated encompassing the coefficient of determination (R^2 = 0.89) and typical errors (standard error of the estimate = 0.377). Also, the analysis of variance (ANOVA) was performed to control the overall significance of the regression. The two-tailed t-test was done to check the significance of independent variables (Table 6-22). Only pavement age was the statistically significant independent variable and the rest (pervious concrete thickness and traffic load) was not significant.

Table 6-21 PCP sections characteristics and their PCDI

Group #	Age	Thickness	Vehicle	PCDI(t)
1	1	152	1	8.1
1	2	152	1	7.5
2	3	152	1	6.9
2	4	152	1	6.3
2	5	152	1	5.8
3	1	203	1	8.3
3	2	203	1	7.9
4	3	203	1	7.4
4	4	203	1	7.0
4	5	203	1	6.8
5	1	203	2	8.0
5	2	203	2	7.4
6	3	203	2	6.6
6	4	203	2	5.9
6	5	203	2	5.2

Table 6-22 Coefficient of the regression model

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	8.74	.228	NA	38.24	.000
	Age	-.69	.069	-.94	-10.02	.000

The prior may also be summarized by plotting the probability distribution function for the regression coefficient “b”, as shown in Figure 6-10.

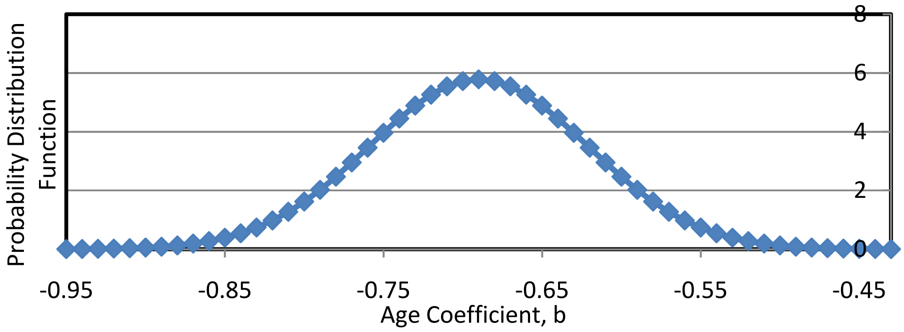


Figure 6-10 Prior Probability Distribution for Coefficient “b”.

Then, the precision matrix (A) for expert data was computed applying Equation 2-17. The precision matrix can be computed applying N-prior and G-prior methods. The only difference is in the way the prior precision matrix is calculated. The G-prior was applied in this research. The G-prior independent variable (X_G) is a set of data similar to data used for regression analysis. The difference is that no associated dependent variable is required. "X_G" and "A" are presented as follows:

$$X_G = \begin{bmatrix} 1 & 1 \\ 1 & 2 \\ 1 & 3 \\ \cdots & \cdots \\ 1 & 5 \end{bmatrix}$$

$$A = \begin{bmatrix} 15 & 45 \\ 45 & 165 \end{bmatrix}$$

6.3.2 Experimental Data

The second step, analyzing the experimental data, is the same as for classical regression except for one additional calculation, the precision matrix for the experimental data. The definitions of "b", "X", "Y", and all other terms are the same as defined for classical regression.

The experimental data includes the PCP condition data which was collected from various sites in the United States. As mentioned earlier, several PCP sections were investigated within this research study and the associated PCDI was computed. Incorporating both the PCP section characteristics and their PCDI, the regression analysis was performed and regression coefficients were estimated using Equation 2-20. The coefficient of an independent variable together with an intercept is presented as follows:

$$b = \begin{bmatrix} 8.825 \\ -0.384 \end{bmatrix}$$

Regression statistics were estimated including the coefficient of determination ($R^2 = 0.72$) and typical errors (standard error of the estimate = 0.322). Also, the analysis of variance (ANOVA) was performed to control the overall significance of the regression. The two-tailed t-test was carried out to control the significance of independent variables (Table 6-23). Similar to the prior data, only pavement age was the significant independent variable.

Table 6-23 Coefficient of the regression model

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	8.82	.119	NA	74.09	.000
	Age	-.38	.049	-.85	-7.83	.000

The experimental data may be also summarized by plotting the probability distribution function for the regression coefficient "b". Figure 6-11 illustrates the probability distribution function of coefficient "b" for prior data and experimental data.

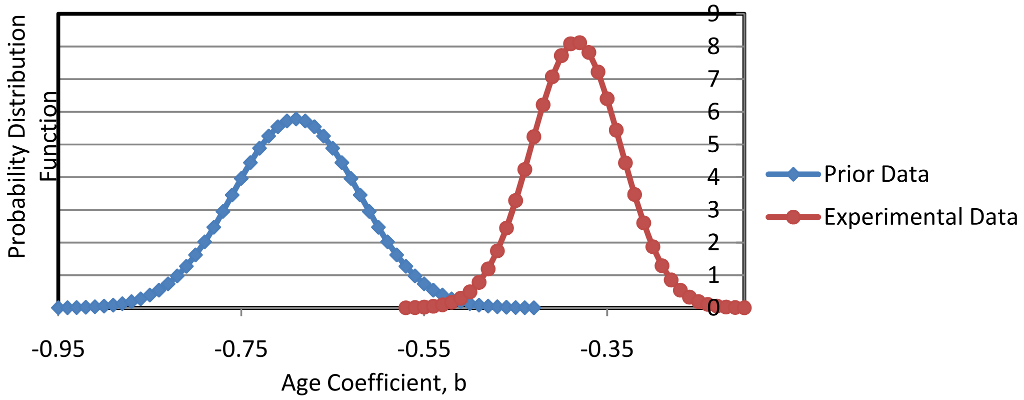


Figure 6-11 Prior and Experimental Data Distributions for Coefficient "b".

The precision matrix (H) was computed applying Equation 2-19. The "X" matrix is required for calculating matrix "H". "X" is a set of data similar to data used for regression analysis. The difference is that no associated dependent variable is required. "X" and "H" are presented as follows:

$$X = \begin{bmatrix} 1 & 1.73 \\ 1 & 0.73 \\ 1 & 5.32 \\ \dots & \dots \\ 1 & 0.47 \end{bmatrix}$$

$$H = \begin{bmatrix} 26 & 54 \\ 54 & 153 \end{bmatrix}$$

6.3.3 Calculate Posterior Results

As mentioned earlier, the final step is to estimate the posterior results by combining the prior data with experimental data. The posterior precision matrix (M) was calculated by adding the prior precision matrix (A) to the experimental data precision matrix (H) incorporating Equation 2-21 and presented as follows:

$$M = \begin{bmatrix} 41 & 99 \\ 99 & 318 \end{bmatrix}$$

Ultimately, the posterior regression coefficient was computed applying Equation 2-22 and represented as follows:

$$b_{pos} = \begin{bmatrix} 8.989 \\ -0.607 \end{bmatrix}$$

The results of applying the Bayesian regression to combine prior data and experimental data to derive posterior data are shown in Figure 6-12. Figure 6-12 shows the probability distribution function of coefficient “b” for posterior data together with prior and experimental data.

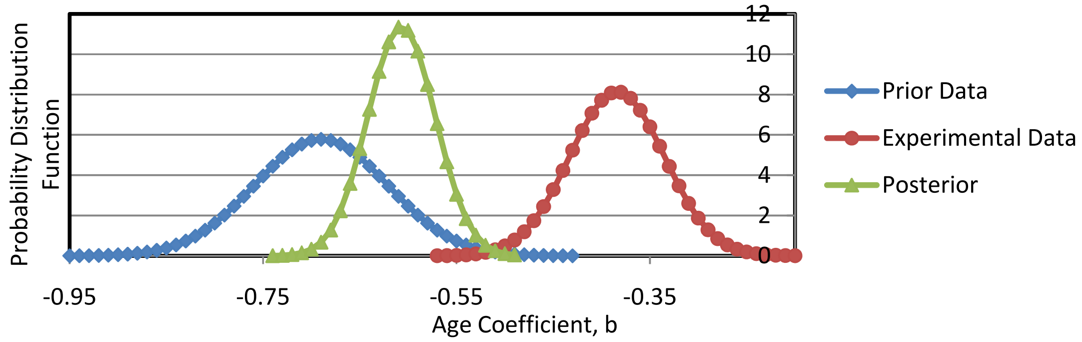


Figure 6-12 Probability Distributions for Bayesian Regression.

Therefore, the posterior performance model for PCP was estimated as follows:

$$PCDI = 8.989 - 0.607 \times T \tag{6-25}$$

Where,

$PCDI$ = Pervious Concrete Distress Index

T = pavement age (year)

Figure 6-12 demonstrates that the probability distribution for the posterior estimate of “b” is “tighter” than either the prior or the experimental data. This is intuitively reasonable as the prior and experimental data reinforce each other with a similar estimate of the mean of “b”. Figure 6-12 clearly shows that the benefit of using the Bayesian regression technique where good prior information is available. Simple classical regression would have resulted in the broad probability distribution based on the data. In general, as long term performance data is added, the posterior will continue to become more and more definitive (i.e., more and more confident in its estimate of “b”).

The question of why one would wish to use Bayesian regression can now be addressed. The difference between classical regression and Bayesian regression is simply that classical regression uses no prior information in making its estimate for the parameter “b”. The classical regression result (the 'Data' result) is lacking compared to the Bayesian result. If no additional data is obtainable, one would certainly prefer the Bayesian approach. Bayesian regression is also very useful where the database is large but of low quality. Potential obstacles include 'noisy data', insufficient data in certain categories, and more complex problems such as multicollinearity. In practice, there are numerous data difficulties that can confound a classical regression analysis. Bayesian regression can be used to overcome some of these problems.

To derive a calibrated PCCI model, Equation 6-25 was entered in Equation 6-10 and represented as follows:

$$PCCI = f(T) = \alpha \times [9.126 - 1.480 \times T] + \beta \times [6.390 - 0.310 \times T] \quad (6\text{-}26)$$

Where,

$PCCI$ = Pervious Concrete Condition Index
T = pavement age (year)
α = weighting factor of FPI
β = weighting factor of SDI

Statistic descriptive measures were used to determine whether the calibrated model is the most appropriate one among the others (Equation 6-16 to 6-19) in terms of model characteristics as shown in Table 6-24.

Table 6-24 Statistic Descriptive for the Calibrated Model

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
Equation 6-26	.924	.854	.838	.669	1.574

Table 6-24 shows that the R^2 value of the calibrated model is the highest among that of other models (Table 6-17). In addition, the standard error of estimate of the calibrated model is the lowest amongst that of other models (Table 6-17). Also, the Durbin-Watson test indicates that there is no significant correlation between the errors of the calibrated model.

6.4 SUMMARY

This chapter has focused on development of performance models for PCP. The performance models have been broadly categorized into empirical and probabilistic models. Several models have been investigated to relate PCDI, SDI, PCI, and K to the pavement age. Then, through substituting of these models in the PCCI models presented earlier in Chapter 5, PCCI models have been presented which is a function of pavement age. All these empirical models, which were developed using field investigations and panel rating data, have provided approximately consistent results with a good R^2 value and low standard error of the estimate. In addition, probabilistic models were developed using the Markov Chain technique. The Markovian model has shown that the deterioration rate of PCP is higher over the initial years of age rather than the remaining service life (short-term prediction i.e., 5 years) which makes engineering sense. The overall performance of groups 3 and 4 (light traffic load and thick pervious concrete thickness) was the best, while that of groups 5 and 6 (heavy traffic load and thick pervious concrete thickness) was the worst which shows that traffic load had the most significant impact on PCDI. Finally, the empirical and probabilistic models provided consistent results. The Bayesian technique has been successfully used to calibrate the performance model. The calibrated model has obtained the highest coefficient of determination and the lowest standard error of the estimate among the performance models developed earlier based only on experimental performance data.

Chapter 7
Conclusions and Recommendation for Future Research

7.1 CONCLUSIONS

This research consisted of a comprehensive study on Pervious Concrete Pavement (PCP) characteristics including the construction of two test sections, laboratory characterization, pavement distress identification, condition index development, and performance modeling. This study has presented a methodology for evaluation of PCP condition. A guideline for pavement condition ratings has been developed. This guideline has been applied by two groups of panel rating to evaluate various PCP sections in this research. A pavement condition evaluation manual has also been designed to identify and describe distress types that occur more frequently on PCP. It can be used by pavement engineers and managers for managing PCP. The pavement surface distress and permeability rate have been evaluated throughout this research in the field (PCP sites located in Canada and the United States). Several models have been examined to provide adequate correlations between panel ratings and field measurements of surface distress and permeability rate. A Pervious Concrete Condition Index (PCCI) has been developed for PCP with incorporation of both the surface distress index (using surface distress evaluation) and functional performance index (using permeability testing). In addition, PCP performance models have been developed by applying both probabilistic and deterministic tools. Various performance modeling techniques have been attempted for prediction of PCP behavior. A survey has been conducted to develop Transition Probability Matrices (TPMs) to develop the Markov Chain model (probabilistic approach). The PCP field performance data together with the proposed PCCI have been applied to develop deterministic performance models. Ultimately, the performance model has been calibrated using the Bayesian method.

The findings and recommendations in this study are expected to assist pavement engineers and managers in PCP design, evaluation, maintenance, and management. The conclusions for this study are summarized in the following sections.

7.1.1 Panel Rating Experiment

1. The panel rating method was successfully applied in the case of surface distress rating. However, it was not successful in the rating of permeability. In other words, the permeability rating was not

statistically significant. Therefore, a subjective permeability rating was not utilized and it was replaced with permeability testing (objective measures).

2. There was no significant difference between the mean of experienced rating and non-experienced rating in the surface distress evaluation at the 95% confidence level.

3. The data collected in the pilot study was of a low quality and high uncertainty (variation) from the engineering perspective although the data was statistically sound at least in terms of surface distress ratings. The high uncertainty and wide variation in the data might happen due to the lack of experience and training in PCP evaluation.

4. There was a strong relationship between the Pervious Concrete Distress Index (PCDI) (i.e., a weighted summation of surface distress) and the Surface Distress Index (SDI) (i.e., the mean of surface distress ratings). They were highly correlated and best described by a linear model.

7.1.2 Pervious Concrete Condition Index

1. The fuzzy Mathematics was found to be an efficient tool to represent the uncertainty which was inherent in assessment of surface distress and permeability rate.

2. The methodology provided by the Ministry of Transportation of Ontario for assessing pavement distress could not capture all distresses with various levels of severity and density so that a new surface distress index (PCDI) and the associated evaluation procedure was proposed.

3. The PCCI was a weighted summation of SDI and the Functional Performance Index (FPI). The objective permeability rate was scaled to a range between 0 and 10 called FPI. The application of various pairs of weighting factors for SDI and FPI have been found to be an efficient approach for calculating PCCI. These pairs of weighting factors depended on the magnitude of FPI.

7.1.3 Pervious Concrete Pavement Performance Model

1. The model that correlated PCDI and pavement characteristics (pavement age, traffic load, and pervious concrete thickness) has shown that pavement age over “Log” of pervious concrete thickness was statistically significant with a good R^2 value of 0.71.

2. For the performance curve (pavement condition over time), PCDI and pavement age have shown a good correlation. The linear and logarithmic trends have shown the best fitness to the data with a good R^2 value of 0.72 and 0.77, respectively.

3. The best model that relates PCDI to pavement age was the logarithmic model. The logarithmic model showed that the deterioration rate during the first few years was higher than the remaining years. The performance predicted from this model would also be consistent with engineering field observations.

4. The service life of PCP was estimated to be approximately 12 years. Alternatively, a range of 8 to 16 years can be estimated to be the expected service life of PCP at the 95% confidence level. It should be noted that this service life is only an estimate (regression extrapolation cannot provide an accurate prediction) and should be validated in the future using in-service data. However, the estimate of 12 years does seem reasonable given current performance levels.

5. The model that correlates SDI and surface distresses concluded that only “ravelling” was statistically significant with a high R^2 value of 0.93.

6. The ravelling index has shown a good to fair correlation with the pavement age. The pavement age was shown to be statistically significant with a R^2 value of 0.62.

7. It would be expected that, if ravelling was observed, it would progress to the point where a major maintenance treatment is required approximately seven years later. It should be noted that this prediction for the maintenance action is only an estimate since a regression model cannot provide an exact prediction via extrapolation. This prediction can be adjusted in future using in-service data.

8. The PCI has shown a good to fair correlation with pavement age with a R^2 value of 0.66 whereas the other performance model that incorporates PCDI and pavement age has shown a better correlation with a good R^2 value of 0.77 indicating that PCDI which uses the proposed pavement evaluation methodology can represent the variation of PCP condition better than PCI.

9. The permeability rate (K) has shown a good correlation with the pavement age. The pavement age was shown to be statistically significant with a good R^2 value of 0.81.

10. In terms of the PCP permeability, it is expected that it should be maintained (e.g., pressure washing and/or vacuuming) at least every six years.

11. The FPI and K have been highly correlated with an excellent R^2 value of 0.99. The best fitted model was the “Ln” trend. This model scaled K to a range from 0 to 10 which is FPI.

12. The model correlating ravelling and pavement age has shown a good to fair correlation with a R^2 value of 0.62. The best fitted model followed the “Ln” trend.

13. The final four performance models which predicted PCCI over time showed consistent results although they have been developed by incorporation of different inputs (e.g., PCDI, PCI, RI).

7.1.4 Survey Experiment

1. Linear performance models with high R^2 values of 0.99 were fitted to the data provided by the Markov Chain process for various PCP groups in a deterministic manner. The models were developed based on the mean rating of survey participants for the Transition Probability Matrices (TPMs). These Markov models provided consistent results with the empirical models (using field investigations and panel rating)

2. The Markov Chain models showed that the uncertainty (standard deviation) of predicted PCDI values increased with increases in pavement age over the planning horizon.

3. In the stochastic Markov Chain analysis, the best probability distribution functions were successfully assigned to both element of TPMs and predicted PCDI.

4. The TPMs have shown that the deterioration rate of PCP in the first few years of age is higher than the deterioration rate of remaining service life. In essence, the deterioration rate slows down after an initial period of time. This trend is consistent with the trend of the PCP performance model presented earlier (empirical models).

5. The TPMs have shown that the deterioration rates of Groups 3 and 4 (thick PCP overlay and light traffic load) were the lowest, while that of Groups 5 and 6 (thick PCP overlay and heavy traffic load) were the highest. The deterioration rates of Groups 1 and 2 (thin PCP overlay and light traffic load) were between the others. This shows that traffic loading had the most significant impact on PCDI.

6. The Bayesian process has been an efficient tool to calibrate the performance model using the Markov model (prior data) with the experimental data. The performance model proposed by the

Bayesian process has shown the best results in terms of the coefficient of determination and standard errors.

7.2 RECOMMENDATION FOR FUTURE RESEARCH

According to field investigations, analysis, and findings in this study, the following recommendations are proposed for future research on PCP:

1. Surface distress investigations and permeability rate measurements should continue to be carried out on a wide range of PCP structural designs with varying loading and environmental conditions. This will provide more comprehensive condition indices and performance models.

2. The pavement condition indices that have been developed in this research should be verified by evaluating an additional set of PCP sections. This could potentially be facilitated through accelerated laboratory testing and field testing.

3. The correlation between SDI and PCDI should be further examined using data from an additional number of PCP sections with various pavement characteristics and conditions.

4. Pavement condition indices should be separately developed for different PCP structural designs through application of following factors: age, pavement thickness, traffic load, and environment.

5. Designated PCP sites in Canada should be continuously tested for their permeability rates on a regular basis for determination of an extensive permeability prediction model which accounts for winter maintenance.

6. Further pavement surface monitoring should be conducted to verify whether the distress types selected for evaluation of PCP in this research are the most probable to occur on PCP and what their impact is on long term performance.

7. Further attempts should be made to verify optimum factors that impact on the PCP performance. In this research, pavement age, pavement thickness, and traffic load have been taken into account. However, other terms such as the number and duration of freeze-thaw cycles, construction techniques, PCP material characteristics (e.g., void ratio and usage of fibers), and maintenance impacts taken to date can be included in the PCP performance evaluation.

8. Questionnaires should be distributed to a wider range of experts with different levels of experience with PCP for further validation and calibration. The Markov Chain model could be further expanded to represent several design situations.

9. Other PCP applications such as walkways, driveways, bike path, and low volume roads should be constructed, monitored, and analyzed. Appropriate pavement condition indices and performance models should be established for various applications of PCP.

10. Appropriate maintenance and rehabilitation treatments should be developed for PCP and associated distresses that may occur on PCP. Applicability, unit costs, performance improvements, and the expected service life of each maintenance action should be estimated.

11. The life cycle cost analysis for PCP structural designs should be developed to provide a decision-making tool for engineers and managers. Overall, this should be incorporated into a pavement management system.

References

AASHTO. (2001). "Pavement Management Guide." *American Association of State Highway And Transportation Officials,* Washington, D.C., United States.

Amador, L., and Mrawira, D. (2008). "Performance modeling for asset management: What to do when you only have two data points*?" Proc., TRB 87Th Annual Meeting CD-ROM.*

American Concrete Institute. (2006). *"Pervious Concrete (ACI 522R-06)".* American Concrete Institute, Michigan, March 2008.

ASTM C 666. (2007). "Standard Test Method for Resistance of Concrete to Rapid Freezing and Thawing." *ASTM International*, Annual Book of ASTM Standards, West Conshohocken, PA.

ASTM D 6433. (2007). "Standard Practice for Roads and Parking Lots Pavement Condition Index Surveys." *ASTM International*, Annual Book of ASTM Standards, West Conshohocken, PA.

Bandara, N., and Gunaratne, M. (2001). "Current and Future Pavement Maintenance Prioritization Based on Rapid Visual Condition Evaluation." *Journal of Transportation Engineering,* 127(2), 116-123.

Briggs, J. F., Roseen, R. M., Ballestero, T. P., Houle, J. P. (2006). "Performance evaluation of porous asphalt as a stormwater treatment strategy." *Proc., TRB 85Th Annual Meeting,* Washington D.C.

Burnham, T., and Load, R. (2004). "Proximity Correlation of Dynamic Strain Measurements in Concrete Pavement." *Proc., Second International Conference on Accelerated Pavement Testing*.

Butt, A. A., Shahin, M. Y., Feighan, K. J., Carpenter, S. H. (1987). "Pavement Performance Prediction Model Using the Markov Process." *Transp. Res. Rec.*, 12-19.

Carey, W. N., and Irick, P. E. (1960). "The Pavement Serviceability-Performance Concepts." *Highway Research Board Bulletin, 250.*

Ceylan, H., Coree, B. J., Gopalakrishnan, K. (2006). "Strategic Plan for Implementing Mechanistic-Empirical Pavement Design Guide in Iowa. CD-ROM." *Proc of the TRB 85th Annual Meeting: Compendium of Papers*.

Chou, C., and Wu, C. (1997). "Evaluation of Panel Characteristics and User-Based Pavement Serviceability." *Transportation Research Record,* (1592), 98-106.

Darter, M. I. (1980). "Requirements for Reliable Predictive Pavement Models." *Transp. Res. Rec.*, 25-31.

De Melo Silva, F., Van Dam, T. J., Bulleit, W. M., Ylitalo, R. (2000). "Proposed Pavement Performance Models for Local Government Agencies in Michigan." *Transportation Research Record,* (1699), 81-86.

Delatte, N., Miller, D., Mrkajic, A. (2007). "*Field Performance Investigation on Parking Lot and Roadway Pavements*." Report to the RMC Research & Education Foundation.

Draper, N. R., and Smith, H. (1981). "*Applied Regression Analysis.",* 2nd ed Ed., Wiley, New York .

Eller, A., and Izevbekhai, B. (2007). "*MnROAD Cell 64 Pervious Concrete First Year Performance Report*." Minnesota Department of Transportation.

Fernando, E. G., and Hudson, W. R. (1983). "Development of a Prioritization Procedure for the Network Level Pavement Management System*" Transp. Res. Rec.,* 28-35.

Fwa, T. F., and Gan, K. T. (1989). "Bus-Ride Panel Rating of Pavement Serviceability." *J. Transp. Eng.,* 115(2), 176-191.

Garg, A., Horowitz, A., Ross, F. (1988). "Establishing Relationships between Pavement Roughness and Perceptions of Acceptability." *Transp. Res. Rec.,* (1196), 276-285.

Gilson Company Inc. (2006). "*Asphalt Field Permeameter Operating Instruction",* Ohio, USA.

Golroo, A., and Tighe, S. (2009). "A methodology for developing a performance model for pervious concrete pavement." *Proc., TRB 88Th Annual Meeting CD-ROM,* Washington, D.C..

Golroo, A., and Tighe, S. (2007). "*Construction Report of Pervious Concrete Pavement of the Georgetown Parking Lot.",* Cement Association of Canada.

Goodwin, A., and Peterson, A. E. (1984). "Guide to Managing Urban Capital Series." *Vol. 2: Guide to Assessing Capital Stock Condition,* The Urban Institute, Washington D.C.

Gorski, M. (1999). "Residual service life of flexible pavements and its impact on planning and selecting priorities for the structural strengthening of road networks." *Proc., XXIst World Road Congress. CD ROM,* PIARC, Kuala Lumpur.

Haas, R. C. G. (1997). "*Pavement Design and Management Guide.",* Transportation Association of Canada, Ottawa.

Haas, R. C. G., Hudson, W. R., Zaniewski, J. P. (1994). "*Modern Pavement Management.",* Original ed Ed., Krieger Pub. Co., Malabar, Fla.

Hajek, J. J., and Bradbury, A. (1996). "Pavement Performance Modeling using Canadian Strategic Highway Research Program Bayesian Statistical Methodology." *Transportation Research Record,* (1524), 160-170.

Haselbach, L. M., Valavala, S., Montes, F. (2006). "Permeability Predictions for Sand-Clogged Portland Cement Pervious Concrete Pavement Systems." *J. Environ. Manage.,* 81(1), 42-49.

Hedfi, A., and Stephanos, P. (2001). "Pavement Performance Modeling: An Applied Approach at the State of Maryland." *Proceedings of the 5th International Conference on Managing Pavements*. Seattle, Washington.

Hillier, F. S., and Lieberman, G. J. (1990). "*Introduction to Operations Research",* 5th ed. McGraw-Hill, New York.

Hudson, W. R. (1978). "Generalized roughness index." TRB Annual Meeting Proceeding, Washington, D.C.

Jackson, N. (1993). "Washington state pavement management system." *Pacific Rim TransTech Conference*, 57-62.

Janoff, M. S. (1986). "Methodology For Computing Pavement Ride Quality From Pavement Roughness Measurements." *Transp. Res. Rec.*, 9-17.

Karan, M. (1977). "Municipal Pavement Management System." PhD thesis, University of Waterloo, Canada.

Karan, M. A., Christison, T. J., Cheetham, A., Berdahl, G. (1983). "Development and Implementation of Alberta's Pavement Information and Needs System." *Transp. Res. Rec.*, 11-20.

Karan, M. A., Haas, R., Walker, T. (1981). "Illustration of Pavement Management: From Data Inventory to Priority Analysis." *Transp. Res. Rec.,* 814, 22-28.

Lee, Y., Mohseni, A., Darter, M. I. (1993). "Simplified Pavement Performance Models." *Transp. Res. Rec.*, (1397) 7-14.

Li, N., Xie, W., Haas, R. (1996). "Reliability-Based Processing of Markov Chains for Modeling Pavement Network Deterioration." *Transp. Res. Rec.,* (1524), 203-213.

Lindsey, J. K. (1997). "Applying Generalized Linear Models"*, Springer*, New York.

Losa, M., Bonomo, G., Licitra, G., Cerchiai, M. (2003). "Performance degradation of porous asphalt pavements." *Proc., MAIREPAV'03 Third International Symposium on Maintenance and Rehabilitation of Pavements and Technological Control,* Guimarães, Portugal.

Lytton, R. L. (1987). "Concepts of Pavement Performance Prediction and Modeling." *Proc., 2nd North American Pavement Management Conference*, 2, pp. 3-19

Madanat, S., Mishalani, R., Ibrahim, W. H. W. (1995). "Estimation of transition probabilities from facility condition ratings." *Transportation Congress, Proceedings* 2, pp. 1658-1669

Mahoney, J. (1990). "Introduction to Prediction Models and Performance Curves", *FHWA Advanced Course on Pavement Management.*

Miradi, M., and Molenaar, A. A. A. (2006). "Application of artificial neural network (ANN) to PA lifespan: Forecasting models." *IEEE International Conference on Neural Networks - Conference Proceedings*, 3679-3685.

Miradi, M. (2004). "Development of intelligent models for ravelling using neural network." Conference Proceedings - IEEE International Conference on Systems, Man and Cybernetics, 3599-3606.

Molzer, C., Felsenstein, K., Litzka, J., Shahm, M. (2001). "Bayesian Statistics for Developing Pavement Performance Models." *Ponencia De La Fifth International Conference on Managing Pavements, Ponencia,* 39.

Montgomery, D. C., and Runger, G. C. (2007). "Applied Statistics and Probability for Engineers.", 4th ed Ed., *Wiley*, Hoboken, NJ.

Montgomery, D. C. (1994). "Applied Statistics and Probability for Engineers.", *John Wiley & Sons,* New York.

Moore, R. K., Clark, G. N., Plumb, G. N. (1987). "Present Serviceability-Roughness Correlations Using Rating Panel Data." *Transp. Res. Rec.*, 152-158.

Murata, Y., Nishizawa, T., Kokubu, K. (2005). "Evaluation of Porous Concrete Pavements in Japan." *Proc., 8Th International Conf. on Concrete Pavement*. Colorado, USA.

Nair, S. K., and Hudson, W. R. (1986). "Serviceability Prediction From User-Based Evaluations of Pavement Ride Quality." *Transp. Res. Rec.*, 66-75.

Nakamura, V., and Michael, H. L. (1963). "Serviceability Ratings of Highway Pavements." *Hwy.Res.Rec. (40)*, 21-36.

NCHRP. (2007). "Mechanistic–empirical Pavement Design Guide (MEPDG)", *National Cooperative Highway Research Program*. *Transportation Research Board*, Washington, D.C.

Nick, J. B., and Janoff, M. S. (1983). "Evaluation of Panel Rating Methods for Assessing Pavement Ride Quality." *Transp. Res. Rec.*, 5-13.

Ningyuan, L., Kazmierowski, T., Marciello, F. (2004). "Monitoring of Road Surface Characteristics and Performance Evaluation of the Pavements in Ontario." *Proceedings of the 5th Symposium on Pavement Surface Characteristics, SURF*.

Ortiz-García, J. J., Costello, S. B., Snaith, M. S. (2006). "Derivation of Transition Probability Matrices for Pavement Deterioration Modeling." *J. Transp. Eng.,* 132(2), 141-161.

Palisade Corporation. (2005). "@Risk Software." New York, NY.

Press, S. J. (2003). "Subjective and Objective Bayesian Statistics: Principles, Models, and Applications.", *Wiley-Interscience*, Hoboken, NJ.

Queiroz, C. (1983). "A Mechanistic Analysis of Asphalt Pavement Performance in Brasil." *Journal of Association of Asphalt Paving Technology,* Vol. 52.

Riverson, J., Sinha, K., Scholer, C., Anderson, V. (1987). "Evaluation of Subjective Rating of Unpaved County Roads In Indiana." *Transp. Res. Rec.,* (1128), 53-61.

Roberts F.L., and Hudson W.R. (1971). "Pavement Serviceability Equations using the Surface Dynamics Profilometer." *Highw Res Bd, Spec Rep* 116, 68-79.

Robinson, R., Danielson, U., Snaith, M. (1998). "Road Maintenance Management: Concepts and Systems.", *Macmillan Press Ltd.* Basingstoke.

Schaefer, V. R., Wang, K., Suleiman, M. T., Kevern, J. (2006). "Mix Design Development for Pervious Concrete in Cold Weather Climates." *A Report from the National Concrete Pavement Technology Center*. Iowa State University, Ames, IA.

Schalkoff, R. J. (1997). "Artificial Neural Network." *McGraw-Hill, International*.

Schmitt, S. A. (1969). "Measuring Uncertainty : An Elementary Introduction to Bayesian Statistics.", *Addison-Wesley, Reading*, Massachusetts.

Shahin, M. Y. (2005). "Pavement Management for Airports, Roads, and Parking Lots.", 2nd Ed., *Springer*, New York.

Shekharan, A. R. (2000). "Solution of Pavement Deterioration Equations by Genetic Algorithms." *Transportation Research Record,* (1699), 101-106.

Shekharan, A. R. (1998). "Assessment of Relative Contribution of Input Variables to Pavement Performance Prediction by Artificial Neural Networks." *Transportation Research Record,* (1655), 35-41.

SHRP. (2003). "*Distress Identification Manual for the Long-Term Pavement Performance Project.*" Report No. SHRP-P-338.

Simpson, P. K. (2007). "Foundation of Neural Networks." *IEEE Technology Update Series, Neural Networks Theory, Technologies and Application*. pp. 1-22.

SPSS Inc. (2009). "SPSS Statistics 17.0." Chicago, IL.

Tack, J. N., and Chou, Y. J. (2001). "Pavement Performance Analysis Applying Probabilistic Deterioration Methods." *Transportation Research Record,* (1769), 20-27.

Tennis, P. D., Leming, M. L., Akers, D. J. (2004). "*Pervious Concrete Pavements.*", Portland Cement Association and the National Ready Mixed Concrete Association.

Tighe, S., Ningyuan, L., Kazmierowski, T. (2008). "Evaluation of Semiautomated and Automated Pavement Distress Collection for Network-Level Pavement Management." *Proc., TRB 87Th Annual Meeting CD-ROM*., Washington, D.C.

Tighe, S. (1997). "The Technical/Performance and Economic Benefits of Modified Asphalt.", Master thesis, University of Waterloo, Canada.

Tsoukalas, L. H., and Uhrig, R. E. (1997). "Fuzzy and Neural Approaches in Engineering.", *Wiley*, New York ; Chichester, England.

U.S. Army Corps of Engineers. (2004). "Software Package Micro PAVER 5.2." *U.S. Army Construction Engineering, Research Lab,* Champaign, United States.

Wang, K., and Liu, F. (1997). "Fuzzy Set-Based and Performance-Oriented Pavement Network Optimization System." *J Infrastruct Syst,* 3(4), 154-159.

Wang, K. C. P., Nguyen, V., Zaniewski, J. P. (2007). "Genetic Algorithms-Based Network Optimization System with Multiple Objectives." *Transportation Research Record,* (2016), 85-96.

Wang, K. C. P., Zaniewski, J., Wag, G. (1994). "Probabilistic Behavior of Pavements." *Journal of Transportation Engineering - ASCE,* 120(3), 358-375.

Wang, Z., and Han, L. D. (2002). "Pavement Distress Deduct-Value Determination: A New Approach." *Road and Transport Research,* 11(1), 22-33.

Water Environment Research Foundation. (2005). "International stormwater best management practices databases." <http://www.bmpdatabase.org> . Accessed September 2009.

Wingerter, R., and Paine, J. E. (1989). "*Field Performance Investigation Portland Cement Pervious Concrete.",* Florida Concrete and Product Associations, Florida.

Winkler, R. L. (2003). "An Introduction to Bayesian Inference and Decision.", 2nd ed., *Probabilistic Publishing*, Gainesville, Florida.

Xu, G., Gao, J., Lu, X. (2006). "An Experimental Method Study on the Water-Purification Properties of Porous Concrete." *China Concrete and Cement Products,* (SUPPL.), 68-70.

Yang, J., and Jiang, G. (2003). "Experimental Study on Properties of Pervious Concrete Pavement Materials." *Cement and Concrete Research,* 33(3), 381-386.

Youngs, A. (2006). "*Pervious Concrete "the California Experience."* California Nevada Cement Promotion Council, California.

Glossary

ACI	American Concrete Institute
ANN	Artificial Neural Network
ANOVA	Analysis of Variance
CDV	Corrected Deduct Value
COG	Center of Gravity
DMI	Distress Manifestation Index
DV	Deduct Value
EPA	Environmental Protection Agency
ESAL	Equivalent Single Axle Load
EV	Expected Value
FWD	Falling Weight Deflectometer
FPI	Functional Performance Index
GA	Genetic Algorithm
IRI	International Roughness Index
MEPDG	Mechanistic-Empirical Pavement Design Guide
MTO	Ministry of Transportation of Ontario
OCI	Overall Condition Index
OR	Operation Research
PCCI	Pervious Concrete Condition Index
PCDI	Pervious Concrete Distress Index
PCI	Pavement Comfort Index
PCP	Pervious Concrete Pavement

PCR	Pavement Condition Rating
PASER	Pavement Surface Evaluation and Rating
PSI	Pavement Serviceability Index
RCI	Riding Condition Index
RI	Ravelling Index
SAI	Structural Adequacy Index
SDI	Surface Distress Index
SHRP	Strategic Highway Research Program
TFN	Triangular Fuzzy Numbers
TPM	Transition Probability Matrix
UPV	Ultrasonic Pulse Velocity

Appendix A
Pervious Concrete Pavement Surface Distress and Permeability Rating Guide

Panel Instruction for Rating of Pervious Concrete Pavements

Pervious Concrete Condition Index (PCCI) is subjectively derived based on evaluation of functional performance of pervious concrete (i.e. permeability) and pavement surface distresses such as spalling, ravelling, cracking, and so on. To estimate PCCI, functional performance index (FPI) and surface distress index (SDI) of pervious concrete pavements should be rated and incorporated in the following equation:

$$PCCI = f\,(FPI, SDI) = \alpha\,(FPI) + \beta\,(SDI)$$

Purpose:

To rate the condition of pervious concrete pavement parking lots in terms of surface distresses and permeability rates. This data will be used to develop a condition index for pervious concrete pavements.

Object of Study:

To obtain your personal opinion of how good or bad a pervious concrete pavement section is in terms of its surface condition and permeability rate based on the pictures provided.

How to rate the pervious concrete pavement:

You are asked to rate eight sections of pervious concrete parking lots. You suppose to assign two rates (surface distress rate and permeability rate) to each section by following the instruction provided below.

1- Please open the Microsoft Word file (Pavement Rating.doc). Fill up your personal information. You will require this file to enter your responses in step 5.

2-Please carefully read the guidelines for estimating <u>surface distress rating</u> and look at the corresponding pictures illustrating various surface conditions of the pavements as follows.

3-Please carefully read the guidelines for estimating <u>permeability rating</u> and look at the corresponding pictures illustrating various permeability conditions of the pavements as follows.

4- Please open the Slabs.pdf file and carefully look at the pictures. Pictures were taken from two different angles of each section (totally eight sections). The number of each section is written on the left top corner of each picture. Note the pictures are of high quality. You can easily zoom in to rate the pavement more precisely.

5- Please rate the surface distress and permeability of each section incorporating the guidelines and two provided pictures. You may use one decimal to accurately rate the sections using values between 0 and 10. Enter two values (surface distress rate and permeability rate) in corresponding table (in Pavement Rating.doc file) in associated cells for Section#1 to Section#8.

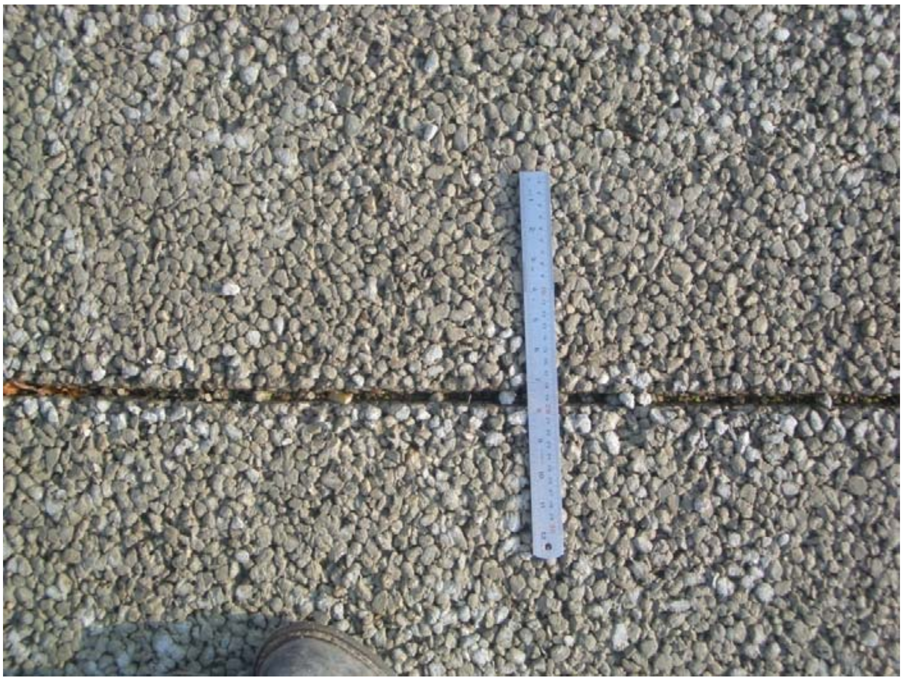
7- Make sure that you have already rated the eight sections and entered two values for each section (in Pavement Rating.doc file). Please save the Pavement Rating.doc file and send it to me (Amir Golroo, agolroo@engmail.uwaterloo.ca).

Appendix A-1 A Guide for Estimating Surface Distress Rating

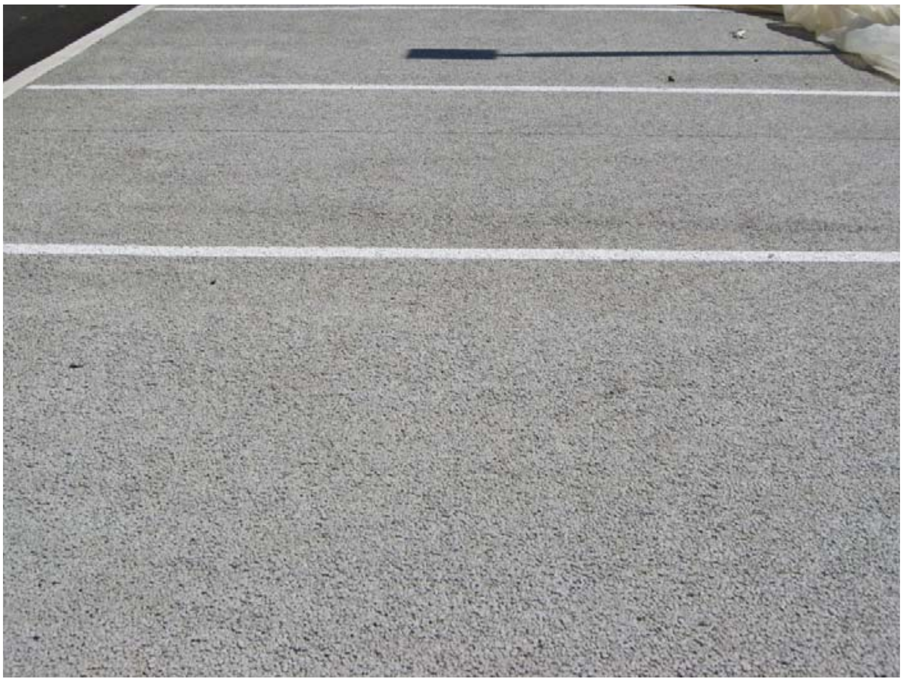
Rate	Condition	Description
8-10	very good	Pavement with no to slight ravelling. No to intermittent slight spalling at joints. Concrete surface has no sign of cracking. The appearance is very good.
6-8	good	Pavement with slight to moderate ravelling. Slight spalling at joints. Concrete surface has no to slight cracking. The appearance is good.
4-6	fair	Pavement with moderate ravelling. Moderate spalling at joints. Concrete surface has slight cracking. The appearance is fair. The surface is slightly rough and uneven.
2-4	poor	Pavement with severe ravelling. Moderate to severe spalling at joints. Concrete surface has slight to moderate cracking. The appearance is poor. The surface is moderately rough and uneven.
0-2	very poor	Pavement with very severe ravelling. Severe spalling at joints. Concrete surface has moderate cracking. The appearance is very poor. The surface is rough and uneven throughout.

Appendix A-2 A Guide for Estimating Permeability Rating

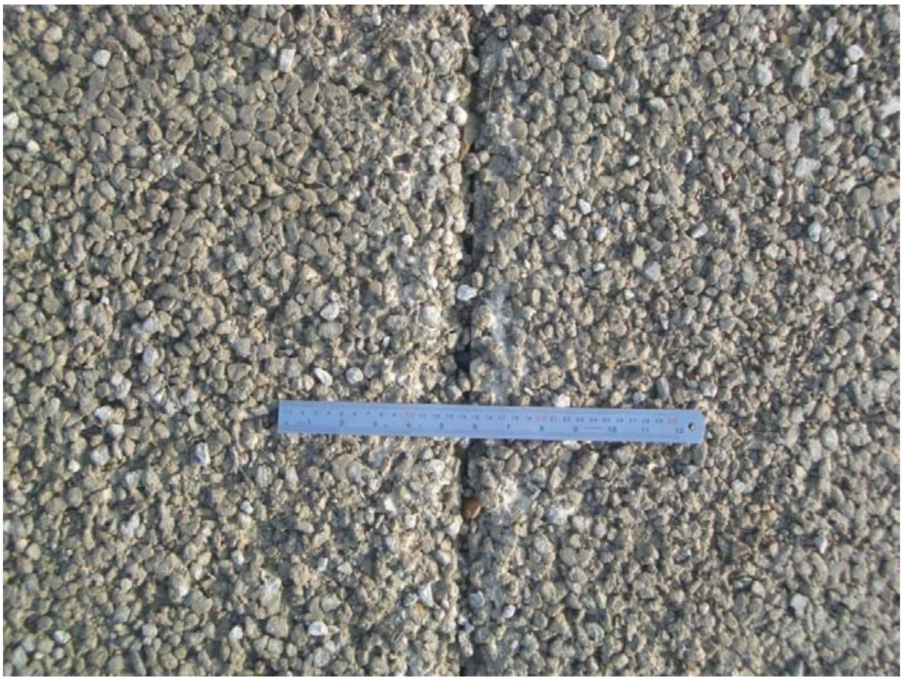
Rate	Condition	Description
8-10	very good	Porous structure of pavement surface can be easily recognized. The surface is free of sand and debris.
6-8	good	Porous structure of pavement surface can be recognized. The surface is slightly covered by sand and debris.
4-6	fair	Porous structure of pavement surface cannot be easily recognized. The surface is moderately covered by sand and debris.
2-4	poor	Porous structure of pavement surface can be barely recognized. The surface is severely covered by sand and debris.
0-2	very poor	Porous structure of pavement surface cannot be recognized. The surface is very severely covered by sand and debris.



Appendix A-3 Surface Distress Rating: Very Good (Close View).

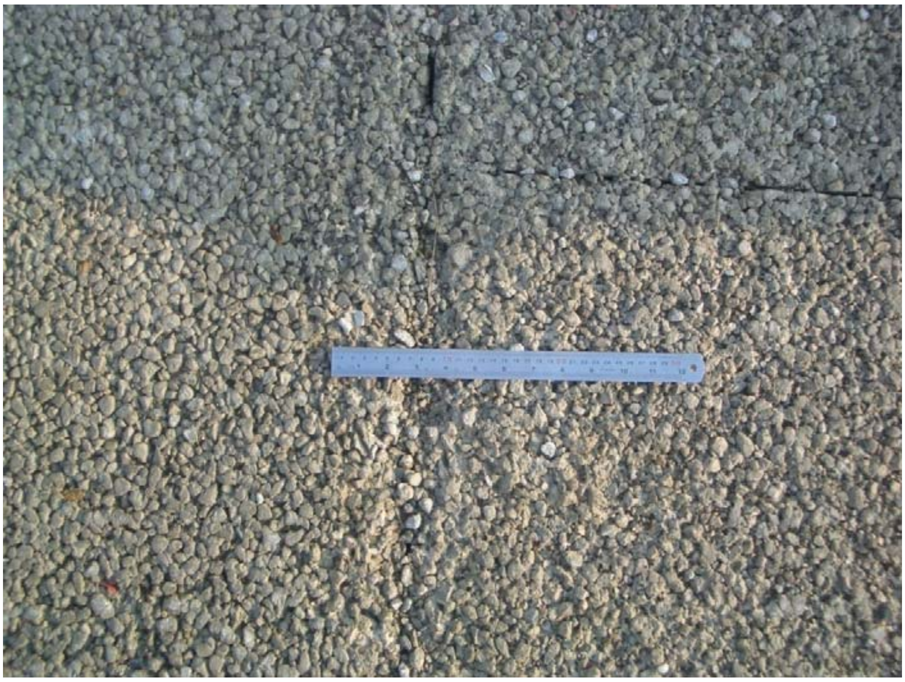


Appendix A-4 Surface Distress Rating: Very Good (Overall View).



Appendix A-5 Surface Distress Rating: Good (Close View).

Appendix A-6 Surface Distress Rating: Good (Overall View).

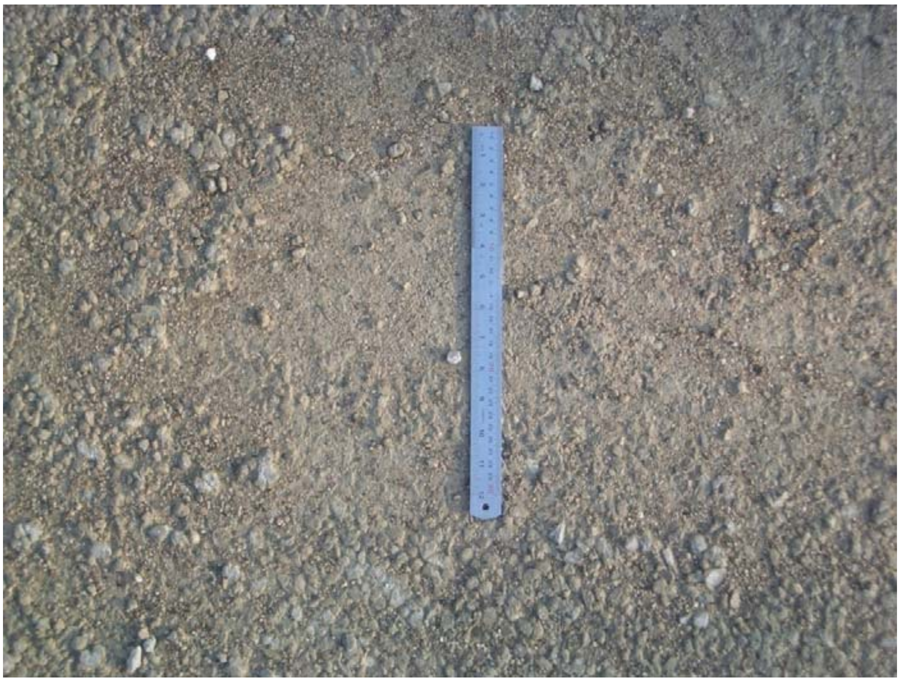


Appendix A-7 Surface Distress Rating: Fair (Close View).

Appendix A-8 Surface Distress Rating: Fair (Overall View).

Appendix A-9 Surface Distress Rating: Poor (Close View).

Appendix A-10 Surface Distress Rating: Poor (Overall View).



Appendix A-11 Surface Distress Rating: Very Poor (Close View).

Appendix A-12 Surface Distress Rating: Very Poor (Overall View).

Appendix A-13 Permeability Rating: Very Good.

Appendix A-14 Permeability Rating: Good.

Appendix A-15 Permeability Rating: Fair.

Appendix A-16 Permeability Rating: Poor.

Appendix A-17 Permeability Rating: Very Poor.

PAVEMENT RATING SURVEY OF PERVIOUS CONCRETE PAVEMENTS

Full Name	
Company/University	
Phone Number	
E-mail Address	
Date	

The following survey is part of a research study on pervious concrete pavement modeling in the Canadian climate. Please enter the surface distress rating and permeability rating figures of each section in associated cells.

Appendix A-18 Pervious Concrete Pavement Rating

Section #	Surface Distress Rating	Permeability Rating	Is pavement of acceptable quality? Choose from Yes, No, and Undecided
1			
2			
3			
4			
5			
6			
7			
8			

Comments:

Please save this file once you fill personal information and TABLE 1 and send it to me (Amir Golroo, amir.golroo@gmail.com).

THANKS FOR YOUR COOPERATION!!!

Appendix B

Pervious Concrete Pavement Condition Survey Data Sheet (Module 1)

PERVIOUS CONCRETE PAVEMENT CONDITION SURVEY DATA SHEET FOR SAMPLE UNIT BASED ON THE MTO PROTOCOL

Section Code ___________ Sample Unit _______________ Sample Area ____________ Date___________ Surveyed by _____________

Section #	Ravelling		Polishing		Potholing		Spalling		Cracking		Stepping	
	Severity	Density	Severity	Density	Severity	Density	Severity	Density	Severity	Density	Severity	Density

SKETCH:

Appendix C

Probabilistic Pervious Concrete Pavement Condition Rating From

Pervious concrete serviceability study

Transportation Group

Department of Civil Engineering

University of Waterloo

Pervious Concrete Condition Rating Form

Section Number: ___________________

Slab Number: _____________________

Rater: ____________________________

Date: ____________________________

Condition	Goodness of fit (out of 10)
Very Good	
Good	
Fair	
Poor	
Very Poor	

Comments

____

____

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____

____

____

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Appendix D

Pervious Concrete Pavement Condition Survey Data Sheet (Module 2)

SKETCH:

PERVIOUS CONCRETE CONDITION SURVEY DATA SHEET

FOR SAMPLE UNIT BASED ON THE MTO PROTOCOL (Adjusted)

Project Name	Thickness	Load Type	Installation date	Date

Slab #	Ravelling					Spalling					Potholing					Polishing					Cracking					Faulting				
	Very Slight	Slight	Moderate	Severe	Very Severe	V.S s. crack with v.s. fracture	S <75, few sm piece miss-loose	M >75 many sm piece miss-loose	S >75 lrg piece miss-loose, patch	VS lrg pothole, damage tire	VS Popout of CA	S Disintegration of surr. martial	M wider & deeper of popout <75	S 75-150 wide & deep	VS wider & deeper 150	VS Barely noticeable	S Noticeable dull finish	M Distinctive dull finish	S Glossy mirror finish	VS highly polished appearance	VS <3mm wide	S 3-12mm wide	M13-19 with /without spall fault	S 20-25 with spall fault	VS >25 with spall fault	VS <3mm Barely noticeable	S 3-6 mm	M17-12 mm	S 13-19 mm	VS >19 mm
	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%
	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%
	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%
	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%
	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%
	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%
	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%
	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%
	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%

Appendix E

Field Investigation: Module 2 (Surface Distress Evaluation and Permeability Test)

Appendix E-1 Pavement Distress Evaluation of the Georgetown Parking Lot (Adjusted MTO Protocol)

	Raveling					Spalling					Potholing					Polishing					Cracking					Faulting				
Slab	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se
1	50	50				40	30				50																			
2	40	60				30	30				60																			
3		10	40	40	10	40	50	10			10	40	40	10																
4		20	10	40	30		100				20	10	40	30																
5		40	30	30			100				40	30	30																	
6			40	50	10	10	70	20				40	50	10																
7			30	60	10		60	40				30	60	10																
8		60	30	10		100					60	30	10																	
9		30	50	20		25	75				30	50	20																	
10		50	50			25	75				50	50																		
11		20	40	30	10	30	50	10	10		20	40	30	10																
12		20	30	30	20	70	30				20	30	30	20																
13		50	40	10		50	50				50	40	10																	
14		50	50			70	30				50	50																		
15		60	40			70	30				60	40																		

Note V-Sl stands for very slight, Sl stands for slight, M stand for medium, Se stands fir severe, and V-Se stands for very severe.

Appendix E-2 Pavement Evaluation based on the ASTM Protocol (Georgetown Parking Lot)

Slab	Popouts	Spalling-Corner	Spalling-Joint	Linear Cracking	Polished Aggregate	Faulting	Patch-Large	Patch-Small	Shrinkage Cracks
1	Extensive		L						
2	Extensive		L						
3	Extensive	L	L						
4	Extensive		L						
5	Extensive		L						
6	Extensive	L	M					L	
7	Extensive		H					L	
8	Extensive		L					L	
9	Extensive		L					L	
10	Extensive		L					L	
11	Extensive		H						
12	Extensive		M					L	
13	Extensive		L						
14	Extensive		L						
15	Extensive		L						

Appendix E-3 Pavement Evaluation based on the Adjusted MTO Protocol (Guelph Line Parking Lot)

	Raveling					Spalling					Potholing					Polishing					Cracking					Stepping				
Slab	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se
1			20	60	20	20	60	20				20	60	20																
2				60	40		80	20					60	40																
3				60	40		80	20					60	40																
4				50	50		70	30					50	50																
5				50	50		70	30					50	50																
6			30	70			80	20				30	70																	
7			80	20			80	20				80	20																	
8				10	90		80	20					10	90																
9				20	80		70	20	10				20	80																
10				20	80		40	40	20				20	80																
11				10	90		80	20					10	90																
12				10	90		30	50	20				10	90																
13			20	40	40			75	15	10		20	40	40													15	10		
14				80	20		40	50	10				80	20																
15				80	20		50	40	10				80	20																
16			70	30			60	30	10			70	30																	
17			20	60	20		70	20	5	5		20	60	20																
18			20	80			60	20	20			20	80																	
19		10	60	20	10		80	10	10		10	60	20	10																
20				20	80		80	20					20	80																
21			60	20	20		70	30				60	20	20																
22				40	60		60	30	10				40	60																
23			70	20	10		50	30	20			70	20	10																
24			30	60	10		70	20				30	60	10																
25				10	90		20	60	10	10			10	90												5	20			
26				40	60		50	50					40	60																
27				20	80		30	70					20	80																
28				50	50		50	50					50	50																
29				50	50		70	30					50	50																
30			50	50			70	30				50	50																	
31				20	80	50		50					20	80																
32				40	60		20	80					40	60																
33				30	70		20	80					30	70																
34				25	75		10	80	10				25	75																
35				80	20		90	10					80	20																
36				80	20		90	10					80	20																

Note V-Sl stands for very slight, Sl stands for slight, M stand for medium, Se stands fir severe, and V-Se stands for very severe.

Appendix E-4 Pavement Evaluation based on the ASTM Protocol (Guelph Line Parking Lot)

Slab	Popouts	Spalling-Corner	Spalling-Joint	Linear Cracking	Polished Aggregate	Faulting	Patch-Large	Patch-Small	Shrinkage Cracks
1	Extensive	L	H			L			
2	Extensive		M						
3	Extensive		M						
4	Extensive		M						
5	Extensive		M						
6	Extensive		M						
7	Extensive		M						
8	Extensive		M						
9	Extensive		H						
10	Extensive		H						
11	Extensive		M						
12	Extensive		H						
13	Extensive	L	H			L			
14	Extensive		M						
15	Extensive		M						
16	Extensive		M						
17	Extensive		H						
18	Extensive		M						
19	Extensive		H						
20	Extensive		M						
21	Extensive	L	M						
22	Extensive	L	M						
23	Extensive		M						
24	Extensive	L	M						
25	Extensive	M	H			L			
26	Extensive		M						
27	Extensive		M						
28	Extensive	M	M						
29	Extensive		M						
30	Extensive		M						
31	Extensive		M						
32	Extensive		M						
33	Extensive	L	M						
34	Extensive	L	H						
35	Extensive		M						
36	Extensive		M						

Appendix E-5 Permeability Rates of Georgetown Parking Lots

Slab	h1 cm	h2 cm	Standpipe cm	t1 sec	t2 sec	t3 sec	K 1 cm/s	K 2 cm/s	K 3 cm/s	K Avg. cm/s	K Std. cm/s
1	30	28	38.32	8.97	9.78	10.47	0.041	0.038	0.035	0.038	0.003
2	30	26	38.32	5.97	7.35	7.78	0.129	0.105	0.099	0.111	0.016
3	32	31	38.32	6.31	7.97	8.62	0.027	0.021	0.020	0.023	0.004
4	30	25	38.32	10.37	10.87	10.03	0.094	0.090	0.098	0.094	0.004
5	32	31	38.32	7.00	8.35	8.57	0.024	0.020	0.020	0.022	0.002
6	28	26	38.32	7.28	8.18	9.22	0.055	0.049	0.043	0.049	0.006
7	32.5	32	38.32	19.03	18.56	17.88	0.004	0.004	0.005	0.005	0.000
8	33	32.5	38.32	31.81	36.28	38.63	0.003	0.002	0.002	0.002	0.000
8	30	26	38.32	5.50	7.47	7.94	0.140	0.103	0.097	0.113	0.023
9	30	25	38.32	8.59	9.00	9.59	0.114	0.109	0.102	0.108	0.006
10	33	32	38.32	53.91	70.69	85.06	0.003	0.002	0.002	0.002	0.001
11	33	32.5	38.32	12.28	12.56	15.78	0.007	0.007	0.005	0.006	0.001
12	25	20	38.32	2.91	3.60	3.50	0.412	0.333	0.342	0.362	0.043
13	30	25	38.32	3.41	3.31	3.25	0.287	0.296	0.301	0.295	0.007
14	15	10	167.53	6.71	13.00	14.19	1.419	0.733	0.671	0.941	0.415
15	32	31	38.32	4.03	5.03	5.65	0.042	0.034	0.030	0.035	0.006

Appendix E-6 Permeability Rates for Guelph Line Parking Lots

Slab	h1 cm	h2 cm	Standpipe cm	t1 sec	t2 sec	t3 sec	K 1 cm/s	K 2 cm/s	K 3 cm/s	K Avg. cm/s	K Std. cm/s
1	25	21	38.32	5.85	7.03	7.65	0.133	0.111	0.102	0.115	0.016
2	28	25	38.32	7.50	9.25	10.71	0.068	0.055	0.047	0.057	0.010
3	12	10	167.53	3.69	3.72	3.94	0.967	0.959	0.906	0.944	0.033
4	30	29	38.32	3.91	4.38	5.25	0.039	0.035	0.029	0.034	0.005
5	27	25	38.32	3.81	4.40	5.46	0.090	0.078	0.063	0.077	0.014
6	33	32	38.32	10.19	12.31	13.97	0.014	0.011	0.010	0.012	0.002
7	32	31	38.32	14.00	19.93	21.18	0.010	0.007	0.007	0.008	0.002
8	32.5	32	38.32	17.16	26.13	32.43	0.004	0.003	0.002	0.003	0.001
9	33	32	38.32	5.03	5.41	6.13	0.027	0.025	0.022	0.025	0.002
10	32	31	38.32	5.06	5.28	5.53	0.028	0.027	0.026	0.027	0.001
11	31.5	31	38.32	19.75	27.56	34.81	0.004	0.003	0.002	0.003	0.001
12	33	32.5	38.32	15.41	15.97	18.37	0.004	0.004	0.004	0.004	0.000
13	32	31	38.32	4.09	4.12	4.19	0.035	0.034	0.034	0.034	0.000
14	32	31	38.32	4.31	3.94	4.06	0.033	0.036	0.035	0.035	0.002
15	33	32.5	38.32	9.81	10.68	11.66	0.007	0.006	0.006	0.006	0.001
16	32	30	38.32	3.44	4.00	4.71	0.084	0.072	0.061	0.073	0.011
17	33	32.5	38.32	14.84	19.35	25.47	0.005	0.004	0.003	0.004	0.001
18	33	32.5	38.32	13.12	15.97	19.97	0.005	0.004	0.003	0.004	0.001
19	33	32.5	38.32	28.37	39.59	49.19	0.002	0.002	0.001	0.002	0.001
20	25	21	38.32	7.53	9.63	10.50	0.104	0.081	0.074	0.086	0.015
21	17	16	167.53	14.31	15.00	16.03	0.083	0.079	0.074	0.079	0.004
22	25	20	38.32	3.72	4.15	4.25	0.269	0.241	0.235	0.248	0.018
23	32	31	38.32	6.88	7.97	8.28	0.021	0.018	0.017	0.019	0.002
24	30	29	38.32	15.15	18.28	20.66	0.010	0.008	0.007	0.009	0.001
25	32	30	38.32	4.13	4.40	4.50	0.070	0.066	0.064	0.067	0.003
26	31.5	31	38.32	7.56	10.12	10.53	0.009	0.007	0.007	0.008	0.001
27	25	20	38.32	3.72	4.15	4.25	0.269	0.241	0.235	0.248	0.018
28	30	26	38.32	5.29	5.66	5.59	0.121	0.113	0.115	0.116	0.004
29	32	30	38.32	4.03	5.31	5.75	0.072	0.054	0.050	0.059	0.011
30	29	27	38.32	5.94	6.82	7.56	0.054	0.047	0.042	0.048	0.006
31	32	31	38.32	10.25	14.16	15.79	0.014	0.010	0.009	0.011	0.003
32	32	30	38.32	5.43	5.78	5.84	0.053	0.050	0.049	0.051	0.002
33	32	30	38.32	6.69	7.12	7.41	0.043	0.041	0.039	0.041	0.002
34	33	32.5	38.32	7.34	8.35	8.94	0.009	0.008	0.008	0.008	0.001
35	32	31	38.32	5.75	7.40	8.34	0.025	0.019	0.017	0.020	0.004
36	32	31	38.32	6.72	10.03	11.28	0.021	0.014	0.013	0.016	0.005

Appendix F

Transition Probability Matrices Questionnaire (Markov Chain Modeling)

UNIVERSITY OF
Waterloo

June 17, 2009

I would like to ask for your assistance with my PhD research that is being conducted by the Centre for Pavement and Transportation Technology (CPATT) located in the Civil and Environmental Engineering Department of the University of Waterloo in conjunction with industry. The research is being directed by Dr.Susan Tighe Associate Professor and Canada Research Chair.

The objective of this research is to develop material, design, construction, and maintenance guidelines for pervious concrete pavements for application in the Canadian climate. Markov models will also be developed. This research has been established to obtain and analyze data in a systematic way for quantifying performance of the pervious concrete pavement technology.

Based on the limited available data, an experience based modeling methods is currently proposed until long term data can be collected. This model was selected as it combines field data with expert opinion to predict pervious concrete pavement performance. The purpose of this survey is to utilize expert opinion in combination with field data to develop a pervious pavement performance model. The individuals selected to fill out this survey are those who have experience in pavements engineering and performance.

Please find the attached pervious concrete pavement questionnaire. Please take your time in filling out the survey and do not hesitate to contact myself, Amir Golroo, agolroo@engmail.uwaterloo.ca or Dr. Susan Tighe at sltighe@uwaterloo.ca .

Your cooperation in this research is greatly appreciated. Thank you for your time.

Sincerely,
Amir Golroo
University of Waterloo

Developing Markov Models

Pavement States

The performance model predicts the condition index of a pavement at any specific time. Pervious Concrete Distress Index (PCDI) is defined herein addresses an overall condition of a pavement affected by surface distresses (including ravelling, spalling, cracking, potholing, polishing, and stepping. The total range of PCDI (0-100) is divided into five discrete ranges (i.e. Very Good, Good, Fair, Poor, and Very Poor), each expressing a state, as shown in Appendix F-1. 0 shows a pavement which unmistakably requires a repair action while 100 presents a pavement like new.

Appendix F-1 PCDI of Different States

State	5 (Very Good)	4 (Good)	3 (Fair)	2 (Poor)	1 (Very Poor)
PCDI	80-100	60-80	40-60	20-40	0-20

Pavement Groups

A pervious concrete pavement group is defined by the combination of specific attributes: pervious concrete thickness, environment condition, pavement age, and traffic load. Two levels of pavement thickness, one type of environment condition (i.e. hard wet freeze climate such as North Ontario, Canada climate), two levels of pavement age, and two traffic load patterns are used resulting in 8 (2 x 2 x 2 x 1) possible combinations, and 8 possible pavement groups. Regarding the fact that a typical design has been used for pervious concrete pavements, groups which have thin overlay and heavy traffic are rarely available. Therefore, the associated groups have been eliminated and totally six groups are analyzed. Appendix F-2 shows the performance factors and their levels, and the 6 most feasible combinations/groups. The implicit assumption is that a change in the level of each aforementioned factors leads to a significant change in the pavement condition index.

Appendix F-2 Different Pavement Groups

Group	Pervious concrete thickness[(1)]	Vehicle Traffic[(2)]	Pavement Age[(3)]	Environment Condition[(4)]
1	Thin	Light	Primary Interval	Hard Wet freeze
2	Thin	Light	Secondary Interval	Hard Wet freeze
3	Thick	Light	Primary Interval	Hard Wet freeze
4	Thick	Light	Secondary Interval	Hard Wet freeze
5	Thick	Heavy	Primary Interval	Hard Wet freeze
6	Thick	Heavy	Secondary Interval	Hard Wet freeze

[(1)] Pervious concrete thickness:

Thin: $100^{mm} < H \leq 150^{mm}$ (4 in.< H ≤ 6 in.)

Thick: $150^{mm} < H < 250^{mm}$ (6 in.< H < 10 in.)

[(2)] Vehicle Traffic:

Light: A pavement section which is generally exposed to ordinary cars, vans, and trucks. The heavy vehicle flow is limited to one vehicle per day (a heavy vehicle is a vehicle which has more than one axle load.)

Heavy: A pavement section that is essentially exposed to heavy vehicles such as a plant which is frequently exposed to construction vehicles.

[(3)] Pavement Age:

First Interval: $1^{year} < T \leq 2^{year}$

Second Interval: $2^{year} < T < 5^{year}$

[(4)] Environmental Condition:

Certain wet freeze areas that undergo a number of freeze-thaw cycles annually (15+) and there is precipitation during the winter where the ground maintains frozen as a result of a long continuous period of average daily temperatures below freezing are referred to as hard wet freeze areas. These areas would have situations where the pervious concrete becomes fully saturated.

Transition Probability Matrices

This section expresses how a specific group of pavement currently in a particular state will change (i.e. make a “transition”) to the lower state or remain in the same state after one year of service assuming that no maintenance action has been carried out. You will be asked to fill out one table for each pavement group on the basis of your own experience. The numbers you report should express your opinion that a pavement which now occupies a specific state will stay in the same state or will degrade to the immediate lower state at end of one year. It is assumed that a pavement cannot degrade more than one state. For instance, a pavement in state 4 cannot degrade to state 2 or 1 after one year of service. Similar conclusion can be extended to other states.

There will be one matrix with 5 columns and 4 rows for each pavement group. The states on the left hand side of the table (row) specify the present state of the pavement and the states along the top of the matrix (column) present possible states after one year of service. Appendix F-3 shows an example transition matrix.

If we represent any box in table by P_{ij} then this P_{ij} represents the number of pavement sections out of one hundred of the same group with initial state i that would be expected to be in state j at the end of one year assuming under a "do nothing" treatment alternative. For instance, if you think that 60 out of one hundred pavement sections in group 3 whose initial state is 3 (PCDI: 40-60) would degrade to the lower state 2 (PCDI: 20-40) at the end of one year then $P_{32} = 35$ and $P_{33} = 65$ as shown in Appendix F-3.

We asked you to apply the following procedure for filling in the blank tables provided for each pavement group.

1-Please read the title of each table to familiarize yourself with the pavement group described.

2- Start with the top row (PCDI: 80-100) and ask yourself the following questions:

If I had 100 pavements of this class in state 5 (PCDI: 80-100) how many of them would I expect to stay in state 5 (PCDI: 80-100)? How many of them would degrade to state 4(PCDI: 60-80) after one year. Your answers should go in the appropriate cells.

Note you don't have to fill all the cells in a row. You are only asked to fill two cells in each row which are the probability of staying in the same state (diagonal cells) and the probability of degrading into the immediate lower state (cells next to diagonal cells).

3-When you finish the top row, please go to the second row (PCDI: 60-80) and ask yourself the following questions:

If I had 100 pavements of this class in state 4 (PCDI: 60-80) how many of them would I expect to stay in state 4 (PCDI: 60-80)? How many of them would degrade to state 3(PCDI: 40-60) after one year. Your answers should go in the appropriate cells.

Note that a pavement cannot be improved (i.e. change to a higher state) because no maintenance action has been performed. Therefore, a pavement in state 3 cannot go up (improve) to state 4 after one year of service. Hence, P_{34}=0. Similar conclusion can be extended to other cells. Namely, the cells below the diagonal line shown in Appendix F-3 will be zero and you can just leave them blank if you wish.

4- Please fill the whole table in a similar way. Remember that sum of each row should be equal to 100.

5-when you complete a table for a pavement group, please select the next pavement group that you are most familiar with and fill out the table with abovementioned procedure.

Note that each cell in the tables presents the number of pavements out of 100 which are now in state i that you expect in state j at the end of one year. Remember that one table is needed for each pavement group. We suggest that you begin by selecting the pavement group which you believe you have had the most experience with.

Appendix F-3 Sample Transition Probability Matrix

			Future Condition				
			State 5 (Very	State 4 (Good)	State 3 (Fair)	State 2 (Poor)	State 1 (Very Poor)
PCDI			80-100	60-80	40-60	20-40	0-20
Present Condition	State 5 (Very Good)	80-100	**50** P_{55}	**50** P_{54}	---	---	---
	State 4 (Good)	60-80	---	**60** P_{44}	**40** P_{43}	---	---
	State 3 (Fair)	40-60	---	---	**65** P_{33}	**35** P_{32}	---
	State 2 (Poor)	20-40	---	---	---	**70** P_{22}	**30** P_{21}

Transition Probability Matrices for six groups of pervious concrete parking lots

Appendix F-4 Group 1, Thickness: Thin / Vehicle Traffic: Light / Pavement Age: Primary Interval

PCDI			Future Condition				
			State 5 (Very	State 4 (Good)	State 3 (Fair)	State 2 (Poor)	State 1 (Very Poor)
			80-100	60-80	40-60	20-40	0-20
Present Condition	State 5 (Very Good)	80-100	P_{55}	P_{54}	---	---	---
	State 4 (Good)	60-80	---	P_{44}	P_{43}	---	---
	State 3 (Fair)	40-60	---	---	P_{33}	P_{32}	---
	State 2 (Poor)	20-40	---	---	---	P_{22}	P_{21}

Appendix F-5 Group 2, Thickness: Thin / Vehicle Traffic: Light / Pavement Age: Secondary Interval

PCDI			Future Condition				
			State 5 (Very	State 4 (Good)	State 3 (Fair)	State 2 (Poor)	State 1 (Very Poor)
			80-100	60-80	40-60	20-40	0-20
Present Condition	State 5 (Very Good)	80-100	P_{55}	P_{54}	---	---	---
	State 4 (Good)	60-80	---	P_{44}	P_{43}	---	---
	State 3 (Fair)	40-60	---	---	P_{33}	P_{32}	---
	State 2 (Poor)	20-40	---	---	---	P_{22}	P_{21}

Appendix F-6 Group 3, Thickness: Thick / Vehicle Traffic: Light / Pavement Age: Primary Interval

PCDI			Future Condition				
			State 5 (Very	State 4 (Good)	State 3 (Fair)	State 2 (Poor)	State 1 (Very Poor)
			80-100	60-80	40-60	20-40	0-20
Present Condition	State 5 (Very Good)	80-100	P_{55}	P_{54}	---	---	---
	State 4 (Good)	60-80	---	P_{44}	P_{43}	---	---
	State 3 (Fair)	40-60	---	---	P_{33}	P_{32}	---
	State 2 (Poor)	20-40	---	---	---	P_{22}	P_{21}

Appendix F-7 Group 4, Thickness: Thick / Vehicle Traffic: Light / Pavement Age: Secondary Interval

PCDI			Future Condition				
			State 5 (Very	State 4 (Good)	State 3 (Fair)	State 2 (Poor)	State 1 (Very Poor)
			80-100	60-80	40-60	20-40	0-20
Present Condition	State 5 (Very Good)	80-100	P_{55}	P_{54}	---	---	---
	State 4 (Good)	60-80	---	P_{44}	P_{43}	---	---
	State 3 (Fair)	40-60	---	---	P_{33}	P_{32}	---
	State 2 (Poor)	20-40	---	---	---	P_{22}	P_{21}

Appendix F-8 Group 5, Thickness: Thick / Vehicle Traffic: Heavy / Pavement Age: Primary Interval

PCDI			Future Condition				
			State 5 (Very	State 4 (Good)	State 3 (Fair)	State 2 (Poor)	State 1 (Very Poor)
			80-100	60-80	40-60	20-40	0-20
Present Condition	State 5 (Very Good)	80-100	P_{55}	P_{54}	---	---	---
	State 4 (Good)	60-80	---	P_{44}	P_{43}	---	---
	State 3 (Fair)	40-60	---	---	P_{33}	P_{32}	---
	State 2 (Poor)	20-40	---	---	---	P_{22}	P_{21}

Appendix F-9 Group 6, Thickness: Thick / Vehicle Traffic: Heavy / Pavement Age: Secondary Interval

PCDI			Future Condition				
			State 5 (Very	State 4 (Good)	State 3 (Fair)	State 2 (Poor)	State 1 (Very Poor)
			80-100	60-80	40-60	20-40	0-20
Present Condition	State 5 (Very Good)	80-100	P_{55}	P_{54}	---	---	---
	State 4 (Good)	60-80	---	P_{44}	P_{43}	---	---
	State 3 (Fair)	40-60	---	---	P_{33}	P_{32}	---
	State 2 (Poor)	20-40	---	---	---	P_{22}	P_{21}

Appendix G

Field Investigation: Module 3 (Test Strip Layout, Surface Distress Evaluation, and Permeability Testing)

3m	3.7m	3.7m	
3	2	1	3m

Appendix G-1 Pervious Concrete Pavement Layout (Collinwood Concrete Saranac Plant)

Appendix G-2 Pavement Evaluation Results According to the Adjusted MTO Protocol (Collinwood Concrete Saranac Plant)

	Raveling					Spalling					Potholing					Polishing					Cracking					Faulting				
Slab	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se
1		20	80			25	40	10	25		20	80				20	30	50												
2		10	40	50		35	40		10		50	40	10			90	10													
3		80	20				100				20	80				70	30													

Appendix G-3 Pavement Evaluation Results According to the ASTM Protocol (Collinwood Concrete Saranac Plant)

Slab	Popouts	Spalling-Corner	Spalling-Joint	Linear Cracking	Polished Aggregate	Faulting	Patch-Large	Patch-Small	Shrinkage Cracks
1	Extensive	L	M		L			L	
2	Extensive		M		L				
3	Extensive		M		L				

Appendix G-4 Permeability Results (Collinwood Concrete Saranac Plant)

Slab	h1 cm	h2 cm	Standpipe cm	t1 sec	t2 sec	t3 sec	K 1 cm/s	K 2 cm/s	K 3 cm/s	K Avg. cm/s	K Std. cm/s
1	32.5	31.5	38.32	112	150	147	0.001	0.001	0.001	0.001	0.000
2	32.5	30.5	38.32	32	42	51	0.008	0.006	0.005	0.006	0.002
3	32.5	31	38.32	37	47	54	0.005	0.004	0.004	0.004	0.001
									Overall Average	**0.004**	**0.001**

5.2m	6.2m	6m	6.2m	6.5m	
1	2	3	4	5	5.6m
6	7	8	9	10	5.9m

11	12	13	14	15	5.7m
8.7m	6m	6m	8m	8.4m	

Appendix G-5 Pervious Concrete Pavement Layout (Lake County Fairground Parking Lot)

Appendix G-6 Pavement Evaluation Results According to the Adjusted MTO Protocol (Lake County Fairground Parking Lot)

	Raveling					Spalling					Potholing					Polishing					Cracking					Faulting				
Slab	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se
1	100					67					50					50	25	25												
2	100					33					50					20	30	50												
3	100					20					50					20	30													
4	70	30				20	30				50	10				20														
5	70	30				40	30				50					20														
6	60	40				45	15	10			50					20	10									15				
7	80	20				40	20	20			50					20										10				
8	90	10				20	20	10			50					20														
9	90	10				30	20				50					20										5				
10	80	20				40	20				50					20	10													
11	80	20				30	25				50	10				20					10									
12	80	20				30					50					25														
13	70	30				15	10	5			60					20														
14	80	20				25	5				50					30														
15	90	10				50					40					20					5									

Appendix G-7 Pavement Evaluation Results According to the ASTM Protocol (Lake County Fairground Parking Lot)

Slab	Popouts	Spalling-Corner	Spalling-Joint	Linear Cracking	Polished Aggregate	Faulting	Patch-Large	Patch-Small	Shrinkage Cracks
1	Extensive		L		L				
2	Extensive		L		L				
3	Extensive		L						
4	Extensive		M						
5	Extensive		M						
6	Extensive		L			L			
7	Extensive		L			L			
8	Extensive		L						
9	Extensive		L			L			
10	Extensive		L		L				
11	Extensive		L						L
12	Extensive				L				
13	Extensive		L						
14	Extensive				L				
15	Extensive								L

Appendix G-8 Permeability Rate (Lake County Fairground Parking Lot)

Slab	h1 cm	h2 cm	Standpipe cm	t1 sec	t2 sec	t3 sec	K 1 cm/s	K 2 cm/s	K 3 cm/s	K Avg. cm/s	K Std. cm/s
1	15	13	167.53	5.4	5.65	6	0.316	0.302	0.285	**0.301**	0.016
2	15	13	167.53	2.28	2.31	2.56	0.749	0.739	0.667	**0.718**	0.045
3	15	13	167.53	1.5	1.72	1.66	1.138	0.993	1.028	**1.053**	0.076
4	15	13	167.53	1.59	1.69	1.72	1.074	1.010	0.993	**1.026**	0.043
5	15	13	167.53	2.72	2.81	2.84	0.628	0.608	0.601	**0.612**	0.014
6	very fast										
7	8	6	167.53	2.25	2.18	2.19	1.525	1.574	1.567	**1.556**	0.026
8	6	4	167.53	1.25	1.29	1.37	3.870	3.750	3.531	**3.717**	0.172
9	15	13	167.53	1.81	1.89	1.87	0.943	0.903	0.913	**0.920**	0.021
10	13	10	167.53	1.88	1.94	1.9	1.665	1.613	1.647	**1.642**	0.026
11	15	13	167.53	3.66	3.91	4.44	0.466	0.437	0.385	**0.429**	0.041
12	15	13	167.53	3.25	3.12	3.25	0.525	0.547	0.525	**0.533**	0.013
13	12	9	167.53	2.47	2.47	2.34	1.390	1.390	1.467	**1.415**	0.045
14	15	13	167.53	3.56	3.34	3.6	0.480	0.511	0.474	**0.488**	0.020
15	15	13	167.53	1.94	1.69	2.1	0.880	1.010	0.813	**0.901**	0.100
									Overall Average	**1.094**	**0.047**

5.7m	5.7m	5.7m	5.7m	5.7m	5.6m	
	5		3		1	4.7m
6		4		2		4.7m

12		10		8		4.7m
	11		9		7	4.7m

Appendix G-9 Pervious Concrete Pavement Layout (Roush Honda Inventory Lot)

Appendix G-10 Pavement Evaluation Results According to the Adjusted MTO Protocol (Roush Honda Inventory Lot)

	Raveling					Spalling					Potholing					Polishing					Cracking					Faulting				
Slab	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se
1	70	30				20					30																			
2	90	10				30	10	20			10					10	25	25	10											
3	50	40	10			20	10				50					20														
4	50	50				20					50					20														
5	40	40	20			20	10				40	20				10	10													
6	50	25	25			40	20				25	25				10	5									25				
7	80	20				20	5				20					10	25									15				
8	70	30				30	10				30					25														
9	60	25	10	5		20	10				25	10	5			10														
10	70	20	10			25	5				20	10				20										10				
11	10	70	20			30	10				70	20				30														
12	60	30	10			20	10				30	10				20										20				

Appendix G-11 Pavement Evaluation Results According to the ASTM Protocol (Roush Honda Inventory Lot)

Slab	Popouts	Spalling-Corner	Spalling-Joint	Linear Cracking	Polished Aggregate	Faulting	Patch-Large	Patch-Small	Shrinkage Cracks
1					L				
2			L						
3	Extensive		L						
4									
5									
6	Extensive		L			L			
7			L			L			
8			L						
9	Extensive								
10			L			L			
11			L						
12	Extensive		L			L			

Appendix G-12 Permeability Rate (Roush Honda Inventory Lot)

Slab	h1 cm	h2 cm	Standpipe cm	t1 sec	t2 sec	t3 sec	K 1 cm/s	K 2 cm/s	K 3 cm/s	K Avg. cm/s	K Std. cm/s
1	15	12	167.53	2.06	2.31	2.4	1.292	1.152	1.109	**1.185**	0.096
2	7	5	167.53	1.31	1.69	1.56	3.064	2.375	2.573	**2.671**	0.355
3	very fast										
4	7	5	167.53	1.78	1.65	1.66	2.255	2.433	2.418	**2.369**	0.099
5	7	5	167.53	1.34	1.59	1.6	2.996	2.525	2.509	**2.676**	0.277
6	7	5	167.53	1.97	1.9	1.65	2.038	2.113	2.433	**2.194**	0.210
7	7	5	167.53	2.5	2.03	2.28	1.606	1.978	1.761	**1.781**	0.187
8	7	5	167.53	1.06	1.37	1.22	3.787	2.930	3.290	**3.336**	0.430
9	7	5	167.53	1.53	1.54	1.56	2.624	2.607	2.573	**2.601**	0.026
10	7	5	167.53	1.53	1.47	1.38	2.624	2.731	2.909	**2.755**	0.144
11	7	5	167.53	0.56	0.72	0.69	7.168	5.575	5.818	**6.187**	0.858
12	7	5	167.53	2.09	2.31	2.18	1.921	1.738	1.841	**1.833**	0.092
									Overall Average	**2.690**	**0.252**

3.4m	4..3m	1.6m	2.4m	3.7m	
1	2	3	4	5	3.8m

Appendix G-13 Pervious Concrete Pavement Layout (Cleveland State University Parking Lot D)

Appendix G- 14 Pavement Evaluation Results According to the Adjusted MTO Protocol (Cleveland State University Parking Lot D)

	Raveling					Spalling					Potholing					Polishing					Cracking					Faulting				
Slab	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se
1		100				80	20				100																			
2		80	20			80	20				80	20					10													
3		80	20			80	20				80	20					20													
4		80	20			60	40				80	20					20													
5		70	30			80	20				70	30					20													

Appendix G- 15 Pavement Evaluation Results According to the ASTM Protocol (Cleveland State University Parking Lot D)

Slab	Popouts	Spalling-Corner	Spalling-Joint	Linear Cracking	Polished Aggregate	Faulting	Patch-Large	Patch-Small	Shrinkage Cracks
1	Extensive		L						
2	Extensive	L	L		L				
3	Extensive	L	L		L				
4	Extensive	L	L		L				
5	Extensive		L						

Appendix G- 16 Permeability Rate (Cleveland State University Parking Lot D)

Slab	h1 cm	h2 cm	Standpipe cm	t1 sec	t2 sec	t3 sec	K 1 cm/s	K 2 cm/s	K 3 cm/s	K Avg. cm/s	K Std. cm/s
1	30.5	28.5	38.32	47	56	64	0.004	0.003	0.003	**0.003**	0.001
2	30	28	38.32	23	29	29	0.008	0.006	0.006	**0.007**	0.001
3	28.5	26.5	38.32	21	26	31	0.009	0.008	0.006	**0.008**	0.002
4	28.5	26.5	38.32	17	20	21	0.012	0.010	0.009	**0.010**	0.001
5	28.5	26.5	38.32	16	14	16	0.012	0.014	0.012	**0.013**	0.001
									Overall Average	**0.008**	**0.001**

	3.6m	4m	4.5m	4.5m	4.5m	4.5m	5m	2.6m
3.9m	1		2	3		4	5	
1.7m		6	7		8	9		10
3.9m	11	12		13	14		15	

Appendix G- 17 Pervious Concrete Pavement Layout (Cleveland State University Administration Building Parking Lot)

Appendix G-18 Pavement Evaluation Results According to the Adjusted MTO Protocol (Cleveland State University Administration Building Parking Lot)

	Raveling					Spalling					Potholing					Polishing					Cracking					Faulting				
Slab	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se
1		60	40			50	50				60	40																		
2		50	50			30	50	20			50	50																		
3	50	30	20			30	50	20			30	20																		
4	80	20				80	20				80																			
5	90	10				70	30				20										10									
6	80	20				90	10				10																			
7	70	20	10			40	50	10				50	10																	
8		100				80	20				80	20																		
9		100				60	40				80	20																		
10		80	20			60	40				70	30																		
11		20	50	30		40	40	20				70	30				20													
12		80	20			20	50	30				50	50																	
13		50	30	20		50	50					50	50																	
14	10	50	30	10		30	40	20	10		40	20	10				10													
15		40	50	10		80	20				40	40	20				20													

Appendix G-19 Pavement Evaluation Results According to the ASTM Protocol (Cleveland State University Administration Building Parking Lot)

Slab	Popouts	Spalling-Corner	Spalling-Joint	Linear Cracking	Polished Aggregate	Faulting	Patch-Large	Patch-Small	Shrinkage Cracks
1	Extensive		L						
2	Extensive		L						
3	Extensive		M						
4	Extensive		L						
5			L						L
6	Extensive		L						
7	Extensive		L						
8	Extensive		L						
9	Extensive		L						
10	Extensive	L	L						
11	Extensive		M		L				
12	Extensive		M						
13	Extensive		M						
14	Extensive		H						
15	Extensive		L		L				

Appendix G-20 Permeability Rate (Cleveland State University Administration Building Parking Lot)

Slab	h1 cm	h2 cm	Standpipe cm	t1 sec	t2 sec	t3 sec	K 1 cm/s	K 2 cm/s	K 3 cm/s	K Avg. cm/s	K Std. cm/s
1	30.5	28.5	38.32	47	56	64	0.004	0.003	0.003	**0.003**	0.001
2	30	28	38.32	23	29	29	0.008	0.006	0.006	**0.007**	0.001
3	28.5	26.5	38.32	21	26	31	0.009	0.008	0.006	**0.008**	0.002
4	28.5	26.5	38.32	17	20	21	0.012	0.010	0.009	**0.010**	0.001
5	28.5	26.5	38.32	16	14	16	0.012	0.014	0.012	**0.013**	0.001
									Overall Average	**0.008**	**0.001**

5.6m	5.2m	5.4m	5.6m	4.2m	
1	2	3	4	5	6m
10	9	8	7	6	6.3m
11	12	13	14	15	6.2m

Appendix G-21 Pervious Concrete Pavement Layout (Indian Run Falls Park)

Appendix G- 22 Pavement Evaluation Results According to the Adjusted MTO Protocol (Indian Run Falls Park)

	Raveling					Spalling					Potholing					Polishing					Cracking					Faulting				
Slab	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se
1	10	65	25			40	50				65	25																		
2	10	70	20			30	60				70	20																		
3	10	65	25			20	70				80	10																		
4	20	80				80	10				80	20																		
5	80	20				100					20					10														
6		25	25	50		60	40				25	50	10																	
7		30	40	30		80	20				30	50	20																	
8		20	40	20	20	20	80				20	40	20	20													10			
9		40	20	20	10	50	40	10			40	20	20	10																
10	20	30	10	30	20	10	80				30	10	20	20													20			
11		80	10	10		80	20				80	10	10			10														
12		70	20	10		10	80	10			70	20	10																	
13		30	20	20	30	20	30	50			30	20	20	30																
14		30	20	30	20	10	40	50			30	20	30	20							10									
15		20	20	30	30	50	40	10			20	20	30	30																

Appendix G-23 Pavement Evaluation Results According to the ASTM Protocol (Indian Run Falls Park)

Slab	Popouts	Spalling-Corner	Spalling-Joint	Linear Cracking	Polished Aggregate	Faulting	Patch-Large	Patch-Small	Shrinkage Cracks
1	Extensive		L						
2	Extensive		L						
3	Extensive		L						
4	Extensive		L						
5	Extensive		L						
6	Extensive		L						
7	Extensive		L						
8	Extensive		L			L			
9	Extensive		L						
10	Extensive		L			L			
11	Extensive		L						
12	Extensive	L	L						
13	Extensive	L	M						
14	Extensive		M						L
15	Extensive		M						

Appendix G-24 Permeability Rate (Indian Run Falls Park)

Slab	h1 cm	h2 cm	Standpipe cm	t1 sec	t2 sec	t3 sec	K 1 cm/s	K 2 cm/s	K 3 cm/s	K Avg. cm/s	K Std. cm/s
1	14	12	167.53	5.03	4.66	4.59	0.366	0.395	0.401	**0.387**	0.019
2	12	10	167.53	4.88	4.66	4.75	0.446	0.467	0.458	**0.457**	0.011
3	24	23	38.32	2.97	2.78	2.84	0.039	0.042	0.041	**0.041**	0.001
4	15.5	15	167.53	6.15	5.34	4.5	0.064	0.073	0.087	**0.075**	0.012
5	11.5	11	167.53	3.29	3.62	3.75	0.161	0.147	0.141	**0.150**	0.010
6	9	8	167.53	2.85	2.66	2.84	0.493	0.528	0.495	**0.505**	0.020
7	16	15	167.53	3.94	4.06	4.16	0.195	0.190	0.185	**0.190**	0.005
8	25	23	38.32	1.66	1.62	1.57	0.137	0.140	0.145	**0.141**	0.004
9	24	23.5	38.32	3.13	3	3.88	0.018	0.019	0.015	**0.017**	0.002
10	28	27	38.32	2.25	2.62	2.62	0.044	0.038	0.038	**0.040**	0.004
11	13	12	167.53	5.6	6.85	6.63	0.171	0.139	0.144	**0.151**	0.017
12	22	20	38.32	2.9	2.91	3.03	0.090	0.089	0.086	**0.088**	0.002
13	9	7	167.53	4.06	3.94	4.16	0.739	0.761	0.721	**0.740**	0.020
14	9	7	167.53	3.88	4.09	3.9	0.773	0.733	0.769	**0.758**	0.022
15	9	7	167.53	5.22	5.46	5.13	0.574	0.549	0.584	**0.569**	0.018
									Overall Average	**0.287**	**0.011**

5m	5.4m	5.4m	5.4m	5.4m	5.5m	5.4m	5.4m	5.4m	5.4m	4m	4.4m	
1		2		3		4		5		6		5.6m

3m	5.4m	5.4m	5.5m	5.5m	5.4m	5.5m	5.4m	5.4m	5.5m	5.5m	5.1m	
	12		11		10		9		8		7	5.7m

Appendix G-25 Pervious Concrete Pavement Layout (Audubon Parking Lot)

Appendix G-26 Pavement Evaluation Results According to the Adjusted MTO Protocol (Audubon Parking Lot)

	Raveling					Spalling					Potholing					Polishing					Cracking					Faulting				
Slab	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se
1	10	30	40	20		50					30	50																		
2	25	50	30	5		50					50	30																		
3	20	50	30			50	5				50	30																		
4	10	50	30	10		50	10				50	30																		
5	10	40	40	10		50					40	50																		
6	40	30	30			50					30	30																		
7	50	50				70					50					10														
8	20	50	30			40					50	30																		
9	20	70	10			50	10				70	10				10														
10	20	70	10			40					70	10				20	10													
11	10	50	40			40	10				50	40				10														
12	10	50	30	10		40	10	5			60	30	10			10														

Appendix G-27 Pavement Evaluation Results According to the ASTM Protocol (Audubon Parking Lot)

Slab	Popouts	Spalling-Corner	Spalling-Joint	Linear Cracking	Polished Aggregate	Faulting	Patch-Large	Patch-Small	Shrinkage Cracks
1	Extensive								
2	Extensive								
3	Extensive								
4	Extensive								
5	Extensive								
6	Extensive								
7	Extensive								
8	Extensive								
9	Extensive								
10	Extensive								
11	Extensive								
15	Extensive		L						

Appendix G-28 Permeability Rate (Audubon Parking Lot)

Slab	h1 cm	h2 cm	Standpipe cm	t1 sec	t2 sec	t3 sec	K 1 cm/s	K 2 cm/s	K 3 cm/s	K Avg. cm/s	K Std. cm/s
1	15	2	167.53	2			12.020			**12.020**	
2	15	2	167.53	6.12	6.94	7.95	3.928	3.464	3.024	**3.472**	0.452
3	15	2	167.53	4.41	4.28	4.5	5.451	5.617	5.342	**5.470**	0.138
4	15	2	167.53	5.6	4.82	5.5	4.293	4.987	4.371	**4.550**	0.381
5	15	2	167.53	4.97	5.06	4.94	4.837	4.751	4.866	**4.818**	0.060
6	15	2	167.53	3.94	4	4.04	6.101	6.010	5.950	**6.020**	0.076
7	15	2	167.53	5.25	5.19	5.18	4.579	4.632	4.641	**4.617**	0.033
8	15	2	167.53	7.15	7.3	7.2	3.362	3.293	3.339	**3.331**	0.035
9	15	2	167.53	9.63	9.91	9.63	2.496	2.426	2.496	**2.473**	0.041
10	11	2	167.53	7.72			2.635			**2.635**	
									Overall Average	**4.941**	**0.152**

6.1m	6.1m	6.1m	6.1m	
	7		5	6.1m
8		6		6.1m

b	3	a	1	6.1m
4		2		6.1m
6.1m	6.1m	6.1m	6.1m	

Appendix G-29 Pervious Concrete Pavement Layout (Anderson Concrete Plant Parking Lot)

Appendix G-30 Pavement Evaluation Results According to the Adjusted MTO Protocol (Anderson Concrete Plant Parking Lot)

	Raveling					Spalling					Potholing					Polishing					Cracking					Faulting				
Slab	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se
1	40	40	20			70	30				40	20					20													
2		40	30	15	15	40	50	10			40	30	15	15																
3(a-b)	70	30				80	20				30						10													
4	40	40	20			10	80	10			40	20																		
5	50	40	10			100					50	50																		
6		20	20	20	40		40	20	40		20	20	20	40																
7		50	25	25			80	20			50	25	25																	
8		80	20			20	80				80	20																		

Appendix G-31 Pavement Evaluation Results According to the ASTM Protocol (Anderson Concrete Plant Parking Lot)

Slab	Popouts	Spalling-Corner	Spalling-Joint	Linear Cracking	Polished Aggregate	Faulting	Patch-Large	Patch-Small	Shrinkage Cracks
1	Extensive								
2	Extensive		L						
3									
4	Extensive		M						
5	Extensive								
6	Extensive	L	M						
7	Extensive		L						
8	Extensive							L	

Appendix G-32 Permeability Rate (Anderson Concrete Plant Parking Lot)

Slab	h1 cm	h2 cm	Standpipe cm	t1 sec	t2 sec	t3 sec	K 1 cm/s	K 2 cm/s	K 3 cm/s	K Avg. cm/s	K Std. cm/s
1	17	16.5	167.53	10.34	11.97	13.37	0.034	0.030	0.027	0.030	0.004
2	4	3	167.53	0.47	0.38	0.44	7.303	9.032	7.801	8.045	0.890
3	12	11	167.53	4.97	5.06	5.4	0.209	0.205	0.192	0.202	0.009
4	7	5	167.53	1.53	1.37	1.31	2.624	2.930	3.064	2.873	0.226
5	7	5	167.53	2.75	2.9	3	1.460	1.384	1.338	1.394	0.061
6	3	2	167.53	0.34	0.22	0.47	14.228	21.988	10.292	15.503	5.951
7	very fast										
8	11	10	167.53	1.53	1.53	1.68	0.743	0.743	0.677	0.721	0.038
									Overall Average	**4.110**	**1.026**

3.8m	4.3m	4m	4.1m	4.1m	4m	
1	2	3	4	5	6	4.6m
12	11	10	9	8	7	4.6m
13	14	15	16	17	18	4.5m

Appendix G-33 Pervious Concrete Pavement Layout (Bettman Natural Resource Center Parking Lot)

Appendix G-34 Pavement Evaluation Results According to the Adjusted MTO Protocol (Bettman Natural Resource Center Parking Lot)

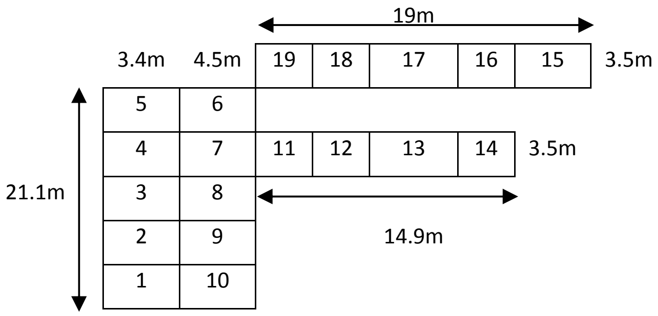
	Raveling					Spalling					Potholing					Polishing					Cracking					Faulting				
Slab	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se
1		100				80	20				80	20				30	20				10									
2		70	30			80	20				70	30					20	50												
3		100				80	20				90	10					40	30												
4	50	20	30			70	10				20	30					10	20	50											
5	80	20				50					20						50	50												
6	20	60	20			50					60	20				20	60	10	10											
7	20	40	30	10		80					40	30	10			30	20				20									
8	20	30	30	20		60	40				20	30	20				20	30												
9	20	60	20			60	40				60	20				20	20									20				
10	30	50	20			60					50	20				30						10								
11	30	50	20			50					50	20				30	20	10												
12			20	80		30	50	10			20	80				20														
13	10	70	20			30	25	5			70	20				20	30	10												
14	10	60	30			40	50				60	30				50														
15	10	50	30	10		40	50	10			50	30	10			40														
16	10	60	20	10		20	80				60	20	10			40	10													
17		10	10	10	70		80	20			10	10	10	70		20														
18		20	20	30	30	20	80				20	20	30	30		10		15												

Appendix G-35 Pavement Evaluation Results According to the ASTM Protocol (Bettman Natural Resource Center Parking Lot)

Slab	Popouts	Spalling-	Spalling-	Linear	Polished	Faulting	Patch-	Patch-	Shrinkage
1	Extensive		L		L				
2	Extensive		L	L	L				
3	Extensive		L		L				
4	Extensive		L		L				
5	Extensive				L				
6	Extensive				L				
7	Extensive			L	L				
8	Extensive		L		L				
9	Extensive		L		L				
10	Extensive			M	L	L			
11	Extensive				L				
12	Extensive		L						
13	Extensive		L		L				
14	Extensive								
15	Extensive		L						
16	Extensive		L		L				
17	Extensive		L						
18	Extensive		L						

Appendix G-36 Permeability Rate (Bettman Natural Resource Center Parking Lot)

Slab	h1 cm	h2 cm	Standpipe cm	t1 sec	t2 sec	t3 sec	K 1 cm/s	K 2 cm/s	K 3 cm/s	K Avg. cm/s	K Std. cm/s
1	12	10	167.53	6.22	6.35	6.53	0.350	0.343	0.333	**0.342**	0.008
3	11	10	167.53	10.5	12.22	12.81	0.108	0.093	0.089	**0.097**	0.010
6	25.5	17.41	38.32	17.41	20.13	25.69	0.060	0.052	0.041	**0.051**	0.010
8	10	8	167.53	3.81	4.28	4.13	0.699	0.622	0.645	**0.655**	0.039
10	24	22	38.32	3.5	3.88	3.87	0.068	0.061	0.061	**0.063**	0.004
12	8	6	167.53	2.56	2.46	2.5	1.341	1.395	1.373	**1.370**	0.027
14	13	12	167.53	9.47	11.84	11.63	0.101	0.081	0.082	**0.088**	0.011
16	10	9	167.53	3.97	4.4	4.53	0.317	0.286	0.277	**0.293**	0.021
18	9	8	167.53	3.91	3.94	4.32	0.359	0.357	0.325	**0.347**	0.019
									Overall Average	**0.367**	**0.017**



Appendix G-37 Pervious Concrete Pavement Layout (Ball Brother Foundation Storage Yard)

Appendix G-38 Pavement Evaluation Results According to the Adjusted MTO Protocol (Ball Brother Foundation Storage Yard)

	Raveling					Spalling					Potholing					Polishing					Cracking					Faulting				
Slab	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se
1		20	50	30			40	30	30		20	40	30	10				20			10									
2		30	60	10			50	20	30		30	60	10				20	30			25									
3		40	50	10			80	20			40	50	10			10	30			10										
4		60	30	10			10	40	50		60	30	10			10														
5		70	20	10			80	10	10		70	20	10			10	10													
6		80	10	10			10	10	80		80	10	10			10														
7		70	30				10	10	80		70	30					20													
8		90	10				60	40			90	10				10														
9		30	40	30			60	40			30	40	30			20					10									
10		70	25	5			100				70	25	5								15									
11	30	60	10				100				60	10																		
12		70	10	20			20	30	50		70	10	20			25														
13		20	40	20	20		70	30			20	40	20	20		10														
14	20	80					100				80					30														
15	20	80					100				80					20														
16	20	80					100				80					10														
17	10	80	10				40	60			80	10				20														
18	15	80	5				100				80	5				20														
19	20	80					100				80						5													

Appendix G-39 Pavement Evaluation Results According to the ASTM Protocol (Ball Brother Foundation Storage Yard)

Slab	Popouts	Spalling-Corner	Spalling-Joint	Linear Cracking	Polished Aggregate	Faulting	Patch-Large	Patch-Small	Shrinkage Cracks
1	Extensive	M	H		L				L
2	Extensive		M	L	L				
3	Extensive		M		L				
4	Extensive		M						
5	Extensive		M						
6	Extensive		M						
7	Extensive		M	L					
8	Extensive		H						
9	Extensive		M						L
10	Extensive		H	M					
11	Extensive		L						
12	Extensive		M		L				
13	Extensive		M						
14	Extensive		L						
15	Extensive		L						
16	Extensive		L						
17	Extensive		M						
18	Extensive		L						
19	Extensive		L						

Appendix G-40 Permeability Rate (Ball Brother Foundation Storage Yard)

Slab	h1 cm	h2 cm	Standpipe cm	t1 sec	t2 sec	t3 sec	K 1 cm/s	K 2 cm/s	K 3 cm/s	K Avg. cm/s	K Std. cm/s
1	30	29.5	38.32	48.24	55.53	79.25	0.0011	0.0010	0.0007	**0.0009**	0.000
2	very slow										
3	32.1	32	38.32	212.21			0.0000			**0.0000**	
4	32.3	32.2	38.32	122.47			0.0001			**0.0001**	
5	32	31.5	38.32	171.18			0.0003			**0.0003**	
6	33.5	32	38.32	35.5	47.31		0.0041	0.0031		**0.0036**	0.001
7	33	32.8	38.32	167.31			0.0001			**0.0001**	
8	33.5	33.1	38.32	107.25			0.0004			**0.0004**	
9	33.2	33	38.32	64.75			0.0003			**0.0003**	
10	33.5	32.5	38.32	106.82			0.0009			**0.0009**	
11	33.5	33.4	38.32	84.97			0.0001			**0.0001**	
12	33	32.9	38.32	76.6			0.0001			**0.0001**	
13	33.5	32.5	38.32	87.06			0.0011			**0.0011**	
14	33.5	32.5	38.32	43.46			0.0022			**0.0022**	
15	33.5	33	38.32	45.34			0.0011			**0.0011**	
16	33	32.9	38.32	104.07			0.0001			**0.0001**	
17	33.5	33.4	38.32	58.81			0.0002			**0.0002**	
18	33.5	33	38.32	100.34			0.0005			**0.0005**	
19	33	32.9	38.32	150.13			0.0001			**0.0001**	
									Overall Average	**0.0015**	**0.000**

	2m	1.6m	1.2m	2.3m	0.8m	3m	3.1m	3.1m	3.1m	3.1m	3.1m	3.1m	3.1m	3.1m
3.8m		7		6		5		4		3		2		1
3.8m	8		9		10		11		12		13		14	
3.2m		21		20		19		18		17		16		15
4.4m	22		23		24		25		26		27		28	

Appendix G-41 Pervious Concrete Pavement Layout (Philips Concrete Parking Lot)

Appendix G-42 Pavement Evaluation Results According to the Adjusted MTO Protocol (Philips Concrete Parking Lot)

	Raveling					Spalling					Potholing					Polishing					Cracking					Faulting				
Slab	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se
1	20	30	20	30		10	30	20			30	30	30																	
2	25	40	20	15		30	20	10			40	20	15																	
3	20	20	30	30		30	20				20	25	30																	
4	50	25	25			30	20				25	25				20														
5	50	25	25			20	30				25	25				30	20	10												
6	30	60	10			30	20				60	10					10									15				
7	10	60	30			50	40				60	30														15				
8		20	50	30		30	50				20	50	30																	
9	10	60	30			30	20				60	30																		
10	10	60	30			50	30				60	30																		
11	20	70	10			30	20				70	10				10														
12	30	50	20			30	30				50	20	5			10										10				
13	10	20	30	40		30	40				20	30	40																	
14	40	30	30			30	50				30	30	30	10																
15		80	20			50	30				80	20					100													
16	20	60	20			40	20				60	20					30	5												
17	20	60	20			25	25				60	20				10														
18	10	70	20			40	10				70	20				10														
19	10	80	10			40	30				80	10				10														
20	10	40	50			60	20				40	50				10														
21		40	40	15	5	80	20				40	40	20													10				
22		20	40	40		20	70	10			20	40	40																	
23	30	70				30	60				70	10				30														
24	20	80				20	60				80	10				20														
25	10	70	20			30	25	5	10		70	20				10										25				
26	10	60	30			40	40				60	30				10														
27	70	15	15			40	10	25			70	30				10														
28	30	40	30			50	30				40	30	10			10														

Appendix G-43 Pavement Evaluation Results According to the ASTM Protocol (Philips Concrete Parking Lot)

Slab	Popouts	Spalling-Corner	Spalling-Joint	Linear Cracking	Polished Aggregate	Faulting	Patch-Large	Patch-Small	Shrinkage Cracks
1	Extensive		L						
2	Extensive		L						
3	Extensive								
4	Extensive								
5	Extensive		L		L				
6	Extensive								
7	Extensive		L			L			
8	Extensive		L						
9	Extensive								
10	Extensive								
11	Extensive								
12	Extensive		L		L				
13	Extensive		L						
14	Extensive		L			L			
15	Extensive		L		L				
16	Extensive		L						
17	Extensive		L						
18	Extensive		L						
19	Extensive		L						
20	Extensive		L						
21	Extensive		L			L			
22	Extensive		L						
23	Extensive								
24	Extensive	L							
25	Extensive	L	L						
26	Extensive		L			L			
27	Extensive		L						
28	Extensive		L						

Appendix G-44 Permeability Rate (Philips Concrete Parking Lot)

Slab	h1 cm	h2 cm	Standpipe cm	t1 sec	t2 sec	t3 sec	K 1 cm/s	K 2 cm/s	K 3 cm/s	K Avg. cm/s	K Std. cm/s
1	28.5	28	38.32	40.84	76.15		0.0012	0.0006		**0.0009**	0.000
2	28	26	38.32	3.09	3.09	3.18	0.0654	0.0654		**0.0654**	0.000
3	26	24	38.32	2.62	2.88	2.87	0.0834	0.0758	0.0761	**0.0784**	0.004
4	26	24	38.32	3.97	4.38	4.37	0.0550	0.0499	0.0500	**0.0516**	0.003
5	26.5	26	38.32	72.35			0.0007			**0.0007**	
6	25.5	25	38.32	32.94	43.38	44.91	0.0016	0.0012	0.0012	**0.0014**	0.000
7	23	22.5	38.32	97.97			0.0006			**0.0006**	
8	27.5	27	38.32	71.1			0.0007			**0.0007**	
9	26	25.5	38.32	50.09	75.53		0.0011	0.0007		**0.0009**	0.000
10	25	24.5	38.32	42.88	75.91		0.0013			**0.0013**	
11	25.5	25.25	38.32	213			0.0001			**0.0001**	
12	27	26	38.32	5.66	6.1	5.56	0.0182	0.0169	0.0185	**0.0179**	0.001
13	16	15	167.53	3.28	3.09	3.06	0.2348	0.2492	0.2516	**0.2452**	0.009
14	26.5	26	38.32	5.5	6.78	6.56	0.0095	0.0077	0.0079	**0.0083**	0.001
15	29.5	29.25	38.32	213			0.0001			**0.0001**	
16	very slow										
17	27	26.5	38.32	112.47			0.0005			**0.0005**	
18	29	28.5	38.32	61.59	101.13		0.0008	0.0005		**0.0006**	0.000
19	28	27.5	38.32	87.47			0.0006			**0.0006**	
20	28.5	28	38.32	16.84	19.75	20.69	0.0029	0.0024	0.0023	**0.0025**	0.000
25	29	28.5	38.32	129.16			0.0004			**0.0004**	
									Overall Average	**0.024**	**0.002**

Appendix H

Field Investigation: Module 3 (Surface Distress Evaluation and Permeability Test)

Appendix H-1 Summary of Raters' Characteristics (Surface Distress Ratings)

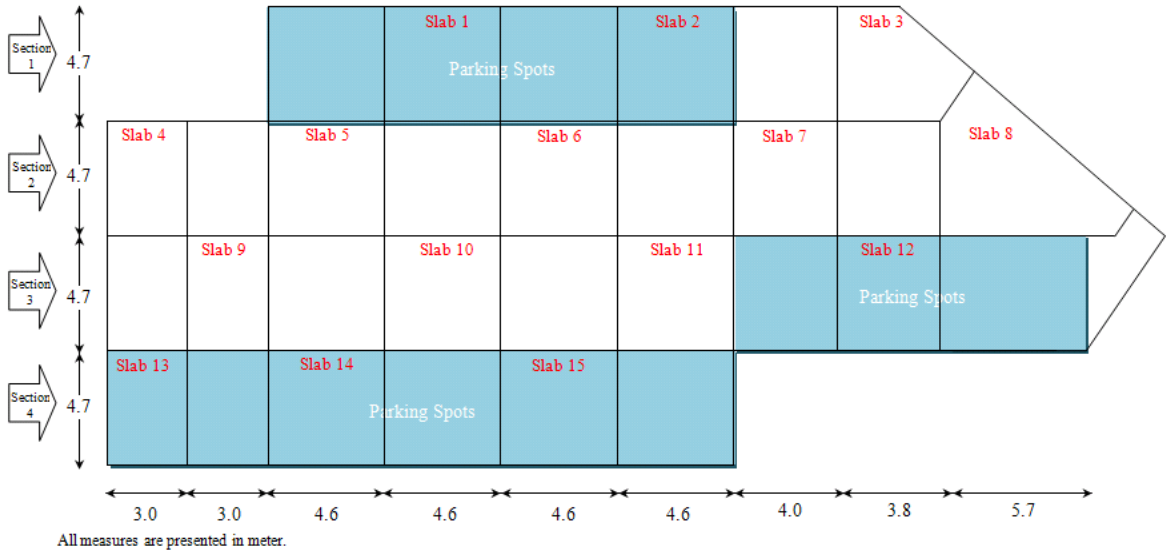
Rater	Range Difference	Avg. Rating	Difference Squared Sum	Difference Squared Sum Ranking	Std.	Std. Ranking
1	7	5.1	35.2	7	2.41	15
2	8	3.7	19.0	10	2.37	13
3	7	4.0	9.2	18	2.50	16
4	6	3.0	26.3	8	2.13	11
5	5	1.9	54.4	2	1.72	6
6	6	4.2	47.5	3	2.81	20
7	7	3.6	16.0	13	2.56	17
8	6	4.7	11.3	16	2.37	13
9	3	4.4	13.0	14	1.30	2
10	5	4.2	5.2	20	1.91	8
11	5	6.8	60.2	1	1.79	7
12	8	3.9	12.5	15	2.64	19
13	4	3.7	6.4	19	1.48	5
14	8	4.5	16.3	12	2.56	18
15	7	4.1	10.9	17	2.37	12
16	3	5.1	17.9	11	1.25	1
17	6	3.2	19.8	9	1.98	9
18	4	6.1	45.9	4	1.45	4
19	5	4.6	45.1	5	2.13	10
20	4	6.5	44.7	6	1.41	3

Appendix H-2 Summary of Raters' Characteristics (Permeability Ratings)

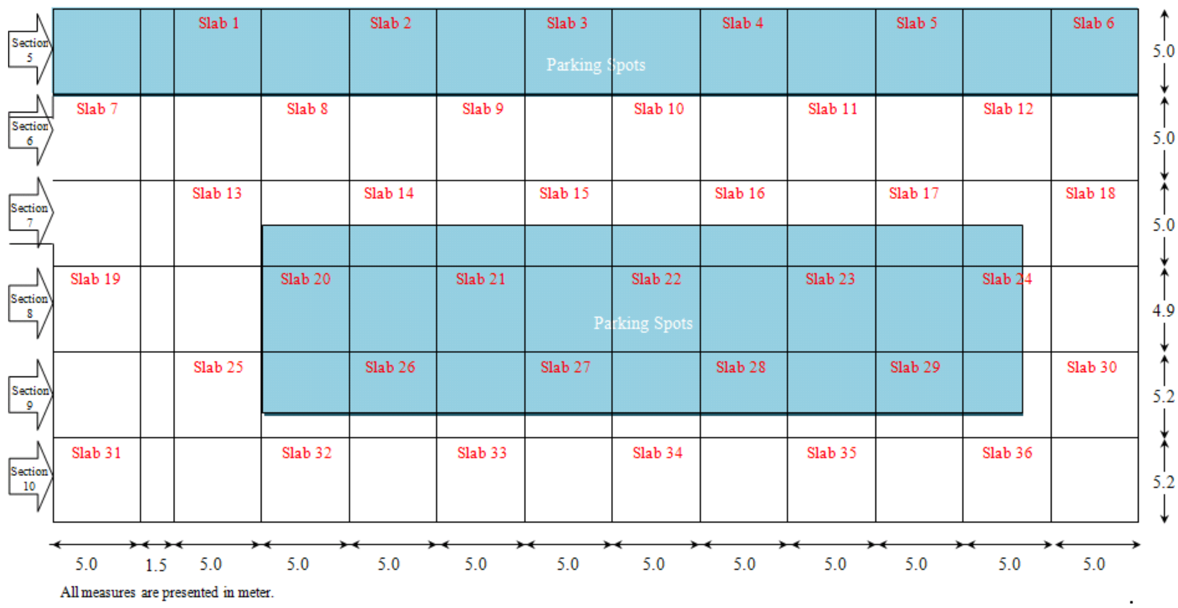
Rater	Range Difference	Avg. Rating	Difference Squared Sum	Difference Squared Sum Ranking	Std.	Std. Ranking
1	7.5	6.625	52.1	4	2.683	14
2	6	3.250	29.8	10	1.982	6
3	9	4.625	24.5	12	3.335	20
4	6	2.750	30.1	9	1.982	6
5	5	1.375	78.6	1	1.996	8
6	4	2.750	31.5	8	1.669	4
7	8	4.125	8.4	19	2.850	17
8	6	4.875	13.8	17	2.642	13
9	7	4.375	9.2	18	2.264	11
10	7	4.375	6.9	20	2.574	12
11	6	6.538	50.9	5	2.066	9
12	9	4.875	16.9	15	2.997	19
13	6	4.000	15.5	16	1.852	5
14	6	3.250	23.3	13	2.712	15
15	9	3.250	19.8	14	2.726	16
16	4	6.125	37.1	7	1.642	3
17	6	3.500	24.8	11	2.070	10
18	4	6.813	57.8	2	1.252	2
19	8	5.125	56.3	3	2.949	18
20	3	6.250	47.3	6	1.165	1

Appendix I

Surface Distress Rating (COG) for the Georgetown Parking Lot and the Guelph Line Parking Lot (Module 2)



Appendix I-1 Georgetown Parking Lot's Plan



Appendix I-2 Guelph Line Parking Lot's Plan

Appendix I-3 Surface Distress Rating (EV) for the Georgetown Parking Lot

		Rater Number					Average
		1	2	3	4	5	
Slab Number	1	7.20	6.80	6.80	5.70	6.40	6.58
	2	7.40	5.80	6.80	6.20	7.20	6.68
	3	6.00	7.00	4.80	3.60	2.70	4.82
	4	5.20	5.40	4.80	2.10	3.80	4.80
	5	5.00	5.00	5.20	1.60	5.00	5.05
	6	4.80	1.80	5.70	1.90	4.80	4.28
	7	3.80	3.80	4.50	1.60	4.20	4.08
	8	7.00	6.20	6.60	4.00	5.00	6.20
	9	6.00	3.40	4.90	1.80	5.60	4.98
	10	5.80	4.70	5.30	2.00	6.00	5.45
	11	5.20	5.00	5.00	2.00	5.20	5.10
	12	6.40	4.00	5.20	3.90	4.20	4.95
	13	7.60	4.50	6.30	5.40	5.80	5.92
	14	7.20	2.20	6.20	5.00	6.20	5.36
	15	7.00	3.60	7.20	6.20	6.00	6.00

Appendix I-4 Surface Distress Rating (EV) for the Guelph Line Parking Lot

		Rater Number					
		1	2	3	4	5	Average
Slab Number	1	7.20	4.40	5.00	6.40	3.00	5.20
	2	5.80	2.00	4.90	4.40	2.80	3.98
	3	6.00	2.00	5.10	4.80	3.00	4.18
	4	6.00	2.80	4.80	4.80	2.60	4.20
	5	5.80	2.80	4.80	4.80	3.60	4.36
	6	5.20	2.60	3.90	3.60	4.00	3.86
	7	6.80	6.50	5.50	7.90	6.40	6.62
	8	4.80	4.50	4.50	4.00	1.40	3.84
	9	5.00	4.60	4.10	5.60	1.80	4.22
	10	3.90	3.00	4.00	3.60	1.80	3.26
	11	5.00	4.50	3.90	3.00	1.60	3.60
	12	4.20	3.80	3.40	2.80	1.40	3.12
	13	7.00	3.00	4.70	3.00	3.80	4.30
	14	6.20	2.40	4.30	3.00	2.20	3.62
	15	6.60	4.80	4.90	5.80	2.40	4.90
	16	7.00	5.00	5.50	6.10	5.20	5.76
	17	6.00	4.00	4.40	5.20	3.20	4.56
	18	6.80	5.50	4.60	5.90	3.80	5.32
	19	7.20	5.80	4.80	4.60	5.80	5.64
	20	6.00	4.30	4.80	4.20	3.00	4.46
	21	5.20	3.60	4.40	6.20	3.60	4.60
	22	6.00	3.50	4.10	3.60	2.60	3.96
	23	6.80	6.20	5.00	6.80	3.60	5.68
	24	6.80	6.00	4.70	6.40	3.00	5.38
	25	4.20	5.00	4.50	3.60	3.00	4.06
	26	4.00	3.00	4.10	3.80	2.20	3.42
	27	5.20	4.80	4.60	3.60	2.40	4.12
	28	6.00	4.00	4.50	3.80	2.60	4.18
	29	7.00	6.00	4.60	5.40	2.80	5.16
	30	7.20	6.00	4.70	4.80	4.60	5.46
	31	6.40	5.20	5.00	2.60	3.00	4.44
	32	4.00	5.50	4.20	2.80	3.40	3.98
	33	3.80	3.50	4.00	2.00	3.20	3.30
	34	3.80	3.80	4.20	2.00	2.60	3.28
	35	6.00	5.50	4.80	3.80	4.20	4.86
	36	5.80	4.80	4.60	4.60	3.60	4.68

Appendix J

Transition Probability Matrices and Standard Deviation

(Deterministic Markov Chain Modeling)

Appendix J-1 Transition Probability Matrix for Group 1

PCDI			Future Condition				
			State 5 (Very	State 4 (Good)	State 3 (Fair)	State 2 (Poor)	State 1 (Very Poor)
			80-100	60-80	40-60	20-40	0-20
Present Condition	State 5 (Very Good)	80-100	0.61	0.39	0.00	0.00	0.00
	State 4 (Good)	60-80	0.00	0.62	0.38	0.00	0.00
	State 3 (Fair)	40-60	0.00	0.00	0.60	0.40	0.00
	State 2 (Poor)	20-40	0.00	0.00	0.00	0.58	0.42

Appendix J-2 Transition Probability Matrix for Group 2

PCDI			Future Condition				
			State 5 (Very	State 4 (Good)	State 3 (Fair)	State 2 (Poor)	State 1 (Very Poor)
			80-100	60-80	40-60	20-40	0-20
Present Condition	State 5 (Very Good)	80-100	0.66	0.34	0.00	0.00	0.00
	State 4 (Good)	60-80	0.00	0.65	0.35	0.00	0.00
	State 3 (Fair)	40-60	0.00	0.00	0.64	0.36	0.00
	State 2 (Poor)	20-40	0.00	0.00	0.00	0.60	0.40

Appendix J-3 Transition Probability Matrix for Group 3

PCDI			Future Condition				
			State 5 (Very	State 4 (Good)	State 3 (Fair)	State 2 (Poor)	State 1 (Very Poor)
			80-100	60-80	40-60	20-40	0-20
Present Condition	State 5 (Very Good)	80-100	0.70	0.30	0.00	0.00	0.00
	State 4 (Good)	60-80	0.00	0.71	0.29	0.00	0.00
	State 3 (Fair)	40-60	0.00	0.00	0.67	0.33	0.00
	State 2 (Poor)	20-40	0.00	0.00	0.00	0.63	0.37

Appendix J-4 Transition Probability Matrix for Group 4

PCDI			Future Condition				
			State 5 (Very	State 4 (Good)	State 3 (Fair)	State 2 (Poor)	State 1 (Very Poor)
			80-100	60-80	40-60	20-40	0-20
Present Condition	State 5 (Very Good)	80-100	0.71	0.29	0.00	0.00	0.00
	State 4 (Good)	60-80	0.00	0.72	0.28	0.00	0.00
	State 3 (Fair)	40-60	0.00	0.00	0.71	0.29	0.00
	State 2 (Poor)	20-40	0.00	0.00	0.00	0.67	0.33

Appendix J-5 Transition Probability Matrix for Group 5

PCDI			Future Condition				
			State 5 (Very	State 4 (Good)	State 3 (Fair)	State 2 (Poor)	State 1 (Very Poor)
			80-100	60-80	40-60	20-40	0-20
Present Condition	State 5 (Very Good)	80-100	0.58	0.42	0.00	0.00	0.00
	State 4 (Good)	60-80	0.00	0.58	0.42	0.00	0.00
	State 3 (Fair)	40-60	0.00	0.00	0.55	0.45	0.00
	State 2 (Poor)	20-40	0.00	0.00	0.00	0.53	0.47

Appendix J-6 Transition Probability Matrix for Group 6

PCDI			Future Condition				
			State 5 (Very	State 4 (Good)	State 3 (Fair)	State 2 (Poor)	State 1 (Very Poor)
			80-100	60-80	40-60	20-40	0-20
Present Condition	State 5 (Very Good)	80-100	0.59	0.41	0.00	0.00	0.00
	State 4 (Good)	60-80	0.00	0.60	0.40	0.00	0.00
	State 3 (Fair)	40-60	0.00	0.00	0.56	0.44	0.00
	State 2 (Poor)	20-40	0.00	0.00	0.00	0.55	0.46

Appendix J-7 Standard Deviation Matrix for Group 1

PCDI			Future Condition				
			State 5 (Very	State 4 (Good)	State 3 (Fair)	State 2 (Poor)	State 1 (Very Poor)
			80-100	60-80	40-60	20-40	0-20
Present Condition	State 5 (Very Good)	80-100	11	11	0	0	0
	State 4 (Good)	60-80	0	11	12	0	0
	State 3 (Fair)	40-60	0	0	14	14	0
	State 2 (Poor)	20-40	0	0	0	18	18

Appendix J-8 Standard Deviation Matrix for Group 2

PCDI			Future Condition				
			State 5 (Very	State 4 (Good)	State 3 (Fair)	State 2 (Poor)	State 1 (Very Poor)
			80-100	60-80	40-60	20-40	0-20
Present Condition	State 5 (Very Good)	80-100	12	12	0	0	0
	State 4 (Good)	60-80	0	10	10	0	0
	State 3 (Fair)	40-60	0	0	13	13	0
	State 2 (Poor)	20-40	0	0	0	18	18

Appendix J-9 Standard Deviation Matrix for Group 3

PCDI			Future Condition				
			State 5 (Very	State 4 (Good)	State 3 (Fair)	State 2 (Poor)	State 1 (Very Poor)
			80-100	60-80	40-60	20-40	0-20
Present Condition	State 5 (Very Good)	80-100	12	12	0	0	0
	State 4 (Good)	60-80	0	10	10	0	0
	State 3 (Fair)	40-60	0	0	12	12	0
	State 2 (Poor)	20-40	0	0	0	17	17

Appendix J-10 Standard Deviation Matrix for Group 4

PCDI			Future Condition				
			State 5 (Very	State 4 (Good)	State 3 (Fair)	State 2 (Poor)	State 1 (Very Poor)
			80-100	60-80	40-60	20-40	0-20
Present Condition	State 5 (Very Good)	80-100	9	9	0	0	0
	State 4 (Good)	60-80	0	10	10	0	0
	State 3 (Fair)	40-60	0	0	13	13	0
	State 2 (Poor)	20-40	0	0	0	19	19

Appendix J-11Standard Deviation Matrix for Group 5

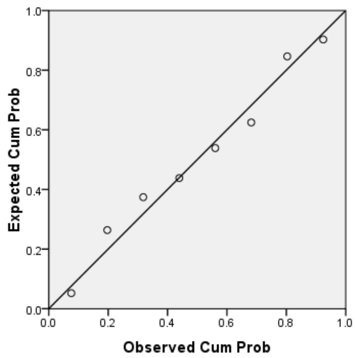
PCDI			Future Condition				
			State 5 (Very	State 4 (Good)	State 3 (Fair)	State 2 (Poor)	State 1 (Very Poor)
			80-100	60-80	40-60	20-40	0-20
Present Condition	State 5 (Very Good)	80-100	16	16	0	0	0
	State 4 (Good)	60-80	0	14	14	0	0
	State 3 (Fair)	40-60	0	0	14	14	0
	State 2 (Poor)	20-40	0	0	0	15	15

Appendix J-12 Standard Deviation Matrix for Group 6

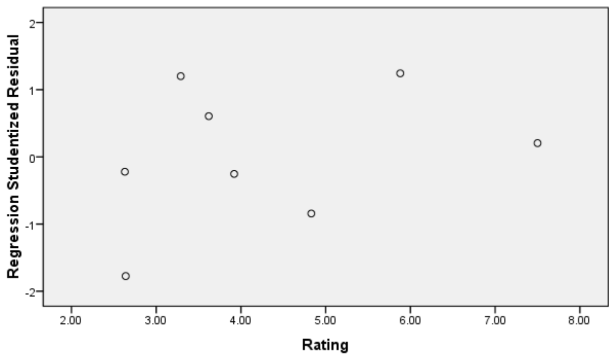
PCDI			Future Condition				
			State 5 (Very	State 4 (Good)	State 3 (Fair)	State 2 (Poor)	State 1 (Very Poor)
			80-100	60-80	40-60	20-40	0-20
Present Condition	State 5 (Very Good)	80-100	13	12	0	0	0
	State 4 (Good)	60-80	0	11	11	0	0
	State 3 (Fair)	40-60	0	0	14	14	0
	State 2 (Poor)	20-40	0	0	0	17	17

Appendix K

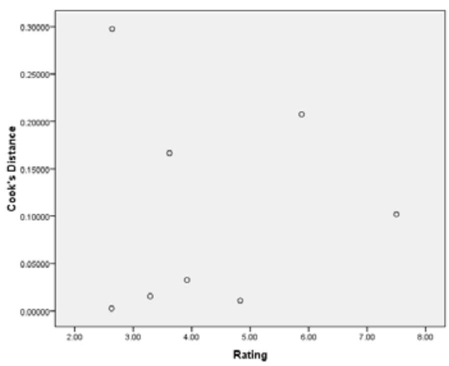
Residual Analysis for the Model for SDI and DMI



Appendix K-1 Normal of Percentile Plot of Standardized Residual.



Appendix K-2 Studentized Residual Versus Predicted Values.



Appendix K-3 Cook's Distances.

Appendix L

Surface Distress Evaluation of Various Slabs at the Georgetown and Guelph Line Parking Lots

Appendix L-1 Objective Evaluation of Surface Distresses of the Georgetown Parking Lot Slabs

Slab	Raveling					Spalling					Potholing					Polishing					Cracking					Stepping					PCDI
	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	
1	50	50				40	30				50																				8.83
2	40	60				30	30				60																				8.80
3		10	40	40	10	40	50	10			10	40	40	10																	6.38
4		20	10	40	30		100				20	10	40	30																	5.90
5		40	30	30			100				40	30	30																		7.07
6			40	50	10	10	70	20				40	50	10																	5.97
7			30	60	10		60	40				30	60	10																	5.67
8		60	30	10		100					60	30	10																		7.90
9		30	50	20		25	75				30	50	20																		7.17
10		50	50			25	75				50	50																			7.67
11		20	40	30	10	30	50	10	10		20	40	30	10																	6.47
12		20	30	30	20	70	30				20	30	30	20																	6.53
13		50	40	10		50	50				50	40	10																		7.62
14		50	50			70	30				50	50																			7.82
15		60	40			70	30				60	40																			7.93

Note V-Sl stands for very slight, Sl stands for slight, M stand for medium, Se stands fir severe, and V-Se stands for very severe.

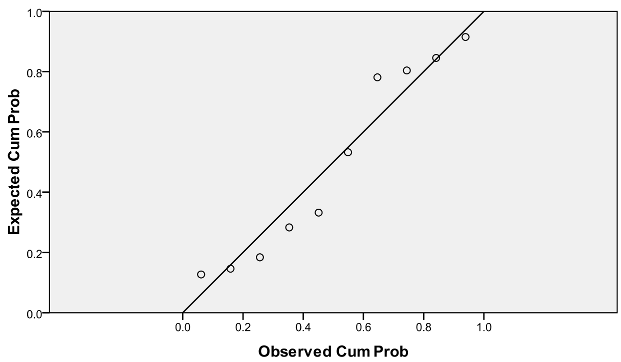
Appendix L-2 Objective Evaluation of Surface Distresses of the Guelph Line Parking Lot Slabs

	Raveling					Spalling					Potholing					Polishing					Cracking					Stepping					
Slab	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	V-Sl	Sl	M	Se	V-Se	PCDI
1			20	60	20	20	60	20				20	60	20																	5.60
2				60	40		80	20					60	40																	5.00
3				60	40		80	20					60	40																	5.00
4				50	50		70	30					50	50																	4.80
5				50	50		70	30					50	50																	4.80
6			30	70			80	20				30	70																		5.93
7			80	20			80	20				80	20																		6.60
8				10	90		80	20					10	90																	4.33
9				20	80		70	20	10				20	80																	4.33
10				20	80		40	40	20				20	80																	4.07
11				10	90		80	20					10	90																	4.33
12				10	90		30	50	20				10	90																	3.87
13			20	40	40			75	15	10		20	40	40													15	10			4.44
14				80	20		40	50	10				80	20																	4.93
15				80	20		50	40	10				80	20																	5.00
16			70	30			60	30	10			70	30																		6.27
17			20	60	20		70	20	5	5		20	60	20																	5.37
18			20	80			60	20	20			20	80																		5.53
19		10	60	20	10		80	10	10		10	60	20	10																	6.38
20				20	80		80	20					20	80																	4.47
21			60	20	20		70	30				60	20	20																	6.00
22				40	60		60	30	10				40	60																	4.53
23			70	20	10		50	30	20			70	20	10																	6.00
24			30	60	10		70	30				30	60	10																	5.73
25				10	90		20	60	10	10			10	90												5	20				3.70
26				40	60		50	50					40	60																	4.53
27				20	80		30	70					20	80																	4.13
28				50	50		50	50					50	50																	4.67
29				50	50		70	30					50	50																	4.80
30			50	50			70	30				50	50																		6.13
31				20	80	50		50					20	80																	4.43
32				40	60		20	80					40	60																	4.33
33				30	70		20	80					30	70																	4.20
34				25	75		10	80	10				25	75																	4.00
35				80	20		90	10					80	20																	5.33
36				80	20		90	10					80	20																	5.33

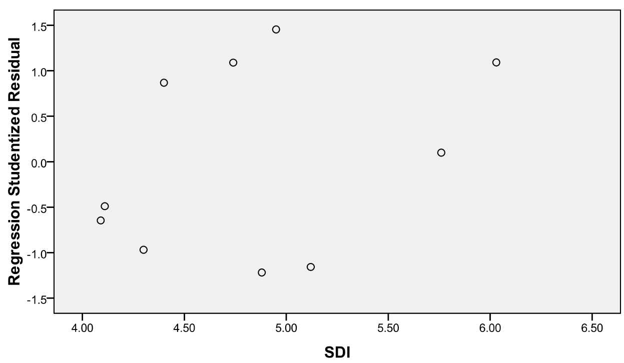
Note V-Sl stands for very slight, Sl stands for slight, M stand for medium, Se stands fir severe, and V-Se stands for very severe.

Appendix M

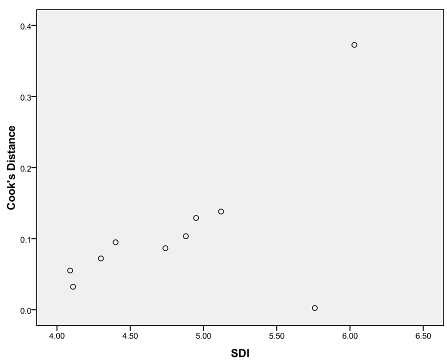
Residual Analysis for the Model for SDI and PCDI



Appendix M-1 Normal of Percentile Plot of Standardized Residual



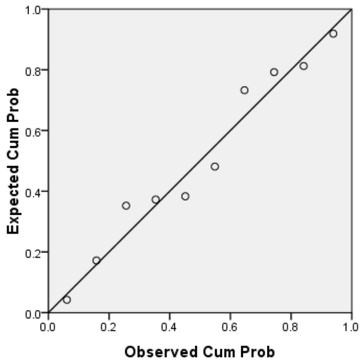
Appendix M-2 Studentized Residual Versus Predicted Values



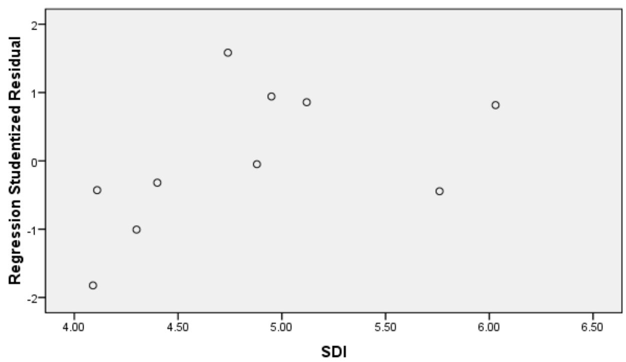
Appendix M-3 Cook's Distances

Appendix N

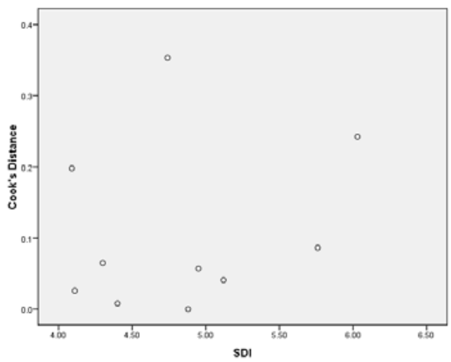
Residual Analysis for the Model for SDI and PCI



Appendix N-1 Normal of Percentile Plot of Standardized Residual



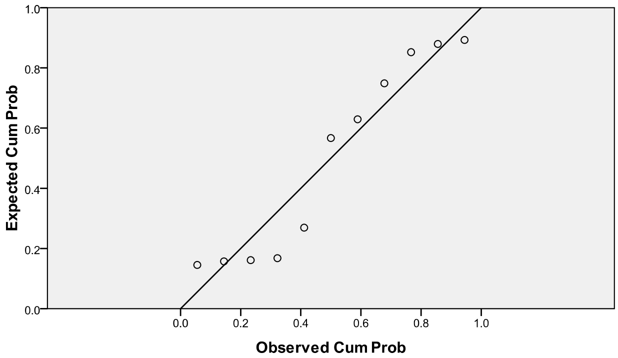
Appendix N-2 Studentized Residual Versus Predicted Values



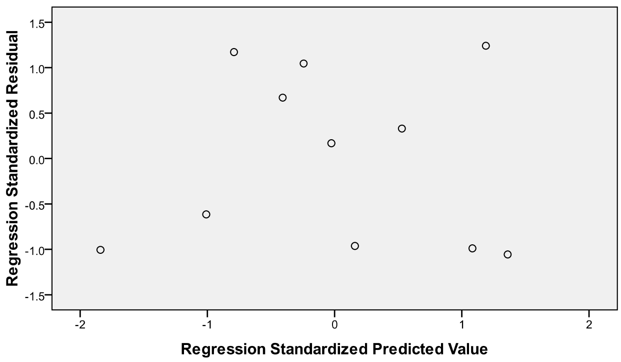
Appendix N-3 Cook's Distances

Appendix O

Residual Analysis for the Model for PCI and Pavement Age



Appendix O-1 Normal of Percentile Plot of Standardized Residual.



Appendix O-2 Scatter Plot of Errors.

Appendix P

Mean and Probability Distribution Functions Associated with Various Transition Probability Matrices (Probabilistic Markov Chain Modeling)

Appendix P-1 Mean Values of the Transition Probability Matrix for Group 1

PCDI			Future Condition				
			State 5 (Very	State 4 (Good)	State 3 (Fair)	State 2 (Poor)	State 1 (Very Poor)
			80-100	60-80	40-60	20-40	0-20
Present Condition	State 5 (Very Good)	80-100	0.62	0.39	0.00	0.00	0.00
	State 4 (Good)	60-80	0.00	0.64	0.37	0.00	0.00
	State 3 (Fair)	40-60	0.00	0.00	0.63	0.39	0.00
	State 2 (Poor)	20-40	0.00	0.00	0.00	0.61	0.41

Appendix P-2 Mean Values of the Transition Probability Matrix for Group 2

PCDI			Future Condition				
			State 5 (Very	State 4 (Good)	State 3 (Fair)	State 2 (Poor)	State 1 (Very Poor)
			80-100	60-80	40-60	20-40	0-20
Present Condition	State 5 (Very Good)	80-100	0.66	0.34	0.00	0.00	0.00
	State 4 (Good)	60-80	0.00	0.66	0.35	0.00	0.00
	State 3 (Fair)	40-60	0.00	0.00	0.66	0.35	0.00
	State 2 (Poor)	20-40	0.00	0.00	0.00	0.62	0.39

Appendix P-3 Mean Values of the Transition Probability Matrix for Group 3

PCDI			Future Condition				
			State 5 (Very	State 4 (Good)	State 3 (Fair)	State 2 (Poor)	State 1 (Very Poor)
			80-100	60-80	40-60	20-40	0-20
Present Condition	State 5 (Very Good)	80-100	0.71	0.30	0.00	0.00	0.00
	State 4 (Good)	60-80	0.00	0.71	0.29	0.00	0.00
	State 3 (Fair)	40-60	0.00	0.00	0.67	0.33	0.00
	State 2 (Poor)	20-40	0.00	0.00	0.00	0.64	0.37

Appendix P-4 Mean Values of the Transition Probability Matrix for Group 4

PCDI			Future Condition				
			State 5 (Very	State 4 (Good)	State 3 (Fair)	State 2 (Poor)	State 1 (Very Poor)
			80-100	60-80	40-60	20-40	0-20
Present Condition	State 5 (Very Good)	80-100	0.71	0.30	0.00	0.00	0.00
	State 4 (Good)	60-80	0.00	0.72	0.28	0.00	0.00
	State 3 (Fair)	40-60	0.00	0.00	0.76	0.30	0.00
	State 2 (Poor)	20-40	0.00	0.00	0.00	0.71	0.31

Appendix P-5 Mean Values of the Transition Probability Matrix for Group 5

PCDI			Future Condition				
			State 5 (Very	State 4 (Good)	State 3 (Fair)	State 2 (Poor)	State 1 (Very Poor)
			80-100	60-80	40-60	20-40	0-20
Present Condition	State 5 (Very Good)	80-100	0.58	0.42	0.00	0.00	0.00
	State 4 (Good)	60-80	0.00	0.59	0.42	0.00	0.00
	State 3 (Fair)	40-60	0.00	0.00	0.56	0.46	0.00
	State 2 (Poor)	20-40	0.00	0.00	0.00	0.54	0.46

Appendix P-6 Mean Values of the Transition Probability Matrix for Group 6

PCDI			Future Condition				
			State 5 (Very	State 4 (Good)	State 3 (Fair)	State 2 (Poor)	State 1 (Very Poor)
			80-100	60-80	40-60	20-40	0-20
Present Condition	State 5 (Very Good)	80-100	0.60	0.41	0.00	0.00	0.00
	State 4 (Good)	60-80	0.00	0.60	0.40	0.00	0.00
	State 3 (Fair)	40-60	0.00	0.00	0.57	0.43	0.00
	State 2 (Poor)	20-40	0.00	0.00	0.00	0.56	0.45

Appendix P-7 Probability Density Functions of the Transition Probability Matrix for Group 1

PCDI			Future Condition				
			State 5 (Very Good)	State 4 (Good)	State 3 (Fair)	State 2 (Poor)	State 1 (Very Poor)
			80-100	60-80	40-60	20-40	0-20
Present Condition	State 5 (Very	80-100	Logistic(61.8894, 6.1067)	Extvalue(34.4106, 8.0356)	0	0	0
	State 4 (Good)	60-80	0	Logistic(63.5886, 5.124)	Extvalue(31.8461, 8.7867)	0	0
	State 3 (Fair)	40-60	0	0	Extvalue(53.245, 16.234)	Extvalue(32.914, 11.135)	0
	State 2 (Poor)	20-40	0	0	0	Extvalue(50.011, 18.525)	Invgauss(32.782, 88.173, RiskShift(8.1465))

Appendix P-8 Probability Density Functions of the Transition Probability Matrix for Group 2

PCDI			Future Condition				
			State 5 (Very Good)	State 4 (Good)	State 3 (Fair)	State 2 (Poor)	State 1 (Very Poor)
			80-100	60-80	40-60	20-40	0-20
Present Condition	State 5 (Very	80-100	Invgauss(65.537, 1936.362,	Extvalue(27.543, 11.645)	0	0	0
	State 4 (Good)	60-80	0	Logistic(66.1605, 5.046)	Extvalue(30.7631, 7.3418)	0	0
	State 3 (Fair)	40-60	0	0	Logistic(65.5273, 6.7212)	Expon(15.714, RiskShift(18.878))	0
	State 2 (Poor)	20-40	0	0	0	Extvalue(51.951, 17.285)	Extvalue(30.755, 15.127)

Appendix P-9 Probability Density Functions of the Transition Probability Matrix for Group 3

PCDI			Future Condition				
			State 5 (Very Good)	State 4 (Good)	State 3 (Fair)	State 2 (Poor)	State 1 (Very Poor)
			80-100	60-80	40-60	20-40	0-20
Present Condition	State 5 (Very	80-100	Extvalue(64.566, 10.563)	Logistic(30.1817, 6.8291)	0	0	0
	State 4 (Good)	60-80	0	Logistic(71.092, 5.4981)	Loglogistic(- 29.506, 58.062,	0	0
	State 3 (Fair)	40-60	0	0	Normal(67.286, 12.156)	Normal(32.714, 12.156)	0
	State 2 (Poor)	20-40	0	0	0	Invgauss(41.079, 231.049, RiskShift(22.492))	Weibull(16.569, 224.66, RiskShift(- 180.98))

Appendix P-10 Probability Density Functions of the Transition Probability Matrix for Group 4

PCDI			Future Condition				
			State 5 (Very Good)	State 4 (Good)	State 3 (Fair)	State 2 (Poor)	State 1 (Very
			80-100	60-80	40-60	20-40	0-20
Present Condition	State 5 (Very	80-100	Logistic(70.7909, 5.3217)	Logistic(30.242, 5.3157)	0	0	0
	State 4 (Good)	60-80	0	Loglogistic(2.2998, 69.511, 13.123)	Logistic(27.9599, 5.3236)	0	0
	State 3 (Fair)	40-60	0	0	Loglogistic(53.408, 13.111, 1.834)	Logistic(30.0252, 7.7433)	0
	State 2 (Poor)	20-40	0	0	0	BetaGeneral(0.35663, 0.31336, 43, 95)	Uniform(1, 61)

Appendix P-11 Probability Density Functions of the Transition Probability Matrix for Group 5

PCDI			Future Condition				
			State 5 (Very Good)	State 4 (Good)	State 3 (Fair)	State 2 (Poor)	State 1 (Very Poor)
			80-100	60-80	40-60	20-40	0-20
Present Condition	State 5 (Very	80-100	Logistic(58.4982, 8.8051)	Logistic(41.5018, 8.8051)	0	0	0
	State 4 (Good)	60-80	0	Normal(58.5, 13.682)	Normal(41.5, 13.682)	0	0
	State 3 (Fair)	40-60	0	0	Extvalue(49.029, 12.121)	Logistic(45.6976, 7.644)	0
	State 2 (Poor)	20-40	0	0	0	Logistic(53.5223, 8.602)	Logistic(46.4777, 8.602)

Appendix P-12 Probability Density Functions of the Transition Probability Matrix for Group 6

PCDI			Future Condition				
			State 5 (Very Good)	State 4 (Good)	State 3 (Fair)	State 2 (Poor)	State 1 (Very Poor)
			80-100	60-80	40-60	20-40	0-20
Present Condition	State 5 (Very	80-100	Weibull(6.9803, 76.872,	Extvalue(35.503, 10.211)	0	0	0
	State 4 (Good)	60-80	0	Logistic(60.2571, 6.1458)	Invgauss(139.76, 24505.13,	0	0
	State 3 (Fair)	40-60	0	0	Logistic(56.8472, 8.004)	Logistic(43.1528, 8.004)	0
	State 2 (Poor)	20-40	0	0	0	Logistic(56.2702, 9.6451)	Loglogistic(-33.127, 75.96, 7.9562)