DEVELOPING A RELATIONSHIP BETWEEN SUBJECTIVE AND OBJECTIVE PAVEMENT CONDITION DATA

By

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ABSTRACT

Several subjective pavement surface distress rating procedures are used by highway departments as an expedient tool to determine the potential need for maintenance work. This manual rating is prone to be biased, causes traffic disruptions and is risky for the assessors required to carry it out. Also, few highly qualified personnel are available to perform it. Therefore, many highway agencies have made efforts to relate subjective ratings to directly measured pavement condition data, in the hope that the need for subjective rating in formulating intervention criteria for road maintenance may be reduced or removed. Studies have revealed that significant differences exist among these ratings due to dissimilarities in the types of distress considered, allocated weighting factors for severity, and the structures of mathematical formulae used.

In Victoria, Australia, Surface Inspection Rating Procedure (SIRP) is performed for major asphalt concrete (AC) and sprayed seal (SS) surfacing road networks based on subjective visual inspection. Subjective data of distresses, for each road segment, are combined into one index denoted as Surface Inspection Rating (SIR) which is used for triggering the periodic resurfacing program. In addition, Pavement Condition Survey (PCS) involves objective surveys, usually accomplished biannually, with measurable outputs of overall pavement condition (functional and structural) which can be used for network condition monitoring to determine if intervention criteria for all types of renewal activities have been met.

The aim of the study is to develop a set of relationships between subjective pavement Surface Inspection Rating (SIR) and automated pavement distresses, with an investigation of interactions between pavement distresses. The pavement condition parameters/distresses include cracking, rutting, texture loss and roughness. In addition, the influences of pavement operating conditions (such as age and heavy vehicle traffic volume) on the measured strength of relationships between subjective rating and objective pavement distresses, are studied.

To accomplish this study, a sample network of granular pavements surfaced with bituminous surfacing (asphalt and sprayed seal) in Victoria, Australia is selected. VicRoads historical data of 2011 and 2013 for 34 highways are screened and compiled for the study. After filtering the data, 160 highway segments of the AC road network and 190 pavement segments of the SS network are prepared for statistical analysis. Initial analysis indicates that the correlations between SIR and some of automated pavement distresses are statistically significant in the AC network. Pearson's correlation coefficients (r) values are found to be 0.526, 0.338 and 0.177 for cracking, rutting and roughness, respectively. However, the 'texture loss' is found to have negligible correlation with SIR for the AC network. In the SS network, the correlations for cracking (r = 0.444) and texture loss (r = - 0.292) are found to be statistically significant. However, 'texture loss' being found to be negatively related to SIR indicates that the texture loss data is not reliable, since SIR is supposed to be positively related with texture loss.

In manual survey, each pavement distress is assessed on a four-level scale with values of 0, 1, 3 and 5 representing good, minor, moderate, and extensive categories respectively, taking severity and extent of the distress into account. Pavement distress data are collected by automated devices such as digital video cameras and multi-laser profilometers. To validate the automated data (cracking, rutting and texture loss) with subjective rating of those distresses, probabilistic logistic regression analysis is performed. The results indicate that automated cracking and rutting data can be validated for the AC network. For the SS network, only cracking data are validated.

In the subjective survey, deformation is evaluated considering localized depressions, not just longitudinal depressions (rutting). Objectively collected rutting data cannot be validated with the subjective ratings of rutting for the SS network. The reason for this may be that local depressions predominate over longitudinal depressions (rutting) in the SS network. Thus, the deformation rating values evaluated by the assessors may perhaps be more related to local depressions than to rutting in the subjective survey. Again, texture loss data cannot be validated with the subjective ratings of texture loss for both networks. The slow deterioration process of texture loss, that is difficult to assess in visual rating, justifies this. Over and above there is a possibility of errors in the objective data due to misreading or misinterpretations. The pavement surface texture loss data, from both types of surveys, should be investigated. Therefore, 'texture loss' is excluded from the analysis for both road networks, and roughness is excluded from analysis for the SS network.

Factorial ANOVA reveals that cracking and rutting interact with each other in predicting the relationships with SIR in the AC network and the interaction is statistically significant [$F(2,138) = 4.282$, $p < 0.05$]. The multiple linear regression model can explain 26% of the variation in SIR when categorical cracking and rutting of automated pavement condition data are used along with their interaction. However, categorical roughness is found to have no statistically significant interaction with cracking and rutting in predicting SIR. Surface inspection rating procedure in Victoria is limited with respect to factors like skid resistance, roughness, structural adequacy, and other environmental conditions. Therefore, the result that 'roughness' is a statistically insignificant predictor, is reasonable. Additionally, Factorial ANOVA tests show that the interaction of pavement distresses with both pavement age and heavy vehicle traffic volume is not statistically significant in predicting SIR for either network.

Multiple Linear Regression (MLR) analysis is performed for each of the AC and SS networks, with SIR as a function of metric/continuous PCS parameters. The best fit model for the AC network contains log-transformed objective cracking and rutting as statistically significant predictors, at the 5% significance level. Moreover, by comparing the standardized beta coefficients, the results prove that the contribution of cracking is more than that of rutting to explaining SIR. However, the prediction level of the model is found to be low (coefficient of determination, $R^2 = 0.305$). Log-transformed objective cracking is found to be a statistically significant predictor of SIR in the SS network and the best fitting model is found to explain only 24% of the variation in SIR. Since both of the AC and SS network MLR results explain relatively little of the variation in SIR, an alternate method is required for the study.

Reviewing previous studies, probabilistic logistic regression analysis is trialed to predict pavement surface condition from objective pavement distresses. Pavement deterioration is associated with the effects of known factors and unknown latent causes. Therefore, probabilistic logistic regression modeling is useful to assess the pavement condition by considering the outcome variable as a stochastic event. The logistic regression analysis is performed by grouping SIR value into different categories (Very Good, Good, Fair, Poor and Very Poor) with two ranking methods: RANK1 (5 categories) and RANK2 (4 categories). The most successful ordinal logistic models prove to be statistically significant (shown by the likelihood ratio and goodness of fit test results) for both networks. The overall success rates of the models are between 46% and 51%, with maximum probabilities in 'Very Good' condition in the AC network and 'Good' condition in the SS network. The developed ordinal models for asphalt and sprayed seal surfacing are validated by comparing the differences in weighted average predicted rating and actual rating of each pavement segment. The scaled squared residuals of SIR are observed to be small for both types of networks. Therefore, the models are validated for both road networks.

The probability table obtained from the logistic models for different condition categories gives the probablity of each pavement segment being in one or other category as a function of objectively collected pavement condition data (rutting / cracking). The pavement condition with the maximum probability is the most likely predicted condition for the pavement segment, and this can help the road asset managers of Victoria to prioritize pavement segments for periodic maintenance resurfacing. It is anticipated that the findings from this study may be able to assist any highway authorities to better understand the interactions between pavement distresses on evaluating overall pavement surface condition, and reduce the time, cost, and risk of evaluators involved in subjective surveys.

The thesis concludes by providing a number of recommendations for future research directions. These include a recommendation to improve ordinal logistic models when more data, covering the full range of SIR, becomes available. Also, it is recommended that future research include automated data of stone loss and patching data in model development, in the expectation that the addition of these variables may improve the models.

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DECLARATION

I declare that this thesis has been written by myself and it contains no materials that have been used for the publication or accomplishment of any other degree apart from where due reference has been made. The findings of this thesis are the views of the author and do not correspond to the views of VicRoads.

I confirm that appropriate recognition has been given within this thesis for the references used and the contributions of associated persons are acknowledged.

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ABBREVIATIONS AND NOTATIONS

Abbreviations

AADT	Average Annual Daily Traffic
AASHO	American Association of State Highway Officials
AASHTO	American Association of State Highway and Transportation Officials
AC	Asphalt Concrete
ANNs	Artificial Neural Networks
ANOVA	Analysis of Variance
ASTM	American Society for Testing and Materials
Austroads	Association of Australian and New Zealand Road Transport and Traffic Authorities
CI	Confidence Interval
DV	Dependent Variable
F	Fair
G	Good
GP	Genetic Programming
HMA	Hot Mix Asphalt
HV	Heavy Vehicle Traffic Volume
IAM	Integrated Asset Management
IRI	International Roughness Index
ISO	International Organization for Standardization
IV	Independent Variable
MC	Markov Chain
MLR	Multiple Linear Regression
MSE	Mean Squared Error
MSE	Metropolitan South East
P	Poor
PIARC	Permanent International Association of Road Congresses

PCI	Pavement Condition Index
PCP	Pervious Concrete Pavement
PCS	Pavement Condition Survey
PCR	Pavement Condition Rating
PIARC	Permanent International Association of Road Congresses
PMS	Pavement Management System
PSI	Present Serviceability Index
PSR	Pavement Serviceability Rating
RMSE	Root Mean Squared Error
SDI	Surface Distress Index
SIR	Surface Inspection Rating
SIRP	Surface Inspection Rating Procedure
SLR	Simple Linear Regression
SPSS	Statistical Package for Social Sciences
SS	Sprayed Seal
U.S.	United States
VicRoads	Victorian Road Authority
WRA	World Road Association
VG	Very Good
VIF	Variance Inflation Factor
VP	Very Poor

CHAPTER ONE

INTRODUCTION

1.1 Background of This Work

Granular pavement is widely used in Australia, New Zealand, and South Africa. Almost 90% of total motorway freight is carried on the sealed granular road network in Australia (T. C. Martin, 2009). This type of pavement consists of granular bases and sub-bases (structural layers) supported by natural soil subgrades, and its top surface layer is coated by bituminous materials that can be either a sprayed seal or a thin layer of asphalt. Both consist of aggregates and bitumen as the binder. For asphalt surfacing, the aggregates and binder are mixed at a plant, laid as a mat over the base and compacted. The sprayed seal involves spraying the binder over the base, after which the aggregate is spread over it and compacted to penetrate the binder film. This type of pavement is considered to be a cost-effective construction for the greater part of the Australian road network (Dickinson, 1982).

The bituminous surfacing assists in maintaining the skid resistance of pavement and acts as a waterproof surface in all-weather conditions. Asphalt surfacing contributes to the pavement structural strength to some extent (Arnold, 2004). Throughout the serviceable life of a pavement, its structural strength decreases, and the bituminous materials deteriorate. The pavement distress on the surface can indicate the condition of the pavement layer's thickness, deformations, traffic loads along with environmental effects (Lijun Sun, 2016). The signs of deterioration can be observed on the surface as different distresses, such as cracking, texture loss, stone loss, potholes, and depressions. The progression of distress in the pavement will consequently compromise its performance later.

Due to aging or oxidation of the bituminous binder, its viscosity increases, and it becomes stiff and cracks under the effect of traffic loading. Cracks may also develop in asphalt due to fatigue under the effect of loading if the mix is not well designed. When these cracks become wider, they allow rainwater to penetrate the lower granular structural layers, leading to reduced strength and higher susceptibility to rutting or deformation by the action of trucks' wheels in their wheel-paths. That may also lead to potholing and stone loss. When the deformation of pavement is approaching to critical state, resurfacing or rehabilitation is necessary.

Most road agencies practise pavement maintenance prioritization using distinct standardized priority indices that are calculated through empirical terms or evaluated through mechanistic-empirical methods. For some of these indices, ratings from manual surveys are considered and in some other indices, automated data are also incorporated into subjective ratings. For interpreting visual condition data for condition indices there are several issues that should be considered, among which the types of distress and the rates of pavement deterioration are most significant (Karim, Rubasi, & Saleh, 2016). Currently, there is no standard survey method for pavement distress assessment. The methods applied differ widely among the highway authorities. Most road authorities have developed their individual distress measurement and evaluation methods depending on their accessible resources, user demand, and network types. Generally, the pavement condition surveys are conducted in two ways: either manually (subjective survey) or automatically (objective survey).

Subjective pavement surface condition evaluation involves a group of experienced engineers giving a rating value. These expert personnel follow the standard manual and visually examine the pavement sections using their experience. Though the manual ratings have the benefit of being simple and easily presentable, they have some limitations too since this type of ratings is costly, inherently subjective and may lack sufficient engineering data which are needed to develop repair strategies (Gharaibeh, Zou, & Saliminejad, 2009).

To abate the constraints of subjective survey data collection procedure like costs for professionals, and discrepancy among the assessors, automated distress survey methods have been developed. Modern advances in computer science offer significant potential for automated detection and categorization of pavement distresses. In this regard, repeatability, accuracy, and the objectivity of pavement distress acquisition and detection in automated processes are significant improvements in condition surveys (Loprencipe & Pantuso, 2017; Zakeri, Nejad, & Fahimifar, 2017). Automated survey at highway increases efficiency as well as lowers potential safety risk associated with subjective field surveys (Ong, Noureldin, & Sinha, 2009).

Considering the cost involved in conducting both surveys, subjectivity, traffic disruption, safety risk to the assessors and the delay caused by subjective survey, road agencies (mostly in the USA) have sponsored many research projects to develop links between the outputs of both surveys. Carey and Irick (1964) were the first to employ the Present Serviceability Index (PSI) by applying a multi-regression fit to AASHO Road Test data (the late 1950s) for both rigid and flexible pavements, to relate the physical characteristics of a road section to the subjective Present Serviceability Rating (PSR), and established a universal standard to evaluate serviceability of roadways without resorting to a panel (C. Liu & Herman, 1996). PSI is the functional prediction of the PSR based on pavement roughness, cracking, rutting and patching. Afterward, several recognized indices such as Pavement Condition Rating (PCR), Pavement Condition Index (PCI) and others have been defined, to evaluate existing pavement condition, compatible with specific road agencies (Saraf, 1998; M. Y. Shahin, 2005).

The VicRoads' freeway and arterial road network provide the State's principal routes for private and commercial on-road transport. These are comprised of 25,000 km of declared roads. The rest of the roads in Victoria (around 150,000 km) are managed by local councils and other government departments (O. Lin, Hassan, & Thananjeyan, 2014). Bituminous surface condition data for Victoria's road network is collected every two to three years for the whole network using surface inspection rating procedures. This is a standardized rating system of pavement surface condition. This evaluation is generally conducted by experienced personnel visually classifying the types of distress and then assigning weighted values to make a suitable estimate for the remaining surfacing service life. Condition data include cracking, loss of aggregate, maintenance patching (localized depression and potholes), deformation and texture loss for asphalt wearing courses in addition to binder condition and level for sprayed seals (VicRoads, 2004). These surface condition ratings are combined into a composite index called Surface Inspection Rating (SIR) which is used to trigger the need for resurfacing or resealing using specified threshold values.

In addition, VicRoads performs objective Pavement Condition Surveys (PCS) to assess the overall performance of the pavement. These are performed biannually. The survey is typically conducted using an automated vehicle to collect condition data to assess overall pavement functional (roughness, texture loss) and structural (rutting, cracking) performance. The measurement method and data aggregation into reporting units are standardized by the Guide to Asset Management of Austroads. PCS data assists in indicating serviceability and physical conditions of road pavements, therefore, it is beneficial for triggering all types of renewal activities.

Most of the pavement condition surveys assesses one or other than the four attributes, distress, roughness, structural strength, and skid resistance (Gramling, 1994). Roughness and pavement distresses are the two key components usually covered in determining overall pavement condition, even though physical capacity and friction can also be included as important measures in the evaluation (Prakash, Sharma, & Kazmierowski, 1994).

An effective pavement maintenance program is important to a nation's infrastructure development. Pavement condition parameters are key inputs for developing short- and long-term maintenance programs. Recently, pavement management has focused on agency budget optimization as well as reducing user cost (Lidicker, Sathaye, Madanat, & Horvath, 2012). Therefore, pavement surface condition prediction and understanding the effects of pavement distress interactions on overall performance of the pavement have become crucial for highway and roads authorities to prioritize renewal and resurfacing needs.

1.2 Aim of The Study

The main aim of the study is to develop the relationship between subjective pavement surface condition rating and automated pavement distresses determined by the combined interactions between pavement distresses including cracking, rutting, texture loss and roughness. In addition, the influence of pavement operating conditions, such as age and heavy vehicle traffic volume, on the strength of relationship between subjective rating and objective pavement distresses is to be investigated.

Efforts are made to develop relationships between subjective surface inspection rating (SIR) and objective pavement condition survey (PCS) parameters to trigger periodic maintenance programs, i.e. resurfacing activities for asphalt concrete (AC) and sprayed seal (SS) surfaced road networks. To achieve the aim of the study, a thorough understanding of the pavement distress mechanisms and the interactions between the distresses, and how they influence overall pavement performance, is required. To undertake this study, a sample network comprising granular pavements surfaced with both asphalt and sprayed seal is selected, and data are provided by VicRoads, the State of Victoria, Australia.

1.3 Research Questions

Research questions of this study include:

1. How do the different surface distresses interact with each other and contribute to assess pavement surface conditions? Is there any influence of pavement operating conditions, such as age and traffic volume, on pavement distresses in determining the pavement surface condition?
2. Can automated survey data be validated with subjective survey data?
    1) Automated cracking measurement is assessed by trained but inexperienced personnel by watching the videos, frame by frame, and judging the area affected. Can this data be validated with visual inspection data?
    2) Deformation includes localized depressions along with rutting whereas rutting is the longitudinal depression in wheel-paths. Can these two measures be related?
    3) Texture loss is a slow deterioration process and thus it may be difficult to assess visually. Can automated texture loss data be validated with subjective rating?
3. Are the relationships of subjective surface inspection rating (SIR) with objective pavement condition survey (PCS) parameters significant? To what extent can SIR be predicted by PCS parameters?

1.4 Objectives of The Study

1. Study pavement surface distress mechanism and investigate how the distresses influence each other in predicting SIR. Simple scatter plot and factorial ANOVA will be used to investigate the interaction effects between pavement distresses and the influence of operating conditions (age and heavy vehicle traffic volume) on the strength of relationship of surface inspection rating (SIR) from objective pavement condition data.
2. Validate automated and subjective survey data using probabilistic logistic regression as below:
   1) Automatic cracking data as statistically significant predictor for subjective cracking evaluation.
   2) Automated longitudinal depression (rutting) data as a statistically significant predictor for rated deformation by considering localized depression data.
   3) Automated texture loss as a statistically significant predictor of manual texture loss rating.
3. Comprehend the relationship between subjective pavement surface condition ratings and the automated distress data. Deterministic and probabilistic models will be trialed and validated to develop models to predict subjective Surface Inspection Rating (SIR) as a function of significant objective Pavement Condition Survey (PCS) parameters. These include cracking, rutting, texture loss and roughness.

1.5 Outcomes and Significance of The Study

The outcomes of the research include:

1. Matrices of correlations between Surface Inspection Rating (SIR) and automated pavement distresses data are found for both asphalt and sprayed seal surfacing road networks. The matrix for each network allows identification of statistically significant correlations between subjective rating and objective pavement distresses, as well as between the distresses. Additionally, interaction effects between automated pavement distresses in predicting SIR and the influence of pavement operating conditions (age and heavy traffic volume) on estimating SIR from automated pavement distress are investigated.
2. The automated pavement distress data (cracking, rutting and texture loss) have been validated with corresponding subjective ratings of pavement surface distress.
3. Statistically significant predictors (automated distresses) are used to predict subjective SIR value using multiple linear regression analysis, and probabilistic logistic models are developed to predict pavement surface condition categories from automated pavement distresses for granular pavements with asphalt surfacing (AC network) and sprayed seal surfacing (SS network) for prioritizing resurfacing programs.

Significant results of the research include:

1. A comprehensive study is presented on how the different pavement distresses interact with each other in predicting subjective pavement surface rating, that is an indicator of overall pavement performance. Additionally, the influence of different operating conditions (age and traffic volume) in assessing the relationship between subjective ratings and the automated pavement distresses has been investigated. The results would provide better understanding of the relationship between visual pavement surface rating and objective pavement surface distresses.

2. The developed ordinal logistic models for asphalt surfacing network and sprayed seal network would provide a useful and practical approach for asset managers of the State Road Authority of Victoria in decision-making regarding prioritization of resurfacing maintenance and as a consideration for other periodic maintenance activities. The results obtained from this study may contribute to cost-reduction and safer assessment conditions for subjective pavement condition monitoring.

1.6 Structure of The Thesis

The thesis is broken into six chapters as follows:

Chapter 1 Introduction

This chapter provides a brief introduction and outline of the motivation and purpose of this specific research in the context of the field, detailing the rationale and significance of this work, as well as the aims and objectives to be accomplished.

Chapter 2 Literature Review

This chapter briefly documents literature associated with pavement surface condition evaluation and assessment for maintenance purposes. A concise description of the pavement behavior that explains the distress initiation, progression and interaction between each distress and the performance measures is presented. The factors contributing to the distresses, and types of pavement distresses in flexible pavements are defined. Subsequently, various methodologies for pavement distress evaluation by subjective survey and assessment through automated survey are discussed. The integration between different pavement condition indices is reviewed to understand the current practice of pavement condition appraisal. Then, the guidelines for rated pavement surface condition survey and objective pavement condition survey procedures in the state of Victoria, Australia are briefly described. Finally, previous relevant studies related to subjective and objective pavement parameters are systematically reviewed in detail and summarized in a table format. Findings from the past studies and research gaps are presented.

Chapter 3 Research Methodology and Data Preparation

Chapter 3 presents the pavement surface condition data collection and evaluation guidelines for subjective and automated survey used in the state of Victoria, Australia. A conceptual framework is developed to address the research objectives. Both metric and discrete data description, preparation and screening assumptions are presented. The pavement condition data incorporates time series data of cracking (percent area affected), rutting, texture loss by left wheel path and roughness (in terms of International Roughness Index). Finally, fundamental statistical methods used in this study are briefly described.

Chapter 4 Deterministic Analysis for Pavement Condition Data

This chapter provides correlation analyses between subjective rating and objective pavement condition data, followed by an investigation of the interaction effects between different automated pavement surface distress performing factorial ANOVA tests. The development of linear regression models for asphalt surfacing and sprayed seal surfacing networks is described separately. The best fit models are presented with significant predictors for subjective rating value.

Chapter 5 Probabilistic Analysis for Pavement Condition Data

At first, the validation of each objective parameter with corresponding subjective rating using probabilistic logistic regression analysis is presented. It details the procedures involved in developing models for subjective rating categories, that predict the pavement surface condition from the objective pavement condition data. The most successful models are described thoroughly with graphical plots and the models are validated with scatter plots of scaled squared residuals of subjective ratings.

Chapter 6: Conclusions and Recommendations

This chapter briefly reviews the research outcomes and major findings. Important conclusions and recommendations for future study are presented as well.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter first presents a brief overview of distress mechanisms, specifying different types of distresses that initiate and progress in flexible pavement/granular pavement. Then pavement distress evaluation by subjective rating and automated measurement of pavement distresses to appraise the condition of the pavement, both locally and internationally, are described briefly. In addition, various modeling approaches to develop relationships between these two types of road condition data are outlined. Lastly, the previous studies in developing relationship between subjective and objective pavement condition data are reviewed in detail and summarized, with a focus on the research gap.

2.2 Pavement Behavior

The key function of a highway is to ensure a riding surface with proper geometric alignment and sufficient skid resistance to guide the traffic while traveling at the desired motion. The pavement is constructed so that roads will achieve these required mobility criteria, both functional and structural, in a reliable and durable way (Symons, 1985). Usually, the pavements can be categorized into three general categories: flexible, rigid, and composite.

Flexible pavements are usually made up of bituminous mixture placed over a granular base or subbase layers that are supported by the compacted natural soil. This type of pavement distributes the imposed loads to the subgrade by the interlocking properties of aggregates from different layers, using friction and cohesion attributes of the particles (Wright & Paquette, 1987). At first, the traffic load is distributed on a small portion of the pavement surface and then with the increase of depth it is transferred over a larger area. In this load transfer process the highest stress takes place at the surface and the stress reduces with depth; when the load is removed the pavement layers rebound (T. F. Fwa, 2005).

Rigid pavements are made up of a Portland cement concrete stratum and sustained on the subgrade with or without any other mid-layer. These pavements have rigidity due to the high modulus of elasticity and distribute loads over a wide area of subgrade soil, thus, foremost structural strength is supported by the slabs themselves (Eldon Joseph Yoder & Witczak, 1975).

Composite pavements include two or more layers with various attributes and perform as single composite element of the structure (Smith, 1963). Here, the Portland concrete and the asphalt concrete are used alternately on each other. In this pavement, the stiffness of the rigid strata (base layer) is more than the flexible strata (surfacing layer) (Flintsch, Diefenderfer, & Nunez, 2008).

2.3 Pavement Performance Measures

The principal considerations of pavement design and maintenance include durability and desired level of service to the users with safety. At the beginning, a newly constructed pavement has an acceptable level of service. With age, due to repeated traffic loads and other factors like inadequate design, lack of construction quality assurance and environmental constraints, the pavement progressively deteriorates, the condition gets poorer and it loses its serviceability.

'Performance' is used to denote how pavements change their ability to ensure necessary functions; usually indicated by initiated or progressed distresses, loss of desired serviceability and thus loss of overall condition of the pavement through the effects of designed traffic and other operating conditions (Lytton, 1987). Hence, performance describes the physical and functional responses of the pavement to vehicle loading, material characteristics and other environmental factors that cause changes to its original structure. Eventually, the collective influence of these contributing factors alters the level of serviceability of the pavement. Thus, the performance of the pavement is evaluated relative to its achievement of standard levels of service. Therefore, the current pavement performance available for the user is an important aspect for road agencies associated with managing road networks and their maintenance development strategies (Bianchini & Bandini, 2010).

To make decisions about maintenance planning, the pavement performance evaluation is very important which necessitates pavement condition to be determined. Pavement condition evaluation can be classified by two main performance terms, functional performance and structural performance (Foley, 1999); functional evaluation is concerned with parameters that affect safety measures and riding comfort of road users (safety is appraised by skid resistance and surface texture, while serviceability is assessed using roughness estimates), whereas structural evaluation is concerned with the impact of wheel loads under different environmental conditions on pavement structure and surface layer(s) due to some specific distress types and structural properties (Bennett, De Solminihac, & Chamorro, 2006). Overall pavement condition is connected to these issues which include structural integrity and capacity, along with functional factors related to riding comfort such as roughness, skid resistance and the rate of deterioration of pavement (M. Y. Shahin & Kohn, 1981).

There are several methods to assess the performance of the pavement. Generally, surface distresses along with roughness are considered as the performance measures that indicate the deterioration of pavements.

The following subsections describe the pavement distress mechanisms, factors influencing the distresses, different types of distresses in flexible pavements and relation of pavement roughness with serviceability.

2.3.1 Mechanisms of Pavement Distress

Pavement distresses develop through a number of different mechanisms. The factors affecting pavement distress mechanisms and interactions between different distresses in flexible pavements are presented in a flow chart, as shown in Figure 2.1, and briefly described below.

Traffic Axle Loadings

Initially, axle loadings from traffic trigger stress and strain in pavement layers that are functions of the material stiffness and thickness of the pavement layers (W. D. Paterson, 1987). When these stresses go under repeated traffic loading, cracking starts through fatigue and deformation in materials, which are strongly dependent on the properties of these materials. Therefore, one of the most important modes of distress in flexible pavement is fatigue, which manifests as cracking in the pavement surface, and it is mostly the result of repetitive traffic loadings and pavement layer thickness (Moghaddam, Karim, & Abdelaziz, 2011; Suo & Wong, 2009).

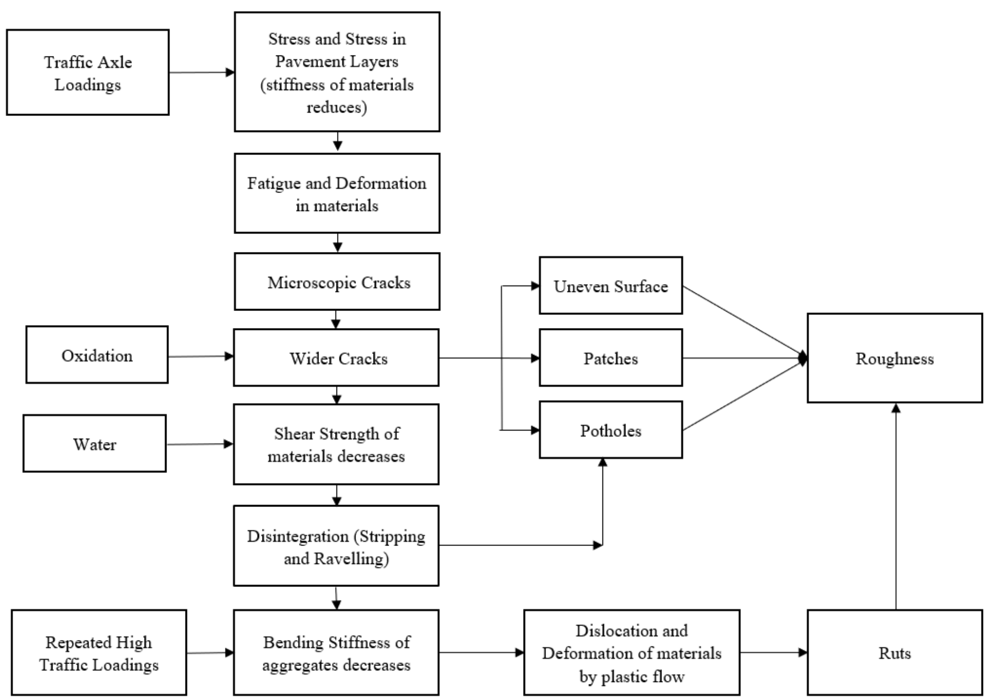


Figure 2.1 Pavement distress mechanisms and interactions in paved roads

Oxidation

In asphalt surfacing mixtures, the binder holds the particles firmly and perform as a sealant to counter moisture ingress (Mashaan, Ali, Koting, & Karim, 2013). During the construction of asphalt mixture and gradual oxidation of the material over its service life, the volatile portion of the bitumen reduces and causes hardening in asphalt surfaced pavement (Airey, 2003). This hardening of bituminous surfacing is also known as ageing of bituminous surfaced pavement. When bituminous surfacing is exposed to air, due to oxidation the viscosity of the binder increases, the aggregate becomes brittle, and thus more vulnerable to cracking, aggregate loss and edge defects. Once initiated, progress in the extent and severity of cracking with age stimulates the development of potholes.

Water

Water can penetrate via cracks on the surface of the pavement via the interconnectivity of the air voids system, or cracks due to rising groundwater level, or from the road shoulders (Hamzah, Kakar, & Hainin, 2015). Exposed cracks on the pavement surface without proper drainage systems allow water to enter the pavement strata. Loss of cohesive bond within the bituminous binder or the reduced adhesion between the binder and the aggregate instigates the disintegration process by decreasing the shear strength of aggregate mixtures. This type of distress in pavement surface due to moisture intrusion is defined as stripping / ravelling and decreases the life cycle of pavement surface by stimulating other distress modes involving fatigue cracking, rutting, flushing, and potholes (Mostafa, 2005).

Repeated Heavy Traffic Loadings

Heavy vehicle traffic causes rapid differential compaction in the top layers of pavement, including fracture of the bituminous surfacing (Sharma, Sitaramanjaneyuiu, & Kanchan, 1995). Repeated high traffic loads cause changes in the shape and size of aggregates in pavement by internal abrasion and, as a consequence reducing bending stiffness prompts the dislocation of material by plastic flow (Symons, 1985). The cumulative progressive deformation all over the pavement depth is exhibited as ruts which are longitudinal depressions in the wheel paths of the pavement. Rutting increases as a result of repeated heavy vehicle traffic loadings that cause gradual progression of deformation due to repetitive tire pressures (Abdulshafi & Kaloush, 1990; Tayfur, Ozen, & Aksoy, 2007).

The irregularities or distortion of surface profile that are the outcome of all other pavement surface distress are known as pavement roughness (W. D. Paterson, 1987). Roughness is associated with riding comfort, vehicle operating cost and higher travel time of the road user (Mactutis, Alavi, & Ott, 2000). Therefore, the pavement distresses discussed above have adverse impacts on overall performance of the bituminous surfacing pavement and reduce the service life of pavement.

2.3.2 Factors Contributing to Pavement Distresses

The factors that influence pavement distresses can be categorized as external causes due to different operating conditions and internal causes which are inherent to the pavement infrastructure (Jameson, 2011). Usually, it is challenging to identify the key cause of any pavement distress because more than one factor may stimulate the contribution of that distress (W. D. Paterson, 1987). A number of these causes are summarized below (T. F. Fwa, 2005; Hamzah et al., 2015; Lay, 2009; Michael Moffatt, 2007a; Papagiannakis & Masad, 2017; W. D. Paterson, 1987).

- Repeated and overloaded traffic on the pavement structure
- Oxidation of bituminous materials on the surface, with age
- Insufficient pavement thickness
- Intrusion of water into pavement strata, mainly through the pavement surface or edges
- Poor compaction or drainage, owing to inappropriate quality control
- Inadequate quality of pavement or surfacing materials
- Mobility of moisture and volume change in subgrade soil
- Inadequate bonding between pavement layers and incorrect asphalt mix design
- Entry of plant roots into the pavement structure
- Settlement of underground structure
- Impact of environmental factors such as temperature and rainfall

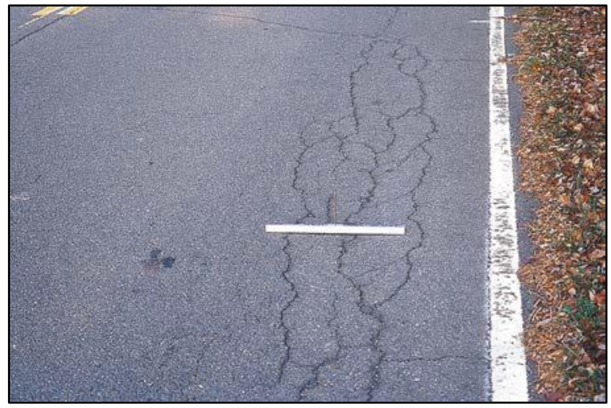
2.3.3 Flexible Pavement Distresses

Recently, to keep up with evolving travel demand and aging road infrastructure, highway agencies are giving attention to finding more efficient means to utilize funds for different types of maintenance programs (A. Ahmed, Bai, Lavrenz, & Labi, 2015). Typically, distresses found in flexible pavements can be classified into four general types (T. F. Fwa, 2005): Cracking, Deformation, Surface Defects and Edge Defects.

i) Cracking

Cracking is one kind of early disease of the pavement that reduces its performance (C. Wang, Sha, & Sun, 2010). The bituminous surfacing is likely to crack at a certain stage of design life; primarily from the combined action of repeated traffic loadings and environmental influences (moisture and temperature). Repeated traffic loadings result in overstressing, whereas environments affect moisture variation, settlement of subgrades, and hardening of the pavement surfacing material by oxidation (M Moffatt & Hassan, 2006). As well, some other factors such as plant roots, landslides, or strong impacts from outside sources have influence on crack initiation, although, they are not the primary sources (Cubero-Fernandez, Rodriguez-Lozano, Villatoro, Olivares, & Palomares, 2017).

(a) Low severity cracking



(b) Medium Severity Cracking

(c) High severity cracking

Figure 2.2 Pavement surface cracking with different severity level (Miller & Bellinger, 2014).

Examples of cracking with different severity levels are presented in Figure 2.2. The direct measurement procedure and evaluation criteria (based on extent and severity level) of pavement cracking are discussed in Chapter 3. In flexible pavements, cracking is a significant indicator of surface failure. Cracks at the surface, small or large, always have damaging effects on the pavement (Colombier, 2014). From the pavement distress mechanism described in section 2.3.1, it is evident that once initiated cracking progress with extent and severity, accelerating the causes of other pavement distresses.

ii) Deformation

Pavement deformation is known as the variation in surface profile from a reference profile of its construction. Traffic loading causes stresses on the pavement materials, reduces shear strength within aggregate mixtures and induces plastic flow in materials that often results in depression along the wheel path and heave around the loadings (W. D. Paterson, 1987). Under the effect of shear stress, material properties and temperature differ with the thickness of asphalt pavement and different types of deformation tend to occur at different sublayers (Sun, 2016). The common pavement deformations which affect pavement service life and riding quality are presented below:

Rutting

Rutting is considered a major distress which causes the failure of flexible pavement. It is the formation of a longitudinal depression (groove or rut) in the pavement surface in the wheel path (Figure 2.3), which is generally caused by traffic wear, abrasion, and displacement of the surface course or base by heavy traffic loads (Brewer, 2007). Rutting in pavement surface may indicate the presence of some structural deformation that is related to 'stress-strain-deflection'.

Two mechanisms within materials are identified as the primary causes of rutting. They are densification of the aggregate mixture (compaction) and plastic deformation by shear failure (Collop, Cebon, & Hardy, 1995). Thus, inadequate compaction during construction or an improper mix design is an important cause of rutting. Besides, moisture causes deformation of road pavement, subgrade or shoulder (e.g. heaving of the road shoulder or pavement edge) which can result in a longitudinal depression reported as rutting (Michael Moffatt, 2007a).

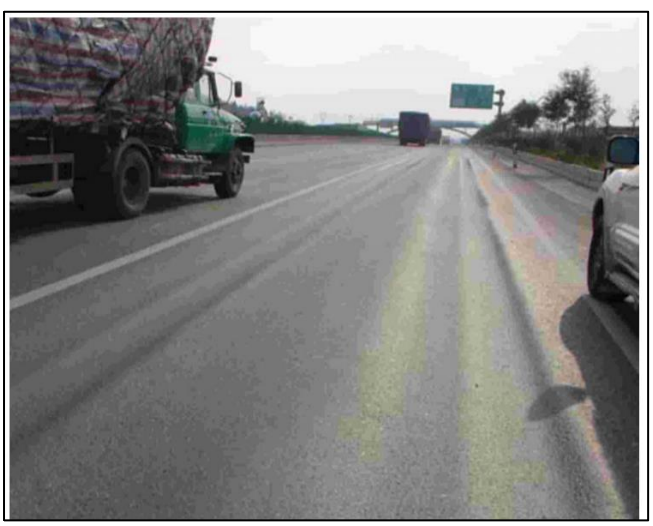


Figure 2.3 Severe rutting in pavement surface (H. Wang, Zhang, & Tan, 2009).

Initially in the designed service life, rutting develops due to compaction of the aggregate mixture by moving traffic, with a declining rate of deformations; after that, rutting growths are reduced, apparently at a static rate where the aggregate mix goes through shear deformations; lastly, materials tend to flow to rupture (Gupta, Kumar, & Rastogi, 2014). Usually, pavement is not allowed to reach rupture in its service life, largely due to carrying out of preventive maintenance and rehabilitation programs. Rutting is a good indicator of pavement behavior since it is less influenced by environmental deterioration (T. F. Henning, 2008). It is established by experiment that permanent deformation in the pavement is proportional to the extent of the ruts (Leiva-Villacorta, Vargas-Nordcbeck, & Aguiar-Moya, 2017). Hence, substantial attention is given to avoid rutting in thinly surfaced asphalted granular pavements and it is the principal design consideration (Arnold, 2004).

The effects of rutting are sources of apprehension for several reasons (T. Fwa, Pasindu, & Ong, 2012; Lijun Sun, 2016):

I. Pavement layer thickness reduction caused by rutting lowers (check this word) pavement strength and instigate pavement structural damage.
II. Water logging in rutting due to poor drainage triggers hydroplaning, which is a potential risk for high-speed travelers.
III. Spread ruts cause difficulties in steering control and become dangerous.
IV. In winter, snow-covered rutted surfaces reduce slippage resistance for vehicles.
V. Reduced riding comfort as rutting has a negative impact on pavement roughness.

Therefore, rutting in the pavement can extensively affect its overall performance and decrease its remaining service life. Following up of the transverse surface profile for rutting is essential as it is an effective measure of pavement structural capacity (J. D. Roberts & Martin, 1998) including its impact on user safety. Most international PMS (Pavement Management Systems) use rutting as a measure of potential need for pavement maintenance (Robinson, Danielson, & Snaith, 1998).

Shoving

Shoving is considered to be a longitudinal shift of a localized portion of the pavement surface, usually caused by sudden impact from vehicles braking or accelerating and normally occurs on hilly areas or through curvatures or at intersections (Miller & Bellinger, 2014). This type of deformation may be related to vertical displacement as well. Shoving takes place in asphalt layers which do not have sufficient stability due to excessive asphalt binder present in the HMA mix, use of low viscosity asphalt binder, smooth textured aggregate, rounded granular particles or a large amount of fine aggregates in the mixture (T. F. Fwa, 2005).

Depression

Depressions are referred to as localized portions of a pavement with heights less than the adjacent area. This type of distress is not limited to wheel paths and could extend through various wheel paths. Likely causes may include subgrade settlement due to compaction of soft materials by repeated traffic or volume variations of subgrade materials (VicRoads, 2004). So, the main reasons for excessive local depressions are related to structural flaws in the underlying subgrade (Gallaway & Rose, 1970). These types of local depressions also trigger hydroplaning like wheel track depressions (rutting).

Corrugations

Corrugation is defined as sequential small gaped ridges and valleys on the pavement at approximately regular intervals. Usually, the crests are upright to the traffic flow. This kind of pavement distress is typically caused by traffic loading accompanying an unsound road surface or base (M. Shahin, 1997). These ripples may be visible in an isolated portion or even over a spreader area of the pavement surface. Developed irregularities on the pavement surface cause instability by escalating the roughness.

iii) Surface Defects

Surface defects are mostly related with functional performance of a pavement and usually do not give an in-depth idea about structural failure in the pavement. These types of distresses are significant to understand the level of service and, without proper maintenance, may cause structural failure of a pavement. The most common surface defects are as follows (T. F. Fwa, 2005):

Ravelling

Ravelling is considered as the displacing of coarse aggregate from the road surface (M. Y. Shahin, 2005). The dislocation of aggregates is result of the loss of cohesive bond between binder and aggregates. Though it begins at the surface, it may progress downward. The term ‘ravelling’ is usually used when aggregate dislocation occurs from asphalt (VicRoads, 2004). This type of surface defect is associated with moisture and affects mixture asphalt (HMA) pavement (You, Zheng, & Ma, 2018). Ultimately it decreases the pavement strength and service life.

Stripping

‘Stripping’ is used to denote the loss of particles from sprayed seal surfacing. This may appear as a loss of a single layer or a substantial number of aggregates in a specific location. The main reason for stripping is the action of water and/or water vapor (Kandahl & Richards, 2001). Even though bound materials of pavement are not affected by moisture extensively, it initiates and progresses stripping in bituminous materials (the binder course) caused by pore water pressure or weakening of the structural strength

(Christopher, Schwartz, & Boudreau, 2010). Usually, these aggregates have an affinity for water and the formation of thin water films on them will tend to reduce initial bonding between the aggregate and bitumen. Poor drainage stimulates these weakly adhered pavement materials susceptibility to stripping under traffic loadings (Kiggundu & Roberts, 1988). Eventually, it adversely affects the pavement performance.

Pothole

Potholes, as an acute pavement distress, are bowl-shaped or irregular-shaped depressions in the road surface (Miller & Bellinger, 2014). The primary cause of potholes is the intrusion of rainwater into the pavement layer (Joubert, Tyatyantsi, Mphahlehle, & Manchidi, 2011). When heavy vehicles pass on that water-intruded weak pavement it causes potholes. Potholes are the consequences of some other distresses too. This distress can be dangerous to drivers when they try to cross or avoid them.

Delamination

Delamination can be simplified as surface lifting from a large area of the asphalt pavement, which may also appear in the full depth of the wearing surface (VicRoads, 2004). In the case of Hot Mix Asphalt (HMA) delamination, it is mainly caused by debonding in layers for lack of proper amount of tack coat (Hoegh, Khazanovich, Maser, & Tran, 2012). This type of distress causes slippage failure in flexible pavement due to the reduction of bonding strength in asphalt layers (Cook, Garg, Singh, & Flynn, 2016) .

Flushing or Bleeding

This type of pavement distress is visible as a reflective surface when an excess amount of bituminous material exists on the surface that may develop into a sticky state at high temperature (Association). Flushing produces soft surface in hot weather and slick top surface in wet or cold weather. Applications of excess binder, flaky aggregate particles, and weak base are the causes for flushing in pavement surface (T. F. Fwa, 2005). Mostly this defect is found in sprayed seal surface; however, it may be visible in asphalt surface also.

Polishing

When the pavement aggregate surface becomes smooth by the action of heavy traffic loading it is called polishing. Fine particles are polished off due to weathering in summer which causes a loss of texture of the pavement; thus this polishing, along with some other pollution from vehicles, results in reduced skid resistance of the pavement (Plati & Georgouli, 2014). In winter, the polishing effects are less due to the presence of moisture film acting as a lubricant on the surface aggregates that reduces the smoothing action (Jayawickrama & Thomas, 1998). Polishing affects skid resistance negatively and therefore results in loss of pavement serviceability and user safety.

Patches

Patches are the portions of pavement surface that has been treated for maintenance purposes or utility cuts. These are also suitable for the mending of several types of surface distress like potholes, alligator cracking, corrugations, shoving, depressions, rutting and some other distresses (Johnson, 2000). Since some roughness is always associated with patching, these are considered as surface defects even though they perform well.

Texture Loss

Surface texture in pavement engineering, is described as "the deviation of a pavement surface from a true planar surface" (ISO, 1997). The terms 'surface texture' and 'texture depth' are often used by practitioners as practical descriptors of the macrotexture (Figure 2.4) of the pavement surface. The surface texture profile of a pavement is also an important consideration (Hillier & Soet, 2009) for maintenance planning.

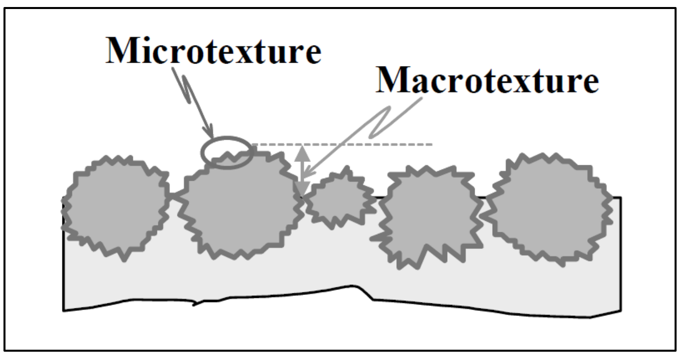


Figure 2.4 Pavement Surface Texture (Flintsch, De León, McGhee, & AI-Qadi, 2003).

According to the World Road Association (WRA), macrotexture is defined as amplitude of deviations from the surface plane, usually with wavelengths between 0.5 mm and 50 mm. This can be influenced by the physical characteristics and spacing of coarse aggregate particles in the surfacing material, and impacts on drainage capacity. Loss of surface texture is the effect of pavement surface flushing and/or bleeding or loss of the aggregate. The surface texture is associated with several pavement characteristics and performances, for example safety issues like dynamic control of vehicle, skid resistance, drainage and also the physical properties of pavement such as distress and deformation (Loprencipe & Cantisani, 2013).

iv) Edge Defects

These types of defects can be found along the pavement edge and shoulder, reducing riding quality and pavement capacity, and permitting moisture intrusion into the pavement. Edge break and edge drop-off defects are visible in flexible pavement due to the absence of proper edge support, insufficient pavement width, and poor adhesion between the surfacing and base layer (T. F. Fwa, 2005).

2.3.4 Concepts of Pavement Serviceability and Relation with Roughness

Since the late 1960s, 'Serviceability' is a well-known concept that is used widely by pavement engineers to evaluate the overall performance of a pavement (Fuentes, Camargo, Arellana, Velosa, & Martinez, 2019). In 1962, the practised personnel of American Association of State Highway and Transportation Officials (AASHO) road test introduced "pavement serviceability concepts" which involve the measurement of pavement behavior under traffic and the capacity to serve that traffic at specific times of its life (BOARD, 1962). Thus, pavement serviceability refers to the functional capacity of a pavement to ensure the adequate riding comfort to the traffic. Pavement serviceability measures the traffic carrying capacity of a pavement section at present condition. This aptitude is largely affected by pavement condition. Carey and Irick employed the present serviceability-performance concept to make a relationship between riding quality and quantifiable pavement parameters (at the AASHO Road Test, in 1962). They developed the Present Serviceability Index (PSI) formula which was a revolution to achieve the purpose (F. L. Roberts & Hudson, 1970). Pavement serviceability is influenced by many attributes. Research has revealed that serviceability is largely associated with roughness and it can be used as a predictor for the level of service of a pavement (Haas, Hudson, & Zaniewski, 1994).

The general condition of a road is objectively measured by pavement roughness, and it is the most commonly used condition variable in pavement deterioration models (Foley, 1999). Roughness is a functional attributes of the pavement that measures states of the longitudinal profile in the wheel path comprising those surface deviations which influence the motion and operation of a moving vehicle; that is, through the user's perception of riding quality, the wear and operating costs of vehicles as well as road safety (W. D. Paterson, 1987). Roughness measurement is the primary tool to assess the functional performance of pavement and combines the consequence of many modes of pavement deterioration (McLean & Ramsay, 1996; W. Paterson, 1986). Usually, pavement roughness (smoothness) conveyed the extent of the presence of surface irregularities to which ride quality is sensitive.

The International Roughness Index (IRI) is a recognized unit of measurement to quantify pavement roughness using several automatic survey devices (Arhin, Williams, Ribbiso, & Anderson, 2015). To measure the roughness a quarter car model simulated with road profilometer is used (Michael Moffatt, 2007b). Austroads has determined that, at the network level, roughness values are to be reported considering Lane IRI or as IRI (m/km). It is measured by averaging two separate single IRI values under wheel track collected by the profilometer.

2.4 Methods for Pavement Distress Evaluation and Measurement

Detailed information of the pavement distresses is generally collected and archived for quantifying, maintenance decision making and research purposes. This information mostly consists of the type, location, extent and/or severity of distress. The detection of distress on pavement involves special attention from the transportation authorities all over the world depending on the surface of transportation. In the United States, the PAVER and Micro PAVER systems (M. Y. Shahin, Cation, & Broten, 1987; M. Y. Shahin & Walther, 1990) are widely used, which are dependent on pavement condition survey and are employed to ensure the efficient use of the maintenance and rehabilitation fund (Ismail, Ismail, & Atiq, 2009). Several states have individual pavement condition survey procedures.

The Distress Identification Manual was established by the Federal Highway Administration in the U.S. to evaluate distress for long term performance prediction (Miller & Bellinger, 2014). In Canada, the Ministry of Transportation and Communications, Ontario developed a separate manual for flexible pavement condition survey (Chong, Phang, & Wrong, 1975). In Australia, Austroads established a standard guide for the visual (subjective) assessment of pavement condition in 1987; the Guide to Asset Management manuals are followed to measure and assess the pavement condition parameters (Sharp & Toole, 2009) and other states have their own rating systems as well. This guide is updated regularly by the member authorities of this organization. Austroads authorities have their individual survey procedures to evaluate and measure the pavement condition. Further, different studies for long term pavement maintenance ("Long-term pavement performance study finalised," 2019) implemented a detailed data collection procedure by Austroads.

2.4.1 Visual Detection and Assessment of Distress (Subjective Survey)

At present, the pavement surface condition evaluation is performed largely by visual inspection where a professional engineer or practised personnel riding on the highway sections by vehicle detects distress by using his or her judgment and collects the relevant data for subjective evaluation such as type, location, extent or severity of distress. Hence, this conventional manual way of distress evaluation is expensive as it is labor-intensive requiring expert persons, takes time, and may be dangerous, tiresome, biased, and unable to give quantitative evidence, and therefore, most of the time it tends to give inconsistent data depending on the verdict of the survey person (Cheng & Miyojim, 1998).

Though automatic distress data collection is widely used nowadays, synchronization of the raw video clips is still largely conducted by trained persons (Huidrom, Das, & Sud, 2013). Subjective pavement surface condition evaluation includes experienced engineers giving rating values. The experienced personnel visually examine the pavement sections based on their experience and following the standard manual.

Though the visual ratings have the benefit of being simple and illustrative, they have some limitations too since this type of ratings is costly, inherently subjective and may lack of sufficient engineering data which are needed to develop repair strategies (Gharaibeh et al., 2009).

2.4.2 Automated Distress Detection and Measurement Survey (Objective Survey)

Automatic data collection processes can be categorized into two broad types: the first one uses images from photography or videotape and the second one uses measurements by various types of sensors or modern electronic devices (McGhee, 2004). There are several procedures and apparatuses available nowadays which include video recording devices and ultra-modern contact-less laser sensors to capture the images of the pavement surface.

Several types of camera (single camera, video camera, line-scan camera and infrared camera), stereo imaging, focus-defocus, photometric stereo, laser, acoustic, pressure sensor, ultrasonic sensor, deflectometers, friction tester, accelerometer and other vibration using contemporary measuring devices have been widely used in automated pavement distress detection and synchronizing all over the world (Coenen & Golroo, 2017; Koch & Brilakis, 2011). The National Cooperative Highway Research program prepared automated pavement condition data collection and processing guidelines for highway practice, investigation, and future development for network-level road management (Tsai, Kaul, & Mersereau, 2009). Typically, automated survey data and images are processed by either fully or semi-automated systems.

Semi-automated Process

Recorded images of pavement distress using cameras or other sensors mounted in moving vehicles, and locations with GPS devices are conveyed to the computer processor to detect and categorize the distress types by the appropriate personnel at the work station (M. B. G. Al-Falahi, 2015). Many road agencies use this type of distress evaluation system.

Fully automated Process

This type of ultra-modern synchronization includes automatic detection of distresses from the input images and the distinct pattern identification. The development of the new technology allowed full automation of pavement crack surveys, reduced the dependency on the traditional manual methods and resulted in wide adoption of automated detection and classification of pavement surface distresses (M. B. G. Al-Falahi, 2015).

According to Austroads' guidelines, automated methods rutting surveys use several vehicle-mounted lasers or ultrasonic sensors (Figure 2.5) in conjunction with taut wire or straight edge models. These devices are typically capable of measuring transverse profiles with as close as 50 mm spacing while the host-vehicle travels at normal traffic speeds (Michael Moffatt, 2007a).

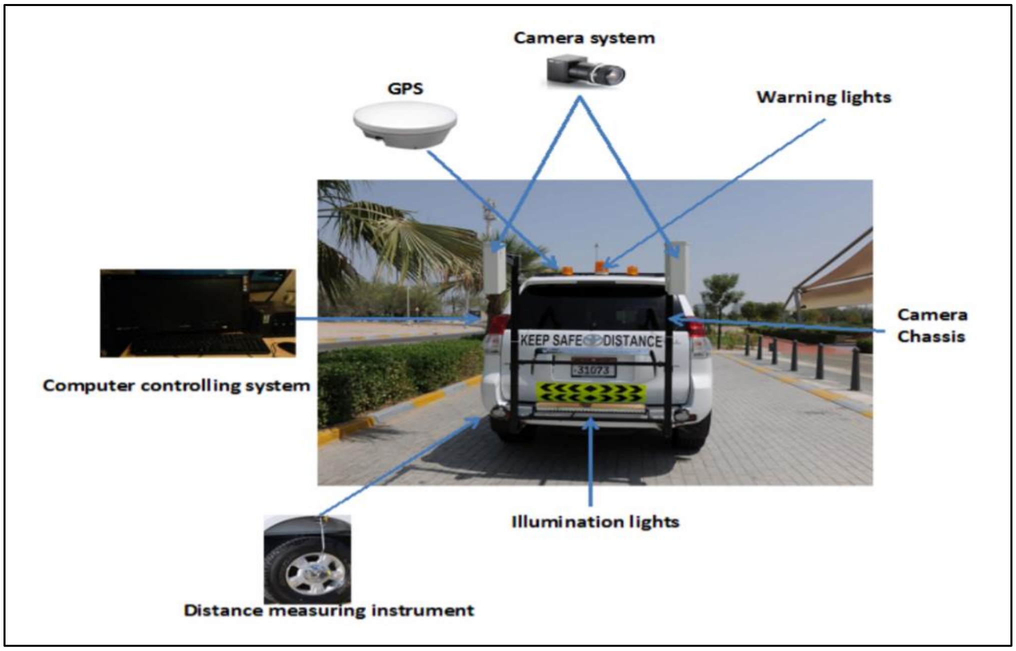


Figure 2.5 Automated pavement condition data collection vehicle (M. Al-Falahi & Kassim, 2019).

At present, high configuration processors with huge memory capacity and various competent software have become cost-effective and useful for maintenance budgets. However, there are still some limitations with the current automated distress detection methods because they are involved with high capital costs and can only assess only specific types of distresses (Cheng & Miyojim, 1998).

2.5 Pavement Maintenance

Effective maintenance planning can ensure an escalation in service life of pavement, accordingly reducing the frequency and the necessity for capital cost (Mohamad, Sinha, & McCarthy, 1997). Usually pavement maintenance has two types of impacts, an instant impact on the road surface condition and the other its effect on future pavement deterioration rate. Maintenance works improve the condition of the pavement and often defer the deterioration process. The major classifications of road maintenance are listed below:

2.5.1. Routine Maintenance

These are small-scale repair works which include: patching, seal coating, crack and joints sealing, repair of shoulders, cleaning of ditches, maintaining side slopes, vegetation control and other regular maintenance of pavement (T. F. Fwa, Sinha, & Riverson, 1988). These types of routine maintenance are useful to slow down the pavement deterioration rate. These operations are expected to be carried out once or more, each year on a pavement section to keep it to its original serviceability.

2.5.2. Resurfacing

Resurfacing is performed on the existing surfacing of the pavement. Full-width or thin resurfacing like reseals, slurry seals, fog seals, thin asphalt surfacing and other surface treatments are used to maintain surface characteristics and structural integrity of the existing pavement (W. D. Paterson, 1987). These are normally large-scale maintenance works and are periodically performed on a segment of road after a number of years. These treatment works also require certain identification and planning.

2.5.3. Rehabilitation

Rehabilitation is referred to as a infrastructural or functional improvement of a pavement that makes a significant increase in service life, by extensively upgrading the condition of pavement and user comfort (Hall, Correa, Carpenter, & Elliot, 2001). This type of maintenance work includes different types of overlays comprising granular and asphalt concrete overlays, granular surfacing, specific types of in-depth patching, surface treatment with substantial shape corrections and some other similar types of repair works. These are conducted for full-width, and full-length of existing road, usually for strengthening.

2.5.4. Reconstruction

Reconstruction is usually done for high capacity improvement of roads, ensuring geometric standards. The process includes removal and replacement of existing pavement surface layers, and often the underlying base and subbase layers with rehabilitation of drainage systems (Hall et al., 2001).

2.5.5. New Construction

New construction is required when road needs to be constructed in a new alignment, or major improvements of existing pavements like conversion of gravel road to paved road or providing an additional lane to the existing right of way are required.

2.6 Granular Pavement Surfacing

Granular road pavements (Figure 2.6) are the most common pavements used in urban and rural areas across Australia, New Zealand, Africa, and some other countries. The main purposes of the surfacings on these granular pavements are to provide a smooth riding path, to protect the underlying weaker base or sub-base from water and to ensure desired (sufficient) skid resistance for riding traffic. There are predominantly two types of bituminous surfacing which are described in the following sub-sections.

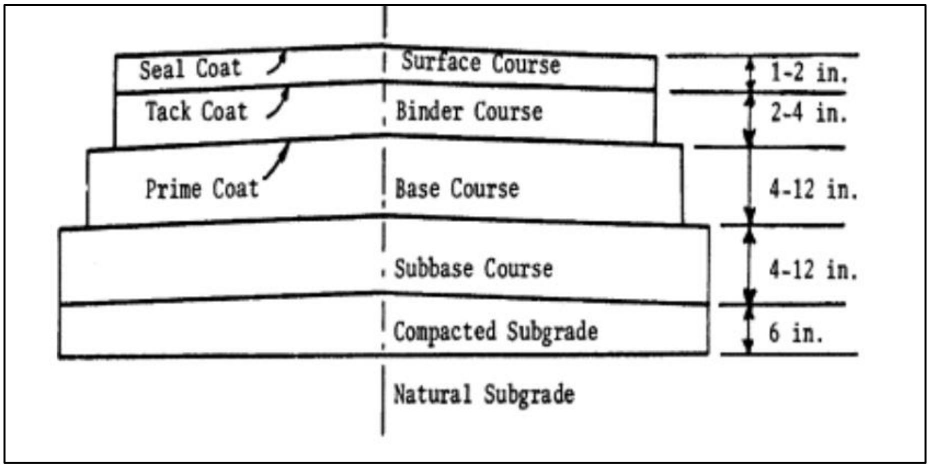


Figure 2.6 Typical cross-section of a granular pavement (Saltan & Fındık, 2008).

2.6.1 Sprayed Seal Surfacing

Sprayed treatments include a layer of aggregate compacted on a thin bituminous binder sprayed on the surface (Figure 2.7). Commonly, surfacing with seals (10 – 20 mm) is made up of an unbound granular base, such as crushed rock or gravel. The performance of sprayed seals depends mainly on the rates at which the aggregate disintegrates under vehicular load and the binder oxidizes (Jameson, 2011). The expected life of a sprayed seal surfacing is 5-15 years, but it can sustain up to 25 years in stable climates. Though many rural roads are surfaced with sprayed seal, the structure is not sufficiently strong to resist shear stresses caused by heavy traffic vertical loads (Gransberg & James, 2005). This type of surfacing is not useful either for sharp grades, at roundabouts or in curvature. To overcome these limitations, asphalt and concrete pavements are used.

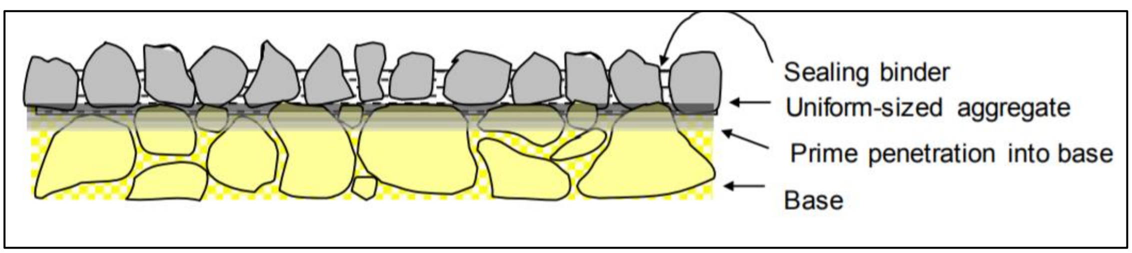


Figure 2.7 Sprayed seal with single application of binder and single layer of aggregates (Patrick, 2018).

During the 1920s, when pneumatic-tired vehicles started to become popular, the demand for cost-effective surface treatment attracted the attention of the highway authorities (Rebecchi & Sharp, 2009). Hence began the use of the sprayed seal (Australian term) or chip seal (New Zealand term) or seal coat (term used in

Africa and some other countries) as a surface treatment. This development of low-cost road surfacing in Australia is a milestone in the road maintenance sector for the international community.

2.6.2 Asphalt Surfacing

'Asphalt wearing course' refers to surfacing where aggregates are mixed with bituminous binder at a plant on site and placed as a carpet on the pavement. The usual thickness of the asphalt wearing course varies in between 20 to 40mm (Rebbechi, 2007). Asphalt surfacing can contribute to the pavement structural strength, provided with Dense Graded Asphalt (DGA) or Stone Mosaic Asphalt (SMA) as a wearing course on an asphalt base, while a sprayed seal surfacing is not able to provide any structural resistance. Asphalt surfacing is selected for urban areas, freeways and arterial roads with high traffic volume, while sprayed sealing is usually used in low trafficked remote areas, on all types of pavements in Australia (Holtrop, 2008).

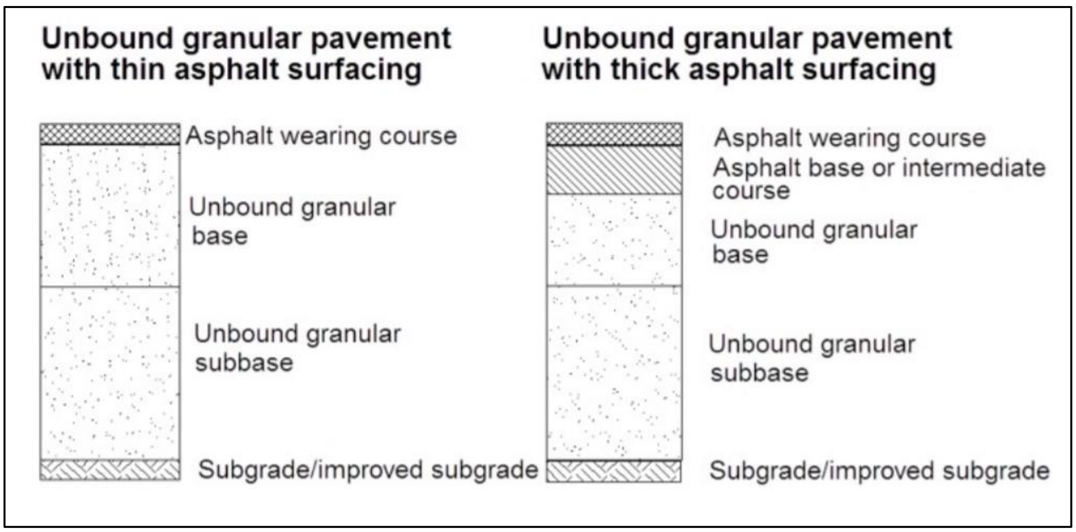


Figure 2.8 Asphalt surfacing on granular pavements (Rebbechi, 2007)

The asphalt is suitable for heavy traffic loading roads and in the city area, because it has a greater durability and resistance to wheel loading effects (Rebecchi & Sharp, 2009). Therefore, it offers a better riding quality for the users. Asphalt surfacing lasts 7 to 25 years depending on traffic loads, environment, developed distresses and type of surfacing (dense graded, and open graded, etc.). The typical cross-sections of asphalt wearing courses are presented in the Figure 2.8.

2.7 Road Maintenance Prioritization

Prioritization of pavement treatments considers those distresses which cause the highest inconvenience, discomfort to road users, and need earlier attention. In the priority ranking of pavement maintenance programs, a convenient practice is to express potential needs of treatments in terms of a priority index developed via some empirical numerical formula or a combined index based on manual ratings. The prioritization practices may be grouped into three categories as below (Shah, Jain, & Parida, 2014).

(1) Priority ranking based on manual judgement

(2) Priority ranking based on financial evaluation and

(3) Priority ranking based on a combined index.

Though mathematical indices are widely used, they often do not convey an understandable physical meaning and cannot articulate the maintenance prioritization precisely (Farhan & Fwa, 2009). This is because integrating various aspects empirically into a single measure tends to suppress the different influences of the pavement condition parameters. However, prioritization of pavement segments becomes essential for selecting a suitable maintenance choice, particularly when budgets are limited.

2.7.1 Agreement Between different Pavement Condition Indices

Pavement surface distress, individually or along with other pavement condition parameters, considered as a significant input for developing integrated road condition index that reflects the overall current condition of pavements. These indices acted as an expedient tool for planning different types of maintenance works and rehabilitation strategies. Pavement maintenance prioritization mainly depends on the accessibility of a standard measuring or evaluating scale for the current condition of each component of the network. Usually, pavement condition indices have been used by transportation agencies to infer the current statuses of pavement to decide whether to intervene as a part of road maintenance programs. Many of these indices are combined measures of the structural and material condition of pavements (Gharaibeh et al., 2009). These indices and methods comprise of simple subjective rating evaluation with mathematical formulations.

Since the subjective rating systems are constrained by various limitations, directly measured data are accumulated to get combined condition indices. These indices are extensively used by many state highway departments. In each type of index, the road agencies considered separate criteria for evaluation. These indices are mainly based on weighting factors like deduct value and statistical analysis. The overall pavement condition index development is more complicated because the ‘roughness’ term is also to be considered, which adds an additional feature to the index (Gharaibeh et al., 2009).

The Present Serviceability Index (PSI) developed on the basis of the Pavement Serviceability Rating (PSR) from AASHO road test results, is a well-recognized index used to define the functional condition of a pavement considering user ride quality (S. Shoukry, D. Martinelli, & J. Reigle, 1997). The Present Serviceability Index (PSI) is determined by a panel of individuals who rate the pavement on a rating scale. The index is correlated with objective measurements made on the pavement surface. These objective measurements include a measure of roughness index, the extent of cracking and patching, and for flexible pavements, the average rut depth in the wheel tracks. The important point here is that an estimation of serviceability can be made by making objective measurements, and then through correlation equations, calculations of the index can be made (Eldon Joseph Yoder & Witczak, 1975). The original AASHO equation of PSI for flexible pavement is as follows (Chastain & Schwartz, 1964):

$$PSI = 5.03 - 1.91\,log\,(1 + SV) - 0.01\ (C + P)^{\frac{1}{2}} - 1.38\ (RD)^2$$

Here,

$SV =$ the mean of the slope variance in the two-wheel paths (measured by longitudinal profilometer)

$C =$ foremost cracking, in ft per 1,000 sq ft of area

$P =$ surfacing patching in sq ft per 1,000 sq ft of area

and

$RD =$ mean rut depth of both wheelpaths in inches

The U.S. Army Corps of Engineers developed PAVER, a pavement management system that improves the maintenance decision-making process at the network and project levels (Nunez & Shahin, 1986). It calculates an arithmetic index between 0 and 100 which is defined as the Pavement Condition Index (PCI) and has been implemented by the American Public Works Association for use by cities and counties. A pavement having a score of 100 is considered to have no defects. On the contrary, pavements in poorer condition would have lower scores (Johnson, 2000). Generally, the PCI encompasses two aspects: 1) user comfort for traveling which is related to roughness, and 2) pavement surface distress rating. The former is based on objective measurements using a roughness profilometer whereas the latter is acquired by subjective evaluation of surface distresses following standard guidelines (Hajek, Phang, Wrong, Prakash, & Stott, 1986). In 2000 in the U.S., the road authorities adopted the developed PCI and use it for evaluating pavement condition for highways and parking lots (ASTM Standard D6433-99). The universal equation for calculating PCI is as follows (M. Shahin, Darter, & Kohn, 1978):

$$PCI = C - \sum Deduct\ Value$$

Here,

$PCI =$ Pavement Condition Index

$C =$ maximum value of overall condition index (i.e. perfect score of 100)

$Deduct\ Value =$ deduct value function that differs with distress parameters

The calibration of the suitable deduct value is a very challenging and crucial part in the development of an effective PCI. The PCI is considered the most specific index that integrates several types of distresses with their magnitudes and severity (M. Y. Shahin, 2005).

Another subjective rating named Pavement Condition Rating (PCR) is also used by some authorities as a procedure to detect pavement distress and to comprehend the combined effects of several distress types to describe the overall pavement condition, with their severity and extent (Saraf, 1998). These composite indices are derived from their constituent elements while the contributions of individual elements to the overall index depends largely upon the weightings assigned to each distress in the equation for calculating the composite index.

To determine the agreement among several indices which are used by different highway authorities, six indices from five transportation departments in the United States were compared using available relevant data collected from the concerned information system. It was found that there are significant variations among the commonly used pavement condition indices due to the weighting factors, types of distress considered and the arithmetic forms of the indices (Gharaibeh et al., 2009).

2.8 Surface Inspection Rating (SIR) Survey in Victoria

In Victoria, surface inspection rating surveying is performed based on some core criteria. The assessed fundamental criteria for asphalt surfacing are cracking, ravelling, patching. In the case of sprayed seals, binder condition and binder level are considered as well. The non-core criteria for assessment are loss of surface texture and deformation (rutting, shoving, corrugations, and depressions). Hence, detection and evaluation of distress considers the several modes of distress which are expressed in terms of extent of area affected, severity of widths of cracks and background of the pavement or surfacing treatment (VicRoads, 2004).

According to the guidelines of VicRoads, the scale used by the practised personnel to give rating is from 0 to 5 where 0 is considered as good (no distress), 1 is to be rated for minor defects, 3 is for moderate distress and lastly, for extensive condition the ranting is 5. The scale used for the rating depicts the effect of the level of distress and able to assess the remaining life of pavement. The given ratings from the experts for the mentioned five types of core distress parameters are then integrated into one measure termed the Surface Inspection Rating (SIR). The calculation of SIR considering all five types of distresses assessed in the pavement surface inspection rating method (VicRoads, 2004) can be expressed as:

$$SIR = \sum \frac{Rating\ Values\ of\ all\ Distresses}{(5 \times Number\ of\ Distresses)} \times 100$$

For example, if the ratings for cracking, texture loss, stone loss, deformation and patching are 1, 3, 1, 3 and 3 respectively, the value of SIR will be equal to [(1 + 3+ 1 + 3 + 3) / (5 × 5)] ×100 = 44. SIR is very useful to trigger the periodic resurfacing programs using a threshold value of SIR = 30 (Hassan, Lin, & Thananjeyan, 2014). SIR values are used to determine the potential need for pavement resurface treatment and not for the selection of treatment method. Visual inspection rating is used to categorize individual road segments' condition as 'critical', 'needed' and 'desired', for the purpose of prioritization in the resurfacing program.

The subjective condition ratings are also considered with objectively collected automated pavement condition data for decision making of other periodic maintenance works (renewal activities), in addition to triggering resurfacing programs at the network level. The recommended maintenance period and choices are mainly based on assessors' individual experience and preference. Hence, this approach is not sustainable and does not enable the asset managers to develop a long-term asset management strategy.

2.9 Pavement Condition Survey (PCS) in Victoria

Additionally, Pavement Condition Survey (PCS) is carried out biannually for Victoria's road network using digital survey vehicles monitored by practised personnel, giving quantifiable condition data. PCS assesses overall pavement condition, functional (roughness, texture loss, strength, and skid resistance) and structural (rutting and cracking). Hence, this objective survey supports understanding of the pavement performance and triggers required renewal activities.

2.10 Modeling Approaches

2.10.1 Deterministic Models

Many studies prefer to use deterministic approaches for prediction because they are the most popular models, of great practical value, and easy to use and understand (Lu & Tolliver, 2011). Linear models to predict pavement condition have been developed by many researchers (Hunt, 2002; T. Martin & Choummanivong, 2008; Stephenson, 2010), considering the relationship between pavement condition (dependent variable) and each of the included factors (independent variables) as linear. Research conventionally predict the serviceability of pavements using Multiple Linear Regression (MLR) analysis (N. O. Attoh-Okine, 2002). This is one of the comprehensive forms of deterministic models and is very effective when more than one cause affects the dependent variable (Ens, 2012). It provides information about the model as a whole and the relative contribution of each of the variables.

Theoretically, the pavement deterioration process is the combined effect of many factors that are related to the mechanistic properties of pavements, which include traffic volume, aggregate properties, and the level of performed maintenance. However, pavement performance is associated with some other latent influencing factors as well that are challenging to incorporate in the pavement condition assessment (Madanat, Mishalani, & Ibrahim, 1995). Thus, pavement deterioration is a complex stochastic process. Furthermore, the rate of deterioration is not fixed, it changes with time which proves it is a dynamic process (Li, 2005). To capture the uncertainty and dynamism associated with the pavement deterioration process, the demand for probabilistic approaches are getting attention over deterministic models (T. Martin, Choummanivong, Thoresen, & Kadar, 2015).

2.10.2 Probabilistic Models

Pavement deterioration is associated with the effect of known factors and unknown latent causes. Therefore, probabilistic modeling is useful to assess the pavement condition by considering the outcome variable as a stochastic event. There are four probabilistic methods in modeling absolute pavement deterioration, including survivor curves, Markov Chain (MC) models, semi-Markov models, and continuous logistic models. The following sections describe most widely used probabilistic methods for modeling subjective pavement condition from objective pavement condition parameters.

2.10.2.1 Logistic Model

Logistic modeling is one type of continuous probability approach that has been used in several current research in modeling pavement deterioration considering distresses progression (Choummanivong & Martin, 2014; T. Henning & Roux, 2012; T. F. Henning, 2008; Khraibani, Lorino, Lepert, & Marion, 2010; Y. Wang, 2012). Usually, this type of method is suitable for explaining and testing hypotheses that relate a categorical response variable with one or more categorical or metric explanatory variables (Peng, Lee, & Ingersoll, 2002). Additionally, the assumption of probabilistic logistic regression is more flexible with data distribution since it does not assume a linear correlation between untransformed DV and IVs. A common limitation of these types of models is that they were easier to apply to an entire network rather than individual road sections, whereas the deterministic and incremental deterministic models are of greater use in this regard (T. F. Henning, 2008).

2.10.2.2 Markov Chain Model

Markov Chain is a probabilistic modeling approach that considers the stochastic pavement deterioration process with age by using a Transition Probability Matrix (TPM) for predicting the future condition of pavement depending on the existing condition (Osorio-Lird, Chamorro, Videla, Tighe, & Torres-Machi, 2018). This model uses a base condition vector showing the present condition of a pavement segment and a TPM (Amador-Jiménez & Mrawira, 2009). This method is a time-dependent model and disregards non-load and other environmental effects (Lytton, 1987).

2.10.3 Other Models

Other models used in the relevant studies for predicting pavement conditions include Artificial Neural Networks (ANNs) and Genetic Programming (GP).

2.10.3.1 Artificial Neural Networks (ANNs)

ANNs are statistical models that have similar functional and structural concepts of the living neurological system (Hill, Marquez, O'Connor, & Remus, 1994). This structure consists of processing components through nodes, links between the components, and processing the information (Alsugair & Al-Qudrah, 1998). This approach is used for forecasting and decision making in pavement condition assessment to trigger maintenance work (Abiola & Kupolati, 2014; Alsugair & Al-Qudrah, 1998; Chandra, Sekhar, Bharti, & Kangadurai, 2012). However, it is hard to interpret and to understand the physical meaning of this type of model (Hill et al., 1994).

2.10.3.2 Genetic Programming (GP)

Genetic Programming (GP) is a recent approach in the pavement condition modeling arena. The key feature of this approach is the ability to create prediction equations without presuming the previous form of the current relationships (Alavi, Ameri, Gandomi, & Mirzahosseini, 2011). Some studies applied GP optimization based on genetic algorithms in modeling pavement condition parameters (Hsie, Ho, Lin, & Yeh, 2012; Tapkin, Çevik, Uşar, & Gülşan, 2013).

2.10.3.3 Fuzzy Mathematics

The theory of fuzzy mathematics is introduced in 1965 (Goguen, 1973). This theory provides an effective approach to measure the subjectivity in pavement condition evaluation and model the uncertainty related to the pavement deterioration process (Kaufmann and Gupta 1991). This is achieved by the combination of a fuzzy set associated with several variables with the assessment of their significance (S. N. Shoukry, D. R. Martinelli, & J. A. Reigle, 1997). Fuzzy mathematics is applied in various recent studies for pavement condition assessment for maintenance planning (Bandara & Gunaratne, 2001; Singh, Sharma, Mishra, Wagle, & Sarkar, 2018; Lu Sun & Gu, 2011).

2.10.4 Modeling Approach in the PMS of VicRoads

VicRoads uses a Pavement Management System (PMS) to enhance management of its pavement assets. Austroads deterioration models have been adopted by VicRoads as the primary models to predict future network performance. Pavement performance prediction is applied directly throughout phase 2 (Form asset strategies), phase 3 (Define investment program) and phase 4 (Identify asset requirements) of the Austroads Integrated Asset Management (IAM) framework (Toole, Martin, Roberts, Kadar, & Byrne, 2007) to optimize pavement and economic performance through minimizing whole-of-life cycle costs. In addition to the Austroads deterioration models, PMS can accommodate further models such as probabilistic models.

2.11 Previous Relevant Studies

Initially, in 1962 Carey and Irick employed the Present Serviceability Index (PSI), obtained by accumulating subjective ratings with measurements of road roughness by applying a multi-regression fit to AASHO Road Test data (Eldon J Yoder & Milhous, 1965). Since its original establishment, the PSI concept has been adopted by many state road authorities for triggering maintenance programs and priority ratings. Later, different state highway departments developed their individual pavement condition indices based on their rating systems. Pavement Condition Index (PCI), developed by the U.S. Army Corps of Engineers (1976) (N. Attoh-Okine & Adarkwa, 2013) and International Roughness Index (IRI) established by the World Bank (1968) are well-acknowledged indices as they are easily comprehensible and convenient to monitor the overall condition of the roads and ensure efficient use of road maintenance budgets.

The recent studies that model the association between pavement condition ratings and distress parameters are observed from various aspects. Regression analysis was applied to establish relationships between Present Serviceability Rating (PSR) and pavement distress (AL & DARTER, 1995). The study also investigated the correlation between PSR and International Roughness Index (IRI). Two multiple linear regression models have been established for of Saudi Arabia's inter-city roads (Mubaraki, 2009). First one is for Pavement Condition Rating (PCR) that used traffic loading, age, and IRI as predictors. The other one predicts IRI from rutting, ravelling, and cracking. These statistically significant models showed coefficients of determination (R^2) = 0.799 and 0.93 respectively, which suggests the acceptability of the models. A study showed the relationships between PCR and roughness or pavement distresses (rutting or cracking) can be developed by a polynomial regression analysis (Hozayen & Alrukaibi, 2008).

In one study rutting, patching, and slope variance along with cracking are used as explanatory variables in developing Artificial Neural Network (ANN) model to estimate subjective PSR, and achieved better results than AASHO panel data of PSR (Terzi, 2007). Another regression study considered 21 pavement distresses to predict IRI in the roads of the urban and rural areas of the San Francisco Bay (U.S.) and results confirm the acceptability of the PCI as a predictor of IRI with an R^2 value of 0.53 in the model (Dewan & Smith, 2002). For the District of Columbia, linear regression models to predict PCI from IRI were found to be statistically significant at the 5% level of significance with R^2 values between 0.56 and 0.82 where functional classifications of the pavement are considered (Arhin et al., 2015) which can be considered a good prediction level. For the North Atlantic Region, a power regression result showed 59% dependency of variation in PCI on IRI (Park, Thomas, & Wayne Lee, 2007). This model predicts the variation of PCI for comparatively low IRI values (0.725 to 2.0 m/km).

Probabilistic logistic regression analysis and developed Markov Chain (MC) models for subjective pavement surface distress rating as a function of age in Australia indicated a moderate success rate (48% - 65%) for sprayed seal surfacing and 57% to 90% for Asphalt wearing course road network (Hassan, Lin, & Thananjeyan, 2017b). In the case of the AC network, probabilistic Markov models and the logistic models both predict SIR values that are higher than the deterministic regression model and for the SS network it is found that the regression and Markov Chain models reflect greater rates of deterioration than logistic models, but the second one has a higher prediction ability for below the age of 7 years (Hassan, Lin, & Thananjeyan, 2017a). When the age is above 7 years, developed three types of models produce almost similar rates including the Markov model is showing a higher prediction level. Further, age is found to be a very significant predictor for surface inspection rating (SIR) explaining 85% to 95% variation in SIR, where linear regression analysis and Markov methods prove that both models predict a similar rate but the MC model using weighted mean probabilities predicts more at all ages (Hassan et al., 2014).

Artificial Neural Network (ANN) and regression analysis were used to explore the relationship between subjective PSR and objective Present Serviceability Index (PSI), which is a function of measurement of roughness and distress (rutting, cracking and patching), for highway sections in South-East Nigeria (Abiola & Kupolati, 2014). In India, the IRI model as a function of pavement condition yields a R^2 value of 0.86 and Mean Squared Error (MSE) = 0.041 indicating that the performance of ANN is satisfactory, and it is feasible for IRI prediction. Another study in India to predict pavement roughness from pavement distress parameters revealed that the non-linear relation is better that the linear model ($R^2 = 0.73$ and 0.77) and ANN models yield better forecast ($R^2 = 0.86$) of road roughness for a given set of distress parameter (Chandra et al., 2012). A summary of reviewed previous models on predicting subjective pavement data is presented below (Table 2.1).

From the previous studies it is observed that a lot of effort has been employed to develop models for forecasting pavement surface condition from present pavement condition parameters and subjective rating integrated with measured influencing factors, with varying levels of involvedness. The reason for this interest from a pavement management program perspective is that modeling and predicting pavement condition enables optimization of available funds and provision of the required level of service to the users. However, selection of the appropriate modeling approaches depends upon available data and the relevant pavement management system.

A comprehensive review of existing relevant pavement condition models indicates that different analytical approaches have been recommended for developing relationships between subjective rating and directly measured condition data. The mainstream of accepted approaches from the existing statistical prediction models are based on observed local historical condition of pavements to estimate future pavement condition. Different predictors have been included, signifying their contributions to pavement surface condition. These factors generally are pavement distress (rutting, cracking, ravelling, patching and potholes), slope variance (a function of profile roughness), IRI (International Roughness Index), pavement age and traffic loading. Numerous studies have been developed using various linear or non-linear regression models or by using probability models based on individual distresses considered by the relevant road authority. In the literature, researchers adopt three kinds of modeling approaches: deterministic, probabilistic (logistic regression and Markov chains) and others (artificial neural network and genetic programming) to evaluate the relationship between subjective rating and objective pavement condition parameters.

To prioritize road maintenance activities, several decision-making approaches have been incorporated and employed in the pavement management study (S. Ahmed, Vedagiri, & Rao, 2017). However, in the past, very few studies focused on the interaction effects between pavement distresses in determining the association between automated pavement distresses and subjective ratings in detail. Therefore, the current study attempts to investigate the interactions between various pavement distresses in developing relationships between objective (automated) pavement surface condition data and visual pavement surface rating, that is a useful indicator of pavement surface performance. Finally, some sets of relationship between subjective and objective pavement condition data are developed for each of the sprayed seal and asphalt surface road networks.

Table 2.1 Summary of reviewed prediction models for subjective rating data from objective data of pavement

Authors, Location	DV and Predictors	Sample Size	Modeling approaches	Findings
(Abiola & Kupolati, 2014) South East, Nigeria	DV: Subjective Present Serviceability Rating (PSR) Predictor: Objective parameters [rut depth, cracking, patching and slope variance (function of profile roughness)] of Present Serviceability Index (PSI)	247 road sections	1. Multiple Linear Regression (MLR) Analysis 2. Artificial Neural Network (ANN)	The results showed that R^2 for ANN model is 0.90 compared to 0.34 for regression model. ANN has demonstrated its ability to model non-linear data. This result confirms that the input variables are non-linear, and the ANN has been shown to forecast with high degree of accuracy over regression analysis.
(Terzi, 2007) AASHTO Test Results are used	DV: Pavement Serviceability Rating (PSR) Predictors: slope variance, rut depth, patches, cracking, and longitudinal cracking	74 samples	Artificial Neural Networks (ANNs), (Logarithmic Sigmoid transfer function is used)	The developed model gives better results for PSR than the AASHO panel estimation for PSI. The result shows that the R^2 values for training set are 0.83 and 0.99 whereas for testing set the vales are 0.82 and 0.87 in the developed ANN model.
(Mubaraki, 2009) Saudi Arabia	DV1: PCR, IVs: pavement age (T), average annual daily traffic (AADT), IRI DV2: IRI, IVs: rutting, ravelling, and cracking	10 years data, sample size is not mentioned	Multiple Regression Analysis	The MLR model for PCR explains 79.9% of the variation in the outcome variable. For IRI model the R^2 indicates 93% of the variation in the outcome variable from the pavement distresses.

Table 2.1 Summary of reviewed prediction models for subjective rating data from objective data of pavement

Authors, Location	DV and Predictors	Sample Size	Modeling approaches	Findings
(Shah, Jain, Tiwari, & Jain, 2013), India	DV: Overall pavement condition index (combined form of $PCI_{distress}$+ $PCI_{Roughness}$+ $PCI_{Structure}$+ PCI_{Skid}) IVs: For $PCI_{distress}$ IVs are cracking, patching, ravelling, rutting and potholes, for $PCI_{Roughness}$ IV is IRI, for $PCI_{Structure}$ IVs are effective and original pavement structural numbers, for PCI_{Skid} subjective rating values are used.	10 arterial/ sub-arterial road sections having 29.92 km road length with four and six lanes divided carriageway.	Subjective and Objective surveys	In this model four pavement performance indices are developed separately. After that, all of them are combined to give an overall pavement condition index. Here, each indicator has been given importance is estimating the final index. The offered combined index is likely to be a good tool for the evaluation of overall pavement condition. This index was used in pavement maintenance prioritization.
(Arhin et al., 2015), USA	DV: Pavement Condition Index (PCI) Predictor: IRI	Freeways = 20 Arterials = 149 Collectors = 140 and Locals = 157	Regression Analysis	The regression models yielded statistically significant regression models at 5% level of significance where R^2 values are found between 0.56 and 0.82.

Table 2.1 Summary of reviewed prediction models for subjective rating data from objective data of pavement

Authors, Location	DV and Predictors	Sample Size	Modeling approaches	Findings
(Park et al., 2007), North Atlantic Region	DV: Pavement Condition Index (PCI) Predictor: IRI	62 observations	Power Regression Analysis	Developed power regression model indicates that 59% of the variations in the outcome variable (PCI) can be explained by IRI. The model is suitable for relatively smaller values of IRI (0.725 to 2.0 m/km).
(J.-D. Lin, Yau, & Hsiao, 2003), Taiwan	DV: Improvement of IRI IVs: Distress and non-distress parameters	125 samples	Artificial Neural Network (ANN) Successful transfer of function was sigmoid function	The correlation coefficient between improvement of IRI and pavement distresses is found to be 0.944. This indicates that IRI can be predicted by distresses to a large extent.
(Hassan et al., 2017b), Australia	DV: Subjective Pavement Surface Distress (cracking, stone loss, Texture Loss) Rating IV: Age	AC: 3848 road sections SS: 1994 road Sections	Logistic Regression, Markov Chains	For asphalt surfaced network, all the distresses used in developing models are proved to be significant and the R^2 value ranges from 0.57 to 0.90. For, SS network- R^2 value is in between 0.48 to 0.65 and the parameters are significant. It is also perceived that predictions of surface distresses from age are higher for Markov Chain models than the logistic regression models and observed average data.
(Chandra et al., 2012), India	DV: Pavement Roughness	Total 510 km	Multiple Linear Regression, Non-Linear Regression,	ANOVA test results indicate that for the developed models, nonlinear model gives higher prediction (R^2 = 0.8) than a linear relation (R^2 values are 0.73 and 0.77).

Table 2.1 Summary of reviewed prediction models for subjective rating data from objective data of pavement

Authors, Location	DV and Predictors	Sample Size	Modeling approaches	Findings
	IVs: distress parameters (potholes, ravelling, rut depth, cracked areas, and patch work)		Artificial Neural Network (ANN)	For this study, the mean error terms also supported the developed nonlinear models.
(Hassan et al., 2014), Australia	DV: Surface Inspection Rating (SIR) IV: Age	3848 road sections (3258.4 mm)	Linear Regression, Markov Chains	All the linear regression models proved to be significant at the 5% level in explaining 85% to 95% of the variation in SIR from age (without constant). The study reveals that both models predict the similar rate of deterioration in pavements. However, MC models predict higher SIR than the linear models.
(Vidya, Santhakumar, & Mathew, 2013), India	DV: IRI IVs: Pavement condition	56.49 km National Highway	Artificial Neural Network with sigmoid transfer function	The model yields an R^2 value of 0.86 and MSE of 0.041. The results indicate that the performance of neural network is satisfactory, and it is feasible for IRI prediction. Higher precision can be obtained with large database and with more Input variables.
(Golroo & Tighe, 2010), Canada	DV: Surface Distress Index (SDI) Predictor: Pervious Concrete Distress Index (PCPDI) Predictor: Pervious Concrete Condition Index (PCCI)	Eight PCP sections (objectively evaluated) and Twenty qualified pavement engineers gave	Regression Analysis	The results show that 94% of variability can be explained by the predictor. The F value of the model indicates that the IV was significant at the 5% level. Fuzzy theory was proved to be an effective means to incorporate the stochastic pavement behavior.

Table 2.1 Summary of reviewed prediction models for subjective rating data from objective data of pavement

Authors, Location	DV and Predictors	Sample Size	Modeling approaches	Findings
	Predictors: SDI and Functional Performance Index (FPI) (Rigid Pavement)	rating to the PCP Sections through digital visual evaluation.		

2.11 Summary

This chapter presented the distress mechanisms for granular pavement with pavement behavior and performance measures. Contributing factors that stimulate these distresses are discussed. Agreement between different pavement condition indices all over the world are outlined. Subjective evaluation survey and objective automated pavement condition surveys are described and compared. Therefore, relevant previous studies related to modeling approaches with subjective and objective pavement condition data are reviewed in detail. Finally, the findings from the past studies are compiled in a table format and research gaps from the literature reviews are specified.

CHAPTER THREE

RESEARCH METHODOLOGY AND DATA PREPARATION

3.1 Introduction

The aim of the study is to develop relationships between subjective rating and automated pavement surface distresses. To achieve this goal, the conceptual framework is developed and accordingly, the data set is prepared for analysis. This chapter outlines the research methodology and the data preparation process, and describes the approaches for statistical analysis.

The guidelines for pavement condition data collection for both subjective Surface Inspection Rating Procedure (SIRP) and objective Pavement Condition Survey (PCS) in Victoria, Australia are reviewed here. The conceptual framework of the research is presented here to address the objectives of the study. The study area, data description, data preparation and data filtration assumptions are briefly explained. Lastly, the modeling approaches suitable for the study are discussed in detail in this chapter.

3.2 Pavement Surface Distresses Data Evaluation Guidelines for Subjective Survey

In the subjective SIRP conducted by VicRoads, the practised personnel select and record a rating by examining uniform sections on foot at approximately 300 to 500 m intervals, together with a very slow 'drive-over'. The manual rating guidelines are described below for the distresses used in this study (VicRoads, 2004).

Cracking

The percentage of carriageway area affected by cracking, including both untreated and treated cracks, is determined and rated. Normally, the more connected cracks that make polygonal shapes are assumed to have larger affected area, which affects their rating. Usually in the evaluation process no cracking, area affected by cracking < 10%, 10 – 20%, or > 20% are categorized as Nil, Minor, Moderate and Extensive, and given rating values as of 0, 1, 3 and 5, respectively.

Deformation

In SIRP the assessment of deformation (rutting, shoving, corrugations, and depressions) is conducted for each type of deformation. No deformation, deformation affected area < 10%, 10 – 30%, > 30% of area in wheel path are regarded as Good, Minor, Moderate and Extensive, which corresponds to 0, 1, 3 and 5, respectively.

Texture Loss

In sprayed seal surface, ratings of 0, 1, 3 and 5 for loss of texture correspond to binder levels less than two thirds up the aggregate, from two thirds up the aggregate to just underneath the top of the aggregate, just below the top of the aggregate, and over the top of the aggregate, respectively. In case of asphalt surfacing, no loss of surface texture, loss < 5% of area, loss 5 - 15% of area, loss > 15% of area are considered as Good, Minor, Moderate, Extensive conditions and rated as 0, 1, 3 and 5, respectively.

3.3 Pavement Condition Survey Data Measurement and Assessment Guidelines

The Austroads guidelines for pavement distress measurement procedures and the adopted methods for pavement condition survey in Victoria are described in this section (Foley, 1999; Hillier & Soet, 2009; Hussein, 2016; Michael Moffatt, 2007a; M Moffatt & Hassan, 2006; Prem, 1989; Sharp & Toole, 2009; Toole et al., 2007).

Cracking

In an automatic survey, cracking is assessed by trained but inexperienced personnel. They watch the videos of the distress, frame by frame and judge the area affected and in addition to performing electronic crack recognition and interpretation according to the Austroads Guidelines (M Moffatt & Hassan, 2006). The data is collected using high speed (maximum speed of 105 km/h) data acquisition modules mounted beneath a vehicle chassis to collect digital images of the pavement surface. In the context of pavement cracking extent, the area affected by cracking is expressed as a percentage of lane area (lane width by length). The percentages of cracked areas are categorized into five bins as follows: < 1%, 1 - 5%, > 5 - 10%, > 10 - 25% and > 25%.

In Victoria, cracking is assessed by a manual crack recording method, where data is collected by watching digital videos and judging the area affected. Detected cracks are classified by an onboard data synchronizing unit and reported by cracking type (transverse, longitudinal and crocodile), crack width (mm), location, and cracking severity (average crack width in mm) or extent (area affected by cracking as a percentage of lane area). This data collection process is performed twice a year for arterial roads with full lane width in 100 m intervals between the centers of the lane lines. In pavement condition survey, cracking condition is considered as ‘Good’ when the percent affected by cracking is less than 10% and ‘Poor’ when it is greater than or equal to 10%.

Rutting

According to Austroads’ Guidelines (Michael Moffatt, 2007a), the automated methods for rutting surveys use several vehicle-mounted lasers or ultrasonic sensors, in conjunction with taut wire or straight edge models. These devices are typically capable of measuring transverse profiles with as close as 50 mm spacing while the host-vehicle travels at normal traffic speeds.

Most Austroads member authorities (MAs) record rutting in the left lane in one direction only, the assumption being that, in more than 95% of the road network, the left or slow lane carries the highest gross freight mass. For each reporting interval, the rut depth is reported as mean rut depth in mm/standard deviation. The proportion of Australian and New Zealand roads with rut depths in excess of 20 mm is small (< 3%). Additionally, the severity of rutting is measured by mean rut depth (mm) and the extent is expressed as a percentage of pavement length. The maximum rut depths (mm) are categorized in 'bins' as follows: 0 - 5, > 5 -10, > 10 - 15, > 15 - 20, > 20 - 25, > 25 - 30, > 30 - 35, > 35 - 40 and > 40mm. A sample of automated rutting survey reports prepared by Austroads is presented in Appendix C.

In Victoria, a multi-laser profilometer is used to assess pavement rutting, which is an automated method. Pavement rutting data is reported for each 100 m in terms of rut depth in mm, as an average of both lane wheel paths for the whole section. To keep consistency with other pavement condition parameters, 100 m sections are adopted to report pavement condition survey data. Rut depth is binned as Good (< 10 mm), Fair (≥ 10 - 15mm), Poor (> 15 - 20mm), and Very Poor (> 20mm) in Victoria.

Roughness

According to Austroads Guidelines to measure the roughness a quarter car model equipped with road profilometer is used. At a road network level, roughness is to be reported as Lane IRI or simply as IRI (m/km). IRI is an important general pavement performance index because it takes into account most of the pavement defects that affect riding quality (West, Michael, Turochy, & Maghsoodloo, 2011).

In Victoria, roughness is measured with a multi-laser profilometer. Roughness is reported in terms of single wheel path IRI (m/km) and is determined by averaging two individual wheel path IRI. The results are reported at 100 m intervals, with IRI results reported to no more than two decimal places (m/km). A travel speed of 80 km/h is built into the definition of IRI. The roughness data is collected once every two years.

Texture Loss

Austroads uses a laser profilometer to measure pavement surface texture loss. The term 'texture loss' introduced by the Road Transport Authority of New South Wales, describes the difference between center lane surface texture and wheel path surface texture, to compare the wear and loss of texture in minimal trafficking areas with the most trafficked area. Thus, the rate and extent of pavement surface texture loss can be examined.

In Victoria, the texture loss data is measured by a profilometer at 50 mm intervals, estimating the difference in surface texture between ‘left wheel path’ and ‘between wheel path’. The data is aggregated to give average values per 100 m segment, to be reported in pavement condition survey. The difference is then expressed as a percentage of left wheel path texture. In Victoria, texture loss > 20% is considered as poor condition.

3.4 Conceptual Framework of This Research

The overall research plan used in this study to address the aim and objectives stated in Chapter One is presented in the flow chart (Figure 3.1). The flow chart of the conceptual framework shows the data analysis approach and statistical techniques used to achieve the aim of the study.

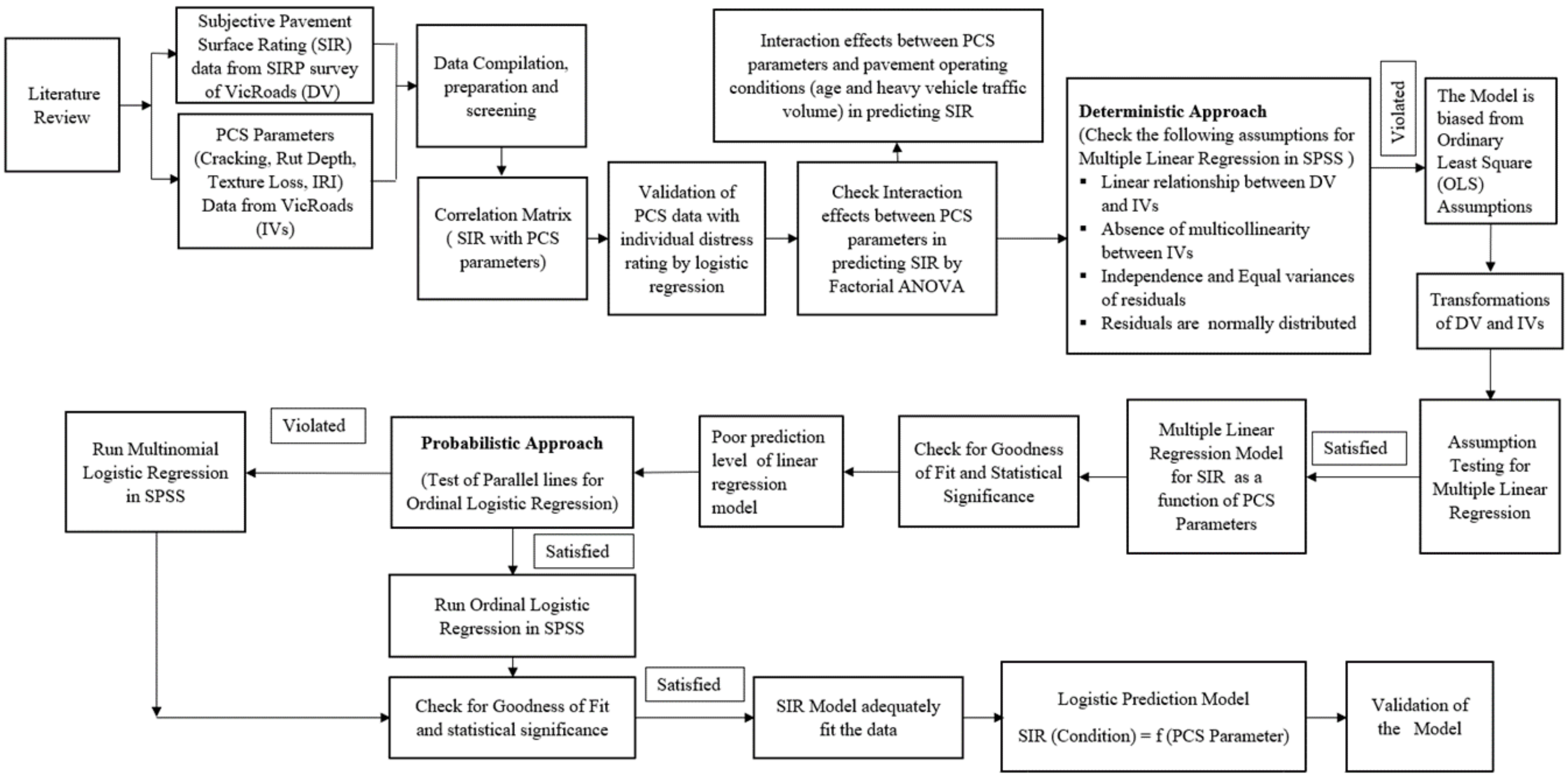


Figure 3.1 Conceptual Framework of Research Methodology

3.5 Study Location

VicRoads Metropolitan South Eastern (MSE) Region is located at the south eastern part of Metropolitan Melbourne and covers 16 municipal councils. The region's network consists of about 39% sprayed seal and 61% asphalt surface roads (O. Lin et al., 2014). The average traffic volume of this region is approximately 17,000 Annual Average Daily Traffic (AADT) on arterial roads and 74,000 AADT on Freeways/Highways (O. Lin et al., 2014). Over the years, about 6% and 3% of the sealed and asphalt network have been resurfaced annually.

Figure 3.2 Location Map of Study Area

With increasing traffic volumes in the urban MSE area, it is becoming problematic to conduct SIRP from the viewpoint of survey personnel safety, which necessitates finding alternatives. Hence, this study attempts to develop relationships between SIR and PCS parameters to predict subjective SIR values from corresponding objectively collected PCS data for VicRoads' MSE Regions.

3.6 Data Description and Preparation

Years 2011 and 2013 data of subjective surface inspection rating (SIR) and objective pavement condition survey (PCS) parameters (cracking, rut depth, roughness, and texture loss) from VicRoads are used for this study. Initially, 247 road sections of the asphalt surfacing (AC) network and 256 road sections of the sprayed seal (SS) network are organized for the study. After filtering the compiled pavement condition data of 2011 and 2013, from subjective and automated survey, 160 road sections for the AC network and 190 road sections for the SS network are prepared for analysis.

3.6.1 Pavement Condition Data

Cracking

Objective cracking data (metric) from the pavement condition survey are used in correlation analysis, to investigate the interaction effects between pavement distresses in determining subjective rating, SIR, and develop probabilistic models for subjective rating as a function of objective pavement distress parameters. Factorial ANOVA is performed to find the interaction between pavement distresses. The cracking data is categorized into two groups: Good (< 10% area affected by cracking) and Poor (≥ 10% area affected by cracking) if the pavement condition survey data binning procedure proposed by VicRoads is followed.

Rut Depth

Automated rutting data (metric) is used for initial correlation analysis, interaction effects analysis and developing probabilistic logistic models for SIR. To investigate interactions between pavement distresses rut depth is binned as Very Good (0 – 5 mm), good (6 – 9 mm) and fair (10 – 15 mm) according to the Austroads guidelines. Here, VicRoads' binning system is not used since most of the rut depths in the data set are below 10 mm and there is no rutting value with poor (15 < rutting ≤ 20 mm) or very poor (> 20 mm) conditions for the asphalt concrete (AC) surfacing network. For the sprayed seal (SS) network, the rutting data cannot be validated with subjective rating and the correlation of rutting with SIR is found to be negligible. Hence, rutting data is excluded from the analysis for SS network.

Texture Loss

Objectively collected texture loss data (metric/continuous) from VicRoads are used for the correlation analysis and validation of data. Since the automated data cannot be validated (Chapter 5) with subjective texture loss rating, 'texture loss' as an explanatory variable is excluded from further analysis.

Roughness

In the pavement condition survey, roughness is reported in terms of IRI (m/km). The automated roughness data (metric) is used for the correlation analysis, to find the interactions between pavement distresses and develop probabilistic models for the AC network. Roughness is grouped into three categories: good condition (IRI < 3.4 m/km), fair condition (IRI ≥ 3.4 - 4.2 m/km) and poor condition (IRI > 4.2 m/km) for the factorial ANOVA test, to examine the interaction effects between other pavement distresses and roughness. In the data set (after filtering), no pavement segment is found to be in very poor condition (IRI ≥ 5.3). The grouping of parameters is selected based on the VicRoads' data binning procedure.

3.6.2 Pavement Operating Condition Data

Heavy Vehicle Traffic Volume

The wheel load of heavy vehicles like trucks is an important factor behind the formation of pavement distresses. Repetitive heavy traffic loading, due to fatigue, causes rapid differential compaction in the pavement upper layer involving failure of the bituminous surfacing, due to fatigue. For road maintenance purposes, often traffic volume is used because it is simple, and it is useful to understand how busy a highway is. 'Trucks' are considered as commercial vehicles and separate traffic volume/Annual Average Daily Traffic (AADT) values are computed for trucks, considered as heavy vehicle traffic. VicRoads guidelines (VicRoads, 2013) for heavy vehicle traffic volume are considered in grouping the traffic data. Thus, heavy vehicle traffic volume (HV) is divided into three groups ($HV \leq 500$, $500 < HV \leq 1000$ and $HV > 1000$) to observe the effects of traffic volume on the relationship between SIR and PCS parameters by the factorial ANOVA test.

Age

Age is an important aspect of bituminous surfacing because bituminous binder becomes brittle due to gradual hardening, due to oxidation, with aging. However, the age of pavement surfacing, by itself, alone is not an adequate cause for resurfacing or treatment work of a surface, it, together with distress condition and pavement performance, is used as an important guide to detect potential need for maintenance. The desired service lives of asphalt and sprayed seal surfacings are 7 to 25 years and 5 to 15 years, respectively (Jameson, 2011). Considering the expected service lives of both types of surfacing, DV and IVs are put into two groups (age ≤ 7 years and age > 7 years) to investigate the impact of age in developing relationship with manual rating and automated distress parameters by factorial ANOVA testing.

3.6.3 Surface Inspection Rating (SIR)

Subjective SIR is used by the road authority of Victoria to trigger periodic resurfacing of pavement and is described briefly in Chapter Two (section 2.7). For deterministic analysis, SIR values (continuous) obtained from the subjective survey data, are to be used as dependent variable (DV). In the case of the probabilistic approach, the SIR values (DV) are categorized using two major rankings (4 and 5 categories) considering the grouping of pavement surface conditions according to previous VicRoads study. Examples of SIR as a categorical variable with 4 categories are:

- VG (Very Good): SIR = 0 - 10,
- G (Good): SIR = 11 - 20,
- P (Poor): SIR = 21 - 30,

- VP (Very Poor): SIR > 30

3.6.4 Data Compilation

The following issues should be considered during data compilation:

- The 'same years' from both types of surveys are considered in data preparation.
- The subjective survey is conducted for each 300 to 500 m road segment and PCS data is collected for 100 m segments.
- To get the equivalent pavement distress data, chainages of through lanes from PCS data collection are matched with corresponding pavement segments from the subjective survey.
- Then the mean value of those PCS parameters (cracking, rutting, IRI and texture loss) are estimated, to get the PCS distress data, corresponding to the SIR value for each pavement segment.

3.6.5 Data Screening Assumptions

Years 2011 and 2013 pavement condition data (cracking, rut depth, roughness, and texture loss) of the MSE region of Victoria for the asphalt surfacing and sprayed seal surfacing networks are compiled for this study. Available subjective rating values of corresponding pavement segments are considered in compiling the data. The data set is screened to run the analysis following the conceptual framework of the research plan. To filter the data set, the following assumptions are considered.

1. The network is divided into two sub-networks based on surface types. The two sub-networks are as below:
   i) Asphalt wearing courses ii) Sprayed seals
2. Ages up to 25 years are considered. The reason for this is the expected average surfacing service life of asphalt is 7 to 25 years depending on the category of asphalt surfacing (open graded, thin open graded, dense graded or other) and road function. For the sprayed seal network, the average service life is expected to be 5 to 15 years, depending on surfacing type (thickness and double application) and road function.
3. Pavement sections with SIR ≤ 40 are selected for the analysis. Greater SIR values are considered outliers since they are assumed to be for major rehabilitation or reconstruction.
4. Sections that were subjected to repair over the study period are excluded to avoid the misleading improved performance.
5. The data set includes only sections of through lanes, to limit the variability of SIR data due to geometry.

6. Extreme values of Cracking, rutting, texture loss and IRI data are found to be as outliers in the analysis and therefore excluded from the study.

3.6.6 Validation of Objective Pavement Condition Data

The pavement condition survey distress data is collected objectively, whereas SIR is estimated by the combined evaluation of the visual ratings of different pavement surface distresses. The objective distress data are to be validated with the corresponding distress rating using logistic regression analysis. Based on the severity and extent of the cracking the subjective cracking in the manual survey, is evaluated on a four-level scale with the values of 0, 1, 3 and 5 for nil, minor, moderate, and extensive distress categories respectively. Additionally, objective PCS cracking (automated) data (metric) are used to intervene for different maintenance renewal activities. To find the relationship between these two types of cracking data for the same set of pavement segments, logistic regression analysis is performed, and objective cracking data are validated to use in the analysis. Similarly, automated rutting data are validated with subjective ratings of deformation for both the AC and SS networks (Chapter 5).

3.7 Statistical Approaches

3.7.1 Correlation Analysis for Pavement Condition Data

The correlation coefficient is a convenient statistical measure when investigating the relationship between one dependent (response/or outcome) variable and one or more independent (explanatory or predictor) variables. Pearson's correlation coefficient, denoted by 'r', is a well-known measure that estimates the strength and direction of association between two metric (interval/ratio) variables. It is a simple measure of the statistical fit of a linear regression model. The square of this value is called the coefficient of determination (R^2) which is often used as a measure of goodness-of-fit of any linear model (Bolboaca & Jäntschi, 2006).

SPSS statistics software is used to perform correlation analysis with the available data for surface inspection rating (DV) and corresponding PCS distresses (IVs) from 2011 and 2013 to investigate the linear association between the DV and IVs.

3.7.2 Interaction Effects between Pavement Distresses

Interaction effects indicate that the relationship between two variables depends on another variable's value (Aguinis & Gottfredson, 2010). It means that the association between one independent variable and the dependent variable is influenced by a third variable. Factorial ANOVA testing is performed to find the interaction effects between pavement distresses on modeling subjective rating. The overall ANOVA 'F statistic' determines only if there are significant differences in the means across all the groups (Kao &

Green, 2008). In this study the differences in the means of subjective rating across the groups of pavement distresses are investigated through the ANOVA test.

3.7.3 Modeling Approaches

3.7.3.1 Deterministic Approach to Develop Subjective Rating Model

The widely used deterministic model is a mathematical function that is used to predict the precise value of a dependent variable (DV) such as pavement condition (Abaza, 2004). Generally deterministic models can be categorized into three types based on their purposes: mechanistic (based on mechanics theories), empirical (based on observed or experimental data) and mechanistic-empirical models (Alaswadko, 2016).

Regression analysis (a type of empirical modeling) is performed to determine the correlation between two or more variables and to make predictions (Uyanık & Güler, 2013). Simple linear regression models are favored with the asset managers due to their easy comprehension and application procedure (Hassan et al., 2017a). In this study, regression analysis is selected based on a literature review of previous years' research work and the initial correlation analysis. From the preliminary correlation analysis, it is found that the correlations of subjective surface inspection rating (SIR) with automated distresses are significant for some parameters. Therefore, regression analysis is found to be a suitable approach to try to estimate SIR values directly from the automated pavement condition data.

Multiple Linear Regression (MLR) is a common analysis method to develop the relationship between single continuous outcome variable and more than one explanatory variable (Field, 2013). Here, linear transformation of independent variables (IVs) is done to minimize the summation of squared residuals (deviations of the predicted values from actual values) of the dependent variable. The general form of the multiple linear regression model is as follows (Myers & Myers, 1990):

$$Y = a_0 + a_1 x_1 + a_2 x_2 + a_3 x_3 + \cdots + a_n x_n + \varepsilon$$

Where, Y = dependent variable (DV) / Outcome Variable

a_0 = constant / Y-intercept

a_i = regression coefficient, $i = 1, 2, 3, \ldots \ldots .., n$

x_i = independent variable (IV), $i = 1, 2, 3, \ldots \ldots .., n$

ε = error

As the number of independent variables (PCS parameters) is more than one, MLR is an expedient deterministic approach for this study. Using SPSS statistics software, multiple linear regression analyses are performed with relevant available PCS distress data from 2011 and 2013 to develop best fit models with SIR as DV and PCS parameters as IVs.

3.7.3.2 Probabilistic Approach for Subjective Rating Condition Model

Though the deterministic approach is extensively used in developing relationships between different variables and can provide good prediction results (T. Martin & Choummanivong, 2010), this method cannot incorporate the stochastic nature of pavement effectively, in the assessment of its performance (Toole et al., 2007). To overcome this limitation, probabilistic approaches are considered for modeling the pavement performance (Hong & Wang, 2003; Porras-Alvarado, Zhang, & Salazar, 2014). Logistic models are useful to explain regression with one categorical dependent variable and various independent variables (IVs).

Ordinal logistic regression (probabilistic approach) has been used herein for the following reasons:

1. In the multiple linear regression analysis, the coefficient of determination (R^2) values are found to be low (0.305 and 0.235 for the AC and SS networks, respectively) indicating that the models explain only small amounts of variation (31% and 24%) in SIR.
2. Ordinal logistic models are used when more than two categories of the dependent variables (DVs) are available having a reasonable order between the DV categories (Field, 2013). The dependent variable (SIR value) can be grouped in more than two categories and treated as categorical.

The probabilistic approach of ordinal logistic regression is to be used for predicting subjective SIR values from objective PCS data. At first the assumptions of parallel lines are to be tested for ordinal logistic regression. If the same slope (parallel lines) assumption is violated, then multinomial logistic regression will be conducted. Considering the practice in the relevant studies, the application of logistic regression involves ranking of SIR (DV) into the following categories:

RANK1

- Very Good (VG): SIR = 0 – 10
- Good (G): SIR = 11 – 15
- Fair (F): SIR = 16 – 20
- Poor (P): SIR = 21 – 30
- Very Poor (VP): SIR > 30

RANK2

- Very Good (VG): SIR = 0 – 10
- Good (G): SIR = 11 – 20
- Poor (P): SIR = 21 – 30

- Very Poor (VP): SIR > 30

The required number of logistic equations is normally decreased by one category, because in developing logistic model one of the categories is selected as a base or reference category in each case. Usually the reference category for prediction is the category with highest values. Here VG will be the reference category. SPSS statistical software output of logistic regression analysis includes the following statistical measures (Wuensch, 2014).

- Regression coefficients (slopes) are available. The test of parallel lines is used to select the appropriate logistic model (ordinal or multinomial).
- Likelihood ratio test specifies the significance of adding the explanatory variables (PCS parameters) to the model which is based on the variation in likelihood ratio (-2 log-likelihood) when the predictors are added to a model that contains the intercept only.
- Nagelkerke measure will denote the variation in SIR explained by the PCS parameters. This test statistic ranges from 0 to 1 and is one of the measures to assess the relationships.
- Significance of Logit model parameters for each category will be assessed using the Wald statistic.
- Classification tables are available in SPSS that show the number of events or cases where the DV categories have been predicted correctly. The success rate of the model will be expressed as a percentage and calculated as the ratio of the number of events correctly predicted to the total observed number of events.

3.8 Summary

This chapter briefly describes the standard measurement practised in Victoria, Australia for subjective and objective surveys. The research plan is presented as a flow diagram to address the objectives to be achieved in this study. Then, the considerations for pavement condition data preparation, compilation and filtration are briefly explained. Lastly, suitable methods to investigate interactions between pavement condition parameters and modeling approaches to develop relationships between subjective rating and automated pavement distresses are discussed.

CHAPTER FOUR

DETERMINISTIC ANALYSIS FOR PAVEMENT CONDITION DATA

4.1 Introduction

This chapter documents the analysis involved in investigating whether there is a linear relationship between subjective pavement surface inspection rating (SIR) and objectively collected pavement condition survey (PCS) data. From the initial correlation analysis, data validation, and assumption testing for linear regression models, the significant predictors from PCS parameters are selected to determine SIR. Interaction effects between pavement surface distresses are investigated by ANOVA tests. The development of the best fit model as a function of automated (objective) pavement condition distress parameters is described briefly for AC and SS network separately. Statistical Package for Social Sciences (SPSS) software is used for the analysis.

4.2 Deterministic Analysis of pavement condition data

4.2.1 AC Network

4.2.1.1 Correlation Analysis of pavement condition data (AC Network)

From the initial correlation analysis, it is found (Table 4.1) that the correlations of subjective SIR with automated cracking (Pearson's correlation coefficient, r = 0.53) and rutting (r = 0.34) are significant at the 0.01 level, while the correlation with IRI (r = 0.177) is significant at the 0.05 level. The results also indicate that cracking has a significant correlation with rutting and roughness.

Table 4.1 Correlation (Pearson's Coefficient) SIR and untransformed PCS parameters (AC network)

	SIR	Cracking	Rutting	IRI /Roughness	TL
SIR	1	0.526**	0.338**	0.177*	- 0.048
cracking	0.526**	1	0.419**	0.292**	- 0.079
rutting	0.338**	0.419**	1	0.315**	0.005
IRI	0.177*	0.292**	0.315**	1	- 0.086
Texture loss	- 0.048	- 0.079	0.005	- 0.086	1

** Correlation is significant at the 0.01 level (2-tailed)

* Correlation is significant at the 0.05 level (2-tailed)

In addition, rutting is also significantly correlated with roughness. The correlation results show that texture loss has a very weak correlation (r = - 0.048) with SIR. Loss of surface texture is a slow deterioration process and thus it is very difficult to assess visually.

Hence, the result (low correlation with SIR) justifies that 'loss of surface texture' is a non-core criterion for evaluation in subjective survey. From the correlation analysis results and studied pavement distress mechanisms, it can be presumed that there are some interactions between the pavement distresses. The interactions between pavement distresses and interactions between distress and different operating conditions are discussed in the following sections.

4.2.1.2 Multiple Linear Regression Analysis for pavement surface condition (AC Network)

Multiple linear regression is widely used to understand the influence of more than one variable on a single outcome. This method is easy to apply and comprehend. Since the number of available IVs (PCS parameters) is more than one for developing the model, multiple linear regression (MLR) is an expedient deterministic approach for this study. Therefore, to find the combined influence of these four PCS parameters on SIR, stepwise multiple regression analysis is trialed.

Assumptions Testing for Multiple Linear Regression

In this study the AustRoads recommended minimum set of condition parameters (cracking,rutting, texture loss and roughness) are considered ("Pavement management systems : national pavement indicators. - Version details," 2019). For a multiple linear regression model to be correct the dependent variable (DV) should be a linear function of the independent variables (IVs) with no multicollinearity in IVs, values of the residuals should be normally distributed and independent, variance of the residuals should be constant with no influential cases to bias the model.

For the prepared data set, the linearity assumption and the normality assumption for residuals are found to be violated. Hence, different transformations are applied to the DV and the IVs to improve the accuracy of the predictive models. The successful ones include logarithmic (base 10 logarithms) transformation of the IVs. To facilitate such logarithmic transformation all cracking and rutting values were increased by 1 point to remove undefined values. Since there is always some roughness in a pavement surface, it was not necessary to change roughness values before taking their logarithm in the analysis.

The partial regression plots for SIR vs. PCS parameters suggest that SIR is linearly associated with Log_{10}(cracking + 1) and Log_{10} (rutting + 1) when other IVs are statistically controlled (Figures 4.1, 4.2 and 4.3). The partial correlation coefficients for log-transformed cracking and rutting are 0.45 and 0.24 respectively (Figures 4.1 and 4.2).

Figure 4.1 Checking the linearity assumption (Partial Regression Plot) for SIR and transformed PCS parameter (cracking) in the AC network.

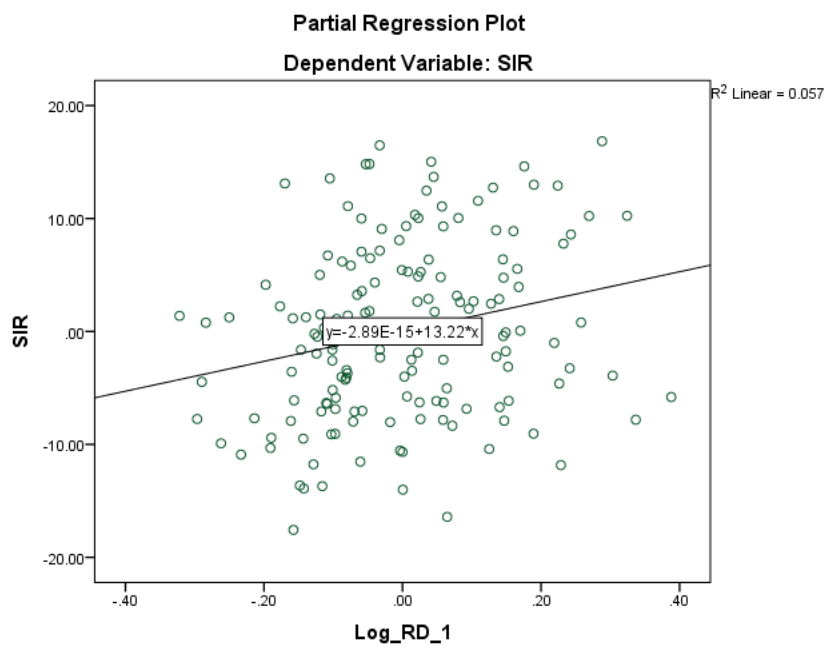


Figure 4.2 Checking the linearity assumption (Partial Regression Plot) for SIR and transformed PCS parameter (rutting) in the AC network.

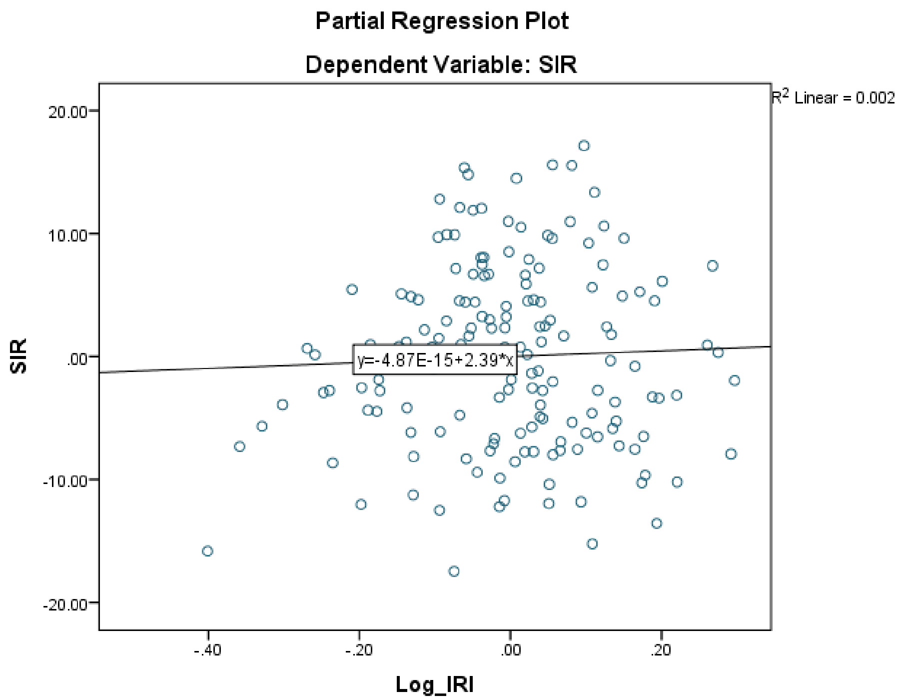


Figure 4.3 Checking the linearity assumption (Partial Regression Plot) for SIR and transformed PCS parameter (roughness) in the AC network.

For roughness, the linearity assumption is violated (Figure 4.3), and the partial correlation coefficient is very low (0.042). Though roughness has a very weak partial correlation with SIR, the zero-order correlation (Pearson's correlation coefficient) is significant. Hence it is included in the analysis to see the combined influence of roughness with cracking and rutting in predicting subjective rating.

Table 4.2 Checking multicollinearity assumption for SIR (DV) and transformed PCS parameters (IVs) of AC network (2011 and 2013) using Pearson's Correlation Coefficient

	SIR	Log_{10}(cracking + 1)	Log_{10}(rutting + 1)	Log_{10}(IRI)
SIR	1.000	0.505	0.345	0.203
Log_{10}(cracking + 1)	0.505	1.000	0.256	0.212
Log_{10}(rutting + 1)	0.345	0.256	1.000	0.301
Log_{10}(IRI)	0.203	0.212	0.301	1.000

It is found (Table 4.2 and Table 4.7) that predictors are not highly correlated with each other (correlation values are less than 0.8, VIF is well below 10, and tolerance is greater than 0.2). Thus, the multicollinearity assumption is also satisfied for the data set.

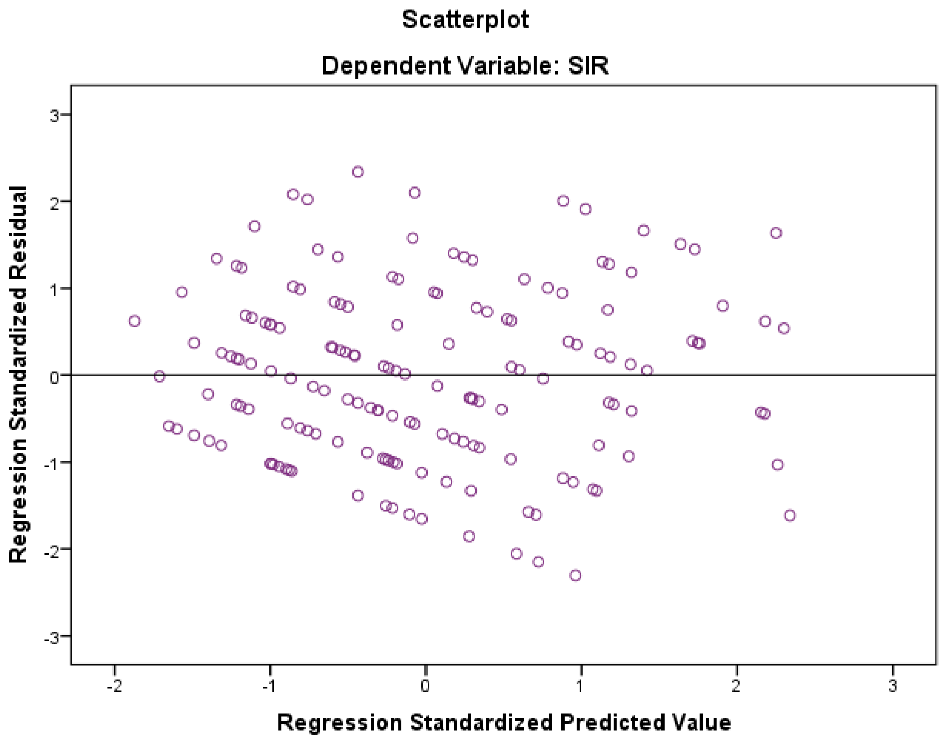


Figure 4.4 Investigating the independence and equal variance of residuals for SIR vs. transformed PCS parameters (IVs) in the AC network.

Figure 4.4 presents the graph of residuals (staderdized) vs. predicted (standardized) values and generally appears more random than funneled. So the independence and equal variance assumptions are satisfied. Further, the histogram (Figure 4.5) and Normal Probability plot (Figure 4.6) of the standardized residuals clearly indicate that the normality assumption is satisfied. The residuals being examined here are for the best fitting linear model for the AC network, which will be discussed in section 4.2.1.4.

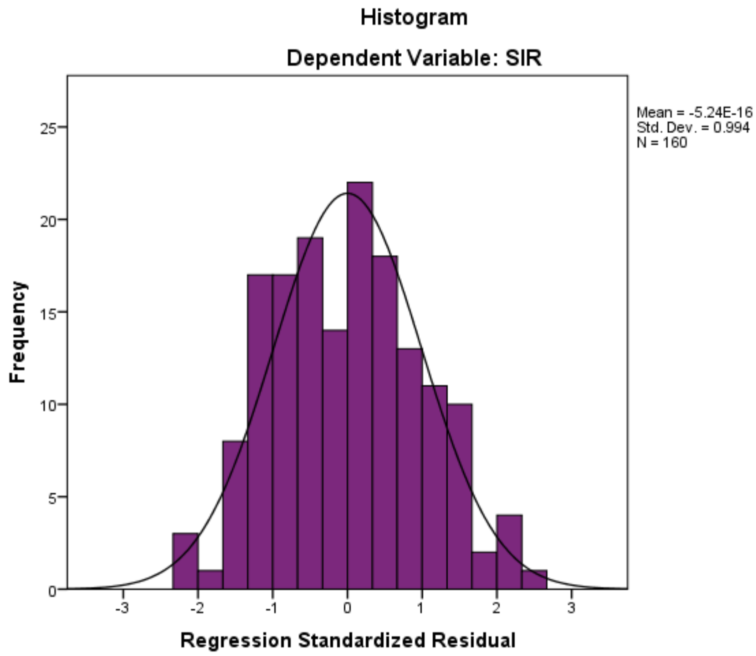


Figure 4.5 Investigating normality assumption for SIR regressed on transformed PCS parameters in the AC network.

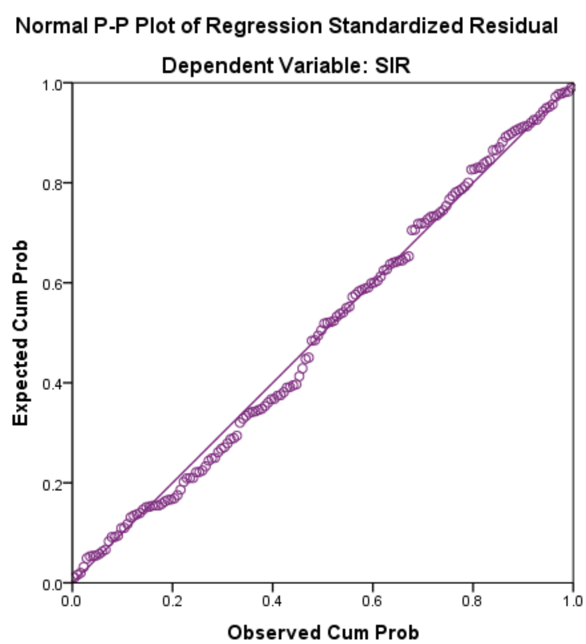


Figure 4.6 Investigating normality assumption for SIR regressed on transformed PCS parameters in the AC network.

Further, in the normal P-P plot (Figure 4.6), the close the dots lie to the diagonal line, the closer to normal the residuals are distributed. Here, the plot of residuals is closer to the diagonal line, and indicating that the normality assumptions are retained for the filtered data in the AC network.

4.2.1.3 Interaction Effects between Pavement Distresses (continuous variables) in AC Network

When the nature or strength of relationship between two variables changes as a function of another variable it is called interaction. In applied researches, interaction terms are often used to explore the magnitude of one independent variable effects the relationship between another independent variable and the outcome variable (Norton, Wang, & Ai, 2004). In the real world, the initiation and progression of pavement surface distresses are stochastic in nature. Hence, these distress mechanisms cannot be predicted precisely. A cause of one distress initiation might be associated with the influence of other distresses. Therefore, interaction effects between pavement distresses in determining subjective rating are investigated with ANOVA tests.

To increase the interpretability of coefficients in an interaction model, it is recommended that the variables used in the regression analysis are to be centered (Afshartous & Preston, 2011). Therefore, all continuous independent variables [Log_{10}(Cracking + 1), Log_{10}(Rutting + 1) and Log_{10}(IRI)] are centered by subtracting corresponding mean values from actual values. Multiple linear regression with interaction effects is performed. The results (Table 4.3 and Table 4.4) indicate that the interaction effects are not statistically significant for any set of independent variables (continuous).

Table 4.3 Multiple Linear Regression with interaction effects (continuous variables) in the AC network

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	12.505	0.633		19.745	0.000	11.254	13.756
	$Log_{10}(cracking + 1)_{centered}$	7.642	1.309	0.421	5.837	0.000	5.055	10.228
	$Log_{10}(rutting + 1)_{centered}$	12.451	4.368	0.207	2.850	.005	3.821	21.080
	$Log_{10}(IRI)_{centered}$	2.736	4.553	0.043	0.601	0.549	-6.258	11.730
	$Log_{10}(cracking + 1)_{centered} \times Log_{10}(rutting + 1)_{centered}$	12.872	8.216	0.121	1.567	0.119	-3.359	29.103
	$Log_{10}(rutting + 1)_{centered} \times Log_{10}(IRI)_{centered}$	- 13.453	27.896	-0.034	-0.482	0.630	-68.563	41.658
	$Log_{10}(cracking + 1)_{centered} \times Log_{10}(IRI)_{centered}$	- 6.524	10.107	-0.048	-0.645	0.520	-26.491	13.444

a. Dependent Variable: SIR

Table 4.4 Multiple Linear Regression with interaction effects (continuous variables) in the AC Network

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	12.360	0.609		20.311	0.000	11.158	13.562
	$Log_{10}(cracking + 1)_{centered}$	7.652	1.285	0.422	5.957	0.000	5.115	10.190
	$Log_{10}(rutting + 1)_{centered}$	12.916	4.179	0.215	3.090	0.002	4.661	21.172
	$Log_{10}(cracking + 1) \times Log_{10}(rutting + 1)_{centered}$	10.342	7.456	0.097	1.387	0.167	-4.386	25.070

a. Dependent Variable: SIR

4.2.1.4 Multiple Linear Regression Model for SIR with main effects (Continuous Variables) in the AC network

Since deterministic models are easy to interpret and our study interest is to predict the SIR value from the collected numerical (continuous) values of PCS parameters, the linear regression model with continuous variables is preferred to categorical independent variables. Since interaction effects with continuous variables are found not to be significant, only the main effects are considered for the analysis. The general expression of the multiple linear model for the AC network is as follows:

$$SIR = a_0 + a_1 Log_{10}(cracking + 1) + a_2 Log_{10}(rutting + 1) + a_3 Log_{10}(IRI) + \varepsilon$$

Here,

SIR = Surface Inspection Rating (SIR), Dependent Variable

$cracking, rutting, IRI$ = Pavement Condition Survey (PCS) parameters, Independent Variables

a_i = regression coefficient; $i = 0,1,2,3$

ε = random error component that reflects the difference between observed data and fitted values

Several trials have been made to develop a best fit multiple linear regression equation. From the stepwise multiple linear regression analysis, it is found that roughness is not a statistically significant predictor and so it is excluded from the models (Tables 4.3 and 4.6). The best fit model (Model 2 in Table 4.7) is found to include $\log_{10}$ (cracking + 1) and $\log_{10}$ (rutting + 1) as statistically significant predictors [Standardized Beta coefficient for $\log_{10}$ (cracking + 1) = 0.446 and for $\log_{10}$ (rutting+1) = 0.231 ($p < 0.05$)]. So, the contribution of cracking is more than rutting in predicting the variation of SIR. The coefficient of determination (R^2) is 0.305 (Table 4.5), meaning that the model explains about 31% of the variation in SIR. By itself, log-transformed rutting accounts for 34.5% of variability in SIR value (Model 2 in Table 4.7). However, once log-transformed cracking is taken into account, log-transformed rutting accounts for 22.3% of the variability in SIR value over and above the variability explained by log-transformed cracking. Log-transformed cracking contributes 43.1% to the variability of SIR value in addition to the variability explained by the log-transformed rutting.

The fitted equation has the following form:

$$SIR = -3.136 + 8.093\, Log_{10}\,(cracking + 1) + 13.862\, Log_{10}\,(rutting + 1)$$

The constant term is not statistically significant, but is included in the best fit equation for reasons of practicality. SIR is dependent on other parameters also, such as maintenance patching, stone loss, potholes, local depression and other factors that are not considered in the analysis. At initial stage with new surfacing or after maintenance treatment, the SIR value is expected to be zero. Here, negative value of the constant can be justified by effects of other distresses that are not considered in developing the best fit equation.

Table 4.5 Model Summary for SIR regressed on transformed PCS parameters (AC network)

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	0.505[a]	0.255	0.250	7.75650	0.255	54.141	1	158	0.000	
2	0.552[b]	0.305	0.296	7.51686	0.050	11.235	1	157	0.001	1.355

a. Predictors: (Constant), $\log_{10}$(cracking + 1)

b. Predictors: (Constant), $\log_{10}$(cracking + 1), $\log_{10}$(rutting + 1)

c. Dependent Variable: SIR

Table 4.6 Summary of Excluded Variables from MLR Model for SIR regressed on transformed PCS parameters (AC network)

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics		
						Tolerance	VIF	Minimum Tolerance
1	Log_{10}(rutting + 1)	0.231[b]	3.352	0.001	0.258	0.935	1.070	0.935
	Log_{10}(IRI)	0.100[b]	1.429	0.155	0.113	0.955	1.047	0.955
2	Log_{10}(IRI)	0.043[c]	0.615	0.539	0.049	0.890	1.124	0.871

a. Dependent Variable: SIR

b. Predictors in the Model: (Constant), Log_{10}(cracking + 1)

c. Predictors in the Model: (Constant), Log_{10}(cracking + 1), Log_{10}(rutting + 1)

Table 4.7 Coefficients of Multiple Linear Regression Model (MLR) for SIR regression on transformed PCS parameters (AC network)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	6.067	1.076		5.637	0.000	3.942	8.193					
	Log_{10}(cracking + 1)	9.163	1.245	0.505	7.358	0.000	6.703	11.622	0.505	0.505	0.505	1.000	1.000
2	(Constant)	-3.136	2.937		-1.068	0.287	-8.938	2.665					
	Log_{10}(cracking + 1)	8.093	1.248	0.446	6.483	0.000	5.627	10.559	0.505	0.460	0.431	0.935	1.070
	Log_{10}(rutting + 1)	13.862	4.136	0.231	3.352	0.001	5.693	22.030	0.345	0.258	0.223	0.935	1.070

a. Dependent Variable: SIR

4.2.1.5 Interaction Effects between Pavement Distresses (categorical independent variables) in AC network

In this section, at first the influences of different distresses on predicting subjective rating are visualized with simple scatter plots and then the statistical significance of the interaction effects between pavement distresses in predicting SIR are tested with Factorial ANOVA. The operating conditions are also considered to understand the effects of age and heavy vehicle traffic volumes (trucks) in measuring the strength of relationship between SIR and automated pavement distresses.

SIR vs. Cracking (AC Network)

To investigate the influence of rutting on cracking in measuring the relationship between SIR and cracking, the conditions of rutting are coded as 'Very Good' when rutting = 0 - 5mm, as 'Good' for rutting = 6 - 9mm and 'Fair' when rutting = 10 - 15mm. In the AC network, there is no pavement segment in our data with poor rutting condition (15 < rutting ≤ 20mm) or very poor condition (rutting > 20mm).

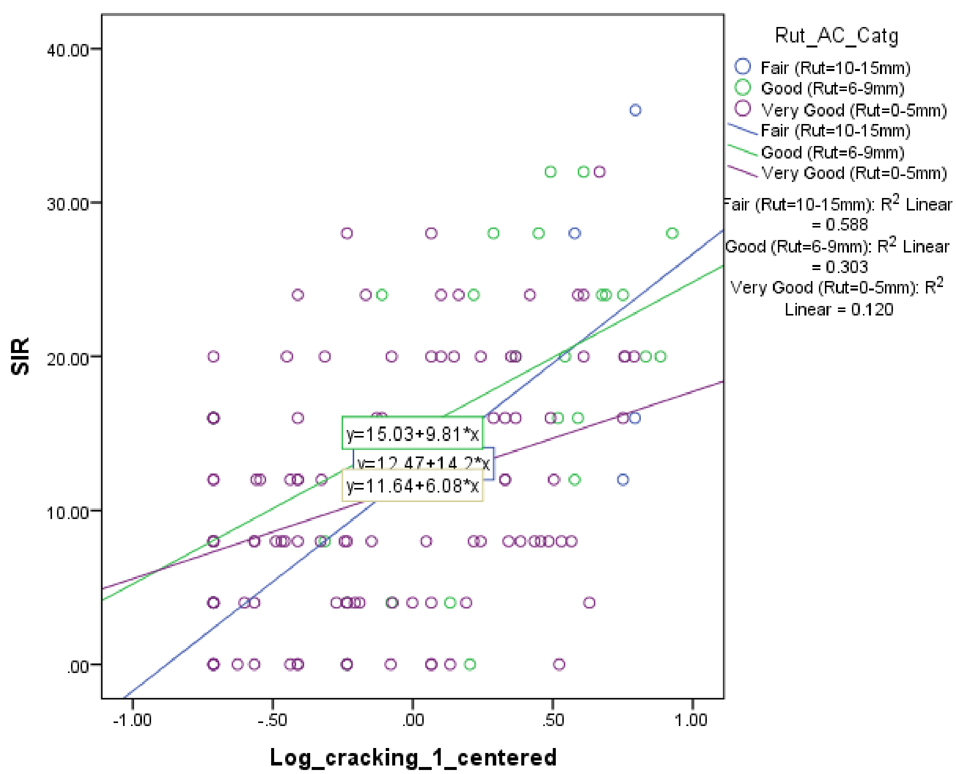


Figure 4.7 Influence of rutting on cracking in predicting subjective rating (SIR) in the AC network.

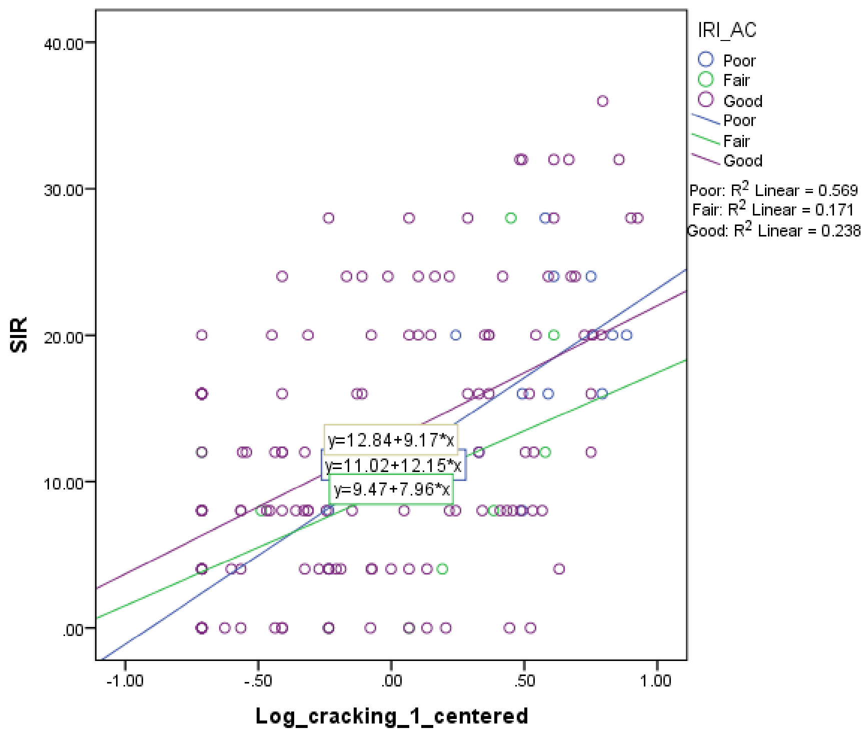


Figure 4.8 Influence of roughness on cracking in predicting subjective rating (SIR) in the AC network.

From Figure 4.7 it is found that the slopes of the fitted lines are different for the three categories of rutting, indicating possible interaction between cracking and rutting. The coefficient of determination is greater ($R^2 = 0.588$) in predicting SIR from automated cracking for 'Fair' condition of rutting than for 'Good' and 'Very Good' conditions ($R^2 = 0.303$ and 0.12).

Therefore, these results indicate that for the data, 59% of the variation in SIR is predicted by automated cracking when the pavement section has fair rutting condition and 30% of variation can be explained in the case of good rutting condition, but only 12% for 'Very Good' condition. This seems right, because the influence of rutting on cracking is greater when road conditions are deteriorating.

Further, Figure 4.8 illustrates that though the difference of the slopes in the fitted lines is not very high, the coefficients of determination indicate that roughness has an influence on the relationship of cracking with SIR. The results show that 57% of the variation in subjective rating (SIR) can be explained by automated cracking data when roughness is in poor condition (IRI > 4.2 m/km, coded as 'Poor'), 17% of the variation can be explained when roughness is in fair condition (IRI = 3.4 - 4.2m/km, coded as 'Fair') and 24% of the variation can be explained for good condition (IRI = 0 - 3.4m/km, coded as 'Good'). Hence, these results indicate that roughness has an influence in measuring the strength of relationship between cracking and

SIR. However, the ANOVA tests indicate that the interaction between cracking and roughness in determining SIR is not statistically significant (Appendix A).

SIR vs. Rutting (AC Network)

The simple scatterplots (Figures 4.9 and 4.10) reveal that the strength of relationship between SIR and rutting also changes with the influence of cracking and roughness. Here, cracking is grouped as 'Good' condition when the area affected by cracking < 10% and 'Poor' when the area affected by cracking ≥ 10%. Since the slopes of the lines of best fit are different, it seems that rutting values are dependent on cracking condition to some extent in predicting SIR, which is a measure of overall condition of a pavement surface.

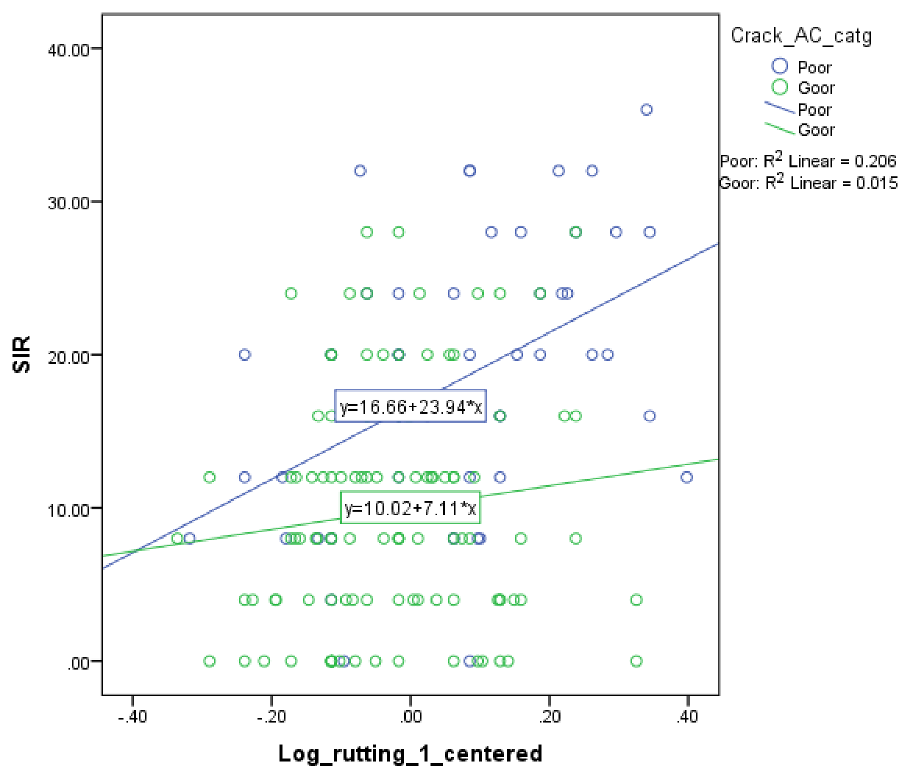


Figure 4.9 Influence of cracking on rutting in predicting subjective rating (SIR) in the AC network.

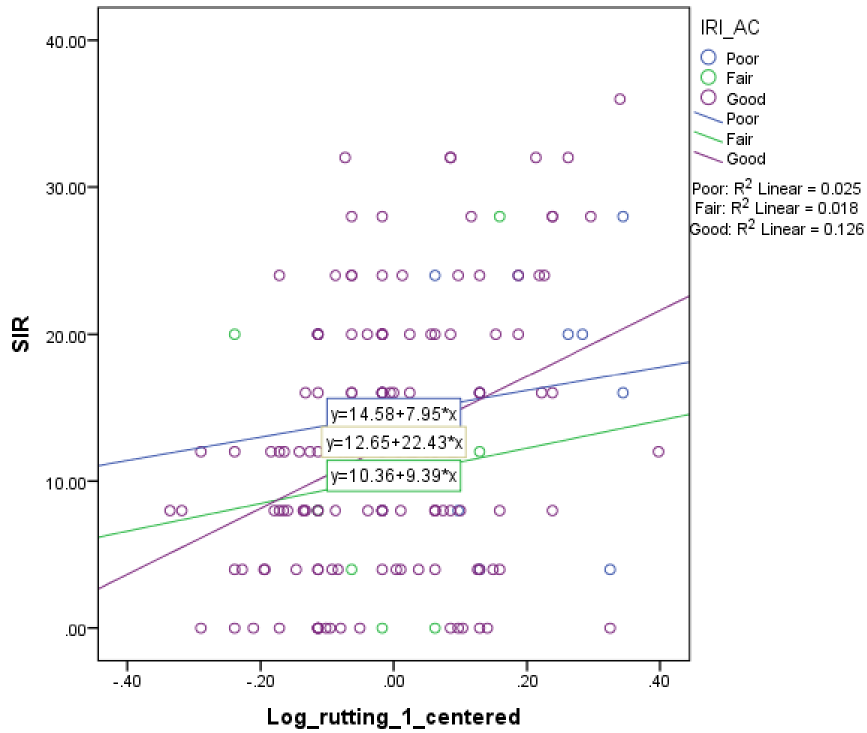


Figure 4.10 Influence of roughness on rutting in predicting SIR in the AC network.

The coefficient of determination is higher in the case of poor cracking condition. In real life, when cracking condition is poor (wider crack) the water penetrates the pavement layers and decreases the shear strength of materials, causing disintegration of materials. Repeated high traffic load reduces the bending stiffness of aggregates and causes dislocation of materials, which manifests as rutting in the pavement. Therefore, it makes sense that poor cracking condition influences the relationship of rutting with SIR. The Two-way ANOVA Test shows that the interaction effect between categorical cracking and rutting is statistically significant (Table 4.9). Although it seems from Figure 4.10 that roughness and rutting interact in predicting SIR, the interaction is found not to be statistically significant (Appendix A).

4.2.1.6 Two-way ANOVA Test for interaction effects (AC Network)

The interaction effects between cracking and rutting (as categorical variables) are found to be significant in predicting SIR. The Levene's Test statistic ($p > 0.05$) shows (Table 4.8) that equal variances can be assumed. Factorial ANOVA reveals (Table 4.9) that there are significant differences in mean SIR across the different conditions of cracking, $F(1,138) = 25.608$, $p < 0.05$. The relationship between mean SIR and cracking is different for different rutting conditions. Further, the results show that there are significant differences in mean SIR across the different rutting conditions, $F(2,138) = 3.691$, $p < 0.05$. In addition, there is a statistically significant interaction between cracking and rutting, on determining the SIR value, F (2,138) = 4.282, $p < 0.05$. Thus, the results from the two-way ANOVA test (Table 4.9) show that the interaction effect between cracking and rutting is statistically significant at the 5% level.

Table 4.8 Levene's Test of equality of error variance for cracking and rutting in the AC network

Dependent Variable: SIR

F	df1	df2	Sig.
1.818	5	138	0.113

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

a. Design: Intercept + cracking + rutting + cracking * rutting

Table 4.9 Interaction effects (Tests of Between-Subjects Effects) between cracking and rutting in the AC network

Dependent Variable: SIR

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	2785.432[a]	5	557.086	9.700	0.000
Intercept	7380.594	1	7380.594	128.511	0.000
cracking	1470.724	1	1470.724	25.608	0.000
rutting	423.942	2	211.971	3.691	0.027
cracking * rutting	491.831	2	245.916	4.282	0.016
Error	7925.568	138	57.432		
Total	32912.000	144			
Corrected Total	10711.000	143			

a. R Squared = 0.260 (Adjusted R Squared = 0.233)

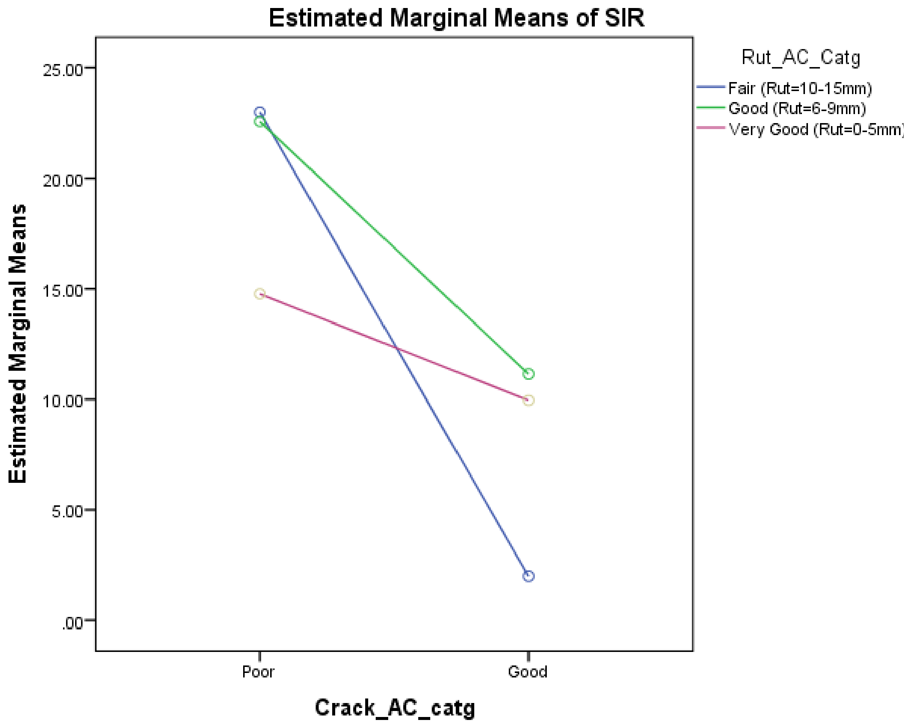


Figure 4.11 Comparison of means in predicting SIR from cracking showing interaction effects between cracking and rutting in the AC network.

The interaction plot (Figure 4.11) clearly reveals a difference between ‘Fair’ and ‘Very Good’ rutting condition in the way that cracking affects SIR, since the lines are not parallel and intersect each other. The difference between the mean SIR on the cracking is much wider for ‘Fair’ rutting condition than for ‘Very Good’ and ‘Good’ conditions. Outcomes from previous studies indicate that due to the stresses generated for rutting geometry, the greater the existing rut severity is in pavement, the more expected is top-down cracking in the pavement (De Freitas, Pereira, Picado–Santos, & Papagiannakis, 2005; G. Wang, Roque, & Morian, 2012). In this study, most of the pavement segments are in “Very Good’, ‘Good’ and ‘Fair’ condition for the asphalt surfacing network. The number of pavement segments with poor rutting condition (rutting = 15 - 20mm) or very poor condition (rutting > 20mm) was very few and these are deemed as outliers in the analysis. Hence, the comparison is made based on ‘Very Good’, ‘Good’ or ‘Fair’ conditions. The comparison of means supports the findings from previous studies.

4.2.1.7 Interaction between pavement distress and operating conditions (AC Network)

SIR vs. Cracking

The simple scatter plot (Figure 4.12) indicates that age may influence the strength of the relationship between cracking and SIR. Almost 30% of the variation in SIR in the data is explained by cracking when pavement age is greater than seven years. The slope is greater for age > 7 years. Thus, the variation of means of SIR is greater for age > 7 years. However, the results from the two-way ANOVA test show (Appendix A) that the interaction effect between cracking and age is not statistically significant ($p > 0.05$).

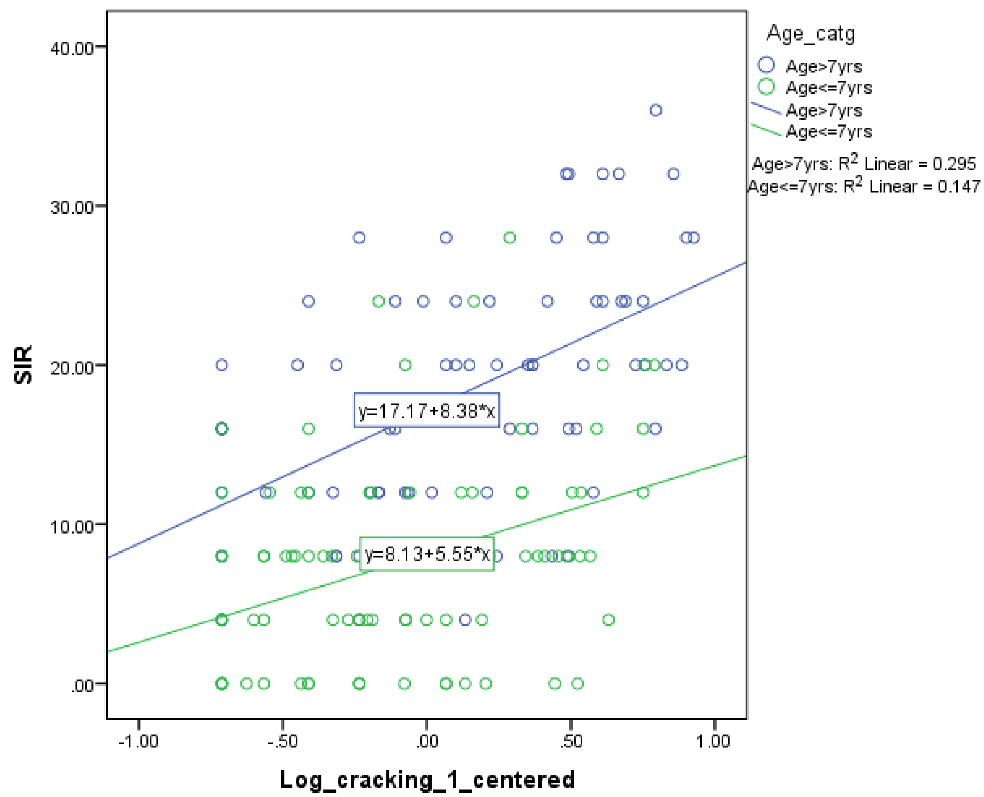


Figure 4.12 Influence of operating condition (age) on cracking in predicting SIR in the AC network.

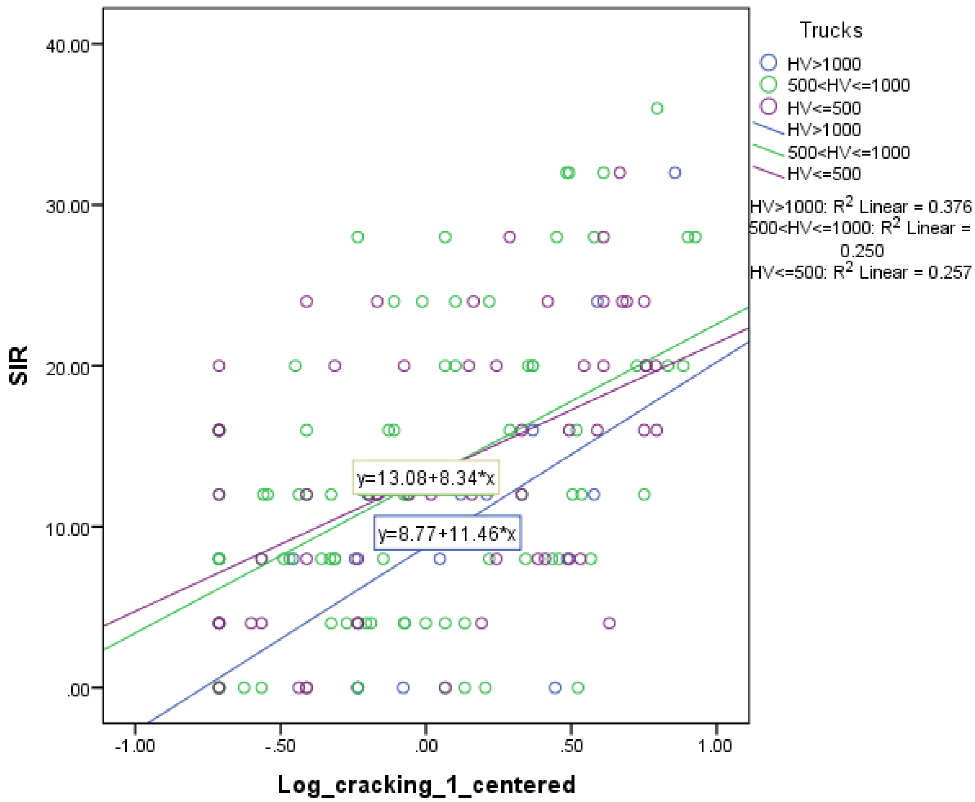


Figure 4.13 Influence of operating condition (heavy vehicle traffic volume) on cracking in predicting SIR in the AC network.

In the asphalt surfacing network, usually the traffic volume is high and thus the heavy traffic volume is grouped into three categories. The slope for heavy vehicle traffic volume > 1000 is greater than for the other two categories with less traffic. So, there is an influence of heavy traffic volume on cracking when the traffic volume > 1000. The slopes for traffic volume ≤ 500 and 501-1000 are similar. Almost 38% of the variation in SIR can be explained by cracking at heavy vehicle traffic volume > 1000. The plot (Figure 4.13) indicates that when the commercial traffic volume is high, it has an influence in determining the strength of association between subjective rating and objective cracking. To find whether the interaction effects are statistically significant, univariate analysis of variance (factorial ANOVA) is performed and the interaction effect is found not to be statistically significant for truck volume (Appendix A).

SIR vs. Rutting

The graph (Figure 4.14) indicates that the slope is different depending on the age of the pavement but the R^2 is very small for each age group. Moreover, ANOVA test results indicate that interaction between rutting and age is not statistically significant when measuring the strength of the relationship between SIR and rutting (Appendix A).

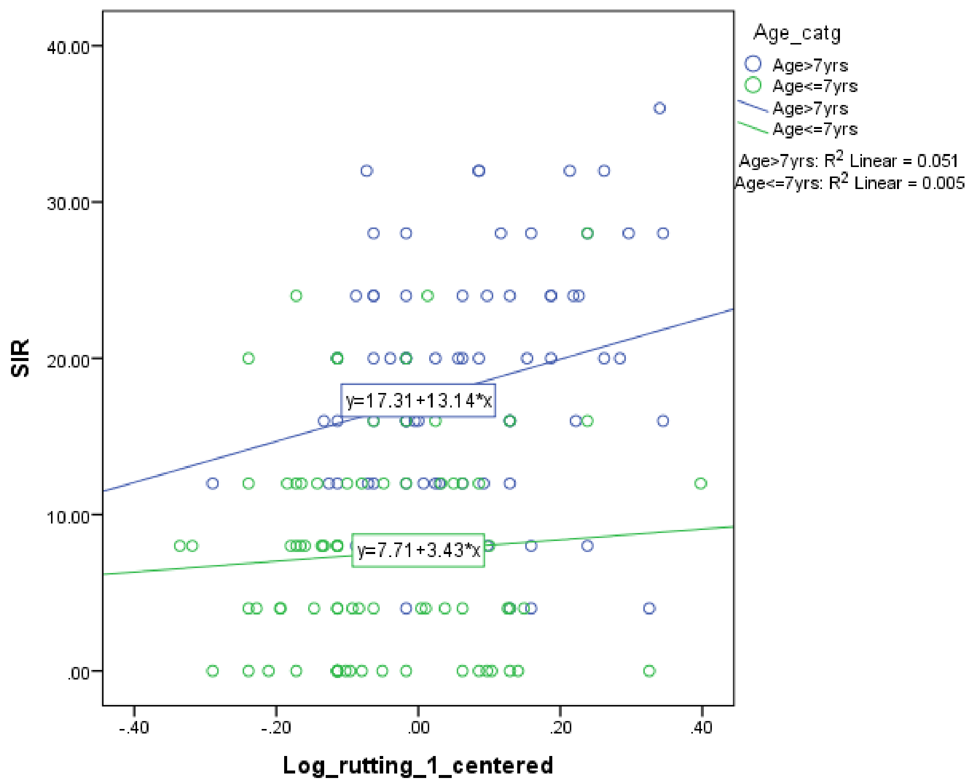


Figure 4.14 Influence of operating condition (age) on rutting in predicting SIR in the AC network.

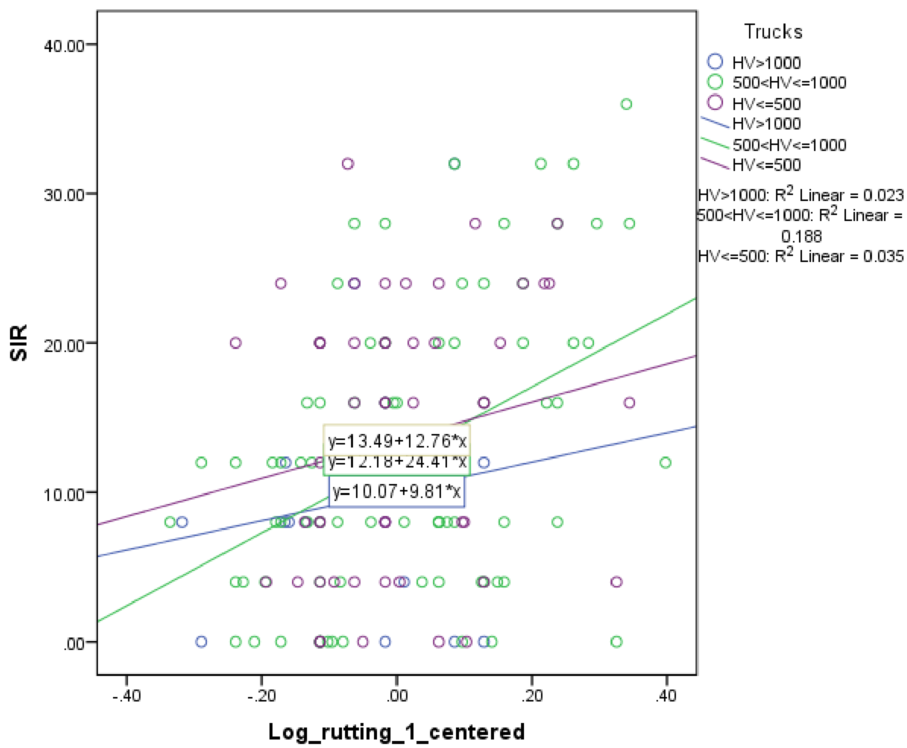


Figure 4.15 Influence of operating condition (heavy vehicle traffic volume) on rutting in predicting SIR in the AC network.

For heavy vehicle traffic volume below 500 or above 1000, there is no influence of traffic because the difference in the variation of SIR that can be explained from rutting is negligible (Figure 4.15). For Heavy vehicle volume between these values, 19% of variation in the SIR data is explained by rutting. Though rutting is usually caused by repeated and high traffic loadings in asphalt surfacing, the non-traffic associated variables like consolidation of underlying materials or expansion of subgrade soil may have impacts on the progression of rutting for the pavements with heavy vehicle traffic volume more than 1000. Further ANOVA results show that the interaction effect between rutting and heavy traffic volume in predicting SIR is not statistically significant (Appendix A).

4.2.3 SS Network

From the initial analysis it is found (Table 4.10) that the correlations of subjective SIR with automated cracking (Pearson's correlation coefficient, r = 0.444) and texture loss (r = - 0.292) are significant at the 0.01 level. From the correlation analysis and studied pavement surface distress mechanisms, it can be assumed that there may be some interactions between the pavement distresses. The interactions between pavement distresses and interactions between distress and different operating conditions (age and heavy vehicle traffic volume) are discussed in the following sections.

Table 4.10 Correlation analysis (Pearson's Correlation Coefficients) of SIR and PCS parameters (SS network)

	SIR	cracking	rutting	IRI	texture Loss
SIR	1	0.444**	-0.002	-0.037	-0.292**
cracking	0.444**	1	0.128	0.232**	-0.071
rutting	-0.002	0.128	1	0.379**	0.042
IRI	-0.037	0.232**	0.379**	1	0.180*
texture loss	-0.292**	-0.071	0.042	0.180*	1

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

In practice, the correlation between texture loss and surface inspection rating should be positive. The negative significant correlation result between SIR and texture loss indicates an unrealistic relationship. The automated pavement condition survey data for cracking, rutting and texture loss are tested to validate the corresponding subjective ratings of the distresses from surface inspection rating survey using logistic regression analysis (Chapter 5; Sections 5.6, 5.7 and 5.8). The detailed analysis process of probabilistic logistic regression is described in Chapter 5. From the logistic regression, it is found that automated cracking data can be validated with subjective cracking (Chapter 5) but rutting and texture loss data cannot be validated. Therefore, surface texture loss is considered unreliable and excluded from the analysis in developing a deterministic model.

The correlation coefficients for SIR with rutting and roughness are very low (r = - 0.002 and - 0.037) and not statistically significant. Rutting gradually develops in asphalt pavements with the traffic growth (Alavi et al., 2011). The subjective deformation ratings judged by the assessors may possibly more associated with local depressions than rutting in the subjective survey. The subjective Surface Inspection Rating Procedure (SIRP) is limited with respect to factors such as roughness, skid resistance, pavement structural adequacy and other environmental aspects (VicRoads, 2004). Hence, the weak correlation between SIR and roughness makes sense. Therefore, rutting and roughness are also excluded from the analysis, along with texture loss.

4.2.3.1 Simple Linear Regression analysis (SS Network)

After several trials of different transformations of variables, the logarithmic (base 10 Logarithm) transformation of cracking with an increase of 1 point met the linearity assumption. The linear trend between SIR and Log_{10} (cracking+1) is seen in Figure 4.16. The correlation between the two variables is 0.485 (Figure 4.16, Tables 4.11 and 4.12).

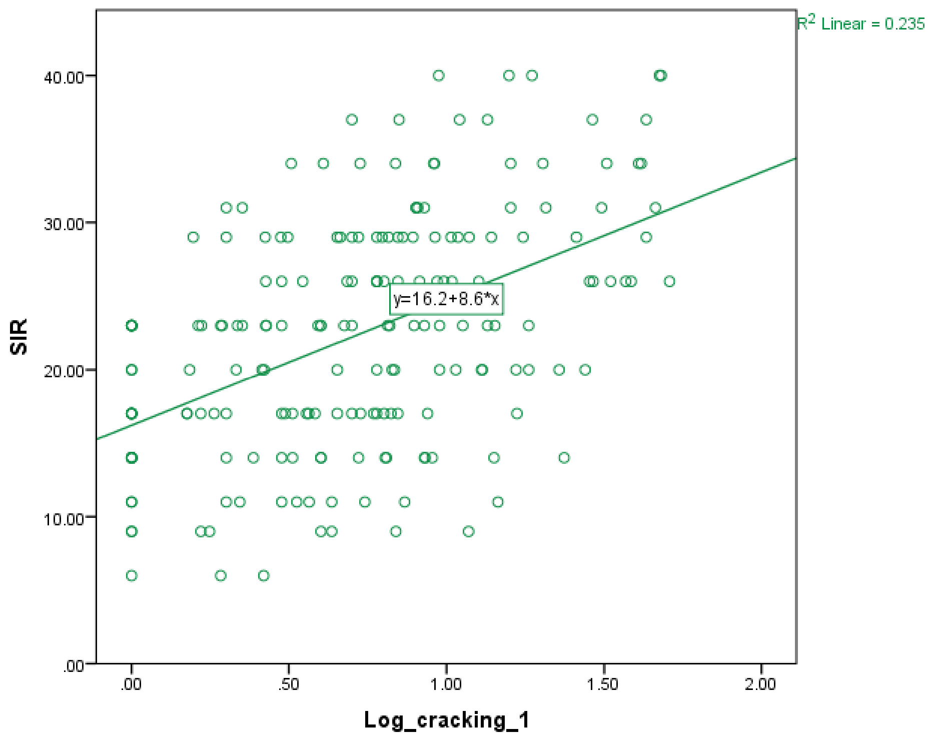


Figure 4.16 Checking linearity assumption for SIR (DV) and Log_{10}(cracking + 1) in the SS network.

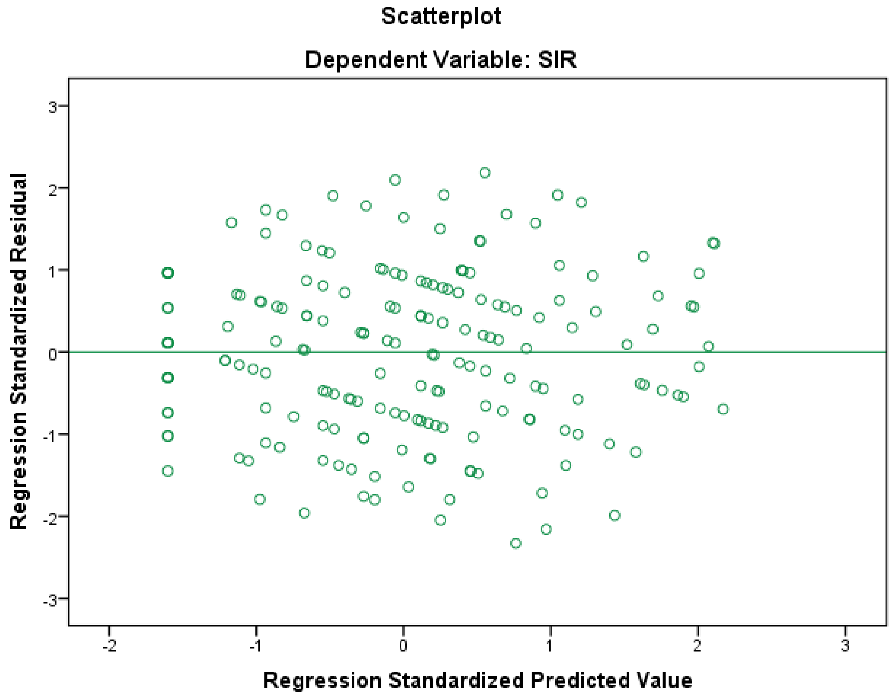


Figure 4.17 Checking the independence of residuals for SIR regressed on Log_{10} (cracking + 1) in the SS network.

In this section the investigations into residuals being independent and normally distributed are for the best fitting linear model for the SS network which will be discussed in the following section (Section 4.2.3.2). Figure 4.17 presents the graph of residual (standardized) vs. predicted (standardized) values and generally appears more random than funneled. So the independence and equal variance assumptions are satisfied. Further, the histogram (Figures 4.18) and Normal Probability plot (Figure 4.19) of the residuals indicate that the normality assumption is satisfied.

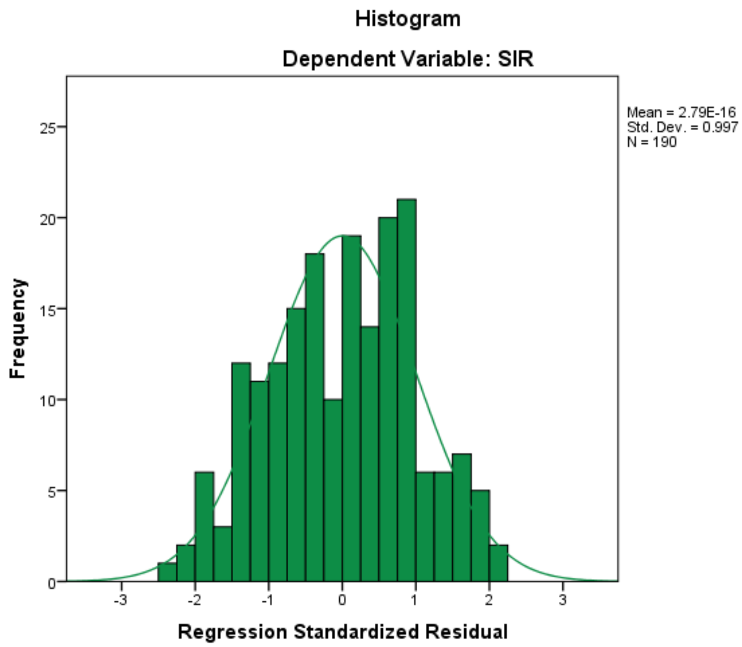


Figure 4.18 Investigating normality assumption for SIR regressed on Log_{10}(cracking + 1) in the SS network.

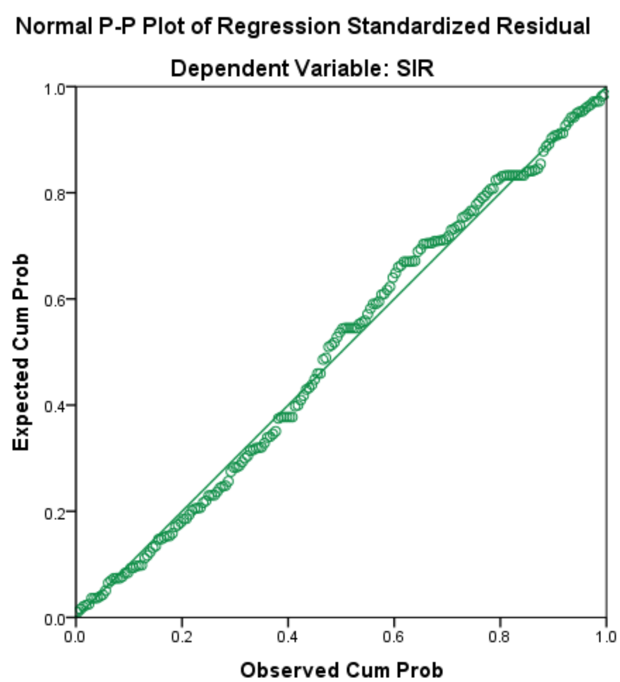


Figure 4.19 Investigating normality assumption for SIR regressed on Log_{10}(cracking + 1) in the SS network.

4.2.3.2 Linear Regression Model for SIR with main effects (Continuous Variables) in the SS Network

Since only log transformed cracking data is found to satisfy the assumption testing of linear regression, the general expression of the simple linear model for the SS network becomes:

$$SIR = a_0 + a_1 Log_{10}(cracking + 1) + \varepsilon$$

Here,

SIR = Surface Inspection Rating, Dependent Variable

$cracking$ = Pavement Condition Survey (PCS) parameter, Independent Variable

a_i = regression coefficient

ε = random error component that reflects the difference between observed data and fitted values

The predicted regression equation for the relationship between SIR and cracking in the SS network is as below and explains about 24% (coefficient of determination, $R^2 = 0.235$) of the variation in SIR (Table 4.11 and Table 4.12).

$$SIR = 16.202 + 8.603 \times Log_{10}\,(cracking + 1)$$

Table 4.11 Summary for Linear Model of SIR in terms of PCS parameters for the SS network

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	0.485[a]	0.235	0.231	7.04880	0.235	57.684	1	188	0.000	1.237

a. Predictors: (Constant), $\log_{10}$(cracking + 1)

b. Dependent Variable: SIR(Porras-Alvarado et al., 2014)

Table 4.12 Parameter Estimates for Linear Model of SIR in terms of PCS parameters for the SS network

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
	B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1. (Constant)	16.202	0.968		16.731	0.000	14.291	18.112					
Log_{10}(cracking + 1)	8.603	1.133	0.485	7.595	0.000	6.369	10.838	0.485	0.485	0.485	1.000	1.000

a. Dependent Variable: SIR

4.2.3.3 Interaction between pavement distress (cracking) and operating conditions in predicting SIR for SS Network

SIR vs. Cracking

The simple scatter plot (Figure 4.20) demonstrates that age has not much influence in determining the strength of relationship between cracking and SIR. Almost 30% of the variation in SIR can be explained by cracking when pavement age is more than 7 years, which is only 3% greater than for pavement age ≤ 7 years. From the different slopes for three categories of heavy vehicle traffic volume, it might be assumed that there is some influence of heavy truck volume (Figure 4.21) on the relationship between cracking and pavement surface condition rating, but factorial ANOVA testing shows that the interaction of cracking with age and truck volume is not statistically significant (Appendix A).

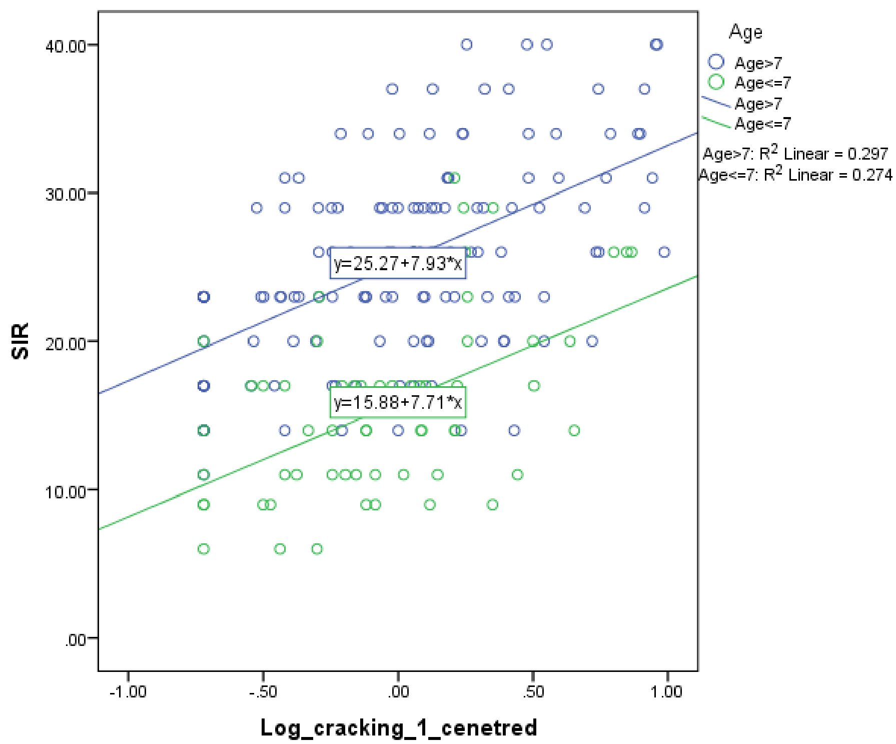


Figure 4.20 Influence of operating condition (age) on cracking in predicting SIR in the SS network.

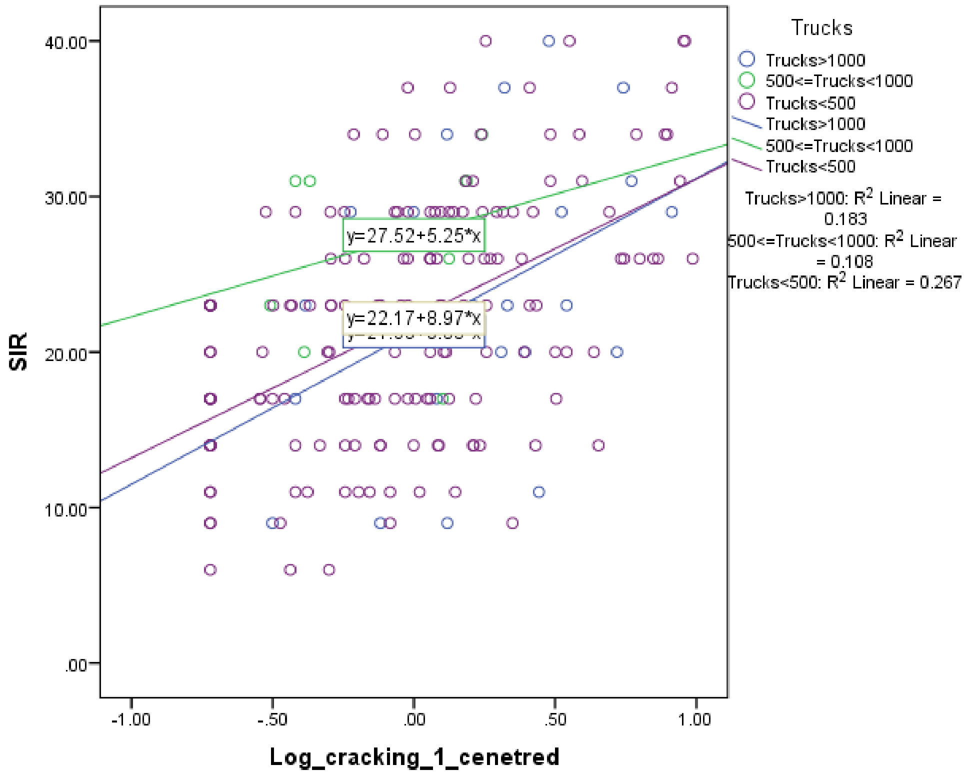


Figure 4.21 Influence of operating condition (heavy vehicle traffic volume) on cracking in predicting SIR in the SS network.

4.2.3.4 One-way ANOVA Test for SIR with cracking (categorical IV)

One-way ANOVA testing reveals (Table 4.13) that there are significant differences in mean SIR across the different conditions of cracking, $F(1,184) = 25.302$, $p < 0.05$. The result indicates that mean SIR is different (Figure 4.22) for two different cracking groups (Good and Poor) as was expected. But the coefficient of determination for the model from categorical cracking ($R^2 = 0.121$) is lower than for the continuous one ($R^2 = 0.235$).

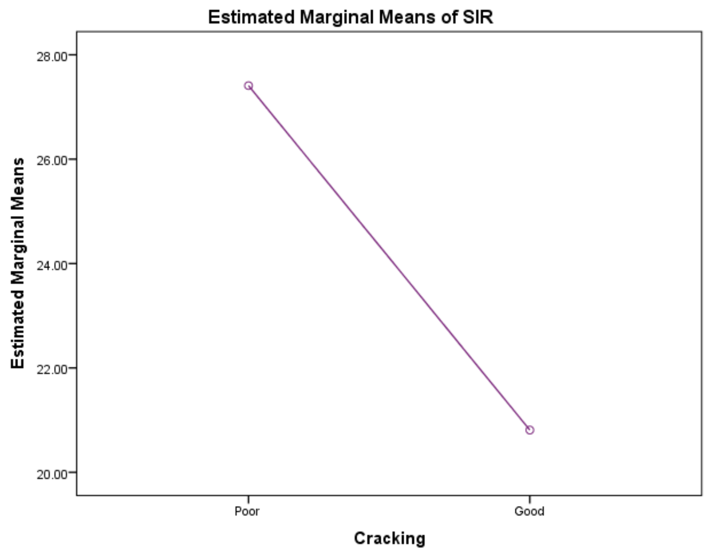


Figure 4.22 Comparison of means in predicting SIR from PCS cracking in the SS network.

Table 4.13 Main effects (Tests of Between-Subjects Effects) of cracking in Predicting SIR in the SS network

Dependent Variable: SIR

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	1462.901[a]	1	1462.901	25.302	0.000
Intercept	78102.256	1	78102.256	1350.831	0.000
cracking	1462.901	1	1462.901	25.302	0.000
Error	10638.503	184	57.818		
Total	105187.000	186			
Corrected Total	12101.403	185			

a. R Squared = 0.121 (Adjusted R Squared = 0.116)

4.3 Summary

In this chapter, the development of a multiple linear regression model (AC network) and a simple linear regression model (SS network) for predicting surface inspection rating (SIR) from objective pavement condition survey (PCS) parameters (for 2011 and 2013) is documented, with assumption testing. Initially, correlation analyses between SIR and PCS parameters are performed. After that, interaction effects of pavement surface distresses are investigated. Pavement operating conditions (age and heavy traffic volume) are also considered, to investigate the influence of pavement distresses on subjective rating. Various transformations of DV (SIR) and IVs (PCS Parameters) were explored in search of the best model. Lastly, the results for the best-fitting models based on available data for asphalt surfacing and sprayed seal surfacing networks in the MSE region of Victoria are presented.

Correlation Analysis

The initial correlation analysis (Pearson's correlation coefficient, r) revealed that the correlations of subjective SIR with objective cracking ($r = 0.53$), rutting ($r = 0.34$) and IRI ($r = 0.177$) are statistically significant in the AC network. The correlation results show that texture loss has a very weak correlation ($r = -0.048$) with SIR. Further, the results from the SS network show that the correlations of subjective SIR with automated cracking ($r = 0.444$) and texture loss ($r = - 0.292$) are statistically significant. However, the negative value for texture loss indicates unreliable objective texture loss data because SIR value will be high for poor condition of surface texture. Since loss of pavement surface texture is a gradual deterioration process, it is hard to evaluate texture loss visually. Moreover, the objective texture loss data cannot be validated (Chapter 5) with subjective texture loss rating for any of the network and so is excluded from the analysis.

For the SS network, the correlation coefficients for SIR with rutting and roughness are very low ($r = - 0.002$ and $- 0.037$) and not statistically significant. As discussed in Chapter 2, rutting initiates and progresses in asphalt pavements with growing traffic load. The SS network is usually designed for low traffic volume. It is assumed that rutting is not correlated with SIR due to the presence of local depressions predominantly over longitudinal depression (rutting) in the SS network. The subjective rating of deformation given by the evaluators may perhaps more associated with local depressions than longitudinal depression (rutting).

Further, the subjective rating survey does not consider roughness and other factors. Hence, the weak correlation between SIR and roughness is understandable. Therefore, rutting and roughness are also excluded from the analysis, along with texture loss in the SS network. Only cracking is considered as the independent variable.

Interaction Effects between Pavement Distresses

The strength of relationship between SIR and objective pavement distresses may change as a function of some other pavement distress. The distresses' initiation and progression are stochastic in nature, and the reason for one distress initiation may be related to the influence of other distress or distresses. To investigate the interaction effects, objective cracking data is coded as 'Good' when cracking % area affected < 10% and 'Poor' for cracking % area affected ≥ 10%. Further, rutting data is coded as 'Very Good" when rutting = 0 - 5mm, as 'Good' for rutting = 6 - 9mm and 'Fair' when rutting = 10 - 15mm. In the AC network, there is no pavement segment in the data set with poor rutting condition (15 < rutting ≤ 20mm) or very poor condition (rutting > 20mm). In the subjective rating, roughness is not considered to determine SIR. Objective roughness is coded as 'Good' (IRI = 0 - 3.4m/km), 'Fair' (IRI = 3.4 - 4.2m/km) and 'Poor' (IRI > 4.2m/km).

The factorial ANOVA results revealed that there are statistically significant differences in mean SIR across the different conditions of cracking and rutting [$F_{\mathbf{cracking}}$ (1,138) = 25.608, $p < 0.05$ and $F_{\mathbf{rutting}}$ (2,138) = 3.691, $p < 0.05$] in the AC network. Further, two-way ANOVA indicates that the interaction effect between objectively collected cracking and rutting in determining subjective rating is statistically significant [F (2,138) = 4.282, p <0 .05] for the AC network. The coefficient of determination is found to be 0.26. So, 26% of the variation in SIR is explained by categorical cracking and rutting with interaction effects between these two pavement distresses.

Roughness has no statistically significant interactions with cracking and rutting in predicting SIR. As mentioned in this Chapter (Section 4.2.3), subjective ratings in Victoria do not consider riding quality or skid resistance, which are both related to roughness. This explains why roughness is not a statistically significant predictor of subjective SIR.

Interaction Effects between Pavement Distress and Operating Conditions

Since the desired service life of asphalt surfacing is 7 to 25 years and for sprayed seal surfacing 5 to 15 years, the pavement service life age is categorized into two groups (age ≤ 7years and age > 7years). Though the slope is little different for the two groups of age in predicting SIR from automated cracking and rutting for the AC network, the two-way ANOVA test shows that the interaction effects are not statistically significant for different age groups for AC. The slope difference in simple scatter plots for different age groups are found to be negligible for the SS network and the ANOVA result shows that the interaction is not statistically significant.

In addition, the simple scatter plots indicate that the heavy traffic volume grouping has an influence in determining the strength of relationship between visual rating and automated distresses, but the interaction effect is found not to be statistically significant from two way ANOVA tests for both AC and SS networks. In this study, age and heavy vehicle traffic volume are not used as predictors in developing the models for SIR as they are associated with the pavement deterioration process and thus embodied in the pavement surface distresses used as independent variables in developing the models.

AC Network (MLR)

Since linear regression with metric variables is the most precise and simplest way to estimate the outcome variable, linear regression with continuous variables is trialed to get the best fit model. The best regression models are found with the application of a logarithmic transformation (base 10 Logarithm) to IVs. From stepwise multiple linear regression analysis, it is found that PCS cracking and rutting are two statistically significant ($p < 0.05$) predictors [Standardized Beta coefficient for $\text{Log}_{10}(\text{cracking} + 1) = 0.446$ and $\text{Log}_{10}(\text{rutting} + 1) = 0.231$] for the AC network. PCS roughness [$\text{Log}_{10}(\text{IRI})$] is found not to be statistically significant in explaining the variation of SIR. This indicates that cracking and rutting make significant contributions to estimating SIR value. Coefficient of determination (R^2) is 0.305 meaning that about 31% of the variation in SIR for the AC network is explained by the model.

SS Network (SLR)

For the SS network, only PCS cracking [$\text{Log}_{10}(\text{cracking} + 1)$] is found to be statistically significant ($p < 0.05$) with Standardized Beta coefficient = 0.485. The results indicate that objective cracking contributes significantly to predicting SIR value. In the regression output the coefficient of determination (R^2) is 0.235, so only about 24% of the variation in SIR for the SS network is explained.

Model Evaluation

The developed multiple linear regression model (AC network) and simple linear regression model (SS network) for subjective rating of pavement surface condition as a function of automated pavement condition parameters are found to have poor prediction ability since the coefficients of determination are 31% and 24% for the AC and SS network, respectively. This necessitates finding alternative methods to develop more applicable models. Considering the previous relevant studies, probabilistic logistic regression analysis is trialed to develop the relationship between subjective SIR conditions and objective pavement distresses.

CHAPTER FIVE

PROBABILISTIC MODELS FOR PAVEMENT SURFACE CONDITION

5.1 Introduction

This chapter initially outlines the concepts of probabilistic logistic regression. Automated distress data (cracking, rutting and texture loss) are validated individually with the corresponding subjective rating through logistic regression analysis before developing the models for overall pavement surface condition rating. After that, logistic models for surface inspection rating (SIR) conditions are developed as a function of automated distresses considering two types of category ranks of the SIR for both AC and SS networks. Finally, the developed models are validated by considering the scaled squared of residuals of SIR for each pavement segment.

5.2 Logistic Regression

Linear regression analysis uses least squares deviation criteria to get the best fit model, with the dependent variable (DV) being continuous (interval/ratio). Logit models are used to perform regression with a single categorical DV and various independent variables (IVs). Moreover, logistic regression is more flexible with data distribution because it does not assume a linear relationship between untransformed DV and IVs. Here, the parameter estimates of the models are determined by maximum likelihood estimation (Fan, Kane, & Haile, 2015).

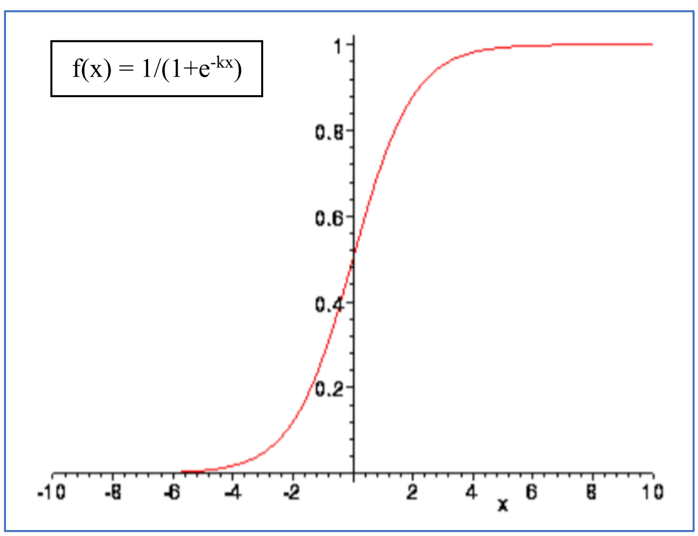


Figure 5.1 The standard logistic function f(x) ϵ (0, 1) for all value of x (Bonnell, 2011).

Since the pavement deterioration process is the combined effect of known factors and unknown latent causes, the pavement condition assessment needs to capture the uncertain stochastic nature of the pavement. Therefore, logistic regression analysis is useful to present the pavement deterioration process by considering the DV as a stochastic event. The logistic regression approach also solves the difficulties with simple linear regression analysis in modeling the situation where categories of outcome variables are of interest.

In logistic regression the DV describes the outcome of this stochastic event with function of cumulative probabilities ranging from 0 to 1 (Figure 5.1). Here the best fit model is established using the maximum likelihood method. In this type of model, natural logarithm of odds considering a ranked outcome variable is expressed in the form of a linear function of IVs (Erkan & Yildiz, 2014).

In logistic regression analysis, the logit or natural logarithm of the odds acts as dependent variable. $Logit\ (p)$ is defined as the logarithm (usually with base e) of odds or 'likelihood'. This likelihood or probability is for any event occurring is compared to that event not occurring. Here the likelihood ration of the DV is considered as 1. If p is the probability, then $p/(1-p)$ is the corresponding odds. Thus, the form of the logistic regression equation is:

$$Logit\ [p(x)] = \ log_e \left[\frac{p(x)}{1-p(x)}\right] = \ b_0 + b_1 x_1 + b_2 x_2 + \cdots + b_n x_n$$

Where,

$b_0\ $ = constant

$b_i\ $ = regression coefficient; $i = 1, 2, 3, \ldots\ldots, n$

x_i = independent variable; $i = 1, 2, 3, \ldots\ldots, n$

The best fit model is achieved by finding the fitted regression coefficient values which maximize the probability of obtaining the observed results, using maximum likelihood method. Here, negative value of logit indicates that probability for DV category is smaller than 0.5.

There are generally three types of logit models:

1. Binary Logistic Model: applied when DV is dichotomous (e.g. Yes vs. No).

2. Ordinal Logistic Model: used in the case where ordering (e.g. very low, low, medium, high, and very high) of DV categories is present.

3. Multinomial (Polytomous) Logistic Model: like ordinal logistic regression but assumes no "ranking ordering" of categorical outcomes.

5.3 Ordinal Logistic Regression

In general, the proportional odds method is used to determine the cumulative probability of any category to be at or below a specific category of the outcome variable in ordinal logistic regression analysis. Here, the influence of each explanatory variable is presumed to be the same within different categories of the ordinal outcome variable. Therefore, the effect of each predictor on the odds to be at or below a particular category of DV, remains the same within the model (X. Liu & Koirala, 2012).

Thus, in ordinal logistic regression the underlying assumption is that the slope parameters must not change for different categories; i.e. correlation between dependent variable and independent variable does not vary for DV categories (Erkan & Yildiz, 2014). Therefore, the values of $b_1, b_2, \dots, b_i$ remain constant across DV categories i.e. DV categories are parallel to each other. The second assumption is that the intercepts will differ only. So, the b_0 values will be different for each category.

5.4 Test of Parallel Lines

The assumption of unchanged regression coefficient or proportional odds or parallel lines for ordinal regression is tested for all five categories of DV. The aim of this test is to compare the improvement in the general model for model fit from the null model. If the Chi square statistic is significant ($p < 0.05$), it means that there is sufficient evidence to reject the parallelism assumption i.e. unvarying regression coefficient for all logistic equations. If this assumption of same slope is rejected, then multinomial regression should be trialed as it estimates different coefficients (slopes) for each category.

5.5 Multinomial Logistic Regression

Multinomial logistic regression is used when prediction of the probabilities of DV categories are required having no natural order in them for more than one independent variables. Multinomial logistic regression analysis is like ordinal logistic regression analysis but differs as the former assumes that there is no "ranking ordering" is the categorical outcomes.

Being the test of parallel lines is violated for ordinal logits or the dependent variable is not in ordered form, multinomial logistic models are needed to achieve acceptable results. This approach makes the assumption that the choices of dependent variable categories are independent (Starkweather & Moske, 2011). Therefore, multinomial logistic regression assumes that belonging in one category of DV is not dependent on the belonging of another category of DV. Thus, the assumption of choice of one category is not interrelated to the choice of belonging in another category of DV. Hence, dependent variable categories are not parallel to each other for multinomial models, which generate different coefficients for each independent variable, with different intercepts. Hence, the slopes are potentially different for each DV category i.e. $b_1, b_2, \ldots\ldots, b_i$ can vary across the model. These coefficients are the projected amount of variation in the logit per unit change in the independent variable.

5.6 Development of logit models to validate the automated cracking data (used in developing the deterministic and probabilistic models) with subjective rating of cracking

The subjective cracking in the surface inspection rating survey is evaluated in a four-level scale with values of 0, 1, 3 and 5 for nil, minor, moderate, and extensive distress categories, respectively. The allocated rating value is based on the evaluation of cracking severity along with its extent, which implies the effect of the level of cracking on the determined remaining life of the pavement surface and is thus used for prioritizing resurfacing programs. In addition, from pavement condition survey (PCS) the measured (automated) cracking data are used to intervene for different renewal activities. To find the relationship of these two types of cracking data and validation of automated cracking data, logistic regression analysis is performed.

5.6.1 AC Network

The test of parallel lines is not significant and the null hypothesis of same regression coefficients for all logit models cannot be rejected. Hence, ordinal regression analysis is performed. From the ordinal logistic regression analysis, as seen in the model fitting table (Table 5.1), it is found that subjective cracking models for AC network are significantly improved ($p < 0.05$) by adding objective cracking as predictor compared to the intercept only. The likelihood ratio test is also significant.

Table 5.1 Model Fitting Information for validation of cracking data in AC network

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	291.447			
Final	223.162	68.285	1	0.000

Link function: Logit.

The parameter estimates (Table 5.2) stipulate that intercept is significant for ‘Moderate’ and ‘Extensive’ categories of the subjective cracking model. Here, good cracking condition is the reference category. The classification table results (Appendix B) indicate that the overall success rate of the cracking models is 55% with highest success rate in the ‘Minor’ category.

Table 5.2 Parameter Estimates for validation of cracking data in AC network

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[cracking (Extensive)]	-5.612	0.650	74.629	1	0.000	-6.885	-4.339
	[cracking (Moderate)]	-2.879	0.342	70.964	1	0.000	-3.548	-2.209
	[cracking (Minor)]	0.137	0.209	.429	1	0.513	-0.273	0.547
Location	cracking	-0.149	0.021	51.222	1	0.000	-0.189	-0.108

Link function: Logit.

Therefore, the Logit models are as follows:

$$Logit\ (\leq Extensive) = -5.612 + 0.149\ \times\ cracking$$
$$Logit\ (\leq Moderate) = -2.879 + 0.149\ \times cracking$$
$$Logit\ (\leq Minor) = 0.137 +\ 0.149\ \times cracking$$

The results of the logistic regression show (Table 5.2) that subjective cracking conditions can be predicted from automated cracking since automated cracking found to be a statistically significant predictor. Hence, automated cracking data from pavement condition survey can be used to trial deterministic and probabilistic models to predict SIR for AC network.

5.6.2 SS Network

The model fitting table (Table 5.3) shows that subjective Cracking models for SS network give significantly better predictions ($p < 0.05$) by adding objective cracking as predictors to the model with intercept only. The likelihood ratio test is also significant.

Table 5.3 Model Fitting Information for validation of cracking data in SS network

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	316.444			
Final	267.076	49.368	1	0.000

Link function: Logit.

Table 5.4 Parameter Estimates for validation of cracking data in SS network

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[cracking (Extensive)]	-5.170	0.602	73.867	1	0.000	-6.349	-3.991
	[cracking (Moderate)]	-3.165	0.347	83.429	1	0.000	-3.845	-2.486
	[cracking (Minor)]	0.384	0.187	4.211	1	0.040	0.017	0.752
Location	cracking	-0.101	0.016	39.565	1	0.000	-0.133	-0.070

The results of the ordinal logistic regression show (Table 5.4) that rating value of cracking can be predicted from objective cracking data because automated cracking is found to be a statistically significant predictor. Therefore, objective cracking data are validated to develop deterministic and probabilistic models to predict SIR for SS network.

5.7 Development of Logit models to validate the automated rutting data (used in developing the deterministic and probabilistic models) with subjective rating of Deformation

The current practice of two types of rutting data collection in Australia include manual rating and using the automated multi-laser profilometer which employs optical or ultrasonic sensors to measure the depth of ruts (Michael Moffatt, 2007a). The subjective deformation ratings of local depressions (patching and potholes) are evaluated in addition to rutting in a guided scale including rating values of 0, 1, 3 and 5 used for good, minor, moderate, and extensive categories of distress respectively in Victoria. The rated value is allocated depending on the severity and extent of observed rutting. This rating value used with other distress ratings to calculate the combined index, SIR which indicates the estimated remaining life of the pavement surface and is used for prioritizing resurfacing programs. Thus, rut depth is widely used as an intervention trigger for bi-annual or three-year periodic maintenance to improve skid resistance.

In addition, from PCS, the directly measured rutting data (longitudinal depression in the pavement surface) are used to trigger different renewal activities (resurfacing, rehabilitation, reconstruction etc.). Hence, this type of automated data is also used to trigger reseal and rehabilitation activities that improve functional and structural capacity of pavement along with other pavement condition parameters. To find the relationship of these two types of data used for deformation assessment and validate the automated rutting data to develop deterministic and probabilistic models, logistic regression analysis is performed.

5.7.1 AC Network

The test of parallel lines is found to be significant for the deformation model. Therefore, the null hypothesis of parallelism is rejected, and multinomial logistic regression is trialed to investigate the relationship between subjective deformation and automated rutting. From the following model fitting table (Table 5.5), it is found that subjective Deformation models for AC network are significantly improved ($p < 0.05$) by adding objective rutting as predictor, compared to the intercept only. The data are fitted well by the model and the likelihood ratio test is also significant. The parameter estimates indicate that objective rutting is a significant logit parameter (Table 5.6) for 'Minor', and 'Moderate' categories of the subjective Deformation model. Here, 'Good' condition is used as reference category. The classification table results (Appendix B) indicate that the overall success rate of the multinomial logistic regression model is almost 58% with maximum success rate in the 'Minor' category. Therefore, the Logit models for deformations are as follows:

$$Logit\ (\leq Minor) = -0.656 + 0.215 \times rutting$$
$$Logit\ (\leq Moderate) = -5.791 + 0.718 \times rutting$$

Table 5.5 Model Fitting Information for validation of rutting data in AC network

	Model Fitting Criteria	Likelihood Ratio Tests		
Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	183.650			
Final	161.005	22.645	2	0.000

Table 5.6 Parameter Estimates for validation of rutting data in AC network

								95% Confidence Interval for Exp(B)	
Deformation (Rating)[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	Lower Bound	Upper Bound
Minor	Intercept	-0.656	0.450	2.130	1	0.144			
	rutting	0.215	0.099	4.721	1	0.030	1.240	1.021	1.506
Moderate	Intercept	-5.791	1.126	26.446	1	0.000			
	rutting	0.718	0.167	18.503	1	0.000	2.050	1.478	2.844

a. The reference category is: Good.

For the 'Extensive' category the number of pavement segments is small, and the model cannot predict deformation condition from automated rutting data. However, the focus of the study is not is on the 'Extensive' category and thus for our purposes, the automated rutting data are validated to use to develop deterministic and probabilistic models to predict SIR.

5.7.2 SS Network

For the sprayed seal network, deformation condition can be predicted from objective rutting data only for 'Moderate' condition because the number of pavement segments is nil for the 'Good' and 'Extensive' conditions of deformation and the 'Minor' category is used as reference category. Therefore, binary logistic regression analysis is performed to find the relationship. The results (Table 5.7 and Table 5.8) show that there is no variation in prediction success rate (94.2%) with the addition of the predictor to the base model (with intercept only). This is because of the small number of pavement segments in the moderate category present in the SS network. So, the automated rutting data for SS network cannot be validated for developing the deterministic and probabilistic models.

Table 5.7 Classification Table[a] for deformation model with intercept only (SS network)

Observed			Predicted		
			Deformation		Percentage Correct
			Moderate	Minor	
Step 0	Deformation	Moderate	0	11	0.0
		Minor	0	179	100.0
	Overall Percentage				94.2

a. Constant is included in the model.

Table 5.8 Classification Table for deformation model including the predictor (SS network)

Observed			Predicted		
			Deformation		Percentage Correct
			Moderate	Minor	
Step 1	Deformation	Moderate	0	11	0.0
		Minor	0	179	100.0
	Overall Percentage				94.2

5.8 Validation of automated texture loss data with subjective rating of texture loss

Texture loss of pavement surface is a slow deterioration process. Hence, it is very difficult to assess this distress visually. To validate the automated texture loss from pavement condition survey with the subjective rating of texture loss used in surface inspection rating survey, ordinal logistic regression is trialed for both AC and SS networks.

5.8.1 AC network

The model is found not to be statistically significant (Table 5.9) and the parameter estimate (Table 5.10) indicates that objective texture loss is not a statistically significant predictor (at the 0.05 level) for subjective deformation, which is used to compute SIR. Therefore, the subjective rating cannot be related with automated texture loss data for AC network and it is excluded from the analysis to develop the models for SIR.

Table 5.9 Model Fitting Information for validation of texture loss data in the AC network

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	97.161			
Final	93.972	3.189	1	0.074

Link function: Logit.

Table 5.10 Parameter Estimates for validation for texture loss data in the AC network

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[texture loss (Extensive)]	-4.079	0.573	50.678	1	0.000	-5.203	-2.956
	[texture loss (Moderate)]	-2.401	0.353	46.284	1	0.000	-3.092	-1.709
Location	texture loss	-0.062	0.034	3.398	1	0.065	-0.128	0.004

Link function: Logit.

5.8.2 SS Network

The texture loss model is found not to be statistically significant (Table 5.11) for the SS network. The parameter estimates (Table 5.12) indicate that automated texture loss is not a statistically significant explanatory variable to predict subjective deformation. Hence, the manual rating cannot be related with objective texture loss data for the SS network also and it is excluded from developing the models to predict SIR.

Table 5.11 Model Fitting Information for validation of texture loss data in the SS network

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	373.207			
Final	373.006	0.200	1	0.655

Link function: Logit.

Table 5.12 Parameter Estimates for validation of Texture loss data in the SS network

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[texture loss (Extensive)]	-1.114	0.252	19.572	1	0.000	-1.608	-0.621
	[texture loss (Moderate)]	0.985	0.248	15.712	1	0.000	0.498	1.472
Location	texture loss	0.004	0.008	0.201	1	0.654	-0.012	0.020

Link function: Logit.

5.9 Logistic Regression Analysis and Interpretation of Outputs to Predict Pavement Surface Condition Category from automated distress data

Since categorical variables are qualitative, to analyze the data the coding of categorical variable is important. At the time of coding, ranking, or ordering is considered as it influences the odds ratios and slope estimates. The DV category of highest value is considered as reference category (here VG) and is given the highest code. The input data into SPSS includes SIR values for all sections in the AC and SS network and their corresponding PCS parameters.

The interpretation of SPSS outputs from the analysis and the best fit models for two ranks are described in the following sections for modeling subjective SIR from the measured PCS data of the AC and SS network. The pertinent SPSS outputs are shown in Appendix B.

5.10 Ordinal Logistic Models

For ordinal logistic regression to predict SIR value from objective PCS parameters, values of the Dependent Variable SIR are categorized (ranked) in two ways.

- RANK1 (5 categories): VG (Very Good) = 0 – 10 = coded as ‘4’; G (Good) = 11 – 15 = coded as ‘3’; F (Fair) = 16 – 20 = coded as ‘2’; P (Poor) = 21 – 30 = coded as ‘1’; VP (Very Poor) > 30 = coded as ‘0’.
- RANK2 (4 categories): VG (Very Good) = 0 - 10 = ‘3’; G (good) = 11 – 20 = ‘2’; P (Poor) = 21 - 30 = ‘1’; VP (Very Poor) > 30 = ‘0’.

The necessary number of logit equations/models is generally reduced by one type of prediction category because one of the outcome variable categories is selected as a base category. Here VG has been chosen as the base or reference category because of its highest rating.

In ordinal logistic modeling, the event of interest is observing a specific score or less (Y. Wang, 2012). Hence, the fitted equations for predicting the condition of a pavement segment from corresponding measured PCS parameters have the following forms for the AC network (RANK1):

$$Logit\ (\leq\ G) = a_G - b_G \times cracking - c_G \times rutting - d_G \times IRI$$

$$Logit\ (\leq\ F) = a_F - b_F \times cracking - c_F \times rutting - d_F \times IRI$$

$$Logit\ (\leq\ P) = a_P - b_P \times cracking - c_P \times rutting - d_P \times IRI$$

$$Logit\ (\leq\ VP) = a_{VP} - b_{VP} \times cracking - c_{VP} \times rutting - d_{VP} \times IRI$$

Here, slopes are same for all regression equation e.g. $b_G = b_F = b_P = b_{VP}$. It means that DV categories are parallel to each other. The second assumption is that the intercepts will differ only. Thus, the intercepts of the ordinal logistic regression equations are $a_G \neq a_F \neq a_P \neq a_{VP}$.

In the above logit equations, objectively collected PCS parameters - cracking, rutting and IRI (International Roughness Index) are the Independent Variables (IVs). The minus sign is used to indicate that a larger coefficient is related with a larger score. For the SS network, only cracking is considered since rutting data cannot be validated and roughness has negligible correlation with SIR. The development of logistic models for predicting pavement surface conditions is described in the following sections.

5.10.1 AC Network (RANK1)

In this study for RANK1 from the following table (Table 5.13) it is found that $p > 0.05$ i.e. the assumption of parallel lines is satisfied, and ordinal regression is tested to get suitable logistic models for RANK1, briefly described in the next section.

Table 5.13 Test of Parallel Lines[a] for SIR model in AC network (RANK1)

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	398.994			
General	391.751	7.243	9	0.612

The null hypothesis states that the location parameters (slope coefficients) are the same across response categories.

a. Link function: Logit.

5.10.1.2 Data Distribution (RANK1)

For RANK1, SIR is categorized into five groups for the logit models. Here, 'Very Good' is considered as the reference category. For each case, the SIR condition category that is predicted is taken as the category for which the predicted probability is maximum. The following table (Table 5.14) presents the number and percentage of sections in each category of the AC network (observed data).

Table 5.14 Case Processing Summary (AC Network)

		N	Marginal Percentage
SIR_RANK1	VP	6	3.8%
	P	21	13.1%
	F	36	22.5%
	G	26	16.3%
	VG	71	44.4%
Valid		160	100.0%
Missing		0	
Total		160	

5.10.1.3 Likelihood Ratio Test (RANK1)

The following model fitting table (Table 5.15) presents the results of the test of the null hypothesis that the slopes of the regression equation for all variables in the model are 0. The likelihood ratio test is used to decide whether adding an explanatory variable (or predictor) improves our ability to predict the outcome. The table gives the -2log-likelihood (-2LL) values for the null model (containing intercept only) and the final model. We compare our model against the null model to check whether it has significant Chi-square statistic ($p < 0.05$), indicating a real improvement in the model fit.

Table 5.15 Model Fitting Information for SIR model in the AC network (RANK1)

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	441.950			
Final	398.994	42.955	3	0.000

Link function: Logit.

The model fitting table (Table 5.15) shows a significant Chi-square statistic value ($p < 0.05$) which indicates that SIR models give significantly better predictions by adding PCS parameters (cracking, rutting and IRI) as predictors, compared to the Intercept only (baseline model/null model) for RANK1 in AC network.

5.10.1.4 Measuring Strength of Association Goodness-of-Fit (RANK1)

The Goodness-of-Fit table represents the model fits (Table 5.16). It comprises Pearson's chi-square statistics and another chi-square result based on Deviance. These statistics are used to test whether the data are consistently fitted by the model. When the model fits well, the value of each statistic is small, and the significance probability is large. The null hypothesis can be rejected if the observed significance probability for the goodness of fit statistics is small. The following table shows that the significance probability is > 0.05 which indicates that the Null hypothesis of good model fit cannot be rejected for RANK1. Therefore, it can be concluded that the SIR models adequately fit the data for the AC network in RANK1.

Table 5.16 Goodness-of-Fit for SIR model in the AC network (RANK1)

	Chi-Square	df	Sig.
Pearson	554.802	633	0.989
Deviance	398.994	633	1.000

Link function: Logit.

Table 5.17 Pseudo R-Square for SIR model in the AC network (RANK1)

Cox and Snell	0.235
Nagelkerke	0.251
McFadden	0.097

Link function: Logit.

Here, the Coefficient of Determination (R^2) in maximum likelihood logistic regression is calculated by equivalent formula. However, it is not conceptually alike to R^2 in Ordinary Least Square Regression (OLSR). Thus, R^2 in this case is not the observed proportion of variation of the dependent variable explained by the model but rather the variation of the log likelihood of the fitted model compared to the log likelihood of the null model, and ranges from 0 to 1. When the R^2 value is 1, it indicates perfect fit of the model and 0 indicates no relationship. Therefore, R^2 satisfies the criterion of measuring strength of association partially with an intuitive interpretation here, but these R^2 values are not really the most important estimate in which we are interested (Menard, 2000). The Pseudo R-Square Table (Table 5.17) presents the Nagelkerke statistics value (0.251) indicating medium-low association between predictors and prediction. A Nagelkerke R^2 value greater than 0.2 is considered as indicating a relatively good fit of the model for any kind of logistic analysis (Clark & Hosking, 1986).

5.10.1.5 Parameter Estimates (RANK1)

In this analysis the DV is categorized as SIR > 30 (VP), SIR = 21 - 30 (P), SIR = 16 - 20 (F), SIR = 11 - 15 (G) and SIR = 0 - 10 (VG). From the result table it is found that cracking and rutting both are statistically significant predictors (Table 5.18). PCS roughness (IRI) is statistically insignificant ($p > 0.05$) and is removed from the model i.e. its coefficient is assumed to be zero. Therefore, rating of 'Very Good' category is used as the base category and Logits (function of PCS parameters) for the remaining four categories of ratings are considered. The fitted equations are:

$$Logit\ (\leq VP) = -5.274 - (-0.083 \times cracking) - (-0.167 \times rutting)$$
$$Logit\ (\leq P) = -3.345 - (-0.083 \times cracking) - (-0.167 \times rutting)$$
$$Logit\ (\leq F) = -1.875 - (-0.083 \times cracking) - (-0.167 \times rutting)$$
$$Logit\ (\leq G) = -1.077 - (-0.083 \times cracking) - (-0.167 \times rutting)$$

Table 5.18 Parameter Estimates for SIR model in the AC network (RANK1)

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[SIR (VP)]	-5.274	0.756	48.677	1	0.000	-6.755	-3.792
	[SIR (P)]	-3.345	0.603	30.759	1	0.000	-4.527	-2.163
	[SIR (F)]	-1.875	0.551	11.580	1	0.001	-2.955	-0.795
	[SIR (G)]	-1.077	0.539	3.989	1	0.046	-2.134	-0.020
Location	cracking	-0.083	0.018	21.856	1	0.000	-0.117	-0.048
	rutting	-0.167	0.082	4.213	1	0.040	-0.327	-0.008
	IRI	0.003	0.188	0.000	1	0.988	-0.366	0.372

Each equation gives the logit of the probability of being in one or below the stated category, predicted from the PCS parameters. If a road segment with cracking value = 30% and rutting value = 10mm, then the logit value for the estimation of probabilities for 'Poor' pavement surface condition are to be calculated as follows: Logit ($\leq$P)= - 3.345 - (- 0.083 × cracking)- (- 0.167× rutting)= - 3.345- (- 0.083× 30) - (- 0.167 × 10) = 0.815.

Table 5.19 SIR (RANK1) Predicted Response Category Crosstabulation (AC network)

			Predicted Response Category			Total
			P	F	VG	
SIR (RANK1)	VP	Count	2	4	0	6
		% within SIR (RANK1)	33.3%	66.7%	0.0%	100.0%
	P	Count	6	5	10	21
		% within SIR (RANK1)	28.6%	23.8%	47.6%	100.0%
	F	Count	3	11	22	36
		% within SIR (RANK1)	8.3%	30.6%	61.1%	100.0%
	G	Count	1	2	23	26
		% within SIR (RANK1)	3.8%	7.7%	88.5%	100.0%
	VG	Count	0	6	65	71
		% within SIR (RANK1)	0.0%	8.5%	91.5%	100.0%
Total		Count	12	28	120	160
		% within SIR (RANK1)	7.5%	17.5%	75.0%	100.0%

The classification table (Table 5.19; from SPSS crosstab), allows us to determine the number of events where the observed SIR values are predicted correctly. The cross tabulation indicates that 29% of P cases have been correctly assigned. The corresponding percentages for categories F and VG are 31% and 92% respectively. These results indicate that the success rate of logistic regression model for AC network with RANK1 is (6 + 11 + 65) / 160 = 0.513 ≈ 51%.

5.10.1.6 Calculating the Probabilities for Pavement Surface Conditions in the AC network

Using the predicted logit equations of the five cumulative condition categories the estimated individual probabilities of RANK1 are found with the following formulas and reported in the Table (Appendix B). The logit equations for the four cumulative condition categories can be used to predict the probability of a road segment being in each category as a function of automated cracking and rutting. For plotting the results in a graph, one independent variable acts as a predictor and the other IV is to be considered as constant at its mean value.

Since the correlation between SIR and cracking is greater than the correlation between SIR and rutting, cracking is considered as the predictor and the mean value of rutting (keeping rutting constant at mean value = 4.56 mm) is used in the logit prediction equations to calculate probabilities and present them graphically. In a real case, automated data values for both cracking and rutting are to be used to calculate the probabilities.

In ordinal logistic regression the estimated probabilities are cumulative scores where the probability of an occurrence and all occurrences that are ordered before it is considered, rather than estimating the probability of an individual occurrence. Hence, the cumulative predicted probabilities for the five pavement surface conditions can be computed as follows:

$$Probability\ of\ pavement\ surface\ condition\ being\ in\ the\ VP\ category = e^{logit\ VP} / [1 + e^{logit\ VP}]$$

$$Probability\ of\ pavement\ surface\ condition\ being\ in\ or\ below\ the\ P\ category = e^{logit\ P} / [1 + e^{logit\ P}]$$

$$Probability\ of\ pavement\ surface\ condition\ being\ in\ or\ below\ the\ F\ category = e^{logit\ F} / [1 + e^{logit\ F}]$$

$$Probability\ of\ pavement\ surface\ condition\ being\ in\ or\ below\ the\ G\ category = e^{logit\ G} / [1 + e^{logit\ G}]$$

From the above computed probabilities, the probabilities of the individual condition categories can be estimated as follows:

- $Probability\ (VP\ condition)\ =\ cum\ probability\ (VP)$
- $Probability\ (P\ condition)\ =\ cum\ probability\ (P) - cum\ probability\ (VP)$
- $Probability\ (F\ condition)\ =\ cum\ probability\ (F) - cum\ probability\ (P)$
- $Probability\ (G\ condition)\ =\ cum\ probability\ (G) - cum\ probabilities\ (F)$
- $Probability\ (VG\ condition)\ =\ 1 -\ cum\ probability\ (G\ condition)$

The probabilities from the model are presented graphically in Figure 5.2. The probabilities for VG, G and P conditions are calculated using the above equations to plot the model graphically. The category with the maximum estimated probability for a given cracking value is taken to be the predicted condition for a road segment with that cracking value.

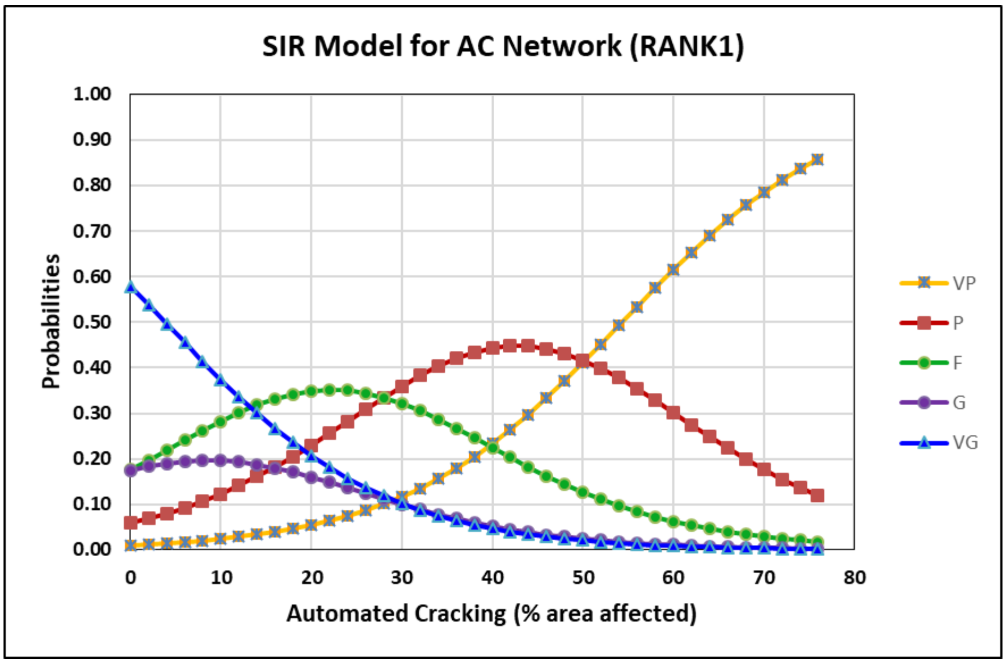


Figure 5.2 Predicted SIR category probabilities for SIR as a function of automated cracking (automated rutting is considered as constant at mean value) using logistic model in the AC network.

Figure 5.2 indicates that an AC network pavement segment is most likely to be in ‘Very Good’ condition up to about 15% area affected by cracking, then fair condition up to 28% and then in poor condition up to 50%. After 50% area affected, the probability of being in ‘Very Poor’ condition dominates, as we would expect in real life. The results show that for the ‘Good’ category the developed model fails to correctly predict the pavement surface condition. This may be because the number of pavement sections with good (SIR = 11 - 15) ratings is smaller than with VG and Fair conditions. Most of the pavement sections of AC networks are found to be in 'Very Good' (SIR = 0 - 10) and 'Fair' (SIR = 16 - 20) conditions according to the surface inspection ratings.

5.10.1.7 Validation of the Ordinal Logistic Model for the AC network (RANK1)

The developed model for prediction of SIR from automated cracking and rutting is validated by comparing expected weighted average condition rating (predicted) with observed (actual) rating of the pavement segments. Thus, the scaled squared residual of SIR is calculated for each pavement segment to investigate the difference between observed and expected SIR value.

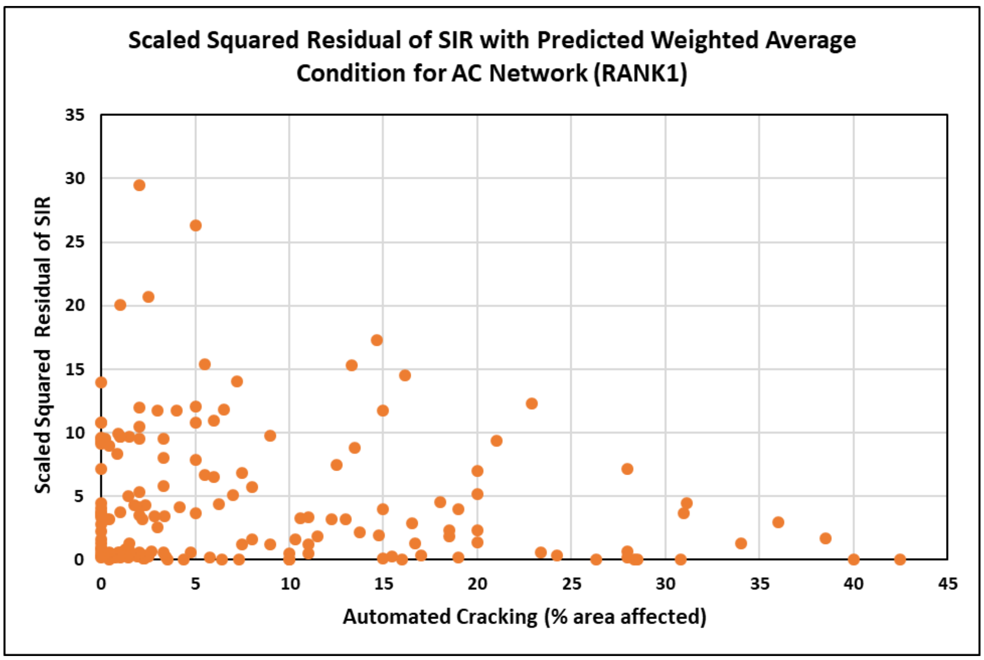


Figure 5.3 Scaled Squared Residual of SIR with Predicted Weighted Average Condition for the AC network (RANK1)

To estimate the weighted average condition rating, the probabilities of each condition category are multiplied by the corresponding SIR category midpoint and added. The predicted probabilities of the five condition categories of pavement segments are obtained from the SPSS output. For RANK1 the SIR category midpoints are: Very Good = 5, Good = 13, Fair = 18, Poor = 25.5, Very Poor = 35.5. The table of probabilities for validation are presented in Appendix B.

Thus, weighted average condition rating (expected rating) is estimated for the first row of the probability table (Appendix B) as below:

For the first case in the Table (Appendix B), where cracking = 2.50 and actual SIR = 12, the expected SIR is calculated as:

$$Expected\ SIR = 0.01 \times 35.5 + 0.06 \times 25.5 + 0.18 \times 18 + 0.18 \times 13 + 0.57 \times 5 = 10.315$$

Hence,

$$Scaled\ Squared\ Residual\ of\ SIR = (Observed\ SIR - Expected\ SIR)^2 / Expected\ SIR$$

$$= (12 - 10.315)^2/10.315 = 0.2753$$

From the scatter plot (Figure 5.3) it is seen that the squared difference between actual SIR value and expected SIR value is relatively small (scaled squared residual < 10) for more than 86% of pavement segments and small (scaled squared residual < 5) for more than 66% of pavement segments. Therefore, the developed ordinal logistic model with RANK1 is validated for the AC network.

5.10.2 SS Network

5.10.2.1 Test of Parallel Lines (RANK1)

From the following table (Table 5.20) it is evident that for RANK1 the test of parallel lines is not significant ($p > 0.05$). The assumption of parallel lines is therefore justified, and ordinal regression is used to get significant logistic models for RANK1. From the analysis it is found that (Appendix B) SIR models for the SS network give significantly better predictions by adding PCS parameters as predictors, compared to the intercept, only for RANK1.The likelihood ratio test shows that PCS cracking is a statistically significant predictor in the SS network (for RANK1). The success rate of the models is 40% but it can predict only the 'Good' condition correctly. Hence, RANK2 for SIR is trialed in search of a better model.

Table 5.20 Test of Parallel Lines for SIR model in the SS network (RANK1)

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	413.612			
General	412.370	1.241	3	0.743

The null hypothesis states that the location parameters (slope coefficients) are the same across response categories.

5.10.2.2 Data Distribution (RANK2)

The following table (Table 5.21) presents the number and percentage of sections in each category of the SS network where SIR > 30 is coded as "0" Very Poor), SIR = 21 - 30 as "1" (Poor), and SIR = 11 - 20 as "2" (Good) and SIR = 0 - 10 as '3' (Very Good).

Table 5.21 Case Processing Summary for SIR model in the SS network (RANK2)

		N	Marginal Percentage
SIR_RANK2	VP	32	16.8%
	P	73	38.4%
	G	74	38.9%
	VG	11	5.8%
Valid		190	100.0%
Missing		0	
Total		190	

5.10.2.3 Test of Parallel Lines (RANK2)

The test for parallel lines is satisfied for SS network and ordinal logistic regression is performed to get the models. Table 5.22 shows that the parallel line test for having different slopes is not statistically significant ($p > 0.05$) which indicates that the Null hypothesis of same slope cannot be rejected for RANK2.

Table 5.22 Test of Parallel Lines[a] for SIR model in the SS network (RANK2)

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	336.340			
General	335.165	1.175	2	0.556

a. The null hypothesis states that the location parameters (slope coefficients) are the same across response categories.

5.10.2.4 Likelihood Ratio Test (RANK2)

The following model fitting information table (Table 5.23) shows a significant Chi-square statistic value ($p < 0.05$) which indicates that the model gives better predictions than the model without adding any predictor. Thus, it is found that the SIR models for the SS network give significantly better predictions by adding cracking as predictor, compared to the intercept only (baseline model/null model) for RANK2. Table 5.24 indicates a non-significant result ($p > 0.05$) and so the null hypothesis of good model fit cannot be rejected for RANK2.

Table 5.23 Model Fitting Information for SIR model in the SS network (RANK2)

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	369.163			
Final	336.340	32.823	1	0.000

Link function: Logit.

Table 5.24 Goodness-of-Fit for SIR model in the SS network (RANK2)

	Chi-Square	df	Sig.
Pearson	351.111	374	0.797
Deviance	294.952	374	0.999

Table 5.25 Pseudo R-Square for SIR model in the SS network (RANK2)

Pseudo R-Square	
Cox and Snell	0.159
Nagelkerke	0.174
McFadden	0.072

Link function: Logit.

Table 5.26 Parameter Estimates for SIR model in the SS network (RANK2)

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[SIR (VP)]	-2.427	0.270	80.616	1	0.000	-2.957	-1.897
	[SIR (P)]	-0.337	0.181	3.487	1	0.062	-0.691	0.017
	[SIR (G)]	2.359	0.322	53.756	1	0.000	1.728	2.990
Location	cracking	-0.078	0.015	27.103	1	0.000	-0.108	-0.049

This parameter estimates (Table 5.26) give the following predicted logit equations for SS network (RANK2):

$$Logit\ (\leq VP)\ =\ -2.427 - (-0.078 \times cracking)$$
$$Logit\ (\leq P)\ =\ -0.337 - (-0.078 \times cracking)$$
$$Logit\ (\leq G)\ =\ 2.359 - (-0.078 \times cracking)$$

The following classification table (Table 5.27) presents the number of correctly predicted overserved values of SIR (DV). Here, 28% of VP cases are correctly predicted, 30% of P cases are correctly predicted, with 77% of G cases correctly assigned while 0% of the VG cases are identified correctly. These results indicate that the overall categorization success rate of the logistic regression model for the SS network with RANK2 is = (9 + 22 + 57) / 190 = 0.463 ≈ 46%.

Table 5.27 Predicted Response Category Crosstabulation for SIR in the SS network (RANK2)

			Predicted Response Category			Total
			VP	P	G	
SIR_RANK2	VP	Count	9	15	8	32
		% within SIR_RANK2	28.1%	46.9%	25.0%	100.0%
	P	Count	6	22	45	73
		% within SIR_RANK2	8.2%	30.1%	61.6%	100.0%
	G	Count	0	17	57	74
		% within SIR_RANK2	0.0%	23.0%	77.0%	100.0%
	VG	Count	0	1	10	11
		% within SIR_RANK2	0.0%	9.1%	90.9%	100.0%
Total		Count	15	55	120	190
		% within SIR_RANK2	7.9%	28.9%	63.2%	100.0%

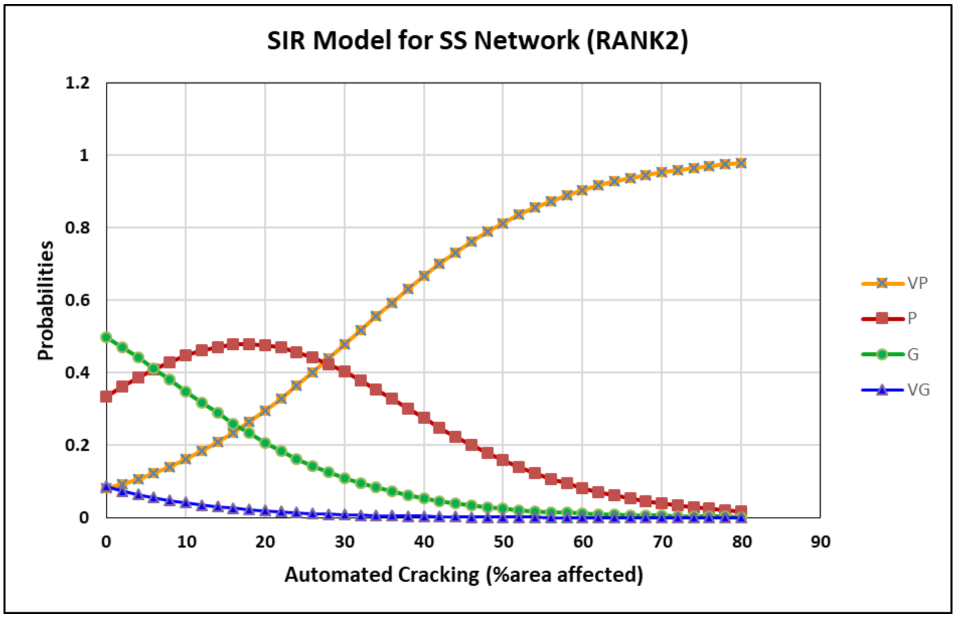


Figure 5.4 Logistic models for SIR as a function of automated cracking (% area affected) for the SS network (RANK2).

From Figure 5.4 it is seen that the model does not predict well for 'Very Good' condition, perhaps because the number of pavement segments in VG condition is small for the SS network. In addition, the model predicts that the probability of pavement segments being in good condition is high up to 6% area affected by cracking. For cracking between 6% and 26% of the area, poor surface condition is predicted. Once cracking area is more than 26%, 'Very Poor' condition is most likely. The computed table of probabilities from the model is presented in Appendix B.

5.10.2.5 Validation of the Ordinal Logistic Model for the SS network (RANK2)

The logistic model for SIR from automated cracking is validated by comparing weighted average condition rating (predicted/expected rating) with the observed rating of each pavement segment in the SS network. The scaled squared residual of SIR is estimated for each pavement segment. Here, the mid values for RANK2 condition categories are: VG=5, G=15.5, P=25.5, VP=35.5. The corresponding predicted probabilities of the four pavement surface condition categories are obtained from the SPSS output and are multiplied by the mentioned mid values to calculate the expected SIR value. The table of probabilities for validation are presented in Appendix B.

For the first case in the Table (Appendix B), where cracking = 22.66 and actual SIR = 14, the expected SIR is calculated as:

$$Expected\ SIR\ =\ 0.34 \times\ 35.5\ +\ 0.47\ \times\ 25.5\ +\ 0.18\ \times\ 15.5\ +\ 0.02\ \times\ 5\ =\ \ 26.945$$

Hence,

$$Scaled\ Squared\ Residual\ of\ SIR\ =\ (Observed\ SIR - Expected\ SIR)^2/Expected\ SIR$$

$$=\ (14 - \ 26.945)^2/26.945 = \ 6.22$$

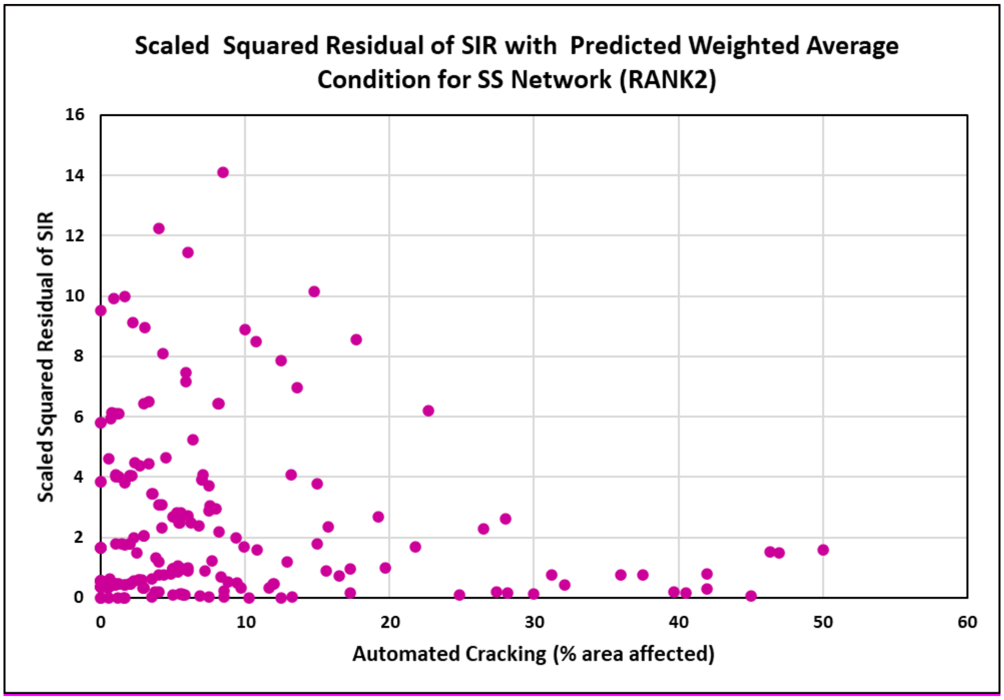


Figure 5.5 Scaled Residual Square of SIR with Predicted Weighted Average Condition in the SS network (RANK2)

From the scatter plot (Figure 5.5) it is seen that scaled squared difference between actual SIR value and expected SIR value is small for more than 84% pavement segments (scaled residual square is less than 5). Therefore, the ordinal logistic model with RANK2 is validated for the SS network.

Table 5.28 Summary of Logistic Regression outputs for SIR as a function of PCS Parameters (AC Network)

	Model Type	Goodness of fit	Likelihood ratio test	Nagelkerke measure	Significant Logit parameters	% success	Categories with maximum probabilities
RANK1	Ordinal	Retained	Significant	25%	cracking and rutting	51%	SIR = 0 - 10 (Very Good)
RANK2	Ordinal	Retained	Significant	23%	cracking and rutting	49%	SIR = 0 - 10 (Very Good)

Table 5.29 Summary of Logistic Regression outputs for SIR as a function of PCS Parameters (SS Network)

	Model Type	Goodness of fit	Likelihood ratio test	Nagelkerke measure	Significant Logit parameters	% success	Categories with maximum probabilities
RANK1	Ordinal	Retained	Significant	17%	cracking	40%	SIR = 21 - 30 (Poor)
RANK2	Ordinal	Retained	Significant	17%	cracking	46%	SIR = 11 - 15 (Good)

5.11 Summary

In this chapter, the pavement condition survey (PCS) distress data are validated with the corresponding subjective distress ratings before using the automated PCS distress data in developing probabilistic models for Surface Inspection Rating (SIR) condition categories, to understand the overall performance of the pavement surface. Then, the development of Logit models for SIR condition as a function of PCS parameters for asphalt surfacing (AC) and sprayed seal surfacing (SS) network are documented separately.

Validation of objective cracking data

At first, objective PCS distress data are validated with subjective rating of the corresponding distresses by logistic regression analysis. Ordinal logistic regression analysis is performed to find automated PCS data (% area affected by cracking) is a significant predictor of subjective rating of the cracking for each pavement segment. The subjective cracking is evaluated on a scale with ratings of 0, 1, 3 and 5 for the categories - nil, minor, moderate, and extensive cracking, respectively. The nil category with rating 0 is considered as the reference category. The ordinal models give significant likelihood ratio tests indicating a reasonable fit to the data for cracking in the AC network. Automated cracking is a significant logit parameter of subjective cracking models for both AC and SS networks.

Validation of objective rutting data

In subjective deformation rating, local depressions (patching and potholes) are evaluated as well as rutting whereas, in automated deformation data, rutting is measured as the longitudinal depression of the pavement surface. The subjective deformation in surface inspection rating surveys is rated as 0, 1, 3 and 5 for good, minor, moderate, and extensive rutting condition, respectively. The multinomial logit model testing results show that automated rutting is a statistically significant predictor of subjective deformation for the AC network.

Binary logistic regression results show that, for the dataset, there is no variation in prediction success rate with the addition of rutting as a predictor in the base model (with intercept only) for the SS network. This may be because of the small number of pavement segments in the moderate category, most of the pavement segments being in the 'Minor' rating category, making it difficult for the model to predict other conditions. So, the automated rutting data for SS network cannot be validated for developing deterministic and probabilistic models.

Validation of objective texture loss data

Objective texture loss is found not to be a statistically significant predictor of subjective deformation, used to compute SIR. Since pavement surface texture loss is a slow deterioration process it makes sense that the visual rating is different from automated data and cannot be validated. Hence, texture loss is excluded from developing deterministic (Chapter 4) and probabilistic (Chapter 5) models.

Ordinal Logistic Models for Pavement Surface Condition

Probabilistic logistic regression is employed to determine which PCS parameters can be used to predict SIR categories, using two types of ranking. The ranking of SIR rating for the analysis depends on the resurfacing or renewal activities triggering strategy for Victoria. Ordinal logistic regression is conducted by ranking SIR value into different categories (Very Good, Good, Fair, Poor and Very Poor). Cracking, rutting and IRI as PCS data are investigated as independent variables in the AC network, with only cracking being included in logistic models for the SS network. The roughness (IRI) parameter is found not to be statistically significant for the AC network. From the initial correlation analysis, the roughness data is found not to be reliable for the SS network and excluded from developing the models. Since the assumptions of parallel lines are satisfied, ordinal logistic regression is performed using two types of ranking of SIR as a function of original compiled PCS data from year 2011 and 2013.

The overall success rates of these models (with metric IVs) in predicting SIR condition membership from PCS parameters lie between 46% and 51% (Table 5.28 and Table 5.29). The model with highest overall success rate (51%) is for RANK1(five categories of SIR condition) in the AC network. To plot the model graphically, cracking is used as the independent variable, keeping rutting value constant at its mean. This is done because the correlation between SIR and cracking was higher than rutting. In practice, both objectively collected cracking and rutting data are to be used to estimate the pavement surface condition category. The developed model for the AC network indicates that pavement segments are most likely to be in 'Very Good' condition up to 15% area affected by cracking, in fair condition up to 28% and in poor condition up to 50%. Above 50% area affected by cracking, the probability of being in 'Very Poor' condition is high, as we expect in real life.

The model with RANK1 can predict 'Very Poor' and 'Poor' surface condition and failed to predict 'Very Good', 'Good' and 'Fair' conditions in the SS network. Hence, the analysis is performed with four categories of SIR condition (RANK2) and the most successful model has success rate of 46% in the SS network. Here, percentage of cracking area affected is the only predictor in the model. The developed ordinal logistic model shows that probability of pavement segments being in good condition is high when the area affected by cracking is up to 6%. When between 6% and 26% pavement surface area is affected by cracking, poor surface condition is predicted. 'Very Poor' condition probability is greatest when cracking area affected is more than 26%. This model cannot predict 'Very Good' condition of the pavement surface. The cause may be that the number of pavement segments in 'Very Good' condition is small for the SS network dataset.

Model Evaluation

AC Network

The likelihood ratio test and goodness of fit test results show that the models for both types of ranking fit the data quite well for the AC network. The model can predict properly the 'Very Good (SIR = 0-10)' condition category and to some extent the 'Fair (SIR = 16 - 20)' category of surface condition rating. The developed ordinal logistic model fails to correctly identify 'Good (SIR = 11 - 15)' pavement surface condition for the AC network. The reason may be the smaller number of pavement sections with 'Good' ratings than 'Very Good' and 'Fair' conditions.

Most pavement sections of the AC network are found to be in 'Very Good' or 'Fair' conditions according to the surface inspection ratings. In practice 'Poor' and 'Very Poor' condition pavement segments will obviously need to be repaired by the road authorities. The main interest of this study is in the 'Very Good', 'Good' and 'Fair' condition pavement surfaces, for resurfacing prioritization. The 'Poor' and 'Very Poor' conditions are also required in order to evaluate the model and priority ranking procedure.

Validation of the models is performed by comparing the weighted average predicted rating with actual rating for each pavement segment. The estimated scaled squared residual of SIR for pavement segments is found to be relatively small (< 10) for more than 86% of pavement segments and small (< 5) for more than 66% of pavement segments. Further, the Nagelkerke measure is found to be 0.25 for this model, which indicates that the model is a relatively good fit. Hence, it can be concluded that the developed ordinal logit model with RANK1 for the AC network is validated.

SS Network

For the SS network model, the likelihood ratio and goodness of fit tests indicate that the model fits reasonably well. The model can predict well 'Good (SIR = 11 - 15)' pavement surface condition and to a lesser extent 'Poor (SIR = 21 - 30)' and 'Very Poor (SIR > 30)' conditions. However, the model does not predict well for 'Very Good condition', perhaps because the number of pavement segments in VG condition is small for the SS network. Since 'Very Good' and 'Good' conditions are important for the ranking of potential need for resurfacing, the maximum probabilities found for Good condition category can be used in this regard.

From the scatter plot and calculation of the squared scaled residual of SIR it is observed that the values are small (< 5) for more than 84% of pavement segments. In addition, the Nagelkerke measure is found to be 0.17 for this model. Since the Nagelkerke measure is not a precise measure of goodness of fit, and its value is close to 0.2, it is reasonable to consider the developed ordinal logistic model for the SS network as being validated.

Application of the Models

In the AC network, the objective (automated) cracking and rutting data from pavement condition surveys are to be used in the logit models and the corresponding probabilities of the pavement segments are to be calculated using the logistic function. For the SS network only objective cracking data is to be used in the logit model. Based on the probabilities of being in particular condition categories, the pavement segments can be ranked in order of priority for resurfacing, in both type of road networks. Therefore, it is anticipated that these models can be used in the prioritization of pavement segments for resurfacing in the AC and SS networks.

CHAPTER SIX

CONCLUSIONS AND RECOMMENDATIONS

6.1 Introduction

This study investigated the interactions between different pavement surface distresses in determining subjective rating and developed models (deterministic linear regression model and probabilistic logistic model) to predict the surface condition rating from the objectively collected pavement distress data for granular pavements with asphalt and bituminous surfacing. This chapter briefly reviews the research methods, results and findings followed by important conclusions and recommendation for future study.

6.2 Summary and Findings

Developed relationships from the study would help asset managers of the different road authorities in reducing time and cost of periodic visual condition monitoring in addition to giving an in-depth understanding of the interactions between different pavement surface distresses to assess the overall performance of the pavement. The research focuses on understanding pavement distress mechanisms and the interactions between different surface distresses that impact on the overall performance of pavement. The distress parameters are assessed in asphalt surfacing and sprayed seal surfacing separately.

Chapter One briefly describes background information regarding the integration of subjective pavement condition rating and directly measured condition data around the world. The merits and demerits of manual and automated pavement condition survey are presented, to understand the current conventional pavement condition survey procedure. Then subjective rating and automated pavement condition data collection procedures used in Victoria/Australia are mentioned. The aim of the study: to investigate the relationship between subjectively rated surface condition and directly measured pavement condition parameters is stated precisely. These parameters comprise: cracking, rutting, texture loss and roughness. To achieve the aim of this research, the required objectives are defined in this chapter. Lastly, the significant and important outcomes of the research are pointed out. The main significances of the study include:

i. In this research a detailed study is performed to find the interactions of different pavement distresses in predicting subjective pavement surface rating, that is an indicator of overall performance of the pavement. In addition, very few studies have examined the influence of different operating conditions (age and traffic volume) on the relationship between subjective ratings and objective pavement distresses data. Investigated relationships will be useful to better understand the association between manual pavement surface rating and automated pavement distresses.

ii. The developed ordinal logistic models for the asphalt surfacing and sprayed seal networks would help road asset managers of Victoria in decision-making regarding the potential need for resurfacing maintenance. Therefore, it is anticipated that the findings from the study will reduce the time, cost and risk of evaluators associated with condition monitoring, by reducing visual inspection surveys.

The review of related literature documented in Chapter Two concisely describes the pavement distress mechanism to measure the performance of the pavement. Different types of pavement distresses to which flexible pavements are susceptible are defined and the concept of pavement serviceability and its relationship with roughness is reviewed as well. A comprehensive study of the methods for pavement distress evaluation by manual survey and pavement distress measurement through automated survey are presented in this chapter. Integrations between pavement condition indices used in different countries are reviewed to understand the recent practice of pavement condition evaluation. Then, manually-rated pavement surface inspection survey and objectively-collected overall pavement condition survey procedures for Victoria/Australia are described briefly. Lastly, relevant past studies related to subjective and objective pavement condition data are reviewed thoroughly and summarized in a table format. Research gaps found from the past research are mentioned in the conclusion.

Chapter Three includes the current standard practice of subjective evaluation of pavement surface inspection rating and objective pavement condition survey in Victoria, Australia. Afterwards, the conceptual framework of the research is depicted precisely. Then the available data description, considerations for data preparation and assumptions in data filtering are presented. Historical data of 2011 and 2013 for 34 highways of the MSE region of Victoria are filtered to conduct the analysis for the study. Therefore, 160 highway segments of AC network and 190 segments of SS network are filtered for the study. Lastly, applied statistical approaches to address the objectives of the study are described briefly.

6.2.1 Correlation Analysis

The correlations (Pearson's correlation coefficient, r) between subjective SIR and objective cracking ($r = 0.53$), rutting ($r = 0.34$) and IRI ($r = 0.18$) are found to be statistically significant in the AC network. Further, the results indicate that texture loss has a negligible correlation ($r = - 0.048$) with subjective rating. In the SS network, the results show that the correlations of visual rating with objective cracking ($r = 0.444$) and texture loss (r = - 0.292) are statistically significant. However, the negative value for texture loss indicates unreliable objective texture loss data to develop the SIR model, because the visual rating is positively related to pavement distresses. That means, SIR value should be high for poor condition of surface texture. Therefore, it is necessary to validate the objective pavement condition data with the corresponding subjective surface condition data before developing the models.

6.2.2 Validation of automated and subjective distress data

Objective PCS distress data are validated with the visual rating of the same pavement segment by logistic regression analysis. Automated cracking is measured and assessed by comparatively inexperienced personnel depending on digital videos, whereas subjective rating is recommended by experienced personnel who use their judgement. Logistic regression analysis is carried out to find the objective PCS parameter, % area affected by cracking as a significant predictor of subjective rating of cracking for each pavement segment. The subjective evaluation of cracking is done on a scale of 0, 1, 3 and 5 for nil, minor, moderate and extensive condition categories respectively, depending on the severity and extent of the distress. Likelihood ratio tests for the ordinal models are found to be significant and the models fit well the cracking data in AC network, and automated cracking is a significant logit parameter of subjective cracking models for both AC and SS networks.

In subjective rating, deformation is evaluated considering local depressions like patching and potholes, including rutting. On the other hand, in objective pavement condition surveys, rutting is quantified as the longitudinal depression of the pavement surface. Automated rutting is found to be a good predictor of manual rating and the multinomial model is found to be statistically significant by likelihood ratio tests for the AC network. Thus, the automated data is validated by logistic regression analysis to use in developing deterministic and probabilistic models for the AC network. In the SS network, the automated rutting data cannot be validated with subjective rating data. This may be because of the evaluation priority considerations of the local depressions than rutting, by the assessors in the subjective survey.

Further, objective texture loss data cannot be validated for either of the road networks. The slow deterioration process in texture loss may be the cause of this discrepancy. Manual rating may not be able to detect this gradual deterioration precisely. Therefore, rutting is excluded from the SS network and texture loss is excluded from both networks in developing deterministic and probabilistic models.

6.2.3 Deterministic Approach for Pavement Condition Data

Interaction Effects between Pavement Distresses

To investigate the interaction effects, objective pavement distresses are grouped to transform the data into categorical variables. Automated cracking data is grouped into two categories - 'Good (% area affected < 10%)' and 'Poor (area affected ≥ 10%)'. Since in the AC network, there is no pavement segment available with poor rutting condition (rutting = 16-20mm) or very poor condition (rutting > 20mm), rutting data is grouped into three categories 'Very Good (rutting = 0-5mm)', 'Good (rutting = 6 - 9mm)' or 'Fair (rutting = 10-15mm)'. Additionally, objective roughness is categorized as 'Good (IRI = 0 - 3.4m/km)', 'fair (IRI = 3.4 - 4.2m/km') or 'Poor (IRI > 4.2m/km)'.

The two-way ANOVA test results show that statistically significant differences are present in mean subjective rating within the different conditions of automated cracking and rutting [$F_{\textbf{cracking}}$ (1,138) = 25.608, $p < 0.05$ and $F_{\textbf{rutting}}$ (2,138) = 3.691, $p < 0.05$] in the AC network. In addition, the ANOVA test indicates that a statistically significant interaction [F (2,138) = 4.282, $p < 0.05$] is present between objectively collected cracking and rutting in predicting subjective SIR for the AC network. The model can explain 26% of the variation in SIR from the categorical cracking and rutting considering the interaction effects. Categorical roughness is found to have no statistically significant main effect or interaction effects with cracking and rutting in predicting SIR.

Interaction Effects between Pavement Distress and operating conditions

Considering the desired service life of asphalt surfacing and sprayed seal surfacing the pavement age is classified into two groups (age ≤ 7 years and age > 7 years). The two-way ANOVA test shows that interactions of age with pavement distresses are not statistically significant for both networks. Further, the interaction effect of heavy traffic volume with pavement distress is also found not to be statistically significant in ANOVA tests in both AC and SS networks. Age and traffic volume are not used as explanatory variables in developing the SIR models because they are reflected in the related pavement condition variables used as predictors in developing the models.

Linear Regression Models

After several trials, the best fit linear models are observed when logarithmic transformation (base 10 logarithm) is applied to the independent variables. Stepwise multiple linear regression analysis is used for the AC network and it is found that $\log_{10}$(cracking + 1) and $\log_{10}$(rutting + 1) are two statistically significant ($p < 0.05$) predictors of SIR. However, roughness is found not to be a significant parameter in the model. The model indicates that cracking and rutting make significant contributions to determining SIR value, where the contribution of cracking is more than rutting. The coefficient of determination (R^2) is 0.305, meaning that the predictors explain about 31% of the variation in SIR for the AC network. Additionally, after correlation analysis and validating the data, cracking is found as the only explanatory variable that can be used for developing a model for SIR in the SS network. The results show that $\log_{10}$(cracking + 1) is a statistically significant predictor of SIR. However, the model can explain only 24% of the variation in the subjective rating.

Model Evaluation

The developed deterministic models for SIR, as a function of objectively collected pavement condition parameters are observed to have low coefficienst of determination, predicting only 31% and 24% of the variation of SIR in the AC and SS networks, respectively. This necessitates alternative methods to develop more applicable models. After reviewing past studies, a probabilistic logistic regression approach is emplyed to investigate the relationship between subjective pavement surface rating conditions and automated pavement distresses.

6.2.4 Probabilistic Approach for Pavement Condition Data

Ordinal Logit Models for Pavement Surface Condition

Probabilistic Logistic Regression analysis is used to model SIR conditions from automated pavement condition data. Reviewing the previous studies and considering the surface inspection rating procedure in Victoria the rating values are categorized into five groups for RANK1 and four groups for RANK2. This ranking is based on resurfacing or renewal triggering in Victoria. The assumption of parallel lines for different levels of each variable is used and retained, and ordinal logistic regression is conducted using two types of ranking of SIR. For the AC network, roughness is found not to be a statistically significant predictor. Considering initial correlation analysis, the roughness data is excluded when developing the models for SS network.

The overall success rates of these models (with automated cracking and rutting as metric IVs) in categorizing SIR are between 46% and 51%. The most successful model (with success rate 51%) is with RANK1 (five categories of SIR) in the AC network. Since cracking is more correlated with SIR than other parameters, it is used as the independent variable in presenting the models graphically, holding rutting value constant at its mean value. Practically, both automated cracking and rutting are to be used to predict the pavement surface condition. The most successful model for the SS network is found for RANK2 (four groups of SIR condition) and has a success rate of 46%. Here, the percentage of area affected by cracking is the only predictor of SIR condition.

Model Evaluation

For the AC network, the most successful model gives a statistically significant likelihood ratio test and this result is confirmed by the goodness of fit test. The model can predict 'Very Good' and 'Fair' condition pavement surfaces and fails to predict 'Good' condition correctly. The reason may be the lesser number of pavement segments in the data set with 'Good' condition than 'Very Good' and 'Fair' conditions. Poor and 'Very Poor' condition pavement segments will readily be identified and repaired by the highway agencies, so this study is mostly concerned with the 'Very Good', 'Good' and 'Fair' condition pavement surfaces for resurfacing prioritization. Validation of the ordinal logistic model is done by comparing the scaled squared differences in weighted average predicted rating of pavement surface and actual rating. These measures are very small for 'Very Good' and 'Fair' conditions. Hence, the model is validated to use.

In the SS network, the likelihood ratio test and goodness of fit test for the developed ordinal logistic model with RANK2 show that it is a good fit. The scaled squared difference of actual condition rating and average predicted rating are small with minor differences when pavement segment is in 'Good', 'Poor' and 'Very Poor' conditions. The measurement is large for 'Very Good' condition, possibly because of the small number of pavement segments in the data set with 'Very Good' condition. Since 'Very Good' and 'Good' conditions are important for the ranking of potential needs for resurfacing activities, the maximum probabilities found for the 'Good' condition category can be used in this regard. Hence, it can be concluded that the SS network ordinal logistic model can be validated.

Application of the Probabilistic Models

The automated cracking and rutting data from pavement condition surveys are to be used in the ordinal logit models and the corresponding condition category probabilities of the pavement segments are to be calculated for the AC network pavement surface conditions. For the SS network, only objective cracking data is to be used in the logit model. These categorizations of conditions for pavement segments are to be used for prioritizing resurfacing in both asphalt surfacing and sprayed seal road networks.

6.3 Conclusions

A set of relationships between Surface Inspection Rating (SIR) and objective/quantified pavement distresses (cracking/rutting) are developed for granular pavements to help the practitioners of Victoria, Australia to trigger periodic resurfacing activities at the network level. In the current study, 160 asphalt surfaced pavement sections and 190 sprayed seal surfaced pavement sections, from the MSE region of Victoria, are used to develop deterministic and probabilistic models. In addition, the present study involves a detailed investigation to find the interactions between different pavement distresses in determining subjective pavement surface rating, an indicator of overall performance of the pavement.

The conclusions mentioned below can be drawn from the findings of the current study:

1. Initial correlation analysis indicates that statistically significant correlation exists between Surface Inspection Rating (SIR) and automated pavement condition parameters (cracking, rutting and roughness) for the asphalt surfacing network. In the sprayed seal network, cracking and texture loss are found to have significant correlations with SIR. However, 'texture loss' is found to have negligible correlation with SIR for the AC network and negative correlation for the SS network, indicating that the texture loss data is unreliable for the purpose of modeling SIR.
2. Validation of automated pavement condition data (distress data) with corresponding subjective rating of each individual distress indicates that automated cracking and rutting data can be used to develop models for subjective rating in the AC network. For the SS network, only cracking data are validated and can be used to model SIR. In the manual survey, deformation is evaluated considering localized depressions together with longitudinal depression (rutting). Objectively collected rutting data cannot be validated with the subjective ratings of rutting for the SS network. The reason may be the rating values evaluated by the engineers are more related to local depressions than rutting. Again, texture loss data cannot be validated with subjective rating of texture loss. The slow deterioration process of texture loss is difficult to assess in visual rating, consistent with this result. Misreading or misinterpretation in objective data collection may also be the reasons for generating unreliable data.
3. Cracking and rutting interact statistically significantly with each other when measuring the strength of their association with SIR in the AC network. Therefore, it can be concluded that the interaction effect between cracking and rutting should be considered in decision making with regard to their relationship with subjective ratings. The investigated relationships are

useful to better understand the pavement distress mechanisms when evaluating manual pavement surface rating in an asphalt surfacing road network.

4. The developed multiple linear regression model for the AC network shows that objectively collected log-transformed cracking and rutting are statistically significant predictors of SIR value. The contribution of cracking is greater than rutting in this regard. However, the amount of variation explained is relatively low (coefficient of determination, $R^2 = 0.305$). For the SS network, log-transformed cracking is found to be a statistically significant predictor of SIR. Again, the R^2 value is low with only 24% of the variation in SIR being explained by automated cracking data. This low predictive results necessitate alternative approaches. Reviewing the past studies, probabilistic logistic regression analysis is trialed in the hope of better results.
5. The overall success rates of the developed ordinal logistic models for asphalt surfacing and sprayed seal surfacing networks are between 46% and 51% for predicting pavement surface condition categories. In the study, the most successful ordinal logistic model has a success rate of 51% with RANK1 (five groups of SIR) for the AC network. For SS network the best model is with RANK2 (four groups of SIR) with success rate of 46%. Here, the percentage of area affected by cracking is the only predictor of SIR condition.
6. Likelihood ratio and goodness of fit tests for both networks indicate that the developed ordinal logistic models are good fits to the data. The ordinal logit model can predict ‘Very Good’ and ‘Fair’ condition of pavement surface in the AC network but fails to predict ‘Good’ condition correctly. The reason may be the small number of pavement segments with good condition, compared to the number with ‘Very Good’ and ‘Fair’ conditions in this road network. The SS network logistic model can predict the ‘Good’ condition category of pavement segments and fails to predict ‘Very Good’ condition. The reason may be that the pavement segments with ‘Very Good’ condition are very few in the SS network. Since ‘Poor’ and ‘Very Poor’ condition pavement segments will be obvious to be treated by the concerned road agencies, predictions for the other three categories- ‘Very Good’, ‘Good’ and ‘Fair’ conditions are what is most needed for prioritizing maintenance resurfacing. However, all condition categories are necessary to evaluate the entire model.
7. The developed models are validated by comparing the scaled squared differences in pavement surface average predicted rating with actual rating. These values are found to be very small for correctly predicted conditions. Thus, the models are validated for both networks.
8. The probability tables obtained from these ordinal logistic models for different condition categories present the probablilities of pavement segments being in each category, as a function of automated pavement condition parameters (rutting / cracking).

9. These probabilistic models can be used to predict, with any automated cracking or rutting data, the probability of a road section being in any particular condition for the AC and the SS network separately.
10. The category with the maximum probability in each case is the most likely condition for the segment and that can assist the road asset managers of Victoria in ranking the pavement segments for potential need of resurfacing.
11. Thus, it is anticipated that the findings from this research will be able to reduce the time, cost and risk of evaluators associated with condition monitoring, by reducing the need for visual inspection surveys.

6.4 Recommendations

To apply and improve the developed ordinal logistic models for practical pupose some reccomendations are provided below:

1. The ordinal logistic models developed in this study do not predict subjective ratings that consider the full range of subjective Surface Inspection Rating (SIR) due to the dataset's lack of pavement segments with high ratings. Moreover, the asphalt surfacing road network model fails to predict the 'Good' condition and the sprayed sealed network model cannot predict well the 'Very Good' condition. Therefore, it is suggested that these ordinal logistic models should be improved on the availabiltiy of a greater number of data, covering the total range of SIR.

2. Additional relevant historical data should generate more powerful regression models. The linear regression models may give better prediction if provided with a larger amount of relevant data.

3. The pavement distresses used in the calculation of SIR include stone loss and patching (not used in the current study), in addition to cracking, rutting and texture loss, which are used in this study for developing the models. The variables considered in this study are based on the minimum standard set of pavement condition measures recommended by the road authorities in Australia. Therefore, it is advised to include automated data of stone loss and patching data in model development, in the expectation that the addition of these variables may improve the models.

4. Determining subjective SIR is limited to some factors that are associated with the serviceability of pavement surfacing. These factors include roughness and skid resistance. The studied pavement distress mechanisms show that roughness is largely associated with other distress modes. It is a measure of functional performance or serviceability of a pavement. Though objectively collected

roughness is proved not to be a statistically significant predictor of SIR they are found to be correlated (r = 0.18) for asphalt surfacing network. Therefore, roughness data from more number of years can be trialed to develop a relationship between SIR and IRI to predict pavement surface condition for asphalt surfacing network from automated roughness data.

5. Objectively collected texture loss data cannot be validated with the manual ratings of texture loss for both networks. The slow deterioration process of texture loss, that is difficult to assess in visual rating, justifies this. There is a probability of errors in the quantified data due to misconceived interpretation as well. Therefore, the pavement surface texture loss data, from both types of surveys, should be examined.

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APPENDIX A

Deterministic Analysis (SPSS outputs) for Pavement Condition Data

1. Interaction Effects with continuous DV and IVs in the AC network

AC Network

Table A.1 Multiple Linear Regression with interaction of cracking, rutting and roughness (uncentered untransformed data) in the AC network

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	5.969	6.928		.862	.390
	cracking	.083	.592	.092	.141	.888
	rutting	.485	1.386	.111	.350	.727
	IRI	-.002	2.685	.000	-.001	1.000
	cracking*rutting	.083	.089	.707	.935	.351
	cracking*IRI	.128	.219	.480	.583	.561
	rutting*IRI	.069	.506	.065	.136	.892
	cracking*rutting*IRI	-.029	.031	-.875	-.927	.355

a. Dependent Variable: SIR

Table A.2 Multiple Linear Regression with interaction of cracking, rutting and roughness (uncentered log transformed data) in the AC network

Coefficients[a]

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Correlations		
	B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part
1 (Constant)	.926	16.493		.056	.955	-31.659	33.510			
Log (cracking+1)	-2.889	18.976	-.159	-.152	.879	-40.379	34.602	.505	-.012	-.010
Log(rutting+1)	4.602	22.327	.077	.206	.837	-39.510	48.714	.345	.017	.014
Log (IRI)	8.967	42.152	.141	.213	.832	-74.312	92.246	.203	.017	.014
Log (cracking+1) × Log(rutting+1)	18.078	24.948	.866	.725	.470	-31.212	67.369	.555	.059	.049
Log (cracking+1) × IRI	3.240	45.311	.095	.072	.943	-86.281	92.762	.487	.006	.005
Log(rutting+1) × IRI	-2.868	55.452	-.043	-.052	.959	-112.424	106.688	.316	-.004	-.003
Log (cracking+1) × Log(rutting+1) × IRI	-12.621	57.087	-.332	-.221	.825	-125.407	100.164	.510	-.018	-.015

a. Dependent Variable: SIR

Table A.3 Multiple Linear Regression with interaction of cracking, rutting and roughness (centered data) in the AC network

Coefficients[a]

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
	B	Std. Error	Beta			Lower Bound	Upper Bound
1 (Constant)	12.505	.633		19.745	.000	11.254	13.756
Log (cracking+1) centered	7.642	1.309	.421	5.837	.000	5.055	10.228
Log(rutting+1) centered	12.451	4.368	.207	2.850	.005	3.821	21.080
Log (IRI)centered	2.736	4.553	.043	.601	.549	-6.258	11.730
Log (cracking+1) × Log(rutting+1) centered	12.872	8.216	.121	1.567	.119	-3.359	29.103
Log(rutting+1) × Log (IRI)centered	-13.453	27.896	-.034	-.482	.630	-68.563	41.658
Log (cracking+1) × Log (IRI)centered	-6.524	10.107	-.048	-.645	.520	-26.491	13.444

a. Dependent Variable: SIR

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	12.360	.609		20.311	.000	11.158	13.562
	Log(cracking+1) centered	7.652	1.285	.422	5.957	.000	5.115	10.190
	Log(rutting+1) centered	12.916	4.179	.215	3.090	.002	4.661	21.172
	Log (cracking+1) × Log(rutting+1) centered	10.342	7.456	.097	1.387	.167	-4.386	25.070

a. Dependent Variable: SIR

2. Interaction Effects with continuous DV and Categorical IVs in the AC network

AC Network

Table A.4 Parameter Estimates with interaction effects between cracking, rutting and roughness in predicting SIR in the AC network

Tests of Between-Subjects Effects

Dependent Variable: SIR

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	3114.071[a]	14	222.434	3.777	.000
Intercept	4622.570	1	4622.570	78.494	.000
cracking	1250.858	1	1250.858	21.240	.000
rutting	28.137	2	14.068	.239	.788
IRI	112.816	2	56.408	.958	.386
cracking * rutting * IRI	19.693	2	9.847	.167	.846
cracking * rutting	385.907	2	192.954	3.276	.041
rutting * IRI	156.785	3	52.262	.887	.450
cracking * IRI	31.857	2	15.929	.270	.763
Error	7596.929	129	58.891		
Total	32912.000	144			
Corrected Total	10711.000	143			

a. R Squared = .291 (Adjusted R Squared = .214)

Table A.5 Parameter Estimates with interaction effects between cracking and rutting in predicting SIR

Tests of Between-Subjects Effects

Dependent Variable: SIR

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	2785.432[a]	5	557.086	9.700	.000
Intercept	7380.594	1	7380.594	128.511	.000
cracking	1470.724	1	1470.724	25.608	.000
rutting	423.942	2	211.971	3.691	.027
cracking * rutting	491.831	2	245.916	4.282	.016
Error	7925.568	138	57.432		
Total	32912.000	144			
Corrected Total	10711.000	143			

a. R Squared = .260 (Adjusted R Squared = .233)

Parameter Estimates

Dependent Variable: SIR

Parameter	B	Std. Error	t	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Intercept	9.952	.827	12.036	.000	8.317	11.587
[cracking=.00]	4.817	1.701	2.832	.005	1.454	8.180
[cracking=1.00]	0[a]	.	.	.	.	.
[rutting=1.00]	-7.952	5.422	-1.467	.145	-18.674	2.769
[rutting=2.00]	1.190	2.188	.544	.587	-3.135	5.516
[rutting=3.00]	0[a]	.	.	.	.	.
[cracking=.00] * [rutting=1.00]	16.183	6.780	2.387	.018	2.777	29.589
[cracking=.00] * [rutting=2.00]	6.612	3.331	1.985	.049	.025	13.199
[cracking=.00] * [rutting=3.00]	0[a]	.	.	.	.	.
[cracking=1.00] * [rutting=1.00]	0[a]	.	.	.	.	.
[cracking=1.00] * [rutting=2.00]	0[a]	.	.	.	.	.
[cracking=1.00] * [rutting=3.00]	0[a]	.	.	.	.	.

a. This parameter is set to zero because it is redundant.

Table A.6 Factorial ANOVA test results with interaction of cracking and roughness (IRI)

Tests of Between-Subjects Effects (AC Network)

Dependent Variable: SIR

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	2574.292[a]	5	514.858	7.782	.000
Intercept	7181.446	1	7181.446	108.545	.000
cracking	1050.457	1	1050.457	15.877	.000
IRI	86.743	2	43.372	.656	.521
cracking * IRI	38.705	2	19.353	.293	.747
Error	10188.808	154	66.161		
Total	38064.000	160			
Corrected Total	12763.100	159			

a. R Squared = .202 (Adjusted R Squared = .176)

Table A.7 Factorial ANOVA test results with interaction effects between cracking and age (Categorical IVs)

Tests of Between-Subjects Effects

Dependent Variable: SIR

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	6053.031[a]	3	2017.677	46.908	.000
Intercept	25631.786	1	25631.786	595.904	.000
cracking	1349.823	1	1349.823	31.382	.000
Age	3519.282	1	3519.282	81.819	.000
cracking * Age	116.748	1	116.748	2.714	.101
Error	6710.069	156	43.013		
Total	38064.000	160			
Corrected Total	12763.100	159			

a. R Squared = .474 (Adjusted R Squared = .464)

Table A.8 Factorial ANOVA test results with interaction effects between cracking and heavy vehicle traffic volume (Categorical IVs)

Tests of Between-Subjects Effects

Dependent Variable: SIR

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	2694.082[a]	5	538.816	8.241	.000
Intercept	15746.458	1	15746.458	240.833	.000
cracking	1643.943	1	1643.943	25.143	.000
Trcuks_500_1000	189.486	2	94.743	1.449	.238
crack * Trcuks_500_1000	51.748	2	25.874	.396	.674
Error	10069.018	154	65.383		
Total	38064.000	160			
Corrected Total	12763.100	159			

a. R Squared = .211 (Adjusted R Squared = .185)

Table A.9 Factorial ANOVA test results with interaction effects between rutting and age (Categorical IVs)

Tests of Between-Subjects Effects

Dependent Variable: SIR

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	3710.899[a]	5	742.180	14.631	.000
Intercept	6580.902	1	6580.902	129.736	.000
rutting	98.610	2	49.305	.972	.381
Age	1149.306	1	1149.306	22.657	.000
rutting * Age	45.556	2	22.778	.449	.639
Error	7000.101	138	50.725		
Total	32912.000	144			
Corrected Total	10711.000	143			

a. R Squared = .346 (Adjusted R Squared = .323)

Table A.10 Factorial ANOVA test results with interaction effects between rutting and heavy vehicle traffic volume (Categorical IVs)

Tests of Between-Subjects Effects

Dependent Variable: SIR

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	1475.882[a]	7	210.840	3.105	.005
Intercept	4878.684	1	4878.684	71.845	.000
rutting	134.543	2	67.272	.991	.374
Trcuks_500_1000	357.611	2	178.806	2.633	.076
rutting * Trcuks_500_1000	325.491	3	108.497	1.598	.193
Error	9235.118	136	67.905		
Total	32912.000	144			
Corrected Total	10711.000	143			

a. R Squared = .138 (Adjusted R Squared = .093)

3. Interaction Effects with continuous DV and Categorical IVs (operating conditions) in the SS network

SS Network

Table A.11 Factorial ANOVA test results with interaction effects between cracking and age (Categorical IVs) in the SS network

Tests of Between-Subjects Effects

Dependent Variable: SIR

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	4985.884[a]	3	1661.961	42.509	.000
Intercept	48178.166	1	48178.166	1232.296	.000
cracking	732.262	1	732.262	18.730	.000
Age_7yrs	2288.997	1	2288.997	58.548	.000
cracking * Age_7yrs	1.579	1	1.579	.040	.841
Error	7115.519	182	39.096		
Total	105187.000	186			
Corrected Total	12101.403	185			

a. R Squared = .412 (Adjusted R Squared = .402)

Table A.12 Factorial ANOVA test results with interaction effects between cracking and Trucks (Categorical IVs) in the SS network

Tests of Between-Subjects Effects

Dependent Variable: SIR

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	1836.791[a]	4	459.198	8.097	.000
Intercept	42320.877	1	42320.877	746.261	.000
cracking	910.474	1	910.474	16.055	.000
Trucks_500_1000	344.912	2	172.456	3.041	.050
cracking * Trucks_500_1000	.001	1	.001	.000	.996
Error	10264.612	181	56.711		
Total	105187.000	186			
Corrected Total	12101.403	185			

a. R Squared = .152 (Adjusted R Squared = .133)

Table A. 13 Pearson's Correlation Matrix from Weighted Least Square Regression (AC Network)

Correlations[a]

		SIR	Log_{10}(cracking+1)	Log_{10}(rutting+1)	Log_{10}(IRI)
Pearson Correlation	SIR	1.000	0.472	0.334	0.220
	Log_{10}(cracking+1)	0.472	1.000	0.196	0.153
	Log_{10}(rutting+1)	0.334	0.196	1.000	0.301
	Log_{10}(IRI)	0.220	0.153	0.301	1.000
Sig. (1-tailed)	SIR	.	0.000	0.000	0.003
	Log_{10}(cracking+1)	0.000	.	0.006	0.027
	Log_{10}(rutting+1)	0.000	0.006	.	0.000
	Log_{10}(IRI)	0.003	0.027	0.000	.
N	SIR	160	160	160	160
	Log_{10}(cracking+1)	160	160	160	160
	Log_{10}(rutting+1)	160	160	160	160
	Log_{10}(IRI)	160	160	160	160

a. Weighted Least Squares Regression - Weighted by Weight

Table A. 14 Pearson's Correlation Matrix from Weighted Least Square Regression (SS Network)

Correlations[a]

		SIR	Log_{10}(cracking+1)
Pearson Correlation	SIR	1.000	0.480
	Log_{10}(cracking+1)	0.480	1.000
Sig. (1-tailed)	SIR	.	0.000
	Log_{10}(cracking+1)	0.000	.
N	SIR	190	190
	Log_{10}(cracking+1)	190	190

a. Weighted Least Squares Regression - Weighted by Weight

APPENDIX B

Probabilistic Models (SPSS outputs) for Pavement Surface Condition

1. Logistic regression outputs to find the relationship with subjective cracking evaluation with the automatic cracking data

AC Network

Table B.1 Ordinal logistic regression model information for validating automated cracking data with subjective rating of cracking in the AC network

Case Processing Summary

		N	Marginal Percentage
cracking	Extensive	7	4.4%
	Moderate	28	17.5%
	Minor	80	50.0%
	Nil	45	28.1%
Valid		160	100.0%
Missing		0	
Total		160	

Test of Parallel Lines[a]

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	223.162			
General	222.026	1.137	2	.566

The null hypothesis states that the location parameters (slope coefficients) are the same across response categories.

a. Link function: Logit.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	291.447			
Final	223.162	68.285	1	.000

Link function: Logit.

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	273.562	266	.362
Deviance	188.008	266	1.000

Link function: Logit.

Pseudo R-Square

Cox and Snell	.347
Nagelkerke	.387
McFadden	.186

Link function: Logit.

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Threshold	[cracking = .00]	-5.612	.650	74.629	1	.000	-6.885	-4.339
	[cracking = 1.00]	-2.879	.342	70.964	1	.000	-3.548	-2.209
	[cracking = 2.00]	.137	.209	.429	1	.513	-.273	.547
Location	cracking	-.149	.021	51.222	1	.000	-.189	-.108

Link function: Logit.

Crack_ordinal * Predicted Response Category Crosstabulation

			Predicted Response Category			Total
			Extensive	Moderate	Minor	
cracking	Extensive	Count	0	6	1	7
		% within cracking	0.0%	85.7%	14.3%	100.0%
	Moderate	Count	3	10	15	28
		% within cracking	10.7%	35.7%	53.6%	100.0%
	Minor	Count	0	2	78	80
		% within cracking	0.0%	2.5%	97.5%	100.0%
	Nil	Count	0	1	44	45
		% within cracking	0.0%	2.2%	97.8%	100.0%
Total		Count	3	19	138	160
		% within cracking	1.9%	11.9%	86.3%	100.0%

SS Network

Table B.2 Ordinal logistic regression model information for validating automated cracking data with subjective rating of cracking in the SS network

Case Processing Summary

		N	Marginal Percentage
Cracking	Extensive	6	3.2%
	Moderate	19	10.0%
	Minor	113	59.5%
	Good	52	27.4%
Valid		190	100.0%
Missing		0	
Total		190	

Test of Parallel Lines[a]

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	267.076			
General	264.131	2.945	2	.229

The null hypothesis states that the location parameters (slope coefficients) are the same across response categories.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	316.444			
Final	267.076	49.368	1	.000

Link function: Logit.

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	375.499	374	.468
Deviance	239.984	374	1.000

Link function: Logit.

Pseudo R-Square

Cox and Snell	.229
Nagelkerke	.264
McFadden	.130

Link function: Logit.

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[Cracking = .00]	-5.170	.602	73.867	1	.000	-6.349	-3.991
	[Cracking = 1.00]	-3.165	.347	83.429	1	.000	-3.845	-2.486
	[Cracking = 2.00]	.384	.187	4.211	1	.040	.017	.752
Location	Cracking	-.101	.016	39.565	1	.000	-.133	-.070

Link function: Logit.

Cracking* Predicted Response Category Crosstabulation

			Predicted Response Category			Total
			Extensive	Moderate	Minor	
Cracking	Extensive	Count	0	2	4	6
		% within Cracking	0.0%	33.3%	66.7%	100.0%
	Moderate	Count	1	5	13	19
		% within Cracking	5.3%	26.3%	68.4%	100.0%
	Minor	Count	0	2	111	113
		% within Cracking	0.0%	1.8%	98.2%	100.0%
	Good	Count	0	0	52	52
		% within Cracking	0.0%	0.0%	100.0%	100.0%
Total		Count	1	9	180	190
		% within Cracking	0.5%	4.7%	94.7%	100.0%

2. Development of Logit models to find the relationship with subjective Deformation evaluation with the automatic rutting data

AC Network

Table B.3 Multinomial logistic regression model information for validating automated rutting data with subjective rating of deformation in the AC network

Test of Parallel Lines[a]

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	164.966			
General	161.030	3.936	1	.047

The null hypothesis states that the location parameters (slope coefficients) are the same across response categories.

a. Link function: Logit.

Case Processing Summary

		N	Marginal Percentage
Deformation	.00	65	40.6%
	1.00	85	53.1%
	3.00	10	6.3%
Valid		160	100.0%
Missing		0	
Total		160	
Subpopulation		75[a]	

a. The dependent variable has only one value observed in 58 (77.3%) subpopulations.

Model Fitting Information

	Model Fitting Criteria	Likelihood Ratio Tests		
Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	183.650			
Final	161.005	22.645	2	.000

Pseudo R-Square

Cox and Snell	.132
Nagelkerke	.160
McFadden	.081

Likelihood Ratio Tests

Effect	Model Fitting Criteria: -2 Log Likelihood of Reduced Model	Likelihood Ratio Tests: Chi-Square	df	Sig.
Intercept	209.097	48.092	2	.000
Rutting	183.650	22.645	2	.000

Parameter Estimates

Deformation[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B): Lower Bound	95% Confidence Interval for Exp(B): Upper Bound
1.00	Intercept	-.656	.450	2.130	1	.144			
	rutting	.215	.099	4.721	1	.030	1.240	1.021	1.506
3.00	Intercept	-5.791	1.126	26.446	1	.000			
	rutting	.718	.167	18.503	1	.000	2.050	1.478	2.844

a. The reference category is: .00.

Classification

Observed	Predicted: .00	1.00	3.00	Percent Correct
.00	26	39	0	40.0%
1.00	19	64	2	75.3%
3.00	0	8	2	20.0%
Overall Percentage	28.1%	69.4%	2.5%	57.5%

SS Network (Binary Logistic Regression)

Table B.4 Binary logistic regression model information for validating automated rutting data with subjective rating of deformation in the SS network

Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	190	100.0
	Missing Cases	0	.0
	Total	190	100.0
Unselected Cases		0	.0
Total		190	100.0

a. If weight is in effect, see classification table for the total number of cases.

Dependent Variable Encoding

Original Value	Internal Value
Moderate	0
Minor	1

Classification Table[a,b]

	Observed		Predicted		
			Deformation		Percentage Correct
			Moderate	Minor	
Step 0	Deformation	Moderate	0	11	.0
		Minor	0	179	100.0
	Overall Percentage				94.2

a. Constant is included in the model.

b. The cut value is .500

Classification Table[a]

	Observed		Predicted		
			Deformation		Percentage Correct
			Moderate	Minor	
Step 1	Deformation	Moderate	0	11	.0
		Minor	0	179	100.0
	Overall Percentage				94.2

a. The cut value is .500

3. Development of Logit models to find the relationship with subjective texture loss rating with the automatic texture loss data

AC Network

Table B. 5 Ordinal logistic regression model information for validating automated texture loss data with subjective rating of texture loss in the AC network

Case Processing Summary

		N	Marginal Percentage
Texture loss	Moderate	4	2.5%
	Minor	15	9.4%
	Good	141	88.1%
Valid		160	100.0%
Missing		0	
Total		160	

Test of Parallel Lines[a]

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	93.972			
General	93.473	.500	1	.480

The null hypothesis states that the location parameters (slope coefficients) are the same across response categories.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	97.161			
Final	93.972	3.189	1	.074

Link function: Logit.

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	127.510	165	.986
Deviance	80.611	165	1.000

Link function: Logit.

Pseudo R-Square

Cox and Snell	.020
Nagelkerke	.034
McFadden	.023

Link function: Logit.

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[Texture loss = 1.00]	-4.079	.573	50.678	1	.000	-5.203	-2.956
	[Texture loss = 2.00]	-2.401	.353	46.284	1	.000	-3.092	-1.709
Location	Texture loss	-.062	.034	3.398	1	.065	-.128	.004

Link function: Logit.

Texture loss * Predicted Response Category Crosstabulation

			Predicted Response Category	Total
			Good	
Texture loss	Moderate	Count	4	4
		% within Texture loss	100.0%	100.0%
	Minor	Count	15	15
		% within Texture loss	100.0%	100.0%
	Good	Count	141	141
		% within Texture loss	100.0%	100.0%
Total		Count	160	160
		% within Texture loss	100.0%	100.0%

<u>SS Network</u>

Table B.6 Ordinal logistic regression model information for validating automated texture loss data with subjective rating of texture loss in the SS network

Case Processing Summary

		N	Marginal Percentage
Texture loss	Moderate	44	23.2%
	Minor	91	47.9%
	Good	55	28.9%
Valid		190	100.0%
Missing		0	
Total		190	

Test of Parallel Lines[a]

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	373.006			
General	371.259	1.747	1	.186

The null hypothesis states that the location parameters (slope coefficients) are the same across response categories.

a. Link function: Logit.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	373.207			
Final	373.006	.200	1	.655

Link function: Logit.

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	323.997	321	.443
Deviance	351.917	321	.113

Link function: Logit.

Pseudo R-Square

Cox and Snell	.001
Nagelkerke	.001
McFadden	.001

Link function: Logit.

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[Texture loss = 1.00]	-1.114	.252	19.572	1	.000	-1.608	-.621
	[Texture loss = 2.00]	.985	.248	15.712	1	.000	.498	1.472
Location	TL	.004	.008	.201	1	.654	-.012	.020

Link function: Logit.

4. Ordinal Logistic Regression Model for SIR (RANK2)

AC Network (RANK2)

SIR is categorized into four groups for the logit models. VG is given highest code=3 as used as the reference category.

Table B.7 Ordinal logistic regression model information for surface inspection rating (SIR) with RANK2 in the AC network

Case Processing Summary

		N	Marginal Percentage
SIR_RANK2	.00	6	3.8%
	1.00	21	13.1%
	2.00	62	38.8%
	3.00	71	44.4%
Valid		160	100.0%
Missing		0	
Total		160	

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	357.619			
Final	320.144	37.476	3	.000

Link function: Logit.

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	390.377	474	.998
Deviance	320.144	474	1.000

Link function: Logit.

Pseudo R-Square

Cox and Snell	.209
Nagelkerke	.234
McFadden	.105

Link function: Logit.

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Threshold	[SIR_RANK2 = .00]	-5.073	.760	44.616	1	.000	-6.562	-3.585
	[SIR_RANK2 = 1.00]	-3.161	.613	26.617	1	.000	-4.362	-1.960
	[SIR_RANK2 = 2.00]	-.952	.551	2.990	1	.084	-2.031	.127
Location	cracking	-.079	.018	19.000	1	.000	-.115	-.044
	rutting	-.165	.084	3.852	1	.050	-.329	.000
	IRI	.044	.194	.052	1	.820	-.336	.425

Link function: Logit.

Test of Parallel Lines[a]

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	320.144			
General	315.851	4.293	6	.637

The null hypothesis states that the location parameters (slope coefficients) are the same across response categories.

a. Link function: Logit.

SIR_RANK2 * Predicted Response Category Crosstabulation

			Predicted Response Category 1.00	2.00	3.00	Total
SIR_RANK2	.00	Count	2	4	0	6
		% within SIR_RANK2	33.3%	66.7%	0.0%	100.0%
	1.00	Count	2	11	8	21
		% within SIR_RANK2	9.5%	52.4%	38.1%	100.0%
	2.00	Count	4	20	38	62
		% within SIR_RANK2	6.5%	32.3%	61.3%	100.0%
	3.00	Count	0	15	56	71
		% within SIR_RANK2	0.0%	21.1%	78.9%	100.0%
Total		Count	8	50	102	160
		% within SIR_RANK2	5.0%	31.3%	63.8%	100.0%

5. Ordinal Logistic Regression Model for SIR (RANK1)

SS Network

Table B.8 Ordinal logistic regression model information for surface inspection rating (SIR) with RANK1 in the SS network

Case Processing Summary

		N	Marginal Percentage
SIR_RANK1	.00 (VP)	32	16.8%
	1.00 (P)	73	38.4%
	2.00 (F)	44	23.2%
	3.00 (G)	30	15.8%
	4.00 (VG)	11	5.8%
Valid		190	100.0%
Missing		0	
Total		190	

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	447.022			
Final	413.612	33.410	1	.000

Link function: Logit.

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	468.937	499	.829
Deviance	364.467	499	1.000

Link function: Logit.

Pseudo R-Square

Cox and Snell	.161
Nagelkerke	.170
McFadden	.060

Link function: Logit.

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Threshold	[SIR_RANK_1 = .00]	-2.429	.270	81.189	1	.000	-2.958	-1.901
	[SIR_RANK_1 = 1.00]	-.339	.180	3.567	1	.059	-.692	.013
	[SIR_RANK_1 = 2.00]	.816	.197	17.151	1	.000	.430	1.203
	[SIR_RANK_1 = 3.00]	2.358	.322	53.745	1	.000	1.728	2.989
Location	Crack	-.078	.015	27.485	1	.000	-.108	-.049

Link function: Logit.

Test of Parallel Lines[a]

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	413.612			
General	412.370	1.241	3	.743

The null hypothesis states that the location parameters (slope coefficients) are the same across response categories.

SIR_RANK1 * Predicted Response Category Crosstabulation

			Predicted Response Category .00	Predicted Response Category 1.00	Total
SIR_RANK1	.00 (VP)	Count	9	23	32
		% within SIR_RANK1	28.1%	71.9%	100.0%
	1.00 (P)	Count	6	67	73
		% within SIR_RANK1	8.2%	91.8%	100.0%
	2.00 (F)	Count	0	44	44
		% within SIR_RANK1	0.0%	100.0%	100.0%
	3.00 (G)	Count	0	30	30
		% within SIR_RANK1	0.0%	100.0%	100.0%
	4.00 (VG)	Count	0	11	11
		% within SIR_RANK1	0.0%	100.0%	100.0%
Total		Count	15	175	190
		% within SIR_RANK1	7.9%	92.1%	100.0%

6. Validation of Ordinal Logistic SIR Model for AC network

The predicted probabilities are used from the SPSS outputs. The weighted average SIR (expected SIR) is determined by multiplying the predicted probability with the middle value of the corresponding SIR category. For RANK1, the mid values are: VG=5, G=13, F=18, P=25.5, VP=35.5 that are considered for the average condition. Then the difference between observed rating (actual rating) and expected rating (predicted rating) are compared to validate the developed model using scaled squared residual of each pavement segment is estimates as follows:

$$Scaled\ Squared\ Residual\ of\ SIR\ =\ (Observed\ SIR - Expected\ SIR)^2/Expected\ SIR$$

Table B.9 Scaled Squared Residuals of SIR with estimated response probability of each category from ordinal logistic regression in the AC Network (RANK1)

SIR	Cracking (% area affected)	Estimated Response Probability VP	Estimated Response Probability P	Estimated Response Probability F	Estimated Response Probability G	Estimated Response Probability VG	Weighted Average Predicted SIR	Scaled Squared Residuals of SIR
12	2.50	.01	.06	.18	.18	.57	10.315	0.28
0	.00	.01	.07	.20	.18	.54	10.78	10.78
4	21.00	.05	.20	.34	.17	.24	16.405	9.38
24	24.25	.12	.37	.32	.10	.10	21.255	0.35
0	1.00	.01	.05	.16	.16	.62	9.69	9.69
12	3.50	.02	.08	.22	.19	.49	11.63	0.01
4	7.00	.02	.08	.23	.19	.48	11.76	5.12
4	.40	.01	.05	.15	.16	.63	9.56	3.23
20	30.80	.10	.33	.34	.11	.12	20.115	0.00
4	2.00	.02	.09	.23	.19	.48	12.015	5.35
12	.00	.01	.06	.19	.18	.56	10.445	0.23
4	5.00	.01	.06	.17	.17	.58	10.055	3.65
0	.22	.01	.05	.15	.16	.63	9.56	9.56
16	.00	.01	.06	.17	.17	.60	10.155	3.36
8	13.00	.03	.16	.32	.19	.30	14.875	3.18
4	6.00	.02	.12	.28	.20	.38	13.31	6.51
8	1.50	.01	.07	.20	.19	.52	10.81	0.73
24	4.00	.02	.09	.24	.19	.46	12.095	11.72
0	2.00	.01	.05	.15	.16	.63	9.56	9.56
8	.75	.01	.05	.14	.16	.65	9.48	0.23
0	.00	.01	.07	.20	.18	.54	10.78	10.78
8	1.50	.02	.09	.23	.19	.47	11.965	1.31

SIR	Cracking (% area affected)	Estimated Response Probability VP	Estimated Response Probability P	Estimated Response Probability F	Estimated Response Probability G	Estimated Response Probability VG	Weighted Average Predicted SIR	Scaled Squared Residuals of SIR
0	5.00	.01	.07	.20	.18	.54	10.78	10.78
20	11.00	.04	.18	.33	.18	.27	15.64	1.22
28	18.50	.12	.36	.32	.10	.10	21	2.33
4	4.14	.01	.07	.19	.18	.55	10.65	4.15
0	.00	.03	.13	.29	.20	.36	14	14.00
16	.00	.02	.09	.24	.19	.45	12.045	1.30
8	1.41	.01	.06	.17	.17	.58	10.055	0.42
16	9.00	.02	.09	.24	.19	.46	12.095	1.26
8	7.50	.02	.08	.23	.19	.48	11.76	1.20
28	40.00	.40	.42	.13	.03	.02	27.74	0.00
16	.00	.01	.05	.17	.17	.60	9.9	3.76
8	.00	.02	.10	.25	.20	.44	12.56	1.66
8	.00	.01	.06	.19	.18	.56	10.445	0.57
16	3.00	.01	.07	.20	.18	.53	10.73	2.59
12	1.43	.01	.06	.19	.18	.56	10.445	0.23
0	.00	.01	.05	.15	.16	.64	9.61	9.61
20	11.00	.02	.12	.28	.20	.38	13.31	3.36
0	.40	.01	.04	.13	.15	.67	9.015	9.02
12	3.44	.01	.06	.18	.17	.58	10.235	0.30
12	28.00	.28	.45	.19	.04	.04	25.555	7.19
0	6.00	.01	.07	.21	.19	.52	10.99	10.99
0	.00	.01	.04	.14	.15	.66	9.145	9.15
0	.00	.01	.05	.15	.16	.63	9.56	9.56
4	2.20	.01	.05	.15	.16	.63	9.56	3.23
8	1.25	.01	.07	.21	.19	.52	10.99	0.81
4	3.36	.01	.05	.16	.17	.61	9.77	3.41
0	7.24	.03	.13	.29	.20	.37	14.05	14.05
4	2.00	.01	.05	.17	.17	.60	9.9	3.52
0	3.30	.01	.05	.15	.16	.63	9.56	9.56
0	2.00	.02	.09	.23	.19	.48	12.015	12.02
12	7.33	.02	.09	.24	.19	.45	12.045	0.00
0	13.33	.04	.17	.32	.18	.29	15.305	15.31
12	18.50	.06	.25	.35	.15	.19	17.705	1.84
16	11.00	.02	.12	.28	.20	.38	13.31	0.54
0	2.00	.01	.06	.19	.18	.56	10.445	10.45

SIR	Cracking (% area affected)	Estimated Response Probability VP	Estimated Response Probability P	Estimated Response Probability F	Estimated Response Probability G	Estimated Response Probability VG	Weighted Average Predicted SIR	Scaled Squared Residuals of SIR
8	1.94	.01	.05	.16	.16	.62	9.69	0.29
0	.88	.01	.05	.17	.17	.60	9.9	9.90
4	2.00	.01	.07	.19	.18	.55	10.65	4.15
8	12.22	.03	.16	.32	.19	.30	14.875	3.18
4	2.33	.01	.07	.20	.19	.53	10.86	4.33
0	16.17	.03	.15	.31	.19	.31	14.49	14.49
4	3.33	.02	.10	.25	.20	.44	12.56	5.83
12	1.00	.01	.06	.19	.18	.56	10.445	0.23
16	.00	.01	.05	.16	.16	.62	9.69	4.11
24	12.50	.03	.13	.29	.19	.35	13.82	7.50
20	17.00	.06	.24	.35	.16	.20	17.63	0.32
24	2.50	.01	.05	.16	.17	.61	9.77	20.73
4	.00	.01	.04	.13	.15	.67	9.015	2.79
8	15.00	.04	.19	.34	.18	.25	15.975	3.98
12	2.27	.01	.06	.17	.17	.58	10.055	0.38
0	1.00	.01	.05	.16	.16	.62	9.69	9.69
0	5.00	.02	.09	.24	.19	.46	12.095	12.10
8	8.00	.02	.10	.25	.20	.44	12.56	1.66
16	28.00	.09	.32	.34	.12	.13	19.685	0.69
24	28.00	.14	.39	.30	.08	.08	21.755	0.23
24	23.40	.11	.35	.33	.10	.11	20.62	0.55
12	4.36	.02	.09	.24	.19	.45	12.045	0.00
16	19.00	.06	.25	.35	.15	.18	17.655	0.16
20	28.33	.09	.32	.34	.12	.13	19.685	0.01
12	6.40	.02	.10	.24	.20	.45	12.43	0.01
20	28.50	.08	.30	.35	.13	.14	19.18	0.04
8	16.50	.03	.15	.31	.19	.31	14.49	2.91
20	3.33	.01	.07	.20	.18	.53	10.73	8.01
8	11.50	.02	.11	.26	.20	.41	12.845	1.83
8	.40	.01	.05	.15	.16	.64	9.61	0.27
8	2.00	.01	.06	.19	.18	.56	10.445	0.57
16	.00	.01	.07	.21	.19	.52	10.99	2.28
12	10.00	.02	.08	.23	.19	.48	11.76	0.00
12	.88	.01	.05	.16	.16	.62	9.69	0.55
20	.83	.01	.07	.19	.18	.54	10.6	8.34

SIR	Cracking (% area affected)	Estimated Response Probability VP	Estimated Response Probability P	Estimated Response Probability F	Estimated Response Probability G	Estimated Response Probability VG	Weighted Average Predicted SIR	Scaled Squared Residuals of SIR
20	26.33	.10	.33	.34	.11	.12	20.115	0.00
16	16.00	.05	.21	.35	.17	.22	16.74	0.03
12	2.29	.01	.07	.20	.18	.53	10.73	0.15
28	5.00	.01	.07	.21	.19	.52	10.99	26.33
8	.40	.01	.04	.12	.14	.69	8.805	0.07
12	.42	.01	.05	.16	.16	.62	9.69	0.55
8	2.67	.01	.07	.20	.18	.53	10.73	0.69
20	5.00	.01	.07	.20	.18	.54	10.78	7.89
16	1.00	.01	.05	.17	.17	.60	9.9	3.76
32	14.67	.04	.18	.33	.18	.26	15.59	17.27
32	15.00	.06	.24	.35	.16	.20	17.63	11.71
20	10.57	.02	.12	.28	.20	.39	13.36	3.30
8	.00	.01	.05	.15	.16	.64	9.61	0.27
24	3.00	.02	.09	.24	.19	.46	12.095	11.72
12	.47	.01	.05	.16	.17	.61	9.77	0.51
24	5.50	.01	.07	.21	.19	.52	10.99	15.40
12	3.33	.01	.05	.15	.16	.63	9.56	0.62
36	31.13	.27	.45	.20	.04	.04	25.38	4.44
28	2.00	.01	.06	.19	.18	.56	10.445	29.50
20	5.50	.01	.08	.22	.19	.50	11.325	6.65
16	2.83	.01	.06	.17	.17	.59	10.105	3.44
16	.00	.02	.10	.25	.20	.44	12.56	0.94
24	7.50	.03	.14	.30	.19	.33	14.155	6.85
12	.00	.01	.04	.14	.15	.65	9.095	0.93
4	.00	.01	.07	.21	.19	.52	10.99	4.45
8	13.76	.02	.12	.28	.20	.39	13.36	2.15
12	2.25	.01	.07	.21	.19	.52	10.99	0.09
12	15.44	.03	.13	.29	.20	.36	14	0.29
4	1.43	.02	.08	.22	.19	.49	11.63	5.01
8	.67	.01	.05	.15	.16	.63	9.56	0.25
8	14.75	.02	.11	.27	.20	.40	12.975	1.91
8	.00	.01	.05	.17	.17	.60	9.9	0.36
24	19.00	.04	.19	.34	.18	.25	15.975	4.03
4	.00	.01	.06	.17	.17	.59	10.105	3.69
32	36.00	.20	.43	.25	.06	.06	23.645	2.95

SIR	Cracking (% area affected)	Estimated Response Probability VP	Estimated Response Probability P	Estimated Response Probability F	Estimated Response Probability G	Estimated Response Probability VG	Weighted Average Predicted SIR	Scaled Squared Residuals of SIR
12	5.78	.01	.07	.19	.18	.54	10.6	0.18
4	.29	.01	.05	.14	.16	.65	9.48	3.17
16	10.00	.02	.12	.28	.20	.38	13.31	0.54
4	.00	.03	.13	.29	.20	.36	14	7.14
32	22.90	.06	.23	.35	.16	.20	17.375	12.31
8	10.33	.02	.10	.25	.20	.44	12.56	1.66
12	16.67	.05	.21	.34	.17	.23	16.61	1.28
12	1.00	.01	.05	.15	.16	.64	9.61	0.59
8	4.75	.01	.06	.19	.18	.55	10.395	0.55
8	.80	.01	.05	.15	.16	.64	9.61	0.27
8	18.00	.05	.21	.35	.17	.22	16.74	4.56
4	1.75	.01	.07	.20	.19	.53	10.86	4.33
28	42.50	.39	.42	.13	.03	.02	27.385	0.01
28	13.50	.04	.20	.34	.17	.25	16.1	8.80
20	38.50	.34	.44	.16	.03	.03	26.71	1.69
20	34.00	.28	.45	.20	.04	.04	25.735	1.28
32	20.00	.10	.33	.34	.11	.12	20.115	7.02
20	8.00	.02	.08	.23	.19	.48	11.76	5.77
24	1.00	.01	.05	.17	.17	.60	9.9	20.08
20	1.50	.01	.06	.17	.17	.59	10.105	9.69
28	20.00	.07	.26	.35	.15	.18	18.265	5.19
24	20.00	.06	.24	.35	.16	.20	17.63	2.30
24	6.50	.02	.09	.24	.19	.45	12.045	11.87
28	9.00	.04	.18	.33	.18	.27	15.64	9.77
8	1.00	.01	.06	.18	.17	.58	10.235	0.49
12	2.50	.01	.06	.17	.17	.59	10.105	0.36
20	.00	.01	.06	.18	.17	.58	10.235	9.32
16	15.00	.03	.16	.32	.19	.30	14.875	0.09
16	31.00	.28	.45	.20	.04	.04	25.735	3.68
12	10.00	.02	.11	.27	.20	.40	12.975	0.07
20	20.00	.04	.17	.32	.19	.29	15.435	1.35
20	6.23	.02	.10	.25	.20	.44	12.56	4.41
4	.00	.01	.05	.17	.17	.60	9.9	3.52

7. Validation of Ordinal Logistic SIR Model for the SS network

The predicted probabilities are used from the SPSS outputs. The weighted average SIR (expected SIR) is determined by multiplying the predicted probability with the middle value of the corresponding SIR category. For RANK2 the mid values are: VG=5, G=15.5, P=25.5, VP=35.5 that are considered for the average condition. Then the difference between observed rating (actual rating) and expected rating (predicted rating) are compared to validate the developed model using scaled squared residual of each pavement segment is estimates as follows:

$$Scaled\ Squared\ Residual\ of\ SIR\ =\ (Observed\ SIR - Expected\ SIR)^2/Expected\ SIR$$

Table B.10 Scaled Squared Residuals of SIR with estimated response probability of each category from ordinal logistic regression in the SS Network (RANK2)

SIR	Cracking	Estimated Response Probability VP	Estimated Response Probability P	Estimated Response Probability G	Estimated Response Probability VG	Weighted Average Predicted SIR	Scaled Squared Residuals of SIR
14	22.66	0.34	0.47	0.18	0.02	26.95	6.22
17	0.66	0.09	0.34	0.49	0.08	19.86	0.41
26	8.33	0.14	0.43	0.38	0.05	22.08	0.70
34	39.67	0.66	0.28	0.06	0	31.50	0.20
26	27.4	0.43	0.43	0.13	0.01	28.30	0.19
34	31.2	0.5	0.39	0.1	0.01	29.30	0.76
20	5	0.12	0.4	0.43	0.06	21.43	0.09
26	28.16	0.44	0.42	0.12	0.01	28.24	0.18
23	13.25	0.2	0.47	0.3	0.03	23.89	0.03
23	1.25	0.09	0.35	0.48	0.08	19.96	0.46
14	3	0.1	0.37	0.46	0.07	20.47	2.04
14	0	0.08	0.34	0.5	0.09	19.71	1.65
14	13.16	0.2	0.47	0.3	0.03	23.89	4.09
17	15.75	0.23	0.48	0.26	0.03	24.59	2.34
14	7.5	0.14	0.42	0.39	0.05	21.98	2.89
11	6.36	0.13	0.41	0.41	0.05	21.68	5.26
26	2.5	0.1	0.37	0.46	0.07	20.47	1.50
17	4	0.11	0.39	0.44	0.06	20.97	0.75
20	0	0.08	0.34	0.5	0.09	19.71	0.00
20	1.15	0.09	0.35	0.48	0.08	19.96	0.00
31	7	0.13	0.42	0.4	0.05	21.78	3.91

SIR	Cracking	Estimated Response Probability VP	Estimated Response Probability P	Estimated Response Probability G	Estimated Response Probability VG	Weighted Average Predicted SIR	Scaled Squared Residuals of SIR
31	1.25	0.09	0.35	0.48	0.08	19.96	6.11
31	7.1	0.13	0.42	0.39	0.05	21.62	4.07
31	1	0.09	0.35	0.48	0.08	19.96	6.11
11	13.57	0.2	0.47	0.3	0.03	23.89	6.95
29	42	0.7	0.25	0.05	0	32.00	0.28
23	10.26	0.16	0.45	0.35	0.04	22.78	0.00
9	0.66	0.09	0.34	0.49	0.08	19.86	5.94
9	5.9	0.12	0.41	0.41	0.06	21.37	7.16
9	3	0.1	0.37	0.46	0.07	20.47	6.42
20	26.5	0.41	0.44	0.14	0.01	28.00	2.28
20	12	0.18	0.46	0.32	0.04	23.28	0.46
20	9.7	0.16	0.45	0.35	0.04	22.78	0.34
31	30	0.48	0.4	0.11	0.01	29.00	0.14
29	16.52	0.24	0.48	0.25	0.03	24.79	0.72
26	4	0.11	0.39	0.44	0.06	20.97	1.21
11	1.21	0.09	0.35	0.48	0.08	19.96	4.02
11	2.35	0.1	0.37	0.47	0.07	20.62	4.49
14	0	0.08	0.34	0.5	0.09	19.71	1.65
17	2.66	0.1	0.37	0.46	0.07	20.47	0.59
31	15	0.22	0.48	0.27	0.03	24.39	1.79
6	0	0.08	0.34	0.5	0.09	19.71	9.54
23	12.5	0.19	0.46	0.31	0.03	23.43	0.01
6	1.63	0.09	0.36	0.48	0.08	20.22	10.00
26	9.4	0.16	0.44	0.36	0.04	22.68	0.49
23	0	0.08	0.34	0.5	0.09	19.71	0.55
23	6.88	0.13	0.42	0.4	0.05	21.78	0.07
14	2	0.09	0.36	0.47	0.07	20.01	1.81
23	0.94	0.09	0.35	0.48	0.08	19.96	0.46
34	2.22	0.1	0.36	0.47	0.07	20.37	9.13
17	0	0.08	0.34	0.5	0.09	19.71	0.37
29	0.57	0.08	0.34	0.49	0.08	19.51	4.62

SIR	Cracking	Estimated Response Probability VP	Estimated Response Probability P	Estimated Response Probability G	Estimated Response Probability VG	Weighted Average Predicted SIR	Scaled Squared Residuals of SIR
17	0	0.08	0.34	0.5	0.09	19.71	0.37
29	4	0.11	0.39	0.44	0.06	20.97	3.07
17	2	0.09	0.36	0.47	0.07	20.01	0.45
23	4	0.11	0.39	0.44	0.06	20.97	0.20
23	2	0.09	0.36	0.47	0.07	20.01	0.45
29	5.24	0.12	0.4	0.42	0.06	21.27	2.81
9	3.33	0.1	0.38	0.45	0.07	20.57	6.50
23	1.68	0.09	0.36	0.47	0.08	20.06	0.43
14	2.25	0.1	0.36	0.47	0.07	20.37	1.99
17	5	0.12	0.4	0.43	0.06	21.43	0.91
26	11.66	0.18	0.46	0.32	0.04	23.28	0.32
23	0.67	0.09	0.34	0.49	0.08	19.86	0.50
20	11.92	0.18	0.46	0.32	0.04	23.28	0.46
20	17.25	0.25	0.48	0.24	0.02	24.94	0.98
20	0.53	0.08	0.34	0.49	0.08	19.51	0.01
31	19.69	0.29	0.48	0.21	0.02	25.89	1.01
29	1	0.09	0.35	0.48	0.08	19.96	4.09
26	5	0.12	0.4	0.43	0.06	21.43	0.98
17	4.86	0.11	0.4	0.43	0.06	21.07	0.79
23	3.73	0.11	0.38	0.45	0.07	20.92	0.21
17	0.5	0.08	0.34	0.49	0.08	19.51	0.32
11	0	0.08	0.34	0.5	0.09	19.71	3.85
14	5.38	0.12	0.4	0.42	0.06	21.27	2.48
14	5.44	0.12	0.4	0.42	0.06	21.27	2.48
11	0	0.08	0.34	0.5	0.09	19.71	3.85
14	0	0.08	0.34	0.5	0.09	19.71	1.65
11	2	0.09	0.36	0.47	0.07	20.01	4.06
11	3.33	0.1	0.38	0.45	0.07	20.57	4.45
9	10.75	0.17	0.45	0.34	0.04	22.98	8.50
11	4.5	0.11	0.39	0.43	0.06	20.82	4.63
20	8.5	0.15	0.43	0.37	0.05	22.28	0.23

SIR	Cracking	Estimated Response Probability VP	Estimated Response Probability P	Estimated Response Probability G	Estimated Response Probability VG	Weighted Average Predicted SIR	Scaled Squared Residuals of SIR
20	21.81	0.33	0.47	0.19	0.02	26.75	1.70
26	36	0.6	0.33	0.07	0.01	30.85	0.76
9	0	0.08	0.34	0.5	0.09	19.71	5.82
14	8	0.14	0.43	0.38	0.05	22.08	2.95
26	50	0.81	0.16	0.03	0	33.30	1.60
14	7.55	0.14	0.43	0.39	0.05	22.23	3.05
20	3.5	0.1	0.38	0.45	0.07	20.57	0.02
14	0	0.08	0.34	0.5	0.09	19.71	1.65
6	0.92	0.09	0.35	0.49	0.08	20.12	9.90
11	1	0.09	0.35	0.48	0.08	19.96	4.02
11	2.67	0.1	0.37	0.46	0.07	20.47	4.38
26	32.14	0.52	0.38	0.09	0.01	29.60	0.44
29	10.8	0.17	0.45	0.34	0.04	22.98	1.58
31	7.5	0.14	0.42	0.39	0.05	21.98	3.71
40	46.33	0.77	0.2	0.03	0	32.90	1.53
34	40.5	0.68	0.27	0.05	0	31.80	0.15
40	47	0.78	0.19	0.03	0	33.00	1.48
23	0	0.08	0.34	0.5	0.09	19.71	0.55
29	24.83	0.38	0.45	0.15	0.01	27.34	0.10
29	12.88	0.19	0.47	0.31	0.03	23.69	1.19
20	1.64	0.09	0.36	0.48	0.08	20.22	0.00
17	4.33	0.11	0.39	0.44	0.06	20.97	0.75
20	5.83	0.12	0.41	0.41	0.06	21.37	0.09
23	8.5	0.15	0.43	0.37	0.05	22.28	0.02
17	2.25	0.1	0.36	0.47	0.07	20.37	0.56
29	1.66	0.09	0.36	0.48	0.08	20.22	3.82
26	7.21	0.13	0.42	0.39	0.05	21.62	0.89
29	3.5	0.1	0.38	0.45	0.07	20.57	3.46
23	0.63	0.08	0.34	0.49	0.08	19.51	0.63
23	0	0.08	0.34	0.5	0.09	19.71	0.55
34	8.16	0.14	0.43	0.38	0.05	22.08	6.44

SIR	Cracking	Estimated Response Probability VP	Estimated Response Probability P	Estimated Response Probability G	Estimated Response Probability VG	Weighted Average Predicted SIR	Scaled Squared Residuals of SIR
17	5.33	0.12	0.4	0.42	0.06	21.27	0.86
37	10	0.16	0.45	0.35	0.04	22.78	8.88
29	4.25	0.11	0.39	0.44	0.06	20.97	3.07
23	3	0.1	0.37	0.46	0.07	20.47	0.31
23	1.17	0.09	0.35	0.48	0.08	19.96	0.46
17	1	0.09	0.35	0.48	0.08	19.96	0.44
23	17.25	0.25	0.48	0.24	0.02	24.94	0.15
23	7.5	0.14	0.42	0.39	0.05	21.98	0.05
37	28	0.44	0.42	0.13	0.01	28.40	2.61
29	2.14	0.09	0.36	0.47	0.07	20.01	4.04
34	5.88	0.12	0.41	0.41	0.06	21.37	7.46
40	14.8	0.22	0.47	0.28	0.03	24.29	10.17
29	6.82	0.13	0.42	0.4	0.05	21.78	2.40
14	1	0.09	0.35	0.48	0.08	19.96	1.78
20	5.71	0.12	0.41	0.42	0.06	21.53	0.11
17	0	0.08	0.34	0.5	0.09	19.71	0.37
23	0	0.08	0.34	0.5	0.09	19.71	0.55
34	15	0.22	0.48	0.27	0.03	24.39	3.79
9	0	0.08	0.34	0.5	0.09	19.71	5.82
23	1.67	0.09	0.36	0.47	0.08	20.06	0.43
23	3	0.1	0.37	0.46	0.07	20.47	0.31
34	4.31	0.11	0.39	0.44	0.06	20.97	8.10
37	12.5	0.19	0.46	0.31	0.03	23.43	7.86
17	5.66	0.12	0.41	0.42	0.06	21.53	0.95
26	6	0.12	0.41	0.41	0.06	21.37	1.00
14	0	0.08	0.34	0.5	0.09	19.71	1.65
14	1.44	0.09	0.35	0.48	0.08	19.96	1.78
17	3.5	0.1	0.38	0.45	0.07	20.57	0.62
29	3.6	0.1	0.38	0.45	0.07	20.57	3.46
26	1.67	0.09	0.36	0.47	0.08	20.06	1.76
26	8.8	0.15	0.44	0.37	0.05	22.53	0.53

SIR	Cracking	Estimated Response Probability VP	Estimated Response Probability P	Estimated Response Probability G	Estimated Response Probability VG	Weighted Average Predicted SIR	Scaled Squared Residuals of SIR
17	2.6	0.1	0.37	0.46	0.07	20.47	0.59
29	1.98	0.09	0.36	0.47	0.07	20.01	4.04
37	6.06	0.12	0.41	0.41	0.06	21.37	11.43
23	0	0.08	0.34	0.5	0.09	19.71	0.55
23	0	0.08	0.34	0.5	0.09	19.71	0.55
37	4	0.11	0.39	0.44	0.06	20.97	12.25
26	3.83	0.11	0.38	0.44	0.07	20.77	1.32
26	5	0.12	0.4	0.43	0.06	21.43	0.98
40	8.44	0.15	0.43	0.37	0.05	22.28	14.10
26	5	0.12	0.4	0.43	0.06	21.43	0.98
23	5.5	0.12	0.4	0.42	0.06	21.27	0.14
29	5	0.12	0.4	0.43	0.06	21.43	2.68
26	2	0.09	0.36	0.47	0.07	20.01	1.79
17	6	0.12	0.41	0.41	0.06	21.37	0.89
29	6.26	0.13	0.41	0.41	0.05	21.68	2.48
23	2.92	0.1	0.37	0.46	0.07	20.47	0.31
40	17.69	0.26	0.48	0.24	0.02	25.29	8.56
29	6	0.12	0.41	0.41	0.06	21.37	2.72
29	8.19	0.14	0.43	0.38	0.05	22.08	2.17
29	5.54	0.12	0.4	0.42	0.06	21.27	2.81
20	1.6	0.09	0.36	0.48	0.08	20.22	0.00
29	9.88	0.16	0.45	0.35	0.04	22.78	1.70
26	5.33	0.12	0.4	0.42	0.06	21.27	1.05
17	0.5	0.08	0.34	0.49	0.08	19.51	0.32
17	0	0.08	0.34	0.5	0.09	19.71	0.37
17	0	0.08	0.34	0.5	0.09	19.71	0.37
23	0.92	0.09	0.35	0.49	0.08	20.12	0.41
20	0	0.08	0.34	0.5	0.09	19.71	0.00
17	2.83	0.1	0.37	0.46	0.07	20.47	0.59
14	4.25	0.11	0.39	0.44	0.06	20.97	2.32
14	3	0.1	0.37	0.46	0.07	20.47	2.04

SIR	Cracking	Estimated Response Probability VP	Estimated Response Probability P	Estimated Response Probability G	Estimated Response Probability VG	Weighted Average Predicted SIR	Scaled Squared Residuals of SIR
29	9.33	0.15	0.44	0.36	0.04	22.33	2.00
34	19.24	0.28	0.48	0.22	0.02	25.69	2.69
31	45	0.75	0.21	0.04	0	32.60	0.08
31	7	0.13	0.42	0.4	0.05	21.78	3.91
23	5.6	0.12	0.4	0.42	0.06	21.27	0.14
37	42	0.7	0.25	0.05	0	32.00	0.78
20	15.63	0.23	0.48	0.27	0.03	24.74	0.91
17	7.7	0.14	0.43	0.39	0.05	22.23	1.23
34	3.07	0.1	0.37	0.46	0.07	20.47	8.95
26	37.5	0.62	0.31	0.06	0.01	30.90	0.78
34	8.09	0.14	0.43	0.38	0.05	22.08	6.44
9	0.77	0.09	0.35	0.49	0.08	20.12	6.14
17	0.83	0.09	0.35	0.49	0.08	20.12	0.48
17	2.08	0.09	0.36	0.47	0.07	20.01	0.45

Table B.11 Probability Table from the Ordinal Logistic Model for SIR in SS Network (RANK2)

Cracking (%area affected)	Logit (VP)	Probability (VP)	Logit (P)	Probability (P)	Logit (G)	Probability (G)	Probability (VG)
0	-2.427	0.081137	-0.337	0.335402	2.359	0.497109	0.086353
2	-2.271	0.093553	-0.181	0.36132	2.515	0.470314	0.074813
4	-2.115	0.107647	-0.025	0.386103	2.671	0.441543	0.064706
6	-1.959	0.123575	0.131	0.409128	2.827	0.411414	0.055882
8	-1.803	0.141486	0.287	0.429775	2.983	0.380539	0.0482
10	-1.647	0.161515	0.443	0.447459	3.139	0.349499	0.041527
12	-1.491	0.183772	0.599	0.461656	3.295	0.318829	0.035743
14	-1.335	0.208334	0.755	0.471934	3.451	0.288994	0.030739
16	-1.179	0.235232	0.911	0.477973	3.607	0.260379	0.026416
18	-1.023	0.264443	1.067	0.479583	3.763	0.233287	0.022687
20	-0.867	0.295879	1.223	0.476712	3.919	0.207935	0.019474
22	-0.711	0.329378	1.379	0.469452	4.075	0.184461	0.016708
24	-0.555	0.364705	1.535	0.458032	4.231	0.162934	0.01433
26	-0.399	0.401553	1.691	0.442803	4.387	0.143359	0.012285
28	-0.243	0.439547	1.847	0.424227	4.543	0.125696	0.010529
30	-0.087	0.478264	2.003	0.402848	4.699	0.109866	0.009022
32	0.069	0.517243	2.159	0.379264	4.855	0.095764	0.007729

34	0.225	0.556014	2.315	0.354098	5.011	0.083268	0.00662
36	0.381	0.594114	2.471	0.327969	5.167	0.072247	0.005669
38	0.537	0.631114	2.627	0.301465	5.323	0.062566	0.004854
40	0.693	0.666634	2.783	0.275116	5.479	0.054094	0.004156
42	0.849	0.700357	2.939	0.249384	5.635	0.046701	0.003558
44	1.005	0.732041	3.095	0.224646	5.791	0.040268	0.003046
46	1.161	0.761514	3.251	0.201195	5.947	0.034684	0.002607
48	1.317	0.788682	3.407	0.17924	6.103	0.029846	0.002231
50	1.473	0.813513	3.563	0.158915	6.259	0.025662	0.00191
52	1.629	0.836033	3.719	0.140284	6.415	0.02205	0.001634
54	1.785	0.856313	3.875	0.123354	6.571	0.018934	0.001398
56	1.941	0.874462	4.031	0.108091	6.727	0.01625	0.001197
58	2.097	0.890611	4.187	0.094424	6.883	0.01394	0.001024
60	2.253	0.904909	4.343	0.08226	7.039	0.011954	0.000876
62	2.409	0.917511	4.499	0.071491	7.195	0.010248	0.00075
64	2.565	0.928575	4.655	0.062001	7.351	0.008783	0.000642
66	2.721	0.938254	4.811	0.053672	7.507	0.007525	0.000549
68	2.877	0.946698	4.967	0.046386	7.663	0.006446	0.00047
70	3.033	0.954043	5.123	0.040034	7.819	0.005521	0.000402

APPENDIX C

Road location reference				Road surface temperature (°C)	Comments	Percentage area and average width (mm) of crack by type						
Road No.	Link No.	Chainage (km)				Transverse		Longitudinal		Crocodile		Straight
		From	To			%	Avg width	%	Avg width	%	Avg width	%
373	0010	0.0	0.1	23	Start of test	5.5	2.28	14.1	2.29	1.2	1.90	5.2
373	0010	0.1	0.2	23		0.0	0.00	35.5	2.38	8.1	2.05	0.0
373	0010	0.2	0.3	23		1.3	2.30	3.9	2.98	0.0	0.00	0.0
373	0010	0.3	0.4	23		1.7	1.90	16.1	2.11	3.0	2.20	1.1
373	0010	0.4	0.5	23		0.0	0.00	8.1	2.01	1.9	2.40	0.0
373	0010	0.5	0.6	23		3.2	1.78	6.9	2.48	1.2	2.20	1.6
373	0010	0.6	0.7	24		8.3	2.66	6.9	2.27	1.3	2.00	1.4
373	0010	0.7	0.8	24		10.9	2.12	8.2	1.84	8.4	1.92	1.4
373	0010	0.8	0.9	24		15.0	1.71	8.9	2.08	5.8	1.92	1.3
373	0010	0.9	1.0	24		8.5	2.04	20.6	1.98	2.9	1.75	0.0
373	0010	1.0	1.1	24		14.4	1.80	6.4	1.97	4.6	1.99	0.0
373	0010	1.1	1.2	24		8.7	1.96	10.1	2.09	6.9	1.99	1.7
373	0010	1.2	1.3	24		9.8	1.99	30.0	2.70	12.8	2.26	2.0
373	0010	1.3	1.4	25		13.2	2.05	26.8	2.42	11.3	2.11	2.1
373	0010	1.4	1.5	25		2.3	1.87	18.7	2.10	1.6	2.00	0.0
373	0010	1.5	1.6	23	Change of seal	1.2	1.50	0.0	0.00	0.0	0.00	0.0
373	0010	1.6	1.7	23		0.0	0.00	7.0	2.42	0.0	0.00	0.0
373	0010	1.7	1.8	22		1.7	2.80	2.8	1.77	0.0	0.00	0.0
373	0010	1.8	1.9	22		0.0	0.00	2.3	2.10	0.0	0.00	0.3
373	0010	1.9	2.0	22		1.1	1.80	3.2	2.07	1.3	2.05	0.0

Source: RTA NSW – this is a sample extract from a RoadCrack survey report.

Notes:

1. '% area' corresponds with 'extent', as defined in these guidelines.
2. 'Average width' corresponds with 'severity', as defined in these guidelines, and is expressed in millimetres.
3. 'Straight' means 'straight crack-like features', which are identified by a 'straightness' test in the crack recognition software, and are mostly joints and include saw cuts, such as traffic detector loops at traffic signals.

Figure C.1 Automated cracking survey report sample (M Moffatt & Hassan, 2006).

COMMENTARY G SAMPLE EXTRACT FROM A REPORT ON A RUTTING SURVEY

Road Agency: … RCA …............... **LGA:** … Vera City .... **Road Name:** … Arterial Rd .... **Road No:** …SH No 1 ………
Rutting Survey Device: …13 laser MLP (Xyz Pty Ltd) .... **Operator's Name:** …Mr D Rutter .... **Test Date:** …11 Nov 2004 ..
Road Surface: … Dry .... **Weather:** … Fine, light wind, overcast .... **Air Temp:** … 23 Deg C ....

Location	Left wheel path rutting (2 m straight edge)					Lane rutting (3.0 m taut wire model)					Comments
	Severity (mm)		Extent (%)			Severity (mm)		Extent (%)			
	Mean max rut depth	Standard deviation	0 – 10 mm	10 - 20 mm	20 - 30 mm	Mean max rut depth	Standard deviation	0 – 10 mm	10 - 20 mm	20 - 30 mm	
100	4	3.3	100	0	0	4	3.5	100	0	0	
200	4	2.9	95	5	0	6	3.2	94	6	0	
300	12	4.7	62	23	15	10	4.4	58	26	16	
400	17	6.0	67	22	11	22	7.2	60	31	9	
500	24	7.2	48	32	20	28	8.0	42	30	18	Kerb on left side
600	21	7.7	56	40	4	30	3.5	51	34	15	
700	23	5.4	34	38	28	19	5.4	37	40	23	
800	14	5.0	65	30	5	18	5.0	62	31	7	
900	8	3.0	81	18	1	12	3.7	74	22	4	Change of seal
1000	6	3.1	86	14	0	8	2.7	83	17	0	
1100	7	2.7	92	8	0	5	3.1	90	9	1	
1200	3	1.2	96	4	0	6	1.6	89	11	0	
1300	4	2.3	97	3	0	4	1.9	94	6	0	
1400	3	2.1	98	2	0	4	2.4	98	2	0	
1500	5	2.6	94	5	1	7	2.7	94	5	1	
Averages	10	3.9	78	16	6	12	3.9	75	18	6	
Std dev'n	7.6					9.0					

Notes:

1. Mean maximum rut depth within each 100 m section is as described in Section C5.
2. The right hand part of this pro-forma could be used to refer to 'right wheel path rutting', in lieu of 'lane rutting', or the pro-forma could be modified to incorporate LWP rutting, RWP rutting, and Lane rutting, as required.

Figure C.2 Automated rutting survey report sample (Michael Moffatt, 2007a).