

**INCORPORATION OF AUTOMATED SURFACE CONDITION
DATA IN PAVEMENT INFORMATION SYSTEMS**

by

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A Thesis

Submitted to the Faculty of Graduate Studies in Partial Fulfillment of the Requirements
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A Thesis/Practicum submitted to the Faculty of Graduate Studies of The University of

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Of

MASTER OF SCIENCE

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ABSTRACT

The purpose of this research is to provide recommendations for the collection and use of automated pavement surface condition data in pavement information systems and pavement management systems. Life cycle costs of the pavement network are minimized when decisions are based on a pavement management system and the concepts of asset management. Pavement condition data quality and consistency must be maintained as decisions made based on inadequate, unreliable, or inconsistent data can lead to costly errors.

Automated and manually collected data elements from two different road networks, the Winnipeg regional street network and the Manitoba highway network were utilized. The data elements used are roughness as represented by the International Roughness Index (IRI), rut depth, and surface distresses including cracking and joint spalling.

Analyses showed that automated data elements, IRI and rut depth, can be measured accurately with an inertial profiler equipped with a rut-bar. Analyses also showed that there was little agreement between cracking and spalling data measured manually and that measured at the speed of traffic with automated data collection equipment.

Attempts were made to use linear regression, maximum likelihood classification, and artificial neural networks to predict manual surface distress ratings. The analyses were unable to find significant relationships in the data to allow for the replacement of manual ratings with ratings predicted based on IRI and rut depth.

Specific attention was paid to analyzing and quantifying the factors that affect the roughness of urban road networks. The roughness of urban road networks is affected by several factors that are not present or are comparatively infrequent in rural pavement networks. The effect of false-grades, frequent intersections, and numerous railway crossings were analyzed. Each of these factors increases IRI and makes the roughness statistics less representative of the pavement condition; understanding these factors can make IRI statistics more meaningful.

The thesis also presents an IRI Information System, developed during the course of the research, and the use of geographic information systems to analyze and display pavement condition data. These systems are necessary to facilitate the analysis of the extensive datasets that result from automated data collection activities.

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NOMENCLATURE

AADT: Average Annual Daily Traffic
AASHTO: American Association of State Highway and Transportation Officials
ANN: Artificial Neural Network
APC: Asphalt over Portland Cement Concrete
ASTM: American Society for Testing and Materials
BBR: Benkelman Beam Rebound
CDA: Cumulative Difference Approach
C-SHRP: Canadian Strategic Highway Research Program
DOT: Department of Transportation
FCNY: Fund for the City of New York
FHWA: Federal Highway Administration (U.S.)
GIS: Geographic Information System
GPS: Global Positioning System
IRI: International Roughness Index
IRIIS: IRI Information System
JPCP: Jointed Plain Concrete Pavement
LTPP: Long Term Pavement Performance
LWP: Left Wheel Path
M & R: Maintenance and Rehabilitation
MLC: Maximum Likelihood Classification
MRI: Mean Roughness Index (average IRI of left and right wheel paths)
MTGS: Manitoba Transportation and Government Services
n: Sample size
NCHRP: National Cooperative Highway Research Program (U.S.)
PASER: Pavement Surface Evaluation Rating
PCC: Portland Cement Concrete
PMS: Pavement Management System
R²: Coefficient of Determination
RMS: Root-Mean-Square
RTRRMS: Response Type Road Roughness Measuring System
RWP: Right Wheel Path
SHT: Saskatchewan Highways and Transportation
TAC: Transportation Association of Canada
TRL: Transportation Research Laboratory

Chapter 1

INTRODUCTION

1.1 Background

In recent years, the use of pavement management systems by highway agencies has grown considerably. An operational pavement management system can: facilitate the efficient and cost-effective planning of maintenance and rehabilitation activities at both the network and project-levels, encourage decision making based on measured conditions, predicted future conditions, and life-cycle cost, and have the ability to generate alternate scenarios of pavement condition based on various levels of funding and different management approaches (Zimmerman and Peshkin, 2004).

Some of the essential data elements required for a pavement management system are the evaluation of pavement surface roughness, distresses, and structural capacity. Road roughness (or ride quality) is becoming the index of choice for characterizing the serviceability of a pavement. Several agencies use roughness to set priorities in the planning of road maintenance and repair, and to decide how the deterioration of specific roads should be corrected (Karamihas et al., 1999). Automated laser survey and video logging from vehicles travelling at normal traffic speeds have promising potential to provide the needed information in a productive and cost effective manner while protecting the operator from exposure to hazardous traffic conditions. These systems are being implemented by several transportation agencies and appear to provide advantages in the areas of safety, consistency of data quality, objectivity, and cost-effectiveness.

1.2 Research Objectives

The purpose of this research is to provide recommendations for the collection and use of automated pavement surface condition data; with the objectives of:

1. Maintaining data quality and consistency,
2. Optimizing data collection needs,
3. Quantifying and explaining the unique factors that affect the use of automated data for urban networks such as the Winnipeg regional street network, and
4. Demonstrating the linking and use of various data elements in a pavement information system through user-friendly software developed during the course of this research.

To accomplish these objectives, this research utilizes several pavement data elements from manual and automated data sources collected on two different road networks; the Winnipeg regional street network and the Manitoba highway network.

1.3 Organization of the Thesis

The thesis is organized as follows:

Chapter 1: Introduction

The remainder of Chapter 1 provides a review of the major components of pavement management systems (PMS). The focus of this research is the assessment of the quality and consistency of data provided to the PMS and the optimization of data collection needs. This background information on pavement management systems provides explanations of how the data can be utilized.

Chapter 2: Data Elements and Sources

This chapter provides explanations of the pavement condition data elements and data sources used throughout the research. The research utilizes pavement condition data from automated and manual pavement condition surveys of the Winnipeg regional street network and multi-year surveys of the Manitoba highway network. The automated pavement condition data elements include the International Roughness Index (IRI), rut depth, and surface distresses while the manual data elements include visually observed cracking, spalling, and general condition data.

Chapter 3: Data Quality and Consistency

Chapter 3 documents several analyses of data quality and consistency. Data quality refers to the accuracy of the data, and consistency refers to the agreement between different measures of pavement condition or the changes in reported condition from year-to-year.

Chapter 4: Optimizing Data Collection Needs

Chapter 4 documents attempts to minimize data collection needs while maintaining data quality and consistency. Optimizing data collection needs is important to reduce the cost and time required to collect data while ensuring that the data can still perform its necessary functions as part of a pavement management system.

Chapter 5: Urban Considerations for the Utilization of IRI

Laser-based roughness measurements are commonly used in the evaluation of rural road networks, and to a lesser extent the evaluation of urban road networks. There are several factors unique to urban street networks that can affect IRI statistics. This section seeks to explain factors unique to urban areas through the use of IRI data collected in Winnipeg and through simulations of different pavement conditions that influence IRI.

Chapter 6: Pavement Information Systems

This chapter documents a software package, IRIIS (IRI Information System), which was developed and used during the course of this research. IRIIS was used to perform quality control of automated pavement condition data in Chapter 3. This software also automated the process of dynamic segmentation, which was used to ensure that segments were homogeneous for the analysis of Chapter 4. The software also links automated pavement condition indicators to manual condition data, structural condition, traffic data, and construction history databases.

This chapter also demonstrates the benefits of the use of pavement condition data in a GIS (Geographic Information System). The use of a GIS enables the spatial analysis of pavement condition and facilitates the communication of pavement condition, budget needs, and predicted condition to engineers, elected officials, and the public.

Chapter 7: Conclusions and Recommendations

This chapter provides a very brief summary of the research, conclusions and recommendations for the collection and utilization of automated pavement condition data, and recommendations for further research in this field.

References and the appendices follow.

1.4 Pavement Management Systems

“Pavement management includes activities and decisions related to providing and maintaining pavements, many of which must be made with supporting information that should be generated from a pavement management system (PMS).” (ASTM, 2003) Pavement management systems function at two different levels, the network-level and the project-level. Network-level management, sometimes called the program-level, involves the making of key administrative decisions that affect programming and planning for the entire road network. Network-level management considers an agency’s short-term and long-term budget needs, present and future

overall network condition, and the identification and prioritization of potential projects. (Shahin, 1994)

Project-level management systems help to ensure that adequate consideration is given to alternative designs, construction, preservation, and maintenance of individual sections or roadways within the network. By comparing the benefits and costs associated with several alternative activities (design and maintenance), an optimum strategy is identified that will provide the desired benefits or service levels at the least cost over an analysis period (SHT, 2000). This research is primarily focused on the data needs and quality of data to be utilized at the network-level.

1.5 Network-Level Pavement Management

For the PMS, it is cost prohibitive to perform a detailed inspection of each pavement in the network. Instead, the pavement network must be inspected in less detail and more quickly (Shahin, 1994). Pavement management systems are composed of the following parts: pavement network definition, pavement condition surveys and ratings, pavement condition prediction, budget forecasting, and prioritization of projects.

1.5.1 Pavement Network Definition

The first step in the establishment of a PMS is identifying and defining the network. A pavement management engineer may be responsible for the management of many different facilities in an area. Separate networks are usually defined based on the network's primary function, funding source, and minimum operational standards. In the City of Winnipeg, roadway pavements are divided into two separate networks, the regional street network and the residential street network. The Winnipeg regional street network and the Manitoba highway network are the primary focus of this research.

Once the network is identified, it is defined by branches and sections or segments. A branch is a readily identifiable part of the network such as a given street. For the Manitoba highway network, branches are identified by control section number, control sections are defined so that they have uniform conditions with respect to traffic. Each branch is subdivided into one or more uniform sections or segments to perform the management functions at the network and project-levels. At the network-level data are collected, summarized, and analyzed for the segments. At the project-level an entire segment usually receives the same maintenance or rehabilitation

treatment. For the Manitoba highway network, the control sections are divided into subsections based on pavement condition.

The City of Winnipeg has developed segmenting guidelines for the identification of uniform segments of the regional street network (City of Winnipeg, 2002).

- The minimum length of individual segments is one block.
- A segment changes when the pavement type changes, except for short lengths of different pavement type.
- A segment continues until the pavement conditions change, except for localized defects.
- A segment continues until the street name changes.
- A segment continues until the width of the street changes. This includes changes from divided to undivided roadways or vice versa. Each direction of a divided street is defined as an individual segment.
- A segment will not cross a street with a higher classification.
- Intersections are included in the streets in the following order: the intersection is included with the street with the higher functional classification, when two streets with the same classification intersect; the intersection is included with the street with the same surface type. If surface type is the same, the intersection is included with the street with the same condition.

1.5.2 Pavement Condition Surveys and Ratings

An essential feature of a PMS is the ability to determine both the current condition of the pavement network and to predict its future condition. To predict condition reliably, an objective, repeatable rating system for identifying the pavement's condition must be used. One of the primary objectives of this research is the assessment of the quality and consistency of data collected with automated pavement condition assessment vehicles.

The City of Winnipeg has a well-defined rating system based on visual inspections of pavement conditions. Quality control (QC) and quality assurance (QA) are essential elements of the rating system. The City of Winnipeg's QC and QA procedures include:

- Training and field evaluation of the Raters in the performance of the surface condition rating.

- Checking data for obvious errors.
- Ensuring that data collection is done by two people, a rater and a recorder.
- Developing training modules and visual aids to enhance training.
- Standardizing training for all Raters.
- Carrying out sensitivity analyses of surface condition data to determine the inherent variability of various distress measurements and determining the degree to which the natural variability of the data will affect decisions based on the data.

Surface condition of the network is the most important input to the PMS; however, it is also important to determine the structural condition of the pavement network. Assessing the structural condition of pavements is not the focus of this research so it is mentioned only briefly. At the network-level, non-destructive testing is important for the definition of the pavement management sections. Without non-destructive testing there is a great risk of defining sections that appear to be uniform based on observed distress but in reality are not uniform. The grouping of structurally similar sections is important for the development of meaningful pavement condition prediction models. Non-destructive testing can also be used for the establishment of load limits, determining the remaining structural life, and overlay design. (Shahin, 1994)

1.5.3 Pavement Condition Prediction

Condition prediction models are used at both the network and project-levels to analyze the condition and determine maintenance and rehabilitation requirements. At the network-level condition prediction models are used for condition forecasting, budget planning, inspection scheduling, and work planning. One of the uses of prediction models is to study the effect of various budget levels on future pavement condition. (Shahin, 1994) Many of the prediction models are based-on constrained regression, probability distribution, and Markovian transition matrices.

The condition prediction models can be based on IRI, rut depth, or a composite index based on surface distresses such as the pavement condition index (PCI). A road with a PCI of 100 is considered to be in perfect condition, while a road with a PCI of 0 has failed. Models used by the City of Winnipeg PMS incorporate visual ratings of general condition, cracking, and joint spalling rather than the formally defined PCI. The deterioration models described in this chapter use PCI for discussion purposes, however it is important to note that any relevant pavement condition indicator could be used.

Constrained Regression Models

Constrained regression models minimize the error between empirical data and a model while incorporating constraints based on engineering judgement or an expert knowledge base. Figure 1.1 compares examples of constrained and unconstrained fourth-degree polynomial deterioration curves for a set of hypothetical PCI data. The constraints or engineering judgement applied in this model are that the pavement was in perfect condition, $PCI = 100$, at age zero, and that the pavement condition only improves after work has been performed (not spontaneously).

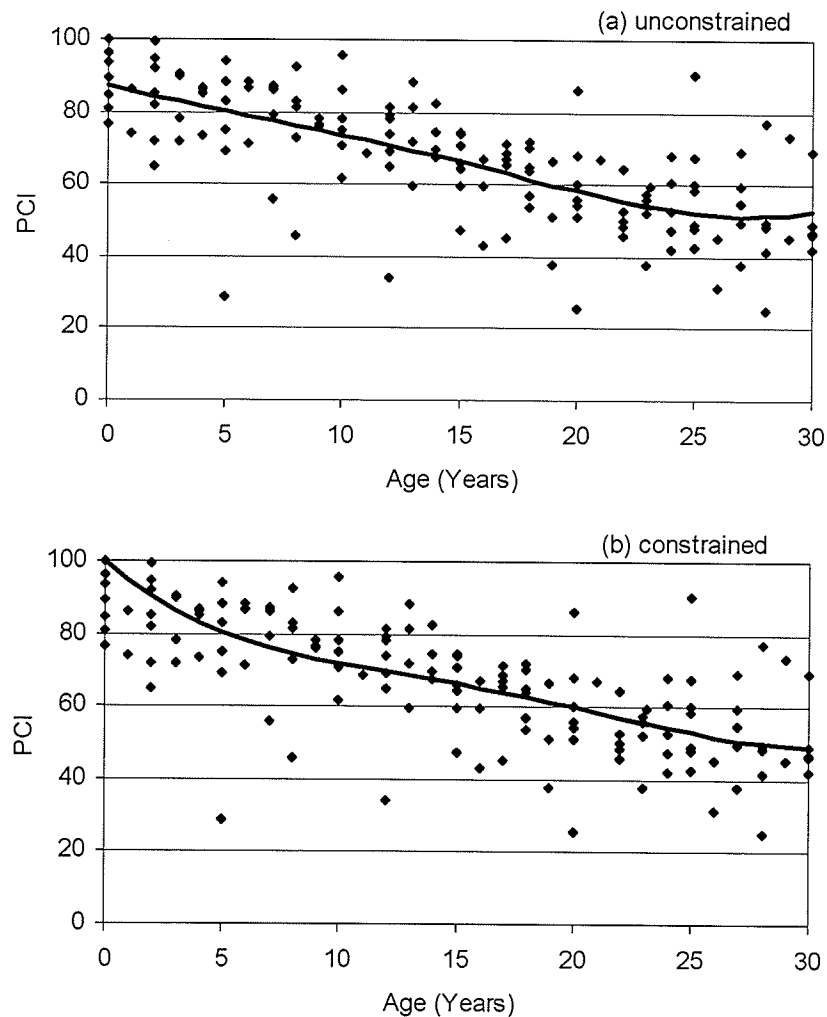


Figure 1.1: Example of unconstrained and constrained fourth-degree deterioration curves

Probability Distribution

A pavement condition measure such as IRI, rut depth, or PCI can be used to develop cumulative distribution functions of the probability that a pavement condition is better or worse than a

specified value. Figure 1.2 shows an example of cumulative distribution function of PCI at different times in pavement life. Cumulative distributions can be used to develop “survivor curves” which forecast the percentage of pavement remaining with condition greater than a specified value at any age.

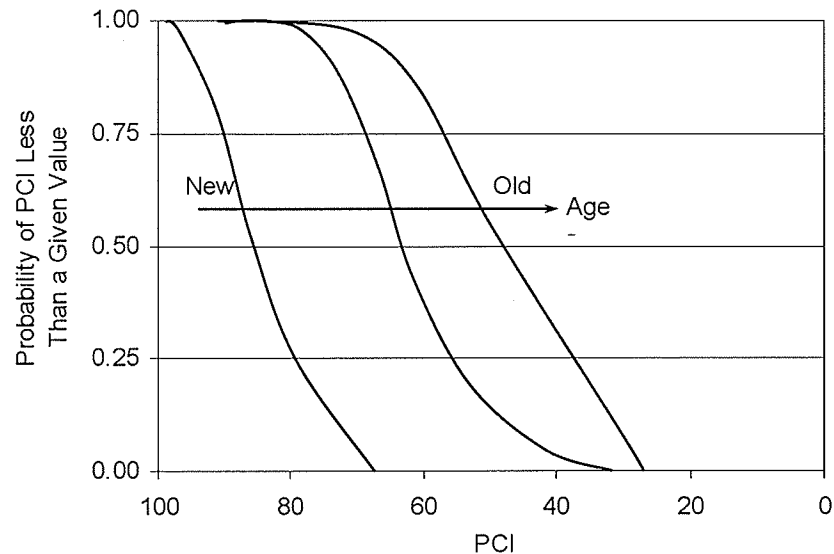


Figure 1.2: Cumulative distribution function of PCI at different times in pavement life (Shahin, 1994)

Markovian Transition Matrices

The Markovian technique is a form of probabilistic prediction. A pavement condition measure, such as IRI, rut depth, or PCI, is divided into several condition states. The technique requires the development of a probability transition matrix to predict the way pavements deteriorate with time. To simplify the development of these matrices it is usually assumed that the pavement condition will either remain the same from year-to-year or decrease by only one condition state. Empirical data and the experience of experts are used to assign the probability that the pavement will remain in its present state or deteriorate to the next state within one year.

1.5.4 Budget Forecasting

An annual budget must be established to maintain the pavement above a minimum operational standard or condition. It is important to analyze different scenarios when conducting budget forecasting. It is necessary to predict the impact on the budget of increasing or decreasing the

minimum operational standard or the impact that changes in the annual budget will have on the condition of the pavement network.

The cost for each segment is estimated by forecasting the year at which the segment will deteriorate to the minimum allowable condition and multiplying an estimated unit cost by the segment's area. Two types of budget are usually required, one for local maintenance and rehabilitation (M & R), and another for annual and long-range work plans.

Localized M & R

The localized M & R program is based on the existing pavement distress and the agency's policy. Most agencies have different M & R policies for pavements with different condition. Pavements in good condition should receive comprehensive localized M & R as a preventive measure. Applying the same policy to heavily deteriorated pavements will not be cost effective. Heavily damaged pavements require major reconstruction and receive little benefit from preventive treatments. They should only receive the localized M & R needed to keep the pavement operational in a safe condition. (Shahin, 1994)

The City of Winnipeg has four localized M & R policies. New pavements with no distress receive no maintenance, segments in good condition receive maintenance such as crack sealing and small patches, pavements in fair condition require significant rehabilitation such as joint repairs or overlay, and pavements in poor condition receive only safety maintenance since they usually require reconstruction. (City of Winnipeg, 2002)

Annual and Long-Range Work Plans

The critical PCI procedure is often used for annual and long-range work plans. The critical PCI procedure is based on the concept that it is more economical to maintain pavements before they deteriorate to a critical value. IRI, rut depth, or another measure of cracking and joint condition can also be used as an alternative to the PCI. The procedure was developed by studying results from network optimization analysis and by performing many life-cycle cost analyses on many projects. (Shahin, 1994)

The critical PCI is defined as the PCI at which the rate of loss of condition increases with time. The cost of applying localized preventive M & R increases significantly at this time. Figure 1.3 shows an example of the critical PCI range. The applicable treatment is selected based on the relationship of the segment's actual or predicted PCI to the critical PCI. Generally, pavements

with PCI above critical receive preventive M & R to keep their condition from deteriorating, while those with PCI less than critical need major M & R or reconstruction if adequate funds are available, otherwise they receive maintenance for safety only. The exception is segments with PCI above critical and structural inadequacies; these segments usually need major M & R to correct structural defects. If adequate funds are not available for major M & R, these segments usually require preventive maintenance to keep the surface condition from further deteriorating.

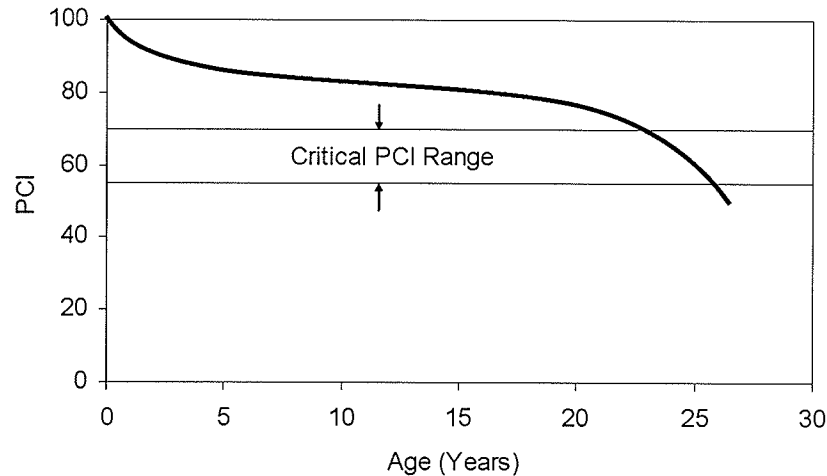


Figure 1.3: Typical deterioration curve showing critical PCI range (Shahin, 1994)

1.5.5 Prioritization (Shahin, 1994)

The factors used to assign M & R priorities include the type of M & R, segment use (traffic), pavement rank, and PCI value. There are three steps in the setting of priorities

Step1: Divide M & R into the following types:

1. Localized safety only,
2. Localized preventive,
3. Global preventive, treatment such as chip seal or thin overlay applied to the entire segment,
4. Major M & R with PCI at or above critical,
5. Major M & R with PCI below critical.

Step 2: M & R types with the lowest numbers from Step 1 are given the highest priority. For M & R types 1 through 3, priorities are assigned within each type based on the segment PCI; the lower PCI receives higher priority.

Step 3: For major M & R types 4 and 5, priorities are assigned based on user-defined criteria. These criteria are based on the segment's use (traffic) and pavement rank (priority based on the importance of the segment to the network). Within each priority group, those segments with the lower PCI receive higher priority.

1.6 City of Winnipeg Pavement Management System

Street surface condition information is the foundation of the pavement management system. The PMS makes use of visual ratings of surface condition that are reported as general condition scores, cracking scores, and joint spalling scores. The visual inspection of the regional street network is time consuming and costly and has the potential to be hazardous to the rating crews. On the heavily trafficked regional street network ratings crews keep off the street, maintain a high-degree of visibility, face oncoming traffic, and watch out for each other; yet it is still unnerving to be in close proximity to large volumes of high-speed traffic. The visual inspection of the regional street network took four rating crews (eight raters) six to eight weeks while a survey with automated equipment can be conducted in just a few days.

Therefore, the City of Winnipeg is examining the potential for the replacement of the visual rating of regional streets with automated surveys operating at the speed of traffic. To allow for the replacement of the visual rating system, the automated data must be of high-quality and capable of providing information comparable to the manually collected data. This thesis documents an analysis of the quality and consistency of automated data, attempts to relate the automated data to manual ratings, and distinguish factors that influence automated data elements in urban areas.

Chapter 2

DATA ELEMENTS AND SOURCES

2.1 Introduction

This research utilizes several pavement condition data elements from two different road networks, the Winnipeg regional street network and the Manitoba highway network. The data elements used are roughness as represented by the International Roughness Index (IRI), rut depth, and surface distresses including cracking and joint spalling.

The sources of data in the City of Winnipeg include automated data collected by a consultant in the fall of 2001 under a pilot testing program, data collected manually by the University of Manitoba and the City of Winnipeg on selected sections in the summer of 2002, and parallel automated and manual surveys of the regional street network conducted by another consultant and the City of Winnipeg in the summer of 2002.

The sources of data for the Manitoba highway network are annual surveys conducted by a consultant from 1999 to 2003 and databases of traffic, pavement structure, and construction history maintained by Manitoba Transportation and Government Services (MTGS).

2.2 Data Elements

This research utilizes several different measures of pavement condition including IRI, rut depth, and surface distresses, including cracking and joint spalling.

2.2.1 International Roughness Index

Roughness has been defined as, "a distortion of the pavement surface that contributes to an undesirable or uncomfortable ride." (TAC, 1997) The distortion of the pavement may have been present in the original construction or the result of deterioration due to traffic and environmental conditions. Roughness is a key indicator of pavement riding comfort and safety (Shahin, 1994).

Rough roads increase passenger discomfort, vehicle operating cost, and the potential for vehicle damage while decreasing vehicle speed. A literature review of pavement roughness effects on the road user by Papagiannakis et al. (1999) found that vehicle maintenance/repair costs, both in parts and labour, are significantly affected by pavement roughness. The consensus in the literature is that tire cost is likely to be significantly affected by pavement roughness in addition to other factors such as pavement texture, operating conditions, and hazards. There is disagreement

among empirical studies on the effect of roughness of fuel consumption for paved roads and no clear trend between roughness and oil consumption. There is no agreement in the reviewed literature on the effect of pavement roughness on the mileage-life of vehicles and hence on vehicle depreciation.

Roughness measurement can be used in pavement management at both the network-level and the project-level. At the network-level, roughness measurements are useful for dividing the network into homogeneous sections, establishing limits for acceptable pavement condition, and determining maintenance and rehabilitation priorities. Several agencies use roughness in combination with other condition measures such as rutting and surface distress. At the project-level, roughness measurements are useful for locating critical areas for repair and for construction quality control. All Canadian provincial highway agencies employ roughness or smoothness (the lack of roughness) specifications for new construction (C-SHRP, 1999).

Description of the IRI

The International Roughness Index is a roughness statistic that is calculated by simulating the motion of a linear “quarter-car” model, shown in Figure 2.1. The IRI is defined as the accumulated suspension motion divided by the distance travelled. The IRI is calculated using an algorithm that moves the model at a constant 80 km/h over the measured pavement profile. It is important to note that while the pavement profile can be measured at any speed, the simulation is always run at 80 km/h. Simulations at other speeds do not yield IRI.

The quarter-car model includes a sprung mass to model the body, an unsprung mass to model the axle, a damper and spring to model the suspension, and a spring to model the tire. The damper rate, spring rate, and unsprung mass are defined as ratios of the sprung mass.

The IRI has been reported to be, (a) relevant as an indicator of pavement serviceability, (b) independent of the particular equipment used to measure it, (c) internationally and geographically transferable, and (d) time stable. (Hajek, et al., 1998) The IRI has these desirable properties because it is based on a measured pavement surface profile and not on a measuring system or method. Response type road roughness measuring systems (RTRRMS) and subjective ratings are less repeatable. “Response-type indices are vehicle dependent and are not repeatable, even when the same vehicle is used, due to a change in the vehicle’s characteristics over time.” (Shahin, 1994)

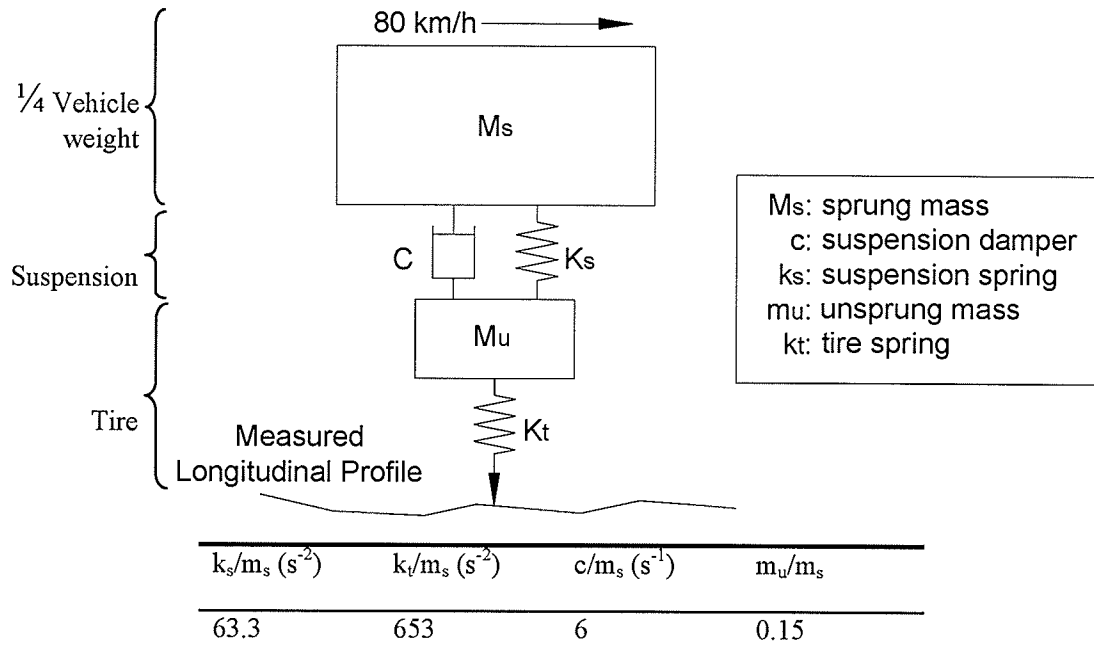


Figure 2.1: The IRI quarter-car model (Karamihas et al.: 1999)

The IRI is sensitive to wave numbers between 0.033 and 0.75 cycles per meter, as shown in Figure 2.2, which corresponds to wavelengths between 30 and 1.3 m (wavelength = 1/wave number). However, there is still some sensitivity to wave numbers outside this range. The IRI has maximum sensitivity to sinusoids with wave numbers near 0.065 cycles/m and 0.42 cycles/m, corresponding to wavelengths of 15 m and 2.4 m, respectively.

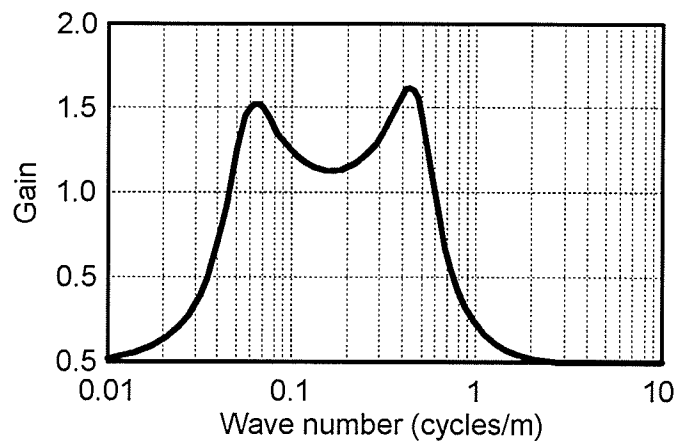


Figure 2.2: Sensitivity of the IRI to wave number (Sayers and Karamihas, 1998)

Calculation of the IRI

The preceding discussion describes what the IRI is intended to simulate, the IRI itself is defined as a specific mathematical transform of a true profile. The IRI is calculated for a single profile, generally the left or right wheel path; however, any line along a road surface can be used to calculate the IRI. When the IRI from the left and right wheel paths are averaged, the result is often reported as MRI (mean roughness index).

The IRI is calculated with a computer program that performs several functions. The measured profile is first filtered using a moving average with a base length of 250 mm. This filter is not applied for profiles with a sampling interval larger than 167 mm. Secondly, the profile is further filtered using an algorithm, found in Appendix F of World Bank Technical Paper Number 45, with the quarter car parameters shown in Figure 2.1 (Sayers et al., 1986a). The results of the second filter represent the suspension motion of the simulated quarter-car. The total suspension motion is summed and divided by the profile length to give IRI in units of slope, commonly in inches/mile or m/km.

2.2.2 Rut Depth

Rutting is the depression of the pavement surface in the wheel paths. Rutting is attributable to the permanent deformation of the pavement due to traffic loads. Significant rutting can lead to major structural failures of the pavement (Shahin, 1994). Deep rutting is a safety issue for drivers manoeuvring vehicles across their lanes (Chen et al., 2001). Deep ruts can hold water and contribute to hydroplaning. Indeed, in many instances, ruts are more visible after a rainfall when the wheel paths are filled with water.

The most important types of road damage due to heavy vehicles are fatigue cracking and rutting (Cebon, 1999). Rut depth is one of the primary indicators used in Texas DOT's pavement management information system (Chen et al., 2001). Rutting alone can trigger the decision to rehabilitate or reconstruct a pavement.

Rutting can be measured by the placing of a straightedge across a pavement and recording the rut depth as the maximum distance between the straightedge and the pavement. Alternatively, a transverse profile can be measured and the rut depth can be calculated with the simulation of a straightedge, as shown in Figure 2.3. A straightedge of 1.8 m is used for the measurement and calculation of rut depth throughout this research; for manually collected data an actual physical straightedge is used, while a simulated straightedge is used for data collected with the automated

data collection vehicle. Rut depths measured using shorter straightedges, such as 1.2 m in length, have demonstrated a lack of repeatability (Simpson, 1999). The lack of repeatability for shorter straightedges is caused by the difficulty of determining where to place the straightedge to yield the largest rut depth.

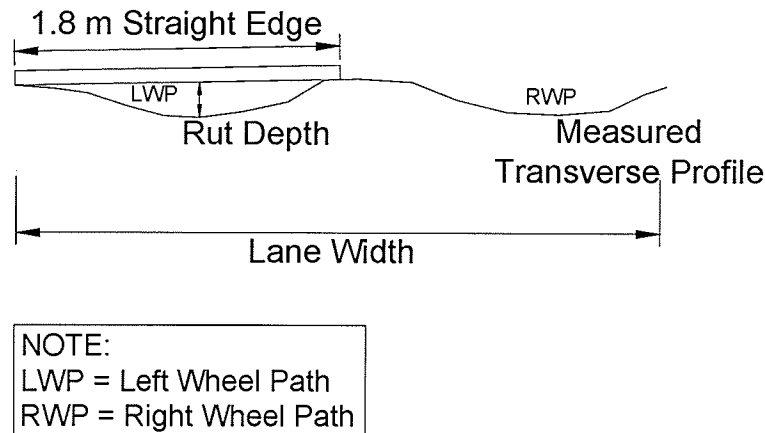


Figure 2.3: Simulation of a 1.8 m straightedge

2.2.3 Cracking

Cracking can be caused by the repetition of heavy traffic loads, climatic conditions, and moisture infiltration or lack of drainage.

Asphalt Concrete Pavements

Fatigue cracking is the failure of the asphalt concrete surface under repeated traffic loading. Cracking begins at the bottom of the asphalt surface, where the tensile strain is the highest under a wheel load. The cracks then propagate to the surface as a series of longitudinal cracks. As traffic loading progresses, the cracks grow and connect, forming many sharp-sided pieces that develop a pattern resembling the skin of an alligator. At this stage the distress is called alligator cracking. Alligator cracking is considered a major structural distress and is usually accompanied by rutting. (Shahin, 1994)

Transverse cracks are approximately perpendicular to the roadway centerline. Transverse cracks may be caused by surface shrinkage due to low temperatures, hardening of the asphalt, or cracks in underlying pavement layers, such as concrete slabs, for composite pavements (Northwest Pavement Management Systems Users Group and Kay, 1992). When transverse cracks occur at

the location of joints of an underlying Portland cement concrete (PCC) layer, they are often referred to as joint reflection cracks (Shahin, 1994).

In addition to fatigue cracks, cracks known as longitudinal cracks can form parallel to the roadway centerline. Like transverse cracks they may be caused by surface shrinkage due to temperature cycles, frost action, reflection cracking, or poorly constructed paving lane joints (Shahin, 1994).

Edge cracks run parallel to and are usually within 0.6 m of the edge of the pavement. This distress can be caused by frost-weakened base or subgrade near the edge of the pavement; edge cracking is often accelerated by traffic loading (Shahin, 1994 and ASTM, 2000).

Crack severity and extent are generally recorded along with the type of cracks. Crack severity is often based on crack width or the degree to which an alligator pattern has developed for that type of cracking. Extent is usually recorded as the length of cracking or as an area for alligator cracks.

Portland Cement Concrete (PCC) Pavements

Longitudinal, transverse, and diagonal cracks are usually caused by a combination of repeated traffic loading, thermal gradient curling stresses, and repeated moisture loading; which causes shrinkage and swelling of the slabs (Shahin, 1994). Low severity cracks are usually related to warp or friction and are not considered major structural deficiencies. For these minor cracks aggregate interlock is generally adequate to facilitate load transfer across the crack (Jensen and Hansen, 2001). Medium and high severity cracks are usually working cracks and are considered major structural deficiencies.

Hairline cracks that extend only a few feet are usually shrinkage cracks. They form during the setting and curing of the concrete and usually do not extend through the depth of the slab.

Durability ("D") cracking is caused by the freeze-thaw of the large aggregate, which gradually breaks down the concrete. This type of cracking usually appears as a pattern of cracks running parallel and close to another crack or a joint in the concrete, typically at the corners of the slabs. This type of distress may eventually lead to disintegration of the entire slab.

Corner breaks and punchouts can also occur on PCC pavements. A corner break is a crack that has progressed to the extent that a corner of the slab has broken off. The crack extends through the entire thickness of the slab. A punchout is a localized distress where a portion of the slab has

broken into pieces. Repeated heavy loads, inadequate slab thickness, or a loss of foundation support can cause corner breaks and punchouts.

As with asphalt pavements, the severity and extent of the cracks is usually recorded along with the type of cracks. Severity is based on the crack width while extent is based on the length or area that the cracking covers.

2.2.4 Joint Spalling

PCC and composite APC (asphalt over Portland Cement Concrete) pavements are often subject to spalling at the joints. Spalling is the breakdown of the slab edges near the joint, usually within 0.6 m. Spalling can be caused by excessive stresses at the joint caused by traffic or by the infiltration of incompressible materials at the joint causing bucking. Freeze-thaw action at a joint can also cause spalling. Figure 2.4 shows a spalled joint. A joint spall does not usually extend through the entire slab, as a corner break does; instead it usually intersects the joint at an angle. (Shahin, 1994)



Figure 2.4: A spalled joint filled with patching material

As with surface cracking, the severity and extent of spalling is recorded. The severity is usually defined in terms of the size of the spall and whether pieces of the slab have become loose or are missing. The extent is usually defined in terms of how many slabs have spalled joints or the percentage of spalled joints in a segment.

2.3 Data Sources

This thesis utilizes data from several sources for two different roadway networks, the City of Winnipeg regional street network, and the Manitoba highway network.

2.3.1 City of Winnipeg Regional Street Network

The City of Winnipeg regional street network comprises all arterial streets and several high-volume collector streets within the city limits. This 626 km street network utilizes three different pavement types. The most common pavement type is APC, which accounts for 72% of the network. APC is a composite pavement in which the original concrete pavement has been overlaid with asphalt concrete. Portland Cement Concrete makes up an additional 22% of the regional network with the remaining 6% being asphalt concrete. This thesis utilizes data collected on the APC and PCC segments; typical pavement structure is shown in Figure 2.5.

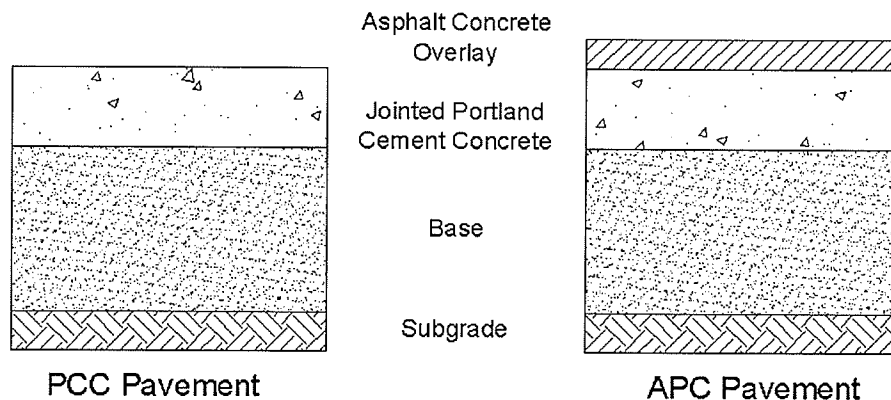


Figure 2.5: Typical APC and PCC Pavement Structure

The City of Winnipeg datasets include automated data collected by a consultant in the fall of 2001 under a pilot testing program, data collected manually by the University of Manitoba and the City of Winnipeg on selected sections in the summer of 2002, and parallel automated and manual surveys of the regional street network conducted by another consultant and the City of Winnipeg in the summer of 2002.

2.3.1.1 Pilot Testing Program: Automated Data

A consultant conducted Road profile and distress surveys of 108 lane-km of arterial and collector streets in the fall of 2001. An inertial profiler, shown in Figure 2.6, was used to collect the profile for calculation of the IRI data and to collect the rut depth data. The operator of the inertial profiler uses a special event keyboard to collect distress data.

The inertial profiler measures pavement elevations relative to an inertial frame of reference at the same speed as other traffic on the highway. The inertial profiler is a vehicle that contains three essential components; (1) accelerometers, (2) laser height sensors, and (3) a distance measuring unit. Most modern profilers are also equipped with a differential GPS receiver for verifying vehicle position. The accelerometers measure the vertical motion of the vehicle; this signal is integrated twice to find the elevation path followed by the vehicle. The distance from the vehicle to the road surface is measured with noncontacting sensors, usually lasers, optical, or infrared transducers. The road profile is obtained by subtracting the distance to the road from the elevation of the vehicle. (Sayers et al., 1986b)



Figure 2.6: Inertial profiling vehicle

The Inertial profiler qualifies as an ASTM Class 2 profiling device. Table 2.1 summarizes the four classes of profiling devices. Class 2 devices are profiling devices that measure non-biased profile elevations. The Dipstick, rod and level, and Transportation Research Laboratory (TRL) Profilometer qualify as Class 1 devices, but lack the productivity and cost effectiveness realized in Class 2 devices (TAC, 1997). Class 3 devices estimate the IRI from correlations; most devices in this category are response-type devices. Roughness measured with these devices is converted to the IRI using a calibration equation that is obtained experimentally for that specific RTRRMS. Class 4 methods of roughness measurement are subjective ratings and uncalibrated measures. (Sayers et al., 1986b)

Table 2.1: Roughness Measurement Methods (TAC, 1997)

Class of Roughness Measurement	Description	Examples
Class 1	Precision Profiles	- Dipstick - rod and level - TRL Profilometer
Class 2	Other Profilometric Methods	- Inertial Profilers
Class 3	Response Type Devices	- K.J. Law Model 8300 Roughness Surveyor - Mays Ride Meter
Class 4	Subjective Ratings	- Riding Comfort Index (from panel ratings) - Present Serviceability Index (from panel ratings) - Measures not correlated to IRI

The inertial profiler also collects a transverse profile of the lane with the use of eleven laser sensors located on a rut-bar mounted on the front bumper of the vehicle. Rut depth is calculated for each wheel path using an eleven-point algorithm that simulates a straightedge (EBA, 2001a). In an analysis of rutting trends at C-SHRP LTPP test sites, EBA (2000), found that rut depths calculated with an eleven-point algorithm are equal-to or less than those calculated by the simulation of a 1.8 m straightedge, when the transverse profile was sampled at 50 mm intervals.

2.3.1.2 Pilot Testing Program: Manually Collected Data

The pilot testing program also involved the manual data collection of IRI, rut depth, and cracking data on three sections that were surveyed with the automated data collection vehicle. Time constraints and limited availability of traffic control restricted the number of sections that could be manually surveyed. The manual survey, conducted by the University of Manitoba and the City of Winnipeg, took place in the summer of 2002.

Manually collected data forms the backbone of the City of Winnipeg asset management system. Rating crews visually examine each predetermined segment and assign it a general condition. They also conduct a detailed survey of a representative gauging area of each segment to determine cracking and joint condition. (City of Winnipeg, 2002)

IRI and Rut Depth

Manual data collection of profile and rutting data was conducted on July 8, 2002 for the segments on Fermor and Grant. Data was collected on July 12, 2002 for the segment on St. Mary's.

Profile data was collected with a Dipstick, shown in Figure 2.7, in the right wheel path of each segment. The Dipstick is a device that is used to accurately measure profiles; it qualifies as a Class 1 ASTM profiling device. Class 1 profiling devices are precision profilers that have negligible measurement error with an accuracy of $\pm 2\%$ for a 320 m long section (TAC, 1997). The Dipstick is an instrument with two feet separated by exactly 300 mm. The difference in elevation between the two feet is shown on the display on top of the dipstick. To obtain a profile the difference in elevation between the two feet are accumulated as the Dipstick is "walked" along the desired path. Table 2.2 summarizes the manually collected IRI and rut depth data.

Table 2.2: Summary of Data Collected

Segment	Segment Length (m)	Dipstick IRI (m/km)	Average Rut Depth LWP (mm)	Average Rut Depth RWP (mm)
Fermor	270	2.97	14	11
Grant	500	4.02	5	4
St. Mary's	345	4.08	1	1

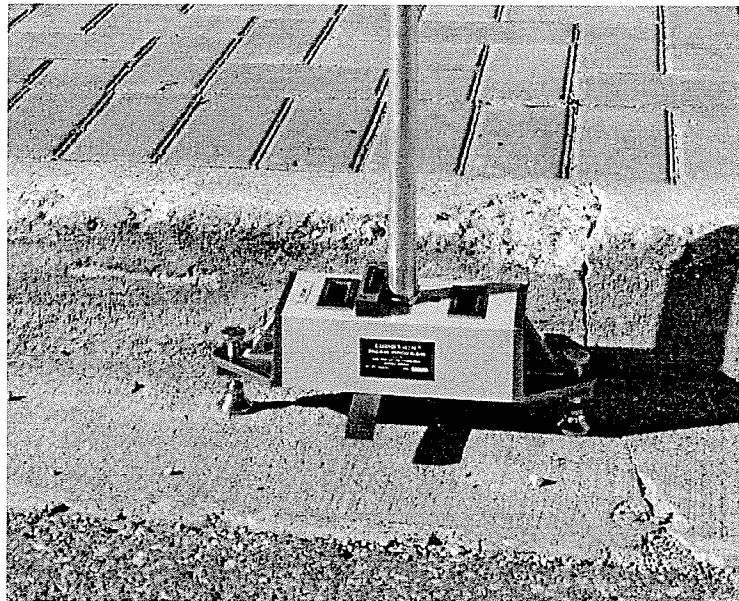


Figure 2.7: The Dipstick device used for manual profile measurement

General Condition

Rating crews assign a rating for each segment based on its general condition. The four categories used are new, good, fair, and poor. New streets are those that are new or were recently overlaid. Good streets usually require minor maintenance, Fair streets usually require major maintenance, and Poor streets are those that need reconstruction and are thus only maintained to keep them safe for the travelling public, not to prevent further deterioration.

For the collection of cracking and spalling data rating crews select a gauging area that is representative of the prevailing conditions of the majority of the segment. At this stage, the rating crew also verifies that the segmentation is valid. The gauging area is chosen so that items such as railway crossings, manholes, and utility patches are excluded unless they are prevalent over the segment. The rating crew then conducts a detailed survey of 10 slabs per lane in the representative gauging area. That is, 20 slabs are surveyed for a two-lane road and 30 slabs are surveyed for a three-lane road.

Cracking Data

The rating crew collects data regarding the number of cracks in each slab, the severity of the cracks, and the number of cracked slabs in the gauging area. Cracks that extend across the full width or length of the slab are considered to be working cracks and are included. Shrinkage cracks are not included in the rating.

Each slab is assigned a crack type based on the number of pieces the slab is broken into and a crack severity based on the size of the cracks and the condition of the sealant. Table 2.3 provides definitions of each crack type and severity. For example, a slab with two unsealed cracks that average a width of 20 mm has a cracking label of BS, branch type with slight severity.

The extent of cracking for a segment is based on the number of cracked slabs in the segment as defined in Table 2.4. Each segment then receives a cracking score based on the predominant distress and the extent. For example, a segment in which 60% of the slabs are cracked and most of the cracked slabs have two or three cracks of extreme severity has a cracking score of BX3.

Table 2.3: Definitions of Crack Type and Severity

Crack Type	Definition	Crack Severity	Definition
N (none)	No Cracking	N (new)	Cracks that are sealed with 75% or more of the sealant in good condition
R (random)	The slab has cracked into 2 pieces	S (slight)	Cracks are not sealed or more than 25% of the sealant is damaged. Width < 25 mm
B (branch)	The slab has cracked into 3 or 4 pieces	M (moderate)	Cracks are not sealed or more than 25% of the sealant is damaged. 25 < Width < 40 mm
P (pattern)	The slab has cracked into 5 or more pieces	X (extreme)	Fully developed cracks are not sealed or more than 25% of the sealant is damaged. Vertical or horizontal displacement > 40 mm

Table 2.4: Crack Extent Definitions

Extent	Lower %	Upper %
0	0	<= 5
1	> 5	<= 20
2	> 20	<= 35
3	> 35	

Slabs with a rating of PX are considered to have failed. As part of the crack ratings, the city maintains data regarding the percentage of slabs with PX ratings, the most extreme crack rating.

Spalling Data

Spalling occurs at the transverse joints of PCC and APC streets. Spalling can be caused by traffic, incompressible materials entering a joint causing it to buckle, or by freeze/thaw action. Spalling data is collected for 10 sets of joints in the gauging area that the rating crew identified while surveying cracking data. Similar to cracking data where the condition of each slab was recorded, the rating crew reports the severity of each joint as defined in Table 2.5.

Table 2.5: Spalling Severity Definitions

Joint Severity	Definition
N (new)	Joints are tight and may have a few minor aggregate pop-outs adjacent to the joint
S (slight)	Parallel cracks adjacent to the joint with some of the cracks forming small pieces, which are tight. Or aggregate pop-outs adjacent to the joint for more than 25% of its length
M (moderate)	Cracks have formed into a pattern and the pieces are loose or missing. The spall is less than 25% of the joint length
X (extreme)	Pieces are extremely loose or missing and the full depth of the spall can be seen. The spall is more than 25% of the joint length

The rating crew then determines the spalling extent based on the number of joints that have spalled. The definitions of spalling extent are shown in Table 2.6. Each segment then receives a joint score based on the predominant severity and the extent. For example, a segment in which 15% of the joints have some type of spalling and where the predominant spall has a slight severity has a joint score of S1.

Table 2.6: Spalling Extent Definitions

Extent	Lower %	Upper %
0	0	<= 5
1	> 5	<= 20
2	> 20	<= 40
3	> 40	

As part of the spall ratings, the city maintains ratings regarding the number of joints with an X rating, the most severe spalling score.

2.3.1.3 Network-Wide Survey: Automated Data

A consultant surveyed the Winnipeg regional street network in August of 2002. Automated data was collected for one lane on each predefined segment. The consultant collected IRI, rut depth, cracking, and faulting data with an automated survey vehicle. The operator also manually

collected patching, pothole, transverse spalling, and slab failure data with an event keyboard. Each segment was assigned a subjective and automated PASER (Pavement Surface Evaluation Rating) value based on its condition.

An inertial profiler was used to collect a longitudinal profile of each wheel path. Profile elevations were then processed and summarized as IRI, which was reported at 20 m intervals.

The same survey vehicle was used to collect rut depth data for each wheel path. The rutting index used was a simulated 1.8 m straightedge. Rut depth was mathematically calculated from a measured transverse profile and reported at the same 20 m intervals as IRI.

Other distress measures were collected and summarized and reported for each predetermined segment. This is in contrast to the IRI and rut depth, which were reported at 20 m intervals throughout the regional street network. Some of these distresses were automatically collected with the laser-based system and others were collected by the operator with an event keyboard.

Those measures collected automatically include faulting, longitudinal cracking, transverse cracking, block cracking, alligator cracking, patching, potholes, and longitudinal spalling. These measures, with the exception of potholes and longitudinal spalling are reported along with a severity of low, medium, or high. Transverse spalling and slab failure data were collected with the event keyboard. The final two measures are designed to be compatible with the City of Winnipeg's Surface Condition Rating System.

The data includes an automated PASER (pavement surface evaluation rating) index based on the distresses collected automatically with the laser-based survey and a subjective PASER index based on the distresses collected with the event keyboard. The PASER index ranges from 1 to 10 with one being failed condition and ten being a newly constructed pavement. Tables 2.7 and 2.8 show how an idealized treatment theoretically relates to the PASER index for APC and PCC pavements. Prior to data collection, the consultant and the City of Winnipeg discussed these definitions. Appendix A shows detailed tables of the amount of each distress that could be expected at each rating level.

Table 2.7: PASER Index for APC Pavement

PASER Index	Theoretical Action
1, 2	Complete Reconstruction
3, 4	Structural Improvement (overlay or recycling)
5, 6	Preservative Treatment (sealcoating)
7, 8	Routine Maintenance (cracksealing, minor patching)
9, 10	No Maintenance Required

Table 2.8: PASER Index for PCC Pavement

PASER Index	Theoretical Action
1, 2	Complete Reconstruction
3, 4	Extensive Slab or Joint Rehabilitation
5, 6	Routine Maintenance (surface repair or partial depth patching)
7, 8	Preventative Maintenance (cracksealing, jointsealing)
9, 10	No Maintenance Required

2.3.1.4 Network-Wide Survey: Manual Data

A parallel manual survey of the regional street network took place in 2002. The manual survey of general condition, cracking, and spalling conditions was conducted in accordance with the City of Winnipeg Surface Condition Rating Manual as discussed in section 2.3.1.2.

2.3.2 Manitoba Highway Network

Manitoba Transportation and Government Services (MTGS) contracted a consultant to collect automated pavement condition data for the paved portion of the Manitoba highway network on an annual basis from 1999 to 2003. These efforts resulted in an extensive dataset with approximately 12 000 km surveyed per year with IRI and rut depth data reported at 100 m intervals. The automated data collection was conducted with an inertial profiler that operates at highway speed to minimize disruption to traffic.

This research also utilizes additional databases maintained by MTGS. Pavement structural information used includes the loading class of the highway, the pavement type and the Benkelman Beam rebound (BBR). The Benkelman Beam rebound is an indicator of the pavement structural condition. The Benkelman Beam test measures the rebound of the pavement

after loading with a standard axle load (80 kN). The Benkelman Beam is placed between the dual wheels of the standard axle and the pavement rebound is measured after the truck is driven forward. (SHT, 2000) Generally, strong roads have lower BBR than weak roads.

Traffic information used includes the functional class of the highway, the average annual daily traffic (AADT), and the percentage of trucks.

Whenever available, construction history data was included and linked to each control section. The construction history data provided by MTGS is the year that the highway was last paved.

Chapter 3

DATA QUALITY AND CONSISTENCY

3.1 Introduction

It is important that the pavement condition data input into a pavement management system be of high accuracy; therefore it is necessary to verify the quality and consistency of pavement condition data. Decisions made based on inadequate, unreliable, or inconsistent data can lead to costly errors (TAC, 1997). Data quality can be thought of as accuracy. For example, accuracy with respect to rut depth means that ruts of 10 mm depth are reported as having 10 mm depth. Data consistency refers to changes in IRI or rut depth from year-to-year or the level of agreement between different measures. For IRI and rut depth to be consistent from year-to-year there should be small annual changes in condition, or a change in condition consistent with construction and maintenance activities. For different measures of pavement distress to be consistent, the measures should each report more distress on segments with more damage.

To analyze data quality and consistency this thesis makes use of three datasets. Automated and manually collected IRI, rut depth, cracking, and spalling data from the pilot testing surveys in the City of Winnipeg are compared. Distress data collected during the parallel network-wide surveys in the City of Winnipeg are compared. Multi-year data from the 1999 to 2003 network-wide surveys of the Manitoba highway network are used to analyze the consistency from year-to-year.

3.2 Pilot Testing Program: Comparison of IRI Data

The IRI obtained from the manual survey was compared to the IRI obtained from the automated survey. The right-wheel path IRI for the segments on Grant Ave, Fermor Ave, and St. Mary's Rd are all compared in Table 3.1 and Figure 3.1. The segment on Fermor has an APC pavement and the segments on Grant and St. Mary's have PCC pavements. The manually measured IRI ranged from 2.97 m/km to 4.08 m/km while the IRI measured with the inertial profiler ranged from 2.90 m/km to 4.49 m/km.

Table 3.1: IRI as measured with manual and automated surveys

Segment	Pavement Type	Segment Length (m)	Manual IRI (m/km)	Automated IRI (m/km)	Difference (%)
Fermor	APC	270	2.97	2.90	- 2%
Grant	PCC	500	4.02	4.49	+ 12%
St. Mary's	PCC	345	4.08	3.37	- 17%

The comparisons show a maximum difference of 17% for the segment on St. Mary's Road. The difference can be thought of as disagreement and does not necessarily imply that either profiler produced errors. The variation in IRI between the two survey methods is within the range that can be expected for different profilers at different times of year.

Several factors can lead to disagreement between profilers including; variation in lateral positioning, daily variations, and seasonal variations. A typical variation in lateral positioning may cause IRI measurements to vary by up to 20% on a 300 m long section (Karamihas et al., 1999). For PCC pavements, IRI variation of 10% is common over a 24-hour cycle, due to daily temperature changes and the corresponding curling of individual slabs (Karamihas et al., 1999). Composite APC pavements are also affected by the thermal gradient in the underlying slabs. Another experiment conducted on eleven LTPP test sections found that the MRI could change by 0.40 m/km throughout the day under extreme circumstances; i.e. a sunny day with a cool morning followed by a warm afternoon (Karamihas et al., 2001).

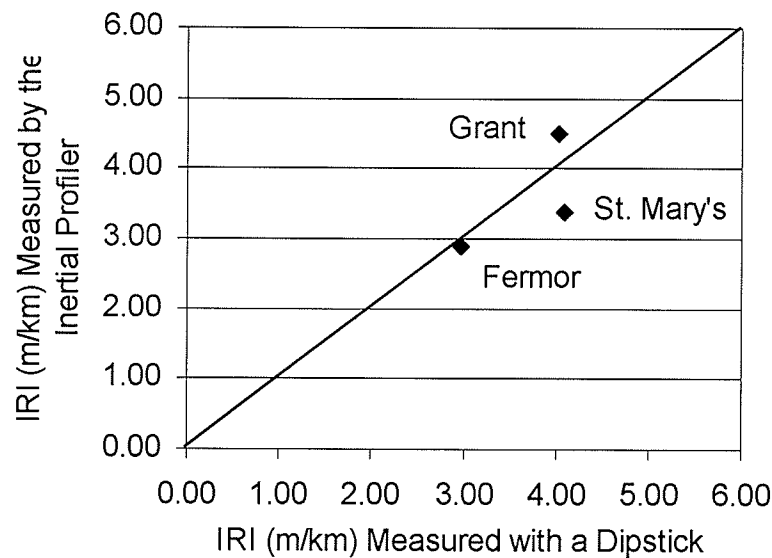


Figure 3.1: Comparison of IRI measured with a Dipstick and inertial profiler

The longitudinal variation of the IRI is shown in Figures 3.2 to 3.4. The manual and automated surveys both show a similar variation although the maximum reported roughness sometimes occurs at different places. This is evident in the survey of St. Mary's Road, shown in Figure 3.4, where the peak measured with the automated equipment occurs approximately 100 m away from the peak measured with the inertial profiler. Reporting the position of the data with coordinates from a GPS receiver would make it possible to verify where the peaks actually occur.

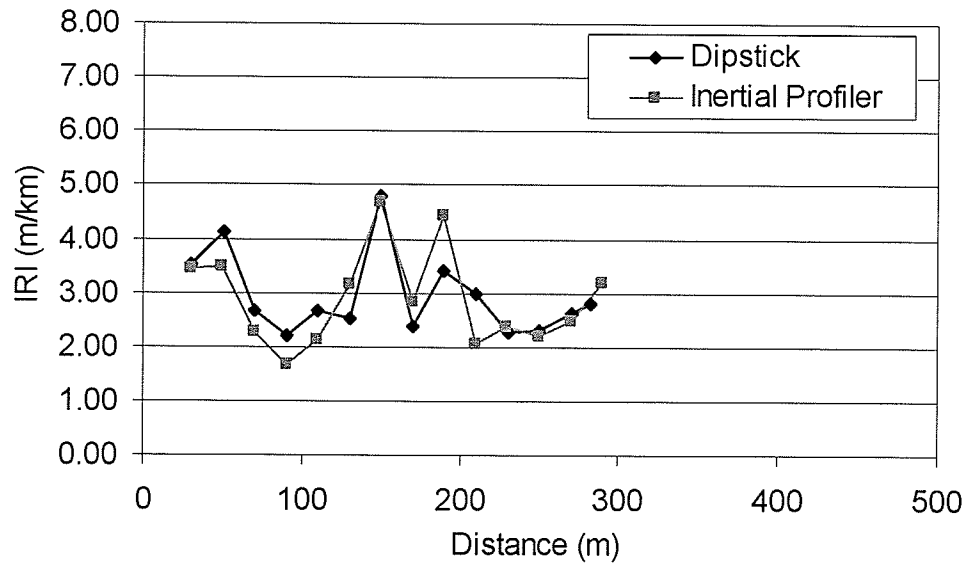


Figure 3.2: IRI comparison of an APC segment on Fermor Ave

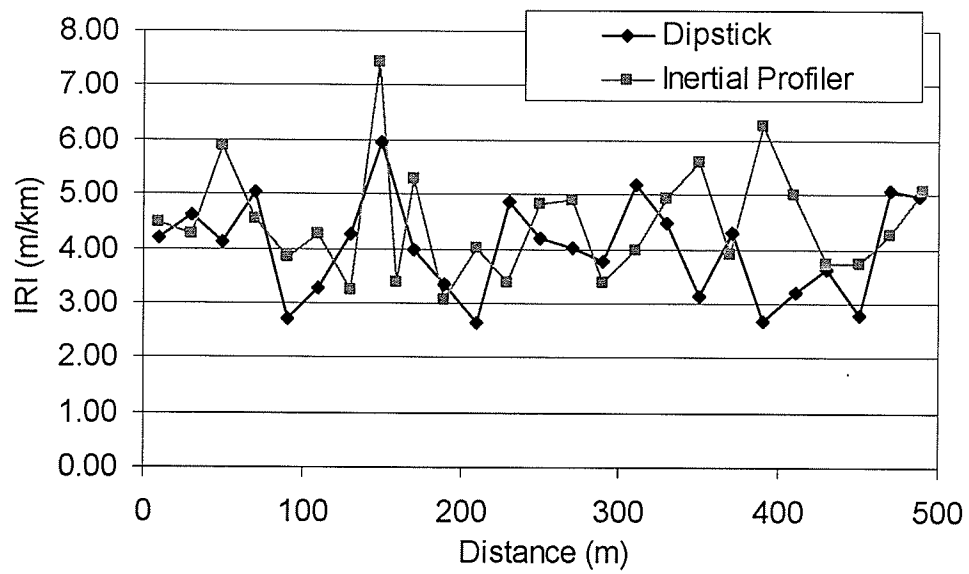


Figure 3.3: IRI comparison of a PCC segment on Grant Ave

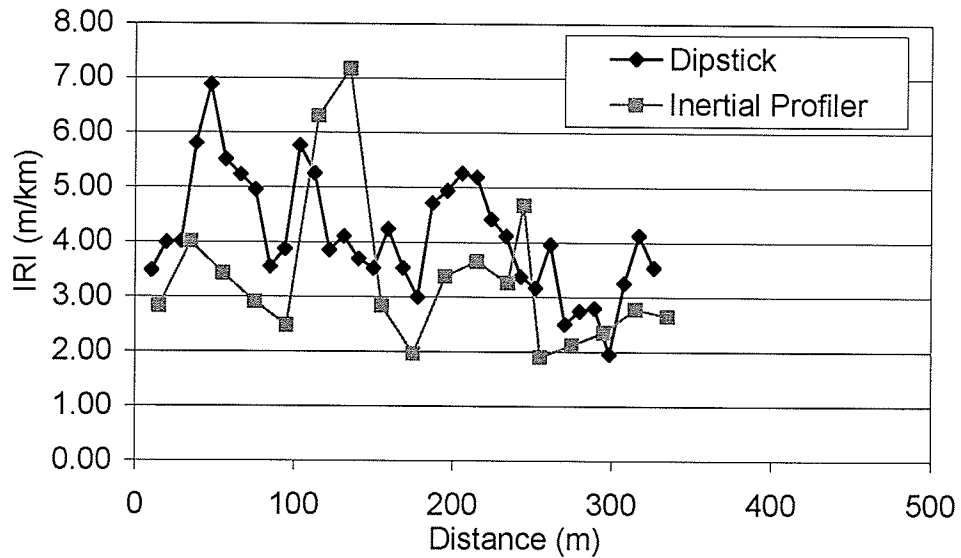


Figure 3.4: IRI comparison of a PCC segment on St. Mary's Rd

3.3 Pilot Testing Program: Comparison of Rut Depth Data

The rut depth obtained from the manual survey with a 1.8 m straightedge is compared to the rut depth obtained from the automated survey. The rut depth measurements for the segments on Grant Ave, Fermor Ave, and St. Mary's Rd are all compared in Figure 3.5 and Table 3.2. The average manually measured rut depth ranged from 1 mm to 13 mm while the average automated rut depth ranged from 2 to 10 mm.

Table 3.2: Rut depth as measured with manual and automated surveys

Segment	Segment Length (m)	Manual Average Rut Depth (mm)	Automated Average Rut Depth (mm)	Difference (mm)
Fermor	270	13	10	- 3
Grant	500	5	4	- 1
St. Mary's	345	1	2	+ 1

Figure 3.5 shows that there is a slight bias towards a somewhat higher manually measured rut depth compared to that with the automated system. This small shift is expected because the automated system uses an eleven-point rut algorithm, which results in reported rut depths equal-to or less-than those measured with a straight edge (EBA, 2000)

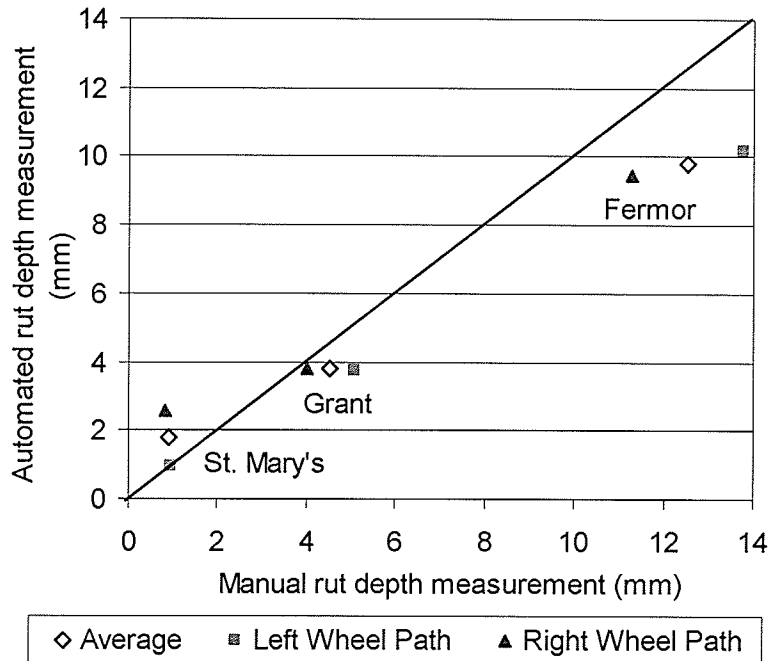


Figure 3.5: Comparison of manual and automated rut depth measurement

The comparisons show an average difference of 1 mm and a maximum difference of 3 mm for the segment on Fermor Ave. This very small error has little practical significance. Information regarding the magnitude of the ruts is necessary for prioritizing rehabilitation and maintenance work. However, the treatment used is often the same for medium and low severity ruts; a shallow, partial, or full depth patch or a mill and overlay could be used for ruts in both severity categories (Shahin, 1994).

The longitudinal variation of rut depth is shown in Figures 3.6 to 3.8. In general, the automated surveys show less variation than the manual survey. The automated survey equipment is likely to give accurate results at the network-level but would be less accurate if the data is intended for use at the project-level. The statistics used at the network-level are the average for the segment while those used at the project-level are the magnitudes throughout the segment.

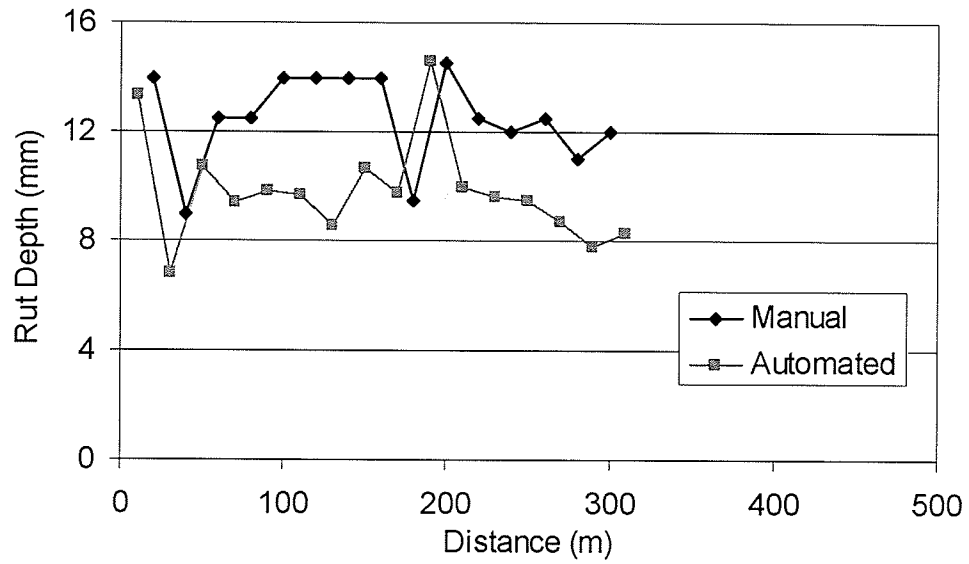


Figure 3.6: Rut depth comparison of an APC segment on Fermor Ave

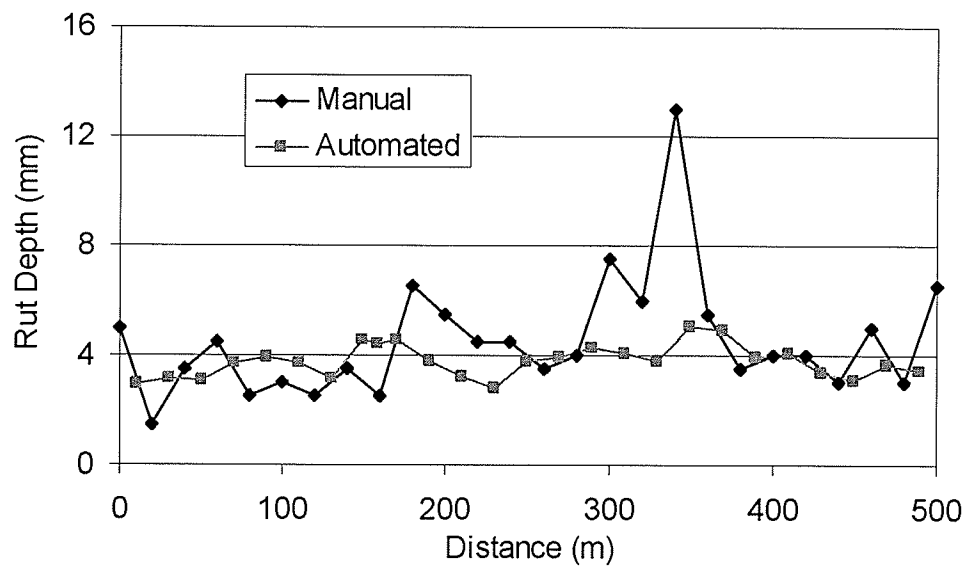


Figure 3.7: Rut depth comparison of a PCC segment on Grant Ave

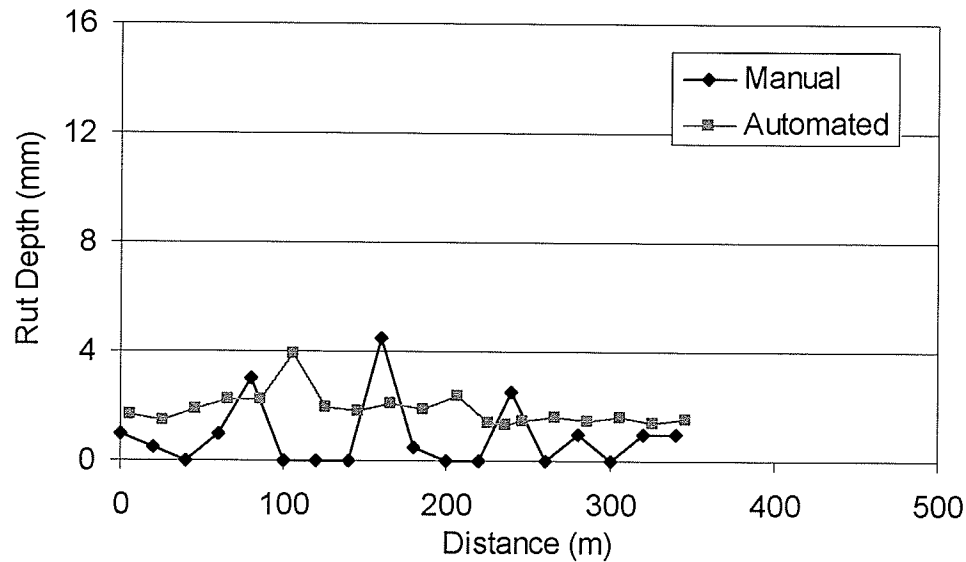


Figure 3.8: Rut depth comparison of a PCC segment on St. Mary's Rd

3.4 Pilot Testing Program: Comparison of Cracking Data

A comparison of the manual distress data and automated distress data was conducted to determine if the automated data is consistent with data collected in accordance with the surface condition rating manual. The cracking data collected manually for the three test segments is summarized in Table 3.3. The segment on Grant had the worst cracking score of RS3; meaning that most slabs had one crack of slight severity. The segment on Fermor had less cracking with a score of RS2 and the segment on St. Mary's had even less cracking with a score of RS1.

Table 3.4 shows the automated surface cracking data collected for the same three segments.

Table 3.3: Manually Collected Cracking Data

Cracking Designation	Grant	Fermor	St. Mary's
N	13	37	60
RN			
RS	13	6	8
RM	6		2
BN			
BS	3		
BM	1		
PN			
PS			
RX	11	5	
PM			1
BX	5		1
PX	4	1	
Number of Slabs	56	49	72
Percent Cracked	77%	24%	17%
Extent	3	2	1
Cracking Score	RS3	RS2	RS1

Table 3.4: Automated Cracking Data Summary

Segment	Segment Length (m)	Lane Width (m)	Low Severity Transverse Cracks (m)	Low Severity Longitudinal Cracks (m)	Medium Severity Longitudinal Cracks (m)	Low Severity Alligator Cracks (m ²)	Total Cracking (m)*
Fermor	280	3.7	18.5	158.0	45.0	1.5	223.0
Grant	500	3.8	0.0	0.0	0.0	0.0	0.0
St. Mary's	370	3.8	0.0	12.0	0.0	0.0	12

* Area calculated assuming a width of 1 m for alligator cracks (City of Winnipeg, 2002)

Direct comparison of the two cracking datasets is complicated by the fact that each data collection system used a unique reporting system; percentage of slabs cracked for the manual ratings and the length of cracking for the automated system. The length of cracking could be used to estimate the number of cracked slabs, however, assumptions regarding the distribution of the cracks and the orientation of the cracks, or the average number of cracks per slab would have to be made. Instead, the normalized total length of cracking is compared to the percentage of slabs cracked. The normalized length of cracking is calculated by dividing the total length of

cracking by the length of the segment and multiplying by 100 to give the length of cracking per 100 m of segment length.

A comparison of the manual and automated cracking data is shown in Figure 3.9. The comparison shows that there is little consistency between the two measures of cracking data. The manual rating method showed that a large percentage of the slabs on Grant are cracked while the automated system showed no cracking at all. On Fermor, the automated system reported a large length of cracking while the manual rating was comparatively low.

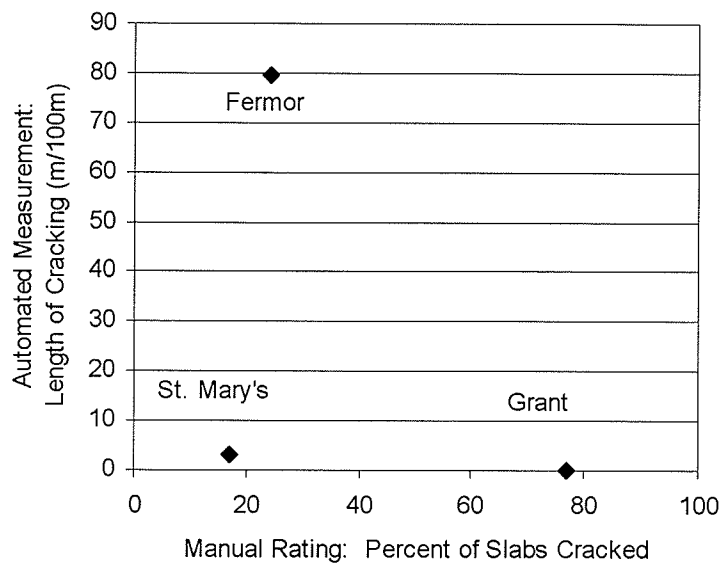


Figure 3.9: Comparison of manual and automated cracking data

3.5 Pilot Testing Program: Comparison of Spalling Data

The manually collected joint data for all three segments is shown in Table 3.5. All three segments had the largest possible extent of 3; meaning that more than 40% of the joints are spalled. Grant had the most severe joints with the majority in extreme condition and a score of X3. Fermor and St. Mary's had each had a score of M3 with less severe spalling and most of the joints in moderate condition.

The automated joint spalling data is shown in Table 3.6. In contrast to the manual data, only one segment measured with the automated equipment showed any joint spalling. The segment on Grant Ave showed a significant amount of joint spalling with the automated and manual data. The test segments on Fermor and St. Mary's showed no joint spalling when measured with the automated equipment, while they both had manual ratings that showed significant joint spalling.

Table 3.5: Manually Collected Joint Spalling Data

Joint Designation	Grant	Fermor	St. Mary's
N	0	0	15
S	1	7	10
M	2	24	29
X	53	18	18
Number of Joints	56	49	72
Percent Spalled	100%	100%	79%
Extent	3	3	3
Joint Score	X3	M3	M3

Table 3.5: Automated Joint Spalling Data Summary

Segment	Segment Length (m)	Low Severity Joint (m)	Medium Severity Joint (m)	Total Joint Spalling (m)
Fermor	280	0.0	0.0	0.0
Grant	500	133.0	121.6	254.6
St. Mary's	370	0.0	3.8	3.8

One reason for the significant discrepancies in the spalling ratings is that the spalling distresses on Grant tend to be fairly obvious while those on Fermor and St. Mary's tend to be more difficult to detect. Figure 3.10 shows a typical spalled joint on Grant. Figure 3.11 shows cracking of the asphalt near a joint on Fermor that indicates spalling of the underlying slab. These small localized cracks can be very difficult to detect with automated data collection equipment travelling at the speed of traffic. Figure 3.12 shows a joint on St. Mary's that has a moderate spall that has been patched. The manual rating system includes such spalls; and they can be difficult to detect at high-speed.



Figure 3.10: A spalled joint on Grant



Figure 3.11: A spalled joint on Fermor



Figure 3.12: A spalled and patched joint on St. Mary's

3.6 Pilot-Testing Program: Summary

Data collected during the pilot-testing program has been analyzed to determine the quality and consistency of IRI, rut depth, cracking, and joint spalling data. Data from the automated pavement survey was compared to data from manual surveys of three segments.

An analysis of the IRI data showed that the inertial profiler could accurately measure IRI data within the variation that can be expected for different profilers on different days. The variation in IRI ranged from +12% to -17% while changes in IRI due to lateral positioning can be up to 20%. As well, daily variation in IRI of 10% is common while larger variation can occur under extreme circumstances.

An analysis of the rut data showed that the automated rut measurements are essentially the same as the manually measured ruts. The simulation of a 1.8 m straightedge using an eleven-point algorithm results in ruts that are equal-to or slightly less than those measured directly with a 1.8 m straightedge. However, this difference has little practical significance.

A comparison of cracking data showed little consistency between the automated system and the manual inspection. There was also little consistency between the joint spalling data measured with the two systems. The manual inspection indicated that all three segments had a significant amount of spalling while the automated data reported no spalling for two of the three segments. The type of spalling evident on those two segments is difficult to detect at high-speed.

3.7 Consistency of Parallel Network-Level Surveys

Distress data collected in the parallel network-level surveys was compared to determine the quality and consistency of the automated dataset. A regression analysis was used to investigate relationships between the manual ratings and the automated PASER index and to determine if there is a significant relationship between data collected with the automated event keyboard and the city's manual pavement distress ratings.

3.7.1 Relationships between Manual Ratings and the PASER Index

The PASER index ranges from 1 to 10 where 1 represents a segment that requires total reconstruction and 10 represents a newly constructed segment. To compare the manual ratings to the PASER index the manual ratings were first converted to a score from 1 to 10. Each crack type and severity was associated with a numerical rating from 4 to 10 as shown in Table 3.6. To arrive at a rating on a scale of 1 to 10, the crack extent was then subtracted from the value in the table. For example, a segment with a crack score of BM2 is assigned a rating of $7-2 = 5$ on the 1 to 10 scale.

Table 3.6: Conversion of Crack Score to PASER

Manual Rating	PX	BX	PM	RX	PS	PN	BM	BS	BN	RM	RS	RN	N
Assigned PASER	4	4.5	5	5.5	6	6.5	7	7.5	8	8.5	9	9.5	10

Joint scores were converted to a 1 to 10 scale in a similar manner. The spall severity was associated with a PASER index given in Table 3.7 and then the spall extent was subtracted. For example a segment with a joint score of X3 has a rating of 1 on the 1 to 10 scale.

Table 3.7: Conversion of Joint Score to PASER

Manual Rating	X	M	S	N
Assigned PASER	4	6	8	10

The manual PASER is calculated as the minimum of the PASER calculated from the crack score and the joint score. The automated PASER is compared to the manual PASER for APC and PCC segments in Figures 3.13 and 3.14. Each point on the graph represents a single segment. Both of these figures show that there is wide variation between the two methods of pavement assessment. The automated PASER index does not provide the same information as the manual rating system.

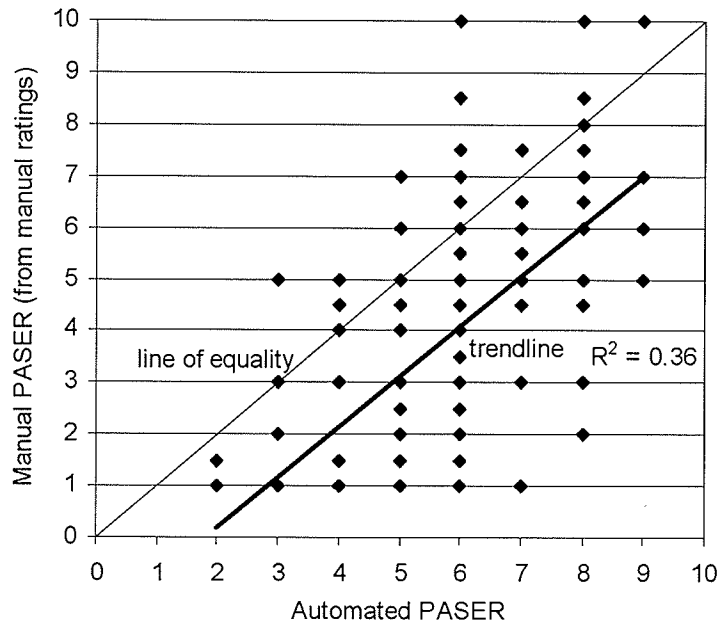


Figure 3.13: Comparison of automated and manual PASER Indices for APC segments (n = 572)

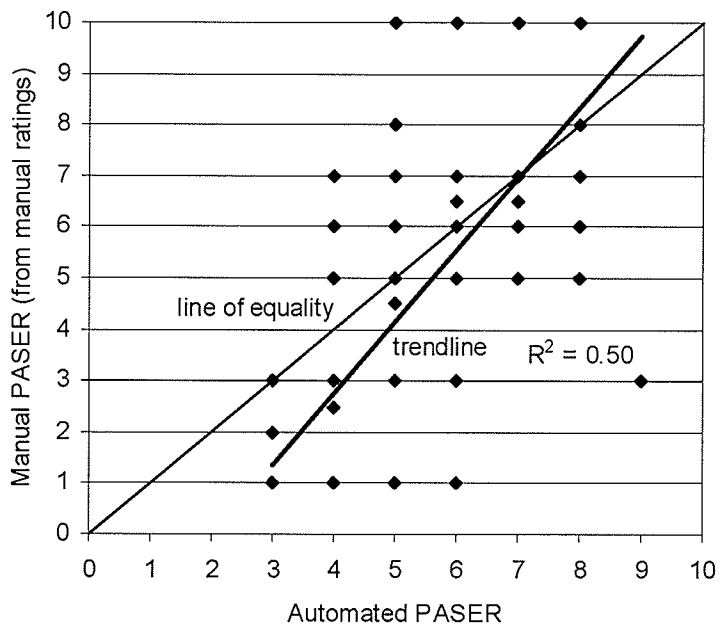


Figure 3.14: Comparison of automated and manual PASER indices for PCC segments (n = 157)

3.7.2 Automated Event Keyboard

The operator of the automated survey equipment uses an event keyboard to collect transverse spalling, slab failure, patching, and pothole data. This analysis was conducted to determine if the transverse spalling and slab failure data matched the manually collected condition data. For this

analysis, the high severity transverse spalling data from the event keyboard was compared to the Percent X rating that city rating crews collect. Also, the slab failure data from the event keyboard was compared to the Percent PX data that the rating crews collect.

Figures 3.15 and 3.16 show a comparison of the %X between the manual and automated (event keyboard) surveys for the APC and PCC segments. These figures show that the data from the event keyboard is not significantly related to the data collected according to the manual rating system.

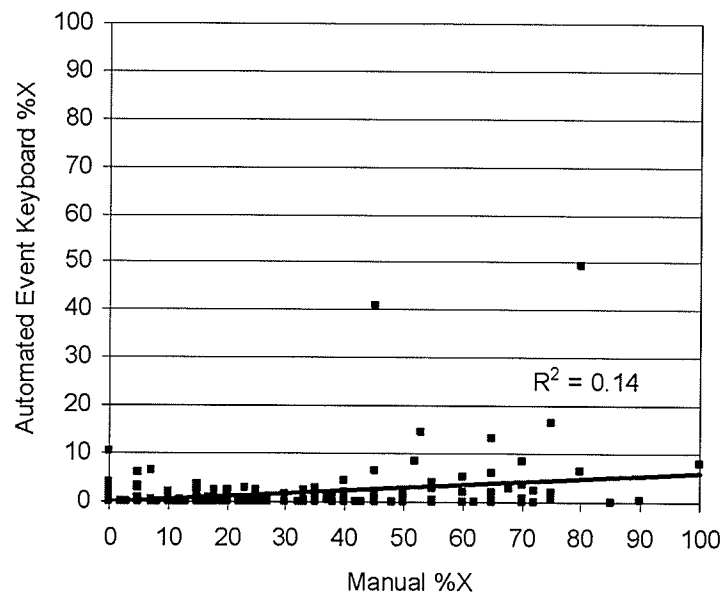


Figure 3.15: Comparison of manual and automated %X for APC segments (n = 572)

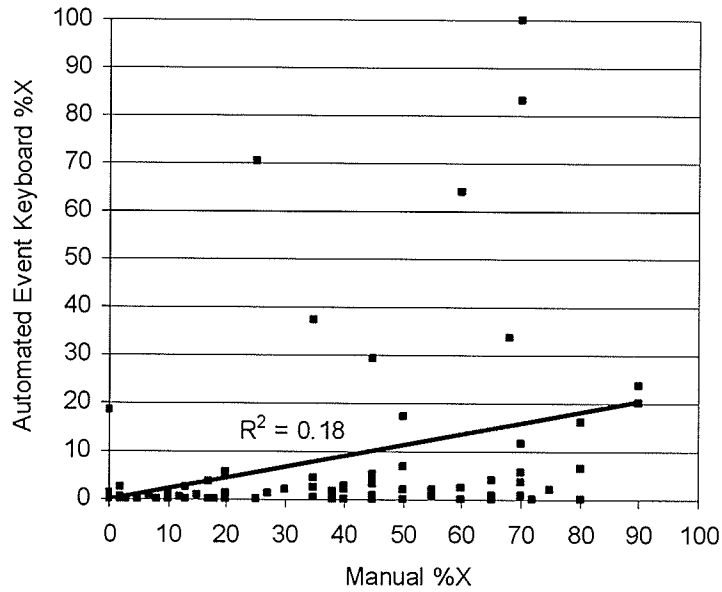


Figure 3.16: Comparison of manual and automated %X for PCC segments (n = 157)

Figure 3.17 shows a comparison of the %PX between the manual and the automated survey of PCC segments. The automated survey of APC segments did not include slab-failure data. Figure 3.16 shows that these two datasets are unrelated. The lack of relationship is probably due to the difficulty of determining the number of pieces a slab has broken into while travelling at the speed of traffic.

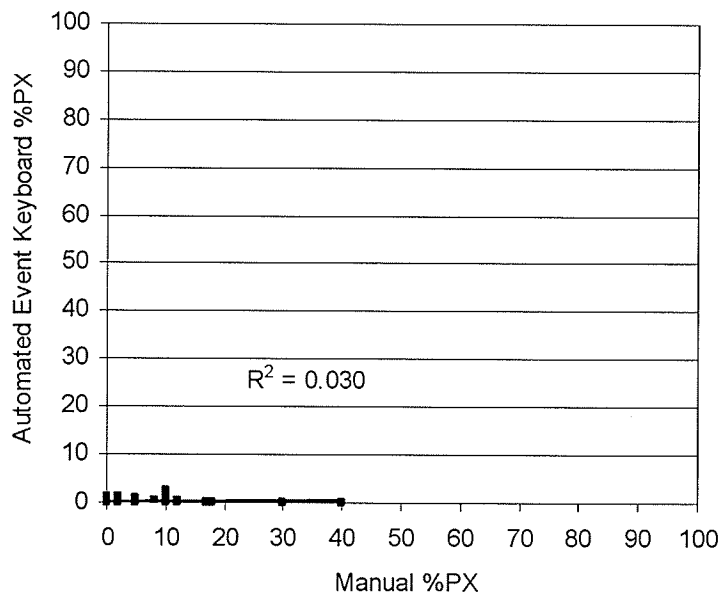


Figure 3.17: Comparison of manual and automated %PX for PCC segments (n = 157)

3.7.3 Summary of the Consistency of Parallel Network-Level Surveys

Regression analyses failed to find significant relationships between the distress data measured manually and with the automated survey equipment. Manual ratings of cracking and joint spalling were converted to a 1 to 10 scale and compared to the automated PASER index. These comparisons showed a large variation between the two methods of pavement assessment.

Comparisons between the automated and manual high severity transverse spalling and slab failure data showed a lack of relationship between the two methods of pavement assessment. Coefficients of determination (R^2) for these comparisons ranged from 0.03 to 0.18; meaning that only 3% to 18% of the variation in the automated event keyboard data was explained by the variation in the manual ratings.

3.8 Consistency of Multi-Year Surveys

Throughout this chapter, the quality and consistency of data has been assessed through the comparison of manual surveys with automated surveys. Another method of assessing the consistency of data is through the use of data collected on an annual basis. This research utilizes IRI and rut depth data of the Manitoba highway network collected on annual basis from 1999 to 2003.

Quality control and quality assurance of automated pavement condition data requires significant efforts on behalf of the data supplier (agency or consultant) and the data user (agency). Most agencies require pre-qualification or qualification of the data supplier. That is, the data supplier is required to demonstrate that agency performance requirements can be met before data collection begins. Secondly, data suppliers must perform checks of the automated data collection equipment on a daily basis. (EBA, 2001b) In addition, the agency establishes blind or unknown verification sites, known verification sites, and closure verification sites. Blind verification sites are generally considered to provide the most meaningful assessment of survey crew and profiler performance.

3.8.1 Manitoba Highway Network Properties

The Manitoba highway network comprises 18 875 two-lane-km of which 13 100 two-lane-km are paved. (Kass et al., 2002) The province is divided into five regions, Regions 1, 2, and 3 are in the southern part of the province, Region 4 is in the central part, west of Lake Winnipeg, and Region 5 comprises the northern part of Manitoba. Region 1 has the heaviest traffic as it includes busy highways surrounding the City of Winnipeg. For planning purposes, the network is divided into

control sections that are homogeneous with respect to traffic volumes. These control sections are further divided into subsections that are considered to have homogeneous conditions with respect to pavement conditions. Figure 3.18 shows the number of subsections in each region while Figure 3.19 shows the length (in lane-km) of the automated survey in 2003.

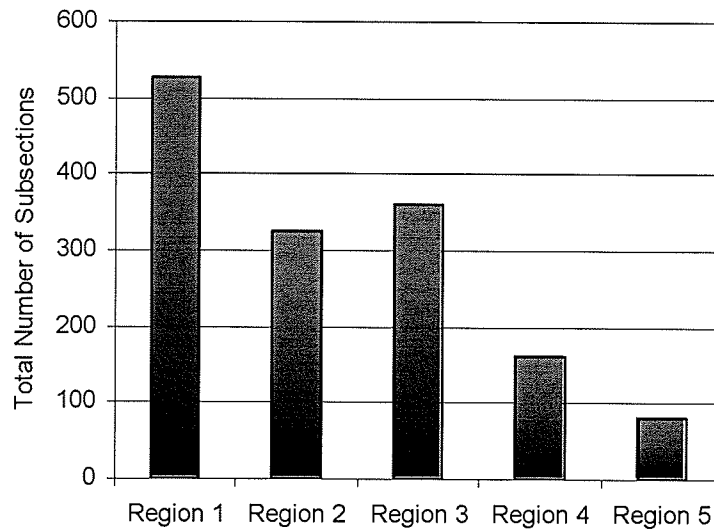


Figure 3.18: Distribution of subsections in the Manitoba highway network

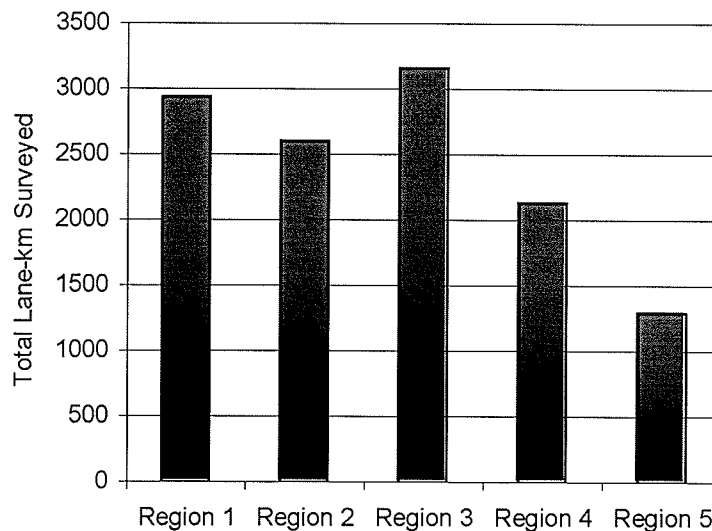


Figure 3.19: The automated survey length (2003)

3.8.2 Data Quality and Consistency: Individual Segments

The availability of multi-year data provides the means of checking the consistency of the data through the use of deterioration graphs. A software package, IRIIS (IRI Information System)

developed at the University of Manitoba during the course of this research can plot the deterioration rates together with pavement history. The IRIIS software package is more fully documented in a subsequent chapter.

The analysis of these deterioration graphs facilitates the screening of suspect data elements, such as unexpectedly large annual increases or decreases in IRI or rut depth; since pavement condition is not expected to undergo significant changes on an annual basis. Figure 3.20, for example, shows a segment that has relatively consistent IRI data. There are small annual increases in IRI, as would be expected. The user can show rutting on the same graph by clicking on the Rut command button.

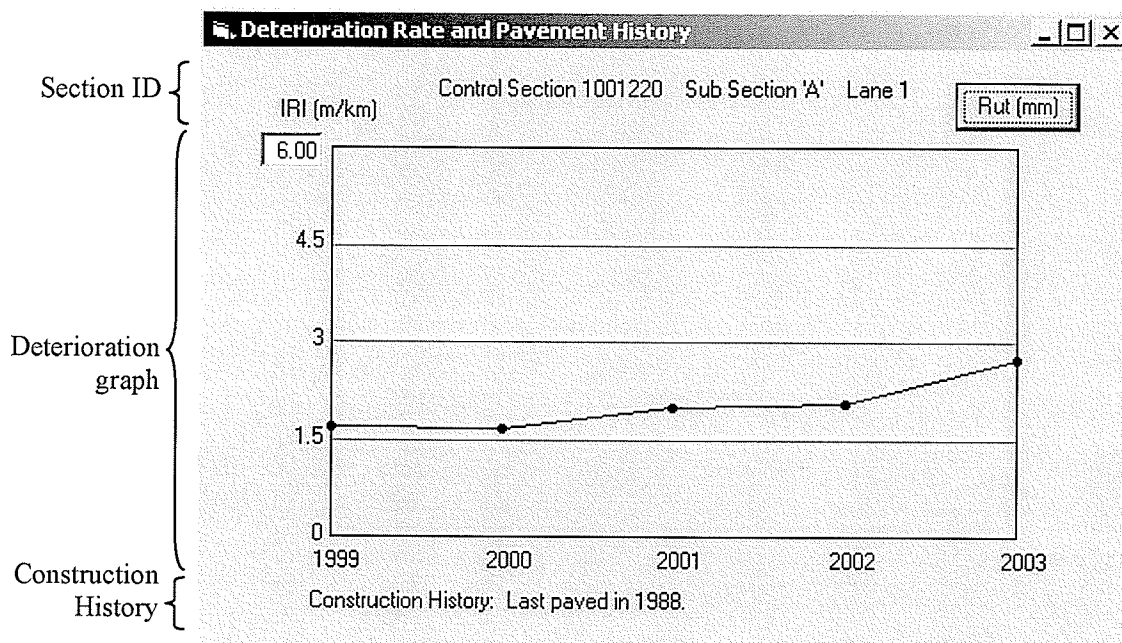


Figure 3.20: Deterioration rate display showing a relatively consistent subsection

Segments that have large changes in condition could indicate that the data is inconsistent. However, if the change can be explained by construction or maintenance interventions, such as improvement in condition following an overlay, the data can be accepted. Figure 3.21 shows a subsection where the IRI decreased significantly between two consecutive surveys conducted in 2000 and 2001. This figure demonstrates the advantage of displaying pavement history data on the same graph to explain why a change in condition occurs.

Figures 3.20 and 3.21 showed subsections where the IRI is consistent, with small changes or a change explained by highway construction. There are also those subsections where there are

large changes in condition that are inconsistent with the construction history. The cause could be inconsistent IRI data or the information regarding the construction history may not be up-to-date.

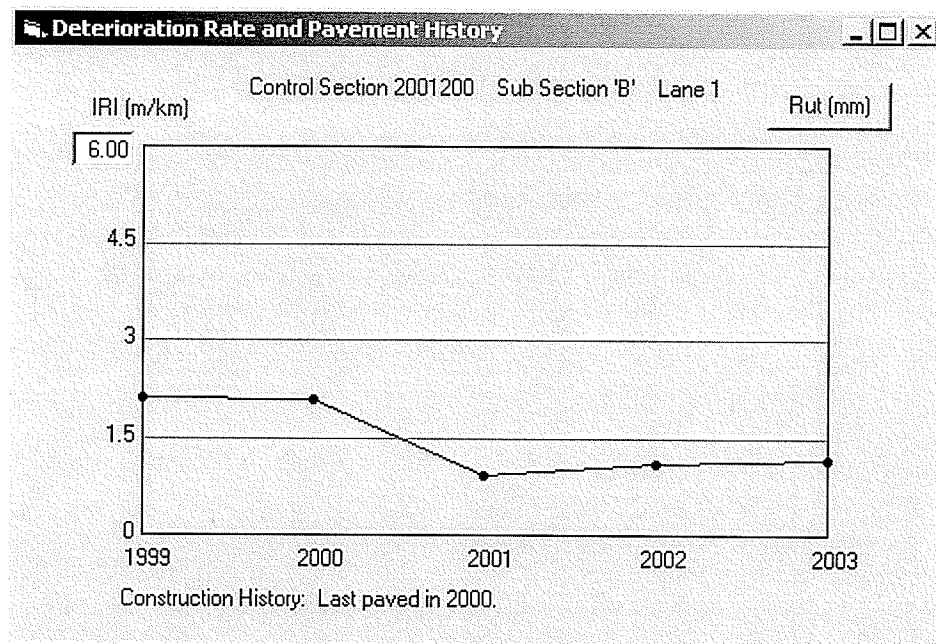


Figure 3.21: Deterioration rate display of a segment with a decrease in IRI after paving in 2000

Figure 3.22 shows the deterioration rate and construction history of a subsection where the change in IRI cannot be explained by construction history records. This subsection had relatively constant reported IRI from 1999 to 2002 and then a large decrease in reported IRI in the 2003 survey. The cause of the discrepancy could be inconsistent IRI data, the construction history may not be up-to-date, or the change in IRI could be the result of unreported maintenance work on the subsection.

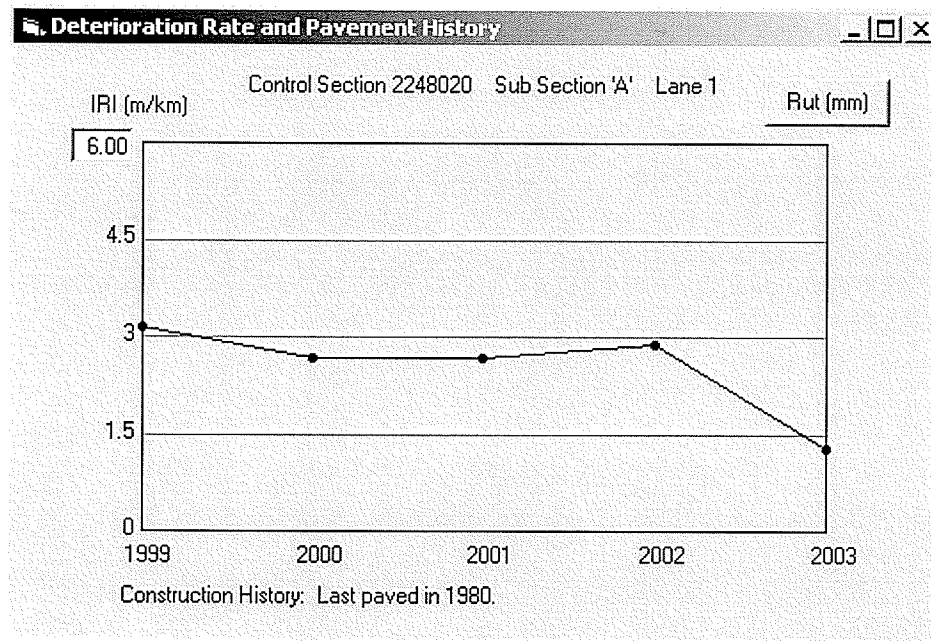


Figure 3.22: Inconsistent IRI data based on the year the segment was last paved.

3.8.3 Data Quality and Consistency: the Network

For the network as a whole, the consistency of automated data can be assessed by determining the number of segments where large annual changes in IRI or rut depth are explained by the construction history and those where the available construction history is inadequate to explain the change in reported condition. To determine if the inconsistency is attributable to the automated data or incomplete construction history or maintenance records, the user would have to examine other subsection properties, such as segment length or other factors that could affect IRI, through the examination of video logs or a visual inspection.

One of the features of the IRIIS software is the ability to filter the database and show only those subsections that have large annual changes in reported condition and then determine which of those irregularities can be attributed to construction or maintenance activities. The statistics of this section are based on the 1456 subsections that were surveyed in 2003 and have available data regarding the last time they were paved. An additional 125 subsections did not have construction history data available.

A change in IRI larger than 1.0 m/km is considered significant and it would not normally occur unless there had been some major rehabilitation of the segment. Figure 3.23 shows the number of subsections in each region that had an annual change (increase or decrease) in IRI greater than 1.0 m/km and the number of subsections where the change in IRI is explained by the highway being

paved. In general, only a few subsections have the large change in IRI explained by the highway being paved. This inconsistency could be attributable to the IRI data or the data regarding highway construction, for example, maintenance work, not included in the construction history database, could also affect IRI.

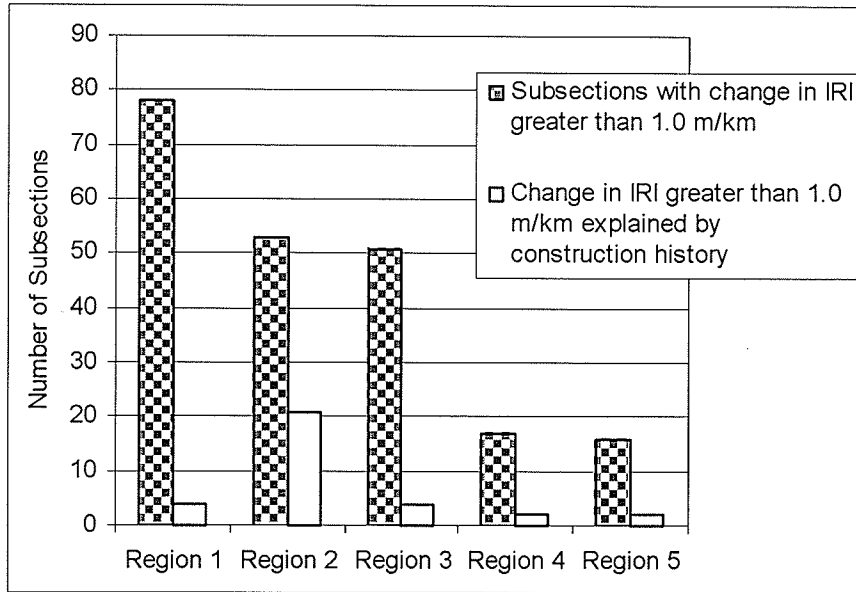


Figure 3.23: Total subsections with a large change in IRI and those with the change explained by construction history data

Similar to annual changes in IRI larger than ± 1.0 m/km, a change in rut depth larger than ± 5 mm would not normally occur in the span of one year unless there had been some construction on the highway. Figure 3.24 shows the number of subsections in each region that had an annual change in rut depth larger than ± 5 mm and the number of subsections where the change was explained by the highway being paved.

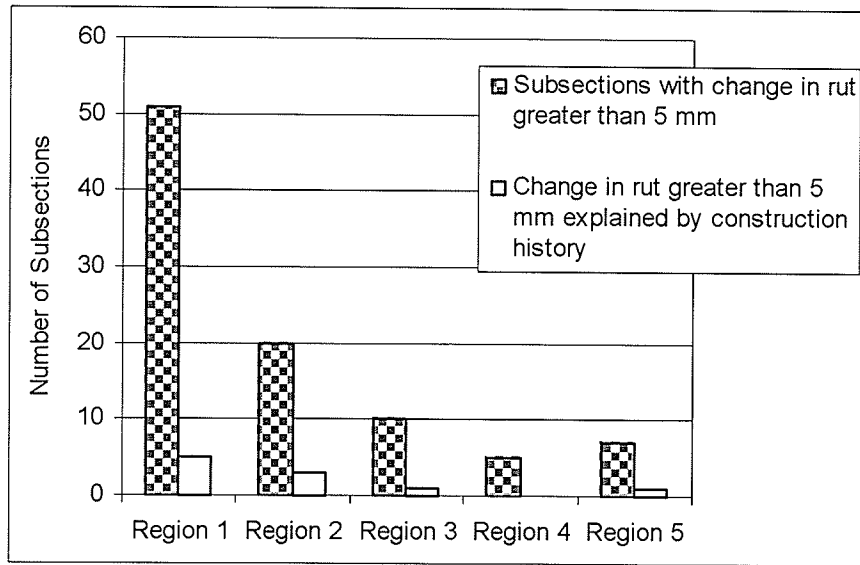


Figure 3.24: Total subsections with a large change in rut depth and those with the change explained by construction history data

As with the IRI data, in general, only a few subsections have the large change in rut depth explained by the highway being paved.

3.8.4 Summary of Consistency of Multi-Year Survey Data

Subtracting the number of subsections with a large, but explainable, change in condition from the total number of subsections with a large change in condition and then dividing the result by the total number of subsections determines the percentage of flagged subsections. For the entire network, 12.5% of subsections had annual changes in IRI data that did not match the year paved. With respect to rutting and the year paved, 5.7% of segments had an annual change in rut depth that did not match the year paved. Figure 3.25 summarizes the percentage of inconsistencies based on IRI and rut depth per region.

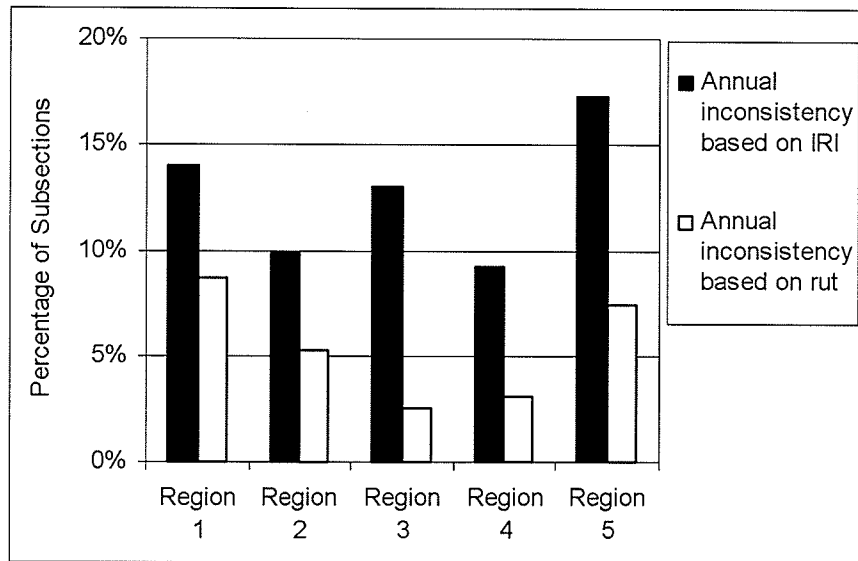


Figure 3.25: Summary of inconsistencies based on IRI and rut depth

IRIIS can identify sections where the changes in reported condition do not seem to match the construction history. The software can be used to produce an annual report regarding data quality and consistency. The software also allows the user to specify what change in IRI or rut depth needs explanation based on construction history or other factors.

3.9 Summary

Analyses of several automated and manual pavement condition datasets were conducted to investigate the consistency and quality of automated survey data.

An analysis of IRI and rut depth data collected in the City of Winnipeg during a pilot testing program showed that both of these data elements can be measured accurately with the inertial profiler equipped with a rut-bar. The variation in IRI between the automated and manual profilers is within the range of variability that should be expected due to a variation in lateral positioning and daily and seasonal changes in IRI. The rut depth calculated for the simulation of a 1.8 m straightedge using an eleven-point algorithm is less than or equal to that measured with a 1.8 m straightedge. The differences in measured rut depth are small and have little practical significance.

A comparison of the cracking and spalling data collected during the pilot-testing program showed that there is little consistency between the two methods. The manual inspection indicated that all three segments had a significant amount of spalling while the automated data reported no spalling

for two of the three segments. The type of spalling evident on those two segments is difficult to detect at high-speed.

Regression analyses of data collected during parallel network-level surveys in the City of Winnipeg in 2002 failed to find significant relationships between the distress data measured manually and with the automated survey equipment. Manual ratings of cracking and joint spalling were converted to a 1 to 10 scale and compared to the automated PASER index. These comparisons showed a large variation between the two methods of pavement assessment. Comparisons between the automated and manual high severity transverse spalling and slab failure data showed a lack of relationship between the two methods of pavement assessment. Coefficients of determination for these comparisons showed that 3% to 18% of the variation in the automated event keyboard data was explained by the variation in the manual ratings.

The consistency of multi-year survey data collected on the Manitoba highway network was analyzed. The analysis showed that 12.5% of subsections had annual changes in IRI data that did not match the year paved and 5.7% of subsections had an annual change in rut depth that did not match the year paved. These inconsistencies may be due to incomplete pavement history data, suspect IRI and rutting data, or maintenance work that is affecting these two measures of pavement condition. Over the five-year survey period, these percentages represent annual inconsistencies of 3.2% per year for IRI and 1.4% per year for rut depth. The data is relatively consistent on an annual basis.

Chapter 4

OPTIMIZING DATA COLLECTION NEEDS

4.1 Introduction

One of the primary objectives of this research is to minimize the data collection needs of the City of Winnipeg's pavement management system while preserving data quality, consistency, and repeatability. Optimizing data collection needs is important to reduce the cost and time required to collect data while ensuring that the data can still perform its necessary functions as part of a pavement management system. The visual inspection of the entire regional street network took four rating crews (eight raters) six to eight weeks, while the automated survey required only two days.

There are two methods of reducing the volume of data collected on an annual basis. The first is to collect data for fewer lane-kilometres of the network. This chapter documents an analysis of the transverse variability of pavement distresses to determine if a single lane can be taken as representative of all of the lanes of multilane segments, and therefore eliminate the need to collect data for each lane. Sampling can often provide sufficient data for the network-level PMS but not for project-level. Additional detailed surveys are necessary at the project-level.

The second method of minimizing data collection needs is to collect fewer variables. The number of variables can be minimized by eliminating the collection of those that are of little use and those that can be estimated from other variables. This chapter documents attempts to use maximum likelihood classification (MLC) and artificial neural networks (ANN) to predict manual ratings based on the automated IRI and rut depth data to determine if the manual ratings could be calculated rather than collected. The analysis of parallel network-level surveys documented in chapter 3 showed that regression cannot be used to determine the manual pavement condition ratings based on the automated distress data.

4.2 Transverse Variability of Surface Distresses

Knowledge of the transverse variability of surface distress is useful for determining data collection needs for manual and automated pavement surveys. Transverse variability is the variation between adjacent lanes of a segment. In 2002 manual distress data was collected by the City of Winnipeg for all lanes of the regional street network while a consultant collected automated data on the second lane from the curb (referred to in this thesis as the "automated lane")

because this lane was surveyed with the automated data collection equipment). An analysis of the transverse variability was conducted to ascertain the differences in manual distress data collected on the automated survey lane and manual distress data collected on all lanes.

4.2.1 Transverse Variability Analysis and Results

An analysis was conducted for 54 segments that were randomly selected with a random number generator. The segments have a total length of 49 km. 25 segments were two-lane, 16 were three-lane, and 13 were four-lane. For each segment and each survey (automated lane and all lanes) the percentage of each type and severity of distress was calculated. Figure 4.1 shows a comparison of cracking data.

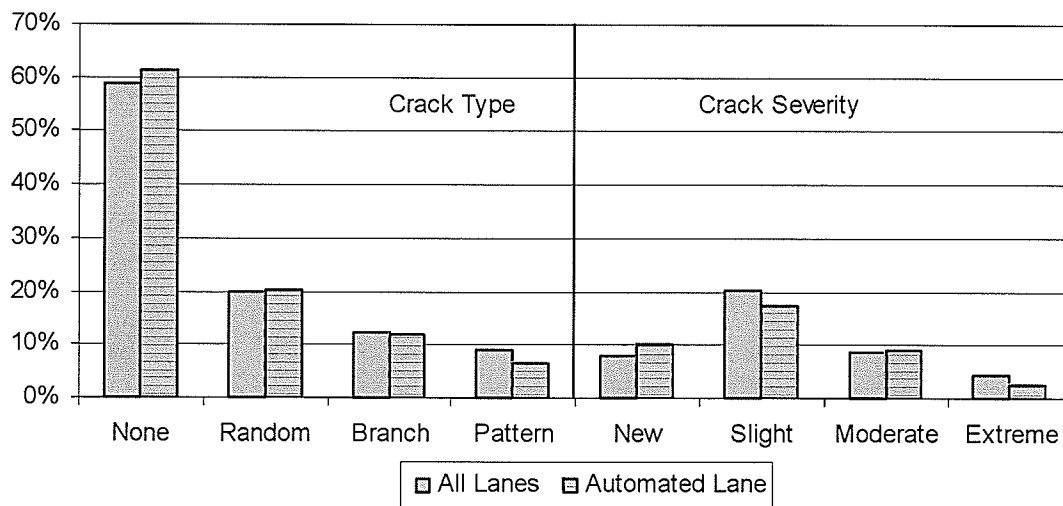


Figure 4.1: The percentage of slabs with each type and severity of cracking

The type and severity of cracking is very similar for the two datasets, although, there are a few differences. There is a slight shift in the type of cracking with more slabs having an absence of cracking on the automated lane and more slabs having pattern cracking on all lanes. There is also a slight shift in the crack severity with more slight and extreme cracking on all lanes but more new cracks on the automated lane.

Figure 4.2 shows a similar comparison of spall data. There were more joints with moderate and extreme spalling on all lanes and more joints with new or slight spalling on the automated lane.

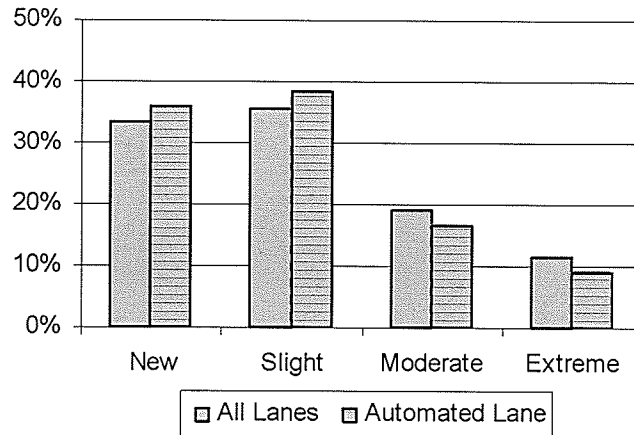


Figure 4.2: The percentage of joints with each severity of spall

4.2.2 Statistical Hypothesis Testing

A non-parametric statistical analysis was conducted to determine if the medians of the two populations are the same. Each of the 54 sample segments has a pair of data, the manual rating for all lanes and the manual rating for the automated measurement lane. A sample of the differences between the lanes is obtained by subtracting the percentage of each distress on the automated lane from the distress on all lanes. A positive difference between the lanes indicates more distress on all lanes, and negative numbers indicate more distress on the automated lane. If a confidence interval is entirely positive, then all of the lanes had more distress than the automated lane. Conversely, if a confidence interval is entirely negative, then the automated lane had more distress than all of the lanes.

As always, two hypotheses are set up:

- The null hypothesis (H_0): the two datasets have the same median amount of distress,
- The alternative hypothesis (H_a): the two datasets have different median amounts of distress.

A binomial distribution can be used to calculate a confidence interval on the median of a population without any assumptions regarding the distribution of the data (Salvia, 1990). There is a 0.50 probability that any single randomly selected sample will fall below the median. For a sample size of 54 we can calculate the probability that any number of samples (up to 54) lie below the population median using the binomial distribution (Equation 4.1).

$$f(x) = \binom{n}{x} p^x (1-p)^{n-x} \quad (\text{Equation 4.1})$$

where,

$f(x)$ = the probability that exactly x number of elements are below the population median

n = sample size

x = the number of elements below the median

p = the probability that a single element is below the median

For example, the probability that exactly 20 of the 54 samples lie below the median is calculated as:

$$f(20) = \binom{54}{20} 0.5^{20} (1-0.5)^{54-20}$$

or

$$f(20) = 0.0178$$

For a sample size of 54, there is 92.4% probability that the median of the population lies between the 21st and 34th elements. The 92.4% probability for this confidence interval is calculated as:

$$1 - \sum_{x=1}^{20} f(x) - \sum_{x=34}^{54} f(x)$$

Alternative confidence intervals that could have been used include the median lying between the 20th and 35th elements with 96.0% probability or the 22nd and 33rd elements with 86.6% probability. For this research, the 92.4% confidence interval was selected to balance the probability of making a statistical Type I error with the probability of a Type II Error. The probability of Type II Errors must not be ignored as evidenced by Washington (1999). The Type I Error probability is one minus the confidence interval, $1 - 92.4\% = 7.6\%$. Increasing the probability of Type I Errors decreases the probability of Type II Errors. The actual probability cannot be calculated unless the actual population median is known.

The Type I Error is the probability of rejecting the null hypothesis when it is true. Practically, this error is the conclusion that the medians are different when they are, in fact, the same. There is a strong desire to avoid this type of error because it could lead to excess data collection, that is the collection of data for multiple lanes when a single lane is sufficient.

The Type II Error is the probability of accepting the null hypothesis when it is false. Practically, the Type II Error is the probability of concluding the medians are the same when they are in-fact different. There is also a strong desire to avoid this error because it could lead to inaccurate data. The 92.4% confidence interval was selected to balance the different types of errors based on the consequences of the errors.

The analysis showed that the medians of the two populations, the automated lane and all lanes, are not statistically different with respect to each category of crack type, crack severity, and spall severity.

Influence on Crack and Joint Score

The differences between the lanes, shown in Figures 4.1 and 4.2, appear to be quite small. However, these are averages and some individual segments had large differences, which become evident when the rating scores are analyzed. Of the 54 randomly selected segments that were analyzed, 30 had the same crack score on all lanes as the automated lane. The differences in the 24 segments that had different scores are summarized in Table 4.1. There appears to be little overall difference in cracking score, however some individual segments had large differences. For example one segment had a score of RS2 on all lanes and PX1 on the automated lane while another had a score of PX3 on all lanes and RM3 on the automated lane.

Table 4.1: Cracking Score Differences between the Automated Lane and All Lanes*

	Type	Severity	Extent
Same	12	10	11
Automated lane was better	5	6	8
Automated lane was worse	7	8	5
Total	24	24	24

*For the 24 of the 54 sample segments that did not have the same crack score

Table 4.2: Joint Spall Score Differences between the Automated Lane and All Lanes*

	Severity	Extent
Same	5	4
Automated lane was better	7	8
Automated lane was worse	0	0
Total	12	12

*For the 12 of the 54 sample segments that did not have the same joint score

Of the 54 segments analyzed, 42 had the same joint score on all lanes and the automated lane. The 12 that had different scores are summarized in Table 4.2. The results show that the automated lane exhibited less joint spalling.

4.2.3 Summary of Transverse Variability Analysis

There is little overall difference between the cracking scores measured on all lanes compared to the automated lane. However, individual segments can have large differences. The automated lane had less severe spalling scores than all lanes, which would result in a bias if it were to be the only lane surveyed.

Given the high cost of automated data collection for multiple lanes, it is recommended that automated data only be collected for a single lane and that this lane be chosen randomly to eliminate the bias that was discovered in the spalling scores. For network-level planning purposes automated data collected on one lane is sufficient to represent the entire segment. While the conditions between adjacent lanes are the same to a statistically significant degree, at the project-level, a detailed survey is required for all lanes.

4.3 Maximum Likelihood Classification

Data collection needs can be further optimized by eliminating the collection of variables that are significantly related to other variables and can thus be estimated rather than collected. One of the methods explored for the determination of these relationships is maximum likelihood classification. This approach to classification assigns segments to classes based on the probability that the segment belongs to that class. Each segment is assigned a general condition, cracking score, and joint score based on the probability that its IRI and rut depth belong to a particular class. MLC is commonly used in remote sensing applications to determine the type of ground cover based on satellite imagery (Lillesand et al., 2004).

4.3.1 Filtering Non-Homogeneous Segments

For the classification approach to be fundamentally sound, it is necessary to have statistically homogeneous segments. To illustrate, Figure 4.3 shows a segment of St. Mary's Road from Burland to Greendell. This segment has three distinct portions with respect to roughness. The first portion has an IRI of 3.26 m/km, the second has an IRI of 1.65 m/km, and the third has an IRI of 3.24 m/km while the segment as a whole has an IRI of 2.61 m/km. The general condition of this segment is poor, the crack score is RM1, and the spall score is X3. The problem of using non-homogeneous segments becomes apparent. This segment's IRI of 2.61 m/km does not match

its general condition of Poor; an IRI of 2.61 m/km is not particularly rough. However, the portion with an IRI of 3.24 m/km, where the rating occurred, was in poor condition. Including such non-homogeneous segments in the MLC has the potential to confound the results. Dynamic segmentation can be used to identify segments with non-homogeneous conditions.

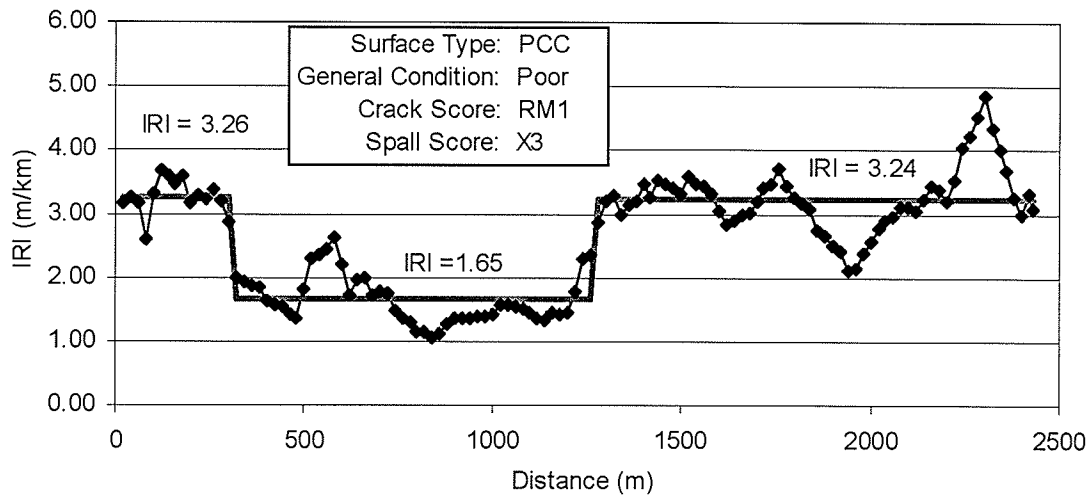


Figure 4.3: IRI on a segment of St. Mary's Rd showing three distinct segments

4.3.1.1 Dynamic Segmentation

Dynamic segmentation is the determination of statistically homogeneous units based on pavement response or condition measurements. A pavement management system depends on segments with relatively uniform conditions. Data collection and storage needs are optimized by eliminating redundant collection of data on segments with relatively uniform conditions. Dynamic segmentation of the regional street network allows for the quick and easy verification of the current segmentation based on data collected with the high-speed laser-based survey equipment.

4.3.1.2 Cumulative Difference Approach

A commonly used method of determining homogeneous units is the cumulative difference approach. The cumulative difference approach (CDA) is fundamentally easy to visualize and can be implemented for large databases with a programming solution. (AASHTO: 1993) The approach can be used for almost any pavement response variables such as roughness, rutting, skid resistance, deflection, etc. For this study, the street network is segmented based on roughness, since roughness is a general indicator of pavement condition.

4.3.1.3 CDA Example: St. Mary's Road from Burland Ave to Greendell Ave

The cumulative difference approach is best explained within the context of an example. The example given here is northbound St. Mary's Road from Burland Ave to Greendell Ave. This segment, shown in Figure 4.4 is a 2.5 km PCC segment located in St. Vital.

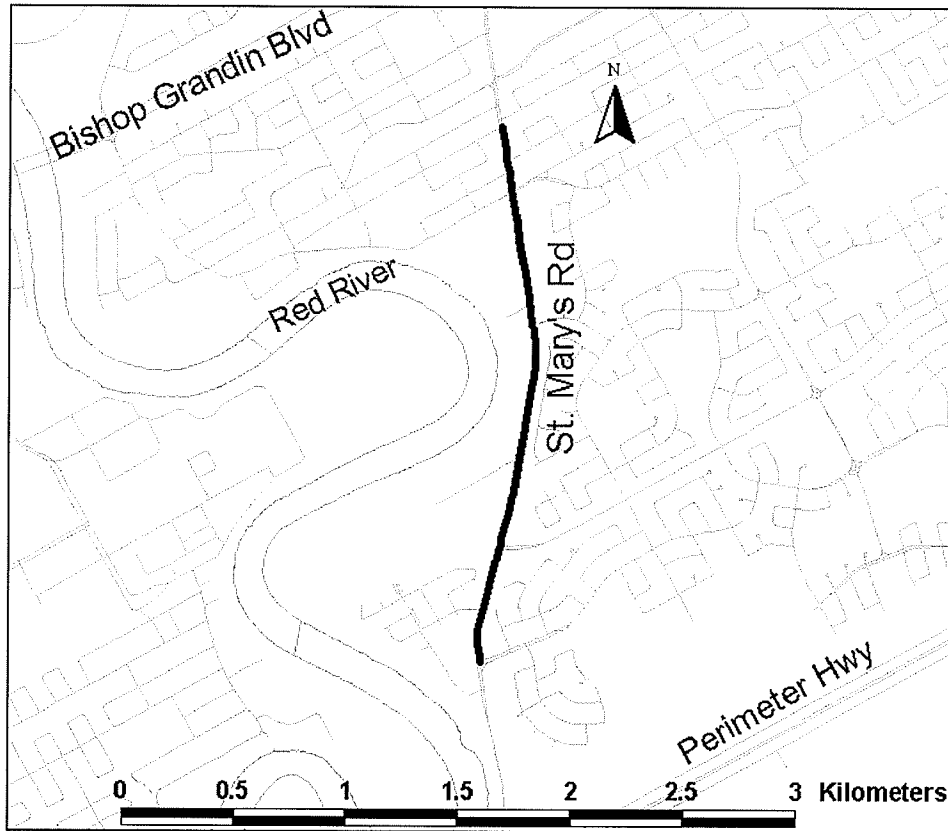


Figure 4.4: Location of the St. Mary's Road example segment

The cumulative difference example is shown in Figure 4.5. Figure 4.5a shows the unprocessed IRI data. The unprocessed IRI data is numerically integrated at each point to give the cumulative area (A_x) shown in Figure 4.5b. Figure 4.5b also shows the average cumulative area ($A_{x,\text{bar}}$) under the curve. The cumulative difference ($A_x - A_{x,\text{bar}}$) is shown in Figure 4.5c; the local maxima and minima of this graph indicate where the borders of statistically uniform regions exist. (AASHTO, 1993)

Figure 4.6 shows the results of the dynamic segmentation on St. Mary's Road. Post-processing is required to address two issues, (i) short insignificant segments such as at 2000 m in the example,

and (ii) segmentation that occurs where there is an insignificant change in pavement condition, as at 600 m in the example.

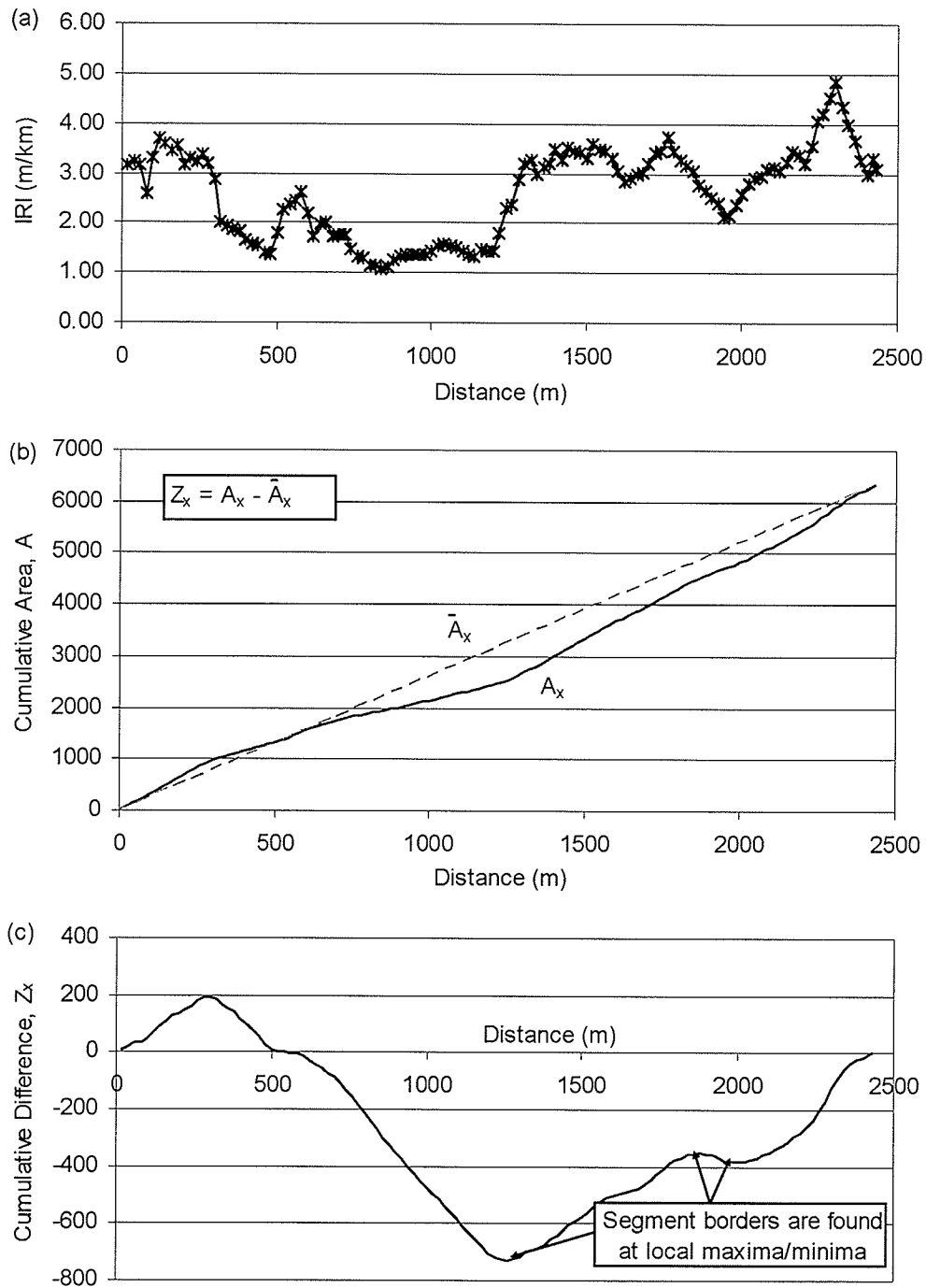


Figure 4.5: Cumulative difference approach on St. Mary's Road. (a) unprocessed IRI data, (b) cumulative area, (c) cumulative difference

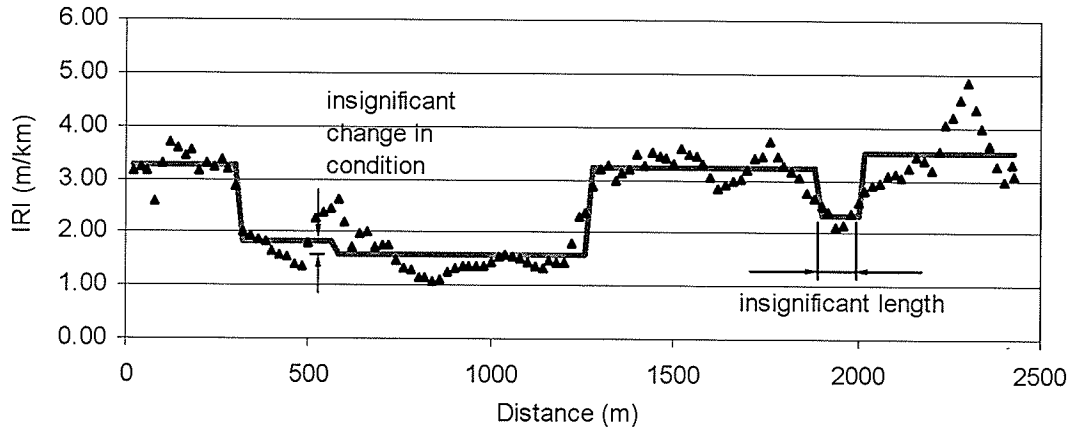


Figure 4.6: St. Mary's Road segmentation based on IRI

4.3.1.4 Dynamic Segmentation Software

A software package, IRIIS (IRI Information System), was developed during the course of this research to automate the segmentation process. Additional capabilities of the software are discussed in a subsequent chapter. The software has the capability to solve each of the two problems associated with the cumulative difference approach. IRIIS applies user-defined criteria to set the minimum significant segment length and the minimum significant change in IRI. A segment is subdivided only if the resulting change in condition and length of segment exceed those of the user-defined criteria, shown in Figure 4.7. Ping et al. (1999) used a similar procedure for setting a minimum segment length and minimum change in rut depth when using the cumulative difference approach to segment based on rutting data.

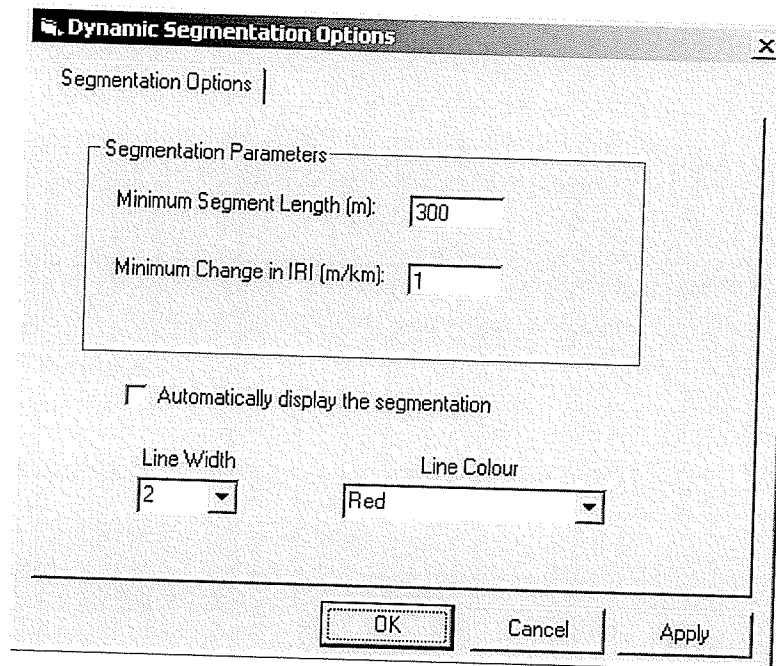


Figure 4.7: User-defined segmentation criteria

Figure 4.8 shows the dynamic segmentation output when applied to the same segment on St. Mary's Road with a minimum segment length of 300 m and a minimum change in IRI of 1.00 m/km. The minimum length and change in condition parameters eliminated the segmentation that occurred at 600 m and 2000 m in Figure 4.6.

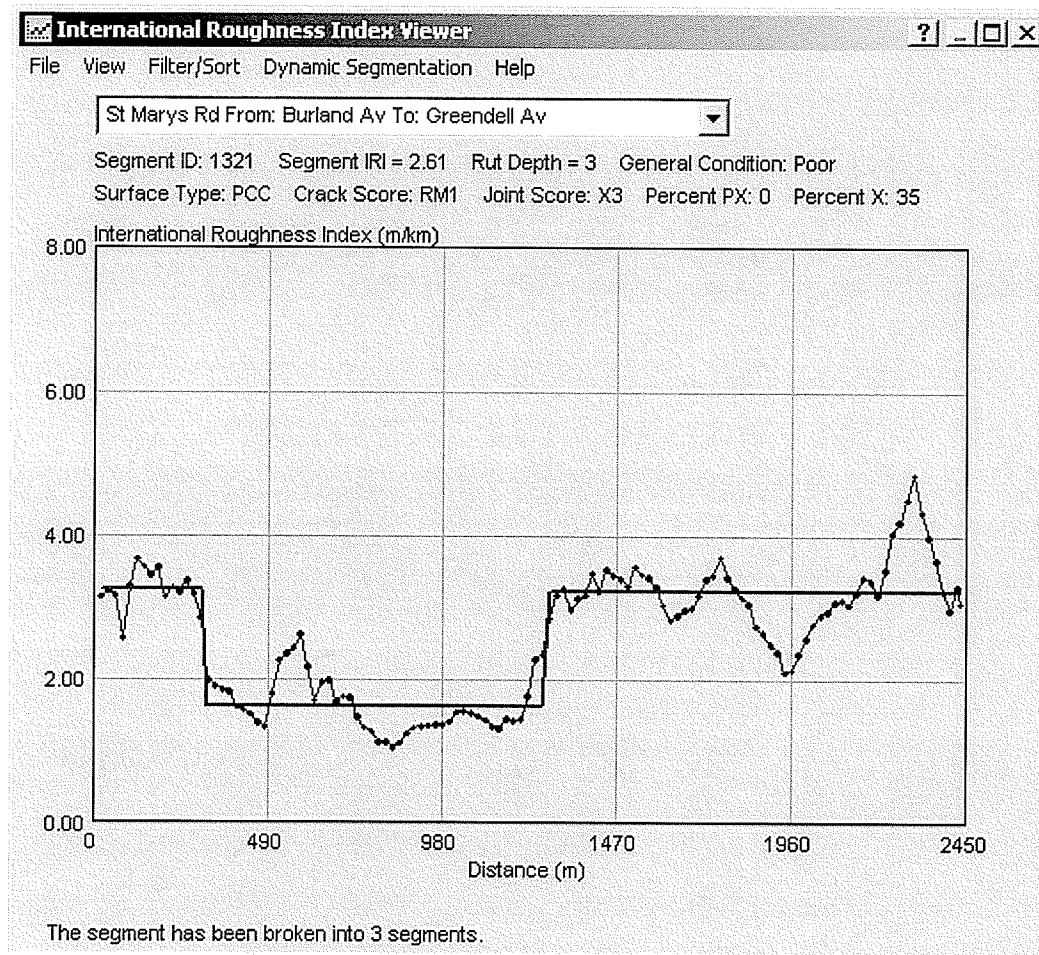


Figure 4.8: Dynamic segmentation output of IRIIS on St. Mary's Rd

4.3.1.5 Dynamic Segmentation Results

IRIIS enables the segmentation of the entire network based on user-defined parameters. Through trial and error, the user can select optimum segmentation parameters, and be able to view the resulting segments without performing tedious calculations. Figure 4.9 illustrates the number of non-homogenous segments found in the original 836 segments using IRIIS and various user-specified minimum segment length and minimum change in IRI. Excessive segmentation of the existing network can result when extremely short segments are allowed or when new segments are formed for small changes in condition.

Based on practical uses of the data, it is recommended to select a minimum segment length of 300 m and a minimum change in IRI of 1.00 m/km. It is possible that data collected with other equipment would produce results with more or less longitudinal variation, which would make it necessary to increase or decrease the minimum change in IRI.

The minimum segment length of 300 m prevents the addition of extremely short segments, which would increase the cost of manual surveys and could be problematic for additional automated surveys. The minimum change in IRI of 1.00 m/km reduces the chance that a segment will be added due to noise in the data. The recommended parameters result in 59 of the 836 segments being broken into new segments that are homogeneous with respect to IRI.

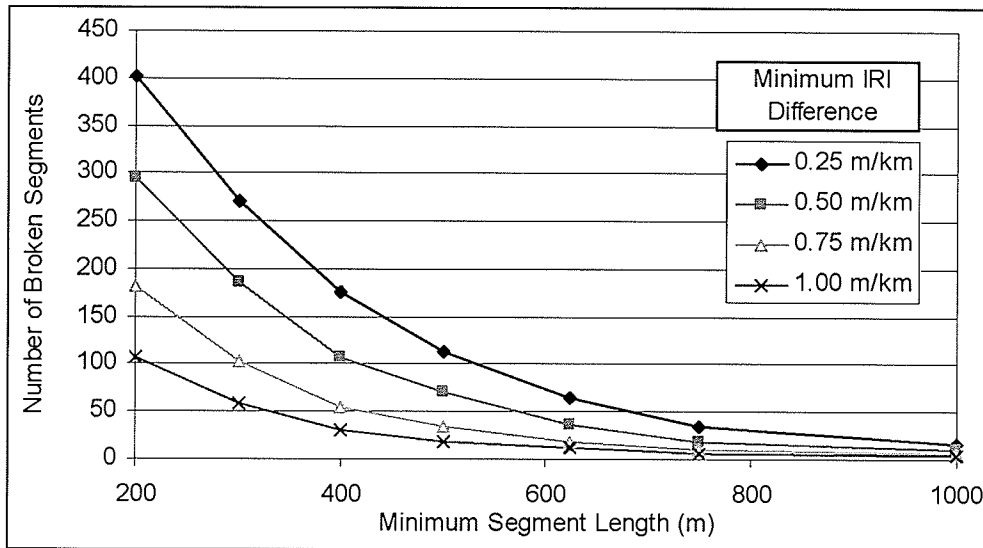


Figure 4.9: The number of segments broken based on different segmentation criteria

IRIIS was used to identify those segments, such as St. Mary's Rd in the example, so that they can be eliminated from the analysis of relationships between the automated and manually collected data elements. Any segment that required segmentation based on a minimum segment length of 300 m and a minimum change in IRI of 1.00 m/km was excluded from the training and test data. This process filtered 59 of the 836 segments, which were not homogeneous with respect to IRI. There were 550 APC segments and 140 PCC segments remaining after the identified segments were removed from the original dataset.

4.3.2 Bayes' Theorem

Bayes' theorem provides a method for the calculation of conditional probabilities. That is, the probability that the segment belongs to a pavement condition class given that it has specific IRI and rut depth, $P(\text{Class}|\text{IRI and Rut Depth})$.

$$P(C_k | x) = \frac{p(x | C_k)P(C_k)}{p(x)} \quad (\text{Equation 4.2})$$

where,

- C_k = class of measurement such as new, good, fair, and poor
- x = a measurement value of pavement condition such as rut depth or IRI
- $P(C_k)$ = prior probability of class k
- $p(x|C_k)$ = conditional probability density of class k at measurement x
- $p(x)$ = unconditional probability density of x regardless of class
- $P(C_k|x)$ = posterior probability of class k given measurement x

4.3.2.1 Probability Density Estimation

To implement Bayes' theorem it is necessary to determine the class conditional probability densities as well as unconditional probability densities. A randomly selected 80% of the segments were used to train the decision space, that is, to find prior probabilities and probability densities. The remaining 20% of the segments were used to test the validity of the classification technique. Typically, 67% to 90% of a dataset is used for the training of MLC decision spaces and artificial neural networks. Shekharan (1999) used a training/testing split of 80/20 when using ANNs to assess the relative contribution of input variables on pavement performance prediction.

The log-normal distribution is more appropriate than a normal distribution for estimating probability density because it is bounded at zero, as are IRI and rut depth. Reggin and Shalaby (2003) concluded that a log-normal distribution can reasonably represent IRI and rutting data. Figures 4.10 and 4.11 show that a log-normal distribution gives a fairly good estimate of probability density for IRI and rutting on APC and PCC segments, respectively.

Probability density was estimated using log-normal distributions for IRI and rut depth, for each class of each rating category; using the training data. The six categories are summarized in Table 4.3, each category contains four classes. The same classification procedure was completed for APC and PCC segments independently.

Table 4.3: Summary of Classification Categories

General Condition	Cracking Score			Joint Score	
	Type	Severity	Extent	Severity	Extent
New	None	New	0	New	0
Good	Random	Slight	1	Slight	1
Fair	Branch	Moderate	2	Moderate	2
Poor	Pattern	Extreme	3	Extreme	3

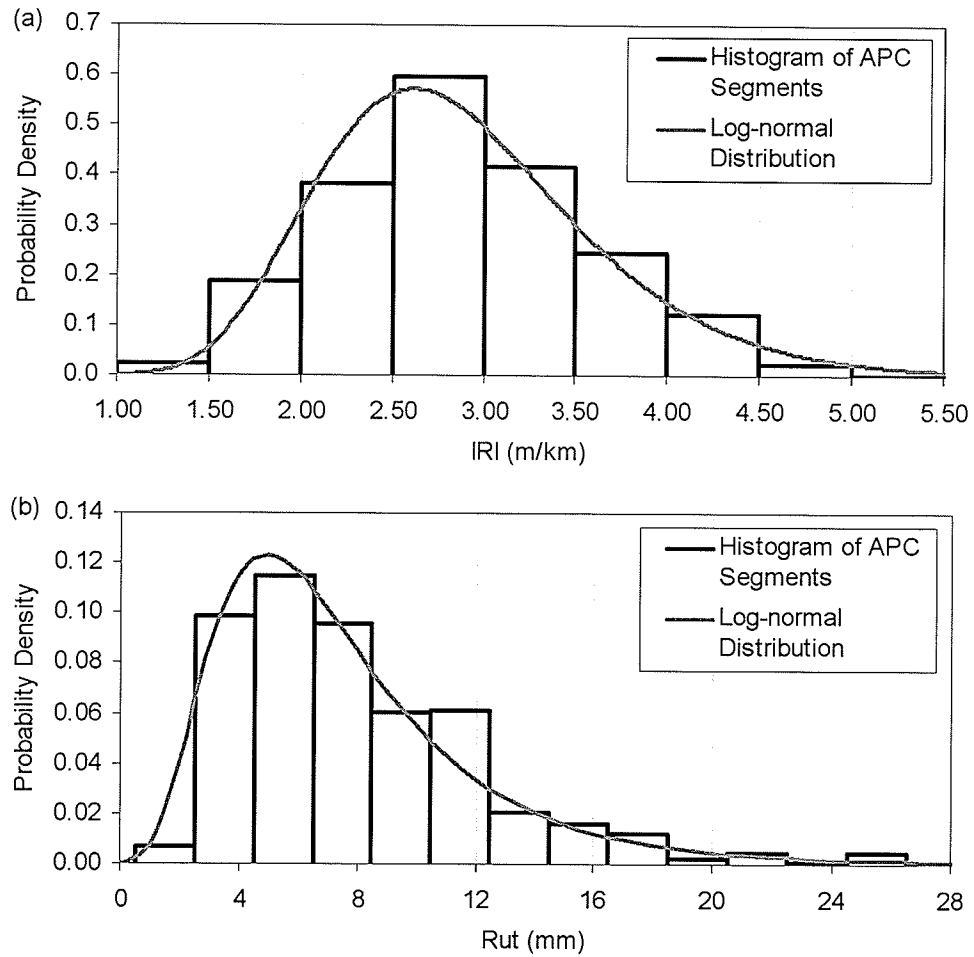


Figure 4.10: Use of a log-normal distribution to estimate the probability density for, (a) IRI on APC segments, (b) rutting on APC segments ($n = 440$)

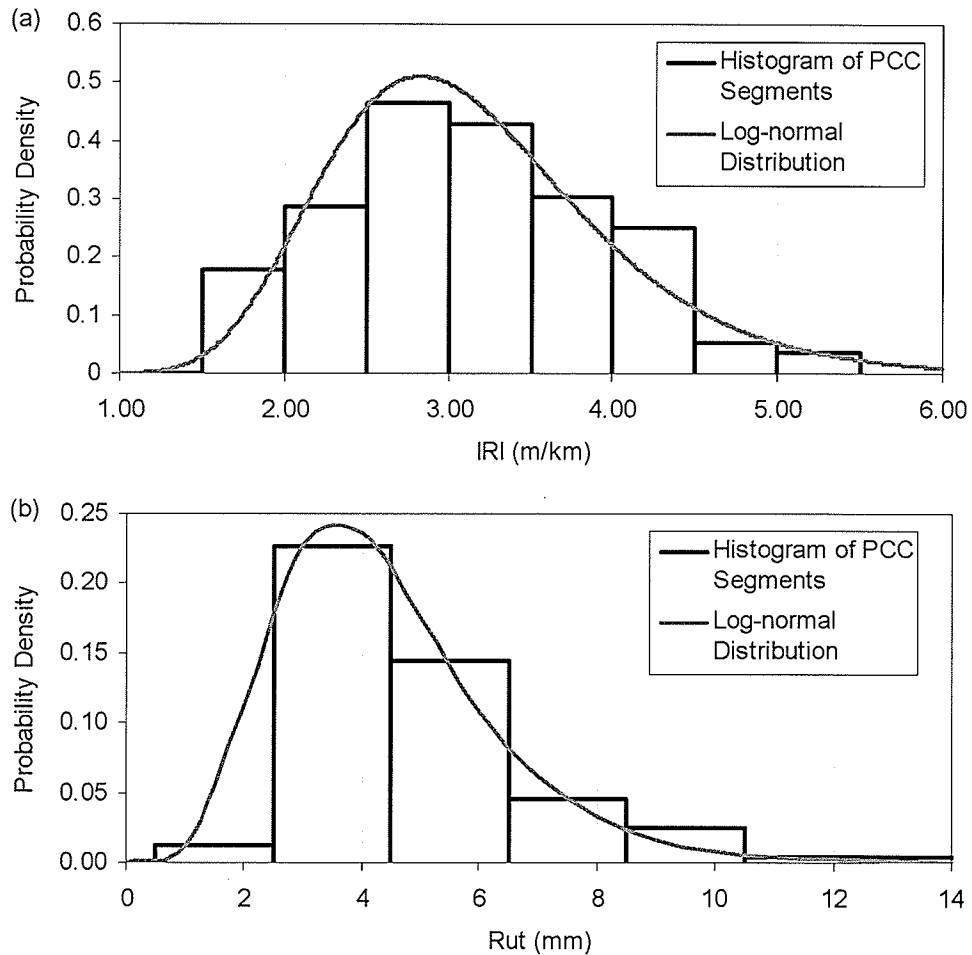


Figure 4.11: Use of a log-normal distribution to estimate the probability density for, (a) IRI on PCC segments, (b) rutting on PCC segments ($n = 112$)

4.3.3 Probability Calculation Example

The use of Bayes' theorem is best explained in the context of an example. In this example, Bayes' theorem is used to predict the general condition of APC segments based on IRI. The test data was used to calculate the parameters for each class of the general condition category; they are summarized in Table 4.4. The prior probability of each class was calculated as the number of samples in that class divided by the total sample size.

Probability density was calculated for each class based on its sample average and standard deviation. Figure 4.12 shows the probability density curves for each class as well as the unconditional probability, or the probability density regardless of class.

Table 4.4: Class Parameters of General Condition on APC Segments

Class	New	Good	Fair	Poor
Average of $\text{Log}_e(\text{IRI})$	0.762	0.946	1.132	1.215
Std Dev of $\text{Log}_e(\text{IRI})$	0.217	0.250	0.190	0.179
Sample Size	18	246	87	89
Prior Probability	0.041	0.559	0.198	0.202

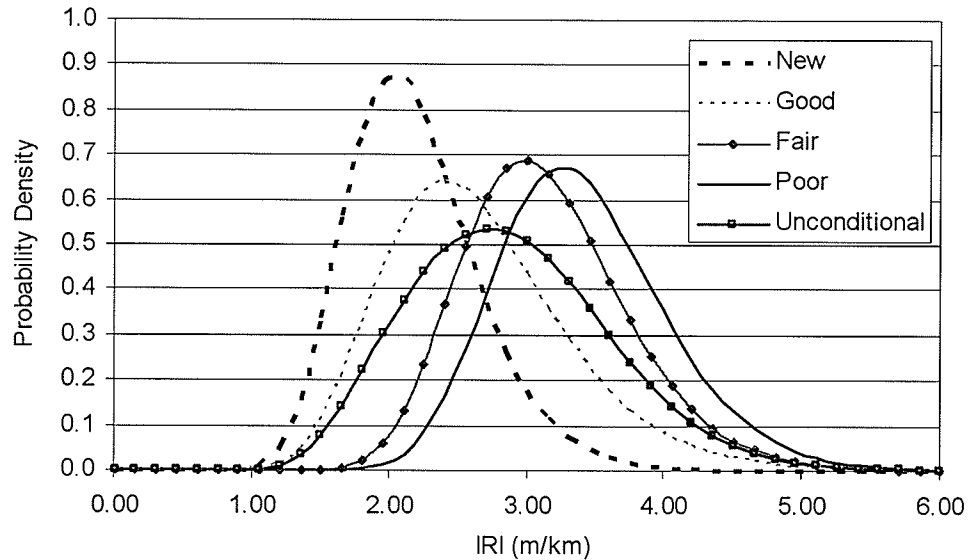


Figure 4.12: Class conditional probability densities (New, Good, Fair, and Poor) and the unconditional probability density for general condition of APC segments

Bayes' theorem was used to obtain the probabilities and decision boundaries shown in Figure 4.13. These decision boundaries are clearly undesirable. The overlap of the boundaries means that only a decision of whether a street is good or poor can be made on the basis of IRI smaller or greater than 3.45 m/km. There are no distinguishable boundaries that can lead to an assignment of fair or new condition.

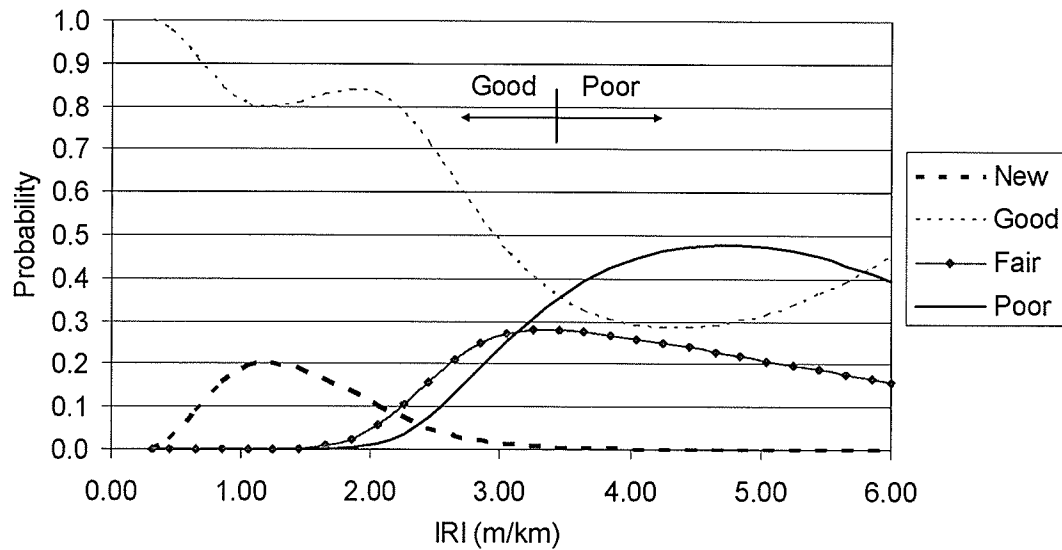


Figure 4.13: Probabilities and decision boundaries for APC general condition classification

4.3.4 Sensitivity Analysis

The inadequate decision boundaries resulted because of the lack of distinction between the probability density curves. A sensitivity analysis of the example demonstrates this phenomenon. Completely different decision boundaries would result if the class conditional probability density curve of new streets in Figure 4.13 were shifted by 0.1 m/km to the left. Applying Bayes' theorem to the shifted probability density curve results in the decision boundaries shown in Figure 4.14. The small shift in IRI resulted in a rather large change in the decision boundaries, showing that the decision boundaries are very sensitive to the estimates of probability density because the probability density curves of the different classes do not exhibit sufficient heterogeneity.

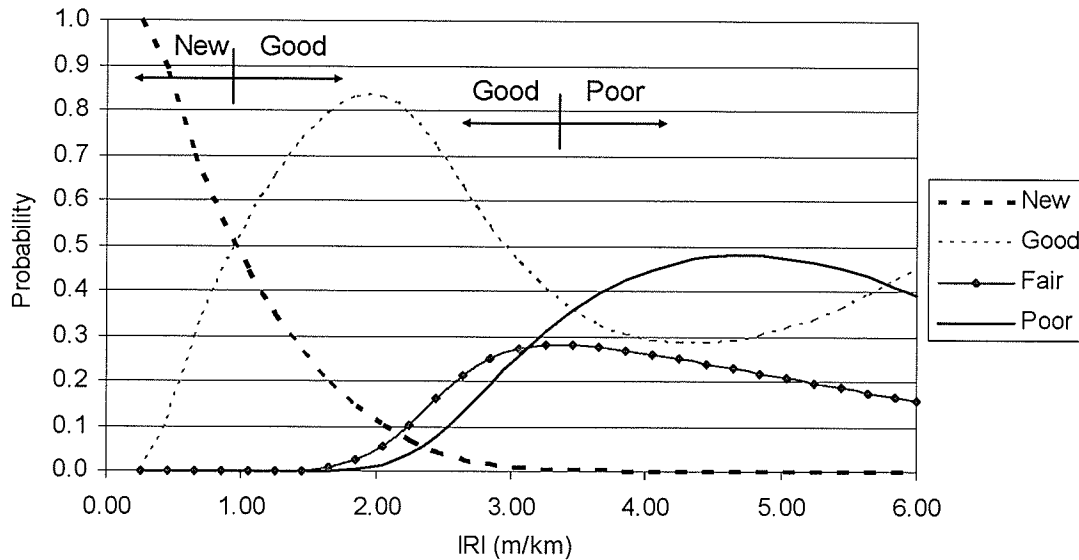


Figure 4.14: Decision boundaries resulting from sensitivity analysis

4.3.5 Classification Based on IRI and Rut Depth

The maximum likelihood classification technique was unable to predict the general condition from the manual rating based on IRI alone; due to a lack of separation between the probability density curves, also known as a lack of clustering. It is possible that classification in two dimensions, IRI and rut depth, could yield more favourable results. Bayes' theorem holds for multiple dimensions where the measurement (x) becomes a vector of IRI and Rut Depth.

Joint probability densities were calculated by multiplying the probability density of IRI by the probability density of rut depth. This method of calculating joint probability density is valid if the two variables are independent. Figures 4.15 and 4.16 show that there is not a significant relationship between the IRI and rut depth data for the APC and PCC segments respectively.

There are also numerous examples of streets throughout the regional street network that have high roughness and low rut depth or vice versa. For example, the PCC segment of McGillivray Blvd. from Waverley St. to Fennell St. has an IRI of 5.06 m/km and an average rut depth of 4 mm, while the PCC segment of Main St. from McAdam Ave. to Partridge Ave. has an IRI of 2.89 m/km and an average rut depth of 8 mm. Other examples of the independence of IRI and rut depth are the APC segment of Edmonton St. from Broadway Ave. to St. Mary Ave. which has a high IRI of 4.41 m/km and a low rut depth of 4 mm and a segment of St. Mary's Rd. from St. Anne's Rd to Morier Ave with a low IRI of 2.03 m/km and a high rut depth of 22 mm.

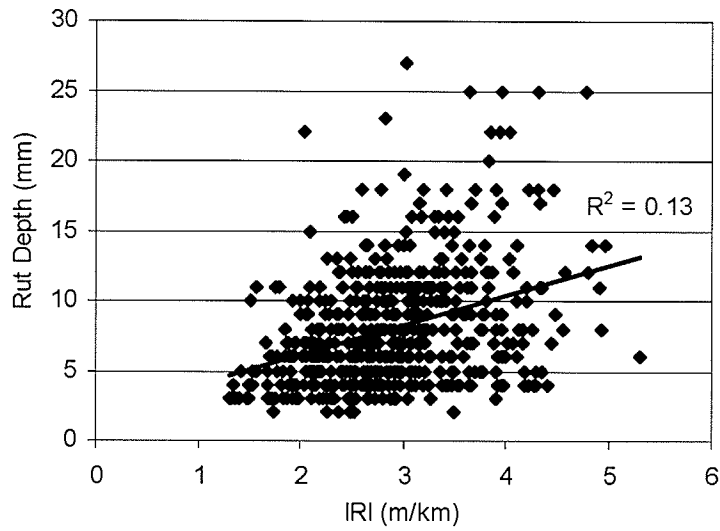


Figure 4.15: Scatter-plot of IRI and rut depth for APC segments (n=572)

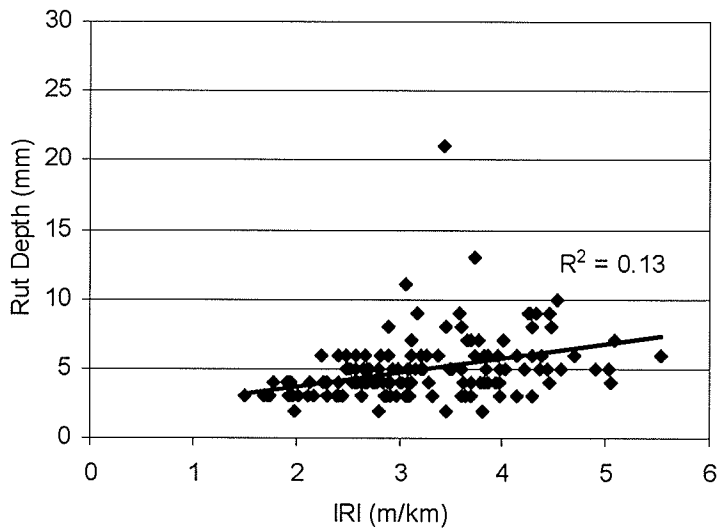


Figure 4.16: Scatter-plot of IRI and rut depth for PCC segments (n=157)

The resulting decision boundaries for the classification of general condition based on IRI and rut depth are shown in Figure 4.17.

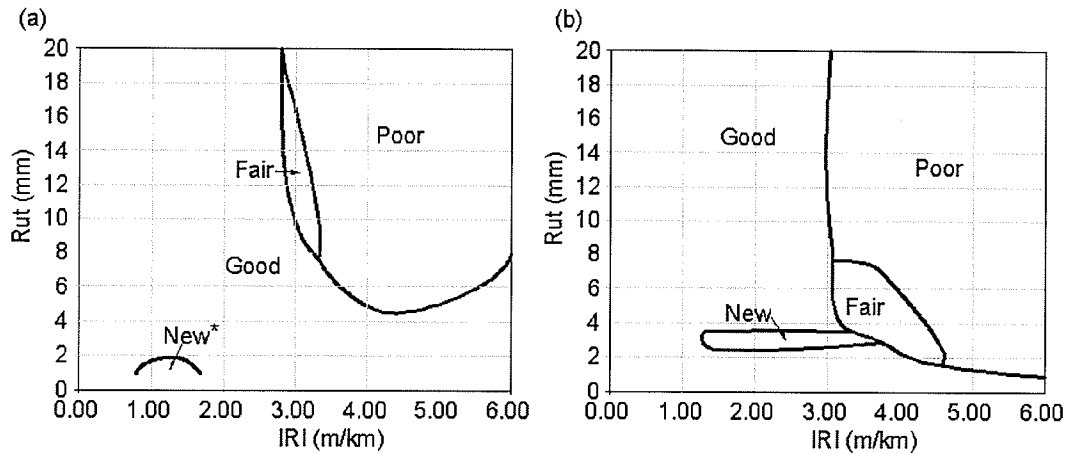


Figure 4.17: General condition MLC decision space for, (a) APC streets and (b) PCC streets.

* The decision boundary does not extent to the IRI axis because probability density cannot be calculated for rut depths equal to zero. Probability density at zero is equal to zero for log-normal distributions, which results in division by zero when Bayes' theorem is used.

The addition of rut depth to the classification method has resulted in a more reasonable decision space. There are combinations of IRI and rut depth that lead to streets being classified in each of the general condition categories.

The problem is that some of the decision boundaries are counterintuitive. For example, if an APC street (Fig. 4.17a) has an IRI of 4.5 m/km and a rut depth of 5 mm, it would be classified as 'Poor'. However, if the IRI of this segment were 5.3 m/km the segment would be classified as 'Good'. Similar problems exist for the PCC streets, if a PCC street has an IRI of 2.0 m/km and a rut depth of 3 mm, it would be classified as 'New'. However, if the rut depth were slightly less, the street would be classified as 'Good'. It is counterintuitive to have an improvement in condition when either IRI or rut depth increase.

Figures 4.18 to 4.22 show the resulting maximum likelihood decision space for all of the other categories: crack type, crack severity, crack extent, joint severity, and joint extent.

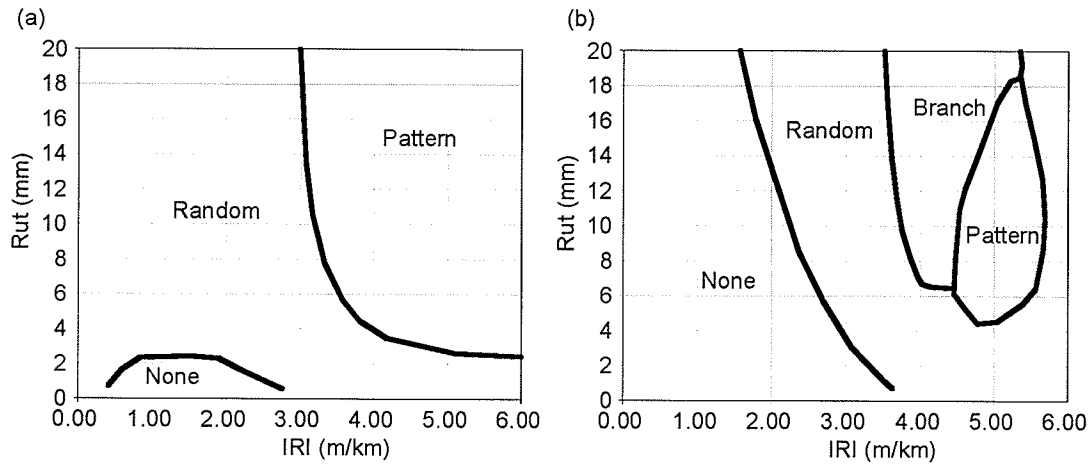


Figure 4.18: Crack type MLC decision space for, (a) APC, and (b) PCC streets

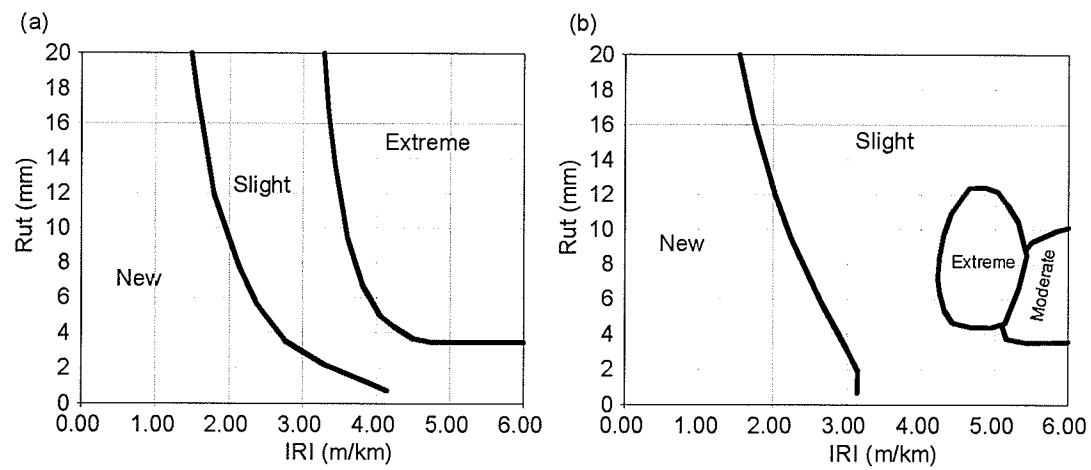


Figure 4.19: Crack severity MLC decision space for, (a) APC, and (b) PCC streets

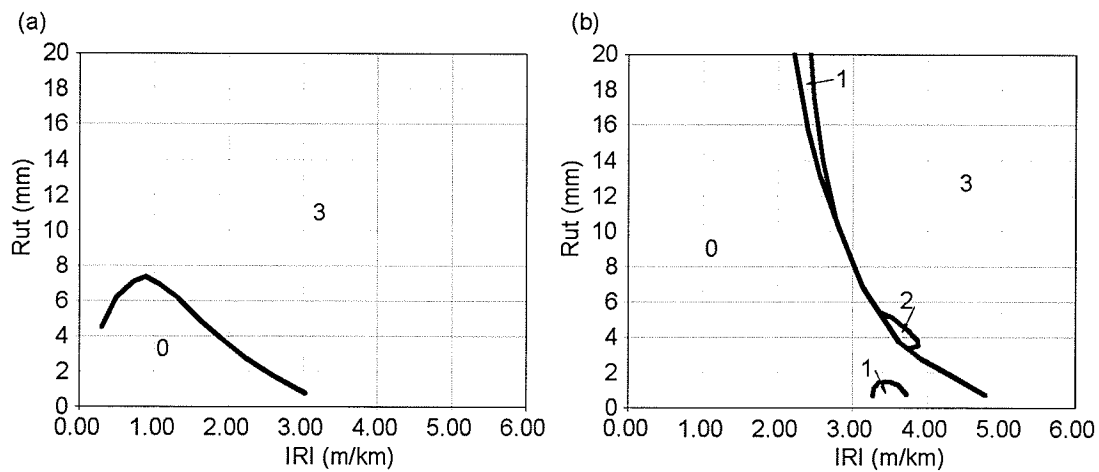


Figure 4.20: Crack extent MLC decision space for (a) APC, and (b) PCC streets

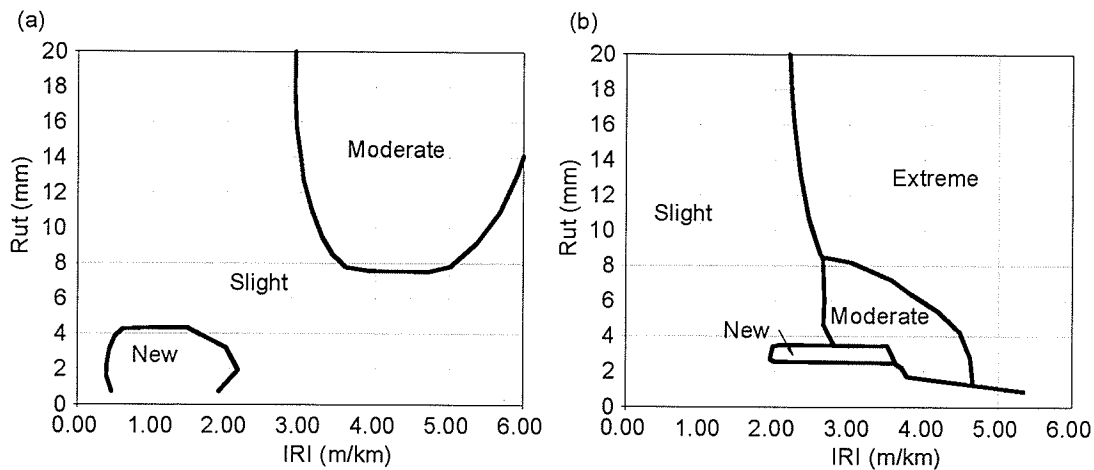


Figure 4.21: Joint severity MLC decision space for (a) APC, and (b) PCC streets

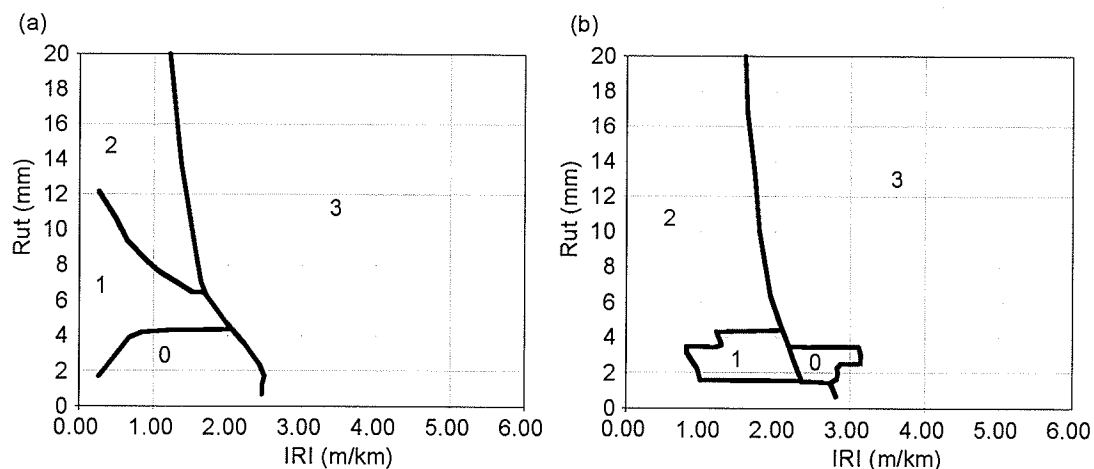


Figure 4.22: Spall extent MLC decision space for (a) APC, and (b) PCC streets

4.3.6 Assessment of Agreement

The training data was used to develop the maximum likelihood decision spaces while the test data was used to assess the agreement between the classification method and the manual rating method using contingency tables and the Kappa coefficient.

Contingency Tables

Contingency tables are useful for assessing the overall agreement between the manual rating and the maximum likelihood classification as well as the agreement for each specific class.

To illustrate, Table 4.5 is the error assessment contingency table for classification of general condition on APC streets based on IRI and rut depth. The contingency table shows an overall

agreement of 52.7% (58/110). The table also shows that the method was fairly effective at classifying 'Good' segments but rather ineffective at classifying all other segments. The classification technique correctly identified 86% of the Good segments, 0% of the 'New' segments, 6% of the 'Fair' segments, and 38% of the 'Poor' segments.

Table 4.5: Error Assessment of General Condition on APC Segments

		Subjective Rating			
		New	Good	Fair	Poor
Maximum Likelihood Classification	New	0	0	0	0
	Good	3	50	23	8
	Fair	0	3	2	2
	Poor	0	5	8	6
Percent matching		0%	86%	6%	38%

Tables 4.6 to 4.17 show the error assessment contingency tables for each category of distress on each type of pavement. The tables show that MLC was an adequate predictor for only one or two of the four classes for each of the twelve categories.

Table 4.6: Agreement between manual ratings and MLC ratings based on IRI and rut depth for **Crack Type** on APC Segments

		Manual Rating			
		None	Random	Branch	Pattern
Maximum Likelihood Classification	None	0	0	0	0
	Random	10	55	11	10
	Branch	0	0	0	0
	Pattern	0	13	4	7
Percent matching		0%	81%	0%	41%

Table 4.7: Agreement between manual ratings and MLC ratings based on IRI and rut depth for **Crack Severity** on APC Segments

		Manual Rating			
		New	Slight	Moderate	Extreme
Maximum Likelihood Classification	New	17	9	0	1
	Slight	24	27	10	8
	Moderate	0	0	0	0
	Extreme	0	5	5	4
Percent matching		41%	66%	0%	31%

Table 4.8: Agreement between manual ratings and MLC ratings based on IRI and rut depth for **Crack Extent** on APC Segments

		Manual Rating			
		0	1	2	3
Maximum Likelihood Classification	0	0	3	0	3
	1	0	0	0	0
	2	0	0	0	0
	3	10	6	5	83
Percent matching		0%	0%	0%	97%

Table 4.9: Agreement between manual ratings and MLC ratings based on IRI and rut depth for **Joint Severity** on APC Segments

		Manual Rating			
		New	Slight	Moderate	Extreme
Maximum Likelihood Classification	New	1	2	0	0
	Slight	6	51	23	6
	Moderate	0	10	9	2
	Extreme	0	0	0	0
Percent matching		14%	81%	28%	0%

Table 4.10: Agreement between manual ratings and MLC ratings based on IRI and rut depth for **Joint Extent** on APC Segments

		Manual Rating			
		0	1	2	3
Maximum Likelihood Classification	0	1	2	1	1
	1	1	0	0	2
	2	0	0	0	0
	3	5	4	8	85
Percent matching		14%	0%	0%	97%

Table 4.11: Agreement between manual ratings and MLC ratings based on IRI and rut depth for **General Condition** on PCC Segments

		Manual Rating			
		New	Good	Fair	Poor
Maximum Likelihood Classification	New	3	2	1	0
	Good	2	1	3	1
	Fair	1	5	3	1
	Poor	0	1	1	3
Percent matching		50%	11%	38%	60%

Table 4.12: Agreement between manual ratings and MLC ratings based on IRI and rut depth for **Crack Type** on PCC Segments

		Manual Rating			
		None	Random	Branch	Pattern
Maximum Likelihood Classification	None	12	3	0	0
	Random	5	7	1	0
	Branch	0	0	0	0
	Pattern	0	0	0	0
Percent matching		71%	70%	0%	N/A

Table 4.13: Agreement between manual ratings and MLC ratings based on IRI and rut depth for **Crack Severity** on PCC Segments

		Manual Rating			
		New	Slight	Moderate	Extreme
Maximum Likelihood Classification	New	11	2	0	1
	Slight	6	8	0	0
	Moderate	0	0	0	0
	Extreme	0	0	0	0
Percent matching		65%	80%	N/A	0%

Table 4.14: Agreement between manual ratings and MLC ratings based on IRI and rut depth for **Crack Extent** on PCC Segments

		Manual Rating			
		0	1	2	3
Maximum Likelihood Classification	0	14	5	0	0
	1	0	0	0	0
	2	1	0	0	0
	3	2	3	1	2
Percent matching		82%	0%	0%	100%

Table 4.15: Agreement between manual ratings and MLC ratings based on IRI and rut depth for **Joint Severity** on PCC Segments

		Manual Rating			
		New	Slight	Moderate	Extreme
Maximum Likelihood Classification	New	1	3	1	0
	Slight	2	3	2	1
	Moderate	0	6	3	3
	Extreme	0	1	1	1
Percent matching		33%	23%	43%	20%

Table 4.16: Agreement between manual ratings and MLC ratings based on IRI and rut depth for **Joint Extent** on PCC Segments

		Manual Rating			
		0	1	2	3
Maximum Likelihood Classification	0	1	1	1	1
	1	0	1	1	0
	2	0	3	0	0
	3	2	0	0	17
Percent matching		33%	20%	0%	94%

The Kappa Coefficient

The Kappa coefficient is a more precise method for assessing agreement because it accounts for chance agreement. Landers et al (2003) used the Kappa coefficient for quality assurance of manual pavement surveys by assessing the agreement between different pavement raters. Goodman (2001) also used the Kappa coefficient to compare the variability between pavement distress surveys. An example calculation of chance agreement is shown in Table 4.17.

$$\kappa = \frac{\text{observed accuracy} - \text{chance agreement}}{1 - \text{chance agreement}} \quad (\text{Equation 4.3})$$

To calculate prior probability, the number of segments in each subjective rating class is multiplied by the prior probability of that class. In other words, for ‘Good’ streets 55.9% (the prior probability from Table 4.4) of the 58 in the test data set would be classified as ‘Good’ purely by chance.

Table 4.17: Example calculation of chance agreement for general condition on APC segments

Class	New	Good	Fair	Poor
Number of Segments	3	58	33	16
Prior Probability (from Table 4.4)	0.041	0.559	0.198	0.202
Chance Agreement = (number of segments) * (prior probability)	0	32	7	3
% Chance agreement = (0 + 32 + 7 + 3)/110 = 38.1%				

The observed accuracy for the classification of general condition of APC segments was 52.7% and the chance agreement was 38.1%. The Kappa coefficient is calculated as $(0.527 - 0.381)/(1 - 0.381) = 0.24$. This represents fair agreement according to the guidelines given in Table 4.18. The agreement is only 24% better than chance agreement.

Table 4.18: Interpretation of Agreement from the Kappa Coefficient (Landis and Koch, 1977)

Kappa Value	Strength of Agreement
Below 0.00	Poor
0.00 - 0.20	Slight
0.21 - 0.40	Fair
0.41 - 0.60	Moderate
0.61 - 0.80	Substantial
0.81 - 1.00	Almost perfect

Figures 4.23 and 4.24 summarize the agreement for maximum likelihood classification for all of the manual rating categories of APC and PCC segments. For the APC segments the agreement ranged from slight to moderate while for PCC segments the agreement ranged from poor to moderate. The Kappa coefficient was less than 0.5 (50% better than chance) for all categories.

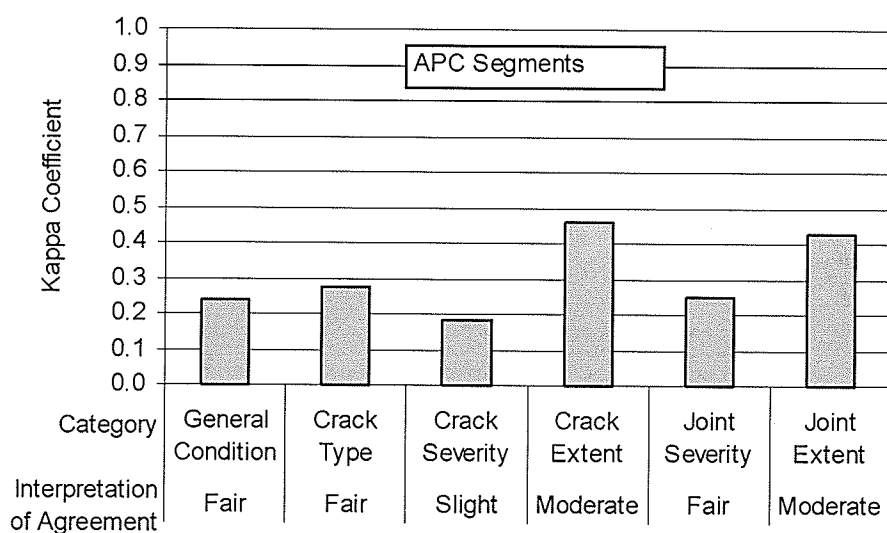


Figure 4.23: Strength of agreement for maximum likelihood classification of APC segments

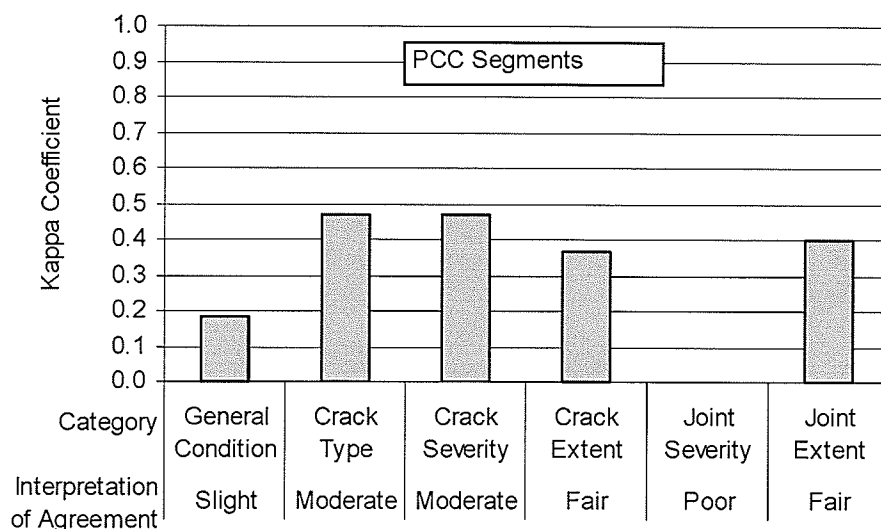


Figure 4.24: Strength of agreement for maximum likelihood classification of PCC segments

4.3.7 Summary of Maximum Likelihood Classification

The MLC analysis highlights the weakness of the agreement between the manual ratings conducted on representative sample units and the automated continuous surveys. The analysis first filtered segments with inconsistent conditions according to the cumulative difference approach and criteria specified for minimum segment length and minimum change in condition. The remaining sections were used to create decision boundaries for each category of the manual rating system. The analysis demonstrated that the lack of data clustering significantly reduces the predictive ability of this method based on IRI or rut depth alone. However, the maximum likelihood classification method produces more reasonable decision boundaries when the decision space includes both IRI and rut depth.

Error was assessed using contingency tables and the Kappa coefficient. The contingency tables show that the classification method could usually only accurately predict one or two classes for any category. The Kappa coefficient tested the agreement between the classification method and the manual rating system and showed that the agreement is at best moderate when compared to chance agreement alone. A substantial agreement, $Kappa > 0.7$, would be necessary to justify the use of automated surveys to predict manual ratings and thus replace them. The condition of the network cannot be based entirely on IRI and rut depth from automated surveys.

4.4 Artificial Neural Networks

Artificial Neural Networks (ANN) have been used in many fields for pattern recognition, from speech and handwriting recognition, to fault detection in machinery and medical diagnosis (Bishop, 1995).

ANNs have also been used numerous times in transportation and pavement engineering applications. Mohammadian and Miller (2002) assessed the ability of neural networks to predict household vehicle choice. Fernandes et al. (2001) used neural networks for the programming of maintenance and rehabilitation of unpaved roads. Abdallah et al. (2001) used artificial neural networks in real-time to predict pavement layer thicknesses and moduli based on deflection and seismic data.

Artificial neural networks are another method explored for the optimization of data collection needs. This section documents attempts to use ANNs to predict manual ratings based on IRI and rut depth collected with automated equipment. Neural networks are composed of many single units operating in parallel. These units are inspired by biological nervous systems. (Demuth and Beale, 2002) The neural network “learns” through a training process that utilizes training data to adjust the weights and biases of the connections between elements to achieve the desired output.

4.4.1 Neural Network Architecture

Determining the neural network architecture requires significant effort; including the determination of input and output variables, the number of hidden layers, and the number of hidden neurons in each hidden layer. In practice, most neural network applications use only one hidden layer and trial and error is employed to select the number of neurons for the hidden layer (Yang et al., 2003). Yang et al. also found that processing time increases significantly when two hidden layers are used. Keeping processing time to a minimum is necessary for this research because of the significant number of pavement condition variables to predict; six for each of the two pavement types.

This research utilizes multilayer perceptrons (MLP) to predict the classes of distress for segments based on the segment's IRI and average rut depth. The training of an MLP is usually accomplished by a back-propagation algorithm that involves two phases, the forward phase and the backward phase. During the forward phase the network weights and biases are fixed as the inputs are passed through the network and the outputs are calculated. The error is computed as the desired response minus the actual response (equation 4.4). During the backward phase, the

error, e_i , is passed backward through the network and the network weights and biases are adjusted to minimize e_i , usually as represented by root-mean-square (RMS) error. (Haykin, 1994)

$$e_i = d_i - y_i \quad (\text{Equation 4.4})$$

where,

e_i = the error for the i^{th} element

d_i = the desired response

y_i = the calculated network output

The Matlab Neural Network Processing toolbox was used to train and test the multilayer perceptrons. The Matlab 'trainrp' function was used as the training function. This resilient back-propagation function is the fastest algorithm on pattern recognition problems. (Demuth and Beale, 2002) The Matlab documentation also recommends that sigmoid transfer functions be used in the output layer for pattern recognition problems.

The initial bias and layer weights are randomly selected, which can lead to different decision boundaries each time the network is trained. To overcome this problem, the network was trained 100 times for 500 epochs each, the error and the decision space had stabilized after 500 epochs. Only the training run that achieved the lowest RMS error was retained. As an example, the Matlab code for the training of General Condition of APC segments is provided in Appendix B. As with the MLC analysis, a randomly selected 80% of the data was used to train the network and 20% of the data was used to test the effectiveness of the decision space.

This analysis uses neural networks with one hidden layer with the number of neurons in the hidden layer selected to maximize the potential for learning while minimizing the risk of over-fitting the model. A neural network with too few hidden neurons is incapable of sufficiently learning from the training set, while one with too many hidden neurons will attempt to memorize the training set and perform poorly for previously unseen data (Yang et al., 2003). The selection of a network with too many hidden neurons is analogous to the fitting of a polynomial of too high an order; over-fitted models are unable to generalize to new data (Bishop, 1995). For example, Figure 4.25 shows an over-fitted polynomial to linear training data (x, y) that had random error added to it. The sixth order polynomial provides lower error for the training data but higher error than a linear model for the test data.

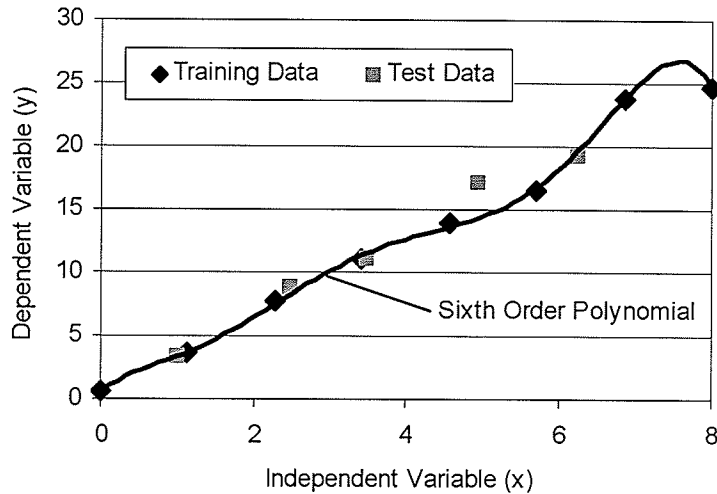


Figure 4.25: Example of over-fitting a polynomial to linear data; test data RMS error = 1.45 for the sixth order model and RMS error = 0.726 for the linear model

To avoid the problem of over-fitting the neural network by using too many hidden neurons, a number of networks were trained, with varying numbers of hidden neurons. The RMS error of the training and test data was calculated for each network. The results of these trials for the prediction of General Condition of APC streets based on IRI and rut depth are shown in Figure 4.24. This figure shows that the error for the training set decreases with increasing numbers of hidden neurons as the network attempts to memorize the training data. The RMS error for the test data reaches a minimum at five hidden neurons, after which point the model is over-fitted and the error for the test data increases. Thus, neural networks with a single layer of five hidden neurons were selected for this research.

The two network architectures used are shown in Figure 4.27. Each of these artificial neural networks utilizes IRI and rut depth as inputs, five neurons in the hidden layer, sigmoid transfer functions at each layer, and is fully connected. Neural Network 1 uses four output neurons and thus an output in the form of a four-element vector. For new streets, the target output vector is $\{1, 0, 0, 0\}$, for good streets the target output vector is $\{0, 1, 0, 0\}$, for fair streets the target output vector is $\{0, 0, 1, 0\}$, and for poor streets the target output vector is $\{0, 0, 0, 1\}$.

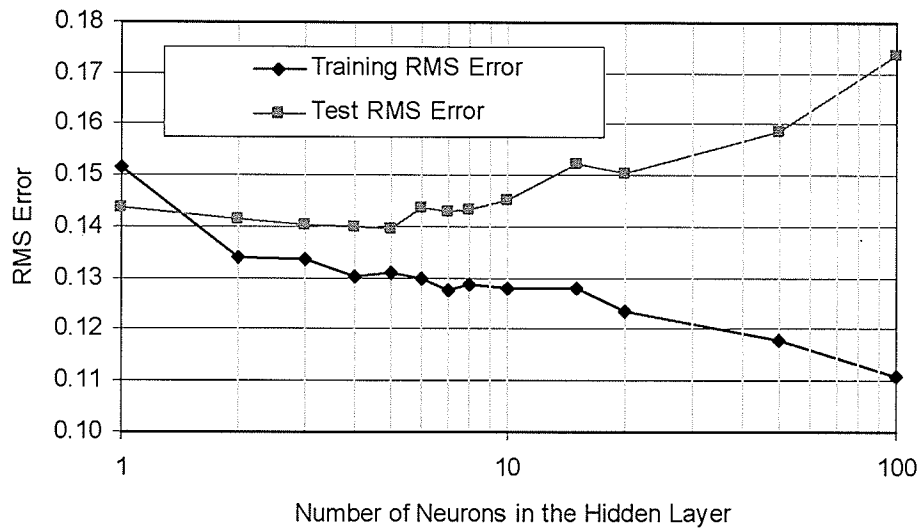


Figure 4.26: Training and test RMS errors for the prediction of General Condition of APC segments

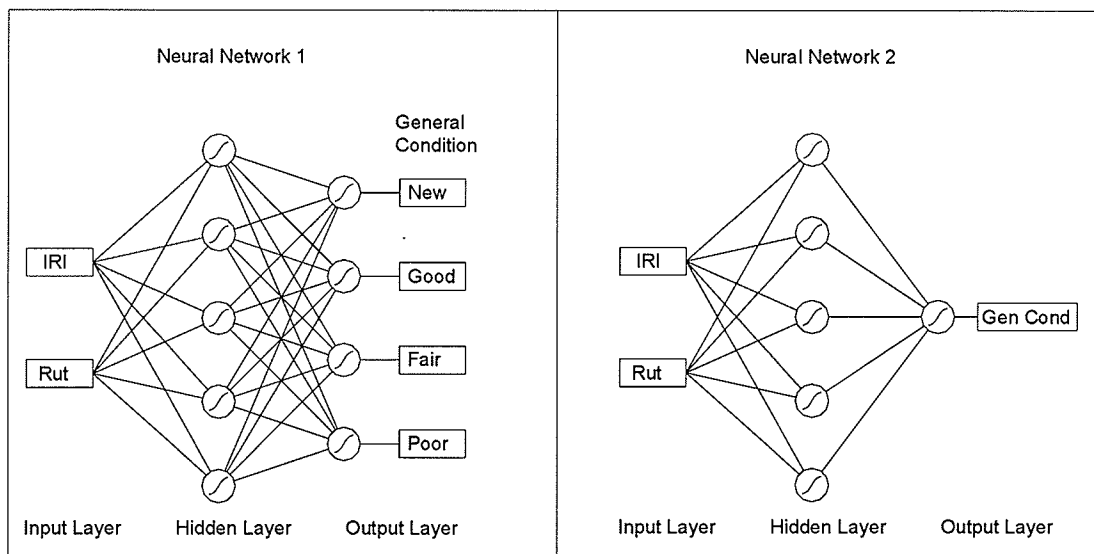


Figure 4.27: Neural Network Architectures

Neural Network 2 uses a single output neuron. The potential disadvantage of this network is that there are far fewer weights to adjust between the hidden layer and the output layer; however it has the advantage of the ability to utilize the ordinal nature of the data. The classes of each category are ordered and so are the target outputs. For General Condition the classes are {new, good, fair, poor} and the targets for the classes are {0.125, 0.375, 0.625, 0.875}.

4.4.2 Neural Network Results

As with the maximum likelihood classification analysis, the Kappa coefficient and contingency tables are used for the assessment of agreement between the manual subjective survey and the neural network results. Tables 4.19 to 4.22 summarize the Neural Network 1 and Neural Network 2 classification results for APC and PCC segments. For the classification based on Neural Network 1, the Kappa coefficients ranged from 0.15 to 0.48, at best moderate agreement between the ratings and the classification method. For the classification based on Neural Network 2, the Kappa coefficients ranged from a surprisingly low -0.42 to 0.40. The negative Kappa coefficient represents disagreement between the two methods.

Table 4.19: Neural Network 1 Classification Results for APC Segments

Parameter	Chance Agreement	Observed Agreement	Kappa Coefficient	Interpretation of Agreement
General Condition	38%	48%	0.16	Slight
Crack Type	40%	59%	0.32	Fair
Crack Severity	31%	44%	0.18	Slight
Crack Extent	55%	76%	0.48	Moderate
Joint Severity	41%	50%	0.15	Slight
Joint Extent	62%	80%	0.48	Moderate

Table 4.20: Neural Network 1 Classification Results for PCC Segments

Parameter	Chance Agreement	Observed Agreement	Kappa Coefficient	Interpretation of Agreement
General Condition	21%	57%	0.45	Moderate
Crack Type	39%	64%	0.41	Moderate
Crack Severity	39%	50%	0.18	Slight
Crack Extent	32%	54%	0.32	Fair
Joint Severity	29%	46%	0.25	Fair
Joint Extent	46%	68%	0.40	Fair

Table 4.21: Neural Network 2 Classification Results for APC Segments

Parameter	Chance Agreement	Observed Agreement	Kappa Coefficient	Interpretation of Agreement
General Condition	38%	59%	0.34	Fair
Crack Type	40%	52%	0.20	Slight
Crack Severity	31%	41%	0.14	Slight
Crack Extent	55%	35%	-0.42	Poor
Joint Severity	41%	56%	0.26	Fair
Joint Extent	62%	61%	-0.02	Poor

Table 4.22: Neural Network 2 Classification Results for PCC Segments

Parameter	Chance Agreement	Observed Agreement	Kappa Coefficient	Interpretation of Agreement
General Condition	21%	39%	0.23	Fair
Crack Type	39%	43%	0.06	Slight
Crack Severity	39%	50%	0.18	Slight
Crack Extent	32%	32%	0.00	Poor
Joint Severity	29%	57%	0.40	Fair
Joint Extent	46%	61%	0.27	Fair

As with the MLC analysis, neither ANN produced agreement strong enough to allow for replacement of the manual rating system with a classification based on IRI and rut depth. The agreement was moderate at best, while substantial agreement would be necessary to allow for the replacement of the manual ratings with neural network based ratings. A comparison of the agreement between the different classifications is shown in Figures 4.28 and 4.29 for the APC and PCC segments respectively.

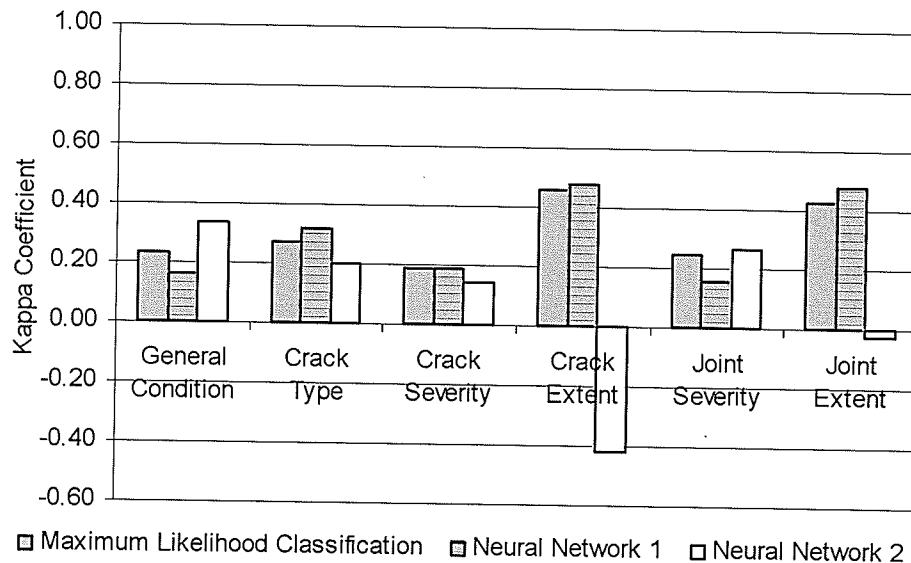


Figure 4.28: Strength of agreement for classification of APC segments based on IRI and rut depth

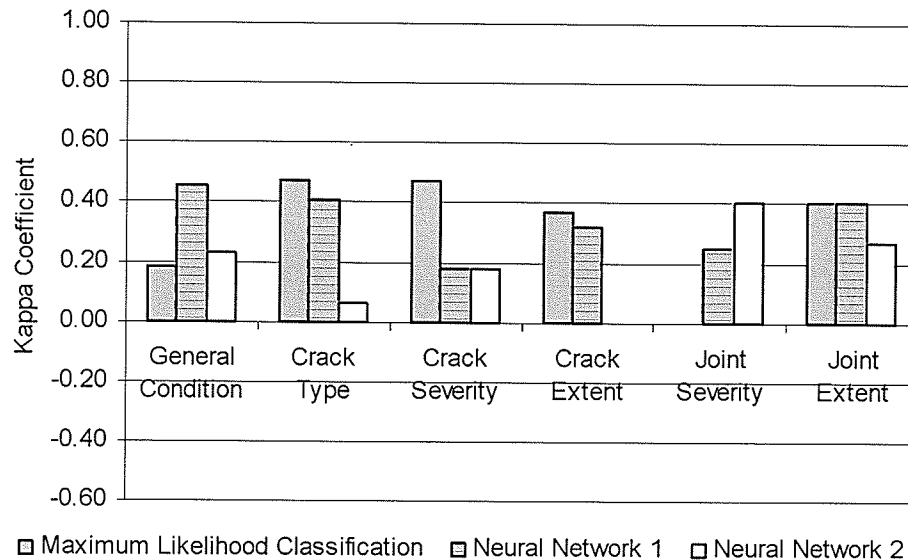


Figure 4.29: Strength of agreement for classification of PCC segments based on IRI and rut depth

4.5 Summary

This chapter documents analyses that were conducted with the objective of optimizing data collection needs by minimizing the quantity of data collected while maintaining data quality and consistency.

An analysis of the transverse variability of surface distresses collected in 2002 for the automated lane and all lanes showed that a survey of one lane of a segment is representative of the entire segment to a statistically significant degree. A non-parametric statistical analysis showed that the medians of the two datasets, the automated lane and all of the lanes are the same with 92% confidence. The analysis also showed that the lane to be surveyed in future automated surveys should be randomly selected to eliminate any bias in cracking and joint scores and that one lane is sufficient for network-level pavement management purposes. There was little overall difference in crack and joint scores, however a few segments exhibited significant differences between the lanes, which would affect decision making at the project-level.

Maximum likelihood classification and artificial neural networks were used to predict the manual rating scores based on IRI and rut depth. Non-homogeneous segments were filtered from the dataset and a randomly selected 80% of the data was used for training the maximum likelihood classifier and the ANNs. The remaining 20% of the data was used to test the ability of the classifier to predict manual ratings based on IRI and rut depth. Agreement between the manual

ratings and the predicted ratings was assessed with contingency tables and the Kappa coefficient. The Kappa coefficients showed at best moderate agreement for the MLC, Neural Network 1, and Neural Network 2. Classification based on MLC and ANNs cannot be used to predict the manual ratings based on IRI and rut depth with sufficient confidence.

Chapter 5

URBAN CONSIDERATIONS FOR THE UTILIZATION OF IRI DATA

5.1 Introduction

Laser based roughness measurements are commonly used in the evaluation of rural road networks, and to a lesser extent the evaluation of urban road networks. There are several key differences between urban and rural road networks that can affect IRI measurement. Urban networks have shorter segments with curbed cross-sections, frequent intersections, and numerous at-grade railway crossings. This chapter seeks to quantify these factors that affect IRI as well as to document the magnitude of IRI that should result from various road conditions using two analysis approaches.

The first approach involves analysis of the manual profile elevations collected in 2002 and the extensive parallel automated and manual datasets collected in the same year. An analysis of profile elevations of the section on Grant Ave quantifies the amount of roughness that can be attributed to false grades, or reversing longitudinal grades that facilitate drainage. An analysis of IRI at railway crossings of various conditions (good, fair, and poor) demonstrates the effect of railway crossings on the IRI of individual segments and the network. Segment length was also analyzed geographically to demonstrate that segment length often affects roughness and to explain this phenomenon.

The second approach involves simulations to show how much roughness should be expected from rutted intersections and different degrees of slab faulting; i.e. a segment with one faulted slab and a segment with faulting at every slab.

5.2 Literature

An extensive search for literature documenting the issues in pavement roughness unique to urban areas yielded relatively few papers on the subject. Recent research by La Torre et al. (2002) documented some of the inadequacies of the IRI in Florence Italy, among them were: (i) the available length of homogeneous sections is often shorter than the 320 m typically used in the World Bank roughness experiments that led to the development of the IRI, (ii) the speed of urban networks is typically less than the 80 km/h used in the IRI quarter-car model, (iii) the type of paving materials used in urban pavements is often different than those used in rural highways

which can result in a different type of roughness, especially for stone block pavements common in historical areas of Florence.

In 1997 and 1999 the Fund for the City of New York (FCNY) measured the roughness of streets throughout that city. The roughness statistic used by the FCNY was the City Roughness Index (CRI); the CRI is mathematically identical to the IRI. The statistics were reported as CRI to highlight the reality that urban streets do not operate at the 80 km/h used by the quarter-car model. (FCNY, 2001)

A workshop conducted by the National Cooperative Highway Research Program (NCHRP) in 2001 identified several issues in pavement smoothness and recommendations for further research. Workshop participants included individuals from state highway agencies, the Federal Highway Administration (FHWA), asphalt concrete and Portland cement concrete paving industries, academia, consulting firms, and research organizations. Included in the recommendations was the need for further research on urban issues in pavement roughness to gain understanding of IRI statistics and to examine the possibility of using different roughness indices or adjusting the simulation speed of the quarter-car model based on the roadway's functional classification or location (urban or rural). (Perera and Kohn, 2002)

5.3 False Grades

False grades are the longitudinal slope that has been built into a road to facilitate drainage. Profile changes due to drainage design can have a large influence on IRI values. Figure 5.1 shows the raw profile of Grant and the profile of Grant with all of the pavement roughness removed. Longitudinal slopes on this section average 0.37% and the average distance between changes in slope is 83 m. The change in slope at the points of intersection varies from 0.66% to 0.82%. These slopes are consistent with those typical of urban areas; the TAC Urban Supplement to the Geometric Design Guide for Canadian Roads recommends a minimum longitudinal grade of 0.35% to facilitate the movement of water to catchbasins (TAC, 1995).

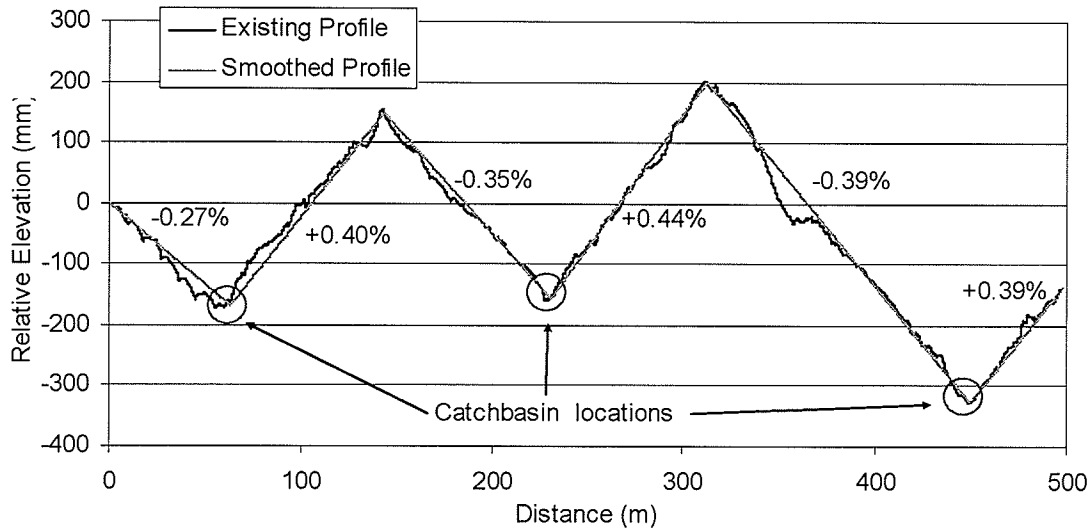


Figure 5.1: Profile of Grant Ave with roughness removed

The elevations of the smoothed profile were processed at each point to give IRI based on 20 m of profile data, 10 m before and 10 m after each point. Figure 5.2 shows that the IRI of the smooth profile reaches peak values of 1.5 to 2.0 m/km at each change in slope.

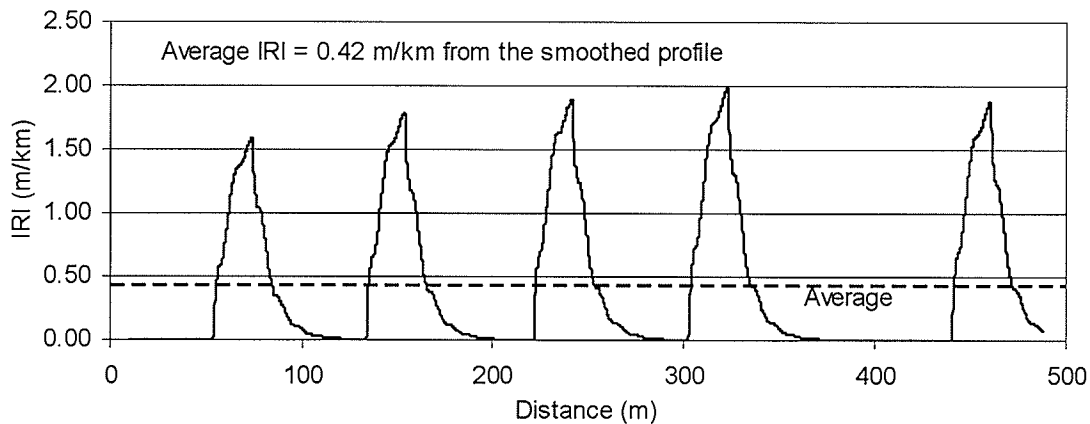


Figure 5.2: The effect of false grades on IRI

The average IRI for the smoothed profile of the 500 m section is 0.42 m/km, while the IRI for the segment as a whole is 4.02 m/km. The reversing longitudinal grades built into the segment account for about 10% of the roughness on Grant. Rural highways are not faced with a similar problem because they generally do not have curbs and thus do not need slope reversal as often to direct water towards catchbasins. The effect of false grades can be even more significant on

smoother roadways. For example, on a road with an IRI of 2.00 m/km, false grades could account for more than 20% of the roughness.

5.4 Railway Crossings

There are currently 106 at-grade railway crossings of the Winnipeg regional street network. Crossings in which the street is undivided were counted once and those where the street is divided were counted twice. In 2002, the same year as the parallel automated and manual street surveys, the City of Winnipeg manually inspected each crossing and assigned each a rating of good, fair, or poor. The rating is based on the condition of the street at the crossing, not the condition of the railway. Figure 5.3 shows the number of crossings of the regional street network that were rated in each condition; 58 were in good condition, 35 were in fair condition, and 13 were in poor condition.

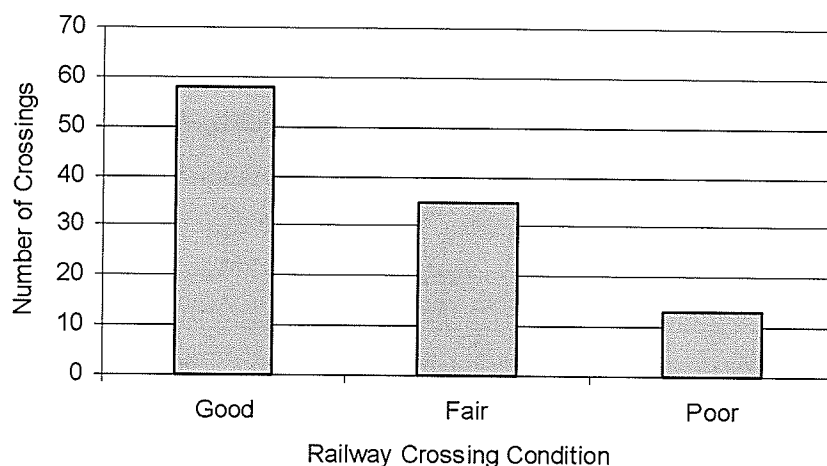


Figure 5.3: The condition of railway crossings of the Winnipeg regional street network

To determine the impact of railway crossing on the IRI of a segment, IRI data was analyzed from ten crossings in good condition, ten crossings in fair condition, and ten crossings in poor condition. The ten crossings in each condition category were selected randomly. The IRI of the railway crossing was calculated as the average of the four highest readings at that location. To illustrate, Figure 5.4 shows a segment of Fermor Avenue from Archibald to Lakewood that intersects the CP Emerson line. The IRI of the railway crossing is 5.14 m/km while the IRI of the segment as a whole is 2.63 m/km, including the roughness of the railway crossing.

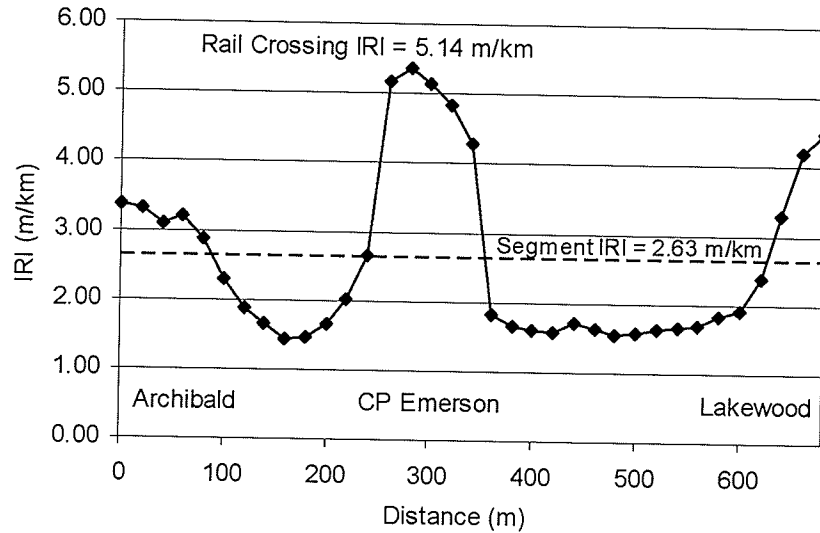


Figure 5.4: Increase in IRI at the CP Emerson crossing of Fermor Ave between Archibald and Lakewood

The average IRI of the ten crossings in each condition were calculated as were the IRI of the segments including the railway crossing; they are shown in Figure 5.5. This figure indicates that the IRI of railway crossings in poor condition is higher than those with IRI in good and fair condition. The average IRI of the railway crossings for each condition were 3.59 m/km for good crossings, 3.63 m/km for fair crossings, and 4.46 m/km for poor crossings. These IRI values represent roughness of 1.15 m/km, 1.06 m/km, and 1.66 m/km higher than the segment IRI.

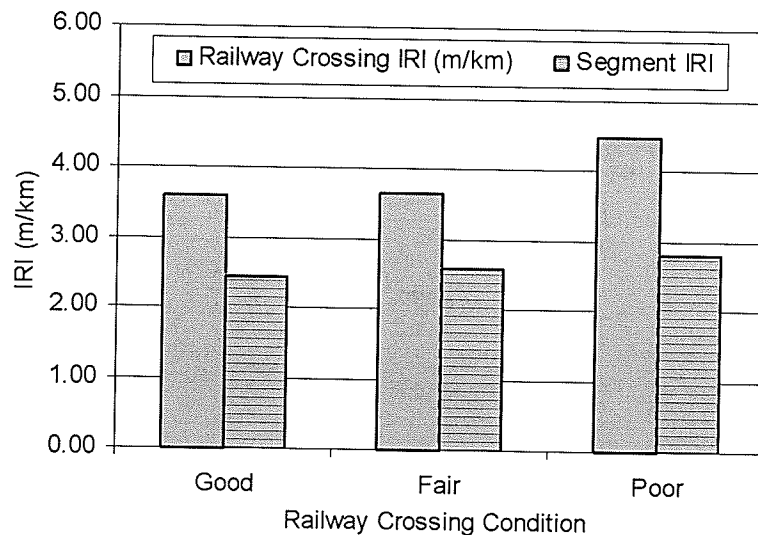


Figure 5.5: Average IRI of railway crossings and the segment containing the crossings

The effect of railway crossings on the IRI of individual segments can be significant. The effect is more significant for short segments than long segments where the increase in roughness tends to be averaged out. The effect of railway crossings on network-wide roughness statistics is almost insignificant. The following approximate calculation regarding the effect of railway crossings demonstrates this finding. In 2002, the IRI of the 535 km regional street network was 2.71 m/km and there were 106 railway crossings. If the average increase in IRI associated with a railway crossing is assumed to be 1.5 m/km and this increase affected the segments for 140 m (similar to Figure 5.4) the network IRI with railway crossings removed can be estimated in this way:

$$\text{Network IRI} = \frac{(2.71 \text{ m/km})(535 \text{ km}) - (1.5 \text{ m/km})(0.14 \text{ km})(106 \text{ crossings})}{535 \text{ km}}$$

$$\text{Network IRI} = 2.67 \text{ m/km}$$

The estimated effect of railway crossings on network IRI is only 0.04 m/km, or 1.5% of the network IRI.

5.5 Rutted Intersections

When a vehicle crosses a rutted street the vehicle perceives the rutting as roughness. For intersecting streets, the transverse profile of the cross street is a longitudinal profile. A simulation of the theoretical impact of a rutted intersection on IRI is presented. Figure 5.6 shows the transverse profile of a theoretical two-lane road with 10 mm of rutting; the IRI calculations are based on the profile points shown in the figure, which are equally spaced at 300 mm.

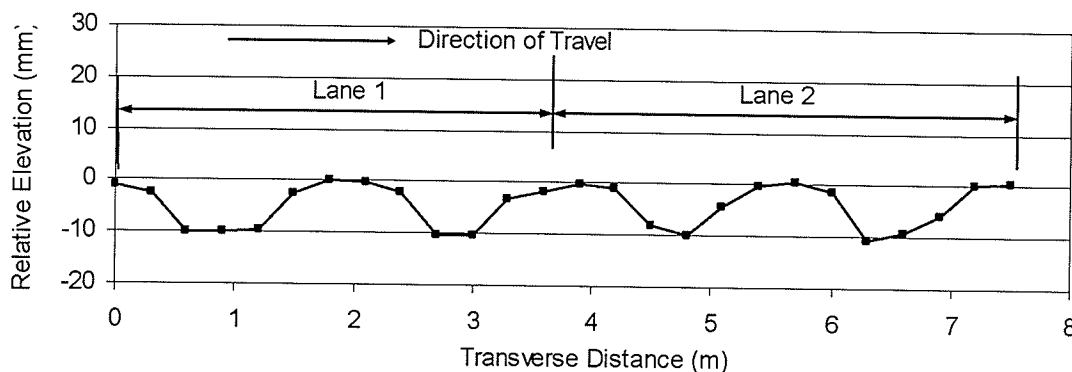


Figure 5.6: Rutting of a theoretical road

If a road with an IRI of 2.0 m/km intersected a road characterized by the transverse profile in Figure 5.6, the IRI would increase significantly in the vicinity of the intersection as shown in

Figure 5.7. The IRI shown in this figure is that calculated for 20 m profiles, 10 m on each side of each reading.

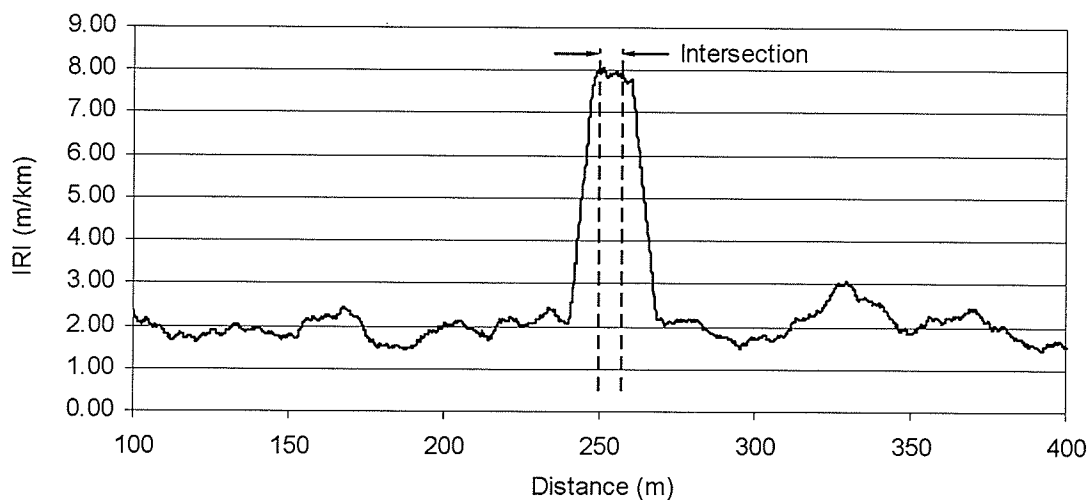


Figure 5.7: The effect of a rutted intersection on the IRI of a crossing street

The effect of rutted intersections on roughness partially explains the higher IRI values often found on urban streets as compared to rural highways. This roughness can have a significant impact on the reported roughness for individual segments and for the network as a whole due to the large number of intersections in urban networks.

It is often difficult to determine the proportion of the roughness of a segment that is attributable to the effect of intersections. Figure 5.8 shows an example of a segment which increases in roughness at certain locations that are similar to the increase expected for rutted intersections. However, the increases do not occur at the exact location of the intersections, which are shown in Figure 5.9. If future surveys report and calculate roughness for 20 m intervals and report GPS coordinates for each 20 m interval it will be easier to ascertain the cause of the roughness.

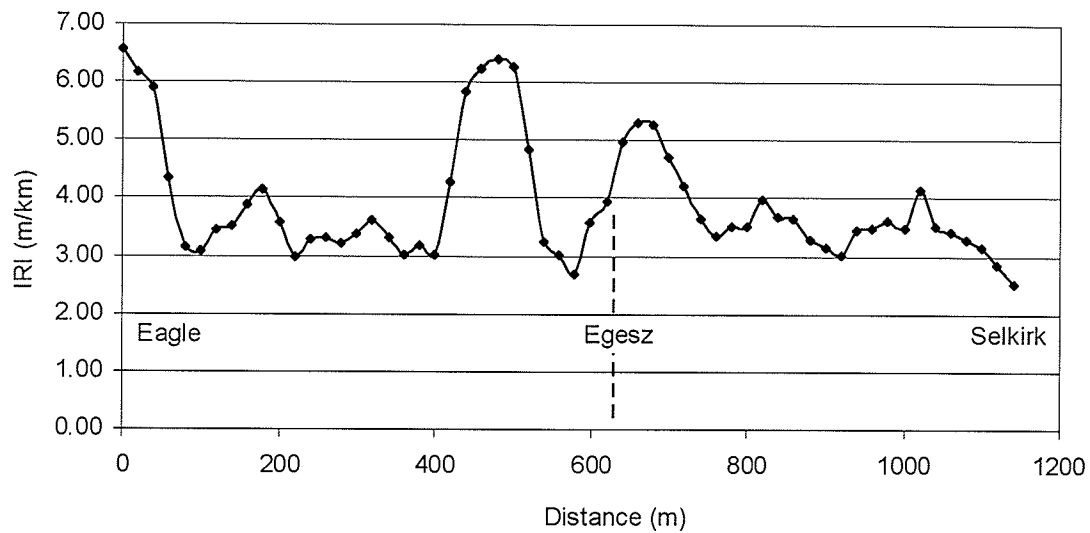


Figure 5.8: Oak Point Highway from Eagle Drive to Selkirk Avenue

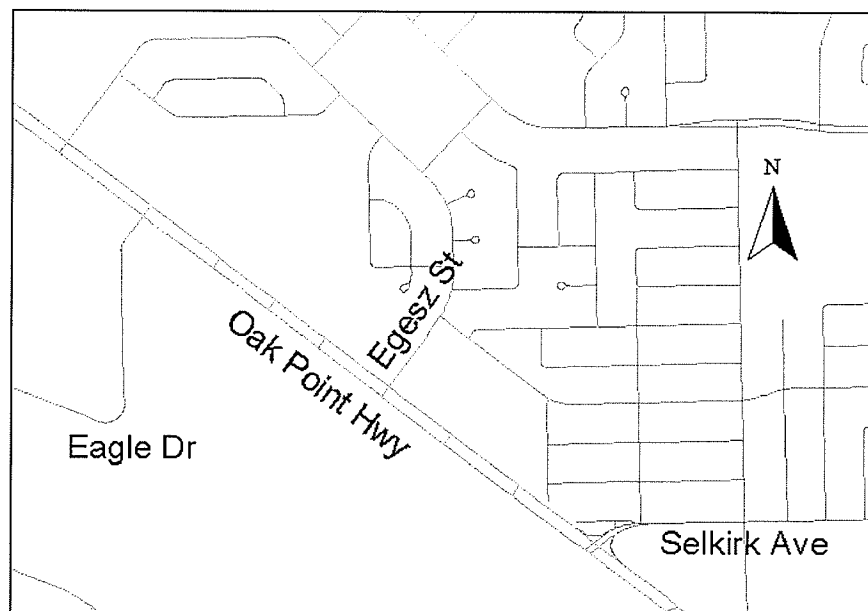


Figure 5.9: A segment of Oak Point Highway from Eagle Drive to Selkirk Avenue

5.6 Segment Length

The previous two factors that can affect IRI, railway crossings and rutted intersections, tend to have a larger effect on shorter segments. The City of Winnipeg segmenting guidelines specify that segments always end and begin at intersections. Thus, segments often start with a high IRI at the beginning and finish with a high IRI at the end. An example of a street that demonstrates a

higher IRI at the beginning and end is Arlington Street from Sargent Avenue to Notre Dame Avenue, shown in Figure 5.10.

The impact of this phenomenon is that the IRI of a segment can be higher than its condition, based on manual ratings, would indicate. This is one of the types of anomalies that can occur.

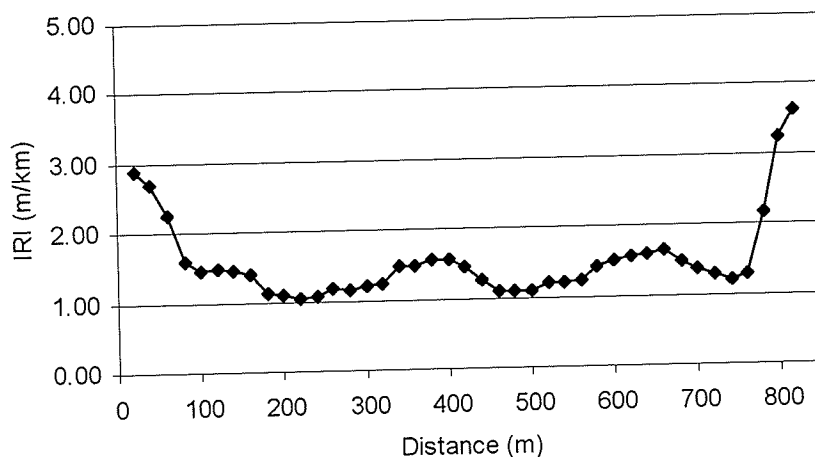


Figure 5.10: Arlington from Sargent to Notre Dame showing high IRI at the beginning and end

5.6.1 Analysis of Anomalies

There are two types of anomalies between the manual and automated rating systems. The first is that a segment can have a higher IRI than its manual rating indicates, as explained by railway crossings or the effect of intersections. The second type of anomaly is that a segment has lower IRI than its manual ratings indicate. One of the reasons for this type of anomaly is that cracking and spalling should only affect IRI if there have been changes in elevation in either the left or right wheel paths as a result of the distress. The International Roughness Index is a simulation of the suspension motion of a quarter-car model. The tire component of the model will simply bridge over any small cracks or joint openings without a vertical displacement unless the cracks have caused the slab to fail or if the joints have spalled enough to change the vertical profile of the road.

It is useful to plot the anomalies in a Geographic Information System (GIS) to enable the detection of spatial patterns in the data. Figure 5.11 shows a plot of all of the anomalies and Figure 5.12 shows an enlargement of this plot in the downtown area. The first type of anomaly, in which a segment has a higher IRI than its manual rating indicates, is plotted in blue. These segments have IRI > 3.00 m/km and a general condition of good. The second type of anomaly, in

which a segment has a lower IRI than its manual rating indicates, is plotted in red. These segments have $IRI < 3.00$ m/km and a general condition of poor.

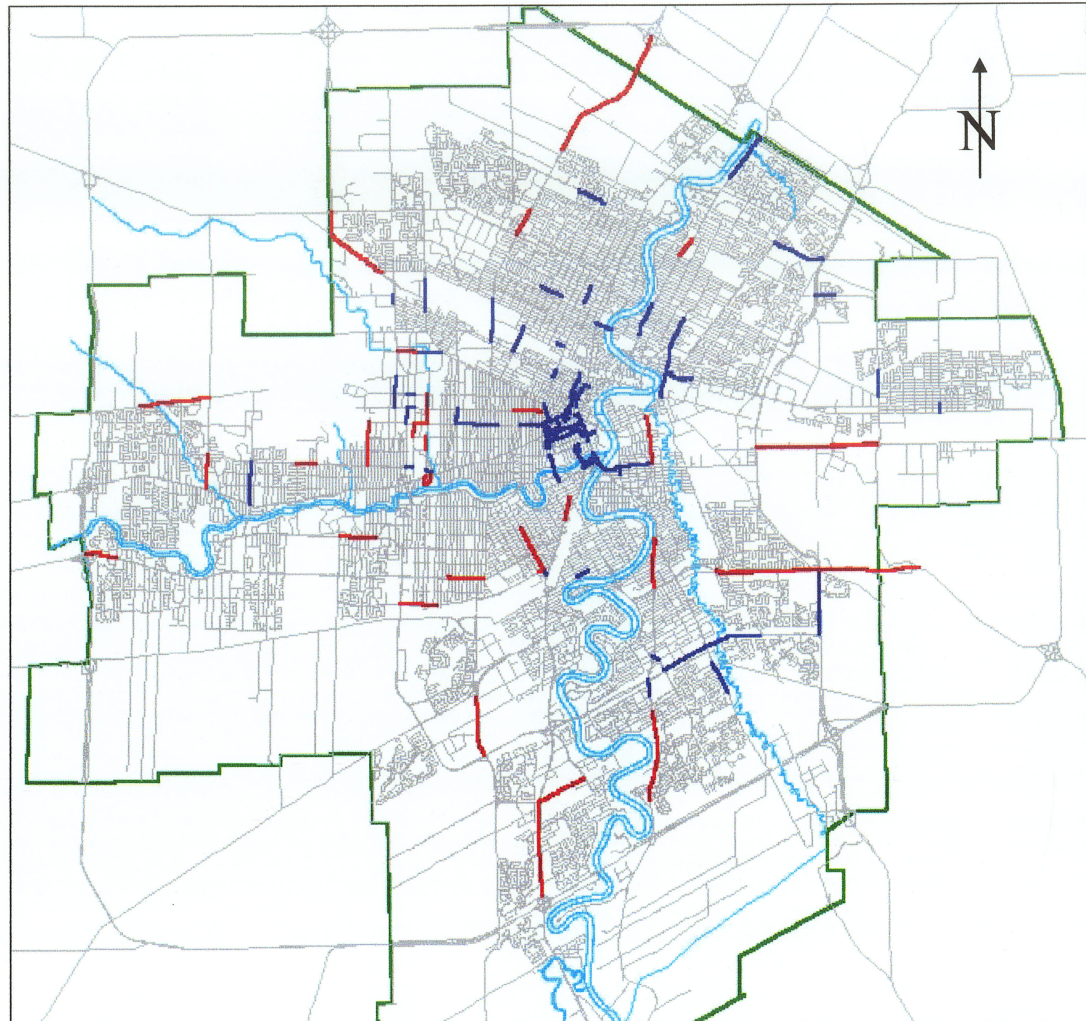


Figure 5.11: Winnipeg regional street network showing anomalies between the manual and automated rating systems. Blue segments have $IRI > 3.00$ m/km and a general condition of good.

Red segments have $IRI < 3.00$ m/km and a general condition of poor.

The clustering of blue streets in the downtown area, where segments are generally short, further demonstrates that segment length plays a role in the measurement of IRI. The average lengths of segments with each type of anomaly are shown in Table 5.1. This table shows that segments with different types of anomalies have different average lengths. The average segment length of poor APC segments with $IRI < 3.00$ m/km was more than twice as long as the average segment length of good and new APC segments with $IRI > 3.00$ m/km. Similarly, for PCC segments, the average

length of segments in poor condition with IRI < 3.00 m/km was more than twice the average length of segments in good and new condition with IRI > 3.00 m/km. The impact of segment length on reported IRI provides further explanation for the weakness of the agreement between the automated and manual distress measures that was discussed in Chapter 4.



Figure 5.12: Enlargement of downtown Winnipeg showing anomalies between the manual and automated rating systems. Blue segments have IRI > 3.00 m/km and a general condition of good.

Red segments have IRI < 3.00 m/km and a general condition of poor.

Table 5.1: Average Segment Length for each General Condition Anomaly

Anomaly	Average Segment Length (m)	Number of Segments
APC in New or Good Condition with IRI > 3.00 m/km	472	66
APC in Poor Condition with IRI < 3.00 m/km	975	32
PCC in New or Good Condition with IRI > 3.00 m/km	523	24
PCC in Poor Condition with IRI < 3.00 m/km	1246	10

5.7 Simulation of the Effect of Slab Faulting on IRI

The purpose of this section is to analyze and document the amount of roughness that should be expected from different amounts of faulting and provide evidence for how much roughness could be expected on a failed segment. Two segments are simulated for this analysis. The first has 10 mm of faulting at every joint, joints are 4.5 m apart, and would have an IRI of 1.0 m/km if the faulting is removed. The second segment only has one joint with 10 mm of faulting (simulated as a 10 mm step) and also would have an IRI of 1.0 m/km if the faulting is removed.

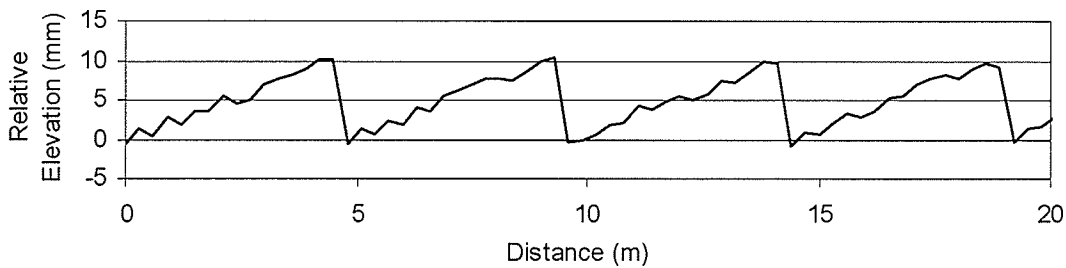


Figure 5.13: Simulated 10 mm faulting of all slabs

Figure 5.13 shows the 10 mm faulting of all of the slabs in a segment and Figure 5.14 shows the IRI resulting from the faulting. Just as with the simulated analysis of IRI resulting from a rutted intersection, the IRI used here is for a 20 m profile, 10 m to each side of any point. IRI of approximately 5 m/km could be expected from 10 mm of faulting of every slab in a segment.

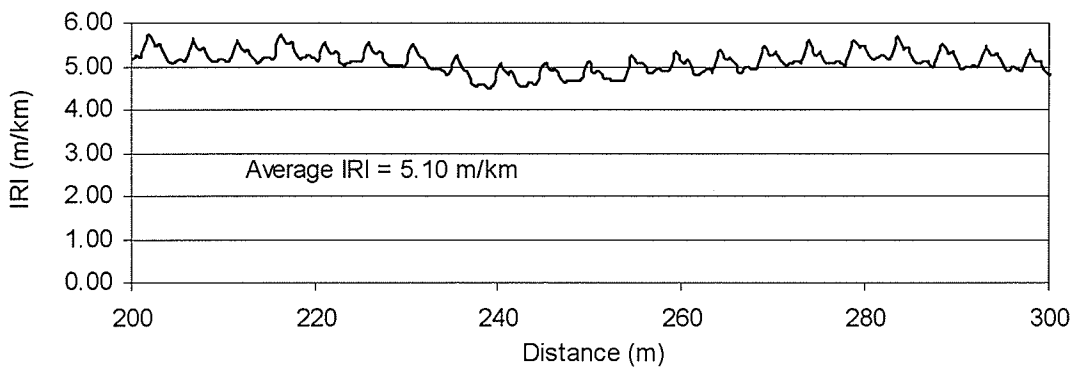


Figure 5.14: IRI resulting from 10 mm of faulting at every joint

Figure 5.15 shows a simulated 10 mm step, which represents a single slab having 10 mm of faulting. Figure 5.16 shows the IRI resulting from the simulated 10 mm step. The IRI increases to 2.0 m/km in the vicinity of the step and the segment IRI also shows an increase inversely proportional to the segment length.

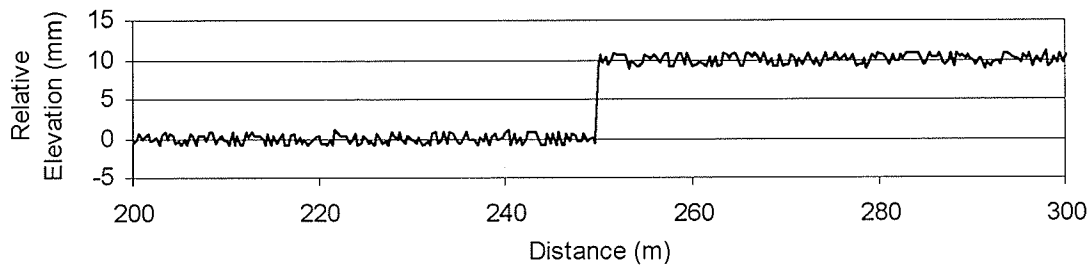


Figure 5.15: Simulated 10 mm step

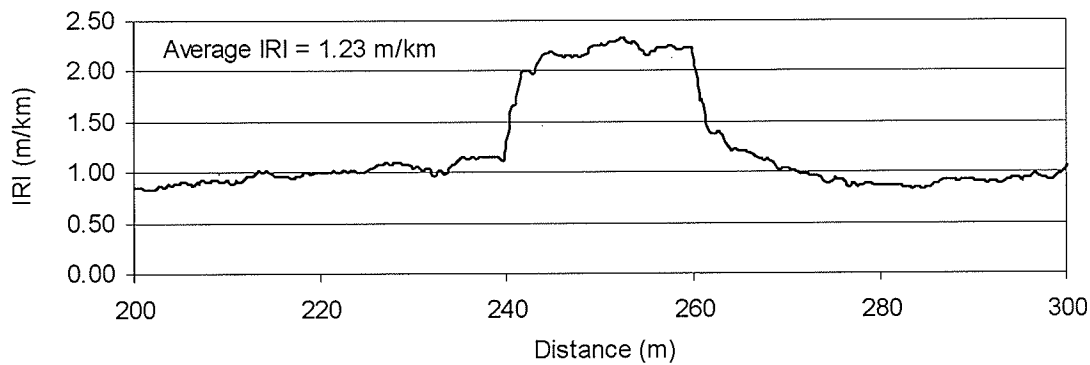


Figure 5.16: IRI resulting from a simulated 10 mm step

5.8 Summary

Two approaches were used to explain the effect of several factors on IRI measured in urban areas. Understanding these factors can make IRI statistics more meaningful. Analyses of manually collected profile data and the extensive automated dataset were used to examine the effect of false grades on IRI, to determine the magnitude of IRI increases at railway crossings of varying condition, and to explain the effect of segment length on IRI measurements. Simulations of various conditions were conducted to demonstrate the effect of rutted intersections on the IRI of the crossing street and to demonstrate the effect of heavily faulted and slightly faulted pavement on the IRI of a segment.

False Grades

False grades are the reversing longitudinal slopes that are built into roads to facilitate drainage. An analysis of longitudinal profile data collected on Grant showed that the false grades account for 10% of the roughness on this section. The effect can be as high as 20% for smoother sections in urban areas.

IRI Increases at Railway Crossings

An analysis of 30 randomly selected railway crossings showed that roughness increases at these locations; this is especially true for railway crossings that are in poor condition. Most railway crossings had an IRI approximately 1 m/km higher than that of the segment while those in poor condition had an IRI approximately 1.5 m/km higher than the segment.

The effect of railway crossings is significant for the IRI of individual segments, especially short segments. An approximate calculation showed that the reported IRI of the network as a whole would only be slightly lower if railway crossings were excluded.

The Effect of Rutted Intersections on IRI

A simulation of a vehicle driving across an intersection with 10 mm of rutting showed that the increase in IRI could be significant. The prevalence of intersections in urban areas provides an additional explanation as to why the IRI is often higher in urban areas than for rural highways.

The Effect of Segment Length on IRI

An analysis of the anomalies between the automated and manual surveys was conducted to demonstrate the effect of segment length on IRI. An anomaly was defined as a good segment with $IRI > 3.00$ m/km or a poor segment with $IRI < 3.00$ m/km. A GIS plot of these anomalies showed that good segments with $IRI > 3.00$ m/km were clustered in the downtown area where segments were short. The effect of intersections on IRI is magnified for short segments, which indicates that the IRI can become less affected by pavement condition than by other factors.

The Effect of Slab Faulting on IRI

Two simulations were conducted to demonstrate the effect of slab faulting on IRI. The first simulation of a segment with faulting between all slabs showed that the IRI would increase to 5.00 m/km compared to the 1.00 m/km expected for a segment with no faulting or other roughness.

A simulation on the effect of faulting of a single slab showed that there is a noticeable increase in IRI but the increase is much less than that for a segment with all slabs faulted and would be insignificant for long segments.

Chapter 6

PAVEMENT INFORMATION SYSTEMS

6.1 Introduction

This chapter describes two types of pavement information systems that utilize automated pavement condition data. The first is a software package, IRIIS (IRI Information System), which was developed during the course of this research. Two versions of IRIIS were developed for the unique datasets available for the Winnipeg regional street network and the Manitoba highway network. The second is a geographic information system (GIS) that facilitates the viewing and analysis of pavement condition data of the City of Winnipeg regional street network. GIS enables the spatial analysis of the data, such as the analysis of anomalies between the manual and automated systems that is documented in Chapter 5.

6.2 IRIIS (IRI Information System)

IRIIS was developed as a tool that enables the graphical analysis of automated pavement condition data and the linking of this data to other relevant data elements including: manual pavement condition ratings, pavement structural condition, traffic data, and construction history data. IRIIS was used in Chapter 3 to assess the consistency of multi-year survey data and Chapter 4 to ensure that homogeneous segments were used for the maximum likelihood classification and the artificial neural network analysis. IRIIS was customized for each road network, the Winnipeg regional street network and the Manitoba highway network, to utilize the unique data sources available on those networks.

6.2.1 Data Viewing Capabilities

Software is required to view the extensive datasets that result from automated data collection activities. The 2002 automated survey of the Winnipeg regional street network resulted in 836 segments. The five years of surveys of the Manitoba highway network resulted in 8655 subsections. The ability to quickly view these large datasets in a user-friendly environment is necessary for the users of the data to gain confidence in the data and perform reality checks on the data.

Figure 6.1 shows the program display of a typical segment of the Winnipeg regional street network, Corydon Avenue from Shaftesbury Boulevard to Tuxedo Avenue. The display shows the automated pavement condition data with IRI on the left axis and rut depth on the right axis.

The header, at the top displays the segment name, identification number, and pavement type as well as the overall segment IRI (in m/km), rut depth (in mm), and ratings from the manual survey, including: general condition, crack score, joint score, percent PX, and percent X.

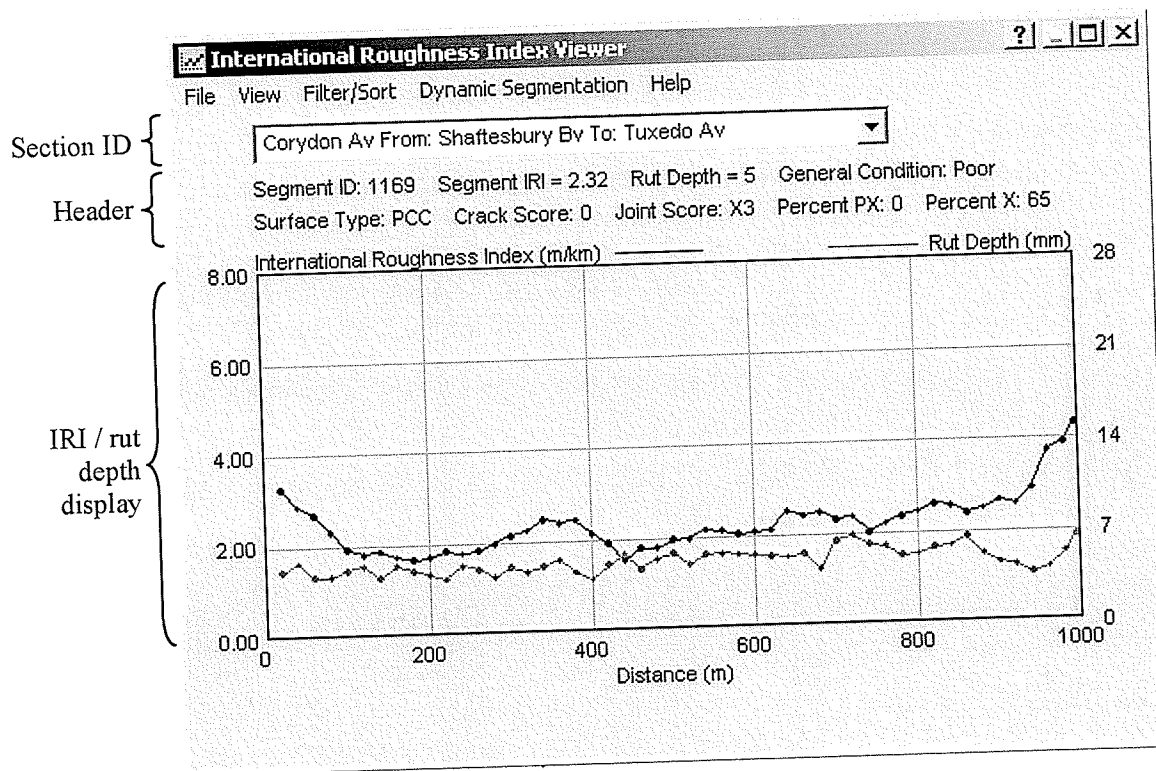


Figure 6.1: IRIIS display of a segment on Corydon Avenue

The version of IRIIS developed for the Manitoba highway network shows similar information. A typical display of a subsection is shown in Figure 6.2. The subsection's identification is shown at the top of the display followed by the header and graphs of IRI and rut depth. The first line of the header shows the subsection's location, in this case 8.0 km east of provincial road 248 to provincial trunk highway 26. Next, the second line of the header shows the surface type, subsection IRI and rut depth from the current survey, and the subsection length in kilometers. The final line of the header displays the functional and loading class of the highway, traffic information (AADT and percent trucks), and a representative Benkelman beam rebound, when available.

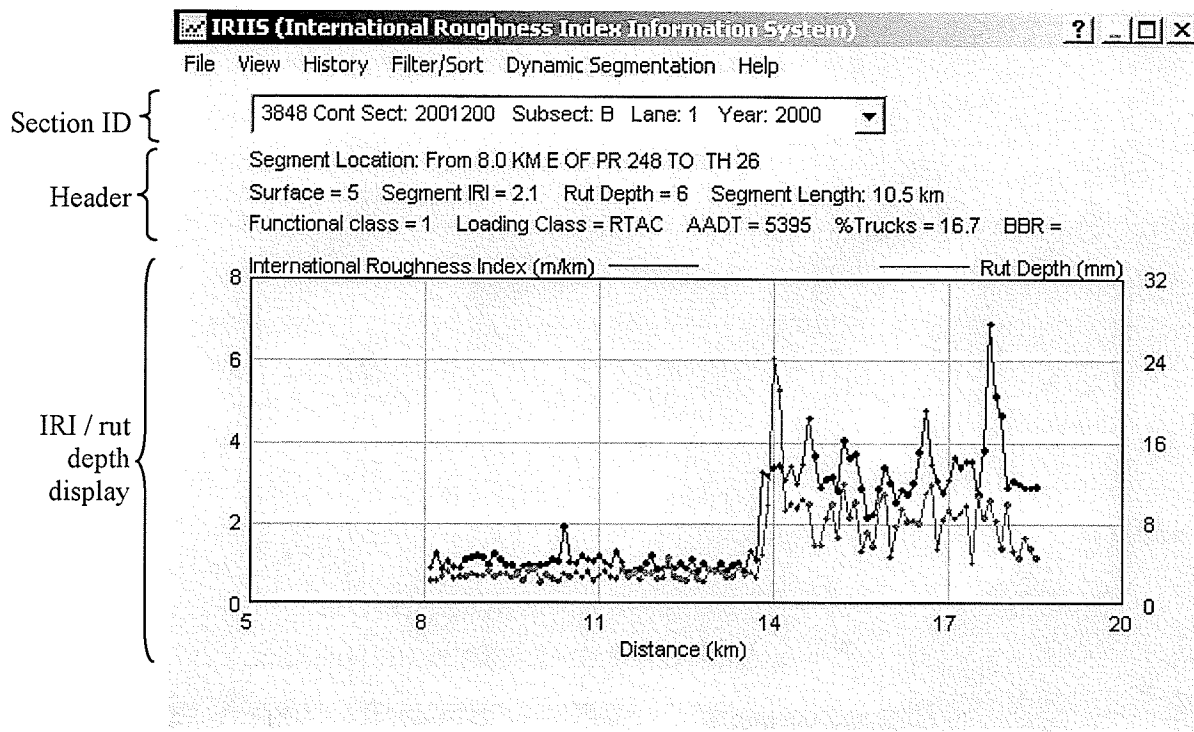


Figure 6.2: Typical IRIIS display of a subsection

6.2.2 Dynamic Segmentation

Dynamic segmentation is the determination of statistically homogeneous units based on pavement response or condition measurements. For network-level pavement management it is necessary to divide the pavement network into segments, each one having homogeneous conditions. When pavement management systems include significant numbers of non-homogeneous segments, the accuracy of pavement condition prediction models is reduced.

IRIIS uses the cumulative difference approach because it is fundamentally easy to visualize and because it can be implemented for large databases. Section 4.3.1 explained the CDA and showed examples of segmentation with IRIIS for the Winnipeg regional street network. The version of IRIIS developed for the Manitoba highway network has the capability of segmenting based on IRI, rut depth, or both. Figure 6.3 shows the user-specified segmentation parameters.

Dynamic Segmentation Options

Segmentation Options

Segmentation Parameters

Minimum Segment Length (km): 1

Minimum Change in IRI (m/km): 1

Minimum Change in rut (mm): 5

Dynamically Segment: ☐ IRI ☐ Rut Depth ☒ Both

☒ Automatically display the segmentation

	Line Width	Line Colour
IRI	2	Red
Rut	2	Black

OK Cancel Apply

Figure 6.3: User-specified dynamic segmentation parameters

An example of a segmentation break resulting from IRI and rut depth is shown in Figure 6.4. There are statistically significant changes in condition at the 2.3 km point and at the 7.3 km point. Each of the resulting segments has relatively uniform conditions and meets the criteria for minimum segment length.

The advantage of displaying a graph of pavement condition data along with the resulting segmentation is that the pavement management engineer can apply judgement and experience to decide if a new segment is warranted or not. New segments may be justified for the pavement condition shown in Figure 6.4 based on the fact that IRI and rut depth both had condition changes and that the resulting segments were significantly long.

A new segment is probably not necessary for the example shown in Figure 6.5. The portion with increased roughness has a length of 1 km so it is long enough to meet the requirement for minimum significant segment length. However, the rut depth does not increase at this location so the pavement management engineer may decide to simply note this as a localized defect rather than a new segment.

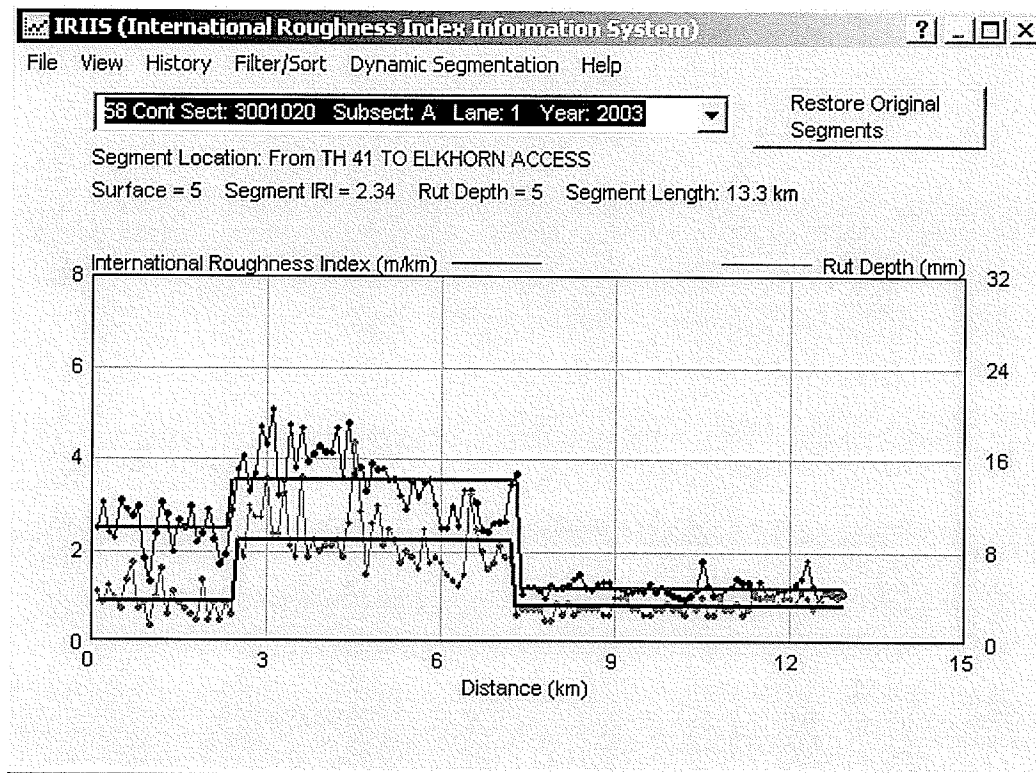


Figure 6.4: Segmentation based on both IRI and rut depth

Another dynamic segmentation option included in IRIIS is the “segment all” feature. This option automatically implements the CDA for each segment based on the user-specified segmentation parameters. The segments that had a break are automatically added to the drop-down box where they can be viewed and analyzed.

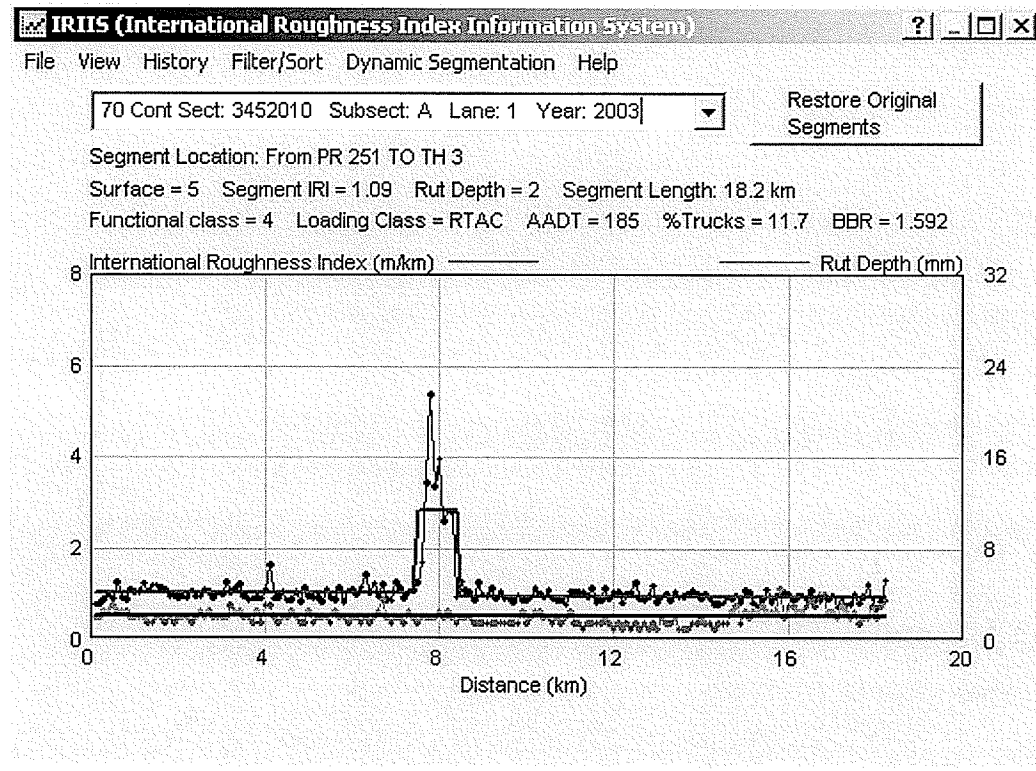


Figure 6.5: A segment with a localized defect

6.2.3 Filtering and Sorting Tools

IRIIS has filtering and sorting capabilities that allow the user to limit the database to segments that match various criteria. This will allow the user to diagnose pavement deterioration problems. For example, if a section of highway is showing premature decline, the user can filter the database to display only those sections with similar structure, traffic, road class, and construction history. A review of these filtered sections would help to identify the problem.

The filtering options available for the Winnipeg version of IRIIS include:

- Pavement type,
- General condition,
- IRI,
- Rut depth,
- Cracking, and
- Spalling.

An example of the filtering is shown in Figure 6.6. In this example the user has decided to identify all APC and PCC segments with IRI greater than 4.0 m/km and percent PX between 40% and 60% (no segments had percent PX greater than 60); that is, segments with high roughness and a large amount of high severity cracking. The twelve segments that match these criteria will be added to the drop-down list for further viewing and analysis. The default values for rut depth and percent X indicate the minimum and maximum values for these pavement condition indicators in the database.

Advanced Filter

Pavement Type and Condition

APC	New
PCC	Good
AC	Fair
Chip Seal	Poor
N/A	N/A

IRI, Rut Depth, Cracking, Spalling

	MIN	MAX	
☒ IRI (m/km)	4	5.72	IRI, RUT ☐ AND ☐ OR
☐ Rut Depth (mm)	1.73	22	
☒ Percent PX	40	60	☒ AND ☐ OR
☐ Percent X	0	100	

Cracking, Spalling
☐ AND ☐ OR

Sort
☒ Alphabetical ☐ IRI ☐ Rut ☐ %PX ☐ %X

OK Cancel Apply

Figure 6.6: Filtering and sorting options for the Winnipeg regional street network

The data available for the Manitoba highway network includes five years of survey data and additional segment information. Therefore, the version of IRIIS developed for the Manitoba highway network includes additional filtering criteria. The user can filter based on multiple criteria:

- Survey year,

- Region,
- Surface type,
- Functional classification; codes 1 though 4 represent Expressways, Primary Arterials, Secondary Arterials, and Collectors,
- Loading class; roads are classified based on the loads they are designed to carry, with RTAC roads designed to carry the heaviest lowest loads, followed by A1 and B1,
- Pavement condition, IRI and/or rut depth in specific ranges,
- Year paved, and
- Traffic data including, AADT (average annual daily traffic) and percent trucks.

An example is shown in Figure 6.7. In this example the user is filtering the database to show only those RTAC highways surveyed in 2003 with IRI greater than 3.0 m/km or rut depth greater than 5 mm and paved after 1990. The 76 segments that match these criteria are added to the drop-down list for further viewing and analysis.

Advanced Filter

Survey Year: 1999, 2000, 2001, 2002, **2003**

Region: 1, 2, 3, 4, 5

Functional Class: 1, 2, 3, 4, **ALL**

Surface Type: 1, 2, 3, 4, 5, 6

Loading Class: **RTAC**, A1, B1, ALL

IRI and Rut Depth

	MIN	MAX
☒ IRI (m/km)	3	10.07
☒ Rut Depth (mm)	5	20

IRI, RUT
☐ AND ☒ OR

Construction History and Traffic (Available for Subsections Only)

☒ Year Paved	1990	2002
☐ AADT	20	12335
☐ Percent Trucks	1	35.2

Sort

☒ Numerical ☐ IRI ☐ Rut ☐ Year Paved ☐ AADT ☐ % Trucks

OK Cancel Apply

Figure 6.7: Filtering and sorting options for the Manitoba highway network

Figures 6.6 and 6.7 also show the useful sorting tools included in each version of IRIIS. Sorting alphabetically makes it easy to find a particular segment. Sorting by pavement condition makes it easy to find segments with the best or worst conditions. Sorting by year paved enables the user to find the oldest or newest segments and observe their conditions. Sorting by traffic, AADT or percent trucks enables the identification of the most heavily trafficked segments.

6.2.4 Pavement History

The pavement history feature of IRIIS was used in section 3.8 to assess the consistency of automated pavement condition data based on multi-year surveys. The pavement history is also a valuable tool that enables the pavement management engineer to observe how specific segments deteriorate as a function of time and to observe the effectiveness of a maintenance or rehabilitation activity towards reducing IRI and rut depth.

Figure 6.8 shows an example of the deterioration rate and pavement history for a subsection repaved in stages from 2000 to 2002. The IRI was reduced from 3.27 m/km in 1999, before the construction, to 1.50 m/km in 2000, between the construction stages, and finally to 0.89 m/km in 2002, after the construction.

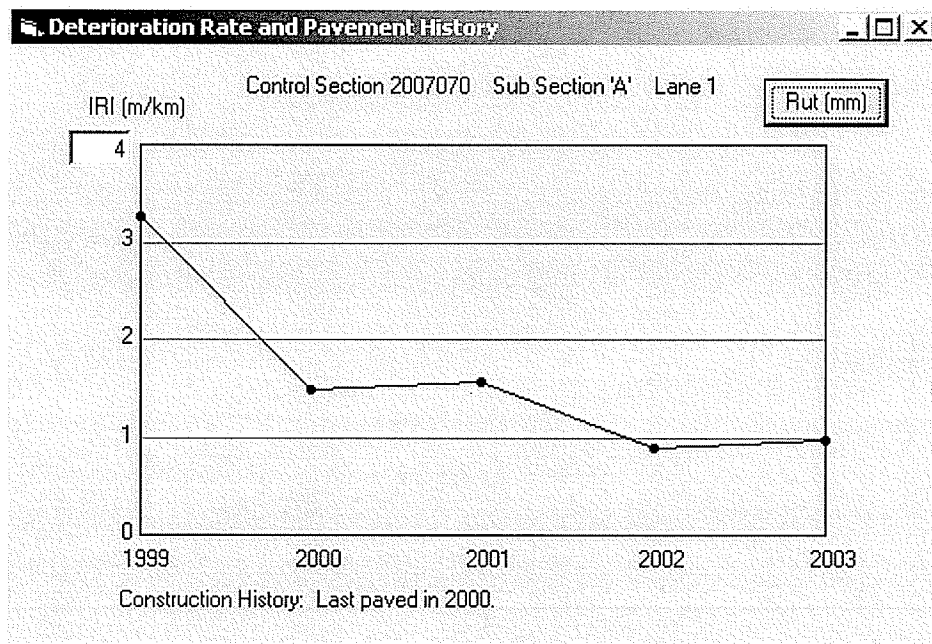


Figure 6.8: Construction history of a segment repaved in stages from 2000 to 2002

Figure 6.9 shows the IRI of the same segment at the various stages of construction. This figure also demonstrates the 'Hold' feature of the software. The figure was created by invoking the

'Hold' command, changing the line colour and then plotting the same segment surveyed in a different year. The hold feature is useful for comparing IRI data along a segment from multiple surveys or for comparing different segments.

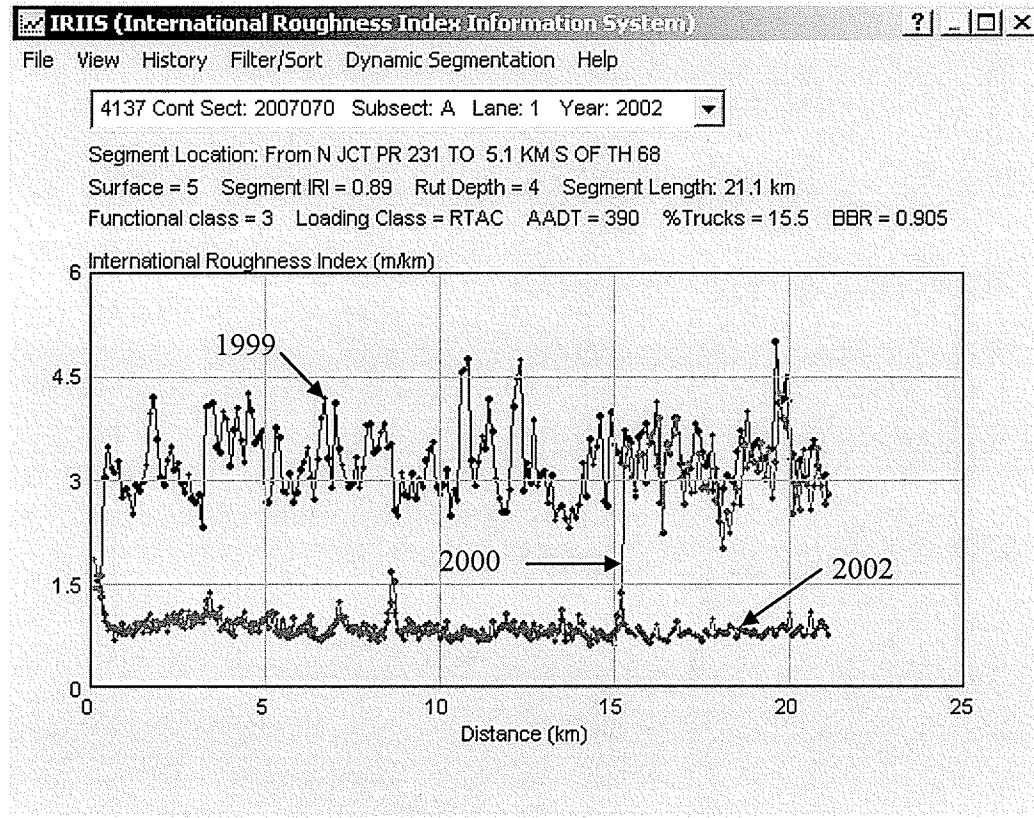


Figure 6.9: Changes in IRI of the segment shown in Figure 6.8

6.2.5 IRIIS Summary

IRIIS is a tool that provides for the graphical display and analysis of the massive amounts of data collected during automated pavement condition surveys. IRIIS was customized for the two networks used during this research, the Winnipeg regional street network and the Manitoba highway network. Displays show automated pavement condition data and other relevant data including manual ratings, highway classification, traffic, and structural information.

The linking of the automated datasets with other databases allows for the filtering and sorting capabilities included in IRIIS. The program also performs other functions including dynamic segmentation based on IRI or rut depth, graphical display of pavement history, and analysis of the consistency of automated data based on multi-year surveys.

6.3 Geographic Information Systems

Geographic information systems facilitate the spatial analysis of patterns in pavement condition data and the production of maps to communicate pavement condition and budget needs to elected officials and the public. Maps can show surface type, existing pavement condition, future pavement condition under a given funding scenario, deferred projects under a given funding scenario, and locations of scheduled projects. (Brotten, 1996)

Pavement type and condition data were linked to the City of Winnipeg Public Works Road Centre Line database. Geographic information systems are a tool that allow for the identification of spatial patterns in the condition of the network. The following pages show maps of the regional street network that display information regarding surface type, general condition, roughness, and rutting. Cracking and spalling data that were collected by City of Winnipeg rating crews in 2002 are also shown.

A number of observations about the GIS maps are provided:

- The GIS map of general condition does not show any obvious clustering in any area of the city.
- The GIS map of roughness shows that the IRI in the downtown area tends to be higher than in other areas of the city. Through a simulation of the effect of rutting at intersections and a geographical analysis of anomalies, Chapter 5 provided explanations of the reasons why these streets are rougher than those in the rest of the city and why this roughness is not reflected in the general condition ratings.
- The GIS map of rutting shows that streets in the downtown area tend to have less rutting than the network as a whole. The map also shows that several heavily trafficked corridors have segments with large rut depth; notably segments of: Pembina, Portage, McPhillips, Logan, Henderson, Fermor, and St. Mary's.
- The maps also show that, for the regional street network as a whole, a large percentage of slabs are cracked and a large percentage of joints are spalled.

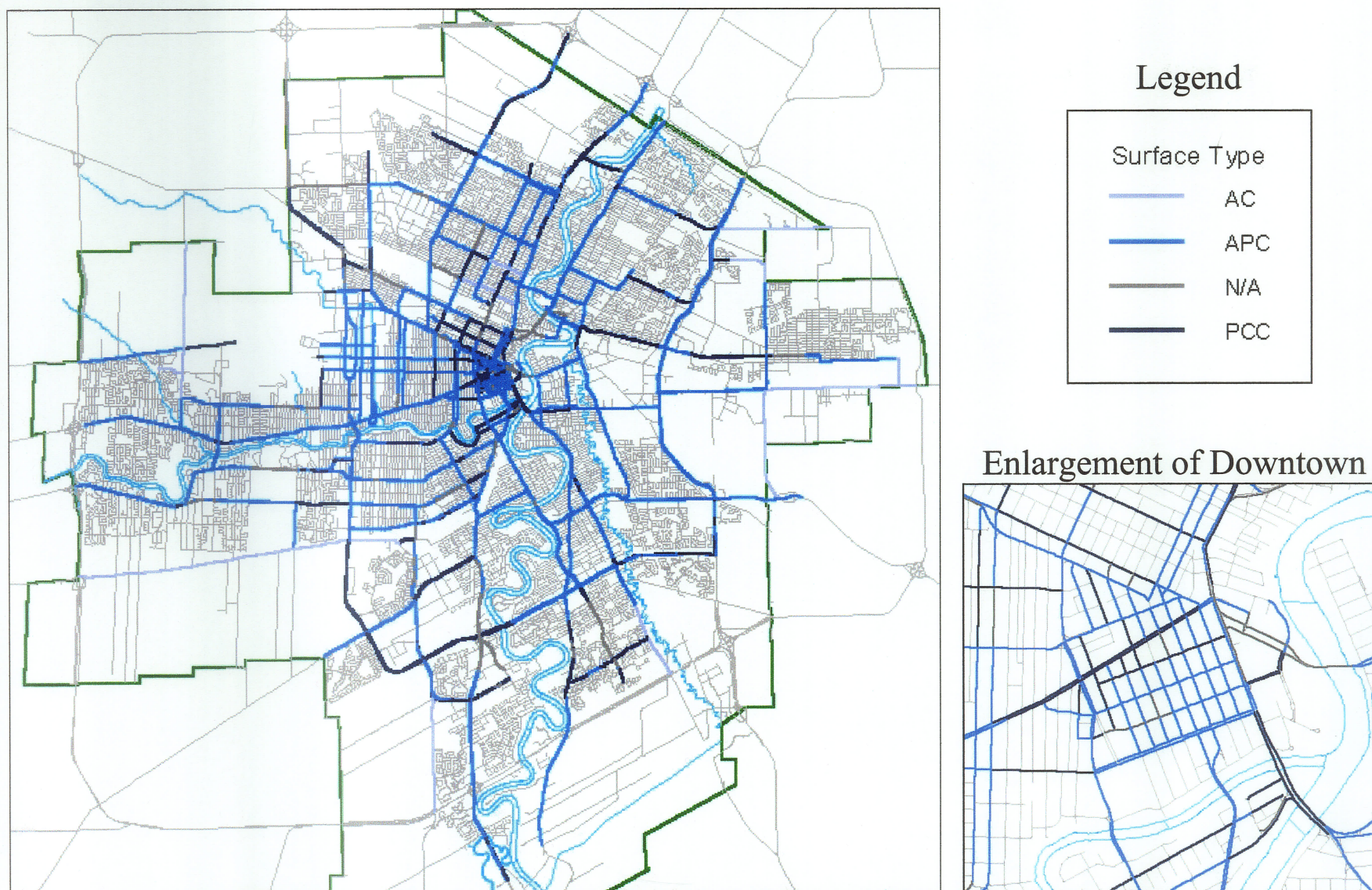


Figure 6.10: Surface Type of the Winnipeg Regional Street Network (2002)

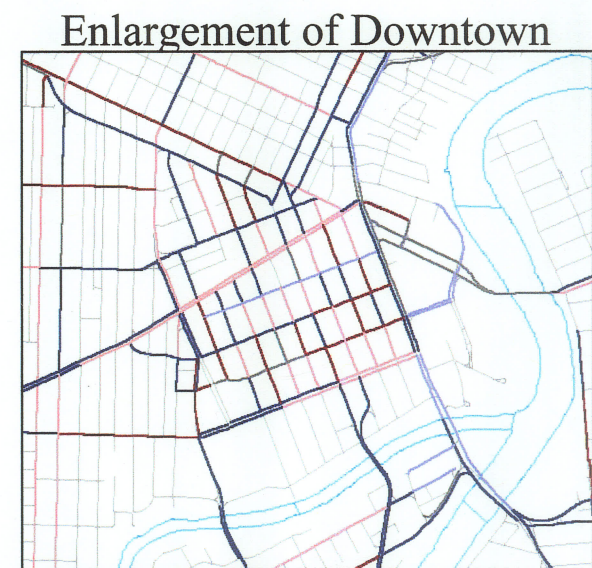
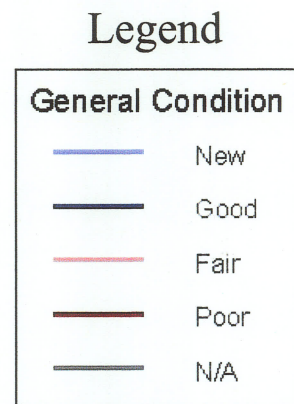
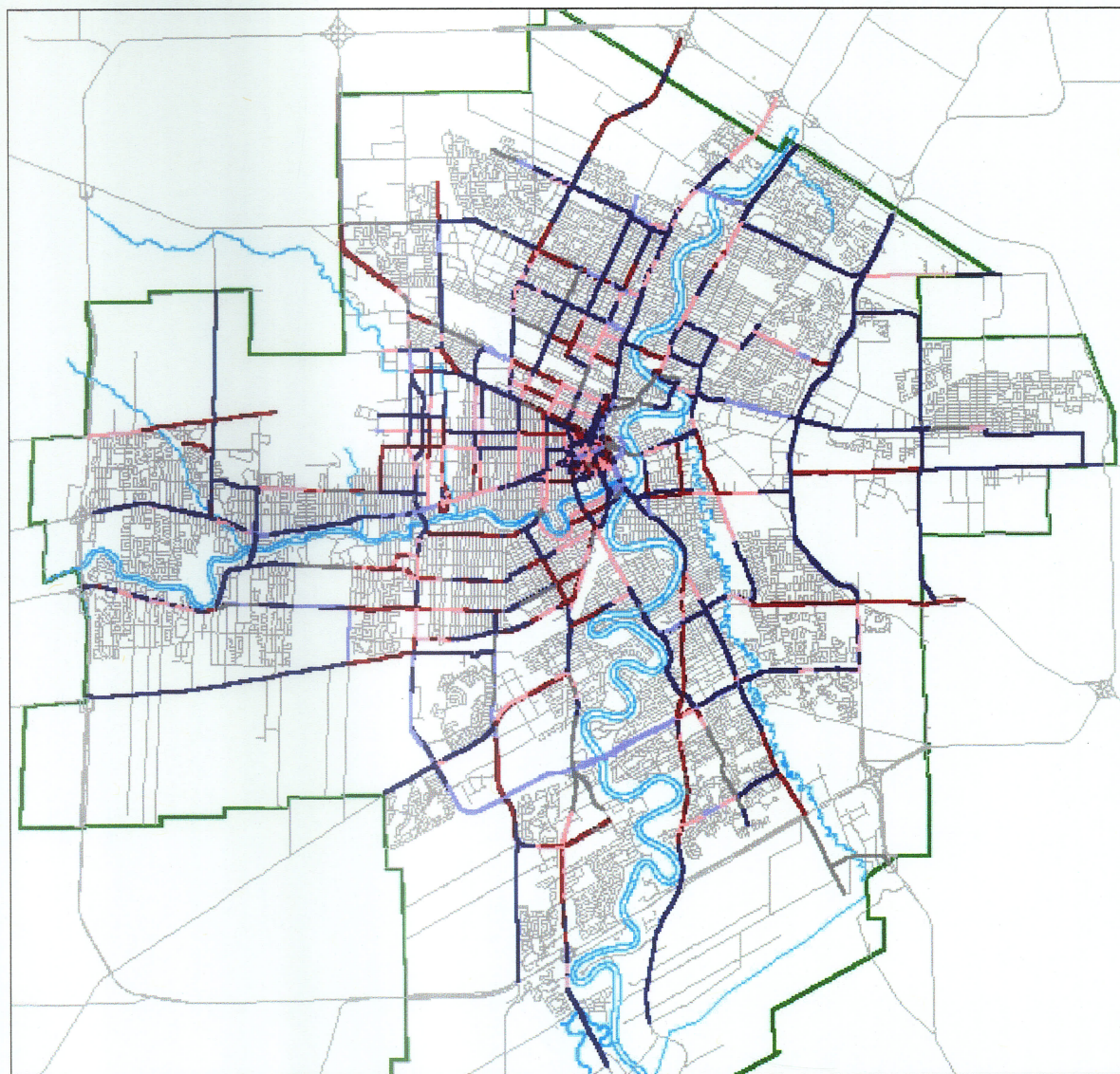
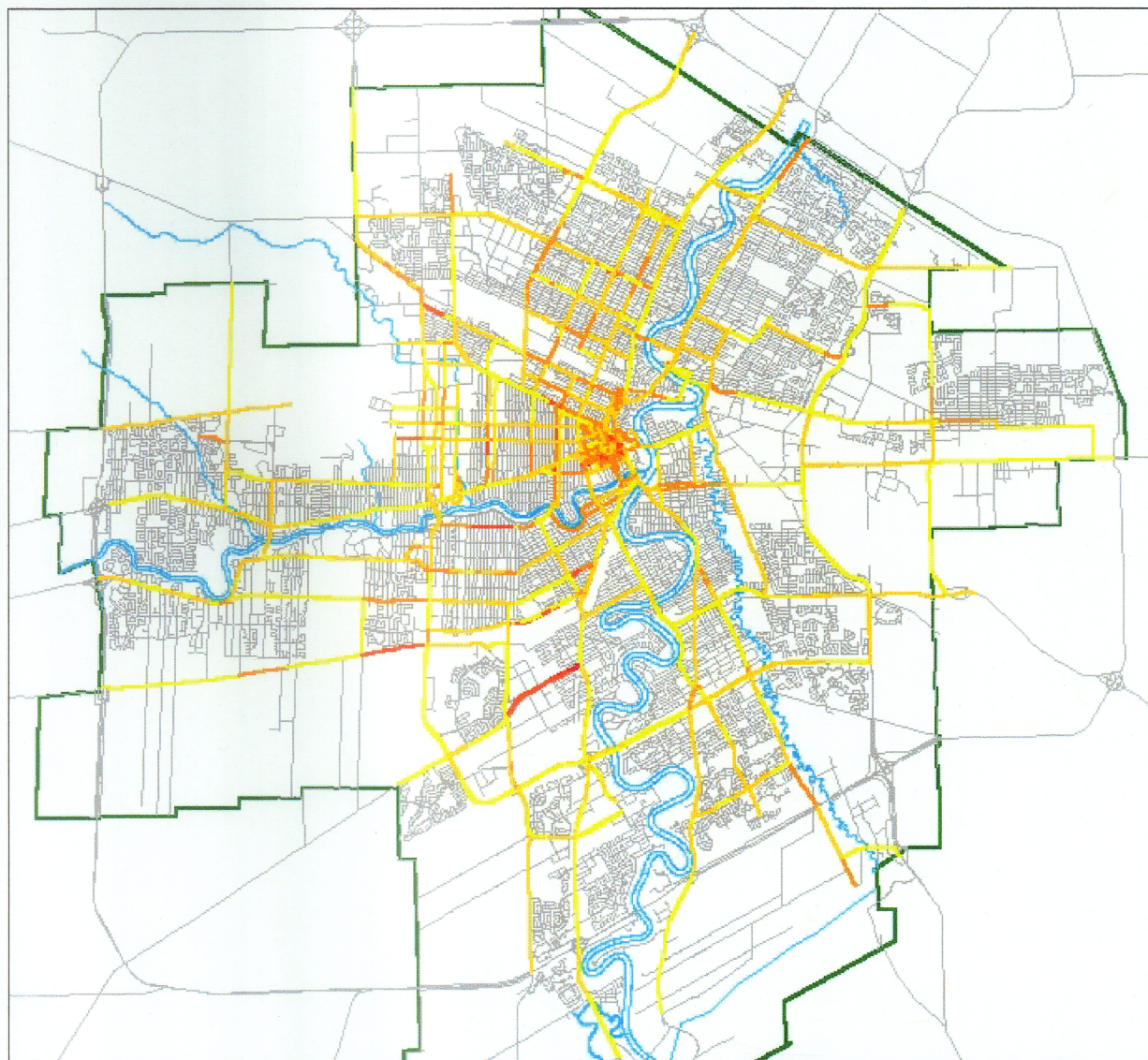


Figure 6.11: General Condition of the Winnipeg Regional Street Network (2002)



Legend

IRI (m/km)	
—	1 - 2
—	2 - 3
—	3 - 4
—	4 - 5
—	5 - 6

Enlargement of Downtown



Figure 6.12: Roughness of the Winnipeg Regional Street Network (2002)

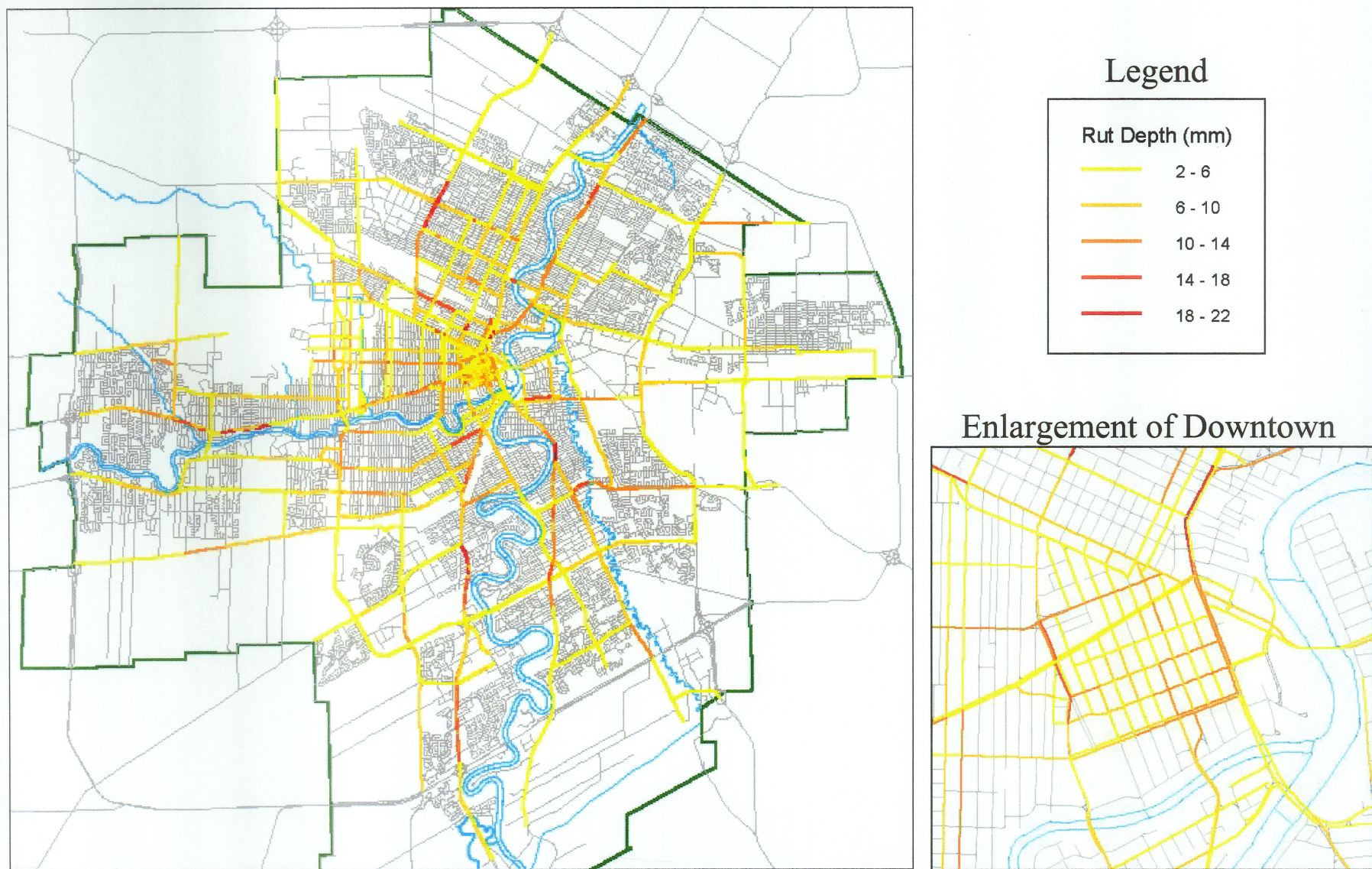
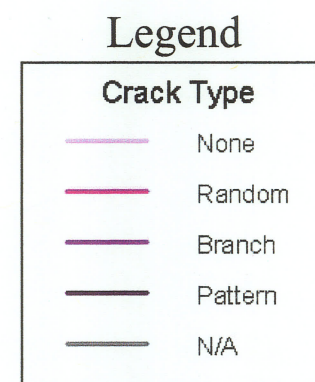
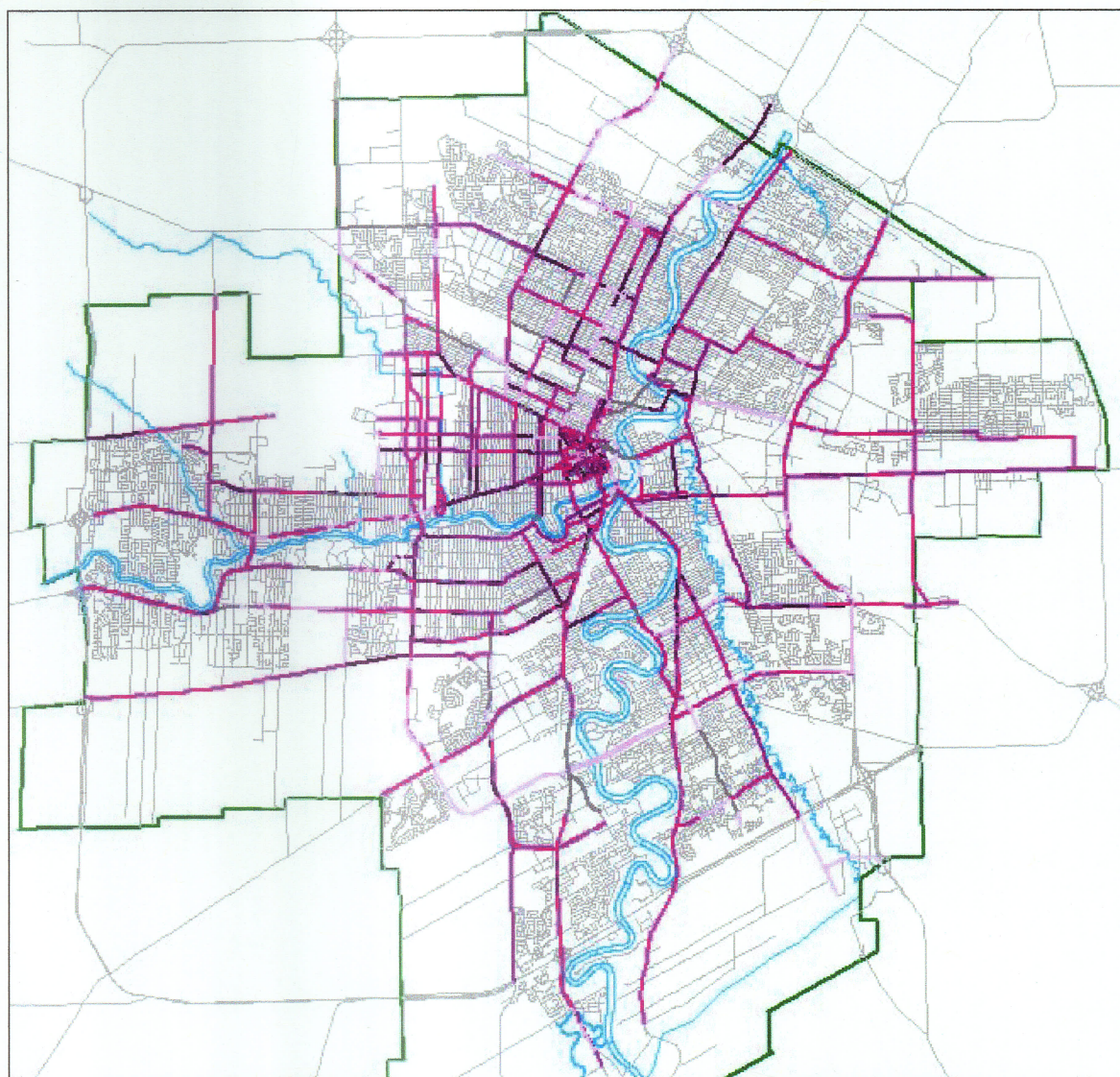


Figure 6.13: Rutting of the Winnipeg Regional Street Network (2002)



Enlargement of Downtown

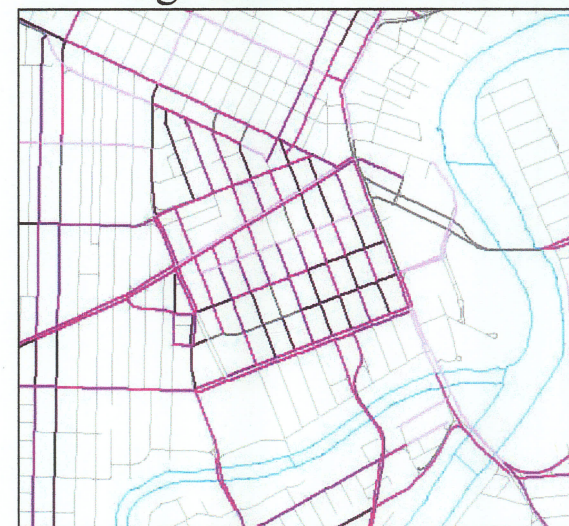
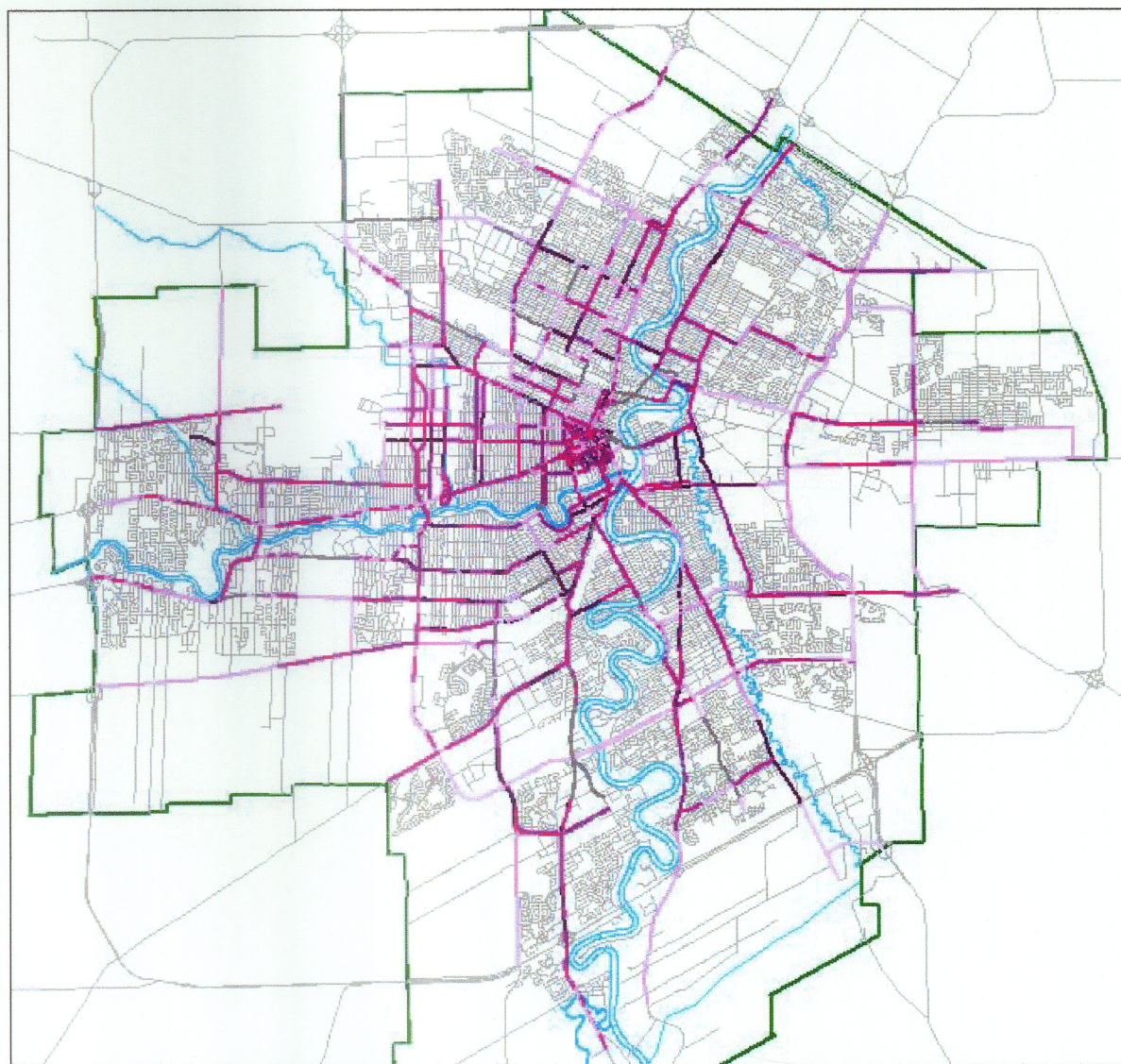


Figure 6.14: Crack Type (2002)



Legend

Crack Severity

- None
- New
- Slight
- Moderate
- Extreme
- N/A

Enlargement of Downtown

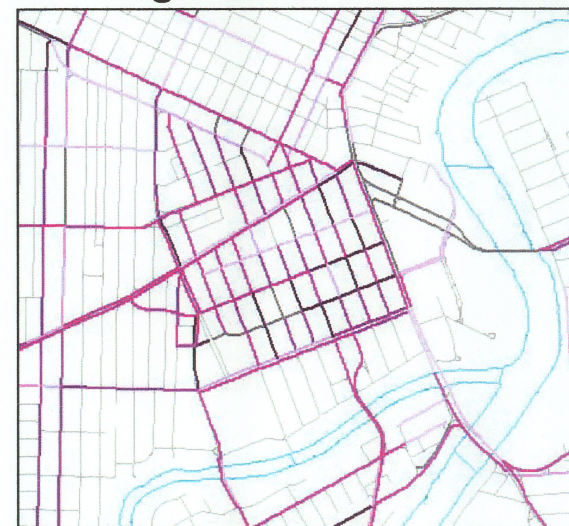


Figure 6.15: Crack Severity (2002)

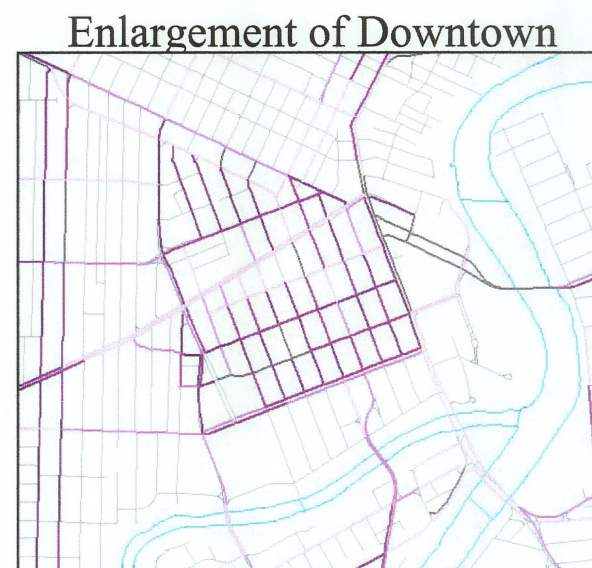
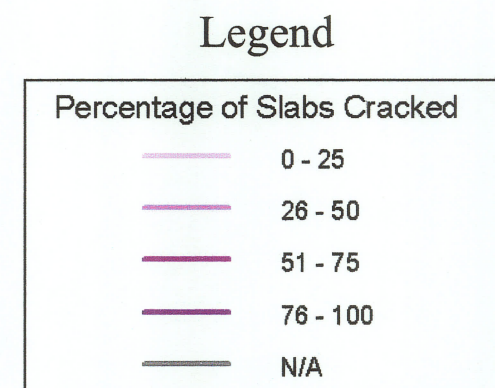
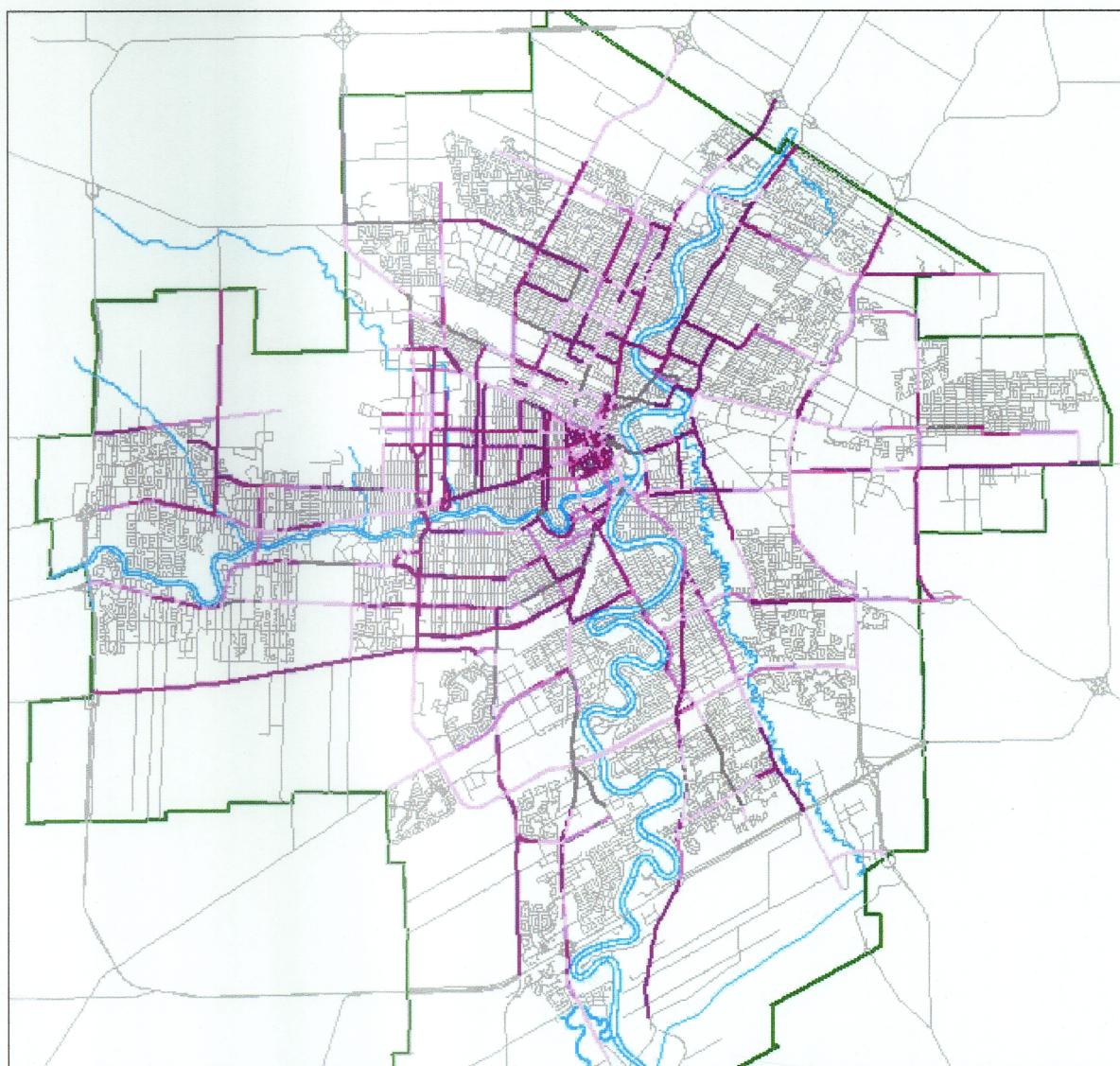
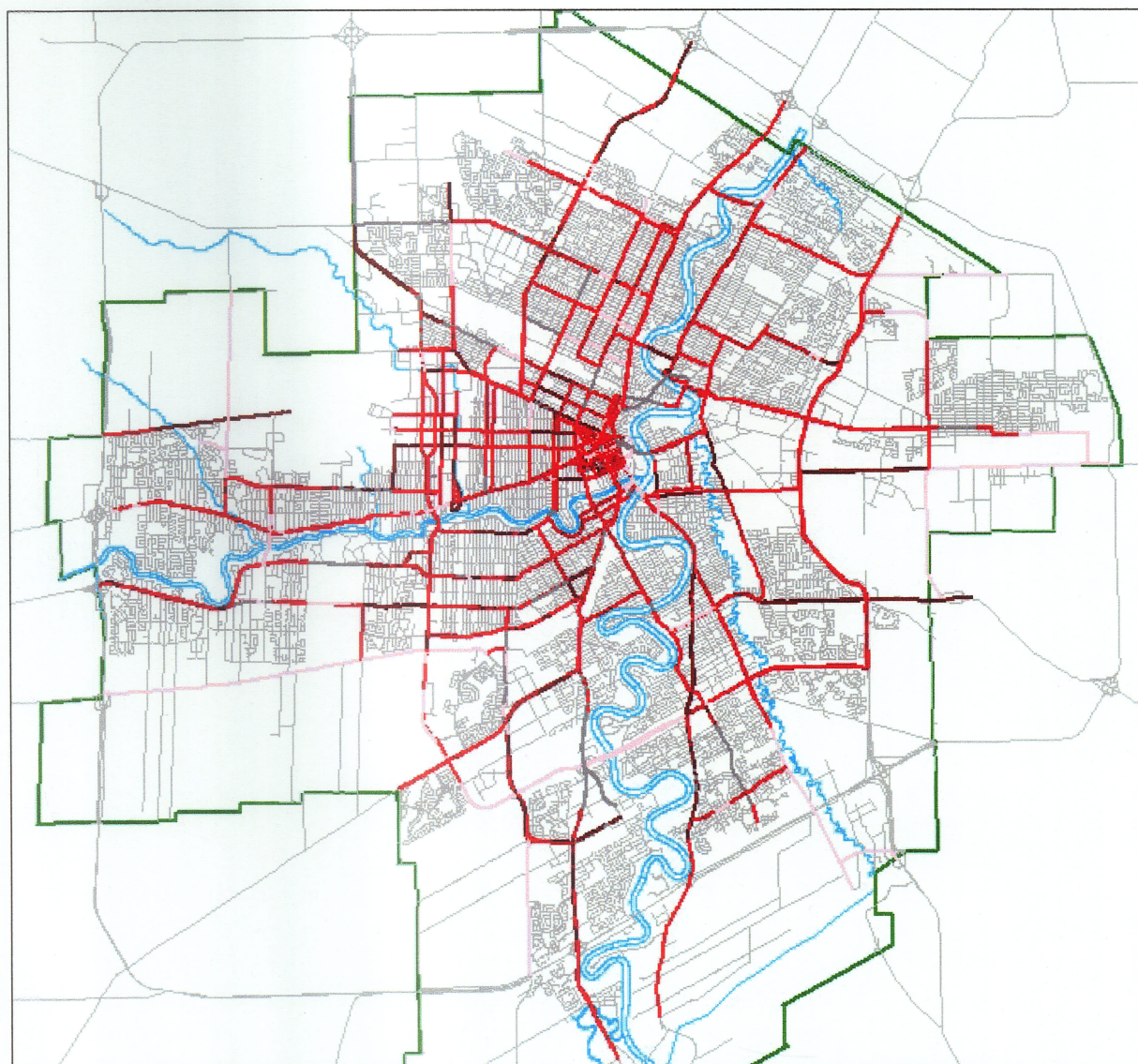


Figure 6.16: Percentage of Slabs Cracked (2002)



Legend

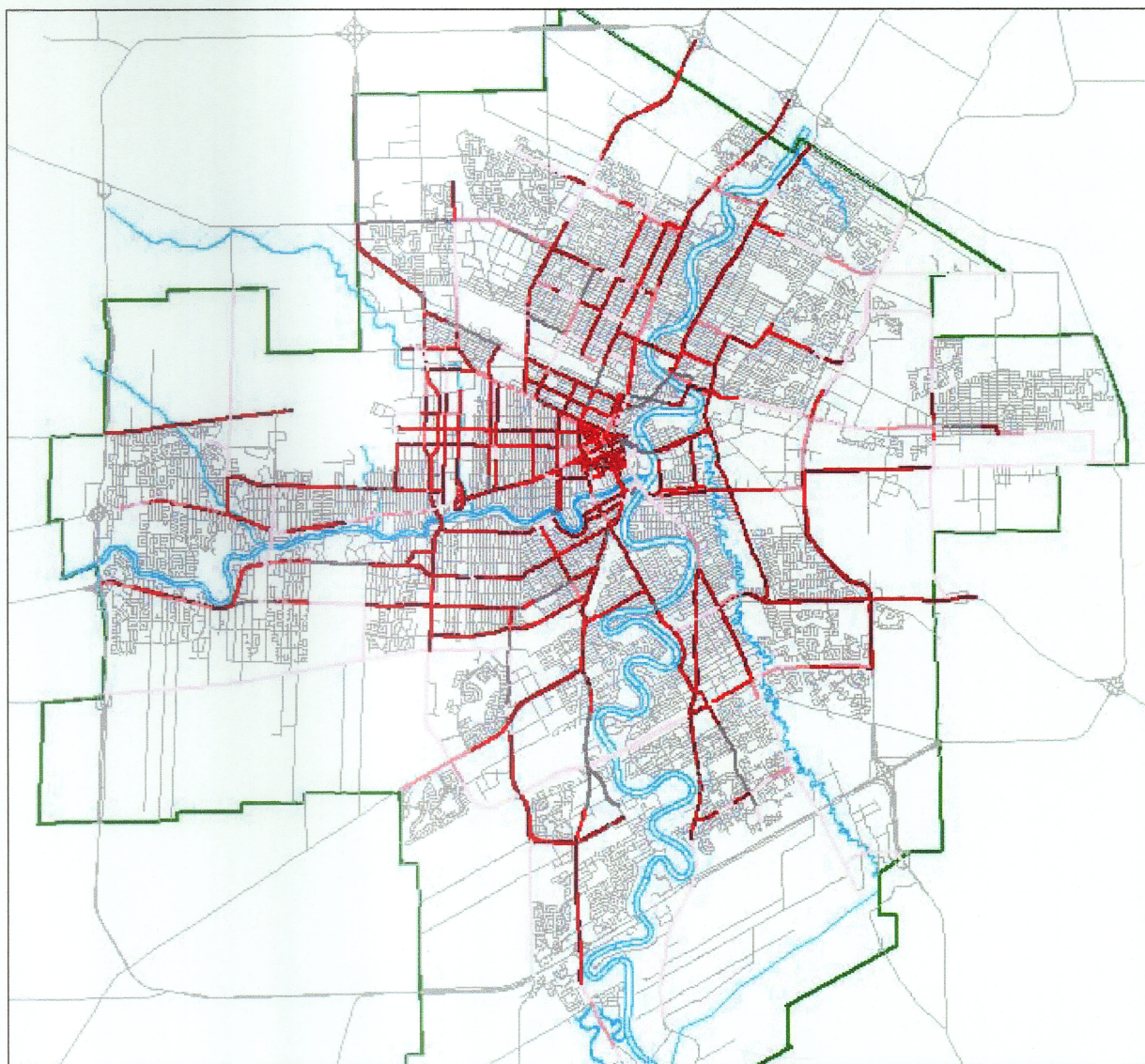
Joint Severity

- New
- Slight
- Moderate
- Extreme
- N/A

Enlargement of Downtown



Figure 6.17: Joint Severity (2002)



Legend

Percentage of Joints Spalled

- 0 - 25
- 26 - 50
- 51 - 75
- 76 - 100
- N/A

Enlargement of Downtown

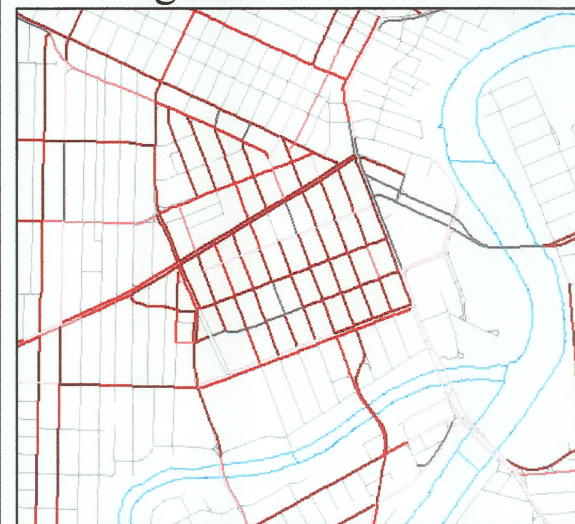


Figure 6.18: Percentage of Joints Spalled (2002)

Chapter 7

CONCLUSIONS AND RECOMMENDATIONS

7.1 Summary

Network-level pavement management systems are necessary for making decisions that affect the programming and planning of the road network. The PMS gives consideration to an agency's short and long-range budgets, present and future network condition, and the identification and prioritization of potential projects. To accomplish these tasks in a timely and cost effective manner at the network-level, data must be collected more quickly and with less detail than at the project level; yet data quality and consistency must be maintained. Decisions made based on inadequate, unreliable, or inconsistent data can lead to costly errors (TAC, 1997).

This research utilized pavement condition data from two unique networks, the Winnipeg regional street network and the Manitoba highway network. The datasets obtained on the Winnipeg regional street network include automated and manually collected data elements from pilot surveys and from parallel network-wide surveys. The dataset obtained for the Manitoba highway network includes automated data from multiple years of surveys, 1999 to 2003.

The data elements used include IRI, rut depth, and surface distresses including cracking and joint spalling data. Chapter 2 provided details about each of the data sources and data elements.

Data quality and consistency were analyzed through the comparison of automated and manual data collected during the pilot testing surveys and parallel network-wide surveys conducted in the City of Winnipeg. Multi-year data collected on the Manitoba highway network were also used to assess the consistency of the data from year-to-year.

Two approaches were used to analyze the potential for optimizing data collection needs; that is, minimizing the volume of data collected while maintaining data quality. The first approach is the collection of data for fewer lane-kilometers. The transverse variability of surface distresses were analyzed to determine if data selected for a single lane is representative of all of the lanes. The second approach is the collection of fewer variables by searching for relationships between the many data elements collected. Linear regression, maximum likelihood classification, and artificial neural networks were used to determine if manually collected data elements are significantly related to automated data elements which would allow for the replacement of the manual data collection with the automated data elements.

The roughness of urban road networks is affected by factors that do not exist or are more infrequent on rural highway networks. These factors include false-grades to facilitate drainage, frequent intersections, and numerous at-grade railway crossings. Two approaches were used to analyze these factors, analyses of the parallel network-wide surveys conducted in Winnipeg and simulations of the effect of rutted intersections on IRI. The effect of slab faulting on IRI was simulated for slightly faulted and heavily faulted segments to quantify the effect that this pavement distress can have on IRI.

This thesis presents a software package, IRIIS, which was developed and used during the course of this research. IRIIS is a tool that facilitates the graphical display and analysis of the massive amounts of data collected during automated pavement condition surveys. Displays show automated pavement condition data and other relevant data including manual ratings, highway classification, traffic, and structural information. The linking of the automated datasets with other databases allows for the filtering and sorting capabilities included in IRIIS. IRIIS performs several other functions including dynamic segmentation based on IRI or rut depth, graphical display of pavement history, and analysis of the consistency of automated data based on multi-year surveys.

GIS was used to analyze the spatial relationships in pavement condition data and to produce maps of pavement condition. GIS can be a very effective tool in the production of maps to communicate present network condition, future network condition, and budget needs to elected officials and the public. Maps of pavement type and condition were presented.

7.2 Conclusions and Recommendations

The analysis contained in this thesis supports a number of conclusions and recommendations for the collection and use of automated pavement condition data.

Data Quality and Consistency

An analysis of IRI and rut depth data collected in the City of Winnipeg during a pilot-testing program showed that both data elements can be measured accurately with an inertial profiler equipped with a rut-bar. The variation in IRI between the automated and manual profilers is within the range of variability that should be expected due to variation in lateral positioning as well as daily and seasonal changes in IRI. The differences in measured rut depth are small and have little practical significance.

A comparison of the cracking and spalling data collected during the pilot-testing program showed that there is little consistency between the two methods. The manual inspection indicated that all three segments had a significant amount of spalling while the automated data reported no spalling for two of the three segments. The type of spalling evident on those two segments is difficult to detect at high-speed.

Regression analyses of data collected during parallel network-level surveys in the City of Winnipeg in 2002 failed to find significant relationships between the distress data measured manually and with the automated survey equipment. Manual ratings of cracking and joint spalling were converted to a 1 to 10 scale and compared to the automated PASER index. These comparisons showed a large variation between the two methods of pavement assessment. Comparisons between the automated and manual high severity transverse spalling and slab failure data showed a lack of relationship between the two methods of pavement assessment.

The consistency of multi-year survey data collected on the Manitoba highway network was analyzed. The analysis showed that, over the five-year period, 12.5% of subsections had annual changes in IRI data that did not match the year paved and 5.7% of subsections had an annual change in rut depth that did not match the year paved. The annual inconsistencies of 3.2% of subsections per year for IRI and 1.4% of subsections per year for rut depth are of little concern given that network-level surveys must be conducted more quickly and in less detail than project-level evaluations. The inconsistencies may be due to incomplete pavement history data, suspect IRI and rutting data, or maintenance work that is affecting these two measures of pavement condition. This method could be very effective at detecting suspect data if the pavement history database was kept up-to-date and if maintenance activities were included in the database.

Optimizing Data Collection Needs

An analysis of the transverse variability of surface distresses collected in 2002 for the automated lane and all lanes showed that a survey of one lane of a segment is representative of the entire segment to a statistically significant degree. The analysis also showed that the lane to be surveyed in future automated surveys should be randomly selected to eliminate any bias in cracking and joint scores and that one lane is sufficient for network-level pavement management purposes. There was little overall difference in crack and joint scores, however a few segments exhibited significant differences between the lanes, which would affect decision making at the project-level.

Maximum likelihood classification and artificial neural networks were used to predict the manual rating scores based on IRI and rut depth. Agreement between the manual ratings and the predicted ratings was at best moderate for the MLC and both neural network architectures. Classification based on MLC and ANNs cannot be used to predict the manual ratings based on IRI and rut depth alone with sufficient confidence to justify replacing manual ratings with ratings predicted based on IRI and rut depth.

For the City of Winnipeg's pavement management system, it is recommended that the manually measured pavement ratings continue to be used until cracking and joint spalling distresses can be accurately measured with automated equipment. IRI and rut depth data also provide valuable pavement information; these automated data elements can be used for dynamic segmentation are transferable between jurisdictions (for comparing pavement condition with other cities), time-stable, and independent of the equipment used to measure them.

Urban Considerations

False grades are the reversing longitudinal slopes that are built into roads to facilitate drainage. Curbed roads in urban areas typically require catchbasins every 50 to 150 m to facilitate drainage (TAC, 1995). An analysis of the longitudinal profile data collected on Grant Avenue showed that the false grades account for 10% of the roughness on this section. The effect can be as high as 20% for smoother sections in urban areas.

An analysis of 30 randomly selected railway crossings showed that roughness increases at these locations; this is especially true for railway crossings that are in poor condition. Most railway crossings had an IRI approximately 1 m/km higher than that of the segment while those in poor condition had an IRI approximately 1.5 m/km higher than the segment. The effect of railway crossings is significant for the IRI of individual segments, especially short segments. An approximate calculation showed that the reported IRI of the network as a whole would only be slightly lower if railway crossings were excluded.

A simulation of a vehicle driving across an intersection with 10 mm of rutting showed that the increase in IRI could be significant. The prevalence of intersections in urban areas provides an additional explanation as to why the IRI is often higher in urban areas than for rural highways.

A reporting interval of 20 m is recommended for IRI and rut depth in urban areas and the coordinates of each data point from a GPS receiver should also be reported. Larger reporting intervals tend to filter out extreme high and low roughness values and obscure useful results.

Extreme and valid data values are essential for the execution of rehabilitation and maintenance programs. The effect of rehabilitating short sections with high IRI values can be studied during the analysis of maintenance and rehabilitation alternatives. GPS coordinates will aid in the diagnosis of roughness problems by making it easy to determine if an intersection, railway crossing, or bridge deck caused the high roughness.

An analysis of anomalies between the automated and manual surveys was conducted to demonstrate the effect of segment length on IRI. A GIS plot of these anomalies showed that good segments with high roughness are clustered in the downtown area where segments are short. The effect of intersections on IRI is magnified for short segments, which indicates that the proportion of IRI attributable to pavement condition is reduced and the proportion caused by intersections and railway crossings increases.

Pavement Information Systems

The IRI Information System, IRIIS, provides for the graphical display and analysis of the massive amounts of data collected during automated pavement condition surveys. IRIIS was customized for the two networks used during this research, the Winnipeg regional street network and the Manitoba highway network. Displays show automated pavement condition data and other relevant data including manual ratings, highway classification, traffic, and structural information.

The linking of the automated datasets with other databases, including traffic, classification, and pavement history, provides for filtering and sorting based on various criteria, which aids in the diagnosis of specific pavement problems. The program also performs other functions including dynamic segmentation based on IRI or rut depth, graphical display of pavement history, and analysis of the consistency of automated data based on multi-year surveys.

Geographic information systems facilitate the spatial analysis of patterns in pavement condition data and the production of maps to communicate pavement condition and budget needs to engineers, elected officials, and the public. Maps can show surface type, existing pavement condition, future pavement condition under a given funding scenario, deferred projects under a given funding scenario, and locations of scheduled projects.

7.3 Recommendations for Further Research

This research addressed some of the questions related to urban pavement roughness that were raised by an NCHRP workshop. (Perera and Kohn, 2002) Additional research on roughness in

urban areas is necessary as indicated by Perera and Kohn. In particular, research on the possibility of using other roughness indices or adjusting the simulation speed of the quarter-car model based on the roadway's functional classification (expressway, arterial, collector, or local) and location (urban or rural).

This thesis concluded that there was little agreement between surface distress data measured manually by rating crews and the distress data obtained at the speed of traffic with automated surveys. The disagreement between the two methods is partially due to the differences in the definitions of surface distress used by the operators and partially due to the difficulty of detecting these distresses at high-speed. Additional research to improve the automated detection of cracking and joint spalling and to provide recommendations for data collection procedures and reporting should be conducted.

Life cycle costs of the pavement network are minimized when decisions are based on a pavement management system and the concepts of asset management. Further research on the use of integrated infrastructure management systems, which consider the needs of the entire transportation infrastructure and not just the pavement network, should be conducted. An integrated system can manage all of the physical components of a transportation system including: pavements, bridges, transit vehicles and shelters, non-motorized multiuse paths, sidewalks, and traffic signals. A recent case study by Sadek, et al. (2003) showed how an integrated infrastructure management system could be applied to a small urban area, the City of South Burlington, Vermont.

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Appendix A

PASER DEFINITIONS FOR APC AND PCC SEGMENTS

Table A.1: Detailed PASER Definitions for APC Segments (GIE, 2002)

	Reconstruction required		Structural improvement (Overlay or recycling)		Preservative treatments (Sealcoating)		Routine maintenance (Cracksealing, minor patching)		No maintenance required	
	1 *	2	3	4	5	6	7	8	9 **	10 ***
Longitudinal Crack	> 1/2"	> 1/2"	> 1/2"	> 1/2"	> 1/2"	1/4 " to 1/2"	< 1/4"	Sealed or < 1/4" At paving Joint only		
Transverse Crack	> 1/2"	> 1/2"	> 1/2"	> 1/2"	> 1/2"	1/4 " to 1/2" (Some <10' apart)	< 1/4" (>10' apart)	Sealed or < 1/4" (≥ 40' apart)		
Block Cracking	>50% area	>50% area	>50% area	>50% area	Up to 50% area	First sign...				
Alligator Cracking	>25% area	>25% area	<25% area							
Patch	High	High	High	Medium	Low	Occasional in good condition				
Pothole	Several	Some	Occasional							

* Loss of surface integrity, failed

** Recent overlay, like new

*** New construction

Table A.2: Detailed PASER Definitions for PCC Segments (GIE, 2002)

	Complete reconstruction		Extensive slab or joint rehabilitation		Routine Maintenance (Surface repair or partial depth patching)		Preventative Maintenance (Crack, joint sealing)		No maintenance required	
	1 *	2	3	4	5	6	7	8	9 **	10 ***
Longitudinal Crack	> ½"	> ½"	> ½"	> ½"	¼ " to ½"	< ¼"	Isolated Sealed or < ¼ "	Sealed		
Transversal Crack	> ½"	> ½"	> ½"	> ½"	¼ " to ½"	More frequent < ¼"	Isolated < ¼"			
Spalling	High	High	High	Medium	Low	Isolated Low				
Faulting	High	High	High	Medium	Low	Isolated Low				
Broken Slab	High	High	Medium Frequent	Medium Seldom	Low Frequent	Low Seldom				
Patch	High	High	High	Medium	Low	Occasional In good condition				
Pothole	Several	Some	Occasional							

* Pavement failure

** Recent concrete rehabilitation, like new

*** New construction

Appendix B

MATLAB CODE FOR TRAINING THE NEURAL NETWORK

```
%P = Input IRI and Rut Depth
%T = Target New, Good, Fair, Poor

net = newff(minmax(P'),[5,4],{'tansig' 'tansig'}, 'trainrp');

% set training parameters
net.trainparam.goal=1e-6;
% net.trainparam.lr=0.5;
net.trainparam.show=500;
net.trainparam.epochs=500;

%train the network
[net, tr]=train(net, P', GenCond4');

% store input weights, layer weights, and bias
inputweights=net.iw{1,1};

for i=1:2
    networkbias{i} = net.b{i};
end
for i =2:2
    layerweight{i-1}=net.lw{i,1};
end

%y = simulated output of network based on P
y=(sim(net, P'))';
e = GenCond4-y; % the error
perf = mse(e) %the mean squared error
perfarray(1,1)=1;
perfarray(1,2)=perf;

% run several more times and store weights and biases if new error is
less
% error can be reduced
for i = 1:100
    i
    net = newff(minmax(P'),[5,4],{'tansig' 'tansig'}, 'trainrp');

    % set training parameters
    net.trainparam.goal=1e-6;
    % net.trainparam.lr=0.5;
    net.trainparam.show=500;
    net.trainparam.epochs=500;

    [net, tr]=train(net, P', GenCond4');

    %y = simulated output of network based on P
    y=(sim(net, P'))';
```

```

    e = GenCond4-y; % the error
    tempperf = mse(e); %the mean squared error
    if tempperf < perf %then replace weights and biases
        inputweights=net.iw{1,1};

        for j=1:2
            networkbias{j} = net.b{j};
        end
        for j =2:2
            layerweight{j-1}=net.lw{j,1};
        end
        perf=tempperf;
        perfarray(i+1,1)=i+1;
        perfarray(i+1,2)=perf;
    end
    perfarray2(i+1)=tempperf;
end

% load the weights and biases that produced the lowest error into
% the neural network
net.iw{1, 1} =inputweights;
for i=1:2
    net.b{i}=networkbias{i};
end
for i =2:2
    net.LW{i,1}=layerweight{i-1};
end

y=(sim(net, P'))';
e = GenCond4-y; % the error
perf = mse(e) %the mean squared error
a=(sim(net, F'))';
b=(sim(net, Ftest'))';

```


Appendix C

CONTINGENCY TABLES FOR ERROR ASSESSMENT OF NEURAL NETWORK 1 AND NEURAL NETWORK 2

Table C.1: Agreement between manual ratings and **Neural Network 1** classification based on IRI and rut depth for **General Condition** on APC Segments

		Subjective Rating			
		New	Good	Fair	Poor
Neural Network 1 Classification	New	0	0	0	0
	Good	3	48	24	10
	Fair	0	2	1	2
	Poor	0	8	8	4
Percent matching		0%	83%	3%	25%

Table C.2: Agreement between manual ratings and **Neural Network 1** classification based on IRI and rut depth for **Crack Type** on APC Segments

		Subjective Rating			
		None	Random	Branch	Pattern
Neural Network 1 Classification	None	0	0	0	0
	Random	10	58	11	10
	Branch	0	0	0	0
	Pattern	0	10	4	7
Percent matching		0%	85%	0%	41%

Table C.3: Agreement between manual ratings and **Neural Network 1** classification based on IRI and rut depth for **Crack Severity** on APC Segments

		Subjective Rating			
		New	Slight	Moderate	Extreme
Neural Network 1 Classification	New	13	6	0	1
	Slight	28	31	9	8
	Moderate	0	0	0	0
	Extreme	0	4	6	4
Percent matching		32%	76%	0%	31%

Table C.4: Agreement between manual ratings and **Neural Network 1** classification based on IRI and rut depth for **Crack Extent** on APC Segments

		Subjective Rating			
		0	1	2	3
Neural Network 1 Classification	0	0	2	0	2
	1	0	0	0	0
	2	0	0	0	0
	3	10	7	5	84
Percent matching		0%	0%	0%	98%

Table C.5: Agreement between manual ratings and **Neural Network 1** classification based on IRI and rut depth for **Joint Severity** on APC Segments

		Subjective Rating			
		New	Slight	Moderate	Extreme
Neural Network 1 Classification	New	0	2	0	0
	Slight	7	48	25	6
	Moderate	0	13	7	2
	Extreme	0	0	0	0
Percent matching		0%	76%	22%	0%

Table C.6: Agreement between manual ratings and **Neural Network 1** classification based on IRI and rut depth for **Joint Extent** on APC Segments

		Subjective Rating			
		0	1	2	3
Neural Network 1 Classification	0	1	2	1	1
	1	0	0	0	0
	2	0	0	0	0
	3	6	4	8	87
Percent matching		14%	0%	0%	99%

Table C.7: Agreement between manual ratings and **Neural Network 1** classification based on IRI and rut depth for **General Condition** on **PCC Segments**

		Subjective Rating			
		New	Good	Fair	Poor
Neural Network 1 Classification	New	6	3	2	1
	Good	0	3	0	0
	Fair	0	3	6	3
	Poor	0	0	0	1
Percent matching		100%	33%	75%	20%

Table C.8: Agreement between manual ratings and **Neural Network 1** classification based on IRI and rut depth for **Crack Type** on **PCC Segments**

		Subjective Rating			
		None	Random	Branch	Pattern
Neural Network 1 Classification	None	12	4	0	0
	Random	5	6	1	0
	Branch	0	0	0	0
	Pattern	0	0	0	0
Percent matching		71%	60%	0%	N/A

Table C.9: Agreement between manual ratings and **Neural Network 1** classification based on IRI and rut depth for **Crack Severity** on **PCC Segments**

		Subjective Rating			
		New	Slight	Moderate	Extreme
Neural Network 1 Classification	New	8	4	0	1
	Slight	9	6	0	0
	Moderate	0	0	0	0
	Extreme	0	0	0	0
Percent matching		47%	60%	N/A	0%

Table C.10 Agreement between manual ratings and **Neural Network 1** classification based on IRI and rut depth for **Crack Extent** on PCC Segments

		Subjective Rating			
		0	1	2	3
Neural Network 1 Classification	0	11	4	0	0
	1	5	2	0	0
	2	0	0	0	0
	3	1	2	1	2
Percent matching		65%	25%	0%	100%

Table C.11: Agreement between manual ratings and **Neural Network 1** classification based on IRI and rut depth for **Joint Severity** on PCC Segments

		Subjective Rating			
		New	Slight	Moderate	Extreme
Neural Network 1 Classification	New	2	3	1	0
	Slight	1	5	1	1
	Moderate	0	4	5	3
	Extreme	0	1	0	1
Percent matching		67%	38%	71%	20%

Table C.12: Agreement between manual ratings and **Neural Network 1** classification based on IRI and rut depth for **Joint Extent** on PCC Segments

		Subjective Rating			
		0	1	2	3
Neural Network 1 Classification	0	3	2	1	3
	1	0	1	1	0
	2	0	0	0	0
	3	0	2	0	15
Percent matching		100%	20%	0%	83%

Table C.13: Agreement between manual ratings and **Neural Network 2** classification based on IRI and rut depth for **General Condition** on APC Segments

		Subjective Rating			
		New	Good	Fair	Poor
Neural Network 2 Classification	New	0	0	0	0
	Good	3	43	12	3
	Fair	0	15	20	11
	Poor	0	0	1	2
Percent matching		0%	74%	61%	13%

Table C.14: Agreement between manual ratings and **Neural Network 2** classification based on IRI and rut depth for **Crack Type** on APC Segments

		Subjective Rating			
		None	Random	Branch	Pattern
Neural Network 2 Classification	None	0	0	0	0
	Random	8	46	7	5
	Branch	2	19	7	8
	Pattern	0	3	1	4
Percent matching		0%	68%	47%	24%

Table C.15: Agreement between manual ratings and **Neural Network 2** classification based on IRI and rut depth for **Crack Severity** on APC Segments

		Subjective Rating			
		New	Slight	Moderate	Extreme
Neural Network 2 Classification	New	8	2	0	0
	Slight	31	28	7	7
	Moderate	2	11	7	4
	Extreme	0	0	1	2
Percent matching		20%	68%	47%	15%

Table C.16: Agreement between manual ratings and **Neural Network 2** classification based on IRI and rut depth for **Crack Extent** on **APC** Segments

		Subjective Rating			
		0	1	2	3
Neural Network 2 Classification	0	0	0	0	0
	1	0	2	0	4
	2	7	4	3	48
	3	3	3	2	34
Percent matching		0%	22%	60%	40%

Table C.17: Agreement between manual ratings and **Neural Network 2** classification based on IRI and rut depth for **Joint Severity** on **APC** Segments

		Subjective Rating			
		New	Slight	Moderate	Extreme
Neural Network 2 Classification	New	1	2	0	0
	Slight	6	43	14	2
	Moderate	0	18	18	6
	Extreme	0	0	0	0
Percent matching		14%	68%	56%	0%

Table C.18: Agreement between manual ratings and **Neural Network 2** classification based on IRI and rut depth for **Joint Extent** on **APC** Segments

		Subjective Rating			
		0	1	2	3
Neural Network 2 Classification	0	0	1	0	1
	1	1	1	1	1
	2	5	3	5	25
	3	1	1	3	61
Percent matching		0%	17%	56%	69%

Table C.19: Agreement between manual ratings and **Neural Network 2** classification based on IRI and rut depth for **General Condition** on **PCC Segments**

		Subjective Rating			
		New	Good	Fair	Poor
Neural Network 2 Classification	New	0	1	0	0
	Good	6	5	2	1
	Fair	0	3	6	4
	Poor	0	0	0	0
Percent matching		0%	56%	75%	0%

Table C.20: Agreement between manual ratings and **Neural Network 2** classification based on IRI and rut depth for **Crack Type** on **PCC Segments**

		Subjective Rating			
		None	Random	Branch	Pattern
Neural Network 2 Classification	None	7	4	0	0
	Random	10	5	1	0
	Branch	0	1	0	0
	Pattern	0	0	0	0
Percent matching		41%	50%	0%	N/A

Table C.21: Agreement between manual ratings and **Neural Network 2** classification based on IRI and rut depth for **Crack Severity** on **PCC Segments**

		Subjective Rating			
		New	Slight	Moderate	Extreme
Neural Network 2 Classification	New	9	4	0	1
	Slight	8	5	0	0
	Moderate	0	1	0	0
	Extreme	0	0	0	0
Percent matching		53%	50%	N/A	0%

Table C.22: Agreement between manual ratings and **Neural Network 2** classification based on IRI and rut depth for **Crack Extent** on **PCC Segments**

		Subjective Rating			
		0	1	2	3
Neural Network 2 Classification	0	4	2	0	0
	1	12	4	0	0
	2	1	2	1	2
	3	0	0	0	0
Percent matching		24%	50%	100%	0%

Table C.23: Agreement between manual ratings and **Neural Network 2** classification based on IRI and rut depth for **Joint Severity** on **PCC Segments**

		Subjective Rating			
		New	Slight	Moderate	Extreme
Neural Network 2 Classification	New	0	1	0	0
	Slight	3	9	1	1
	Moderate	0	3	6	3
	Extreme	0	0	0	1
Percent matching		0%	69%	86%	20%

Table C.24: Agreement between manual ratings and **Neural Network 2** classification based on IRI and rut depth for **Joint Extent** on **PCC Segments**

		Subjective Rating			
		0	1	2	3
Neural Network 2 Classification	0	0	0	0	0
	1	2	3	1	2
	2	1	2	1	3
	3	0	0	0	13
Percent matching		0%	60%	50%	72%