PAVEMENT MANAGEMENT SYSTEMS: INTEGRATION OF TRANSPORTATION MODELING, LAND USE, ECONOMY AND INDICATORS OF DEVELOPMENT

Md. Shohel Reza Amin

A Thesis
In the Department
of
Building, Civil and Environmental Engineering

Presented in Partial Fulfillment of the Requirements
For the Degree of
Doctor of Philosophy (Civil Engineering) at
Concordia University
Montreal, Quebec, Canada
October 2015

CONCORDIA UNIVERSITY

SCHOOL OF GRADUATE STUDIES

This is to certify that the thesis prepared

By: **Md. Shohel Reza Amin**

Entitled **Pavement Management Systems: Integration of Transportation Modeling, Land Use, Economy and Indicators of Development**

and submitted in partial fulfillment of the requirements for the degree of

Doctor of Philosophy (Civil Engineering)

Complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

Signed by the final examining committee:

______________________ Chair
Dr. Nabil Esmail

______________________ External Examiner
Dr. Ming Zhong

______________________ External to Program
Dr. Amin Hammad

______________________ Examiner
Dr. Osama Moselhi

______________________ Examiner
Dr. Ciprian Alecsandru

______________________ Thesis Supervisor
Dr. Luis Amador

Approved by

____
Chair of Department or Graduate Program Director

____
Dean of Faculty

Date ______________________________________

Abstract

Pavement Management Systems: Integration of Transportation Modeling, Land Use, Economy and Indicators of Development

Md. Shohel Reza Amin, Doctor of Philosophy,
Concordia University, 2015

The physical condition of road infrastructure in Canada is not good and roads are in critically condition in many regions. Canadian transportation agencies still require a comprehensive pavement management system (PMS) to guide and recommend the best practices for their appropriate application and communication. The general objective of this research is to extend PMS by incorporating dynamic states of land use, regional economics, travel modeling, and socio-economic development criteria. The specific objectives at regional scale is to integrate regional economy, transport modeling and community development criteria to simulate freight-traffic distribution between Atlantic Provinces of Canada to improve pavement-deterioration modeling and overall province-wide PMS. The specific objective at urban scale is to develop PMS for the road network of Montreal city incorporating simulated traffic and measurement errors free pavement performance curves. Comparison of current practices and proposed PMS based on simulated truck traffic reveals that incorporation of simulated truck traffic into PMS resulted in a more accurate estimation of required levels of funding for maintenance and rehabilitation (M&R). Socio-economic factors of the communities of Atlantic Provinces of Canada are integrated with regional economy and transportation modeling to support multi-criteria based PMS considering that policy makers are not only guided by the engineering characteristics but also by socio-economic benefits of the communities to allocate M&R budget. With and without scenarios of community development criteria into PMS have different implications on M&R budgets. The Backpropagation Neural Network (BPN) method with Generalized Delta Rule (GDR) learning algorithm is applied to develop pavement performance curves for Montreal road network reducing the measurement errors. Finally, a linear programming of PMS is developed for Montreal city incorporating the simulated traffic and

pavement performance curves developed by BPN networks. Lifecycle optimization of PMS estimates that CAD 150 million is the minimum annual budget to achieve most of arterial and local roads are at least in good condition (PCI>70) in Montreal city. This research will provide the transportation agencies with an improved decision-making framework capable of delivering a more balanced M&R budget for the achievement of global objectives, such as cost, condition, service, accessibility, and community benefits.

Acknowledgements

First and foremost all praises belong to Almighty God, the most merciful, most kind and generous to mankind.

I want to thank my advisor Dr. Luis Esteban Amador-Jiménez. I appreciate all his contributions of time, ideas, and funding to make my Ph.D. experience productive and motivating. Dr. Amador-Jiménez gave me the freedom to carry on my research, at the same time continuing to contribute valuable feedbacks, advices, and encouragement. In addition to our academic collaboration, I greatly value the close personal relationship that Dr. Amador-Jiménez and I have developed over the years.

I would like to thank Ville de Montréal for providing data on pavement condition of Montreal road network. I extend my special thanks to Nathalie Oum (Direction de la Gestion Stratégique des Réseaux d'Eau, Unité Plan directeur, Ville de Montréal) for helping me to get data from Ville de Montréal.

I would like to thank my beloved wife Umma Tamima. I cannot think of completing my Ph.D. degree without her relentless supports. Her support, encouragement, quiet patience and unwavering love were undeniably the bedrock upon which the past ten years of my life have been built. Her tolerance of my occasional impatience and frustration is a testament in itself of her unyielding devotion and love.

I am sincerely thankful of my kind, caring and wonderful parents who have always supported me in all aspects of my life even from a long distance.

Finally, and most importantly, I am blessed with a daughter (IBTISAM ZUNAIRAH AMIN) on January 2015. I am thankful to my daughter allowing me to write the thesis when she used to sleep on my lap and encouraging me with heavenly smiles.

Table of Contents

List of Tables

List of Figures

List of Abbreviations

AADT .... Annual Average Daily Traffic
AADTT ....Annual Average Daily Truck Traffic
AASHTO ....American Association of State Highway and Transportation Official
ADOT ....Arizona Department of Transportation
AHP... Analytical Hierarchy Process
ALGA ....Australian Local Government Association
AON .... All-or-Nothing
ANN ....Artificial Neural Network
APAS ....Action de Préparation, d'Accompagnement, et de Suivi
ASU...Arizona State University
BCR.. Benefit-Cost Ratio
BIC .... Bayesian information criterion
BMS ....Bridge Management System
BPN... Backpropagation Neural Network
BPR .... Bureau of Public Roads
Caltrans .... California Department of Transportation
CDI... Community Development Indicator
CLPL...Candidate Locations Priority List
CMA .... Census Metropolitan Area
COPACES...............................Computerized Pavement Condition Evaluation System
CRC...Cooperative Research Centre
CRCI .... Condition Ride Comfort Index
CSD...Census Subdivision
DI .... Distress Index
DOT ....Department of Transportation
DRAM...Disaggregated Residential Allocation Model
DSS .... Decision-Support System
DUE ....Deterministic User Equilibrium
ELECTRE .... Elimination et Choix Traduisant la Realité

EMPAL .... Employment Allocation Model
ESALs .... Equivalent Single Axle Loads
FDOT .... Florida Department of Transportation
FHWA .... Federal Highway Administration
FWD .... Falling Weight Deflectometer
GA .... Genetic Algorithm
GDOT .... Georgia Department of Transportation
GDR .... Generalized Delta Rule
GHG .... greenhouse gas
GIS .... Geographic Information System
H-Index .... Herfindahl index
HMA .... Hot Mix Asphalt
HDM .... Highway Design and Maintenance Model
HLM .... habitation à loyer modéré
HMMS .... Highway Maintenance Management System
HSOP .... Highway System Operations Plan
ILUT .... Integrated Land Use Transportation
ILUTTAM. Integrated Land Use and Transport for Transportation Asset Management
IM-PMM .... Infrastructure Management-Process Maturity Model
IMREL .... Integrated Model of Residential and Employment Location
IOWADOT .... Iowa Department of Transportation
IPWEA .... Institute of Public Works Engineering Australia
IRI .... International Roughness Index
ISO .... International Standardization Organization
ISTEA .... Intermodal Surface Transportation Efficiency Act
ITS .... Intelligent Transportation System
ITLUP .... Integrated Transportation Land Use Package
ILUTE .... Integrated Land Use, Transportation, Environment modeling system
KBS .... Knowledge-Based System
LCCA .... Life-Cycle Cost Analysis
LEF .... Load Equivalency Factor

LILT .... Leeds Integrated Land Use- Transport

LOS .... level-of-service

LRRS... Local Roads of Regional Significance

LUT ....Land Use & Transport Modeling

MCA .... Multicriteria Analysis

MCI .... Maintenance Control Index

MDP .... Markov Decision Process

MDOT .... Michigan Department of Transportation

MLP .... Multi-Layer Perceptron

MMS .... Maintenance Management System

MnDOT ....Minnesota Department of Transportation

MNL...Multinomial Logit

M&R .... Maintenance and Rehabilitation

MRP .... Maintenance Rating Program

MRWA...Main Roads Western Australia

MUC ....Montreal Urban Community

MUSSA...Modelo de Uso de Suelo de Santiago

NCHRP ....National Cooperative Highway Research Program

NDOT .... Nevada Department of Transportation

NDDOT...North Dakota Department of Transportation

NLRDS ....National Local Roads Database System

NYMTC-LUM...........New York Metropolitan Transit Commission- Land Use Model

NZTA..New Zealand Transport Agency

OBNL..organisme à but non lucrative

ODOT ....Ohio Department of Transportation

OECD.............................. Organisation for Economic Co-operation and Development

OPAC.. Ontario Pavement Analysis of Costs

PCA.. Principal Component Analysis

PCC ....Portland Cement Concrete

PCEs..Passenger Car Equivalents

PCI .... Pavement Condition Index

PECAS .... Production, Exchange and Consumption Allocation System
PLR .... Polynomial Linear Regression
PennDOT .... Pennsylvania Department of Transportation
POLIS .... Projective Optimization Land Use Information System
PMS .... Pavement Management System
PPS&O .... Pavement Performance Simulation and Optimization
PQEM .... Pavement Quality Evaluation Model
PQI .... Pavement Quality Index
PRISM .... Pavement Rehabilitation and Improvement Strategic Model
PRP .... Program and Resource Plan
PSI .... Present Serviceability Index
QLDRA .... Queensland Road Alliance
RAMM .... Road Assessment and Maintenance Management
RCI .... Roadway Characteristics Inventory
RDI .... Regional Development Indicator
RE .... Relative Error
RIAMS .... Road Infrastructure Asset Management System
RIDB .... Roadway Information Data Base
RPP .... Rehabilitation Project Prioritization
RQFS .... Roadway Quality Forecasting System
RQI .... Ride Quality Index
RRGs .... Regional Road Groups
RSL .... Remaining Service Life
RSMS .... Road Surface Management System
RURBAN .... Random-Utility Urban
SAI .... Standard Application Inquires
SIO .... Spatial Input-Output
SNC .... Structural Number Coefficient
SO .... System Optimum
SSE .... Sum of Squares Error
STIP .... State Transportation Improvement Program

SUDI ....Sustainable urban development Indicator
SUE .... Stochastic User Equilibrium
TAC...Transportation Association of Canada
TARUT .... Transportation Application of Restricted Use Technology
TAZs .... Traffic Analysis Zones
TF ....Truck Factor
TFCP ....Transportation Facilities Construction Program
TPM .... Transition Probability Matrix
TRESIS .... Transportation and Environment Strategy Impact Simulator
UTPS...Urban Transportation Planning System
VII ....Vehicle Infrastructure Initiative
WALGA.. Western Australia Local Government Association

Chapter 1
Introduction

1.1. Background

The pavement management system (PMS) is an approach that incorporates the economic assessment of trade-offs between competing alternatives at both the network and project levels (Ouertani, et al., 2008). A PMS can provide an organized methodology to assist decision makers at all management levels with strategies derived through clearly established rational procedures (Hudson, et al., 1979). The idea behind the PMS is to improve efficiency of decision making, expand its scope, provide feedback as to the consequences of decisions, and ensure consistency of decisions made at different levels within the same organization. A complete PMS has applications in virtually every division within a transportation agency (Peterson, 1987).

The PMS integrates and simulates the pavement activities with roadways evaluation; and achieves the optimum use of available funds by comparing investment alternatives and coordinating design, construction and maintenance. In other words, a PMS systematically integrates the activities relating to data collection, processing and analysis; identification of current and future needs; and development of rehabilitation and maintenance programs to implementation of the programs through design, construction and maintenance (Haas & Hudson, 1987). This ensures a safe, comfortable and economic transportation. The 1986 AASHTO 'Guide for Design of Pavement Structures' states that 'pavement management in its broadest sense encompasses all the activities involved in the planning, design, construction, maintenance, evaluation, and rehabilitation of the pavement portion of a public works program' (Allen, et al., 1992).

The methodology of the PMS uses the prediction models to estimate the structural and functional deteriorations of the pavement. The PMS methods consider both the historic pavement performance data and engineering considerations. The materials in the pavement layers, and their degradation under the effects of time and loading, are of primary concerns to those highway engineers responsible for the maintenance and performance of the pavement network (Ullidtz & Stubstad, 1992). Therefore, the pavement performance modeling by extrapolating future condition from historical data is a technically unacceptable simplification because the effects of material degradation, maintenance, or rehabilitation measures cannot be considered (Ullidtz & Stubstad, 1992).

The overall structure and the logical sequences of the activities of a PMS can be outlined by Figure 1.1. This activities-based framework of the PMS assumes that route selection, feasibility studies and functional planning of the highway or street have already been conducted (Roads and Transportation Association of Canada, 1977). There are five phases in the PMS framework – planning or programming, design, construction, maintenance and in-service evaluation.

The planning or programming phases includes the acquisition of dynamic traffic load data, an assessment of the deficiencies on a network basis, the establishment of priorities, the development of a schedule for carrying out the needed works, and the determination of any extra property required. The basic investment decisions within the budget constraints are taken in this phase (Roads and Transportation Association of Canada, 1977).

The design phase initially acquires data on the pavement materials, traffic loads of different categories of vehicles, and costs, etc. The alternative designs are developed, analyzed and compared with respect to their costs and benefits. Finally, the best alternative is selected for construction. The construction phase includes specifications and contracts, work scheduling, construction operations, quality control, and processing of data (Roads and Transportation Association of Canada, 1977).

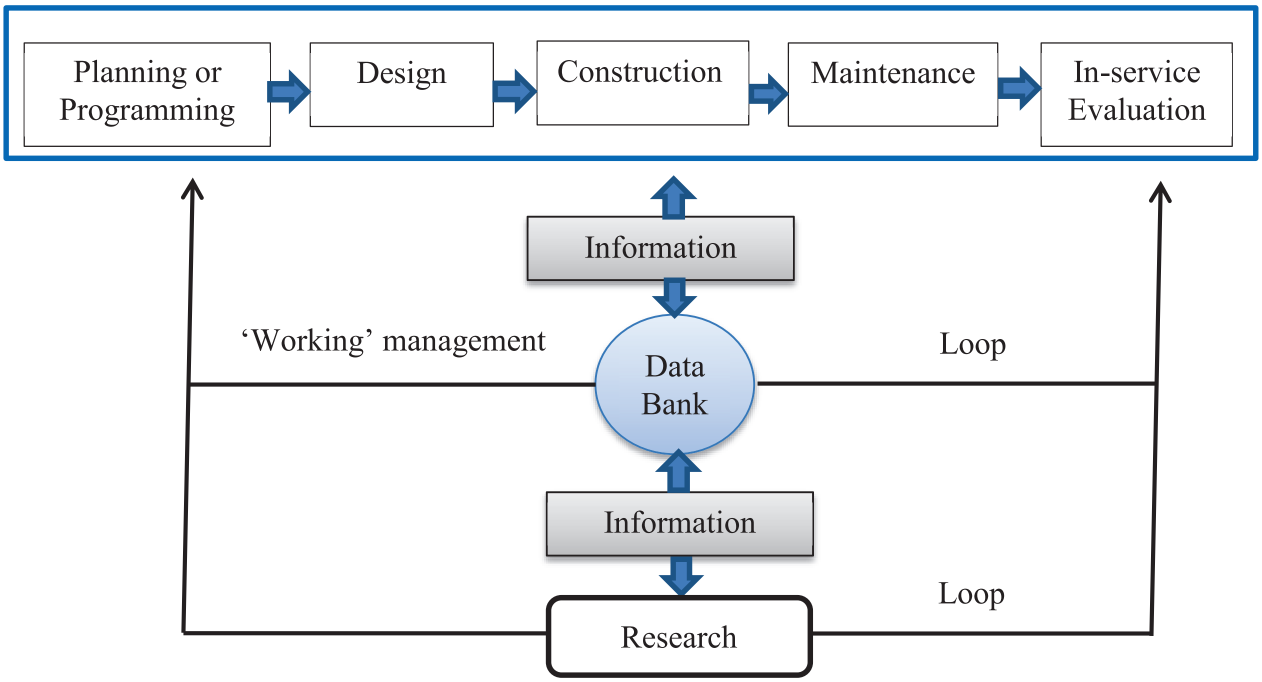


Figure 1.1: The activities-based framework of the PMS

The maintenance phase includes the establishment of a standard program and schedule within the budget constraints, the Maintenance and Rehabilitation (M&R) operations, and the acquisition and processing of data (Roads and Transportation Association of Canada, 1977).

The in-service evaluation of pavements includes the establishment of control selections, the periodic measurement of the pavement structural capacity, roughness, condition, and skid resistance under dynamic traffic loads. It also includes the input data, which are stored in the data bank, for use in the other cycle of the PMS (Roads and Transportation Association of Canada, 1977).

The PMS framework has separately identified the data bank to emphasize its central role as an information base for all activities. Data banks can range from simple manual record files to sophisticated computer systems. The importance of research as a major phase of the pavement management system depends largely upon the available resources and the particular requirements of each transportation agency (Roads and Transportation Association of Canada, 1977).

1.2. Problem statement

Internationally, the practices of PMS are moving from condition-based approaches towards service-based approaches focusing more on customer-driven priorities. A service-based approach that expands traditional condition-based methods has to be balanced against the budget constraint, level of service and risk tolerance. However, transportation agencies have not yet address how dynamic traffic loads vary during the life-span of the pavement as a result of the economic evolvement. Currently, capital investments are somehow disconnected from PMS and must be fully incorporated within the decision making framework. Even though some research has looked into uncertainty, few state of the practice models incorporate it on the performance curves. The economic impact of multiple strategies (i.e., rehabilitation versus capital investments) for condition, congestion, pollution and social cost, has not been addressed. The perception of congestion combined with condition, highway capacity, and accessibility impact the personal choices of modes, routes and links (Donaghy and Schintler, 1998) and must be included in a wider PMS framework.

In most cases, the PMS is based on the Markov Decision Process (MDP) optimization method that has some limitations. The optimization programming of M&R strategies are calculated from the steady-state probabilities. However, in reality, the pavements under a given maintenance policy usually takes many years to reach the steady state and the proportion of the pavements are changing year by year. Therefore, the use of steady-state probabilities in the optimization objective function does not fully reflect reality, especially when this transition period is very long (Li, et al., 2006).

Transportation agencies usually minimize the agency and user costs; and maximize the pavement condition in the life-cycle cost optimization of the PMS. They are giving little attention on the effect of M&R strategies on the other road users such as residents in close proximity from the road, industrial settlements, trade centres, etc. (Cafiso, et al., 2002).

Transportation agencies should develop a performance-based PMS which ensures the serviceability, accountability, stewardship, long-term financial plans, transparent investments, and the betterment of the communities.

A framework that incorporates the states of land use, regional economies and trade flow, transportation modeling, pavement condition, environmental costs and socio-economic development indicators into the performance-based PMS is required.

1.3. Objectives

1.3.1. General Objective

The general objective of this research is to extend PMS by incorporating dynamic states of land use, regional economics, travel modeling, and socio-economic development criteria into pavement management systems.

There are two groups of specific objectives: one for regions and another for cities.

1.3.2. Specific Objectives at regional scale

i. To integrate regional economy and transport modeling at a regional scale to forecast freight-traffic distribution to improve pavement-deterioration modeling and overall province-wide PMS.
ii. To expand multi-criteria based PMS incorporating community development criteria.

1.3.3. Specific Objectives at urban scale

i. To develop pavement performance model for the road network of a city that integrates land use and transport modeling and reduces the measurement error of pavement performance model
ii. To develop a linear programming of PMS for the road network of a city that accommodates the simulated traffic during a long term period and deals with the measurement error of the pavement performance modeling.

1.4. Tasks

1.4.1. Tasks for Specific Objectives at regional scale

i. Collect data on historical pavement condition and regional economies.
ii. Estimate traffic flow on the regional networks of the Atlantic Provinces by integrating the spatial input-out and transportation models.
iii. Develop pavement performance curves
iv. Calculate the community development criteria for each census subdivision (CSD) of Atlatic Provinces of Canada.

v. Develop a multi-criteria PMS incorporating the regional economies, travel modeling, pavement performance, and community development criteria.

1.4.2. Tasks for Specific at urban scale

i. Collect data on the historical pavement condition, land uses, urban development and economic characteristics.

ii. Anticipate the traffic flow on the different road networks by applying travel demand model of urban transportation planning package (UTPS) during the period of 2009-2058.

iii. Apply the Backpropagation Neural Network (BPN) method with Generalized Delta Rule (GDR) learning algorithm for reducing the measurement errors of the pavement performance modeling.

iv. Develop pavement performance curves for flexible arterial, flexible local, rigid arterial and rigid local roads of Montreal city durng the period of 2009-2058.

v. Develop the linear programming of PMS for the road network of Montreal city that accommodates the simulated traffic during the period of 2009-2058 and deals with the measurement error of the pavement performance modeling

1.5. Expected contributions

This research provides new methods to address drawbacks of current transportation management systems. The input of the dynamic traffic loads resulted from the integration of Land Use and Transport Modeling into the PMS enables a significant improvement in the allocation of economic resources.

The periodic incorporation of the travel demand models into the PMS will not only make it accommodative to most growth-theory frameworks and distribution models, but also provide a better way of depicting ongoing aggregate behavior and a more satisfactory PMS (Donaghy and Schintler, 1998). The improved performance models of the PMS will reflect a more realistic measure of travel demand and trip redistribution, therefore, improving the user's satisfaction and ability to generate and support economical activities. The integration of these modeling frameworks represents the opportunity to deploy performance-based trade-off analysis (as oppose to lifecycle cost-benefit) for the monetary allocation of resources among competing alternatives for maintenance and rehabilitation, safety retrofitting, mobility and accessibility improvements, network expansion and capital upgrades.

The inclusion of the community development criteria within the PMS addresses the effect of M&R strategies on other road users such as residents in close proximity from the road, industrial settlements, trade centres, etc. This helpes the transportation planner and policy makers to understand the positive impact of transport infrastructure maintenance on the community development.

Overall, the possible integration of these frameworks will represent the opportunity of a more comprehensive representation of the economic development of city and region. It will provide us with an improved decision-making framework capable of delivering a more balanced budget for the achievement of global objectives (cost, condition, service, accessibility, and pollution). The final product of this research should provide transportation authorities with the capacity to build alternative scenarios to assess the impact of policies intended to address major transportation issues such as pricing traffic congestion and to estimate the environmental impact of vehicle emissions. Ultimately, the research can be extended to cover all infrastructure systems and to identify viable means to estimate performance measures to be used to evaluate how well the infrastructure systems support urban and economic development strategies.

1.6. Limitations and scope for future research work

This study simulates the commercial and urban traffics based on the aggregate data of travel behavior. People travel in order to satisfy a need undertaking an activity at particular locations. This is equally significant for goods movements. In order to understand the demand for transport, we must understand the way in which these activities are distributed over space, in both urban and regional contexts. There is a whole range of specific demand for transport which are differentiated by time of day, day of week, journey purpose, type of freight transport, importance of speed and frequency, and so on. Transport demand modeling has very strong dynamic elements. Future study should develop a travel demand modeling considering disaggregate data and dynamic attributes of travel behavior.

Pavement deterioration is caused not only by vehicles induced deformations but to a large extent by the interaction of traffic and climate. Climate effects, particularly during spring-thaw cycles, must be addressed to attain comprehensive and long-term PMS in cold regions. Future study should simulate the climate change and traffic growth and estimate the implications of climate change and traffic growth on PMS in cold region. This will have two-fold contributions to the currently practicing PMSs. First, it will accommodate the climate change induced seasonal variability in the traditional PMS for the road network of cold regions. Second, it includes dynamic traffic loads into PMS rather than simply based on anticipate traffic growth during the life-span of pavement structures.

1.7. Organization of the thesis

This dissertation is prepared into ten chapters as follows. Chapter 1 defines the problem and presents the objectives of the research and structure of the thesis. Chapter 2 discusses the practices of Road Infrastructure Asset Management System (RIAMS) adopted in different countries. This discussion mainly focuses on PMS. Chapter 3 discusses the methods of PMS and outlines a conceptual framework of a PMS that incorporates dynamic states of land use, traffic volumes, design capacities, and pavement conditions. Chapter 4 discusses various deterministic and stochastic approaches for calculating pavement performance curves. This chapter discusses the Backpropogation Artificial Neural Network (BPN) method with generalized delta rule (GDR) learning algorithm to reduce the measurement error of the pavement performance model. This chapter also argues for the application of reliability analyses dealing with the randomness of pavement condition and traffic data. Chapter 5 presents the methodology employed for the collection, processing and analysis of the data. Chapter 6 integrates the spatial input-output and transportation models to simulates freight traffic distribution in order to improve pavement deterioration modeling. A case study of trade flows between Canada's Atlantic Provinces and Quebec is used to show the pitfall of current management models to estimate rates of deterioration underfunding maintenance and rehabilitation strategies. Chapter 7 integrates the regional economy and socio-economic factors of communities with transportation to support multi-criteria based PMS for the regional road network of Atlantic Canada provinces. Chapter 8 applies the BPN method with GDR learning algorithm for reducing the measurement errors of the pavement performance modeling. The Multi-Layer Perceptron (MLP) network and sigmoid activation function are applied to build the BPN network. Local and arterial roads of both flexible and rigid pavements in Montreal City are taken as a case study. Chapter 9 develops the linear programming of PMS for the road network of Montreal City that accommodates the simulated traffic during the period of 2009-2058 and deals with the measurement error of the pavement performance modeling. Chapter 10 includes the concluding remarks of the overall research.

Chapter 2

Discussion on Road Infrastructure Management Practices

Amin, M.S.R., and Amador, L. (2014). Discussion on Road Infrastructure Management Practices. International Journal of Built Environment and Asset Management, 1(3), pp. 236-251.

Abstract

The objective of this study is to discuss the practices of Road Infrastructure Asset Management System (RIAMS) adopted in different countries. This discussion mainly focuses on the pavement management system. Internationally, the RIAMS approach is moving from the condition-based towards the service-based approach focusing on the customer-driven priorities. This service-based approach needs to be balanced with the budget constraints, level of service and risk tolerance. The transportation agencies have not yet addressed the integrated land use and transportation modelling, the comparison of the relative advantages between capital and operating investments, the risk-based estimation, and the identification of a range of costs associated with the failure within the RIAMS. The transportation agencies should develop a performance-based RIAMS ensuring the serviceability, accountability, stewardship, long-term financial plans, and transparent investments. The RIAMS is still emerging and needs to incorporate the local mission, budget and other constraints within the scope of the local context.

Keywords

Infrastructure Planning, Roads & Highways, Transport management, Transport planning.

2.1. Introduction

The Road Infrastructure Asset Management System (RIAMS) is a systematic process of maintaining, upgrading, and operating different components of road infrastructures in a most cost-effective manner. It provides a concrete foundation to periodically monitor the performance and to optimise the maintenance and rehabilitation (M&R) actions through cost-effective management, programming and resource allocation decisions (Karlsson, et al., 2007). The RIAMS can be explained in different terms such as ‘ensure desirable driving standards’, ‘maintain performance standards involving pavement smoothness and riding comfort’, ‘foster a competitive business environment supported by a safe, efficient, and accessible transportation network', 'ensure appropriate levels of quality and accessibility', and 'minimise the long-term costs of preserving the highway system', and so on (Falls, et al., 2001).

The Federal Highway Administration (FHWA) defines RIAMS in the Asset Management Primer (Federal Highway Administration, 1999). The Asset Management Primer points out that the parameters or characteristics of any infrastructure system must match with the goal, ability and scope of the relevant infrastructure agency; and should be flexible enough for future change (FHWA, 1999). The Transportation Association of Canada (TAC) (1999) also indicates the flexibility of RIAMS to capture the needs, resources and policies of an involved agency (Falls & Haas, 2010). The TAC framework explains that a comprehensive RIAMS should have the ability to identify future deterioration, to identify the possible alternative programs along with their costs and economic rate of returns on investments, and to calculate future asset values of these alternatives (Falls, et al., 2001).

The RIAMS is still an emerging concept and facing diversified challenges because of the growing demand for investment in the construction and M&R operations under the budget constraints. Moreover, it is estimated that the infrastructure investment on M&R operations is more beneficial for the economic growth of a country comparing to the investment on new infrastructure (Rioja, 2003).

Many countries have experienced a wide spectrum of challenges and possible alternative options for the RIAMS during the last couples of decades. The RIAMS has experienced advanced technical and methodological improvements with a wide spectrum of functionalities such as inspection and data collection, condition assessment, performance evaluation, prediction of future performance, planning and prioritising M&R operations, and evaluating alternative technical and economic policies (Halfawy, et al., 2002). These advanced techniques and methods have developed and applied to support management activities for different components of road infrastructures such as pavement and bridge etc. The most well-known RIAM model is the Highway Design and Maintenance Standards Model (HDM) III developed by the World Bank for evaluating the road projects in developing countries (Watanatada, et al., 1985; Watanatada, et al., 1987). The HDM-III model provides an annual expenditure for a particular strategy including construction, M&R operations. It also generates vehicle operation costs, agency costs and user costs (Ockwell, 1990).

The objective of this study is to discuss the practices of RIAMS adopted in different countries. This discussion mainly focuses on the Pavement Management System (PMS).

2.2. United States approaches

The Department of Transportation (DOT) of different States in the United States has adopted its own PMS practice as a part of the RIAMS. This section focuses on the RIAMS practices in Arizona, Ohio, Michigan, Minnesota, Georgia, Florida, California, Iowa, Maine, Pennsylvania, and North Dakota States.

2.2.1. Arizona Department of Transportation (ADOT)

The ADOT has developed a Five-Year Transportation Facilities Construction Program (TFCP) for highways and airports. The PMS, which was first developed in early 1980s, is one of the key elements of TFCP. The ADOT applied network optimisation PMS by using Markov decision process (MDP) (Li, et al., 2006).The ADOT calculates pavement performance prediction curves based on the historical performance (condition) data. The PMS operates the decision tree to determine the M&R operations, calculates the post-treatment future performance, and determines the strategy of cost-effectiveness for each of the section of the road network (Li, et al., 2006).

Medina et al. (1999) integrated the decision-support system (DSS) tools of the Geographic Information System (GIS) with PMS to improve the PMS. This DSS model adopts the Road Surface Management System (RSMS) package, which is based on the general framework of PMS proposed by Monismith et al. (1987) for local governments and developed at Arizona State University (ASU) (Flintsch, 1991; Medina, et al., 1999).

2.2.2. Ohio Department of Transportation (ODOT)

Every two years, the ODOT management updates the goals of infrastructure system; and develops a new 10-year infrastructure system preservation plan. Two-year strategic plan outlines the short-term activities to achieve the 10-year goals. The condition of the infrastructures determines the districts' budgets (National Cooperative Highway Research Program, 2007). The ODOT uses a "mix of fixes" to provide the infrastructure a condition state as close to a steady state as possible. The targeted value of pavement condition depends on the satisfactory ride quality and the budget affordability of ODOT (NCHRP, 2007). The ODOT has also adopted the sensitivity analysis of the infrastructure investments due to the increasing construction costs and budget constraints. The ODOT includes the importance of economic development along with the transportation efficiency and effectiveness into the PMS. For example, 70 percent weight is assigned to transportation efficiency and effectiveness factors, and 30 percent weight is assigned to economic development factors to decide the infrastructure investments (NCHRP, 2007).

2.2.3. Michigan Department of Transportation (MDOT)

Initially, the MDOT prioritised the projects and recommended M&R operations by developing a priority assessment model and performing the life-cycle cost analysis (LCCA). The projects were ranked based on the sufficiency, PMS, traffic, and economic data (Zimmerman, 1995). This methodology was later revised to adapt the Roadway Quality Forecasting System (RQFS). The RQFS uses the planning and technical processes to develop the PMS (Zimmerman, 1995). The planning process consists of a needs assessment, the long-range plan, and budget setting. The technical process consists of design, construction, maintenance, and research. The projects are selected based on fulfilling the constraints, and attaining the efficiency and benefits (Zimmerman, 1995).

The MDOT calculates the Remaining Service Life (RSL) of a pavement section processing the historical distress data, project type history, and the distress growth curves. In case of insufficient distress data, the MDOT calculates RSL based on the engineering judgements and the historic performance data of similar pavement (NCHRP, 2007). The MDOT applies the transition probability matrix (TPM) to define the pavement performance. The applied method is unable to answer the behaviour of the transition probabilities under modified strategies or M&R operations (NCHRP, 2007). Another disadvantage of the PMS is that the decision of M&R operations are based on long-term pavement strategies rather than life-cycle costs, although the LCCA is used to choose between comparable M&R alternatives (NCHRP, 2007). The MDOT is facing the difficulties of accurately and timely updating the infrastructure databases; especially with the new projects and heavy M&R operations. The MDOT has been carrying out different studies to overcome these difficulties (NCHRP, 2007).

The main advantage of the MDOT is that all of the asset management systems (AMSs) are integrated because of MDOT's commitment to the Intermodal Surface Transportation

Efficiency Act (ISTEA) management systems. The AMSs use the same set of standards, data collection methods, mapping and referencing systems, and technical platforms, etc. This enables the improvement of the facilities at the appropriate time, and saves the time and money (NCHRP, 2007).

2.2.4. Minnesota Department of Transportation (MnDOT)

The MnDOT has developed the Highway System Operations Plan (HSOP) for defining the needs, implementing the performance-based district plans, and articulating the needs of historical funding level. The MnDOT adjusts the district plans with respect to the available funding in the State Transportation Improvement Program (STIP) (NCHRP, 2007). The MnDOT has developed a RIAMS formula to distribute the funds consistent with the state policies. The formula assigns the weights of 60 percent, 10 percent and 30 percent to the preservation, safety and mobility, respectively. The formula also assigns weight to individual factors such as: 20 percent for the average bridge needs, 5 percent for the heavy commercial vehicle miles travelled, 35 percent for the average pavement needs, 10 percent for the fatal-injury crashes, 15 percent for the congested vehicle miles travelled, 5 percent for the transit use, and 10 percent for the future vehicle miles travelled (NCHRP, 2007).

The HSOP performance measures include the public opinion on the level of performance, such as: Ride Quality Index (RQI). The RQI is a measure of pavement smoothness perceived by the road users. The MnDOT develops a pavement quality index (PQI) for the entire road system each year relating the RQI and the surface rating (SR). The SR rates each road segment based on the pavement cracking (NCHRP, 2007). The MnDOT also estimates the benefit-to-cost ratio (BCR) for the HSOP investments and ranks the projects based on the public opinion.

2.2.5. Georgia Department of Transportation (GDOT)

The GDOT has developed the Computerised Pavement Condition Evaluation System (COPACES). The COPACES has several modules such as; data collection, network-level data management and analysis, network-level GIS, highway maintenance management system (HMMS), knowledge-based system (KBS), pavement profile, pavement performance, pavement performance simulation and optimisation (PPS&O), and rehabilitation project prioritisation (RPP) (Tsai & Lai, 2002).

The data collection module incorporates many features such as automatic data input and built-in data validation schemes. The GDOT also develops a quality control program to perform the screening and filtering the historical data before using for other applications, such as: network analysis data management and reporting, network-level GIS spatial analysis and visualisation, and development of deterioration models (Tsai & Lai, 2002). The Network-level data management and analysis module provides the query forms to query on the selected information from the centralised database, and to perform various statistical and temporal analyses (Tsai & Lai, 2002).

The Network-level GIS module analyses and visualises the pavement condition. The spatial analysis allows evaluating the pavement condition for different jurisdiction levels, such as: state, county, congressional district, and engineering district (Tsai & Lai, 2002).

The HMMS module provides an effective tool for planning and scheduling maintenance activities utilising the internal resources of the GDOT. The module tracks various operational activities; and compares them with the historical data. The comparison helps the module to evaluate and optimise the operation efficiency on a daily basis (Tsai & Lai, 2002).

The pavement profile information module allows the storage and retrieval of all relevant pavement information, such as: pavement structure properties, material properties constituting each pavement layer, and pavement construction and rehabilitation history on a system-wide basis. The KBS module diagnoses the causes of pavement distresses and suggests additional investigations if the queried information is insufficient for the system to render the diagnosis (Tsai & Lai, 2002).

The pavement performance module is developed to generate more accurate pavement deterioration models for predicting the network-level pavement system performance. The models are developed on the basis of the historical pavement performance and distress data currently available in the database (Tsai & Lai, 2002).

The PPS&O module balances the distribution of the funding and number of projects among different districts. The RPP module develops a systematic decision-making process to assist the decision makers in prioritising M&R projects; and to estimate the costs for the M&R projects (Tsai & Lai, 2002).

2.2.6. Florida Department of Transportation (FDOT)

The FDOT develops a 20-year Florida Transportation Plan (FTP) for enhancing the safety and system preservation, promoting the economic competitiveness, and providing mobility. The FDOT also develops a 10-year Program and Resource Plan (PRP). The PRP contains program funding levels, and have the financial and production targets balancing against the anticipated revenues. In addition, a five-year listing of projects (known as the work program) is developed annually based on the existing plans, district and public involvement, and collaborative decision (NCHRP, 2007).

The FDOT does not have a separate RIAMS rather it considers asset management as the entire process of planning, programming, and system monitoring. The FDOT depends on four major management systems for providing information to investment decisions: the PMS, the Bridge Management System (BMS), the Maintenance Management System (MMS) and the Maintenance Rating Program (MRP). The asset management approach depends on the adopted operational policies. The adopted operational policies are linked to customer opinions and expectations on road conditions and maintenance levels. The FDOT has also defined the Roadway Characteristics Inventory (RCI) as the indicator of obtaining and disbursing the transportation funds (NCHRP, 2007).

2.2.7. California Department of Transportation (Caltrans)

The district offices of Caltrans use the 'Candidate Locations Priority List (CLPL)' to develop and design the projects. The districts establish the project priority number by giving weighted average to the individual segments of the entire road network and finally submit it to the Caltrans headquarters for the compilation of a state-wide priority list (Paterson, 1987). The CLPL is an array of 14 priority categories by combining ride score, distress ratings, and average daily traffic in different ways (Paterson, 1987).

2.2.8. Pennsylvania Department of Transportation (PennDOT)

The PennDOT develops a RIAMS to improve management control of the road network. The major components of the RIAMS are: the Roadway Information Data Base (RIDB), the pavement management function, the Standard Application Inquires (SAI), the ad-hoc query language and function, and the batch reporting. The SAI contains planned and approved projects, accident details, accident summary, planned maintenance activities, Annual Average Daily Traffic (AADT) and pavement conditions, planned and approved projects affecting a structure or accident details by structure, AADT and pavement condition ranking, and state route sequential listing (Paterson, 1987).

2.2.9. North Dakota Department of Transportation (NDDOT)

The NDDOT uses the pavement performance models to develop a multiyear prioritised program for pavement families with consistent deterioration patterns. The decision matrices are established to determine the appropriate rehabilitation treatments for various functional classifications, condition levels, and geometric situations. The NDDOT applies the BCR to determine the timing and level of rehabilitation that provides the agency with the most cost-effective strategy over the analysis period (Paterson, 1987).

The U.S. transportation agencies address several transportation issues in the RIAMS, such as: the performance data and systematic processes are used to evaluate investment strategies. This enables the transportation agencies responding effectively to the budget constraints, and to the government efforts improving efficiency and increasing customer expectations (FHWA, 2012). The incorporation of LCCA into the RIAMS enhances the efficiency of asset management and improves the accountability of the transportation agencies. The adopted RIAMS determines the financial sustainability of the investment programs by evaluating the percentage of depreciation funded each year and accounting for any unfunded depreciation as an agency liability (FHWA, 2012). The transportation agencies have not yet address the dynamic traffic loads during the life-span of the pavement, the comparison of the relative advantages between capital and operating investments, and the risk-based estimating, and the identification of a range of costs associated with the failure.

2.3. Canadian approaches

Very few transportation agencies have developed means of evaluating performance of the overall RIAMS (Falls, et al., 2001) (OECD, 2001). The Saskatchewan Department of Highways and Transportation adopted the asset management guiding principles, such as: developing methodology based on an objective assessment of needs, collecting the condition data on an objective and repeatable basis, considering the M&R operations in the overall optimisation to preserve the infrastructure, and finalising the district-level preservation treatment decisions within an overall policy framework to collectively manage the provincial budget (Saskatchewan Department of Highways and Transportation, 1994).

The condition indicators vary from jurisdiction to jurisdiction, making it difficult to benchmark, or compare network performance among transportation agencies. In addition, the results from existing performance measures are not always analysed and represented in a manner understandable or useful to senior management and technical personnel. The transportation agencies still require compiling and evaluating the range of performance indicators for road networks, and provide guidance and recommended best practices for their appropriate application and communication (OECD, 2001).

2.4. Australian approaches

The RIAMS of Australia applies different performance indicators at upper, internal management, and lower levels. At the upper level, the transportation agencies annually publishes national performance indicators including road safety, registration and licensing, road construction and maintenance, environment, programme and project assessment, travel time, lane occupancy rates and user costs (OECD, 2001).

At the internal management level, the agencies use a variety of performance indicators of the RIAMS, such as: program efficiency, user satisfaction, road-user costs, freight movement and heavy vehicle access, route reliability with respect to flooding, levels of private investment from developers and on toll-ways, environmental performance, contracting performance, administrative overheads, and stakeholder acceptance of the road implementation program (OECD, 2001). At the local level, the transportation agencies use the performance indicators including the trend in road pavement or bridge condition, and measurement parameters for a route, sub-network, road category or region (OECD, 2001). Different transportation agencies practice different types of RIAMS, which are explained in the following sections:

2.4.1 Australian Local Government Association (ALGA)

The ALGA has developed the National Local Roads Database System (NLRDS). The system utilises existing data collected annually by the State Grants Commissions; and calculates the sealing of gravel roads, state of assets, expenditure on roads and bridges, road asset consumption, road asset sustainability and road safety measures (Australian Local Government Association, 2010).

2.4.2 Western Australia Local Government Association (WALGA)

The WALGA uses the ROMAN software as a tool to the RIAMS of the Western Australian local road network. The ROMAN II provides road inventory (age and current condition rating), valuation package and an indicative works program feature (Haider, et al., 2011). The key features of the ROMAN II includes a detailed and accurate road asset register incorporating financial values, a data collection and record keeping repository with GIS functionality, comprehensive works programming and deterioration modelling, road asset reporting to the Grants Commission, 'phase in' with minimal loss of data and disruption, and value for money and system longevity (National Research Centre for Local Roads, 2009). The ROMAN II prepares a RIAMS report compatible with State and Commonwealth Government road asset reporting. The report is used by the Western Australian Local Government Grants Commission to distribute the road grant portion of the Australian government grants to local governments (Haider, et al., 2011).

2.4.3 Queensland Road Alliance (QLDRA)

The QLDRA, developed by the Queensland Department of Main Roads and Local Governments, is a state-wide framework that guides the decision making through a set of parameters for investment and road management strategies. The QLDRA is a voluntary alliance, which manages Local Roads of Regional Significance (LRRS). The LRRS includes the lower order state roads and the higher order local government roads. The aim of the QLDRA is to improve the asset management data and practice for Queensland roads. The key functions of QLDRA are investment strategies, project prioritisation, asset management, resource sharing, joint purchasing, and capability improvement. The Queensland approach does not use a common system rather it establishes the definitions of the standard data. It also transfers the specifications to facilitate the exchange of data between systems within a central repository – known as the Road Alliance Hub (Haider, et al., 2011).

The Institute of Public Works Engineering Australia (IPWEA) supports the implementation of financially sustainable public works programs. The Department of Planning, Transport and Infrastructure of South Australia determines the performance requirements from a road user perspective; and links the performance requirements to the pavement condition characteristics (FHWA, 2012).

2.5. New Zealand approaches

The Road Assessment and Maintenance Management (RAMM) System is the main RIAMS tool in New Zealand. The use of RAMM is mandatory to obtain financial assistance from the New Zealand Transport Agency (NZTA). The RAMM is updated annually with changes made to the network. The RAMM also incorporates a treatment selection programme which utilises condition and road inventory data to identify road sections (Haider, et al., 2011).

The NZTA is moving toward a service-based approach for managing their road networks rather than a condition-based approach. The service-based approach focuses the customer-driven priorities. The NZTA argues that the condition-based approach does not allow the roads to carry an unusually heavy load because of existing road conditions; however, the service-based approach allows the heavy vehicles to use the road infrastructure. The problem of service-based approach is that the highway users are not well aware of the bridge and road conditions; therefore, the risk and LCCA are the key decision drivers for the RIAMS (FHWA, 2012).

2.6. Portuguese approach

The Portuguese RIAMS has some drawbacks, such as: lack of historical data and unreliable empirical models. There are two problems of the traditional empirical models. First, the direct simulation of transition probabilities has been costly and unsuccessful in the long-term. Second, these methods do not address how to incorporate the engineering knowledge in models, and to address the overall budget constraints without meaningless subjective trade-off among road categories (Golabi & Pereira, 2003).

Golabi and Pereira (2003) propose the Portuguese Pavement Management System (PPMS). This system effectively addresses (1) how to deal with data inadequacies; (2) how to bridge the gap between the network optimisation and practical projects; (3) how to correctly incorporate engineering knowledge in models; and (4) how to address overall budget constraints without meaningless subjective trade-offs among road categories (Golabi & Pereira, 2003).

The PPMS comprises several modules, such as: the data bank, Pavement Rehabilitation and Improvement Strategic Model (PRISM), a GIS, and the Pavement Quality Evaluation Model (PQEM) (Golabi & Pereira, 2003). The PPMS does not need any historical data to start, but it can use the historical data and incorporate the engineering opinion easily. The PPMS system introduces an interactive budget planning model that allows the users to introduce flexibility on performance level and budget constraints, for both short-term and long-term planning horizons. The system would then find the optimal solution within feasible scenarios (Golabi & Pereira, 2003).

2.7. Japanese approaches

In Japan, the technical and detailed discussions on defining the road infrastructure and the RIAMS are at their initial stage. At present, there are no general-objective indicators available to quantify the performance of the road network and transportation system. A Maintenance Control Index (MCI) is calculated based on cracking, rutting, and roughness of pavement surfaces. The RCI is calculated based on roughness (OECD, 2001).

2.8. Polish approaches

Poland uses a combination of bearing capacity, evenness, ruts, skid resistance and surface condition resulting in condition classes. This indicator is used for strategic planning of the road budget at the network level, and for budget allocation among regional road administrations. On the other hand, a technical condition of engineering structure performance indicator is issued in the bridge management system (OECD, 2001).

2.9. Comparative evaluation

The management of road infrastructure systems is a complex task as it concerns more stakeholder perspectives, wider-ranging objectives, and longer time-horizons (Zeb, et al., 2013). It is difficult to evaluate to what extent the existing RIAMS practices reach the maturity level. The ISO 55000 includes the generally applicable ‘must do’ items for asset management (Woodhouse, 2013). The key themes of the ISO 55000 are: (1) alignment of organisational objectives feeding clearly into asset management strategies, objectives, plans and day-to-day activities; (2) whole life-cycle asset management planning and cross-disciplinary collaboration to achieve the best value combined outcome; (3) risk management and risk-based decision-making; and (4) establishment of a discipline at multiple levels of learning, innovation and feedback (Woodhouse, 2012; 2013). However, the ISO 55000 does not attempt to define the 'how to' implement the 'must do' items of asset management system (Woodhouse, 2013). The ISO 55000 does not provide financial, accounting or technical guidance for managing specific asset types (Woodhouse, 2013).

This study adopts the Infrastructure Management-Process Maturity Model (IM-PMM), developed by Zeb et al. (2013), to quantify and compare the RIAMS practices and to find out the scope of improvements. The IM-PMM framework is defined by the asset inventory management, condition management, service life analysis, LCCA, risk analysis, and decision-making analysis (Vanier et al., 2009; Zeb et al., 2013).

The above-mentioned functions of the IM-PMM are assessed against five stages of maturity that reflect increasing levels of formalisation or process maturity. In the *Infancy* stage, the particular function of the IM-PMM has not started; or started but at a very beginning level. The function is just defined but is not practicing. The *Preliminary* stage implies that the function is at the beginning level e.g. the definition is documented but practicing at an initial stage. In the *Reactive* stage, the definitions of the functions are specific to a particular situation and are not documented for the purpose of future re-use. They are dynamic and changing frequently with time and context. In the *Proactive* stage, the definitions of the functions are documented and standardized for future re-use. In the *Integrated* stage, the functions are actively managed against the standardised process definitions. Data are collected to determine the success and effectiveness of the functions, and on-going improvements are pursued (Zeb, et al., 2013).

Table 2.1: Infrastructure Management-Process Maturity Model (IM-PMM) framework for evaluating the maturity of RIAMS practices

Functions	Details	Approaches						
		U.S.	Canadian	Australian	New Zealand	Portuguese	Japanese	Polish
Inventory management	Enumerating, listing and storing of the information	Integrated	Proactive	Proactive	Proactive	Preliminary	Proactive	Proactive
Condition assessment	Evaluation of the existing condition based on the historical data, engineering model and customer priorities	Proactive	Reactive	Proactive	Proactive	Preliminary	Infancy	Proactive
Service life analysis	Determination of the remaining or residual life of the assets based on the prevailing condition assessment of the asset	Integrated	Reactive	Integrated	Integrated	Preliminary	Infancy	Preliminary
Life-cycle cost analysis (LCCA)	Assessment of the cost over the life cycle of the asset based on proposed maintenance scenarios	Integrated	Preliminary	Integrated	Integrated	Preliminary	Infancy	Preliminary
Risk analysis	Evaluation of the risks associated with the asset over its life cycle	Proactive	Preliminary	Reactive	Reactive	Infancy	Reactive	Infancy
Decision making analysis	Analysis of proposed alternatives and selection of the best alternative for M&R of the asset including the agency cost, road user costs and socio-economic developments	Reactive	Preliminary	Reactive	Reactive	Infancy	Infancy	Preliminary

The IM-PMM framework for evaluating the RIAMS practices in different countries is summarised in Table 2.1. The U.S. transportation agencies use the performance data and systematic processes to evaluate investment strategies. This enables the transportation agencies responding effectively to the budget constraints, and to the government efforts improving efficiency and increasing customer expectations (FHWA, 2012). The transportation agencies have not yet addressed the dynamic traffic loads, the comparison of the relative advantages between capital and operating investments, and the risk-based estimating, and the identification of a range of costs associated with the failure. The U.S. transportation agencies are at *Integrated* stage in the inventory management, service life analysis, and LCCA. They are at *Proactive* stage in the condition assessment and risk analysis because they still primarily considering the historical data and engineering models to assess the existing pavement conditions. The 'Decision making analysis' function of the IM-PMM is at the *Reactive* stage as the agencies have not yet developed a comprehensive multi-criteria RIAMS (Table 2.1).

Different States of Australia use different approaches to distribute the State infrastructure grants. For example, the ALGA uses the NLRDS, the WALGA uses the ROMAN II software, and the QLDRA establishes the standard indicator to distribute the State infrastructure grants. The transportation agencies in the New Zealand use the RAMM system to obtain financial assistance from the NZTA. The RAMM system is a service-based approach and focuses on the customer-driven priorities. The problem of service-based approach is that the highway users are not well aware of the bridge and road conditions; therefore, the risk and LCCA are the only key decision drivers for the RIAMS. The transportation agencies of Australia and New Zealand are at the *Integrated* stage in the service life analysis and LCCA, however, in case of other functions of the IM-PMM they are at either *Proactive* or *Reactive* stage (Table 2.1).

The Canada, Portugal, Japan and Poland are still developing their own RIAMS. Therefore, most of the functions of IM-PMM for the transportation agencies of these countries are at the *Infancy*, *Preliminary*, and *Reactive* stages (Table 2.1).

In most cases, the PMS of RIAMS is based on the Markov Decision Process (MDP) optimisation model. The problem with the MDP is that the optimisation programming of M&R strategies is determined for a group of pavement sections rather than an individual section under a given budget. Moreover, this optimisation programming is calculated from the steady-state probabilities. However, in reality, the pavements under a given maintenance policy usually takes many years to reach the steady state and the proportion of the pavements are changing year by year. Therefore, the use of steady-state probabilities in the optimisation objective function does not fully reflect reality, especially when this transition period is very long (Li, et al., 2006).

Moreover, the RIAMS methods didn't consider the variability and uncertainties of road data in investment analysis. The practicing RIAMSs have not yet incorporated the effect of M&R strategies on other road users.

2.10. Conclusion

The RIAMS is a systematic process for road infrastructures which is performed through cost-effective manner, optimisation programming algorithm and resource allocation decisions. The RIAMS is still an emerging concept and facing diversified challenges because of the growing demand for investment in the construction, and M&R operations under the budget constraints. The objective of this study is to discuss the practices of RIAMS adopted in different countries. This discussion mainly focuses on the pavement management system (PMS).

The incorporation of performance data, systematic processes and LCCA within the RIAMS enables the transportation agencies of the United States responding effectively to the budget constraints, and to the government efforts improving efficiency and increasing customer expectations. The transportation agencies of Australia and New Zealand also developed their own methods to distribute the infrastructure grants. The Portugal, Japan and Poland are still developing their own RIAMS.

Internationally, the RIAMS approach is moving from the condition-based towards the service-based approach focusing on the customer-driven priorities. This service-based approach has to be balanced with the budget constraints, level of service and risk tolerance. The transportation agencies should address the dynamic traffic loads during the life-span of the pavement, the comparison of the relative advantages between capital and operating investments, and the risk-based estimating, and the identification of a range of costs associated with the failure within the RIAMS. Moreover, in most cases, the PMS of RIAMS is based on the Markov Decision Process (MDP) that has some limitations.

The transportation agencies should develop a performance-based RIAMS which ensures the serviceability, accountability, stewardship, long-term financial plans, and transparent investments. In conclusion, the RIAMS is still emerging; and different researchers and organisations in different parts of the world are modifying, upgrading and improving the RIAMS models in order to incorporate the local mission, budget and other constraints within the scope of the local context.

Chapter 3

Pavement Management System (PMS)

Chapter 2 discusses that Canadian transportation authorities are still developing their own RIAMS. The inventory management of PMS is at proactive stage and is documented and standardized for future re-use. The definitions of condition assessment and service life analysis of PMS are specific to a particular situation and are not documented for the purpose of future re-use. Life-cycle cost, risk and decision making analyses of PMS are at the beginning level and practicing at an initial stage. Transportation authorities in Canada require a holistic PMS that overcomes these drawbacks. Chapter 3 discusses the methods of PMS and outlines a conceptual framework of a PMS incorporating dynamic states of land use, traffic volumes, design capacities, and pavement conditions. Although this chapter develops a conceptual model of PMS for Montreal city, this model is applicable for all geographical contexts.

Amin, M.S.R., and Amador-Jiménez, L. (2014). A performance-based Pavement Management System for the road network of Montreal city—a conceptual framework. Y. Richard Kim (ed.), Asphalt Pavements, Taylor & Francis Group, London, pp. 233-244.

Abstract

Arterial roads of Montreal city, mostly constructed in 1950's, are at an advanced state of deterioration and need major rehabilitation, upgrading, or even reconstruction. The City of Montreal has allocated over $1.6 billion for road infrastructure in its' 2012-2014 Three-year Capital Work Program. This investment can be wasted without proper infrastructure asset management system. The current practice of mill and asphalt overlay method by the City of Montreal to rehabilitate the pavement is inadequate to repair potholes, fatigue and cracking. A performance-based pavement management system (PMS) can predict the response and performance of pavement under actual dynamic traffic loads. As of today, implementations of PMS are dedicated to achieve optimal levels of condition under budget restrictions. Other important objectives (e.g. mobility, safety, accessibility and social cost), along with investments to upgrade and expand the road network, are normally left outside the modelling. This paper presents a conceptual framework of a dynamic PMS for the road network of Montreal City. This

dynamic PMS will manage continuous aggregate behaviour of transportation system and can solve optimization problems of pavement management at any time interval.

Keywords

Pavement Management System, Dynamic, Performance Modelling, Optimization.

3.1. Introduction

The pavement management systems is an approach that incorporates the economic assessment of trade-offs between competing alternatives (Hudson et al. 1997; Haas and Hudson 1978). Historically, pavement management tools such as PAVER and HDM3 (Watanatada et al. 1987) were based on cost-benefit analysis incapable of trading-off decisions across asset types and modes of transportation (NCHRP 2005). The adaptation of linear programming and other heuristic optimization techniques for asset management came to address most of these issues (Robelin and Madanat 2007; Chootinan et al. 2006). These techniques are capable of finding the optimal path to take full advantage of cost-effectiveness of individual treatments, associated with individual asset elements, and the benefits of advancing or deferring a certain treatment (Hudson et al. 1997; NAMS 2006). However, the economic impact of multiple strategies (i.e., rehabilitation versus capital investments) has not yet been addressed for safety, pavement condition, congestion, pollution and social cost. The perception of congestion combined with pavement condition, highway capacity, accessibility, financial incentives, personal safety, and to a lesser degree environmental responsibility impacts personal choices of modes, routes and links (Donaghy and Schintler 1993). Periodic incorporation of choice models into the pavement management system (PMS) will not only render it more tractable mathematically and more consistent with most growth-theory frameworks and distribution models, but also provide a better way of depicting on-going aggregate behavior and a more satisfactory PMS (Donaghy and Schintler 1993).

Most of the arterial roads of Montreal city are constructed in 1950's and are at an advanced state of deterioration. The commonly cited factors of this advanced state of deterioration are improper maintenance, low priority on infrastructure maintenance, inadequate funding, and the use of poor materials in the original construction. The City of Montreal seems to focus more on improving patching technology and execution, which don't appear to survive beyond two to five years. Moreover, the investments of City of Montreal on road system have increased more than 560% since 2001. The Three-year Capital Works Program (TCWP) 2012-2014 allocated over $130 million for maintaining and upgrading the city's roads, including $2.5 million that will be used solely for minor bridge and tunnel repairs (City of Montreal 2012). A performance-based PMS can predict the response and performance of pavement under actual dynamic traffic loads, and can ensure cost effective scheduling of maintenance and rehabilitation operations. The objective of this paper is to outline a conceptual framework of a PMS for the road network of Montreal City incorporating dynamic states of land use, traffic volumes, design capacities, and pavement conditions of arterial roads.

3.2. Measurement of the road infrastructure productivity

The pavement investment policies face important policy questions regarding the uses of pavement maintenance and rehabilitation (M&R) funds such as: What is the optimal level of pavement M&R funding? How can the need for this level of M&R funding be validated persuasively? What choices of M&R sections in the current budget period would most effectively move pavement conditions toward an optimal level in the long-term (Thompson et al. 2013)? There is a wide range of options to achieve an appropriate investment policy. They are: construction with a low initial cost followed by frequent low cost strengthening by overlays, construction of high quality pavements with higher initial costs but lower future maintenances costs, and construction of higher strength initial pavement followed by frequent thin overlays (Ockwell 1990; Potter and Hudson 1981). The first option is applicable when initial capital is limited but a steady flow of maintenance funds are available, however, the second and third options are supported by optimization and design studies.

The productivity of a road infrastructure needs to be understood before developing the optimization and design studies for pavement investment strategies. There is no universally accepted methodology to measure the productivity of a road infrastructure probably because of the lack of methodological consensus and the complexity of the hierarchical characteristics of many sub-systems within the road infrastructure system (Karlsson 2007). The development of cost efficiency analysis methods and methods for analyzing deterioration, maintenance and renewal under a budget constraint is necessary (Karlsson 2007). An economic optimization model, with given budget constraints, can differentiate different maintenance scenarios while identifying optimal actions and scheduling schemes (Karlsson 2007).

The economic optimization model for PMS consists of pavement deterioration model; user cost model; and construction, maintenance and rehabilitation cost model under possible budgets constraints (Thompson et al. 2013). Life-cycle cost analysis (LCCA), which is associated with the evaluation of an asset with a definite life expectancy, is an appropriate economic optimization model to examine the subsequent maintenance works on the pavement (Ockwell 1990).

3.3. Studies on life-cycle cost analysis (LCCA)

LCCA is a tool to assess total cost of M&R operations, to distinguish between alternatives, and to provide a basis for identifying trade-offs related to alternatives (Christensen et al. 2005). LCCA for PMS have been applied in a number of studies (Watanatada et al. 1987; Uddin et al. 1983). Uddin et al. (1983) describe a LCCA program developed for the Pennsylvania Department of Transportation (DOT). The program economically evaluates a range of strategies for design and rehabilitation of road pavements by applying BASIC and FORTRAN components. However, the pavement deterioration algorithm is somehow simplistic (Uddin et al. 1983).

Haas and Hudson (1978) suggest a pavement management working system, including pavement deterioration prediction, decision optimization and feedback, and minimum serviceability index. The minimum serviceability index can be computed by Markov decision process (MDP) which may also minimize the long-term maintenance costs (Carnahan 1988). Kher and Cook (1985) describe the Program Analysis of Rehabilitation System (PARS) model developed by the Ontario Ministry of Transportation and Communication. The application of maintenance treatments and action timings can also be optimized by MDP (Carnahan 1988).

The Texas Transportation Institute has developed optimization models to allocating M&R funds and other resources among highway districts. Under the budget constraints, the models attempt to maintain the quality of the road segments to some pre-specified level (Carnahan 1988). The use of a MDP would take a different approach to optimization since the specified quality of road segments would be calculated in determining the optimal (minimum cost) maintenance policy; an optimum (minimum) budget would then be computed (Carnahan

1988). Scullion and Stein (Scullion and Stein 1985) use the pavement deterioration matrices in planning M&R needs, however, the threshold levels of pavement deterioration for taking certain maintenance actions are determined exogenously (Carnahan 1988).

Artman and Liebman (1983) develop a dynamic optimization programming to schedule the rehabilitation projects of the airfield pavement. The rehabilitation projects are scheduled by maximizing the area under a utility-weighted pavement condition (PCR) versus time curve. The optimization programming is somehow similar to MDP; however, it uses the maximization of utility function of pavement condition rather than minimization of cost measures. Another drawback of this method is that the pavement condition rating (PCR) prediction is based on the regression analysis, which does not include current or recent pavement condition data (Carnahan 1988).

The discussion of the above-mentioned studies explains that the optimization of PMS can better be addressed by MDP, as it results in optimal solution of preventive maintenance strategies depending on the pavement conditions. The conventional MDP applies an infinite horizon probabilistic dynamic programming (DP) to solve the optimization problems in which LCCA is performed on the basis of long-term behavior of the pavement structure (Winston 2004).

The applications of MDP for optimization problems of PMS are justifies by various studies. Golabi et al. (1982) determine the implications of implementing MDP for the Arizona DOT. Golabi et al. (1982) identify that a total of $40 million was saved from the road preservation budget because of applying MDP optimization method. The Arizona MDP model applies two-steps linear programming to get a steady-state solution. A set of steady state maintenance actions was calculated to minimize the expected long-term average costs. If a road was found to be in a particular state, there was a specified probability that a particular maintenance action would be taken. Golabi et al. (1982) argue that the PMS has provided a ‘defensible procedure for preparing one-year and five-year budgets’ and has helped to ‘justify the revenue requests before oversight legislative committees.’ However, the maintenance policy was found to be stationary, and random and long-term performance standards were not included (Carnahan 1988).

Carnahan et al. (1987) develop MDP model for optimal decision-making capability of PAVER, which is a PMS developed by the U.S. Army Corps of Engineers Construction

Engineering Research Laboratory (CERL). Unlike Arizona MDP model, this model incorporates pavement data as a pavement condition rating (PCR) based inventory at a single point in time. A transition matrix is developed to identify a Markov chain for each pavement type (Carnahan 1988). Feighan et al. (1987) also employed dynamic programming in conjunction with a Markov chain probability-based prediction model to obtain minimum cost maintenance strategies over a given LCCA period.

The main drawback of MDP approach is that it does not accommodate budget constraints (Li et al. 2006). Another important drawback of this approach is that pavement sections have to be grouped into a large number of roughly homogeneous families based on pavement characteristics (Li et al. 2006). A large number of families mean fewer sample of pavement sections in each family, which compromises the reliability and validity of the transition probability matrix (TPM) generated for each family (Li et al. 2006). There are equally large numbers of M&R treatments for each family of pavement sections. It is suggested that all pavement sections should be categorized into small numbers of families. As the MDP addresses the performance evaluation of the pavement section as a group, it is not possible to address the performance condition of individual pavement section. Similarly, the optimization programming of M&R strategies are determined for a group of pavement sections rather than an individual section under a given budget. Moreover, the optimization programming of M&R strategies are calculated from the steady-state probabilities. However, in reality, the pavements under a given maintenance policy usually takes many years to reach the steady state and the proportion of the pavements are changing year by year. Therefore, the use of steady-state probabilities in the optimization objective function does not fully reflect reality, especially when this transition period is very long (Li et al. 2006).

3.4. Project-based PMS: can it be an alternative to network-based PMS?

The project-based modelling approach is based on the analysis of historical performance data stored in the database to develop model coefficients for individual pavement section. For each individual section, the available historical performance data since the last rehabilitation or construction are analysed to determine the model that matches the observed performance of the section and thus predict the future performance. The cost effectiveness, later on, derived from the prediction performance curve. The pioneer of project-based optimization method for pavement M&R strategies and projects is Arizona DOT (Li et al. 2006).

The major drawback to practice project-based optimization is that the complexity of pavement management problems increases exponentially with the size of the problem. For example, the number of possible solutions for project-based optimization problems is MT, where M is the number of maintenance actions to be considered and T is the number of years (or periods) in the analysis period. If the solution space size for a single section given a certain analysis period and number of available maintenance actions (project level) is C, the solution space size of the network problem, assuming S similar sections, is CS. With the general project-level complexity, therefore, this equates to (AT) CS (Pilson et al. 1999).

Pilson et al. (1999) propose a genetic algorithm (GA) optimization model to overcome this complexity. The GA optimization model considers each analysis period as a 'gene' and maintenance actions as 'allele' values. A chromosome represents a maintenance strategy for a particular period. The second step of GA optimization model is to measure the 'fitness' of the chromosomes (Pilson et al. 1999). However, the major drawback of GA optimization model for PMS is that the chromosome has one gene for each pavement section and each gene can take on any value from that section's efficient set. This decomposition of the network problem relies on the independence of the project-level problems, which is not theoretically acceptable for annual budgets (Pilson et al. 1999).

The project-based PMS is still struggling with the large size of problems and solutions. Although we can solve this problem by GA optimization model, there is a decomposition problem of the independence of the project-based PMS. This is not suitable under an annual budget for the whole road network. Moreover, the above-mentioned models optimize the PMS by minimizing the cost, ignoring the maximization of pavement condition.

3.5. Pavement performance modelling

The appropriate and effective pavement performance models are the foundation for the long-term analysis of PMS. The performance models calculate the future condition of the pavement based on which PMS optimizes several maintenance treatments in the long-term maintenance process. The pavement performance prediction (PPP) models have significant features in the PMS such as (1) they are used when the prioritization of maintenance treatments is required for each segments of road network, (2) they enable the transportation agencies to estimate long-range investment requirement during the life-span of the pavement, (3) they also estimate the consequences of budget allocation for maintenance treatments of a particular road segment on the future pavement condition of that road segment, (4) they can be applied for life-cycle economic evaluation of the pavement as they relate the pavement exposure variables to pavement deteriorations in the performance indicators, (5) many components of PMS such as pavement structural design, maintenance treatment strategies, and priority programming are directly related to the output of the PPP models (George et al. 1989; Li et al. 1997).

3.5.1 Methods of pavement performance modelling

The PPP models should be selected carefully. Otherwise they may make the road infrastructure system costly; and may cause the optimal pavement design, the selection of optimal rehabilitation strategies and the timing of projects impossible (Johnson and Cation 1992; Attoh-Okine 1999). Early PMS did not have PPP models rather they evaluated only the current pavement conditions. Later, simplified PPP models, usually based on the engineering opinions on the expected design life of different M&R actions, were introduced by considering age of the pavement as the only predictive variable (Kulkarni and Miller 2002). The PPP modelling is explicitly complicated as it is very difficult to estimate a large number of dynamic parameters of pavement performance. A variety of approaches can be used to predict pavement performance such as regression, survivor curves, latent variable models, mechanistic models and Markov chain probabilistic models (Humplick 1986; McNeil et al. 1992; Ramaswamy 1989; Paterson 1988; Wang et al. 1994).

Probabilistic models recently have received considerable attention from pavement engineers and researchers. Typically, a probabilistic model is represented by the Markov transition process, which is a knowledge-based expert decision model for the prediction of pavement deterioration (Li et al. 1997). Knowing the 'before' condition' or state of pavement in probabilistic form, one can employ the Markov process to predict the 'after' state, again in probabilistic forms, for as many time steps as are desired (George et al. 1989). The major challenge, facing the existing stochastic PPP models, includes difficulties in establishing transition probability matrices (TPMs).

The TPMs are estimated using a non-linear programming approach. The objective function of TPMs is to maximize the absolute distance between the actual pavement condition rating (PCR) versus age data points and the predicted PCR for the corresponding age generated by the Markov chain (Feighan et al. 1987). The assumption is that the pavement condition will not drop by more than one state in a single year. Thus, the pavement will either stay in its current state or transit to the next lowest state in one year. The probability transition matrix has a diagonal structure. The pavement condition cannot transit from this state unless repair action is performed (Feighan et al. 1987).

Several studies (George et al. 1989; Smadi and Maze 1994) applied empirical-mechanistic pavement performance model to calculate the PCR. George, et al. (1989) executed various regression analyses to develop and evaluate the empirical-mechanistic performance models for the highways in Mississippi based on the pavement condition data during the period of 1986-1988. The evaluation was based on rational formulation and behaviour of the model and on its statistical parameters. Exponential and power functions of both concave and convex shapes are identified as statistically significant. The best-fit models for the performance prediction (PCR_t) of flexible pavement with no overlay (Equation 3.1), flexible pavement with overlay (Equation 3.2) and composite pavement (Equation 3.3) are given below (George et al. 1989).

$$PCR_t = 90 - a[\exp(t^b) - 1]\log\left[\frac{ESAL}{SN^c}\right] \ \forall a = 0.6349; b = 0.4203; C = 2.7062 \tag{3.1}$$

$$PCR_t = 90 - a[\exp(t^b) - 1]\log\left[\frac{ESAL}{SN^c \times T}\right] \ \forall a = 0.8122; b = 0.3390; C = 0.8082 \tag{3.2}$$

$$PCR_t = 90 - a[\exp\left(\left(\frac{t}{T}\right)^b\right) - 1]\log[ESAL] \ \forall a = 1.7661; b = 0.2826 \tag{3.3}$$

The prediction models recognized that the yearly equivalent single axle load (*ESAL*) and structural number (*SN*) were of only minor importance, while age (*t*) being the most important factor of pavement performance modelling. George, et al. (1989) argued that the *ESAL* would be the weakest link in the cumulative traffic computation because several questionable input parameters (e.g. traffic count, the growth factor, the truck factor) are associated with the *ESAL* estimation. George, et al. (1989) applied the same argument for the exclusion of the environmental loads which include thermal effects, subgrade movements in expansive clays if applicable, freeze-thaw effects, and bitumen aging. George, et al. (1989) found out that computational accuracy along with the direct influence of *SN* and asphalt concrete thickness (*T*) on the mechanistic parameters (e.g. stress, strain and deflection) were the reasons for its significance in the performance model (George, et al. 1989).

Lee, et al. (1997) developed the present serviceability rating (PSR) of flexible pavements as a function of *SN*, age, and cumulative *ESAL*s (Equation 3.4).

$$\log_{10}(4.5 - PSR) = 1.1550 - 1.8720 \times \log_{10} SN + 0.3499 \times \log_{10} t + 0.3385 \times \log_{10} ESAL \tag{3.4}$$

Smadi and Maze (1994) determined the PCR for the Iowa Interstate 80 based on the 10 years traffic data. The performance curve of PCR is assumed to be a function of only the total number of 18 kip *ESAL*s that the pavement has experienced (Equation 3.5).

$$PCR = 100 - a(ESAL), \text{a is constant depends on surface type} \tag{3.5}$$

Traffic volumes, which are converted to *ESAL*s, can be calculated for each road link by applying four-step transportation modelling – trip production, trip distribution, modal split and choice analysis, and traffic assignment. Trip production is performed by relating the number or frequency of trips to the characteristics of the individuals, of the zone, and of the transportation network. Discrete choice models use disaggregate household or individual level data (personal, household, zonal and transportation network characteristics) to estimate the probability with which any household or individual may make trips. The outcome can then be aggregated to predict the number of trips produced.

Trip distribution models (e.g. growth factor models and gravity models) are used to predict spatial pattern of trips or other flows between origins and destinations. Modal choice model estimation and application is done to predict the zonal shares of trips by mode. The Multinomial Logit (MNL) model relates the probability that a decision unit chooses a given alternative from a set of modes to the utility of these modes.

The traffic assignment models (All-or-Nothing, STOCH, Incremental, Capacity Restraint, User Equilibrium, Stochastic User Equilibrium, and System Optimum) predict the network flows that are associated with future planning scenarios, and estimate the link travel times and related attributes that are basis for benefits estimation and air quality impacts. The traffic assignment model is also used to generate the estimates of network performance that are used in the mode choice and trip distribution stages of many models.

3.5.2. Uncertainty with pavement performance curve

To include the diversified characteristics of pavement, Thompson et al. (1987) divided the Finnish highway network into six regional class sub-networks and proposed an individual optimization model for each of the sub-network group rather than for an individual road segment. Each model is classifed among four dimensions, such as: bearing capacity, pavement defects, rutting, and pavement roughness.

The proposed models by Arizon DOT and Thompson et al. (1987) solved the opitmization problem at an individual or group of pavement section, however, the deterioration uncertainty has not yet been resolved. The required budget should treat the uncertainty of deterioration carefully by incorporating stochastic characteristics of road data.

Butt et al. (1994) introduced different duty cycles to allow the changes in traffic loads and maintenance polices over the pavement life. That nonhomogeneous Markov model divided the life of the pavement into different zones assuming a constant rate of deterioration for each of these zones. A homogeneous Markov chain and a separate TPM were developed for each zone. On the other hand, a nonhomogeneous Markov chain had been used for transition from one zone to another (Butt et al. 1994).

A research project titled ‘Maintenance Cost Prediction for Road’ under the cooperative Research Centre (CRC) for Construction Innovation has also developed a method that takes into account the variability and uncertainties of road data in investment analysis (Piyatrapoomi et al. 2006). Piyatrapoomi et al. (2006) identify the variability parameters of the predicted budget, which includes rut depth, AADT, initial roughness and pavement strength (Piyatrapoomi et al. 2006). The variability of these parameters was quantified by probability distributions, means and standard deviation for each category. The best fitted probability distribution functions (pdf) for IRI, rut depth, and AADT of the Queensland road network are Beta General, log normal and exponential distributions, respectively (Piyatrapoomi et al. 2006). Piyatrapoomi et al. (2006) apply Latin-hypercube sampling technique to simulate the variability of above-mentioned parameters.

3.6. Dynamic programming process of pavement management system

The dynamic programming process starts with the calculation of the routine maintenance cost for each state condition in every family (categorized based on the pavement characteristics e.g. type, structure, construction history, condition, use, and rank) in a particular year. Routine maintenance is not feasible if $R_{ijk} = 0$ or state condition $S_j \geq i$ for family j. R_{ijk} is the feasibility indicator for alternative maintenance operation k when in state i of family j. R_{ijk} =1 if maintenance alternative is feasible and 0 for infeasible alternative. S_j is the minimum allowable state for each j family, i.e. the lowest state that the network manager will allow a particular family to deteriorate to before performing some major maintenance. The state vector of any period n, S_{jn}, is obtained by multiplying the initial state vector, S_0 by the transition matrix (P_{ij}) raised to the power of n (Feighan et al. 1987).

For all feasible states, the cost of routine maintenance is obtained from $C_{ijk,N} = C_{ijk}$, where k is the maintenance alternatives (Feighan et al. 1987). The cost of all feasible maintenance alternatives for year N-n is given by Equation 3.6 (Feighan et al. 1987).

$$C^*_{ijk,N-n} = C_{ijk} + \left[P^1_{ij} * C^*_{ij^1,N-n+1} + \left(1 - P_{ij^11}\right) * C^*_{2j^1,N-n+1}\right] * \frac{1}{(1+i^*)} \qquad (3.6)$$

Where P_{ij} is the Markov Transition probabilities for state i (1…10 states) of matrix j (1…. m families). P_{ij} transition matrix probabilities are estimated using a non-linear programming approach which has its objective function the minimization of absolute distance between the actual pavement condition versus pavement age and the expected pavement condition. C_{ijk} is the cost of applying treatment k (1…n maintenance alternatives) to family j in state i (Feighan et al. 1987).

The first part (C_{ijk}), of the right side of Equation 3.6, is the immediate cost of routine maintenance in year n. The second part ($\left[P^1_{ij} * C^*_{ij^1,N-n+1} + \left(1 - P_{ij^11}\right) * C^*_{2j^1,N-n+1}\right] * \frac{1}{(1+i^*)}$) is the total expected cost to be incurred in the remaining years as a consequence of applying routine maintenance operations. This expected cost is obtained by identifying the probability of remaining in a given state and multiplying this probability by the expected cost of that state and then finding the associated probability of dropping a state if routine maintenance is applied and multiplying this by the expected cost of the lower state. This sum is then discounted by the effective interest rate, i*, to calculate the present net value in the year *N-n* (Feighan et al. 1987).

The optimum maintenance strategy is then given by Equation 3.7 (Feighan et al. 1987).

$$C^*_{ijk,N-n} = Min\ [C_{ij1,N-n}, C_{ijk,N-n}] \text{ for all } k. \tag{3.7}$$

With the related optimal maintenance alternative to be performed for this (*i,j*) family or state combination in year *N-n* being the choice of k that minimizes the cost in Equation 1. This backward recursion is performed for every successive year of the analysis period until the analysis for year 0, or stage *N*, is reached. (Feighan et al. 1987).

3.6.1. Road user costs of pavement management system

The objective function of life-cycle cost optimization is not only to reduce the maintenance costs but also to reduce the user costs. The road user costs are defined as the consequences of the periodic M&R strategies of pavement section on the road users. Moreover, the vehicle, accident and time costs are directly associated with pavement condition deterioration. Vehicles costs for fuel, lubricants, tires, repairs and depreciation are proportionately related to the pavement surface condition. For example, fuel consumption is a function of vehicle's speed and the road geometry (mainly vertical upgrade and downgrade) (Haugodegard et al. 1994). Although an increase of international roughness index (*IRI)* has very insignificant impact on fuel consumption and lubricant costs, the impact of rutting is high during the wet season. In rain, when the ruts are full of water, the rolling resistance increases as a function of water depth. The average water depth is a result of cross-fall, rut depth, precipitation levels and intensity, traffic volume, and the driver's behavior. The increase in rolling resistance gives an increase in fuel consumption when driving on wet surfaces (Haugodegard et al. 1994). However, repair costs of vehicles are related to *IRI* rather than rutting. For example, the roughness can affect 50% of repair costs for passenger cars and 25% for heavy goods vehicles in Norway road network (Haugodegard et al. 1994).

The cost of travel time is a product of value of time and the time to travel a certain distance. Traveling time is a result of traveling speed, which is the function of speed limit, road width, and curvature. Speed limit, road width, and curvature generate a speed of 70 km/hr at an average roughness of 2.7 (*IRI*) (Haugodegard et al. 1994). The commuters also drive additional travel distances in order to avoid the maintenance links of the road network resulting in additional cost of travel time. The cost of travel time can be estimated by calculating the salary of the equivalent time spends on working hours.

The number of accidents within a road section is a product of various casual factors. The Transportation Association of Canada has categorized causal factors into three main groups: road geometry elements, environmental factors and human characteristics (Sayyadi et al. 2013). De Leur and Sayed (2002) categorized the causal factors into three generic groups such as exposure, consequences and probability. Exposure has been defined as the extent of exposure to road accidents by road users (Sayyadi et al. 2013). Consequences can be expressed by the severity of road accidents and the probability was explained as the likelihood of accidents occurrence (Sayyadi et al. 2013). Sayyadi et al. (2013) identify several road geometrics, traffic and environmental characteristics as the causal factors of road accidents. These are: individual car accident percentage, vehicle's speed, intersections per kilometer, severity of horizontal and vertical alignment, length of the road section, Annual Average Daily Traffic (AADT), light condition, weather-surface condition, road cross-section characteristics, and shoulder and land width.

The objective function (Equation 3.8) is also to minimize user cost along agency cost (maintenance cost plus initial or construction cost) with under budget constraints (Equation 3.9) (Thompson et al. 1987).

$$Min \sum_i \sum_j \sum_k w_{ik}\left(C^*_{ijk,N-n} + U_{ik}\right) \; \forall \; \sum_i \sum_k w_{ik} = 1 \tag{3.8}$$

$\sum_k w_{ik} \leq \varepsilon_i(1+\emptyset)$ for all unacceptable i and $\sum_k w_{ik} \geq \varepsilon_i(1+\emptyset)$ for all acceptable i.

$$B(1-\Omega) \leq \sum_i \sum_j \sum_k w_{ik}\left(C^*_{ijk,N-n}\right) - \beta \leq B(1+\Omega) \tag{3.9}$$

Where w_{ik} is the fraction of area of pavement in state i with action k applied, B is the budget constraint per year, β is the parametric analysis adjustment on budget constraint, Ω is the tolerance on budget constraint, ε_i is the condition constraint for state i, $\emptyset$ is the tolerance on condition constraints (Thompson et al. 1987).

3.6.2. Drawbacks of Markov decision process

The main drawback of Markov decision Process (MDP) approach is that it does not accommodate budget constraints (Liebman 1985). Another important drawback of this approach is that pavement sections have to be grouped into a large number of roughly homogeneous families based on pavement characteristics (Li et al. 2006). A large number of families mean fewer sample of pavement sections in each family, which compromises the reliability and validity of the transition probability matrix (TPM) generated for each family (Li et al. 2006). There are equally large numbers of M&R treatments for each family of pavement sections. It is suggested that all pavement sections should be categorized into small numbers of families. As the MDP addresses the performance evaluation of the pavement section as a group, it is not possible to address the performance condition of individual pavement section. Similarly, the optimization programming of M&R strategies are determined for a group of pavement sections rather than an individual section under a given budget. Moreover, the optimization programming of M&R strategies are calculated from the steady-state probabilities. However, in reality, the pavements under a given maintenance policy usually takes many years to reach the steady state and the proportion of the pavements are changing year by year. Therefore, the use of steady-state probabilities in the optimization objective function does not fully reflect reality, especially when this transition period is very long (Li et al. 2006).

3.6.3. Drawbacks of project-based pavement management system and existing practices to deal with these problems

The project-based modeling approach is based on the analysis of historical performance data stored in the database to develop model coefficients for individual pavement sections. For each individual section, the available historical performance data since the last rehabilitation or construction is analyzed to determine the model that matches the observed performance of the section and thus predict the future performance. The cost effectiveness, later on, is derived from the prediction performance curve. The pioneer of project-based optimization method for pavement M&R strategies and projects is Arizona DOT (Li et al. 2006).

Thompson et al. (1987) divide the Finnish highway network into six regional class sub-networks and propose individual optimization model for each of the sub-network group rather than for an individual road segment. Each model is classified among four dimensions – bearing capacity, pavement defects, rutting, and pavement roughness.

The proposed models by Arizon DOT and Thompson et al. (1987) solve the optimization problem at an individual or group of pavement section, however, the deterioration uncertainty has not yet been resolved. The required budget should treat the uncertainty of deterioration carefully by incorporating dynamic characteristics of road data. The traffic loads on the pavement are uncertain and dynamic in character and need to be included in the maintenance budget.

Butt et al. (1994) introduce different duty cycles to allow the changes in traffic loads and maintenance polices over the pavement life. This nonhomogeneous Markov model divides the life of the pavement into different zones assuming a constant rate of deterioration for each of these zones. A homogeneous Markov chain and a separate TPM are developed for each zone. On the other hand, a nonhomogeneous Markov chain has been used for transition from one zone to another (Butt et al. 1994).

A research project titled 'Maintenance Cost Prediction for Road' under the cooperative Research Centre (CRC) for Construction Innovation has also developed a method that takes into account the variability and uncertainties of road data in investment analysis (Piyatrapoomi et al. 2006). Piyatrapoomi et al. (2006) identify the variability parameters of the predicted budget, which includes rut depth, AADT, initial roughness and pavement strength (Piyatrapoomi et al. 2006). The variability of these parameters was quantified by probability distributions, means and standard deviation for each category. Piyatrapoomi et al. (2006) identify the best fitted probability distribution functions (pdf) for IRI, rut depth, and AADT of the Queensland road network are Beta General, log normal and exponential distributions, respectively. Piyatrapoomi et al. (2006) apply Latin-hypercube sampling technique to simulate the variability of above-mentioned parameters.

Another major drawback to practice project-based optimization is that the complexity of pavement management problems increases exponentially with the size of the problem. For example, the number of possible solutions for project-based optimization problems is M^T, where M is the number of maintenance actions to be considered and T is the number of years (or periods) in the analysis period. If the solution space size for a single section given a certain analysis period and number of available maintenance actions (project level) is ***C*,** the solution space size of the network problem, assuming *S* similar sections, is ***CS***. With the general project-level complexity, therefore, this equates to $(A^T)^{CS}$ (Pilson et al. 1999).

Pilson et al. (1999) propose a genetic algorithm (GA) optimization model to overcome this complexity. The GA optimization model considers each analysis period as a 'gene' and maintenance actions as 'allele' values. A chromosome represents a maintenance strategy for a particular period. The second step of GA optimization model is to measure the 'fitness' of the chromosomes (Pilson et al. 1999). However, the major drawback of GA optimization model for PMS is that the chromosome has one gene for each pavement section and each gene can take on any value from that section's efficient set. This decomposition of the network problem relies on the independence of the project-level problems, which is not theoretically acceptable for annual budgets (Pilson et al. 1999).

The project-based PMS is still struggling with the large size of problems and solutions. Although we can solve this problem by GA optimization model, there is a decomposition problem of the independence of the project-based PMS. This is not suitable under an annual budget for the whole road network. Moreover, the above-mentioned models optimize the PMS by minimizing the cost, ignoring the maximization of pavement condition.

3.6.4. Multi-criteria pavement management system

The construction of new road and maintenance of exiting road network have significant impacts on the surrounding locations such as changes in economic activities, and social and cultural changes. PMS should include the effect of M&R strategies on other road users and surrounding locations such as residents in close proximity from the road, industrial settlements, trade centers, etc. (Cafiso et al. 2002). The Action de Préparation, d'Accompagnement, et de Suivi (APAS) transport research project, funded by the European Commission, develops some indicators for the choice of transport projects using decision criteria optimization (European Commission 1996). The indicators are developed through simplified multi-criteria analysis (MCA) techniques such as Elimination et Choix Traduisant la Realité (ELECTRE III) and the analytical hierarchy process (AHP) (Hokkanen and Salminen 1997). Highway Development and

Management Tool (HDM-4) applies AHP method to integrate multi-criteria factors with the PMS (European Commission 1996).

Cafiso et al. (2002) identify ride comfort and environmental factors as the criteria of PMS along with agency costs and user costs. The ride comfort is defined as ride number (*RN*) values by National Cooperative Highway Research Program (NCHRP). Ride number (*RN*) values for alternative k of the section j are obtained from *IRI* (m/km). The environment parameter for a road segment can be calculated by deriving air quality index (AQI). AQI is a function of emission value of the air pollution substance for an alternative of each section at a particular year, average annual daily traffic for each section at a year, length of the section, concentration limits of a single air pollution substance (Cafiso et al. 2002).

Socio-economic development parameter can have significant relation with the PMS. The residents, in close proximity to the invested road infrastructure, may achieve significant socio-economic benefits from the PMS strategies. The characteristics of development parameters of urban area can be demographic characteristics, economic characteristics, social and community characteristics, transportation facilities, urban services and facilities, and environmental characteristics.

3.7. Conclusion

The pavement management systems incorporate the economic assessment of trade-offs between competing maintenance and rehabilitation alternatives. The conventional techniques are capable of finding the optimal path to take full advantage of cost-effectiveness of individual treatments, however, incapable of addressing safety, condition, congestion, pollution and social cost.

This paper initially describes the life-cycle cost analysis as the economic optimization model for PMS. The methods of appropriate and effective pavement performance modelling are discussed as the pavement deterioration modelling is the foundation for the long-term analysis of PMS. The framework of four-step transportation modelling is explained to predict the future traffic volume during the life-cycle of pavement. Transportation modelling is discussed because the predicted traffic volumes of each segment of road network are transferred to Equivalent Single Axle loads (ESALs).

The proposed dynamic programming process of PMS points out the drawbacks of the Markov decision process of network-based PMS and is brokering the project-based PMS. The project-based PMS is still struggling with exponentially increasing size of problems and M&R solutions. This study proposes a PMS for different categories of road groups with different pavement performance curves for each group. This paper also proposes the incorporation of road user costs, riders' comfort, environmental benefits and socio-economic benefits along with agent costs in the PMS. This dynamic PMS will manage continuous aggregate behavior of transportation system and can solve optimization problems of pavement management at any time interval.

Chapter 4

Pavement Performance Modeling

Amin, M.S.R. (2015). The Pavement Performance Modeling: Deterministic vs Stochastic Approaches. S. Kadry and A. El Hami (eds.) Numerical Methods for Multiscale and Multiphysics in Reliability and Safety, pp. 179-196. Springer: Switzerland

Abstract

Pavement performance modeling is an essential part of pavement management system (PMS). It estimates the long-range investment requirement and the consequences of budget allocation for maintenance treatments of a particular road segment on the future pavement condition. The performance models are also applied for life-cycle economic evaluation and for the prioritization of pavement maintenance treatments. This chapter discusses various deterministic and stochastic approaches for calculating the pavement performance curves. The deterministic models include primary response, structural performance, functional performance, and damage models. The deterministic models may predict inappropriate pavement deterioration curves because of uncertain pavement behavior under fluctuating traffic loads and measurement errors. The stochastic performance models assume the steady-state probabilities and cannot consider the condition and budget constraints simultaneously for the PMS. This chapter discusses the Backpropogation Artificial Neural Network (BPN) method with generalized delta rule (GDR) learning algorithm to offset the statistical error of the pavement performance modeling. This chapter also argues for the application of reliability analyses dealing with the randomness of pavement condition and traffic data.

Keywords

Pavement management system, mechanistic models, mechanistic-empirical models, regression models, Markov transition probability matrix, Artificial Neural Network, backpropagation neural network, pavement condition state, present serviceability index, international roughness index, distress index, pavement thickness, pavement material properties, soil load bearing capacity, equivalent single axle loads, pavement age, performance reliability, average minimum annual air temperature.

4.1. Introduction

The appropriate and effective pavement performance curves are the fundamental components of pavement management system (*PMS*); and ensure the accuracy of pavement maintenance and rehabilitation (*M&R*) operations (Jansen and Schmidt 1994, Johnson and Cation 1992, Attoh-Okine 1999). The performance models calculate the future conditions of pavement based on which *PMS* optimizes several maintenance treatments, and estimates the consequences of maintenance operations on the future pavement condition during the life-span of the pavement (George et al. 1989, Li et al. 1997). Early *PMS*s did not have performance curves rather they evaluated only the current pavement condition. Later, the simplified performance curves were introduced based on the engineering opinions on the expected design life of different *M&R* actions (Kulkarni and Miller 2002). The only predictive variable of these performance curves was the pavement age. The development of performance curve is explicitly complicated as the pavement performance is subjected to a large number of parameters of pavement performance.

There are two streams of pavement performance modeling - deterministic and stochastic approaches. The major differences between deterministic and stochastic performance prediction models are model development concepts, modeling process or formulation, and output format of the models (Li et al. 1996). This study discusses various deterministic and stochastic approaches of pavement performance modeling, and elucidates the advantages and disadvantages of these methods.

4.2. Deterministic Pavement Performance Modeling

The deterministic models include primary response, structural performance, function performance, and damage models (George et al. 1989). Three are different types of deterministic models, such as: mechanistic models, mechanistic-empirical models and regression models. The mechanistic models draw the relationship between response parameters such as stress, strain, and deflection (Li et al. 1996). The mechanistic-empirical models draw the relationship between roughness, cracking, and traffic loading. On the other hand, the regression models draw the relationship between a performance parameter (e.g. riding comfort index, *RCI*) and the predictive parameters (e.g. pavement thickness, pavement material properties, traffic loading, and age) (Li et al. 1996). A large number of deterministic models have been developed for regional or local

*PMS*s such as traffic related models, time related models, interactive-time related models, and generalized models (Attoh-Okine 1999).

The general function of a deterministic pavement performance model can be expressed by Equation 4.1 (Li et al. 1996).

$$PCS_t = f(P_0, ESALs_t, H_e \text{or } SN, M_R, C, W, I) \tag{4.1}$$

Where PCS_t is the generalized pavement condition state (*PCS*) at year *t*, P_0 is the initial pavement condition state, $ESALs_t$ is the accumulated equivalent single axle loads (*ESAL*s) applications at age *t*, H_e is the total equivalent granular thickness of the pavement structure, *SN* is the structural number index of total pavement thickness, M_R is the subgrade soil resilient modulus, W is the set of climatic or environmental effects, I is the interaction effects of the preceding effects, and C is the set of construction effects. The *PCS* represents *RCI*, present serviceability index (*PSI*), pavement quality index (*PQI*), roughness, and cracking. The SN is also known as pavement strength that can be calculated by $\sum a_i h_i + SN_g$, where a_i is the material layer coefficients, and h_i is the layer thicknesses. The SN_g is a subgrade contribution that can be calculated by $3.51 \log CBR - 0.85(\log CBR)^2 - 1.43$; *CBR* is the in situ California bearing ratio of subgrade (Li et al. 1996).

The American Association State Highway and Transportation Officials (1985) developed the *PSI* for the flexible pavement. The *PSI* and 18 kip *ESALs* are the main factors of pavement performance along with other factors such as materials properties, drainage and environmental conditions, and performance reliability (Equation 4.2) (Abaza et al. 2001).

$$\log_{10}(ESAL_t) = Z_R \times S_0 + 9.36 \times \log_{10}(SN+1) - 0.2 + \frac{\log_{10}\left[\frac{\Delta PSI}{4.2-1.5}\right]}{0.40 + \frac{1094}{(SN+1)^{5.19}}} + 2.32 \times \log_{10}(M_R) - 8.07 \tag{4.2}$$

Where ΔPSI is the difference between the initial design serviceability index (PSI_0) and the serviceability index at year *t* (PSI_t), and Z_R and S_0 are the standard normal deviate and combined standard error of the traffic prediction and performance prediction, respectively. Lee et al. (1993) also developed the *PSI* for the flexible pavements shown in Equation 4.3 (Lee et al. 1993).

$$\log_{10}(4.5 - PSI) = 1.1550 - 1.8720 \times \log_{10} SN + 0.3499 \times \log_{10} t + 0.3385 \times \log_{10} ESAL \tag{4.3}$$

The Ontario Pavement Analysis of Costs (OPAC) developed the deterministic flexible pavement deterioration model of pavement condition index (*PCI*), which is expressed by Equation 4.4 (Jung et al. 1975, Li et al. 1997).

$$\Delta PCI = PCI_0 - (P_T + P_E) = PCI_0 - \left[(2.4455\Psi + 8.805\Psi^3) + \left(PCI_0 - \frac{PCI_0}{1+\beta_w}\right)(1 - e^{-\alpha t})\right] \tag{4.4}$$

$$w = \frac{9000 \times 25.4}{2M_s\left(0.9H_e\sqrt[3]{\frac{M_2}{M_R}}\right)\sqrt{1 + \frac{6.4}{0.9H_e\sqrt[3]{\frac{M_2}{M_R}}}}} \quad \text{and} \quad \Psi = 3.7238 \times 10^{-6} w^6 ESAL$$

Where w is subgrade deflection, PCI_0 is as-built *PCI*, P_T and P_E are the traffic and environment induced deteriorations of pavement condition, M_2 is the modulus of granular base layer, β is the regional factor 1 ($\beta = 60$ in southern Ontario), and α is the regional factor 2 ($\alpha = 0.006$ in southern Ontario).

The Nevada Department of Transportation (NDOT) developed sixteen deterministic performance models for different pavement rehabilitation and maintenance treatments in 1992 (Sebaaly et al. 1996). The factors of the performance models are traffic, environmental, materials, and mixtures data in conjunction with actual performance data (*PSI*). The performance model for the asphalt concrete (AC) overlays is given by Equation 4.5 (Sebaaly et al. 1996).

$$PSI = -0.83 + 0.23\,DPT + 0.19\,PMF + 0.27\,SN + 0.078\,TMIN + 0.0037\,FT - (7.1e - 7\,ESAL) - 0.14\,t \tag{4.5}$$

Where *DPT* is the depth of overlay, *PMF* is the percent mineral filler, *TMIN* is the average minimum annual air temperature (°F), and *FT* is the number of freeze-thaw cycles per year. The *PSI* was calculated by using a modified version (Equation 4.6) of the AASHTO performance method (Equation 4.1) (Sebaaly et al. 1996).

$$PSI = 5 \times e^{-0.0041*IRI} - 1.38RD^2 - 0.03(C+P)^{0.5} \quad (4.6)$$

Where IRI is the international roughness index, RD is the rut depth, C is the cracking and P is the patching. The *IRI* is a key property of road condition considered in any economic evaluation of design and maintenance standards for pavements, and also in any functional evaluation of the standards desire of road users (Paterson 1987, Ockwell 1990). Haugodegard et al. (1994) derived that the *IRI* function followed the parabolic distribution (Equation 4.7).

$$IRI_t = IRI_i + (IRI_1 - IRI_0) * \left(\frac{A_d}{A_1}\right)^{1.5} \quad (4.7)$$

Where IRI_t is the predicted roughness at year *t*, IRI_0 is the roughness just after the latest rehabilitation, IRI_1 is the latest recorded roughness, A_t is the age of the pavement surface at year *t*, $A_1$is the age of the pavement surface when the latest roughness recording made.

Saleh, et al. (2000) developed a mechanistic roughness model relating the roughness with the number of load repetitions, axle load, and asphalt layer thickness (Equation 4.8). The model applied vehicle dynamic analysis to estimate the dynamic force profile. The model also used the finite element structural analysis to estimate the change of pavement surface roughness for each load repetition. The statistical relationships in Eq. 8 show that initial roughness (IRI_0) is the most significant factor that affects roughness at later ages. The other important factors are axle load (*P*), asphalt thickness (*T*), and the number of load repetitions ($ESALs$) (Saleh et al. 2000).

$$IRI = -1.415 + 2.923\sqrt{IRI_0} + 0.00129\sqrt{ESALs} + 0.000113T - 5.485 \times 10^{-10}P^4 - 10^{-3}T\sqrt{ESALs} + 5.777 \times 10^{-12}P^4\sqrt{ESALs} \quad (4.8)$$

George et al. (1989) carried out various regression analyses to develop empirical-mechanistic performance models for the highways in Mississippi based on the pavement condition data during the period of 1986-1988. The constructed performance models were evaluated based on the rational formulation, behavior of the models, and statistical parameters. The exponential and power functions of both concave and convex shapes were identified as the statistically significant functions. The best-fit models for the performance prediction (PCI_t) of the flexible pavement with no overlay (Equation 4.9), with overlay (Equation 4.10), and composite pavement (Equation 4.11) are given below (George et al. 1989):

$$PCI_t = 90 - a[\exp(t^b) - 1]\log\left[\frac{ESAL}{SN^c}\right] \ \forall a = 0.6349; b = 0.4203; C = 2.7062 \tag{4.9}$$

$$PCI_t = 90 - a[\exp(t^b) - 1]\log\left[\frac{ESAL}{SN^c \times T}\right] \ \forall a = 0.8122; b = 0.3390; C = 0.8082 \tag{4.10}$$

$$PCI_t = 90 - a[\exp\left(\left(\frac{t}{T}\right)^b\right) - 1]\log[ESAL] \ \forall a = 1.7661; b = 0.2826 \tag{4.11}$$

The prediction models identified *t*, *SN*, and *T* as the most significant factors of pavement performance. The computational accuracy along with the direct influence of *SN* and *T* on the mechanistic parameters (e.g. stress, strain and deflection) were the reasons for their significance in the performance model (George et al. 1989). The attribute *ESALs* was identified as the less important factor of pavement performance. George et al. (1989) argued that *ESALs* would be the weakest link in the cumulative traffic computation because several questionable input parameters (e.g. traffic count, traffic growth factor, and truck factor) are associated with the *ESALs* estimation. George, et al. (1989) applied the same argument for the exclusion of the environmental loads which include thermal effects, subgrade movements in the expansive clays, freeze-thaw effects, and bitumen aging.

Smadi and Maze (1994) determined the *PCI* for the Iowa Interstate 80 based on the 10 years traffic data. The performance curve of *PCI* was a function of only the total number of 18 kip *ESALs* that the pavement had experienced (Equation 4.12) (Smadi and Maze 1994):

$$PCI = 100 - a(ESALs), \ \alpha \text{ is constant depends on surface type} \tag{4.12}$$

De Melo e Siva et al. (2000) proposed the logistic growth pavement performance curve for local government agencies in Michigan. These agencies commonly use a *PMS* called RoadSoft (De Melo e Siva et al. 2000). The model of de Melo e Siva, et al. (2000) was based on the Kuo's pavement model considering the ascending distress index with different design service life values (Kuo 1995). In this formulation, the starting distress index of a reconstructed or resurfaced pavement was established as 0. The boundary condition of Kuo's logistic growth model (Kuo 1995) is expressed by Equation 4.13 (De Melo e Siva et al. 2000).

$$DI = \alpha\left[\frac{(\alpha+\beta)}{(\alpha+\beta e^{-\gamma t})} - 1\right] \tag{4.13}$$

Where DI is distress index, α is the potential initial of *DI*, β is the limiting of DI, *t* is the age (years), $\gamma = -\frac{1}{DSL}\ln\left(\left\{\left[\frac{(\alpha+\beta)}{(\alpha+cDP)}\right]-1\right\}\frac{\alpha}{\beta}\right)$ is the deterioration pattern index, *DSL* is the design service life, and *cDP* is the predetermined *DI* (De Melo e Siva et al. 2000).

De Melo e Siva et al. (2000) argued that the parameter values, in the logistic growth model, had to be inverted to meet the constraints of the PASER and RoadSoft data. In the PASER and RoadSoft data, the values range from 1 to 10, and the starting *DI* of a distress-free pavement (reconstructed or resurfaced) is 10. To reflect this, the boundary condition was reconstructed as Equation 4.14 (De Melo e Siva et al. 2000).

$$PASER\ Rating = \alpha - \beta\left[\frac{(\alpha+\beta)}{(\beta+\alpha e^{-\gamma t})} - 1\right]\ \forall\, \gamma = -\frac{1}{DSL}\ln\left(\left\{\left[\frac{(\alpha+\beta)}{(\alpha+\beta-cDP)}\right]-1\right\}\frac{\beta}{\alpha}\right) \tag{4.14}$$

Sadek, et al. (1996) developed a distress index (*DI*), which was a composite index reflecting severity and frequency of the observed distresses in the pavement surface. This index is a function of average yearly *ESALs*, age (*t*) of the pavement and thickness of the overlay (*T*) (Equation 4.15)

$$DI = 100 - 5.06 \times t^{0.48} ESALs^{1.29} T^{-0.20} \tag{4.15}$$

Robinson et al. (1996) developed a sigmoidal form of the distress model for the Texas Pavement Management Information System, where D_1 predicted the punch-outs per mile and D_2 predicted the Portland cement concrete patches per mile (Equation 4.16) (Pilson et al. 1999).

$$D_1 = 101.517 \exp - \left[\frac{538.126}{t}\right]^{0.438} \text{ and } D_2 = 1293.840 \exp - \left[\frac{399.932}{t}\right]^{0.536} \tag{4.16}$$

Pilson, et al. (1999) developed the pavement deterioration model. The fundamental concept of this model is that the rate of the deterioration of one component of a system is a function of the level of deterioration of itself and other components in the system. The coefficients describing these functions can be summarized as an interactivity matrix (**C**) (Equation 4.17). The additional deterioration of surface (*S*) during the current year (*dS*) is proportional to its own current level of deterioration and the deterioration levels of the base (*B*) and subbase (*Sb*) (Equation 4.18) (Pilson et al. 1999).

$$\mathbf{C} = \begin{bmatrix} C_{s0} & C_{s1} & C_{s2} & C_{s3} \\ C_{B0} & C_{B1} & C_{B2} & C_{B3} \\ C_{Sb0} & C_{Sb1} & C_{Sb2} & C_{Sb3} \end{bmatrix} \tag{4.17}$$

$$dS = C_{s0} + C_{s1}S + C_{s2}B + C_{s3}Sb \tag{4.18}$$

Where C_{s0}, C_{s1}, C_{s2}, C_{s3} are the linear proportional constants for surface. The effect of different maintenance actions on each component can be measured by the same interactivity matrix. The assumption is that the maintenance actions will reduce the deterioration level to a specific fraction of the current value (Pilson et al. 1999).

However, the deterministic approaches of performance model cannot explain some issues such as: (*a*) randomness of traffic loads and environmental conditions, (*b*) the difficulties in quantifying the factors or parameters that substantially affect pavement deterioration, and (*c*) the measurement errors associated with pavement condition, and the bias from subjective evaluations of pavement condition (Li et al. 1997). For example, in the Equation 4.1, each of the factors of pavement performance index can further be subdivided into a set of individual factors. Total equivalent granular thickness of the pavement structure (H_e) is determined by the properties of pavement materials, equivalent layer factors defined for the pavement materials, and construction quality. The effect of *ESALs* applied on the pavement for *t* years is not the same because of the traffic growth rate, percentage of trucks, and traffic distribution on the pavement

(Li et al. 1997). These constraints of deterministic approaches broker for the application of stochastic pavement performance modeling.

4.3. Stochastic Pavement Performance Modeling

The stochastic models recently have received considerable attentions from pavement engineers and researchers (Wang et al. 1994, Karan 1977). Typically, a stochastic model of pavement performance curve is represented by the Markov transition process (Li et al. 1997). Knowing the 'before' condition or state of pavement, the Markov process predict the 'after' state (George et al. 1989). The main challenge for these stochastic models is to develop the transition probability matrices (*TPMs*).

Wang et al. (1994) developed the Markov *TPMs* for the Arizona Department of Transportation by using a large number of observed pavement performance historical data for categorized highways with several initial pavement condition states. The pavement probabilistic behavior is expressed by Equation 4.19 for all i, j, l, n, and $0 \leq v \leq N, 0 \leq n \leq N$ (Wang et al. 1994).

$$P_{ij}{}^{(n)} = \sum_{k=0}^{M} P_{ik}^{(1)} P_{kj}^{(n-1)} \ \forall\, n \leq v \text{ and } P_{ij}{}^{(n)} = \sum_{i=0}^{M} \sum_{k=0}^{M} \left(P_{ik}^{(v)} . P_{kl}^{(1)a} \right) P_{lj}^{(n-v-1)} \ \forall\, n > v \tag{4.19}$$

Where $P_{ij}{}^{(n)}$ is the *n*-step transition probability from condition state *i* to *j* for the entire design period (*N*), *M*+1 is the total number of pavement condition states, *v* is the period when the rehabilitation is applied; $P_{ik}^{(v)}$ is the *v*-step transition probability from condition state *i* to *k* under the routine maintenance; $P_{kl}^{(1)a}$ is the one-step transition probability from condition k to l at period *v*; and $P_{lj}^{(n-v-1)}$ is the $(n - v - 1)$ step transition probability from condition *l* to *j* under the routine maintenance. The *n*-step transition probability matrix ($P^{(n)}$) is given by Equation 4.20 (Wang et al. 1994).

$$P^{(n)} = \begin{bmatrix} P_{00}^{(n)} & \cdots & P_{0M}^{(n)} \\ \vdots & & \vdots \\ P_{M0}^{(n)} & \cdots & P_{MM}^{(n)} \end{bmatrix} = \begin{cases} P_{routine}^{(n)} & n \leq v \\ P_{ik}^{(v)} \times P_{kl}^{(1)a} \times P_{lj}^{(n-v-1)} & n > v \end{cases} \tag{4.20}$$

Where $P_{routine}^{(n)}$ is the n-step transition probability matrix before the rehabilitation when $n \leq v$ (Wang et al. 1994). Equation 4.19 and 4.20 can easily be expanded to analyze pavement probabilistic behavior where more than one rehabilitation actions are applied.

Karan (1977) developed pavement deterioration functions by means of Markov process modeling for the *PMS* of the Waterloo (Ontario) regional road network. In this study, the pavement performance deterioration versus age was modeled as a time-independent Markov process (Equation 4.21).

$$V(n) = V(0) \times M^n \tag{4.21}$$

Where $V(n)$is the predicted condition state matrix at year n; $V(0)$ is the initial condition state matrix at year 0; and M is the one-step transition probability matrix (Wang et al. 1994).

For the stochastic performance modeling for different pavement categories of roads, a large amount of measured performance data for all pavement categories in a road network have to be obtained and processed, which are time-consuming and costly (Li et al. 1997).

4.4. Transition from Deterministic to Stochastic Performance Modeling

Since the deterministic methods are widely applied by different studies and organization for the pavement performance modeling, the provision of transitional process from deterministic to stochastic modeling can be useful. Li et al. (1997) discussed the principles of system conversion from a deterministic to a stochastic model. Li et al. (1997) considered the AASHTO (Equation 4.2) and OPAC (Equation 4.4) deterministic performance models to convert into stochastic models. Li et al. (1997) assumed that the predicted actual traffic ($ESALs$) is normally distributed with $p^{s}_{(ESALs)_t}(ESALs)$ probability density function for a pavement section (s) in t years. The $\overline{ESALs}$ is the mean value of the traffic ($ESALs$) that drives the pavement condition state to deteriorate from the initial state i to state j. The $(ESALs)^{s}_{ij}$, a random variable, can be defined as the maximum numbers of $ESALs$ that a pavement section s can carry before it drops from condition state i to state j. The transition of $(ESALs)^{s}_{ij}$ from deterministic to stochastic numbers can be expressed by Equation 4.22 (Li et al. 1997).

$$P_{ij}^{s}(t) = P\left((ESALs)_{i,j+1}^{s} < \overline{ESALs} < (ESALs)_{i,j}^{s}\right) = P\left(\overline{ESALs} < (ESALs)_{i,j}^{s}\right) - P\left(\overline{ESALs} < (ESALs)_{i,j+1}^{s}\right) = \int_0^\infty \left[\int_0^y p_{(ESALs)_t}^{s}(x)dx\right] P_{(ESALs)_{ij}^{s}}(y)dy - \sum_{k=i}^{j+1} p_{ik}^{s}(t)\,, j < i \quad (4.22)$$

By applying Equation 4.22 to each specific section of pavement in a road network, the non-homogeneous Markov *TPM* for pavement section *s* at stage *t* can be calculated by Equation 4.23 (Li et al. 1997).

$$P^{s}(t) = \begin{bmatrix} P_{10,10}^{s}(t) & P_{10,9}^{s}(t) \dots & P_{10,0}^{s}(t) \\ P_{9,10}^{s}(t) & P_{9,9}^{s}(t) \dots & P_{9,0}^{s}(t) \\ \vdots & \vdots & \vdots \\ P_{0,10}^{s}(t) & P_{0,9}^{s}(t) \cdots & P_{0,0}^{s}(t) \end{bmatrix} \quad (4.23)$$

Traditionally, the *TPMs* have been assumed to be time independent through the analysis period. Li et al. (1997) developed time-dependent non-homogeneous Markov transition process. The modeling process was governed by three components: state, stage, and transition probability. First, stages were considered a series of consecutive equal periods of time (e.g. each year). Second, states were used to measure pavement functional and structural deterioration in terms of *PCS*. Finally, a set of *TPMs* was calculated to predict the pavement condition state (assuming 10 condition states) at year *t* (Equation 4.24) (Li et al. 1997).

$$\boldsymbol{P(t)} = \boldsymbol{P^{(1)}P^{(2)}\dots P^{(t-1)}P^{(t)}}$$

$$p(t) = \begin{bmatrix} P_{10,10}^{(1)} & P_{10,9}^{(1)} \dots & P_{10,0}^{(1)} \\ P_{9,10}^{(1)} & P_{9,9}^{(1)} \dots & P_{9,0}^{(1)} \\ \vdots & \vdots & \vdots \\ P_{0,10}^{(1)} & P_{0,9}^{(1)} \cdots & P_{0,0}^{(1)} \end{bmatrix} \begin{bmatrix} P_{10,10}^{(2)} & P_{10,9}^{(2)} \dots & P_{10,0}^{(2)} \\ P_{9,10}^{(2)} & P_{9,9}^{(2)} \dots & P_{9,0}^{(2)} \\ \vdots & \vdots & \vdots \\ P_{0,10}^{(2)} & P_{0,9}^{(2)} \cdots & P_{0,0}^{(2)} \end{bmatrix} \dots \begin{bmatrix} P_{10,10}^{(t)} & P_{10,9}^{(t)} \dots & P_{10,0}^{(t)} \\ P_{9,10}^{(t)} & P_{9,9}^{(t)} \dots & P_{9,0}^{(t)} \\ \vdots & \vdots & \vdots \\ P_{0,10}^{(t)} & P_{0,9}^{(t)} \cdots & P_{0,0}^{(t)} \end{bmatrix} \quad (4.24)$$

This non-homogeneous Markov transition process can be applied to simulate the probabilistic behavior of pavement deterioration in predicting pavement serviceability level (Li et al. 1997).

4.5. Drawbacks of Markov Decision Process (*MDP*)

The main drawback of *MDP* approach is that it does not accommodate budget constraints (Liebman 1985). Another important drawback of this approach is that pavement sections have to be grouped into a large number of roughly homogeneous families based on pavement characteristics (Li et al. 2006). A large number of families mean fewer sample of pavement sections in each family, which compromises the reliability and validity of the *TPMs* generated for each family (Li et al. 2006). There are equally large numbers of *M&R* treatments for each family of pavement sections. It is suggested that all pavement sections should be categorized into small numbers of families. As the MDP addresses the performance evaluation of the pavement section as a group, it is not possible to address the performance condition of individual pavement section. Similarly, the optimization programming of *M&R* strategies are determined for a group of pavement sections rather than an individual section under a given budget. Moreover, the optimization programming of *M&R* strategies are calculated from the steady-state probabilities. However, in reality, the pavements under a given maintenance policy usually takes many years to reach the steady state and the proportion of the pavements are changing year by year. Therefore, the use of steady-state probabilities in the optimization objective function does not fully reflect reality, especially when this transition period is very long (Li et al. 2006).

4.6. Backpropagation Neural Network for Dealing with Uncertainties

In reality, many uncertain factors are involved in pavement performance curves. Ben-Akiva et al. (1993) developed the latent performance approach to report the problem of forecasting condition when multiple technologies are used to collect condition data. In that approach, a facility's condition is represented by a latent/unobservable variable which captures the ambiguity that exists in defining (and consequently in measuring) infrastructure condition (Durango-Cohen 2007). Unfortunately, this proposed model suffers from computational limitations. The process of finding an optimal action for a given period involves estimating and assigning a probability to every possible outcome of the data-collection process. The number of outcomes, the number of probabilities, and the computational effort to obtain *M&R* policies increases exponentially with the number of distresses being measured (Durango-Cohen 2007).

Durango-Cohen (2007) applied the polynomial linear regression model to define the dynamic system of infrastructure deterioration process. At the start of every period, the agency collects sets of condition data (X_t), and decides to take an action (A_t). The structure of deterioration process is determined by the material and construction quality, environmental conditions, and so on. These factors is represented by the vector $\vec{\beta}_t$. The deterioration model is given in Equation 4.25 (Durango-Cohen 2007).

$$D_t\left(X_t, A_t, \vec{\beta}_t\right) = g_t X_t + h_t A_t + \vec{\beta}_t + \varepsilon_t \tag{4.25}$$

This model assumed that ε_t accounted for the systematic and random errors in the data-collection process. The relationship between the latent condition and the distress measurements can be expressed by Equation 4.26 (Durango-Cohen 2007). The measurement error model not only included the condition data (X_t), but also includes a set of exogenous (deterministic or stochastic) inputs captured in the matrices Γ_t (one vector associated with each distress measurement). The vector $\vec{\xi}_t$ is assumed to follow a Gaussian distribution with finite covariance matrix (Durango-Cohen 2007).

$$M(X_t, \Gamma_t) = H_t X_t + I_t \Gamma_t + \vec{\xi}_t \tag{4.26}$$

The Durango-Cohen's model cannot define the proportion of errors contributed by each of the factors to the distress outcome. This study proposes the Backpropogation Artificial Neural Network (*BPN*) method to estimate the pavement performance for each year during the life-span of the pavement. The estimated pavement performance for each year can, later on, be plotted with respect to the pavement-age to determine pavement-deterioration during the life-span of the pavement.

The fundamental concept of BPN networks for a two-phase propagate-adapt cycle is that predictive variables (e.g. traffic loads, structural number etc.) are applied as a stimulus to the input layer of network units that is propagated through each upper layer until an output (e.g. PCI, IRI etc.) is generated. This estimated output can then be compared with the desired output to estimate the error for each output unit. These errors are then transferred backward from the output layer to each unit in the intermediate layer that contributes directly to the output. Each unit in the intermediate layer will receive only a portion of the total error signal, based roughly on the relative contribution the unit made to the original output. This process will repeat layer-by-layer until each node in the network will receive an error representing its relative contribution to the total error. Based on the error received, connection weights will then be updated by each unit to cause the network to converge toward a state allowing all the training patterns to be encoded (Freeman and Skapura 1991).

Attoh-Okine (1994) proposed the use of Artificial Neural Network (*ANN*) for predicting the roughness progression in the flexible pavements. However, some built-in functions, including learning rate and momentum term of the neural network algorithm were not investigated properly. The inaccurate application of these built-in functions may affect the accuracy capability of the prediction models (Attoh-Okine 1999). Attoh-Okine (1999) analyzed the contribution of the learning rate and the momentum term in *BPN* algorithm for the pavement performance prediction using the pavement condition data from Kansas department of transportation network condition survey 1993 (Kansas Department of Transportation 1993). In that model, *IRI* was the function of rutting, faulting distress, transverse cracking distress, block cracking, and *ESALs* (Attoh-Okine 1999).

Shekharan (1999) applied the partitioning of connection weights for *ANN* in order to determine the relative contribution of structural number, age of pavement, and cumulative 80-KN *ESALs* to the prediction of pavement's present serviceability rating (*PSR*) (Shekharan 1999). The output layer connection weights are partitioned into input node shares. The weights, along the paths from the input to the output node, indicate the relative predictive importance of input variables. These weights are used to partition the sum of effects on the output layer (Shekharan 1999).

The built-in functions of *ANN* proposed by Attoh-Okine (1994) and the partitioning of connecting weights of *ANN* applied by Shekharan (1999) may affect the accurate capability of the prediction models. As we know, a neural network is a mapping network to compute the functional relationship between its input and output; and these functional relationships are defined as the appropriate set of weights (Freeman and Skapura 1991). The generalized delta rule (*GDR*) algorithm of *BPN* can deal with these problems. It is a generalization of the least-square-mean (*LMS*) rule. This chapter discusses the *GDR* to learn the algorithm for the neural network because the relationship is likely to be nonlinear and multidimensional. Suppose we have a set of P vector-pairs in the training set, (x_1,y_1), (x_2,y_2), …….(x_p,y_p), which are examples of a functional mapping $y = \phi(x): x \in R^N, y \in R^M$. We also assume that (x_1,d_1), (x_2,d_2), …….(x_p,d_p) is some processing function that associates input vectors, $\mathbf{x}_k$ (rutting, faulting distress, transverse cracking distress, block cracking, *ESALs*, and environmental conditions etc.) with the desired output value, d_k (e.g. *IRI*). The mean square error, or expectation value of error, is defined by Equation 4.27 (Freeman and Skapura 1991).

$$\varepsilon_k^2 = \theta_k = (d_k - y_k)^2 = (d_k - \mathbf{w}^t\mathbf{X}_\mathrm{N})^2 \text{where } y = \mathbf{w}^t\mathbf{X} \tag{4.27}$$

The weight vector at time-step t is $\mathbf{w}^t$. As the weight vector is an explicit function of iteration, R, the initial weight vector is denoted $\mathbf{w}(0)$, and the weight vector at iteration R is $\mathbf{w}(R)$. At each step, the next weight vector is calculated according to Equation 4.28 (Freeman and Skapura 1991).

$$\mathbf{w}(R+1) = \mathbf{w}(R) + \Delta\mathbf{w}(R) = \mathbf{w}(R) - \mu\nabla\theta_k\big(\mathbf{w}(R)\big) = \mathbf{w}(R) + 2\mu\varepsilon_N\mathbf{X}_N \;\; \forall\, \nabla\theta(\mathbf{w}(R)) \approx \nabla\theta(\mathbf{w}) \tag{4.28}$$

Equation 4.28 is the *LMS* algorithm, where $\Delta\mathbf{w}(R)$ is the change in **w** at the R^{th} iteration, and μ is the constant of negative gradient of the error surface. The error surface is assumed as a paraboloid. The cross-section of the paraboloidal weight surface is usually elliptical, so the negative gradient may not point directly at the minimum point, at least initially. The constant variable (μ) determines the stability and speed of convergence of the weight vector toward the minimum error value (Freeman and Skapura 1991).

The input layer of input variables distributes the values to the hidden layer units. Assuming that the activation of input node is equal to the net input, the output of this input node (I_{pj}) is given by Equation 4.29. Similarly, the output of output node (O_{pk}) is given by Equation 4.30, where the net output from the j^{th} hidden unit to k^{th} output units is net_{pk}(Freeman and Skapura 1991).

$$I_{pj} = f_j\big(net_{pj}\big) \quad net_{pj} = \textstyle\sum_{i=1}^{N} w_{ji}\, x_{pi} + \theta_j \tag{4.29}$$

$$O_{pk} = f_k\big(net_{pk}\big) \quad \forall\, net_{pk} = \textstyle\sum_{j=1}^{L} w_{kj} I_{pj} + \theta_k \tag{4.30}$$

Where net_{pj} is the net input to the j^{th} hidden unit, net_{pk} is the net input to k^{th} output unit, w_{ji} is the weight on the connection from the i^{th} input unit to j^{th} hidden unit, w_{kj} is the weight on the connection from the j^{th} hidden unit to p^{th} output unit, and θ_j is the bias term derived from Equation 4.27. The weight is determined by taking an initial set of weight values representing a first guess as the proper weight for the problem. The output values are calculated applying the input vector and initial weights. The output is compared with the correct output and a measure of the error is determined. The amount to change each weight is determined and the iterations with all the training vectors are repeated until the error for all vectors in the training set is reduced to an acceptable value (Freeman and Skapura 1991).

Equations 4.29 and 4.30 are the expressions of output of input and output nodes, respectively. In reality, there are multiple units in a layer. A single error value (θ_k) is not suffice for *BPN*. The sum of the squares of the errors for all output units can be calculated by Equation 4.31 (Freeman and Skapura 1991).

$$\theta_{pk} = \frac{1}{2}\sum_{k=1}^{M} \varepsilon_{pk}^{2} = \frac{1}{2}\sum_{k=1}^{M} (y_{pk} - O_{pk})^2$$

$$\Delta_p\theta_p(\mathbf{w}) = \frac{\partial(\theta_p)}{\partial w_{kj}} = -(y_{pk} - O_{pk})\frac{\partial}{\partial w_{kj}}(O_{pk}) = -(y_{pk} - O_{pk})\frac{\partial f_k}{\partial(net_{pk})}\frac{\partial(net_{pk})}{\partial w_{kj}} \tag{4.31}$$

Combining Equations 4.29, 4.30, and 4.31, the change in weight of output layer can be determined by Equation 4.32 (Freeman and Skapura 1991).

$$\frac{\partial(\theta_p)}{\partial w_{kj}} = -(y_{pk} - O_{pk})\frac{\partial f_k}{\partial(net_{pk})}\frac{\partial}{\partial w_{kj}}(\sum_{j=1}^{L} w_{kj}I_{pj} + \theta_k) = -(y_{pk} - O_{pk})f_k'(net_{pk})I_{pj} \tag{4.32}$$

In Equation 4.32, $f_k'(net_{pk})$ is the differentiation of Equation 4.30; this differentiation eliminates the possibility of using a linear threshold unit, since the output function for such a unit is not differentiable at the threshold value. Following Equation 4.32, the weights on the output layer can be written as Equation 4.33 (Freeman and Skapura 1991).

$$w_{kj}(R+1) = w_{kj}(R) + \tau\left(y_{pk} - O_{pk}\right) f_k'(net_{pk}) I_{pj} \tag{4.33}$$

Where τ is a constant, and is also known as learning-rate parameter. However, $f_k\ (net_{pk})$ needs to be differentiated to derive f_k'. There are two forms of output functions for paraboloid $\left[f_k\left(net_{jk}\right) = net_{jk}\right]$ and sigmoid or logistic function$\left[f_k\left(net_{jk}\right) = (1 + e^{-net_{jk}})^{-1}\right]$. The sigmoid or logistic function is for binary output units and the paraboloid function is for continuous output units. As the output of this model (pavement condition index) is continuous, paraboloid function can be applied for output function and can be expressed by Equation 4.34 (Freeman and Skapura 1991).

$$w_{kj}(t+1) = w_{kj}(t) + \tau\left(y_{pk} - O_{pk}\right) O_{pk}\left(1 - O_{pk}\right) I_{pj} = w_{kj}(t) + \tau\delta_{pk} I_{pj} \tag{4.34}$$

The estimated output, from connection weight, is compared to the desired output, and an error is computed for each output unit. These errors are then transferred backward from the output layer to each unit in the intermediate layer that contributes directly to the output. Each unit in the intermediate layer receives only a portion of the total error signal, based roughly on the relative contribution the unit made to the original output. This process repeats layer-by-layer until each node in the network has received an error that represents its relative contribution to the total error. Based on the error received, connection weights are then updated by each unit to cause the network to converge toward a state that allows all the training patterns to be encoded. Reconsidering Equation 4.30, 4.31, and 4.34 for Backpropagation algorithm, change of weights on hidden layer is expressed by Equation 4.35 (Freeman and Skapura 1991).

$$\theta_p = \tfrac{1}{2}\textstyle\sum_{k=1}^{M}(y_{pk} - O_{pk})^2 = \tfrac{1}{2}\sum_{k=1}^{M}(y_{pk} - f_k(net_{pk}))^2 = \tfrac{1}{2}\sum_{k=1}^{M}(y_{pk} - f_k(\sum_{j=1}^{L} w_{kj} I_{pj} + \theta_k))^2$$

$$\frac{\partial \theta_p}{\partial w_{ji}} = -\sum_{k=1}^{M}\left(y_{pk} - O_{pk}\right)\frac{\partial O_{pk}}{\partial w_{ji}} = -\sum_{k=1}^{M}\left(y_{pk} - O_{pk}\right)\frac{\partial O_{pk}}{\partial\left(net_{pk}\right)}\frac{\partial\left(net_{pk}\right)}{\partial I_{pj}}\frac{\partial I_{pj}}{\partial\left(net_{pj}\right)}\frac{\partial\left(net_{pj}\right)}{\partial w_{ji}}$$

$$\frac{\partial \theta_p}{\partial w_{ji}} = -\sum_{k=1}^{M} (y_{pk} - O_{pk})\, f_k'(net_{pk}) w_{kj} f_j'(net_{pj}) x_{pi}$$

$$\Delta_p w_{ji} = \frac{\partial \theta_p}{\partial w_{ji}} = \tau f_j'(net_{pj}) x_{pi} \sum_{k=1}^{M} (y_{pk} - O_{pk})\, f_k'(net_{pk}) w_{kj} = \tau f_j'(net_{pj}) x_{pi} \sum_{k=1}^{M} \partial_{pk}\, w_{kj} \tag{4.35}$$

Equation 4.35 explains that every weight-update on hidden layer depends on all the error terms (∂_{pk}) on the output layer, which is the fundamental essence of the backpropagation algorithm. By defining the hidden layer error term as $\delta_{pj} = f_j'(net_{pj}) \sum_{k=1}^{M} \partial_{pk}\, w_{kj}$, we can update the weight equations to become analogous to those for the output layer (Equation 4.36). Equations 4.34 and 4.36 have the same form of delta rule (Freeman and Skapura 1991).

$$w_{ji}(t+1) = w_{ji}(t) + \tau \delta x_{pi} \tag{4.36}$$

4.7. Reliability Analysis of the Traffic Data and estimated pavement deterioration

The *BPN* can properly deal with the statistical randomness. The uncertainty not only associated with the statistical analysis, but also with the pavement condition and traffic data. How can we confirm that the traffic data for each year are reliable? To overcome these uncertainties, the reliability analysis (R_i) of the traffic data (*ESALs*) can be performed. The reliability analysis of *ESALs* is expressed at Equation 4.37 by comparing the potential *ESALs* that the pavement structure can withstand before its condition state drops to a defined level ($ESAL_{pcs(i)}$)and the actual predicted annual *ESALs* (Li et al. 1996).

$$R_{i(ESAL)} = P\left[\left(\log ESAL_{pcs(i)} - \log ESAL_t\right) > 0\right] = \Phi\left[\frac{\log \overline{ESAL_{pcs(\imath)}} - \overline{\log ESAL_t}}{\sqrt{S^2_{\log ESAL_{pcs(\imath)}} + S^2_{\log ESAL_t}}}\right] = \Phi(z) \tag{4.37}$$

Where $\Phi(z)$ is the probability distribution function for standard normal random variable, $\log \overline{ESAL_{pcs(\imath)}}$ is the mean value of $\log ESAL_{pcs(i)}$, $\overline{\log ESAL_t}$ is the mean value of $\log ESAL_t$, and $S^2_{\log ESAL_{pcs(\imath)}}$and $S^2_{\log ESAL_t}$ are the standard deviations of $\log \overline{ESAL_{pcs(\imath)}}$ and $\overline{\log ESAL_t}$respectively.

4.8. Conclusion

The pavement performance modeling is an essential part of pavement management system (*PMS*) because it estimates the long-range investment requirement and the consequences of budget allocation for maintenance treatments of a particular road segment on the future pavement condition. This chapter discusses various deterministic and stochastic approaches for calculating pavement performance curves. The deterministic models include primary response, structural performance, functional performance, and damage models. The deterministic models may predict inappropriate pavement deterioration curves because they cannot explain some issues, such as: randomness of traffic loads and environmental conditions, difficulties in quantifying the factors or parameters that substantially affect pavement deterioration, and the measurement errors. The stochastic performance models, usually apply Markov transition process (*MTP*), predict the 'after' state condition knowing the 'before' state condition of pavement. This chapter also shows the transition methods from deterministic to stochastic pavement performance modeling. These stochastic methods cannot address the performance condition of individual pavement section. Another major drawback of stochastic models is that the optimization programming of *M&R* strategies are calculated from the steady-state probabilities. However, in reality, the pavements under a given maintenance policy usually takes many years to reach the steady state, and the proportion of the pavements are changing year by year. Therefore, the use of steady-state probabilities in the optimization objective function does not fully reflect reality, especially when this transition period is very long. This chapter proposes Backpropogation Artificial Neural Network (BPN) method with generalized delta rule (GDR) learning algorithm to offset the statistical error of pavement performance modeling. This chapter also discusses the application of reliability analyses to deal with the uncertainty of pavement condition and traffic data.

Chapter 5
Methodology

5.1. Introduction

This research simulated frieght and urban traffics on regional and urban road networks, respectively. Regional PMS incorporate simulated freight traffic and community development criteria into PMS. Urban PMS incorporates simulated urban traffic and deals with computation error of pavement performance modeling. The pavement performance curve for regional road network is estimated based on the modeling of roughness progression of the pavement surface. The pavement deterioration of urban road is estimated by applying BPN network. The community development indicator of each road link is developed as a multicriteria indicator by applying the multivariate analysis of the variables relevant to socio-economic development of the regional communities. Linear programming of life-cycle optimization is applied for PMS of urban and regional roads.

5.2. Integration of land use and transportation (ILUT) models

Travel demands are simulated from ILUT models that measure the spatial interaction of land use and transport system. The spatial interaction predicts the traffic flows using the spatial characteristics of different traffic analysis zones (TAZs) such as distribution of works and employment, and travel cost, etc. (Torrens, 2000). The most widely used urban modeling package in USA is the Integrated Transportation Land Use Package (ITLUP). The ITLUP model has three components such as the Disaggregated Residential Allocation Model (DRAM), EMPloyment ALlocation Model (EMPAL) and travel demand model. The travel demand model is the four-step Urban Transportation Planning System (UTPS). Trip generation and distribution are developed within the DRAM, and the modal split and route assignment are estimated by the multinomial logit (MNL) model and trip assignment algorithms, respectively (Hunt, et al., 2005).

The MEPLAN and TRANUS are extensively used in Europe and South America, but have limited application in North America. The MEPLAN is an aggregate model that allocates households and economic activities to TAZs. The MEPLAN develops a spatially disaggregated input–output matrix that includes technical coefficients, labor sectors and space sectors. Travel demand model applies logit function to allocate traffic of a particular time in a multimodal network. Transport disutilities are feed back into the next time period as the lags in response to transport conditions (Hunt, et al., 2005). TRANUS uses a more restricted set of functional forms and modeling options comparing to the MEPLAN model (Hunt, et al., 2005).

Some ILUT models predominantly focus on the land market, land use and development such as MUSSA (Modelo de Uso de Suelo de Santiago), NYMTC-LUM and UrbanSim. The MUSSA is a land use auction equilibrium model and is used to examine various transportation and land-use policies particularly related to transit. MUSSA is a spatial disaggregation model that solves a static equilibrium in the forecast year by adjusting the amount of building stock supplied, supply and demand response and consumers' expectation levels (Hunt, et al., 2005). The NYMTC-LUM model is developed for the New York Metropolitan Transit Commission (MTC) that solves for a static equilibrium in the forecast year. It simulates the interaction among residential housing, commercial floor space, labor and non-work travel markets (Hunt, et al., 2005). The UrbanSim is a disequilibrium model of building stock supply and demand with annual increments. The demand side of the model uses the TAZs as its spatial unit of analysis and the supply side uses the individual land parcel as the unit of land development and redevelopment (Hunt, et al., 2005).

There are several other ILUT models developed by various researchers and organizations such as BOYCE (Boyce et al. 1992), DELTA (Simmonds, 2001), ILUTE (Miller and Salvini, 2001), IMREL (Anderstig and Mattsson, 1998), IRPUD (Wegener, 2004), KIM (Rho and Kim, 1989), LILT (Mackett, 1991), METROSIM (Anas, 1994), PECAS (Hunt and Abraham, 2003), POLIS (Caindec and Prastacos, 1995), RURBAN (Miyamoto and Udomsri, 1996), STASA (Haag, 1990), TLUMIP (ODOT, 2002), TRESIS (Hensher and Ton, 2001).

Among these ILUT models, only the ITLUP, ILUTE, MEPLAN, STASA, PECAS, TRANUS, TLUMIP models include all urban subsystems such as road network, land use, work-places, housing, employment, population, goods transport and travel. The DELTA, MUSSA, POLIS, RURBAN and UrbanSim do not model transport but depend on the interaction with existing transport models. No other ILUT models except the DELTA, ILUTE, IRPUD, LILT and UrbanSim can simulate the demographic change and household formation (Wegener, 2004). The ILUTE, IRPUD, and TLUMIP models are equilibrium models of transport only. The ITLUP, IMREL, MEPLAN, PECAS, TRESIS and TRANUS simulate the transport and activity location separately but BOYCE and LILT simulate the transport and location together. The ITLUP, MEPLAN, STASA and TRANUS have multiple-path assignment approach allowing for route-choice dispersion (Wegener, 2004). For the regional economics, the spatial input-output methods are the standard method of simulating the goods flow. The DELTA, KIM, MEPLAN, PECAS and TRANUS use the input-output coefficients or demand functions for inter-sector flows and random utility or entropy models for their spatial distribution (Wegener, 2004).

This study assesses the widely practiced ILUT models to determine the best applicable ILUT models for travel demand modeling with aggregate data at the urban and regional scale (Table 5.1). The ITLUP, MEPLAN and TRANUS models are Zone-based (typically large zones) because of the data constraint problem for the ITLUP model and non-representation of the technical coefficients for small zones in the MEPLAN and TRANUS models. The NYMTC-LUM model is based on the small zones but it does not represent the micro-scale.

The MEPLAN and TRANUS have built-in network modeling capabilities to estimate the travel demand. The MUSSA, NYMTC-LUM and UrbanSim are 'connected' to four-stage travel demand modeling systems. The ITLUP can function either way. The ITLUP, MEPLAN and TRANUS are fully integrated models that use the composite utilities derived from the mode choice and land use models. These models ensure the internal consistency between the land use and transport components of the modeling system. The MUSSA, NYMTC-LUM, and UrbanSim use the composite utilities derived from destination choice models, either explicitly or implicitly. These models are very practical, and indicate that the residential location processes are relatively long run in nature and depends upon a variety of factors. However, the MUSSA, NYMTC-LUM, and UrbanSim are more applicable to residential choice modeling (Hunt, et al. 2005).

Table 5.1: Comparative evaluation of different land use and transportation modeling

Criteria	ITLUP	ILUTE	MEPLAN	TRANUS	MUSSA	NYMTC-LUM	UrbanSim	BOYCE	DELTA	IMREL	IRPUD	KIM	LILT	METROSIM	PECAS	POLIS	RURBAN	STASA	TLUMIP	TRESIS
Widely practiced ILUT models	X		X	X	X	X	X													
Inclusion of urban subsystems	X	X	X	X											X			X	X	
In-built transport modeling	X	X	X	X		X		X		X	X	X	X	X	X			X	X	X
Simulate demographic change and household formation		X					X		X		X		X							
Static Equilibrium model	X		X	X	X	X														
Equilibrium model of transport & location with endogenous land prices												X		X						
Equilibrium model of transport only		X									X								X	
Equilibrium model of transport and activity location separately	X		X	X						X					X					X
Equilibrium model of transport & location combined without endogenous land prices								X					X							

Criteria	ITLUP	ILUTE	MEPLAN	TRANUS	MUSSA	NYMTC-LUM	UrbanSim	BOYCE	DELTA	IMREL	IRPUD	KIM	LILT	METROSIM	PECAS	POLIS	RURBAN	STASA	TLUMIP	TRESIS
Equilibrium model of transport & location with activities as destination of trips	X		X	X				X		X		X	X	X	X		X			
Disequilibrium model							X													
Trip assignment approach for route choice dispersion	X		X	X														X		
Spatial input-output Coefficients or demand functions for good flows			X	X					X			X			X					
Industries and households as consuming and producing factors			X	X											X					
Large zone-based model	X		X	X	X										X		X	X		X
Small zone-based model		X				X		X			X		X	X					X	
Disaggregate or household level							X								X					

This study applies the UTPS of ITLUP and TRANUS models to simulate the travel demand at urban and regional scales, respectively. The ITLUP and TRANUS models include all urban subsystems, have internal ability to model the transportation, simultaneously determine the transport and location, have multiple-path assignment approach for route-choice, are applicable with the aggregate data, are fully integrated models and use the composite utilities derived from the mode choice model. The major advantages of TRANUS as a regional ILUT model are that it explicitly considers the production and consumption of goods and services and applies spatial input-output (SIO) model that is a standard method of simulating the trade flow in the regional economics.

5.2.1. TRANUS – integration of spatial input-output and transportation models at regional scale

This study predicts interprovincial trade flow and freight movement on the regional highways connecting Atlantic Provinces of Canada during the period of 2013-2062. The SIO model estimates the trade flow of goods and services for which the factors of production are private consumption, gross investment, government spending (both federal and provincial), and net exports. The fundamental assumption of the SIO model is that every sector requires input(s)/production factor(s) from other sector(s) except in the case of basic productive activities. The induced production at each province can be calculated based on the demand from one or more sectors at all other provinces. The induced production is allocated among provinces through spatial distribution functions and demand. The allocation of induced production among different provinces causes trade flows (Amador-Jimenez and Amin 2013).

The total demand for sector *n* in a particular province i (TD_i^n) is calculated by Equation 5.1 (Modelistica 2008; Amador-Jimenez and Amin 2013).

$$TD_i^n = \sum ID_i^{mn} + ED_i^n \qquad \forall\, ID_i^{mn} = \left(E_i^{n,t-1} + \Delta E_i^{n,t} * W_i^{n,t}\right) * PD_i^{mn}$$
$$PD_i^{mn} = PDmin^{mn} + (PDmax^{mn} - PDmin^{mn}) * \exp -\delta^{mn} U_i^n \;\; \forall\, U_i^n = \frac{PD_i^{mn}}{\left[\min(PD_i^{mn})\right]^{\theta^m}} \qquad (5.1)$$

Where ID_i^{mn} is the amount of inputs *n* demanded by sector *m* in zone *i*; $E_i^{n,t}$ is the total production of sector *n* in zone *i* for time *t*; $E_i^{n,t-1}$is the total production of sector *n* in zone *i* for time t-1; $\Delta E_i^{n,t}$is the growth of production of sector n in zone i between time t-1 and t; $W_i^{n,t} = \frac{A_i^{n,t}}{\sum_i A_i^{n,t}}$ is the proportion of the increment of n allocated to province i for time t; ED_i^n is the exogenous demand for n from zone other than five provinces and considered as zero; PD_i^{mn} is the amount of production of sector n demanded by a unit of sector m in zone i; $PDmin^{mn}$ is the minimum amount of n required by a unit production of m; $PDmax^{mn}$ is the maximum amount of n required by a unit production of m; δ^{mn} is the elasticity parameter of m with respect to the cost of input n; U_i^n is the disutility function of sector n in province i; and θ^m = degree of scaling (if utility function is fully scaled $\theta^m = 1$, otherwise zero).

The demand for production of good/sector n in province j is the product of the total demand for n. The probability (P_j^n) that the production of n in province j is demanded by other provinces is given by Equation 5.2 (Modelistica 2008; Amador-Jimenez and Amin 2013).

$$P_j^n = \sum TD_i^n * Pr_{ij}^n \qquad Pr_{ij}^n = \frac{(A_j^n)^{\alpha^n} * \exp - \beta^n \breve{U}_{ij}^n}{\sum_j (A_j^n)^{\alpha^n} * \exp - \beta^n \breve{U}_{ij}^n} \qquad \breve{U}_{ij}^n = \frac{U_{ij}^n}{\left[\min(U_{ij}^n)\right]^{\theta^m}} \tag{5.2}$$

Where Pr_{ij}^n is the probability that the production of sector n demanded in zone i is located in zone j; A_j^n is the attractor term for the production of n in j; $\alpha^n$is a parameter that regulates the relative importance of the attractor versus the utility function in the location of sector n; $\beta^n$is the dispersion parameter of the multinomial logit model; and U_i^n is the utility function of sector n between province i and j.

5.2.2. UTPS - integration of land use and transportation models at urban scale

This study simulates the traffic volume on each road segment of Montreal road network for every 5-years period of 50 years (2013-2062) applying UTPS model. The discrete choice model is applied to estimate the trip generations from different boroughs of Montreal city using disaggregate household or individual level data of origin-destination survey 2008 (Equation 5.3). Trip generation is the function of gender, age, personal and household income, occupation, family size, auto ownership, number of children in the household, land use, and residential density (Caliper 2005). This study considers household size, auto ownership and occupation as the explanatory variables of trips per household for business, works and educational purposes during both peak and off-peak hours. Individual decisions to make trips are aggregated to estimate the total number of trip produced from the boroughs of Montreal city. Equation 5.4 aggregates the individual probabilities of trip making to predict the total number of trips produced from the boroughs (Caliper 2005).

$$P_n(1) = \frac{1}{1+e^{\beta(X_{0n}-X_{1n})}} \tag{5.3}$$

$$S(i) = \frac{\sum_{c=1}^{C} N_c \left[\frac{\sum_{n=1}^{N_{sc}} P_n(i)}{N_{sc}}\right]}{N_T} \tag{5.4}$$

Where $P_n(1)$ is the probability of *n* person make a trip; β is the vector of coefficients that is estimated by the model; X_{0n} is the vector of explanatory variables in person *n* utility of not making a trip; X_{1n} is the vector of explanatory variables in person *n* utility of making a trip; $S(i)$ is aggregate forecast of number of trips; N_s is number of decision makers in the sample; N_{sc} is number of decision makers in different groups *C*; N_T is number of decision makers in the populations; N_c is number of decision makers in the population of groups *C*; *C* is number of groups (Caliper 2005).

The predicted trips are spatially distributed among boroughs of Montreal city by applying a doubly-constrained gravity model (Equation 5.5) (Caliper 2005). The doubly-constrained gravity model is UTPS gravity model. The UTPS model balances the trip productions and then factors the calculated attractions so that they normalize to the input attractions. These two steps are then enveloped in an iterative loop (Caliper 2005).

$$T_{ij} = A_j \times P_i \times f\left(d_{ij}\right) \times a_i \times b_j \tag{5.5}$$

$$a_i = \frac{1}{\sum_{\text{all zones } z} b_z \times A_z \times f(d_{iz})} \quad \text{and} \quad b_j = \frac{1}{\sum_{\text{all zones } z} a_z \times P_z \times f\left(d_{zj}\right)}$$

Where T_{ij} is the predicted traffic flow from zone *i* to *j*; P_i is the predicted number of trips produced in zone *i*; A_j is the predicted number of trips attracted to zone *j*; $f\left(d_{ij}\right)$ is friction factor between zone *i* and *j*. Friction function is the impedance function of travel time and cost (Caliper 2005).

A multinomial Logit (MNL) model is applied to estimate the choice of modes (car driving alone, car share, bus, metro and bicycle) by travelers assuming that the utility of an alternative mode is a function of the choice determinants, unknown parameters and an i.i.d Gumbel-distribution error term. Finally, deterministic User Equilibrium (DUE) model is applied to simulate the annual average daily traffic (AADT) on each road segment of Montreal city. The DUE method applies an iterative process to achieve a convergent solution so that no travelers can improve their travel times by shifting routes (Caliper 2005).

5.3. Pavement performance modeling

5.3.1. BPN for estimating pavement deterioration of urban road network

The fundamental concept of BPN network for a two-phase propagate-adapt cycle is that input variables are applied as a stimulus to the input layer of network units that are propagated through each upper layer until an output is generated. This estimated output are compared with the desired output to estimate the error for each output unit. These errors are transferred backward from the output layer to each unit in the intermediate layer that contributes directly to the output. Each unit in the intermediate layer receives only a portion of the total error signal based roughly on the relative contribution to the original output. This process repeats layer-by-layer until each node receives an error representing its relative contribution to the total error. Based on the error received, connection weights are updated by each unit to cause the network to converge toward a state allowing all the training patterns to be encoded (Freeman and Skapura 1991).

This study applies a GDR learning algorithm of BPN network. The learning process of BPN network for pavement performance modeling is described in this section. Let assume that we have a set of P vector-pairs in the training set $\{(x_1, y_1), (x_2, y_2)\ldots (x_p, y_p)\}$ and the functional mapping is $y = \phi(x)\colon x \in R^N, y \in R^M$. The processing function is $\{(x_1, d_1), (x_2, d_2)\ldots (x_p, d_p)\}$ with input vectors ($\mathbf{x}_k$) and desired output value (d_k). The mean square error (ε_k^2) is defined by Equation 5.1 (Freeman and Skapura 1991).

$$\varepsilon_k^2 = \theta_k = (d_k - y_k)^2 = (d_k - \mathbf{w}^t\mathbf{X}_\mathrm{N})^2 \qquad \text{where } y = \mathbf{w}^t\mathbf{X} \tag{5.1}$$

The weight vector at time t is $\mathbf{w}^t$. Since the weight vector is an explicit function of iteration (R), the initial weight vector is denoted $\mathbf{w}(0)$ and the weight vector at iteration R is $\mathbf{w}(R)$. At each step, the next weight vector is calculated following Equation 5.2 (Freeman and Skapura 1991).

$$\mathbf{w}(R+1) = \mathbf{w}(R) + \Delta\mathbf{w}(R) = \mathbf{w}(R) - \mu\nabla\theta_k\big(\mathbf{w}(R)\big) = \mathbf{w}(R) + 2\mu\varepsilon_N\mathbf{X}_N \;\; \forall\, \nabla\theta(\mathbf{w}(R)) \approx \nabla\theta(\mathbf{w}) \tag{5.2}$$

Equation 5.2 is the Least Mean Square (LMS) algorithm, where $\Delta\mathbf{w}(R)$ is the change in weight vector $(\mathbf{w})$ at the R^{th} iteration, and μ is the constant of negative gradient of the error surface. The error surface is either hyperbolic tangent or sigmoid learning function. The constant variable (μ) determines the stability and speed of convergence of the weight vector toward the minimum error value (Freeman and Skapura 1991).

The input layer distributes the values to the hidden or intermediate layer units. Equation 5.3 defines the output (net_{pj}) of input node (I_{pj}) assuming that the activation of input node is equal to the net input. Similarly, Equation 4 defines the output (net_{pk}) of output node (O_{pk}) (Freeman and Skapura 1991).

$$I_{pj} = f_j\big(net_{pj}\big) \quad net_{pj} = \textstyle\sum_{i=1}^{N} w_{ji}x_{pi} + \theta_j \tag{5.3}$$

$$O_{pk} = f_k\big(net_{pk}\big) \quad \forall\; net_{pk} = \textstyle\sum_{j=1}^{L} w_{kj}I_{pj} + \theta_k \tag{5.4}$$

Where w_{ji} is the weight on the connection from i^{th} input unit to j^{th} hidden unit, w_{kj} is the weight on the connection from j^{th} hidden unit to p^{th} output unit, and θ_j and θ_k are errors at intermediate and output layers respectively. The weight is determined by taking an initial set of weight values representing a first guess as the proper weight for the problem. The output values are calculated applying the input vector and initial weights. The calculated output is compared with the correct output and a measure of the error is determined. The amount of change in each weight is determined. The iterations with all training vectors are repeated until the error in all vectors of training set is reduced to an acceptable value (Freeman and Skapura 1991).

Equations 5.3 and 5.4 define the output of input and output nodes, respectively. In reality, there are multiple units in a layer. A single error value (θ_k) is not suffice for BPN network. The sum of error squares for all output units is shown in Equation 5.5 (Freeman and Skapura 1991).

$$\theta_{pk} = \frac{1}{2}\sum_{k=1}^{M} \varepsilon_{pk}^2 = \frac{1}{2}\sum_{k=1}^{M} (y_{pk} - O_{pk})^2$$

$$\Delta_p\theta_p(\mathbf{w}) = \frac{\partial(\theta_p)}{\partial w_{kj}} = -(y_{pk} - O_{pk})\frac{\partial}{\partial w_{kj}}(O_{pk}) = -(y_{pk} - O_{pk})\frac{\partial f_k}{\partial(net_{pk})}\frac{\partial(net_{pk})}{\partial w_{kj}} \tag{5.5}$$

Change in weight of output layer is expressed in Equation 5.6 by combining Equations 5.3, 5.4 and 5.5 (Freeman and Skapura 1991).

$$\frac{\partial(\theta_p)}{\partial w_{kj}} = -(y_{pk} - O_{pk})\frac{\partial f_k}{\partial(net_{pk})}\frac{\partial}{\partial w_{kj}}(\sum_{j=1}^{L} w_{kj}I_{pj} + \theta_k) = -(y_{pk} - O_{pk})f_k'(net_{pk})I_{pj} \tag{5.6}$$

Where $f_k'(net_{pk})$ is the differentiation of Equation 5.4. This differentiation eliminates the possibility of using a linear threshold unit, since the output function for such a unit is not differentiable at the threshold value. Equation 5.7 estimates the weights on the output layer following Equations 5.2 and 5.6 (Freeman and Skapura 1991).

$$w_{kj}(R+1) = w_{kj}(R) + \tau(y_{pk} - O_{pk})f_k'(net_{pk})I_{pj} \tag{5.7}$$

Where τ is a constant and learning-rate parameter. There are two forms of activation functions such as hyperbolic tangent $[f_k(net_{jk}) = \tan(net_{jk}) = (e^{net_{jk}} - e^{-net_{jk}})/(e^{net_{jk}} + e^{-net_{jk}})]$ and sigmoid or logistic function$[f_k(net_{jk}) = (1 + e^{-net_{jk}})^{-1}]$. The sigmoid or logistic function is for output units in a range of (0, 1) and the hyperbolic tangent function is for output units in a range of (-1, 1). Since the output of this model (e.g. pavement condition index) is positive value, sigmoid or logistic function is applied and can be expressed by Equation 5.8 (Freeman and Skapura 1991).

$$w_{kj}(t+1) = w_{kj}(t) + \tau\big(y_{pk} - O_{pk}\big)O_{pk}\big(1 - O_{pk}\big)I_{pj} = w_{kj}(t) + \tau\delta_{pk}I_{pj} \tag{5.8}$$

The errors, estimated from the difference between calculated and desired output, are transferred backward from the output layer to each unit in the intermediate layer. Each unit in the intermediate layer receives only a portion of the total error based roughly on the relative contribution the unit made to the original output. This process repeats layer-by-layer until each node in the network has received an error that represents its relative contribution to the total error. The connection weights are updated based on the error received by each unit. Reconsidering Equations 5.4, 5.5, and 5.8 for Backpropagation algorithm, Equation 5.9 expresses the change of weights in hidden layer (Freeman and Skapura 1991).

$$\theta_p = \frac{1}{2}\sum_{k=1}^{M}(y_{pk} - O_{pk})^2 = \frac{1}{2}\sum_{k=1}^{M}(y_{pk} - f_k(net_{pk}))^2 = \frac{1}{2}\sum_{k=1}^{M}(y_{pk} - f_k(\sum_{j=1}^{L} w_{kj}I_{pj} + \theta_k))^2$$

$$\frac{\partial\theta_p}{\partial w_{ji}} = -\sum_{k=1}^{M}\big(y_{pk} - O_{pk}\big)\frac{\partial O_{pk}}{\partial w_{ji}} = -\sum_{k=1}^{M}\big(y_{pk} - O_{pk}\big)\frac{\partial O_{pk}}{\partial\big(net_{pk}\big)}\frac{\partial\big(net_{pk}\big)}{\partial I_{pj}}\frac{\partial I_{pj}}{\partial\big(net_{pj}\big)}\frac{\partial\big(net_{pj}\big)}{\partial w_{ji}}$$

$$\frac{\partial\theta_p}{\partial w_{ji}} = -\sum_{k=1}^{M}\big(y_{pk} - O_{pk}\big)\, f_k'\big(net_{pk}\big)w_{kj}f_j'\big(net_{pj}\big)x_{pi}$$

$$\Delta_p w_{ji} = \frac{\partial\theta_p}{\partial w_{ji}} = \tau f_j'\big(net_{pj}\big)x_{pi}\sum_{k=1}^{M}\big(y_{pk} - O_{pk}\big)\, f_k'\big(net_{pk}\big)w_{kj} = \tau f_j'\big(net_{pj}\big)x_{pi}\sum_{k=1}^{M}\partial_{pk}\, w_{kj} \tag{5.9}$$

Equation 5.9 explains that each weight update in hidden layer depends on the error terms (∂_{pk}) in the output layer. The BPN network defines hidden layer error as $\delta_{pj} = f_j'(net_{pj})\sum_{k=1}^{M}\partial_{pk}\, w_{kj}$ to update weight equations analogous to those for the output layer (Equation 5.10). Equations 8 and 10 have the same form of delta rule (Freeman and Skapura 1991).

$$w_{ji}(t+1) = w_{ji}(t) + \tau\delta x_{pi} \tag{5.10}$$

5.3.2. Pavement performance modeling for regional road network

This study estimates the deterioration of pavement structures of regional road network based on the regression modeling of roughness progression given by Equation 5.11 (Paterson and Attoh-Okine 1992; Watanatada et al. 1987). Equation 5.11 shows that roughness (International Roughness Index, IRI) is the function of initial as-built quality (IRI_0), equivalent single axle loads at time t ($ESALs_t$), observed pavement structure number (SN), and mean environmental exposure (Thornthwaite's moisture coefficients, m). The accumulated traffic loads (ESALs) are calculated based on the predicted AADT and locally observed truck distributions combined with truck factors. The Federal Highway administration (2011) defines the distribution and truck factors for truck classes of 4, 5, 6, 7, 8, 9, 10, 11, 12 and 13. As-built quality (IRI_0) is set between 0.7 and 1 m/km depending on the highway and coefficient a is set to 265. The structural number coefficient (SN) follows the computation method developed by the 1993 AASHTO Flexible Pavement Structural Design. The mean environmental exposure is identified as 0.07, 0.074 and 0.08 for the three environmental zones with a moisture index of 60, 80 and 100, correspondingly (Natural Resources Canada 1995).

$$IRI_t = e^{mt}[IRI_0 + a(1+SN)^{-5} \cdot ESAL_t] \tag{5.11}$$

5.4. Life-Cycle Optimization of PMS

The lifecycle optimization to achieve and sustain acceptable mean network level-of-service (LOS) at a minimum cost was used to find required levels of funding for regional roads (Equations 5.12 and 5.13). Maximization of total network level of service (condition) under such a budget was then used to find optimal strategic results for pavement management (Equations 5.14 and 5.15). A comparison of funds allocation was used to measure the differences between current and improved management models (from performance models based on freight traffic simulation). This formulation relied on a decision tree containing all possible paths of asset condition across time, after hypothetically receiving available treatments (Amador-Jiménez and Amin, 2012).

$$Min \sum_i \sum_k w_{ik}\left(C_{ik,N-n} + U_{ik}\right) \; \forall \; \sum_i \sum_k w_{ik} = 1 \tag{5.12}$$

Subject to $\sum_k w_{ik} \leq \varepsilon_i(1 + \emptyset)$ for all acceptable i and $\sum_k w_{ik} > \varepsilon_i(1 + \emptyset)$ for all unacceptable i

$$\sum_{n=1}^{N}\sum_{i=1}^{I} L_i Q_{n,i} \geq (LOS)\sum_{i=1}^{I} L_i \tag{5.13}$$

$$Max \quad \sum_{n=1}^{N}\sum_{i=1}^{I} (W_i * L_i Q_{n,i} + W_2 * MCI_i) \tag{5.14}$$

Where $MCI_i = f(\text{socioeconomic development criteria})$

$$\text{Subject to } \; B\,(1 - \Omega) \leq \sum_i \sum_k w_{ik}\left(C^{*}_{ik,N-n} + U_{ik}\right) \pm \beta \leq B(1 + \Omega) \tag{5.15}$$

Where w_{ik} = fraction of area of pavement in state i with action k applied, B = budget constraint per year, β = parametric analysis adjustment on budget constraint, Ω = tolerance on budget constraint, ε_i = condition constraint for state i, $\emptyset$ = tolerance on condition constraints$Q_{n,i}$ = Condition Index for asset i on year n; MCI_i = multicriteria index for asset i, and W_1 and W_2 = the weights of the condition index and multicriteria index.

Chapter 6

Simulating Freight Traffic between Atlantic Canada and Québec to Support Pavement Management on New Brunswick's Regional Highways

Amador-Jiménez, L. and Reza Amin, M. (2013). "Simulating Freight Traffic between Atlantic Canada and Québec to Support Pavement Management on New Brunswick's Regional Highways." J. Infrastructure Systems, 19(3), 343–350.

Abstract

Traffic loading for pavement deterioration should be modeled as a dynamic indicator based on trip distribution derived from spatial economics. The estimation of modal distribution of trips and land development has been the main focus of integrated land use and transport models. However, no connection with transportation asset management has been established. This paper proposes the use of spatial economic simulation to forecast freight traffic distribution in order to improve pavement deterioration modeling. A case study of trade flows between Canada's Atlantic Provinces and Quebec is used to show the pitfall of current management models to estimate rates of deterioration underfunding maintenance and rehabilitation strategies. It was found that, $25 million could maintain adequate levels of condition under current performance modeling, however, such a budget resulted inadequate when performance is based on forecasted truck traffic. In particular, it was found that meanwhile $25 million could maintain current levels of condition. This budget resulted inadequate when performance is based on forecasted truck traffic. It was also found that, aggregation of pavements in few homogeneous groups resulted in the inability to prioritize investments considering the economic relevance of the road in the region. This study suggests the use of individual deterioration models for strategic roads.

Keywords

Pavement; Deterioration; Management; Decision making; Planning; Spatial; Economics

6.1. Background

The intrinsic relationship between provision of efficient infrastructure and degree of economic development has been long claimed. Infrastructure can be further classified by its function: transportation of goods and people, or support to human activities. Transportation has been deemed to be crucial for local accessibility to reach international markets and therefore correlated to the degree of competitiveness of a nation (Straub 2007). It's widely recognized that the price of any good contains a component of transportation (Iacono *et al.,* 2008). As industrialized countries become more technologically efficient it is transportation the factor that may decline the balance on favor of one country or the other. The extensiveness of a road network is relevant only if complemented with adequate urban planning that encourages development and promotes the establishment of new industries providing easy accessibility. That is the case for Atlantic Canada and especially for New Brunswick; its national highways provide a common and unique link to connect all Atlantic Provinces with the US (New England) and with Quebec. With the exception of mining activities in Labrador, being directly connected to Quebec by rail, the rest of the freight of goods produced by New Scotia, Prince Edward Island, Newfoundland and New Brunswick must be moved through provincial routes to reach its final consumption markets.

The province of New Brunswick is one of Canada's leaders in Transportation Asset Management; their management model was awarded the Franz Edelman Award for Excellence in Operations Research in 2010 (Feunekes *et al.* 2011). However, even the most advanced asset management system uses historical rates of deterioration to support decisions on maintenance and rehabilitation. In the particular case of New Brunswick, the lack of complete sets of traffic observations forced analysts to cluster roads employing functional classification as a proxy for traffic intensity, basing deterioration curves on expert criteria. This assumption was further justified by a local analysis which lacked of an explicit consideration of the relationship between causal factors and performance deterioration (Cunningham 2010). Even when causal factors are incorporated in the analysis, performance models fail to consider the intrinsic feedback of disutility (travel time, cost) between trade, traffic flows and road's performance.

Typical implementations of pavement management systems are dedicated to achieve optimal levels of condition, while dealing with budget restrictions. Other important objectives (mobility, safety, accessibility and social cost) along with investments to upgrade and expand the network, are normally left outside the modeling. In addition, modeling for Transportation Asset Management does not consider the economic relevance of roads as a factor to prioritize. In practice, the establishment of new industries in any region is related to the availability of infrastructure (energy, water) and to the easy access to surface transportation.

Previous work done by Ng, Lin, and Waller (2009) has identified the need to account for traffic dynamics; however such research attempts to minimize travel time ignoring the complex decision choices made by travelers with limited imperfect information. A more evolved method can be found in the work of Ouyang (2007) in which driver route choices are simulated and the effect of pavement condition affect such choices. This paper proposes a connection among regional economy, transport modeling and transportation asset management. Such a connection extends the aforementioned work of Ouyang (2007) by making use of a feedback loop between the utility function of spatial economic models and traditional four step traffic generation and assignment. In particular, a case study of the road network in New Brunswick is proposed to demonstrate how regional interactions in the movement of freight can be used to estimate traffic distribution and this to produce more accurate deterioration models for pavement condition. In theory, traffic could be used to forecast overall performance of a road network (deterioration, road safety, and mobility).

6.2. Objective

To demonstrate how simulation capabilities of trade flow and transport models can be used to improve the prediction of pavement condition to support fund allocation on strategic analysis for maintenance and rehabilitation. A small case study of New Brunswick's regional corridors connecting Atlantic Canada and Quebec was used to compare current and adjusted pavement management models.

6.3. Methodology

This paper presents a case study of New Brunswick’s management system for regional highways, based on pavement deterioration simulated from the regional interactions of trade between Canadian Atlantic Provinces and Quebec. Due to time restrictions and lack of processed data the interactions with New England (US) were left outside the model.

Traffic flow is the dynamic factor in road performance (deterioration, safety and mobility). Typically all other factors remain invariant (structure) or follow predictable cycles (environment) across time. This paper was limited to pavement deterioration; the regional movement of freight traffic, using New Brunswick major highways, was expected to affect the rate of such a response. Passenger cars were not relevant to the computation of equivalent single axle loads (*ESALs*), therefore, neglected from the analysis. Truck traffic volumes were translated into *ESALs* (AASHTO 1993) using truck factors estimated according to Transportation Association of Canada (TAC) (1986); truck factors were 2.65, 3.03, 4.39 and 4.45 for 2-, 3-, 4-, and 5-axles truck, respectively. Average daily truck traffic data from TRANUS was converted into *ESALs* per lane per year by multiplying the truck counts in each lane by the corresponding truck factor by class. Annually accumulated *ESALs* were correlated to deterioration in order to forecast pavement decay used in the decision making system to allocate treatments during their lifespan.

6.4. Mathematical Formulation for Pavement Management

Lifecycle optimization to achieve and sustain acceptable level-of-service (*LOS*) at a minimum cost, was used to find required levels of funding (overall budget) for regional roads (Equations 6.1 and 6.2). Previous work by Ouyang (2007) used a similar formulation, also found at the World Bank (Watanatada et al 1987), in order to minimize lifecycle cost. As a second step, total network level of service (condition) under previously found budget was used to allocate maintenance and rehabilitation activities for pavement management (Equations 6.3 and 6.4). In practice such method is normally further refined incorporating additional constraints to set minimum levels of service per facility (route). However, the flexibility to allocate resources per route, without having to meet a minimum LOS, was required. A comparison of funds allocation was used to measure the differences between current and improved performance models (based on freight traffic simulation). Budget (Equations 6.1 and 6.2) was fixed and two models with different performance curves were compared. A linear programming commercial solver was used to find a solution. The solver relied on an enumeration tree containing all possible paths of asset condition across time, for every asset, after hypothetically receiving available treatments at different points on time.

$$MINIMIZE\ Z = \sum_{t=1}^{T}\sum_{i=1}^{a}\sum_{j=1}^{o} C_{t,j} x_{t,i,j} L_i \tag{6.1}$$

$$Subject\ \text{to}: \sum_{t=1}^{T}\sum_{i=1}^{a} L_i Q_{t,i} \geq (LOS)\sum_{i=1}^{a} L_i \tag{6.2}$$

$$MAXIMIZE \sum_{t=1}^{T}\sum_{i=1}^{a} L_i Q_{t,i} \tag{6.3}$$

$$Subject\ \text{to}: \sum_{t=1}^{T}\sum_{i=1}^{a}\sum_{j=1}^{k} C_t x_{t,i,j} L_i \leq B_t \tag{6.4}$$

$0 \leq Q_{t,i} \leq 100$

$\sum_{j \in J_{t,i}} x_{t,i,j} \leq 1$ {for all times t and for each asset i}

Where: $x_{t,i,j} = \{0, 1\}$; 1 if treatment j is applied on asset i on year t, zero otherwise

$Q_{t,i}$ = Condition Index for asset i on year t

$C_{t,j}$ = Cost ($) of treatment j on year t

L_i = length of asphalt road (km) for segment i.

B_t = Budget on year t

6.5. Pavement Performance

Current pavement performance modeling in New Brunswick's road network is associated with functional classification rather than determined from mechanistic-empirical models based on traffic intensity, environmental exposure and pavement strength (Cunningham *et al.* 2010). The performance modeling of pavements for this paper was based on a simplified version of the expected progression of international roughness index (IRI) as defined by Patterson and Attoh-Okine (1992) and, used in the Highway design manual of the World Bank (Watanatada *et al.* 1987). Equation 6.5 shows the mechanistic modeling of roughness based on accumulated equivalent single axle loads for time t (NE_t), initial as-built quality (IRI_0), modified structural number -pavement strength- (SNC) and mean environmental exposure represented by Thornthwaite's moisture coefficients (m) of 0.07, 0.074 and 0.08 (Paterson and Attoh-Okine 1992) for the three environmental zones with moisture index of 60, 80 and 100, correspondingly (Natural Resources Canada 1995). As-built quality (IRI_0) was set between 0.7 and 1 m/km depending on the route and coefficient a was set to 265, structural number coefficient (SNC)

followed the formulation given by Watanatada *et al.* (1987). These values were all taken as recommended by Amador and Mrawira (2010). Accumulated traffic loading in equivalent single axle loads (NE_t) was the result of predicted number of trucks per year (Annual Average Daily Truck Traffic - *AADTT*) from the spatial economic model, and locally observed fleet distributions combined with truck factors for vehicle classes 5,6,7,8,9,10 and 13 (FHWA 2011).

$$RI_t = e^{mt}[IRI_0 + a(1+SNC)^{-5} \cdot NE_t] \tag{6.5}$$

6.6. Regional Spatial Economic Model

For simulating inter-provincial trade flow, we used the freely available software TRANUS (de la Barra 1989). Trade flow starts with demand-supply link which is followed by locations of origin (production) and destination (demand) of the trade flow. Provincial capital cities were simplified as nodes and used to represent origins and destinations of inter-provincial trade flows.

The spatial input-output model, adopted in this study, considers the trade flow of goods and services for which the factors of production are private consumption, gross investment, government spending (both federal and provincial), and net export. Gross investment includes non-residential investment (expenditure for firms for machines and tools), residential investment (expenditure by households and firms on apartments, buildings and factories), and change in inventories in a given period. Government spending consists of federal expenditure on provinces, provincial expenditure, and federal government transfer fund for individual and provincial government. Net export is the summation of net international export (International export – international import) and net domestic export (domestic export – domestic import). Production of goods and services, and factors of production were included in the spatial input-output model as the sectors. In principle, every sector requires inputs/production factors from other sectors except in the case of basic production or activities. Given a certain amount of final demand in one or more sectors of provinces, the induced production of each province can be calculated, which will be allocated among provinces through spatial distribution functions. The allocation of induced production among different provinces according to demand eventually causes transportation flows of goods and services among different provinces through provincial road infrastructures. Hypothetical flow diagram on the relationship between production and consumption is shown in Figure 6.1.

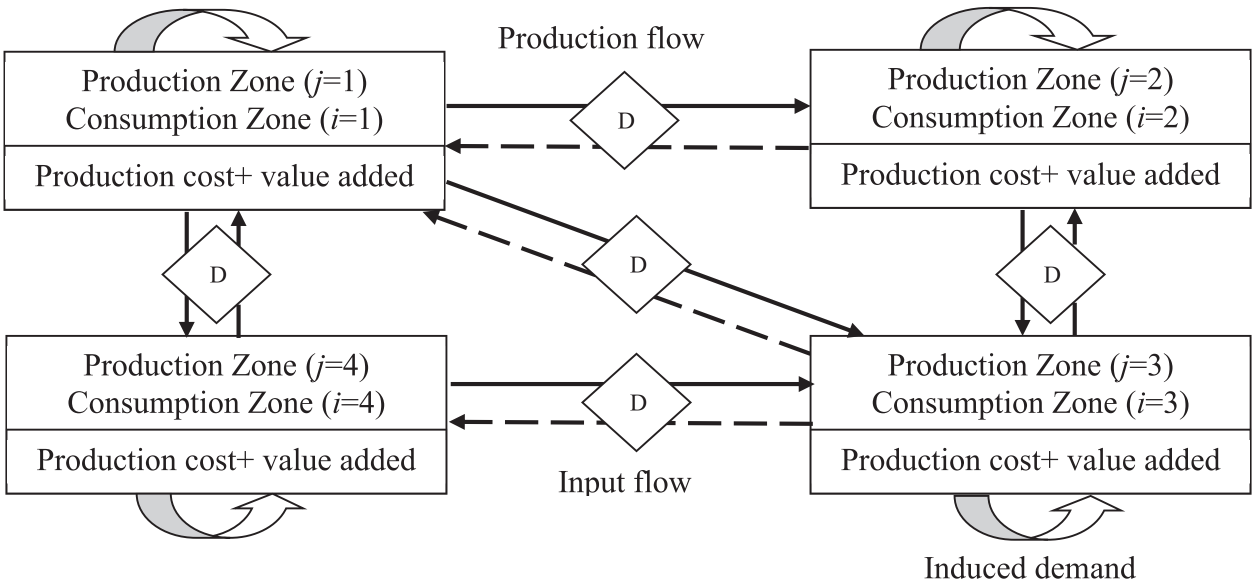


Figure 6.1: Relationship between production and consumption (Modelistica 2008)

Production of sector *n* in province *i* for time *t*

$$p_i^{n,t} = p_i^{n,t-1} + \Delta p_i^{n,t} I_i^{n,t} \qquad \forall \mathrm{I}_\mathrm{i}^{\mathrm{n,t}} = \frac{A_i^{n,t}}{\sum_i A_i^{n,t}} \tag{6.6}$$

$p_i^{n,t-1}$ = Production of sector *n* in province *i* for time (*t*-1)

$\Delta p_i^{n,t}$ = Growth of production of sector *n* in province *i* between time (*t*-1) and *t*

$I_i^{n,t}$ = Proportion of the increment of *n* allocated to province *i* for time *t*.

$A_i^{n,t}$ = Attractor of sector *n* in province *i* for period *t*.

Attraction of selected five provinces out of the total provincial trade flow for the period of 2012-2031 was predicted (Table 6.1) based on the interprovincial trade flow data (1986-1996) collected from the *Institute de la Statistique de Quebec* (2007). As the study is mainly concerned with truck trade flow, truck share of the interprovincial trade flow was incorporated during the calculation.

Table 6.1: Attraction of provinces during the period of 2012-2031

Year	New Brunswick	Nova Scotia	Newfoundland & Labrador	Quebec	Prince Edward
2012	0.0481	0.0293	0.0275	0.0816	0.0074
2013	0.0487	0.0295	0.0287	0.0823	0.0076
2014	0.0493	0.0297	0.0301	0.0831	0.0079
2015	0.0498	0.0298	0.0314	0.0840	0.0081
2016	0.0503	0.0300	0.0328	0.0849	0.0083
2017	0.0508	0.0302	0.0342	0.0859	0.0086
2018	0.0514	0.0303	0.0357	0.0870	0.0089
2019	0.0519	0.0305	0.0373	0.0883	0.0091
2020	0.0524	0.0307	0.0390	0.0896	0.0094
2021	0.0529	0.0309	0.0408	0.0911	0.0098
2022	0.0534	0.0311	0.0428	0.0927	0.0101
2023	0.0539	0.0313	0.0449	0.0945	0.0105
2024	0.0544	0.0316	0.0471	0.0965	0.0109
2025	0.0549	0.0318	0.0496	0.0986	0.0113
2026	0.0555	0.0321	0.0523	0.1009	0.0118
2027	0.0560	0.0324	0.0553	0.1034	0.0123
2028	0.0566	0.0327	0.0586	0.1061	0.0128
2029	0.0572	0.0330	0.0622	0.1090	0.0133
2030	0.0578	0.0333	0.0663	0.1122	0.0139
2031	0.0584	0.0336	0.0708	0.1156	0.0146

The amount of inputs that a unit of production of a sector requires from another sector is determined by a demand function (Equation 6.7 and Table 6.2).

$$PD_i^{mn} = PD_{\min}^{mn} + \left(PD_{\max}^{mn} - PD_{\min}^{mn}\right)e^{-\delta^{mn}U_i^n} \qquad \forall \mathrm{U}_\mathrm{i}^\mathrm{n} = \frac{PD_i^{mn}}{\left[\min\left(PD_i^{mn}\right)\right]^{\theta^m}} \tag{6.7}$$

PD_i^{mn} = amount of production of sector *n* demanded by a unit of sector *m* in zone *i*

$PD_{\min}^{mn}$ = minimum amount of *n* required by a unit production of *m*

$PD_{\max}^{mn}$ = maximum amount of *n* required by a unit production of *m*

δ^{mn} = elasticity parameter of *m* with respect to the cost of input *n*

U_i^n = disutility of *n* in *i*

θ^m = degree of scaling. If the utility function is fully scaled θ^m =1, otherwise 0.

Total demand for sector *n* in a particular province *i* (TD_i^n) is estimated by Equation 6.8.

$$TD_i^n = \sum ID_i^{mn} + ED_i^n \qquad \forall\ ID_i^{mn} = \left(p_i^{n,t} = p_i^{n,t-1} + \Delta p_i^{n,t} I_i^{n,t}\right) PD_i^{mn} \tag{6.8}$$

ED_i^n is exogenous demand for *n* from zone other than selected five provinces and is considered as zero.

Table 6.2: Demand function for sectors in 2012, 2021 and 2031

	Production		**Consumption**		**Investment**		**Govt. spending**		**Export**	
Sector	**2012**	**2031**	**2012**	**2031**	**2012**	**2031**	**2012**	**2031**	**2012**	**2031**
Production			0.37	1.46	0.30	1.50	0.81	3.40	0.25	0.08
Consumption	4.33	3.43			1.30	2.10	2.18	17.62	1.14	0.36
Investment	4.92	5.12	1.74	0.79			3.39	0.16	0.80	0.00
Govt spending	2.37	0.32	0.66	0.48	0.72	0.00			0.63	0.31
Export	3.34	10.43	0.68	2.31	1.07	23.92	1.23	-1.45		

Production of *n* in province *j* demanded by other provinces is the product of total demand for *n* and the probability that production of *n* in province *j* demanded by other provinces (Equation 6.9).

$$p_j^n = \sum_i TD_i^n \Pr_{ij}^n \qquad \forall \Pr_{ij}^n = \frac{\left(A_j^n\right)^{a^n} e^{-\beta^n \breve{U}_{ij}^n}}{\sum_j \left(A_j^n\right)^{a^n} e^{-\beta^n \breve{U}_{ij}^n}} \tag{6.9}$$

6.7. Case Study – The New Brunswick Road Network

This study considered routes 1, 2, 7, 15, 16 in New Brunswick as well as 102, 104 for regional trade flow between New Brunswick, Quebec, Prince Edward Island, Nova Scotia, and Newfoundland and Labrador. The main input variable for the network data was traffic flow (AADT). The calculation of road capacity for each particular link of the selected routes was estimated using the method adopted by the Ministry of Transportation of British Columbia (2011). Peak capacity (vehicle per hour) of a particular road was determined applying Equations 6.10 to 6.13 (Table 6.3).

$$peakCapacity = BaseCapacity * PHF * N * f_{HV} * f_p \tag{6.10}$$

$$BaseCapacity = 1000 + 20FFS \quad \text{If } FFS \le 96.56 km/h \tag{6.11}$$

$$BaseCapacity = 2200$$

$$\text{If } FFS > 96.56 km/h \tag{6.12}$$

$$FFS = BFFS - f_{LW} - f_{LC} - f_M - f_A \tag{6.13}$$

Where

$BFFS$ = speed limit +11 for speed limit 70 km/h = 81 km/h

$BFFS$ = Base free flow speed (km/h)

FFS = Free flow speed (km/h)

f_{LW} = Adjustment factor for lane width = 1.0 km/h

f_{LC} = Adjustment factor for right shoulder lateral clearance =2.0 km/h

f_M = Adjustment factor for number of lanes = 0 km/h

f_A = Adjustment factor for interchange density = 0 km/h

PHF = Peak Hour Factor = 0.95

N = Number of lanes in one direction = 2 for 4-lane divided

f_{HV} = Adjustment factor for heavy vehicles = $f_{HV} = \dfrac{1}{1+P_T(E_T-1)}$

f_p = Adjustment factor for driver population = 0.95 for mixture of regular and non-regular users

P_T = Proportion of trucks

E_T = Passenger car equivalents of trucks= 1.5 for rural freeways in level terrain (HPMS Manual)

The obtained Free Flow Speed (FFS) for multi-land highway (4-land divided) was 78 km/h (Equation 6.13). The base capacity was 1980 passenger cars per hour per lane (*pcphpl)* (Equation 6.11). Table 6.4 summarizes the calculation of peak capacity of each route, based on the proportion of trucks in each road segment, passenger car equivalents (1.5), peak hour factor (0.95), number of lanes (2), adjustment factor for driver population (0.95) and base capacity (1980 *pcphpl*). Truck ratios were based on statistical data (weight in motion) from the department of Transportation of New Brunswick (NBDOT 2006).

Table 6.3: Calculation of peak capacity

Route no.	**Base capacity (*pcphpl*)**	**Truck ratio of AADT**	**Min freq. (veh/hour)**	**Max freq. (veh/hour)**	**Peak capacity (*pcphpl*)**
1	1980	0.1145506	179	1304	3469
2		0.2295673	189	750	3290
7		0.1322844	147	783	3440
15		0.06564	118	1317	3551
16		0.1844828	116	198	3358
102		0.0287909	23	738	3616
104		0.0964361	13	102	3499

Only flows of trucks on the regional network were simulated, passenger cars were neglected from the analysis because of their insignificant contribution to equivalent single axle loads. The first step consisted on developing a GIS database containing all the information of the regional road network.

Transportation attributes of truck were considered for the traffic simulation. The values of travel and waiting time were crucial because it directly affected the behavior of drivers. The waiting and travel time value of truck drivers is assumed to be zero as traveling and waiting time are within their salary.

Operating cost per truck was calculated, including fixed cost, distance-related cost, time-related cost, possible charges and energy cost (Equation 6.14). Used values are summarized in Table 6.4.

$$C_{op} = C_F + C_T + C_D + C_c + C_e \tag{6.14}$$

Where

C_F = Fixed operating cost of a truck once for every trip made; usually refers to administrative costs and loading/unloading cost;

C_T = Operating cost per hour; usually includes drivers' salaries and capital payments;

C_D = Operating cost per km of a truck, usually including tires, spares, maintenance, lubricants, and others; this cost varies by link type;

C_c = Charges paid by driver for tolls, parking, duties, etc.

C_e = energy cost

C_T was calculated by summing driver's salaries (hour wage) and per hour capital payments. According to Economic Analysis Directorate (2005), after 800,000 to 1.2 million km, the truck will either be sold or retired for use, as an urban pickup and delivery unit. This is equivalent to a mean service life of 8 years when assuming 160000 km driven per year.

$$C_T = (126000/8/270/10) + 15.77 = \text{CAD}21.60 \text{ per hour} \tag{6.15}$$

The average purchasing cost of a 6-axle truck for the five provinces is CAD$126,000 (Quebec CAD 130,000, New Brunswick CAD 121,000, Nova Scotia CAD 121,000, Prince Edward Island CAD 133,000, and Newfoundland and Labrador CAD 121,000). Furthermore, the analysis also considered 270 working days per year and 10 hours per day for drivers operating the truck (Economic Analysis directorate 2005).

Table 6.4: Operating cost components

Components	Value (CAD)	Data sources
C_F	1.93	Average fixed cost from Table 6.6
C_T	21.60	Equation 6.15
C_D	1.4	
C_c	0	
C_e	Equation 6.16	

Table 6.5: Fixed cost for 6-axle truck (160000 km)

Province	10% profit margin total cost CAD/km	5% profit margin total cost CAD/km	2.5% profit margin total cost CAD/km
Quebec	2.094	1.984	1.933
New Brunswick	1.885	1.785	1.74
Nova Scotia	1.838	1.741	1.697
Prince Edward Island	1.848	1.751	1.706
Newfoundland	1.985	1.88	1.832

Average operating cost per km was estimated to be CAD 1.4 based on operating cost data collected by Levinson *et al*. (2005). Energy cost (C_e) was estimated by Equation 6.16, which was applied in TRANUS.

$$C_e = \left[ed_o^{\min} + (ed_o^{\max} - ed_o^{\min}) * \exp(-\delta^o V_o)\right] pe_o \tag{6.16}$$

Where

$ed_o^{\min}$ = Minimum consumption of energy per unit distance when truck travels at free flow speed

$ed_o^{\max}$ = Maximum consumption of energy per unit distance when truck travels at a speed close to zero

V_o = Speed of vehicle (km/h)

pe_o = Price of unit of energy (CAD per liter)

The energy cost of each truck was calculated based on the minimum and maximum consumption of energy and optimal speed, which are identified on Table 6.6. Here the price of gas is CAD 0.96 per liter. An aerodynamic 18-wheel truck with a smooth side van trailer, with 36287.39 kg gross vehicle weight, operates at 96.56 kilometers per hour (km/h). This results in a truck getting about 2.55 kilometers per liter (KPL) according to the Transportation Business Association (2011).

Table 6.6: Consumption and expenditure of energy by truck for particular speed

Speed (mph)	Consumption	Expenditure	Speed (mph)	Consumption	Expenditure
5	0.132	2.89	45	0.3648	7.99
10	0.2205	4.83	50	0.3635	7.96
15	0.2804	6.14	55	0.3603	7.89
20	0.3192	6.99	60	0.3534	7.74
25	0.3425	7.5	65	0.3397	7.44
30	0.3557	7.79	70	0.316	6.92
35	0.3621	7.93	75	0.2767	6.06
40	0.3644	7.98	80	0.2164	4.74

Finally, the total demand and production of each province, simulated from TRANUS for the period of 2012-2031 (Table 6.7), were considered in the traffic simulation model.

Different categories of straight truck and Tractor trailer (CAT 5-13 - Federal Highway Administration) were assumed to carry on an average CAD 1million worth of goods and services. According to Canadian Annual Vehicle Survey 2009 (Statistics Canada 2009), 54871 registered trucks (weight 15 tones and over) of the selected five provinces made trips of 4465.1 million vehicle-km. On the other hand, the trade flow among these five provinces was CAD 97125 millions during 2009. If we assume that all inter-provincial trade flows were carried out by truck, an average-size truck tentatively carries CAD 1 million worth of goods and services. A number of additional parameters affecting the way in which truck operates were defined as follows; free-flow speed as 45 Km/hr, distance cost per km as CAD 1.4 (Table 6.6), and passenger car equivalents (PCEs) as 3.5 (Ahuja 2007). Minimum and maximum parameters of the elastic trip generation function in the transport model were taken from Table 6.8 (Transportation Research Board 2001). Maximum trip generation rate was the maximum amount of trips that a trip maker was willing to make in the time period of simulation when travel disutility tends to zero.

Table 6.7: Total demand (TD_i^n) and production (P_j) in millions of dollars

	New Brunswick		Nova Scotia		Newfoundland & Labrador		Quebec		Prince Edward	
Year	**Prod.**	**Dem.**	**Prod.**	**Dem.**	**Prod.**	**Dem.**	**Prod.**	**Dem.**	**Prod.**	**Dem.**
2012	30777	25983	37867	26771	37256	74927	347004	182527	5477	5309
2013	31485	27717	38671	25900	40334	82347	359616	180662	5703	5529
2014	32152	31296	39428	25743	43667	100681	372686	187462	5940	5970
2015	32779	33645	40139	25381	47276	114643	386232	178486	6186	6293
2016	33366	36302	40804	25172	51183	132890	400269	180954	6442	6674
2017	33913	38959	41423	25003	55412	154042	414817	183421	6709	7077
2018	34420	41615	41995	24861	59992	178560	429894	185889	6987	7505
2019	34887	44272	42521	24738	64949	206980	445518	188357	7277	7959
2020	35313	46928	43000	24631	70316	239924	461710	190825	7578	8440
2021	35700	49585	43433	24535	76127	278112	478491	193293	7892	8950
2022	36046	52242	43820	24449	82418	322378	495882	195761	8219	9492
2023	36352	54898	44161	24370	89229	373689	513905	198229	8560	10065
2024	36618	57555	44455	24298	96602	433167	532582	200697	8915	10674
2025	36844	60211	44703	24232	104585	502112	551939	203165	9284	11319
2026	37030	62868	44904	24170	113228	582031	571999	205633	9669	12004
2027	37176	65525	45059	24112	122585	674670	592788	208100	10069	12729
2028	37282	68181	45168	24058	132715	782054	614333	210568	10486	13499
2029	37347	70838	45231	24007	143682	906530	636661	213036	10921	14315
2030	37373	73494	45247	23959	155556	1050818	659801	215504	11373	15180
2031	37358	76151	45217	23914	168410	1218072	683781	217972	11845	16098

Table 6.8: Weekday daily light truck trip generation rates (Fontana CA)

Industry	2 & 3 axle	4 &6 axle
Warehouse	0.17	0.21
Industrial	0.33	0.27

Other indicators used to set-up the model were left to default values. Parameters of capacity restriction such as percentage of speed reduction (by which free-flow speed is reduced and the volume/capacity ratio becomes 1), percentage of maximum speed reduction (maximum percentage by which free-flow speed will be reduced, disregarding the volume) and volume/capacity at maximum speed reduction were considered 50%, 90% and 120% respectively. Demand elasticity parameter of the elastic trip generation function in the transport model was assumed to be 0.05. It is the demand elasticity to trips in the time period of the simulation, from the minimum to the maximum depending on travel disutility. The path overlapping factor was assigned to 3. Path overlapping factor controls the degree of dispersion of paths with respect to the minimum path. If path overlapping factor was zero, path search will only find the minimum path. As this value increases, more paths are generated, and the resulting paths become more distinct, avoiding irrelevant options. Target occupancy rate was assigned to 80%. If the highway gets saturated, operators will consider increasing the trip frequency.

6.8. Available Treatments for Pavements

Five treatments were made available for those roads considered in this case study. Table 6.9 summarizes their range of application (operational window) and cost. Cost was based on that observed during 2006 by New Brunswick's Department of Transportation.

Table 6.9: Treatment and Operational Windows Used in Network-level Trade-off Analysis

Asset	Treatment	Operational Window	Unit Cost (2006 CAN$)
Asphalt pavement	Crack-sealing	IRI <= 1.13 and *Crack*[1] >= 90	2,000 /lane-km
	Micro-surfacing (max. of 2 consecutive)	*Crack* >= 80 and *rutting*[2] <= 10%	80,000 /lane-km
	Minor Rehab (e.g. thin overlay)	Arterial: IRI <= 2 and PSDI[3] >= 65	175,000 /lane-km
	Major Rehabilitation	Arterial: IRI <= 2.5 and PSDI >=50	400,000 /lane-km
	Reconstruction	IRI >= 2.0 SAI[4] <= 65	600,000 /lane-km

Note: *[1] CRACK = % of surface without cracks, [2] rutting = % of surface with rutting, [3] PSDI = pavement distress index and , [4] SAI = structural adequacy index*

6.9. Results and Discussion

The simulation of traffic flow from TRANUS returned 7,834 truck-trips from inter-provincial transportation in 2007. For these total 7,834 trips, trucks drive 2,487,470 km, while total vehicle-distance is 334,722,720 vehicle-km, total vehicle-hour is 4,714,405. TRANUS also simulated the total energy cost and other operating cost as CAD 91.70 millions and CAD 2579.64 millions respectively. Table 6.10 provides further details per route.

Table 6.10: Results from the simulation of TRANUS

Route	Goods-Distance (CAD millions-km)	Vehicle-Distance (No.-km)	Vehicle-Hours
1	62127424	62127424	875034
2	204130880	204130880	2875085
7	24203184	24203184	340890
15	15512944	15512944	218492
16	14747773	14747773	207715
102	5866736	5866736	82630
104	4732085	4732085	66649
2_1[5]	3401880	3401880	47914

Note. [5]*Varnier Highway in the connection of Route 2 with Fredericton, N.B*

Deterioration curves based on the predicted amount of traffic loads (*ESALs* per year) were developed for the pavement management system following those proposed by Paterson and Attoh-Okine (1992) and previously applied in New Brunswick by Amador-Jimenez and Mrawira (2011). Table 6.11 shows the calculation and final values of expected traffic loading. TRANUS predicted nearly 2% annual traffic growth on routes 1 and 2, and nearly 1% for routes 7, 15, 16.

Table 6.11: Predicted ESALs per year for New Brunswick regional highways

Truck category (FHWA)	% trucks	Truck Factor	Route1	Route2	Route7	Route15	Route16
5	8.2	0.45	12,385	41,370	4,825	3,092	2,940
6	5.7	1.18	22,574	75,409	8,794	5,637	5,359
7	0.4	3.25	4,363	14,575	1,700	1,089	1,036
8	2.7	0.99	8,971	29,968	3,495	2,240	2,130
9	52.6	2.33	411,341	1,374,059	160,247	102,710	97,644
10	28.6	5.91	567,302	1,895,035	221,005	141,653	134,666
13	1.8	4.7	28,394	94,849	11,062	7,090	6,740
ESALs per year			**1,055,331**	**3,525,266**	**411,129**	**263,511**	**250,514**

The New Brunswick Road Network exhibited good condition levels for the base year (2006), therefore an initial analysis was conducted to identify required levels of budget to maintain current mean network Levels of Service (LOS) for those observed that year. It was determined that an average of 25 million dollars per year was sufficient to achieve such a goal, while expending as little as possible (Equations 6.1 and 6.2). Expected performance based on road's functional classification, was used for a scenario intended to maximize network LOS (condition) while constrained by a budget of 25 million dollars, called *MAX $25M* (Equations 6.3 and 6.4). This scenario was then compared with a scenario called *integrated land use and transport for transportation asset management* (*ILUTTAM*), based on simulated freight flows and an explicit consideration of causal factors for the performance and in Equations 6.3 and 6.4 for the analysis. ILUTTAM used the same budget restriction of 25 million dollars, and its only difference with MAX$35M came from having a different set of performance curves. Results from both scenarios were limited to the portion of the regional network located within the province of New Brunswick.

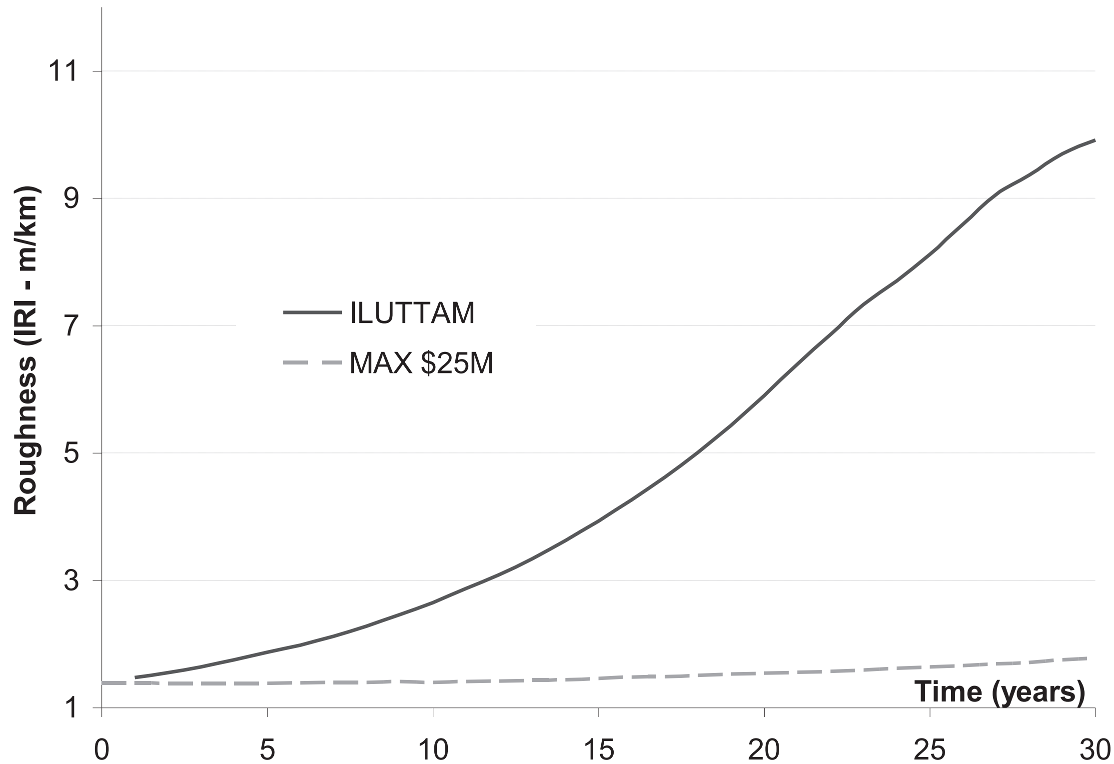


Figure 6.2: Predicted Roughness (IRI) trends for scenarios ILUTTAM and MAX $25M

As shown on Figure 6.2, the simulation of truck-traffic flows returned a much faster decay on surface condition (roughness) if the network remained funded with $25 million dollars. Qualitative progression of poor (IRI > 3.9), fair (1.9 < IRI < 3.9) and good (IRI < 2.15) pavements (Figure 6.3), clearly illustrates the impact of miscalculating the deterioration rate in funding maintenance and rehabilitation; as seen the budget resulted incapable of sustaining a network in good levels of service (condition) as those observed before the analysis.

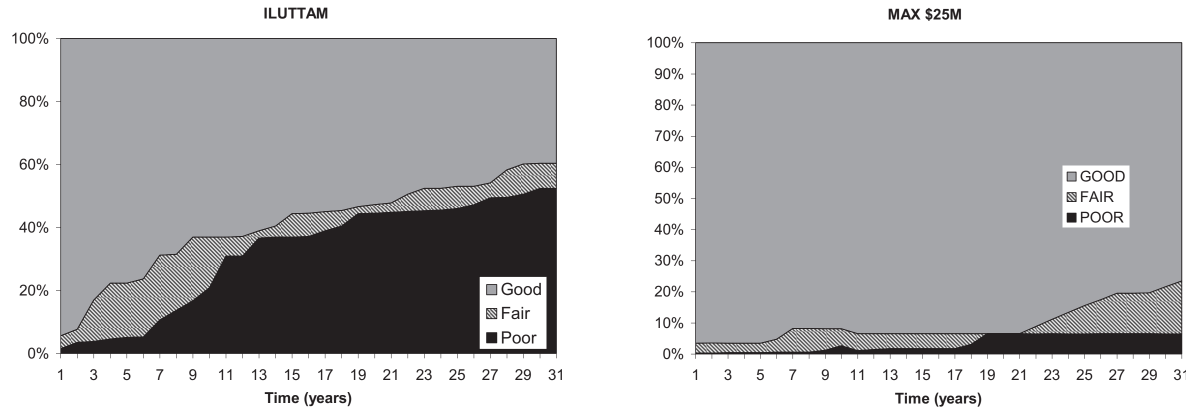
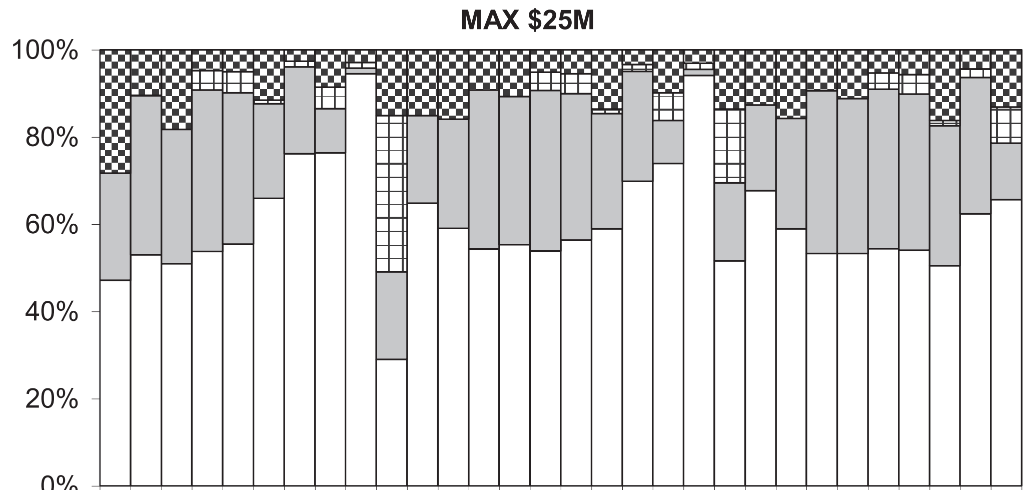


Figure 6.3: Qualitative Levels of Service (Road Condition)

Issues from an inaccurate performance model were not only reflected at the mean network performance but also in the distribution of investments between routes. Originally, the inability to account for dissimilarities in traffic intensities resulted in a somewhat balanced expenditure only shifted by relative importance given by the size (length and number of lanes) of each route (MAX$25). Meanwhile simulated traffic per route (from ILUTTAM) allowed for the incorporation of traffic intensities and refined deterioration models per route, which translated into more resources being invested towards maintenance on those roads moving larger amounts of freight. Figure 6.4 compares the distribution of maintenance and rehabilitation investments for both scenarios. As seen, a significant portion of the budget is being expended on routes 1 and 2 because of its relative size (*MAX $25M* scenario). Results from simulating traffic flows (ILUTTAM scenario) suggest the need to invest more resources into route 1. As seen on Figure 6.4, route 2 maintained similar levels of funding, meanwhile investments dropped for the rest of the regional network. Evidently, the depletion of funding observed in Figure 6.4, leaving some routes with no resources is by no means advisable and is only shown here to proof that levels of funding were underestimated. Therefore, this model suggests the need to used more refined performance models to capture the economic relevance of every route and to estimate more accurate levels of required funding.



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
R07	5	2	4	1	1	3	1	2	1	4	3	3	2	2	1	1	3	1	2	1	3	3	3	2	3	1	1	4	1	3
R16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
R15	0	0	0	1	1	0	0	1	0	9	0	0	0	0	1	1	0	0	1	0	4	0	0	0	0	1	1	0	0	2
R01	4	7	7	9	8	5	5	2	0	5	4	5	8	8	9	8	6	6	2	0	4	4	5	8	8	9	8	7	7	3
R02	9	11	12	13	13	15	18	16	22	7	14	12	12	13	13	13	14	16	15	22	12	15	13	12	12	13	13	12	14	13

Figure 6.4: Distribution of Expenditure per Route (in millions CAN$)

6.10. Conclusions

This paper proposes to use the simulation capabilities of integrated land use and transport modeling as an input into road management systems. A case study based in the simulation of freight flows between the provinces of Newfoundland and Labrador, Nova Scotia, Prince Edward Island, New Brunswick and Quebec, was presented. Two performance models were produced; one based on current practices which use functional classification of roads as a proxy for traffic intensity and, the other one based on simulated truck traffic for each of the main routes within the province of New Brunswick.

The scenario based on current practices was compared with an improved model. Such a model was obtained after adjusting the deterioration curves to account for traffic flow distribution as derived from regional trade flow and locally observed causal factors (environment, traffic loading and pavement's structure strength). As seen, current practices with a mean budget of $25 million dollars per year, were capable of maintaining mean network *LOS* (condition) at acceptable levels, however, once flows of freight were explicitly considered, such a budget became insufficient. In particular, it was demonstrated how performance deterioration modeling based on simulated truck traffic resulted in a more accurate estimation of required levels of funding for maintenance and rehabilitation.

Under current practices, expected budget distribution is well balanced and, the only factor shifting resources is route extensiveness. Under an improved performance model (from simulation) resources are clearly allocated first to those routes that move the majority of the freight (in the case study routes 1 and 2), therefore proofing the need to have an individual performance model per facility based on accurate estimation of truck traffic use and expected growth. Real life applications will require the use of minimum LOS per route.

Future research may examine the sensitivity of factors during the calibration of the multinomial logit discrete choice component of TRANUS. Also future research should look at the creation of a direct linkage between the spatial economic model and the pavement management system. Finally, future research may consider the intrinsic interrelations between simulated traffic flows (vehicles and trucks) with a wider range of objectives such as road safety, highway capacity (mobility), social cost and environmental impact (gas emissions and energy consumption).

Chapter 7

The Multi-Criteria Based Pavement Management System for Regional Road Network in Atlantic Provinces of Canada

Amin, M.S.R., and Amador, L.E. (2014). The Multi-criteria based Pavement Management System for Regional Road Network of Atlantic Provinces of Canada. International Journal of Pavements, Volume 13 Number 1-2-3 January-May-September 2014 [In Press].

Abstract

The infrastructure investment in maintenance and rehabilitation (M&R) of highways is typically done on the basis of pavement condition that is calculated on historical observations of freight traffic. This traditional approach ignores the dynamic nature of land development, economic growth and their connection to traffic growth. This study integrates the regional economy and socio-economic factors with transportation to support multi-criteria based pavement management system (PMS) for the regional road network of Atlantic Canada provinces. This study predicts the movement of freight vehicles as a result of economic and spatial interactions between different provinces. This study optimizes pavement M&R operations of the regional road network based on pavement condition and socio-economic benefits to the surrounding census sub-divisions. The multi-criteria based PMS ensures the relevance of pavement M&R operations in terms of economic and social benefits while providing a network in good condition for the movement of goods and people.

Keywords

Economy, input-output, roughness, maintenance, optimization, community.

7.1. Introduction

7.1.1. Background

Transport infrastructure has a significant impact on regional economics. It generates economic activities through construction, maintenance and rehabilitation (M&R) of transport infrastructure in the short term; transports people and goods and changes the spatial patterns of relative prices and production of goods in the long run (Vickerman 1987). The broader function of regional transport infrastructure can be categorized into two groups – transportation of people by passenger vehicles and transportation of goods by freight transports. Historically, freight travel demand has not been given adequate research interest by regional planners, geographers and scientists as compared to passenger travel demand. Freight travel demand was considered as the classic case of derived demand for goods and assumed that prediction of economic outputs is sufficient enough to determine the demand for freight transports on the regional road network (Vickerman and Monnet 2003).

Transport infrastructure represents major capital infrastructure investments that must be protected in order to ensure adequate return on expenditure. The deterioration of transport infrastructure is progressive and is influenced by several factors including traffic axle loading, environmental exposure, quality of materials, and original design and construction standards. The pavement maintenance is an essential task of transport infrastructure management that should be started immediately after the completion of each stage of the construction and should continue throughout the entire lifespan of the infrastructure. A well-planned maintenance operation is not only the function of accumulated traffic loads and environmental exposure during the life span of road infrastructure, but is also subjected to community benefits.

7.1.2. Objective

This study integrates the regional economy and socio-economic factors of the regional communities with transportation to support multi-criteria based pavement management system (PMS) for the regional road network of Atlantic Canada provinces - New Brunswick, Prince Edward Island, Newfoundland & Labrador, Nova Scotia and Quebec.

7.2. Methodology

This study predicts interprovincial trade flow and freight movement during the period of 2012-2041 by integrating a spatial input-output model with a transportation model. The pavement performance during this design period is estimated based on the modeling of roughness progression of the pavement surface. Finally, community development indicator of each regional road link is developed by multivariate analysis of the variables relevant to community development.

7.2.1. Spatial Input-Output (SIO) Modeling

The provincial capital cities are considered as the points of origins and destinations of trade flow, as this study predicts the impact of inter-provincial trade-flow on regional highways. This study estimates the inter-provincial trade flow based on a SIO model. The SIO model estimates the trade flow of goods and services for which the factors of production are private consumption, gross investment, government spending (both federal and provincial), and net exports. The gross investment includes non-residential investment (expenditure for firms for machines and tools), residential investment (expenditure by households and firms on apartments, buildings and factories), and change in inventories in a given period. The government spending consists of federal expenditure on provinces, provincial expenditure and federal government funds transferred to provincial governments. The net export is the summation of net international export (difference between international export and import) and net domestic export (difference between domestic export and import). The production of goods and services, and factors of production are included in the SIO model as the sectors of regional trade.

The fundamental assumption of the SIO model is that every sector requires input(s)/production factor(s) from other sector(s) except in the case of basic productive activities. The induced production at each province can be calculated given the amounts of final demand from one or more sectors of all other provinces that is allocated among provinces through spatial distribution functions. The allocation of induced production among different provinces according to demand eventually causes trade flows among different provinces through provincial road infrastructures.

The total demand for sector *n* in a particular province i (TD_i^n) is calculated by Equation 7.1 (Modelistica 2008).

$$TD_i^n = \sum ID_i^{mn} + ED_i^n \qquad \forall\, ID_i^{mn} = \left(E_i^{n,t-1} + \Delta E_i^{n,t} * W_i^{n,t}\right) * PD_i^{mn}$$

$$PD_i^{mn} = PDmin^{mn} + \left(PDmax^{mn} - PDmin^{mn}\right) * \exp -\delta^{mn} U_i^n \;\; \forall\, U_i^n = \frac{PD_i^{mn}}{\left[\min\left(PD_i^{mn}\right)\right]^{\theta^m}} \qquad (7.1)$$

$E_i^{n,t}$ = production of sector *n* in zone *i* for time *t*

$E_i^{n,t-1}$= production of sector *n* in zone *i* for time *t*-1

$\Delta E_i^{n,t}$= Growth of production of sector *n* in zone *i* between time *t*-1 and *t*

$W_i^{n,t} = \frac{A_i^{n,t}}{\sum_i A_i^{n,t}}$ = proportion of the increment of *n* allocated to province *i* for time *t*

ED_i^n = exogenous demand for *n* from zone other than five provinces and considered as zero

PD_i^{mn} = amount of production of sector *n* demanded by a unit of sector *m* in zone *i*

$PDmin^{mn}$ = minimum amount of *n* required by a unit production of *m*

$PDmax^{mn}$ = maximum amount of *n* required by a unit production of *m*

δ^{mn} = elasticity parameter of *m* with respect to the cost of input *n*

U_i^n = disutility of sector *n* in province *i*

θ^m = degree of scaling. If utility function is fully scaled $\theta^m = 1$, otherwise zero.

The demand for production of good/sector *n* in province *j* is the product of the total demand for *n*. The probability (P_j^n) that the production of *n* in province *j* is demanded by other provinces is given by Equation 7.2 (Modelistica 2008).

$$P_j^n = \sum TD_i^n * Pr_{ij}^n \quad Pr_{ij}^n = \frac{(A_j^n)^{\alpha^n} * \exp -\beta^n \breve{U}_{ij}^n}{\sum_j (A_j^n)^{\alpha^n} * \exp -\beta^n \breve{U}_{ij}^n} \quad \breve{U}_{ij}^n = \frac{U_{ij}^n}{\left[\min(U_{ij}^n)\right]^{\theta^m}} \tag{7.2}$$

Pr_{ij}^n = probability that the production of sector *n* demanded in zone *i* is located in zone *j*

A_j^n= attractor term for the production of *n* in *j*

α^n= is a parameter that regulates the relative importance of the attractor versus the utility function in the location of sector *n*

β^n= dispersion parameter of the multinomial logit model

U_i^n = utility function of sector *n* between province *i* and *j*

7.2.2. Pavement Performance Modeling

The pavement performance modeling depends on the modeling of roughness progression (Paterson and Attoh-Okine 1992; Watanatada et al. 1987). Equation 7.3 shows that the estimation of international roughness index (IRI). IRI is estimated based on the initial as-built quality (IRI_0), the equivalent single axle load of predicted truck traffic for time *t* ($ESAL_t$), the observed pavement strength (structural number coefficient, *SNC*) and the mean environmental exposure (Thornthwaite's moisture coefficients, *m*). The as-built quality (IRI_0) is set between 0.7 and 1 m/km depending on the route and coefficient *a* is set to 265. The structural number coefficient (*SNC*) follows the formulation given by Watanatada et al. (1987). These values are taken as recommended by Amador-Jiménez and Mrawira (2011). The mean environmental exposure is identified as 0.07, 0.074 and 0.08 for the three environmental zones with a moisture index of 60, 80 and 100, correspondingly (Amador-Jiménez and Mrawira 2011; Natural Resources Canada 1995).

$$IRI_t = e^{mt}[IRI_0 + a(1+SNC)^{-5} \cdot ESAL_t] \tag{7.3}$$

The IRI is rescaled to produce a 0 to 100 performance roughness index (PRI). The measures of rutting and linear cracking are linked to IRI and combined to produce a surface distress index (SDI). The observed historical trends of structural strength (FWD and Dynaflect) are used to produce a structural adequacy index (SAI). These indexes are combined to produce a Pavement Condition Index (PCI) (Amador-Jiménez and Mrawira 2011). The criteria for pavement treatments of regional highways during the 30-years period are presented in Table 7.1 (Amador-Jiménez and Mrawira 2011).

Table 7.1. Treatment and operational windows used in network-level trade-off analysis

Treatment	Operational Window
Crack-sealing	IRI <= 1.13 and *Crack*[6] >= 90
Micro-surfacing (max. of 2 consecutive)	*Crack* >= 80 and *rutting*[7] <= 10%
Minor Rehab (e.g. thin overlay)	IRI <= 2 and PSDI[8] >= 65
Major Rehabilitation	IRI <= 2.5 and PSDI >=50
Reconstruction	IRI >= 2.0 SAI[9] <= 65

Note: *[6]CRACK = % of surface without cracks, [7]rutting = % of surface with rutting, [8]PSDI = pavement distress index and, [9]SAI = structural adequacy index*

7.2.3. Community Development Indicator (CDI)

This study identifies eighteen variables to calculate the community development indicator of each census subdivision (CSD) of Atlantic Canada provinces. The variables are identified based on the community vulnerability report of Statistics Canada (Alasia et al. 2008). The variables are: total population; percentage of agricultural, other primary, manufacturing, production services and distribution services employment; GINI index of income equality; proportion of participation in the labor market (ratio between experience labor force and total working age population); percentage of working age population with post-secondary degree; percentage of individuals who moved from different CSD during last 5 years; proportion of average income working population; Herfindahl Index (H- Index) of the concentration of immigrants; percentage of married population, young (age greater than 15 years) and old (age greater than 65 years); distance from large and small census Metropolitan area (CMA). These variables are standardized in order to ensure the common unit.

The Gini Index of income inequality is usually a standard economic measure of deviation from equal distribution of income among individuals and households within an economy based on Lorenz curve. An economy that scores 0 on the Gini scale has perfect equality in income distribution. The Gini score of greater than 0 to 1 indicates income inequality.

The H-Index is usually applied to measure the market concentration by the industrial organization, economists and public-policy analysts. The H- Index of the concentration of immigrants for each CSD is the sum of square of the proportion of immigrants from different ethnic groups with respect to total population.

This study applies the multivariate analysis technique to identify the variables of principal importance along with the critical correlations. The principal component analysis (PCA), a multivariate analysis technique, is applied to analyze the interrelationships among a large number of variables and to explain these variables in terms of their common underlying dimensions (Hair 1992). The PCA transforms the data to a new set of coordinates that are a linear combination of the original variables. The CDI for each CSD is calculated by multiplying the value of each variable for each CSD, the proportion of variance explained by each variables and the proportion of variance explained by each factor.

7.2.4. Optimization of Pavement Management

The lifecycle optimization to achieve and sustain acceptable mean network condition ($\overline{Q}$) at a minimum cost is used to find required levels of funding for regional roads (Equations 7.4 and 7.5). The maximization of total network condition and community benefits under such a budget is then used to find optimal strategic results for pavement management (Equations 7.6 and 7.7). A comparison of funds allocation is used to measure the differences between current and improved management models (from performance models based on freight traffic simulation). This formulation relied on a decision tree containing all possible paths of asset condition across time, after hypothetically receiving available treatments (Amador-Jiménez and Amin 2013). A transfer function is used to estimate condition (Q_{ti}) as a convex combination based on the decision variable and the effectiveness or decay of the specific link on time t (Equation 7.7a).

The objective function is to minimize cost (Z), $MINIMIZE \quad Z = \sum_{t=1}^{T}\sum_{i=1}^{a}\sum_{j=1}^{o} C_{tj} X_{tij} L_i$ (7.4)

$$\text{Subject to: } \sum_{t=1}^{T}\sum_{i=1}^{a} L_i Q_{ti} \geq \left(\overline{Q}\right)\sum_{i=1}^{a} L_i \qquad (7.5)$$

$$MAXIMIZE \quad \sum_{t=1}^{T}\sum_{i=1}^{a} (W_1 * L_i Q_{ti} + W_2 * CDI_i) \qquad (7.6)$$

$$\text{Subject to: } \quad Z = \sum_{t=1}^{T}\sum_{i=1}^{a}\sum_{j=1}^{k} C_{tj} X_{tij} L_i \leq \mathrm{B_t} \qquad (7.7)$$

$0 \leq Q_{t,i} \leq 100$ and $0 \leq CDI_{,i} \leq 100$

$\sum_{j \in J_{ti}} X_{tij} \leq 1$ {for all times t and for each asset i}

$$Q_{tij} = X_{tij}\,(Q_{(t-1)ij} + E_{ij}) + (1 - X_{tij})\,(Q_{(t-1)ij} + D_{it}) \qquad (7.7a)$$

Where: $X_{tij} = 1$ if treatment j is applied on asset i on year t, zero otherwise; Q_{ti} = condition Index for asset i on year t; Q_{tij} = condition Index of asset i on year t for treatment j; $Q_{(t-1)ij}$ = condition Index of asset i on year (t-1) for treatment j; C_{tj} = cost ($) of treatment j on year t; L_i = length of asphalt road (km) for segment i; $CDI_{,i}$ = community development indicator for asset i, E_{ij} = improvement (+) on asset i from treatment j, D_{it}= deterioration (-) on asset i at time t, B_t = budget on year t, and W_1 and W_2 are the weights of the condition index and community development indicator, respectively.

7.3. Prediction of trade flow and freight movement

The total demand and production of the Atlantic Provinces for the period of 2012–2041 are predicted applying Equations 7.1 and 7.2 (Figure 7.1). Since this study is mainly concerned with the truck trade flow, the truck share of the interprovincial trade flow is only considered during the estimation of track flow.

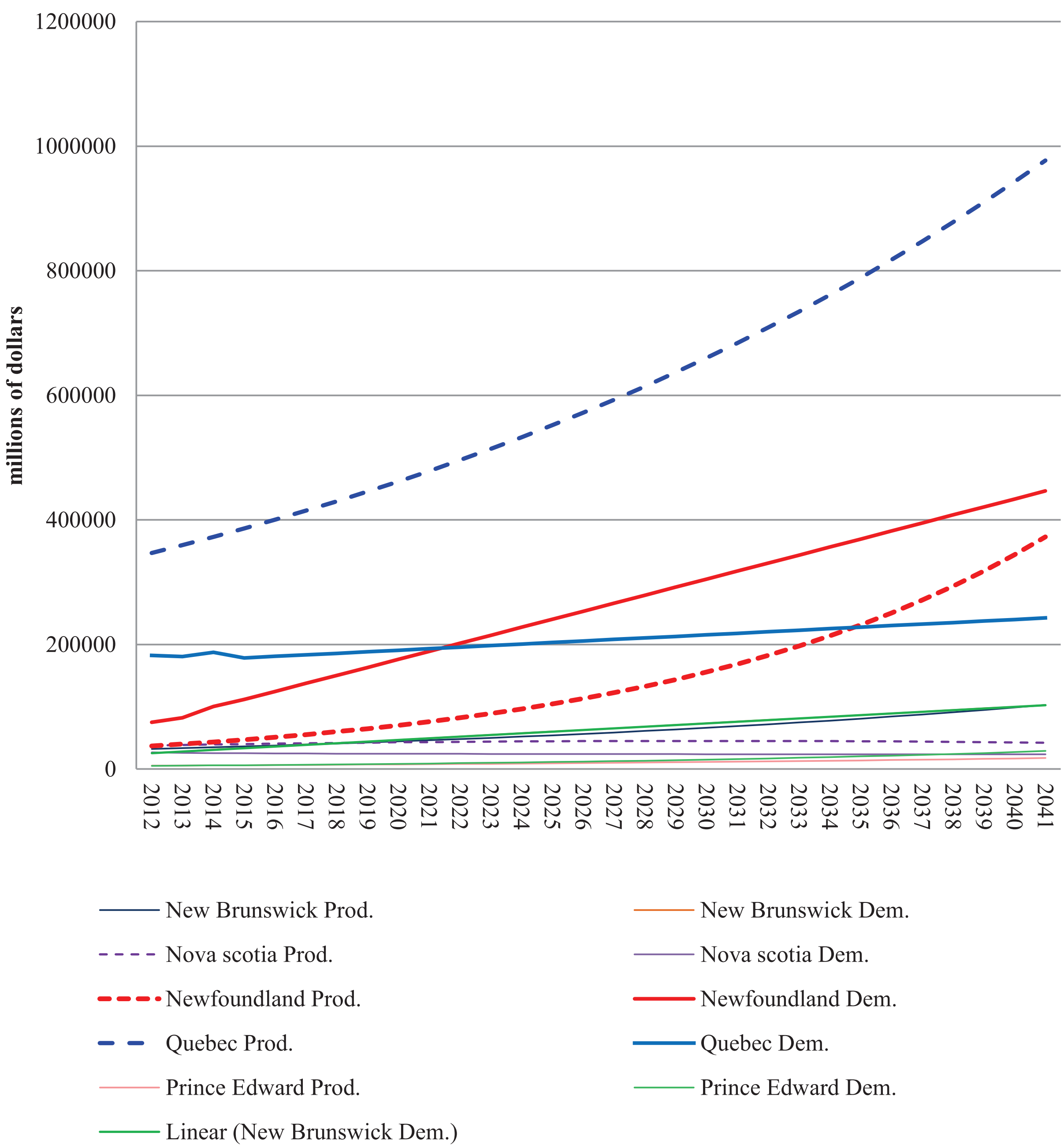


Figure 7.1. Total demand and production of five provinces

Figure 7.1 reveals that the predicted production and demand of goods and services in New Brunswick is indifferent during the period of 2012-2041. In Nova Scotia, the total demand is decreasing while total production is increasing (increasing at an increasing rate until 2030 and then increasing at a decreasing rate) and demand is far lower than production during the same period. In Newfoundland and Labrador, the total demand exceeds total production during the estimation period. The production in Newfoundland and Labrador is exponentially increasing, while demand is linearly increasing. In Quebec, the total production is far higher than total demand and increasing at a higher rate than that of demand during the design period. In Prince Edward Island, the total demand is increasing at a higher rate than that of production (Figure 7.1).

The SIO model estimates the annual average daily truck traffic (AADTT) for interprovincial trade flow. The AADTT for the year of 2012 is estimated as 2397 for highway 1, 8008 for highway 2, 934 for highway 7, 599 for highway 15, 569 for highway 16, 226 for highway 102, and 183 for highway 104.

7.4. Pavement maintenance operations

The accumulated traffic loads ($ESAL_t$) are calculated based on the predicted AADTT and locally observed truck distributions combined with truck factors. The Federal Highway administration (2011) defines the truck factors of 0.45, 1.18, 3.25, 0.99, 2.33, 5.91 and 4.7 for truck classes 5, 6, 7, 8, 9, 10 and 13 respectively. The deterioration curves (IRI) of pavement condition are developed for selected regional highways following Equation 3 (Figure 7.2). Figure 7.2 shows the cumulative IRI of selected highways during the 30-years period for different moisture index zones. For example, Highway 1 geographically locates within 100 and 80 moisture index zones; Highway 2 and 7 locate within 100, 80 and 60 moisture index zones; Highway 15 locates within 80 and 60 moisture index zones; Highway 16 locates within 60 moisture index zone; Highway 102 locates within 100 moisture index zone; and Highway 104 locates within 80 moisture index zone (Natural Resources Canada 1995).

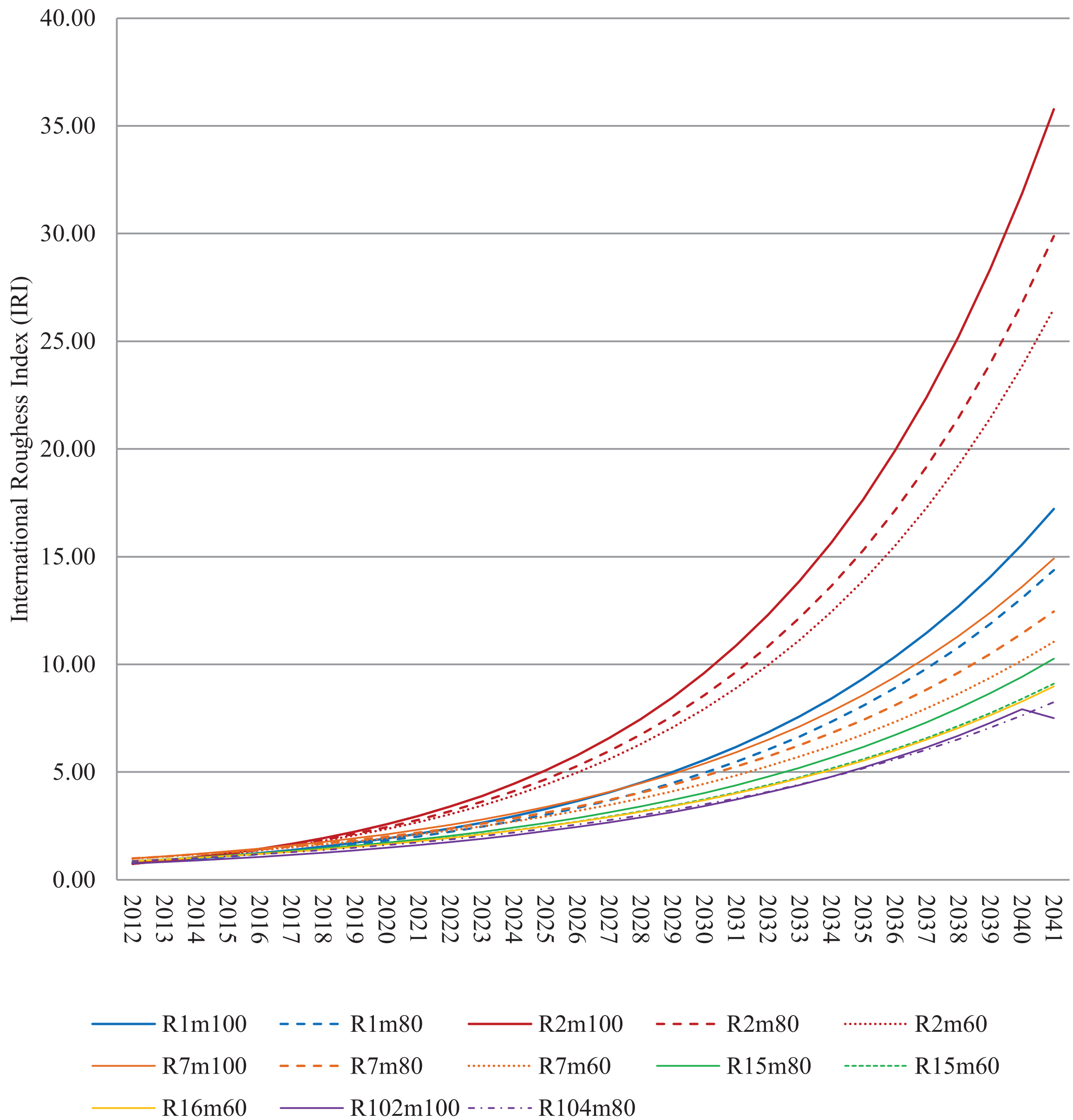


Figure 7.2: International Roughness Index for moisture index of 60, 80 and 100

The pavement treatment operations, for the selected highways during the 30-years period, are defined based on the operation window in Table 7.1. Table 7.2 represents the total length (kilometers) of selected highways that require different types of pavement treatments operations during the 30-years period. The single chip sealing will be required for 15,261.1 km of selected routes during the period of 2012-2041. The double chip sealing, micro-surfacing, minor rehabilitation, major rehabilitation and reconstruction operations will be required for 1,952 km, 515.24 km, 383.3 km, 304.1 km and 84.28 km of highways respectively (Table 7.2).

Table 7.2: Pavement surface treatments of selected highways (km)

Highway No.	One cheap seal	Double cheap seal	Micro surfacing	Minor Rehabilitation	Major Rehabilitation	Reconstruction
1	7073.7	246	18.68	11.48	168	5.44
2	1253.16	14.9	164.8	100.06	113.8	50.26
7	2246.26	1689.06	27.28	32.8	3.84	3.2
15	2985.06	0.56	100.14	58.24	4.36	5.1
16	1.44	1.48	2.64	5.18	6.96	14.48
102	3.68	0	121.22	126.76	1.8	5.8
104	1697.8	0	80.48	48.78	5.34	0

7.5. The multivariate analysis of community development indicator

The first step of performing PCA is to assess the suitability of the data for principal component analysis. The pattern of relationships among variables is identified from the correlation matrix, the determinant of the correlation, the total variance explained (before and after rotation) and the component matrix (before and after rotation) of the variables.

The variables, which have strong correlation (±0.3 and above) with at least three variables, are considered as the significant variables for this multivariate analysis. This study identifies all variables of CDI are strongly correlated except in the case of 'percentage of population', 'percentage of traditional manufacturing employment', 'concentration of immigrants', 'percentage of young people' and 'distance from the large and small CMA'.

The 'Eigenvalues' associated with each linear component (factor) before extraction, after extraction and after rotation are estimated. The eigenvalue associated with each factor represents the variance explained by the linear component. If the total variance of each test is unity, the eigenvalue of the first factors extracted has a theoretical maximum equal to the number of tests (Kinnear et al. 2009). The first factors have the greatest sums and thus account for the greatest part of the total variance. The PCA reveals that the first eleven factors explain 97.57% of variance and have eigenvalues greater than 1 (Table 7.3). The rotation sum of squared loading, representing the effects of optimizing the factor structure, is examined in order to equalize the relative importance of the factors. The rotation sums of squared loadings indicate that 13.25% of the total variance is explained by the 1st factor, followed by 13.03% of the variance by the 2nd factor, 11.82% of the variance by the 3rd factor, 8.98% of the variance by the 4th factor, and 5.56% of the variance by the 5th factor (Table 7.3).

The communality of each variable, which is the total proportion of its variance accounted for by the extracted factors (Table 7.3), is calculated by the squared multiple correlations among the test and the factors emerging from the PCA. The resulting communalities suggest that most of the selected variables describe the main characteristics of the CDI except 'percentage of population', 'percentage of traditional manufacturing employment', 'proportion of young people', and 'distance from the large and small CMA'.

Table 7.3: Total variance explained by the factors

Variables	Initial Eigenvalues			Rotation Sums of Squared Loadings		
	Total	% Variance	Cumulative %	Total	% Variance	Cumulative %
1	959.80	32.46	32.46	2.39	13.25	13.25
2	632.85	21.40	53.86	2.35	13.03	26.29
3	335.94	11.36	65.23	2.13	11.82	38.11
4	267.20	9.04	74.26	1.62	8.98	47.09
5	225.02	7.61	81.87	1.00	5.55	52.64
6	131.26	4.44	86.31			
7	110.79	3.75	90.06			
8	93.21	3.15	93.21			
9	59.51	2.01	95.22			
10	37.55	1.27	96.49			
11	31.75	1.07	97.57			
12	25.13	.85	98.42			
13	14.75	.50	98.92			
14	13.51	.46	99.37			
15	6.58	.22	99.60			
16	6.47	.22	99.81			
17	5.48	.19	100.00			
18	.00	.00	100.00			

It is difficult to interpret the factors on the basis of their factor loadings. The factor loadings explain that the first factor accounts for the maximum part of the variance. The factor rotation is conducted to alter the pattern of the factor loadings and to improve the interpretation. The process of rotation changes the eigenvalues of the factors so that the common factor variance is more evenly distributed among the rotation factors. By orthogonal rotation, it is possible to make clusters of variables load optimally. The communalities of the variables are unchanged by rotation, because their values depend only upon the number of factors and the correlations among the tests (Kinnear et al. 2009).

The 'percentage of agricultural employment', 'percentage of other primary employment', 'proportion of young people', and 'distance from the large and small CMA' are highly correlated with the 1st factor (Table 7.4). The 'percentage of traditional manufacturing employment', 'percentage of distribution service employment', 'percentage of production service employment', 'percentage of working population with post-secondary degree', 'percentage of individuals moved from different CSD during the last 5 years', 'percentage of married people', 'percentage of old population' are associated with 2nd factor (Table 7.4).

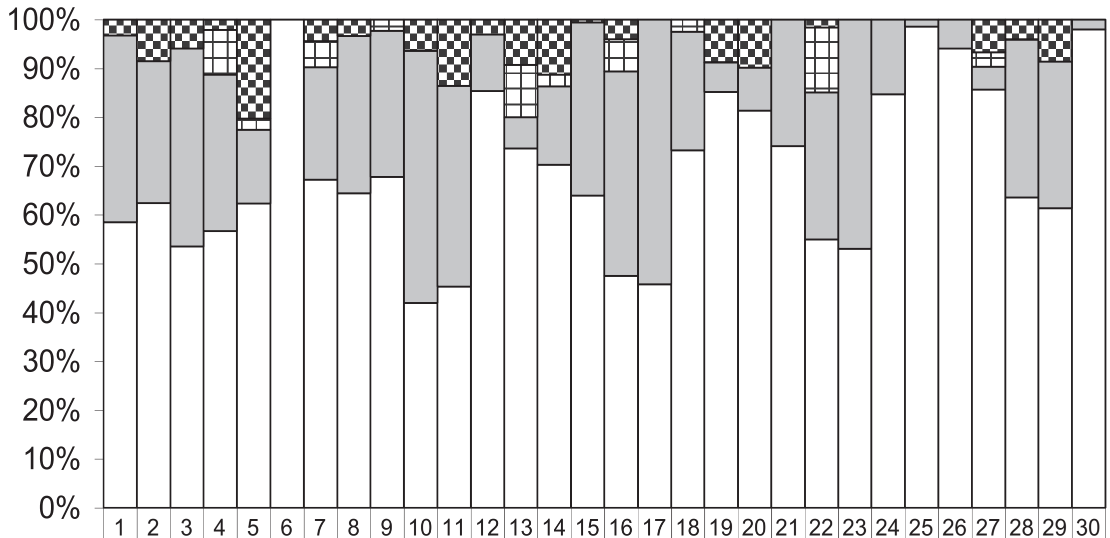
The variables such as 'percentage of employment', 'percentage of population', 'proportion of participation in the labor market' are comparatively more correlated with 3rd factor (Table 7.4). The 'GINI income equality index' and 'average income' are highly correlated with the 4th factor (Table 7.4). The 'H-index concentration of immigrants' is highly correlated with the 5th factor (Table 7.4).

Table 7.4: Rotated component matrix of the variables for CDI

Variables of CDI	Rotated Component Matrix				
	1	2	3	4	5
Percentage of population	-.02	.02	.07	.04	.06
Percentage of employment	-.09	.00	.96	.15	-.06
GINI income equality index	.04	-.01	-.15	-.98	.04
Percentage of agricultural employment	.95	.04	-.01	.02	.01
Percentage of other primary employment	.95	.06	-.02	.00	.01
Percentage of traditional manufacturing employment	.09	.33	.14	.03	-.02
Percentage of distribution service employment	-.24	.58	-.10	.06	.02
Percentage of production service employment	-.32	.42	.08	.04	-.02
Proportion of participation in the labor market	.01	.03	.92	.13	-.03
Percentage of working age population with post-secondary degree	-.36	.62	.20	.05	.00
Percentage of individuals who moved from different CSD during last 5years	-.36	.62	.20	.05	.00
Average income	-.07	.01	.41	.76	.00
Concentration of immigrants	.00	-.03	-.05	-.09	.99
Percentage of married people	.35	.83	-.21	-.07	.01
Proportion of young	-.10	.02	.05	.02	.02
Proportion of old	.10	.52	-.09	.00	.03
Distance to large CMA	-.05	.01	-.01	.04	.01
Distance to Small CMA	-.03	.02	-.02	.03	-.01

7.6. Multi-criteria index of pavement maintenance operations

The lifecycle optimization to achieve and sustain acceptable mean network condition ($\bar{Q}$) at a minimum cost is used to find required levels of funding for regional roads (Equations 7.4 and 7.5). This study compares the pavement M&R budget for two scenarios. The first scenario integrates the regional economy and transportation modeling to simulate the inter-provincial truck flow and the M&R budget is optimized to maximize the pavement condition under the simulated truck flow. The second scenario optimizes the M&R operation budget maximizing the pavement condition and community benefits (CDI). Amador-Jiménez and Amin (2013) estimate that most of the M&R operation budget will be spent on the highway 1 and 2 during the design period (Figure 7.3). Figure 7.4 shows that the regional highways 1, 2, 7, 15, 104 mostly require the single chip seal treatment during the design period. The micro-surfacing, minor rehabilitation and reconstruction are the main M&R operations for highway 16 and 102 (Figure 7.4).



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
R07	1	2	1	0	4	0	1	1	0	2	3	1	2	3	0	1	0	0	2	2	0	0	0	0	0	0	2	1	2	0
R16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
R15	0	0	0	2	0	0	1	0	0	0	0	0	3	1	0	2	0	1	0	0	0	3	0	0	0	0	1	0	0	0
R01	9	6	10	8	3	0	6	8	6	13	10	2	2	4	9	10	14	6	2	2	6	8	12	4	0	1	1	8	8	1
R02	14	14	13	13	13	25	16	16	15	10	11	17	18	18	16	12	11	18	21	20	19	14	13	21	25	24	21	16	15	24

Figure 7.3: Distribution of Expenditure for M&R operations (in millions CAN$) (Amador-Jiménez and Amin 2013)

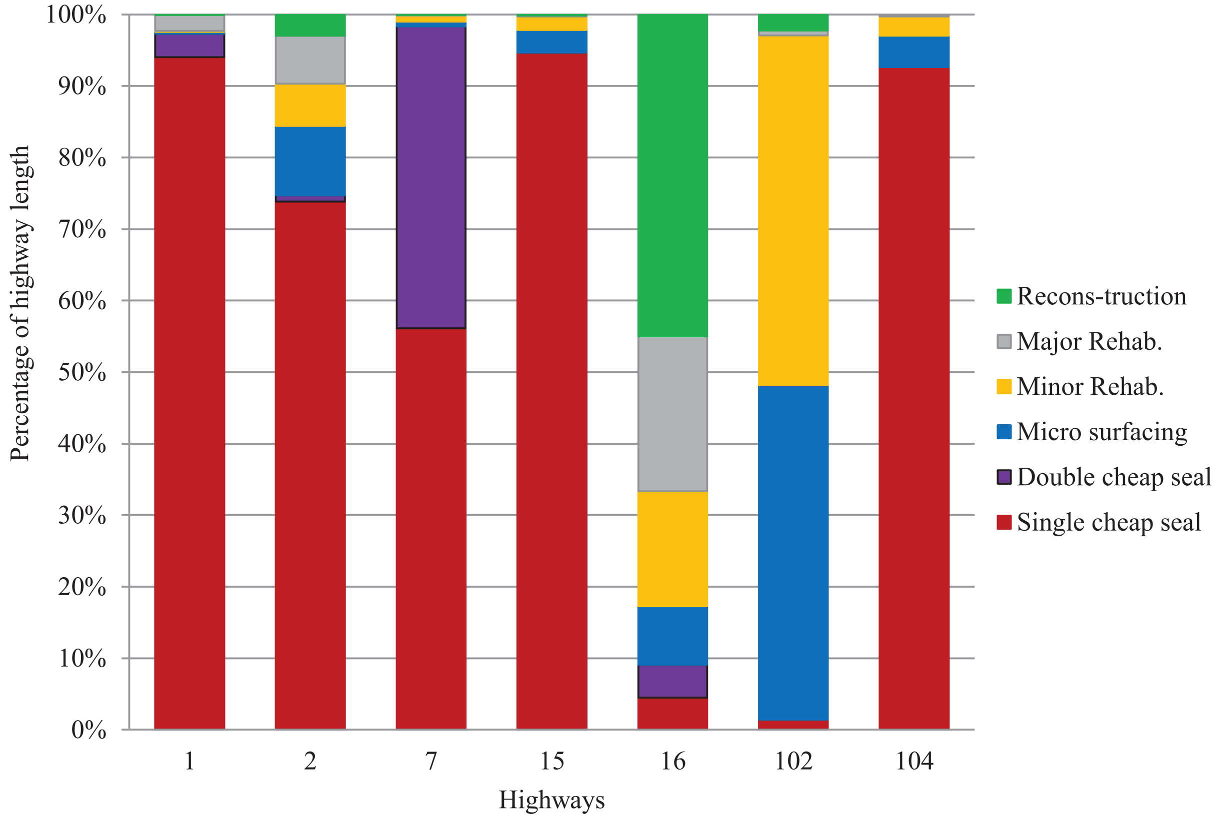


Figure 7.4: Proportion of M&R operations for different highways (Amador-Jiménez and Amin 2013)

The purpose of this study is to include the community benefits within the PMS. This can be determined by measuring the CDI of each CSD and by distributing this CDI to the nearest road link. This study calculates the CDI of each road link by summing up the CDI of all CSDs within the 5 km buffer zone of each road link (Figure 7.5). The 5-km distance, from the centroid of each CSD to the road link, is assumed as the 5-km buffer zone of each road link.

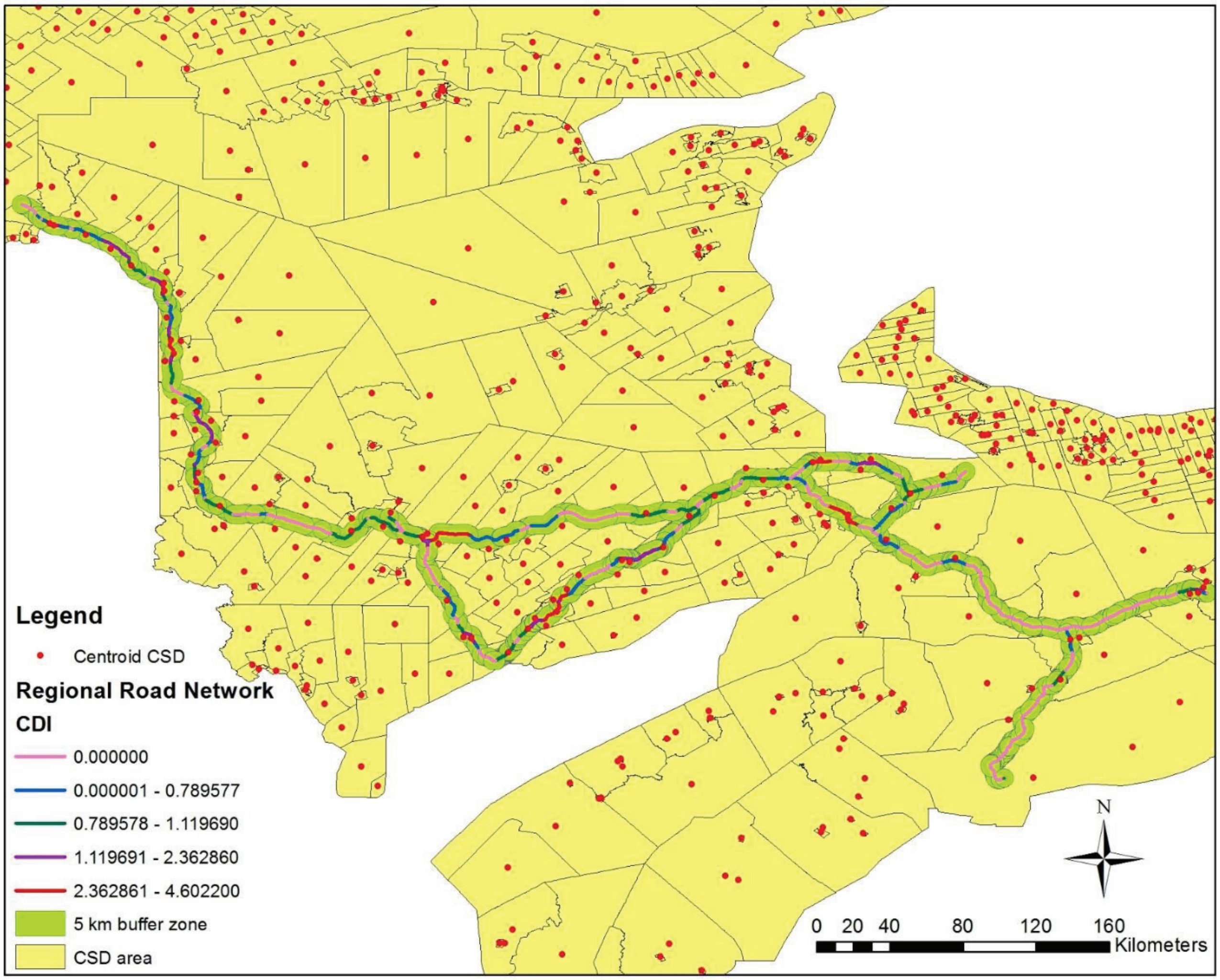


Figure 7.5: Community Development Index map of the regional road network

The prioritization of maintenance operations for each link of regional road network is determined by the summation of weighted value of pavement condition and CDI of each link within the limited budget allocation (Equation 7.4-7.7a). This study iterates the pavement management optimization model by combining the weight values of PCI and CDI from 0-100. However, this study doesn't find any significant budget difference from the outcomes of these iterations. This is why; this study gave the equal weights to the PCI and CDI for each link. This study assumes the annual budget of road maintenance operations is CAD 15 million. Figure 7.6 shows the total length of regional highways requires different types of treatment operations annually. Figure 7.7 shows the annual budget requires for the treatment operations during the design period.

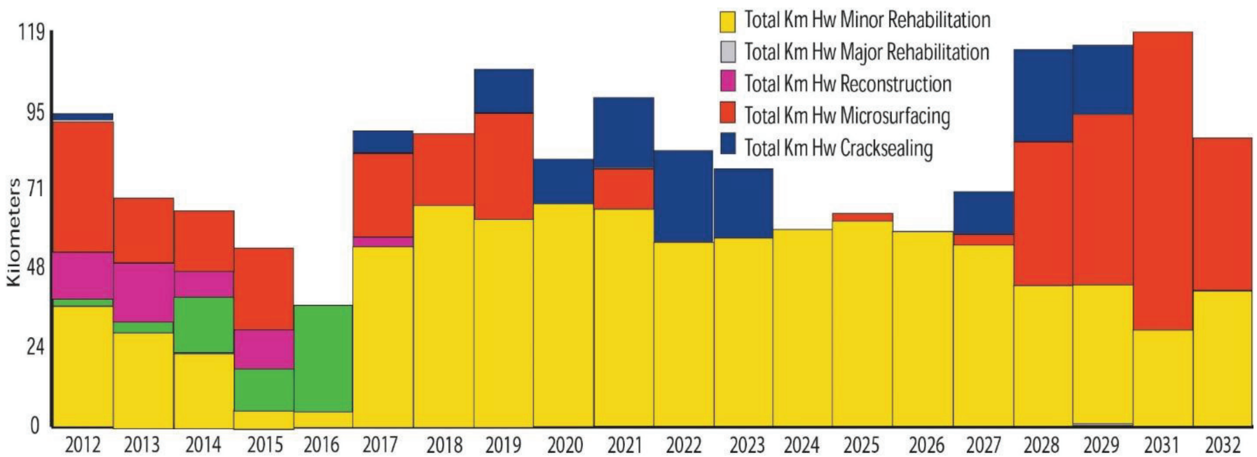


Figure 7.6: Projection of pavement treatment operations during the period of 2012-2041

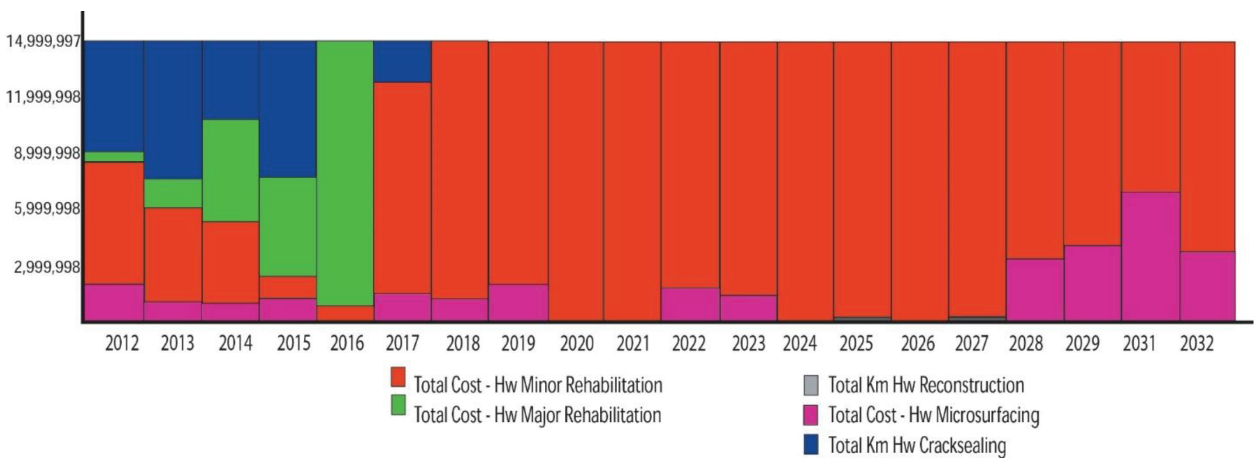


Figure 7.7: Projection of annual budget distributions for different treatment operations

The inclusion of the community benefits within the PMS helps the policy makers (local, provincial or federal government) to consider the community benefits during the pavement maintenance budget allocations. The policy makers are not only guided by the engineering characteristics but also considers the socio-economic benefits of the communities to allocate PMS budget. For example, in a municipality, downtown is given priority comparing to the suburb area for allocating pavement maintenance budget because of the economic and commercial significance. Sometimes different residential areas of a municipality are given different priorities during the municipality maintenance budget allocation based on the socio-economic characteristics and quality of life and neighborhood. The applied model in this study includes both pavement condition and community benefits with weight factors. This study allows the policy makers to weight the pavement condition and community benefits according to their priorities and demands.

7.7. Conclusion

Transport infrastructure has significant association with regional economy as it generates economic activities. The deterioration of transport infrastructure is progressive and is influenced by traffic axle loading, environmental condition, and original design and construction standards. A well-planned PMS is not only the function of accumulated traffic loads and environmental exposure during the life span of road infrastructure, but is also subjected to community development. This study integrates the regional economy and socio-economic factors of the regional communities with transportation to support multi-criteria based PMS for the regional road network of Atlantic Canada provinces - New Brunswick, Prince Edward Island, Newfoundland & Labrador, Nova Scotia and Quebec.

This study predicts interprovincial trade flow and freight movement during the period of 2012-2041 by integrating a SIO model with a transportation model. For example, the AADTT for the year of 2012 is estimated as 2397 for highway 1, 8008 for highway 2, 934 for highway 7, 599 for highway 15, 569 for highway 16, 226 for highway 102, and 183 for highway 104. The accumulated traffic loads are calculated based on the predicted AADTT and locally observed truck distributions combined with truck factors.

The pavement performance during the 30-years period is estimated based on the modeling of roughness progression of the pavement surface. The pavement treatment operations, for the selected highways during the 30-years period, are estimated based on predicted pavement deterioration during the 30-years period. The single chip sealing will be required for 15,261.1 km of selected routes, while 1,952 km, 515.24 km, 383.3 km, 304.1 km and 84.28 km of highways require double chip sealing, micro-surfacing, minor rehabilitation, major rehabilitation and reconstruction during the design period respectively.

The CDI of each regional road link is developed by multivariate analysis of the variables relevant to community development. The lifecycle optimization is performed to maximize the pavement condition and CDI at a minimum budget.

This study compares the pavement M&R budget for two scenarios. The first scenario integrates the regional economy and transportation modeling to simulate the inter-provincial truck flow and the M&R budget is optimized to maximize the pavement condition under the simulated truck flow. The second scenario optimizes the M&R operation budget maximizing the pavement condition and CDI. In the first scenario, the regional highways mostly require the single chip seal and micro-surfacing treatment operations during the design period. In the second scenario, incorporation of CDI within the prevailing system of 1st scenario, the M&R budget will mainly be allocated for minor (overlay) and major rehabilitation treatment operations during the design period.

The integration of regional economy, transportation modeling and community development criteria into the multi-criteria based PMS can help the policy makers and infrastructure managers to understand and include the community benefits within the transport infrastructure maintenance operations. The policy makers are not only guided by the engineering characteristics but also considers the socio-economic benefits of the communities to allocate PMS budget. For example, in a municipality, downtown is given priority comparing to the suburb area for allocating pavement maintenance budget because of the economic and commercial significance. Sometimes different residential areas of a municipality are given different priorities during the municipality maintenance budget allocation based on the socio-economic characteristics and quality of life and neighborhood. The applied model in this study includes both pavement condition and community benefits with weight factors. This study allows the policy makers to weight the pavement condition and community benefits according to their priorities and demands. Future studies can include the socio-economic impacts of the M&R operations on the community instead of only maximizing the generalized value of CDI within the life-cycle optimization of the PMS.

Chapter 8

Application of Backpropagation Neural Network Dealing with Uncertainties in the Pavement Performance Modeling

Amin, M.S.R., and Amador, L.E. Application of Backpropagation Neural Network Dealing with Uncertainties in Pavement Performance Modelling. International Journal of Pavement Engineering. [under review, manuscript no. GPAV-2014-0172]

Abstract

The objective of this study is to apply the Backpropagation Neural Network (BPN) method with Generalized Delta Rule (GDR) learning algorithm for offsetting the statistical errors of the pavement performance modeling. The Multi-Layer Perceptron (MLP) network and sigmoid activation function are applied to build the BPN network. Collector and arterial roads of both flexible and rigid pavements in Montreal City are taken as a case study. Data on pavement condition and age, traffic volume and road characteristics are collected from Ville de Montréal. Ville de Montréal has complete pavement condition data only for 2009 and 2010. The input variables of Pavement Condition Index (PCI) are Average Annual Daily Traffic (AADT), Equivalent Single Axle Loads (ESALs), Structural Number (SN), pavement's age, slab thickness and difference of PCI between current and preceding year (ΔPCI). The BPN networks estimates that the PCI has inverse relationships with AADT, ESALs and pavement's age. The PCI has positive relationships with these variables for roads that have recent treatment operations. The PCI has positive relationships with SN and slab thickness that imply that the increase of structural strength and slab thickness increases the pavement condition. The ΔPCI significantly influences the estimation of PCI values. The AADT and ESALs have considerable importance, however, pavement's age and structural characteristics of pavement have insignificant influence in determining the PCI values except in the case of flexible arterial roads.

Keywords

Pavement management system; pavement condition index; deterministic; stochastic; Backpropagation Neural network; average annual daily traffic; equivalent single axle loads; pavement's age; structural strength; slab thickness.

8.1. Introduction

An appropriate pavement performance curve is the fundamental component of Pavement Management System (PMS) and ensures the accuracy of pavement maintenance and rehabilitation (M&R) operations (Jansen and Schmidt 1994; Johnson and Cation 1992; Attoh-Okine 1999). The pavement performance models help PMS to optimize M&R operations and to estimate the consequences of M&R operations on the future pavement condition during the life span of pavement (George et al. 1989; Li et al. 1997). Early PMSs did not have performance curves rather they evaluated only the current pavement condition. The simplified performance curves were later introduced based on engineering opinions on the expected design life of different M&R operations (Kulkarni and Miller 2002). The only predictive variable of these performance curves was pavement's age. The development of performance curve is explicitly complicated since the pavement performance depends on a large number of dynamic and static attributes.

There are two streams of pavement performance modeling such as deterministic and stochastic. The major differences between deterministic and stochastic performance models are model development concepts, modeling process or formulation and output format of the models (Li et al. 1996). Deterministic models include primary response, structural performance, function performance and damage models for pavements (George et al. 1989). Different methods of deterministic models are mechanistic, mechanistic-empirical and regression models (Saleh, et al. 2000; AASHTO 1985; George et al. 1989; De Melo e Siva et al. 2000). Mechanistic models draw the relationship between response parameters such as stress, strain, and deflection (Li et al. 1996). Mechanistic-empirical models draw the relationship between roughness, cracking, and traffic loading. Regression models draw the relationship between a performance (e.g. riding comfort index) and predictive parameters (e.g. pavement thickness, pavement material properties, traffic loading, and age) (Li et al. 1996). A large number of deterministic models are developed for regional or local PMSs such as traffic related, time related, interactive-time related and generalised models (Attoh-Okine 1999).

Deterministic models cannot address some important issues such as (a) randomness of traffic loads and environmental conditions, (b) difficulties in quantifying the factors or parameters that substantially affect pavement deterioration, (c) measurement errors associated with pavement condition and (d) bias from subjective evaluations of pavement condition (Li et al. 1997). These constraints of deterministic models open the application of stochastic modeling.

Stochastic models recently have received considerable attentions from pavement engineers and researchers (Wang et al. 1994; Karan 1977). Typically, the Markov Decision Process (MDP) defines a stochastic model (Li et al. 1997). The Markov process predicts the 'after' condition of pavement knowing the 'before' condition (George et al. 1989). The main challenges of these stochastic models are to develop the Transition Probability Matrices (TPMs) and to obtain and process a large amount of measured performance data for all pavement categories in a road network (Li et al. 1997). However, the main drawbacks of MDP approach are (a) it does not accommodate budget constraints along with condition state and (b) pavement sections are grouped into a small number of roughly homogeneous families based on pavement or road or traffic characteristics (Liebman 1985; Li et al. 2006). The MDP suggests that pavement sections should be categorized into small numbers of families to avoid dealing with large number of pavement families. Similarly, the optimization programming of M&R strategies are estimates for a group of pavement sections rather than for each road section under a given budget. The optimization programming of M&R strategies are calculated using the steady state probabilities of pavement condition. In reality, pavements under a given maintenance policy usually take many years to reach the steady state and the pavement proportion under a particular state is changing every year. The application of steady state probabilities in the optimization objective function does not fully reflect reality (Li et al. 2006).

8.2. Pavement Performance Models Dealing with Uncertainties

Pavement performance models are associated with data collection and computational uncertainties. Ben-Akiva et al. (1993) developed the latent performance approach dealing with forecasting uncertainties during condition data collection. A latent variable captures the ambiguity in measuring infrastructure condition (Durango-Cohen 2007). This latent model suffers from computational limitations. Finding an optimal action for a given period requires estimating and assigning a probability to every possible outcome of data-collection process. Number of outcomes, probabilities and computational effort to obtain M&R policies increases exponentially with the number of distresses being measured (Durango-Cohen 2007).

Durango-Cohen (2007) applied the Polynomial Linear Regression (PLR) model to define the dynamic system of infrastructure deterioration process. The PLR model includes condition data and a set of exogenous (deterministic and stochastic) inputs. Durango-Cohen's PLR model cannot define the proportion of errors contributed by each of the factors to the distress outcome.

Attoh-Okine (1994) proposed the Artificial Neural Network (ANN) for predicting the roughness progression in flexible pavements. However, some built-in functions of ANN such as learning rate and momentum term of ANN algorithm were not investigated properly. Inaccurate application of these built-in functions may affect the aptness of ANN (Attoh-Okine 1999). Attoh-Okine (1999) analyzed the contribution of learning rate and momentum term in Back Propagation Neural (BPN) algorithm for the pavement performance prediction of Kansas pavement condition data during 1993. The BPN model estimates International Roughness Index (IRI) as a function of rutting, faulting distress, transverse cracking distress, block cracking and Equivalent Single Axle Loads (ESALs) (Attoh-Okine 1999). Shekharan (1999) applied the partitioning of connection weights in ANN to estimate the relative contribution of structural number, age of pavement, and cumulative ESALs to the present serviceability rating (PSR) of pavement. The weights of output layer connection are partitioned into input node shares. The weights, along the paths from input to output nodes, indicate the relative predictive importance of input variables. These weights are used to partition the sum of effects on the output layer (Shekharan 1999). However, Attoh-Okine (1999) and Shekharan (1999) models have not yet overcome the functional limitations of neural network algorithms.

8.3. Objective

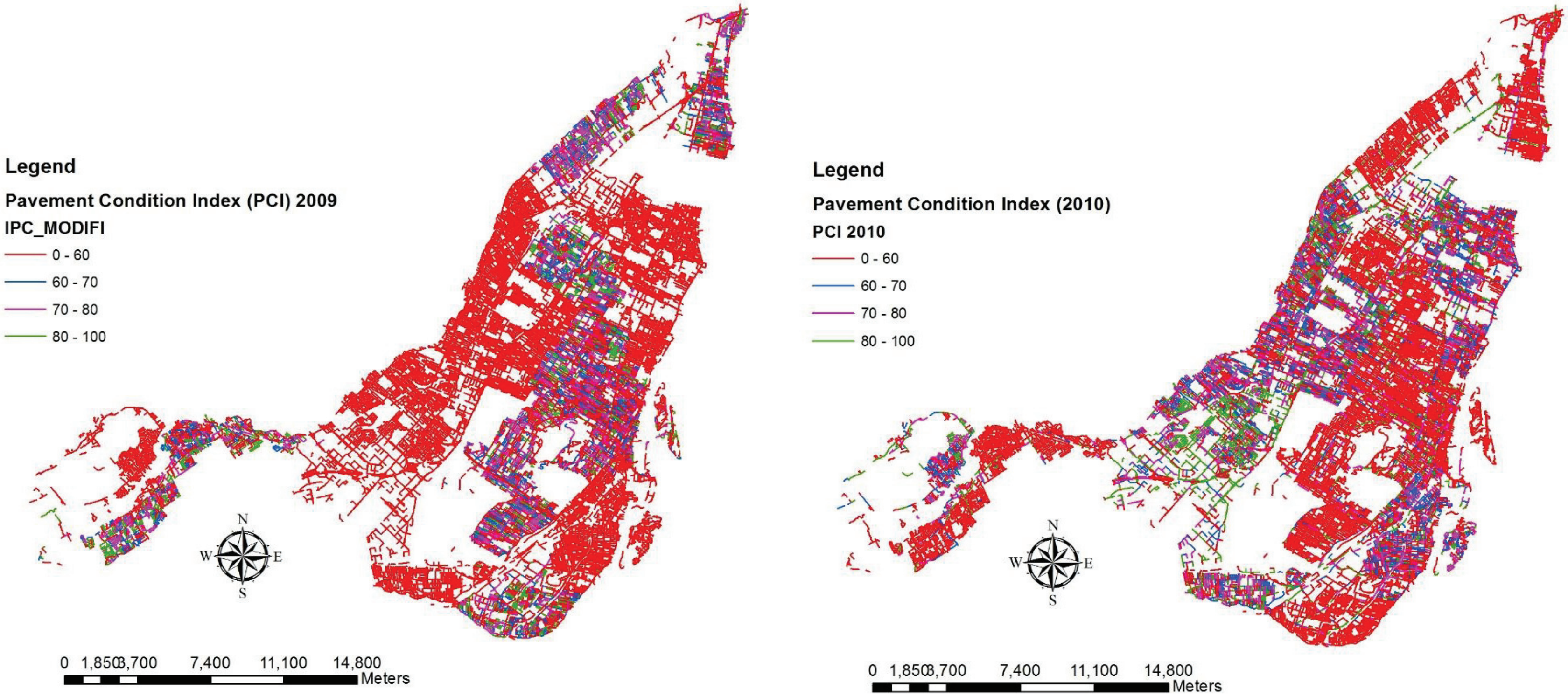
This study applies the Backpropagation Neural Network (BPN) method with Generalized Delta Rule (GDR) learning algorithm to offset the statistical error of the pavement performance modeling. Collector and arterial roads of Montreal City are taken as a case study.

8.4. Methodology

8.3.1. Data Collection

Data on pavement condition and age, traffic volume and road characteristics are collected from the Ville de Montréal. Pavement condition data in 2010 and 2009 are used in this study as the Ville de Montréal has complete pavement condition data only for these two periods (Figure 8.1).

Traffic volume is usually described as the Average Annual Daily Traffic (AADT). The AASHTO Design Guide (AASHTO 1993) terms traffic volume as the 80-KN Equivalent Single Axle Loads (ESALs) that is the total damage of road pavement caused by commercial vehicles. The ESALs are calculated based on number, type and distribution of commercial vehicles, road characteristics and truck growth factor on the road network of Montreal City. Data on type and distribution of trucks on the road network of Montreal City and annual truck growth rate (2 percent) are adopted from the report prepared by the Cement Association of Canada (Cement Association of Canada 2012). Truck distribution and truckloads on the collector and arterial roads are shown in Table 8.1.



(a) PCI in the year 2009

(b) PCI in the year 2010

Figure 8.1: Pavement Condition Index (PCI) of the road network in the Montreal City

Table 8.1: Distribution and Truck Factor (TF) of commercial vehicles on the road network of Montreal city

FHWA Class	Cement Association of Canada	Collector		Arterial	
		Percent (%)	Truck Factor	Percent (%)	Truck Factor
4	Two or Three Axle Buses	2.9	0.0522	1.8	0.046044
5	Two-Axle, Six-Tire, Single Unit Trucks	56.9	13.9974	24.6	0.629268
6	Three-Axle Single Unit Trucks	10.4	0.7904	7.6	0.186808
7	Four or More Axle Single Unit Trucks	3.7	0.0185	0.5	0.01894
8	Four or Less Axle Single Trailer Trucks	9.2	0.46	5	0.1894
9	Five-Axle Single Trailer Trucks	15.3	4.7889	31.3	1.201294
10	Six or More Axle Single Trailer Trucks	0.6	0.0588	9.8	0.324184
11	Five or Less Axle Multi-Trailer Trucks	0.3	0.0024	0.8	0.030704
12	Six-Axle Multi-Trailer Trucks	0.4	0.0132	3.3	0.126654
13	Seven or More Axle Multi-Trailer Trucks	0.3	0.0459	15.3	0.587214

Since data on the thickness of pavement's layers are not available from the Ville de Montréal, thickness data for different layers of Portland Cement Concrete (PCC) and Hot Mix Asphalt (HMA) pavements in Montreal City are also adopted from the report prepared by the Cement Association of Canada (2012). The Structural Number (SN) of the flexible pavements is calculated from the thickness of pavement layers and climate condition of Montreal City.

This study categorizes the road segments into four classes based on pavement types (e.g. flexible and rigid) and road hierarchies (e.g. arterial and collector). These are arterial and flexible, arterial and rigid, collector and flexible, and collector and rigid roads. The predictive variable for all types of pavement is Pavement Condition Index (PCI). The input variables for the flexible pavements are AADT, ESALs, SN, pavement's age (N) and difference of PCI between current and preceding year ($\Delta PCI = PCI_{2009} - PCI_{2010}$). The ΔPCI helps to track the condition deterioration or application of treatment operations during the preceding year. The input variables for the rigid pavements are AADT, ESALs, slab thickness (T), N and ΔPCI. Since AADT and ESALs are log-linearly related to PCI, Log_{10} (AADT) and Log_{10} (ESALs) are taken as input variables of PCI.

8.3.2. Learning Process in the Backpropagation neural network

The fundamental concept of BPN network for a two-phase propagate-adapt cycle is that input variables are applied as a stimulus to the input layer of network units that are propagated through each upper layer until an output is generated. This estimated output are compared with the desired output to estimate the error for each output unit. These errors are transferred backward from the output layer to each unit in the intermediate layer that contributes directly to the output. Each unit in the intermediate layer receives only a portion of the total error signal based roughly on the relative contribution to the original output. This process repeats layer-by-layer until each node receives an error representing its relative contribution to the total error. Based on the error received, connection weights are updated by each unit to cause the network to converge toward a state allowing all the training patterns to be encoded (Freeman and Skapura 1991). Diagrams of BPN networks for flexible and rigid pavements are shown in Figure 8.2 and 8.3 respectively.

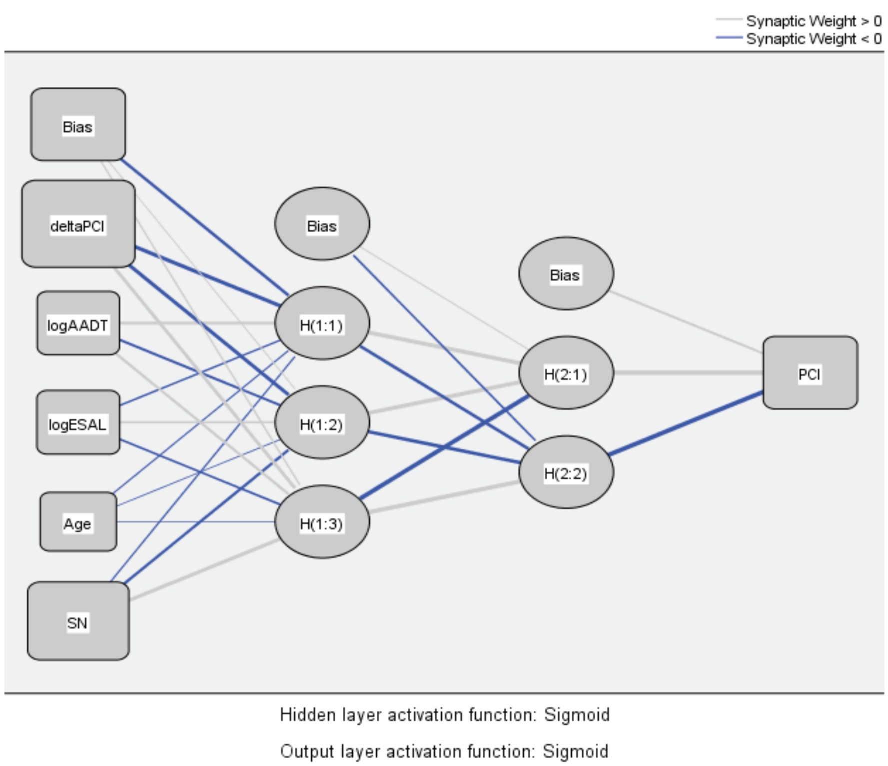


Figure 8.2: BPN network diagram for flexible pavement

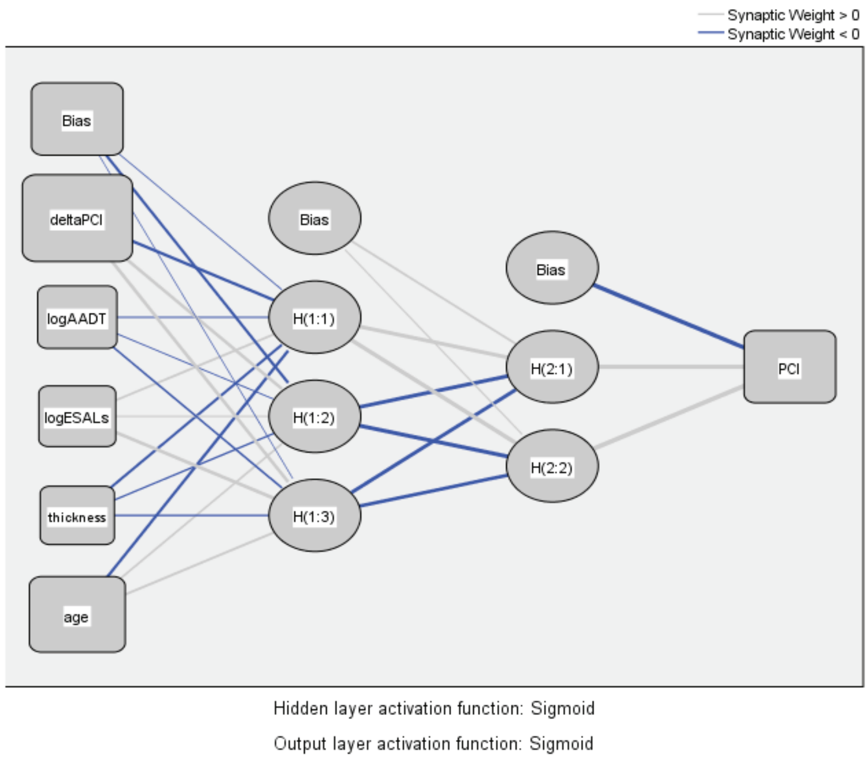


Figure 8.3: BPN network diagram for rigid pavement

This study applies a GDR learning algorithm of BPN network. The learning process of BPN network for pavement performance modeling is described in this section. Let assume that we have a set of P vector-pairs in the training set $\{(x_1, y_1), (x_2, y_2)\ldots (x_p, y_p)\}$ and the functional mapping is $y = \phi(x){:}\, x \in R^N, y \in R^M$. The processing function is $\{(x_1, d_1), (x_2, d_2)\ldots (x_p, d_p)\}$ with input vectors ($\mathbf{x}_k$) and desired output value (d_k). The mean square error (ε_k^2) is defined by Equation 8.1 (Freeman and Skapura 1991).

$$\varepsilon_k^2 = \theta_k = (d_k - y_k)^2 = (d_k - \mathbf{w}^t\mathbf{X}_\mathrm{N})^2 \qquad \text{where } y = \mathbf{w}^t\mathbf{X} \tag{8.1}$$

The weight vector at time t is $\mathbf{w}^t$. Since the weight vector is an explicit function of iteration (R), the initial weight vector is denoted $\mathbf{w}(0)$ and the weight vector at iteration R is $\mathbf{w}(R)$. At each step, the next weight vector is calculated following Equation 8.2 (Freeman and Skapura 1991).

$$\mathbf{w}(R+1) = \mathbf{w}(R) + \Delta\mathbf{w}(R) = \mathbf{w}(R) - \mu\nabla\theta_k\big(\mathbf{w}(R)\big) = \mathbf{w}(R) + 2\mu\varepsilon_N\mathbf{X}_N \;\; \forall\, \nabla\theta(\mathbf{w}(R)) \approx \nabla\theta(\mathbf{w}) \tag{8.2}$$

Equation 8.2 is the Least Mean Square (LMS) algorithm, where $\Delta\mathbf{w}(R)$ is the change in weight vector (**w**) at the R^{th} iteration, and μ is the constant of negative gradient of the error surface. The error surface is either hyperbolic tangent or sigmoid learning function. The constant variable (μ) determines the stability and speed of convergence of the weight vector toward the minimum error value (Freeman and Skapura 1991).

The input layer distributes the values to the hidden or intermediate layer units. Equation 8.3 defines the output (net_{pj}) of input node (I_{pj}) assuming that the activation of input node is equal to the net input. Similarly, Equation 8.4 defines the output (net_{pk}) of output node (O_{pk}) (Freeman and Skapura 1991).

$$I_{pj} = f_j\big(net_{pj}\big) \quad net_{pj} = \sum_{i=1}^{N} w_{ji}x_{pi} + \theta_j \tag{8.3}$$

$$O_{pk} = f_k\big(net_{pk}\big) \quad \forall\, net_{pk} = \sum_{j=1}^{L} w_{kj}I_{pj} + \theta_k \tag{8.4}$$

Where w_{ji} is the weight on the connection from i^{th} input unit to j^{th} hidden unit, w_{kj} is the weight on the connection from j^{th} hidden unit to p^{th} output unit, and θ_j and θ_k are errors at intermediate and output layers respectively. The weight is determined by taking an initial set of weight values representing a first guess as the proper weight for the problem. The output values are calculated applying the input vector and initial weights. The calculated output is compared with the correct output and a measure of the error is determined. The amount of change in each weight is determined. The iterations with all training vectors are repeated until the error in all vectors of training set is reduced to an acceptable value (Freeman and Skapura 1991).

Equations 8.3 and 8.4 define the output of input and output nodes, respectively. In reality, there are multiple units in a layer. A single error value (θ_k) is not suffice for BPN network. The sum of error squares for all output units is shown in Equation 8.5 (Freeman and Skapura 1991).

$$\theta_{pk} = \frac{1}{2}\sum_{k=1}^{M} \varepsilon_{pk}^{2} = \frac{1}{2}\sum_{k=1}^{M} (y_{pk} - O_{pk})^2$$

$$\Delta_p \theta_p(\mathbf{w}) = \frac{\partial(\theta_p)}{\partial w_{kj}} = -(y_{pk} - O_{pk})\frac{\partial}{\partial w_{kj}}(O_{pk}) = -(y_{pk} - O_{pk})\frac{\partial f_k}{\partial(net_{pk})}\frac{\partial(net_{pk})}{\partial w_{kj}} \tag{8.5}$$

Change in weight of output layer is expressed in Equation 8.6 by combining Equations 8.3, 8.4 and 8.5 (Freeman and Skapura 1991).

$$\frac{\partial(\theta_p)}{\partial w_{kj}} = -(y_{pk} - O_{pk})\frac{\partial f_k}{\partial(net_{pk})}\frac{\partial}{\partial w_{kj}}(\sum_{j=1}^{L} w_{kj} I_{pj} + \theta_k) = -(y_{pk} - O_{pk}) f_k'(net_{pk}) I_{pj} \tag{8.6}$$

Where $f_k'(net_{pk})$ is the differentiation of Equation 8.4. This differentiation eliminates the possibility of using a linear threshold unit, since the output function for such a unit is not differentiable at the threshold value. Equation 8.7 estimates the weights on the output layer following Equations 8.2 and 8.6 (Freeman and Skapura 1991).

$$w_{kj}(R+1) = w_{kj}(R) + \tau(y_{pk} - O_{pk}) f_k'(net_{pk}) I_{pj} \tag{8.7}$$

Where τ is a constant and learning-rate parameter. There are two forms of activation functions such as hyperbolic tangent $[f_k(net_{jk}) = \tan(net_{jk}) = (e^{net_{jk}} - e^{-net_{jk}})/(e^{net_{jk}} + e^{-net_{jk}})]$ and sigmoid or logistic function$[f_k(net_{jk}) = (1 + e^{-net_{jk}})^{-1}]$. The sigmoid or logistic function is for output units in a range of (0, 1) and the hyperbolic tangent function is for output units in a range of (-1, 1). Since the output of this model (e.g. pavement condition index) is positive value, sigmoid or logistic function is applied and can be expressed by Equation 8.8 (Freeman and Skapura 1991).

$$w_{kj}(t+1) = w_{kj}(t) + \tau(y_{pk} - O_{pk}) O_{pk}(1 - O_{pk}) I_{pj} = w_{kj}(t) + \tau\delta_{pk} I_{pj} \tag{8.8}$$

The errors, estimated from the difference between calculated and desired output, are transferred backward from the output layer to each unit in the intermediate layer. Each unit in the intermediate layer receives only a portion of the total error based roughly on the relative contribution the unit made to the original output. This process repeats layer-by-layer until each node in the network has received an error that represents its relative contribution to the total error. The connection weights are updated based on the error received by each unit. Reconsidering Equations 8.4, 8.5, and 8.8 for Backpropagation algorithm, Equation 8.9 expresses the change of weights in hidden layer (Freeman and Skapura 1991).

$$\theta_p = \frac{1}{2}\sum_{k=1}^{M}(y_{pk} - O_{pk})^2 = \frac{1}{2}\sum_{k=1}^{M}(y_{pk} - f_k(net_{pk}))^2 = \frac{1}{2}\sum_{k=1}^{M}(y_{pk} - f_k(\sum_{j=1}^{L} w_{kj}I_{pj} + \theta_k))^2$$

$$\frac{\partial\theta_p}{\partial w_{ji}} = -\sum_{k=1}^{M}\left(y_{pk} - O_{pk}\right)\frac{\partial O_{pk}}{\partial w_{ji}} = -\sum_{k=1}^{M}\left(y_{pk} - O_{pk}\right)\frac{\partial O_{pk}}{\partial\left(net_{pk}\right)}\frac{\partial\left(net_{pk}\right)}{\partial I_{pj}}\frac{\partial I_{pj}}{\partial\left(net_{pj}\right)}\frac{\partial\left(net_{pj}\right)}{\partial w_{ji}}$$

$$\frac{\partial\theta_p}{\partial w_{ji}} = -\sum_{k=1}^{M}\left(y_{pk} - O_{pk}\right) f_k'\left(net_{pk}\right)w_{kj}f_j'\left(net_{pj}\right)x_{pi}$$

$$\Delta_p w_{ji} = \frac{\partial\theta_p}{\partial w_{ji}} = \tau f_j'\left(net_{pj}\right)x_{pi}\sum_{k=1}^{M}\left(y_{pk} - O_{pk}\right) f_k'\left(net_{pk}\right)w_{kj} = \tau f_j'\left(net_{pj}\right)x_{pi}\sum_{k=1}^{M}\partial_{pk}\, w_{kj} \qquad (8.9)$$

Equation 9 explains that each weight update in hidden layer depends on the error terms $\left(\partial_{pk}\right)$ in the output layer. The BPN network defines hidden layer error as $\delta_{pj} = f_j'(net_{pj})\sum_{k=1}^{M}\partial_{pk}\, w_{kj}$ to update weight equations analogous to those for the output layer (Equation 8.10). Equations 8.8 and 8.10 have the same form of delta rule (Freeman and Skapura 1991).

$$w_{ji}(t+1) = w_{ji}(t) + \tau\delta x_{pi} \qquad (8.10)$$

8.5. Data analysis

This study partitions the dataset into training, testing, and validation data to estimate the BPN models for all road categories. The BPN network uses the training and testing data to train the network and to track errors during training in order to prevent overtraining respectively. The BPN algorithm finally estimates the predictive ability of the BPN network by using the validation data. This study approximately uses 60 percent, 30 percent and 10 percent data of each road category as training, testing and validation data to estimate the BPN models respectively.

8.5.1. Back Propagation Neural Network Performance

This study evaluates the performance of BPN models to determine the statistically significance of the models. The Sum of Squares Error (SSE) and Relative Error (RE) defines the fitness of BPN models. The SSE is the cross-entropy error when the sigmoid activation function is applied to the output layer. The BPN model minimizes the SSE function during training. The RE is the percentage of incorrect predictions and is associated with dependent variable. In other words, the RE is the ratio of SSE for dependent variable and 'null model'.

Estimation of BPN models has insignificant difference between values implied by estimators and the true values of the output especially for training data (Table 8.2). Testing data, used to track errors during training, also contain minor expected value of squared error loss (Table 8.2). Insignificant errors for validation data explain the accurate prediction ability of the constructed BPN networks (Table 8.2).

Table 8.2: Error Estimation of Backpropagation Neural Network Models

Cases	Statistical significance	Arterial		Collector	
		Flexible	Rigid	Flexible	Rigid
Training	Sum of Squares Error	0.13	0.083	0.516	0.389
	Relative Error	0.051	0.105	0.033	0.036
Testing	Sum of Squares Error	0.135	0.472	1.024	0.741
	Relative Error	0.094	0.225	0.033	0.040
Validation	Relative Error	0.09	0.716	0.037	0.037

The predicted-by-observed and residual-by-observed scatterplot are plotted to understand the relationship between predicted and observed data and residual and observed data respectively. The predicted and observed data of PCI for the combined training and testing samples are plotted on the y-axis and x-axis of the predicted-by-observed scatterplot respectively (Appendix 8.A). Ideally, values should lie roughly along a 45-degree line starting at the origin. The scatterplots for flexible and rigid pavements of arterial and collector roads show that the BPN models do a reasonably good job of predicting PCI (Appendix 8.A).

The residual and predicted values of PCI are also plotted on the y-axis and x-axis of the residual-by-observed scatterplot respectively. Appendix 8.B3 and 8.B4 show that the residual-by-observed scatterplot for flexible and rigid collector roads are well-behaved and fit scatterplots. In case of rigid arterial roads, the residuals roughly form horizontal band and bounce randomly around the '0' line, however, there are few outliers (Appendix 8.B2). These outliers do not have significant influence to estimate the BPN network for PCI values. The scattered distribution of residuals vs. predicted values of PCI questions the statistical significance or fitness of BPN network for flexible arterial roads (Appendix 8.B1).

8.5.2. Parameter Estimation of Input Variables

The predictive variables are initially applied as stimulus to the input layer of network units that is propagated to the hidden (intermediate) layers in the BPN network. This study applies the Multi-Layer Perceptron (MLP) network that is a function of predictors minimizing the prediction error of outputs. The MLP procedure computes the minimum and maximum values of the range and find the best number of hidden layers within the range (IBM 2010). The MLP estimates the number of hidden layers based on the minimum error in the testing data and the smallest Bayesian information criterion (BIC) in the training data (IBM 2010). The MLP estimates that the best number of hidden layers is two. In the first hidden layer of network, the training and testing data are distributed into three sub-layers H (1:1), H (1:2) and H (1:3). The sigmoid activation function is used for the hidden layers so that the activation of the hidden unit is a Gaussian 'bump' as a function of input units (IBM 2010).

In reality, the PCI has inverse relationships with AADT, ESALs and pavement's age for both flexible and rigid pavements. Pavement condition deteriorates with increasing traffic volume, axle loads and pavement's age. For the training and testing data of flexible arterial roads in sub-layers H (1:1) and H (1:2), the PCI has inverse relationships with AADT, ESALs and pavement's age. For example, a one-unit increase in $\log_{10}$ (AADT) will produce an expected decrease in PCI of 0.086 and 0.249 in the hidden sub-layers H (1:1) and H (1:2) respectively (Table 8.3). Similarly, in the same sub-layers, a one-unit increase in $\log_{10}$ (ESALs) and pavement's age will produce an expected decrease in PCI of 0.077 and 0.325, and 2.765 and 1.207 respectively (Table 8.3). In contrary, the PCI has positive relationships with AADT, ESALs and pavement's age in the H (1:3) sub-layer of BPN network for the flexible arterial roads. A one-unit increase in $\log_{10}$ (AADT), $\log_{10}$ (ESALs) and pavement's age will produce an expected increase in PCI of 0.069, 0.005 and 0.415 respectively (Table 8.3). This may be because of the inclusion of training and testing data in this sub-layer that have recent treatment operations. The PCI has increased for treatment operations instead of high AADT, ESALs and pavement's age (Figure 8.4). This assumption is strongly supported by the negative value of ΔPCI in the H (1:3) sub-layer of BPN network for flexible arterial roads (Table 8.3). A one-unit increase in ΔPCI will produce an expected decrease in PCI of 1.031 in H (1:3) sub-layer, however, will increase 3.877 and 1.576 unit of PCI in sub-layers H (1:1) and H (1:2) respectively (Table 8.3). The positive relationship between SN and PCI explains that better structural strength of pavement increases the pavement condition. A one-unit increase in SN will produce an expected increase in PCI of 0.020, 0.052 and 0.622 in H (1:1), H (1:2) and H (1:3) sub-layers respectively (Table 8.3).

For flexible pavement of collector roads, a one-unit increase in ΔPCI will produce an expected decrease in PCI of 0.889 in H (1:2) sub-layer, however, will increase 1.025 and 0.838 unit of PCI in sub-layers H (1:1) and H (1:3) respectively (Table 8.3). A one-unit increase in $\log_{10}$ (AADT) will increase 0.253 unit of PCI in H (1:2) sub-layer and decrease 0.423 and 0.265 unit of PCI in sub-layers H (1:1) and H (1:3) respectively (Table 8.3). Similarly, a one-unit increase in $\log_{10}$ (ESALs) will increase 0.209 unit of PCI in H (1:2) sub-layer and decrease 0.176 and 0.201 unit of PCI in sub-layers H (1:1) and H (1:3) respectively (Table 8.3). The relationship between PCI and pavement's age shows that a one-unit increase in pavement's age will produce an expected decrease in PCI of 0.092, 0.021 and 0.017 in the sub-layers H (1:1), H (1:2) and H (1:3) respectively (Table 8.3). The SN has positive relationship with PCI for flexible collector roads. A one-unit increase in the SN will produce an expected increase in PCI of 0.111, 0.368 and 0.946 in sub-layers H (1:1), H (1:2) and H (1:3) respectively (Table 8.3).

For rigid pavements of arterial roads, a one-unit increase in ΔPCI will produce an expected decrease in PCI of 0.34 in H (1:1) sub-layer, however, will increase 1.288 and 0.971 unit of PCI in sub-layers H (1:2) and H (1:3) respectively (Table 8.4). A one-unit increase in $\log_{10}$ (AADT) will increase 0.661 unit of PCI in H (1:1) sub-layer and decrease 0.059 and 0.097 unit of PCI in sub-layers H (1:2) and H (1:3) respectively (Table 8.4). Similarly, a one-unit increase in $\log_{10}$ (ESALs) will increase 0.348 unit of PCI in H (1:1) sub-layer and decrease 0.121 and 0.059 unit of PCI in sub-layers H (1:2) and H (1:3) respectively (Table 8.4). The relationship between PCI and pavement's age shows that a one-unit increase in pavement's age will produce an expected decrease in PCI of 0.286, 1.85 and 1.268 in sub-layers H (1:1), H (1:2) and H (1:3) respectively (Table 8.4). The slab thickness (mm) of rigid pavement has positive relationship with the PCI. A one-unit increase in slab thickness will produce an expected increase in PCI of 0.44, 0.282 and 0.745 in sub-layers H (1:1), H (1:2) and H (1:3) respectively (Table 8.4).

Table 8.3: Parameter estimation of the independent variables of PCI for Flexible pavements

Predictor		Predicted PCI for Arterial Roads						Predicted PCI for Collector Roads					
		Hidden Layer 1			Hidden Layer 2		Output Layer	Hidden Layer 1			Hidden Layer 2		Output Layer
		H(1:1)	H(1:2)	H(1:3)	H(2:1)	H(2:2)	PCI	H(1:1)	H(1:2)	H(1:3)	H(2:1)	H(2:2)	PCI
Input Layer	(Bias)	-.647	-.541	-.523				-.460	.052	.115			
	ΔPCI	3.877	1.576	-1.031				1.025	-.889	.838			
	Log_{10}(AADT)	-.086	-.249	.069				-.423	.253	-.265			
	Log_{10}(ESALs)	-.077	-.325	.005				-.176	.209	-.201			
	Pavement's Age (N)	-2.765	-1.207	.415				-.092	-.021	-.017			
	Structural Number (SN)	.020	.052	.622				.111	.368	.946			
Hidden Layer 1	(Bias)				.429	.646					.062	-.179	
	H(1:1)				-3.553	-2.520					1.367	-.676	
	H(1:2)				-1.720	-1.303					1.043	-.879	
	H(1:3)				-.712	-.017					-2.341	1.579	
Hidden Layer 2	(Bias)						-2.102						.222
	H(2:1)						4.151						4.063
	H(2:2)						4.034						-2.363

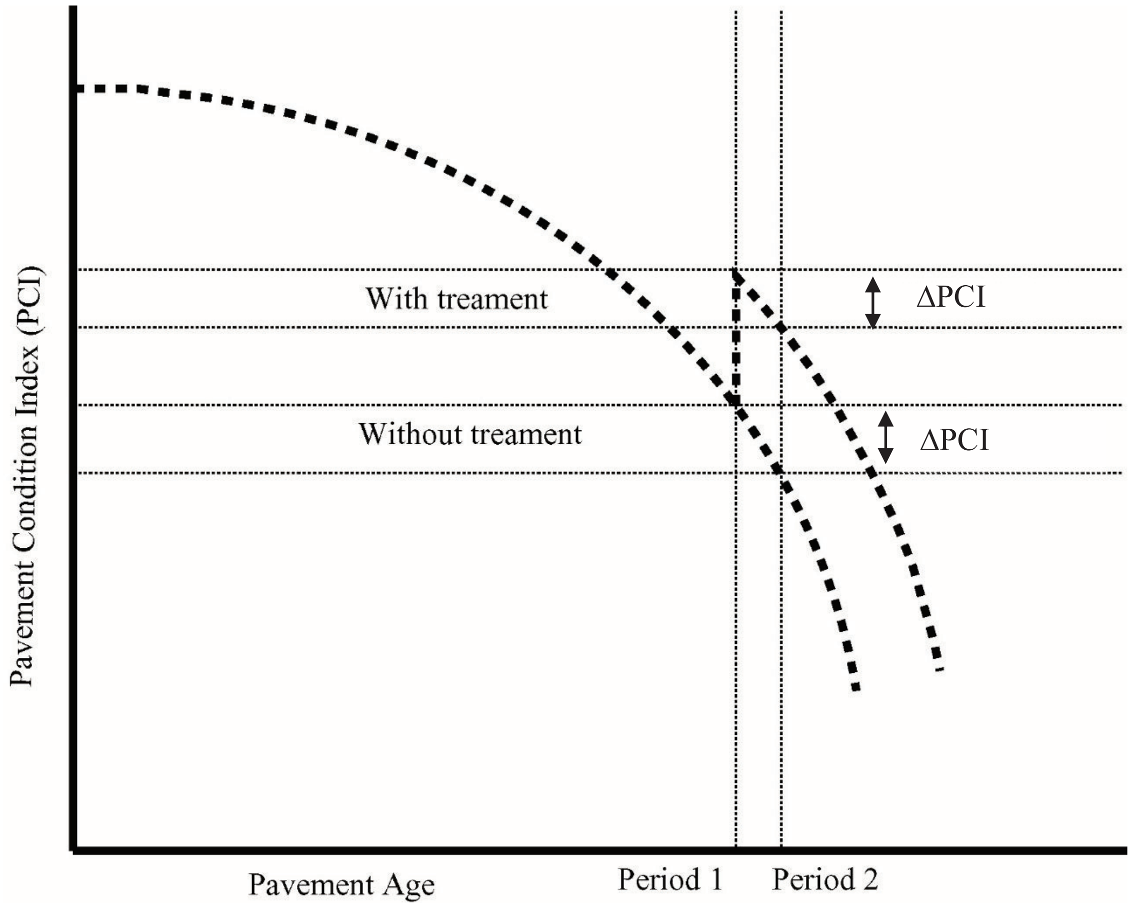


Figure 8.4: Hypothetic scenario of pavement deterioration with or without treatment operations

For rigid pavements of arterial roads, a one-unit increase in ΔPCI will produce an expected decrease in PCI of 0.496 in H (1:1) sub-layer, however, will increase 0.511 and 0.522 unit of PCI in sub-layers H (1:2) and H (1:3) respectively (Table 8.4). A one-unit increase in $\log_{10}$ (AADT) will increase 0.058 unit of PCI in H (1:1) sub-layer and decrease 0.046 and 0.241 unit of PCI in sub-layers H (1:2) and H (1:3) respectively (Table 8.4). Similarly, a one-unit increase in $\log_{10}$ (ESALs) will increase 0.296 unit of PCI in H (1:1) sub-layer and decrease 0.06 and 0.546 unit of PCI in sub-layers H (1:2) and H (1:3) respectively (Table 8.4). The relationship between PCI and pavement's age shows that a one-unit increase in pavement's age will produce an expected decrease in PCI of 0.431, 0.266 and 0.323 in sub-layers H (1:1), H (1:2) and H (1:3) respectively (Table 8.4). Similar to the rigid pavements of arterial roads, the slab thickness (mm) has positive relationship with PCI in the rigid pavements of collector roads. A one-unit increase in slab thickness will produce an expected increase in PCI of 0.327, 0.157 and 0.23 in sub-layers H (1:1), H (1:2) and H (1:3) respectively (Table 8.4).

Each unit of the second hidden layer is a function of the units in the first hidden layer, and each response is a function of the units in the second hidden layer. For example, H (1:1), H (1:2) and H (1:3) sub-layers of hidden layer 1 contribute -3.553, -1.72 and -0.712 to H (2:1) sub-layer of hidden layer 2 for the training and testing data of flexible arterial roads respectively (Table 8.3). The H (1:1), H (1:2) and H (1:3) sub-layers of hidden layer 1 contribute -2.520, -1.303 and -0.017 to the H (2:2) sub-layer of hidden layer 2 respectively (Table 8.3). The H (1:1), H (1:2) and H (1:3) sub-layers of hidden layer 1 contribute 1.367, 1.043 and -2.341 to the H (2:1) sub-layer; and contribute -0.676, -.879 and 1.579 to the H (2:2) sub-layer of hidden layer 2 for the training and testing data of flexible collector roads respectively (Table 8.3).

For the training and testing data of arterial rigid roads, the H (1:1), H (1:2) and H (1:3) sub-layers of hidden layer 1 contribute 0.710, -0.930 and 1.380 to the H (2:1) sub-layer; and contribute 0.685, 1.442 and -0.565 to the H (2:2) sub-layer of hidden layer 2 respectively (Table 8.4). The H (1:1), H (1:2) and H (1:3) sub-layers of hidden layer 1 contribute 1.686, -1.685 and -1.346 to the H (2:1) sub-layer; and contribute 2.079, -1.880 and -1.210 to the H (2:2) sub-layer of hidden layer 2 for the training and testing data of rigid collector roads respectively (Table 8.4).

Table 8.4: Parameter estimation of the independent variables of PCI for Rigid pavements

Predictor		Predicted PCI for Arterial Roads						Predicted PCI for Collector Roads					
		Hidden Layer 1			Hidden Layer 2		Output Layer	Hidden Layer 1			Hidden Layer 2		Output Layer
		H(1:1)	H(1:2)	H(1:3)	H(2:1)	H(2:2)	PCI	H(1:1)	H(1:2)	H(1:3)	H(2:1)	H(2:2)	PCI
Input Layer	(Bias)	-.463	-.393	.115				-.045	-.379	-.041			
	ΔPCI	-.340	1.288	.971				-.496	.511	.522			
	Log_{10}(AADT)	.661	-.059	-.097				.058	-.046	-.241			
	Log_{10}(ESALs)	.348	-.121	-.059				.296	-.060	-.546			
	Pavement's Age (N)	-.286	-1.850	-1.268				-.431	-.266	-.323			
	Slab Thickness (mm)	.440	.282	.745				.327	.157	.230			
Hidden Layer 1	(Bias)				.477	-.070					.284	.151	
	H(1:1)				.710	.685					1.686	2.079	
	H(1:2)				-.930	1.442					-1.685	-1.880	
	H(1:3)				1.380	-.565					-1.346	-1.210	
Hidden Layer 2	(Bias)						3.153						-2.462
	H(2:1)						2.987						3.292
	H(2:2)						-8.442						3.621

For the output layer, the activation function is the sigmoid function. The H (2:1) and H (2:2) sub-layers have almost equal weight to output unit in the flexible arterial roads (e.g. 4.151 and 4.034) and rigid collector roads (e.g. 3.292 and 3.621) (Table 8.3 and 8.4). However, H (2:1) sub-layer has approximately double weight to output units comparing to H (2:2) layer in the flexible collector roads (Table 8.3). The H (2:2) layer has approximately triple weight to output units comparing to H (2:1) layer in the rigid arterial roads (Table 8.4).

The BPN network performs the sensitivity analyses to compute the importance of input variables in determining the PCI based on the combined training and testing samples. The importance of an input variable is a measure of how much the PCI value changes for different values of an input variable. The PCI values for flexible arterial roads are predominantly determined by ΔPCI (36.4 percent) and pavement's age (36.3 percent) (Table 8.5). Other input variable such as $\log_{10}$ (AADT), $\log_{10}$ (ESALs) and SN have 13.8 percent, 12 percent and 1.5 percent contributions in determining the PCI value (Table 8.5). The ΔPCI also significantly influence the PCI values of rigid arterial, flexible collector and rigid collector roads by 33.1 percent, 33 percent and 32.9 percent respectively (Table 8.5). However, pavement's age does not significantly influence the PCI values of rigid arterial (16.2 percent), flexible collector (12.3 percent) and rigid collector (21.1 percent) roads (Table 8.5).

The $\log_{10}$ (AADT) and $\log_{10}$ (ESALs) have considerable importance to estimate the PCI values in BPN models for rigid arterial, flexible collector and rigid collector roads. For example, the $\log_{10}$ (AADT) has 23 percent, 22.6 percent and 20.1 percent importance to estimate PCI values of rigid arterial, flexible collector and rigid collector roads respectively (Table 8.5). The $\log_{10}$ (ESALs) variable contributes 19.4 percent, 22.1 percent and 24.8 percent of PCI values for rigid arterial, collector flexible and collector rigid roads respectively (Table 8.5). The structural characteristics of pavement, SN and slab thickness, for flexible and rigid pavements do not have significant influence in determining the PCI values respectively (Table 8.5). The reason is that the categorical values of thickness of pavement's layers for broader categories of AADT are applied in this study both for flexible and rigid pavements from the report prepared by the Cement Association of Canada (2012). There is a strong potential that the BPN models might estimate the significant or considerable influences of SN and slab thickness on the PCI for flexible and rigid pavements respectively, if the actual data on thickness of pavement's layers for each road segment can be accommodated into the BPN network.

Table 8.5: Importance of input variables to estimate PCI values in BPN networks

Input variables	Arterial		Collector	
	Flexible	Rigid	Flexible	Rigid
ΔPCI	.364	.331	.330	.329
Log_{10}(AADT)	.138	.230	.226	.201
Log_{10}(ESALs)	.120	.194	.221	.248
Pavement's Age (N)	.363	.162	.123	.211
Structural Number (SN)	.015		.100	
Slab Thickness (mm), T		.083		.012

The BPN can properly deal with the statistical randomness. The uncertainty is not only associated with the statistical analysis but also with the traffic data collection process. How can we confirm that the traffic data for each year are reliable? To overcome these uncertainties, the reliability analysis of the traffic data (e.g. AADT and ESALs) can be performed. The reliability analysis of traffic data is defined by comparing the potential traffic data that the pavement structure can withstand before its condition state drops to a defined level and the actual predicted annual traffic data.

A complete historic record on the pavement condition, pavements' structural attributes, pavement age, traffic volume, and road characteristics will enable to estimate more accurate pavement performance model by applying BPN network. The BPN method with GDR learning algorithm overcomes the prevailing functional errors of pavement performance modeling such as stability and speed of convergence of the weight vector toward the minimum error value.

8.6. Conclusion

The pavement performance models optimize treatment operations and estimate the consequences of treatment operations on the future pavement condition during the life span of pavement. Deterministic performance models define primary response, structural performance, function performance and damage models of pavements. On the other hand, the Markov Decision Process (MDP) defines a stochastic model that develops the Transition Probability Matrices (TPMs) and estimates the 'after' condition of pavement knowing the 'before' condition.

The deterministic and stochastic models cannot overcome some key drawbacks. For example, deterministic models cannot address randomness of traffic loads and environmental conditions, difficulties in quantifying factors or parameters that substantially affect pavement deterioration and measurement errors. The stochastic models do not accommodate budget constraints along with condition state and categories pavement sections into small number of roughly homogeneous families. In addition, the existing practiced pavement performance models are still struggling with data collection error and computational uncertainties. The objective of this study is to apply the Backpropagation Neural Network (BPN) method with Generalized Delta Rule (GDR) learning algorithm for offsetting the statistical error of the pavement performance modeling. The Multi-Layer Perceptron (MLP) network and sigmoid activation function are applied to build the BPN network. Collector and arterial roads of both flexible and rigid pavements in Montreal City are taken as a case study. Data on pavement condition and age, traffic volume and road characteristics are collected from Ville de Montréal. Pavement condition data in 2010 and 2009 are used in this study as the Ville de Montréal has complete pavement condition data only for these two periods. The input variables of Pavement Condition Index (PCI) are Average Annual Daily Traffic (AADT), Equivalent Single Axle Loads (ESALs), Structural Number (SN), pavement's age, slab thickness and difference of PCI between current and preceding year are ($\Delta PCI = PCI_{2009} - PCI_{2010}$).

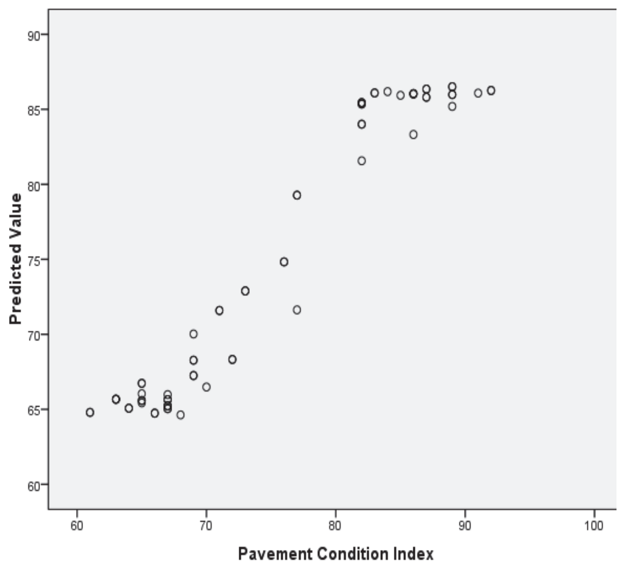
The BPN networks estimates that the PCI has inverse relationships with AADT, ESALs and pavement's age for both flexible and rigid pavements of arterial and collector roads. However, the BPN networks estimates that the PCI has positive relationships with AADT, ESALs and pavement's age for roads that have recent treatment operations. The PCI has positive relationships with SN and slab thickness that imply that the increase of structural strength and slab thickness increases the pavement condition.

The sensitivity analyses of BPN network compute the importance of input variables in determining the PCI values. The ΔPCI significantly influence the PCI values of flexible arterial, rigid arterial, flexible collector and rigid collector roads by 36.3 percent, 33.1 percent, 33 percent and 32.9 percent respectively. The $\log_{10}$ (AADT) and $\log_{10}$ (ESALs) have considerable importance to estimate the PCI values in BPN models. The $\log_{10}$ (AADT) has 13.8 percent, 23 percent, 22.6 percent and 20.1 percent importance to estimate PCI values of flexible arterial, rigid arterial, flexible collector and rigid collector roads respectively. The $\log_{10}$ (ESALs) variable contributes 12 percent, 19.4 percent, 22.1 percent and 24.8 percent of PCI values for flexible arterial, rigid arterial, collector flexible and collector rigid roads respectively. However, pavement's age does not significantly influence the PCI values except in the case of flexible arterial roads (36.3 percent). The structural characteristics of pavement, SN and slab thickness for flexible and rigid pavements do not have significant influence in determining the PCI values respectively. The reason is that the categorical values of thickness of pavement's layers for broader categories of AADT are applied in this study both for flexible and rigid pavements from the report prepared by the Cement Association of Canada. There is a strong potential that the BPN models might estimate the significant or considerable influences of SN and slab thickness on the PCI for flexible and rigid pavements respectively, if the actual data on thickness of pavement's layers for each road segment can be accommodated into the BPN network.

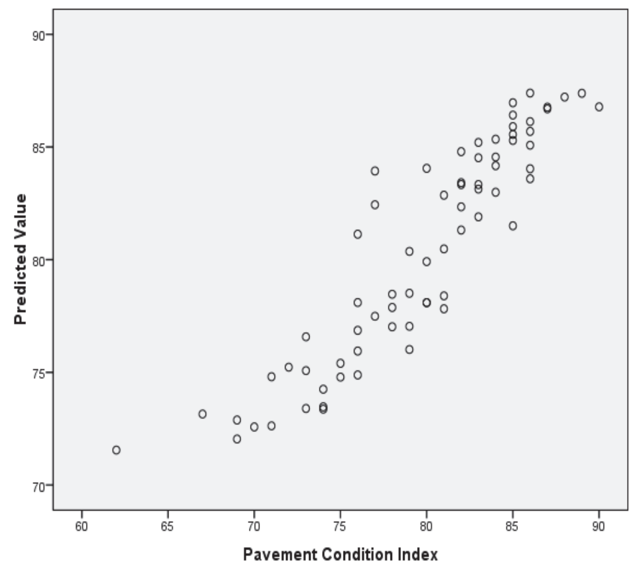
The uncertainties are not only associated with statistical randomness but also with traffic data collection process. The reliability analysis of the traffic data (e.g. AADT and ESALs) overcomes the errors in traffic data collection. The reliability analysis of traffic data is defined by comparing the potential traffic data that the pavement structure can withstand before its condition state drops to a defined level and the actual predicted annual traffic data.

A complete historic record on the pavement condition, pavements' structural attributes, pavement age, traffic volume, and road characteristics will enable to estimate more accurate pavement performance model by applying BPN network. In addition, the BPN method with GDR learning algorithm overcomes the prevailing functional errors of pavement performance modeling.

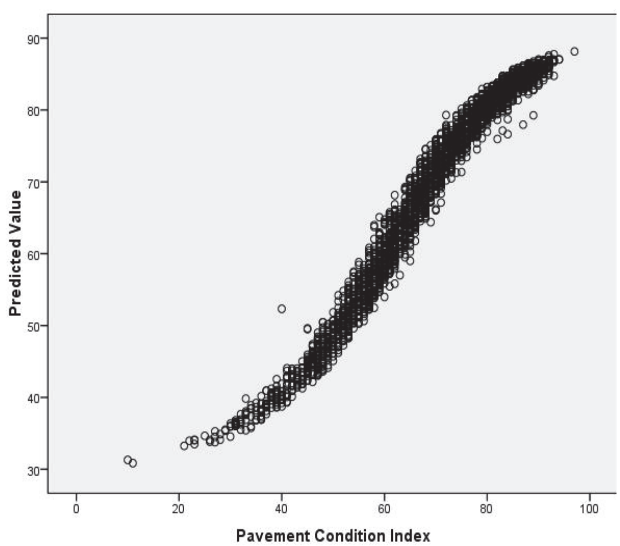
Appendices



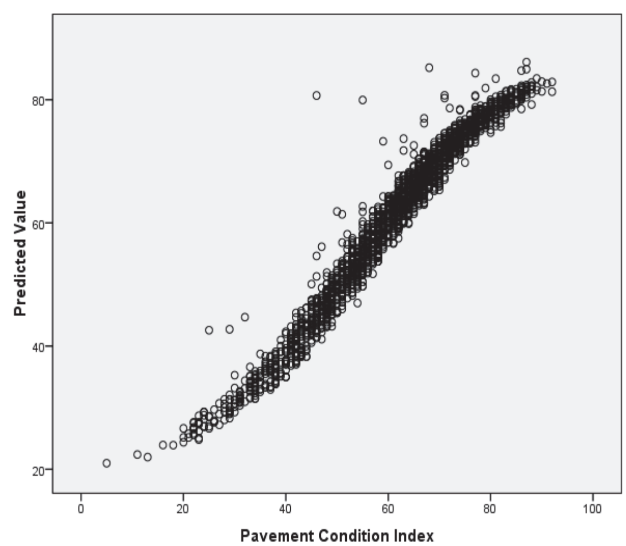
1. Arterial flexible pavement



2. Arterial rigid pavement

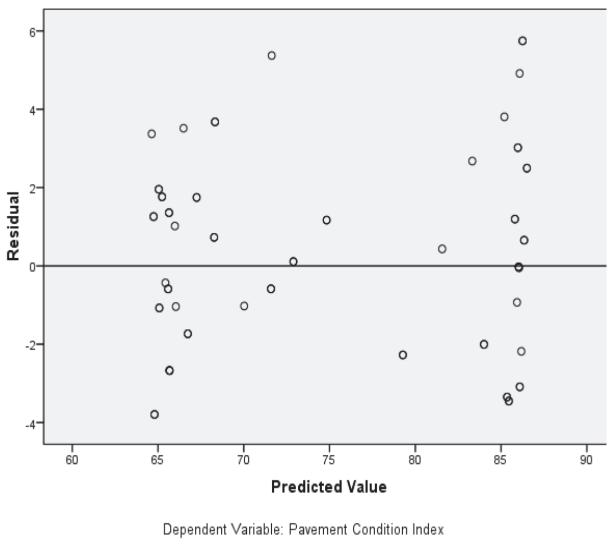


3. Collector flexible pavement

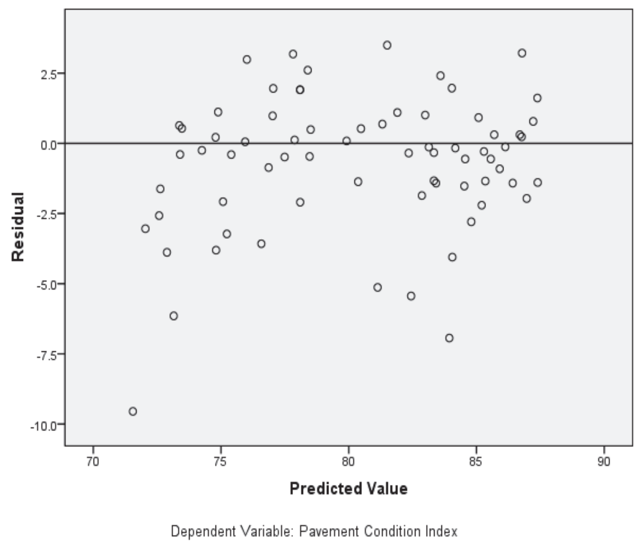


4. Collector rigid pavement

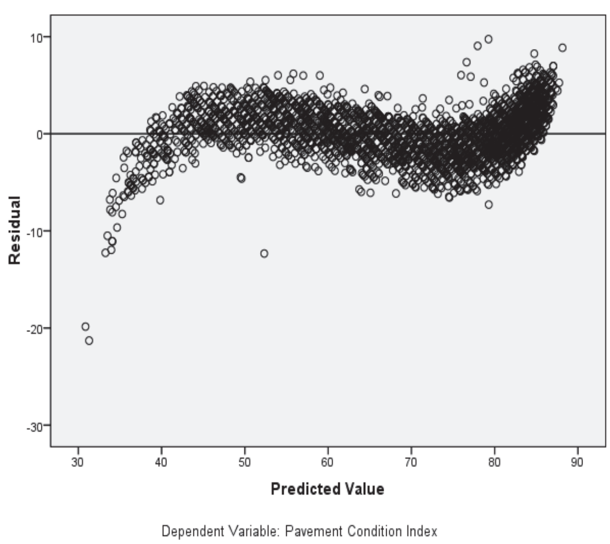
Appendix 8.A: Predicted-by-observed scatterplot of Pavement Condition Index (PCI)



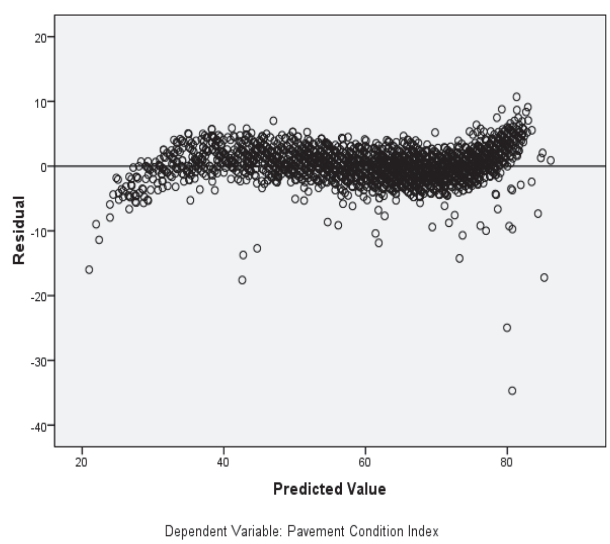
1. Arterial flexible pavement



2. Arterial rigid pavement



3. Collector flexible pavement



4. Collector rigid pavement

Appendix 8.B: Residual-by-predicted scatterplot of Pavement Condition Index (PCI) values

Chapter 9

Improving Pavement Performance Modeling: a case study of Montreal

Amin, M.S.R., and Amador, L.E. A Holistic Model of Pavement Management System for the Road Network of Montreal City. Canadian Journal of Civil Engineering [under review, manuscript no. CJCE-2015-0299].

Abstract

Pavement performance models are based on projections of observed traffic loads, which makes uncertain to study funding strategies in the long run if history does not reapeat. Neural networks can be used to estimate deterioration rates but the learning rate and momentum have not been properly investigated, in addition land use changes could change traffic flows. This study addresses both issues through a case study for roads of Montreal that simulates traffic for a period of 50 years and deals with the measurement error of the pavement deterioration model. Travel demand models are applied to simulate annual average daily traffic (AADT) every 5 years. Accumulated equivalent single axle loads (ESALs) are calculated from the predicted AADT and locally observed truck distributions combined with truck factors. A backpropagation Neural Network (BPN) method with a Generalized Delta Rule (GDR) learning algorithm is applied to estimate pavement deterioration models capable of overcoming measurement errors. Linear programming of lifecycle optimization is applied to identify M&R strategies that ensure good pavement condition while minimazing the budget. It was found that CAD 150 million is the minimum annual budget to good condition for arterial and local roads in Montreal.

Keywords

Pavement management system; traffic simulation; backpropagation neural network; performance modeling; measurement errors; linear programming; lifecycle optimization.

9.1. Introduction

The aging road network in Montreal City is at an advanced state of deterioration. Inappropriate maintenance, low priority on infrastructure maintenance, and inadequate funding are the main factors for this state of deterioration. Lack of a comprehensive pavement management system (PMS) and a long-term plan are responsible for observing an increase in the budget for the City of Montreal of more than 560% since 2001 (Amin and Amador-Jiménez 2014). The City needs a realistic model of PMS to predict the response and performance of its pavements under dynamic traffic loads in order to optimizes the allocation of interventions.

Life-cycle cost analysis (LCCA) for PMS has been applied in a number of studies (Chan et al. 2008; Salem et al. 2003; Li and Madanu 2009). Chan et al. (2008) assessed LCCA practices in the Michigan Department of Transportation and analyzed its accuracy in projecting the actual costs and choosing the best alternatives for the treatments operations during the lifespan of the pavement. Salem et al. (2003) applied risk-based life-cycle cost model that reflected the time to failure of each intervention alternative and reported the uncertainty levels that accompany the estimated life-cycle costs. Li and Madanu (2009) developed an uncertainty-based method for highway project-level LCCA to deal with computational uncertainty from the input factors. Zhang et al. (2013) applied a life-cycle optimization model to develop a new network-level pavement asset management system (PAMS) from historical values of pavement distress.

However, many of these methods are incapable of trading-off decisions between asset types and modes of transportation (Moazami et al. 2011; Jain et al. 2005; Amin and Amador-Jiménez 2014; Humphries 2012). Linear programming and other optimization techniques for PMS are capable of finding the optimal solution of cost-effectiveness of maintenance and rehabilitation (M&R) operations and the benefits of advancing or deferring a certain treatment (Hudson et al. 1997). However they rely on the ability to predict future rates of pavement deterioration.

The Arizona Department of Transportation (ADOT) has applied a Markovian chain–based pavement management systems (PMS) to support its pavement preservation activities (Li et al. 2006). Several other researchers had also applied Markov decision process (MDP) as a PMS tool (Abaza et al. 2004; Golabi and Pereira 2003; Gao and Zhang 2008). The MDP models optimize the M&R strategies but assumes steady-state probabilities. In reality, pavements under a given maintenance policy are not at a steady state, it takes many years to reach the steady state and in reality the proportion of pavements that are deteriorating or improving changes year-by-year (Amin and Amador-Jiménez 2014). It is common to observed steady states after a long initial period of network condition stabilization.

Prediction of pavement deterioration, a crucial part of PMS, is explicitly complicated since pavement performance depends on a large number of dynamic and static attributes. Deterministic and stochastic models have been applied to predict the pavement deterioration. Deterministic models could take the form of mechanistic, mechanistic-empirical and regression models (Archilla 2006; Yu et al. 2007; Santos and Ferreira 2013; Sathaye et al. 2010). Stochastic models apply Markov transition matrices that predict the 'after' condition of a pavement knowing the 'before' condition (Ferreira et al. 2011; Ortiz-García et al. 2006; Kobayashi et al. 2010). Deterministic and stochastic models cannot properly address the uncertainties associated with data collection and computation of deterioration rates. Even the Markov-decision process suffers from somewhat unrealistic assumptions of discrete transition time intervals and dependence of the future facility condition only on the current condition (Morcous 2002; Li et al. 2006). The MDP models lack the flexibility to consider the changes in conditions associated with individual pavement sections (Li et al. 2006), originating from unexpected dynamic changes of traffic loads from economic traffic-flow redistributions.

Ben-Akiva et al. (1993) developed a latent performance approach that dealed with forecasting uncertainties of condition from the data collection. This latent model had computational limitations originated from the number of outcomes, the probabilities and the computational effort used to obtain M&R policies which increased exponentially with the number of distresses being measured. Attoh-Okine (1999) proposed the use of an Artificial Neural Network (ANN) for predicting roughness progression in flexible pavements. However, some built-in functions of his ANN -such as the learning rate and the momentum term of the ANN algorithm- were not properly investigated. Several researchers have applied the ANN as a tool of PMS (Shekharan 1999; Yang et al. 2006). Their models have not yet overcome the functional limitations of the neural network algorithms. This study addresses the measurement errors of the learining rate and ANN momentum term. In addition it simulates traffic for the next 50 years in order to break with the long standing tradition to use historical projections of traffic load to predict future pavement deterioration when no interventions are applied. This study uses linear programming to test different management strategies.

9.2. Methodology

This study has been executed in three main steps: first the simulation of traffic volumes and loads, second pavement performance modeling and third linear programming of pavement management system. The flowchart of the methodology is shown in Figure 9.1.

9.2.1. Simulation of traffic loads

This study simulates the traffic volume on each road segment of Montreal road network for every 5-years for a period of 50 years (between 2009 and 2058) through a travel demand model. Discrete choice model estimates the trip generations from different Traffic Analysis Zones (TAZs) using household data (Equation 9.1). Trip generation is the function of gender, age, personal and household income, occupation, family size, auto ownership, number of children in the household, land use, and residential density (Caliper 2005). Equation 9.2 aggregates the individual probabilities of trip making to predict the total number of trips produced in the TAZs (Caliper 2005). The predicted trips are spatially distributed among TAZs by applying a doubly-constrained gravity model (Equation 9.3) (Caliper 2005).

$$P_n(1) = \frac{1}{1+e^{\beta(X_{0n}-X_{1n})}} \tag{9.1}$$

$$S(i) = \frac{\sum_{c=1}^{C} N_c \left[\frac{\sum_{n=1}^{N_{sc}} P_n(i)}{N_{sc}}\right]}{N_T} \tag{9.2}$$

$$T_{ij} = A_j \times P_i \times f\left(d_{ij}\right) \times a_i \times b_j \tag{9.3}$$

$$a_i = \frac{1}{\sum_{\text{all zones } z} b_z \times A_z \times f(d_{iz})} \quad \text{and} \quad b_j = \frac{1}{\sum_{\text{all zones } z} a_z \times P_z \times f\left(d_{zj}\right)}$$

Where T_{ij} is the predicted traffic flow from zone *i* to *j*; P_i is the predicted number of trips produced in zone *i*; A_j is the predicted number of trips attracted to zone *j*; $f\left(d_{ij}\right)$ is friction factor between zone *i* and *j* (Caliper 2005). Friction function is the impedance function of travel time and cost.

A multinomial Logit (MNL) model is applied to estimate the choice of modes by commuters assuming that the utility of an alternative is a function of the choice determinants, unknown parameters and an i.i.d Gumbel-distribution error term. Choice determinants are travel time and cost. Finally, deterministic User Equilibrium (UE) model is applied to simulate the annual average daily traffic (AADT) on each road segment of Montreal City. The deterministic UE method applies an iterative process to achieve a convergent solution so that no travelers can improve their travel times by shifting routes (Caliper 2005).

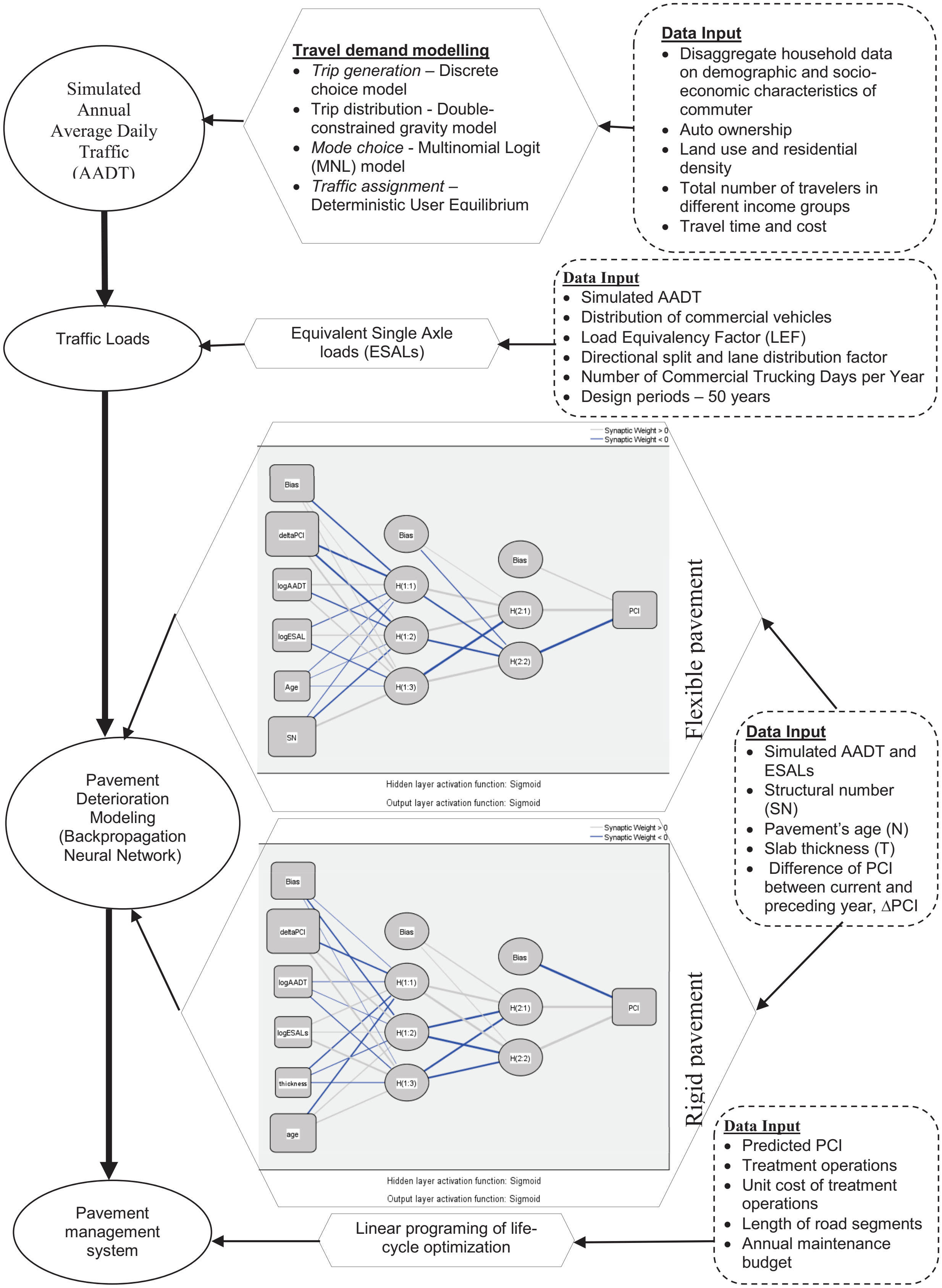


Figure 9.1: Flow chart of methodology

9.2.2. Pavement performance modeling

This study applies a Backpropagation Neural Network (BPN) method with a Generalized Delta Rule (GDR) learning algorithm to minimize the measurement error of the pavement performance modeling. The GDR learning algorithm is applied to the neural network because the relationship is nonlinear and multidimensional. BPN estimates the weights on the output layer by applying Equation 9.4 (Freeman and Skapura 1991).

$$w_{kj}(R+1) = w_{kj}(R) + \tau\left(y_{pk} - O_{pk}\right) f_k'(net_{pk}) I_{pj} \tag{9.4}$$
$$I_{pj} = f_j\left(net_{pj}\right) \quad net_{pj} = \sum_{i=1}^{N} w_{ji} x_{pi} + \theta_j$$
$$O_{pk} = f_k\left(net_{pk}\right) \quad \forall\, net_{pk} = \sum_{j=1}^{L} w_{kj} I_{pj} + \theta_k$$

Where $w_{kj}(R+1)$ and $w_{kj}(R)$ are the weights on the connection from j^{th} hidden unit to k^{th} output unit at the $(R+1)^{th}$ and R^{th} iterations, respectively; y_{pk} is the desire output of k^{th} output node with a set of P vector-pairs in the training set; O_{pk} is the estimated output of k^{th} output node with a set of P vector-pairs in the training set; τ is a constant and learning-rate parameter; net_{pj} is the net input to the j^{th} hidden unit, net_{pk} is the net input to k^{th} output unit; w_{ji} is the weight on the connection from the i^{th} input unit to j^{th} hidden unit; w_{kj} is the weight on the connection from the j^{th} hidden unit to p^{th} output unit; θ_j and θ_k are bias terms for j^{th} hidden unit and k^{th} output unit, respectively; and x_{pi} defines input variables to estimate output (Freeman and Skapura 1991).

The BPN network has two forms of activation functions such as hyperbolic tangent function $\left[f_k\left(net_{jk}\right) = \tan(net_{jk}) = (e^{net_{jk}} - e^{-net_{jk}})/(e^{net_{jk}} + e^{-net_{jk}})\right]$ and sigmoid or logistic function$\left[f_k\left(net_{jk}\right) = (1 + e^{-net_{jk}})^{-1}\right]$. The sigmoid or logistic function is for output units in a range of (0, 1) and the hyperbolic tangent function is for output units in a range of (-1, 1). Since the output of this model (e.g. pavement condition index) is positive value, sigmoid or logistic function is applied and can be expressed by Equation 9.5 (Freeman and Skapura 1991).

$$w_{kj}(t+1) = w_{kj}(t) + \tau\left(y_{pk} - O_{pk}\right) O_{pk}\left(1 - O_{pk}\right) I_{pj} = w_{kj}(t) + \tau \delta_{pk} I_{pj} \tag{9.5}$$

The errors, estimated from the difference between calculated and desired output, are transferred backward from the output layer to each unit in the intermediate layer. Each unit in the intermediate layer receives only a portion of the total error based roughly on the relative contribution the unit made to the estimated output (Freeman and Skapura 1991). This process is repeated layer-by-layer until each node in the network has received a proportion of error that represents its relative contribution to the total error. The connection weights are updated based on the error received by each unit. Each weight update in hidden layer is explained by Equation 9.6 (Freeman and Skapura 1991).

$$\Delta_p w_{ji} = \frac{\partial \theta_p}{\partial w_{ji}} = \tau f_j'(net_{pj}) x_{pi} \sum_{k=1}^{M} (y_{pk} - O_{pk}) f_k'(net_{pk}) w_{kj} = \tau f_j'(net_{pj}) x_{pi} \sum_{k=1}^{M} \partial_{pk} w_{kj} \tag{9.6}$$

The BPN network defines hidden layer error as $\delta_{pj} = f_j'(net_{pj}) \sum_{k=1}^{M} \partial_{pk} w_{kj}$ to update the weight equations analogous to those for the output layer (Equation 9.7). Equations 9.5 and 9.7 have the same form of delta rule (Freeman and Skapura 1991).

$$w_{ji}(t+1) = w_{ji}(t) + \tau \delta x_{pi} \tag{9.7}$$

Pavement performance curves are estimated for four categories of roads based on the road characteristics and pavement types such as arterial-flexible, local-flexible, arterial-rigid and local-rigid. The indicator of condition for all types of pavement is a Pavement Condition Index (PCI). The input variables for flexible pavements are traffic volume in the form of AADT, equivalent single axle loads (ESALs), structural number (SN), pavement's age (N) and difference of PCI between current and preceding year (ΔPCI = PCI2009 – PCI2010). The ΔPCI helps to track the application of treatment operations during the preceding year. The input variables for the rigid pavements are AADT, ESALs, slab thickness (T), N and ΔPCI. Since AADT and ESALs are log-linearly related to PCI, Log10 (AADT) and Log10 (ESALs) are taken as input variables of PCI.

Data on pavement condition, age, thickness and road characteristics was collected from the City of Montreal. Pavement condition data for 2010 and 2009 are used in this study as the

City of Montreal has complete the collection and estimation of pavement condition data only for these two years. The AADT is converted to 80-KN ESALs and only considers the total damage to the pavement caused by commercial vehicles. The ESALs are calculated based on simulated AADT and traffic mixture (number, type and distribution of commercial vehicles). Data on type and distribution of vehicles on the road network of Montreal City are adopted from the report prepared by the Cement Association of Canada (Cement Association of Canada 2012). The SN of the flexible pavements is calculated from the thickness of pavement layers and climate condition of Montreal City following the 1993 AASHTO Guide basic design equation.

9.2.3. Linear programming of pavement management system (PMS)

Lifecycle optimization to achieve and sustain acceptable mean network condition ($\overline{Q}$) at a minimum cost was used to find required levels of funding for Montreal road network (Equation 9.8 and 9.9). The maximization of total network condition under such a budget is then used to find optimal strategic results for pavement management (Equation 9.10 and 9.11). This formulation relied on a decision tree containing all possible paths of pavement condition across time, after hypothetically receiving available treatments (Amin and Amador 2014). This tree is based upon a transfer function used to estimate condition (Q_{ti}) as a convex combination based on the decision variable and the effectiveness or deterioration of the specific link on time t (Equation 9.12).

The objective function is to minimize cost (Z) and maximize pavement condition of the road network [$\sum_{t=1}^{T}\sum_{i=1}^{a}(L_i Q_{ti})$].

$$MINIMIZE \quad \mathrm{Z} = \sum_{t=1}^{\mathrm{T}}\sum_{i=1}^{a}\sum_{j=1}^{o} C_{tj} X_{tij} L_i \tag{9.8}$$

$$\text{Subject to}: \quad \sum_{t=1}^{T}\sum_{i=1}^{a} L_i Q_{ti} \geq \left(\overline{Q}\right)\sum_{i=1}^{a} L_i \tag{9.9}$$

$$MAXIMIZE \quad \sum_{t=1}^{T}\sum_{i=1}^{a}(L_i Q_{ti}) \tag{9.10}$$

$$\text{Subject to}: \quad \mathrm{Z} = \sum_{t=1}^{\mathrm{T}}\sum_{i=1}^{a}\sum_{j=1}^{k} C_{tj} X_{tij} L_i \leq \mathrm{B_t} \tag{9.11}$$

$0 \leq Q_{t,i} \leq 100$ and $\sum_{j \in J_{ti}} X_{tij} \leq 1$ {for all times t and for each asset i}

$$Q_{tij} = X_{tij} \left(Q_{(t-1)ij} + E_{ij}\right) + \left(1 - X_{tij}\right)\left(Q_{(t-1)ij} + D_{it}\right) \tag{9.12}$$

Where X_{tij} is 1 if treatment j is applied on road segment i at year t, zero otherwise; Q_{ti} is condition Index for road segment i at year t; Q_{tij} *is* condition Index of road segment i at year t for treatment j; $Q_{(t-1)ij}$ is condition Index of road segment i at year (t-1) for treatment j; C_{tj} is cost ($) of treatment j at year t; L_i is length of road (km) for road segment i; E_{ij} is improvement (+) on road segment i from treatment j, D_{it} is deterioration (-) on road segment i at time t, B_t is budget at year t.

9.3. Data Analysis

9.3.1. Simulation of traffic loads

The regression coefficients of trip generation model give the change in trips per household for a one unit increase in the predictor variable such as auto ownership, persons per household and occupation (Table 9.1). Table 9.1 shows that the predictor variables are statistically significant for different trip purposes during both peak and off-peak hours. In all the models estimated for working, business and education purposes, the value of the parameter estimates decreases with increasing auto ownership in Montreal city, thus confirming the hypothesis that the number of trips made decreases with auto ownership (Table 9.1). Montrealers prefers public transits for working, business and education trips rather than private cars in order to avoid the traffic congestion, parking fees and inadequate parking spaces at offices, business centers and educational institutions. Number of working and business trips taken increases with increasing number of persons per households but educational trips decrease with increasing persons per households during both peak and off-peak hours (Table 9.1). Employment has significantly positive impact on the business and working trips and negative impact on the educational trips (Table 9.1).

Table 9.1: Estimated effects of explanatory variables on trips per household during peak and off-peak hours

Time	Purpose	Variables	Coefficients	Standard Error	t Stat	P-value	95% confidence interval	
Peak-hour	Working	Intercept	1.082	0.044	24.678	0.000	0.996	1.168
		Auto ownership	-0.023	0.008	-2.969	0.003	-0.039	-0.008
		Persons per household	0.053	0.007	7.909	0.000	0.040	0.066
		Occupation	0.005	0.030	0.171	0.865	-0.054	0.064
	Business	Intercept	1.934	0.304	6.360	0.000	1.335	2.534
		Auto ownership	-0.074	0.092	-0.800	0.424	-0.256	0.108
		Persons per household	0.130	0.062	2.116	0.035	0.009	0.251
		Occupation	0.265	0.063	4.198	0.000	0.389	0.141
	Education	Intercept	1.924	0.154	12.505	0.000	1.622	2.225
		Auto ownership	-0.011	0.005	-2.084	0.037	-0.021	-0.001
		Persons per household	-0.010	0.004	-2.200	0.028	-0.018	-0.001
		Occupation	-0.265	0.051	-5.180	0.000	-0.365	-0.165
Off-peak hour	Working	Intercept	1.118	0.092	12.208	0.000	0.939	1.298
		Auto ownership	-0.009	0.016	-0.562	0.574	-0.039	0.022
		Persons per household	0.019	0.013	1.436	0.151	-0.007	0.044
		Occupation	0.188	0.064	2.930	0.003	0.062	0.313
	Business	Intercept	2.078	0.337	6.163	0.000	1.414	2.743
		Auto ownership	-0.100	0.073	-1.369	0.172	-0.243	0.044
		Persons per household	0.123	0.062	1.994	0.047	0.001	0.245
		Occupation	0.109	0.090	1.208	0.228	0.286	0.069
	Education	Intercept	2.821	0.591	4.778	0.000	1.662	3.981
		Auto ownership	-0.023	0.035	-0.638	0.524	-0.092	0.047
		Persons per household	-0.007	0.030	-0.228	0.820	-0.066	0.052
		Occupation	-0.490	0.196	-2.501	0.013	-0.875	-0.105

The doubly-constrained gravity model (Equation 9.3) spatially distributes the generated trips among different boroughs of Montreal city (Figure 9.2). For example, a total of 132029 trips are generated from Ville-Marie borough in an average day of the year 2013 and 20 percent of these trips are terminated within the same borough (Figure 9.2). The proportions of trips distributed from Ville-Marie to Plateau Mont-Royal, Côte-des-Neiges–Notre-Dame-de-Grâce, Mercier-Hochelaga-Maisonneuve, Rosemont-La Petite Patrie, Ahuntsic-Cartierville, Sud-Ouest and Villeray - Saint-Michel - Parc-Extension are 11 percent, 9 percent, 7 percent, 7 percent, 5 percent, 5 percent and 5 percent in an average day of the year 2013, respectively (Figure 9.2).

The MNL models estimates that the choice determinants (travel time and cost) are statistically significant for all modes. Travel time is inversely related to the utility of all modes except in the case of car-share riding (Table 9.2). Trip makers share ride to reduce the cost for long trip distance.

The DUE model simulates the AADT on each road segment of Montreal city at 5-years interval during the fifty years design period. For example, AADT will be increased by 6.8 percent, 6 percent, 5.8 percent and 5.2 percent on flexible-arterial, rigid-arterial, flexible-local and rigid-local roads during the period of 2008-2013, respectively (Table 9.3). Figure 9.3 shows the projected average AADT for four types of road categories during the design period. The average traffic volume on arterial-flexible roads will increase from 8301 to 16027 during the period of 2009-2058 (Figure 9.3). For arterial-rigid roads, average AADT will increase from 2499 to 4475 during the 50 year period (Figure 9.3). The average AADT will increase from 6435 to 11310 and from 4431 to 7256 on local-flexible and local-rigid roads during the same period, respectively (Figure 9.3).

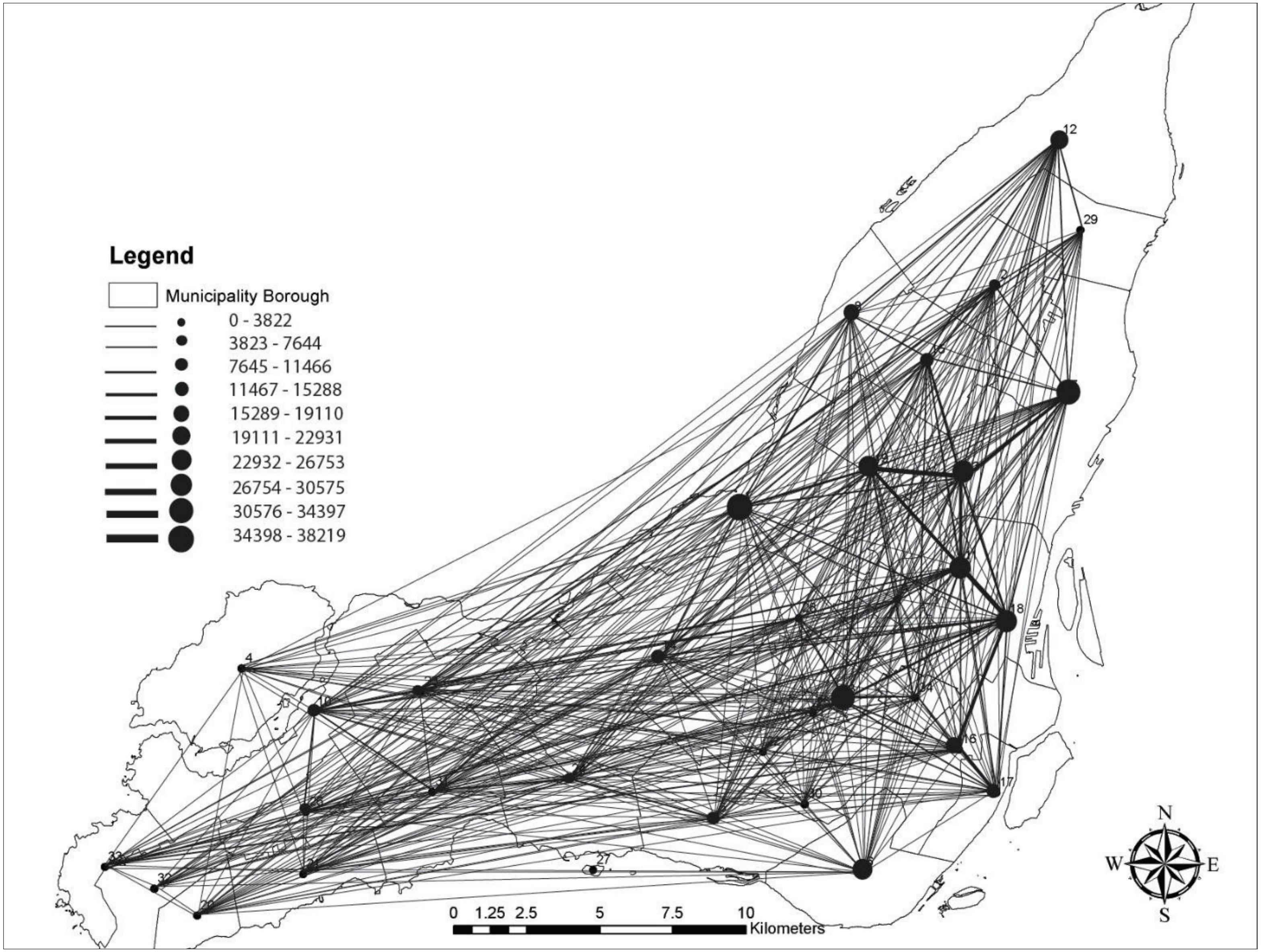


Figure 9.2: Simulated origin-destination map of traffic flow in 2013

Table 9.2: Estimated utility function of choosing different modes

Mode	Variables	Coefficient	Standard error	Z	P>|Z|	95% Confidence Interval	
Car driving alone	Constant	-0.685	0.010	-69.58	0.000	-0.704	-0.666
	Travel time (min)	-0.008	0.001	-12.19	0.000	-0.009	-0.007
	Travel cost ($)	-0.095	0.008	-12.42	0.000	-0.080	-0.110
Car share	Constant	-1.062	0.017	-62.72	0.000	-1.096	-1.029
	Travel time (min)	0.025	0.002	15.93	0.000	0.022	0.028
	Travel cost ($)	-1.016	0.025	-41.34	0.000	-1.064	-0.967
Bus	Constant	-2.451	0.017	-143.96	0.000	-2.485	-2.418
	Travel time (min)	-0.004	0.001	-5.37	0.000	-0.006	-0.003
	Travel cost ($)	0.052	0.009	5.87	0.000	0.035	0.069
Metro	Constant	-2.983	0.023	-131.98	0.000	-3.028	-2.939
	Travel time (min)	-0.067	0.001	-50.58	0.000	-0.069	-0.064
	Travel cost ($)	0.776	0.015	50.73	0.000	0.746	0.806
Bicycle	Constant	-3.585	0.028	-126.48	0.000	-3.640	-3.529
	Travel time (min)	-0.0168	0.002	-0.10	0.000	-0.034	0.0307

Table 9.3: Traffic volume on different road segments of Montreal city during 2008 and 2013

Road Hierarchy	Pavement type	Percentile distribution	Length (meter)	Travel time (min) 2008	AADT 2008	AADTT 2008	AADT growth 2008-2013 (%)
Arterial	Flexible	25^{th}	14.39	0.02	7578	5304	5
		50^{th}	76.76	0.07	11100	7770	6.8
		75^{th}	167.13	0.18	17251	12076	8.5
		99^{th}	683.46	0.67	65000	45500	12.43
	Rigid	25^{th}	15.16	0.02	7047	4933	4.5
		50^{th}	85.57	0.10	9758	6831	6
		75^{th}	180.45	0.21	15927	11149	7.9
		99^{th}	560.14	0.63	65000	45500	10
Local	Flexible	25^{th}	68.67	0.08	8550	2565	4
		50^{th}	84.10	0.10	11702	3511	5.8
		75^{th}	169.03	0.20	14723	4417	7.5
		99^{th}	445.47	0.62	23000	6900	12
	Rigid	25^{th}	71.35	0.08	6030	1809	3.25
		50^{th}	89.00	0.11	8378	2513	5.2
		75^{th}	174.14	0.21	11999	3600	6.9
		99^{th}	476.19	0.84	23000	6900	9.28

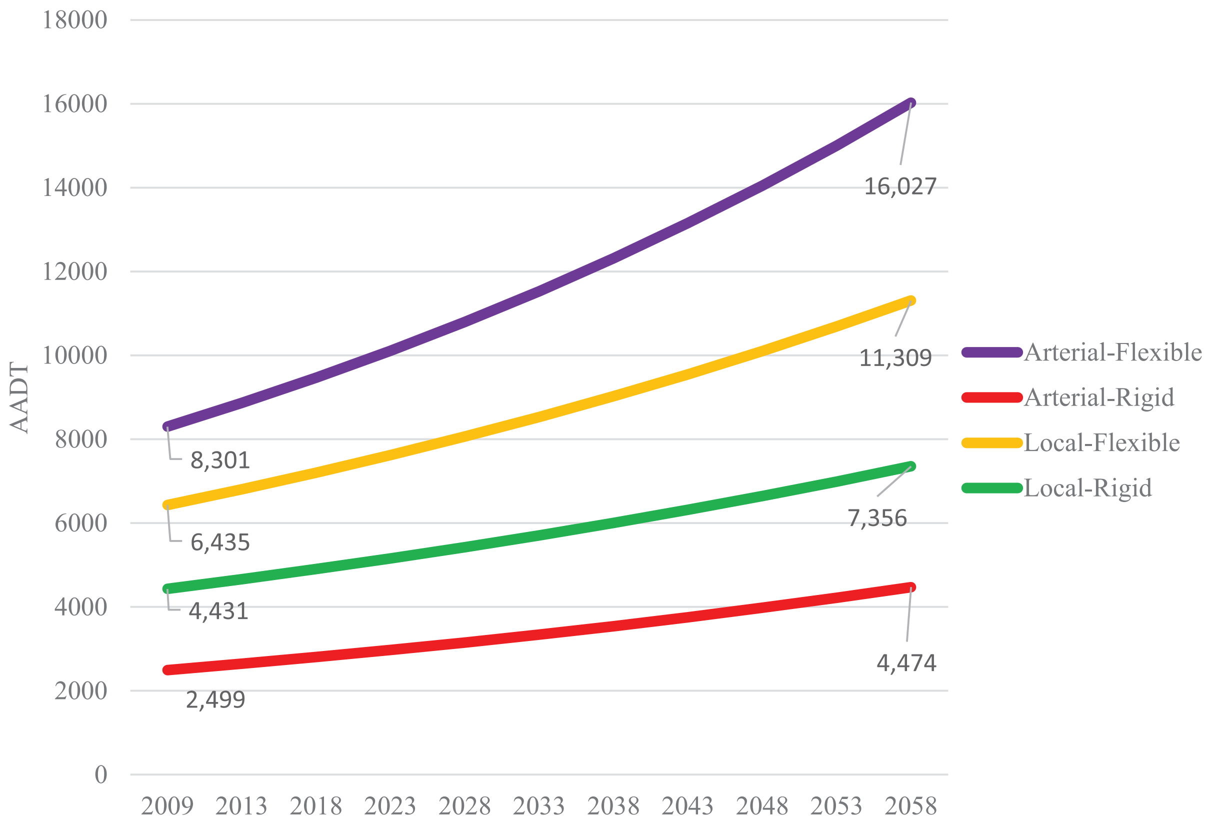


Figure 9.3: Simulated 50-percentile AADT for different road categories during the period of 2009-2058

The accumulated traffic loads (ESALs) are calculated based on the predicted AADT and locally observed truck distributions combined with truck factors (Table 9.4). The Federal Highway administration (2011) defines the distribution and truck factors for truck classes of 4, 5, 6, 7, 8, 9, 10, 11, 12 and 13. The accumulated traffic loads (ESALs) are 31.67, 5.26, 22.64 and 18.61 million on arterial-flexible, arterial-rigid, local-flexible and local-rigid roads during the period of 2009-2058 (Figure 9.4).

Table 9.4: Distribution and Truck Factor (TF) of commercial vehicles on the road network of Montreal city

FHWA Class	Cement Association of Canada	Collector		Arterial	
		Percent (%)	Truck Factor	Percent (%)	Truck Factor
4	Two or Three Axle Buses	2.9	0.0522	1.8	0.046044
5	Two-Axle, Six-Tire, Single Unit Trucks	56.9	13.9974	24.6	0.629268
6	Three-Axle Single Unit Trucks	10.4	0.7904	7.6	0.186808
7	Four or More Axle Single Unit Trucks	3.7	0.0185	0.5	0.01894
8	Four or Less Axle Single Trailer Trucks	9.2	0.46	5	0.1894
9	Five-Axle Single Trailer Trucks	15.3	4.7889	31.3	1.201294
10	Six or More Axle Single Trailer Trucks	0.6	0.0588	9.8	0.324184
11	Five or Less Axle Multi-Trailer Trucks	0.3	0.0024	0.8	0.030704
12	Six-Axle Multi-Trailer Trucks	0.4	0.0132	3.3	0.126654
13	Seven or More Axle Multi-Trailer Trucks	0.3	0.0459	15.3	0.587214

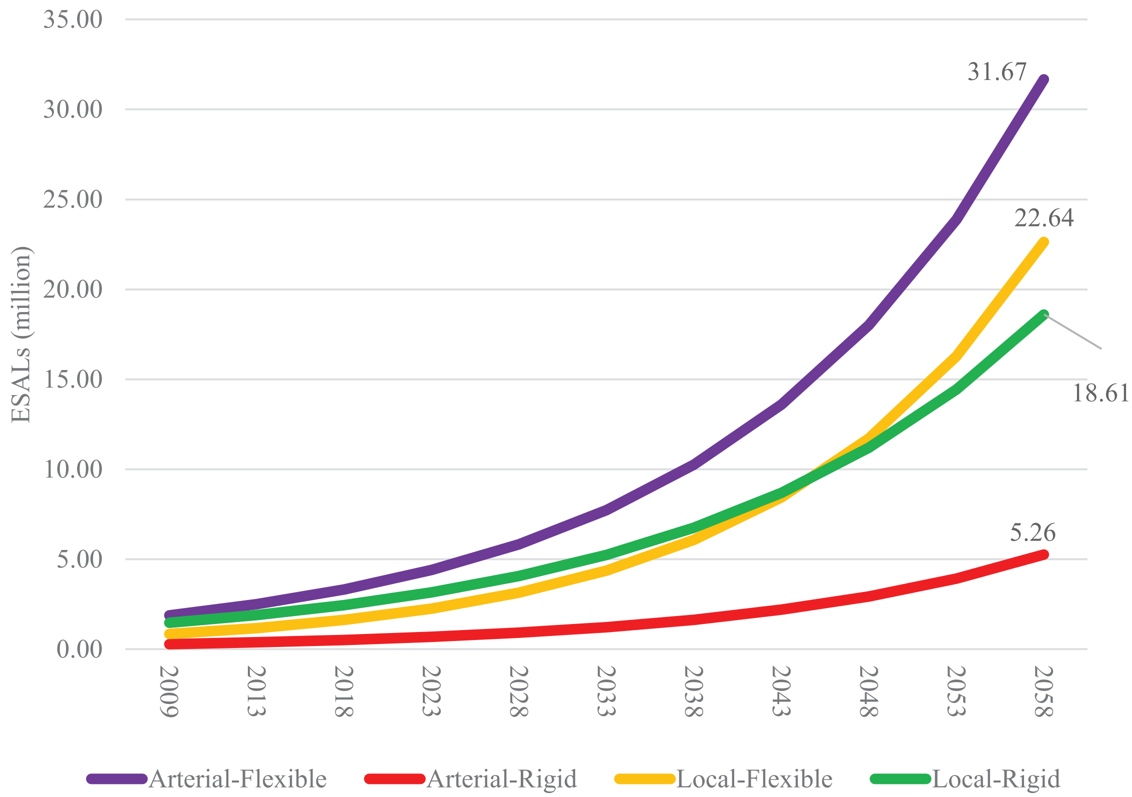


Figure 9.4: Simulated 50-percentile ESALs (million) for different road categories during the period of 2009-2058

9.3.2. Pavement performance modeling

This study applies the Multi-Layer Perceptron (MLP) network that is a function of predictors minimizing the prediction error of outputs. The MLP procedure computes the minimum and maximum values of the range and find the best number of hidden layers within the range (IBM 2010). The MLP estimates the number of hidden layers based on the minimum error in the testing data and the smallest Bayesian information criterion (BIC) in the training data (IBM 2010). The sigmoid activation function is used for the hidden layers so that the activation of the hidden unit is a Gaussian 'bump' as a function of input units (IBM 2010).

The BPN network estimates that The PCI values for arterial-flexible roads are predominantly determined by ΔPCI and pavement's age. Other input variable such as $\log_{10}$ (AADT), $\log_{10}$ (ESALs) and SN have 13.8 percent, 12 percent and 1.5 percent contributions in determining the PCI value. The ΔPCI also significantly influence the PCI values of arterial-rigid, local-flexible and local-rigid roads by 33.1 percent, 33 percent and 32.9 percent respectively. However, pavement's age does not significantly influence the PCI values of arterial-rigid, local-flexible and local-rigid roads.

The $\log_{10}$ (AADT) and $\log_{10}$ (ESALs) have considerable importance to estimate the PCI values in BPN models for arterial-rigid, local-flexible and local-rigid roads. For example, the $\log_{10}$ (AADT) has 23 percent, 22.6 percent and 20.1 percent importance to estimate PCI values of arterial-rigid, local-flexible and local-rigid roads respectively. The $\log_{10}$ (ESALs) variable contributes 19.4 percent, 22.1 percent and 24.8 percent of PCI values for arterial-rigid, local-flexible and local-rigid roads respectively. The structural characteristics of pavement such as SN and slab thickness of flexible and rigid pavements do not have significant influence in determining the PCI values respectively. The reason is that the categorical values of thickness of pavement's layers for broader categories of AADT are applied in this study both for flexible and rigid pavements from the report prepared by the Cement Association of Canada (2012). There is a strong potential that the BPN models might estimate the significant or considerable influences of SN and slab thickness on the PCI for flexible and rigid pavements respectively, if the actual data on thickness of pavement's layers for each road segment can be accommodated into the BPN network.

Pavement performance curves for the selected four categories of roads are developed based on the estimated relationship between the PCI values and input variables applying BPN, and simulated traffic applying travel demand modelling. The estimated pavement performance curves for the four categories of roads are shown in Figure 9.5.

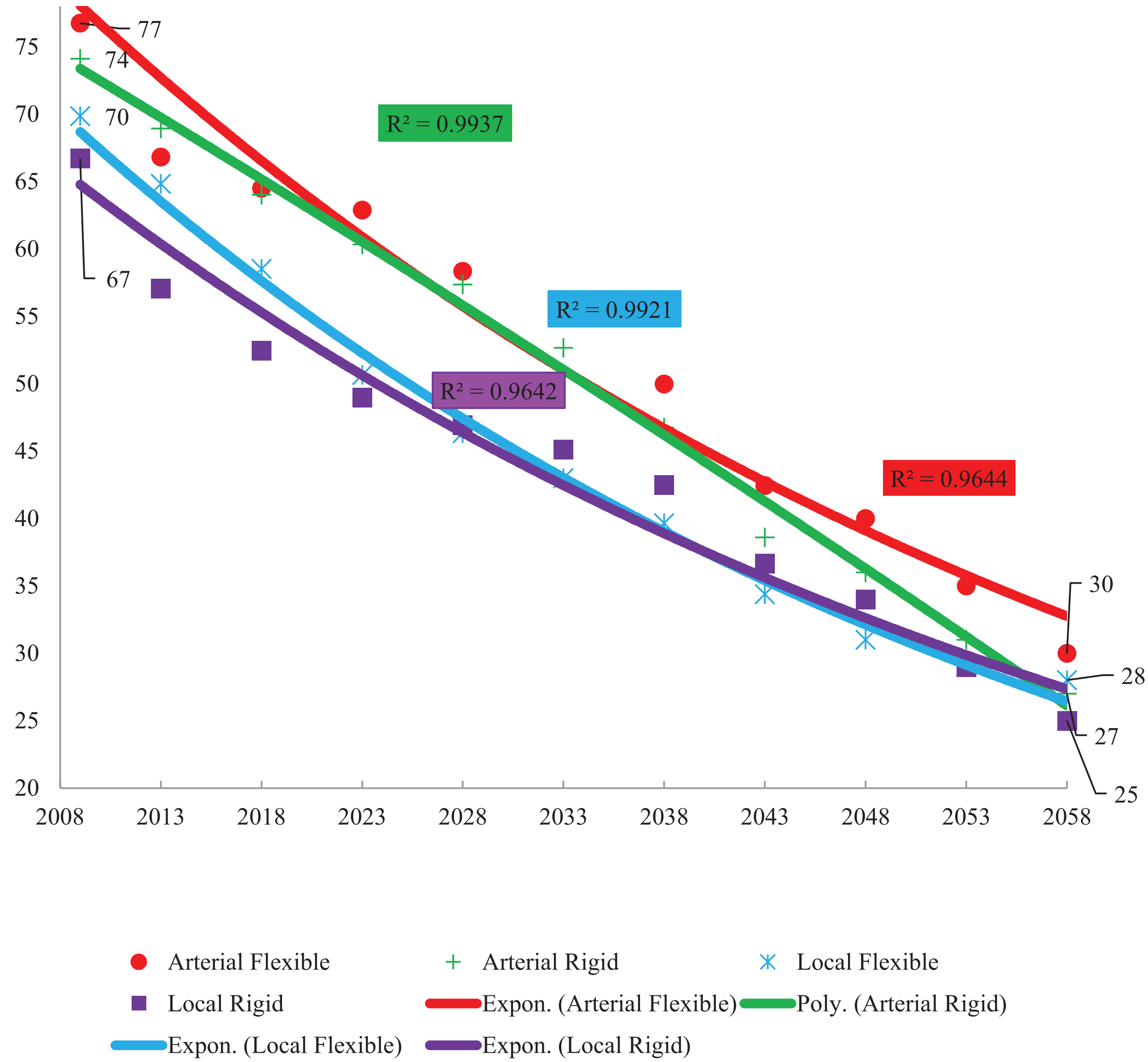


Figure 9.5: Pavement deterioration curves for different road categories during the period of 2009-2058

9.3.3. Pavement treatment operations

The criteria for pavement treatments of four categories of roads in Montreal City are defined based on the operational window presented in Table 9.5 (Cement Association of Canada 2012). Equation 9.6 and 9.7 are applied to estimate the minimum maintenance budget to achieve and sustain good pavement condition of Montreal road network. Dynamic linear programming of lifecycle optimization is applied to estimate the minimum annual budget for maintenance operations ensuring that roads are in good condition. This study categories the pavement condition of roads in four categories such as excellent (PCI $\geq$80), good (80 > PCI $\geq$ 70), fair (70 > PCI $\geq$ 50) and poor (PCI<50). Lifecycle optimization of PMS estimates that CAD 150 million is the minimum annual budget to ensure most of arterial and local roads in Montreal City are at least in good condition (Figure 9.6). Figure 9.7 shows that pavement condition will rapidly deteriorate after 31st year of design period under annual maintenance budget of CAD 125 million. Additional investment in maintenance budget on the top of CAD 150 million will not significantly improve the pavement condition rather the proportion of roads in good condition will be upgraded to excellent condition. Figure 9.8 shows that the overall pavement condition of Montreal road network will not be improved under the annual maintenance budget of CAD 175 million.

Table 9.5: Treatment and Operational Windows Used in Network-Level Trade-Off Analysis

Pavement Type	Treatments	Operational window	Unit cost (CAD$)	
			Arterial	Local
		AGE $\leq$ 5		
	Reseal joints, % length (m)	80 $\geq$ PCI (Arterial) $\geq$ 77; 80 $\geq$ PCI (Local) $\geq$ 73	10	10
		5 $\leq$ AGE $\leq$ 12		
	Partial depth PCC repair, % area, (sq. m.)	76 $\geq$ PCI (Arterial) $\geq$ 68; 72 $\geq$ PCI (Local) $\geq$ 55	150	150
		12 $\leq$ AGE $\leq$ 25		
	Full depth PCC repair, % area, (sq. m.)	67 $\geq$ PCI (Arterial) $\geq$ 56; 54 $\geq$ PCI (Local) $\geq$ 44	125	125
	Reconstruction - Arterial		108	
	200 mm PCC pavement, 25.4mm dowels (m²)		64	
	Base - MG 20, mm (t)		23	
	Subbase - MG 112, mm (t)	AGE $\geq$ 26; PCI (Arterial) < 55	21	
				98.75
				54.75
	Reconstruction - Local	AGE $\geq$ 26; PCI (Local) < 43		23
	175 mm PCC pavement, no dowels (m²)			21
	Base - MG 20, mm (t)			23
Rigid	Subbase - MG 112, mm (t)			21

Pavement Type	Treatments	Operational window	Unit cost (CAD$)	
			Arterial	Local
	Rout and seal, m/km (m)	80 ≥ PCI (Arterial) ≥ 76; 80 ≥ PCI (Local) ≥ 72	5	5
		PCI (Arterial) ≥ 75; PCI (Local) ≥ 71		
	Spot repairs, mill 40 mm/ patch 40 mm, % area (sq. m.)	5 ≤ AGE ≤ 10	20	20
		74 ≥ PCI (Arterial) ≥ 69; 70 ≥ PCI (Local) ≥ 65		
	Mill HMA, mm (t)	10 ≤ AGE ≤ 15	10.4	10.4
		68 ≥ PCI (Arterial) ≥ 64; 64 ≥ PCI (Local) ≥ 59		
	Resurface with ESG 10, mm (t)	15 ≤ AGE ≤ 25	135	135
		63 ≥ PCI (Arterial) ≥ 58; 58 ≥ PCI (Local) ≥ 46		
	Reconstruction - Arterial	AGE ≥ 26; PCI (Arterial) < 58	179	
	HMA - ESG 10, mm (t) 70-28		135	
	Base - MG 20, mm (t)		23	
	Subbase - MG 112, mm (t)		21	
	Reconstruction - Local	AGE ≥ 26; PCI (Local) < 46		173
	HMA - ESG 10, mm (t) 64-28			129
	Base - MG 20, mm (t)			
Flexible	Subbase - MG 112, mm (t)			

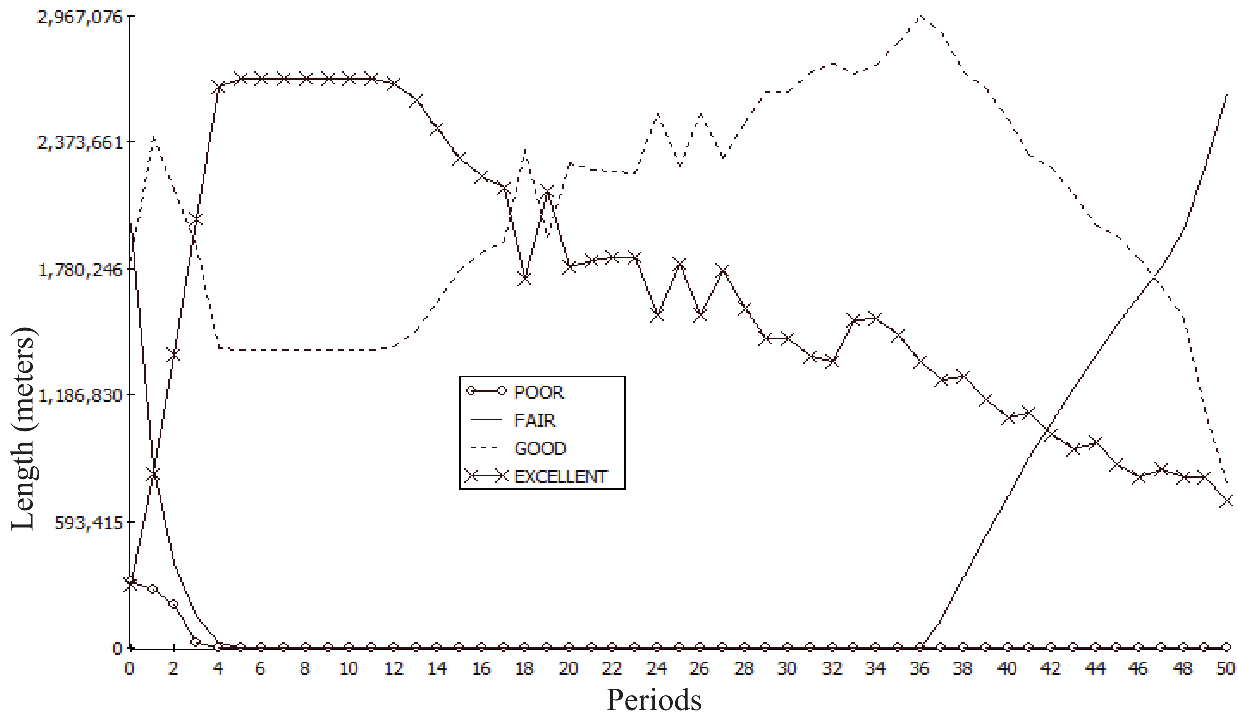


Figure 9.6: Predicted conditions of roads after treatment operations under annual maintenance budget of CAD 150 million

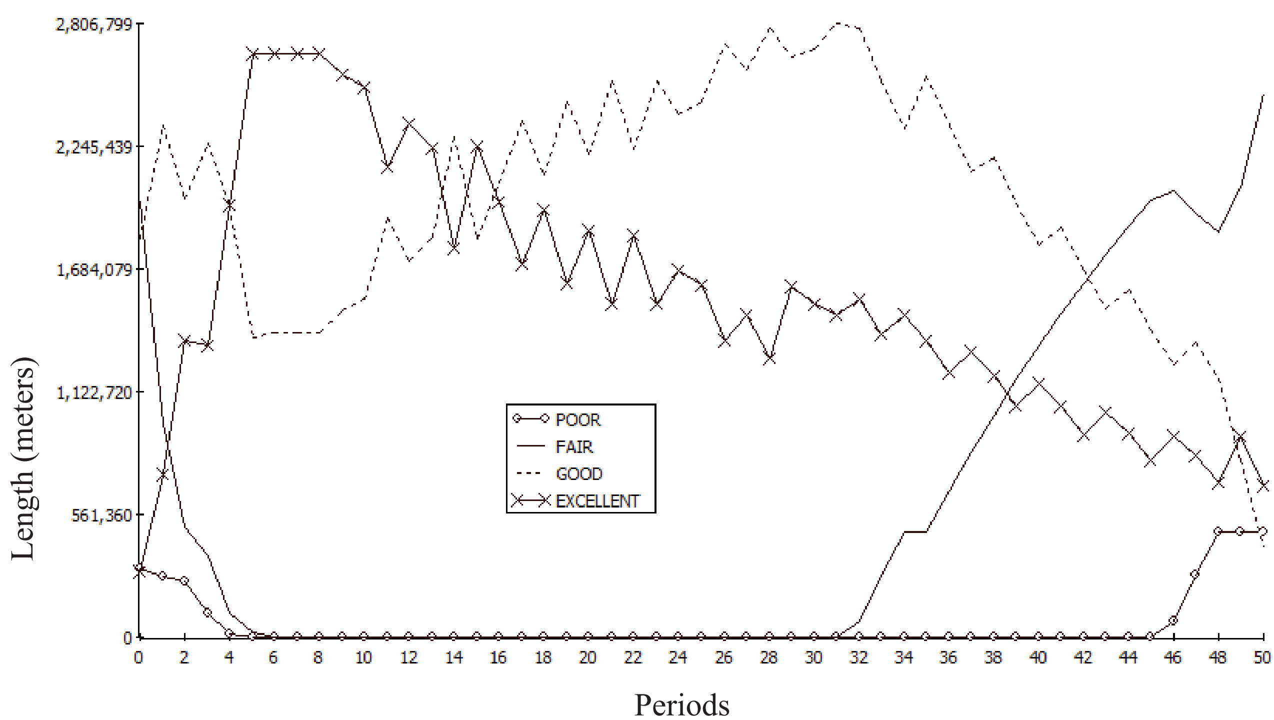


Figure 9.7: Predicted conditions of roads after treatment operations under annual maintenance budget of CAD 125 million

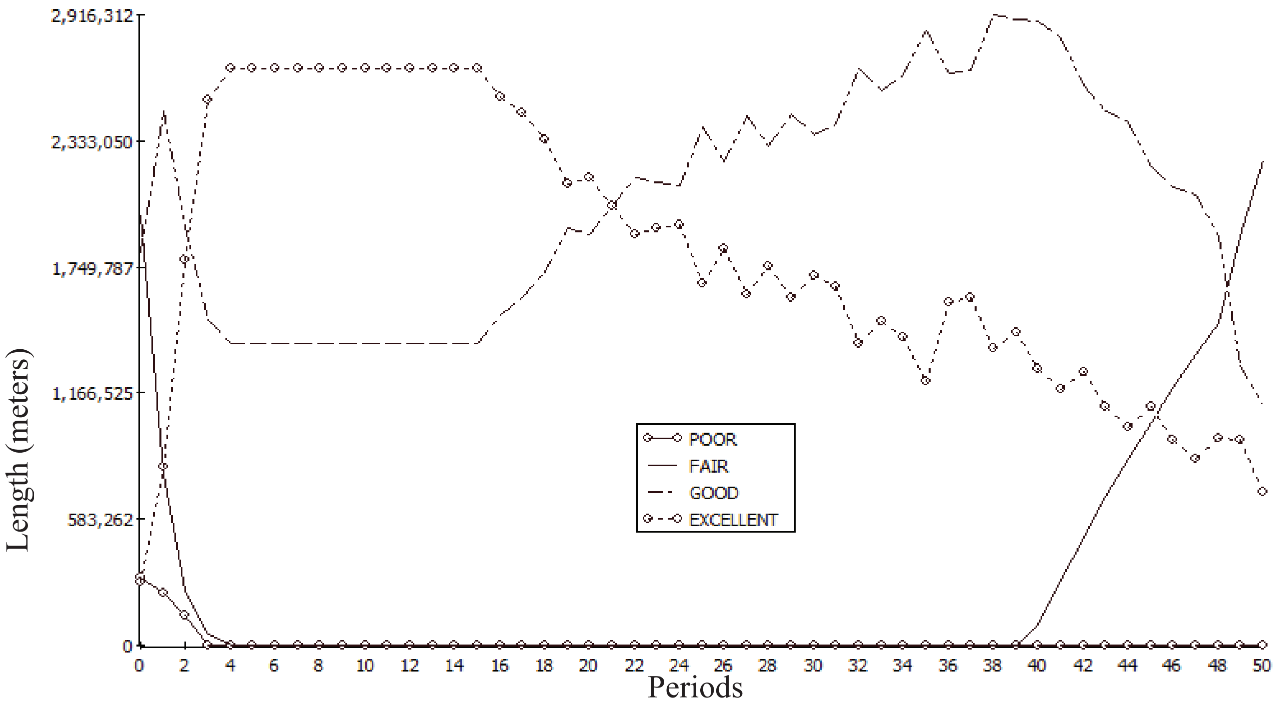


Figure 9.8: Predicted conditions of roads after treatment operations under annual maintenance budget of CAD 175 million

An annual budget of CAD 150 million will almost be equally distributed between treatment operations of flexible and rigid pavements during the first 20 years, but flexible pavements will require more maintenance budget during the period 2029 -2045 (Figure 9.9). Considerably higher maintenance budget will be invested for treating rigid pavements after the year 2044 (Figure 9.9). During the first 6 years, a large portion of the maintenance budget of flexible pavements will be invested in reconstruction (RC), resurfacing (RS), repair and overlay treatments operations. Annual budget for flexible pavements will be invested in rout and crack sealing (CS) during the remaining periods (Figure 9.10). Similar pattern of budget distribution in treatment operations is observed for rigid pavements (Figure 9.11).

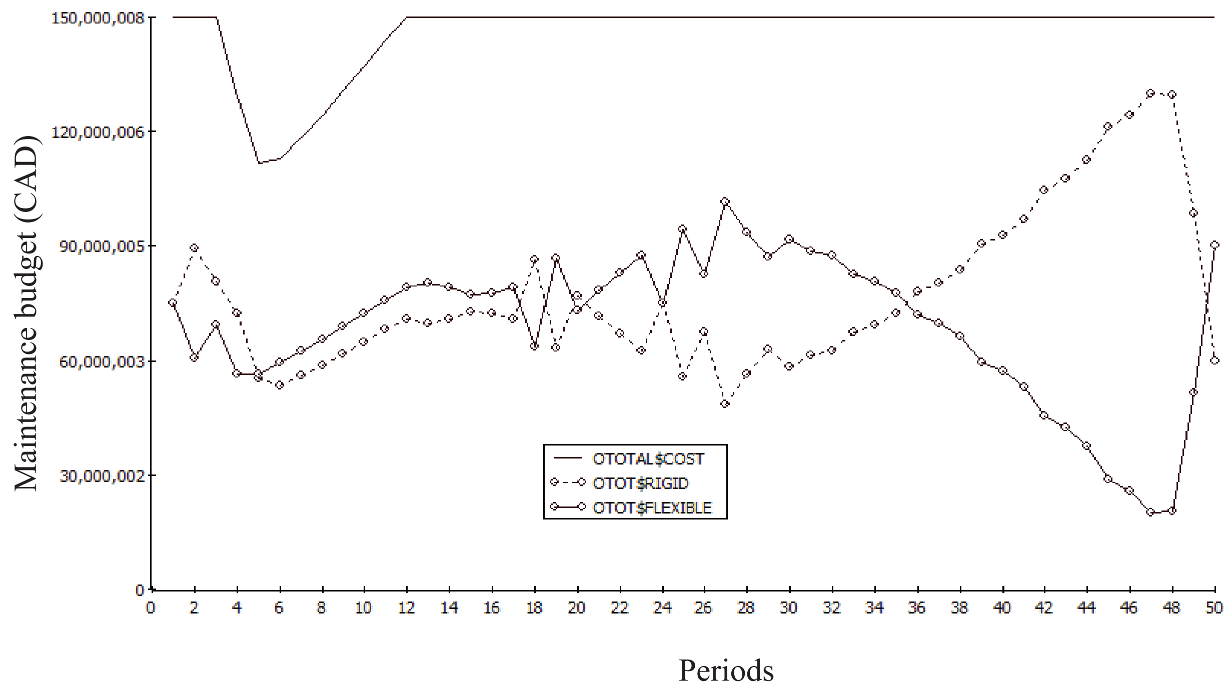


Figure 9.9: Distribution of annual maintenance budget (CAD $150 million) among rigid and flexible pavements

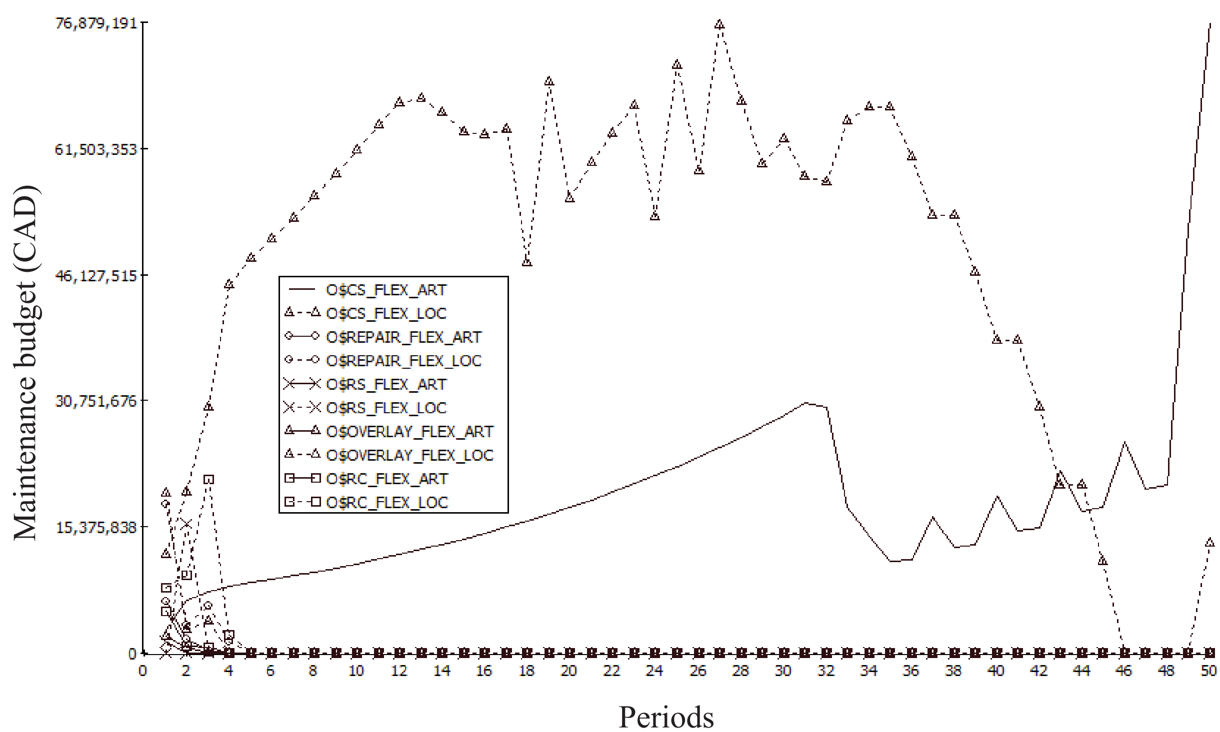


Figure 9.10: Distribution of annual maintenance budget for different treatment operations of flexible pavements

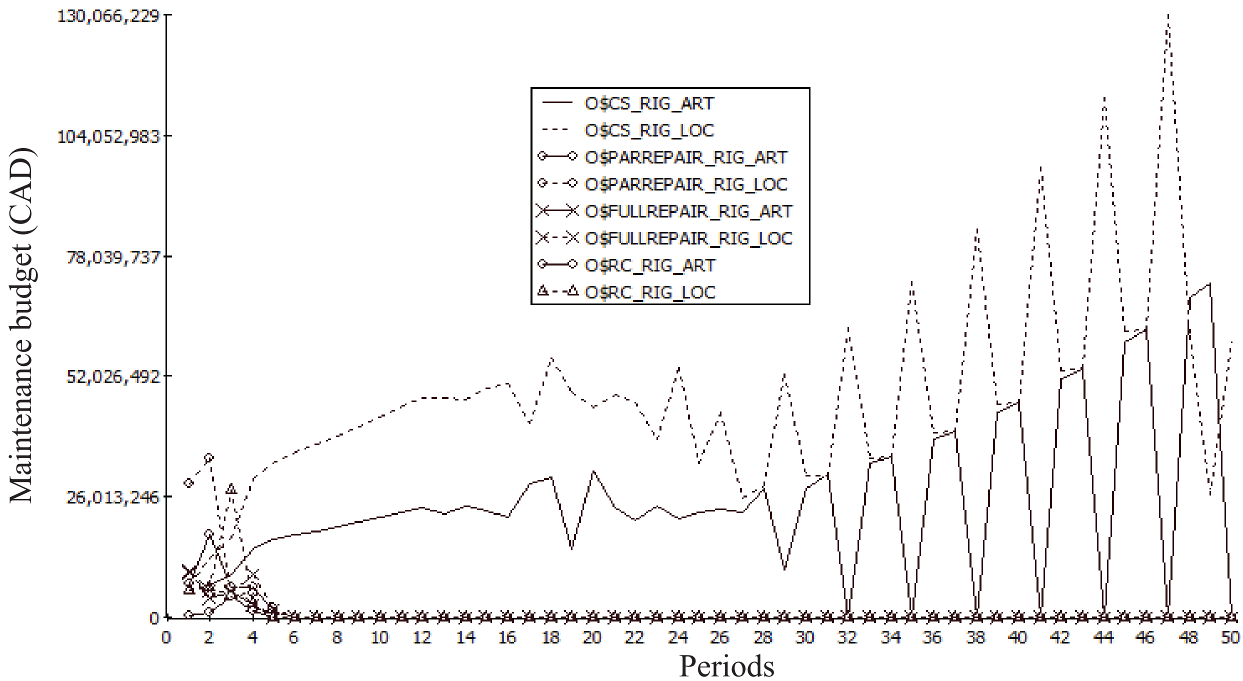


Figure 9.11: Distribution of annual maintenance budget for different treatment operations of rigid pavements

The developed model of PMS has two-fold improvement on the conventional methods of PMS. Firstly, traditional methods of PMS apply the pavement deterioration curves that are based on the historical data on traffic volume or compound traffic growth rate. But traffic volume and distribution is related to land use, economy, employment opportunities, and travel behavior. This study predicts dynamic traffic volume and loads during the fifty-year design period by applying travel demand modeling. Secondly, this proposed model for the road network of Montreal City deals with the computational error of developing the pavement performance curves. Traditional deterministic and stochastic methods of predicting pavement deterioration are not only unable to address dynamic traffic loads, but also have drawbacks of measurement error, subjective evaluations of pavement condition and steady-state probabilities for transition of pavement condition from one state to another. This model helps the transportation authorities to manage continuous aggregate behavior of transportation system, estimate more accurate pavement deterioration and solve lifecycle optimization problems of pavement management at any time interval during the lifespan of pavement.

9.4. Conclusions

Arterial roads of Montreal City, mostly constructed in 1950's, are at an advanced state of deterioration. Montreal City needs a holistic model of PMS predicting the response and performance of pavement under actual dynamic traffic loads and optimizing the treatment operations. Traditional PMS methods have limitations of addressing dynamic traffic loads, measurement errors to predict the pavement deterioration and subjective evaluations of pavement condition. This study develops the linear programming of PMS for the road network of Montreal City that accommodates the simulated traffic during 50 years design period and deals with the measurement error of the pavement performance modeling.

Linear programming of lifecycle optimization method is applied to develop M&R strategies ensuring the good pavement condition of roads at a minimum maintenance budget. Lifecycle optimization of PMS estimates that CAD 150 million is the minimum annual budget to achieve most of arterial and local roads are at least in good condition in Montreal City. The developed model of PMS has two-fold improvement on the conventional methods of PMS. Firstly, this study predicts dynamic traffic volumes and loads during the fifty-year design period by applying travel demand models. Secondly, this model deals with the computational errors of developing the pavement performance curves. This proposed model will help the transportation authorities to manage continuous aggregate behavior of transportation system, estimate more accurate pavement deterioration and solve lifecycle optimization problems of pavement management at any time interval during the lifespan of pavement.

The fast rate of deterioration of Montreal roads is confirmed by the estimations from the model: eventhough overall vehicle traffic is expected to double within 50 years, truck traffic is expected to suffer a much faster increase; doubling the number of ESALs every 15 years, this is a direct result from economic activity and some traffic could be regional. A backpropagation Neural Network (BPN) of the type multilayer perceptron combined with a Generalized Delta Rule (GDR) was able to improve the estimation of future deterioration of pavements. Both rigid and flexible pavements deteriorated at a similar rate, no big differences were observed. A budget of at least CAN$150 millions is required to sustain arterial and local roads of Montreal in good condition.

Roads in the island of Montreal need to undergo through a stabilization period for about 25 years, a steady state seems to be reached after that and only preventive maintenance treatments are applied after that. Future research should study more complex maintenance rules regarding the limited back-to-back application of certain interventions, per instance limiting the number of consecutive crack sealing before enforcing an overlay. Future research can study alternate methods for traffic prediction. Future research should use individual distress indicators of pavement damage instead of PCI.

Chapter 10
Conclusions

The physical condition of the road infrastructure in Canada is not good, and in many regions roads are critically aged. Arterial roads of the City of Montreal, mostly constructed in 1950's, are also at an advanced state of deterioration and need major rehabilitation, upgrading, or even reconstruction. The Canadian transportation agencies still require a comprehensive pavement management system (PMS) to guide and recommend the best practices for their appropriate application and communication. The PMS is an approach that incorporates the economic assessment of trade-offs between competing alternatives at both the network and project levels. The aim of this research is to address major challenges of PMS such as the incapacity of current systems to dynamically forecast performance, the inability to prioritize investments considering economic output, and the absence of a truly optimized decision-making support system based on more that simple asset condition. The general objective of this research is to extend PMS by incorporating dynamic states of land use, regional economics, travel modeling, and socio-economic development criteria into pavement management systems. This research also deals with the measurement error of the pavement performance modeling. The specific objectives implement the general objective at two geographical scales. The specific objectives at regional scale are to integrate regional economy and transport modeling at a regional scale (Atlantic Provinces of Canada) to forecast freight-traffic distribution to improve pavement-deterioration modeling and overall province-wide PMS; and to expand multi-criteria based PMS incorporating community development criteria. The specific objectives at urban scale are to develop the pavement performance model for the road network of Montreal city by integrating land use and transport modeling and reducing the measurement error; and to develop the linear programming of PMS for the road network of Montreal city accommodating simulated traffic and measurement correction of the pavement performance modeling.

This study initially discusses the practices of RIAMS, particularly PMS, adopted in different countries to focus on the issues that need to be addressed in PMS. Discussion on RIAMS reveals that Canadian transportation authorities are still developing their own RIAMS. Life-cycle cost, condition assessment and decision making analyses of PMS are at the beginning level in RIMAS of Canada. Transportation authorities in Canada require a holistic PMS that overcomes these drawbacks. This study develops a PMS incorporating dynamic states of land use, regional economy, traffic volumes, design capacities, and pavement conditions. This study also proposes Backpropogation Artificial Neural Network (BPN) method with generalized delta rule (GDR) learning algorithm to reduce the measurement error of pavement performance modeling.

This study proposes to use the simulation capabilities of integrated land use and transport modeling as an input into road management systems. A case study based in the simulation of freight flows between the provinces of Newfoundland and Labrador, Nova Scotia, Prince Edward Island, New Brunswick and Quebec, is presented. Two performance models are produced and compared; one based on current practices which use functional classification of roads as a proxy for traffic intensity and, the other one based on simulated truck traffic for each of the main routes within the province of New Brunswick by integrating spatial input-output and transportation models. It is demonstrated how performance deterioration modeling based on simulated truck traffic resulted in a more accurate estimation of required levels of funding for maintenance and rehabilitation.

The socio-economic factors of the regional communities are integrated with regional economy and transportation modeling to support multi-criteria based PMS for the regional road network of Atlantic Canada provinces - New Brunswick, Prince Edward Island, Newfoundland & Labrador, Nova Scotia and Quebec. The reason is that the policy makers are not only guided by the engineering characteristics but also considers the socio-economic benefits of the communities to allocate PMS budget. The CDI of each regional road link is developed by multivariate analysis of the variables relevant to community development. The lifecycle optimization is performed to maximize the pavement condition and CDI at a minimum budget. This study compares the pavement M&R budget for two scenarios. The first scenario integrates the regional economy and transportation modeling to simulate the inter-provincial truck flow and the M&R budget is optimized to maximize the pavement condition under the simulated truck flow. The second scenario optimizes the M&R operation budget maximizing the pavement condition and CDI. In the first scenario, the regional highways mostly require the single chip seal and micro-surfacing treatment operations during the design period. In the second scenario, incorporation of CDI within the prevailing system of 1st scenario, the M&R budget will mainly be allocated for minor (overlay) and major rehabilitation treatment operations during the design period.

This study, later on, focuses on the measurement error of the pavement performance modeling. Backpropagation Neural Network (BPN) method with Generalized Delta Rule (GDR) learning algorithm is applied to reduce the measurement error of the pavement performance modeling. The Multi-Layer Perceptron (MLP) network and sigmoid activation function are applied to build the BPN. Collector and arterial roads of both flexible and rigid pavements in Montreal City are taken as a case study. The input variables of Pavement Condition Index (PCI) are Average Annual Daily Traffic (AADT), Equivalent Single Axle Loads (ESALs), Structural Number (SN), pavement's age, slab thickness and difference of PCI between current and preceding year (ΔPCI). BPN networks estimates that the PCI has inverse relationships with AADT, ESALs and pavement's age for both flexible and rigid pavements of arterial and collector roads. However, BPN networks estimates that the PCI has positive relationships with AADT, ESALs and pavement's age for roads that have recent treatment operations. The PCI has positive relationships with SN and slab thickness that imply that the increase of structural strength and slab thickness increases the pavement condition. The ΔPCI significantly influence the PCI values of flexible arterial, rigid arterial, flexible collector and rigid collector roads by 36.3 percent, 33.1 percent, 33 percent and 32.9 percent respectively. The $\log_{10}$ (AADT) and $\log_{10}$ (ESALs) have considerable importance to estimate the PCI values in BPN models. The $\log_{10}$ (AADT) has 13.8 percent, 23 percent, 22.6 percent and 20.1 percent importance to estimate PCI values of flexible arterial, rigid arterial, flexible collector and rigid collector roads respectively. The $\log_{10}$ (ESALs) variable contributes 12 percent, 19.4 percent, 22.1 percent and 24.8 percent of PCI values for flexible arterial, rigid arterial, collector flexible and collector rigid roads respectively. However, pavement's age does not significantly influence the PCI values except in the case of flexible arterial roads (36.3 percent).

The structural characteristics of pavement, SN and slab thickness for flexible and rigid pavements do not have significant influence in determining the PCI values respectively. The reason is that the categorical values of thickness of pavement's layers for broader categories of AADT are applied in this study both for flexible and rigid pavements from the report prepared by the Cement Association of Canada. There is a strong potential that the BPN models might estimate the significant or considerable influences of SN and slab thickness on the PCI for flexible and rigid pavements respectively, if the actual data on thickness of pavement's layers for each road segment can be accommodated into the BPN network.

Finally, a holistic model of PMS is developed for the road network of Montreal city by accommodating the simulated traffic during the period of 2009-2058 and reducing the measurement error of the pavement performance modeling. Urban traffic volume is simulated at 5-year interval during 2009-2058 by applying travel demand modeling of UTPS package. The ESALs are 31.67, 5.26, 22.64 and 18.61 million on arterial-flexible, arterial-rigid, local-flexible and local-rigid roads during the design period. BPN networks simulate that the average PCI values will be reduced from 77 to 30, 74 to 27, 70 to 28 and 67 to 25 for arterial-flexible, arterial-rigid, local-flexible and local-rigid roads during the period of 2009-2058, respectively.

Lifecycle optimization of PMS estimates that CAD 150 million is the minimum annual budget to achieve most of arterial and local roads are at least in good condition (PCI>70) in Montreal City. The developed model of PMS has two-fold improvement on the conventional methods of PMS. Firstly, this study predicts dynamic traffic volumes and loads during the fifty-year design period by applying travel demand models. Secondly, this model deals with the computational errors of developing the pavement performance curves.

This research will improve the allocation of economic resources by combining the output from land use & transport modeling (LUT) and development criteria as a feedback into the PMS. The improved performance models of the PMS will reflect a more realistic measure of travel demand and trip redistribution, therefore improving the user's satisfaction and ability to generate and support economical activities. This research will provide the transportation agencies with an improved decision-making framework capable of delivering a more balanced budget for the achievement of global objectives, such as; cost, condition, service, accessibility, pollution, and community benefits.

Future research may consider the intrinsic interrelations between simulated traffic flows (vehicles and trucks) with a wider range of objectives such as road safety, highway capacity (mobility), social cost and environmental impact (gas emissions and energy consumption). Future studies can include the socio-economic impacts of the M&R operations on the community instead of only maximizing the generalized value of CDI within the life-cycle optimization of the PMS.

References

AASHTO, (1985). *AASHTO Guide for the Design of Pavement Structures (Appendix EE)*. Washington, DC: American Association of State Highway and Transportation Officials.

AASHTO, (1993). *Guide for the Design of Pavement Structures*. Washington, DC: American Association of State Highway and Transportation Officials.

Abaza, K., Ashur, S., and Al-Khatib, I. (2004). Integrated Pavement Management System with a Markovian Prediction Model. *Journal of Transportation Engineering*, 130(1), 24–33.

Abaza, K. A., Ashur, S. A., Abu-Eisheh S. A. (2001). Macroscopic Optimum System for Management of Pavement Rehabilitation. *Journal of Transportation Engineering*, 127(6), 493-500.

Ahuja, A. S. (2007). *Development of passenger car equivalents for freeway merging sections*. MSE Thesis. University of Nevada, Las Vegas.

Alasia, A., Bollman, R., Parkins, J., and Reimer, B. (2008). An *Index of community vulnerability: conceptual framework and application to population and employment changes 1981 to 2001*. Agricultural and Rural Working Paper Series, Statistics Canada, Canada,.

Allen, D. L., Rizenbergs, R. L., and Sharpe, G. W. (1992). History and Implementation of Pavement Management in Kentucky. In: *Pavement Management Implementation*, F. B. Holt and W. L. Gramling (eds.), American Society for Testing and Materials, Philadephia, pp. 167-184.

Amador-Jiménez, L., and Amin, M.S.R. (2013). Simulating freight-traffic between Atlantic Canada and Quebec to support pavement Management on New Brunswick's regional highways. *Journal of Infrastructure Systems*, 19(3), 343-350.

Amador-Jiménez, L,. and Mrawira, D. (2011). Capturing variability in pavement performance models from sufficient time-series predictors: a case study of the New Brunswick road network. *Canadian Journal of Civil Engineering*, 38(2), 210-220.

Amin, M. S. R., and Amador, L. E. (2014). The Multi-criteria based Pavement Management System for Regional Road Network of Atlantic Provinces of Canada. *International Journal of Pavements*, 13(1-2-3) [In Press].

Amin, M. S. R., and Amador-Jiménez, L. (2014). A performance-based Pavement Management System for the road network of Montreal city—a conceptual framework. In *Asphalt Pavements* Y. R. Kim (ed.), 233-244.

Anas, A. (1994). *METROSIM: A Unified Economic Model of Transportation and Land-Use*. Alex Anas & Associates, Williamsville, NY.

Anderstig, C., and Mattsson, L.-G. (1998). Modelling land-use and transport interaction: evaluations and policy analysis. In *Network Infrastructure and the Urban Environment: Recent Advances in Land-Use/Transportation Modelling*, L. Lundqvist, L. Mattsson, and T. J. Kim (eds.), Springer, Berlin/Heidelberg/New York. pp. 308-328.

Archilla, A. E. (2006). Repeated Measurement Data Analysis in Pavement Deterioration Modeling. *Journal of Infrastructure Systems*, 12(3), 163–173.

Artman, D., and Liebman, J. (1983). Optimization of Long-range Major Rehabilitation of Airfield Pavements. *Transportation Research Record*, 938, 1-11.

Attoh-Okine, N. O. (1994). Predicting Roughness Progression in Flexible Pavements Using Artificial Neural Networks. *Proc., Third International Conference on Managing Pavements,* Transportation Research Board, National Research Council, San Antonio, Texas, 55-62.

Attoh-Okine, N. O. (1999). Analysis of Learning Rate and Momentum Term in Backpropagation Neural network Algorithm Trained to Predict Pavement Performance. *Advances in Engineering Software*, 30, 291-302.

Australian Local Government Association (2010). *National Local Roads Database System (NLRDS).* Available at http://www.alga.asn.au/policy/transport/management/nlrds.php (accessed March 7 2013).

Ben-Akiva, M., Humplick, F., Madanat, S., and Ramaswamy, R. (1993). Infrastructure Management under Uncertainty: The Latent Performance Approach. *Journal of Transportation Engineering*, 119(1), 43-58.

Boyce, D., Tatineni, M., and Zhang, Y. (1992). *Scenario Analyses of the Chicago Region with a Sketch Planning Model of Origin-Destination Mode and Route Choice*. Urban Transportation Center, University of Illinois, Chicago, IL.

Butt, A. A., M. Y. Shahin, S. H. Carpenter, and J. V. Carnahan (1994). Application of Markov Process to Pavement Management Systems at Network Level. *3rd International Conference on Managing Pavements.* Transportation Research Board, National Research Council, San Antonio, Texas, 159-172.

Cafiso, S., Di Graziano, A., Kerali, H. R., and Odoki, J. B. (2002). Multicriteria Analysis Method for Pavement Maintenance Management. *Transportation Research Record* 1816, 73-84.

Caindec, E.K., and Prastacos, P. (1995). A *Description of POLIS. The Projective Optimization Land Use Information System*. Association of Bay Area Governments, Oakland, CA.

Caliper (2005). *Travel Demand Modeling with TransCAD 4.8*, Caliper Corporation, Newton, MA.

Carnahan, J. V. (1988). Analytical Framework for Optimizing Pavement Maintenance. *Journal of Transportation Engineering*, 114(3), 307-322.

Carnahan, J., Davis, W., Shahin, M., Keane, P., and Wu, M. (1987). Optimal Maintenance Decisions for Pavement Management. *Journal of Transportation Engineering*, 113(5), 554-572.

Cement Association of Canada (2012). *Methodology for the Development of Equivalent Pavement Structural Design Matrix for Municipal Roadways- Montréal and Québec City: Including Maintenance & Rehabilitation Schedules and Life Cycle Cost Analysis*. Final Report. Applied Research Associates Inc., Ottawa.

Chan, A., Keoleian, G., and Gabler, E. (2008). Evaluation of lifecycle cost analysis practices used by the Michigan Department of Transportation. *Journal of Transportation Engineering*, 134 (6), 236–245.

Chootinan, P., Chen, A., Horrocks, M. R., and Bolling, D. (2006). A multi-year pavement maintenance program using a stochastic simulation-based genetic algorithm approach. *Transportation Research Part A*, 40(9), 725–743 .

Christensen, P. N., Sparks, G. A., and Kostuk, K. J. (2005). A Method-based Survey of Life Cycle Costing Literature Pertinent to Infrastructure Design and Renewal. *Canadian Journal of Civil Engineering*, 32, 250 – 259.

City of Montreal (2012). *Operating Budget at a Glance.* City of Montreal, Montreal.

Cunningham, J., MacNaughton, J., and Landers, S. (2010). Managing the Risk of aging pavement infrastructure in New Brunswick through innovative decision making. *Proceedings of the 2010 Annual Conference of the Transportation Association of Canada*, Halifax, N.S.

De la Barra. (1989). *Integrated Land Use and Transport modeling: Decision Chains and hierarchies*. Cambridge University Press, Cambridge, U.K.

De Leur, P., and Sayed, T. (2002). Development of a Road Safety Risk Index. *Transportation Research Record: Journal of the Transportation Research Board*, 1784, 33–42.

de Melo e Siva, F., Van Dam, T. J., Bulleit, W. M., and Ylitalo, R. (2000). Proposed Pavement Performance Models for Local Government Agencies in Michigan. *Transportation Research Record: Journal of the Transportation Research Board*, 1699, 81-86.

Donaghy, K. P., and Schintler, L. A. (1993). *A Prototype Dynamic Transportation Network Management Model.* Final report , Delaware Department of Transportation, Delaware.

Durango-Cohen, P. L. (2007). An Optimal Estimation and Control Framework for the Management of Infrastructure Facilities. In *The Management and Measurement of Infrastructure: Performance, Efficiency and Innovation*, C. Karlsson, W. P. Anderson, B. Johansson, K. Kobayashi (eds), Edward Elgar, Cheltenham, UK, 177-197.

Economic Analysis Directorate. (2005). *Operating Costs of Trucks in Canada 2005*. Economic Cost Directorate of Transport Canada by Logistic Solution Builder. Available at [http://publications.gc.ca/collections/collection_2011/tc/T46-14-2005-eng.pdf] (Accessed July 18 2011)

European Commission (1996). *Evaluation Methods: APAS Road Transport Research Project.* European Commission, Luxembourg.

Falls, L. C., and Haas, R. (2010). *Measuring and Reporting Highway Asset Value, Condition and Performance*, Transportation Association of Canada, Ottawa, Ontario, Canada.

Federal Highway Administration (1999). *Asset Management Primer*. U.S. Department of Transportation Washington, D.C., USA

Federal Highway Administration (2010). *New Zealand 'RAMM' Asset Management System.* Available at http://international.fhwa.dot.gov/assetmanagement/chp2_b_new_ze.htm (accessed March 7 2013).

Federal Highway Administration. (2011). *FHWA vehicle types*. Available at ⟨http://www.fhwa.dot.gov/policy/ohpi/vehclass.htm⟩ (Accessed April 24 2012).

Federal Highway Administration (2011). *Highway Performance Monitoring System Manual*. US Department of Transport, USA, 2011. Avilable at http://www.fhwa.dot.gov/ohim/hpmsmanl/appn1.cfm (accessed July 18 2011).

Federal Highway Administration (2012). *Managing Pavements and Monitoring Performance: Best Practices in Australia, Europe, and New Zealand,* U.S. Department of Transportation, Washington, D.C., USA.

Feighan, K. J., Shahin, M. Y., and Sinha, K. C. (1987). Dynamic Programming Approach to Optimization for Pavement Management Systems. *Transportation Research Board (TRB) Committee AFD10 on Pavement Management Systems*. Available at http://www.pavementmanagement.org/ICMPfiles/1987039.pdf (accessed June 28, 2013).

Flintsch, G. W. (1991). *A Generic Road Surface Management Program for Local Governments.* Arizona State University, Tempe, USA.

Freeman, J. A., and Skapura, D. M. (1991). *Neural Networks. Algorithms, Applications, and Programming Techniques*, Addison-Wesley, 56-125.

Feunekes, U., Palmer, S., Feunekes, A., MacNaughton, J., Cunningham, J., and Mathisen, K. (2011). Taking the politics out of paving: Achieving Transportation Asset Management Excellence through OR. *Interfaces*, 41(1), 51-65

GAO, L., and Zhang, Z. (2008). Robust Optimization for Managing Pavement Maintenance and Rehabilitation. *Transportation Research Record 2084, Transportation Research Board*, Washington, DC, 55–61.

George, K. P, Rajagopal, A. S., and Lim, L. K. (1989). Models for Predicting Pavement Deterioration. *Transportation Research Record: Journal of the Transportation Research Board*, 1215, 1-7.

Golabi, K., Kulkarni, R., and Way, G. (1982). A statewide pavement management system. *Interfaces*, 12(6), 5-21.

Golabi, K., and Pereira, P. (2003). Innovative Pavement Management and Planning System for Road Network of Portugal. *Journal of Infrastructure Systems*, 9(2), 75–80.

Government of Western Australia, 2010. *Western Australian (Roman) Asset Management System.* Available at http://www.councils.wa.gov.au/directory/walga/index.html/roman (accessed March 7 2013).

Haag, G. (1990). Master equations. In *Urban Dynamics. Designing an Integrated Model* C.S. Bertuglia, G. Leonardi, and A.G. Wilson (eds.), Routledge, London/New York. 69-83.

Haas, R., and Hudson, W. R. (1978). *Pavement management systems.* McGraw-Hill, New York, N.Y..

Haider, A., Koronios, A., and Kumar, A. (2011). An Object Oriented Road Asset Information Model. In *Engineering Asset Management and Infrastructure Sustainability*, J. Mathew, L. Ma, A. Tan, M. Weijnen and J. Lee (eds.), Springer-Verlag London Limited, London, UK, pp. 283-297.

Hair, J. F. (1992). *Multivariate data analysis*, Macmillan, New York.

Halfawy, M. R., Pyzoha, D., and El-Hosseiny, T. (2002). *An Integrated Framework for GIS-based Civil Infrastructure Management Systems.* Canadian Society for Civil Engineering, Montreal, Quebec, Canada.

Hensher, D., and Ton, T. (2001). TRESIS: A transportation, land use and environmental strategy impact simulator for urban areas. In *Proceedings of the 9th World Conference on Transport Research*, Seoul, South Koria, 22-27 July.

Humphries, C. (2012). *Examination of potential cost benefits for converting surfaced roads to unsurfaced roads in Texas*. Unpublished M.Sc thesis, Dept. of Engineering Technology, Texas State University-San Marcos.

Haugodegard, T., Johansen, J. M., Bertelsen, D., and Gabestad, K. (1994). Norwegian Public Roads Administration: A Complete Pavement Management System in Operation. *3rd International Conference on Managing Pavements*, National Research Council, Transportation Research Board, San Antonio, Texas.

Hokkanen, J., and Salminen, P. (1997). ELECTRE III and IV Decision Aids in an Environmental Problem. *Journal of Multi-Criteria Decision Analysis*, 6(4), 215–226.

Hudson, W. R., Haas, R., and Pedigo, D. R. (1979). *Pavement Management System Development*, National Cooperative Highway Research Program, Washington, DC.

Hudson, W. R., Haas, R., and Uddin, W. (1997). *Infrastructure Management.* McGraw Hill, New York, NY.

Hunt, J., and Abraham, J. (2003). Design and application of the PECAS land use modelling system. In Proceedings of the *8th International Conference on Computers in Urban Planning and Urban Management*, Sendai, Japan, 27-29 May, CD-ROM Format.

Hunt, J. D., Kriger, D. S., and Miller, E. J. (2005). Current Operational Urban Land-use–Transport Modelling Frameworks: A Review. *Transport Reviews*, 25(3), 329–376.

IBM, (2010). IBM SPSS Neural Networks 19. Available at <http://www.sussex.ac.uk/its/pdfs/SPSS_Neural_Network_19.pdf> (accessed January 10, 2012).

Iacono, M., Leviston, D., and El-Geneidy, A. (2008). Models of Transportation and Land Use: A Guide to the territory. *Journal of Planning Literature*, 22, 323-340

Institut de la Statistique Quebec. (2007). *Comparaisons interprovinciales*. Available at [http://www.stat.gouv.qc.ca/donstat/econm_finnc/conjn_econm/TSC/index.htm] (accessed March 12 2012).

Jain, S. S., Aggarwal, S., and Parida, M. (2005). HDM-4 Pavement Deterioration Models for Indian National Highway Network. *Journal of Transportation Engineering*, 131(8), 623–631.

Jansen, J. M., and Schmidt, B. (1994). Performance Models and Prediction of Increase Overlay need in Danish state highway pavement management system, BELMA. *Proc., Third International Conference on Managing Pavements*, San Antonio, TX, 74-84.

Johnson, K. D., and Cation, K. A. (1992). Performance Prediction Development Using Three Indexes for North Dakota Pavement Management System. *Transportation Research Record: Journal of the Transportation Research Board*, 1344, 22-30.

Jung, F. W., Kher, R., and Phang, W. A. (1975). *A Performance Prediction Subsystem—Flexible Pavements*, Research Report 200. Ontario Ministry of Transportation and Communications, Downs view, Ontario.

Kansas Department of Transportation (1993). *Pavement Management System NOS Condition Survey.* Kansas Department of Transportation, Kansas.

Karan, M. (1977). *Municipal Pavement Management System.* Dissertation, Department of Civil Engineering, University of Waterloo.

Karlsson, C., Johansson, B., Anderson, W. P., and Kobayashi, K. (2007). Infrastructure Meansurement and Management: An Introduction. In *The Management and Measurement of Infrastructure: Performance, Efficiency and Innovation*, C. Karlsson, W. P. Anderson, B. Johansson and K. Kobayashi (eds.), Edward Elgar Publishing Inc., Massachusetts, USA, 1-24.

Kher, R., and Cook, W. (1985). PARS-the MTC Model for Program and Financial Planning in Pavement Rehabilitation. *North American Pavement Management Conference.* Ontario Ministry of Transportation and Communication, U.S. Federal Highway Administration, Washington DC, 6.24-6.40.

Kinnear, P. R., and Gray, C. D. (2009). *SPSS 16 Made Simple.* Psychology Press, New York, NY.

Kobayashi, K., Do, M., and Han, D. (2010). Estimation of Markovian transition probabilities for pavement deterioration forecasting. *KSCE Journal of Civil Engineering*, 14(3), 343-351.

Kulkarni, R. B., and Miller, R. W. (2002). Pavement Management Systems Past, Present, and Future. *Transportation Research Record: Journal of the Transportation Research Board*, 1853, 65-71.

Kuo, W. H. (1995). *Pavement Performance Models for Pavement Management System of Michigan Department of Transportation*, Michigan Department of Transportation, Lansing.

Lee, Y.-H., Mohseni, A., and Darter, M. I. (1993). Simplified Pavement Performance Models. *Transportation Research Record: Journal of the Transportation Research Board*, 1397, 7-14.

Levinson, D., Corbett, M., and Hashami, M. (2005). *Operating costs for trucks. Working Paper Series (SSRN – 1736159)*. Social Science Research Network. Available at [http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1736159] (accessed July 18, 2011)

Liebman, J. (1985). Optimization Tools for Pavement Management. In proceedings of *North American Pavement Management Conference,* Ontario Ministry of Transportation and Communication and U.S. Federal Highway Administration, Washington D.C., 6.6-6.15.

Li, Z., and Madanu, S., (2009). Highway project level life-cycle benefit/cost analysis under certainty, risk, and uncertainty: methodology with case study. *Journal of Transportation Engineering*, 135(8), 516–526.

Li, N., Xie, W.-C., and Haas, R. (1996). Reliability-Based Processing of Markov Chains for Modeling Pavement Network Deterioration. *Transportation Research Record: Journal of the Transportation Research Board*, 1524, 203–213.

Li, N., Haas, R., and Xie, W.-C. (1997). Investigation of Relationship between Deterministic and Probabilistic Prediction Models in Pavement Management. *Transportation Research Record: Journal of the Transportation Research Board*, 1592, 70-79.

Li, Y., Cheetham, A., Zaghloul, S., Helali, K., and Bekheet, W. (2006). Enhancement of Arizona Pavement Management System for Construction and Maintenance Activities. *Transportation Research Record: Journal of the Transportation Research Board*, 1974, 26–36.

Mackett, R. L. (1991). LILT and MEPLAN: a comparative analysis of land-use and transport policies for Leeds. *Transport Reviews*, 11, 131-154.

Medina, A., Flintsch, G. W., and Zaniewski, J. P. (1999). Geographic Information Systems–Based Pavement Management System A Case Study. *Transportation Research Record*, 1652,151-157.

Miller, E., and Salvini, P. (2001). The Integrated Land Use, Transportation, Environment (ILUTE) Microsimulation Modelling system: Description and current status. In *The Leading Edge in Travel Behaviour Research,* D. A. Henscher (ed.), 9th International Association for Travel Behaviour Research Conference, Gold Coast, Queensland, Australia.

Ministry of Transportation (2007). Trans-Canada Highway 1 - Malahat Corridor Study Area Final Report. Available at [http://www.th.gov.bc.ca/malahat/finalreport/index.htm] (accessed July 18, 2011).

Miyamoto, K., and Udomsri, R. (1996). An analysis system for integrated policy measures regarding land use, transport and the environment in a metropolis. In *Transport, Land Use and the Environment*, Y. Hayashi and J. Roy (eds.), Kluwer, Dordrecht. 259-280.

Moazami, D., Behbahani, H., and Muniandy, R. (2011). Pavement rehabilitation and maintenance prioritization of urban roads using fuzzy logic. *Expert Systems with Applications*, 38, 12869–12879.

Modelistica (2008). Mathematical Descriptions of TRANUS. Available at http://www.tranus.com/tranus-english (accessed January 10, 2011).

Morcous, G., Rivard, H., and Hanna, A. M. (2002). Modeling bridge deterioration using case-based reasoning. *Journal of Infrastructure Systems*, 8(3), 86–95.

NAMS (2006). *International Infrastructure Management Manual.* National Asset Management Steering Group, New Zealand.

National Cooperative Highway Research Program (2007). *U. S. Domestic Scan Program: Best Practices in Transportation Asset Management*. Cambridge Systematics Inc., Cambridge, Massachusetts, USA.

National Research Centre for Local Roads (2009). ROMAN II: ARRB's asset management solution for WALGA. *Local Roads News*, 1.

Natural Resources Canada. (1995). *The National Atlas of Canada 1978-1995: Thornthwaites Classification Moisture Regions* [online]. Available at http://atlas.nrcan.gc.ca/site/english/maps/archives/5thedition/environment/climate/mcr4096 [accessed April 24, 2012]

NBDOT. (2006). *Asset Management Business Framework Project – Pavement Deterioration Curves and Performance Measurement*. Report FR-TAM-06-01. Fredericton, NB.

NCHRP. *Analytical tools for Asset Management.* Report 545, Washington D.C.: Transportation Research Board, National Cooperative Research Program, 2005.

Ng. M, Lin, D.Y. and Waller, T. (2009). Optimal Long-Term Infrastructure Maintenance Planning Accounting for traffic dynamics. *Journal of Computed-Aided Civil and Infrastructure Engineering*, 24, 459-469.

Ockwell, A. (1990). *Pavement Management: Development of a Life Cycle Costing Technique.* Occasional Paper 100, Bureau of Transport and Communications Economics, Department of Transport and Communications, Canberra: Australian Government Publishing Service.

ODOT (2002). Oregon Department of Transportation. [Online] Available at http://www.odot.state.or.us/tddtpau/ [accessed 11 January 2014].

OECD (2001). *Asset Management for the Road Sector.* Organization for Economic Co-operation and Development, Paris, France.

Ortiz-García, J. J., Costello, S. B., and Snaith, M. S. (2007). Derivation of Transition Probability Matrices for Pavement Deterioration Modeling. *Journal of Transportation Engineering*, 132(2), 141-161.

Ouertani, M. Z., Parlikad, A. K., and Mcfarlane, D. (2008). Towards an approach to select an asset information management strategy. *International Journal of Computer Science and Applications*, 5(3b), 25 – 44.

Ouyang, Y. (2007). Pavement resurfacing planning for highway networks: parametric policy iteration approach. *Journal of Infrastructure Systems*, 13(1), 65-71

Paterson, D. E. (1987). *Pavement Management Practices.* Transportation Research Board, National Research Council, Washington, D.C.

Paterson, W. D. O., and Attoh-Okine, B. (1992). Summary of Models of Pavement Road Deterioration Based on HDM-III. *Transportation Research Record: Journal of the Transportation Research Board,* 1344, 99 – 105

Peterson, D. E. (1987). *Comparative Analysis of Several State and Provincial Systems for Managing Pavements*. Transportation Research Board, National Research Council, Toronto, Ontario, Canada.

Pilson, C., Hudson, R., and Anderson, V. (1999). Multiobjective Optimization in Pavement Management by Using Genetic Algorithms and Efficient Surfaces. *Transportation Research Record: Journal of the Transportation Research Board*, 1655, 42-48.

Piyatrapoomi, N., Kumar, A., Robertson, N., and Weligamage, J. (2006). A Framework for Risk-based Analysis of Investment in Maintenance and Rehabilitation of Large Road Networks. *Joint International Conference on Computing and Decision Making in Civil and Building Engineering, June 14 - 16.* Montreal, Canada.

Potter, D. W., and Hudson, W. R. (1981). Optimisation of Highway Maintenance Using Highway Design Model. Australian Road Research 11(1), 3-16.

Rho, J. H., and Kim, T. J. (1989). Solving a three-dimensional urban activity model of land use intensity and transport congestion. *Journal of Regional Science*, 29, 595-613.

Rioja, F. K. (2003). Filling Potholes: Macroeconomic Effects of Maintenance vs. New Investments in Public Infrastructure. *Journal of Public Finance*, 87(9-10), 2281-3004.

Road and Transportation Assocation of Canada (1977). *Pavement Management Guide*, Roads and Transportation Assoc. of Canada, Ottawa, Canada.

Robelin, C. A., and Madanat, S. M. (2007). History-dependent bridge deck maintenance and replacement optimization with Markov decision processes. *Journal of Infrastructure Systems* 13 (3), 195–201.

Robinson, C., Beg, M. A., Dosseu, T., and Hudson, W. R. (1996). Distress Prediction Models for Rigid Pavements for Texas Pavement Management Information System. *Transportation Research Record: Journal of the Transportation Research Board*, 1524, 145-151.

Sadek, A. W., Freeman, T. E., and Demetsky, M. J. (1996). Deterioration Prediction Modeling of Virginia's Interstate Highway System. *Transportation Research Record: Journal of the Transportation Research Board*, 1524, 118-129.

Saleh, M. F., Mamlouk, M. S., and Owusu-Antwi, E. B. (2000). Mechanistic Roughness Model based on Vehicle-Pavement Interaction. *Transportation Research Record: Journal of the Transportation Research Board*, 1699, 114-120.

Salem, O., Abourizk, S., and Ariaratnam, S. (2003). Risk-based life-cycle costing of infrastructure rehabilitation and construction alternatives. *Journal of Infrastructure Systems*, 9 (1), 6–15.

Santos, J., and Ferreira, A. (2013). Life-cycle cost analysis system for pavement management at project level. *International Journal of Pavement Engineering*, 14(1), 71–84.

Sathaye, N., Horvath, A., and Madanat, S. (2010). Unintended impacts of increased truck loads on pavement supply-chain emissions. *Transportation Research Part A*, 44, 1–15.

Saskatchewan Department of Highways and Transportation (1994). *Asset Capitalization and Design and Implementation of an Asset Management System.* Saskatchewan Department of Highways and Transportation, Regina, Saskatchewan, Canada.

Sayyadi, G., Amador, L. E., and Amin, M. S. R. (2013). A Multivariate Analysis of Road Severity Accident Index. Proceedings *23rd Canadian Multidisciplinary Road Safety Conference.* The Canadian Association of Road Safety Professionals, Montréal, Québec, May 26-29.

Scullion, T., and Stein, A. (1985). Predicting Maintenance and Rehabilitation Needs for the State of Texas. Proceedings *North American Pavement Management Conference.* Ontario Ministry of Transportation and Communication and U.S. Federal Highway Administration, Washington DC. 5.54-5.64.

Sebaaly, P. E., Hand, A., Epps, J. (1996). Nevada’s Approach to Pavement Management. *Transportation Research Record: Journal of the Transportation Research Board*, 1524, 109-117.

Shekharan, A. R. (1999). Assessment of Relative Contribution of Input Variables to Pavement Performance Prediction by Artificial Neural Networks. *Transportation Research Record: Journal of the Transportation Research Board*, 1655, 35-41.

Simmonds, D. (2001). The objectives and design of a new land-use modelling package: DELTA. In *Regional Science in Business* G. Clarke and M. Madden (eds.), Springer, Berlin/Heidelberg, 159-188.

Smadi, O. G., and Maze, T. H. (1994). Network Pavement Management System Using Dynamic Programming: Application to Iowa State Interstate Network. Paper presented at *Third International Conference on Managing Pavements,* Transportation Research Board, National Research Council, San Antonio, Texas.

Statistics Canada. (2009). Canadian Vehicle Survey: 2009. Available at [http://publications.gc.ca/Collection/Statcan/53-223-X/53-223-XIE.html] (accessed March 15 2012).

Straub, S. (2007). *Infrastructure and Development: A critical appraisal of the Macro-level literature*. Policy Research Working Paper No. 4590, the World Bank, Washington, D.C.

Thompson, P. D., Neumann, L. A., Niettinen, M., and Talvitie, A. (1987). A Micro-Computer Markov Dynamic Programming System for Pavement Management in Finland. *Pavement Management*. Available at http://www.pavementmanagement.org/ICMPfiles/1987042.pdf (accessed June 28, 2013).

Torrens, P.M. (2000). *How Land-Use-Transportation Models Work. Centre for Advanced Spatial Analysis*, University College London, London, UK.

Transportation Association of Canada (1999). *Primer on Highway Asset Management Systems.* Transportation Association of Canada, Ottawa, Ontario, Canada.

Transportation Business Association. (2011). Operational Costs – Reducing Fuel Use is being Green. Available at [http://www.tbabz.com/wp/fuel/operational-costs-reducing-fuel-use-is-being-green] (accessed August 7, 2011).

Transportation Research Board, National Research Council (2001). *Truck Trip Generation Data. A Synthesis of Highway Practice*. NCHRP Synthesis 298. National Cooperative Highway Research Program. National Academy Press, Washington DC.

Tsai, Y., and Lai, J. S. (2002). Framework and Strategy for Implementing an Information Technology–Based Pavement Management System. *Transportation Research Record: Journal of Transportation Research Board*, 1816, 56-64.

Uddin, W., Carmichael, R. F., and Hudson, W. R. (1986). *Life Cycle Analysis of Pavement Management Decision Making*. Final Report, Department of Transportation, Washington DC.

Ullidtz, P., and Stubstad, R. N. (1992). Standard Enginnering Principles in PMS Applications. In *Pavement Management Implementation*, American Society for Testing and Materials, Philadelphia, PA, 106-116.

Vanier, D. J., Newton, L. A., and Rahman, S. (2009). *Implementation details to support a generalized framework for municipal infrastructure management municipal infrastructure investment planning*. National Research Council Canada, Ottawa, Canada.

Vickerman, R. W. (1987). The Channel Tunnel: Consequences for Regional Growth and Development. *Regional Studies*, 21(3), 187-197.

Vickerman, R., and Monnet, J. (2003). Freight Traffic: Managing the Fundamental Drivers of Transport Demand. Proceedings *European Conference of Ministers of Transport*, *Gérer les déterminants de la demande de transport OECD*, Paris, France, 15-25.

Wang, K. C. P., Zaniewski. J., and Way, G. (1994). Probabilistic Behavior of Pavements. *Journal of Transportation Engineering*, 120(3), 358–375.

Watanatada, T., Dhareswar, A. M., and Rzende-Lima, P. R. S. (1985). *Models for Predicting Vehicles Speeds and Operating Costs based on Mechanistic Principles.* Highway Design and Maintenance Standard Study, World Bank, Washington, USA.

Watanatada, T., Harral, C. G., Paterson, W. D. O., Dhareshwar, A. M., Bhandari, A., and Tsunokawa, K. (1987). *The Highway Design and Maintenance Standard Model*. The John Hopkins University Press, Washington DC, USA.

Wegener, M. (1982a). A multilevel economic–demographic model for the Dortmund Region. *Sistemi Urbani*, 3, 371–401.

Wegener, M. (1982b). Modeling urban decline: a multilevel economic-demographic model of the Dortmund region. *International Regional Science Review*, 7, 21-41.

Wegener, M. (1985). The Dortmund housing market model: A Monte Carlo simulation of a regional housing market. In *Microeconomic Models of Housing Markets*, K. Stahl (ed.), Springer, Berlin/Heidelberg/New York, 144-191.

Wegener, M. (1986). Transport network equilibrium and regional deconcentration. *Environment and Planning A*, 18, 437-456.

Wegener, M. (1996). Reduction of CO2 emissions of transport by reorganisation of urban activities. In *Transport, Land Use and the Environment* Y. Hayashi and J. Roy (eds.), Kluwer, Dordrecht, 103-124.

Wegener, M. (1998). Applied models of urban land use, transport and environment: state-of-the-art and future developments. In *Network Infrastructure and the Urban Environment: Recent Advances in Land-Use/Transportation Modelling*, L. Lundqvist, L. Mattsson and T. J. Kim (eds.), Springer, Berlin/Heidelberg/New York, 245-267.

Wegener, M. (2004). Overview of Land-Use Transport Models. In *Transport Geography and Spatial Systems*, D. A. Hensher and K. Button (eds.), Pergamon/Elsevier Science, Kidlington, UK, 127-146.

Wegener, M. M. R., and Simmonds, D. (1991). One city, three models: comparison of land-use/transport policy simulation models for Dortmund. *Transport Reviews*, 11, 107-129.

Winston, W. (2004). *Operations Research: Applications and Algorithms.* 4th. homson-Brooks/Cole, Belmont, California.

Woodhouse, J. (2012). Setting a good standard in asset management. Available at http://www.assetmanagementstandards.com/resources/Setting+a+good+standard+for+asset+management+Times+2013.pdf (accessed 21/1/2014).

Woodhouse, J. (2013). ISO 55000. Available at http://www.assetmanagementstandards.com/resources/ISO55000+introduction+v1.1.pdf

(Accessed 21/1/2014).

Yang, J., Gunaratne, M., Lu, J. J., and Dietrich, B. (2007). Use of Recurrent Markov Chains for Modeling the Crack Performance of Flexible Pavements. *Journal of Transportation Engineering* 133(6):347–354.

Yang, J., Lu, J. J., Gunaratne, M., and Dietrich, B. (2006). Modeling Crack Deterioration of Flexible Pavements. Comparison of Recurrent Markov Chains and Artificial Neural Networks. *Transportation Research Record: Journal of Transportation Research Board*, 1974, 18–25.

Yu, J., Chou, E. Y. J., and Luo, Z. (2007). Development of Linear Mixed Effects Models for Predicting Individual Pavement Conditions. *Journal of Transportation Engineering*, 133(6), 347–354.

Zeb, J., Froese, T., and Vanier, D. (2013). Infrastructure Management Process Maturity Model: Development and Testing. *Journal of Sustainable Development*, 6(11), 1-15.

Zhang, H., Keoleian, G. A., and Lepech, M. D. (2013). Network-Level Pavement Asset Management System Integrated with Life-Cycle Analysis and Life-Cycle Optimization. *Journal of Infrastructure Systems*, 19(1), 99–107.

Zimmerman, K. A. (1995). *Pavement Management Methodologies to Select Projects and Recommend Preservation Treatments.* Transportation Research Board, National Research Council, Washington, D.C., USA.