Road Management Systems to Support Bicycling: A Case Study of Montreal's Bike Network

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ABSTRACT

Bicycling is a sustainable mode of transportation given its health benefits, reduced air and noise pollution, savings in fuel consumption, and role in shifting demand away from the automobile. A significant increase of bicycle users is an aim of many cities around the world. Responding to this, various cities announced their strategies to extend and/or upgrade their bikeway networks. However, there is a disconnection between the strategies to support bicycles and road management systems, which are typically used for optimal scheduling of maintenance and interventions for roads' infrastructure. Traditional road management systems consider neither the need to sustain bicycle pathways at good levels of service, nor consider bicycling demand to prioritize their selection. This thesis extends road management systems to support bicycling networks. This enables the ability to optimally allocate available resources for sustaining the surface of bicycle pathways in good condition, and implement physically-separated bicycle lanes to enhance safety conditions and encourage bicycle ridership. A simple formulation of bicycle demand is proposed; it employs the capabilities of smartphones for collecting and estimating bicycling demand based on GPS trajectories of cyclists. Goal programming optimization is applied to address scheduling of maintenance and upgrade investments of pathways. Two scenarios are investigated with different annual budgets. The results show that the first scenario allows a rapid upgrade of existing bicycle lanes to protected paths while accomplishing good conditions of pavements. However, the second scenario is not able to prevent the deterioration of pavement segments.

DEDICATION

To my father, mother, sisters and beloved wife: Farah

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LIST OF ABBREVIATIONS

AADB	Annual Average Daily Bicycle
AASHTO	American Association of State Highways and Officials
AMF	Asset Management Framework
BF	Best-first Strategy
BLOS	Bicycle Level of Service
ESAL	Equivalent Single-Axle Load
FDOT	Florida Department of Transportation
FHWA	Federal Highway Administration
GIS	Geographic Information System
GPS	Global Positioning System
ILP	Integer Linear Programming
IRI	International Roughness Index
LOS	Level of Service
M&R	Maintenance and Rehabilitation
OPT	Optimization-based Strategy
PMS	Pavement Management System
PPP	Pavement Performance Prediction
THR	Threshold-based Strategy
WF	Worst-first Strategy

Chapter 1: Introduction

1.1 Background

Bicycling is healthy, environmentally friendly, and affordable solution to crowded transit and congested streets in urban areas. Recently, with the rapid increase of bicycle users since people have become more environmentally and health conscious, bicycle is being regarded as a key component of a sustainable transportation system, rather than just a supporting transportation option. Responding to this change, development and improvement of bicycle networks are now planned in several cities around the world.

Cyclists can utilize various types of roads from cycle tracks to narrow streets because of their size and flexibility. However, bicycle networks that are safe, consistent, immediate, well-connected, and convenient encourage people to consider bicycling as a daily commuting option rather than just for recreational purposes. Bicycling facilities are typically chosen based on vehicular traffic, level of bicycling in area, and cost. The main difference between many types of bicycling infrastructure is whether they are separated or shared with other road users; pedestrians and/or vehicles. In this context, there are many various designations of bicycling infrastructure including singed bicycle routes (also called sharrows); bicycle lanes, cycle tracks (i.e. physically separated bicycle paths), and off-street bicycle facilities.

Across Canada, bicycling is growing in popularity in urban areas and some suburbs. However, not all Canadian cities are investing in bicycling infrastructure to the same degree, particularly when it comes to creating separated lanes and other measures that improve safety and attract new cyclists (Vijayakumar and Burda, 2015). Among five large Canadian cities (Toronto, Montreal, Vancouver, Calgary, and Ottawa), Montreal has most separated bicycling lanes; around 70 kilometres of separated bicycling facilities across the island. Montreal's bicycling infrastructure has increased from 400 km in 2009 to 648 km in 2015; which represents a growth of 162% (Vijayakumar and Burda, 2015). However, Montreal has the highest crash rate among these cities, with seven crashes for every 100,000 bicycling trips (Vijayakumar and Burda, 2015).

In 2017, The City of Montreal announced its commitment to increase the bicycling mode share up to 15% in the coming 15 years, which requires investing $150 million over the first five-year period (Ville de Montréal, 2017). Although the City has been extending the bicycle network covering most of the Island of Montreal, better infrastructure are still required.

Thus, the city has been giving greater attention to the quality of bicycle facilities, especially to the construction of new protected bicycling corridors, in line with the vision of the city at minimizing the serious or fatal traffic accidents until reaching a target of zero (Ville de Montréal, 2017).

Consequently, there is a need to develop a cost-effective decision making procedure to optimal allocation of the available budgets for maintenance and rehabilitation (M&R) interventions and improvement treatments. This procedure should be able to evaluate benefits, economic cost, and associated impacts on bicycling demand, vehicular traffic, environment and society. These projects include repair, upgrade or extend the existing bicycling infrastructure.

1.2 Problem Statement

Many travel plans and strategies associated with transportation impact assessment do recommend supporting bicycling in addition to walking and using transit. Modern Transportation Master Plans contain specific strategies to develop or improve their bicycle networks. However there is a disconnection between them and traditional Asset Management Framework (AMF), often used for optimal scheduling of maintenance and interventions of road infrastructure. Road Management Systems do not explicitly take into consideration the need to sustain shared bicycle paths in good level or surface condition, but most importantly to consider bicycling demand and to encourage more individuals to shift daily commuting to bicycling by providing more convenient, compatible, and safe bicycling facilities, such as separated bicycle lanes, and fully protected bicycling lanes.

1.3 Research Objective

1.3.1 Overall Goal

The overall goal of this research is to propose a decision-making model that is able to allocate the investments to encourage more bicycle riders in the city by considering existing bicycling demand and road condition.

1.3.2 Research Tasks

Two tasks were identified to address the main goal of this research:

Task 1

The motivation of this task is to address the need to take into consideration the maintenance of existing bikeway network. This task will adapt the concepts of traditional pavement management systems. Firstly, Pavement Performance Prediction (PPP) models for bicycle lanes. Such models will be developed based on historical data of pavement surface condition of roads with low traffic load intensity. Moreover, this task will utilize the capabilities of smartphones in collecting pavement surface condition data via built-in accelerometers as done by others before. This task will apply classical linear integer programming to find the optimal selection of intervention and improvement investments given a predetermined annual budget.

Task 2

This task is motivated by the very important need to establish strategies that encourage bicycling as a sustainable mode of transportation, particularly in congested cities, through providing more convenient, compatible, and safe bicycling facilities. This task will introduce an integrated approach by extending traditional road management systems to consider different designations of bicycling facilities. This task will also estimate existing bicycling demand over the network based on cyclists' trip data collected through built-in GPS systems in smartphones. Goal optimization will be applied to deal with conflicting objectives pursuing a trade-off analysis between cost of treatments, road condition, and bicycling rates.

1.4 Scope and Limitations

The scope of this research is limited to applications in road infrastructure management. Only on-street bicycling facilities are considered; off-street facilities, mixed-use trails and on-curb paths are excluded. Optimization is conducted based on pavement surface condition and estimated existing bicycling usage; no considerations are given to structural strength of pavement, vehicular traffic flow, and environmental impact. Moreover, beside the bicycling infrastructure, other factors influencing the bicycling demand including employment rate, land use, bike sharing stations, and social characteristics of urban zones are not considered. Different scenarios are needed to be investigated; pessimistic, optimistic and most probable.

The data required for this research including digital representations of road and bicycle networks, pavement surface condition, GPS trip data are provided by the City of Montreal, except pavement surface condition for *Plateau-Mont-Royal* borough. The latest was collected via smartphones in winter 2017. The pavement was frozen during the data collection which might affect the reliability of condition data.

1.5 Research Significance

This thesis adapts traditional road management methods for bicycle networks. Such adaptation enables not only the ability to allocate resources for sustaining the surface condition of bicycle paths in good condition, but most importantly to implement bicycle pathways that are separated from other road users through physical barriers. Separated bicycle pathways provide more convenient and safe conditions for cyclists, and minimize the interaction with motorized traffic along network segments. This is expected to enhance the safety along network segments through reducing the likelihood of vehicle-bicycle collisions and conflicts, and increase the level of service through reducing the delay induced by the interruption of motorized traffic.

Moreover, such improvement is expected to attract more bicycle riders and therefore accomplishing a larger modal shift encouraging healthier active transportation for people, particularly in congested areas such as in downtown areas. This in turn results in reduced traffic related emissions and noise pollution, and even less congestion for those requiring the use of motorized modes (courier delivery, service vehicles, goods delivery, emergency vehicles, and aged population and/or people with reduced mobility).

1.6 Organization of the Thesis

This thesis is presented in five chapters as follows: Chapter 1 defines the problem and presents the objectives of the research and structure of the thesis. Chapter 2 contains a review of the state of practice in pavement management system and bicycle travel demand modeling: traditional strategic planning approaches and data collection methods are discussed. Traditional management methods are criticized for the lack of bicycling usage considerations. The impact of surface quality and different designations of bicycling facilities on behavior of cyclists is highlighted. Chapter 3 presents the methodology employed to obtain coordinated strategic plans considering the bicycle demand. Chapter 4 presents the work under Task 1 of the research. A case study illustrates the results of long-term strategic analysis of on-street bicycle lanes, and utilize the capabilities of smartphones in collecting surface condition data of pavements. Chapter 5 presents the work covered under Task 2. This chapter is devoted to incorporate bicycling considerations in a road management system. The chapter demonstrates how bicycle counts can be integrated into a multi-criteria decision making procedure to maximize pavement condition, and encourage bicycling among individuals. Chapter 6 presents the conclusions and lessons learnt from the modeling experience, and make recommendations for future research.

The work described in Chapters 4, and 5 have been written as self-contained papers and as such, each chapter has its own abstract. Chapter 4 has been submitted for publication while Chapter 5 will be submitted soon, as follows:

Chapter 4: Elsaid, F., Amador-Jimenez, L., and Alecsandru, C. (2018). Pavement Management System for On-Street Bicycle Network: Plateau-Mont Royal, Montréal. *International Journal of Sustainable Transportation*. Submitted.

Chapter 5: Elsaid, F., Amador-Jimenez, L., and Alecsandru, C. (2018). Towards Convenient Bikeway Networks: Incorporating Bicycling Demand into Road Management Systems.

Chapter 2: Literature Review

2.1 Introduction

The goal of this chapter is to establish the need for a better management system including coordinated planning of Maintenance and Rehabilitation (M&R) actions and considerations of bicycling demand and behaviour.

The chapter is divided in two major sections: the first one (Section 2.2) provides a review of the state of the practice in pavement management systems. This is accomplish by reviewing pavement-condition data collection and evaluation methods, pavement performance prediction models, and optimization approaches of M&R activities at the network-level. The second part (Section 2.3) highlights the impact of bicycling facilities on bicycling travel demand and behaviour of cyclists. This section also provides a review of the development of various methods and the utilization of technologies in conducting travel surveys to understand the current and predict the future demand.

2.2 Pavement Management System

The objective of any Pavement Management System (PMS) is to best utilize the available funding to improve or preserve the roadway pavement. A PMS determines the best point through the life cycle of each pavement section to apply a given maintenance treatment. This strategy aims at maintaining existing pavements in good condition, and keeping the number of roads in poor condition at a minimum. A PMS consists of two essential components: a comprehensive database and a set of tools and optimization techniques to assist policy makers in establishing cost-effective strategies for the evaluation and maintenance of roadway pavement. The database should contain comprehensive information on historical and current road condition (functional and structural), pavement structure (pavement type, number and thickness of layers, etc.), traffic and environmental information. The set of tools and optimization methods help in determining the current and future conditions of roadway segments, estimating necessary financial resources, identifying most cost-effective maintenance treatments, and prioritizing roadway segments for rehabilitation projects.

A PMS addresses questions about which pavement section to treat, which type of treatment to apply, and when this treatment must be applied. PMS must integrate three management levels that vary in terms of information detail and complexity of used models in decision making process: strategic, network and project level. At the network level, the primary purpose is the design of the network maintenance program given overall budget constraints (Torres-Machí, Chamorro, Videla, Pellicer, and Yepes, 2014).

The key elements of an optimization model include pavement deterioration model, maintenance decision making process, cost of M&R actions cost, available budget, functional classification of the roadways, and cost-factor associated with the maintenance treatment type. The system ensures that the overall condition of roadway network is maximized considering other significant factors such as traffic demand and environmental impact. The road maintenance in PMS is a multi-objective optimization problem for several reasons (Saha and Ksaibati, 2017). These reasons are: (1) the objective of engineers or decision makers is to maximize the overall condition of road network under specific budget limitations; (2) preventive and minor rehabilitation treatments are more cost-effective than reconstruction; (3) budget should be more than a certain amount to achieve maximum benefit to society; and (4) the best mix of roadway segments for rehabilitation should include the segments with high traffic volume.

2.2.1 International Roughness Index

Smoothness is a measure of the level of comfort experienced by the traveling public while riding over a pavement surface (FHWA, 2016). Smoothness is used interchangeably with roughness as an important indicator of pavement performance and user satisfaction. Smoothness also relates to other benefits including reduced fuel consumption and vehicle maintenance cost (Dam *et al.*, 2015; Zaabar and Chatti, 2014).

In the 1970s the World Bank supported several wide-ranging projects aimed at proposing cost effective maintenance actions for roadway pavements. The roughness of pavement surface emerged as a key indicator for the costs, such as damage to vehicles, associated with using roadway pavements. The International Roughness Index (IRI) was proposed by the World Bank in Brazil as a standard to correlate and to calibrate pavement surface roughness measurements (Sayers, Gillespie, and Queiroz, 1986). The IRI measures the cumulative movement of suspension in a vehicle traversing a specific distance, and is expressed in units of slope (m/km, in/mi, mm/m etc.). The IRI quantifies the vehicle vibrations resulted from the pavement surface and is linearly proportional to roadway roughness (Park, Thomas, and Wayne Lee, 2007). The flatter of pavement surface the lower measured IRI value; an IRI of 0.0 (m/km) represents a perfectly flat paved road. Though there is no theoretical upper limit on IRI, values above 8 (m/km) practically reflect pavements almost impassible by vehicle at regular speed (Park *et al.*, 2007). A proper pavement surface condition is necessary for reducing dynamic load on vehicle and pavement, and it ensures ride safety and comfort, worldwide, the IRI is the most commonly used index to characterize longitudinal road roughness for managing road systems (Múčka, 2017). The IRI is also implemented in American Society for Testing and Materials (ASTM) E1926-08. The IRI is usually used as a pavement condition performance measure in PMS and in the transportation engineering community (Múčka, 2017).

2.2.2 Measurement of IRI

The several approaches used worldwide for measuring road roughness can be grouped into four generic classes based on how directly their measurements are related to the IRI (Sayers *et al.*, 1986). Class 1 "Precision profiles" provides the most accurate measurement of IRI (Sayers *et al.*, 1986). In this approach, the longitudinal profile of a wheel path is measured as a series of elevation points along the travelled wheel path. Class I includes laser profilers (noncontact lightweight profiling devices and portable laser profilers) and manually operated devices (Dipstick, Walking Profiler) (Múčka, 2017).

The newer devices are equipped with onboard computers for digital analysis, non-contacting height sensors, and software that allows a variable measurement speed. (Múčka, 2017). The measuring wheels have been replaced by non-contacting sensors in modern profilers. These sensors measure the height using more technologically-advanced approaches such as ultrasound, laser beams, and optical images (Perera and Kohn, 2005). According to Múčka (2017), the current most common used equipment for measuring IRI are as follows:

- Inertial profilers
    - High-speed inertial profilers
    - Lightweight inertial profilers
- Inclinometer-based devices (Walking Profiler, Dipstick)

Inertial profilers are vehicle-mounted instrumentation systems that measure vertical deviations of pavement surface along the direction of travel. High-speed inertial profilers are capable of taking measurements at highway speeds and are appropriate for testing long sections of pavement. Modern version of high-speed inertial profilers empowered by laser height sensors are currently prevailed for IRI measurements, shown in Figure 2.1. Lightweight profilers are ideal for testing new pavements, shown in Figure 2.2. Walking profiler is operated manually and can be used at speed up to 5 km/h., and it includes high-resolution incline and position sensors (Múčka, 2017), shown in Figure 2.3. American Association of State Highway and Transportation Officials (AASHTO) standard R 43M/R 43-07 and the ASTM standard E1926 provide standardized methods to compute the IRI. However, for large roadway networks, it is a costly and time-consuming process to collect the necessary data (Patrick and Soliman, 2018).

Figure 2.1 Model 8300: Portable High Speed Profiler (source: amesengineering.com)

Figure 2.2 Model 6200: Lightweight Profiler (source: amesengineering.com)

Figure 2.3 Walking Profiler G3 (source: arrbgroup.net)

2.2.3 Pavement Performance Prediction Models

The pavement performance prediction process involves predicting future pavement conditions under specified traffic loading and environmental conditions (Kulkarni and Miller, 2003). The appropriate and effective pavement performance models are essential for the long-range evaluation process of PMS (Amin and Amador-Jiménez, 2014). The pavement performance prediction (PPP) models aims at estimating the future condition of pavement, both structural and functional. PPP models play a significant role in PMS. They are used in the prioritization of rehabilitation and maintenance actions of road segments in the network; they are used in estimating long-term required investment (budget) during the life-span of the pavement and the consequences of budget allocation for maintenance treatments of a particular road segment on the future pavement condition of that road segment (Amin and Amador-Jiménez, 2014). Early PMS did not have prediction models and the pavement evaluation was based only on the current pavement conditions; any consideration of future pavement conditions was implicit. Later, simplified prediction models, based on the judgment of experts of the expected life-span of different rehabilitation and maintenance actions, were proposed. These models considered the age of pavement as the only predictive variable (Kulkarni and

Miller, 2003). The current PPP models use either deterministic or probabilistic approaches to characterize pavement performance (Mills, Attoh-Okine, and McNeil, 2012).

Deterministic models include empirical, mechanistic, or mechanistic–empirical methods. Empirical models are based on the analysis of time series pavement condition data implicitly considering the impact of different environmental and loading conditions. Mechanistic models involve interactions between traffic loading and pavement strength parameters and between loading and pavement deflections. Mechanistic–empirical models are developed by using regression approaches and pavement responses as dependent variables. These models incorporate time series condition data and interactions between loading and pavement deflections. Empirical models can be reliable for the regions that they are developed for, but they are difficult to be used in other regions that have different traffic and environmental conditions. Mechanistic models need input data from extensive laboratory testing or precise field measurements or both, which is not always practical for planning agencies (Mills *et al.*, 2012).

In probabilistic approaches, the future pavement condition is predicted typically by using stochastic models such as the Markov model (Abaza, 2016; Hong and Wang, 2003; Lethanh and Adey, 2013; Wang, Zaniewski, and Way, 1994). In the Markov model, a transition probability matrix is defined that specifies the probability that a pavement remains in its current condition state or changes to another one in the future. Therefore, the major challenge is to establish a transition probability matrices (TPMs) (Amin and Amador-Jiménez, 2014).

The performance of pavement is significantly influenced by several environmental and load-related factors and their interactions. Most highway agencies express the pavement condition, which is the dependent variable in PPP models, as a numeric value either as an index or a rating. The initial selection of independent variables is based on experience. The prediction of the pavement significantly depends on the following factors: the age of the pavement, traffic volume and load, thickness of last overlay, strength and condition of pavement structure; environmental conditions; and the construction quality. Of all these factors, research suggests that the age of a pavement plays a key role in predicting pavement deterioration (George, Rajagopal, and Lim, 1989). Age is expected to be a good predictor as it can be determined precisely for any pavement while other factors can be more difficult to quantify.

2.2.4 Network-Level Pavement Maintenance Strategies

The widespread pavement M&R strategies are categorized into: worst-first (WF), best-first (BF), threshold-based (THR), and optimization-based (OPT) strategies. (Chu and Huang, 2018) briefly defined these strategies as follows:

- BF strategy: The pavement segments are sorted according to their conditions. The pavement sections in good condition are maintained before the ones in poor condition. The maintenance process continue covering as many pavement segments as possible until the budget is completely spent. The incentive of this strategy is to conduct preventive maintenance to sustain pavement segments in good condition before they deteriorate to poor condition, which requires intensive maintenance actions. However, BF strategies are rarely studied in the literature.
- WF strategy: In the WF strategy, the pavement segments are sorted according to their conditions. The pavement sections in poor condition are maintained before the ones in good condition. The maintenance process continue covering as many pavement segments as possible until the budget is completely spent. The advantage of this strategy is that it is easy to implement.
- THR strategy: In THR strategy, a pavement receives maintenance treatment when its condition reaches a predetermined threshold. In practice, the strategy fits the workflow of transportation agencies well and is therefore widely adopted (Chu and Huang, 2018). However, the maintenance thresholds are often derived on the basis of engineering judgment (Khurshid, Irfan, and Labi, 2011). THR strategy has been studied for a single facility problem and for system-level problem (Chu and Chen, 2012; Gu, Ouyang, and Madanat, 2012; Hajibabai, Bai, and Ouyang, 2014; Lee and Madanat, 2014; Lee, Madanat, and Reger, 2016; Ouyang and Madanat, 2006; Sathaye and Madanat, 2011, 2012).
- OPT strategy: The OPT strategy is defined as using optimization methods to generate optimal or near-optimal maintenance long-term plans for pavements. Several studies have adopted this strategy (Lee and Madanat, 2015; Zhang, Fu, Gu, Ouyang, and Hu, 2017). These optimization approaches usually provide detailed plans of the types and magnitudes of maintenance actions for each pavement segment in each time period. The advantage of the strategy is that pavement segment conditions and the efficiency of budget allocation are optimized.

The optimization of pavement maintenance is frequently conducted under the OPT and THR strategies. A variety of methods have been proposed for the OPT and THR strategies. The main assumptions adopted in these optimization models include facility- and network-level, continuous- and discrete-time, continuous- and discrete-condition state, Markovian- and non-Markovian deterioration, and the set of available M&R actions (Chu and Huang, 2018). Optimization approaches seek an allocation that minimizes costs (or maximizes benefits) within the constraints of good levels of service (or budget) over the whole network for the long term (Faghih-Imani and Amador-Jimenez, 2013).

Various approaches for network-level optimization of M&R actions have been proposed in recent years. Two major classes of optimization approaches have been used in PMS; mathematical and near optimization approaches. Mathematical optimization approaches select alternatives to maximize or minimize a predefined objective function while satisfying given constraints. Objective functions can include technical, economic, and social objectives such as maintenance costs, vehicle operating costs, and effectiveness. Most commonly used mathematical optimization methods for pavement management are linear, nonlinear, integer, and dynamic programming (Harvey, 2012). Linear and nonlinear programming seek optimal solutions using continuous variables. The main difference between the two approaches is that the former considers linear functions correlated with time, while the latter may consider curvilinear dependency. Integer programming simplifies the analysis by considering only two variables in the model: a do nothing alternative or do something. Dynamic programming is used when a number of sequential decisions are required. This optimization approach begins at the desired final solution and works backwards to find optimal values of variables. Near optimization methods, also called heuristic methods, provide solutions that are close approximations to those derived from mathematical optimization. These optimization methods start with an initial solution and search for better solutions within the constraints. Although there are global search and local search methods, applications in PMS often involve global search heuristics (usually population based), such as genetic algorithms (GAs), particle swarm optimization, ant colony optimization, and evolutionary programming (France-Mensah and O'Brien, 2018). A sample of studies are shown in Table 2.1.

Haas and Huot (1998) proposed an approach to multiyear optimization programming for M&R actions in pavement network management. The effects of various treatments were defined in terms of costs, benefits, and performance impacts on the existing pavements. The treatments range from minor and routine maintenance to major rehabilitation or reconstruction. The study proposed a cost-effectiveness-based integer programming for the preservation of deteriorated pavements in a road network with the constraints of budget limitations and a required pavement serviceability level. The objective of the proposed approach is to select the most effective M&R projects for each year. This procedure can also be used to calculate the minimum budget requirements for maintaining a prescribed level of the pavement network performance or serviceability.

Table 2.1 Selected studies on optimization approaches used in PMS

Optimization method	
Linear programming	(Amador-Jiménez and Mrawira, 2009; Davis and Van Dine, 1988; de la Garza, Akyildiz, Bish, and Krueger, 2011; Gao, Xie, Zhang, and Waller, 2012; Grivas, Ravirala, and Schultz, 1993)
Nonlinear programming	(Abaza, Ashur, and Al-Khatib, 2004; Abaza and Ashur, 1999; Gao and Zhang, 2008; Wu and Flintsch, 2009)
Integer programming	(Faghih-Imani and Amador-Jimenez, 2013; Ferreira, Antunes, and Picado-Santos, 2002; Li *et al.*, 1998; Ng, Zhang, and Travis Waller, 2011; Wang, Zhang, and Machemehl, 2003)
Dynamic programming	(Farhan and Fwa, 2012; Feighan, Shahin, Sinha, and White, 1989; Fwa and Farhan, 2012; Yoo and Garcia-Diaz, 2008)
Genetic Algorithms (GA)	(Chootinan, Chen, Horrocks, and Bolling, 2006; Elhadidy, Elbeltagi, and Ammar, 2015; Farhan and Fwa, 2012, 2016; Fwa and Farhan, 2012; Fwa, Tan, and Chan, 1994; Jorge and Ferreira, 2012; Maji and Jha, 2007; Marecos, Fontul, de Lurdes Antunes, and Solla, 2017; Moreira, Fwa, Oliveira, and Costa, 2017; Pilson, Hudson, and Anderson, 1999)

Faghih-Imani and Amador-Jimenez (2013) considered the environmental impacts resulting from M&R actions into strategic planning of pavement sections at network-level. The energy use of such activities and resulting greenhouse gas emissions are explicitly considered. The study followed a three-step procedure to identify the required mean annual budget necessary to achieve target levels of service (e.g. the IRI) process: (1) finding the minimum requirement for the annual budget, (2) maximizing pavement condition, and (3) reducing environmental impacts.

2.3 Bicycle Travel Demand Modeling

2.3.1 The Impact of Bicycle Facilities on Bicycling

Most researchers concluded a positive relationship between the development of bikeway network and bicycling levels (Buehler and Dill, 2016). The bikeway network is composed of links and nodes (intersections). The bicycling links are either shared with motorized traffic or separated. Several interventions are done to accommodate bicycling along with motorized traffic. These interventions include signed routes, extra-wide road travel lanes or shoulders, markings on roadways (sharrows), streets that give priority to cyclists, and traffic calming zones that reduce traffic speed and volume. While separated bicycling pathways are classified into three categories: bike lanes, cycle tracks and bike paths. Bike lanes are separated from motorized traffic by painted lines on the roadway and they are typically located between motorized travel lanes and car parking or the sidewalk. Cycle tracks are physically separated from motorized traffic by a curb or concrete barriers. They are also known as protected or separated bike lanes; they keep cyclists protected from vehicles. Bike paths are also physically separated from motorized traffic but typically run through parks away from the road network. Several studies found a positive relationship between bicycling rates and the presence of bike lanes (Buehler and Pucher, 2012; Dill and Carr, 2003; Goodno, McNeil, Parks, and Dock, 2013). Figures 2.4 and 2.5 illustrate possible configurations of bicycle lanes and cycle tracks.

Dill and Carr (2003) conducted an aggregate study across 42 large US cities (with population more than 250,000) and found that approximately 1% increase in bicycling rates is associated with each additional linear mile of bike lanes per square mile land area.

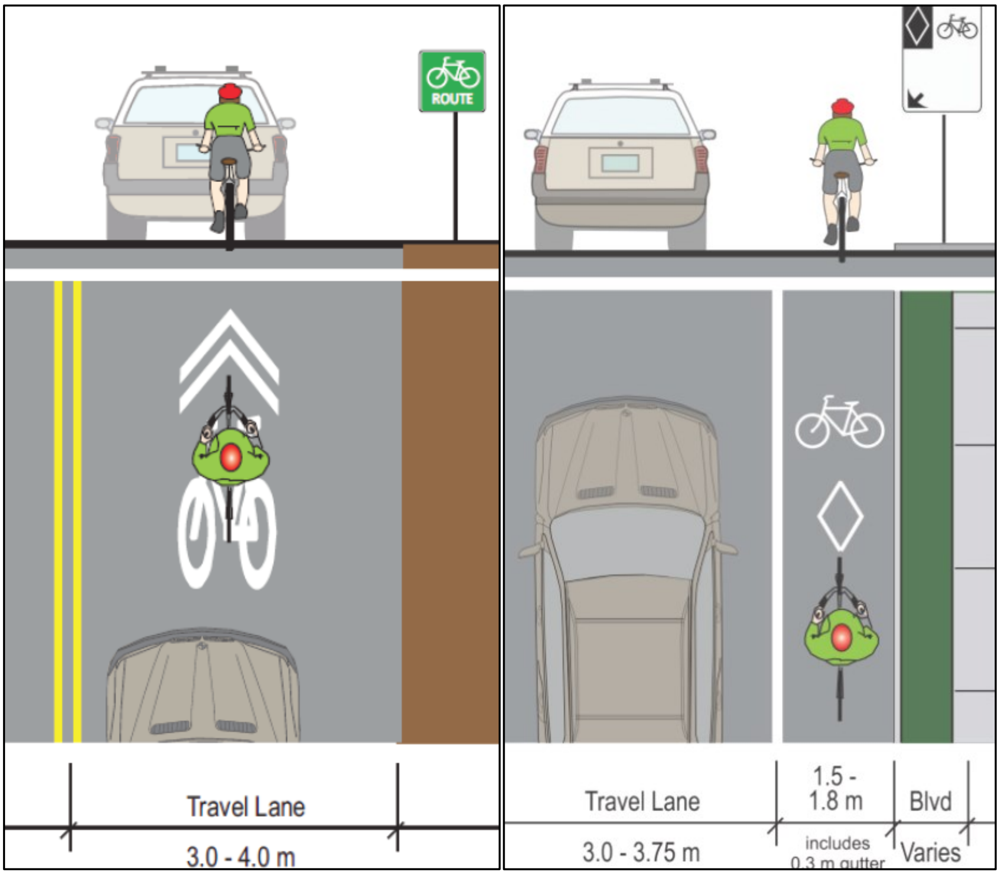


Figure 2.4 Shared singed route (left) and Bicycle lane (right) (source: Ontario Traffic Manual 2013)

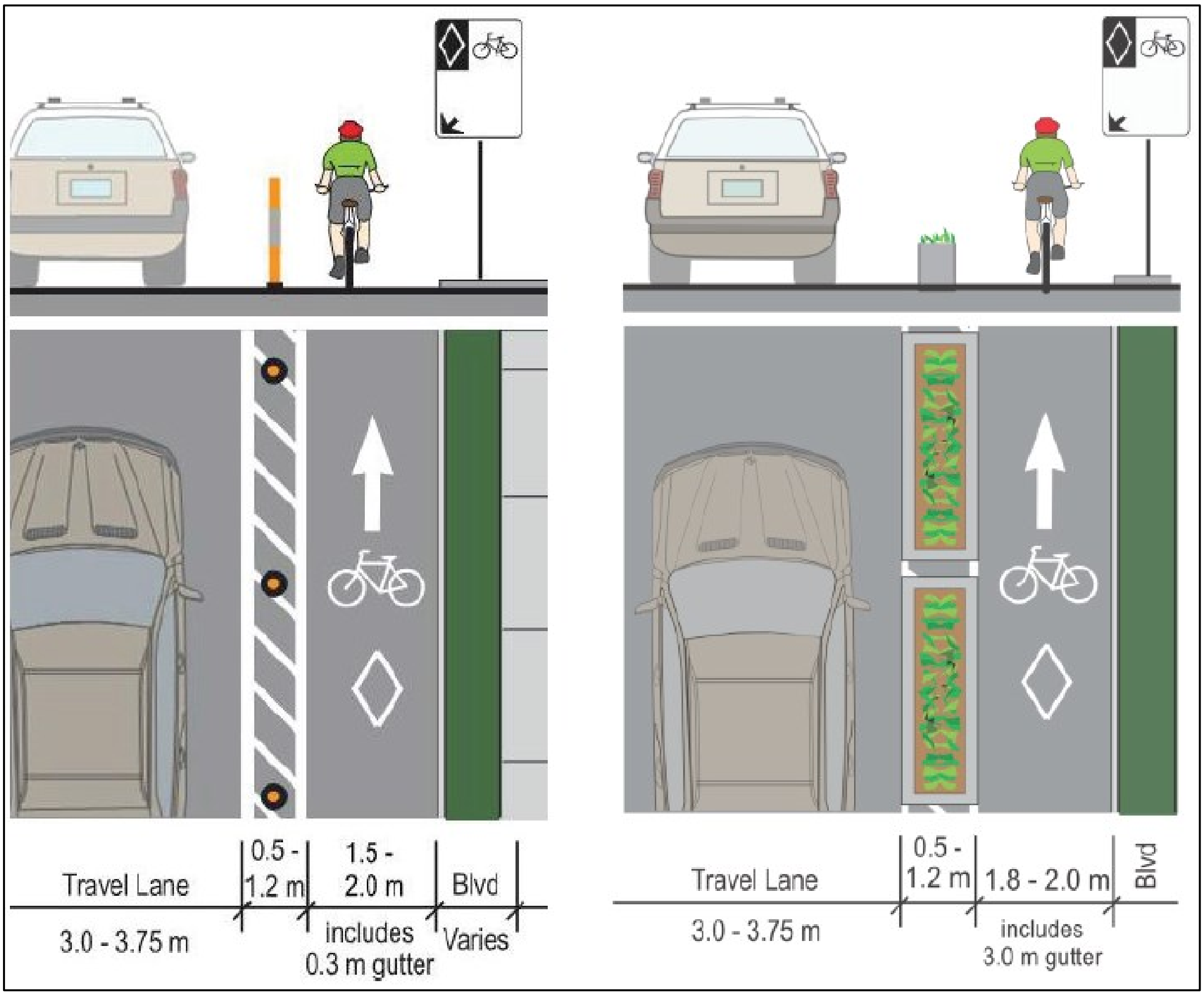


Figure 2.5 Cycle tracks separated with bollards (left); separated with median (right) (source: Ontario Traffic Manual 2013)

Buehler and Pucher (2012) studied the influence of bike paths and lanes on commuting using bicycle based on a dataset contains the length of bike lanes and paths in 2008 collected from 90 large cities in US. The statistical analysis confirmed that cities with a greater supply of both bicycling facilities, both bicycle paths (cycle tracks) and bicycle lanes, have significantly higher bike commute rates even when controlling for other factors. The findings show that 10% greater supply of bicycle lanes is associated with a 3.1% greater number of bike commuters per 10,000 population. Similarly, a 10% greater supply of bike paths is associated with a 2.5% higher level of bike commuting. Among several factors that influence the preferences of cyclists, safety is considered to be significant. Stated-preference studies showed that bike lanes, trails and paths would encourage cyclists and non-cyclists to bike more often as they feel safer (Akar and Clifton, 2009; Landis, Vattikuti, and Brannick, 1997; Monsere *et al.*, 2014; Sener, Eluru, and Bhat, 2009). Nearly 2 in 3 residents across five cities in the US stated their potentiality to bike if bicycle and motorized traffic were physically separated (Monsere *et al.*, 2014).

Landis *et al.* (1997) compared two road segments that are similar with all geometric aspects except that one had a striped bike lane while the other had an unstriped wide outside lane. They found that the corresponding Bicycle Level of Service (BLOS) score of striped bike lane was 50 percent higher than the unstriped even though it had a traffic volume as twice as the unstriped segment. (Sener *et al.*, 2009) conducted a survey that included 1605 individuals across 100 cities in Texas, US to collect detailed information on perceptions of bicyclists. The results showed that commuters found it dangerous to ride in the presence of an unsigned shared roadway. Furthermore, three revealed-preference studies from Copenhagen, Washington, DC, and five US cities found an increase in bicycling levels after the installation of cycle tracks (Goodno *et al.*, 2013; Monsere *et al.*, 2014; Snizek, Nielsen, and Skov-Petersen, 2013).

Lusk *et al.* (2011) studied six cycle tracks (two-way protected bicycle lanes on one side of the street) in Montreal. They compared each cycle track with one or two reference streets without bicycle facilities that were considered alternative bicycling routes. The study found that the cycle tracks were much highly used, 2.5 times (250 % increase in ridership), compared with reference streets, and the risk injury was lower in the cycle tracks.

Several studies investigated the effect of installing separated on-street bicycle infrastructure (cycle tracks or bicycle lanes) on average daily bicycle volumes (Goodno, McNeil, Parks, and Dock, 2013; Monsere *et al.*, 2014; Parker *et al.*, 2013; Parker, Gustat, and Rice, 2011). These studies are summarized in Table 2.2.

Goodno *et al.* (2013) concluded that the bicycle volume roughly quadrupled after the installation of a two-way cycle track, well above the average in the city, and the BLOS was also improved. Monsere *et al.* (2014) studied the effect of installing cycle tracks (protected bicycle lanes) in five cities: Austin, TX; Chicago, IL; Portland, OR; San Francisco, CA; and Washington, D.C in terms of use, perception benefits and impacts, using video, surveys of intercepted bicyclists (n=1,111) and nearby residents (n=2,283), and count data. City database containing counts before and after installation of protected bicycle lanes, along with counts extracted from video observation, were used to analyze change in ridership. They observed a measured increase in ridership ranging from 21% to 171% on all facilities. The increases were greater than overall increases in bicycle commuting in each city. Some of the increase in ridership at each facility likely came from new riders (i.e. riders who, in the absent of the protected bike lane, would have travelled using a different mode or would not have taken the trip) and some from riders diverted from other nearby streets (i.e. riders who were attracted to the route because of the facility, but would have chosen to ride a bicycle for that trip regardless). The study also conducted a stated-preference survey which showed that 10% of the riders shifted from other modes, and 24% switched from other bicycle routes. An increase in the frequency of biking on the installed protected lanes was reported by over a quarter of respondents. A strong support for building protected bicycle lanes at other locations was also reported by 75% of the residents. Approximately 67% of surveyed residents expressed their intention to ride a bicycle if motorized traffic and bicycles were physically separated by a barrier.

Parker, Gustat, and Rice (2011) studied the impact of the installation of the first on-street bicycle lane (3.1 mile dedicated bike lane) in New Orleans, LA during the spring of 2008. The number of cyclists riding on St. Claude Avenue was counted in November of 2007 (before the installation) and again in November 2008 (after the installation). Data were collected for 10 days in 2017: 8 weekdays and 2 weekend days, and 14 days in 2008: 10 weekdays and 4 weekend days. Cyclists were observed over a 9-hour period from 8 AM to 5 PM. The results show an increase in the mean number of cyclists observed per day from 90.0 to 142.5 (58.33%). There was a 133% increase in the average daily number of women riders and a 44% increase in the average number of male riders. The observations were made 6 months after the installation, which reflected a real increase in bicycling observed rather than a temporary one.

Parker *et al.* (2013) similarly studied the impact of installing 1-mile dedicated bike lane on S. Carrollton Avenue in New Orleans, LA in 2010. This study examined the impact through direct observation of one street with a new bike lane and two adjacent streets without bike lanes, before and after the installation. The study found an increase in the average daily number of cyclists after the installation of the bike lane from 79.2 to 257.1 (224.62%), but a reduction on the two adjacent streets from 54.4 to 36.4 (-33.09%). The study concluded that more people rode in the overall neighborhood after the lanes were striped; however, the increase in cyclists was greatest on the street with the new bike lane. The decrease in cyclists on the side streets suggests that few of those cyclists may have started using the dedicated bike lane.

Table 2.2 Summary of studies on the installation of separated bicycle lanes

Year	Intervention	Observed increase in average daily bicycle volume	Location	Reference
2011	Bicycle lane	58.33%	New Orleans, LA	(Parker, Gustat, and Rice, 2011)
2013	Bicycle lane	224.62%	New Orleans, LA	(Parker *et al.*, 2013)
2013	Cycle track	Roughly 400%	Washington, D.C	(Goodno, McNeil, Parks, and Dock, 2013)
2014	Cycle track	21% to 171%	Austin, TX; Chicago, IL; Portland, OR; San Francisco, CA; and Washington, D.C	(Monsere *et al.*, 2014)

2.3.2 The Impact of Pavement Surface Quality on Bicycling

Antonakos (1994) studied the environmental and travel preferences of cyclists through distributing a questionnaire to 552 cyclists at four recreational bicycle tours in Michigan. In the questionnaire, cyclists rated their preferences for different types of bicycling corridors using a five-point scale ranging from 1 (not at all preferred) to 5 (very preferred). Smooth pavement surface, among other factors, was reported to be an important factor for choosing bicycling routes with average ratings of 3.8 and 4.1 reported for commuting and recreational purposes, respectively.

Stinson and Bhat (2003) evaluated the importance of 11 factors affecting commuter cyclists' route choice decision making process, using data from a stated preference survey. Factors at both route-level (e.g. travel time and number of stop signs per mile) and link-level (e.g. roadway class and riding surface) are investigated. The quality of riding surface was included and categorized into three types: rough pavement, smooth pavement, and coarse sand surface. A binary logit model was used in the route choice analysis to estimate the main and interaction effects of included variables. The study also included a comprehensive exploration of interactions of the route attributes with cyclists' characteristics (including demographics, residential location, and experience in bicycling). The final model results showed a clear preference among cyclists for a smooth pavement surface over rough and coarse sand surfaces. This preference for smooth riding surface is found to be stronger among older individuals who are more comfort-conscious.

Kang and Fricker (2013) conducted a study aims at identifying the factors that explain a bicyclist's choice between available facilities; off-street (sidewalk and bicycle path) or on-street (bicycle lane and roadway). The study used revealed preference cross-section choice data collected through intercept surveys of 178 bicyclists heading to Purdue University, West Lafayette, Indiana, USA during fall semesters of years 2006-2008. A mixed logit model was used to analyze the preferences of bicyclists and capture the unobserved heterogeneity across the population. The results showed that effective sidewalk width, traffic signals, segment length, road functional class, street pavement condition, and one-way street configuration were found to be statistically significant. The results also suggested that 57 % of bicyclists are more likely to use an on-street facility if the pavement condition is good or better (the pavement condition rating is greater than 6 according to PASER system). An increase of 0.03 in the likelihood of using on-street facilities instead of sidewalk is expected for improving the street pavement condition.

2.3.3 Travel Surveys Data Collection Methods

Transportation planning models require good-quality travel survey data to forecast and evaluate various transportation system scenarios. Travel surveys started as face-to-face interview in the 1950s, in which interviewers visited the respondents and asked questions about the household's travel behaviour. The answers were recorded using paper and pencil. To minimize the labour and time costs, these interviews were gradually replaced by the mail-back survey in the 1960s, in which households received survey forms by mail and returned them after filling the survey. The major issue of this approach was the low response rate, and it still requires labour to enter the records into computers (Shen and Stopher, 2014). These self-reporting methods as well as telephone interviews have certain limitations. These limitations include lack of reporting of short trips and actual routes traveled; poor data on travel start and end times; total durations of trips; and destination location (Chung and Shalaby, 2005; Murakami, Wagner, and Neumeister, 1997). In order to overcome these disadvantages, computer-assisted surveys were introduced in the 1980s. Computer-assisted surveys include computer-assisted telephone interviewing (CATI), personal interviews (CAPI), self-interviews (CASI). The web-based survey, in which respondents can fill in the travel information in a web interface, is considered one of the CASI approaches (Shen and Stopher, 2014).

Most conventional travel data collection methods including mail-back, CATI, CAPI, CASI, web-based questionnaires, analyses of transport schedule inquires, and traffic counting on cross sections or intersections are intensive in terms of cost and time, therefore, often applied once a decade, particularly for large-scale travel surveys (Nitsche, Widhalm, Breuss, and Maurer, 2012). Nevertheless, issues of underreported trips and nonresponse are significant in surveys, as discussed by Richardson, Ampt, and Meyburg (1996). Sometimes, respondents underreport short trips as well as trips that do not end or start at home. Moreover, car drivers might underestimate their travel time, while people who travel with public transportation might overestimate the time spent on travelling.

Travel surveys, are used to collect the input and calibration data used to derive and validate travel demand models. In this context, the first question is about the validity of using 24-hour travel diary to capture origins, destinations, travel times, and purposes of trips done by various modes of transportation including bicycling. The second is about the accuracy of estimating bicycling demand based only on observing commuting trips on a typical day.

This requires collecting data from thousands of households across the region to be analyzed to estimate current travel demand and to predict future travel demand. Therefore, the accuracy and completeness of the travel data have a critical impact on the developed planning models.

2.3.4 The Utilization of Global Positioning System in Travel Surveys

The Global Positioning System (GPS) is a satellite-based location system. When a GPS device receives signals from at least three satellites, the location of the device can be recorded within approximately 10 m. In addition to location coordinates, GPS devices record the times at which they were situated at these locations. As a result, the accuracy of the collected data depends much less on the memory of respondent. Due to the lower burden on the respondent, the data can be collected over an extended period instead of few days. Moreover, the collected data are available immediately in digital format, therefore avoiding the need for time-consuming data entry, and possible entry errors (Bohte and Maat, 2009).

In the late 1990s, GPS data loggers were used as a supplementary tool to measure individual travel. Several studies were conducted to assess the application of GPS to describe travel behavior (Gong, Chen, Bialostozky, and Lawson, 2012; Murakami *et al.*, 1997; Wolf, Guensler, and Bachman, 2001). The results indicated the potential of using GPS devices (wearable or mounted devices in household vehicles) instead of traditional methods.

GPS technology, which provides second-by-second position data, velocity and time data, introduced a comprehensive and accurate method to be used in travel surveys. The advantages of using GPS technology include automatic recording of trip origin, destination, and route data; accurate recording of trip start and end times as well as trip length; and the potential using of GPS data in the verification of traditionally-collected travel data bases.

Wolf, Guensler, and Bachman (2001) assessed the potential of using GPS-based travel surveys to eliminate travel diaries. They demonstrated that it is feasible to use GPS data loggers to obtain most of the traditional travel diary information. The study used GPS data loggers to collect travel data in personal vehicles. The collected data were processed using a GIS and then were compared with data recorded on paper diaries by participants in the survey and were found to match or exceed the reporting quality of the participants.

GPS technology has also been used in modeling the behaviour of cyclists and assessing the potential impact of infrastructure, environmental, social, and other associated factors on the tendency of cyclists to use specific routes to make their trips. For example, Dill (2009) conducted a study to provide insight on the role of daily bicycling to help US adults meet the recommended levels of physical activity. The study collected data on bicycling behavior from 166 regular cyclists in the Portland, Oregon metropolitan region using GPS devices. This study also demonstrated the potential capabilities of utilizing GPS technology to observe the behavior of cyclists. The advantage of using GPS technology over other measurement tools such as accelerometers (which provide information on speed of travel), is the ability of GPS technology to provide location information. For behavior that is dependent upon infrastructure or otherwise influenced by the physical environment, this information is helpful in evaluating the relative effects of various environments. It was also concluded that a supportive environment appears to be necessary to encourage bicycling for everyday travel, allowing more adults to achieve daily active goals.

As Smartphones have become one of the necessities of daily life and most current smartphones have built-in GPS module, Smartphone-based GPS surveys have been proposed to replace dedicated GPS devices (Shen and Stopher, 2014). Despite the increase use of handheld or dedicated GPS devices for measuring individual trips along with their travel times and distances, other associated travel characteristics such as travel mode and trip purpose cannot be derived directly from GPS logs and require more complex derivation approaches (Bohte and Maat, 2009).

Generally, it is widely accepted that GPS surveys provide more accurate data. However, two main issues GPS units have: signal loss and signal noise. Signal problems occur for several reasons, such as a cold start or warm start, and travelling through blocks of tall buildings (Shen and Stopher, 2014). Cold starts usually occur at the beginning of each day, while warm starts usually occur when GPS devices switch from 'sleep mode' to 'working mode' after a person stops for one or two hours. High rise buildings, usually in downtown area, and tunnels have impacts on GPS signal reception, and cause missing GPS data. Signal problems result in missing trips or parts of trips. A sample of conducted GPS surveys in several places around the world is summarized in Table 2.3.

Table 2.3 A sample of GPS surveys conducted in the world (adapted from Shen, L. and Stopher, P. R., 2014)

Location	Year	Survey purpose	Device	Sample size	Collection period
Greater Copenhagen Area	2013	Part of the research on travel chain and sustainable mobility	Dedicated GPS device, recording data every second	54 households	3-5 days
UK	2011	Test the possibility of replacing travel diaries	Accelerometer-equipped GPS units, recording data every second	429 households	7 days
Beijing, China	2010	Sub-sample of Beijing Household Travel Surveys	Dedicated GPS device, recording data every five seconds	890 persons	1 day
Ohio, US	2009 - 2010	GPS-based household travel survey	Dedicated GPS device, recording data every second	2059 households	3 days

Table 2.4 A sample of GPS surveys conducted in the world (continued)

Graz and Tullnerfeld, Austria	2009-2010	Test an integration of new technologies for a mobility survey	Dedicated GPS device	235 respondents	3 days
Western Cape, South Africa	2008	Assess the reliability of GPS survey	Dedicated GPS device, recording data every second	100 respondents	14 days
Three cities in Switzerland	2008	Explore whether participants pass certain billboards	Dedicated GPS device	4882 respondents	Average 6.6 days
France	2007-2008	Sub-sample of National Travel Surveys	Dedicated GPS device recording data every 10 seconds	9% of the main survey	7 days
Four states in Australia	2007	Travel behaviour changes monitoring	Dedicated GPS device recording data every second	130 households	15 days
Ontario, Canada	2007	Route choice modeling	Smartphone plus a GPS receiver	31 respondents	2 days
Three cities in the Netherlands	2007	Residential selection	Dedicated GPS device, recording data every six seconds	1104 respondents	7 days
Matsuyama, Japan	2004	Compare GPS records and travel diaries	GPS-equipped mobile phone, recording data every 30 seconds	31 respondents	5 days
Borlange, Sweden	1999	Traffic safety	In-vehicle GPS device, recording data every second	310 vehicles	15 – 243 days

2.3.5 Trip Reconstruction Using GPS Travel Surveys

Chung and Shalaby (2005) proposed a procedure for trip reconstruction based on GPS data to transform the GPS data collected for single-purpose trips into a list of links and modes used. The procedure was tested using a sample of sixty records and was able to detect 78.5% of the links traveled correctly. However, the study concluded certain limitations and problems such as the cold or warm start problem (GPS receivers require an initial amount of time to acquire sufficient signals to properly measure the location after being turned on) and incomplete trip data due to signal blockage. They recommended using appropriate estimation rules like shortest path algorithm to identify the full path in the case of GPS signal blockage.

Bierlaire, Chen, and Newman (2013) proposed a robust probabilistic approach for matching GPS data to a set of paths. This approach generates a set of paths, and associates a likelihood of each of them. The likelihood is calculated based on spatial (GPS coordinates) and temporal (speed and time) information.

Dalumpines and Scott (2011) developed a set of tools in ArcGIS for map-matching and processing of GPS traces in which the shortest path algorithm in ArcGIS is utilized. The proposed approach consists of filling any gaps within the GPS data points, creating a buffer around the points, and solving for the shortest route between the origin and destination points within the buffer area using route solver in ArcGIS. If the route solver fails to find a route within the predefined buffer area, the buffer area is increased and the process is started again. The accuracy of the developed GIS-based map-matching algorithm is sensitive to the generated buffer distance around the GPS points. They concluded that the buffer distance for the GPS trajectory should be, more or less, 5x to 6x the horizontal accuracy of GPS data. This range of buffer distance values accounts for the width of the roads, the sharpness of curves, and GPS positioning error.

Chapter 3: Methodology

3.1 Introduction

This chapter presents the methodology employed to obtain long-term plans for interventions and improvements of roads and bicycle pathways that considers bicycling demand. The chapter is divided into three sections. The first section describe briefly the datasets used in this research. The second sections explains the method used to estimate bicycle counts along the network based on GPS trajectories of cyclists. The third section explains the procedure followed to incorporate bicycling demand into performance-based optimization of roads strategic purposes.

3.2 Data Description

This section provides a brief description of datasets used in estimating bicycle counts, developing pavement performance models, and establishing strategic plans of M&R activities.

3.2.1 Road Network

The road network is obtained from the City of Montreal, Open Data Portal (http://donnees.ville.montreal.qc.ca/dataset/geobase). The dataset is a shapefile that contains the centerlines of road segments with several attributes including unique identifier of each road segment, road type, direction of traffic flow, and segment length.

3.2.2 Bikeway Network

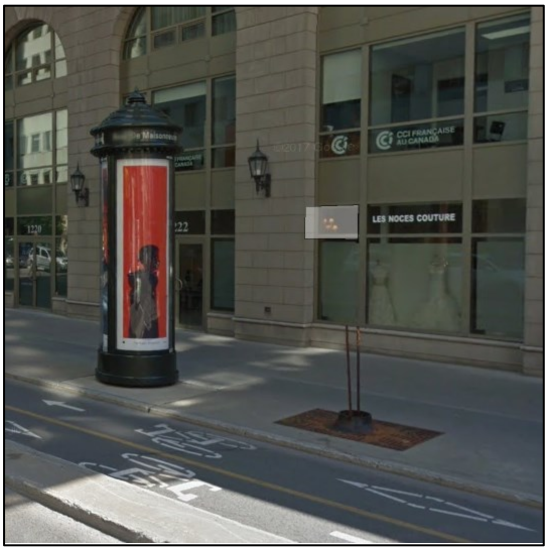
The bikeway network is provided by the City of Montreal on the Open Data Portal (http://donnees.ville.montreal.qc.ca/dataset/pistes-cyclables). The dataset is a shapefile that contains the centerlines of bikeway network segments including several attributes such as a segment identifier, anticipated road segment identifier (where available), facility designation, number of lanes, type of separator (where available) and segment length.

The 2016 GIS representation of bikeways contained the designations listed in Table 3.1 including the category of "no designated facility", along with their total length. Pictures taken from *Google® StreetView* for different designations are shown in Figures 3.1 and 3.2. Together, these designations were grouped into broader categories for the analysis in this research; cycle tracks (protected bicycle paths), bicycle lanes, off-street bicycle facilities, and links shared with motorized traffic. It should be noted that off-street bicycle facilities were excluded from the analysis in this research.

Table 3.1 Different designations of bikeways in Montreal

Category	Designation name	Length (m)
Shared with motorized traffic	Shared street	183,082
	Bicycle boulevard	3,632
Bicycle lane	Bicycle lane	233,405
Cycle track	Cycle track (two-way protected bicycle path)	69,477
Off-street bicycle facilities	Off-street bike path	189,432
	Sidewalk-level bike path	12,852
	Multi-use trail	91,603

Bicycle lane



Cycle track or two-way protected bicycle path

Shared street

Bicycle boulevard

Figure 3.1. Different designations of bikeways in Montreal (taken from Google StreetViewer)

Multi-use trail   Off-street bike path

Figure 3.2. Different designations of bikeways in Montreal (taken from Google StreetViewer)

3.2.3 Smartphone Travel Survey

In this study, GPS observations were collected by a smartphone application, *MTL Trajet*, developed by the City of Montreal. *MTL Trajet* dataset files are accessible on the official website of the City of Montreal (http://donnees.ville.montreal.qc.ca/dataset/mtl-trajet). The GPS trajectories allow tracking the routes of cyclists and provide more cost-effective approach to collect revealed data. Two datasets were used in this research: the "Coordinates" and "Trips" datasets. It is worth mentioning that private information of participants were removed before both datasets were published online. First, "Coordinates" dataset includes GPS-recorded points, with an acceptable positioning quality, collected during the travel survey in 2016. Second, the "Trip" dataset includes each path obtained using the filtered data points. The attributes contained in both dataset files are shown in Table 3.2. The total number of bicycle trips is 3955 and were recorded between September 9th, 2016 and December 1st, 2016.

Table 3.2 Metadata/ Data Dictionary

The "Trips" dataset		
Attribute name	Data type (unit)	Description
id_trip	Numerical	Unique identifier of the trip
avg_speed	Numerical (km/h)	Average speed over the entire trip
duration	Numerical (seconds)	Total trip duration
mode	Text	Mode of transport reported by the participant
purpose	Text	Purpose of making the trip
n_coord	Numerical	Number of GPS points recorded in the "Coordinates" dataset via id_trip
segments	Text	List of traversed segments
geometry	-	Spatial information according to the WGS84 spatial reference system
The "Coordinates" dataset		
id_coord	Numerical	Unique identifier of the point
latitude	Numerical	Point latitude
longitude	Numerical	Point longitude
speed	Numerical (m/s)	Instantaneous speed detected
h_accuracy	Numerical	The accuracy level of the horizontal position of the GPS position
v_accuracy	Numerical	The accuracy level of the vertical position of the GPS position
timestamp	Text	Timestamp of a point (YYYY-MM-DDT HH: MM: SS-TIMEZONE)
id_trip	Numerical	Unique identifier of the trip
geometry	-	Spatial information according to the WGS84 spatial reference system

3.2.4 Pavement surface condition

A dataset containing pavement surface condition in terms of the International Roughness Index (IRI) for 2010 and 2015 was obtained from the City of Montreal (http://donnees.ville.montreal.qc.ca/dataset). This dataset was used to develop Pavement

Performance Prediction (PPP) models. Moreover, to demonstrate the capabilities of smartphone in collecting surface condition of roads, a dataset was collected using the Android-based application, *ANDROSENSOR,* which is available for free on (https://play.google.com/store/apps/details?id=com.fivasim.androsensorandhl=en). The collection process was conducted using two smartphones on January 21st 2017 and January 28th, 2017. In the first session, the application recorded acceleration and speed values every 0.25 seconds. Although the type of smartphone might have an impact on the data collection process, this does not significantly affect the data collected for long-term planning purposes at a network-level scale. For instance, the highest percent of difference between the estimated IRI values using smartphones and those measured by Class 1 profiler was 5.4% (Hanson, Cameron, and Hildebrand, 2014). In the second session, data collection was done every 0.02 seconds, which represented 50 data points collected per second.

3.3 Assignment of GPS Trip Data

GPS cyclist trip data provide large spatial coverage which helps understanding the behaviour of cyclists over the entire network. For instance, it allows identifying those links with high bicycle flows. These capabilities enable urban planners and engineers to develop models that are able to provide more realistic insight about the current demand and more accurate predictions of future demand. The estimation of bicycle counts on various links in the network using a dataset collected through a GPS travel survey was suggested in this research for several reasons: 1) this dataset is provided by the City of Montreal and easily accessible online, 2) this simplified approach in estimating the bicycle counts satisfies the needs of this research, and 3) it is in line with the global tendency to using the GPS technology instead of traditional trip diaries.

Each set of points corresponding to a trip were aggregated based on a unique identifier of each trip (id_trip). These aggregated points were converted to polylines that represent the traveled path. However, GPS systems in smartphone have system errors. These errors could be significant in the presence of tall buildings and tunnels. Most GPS-empowered smartphones have an average horizontal error of 20 meters, but this error can range from 5 to 35 meters (Paek, Kim, and Govindan, 2010). To address this issue, it is necessary to pre-process the GPS data and exclude the outliers from the analysis. The GPS observations were filtered based on average speed, duration and location of the trip, and consequently, some trips were dropped.

3.3.1 Average trip speed

Based on the average speed for the whole trip, those trips having an average speed above 30 km/h were classified as non-bike trips and excluded from the analysis. These trips are more likely were done by motorized vehicle while the application was running and recording (Zangenehpour, Miranda-Moreno, and Saunier, 2015). Similarly, trips with an average speed less than 1 km/h were excluded from the analysis since it is very likely that the application was left collecting the data for hours after the trip ended and the cyclist reached the intended destination (Strauss and Miranda-Moreno, 2017a).

3.3.2 Minimum trip duration

Since the purpose is to estimate bicycle counts, trips with duration less than 1 min were excluded from the analysis as they are too short for our interests.

3.3.3 The location of the trip

The trips that were not recorded entirely within the island of Montreal were excluded from the analysis as they fall outside the scope of our interest.

3.3.4 Assignment of GPS traces

The reconstruction process of trips, from GPS traces, requires complex algorithms to accurately assign the traces (trajectories) to the associated network segments. In this research, a simplified approach was used to assign GPS traces and to estimate bicycle counts on each link in the network. This was accomplished via *ArcGIS* version 10.3 (which is a mapping and analytics platform developed by *Esri*®) by the following steps:

1. Integrate the road and bicycle links into one layer.
2. Create a buffer area around the links in the entire network to enclose the GPS traces of cyclists. This allows to attach each cyclist trace to the nearest segment. The enclosing of GPS traces within this buffer area minimizes the error due to the fact that some GPS traces were irregular and projected far away from the network segments. This issue is caused when GPS signals are hindered by tall buildings, trees and tunnels as well as the accuracy degree of the smartphones' GPS system. The buffer area was chosen to be 25

m around the network segments, this was enough to enclose the most GPS traces, as shown in Figure 3.3.

3. Determine the central point of each segment and create a circular buffer area with a radius of 25m around the central point. This circular buffer area serves to catch the crossing lines (GPS traces), as shown in Figure 3.3. The number of intersecting lines (GPS traces) to each circular buffer area represents the bicycle count on this segment.

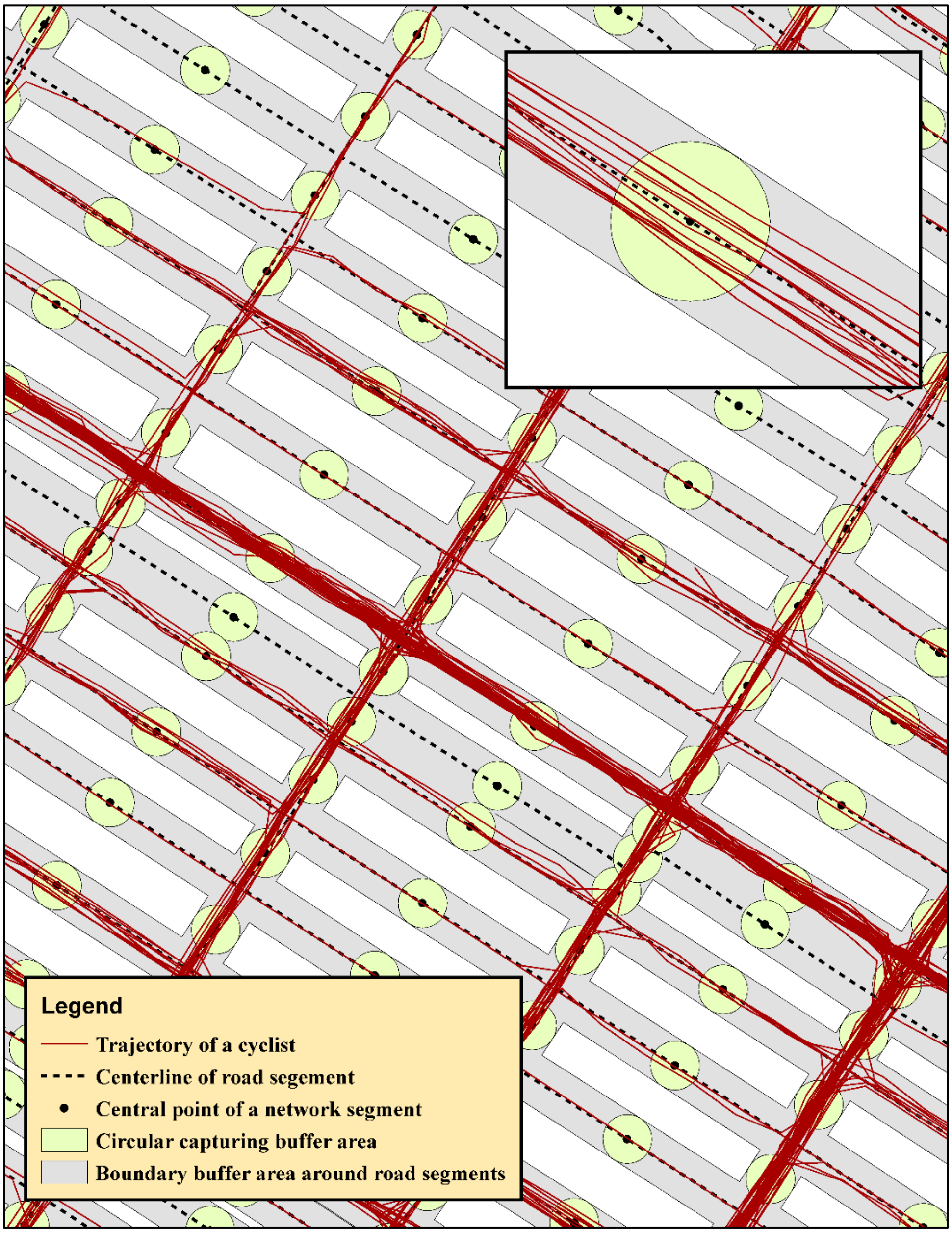


Figure 3.3 Assignment of GPS trajectories of cyclists to network segments

3.4 Coordination of M&R Activities

This section presents the procedure followed to incorporate bicycling demand into road management systems to accomplish long-term performance-based optimal coordinated M&R activities, as illustrated in Figure 3.4.

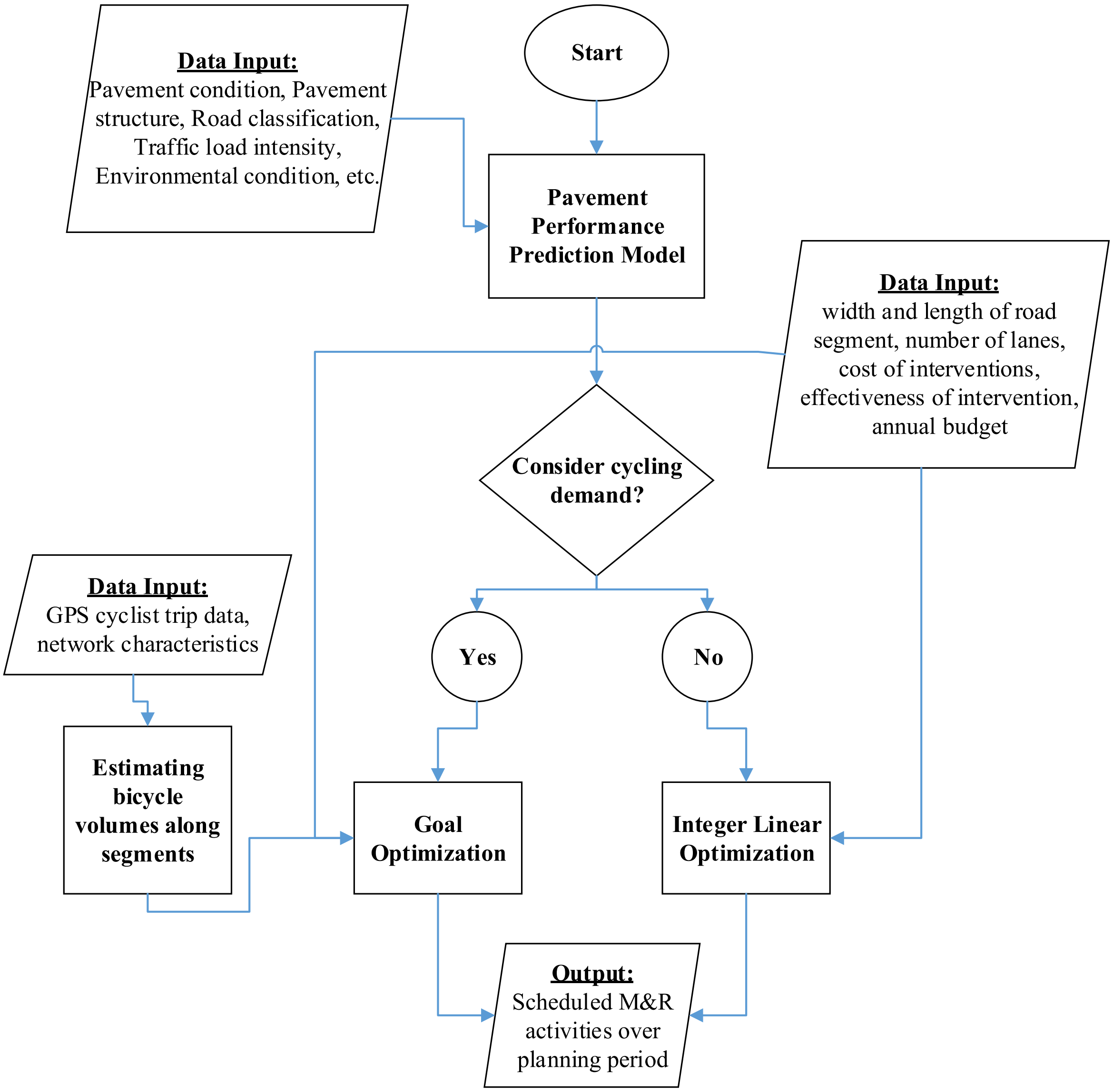


Figure 3.4 The procedure followed to incorporate bicycling demand into road infrastructure management system

3.4.1 Typical Performance-Based Optimization

Mathematical formulations for optimizing M&R activities in a network of spatially distributed assets can be found elsewhere (Amin and Amador-Jiménez, 2015; Faghih-Imani and Amador-Jimenez, 2013; Li, Haas, and Huot, 1998). A typical optimization process attempts to achieve the objectives while subject to constraints. In road management systems, optimization approaches are applied to maximize the aggregated condition at the network-level (Equation 3.1) subject to a given budget over the planning horizon, an annual budget (*Bt*) is usually used. Other traditional constraints include the limitation that every asset can receive no more than one treatment per year, and, in some circumstances, the preclusion of treating assets within a certain period after they have received a specialized intervention.

It should be noted that the binary variable x carries three sub-indices that represent time (t), asset (i) and treatment (j). Solutions for this optimization will enumerate chains of variables $x_{t,i,j}$ that represent sets of assets at different periods of time receiving those treatments that produce the most cost-effective solution in terms of the objectives. The objectives are traditionally related to asset condition or cost.

Maximize

$\sum_{i=1}^{N} L_i Q_{t,i}$ for all values of t [3.1]

Subject to

$\sum_{i=1}^{N} \sum_{j=1}^{K} C_{t,j} x_{t,i,j} L_i \leq B_t$ for all values of t [3.2]

$x_{t,i,j} \in Binary\ Set[0,1]$

Where the following time links connects consecutive periods of times

$Q_{t,i,j} = x_{t,i,j}\,(Q_{(t-1),i,j} + E_{i,j}) + (1 - x_{t,i,,j})\,(Q_{(t-1),i,j} - D_{i,t})$ [3.3]

Z= total aggregated condition at the network-level;

$x_{t,i,j}$ = 1 if treatment j is applied on road segment i at year t, 0 otherwise;

$Q_{i,t}$ = the asset condition index for road segment i at year t;

$Q_{i,(t-1)}$ = the asset condition index for road segment i at year (t-1);

$Q_{t,i,j}$ = the asset condition index of road segment i at year t for intervention j;

$Q_{(t-1),i,j}$ = the asset condition index of road segment i at year (t-1) for intervention j;

$C_{t,j}$ = the cost of intervention j at year t;

L_i = the size of asset i;

$E_{i,j}$ = the improvement of asset i from intervention j;

$D_{i,t}$ = the deterioration of asset i at time t;

B_t = the budget at year t;

N = the total number of assets;

T = the total number of time periods; and

K = the total number of applicable treatments.

This formulation relies on the forward dynamic links of Equation 3.3 which support a decision tree containing all possible paths of asset condition across time, after hypothetically receiving available treatments (Amador-Jiménez and Afghari, 2013; Amin and Amador-Jiménez, 2015; Faghih-Imani and Amador-Jimenez, 2013). This tree is based upon a transfer function used to estimate asset condition ($Q_{t,i}$) as a combination based on the decision variable ($x_{t,i,j}$) and the effectiveness ($E_{i,j}$) or deterioration ($D_{i,t}$) of the specific asset i on time t. This generates chains of alternative decision variables; one of these chains is the optimal set of treatments regarding to particular objectives and constraints which the algorithm would select. Integer linear programming (ILP) is suggested to be used to obtain a solution.

Since the objective is to encourage individuals to bike more through providing safe bicycle paths with smooth surfaces, in this thesis, assists consisted of pavement segments, and the IRI was used as indicator of condition. Lower values of IRI indicate smoother roads, therefore, better condition. Consequently, to maximize the condition, the optimization algorithm should attempt to minimize IRI. Two steps are typically found in pavement management systems (Amin and Amador-Jiménez, 2015; Faghih-Imani and Amador-Jimenez, 2013; Li, Haas, and Huot, 1998). The first step estimates annual budget that is necessary to keep condition of pavements at an appropriate level (Equations 3.4 and 3.5). The constraint that pavement condition index in each year must be better than the one during the previous year results in a non-decreasing level of condition. Due to the nature IRI, it is expected to be a non-increasing function. In the second step, the optimization model attempts to reach the maximum possible level of condition subjected to a fixed annual budget B_t (Equations 3.6 and 3.7).

Minimize

$Z = \sum_{i=1}^{N} \sum_{j=1}^{K} C_{t,j} x_{t,i,j}\, L_i$ for all values of t [3.4]

Subject to

$\sum_{i=1}^{N} L_i IRI_{t,i} \leq \sum_{i=1}^{N} L_i IRI_{t-1,i}$ for all values of t [3.5]

$x_{t,i,j} \in [0,1]$

where

Z= the total aggregated cost of all pavement segments;

$x_{t,i,j}$ = 1 if treatment j is applied on road segment i at year t, 0 otherwise;

$IRI_{t,i}$ = the pavement condition index for road segment i at year t;

$IRI_{(t-1),i}$ = the pavement condition index for road segment i at year (t-1);

$IRI_{t,i,j} = x_{t,i,j}\,(IRI_{(t-1),i,j} - E_{i,j}) + (1 - x_{t,i,j})\,(IRI_{(t-1),i,j} + D_{i,t})$

$IRI_{t,i,j}$ = the pavement condition index of road segment i at year t for intervention j;

$IRI_{(t-1)i,j}$ = the pavement condition index of road segment i at year (t-1) for intervention j;

$C_{t,j}$ = the cost of intervention j at year t;

L_i = the length of road segment i;

$E_{i,j}$ = the improvement in terms of IRI reduction on road segment i from intervention j;

$D_{i,t}$ = the deterioration on road segment i at time t;

N = the total number of road segments;

T = the total number of time periods; and

K = the total number of applicable treatments.

Minimize

$\sum_{i=1}^{N} L_i IRI_{t,i}$ for all values of t [3.6]

Subject to

$\sum_{i=1}^{N} \sum_{j=1}^{K} C_{t,j} x_{t,i,j} L_i \leq B_t$ for all values of t [3.7]

3.4.2 Incorporating Bicycling Usage in Performance-Based Optimization

The steps mentioned in section 3.4.1 can satisfy the economic aspect of sustainability but still do not take into consideration the bicycling usage in the analysis. To address this issue, the mathematical formulation was extended to accommodate bicycling usage across the network. A Goal Programming (GP) was used with three objective functions. The first objective function is to force the pavement condition index in each year to be better than or equal to the one during the previous year. This objective seeks improving the aggregate network pavement condition as possible to achieve and sustain an appropriate level of condition. The second objective function is to consider the budgetary constraints for the analysis period. The third objective function is to increase bicycling rates on network road segments. The last objective is based on the potential impact of various types of bicycling facilities on bicycling rates. Generally, providing compatible, convenient, and safe bicycling facilities is associated with higher bicycling rates in cities. Consequently, the optimization algorithm attempts to either upgrade the existing facilities to more safe and convenient designations or schedule projects to build bicycling facilities on roads where they do not exist. A potential increase ($P_{i,j}$) in bicycling rates can result from upgrading an existing facility (or building a new one) on a road segment i through a specific improvement j.

Objective functions:

$f_1 = \sum_{i=1}^{N} IRI_{t,i} \leq \sum_{i=1}^{N} IRI_{(t-1),i}$ for all values of t [3.8]

$f_2 = \sum_{i=1}^{N} \sum_{j=1}^{K} C_{t,j} x_{t,i,j} L_i \leq B_t$ for all values of t [3.9]

$f_2 = \sum_{i=1}^{N} V_{t,i} \geq \sum_{i=1}^{N} V_{(t-1),i}$ for all values of t [3.10] where

$$V_{t,i,j} = x_{t,i,j}\,(P_{i,j}\,V_{(t\text{-}1),i,j}) + (1\text{-}x_{t,i,j})(V_{(t\text{-}1),i,j}) \qquad [5.11]$$

$V_{t,i}$ = the bicycle volume on road segment *i* at year *t*;

$V_{(t\text{-}1),i}$ = the bicycle volume on road segment *i* at year (*t*-1);

GP approach was applied to find the optimal set of M&R activates over a long-term planning period. This approach is able to accommodate multiple conflicting objectives. Both optimization models in this thesis, ILP and GP, were solved by employing *Remsoft® Spatial Planning System 4.0*; it has the capability of modelling linear binary programming including goal and weighted objective programming, and formulating the long-term planning optimization problem as a standard linear programming problem, generating matrices and solving the problem by using a commercial solver (e.g., *MOSEK*, *LPABO*).

It is worth mentioning that there are a variety of methods to estimate bicycle volume during any desired period of time. Typically, the Annual Average Daily Bicycle (AADB) volume is used in most applications. The AADB volume is typically estimated using daily, hourly, and monthly adjustment factors as well as short-and- long term counts (El Esawey, 2016). Recently, a regression model was proposed to estimate AADB volumes along segments and intersections in the entire network based on short-term, long-term, and GPS data (Strauss, Miranda-Moreno, and Morency, 2015). However, bicycle counts that are estimated based on GPS trip data, collected through smartphones of cyclists, were used as indicators of the current bicycle volumes along segments in this thesis. This satisfies the purposes of this research since it does not mainly focus on calculating bicycle flow rates on road segments.

Chapter 4: Adapting Pavement Management to On-Street Bicycle Networks: Case Study of Plateau-Mont-Royal, Montréal

Feras Elsaid, Luis Amador-Jimenez and Ciprian Alecsandru

Abstract

There are needs maintain on-street bicycle networks on optimal condition and to upgrade certain corridors to higher degrees of protection. This paper develops the foundation of such system for a case study of the *Plateau-Mont-Royal* borough in *Montréal, QC*. The case study borrows concepts of road management systems: historical data of pavement condition, at low-volume roads, and for the years 2010 and 2015, was used to construct performance curves for the bicycle network. The year 2017 was set as baseline and pavement's surface condition data collected using a mobile-phone application, for roads shared between bicycles and automobiles. A long-term plan was developed using a linear programming optimization approach over a span of 40 years. It was found that the optimal strategy allocates resources for the reconstruction of roads and on-street bikeways for the first 13 years, and recommends preventive maintenance thereafter. Future research will investigate the improvement of the degree of protection of on-street bicycle lanes.

Keywords: Pavement Management System; Bicycling; Optimization

4.1 Introduction

4.1.1 Bicycling as a Sustainable Mode of Transportation in Cities

Health benefits of bicycling are significantly greater than its associated risks, by comparison with automobiles (de Hartog, Boogaard, Nijland, and Hoek, 2010). The society as a whole can experience even more benefits due to expected lower levels of air pollution and traffic accidents (de Hartog, Boogaard, Nijland, and Hoek, 2010). A growing body of research supports the advantages of active transportation (bicycling and walking) on individual health; reducing obesity rates, preventing cardiovascular diseases, and reducing Type 2 Diabetes (Andersen, Schnohr, Schroll, and Hein, 2000; Bassett, Pucher, Buehler, Thompson, and Crouter, 2008; Bauman *et al.*, 2008; Brown, 2000; Gordon-Larsen *et al.*, 2009; Hamer and Chida, 2008; Hillman, 1993; Huy, Becker, Gomolinsky, Klein, and Thiel, 2008; Matthews *et al.*, 2007; Nick Cavill, Sonja Kahlmeier, Racioppi., and Organization, 2006;

OECD/International Transport Forum, 2013; Rasmussen *et al.*, 2016; Shephard, 2008). Bicycling also helps reduce traffic congestion (OECD/International Transport Forum, 2013; Transport, 2004).

For these reasons, many government agencies and municipalities around the world have started the implementation of long-term plans to encourage bicycling among individuals. This could be achieved by adopting a wide range of infrastructure, program and policy interventions to promote bicycling in cities. The infrastructure related interventions include; on-street bicycle lanes, off-street bicycle paths, shared bus/bicycle lanes, signed bicycle routes, colored lanes, bicycle boulevards, bicycle boxes (advanced stop lines), bicycle-phases traffic signals, improving quality of pavement, traffic calming zones, car-free zones and bicycle parking (Pucher, Dill, and Handy, 2010).The impact of these interventions on bicycling rates has been studied by several researchers using either stated preference (SP) or revealed preference (RP) studies. SP studies are usually used to evaluate proposed interventions by asking people's opinions or intended behavior. The revealed preference (RP) studies observe the actual behavior either by self-reporting surveys or using technologies such as automatic counters, global positioning systems (GPS) and mobile sensing (Pucher *et al.*, 2010; Strauss and Miranda-Moreno, 2017b). Most of the network-level studies found a positive relationship between bicycle lanes and bicycling levels (Pucher *et al.*, 2010). A positive and significant correlation was also found for levels of bicycle infrastructure and commuting using bicycles (Dill and Carr, 2003; Nelson and Allen, 1997). Cities around the world are increasingly investing in the extension and maintenance of bicycle networks. The City of Berlin, for example, implemented a comprehensive intervention package that extended the bicycling facilities and separated them from the road network. Berlin's bicycle network grew from 271 km to 920 km during the 1970 to 2008 period, and provided 22,600 bicycle parking spots at both metro and rail stations, it added 70 km of bus/bicycle lanes and 100 km of shared-use paths (City of Burlin, 2003; Pucher and Buelher, 2007). In addition, the City of Berlin created training and education programs, and supportive policies for cyclists. Overall, these interventions contributed to increase the bicycle mode share from 5% to 10% during 17-year period starting from 1990 (City of Burlin, 2003; Pucher and Buelher, 2007).

In Canada, several cities are following the same path as Berlin. Toronto in Ontario, Vancouver in British Columbia, Montréal in Quebec, Calgary in Alberta and other cities have set bicycling as a key mode of transportation with a high priority in their long-term plans (Table 4.1).

Table 4.1 Canadian Cities Supporting Bicycling

City	Goal	Bicycle support
Toronto	"To create a safe, comfortable and bicycle-friendly environment, which encourages people of all ages to use bicycles for everyday transportation and enjoyment".	Extend the bicycle network from 166 km in 2001 to 1000 km within 10 years. Bicycle lanes will constitute roughly half (495 km) of the proposed network. This extension was expected to cost $66.8 million as a total, of which $11.6 million were dedicated to the installation of new bicycle lanes (The City of Toronto, 2001)
Vancouver	Shifting to sustainable transportation systems 67% of trips in the city will be made by sustainable modes of transportation including transit, walking or bicycling by 2040.	Building a bicycling bicycle network on which cyclists experience comfortable bicycle trips. More attention is being given to children and elderly cyclists in the proposed network in terms of design, traffic management and supportive education and training programs (The City of Vancouver, 2012).
Calgary	The goal of the city is to become one of the most bicycle-friendly cities in North America	New bicycling strategy: planning, designing and building; operating and maintaining; educating and promoting. So far 205 km of on-street bicycle lanes have been built from 1999 to 2010. The amount of funding allocated for the extension of the network was reported to be approximately $28 million during 2012 to 2014 (The City of Calgary, 2011).
Montreal	Greater attention given to the quality of bicycle facilities, especially to the construction of new protected bicycling corridors,	Increase the bicycling mode share up to 15% in the coming 15 years. Investing $150 million over the first five-year period. Minimizing the serious or fatal traffic accidents until reaching a target of zero (Ville de Montréal, 2017).

4.1.2 Pavement Management System

Pavement Management System (PMS) is an approach that incorporates the economic assessment of trade-offs between competing alternatives (Haas and Hudson, 1978; Hudson, Uddin, and Haas, 1997). PMS operates at two levels; project level (i.e. specific road) and network level. At both levels, field data collection is necessary to evaluate pavement performance to strengthen the decision-making process of appropriate maintenance, preservation and rehabilitation treatments, and priority planning and programming. Pavement performance is evaluated based on several measures: surface and structural. Pavement performance models are generally classified into two categories: deterministic and stochastic (Amador-Jiménez and Mrawira, 2009; George *et al.*, 1989; Prozzi and Madanat, 2003). One of challenges in formulating these models is the lack of time-series data. (Amador-Jiménez and Mrawira, 2009) proposed an approach by which a pavement performance model can be formulated using as little as two time-series points.

4.1.3 Measuring IRI Using Smartphones

One of the surface condition measures used in PMS is the IRI. The IRI was originally developed by World Bank to produce an objective indicator for road roughness that was time-stable, transportable, and relatable to values collected by practitioners regardless of their location (Sayers, Gillespie, and Queiroz, 1986). The roughness of a pavement is defined as the variations in the longitudinal surface profile that cause vibrations in traversing vehicles at a specific point of time (Sayers *et al.*, 1986). The IRI summarizes the longitudinal surface profile in the wheel path and is computed from surface elevation data collected by either a topographic survey or a mechanical profilometer. It is defined by the average rectified slope (ARS), which is a ratio of the accumulated suspension motion to the distance traveled obtained from a mathematical model of a standard car traversing a measured profile at a speed of 50 mph (80 km/h) (Huang, 2004). IRI is typically expressed in vertical distance per horizontal distance of travel (mm/m, m/km, in/mi).

During last decade, researchers have been working on exploring the applicability of sensing capabilities of the smartphone to collect data on an objective performance measures for pavement surface (Aksamit and Szmechta, 2011; Byrne, Parry, Isola, and Dawson, 2013; Mednis, Strazdins, Zviedris, Kanonirs, and Selavo, 2011; Perttunen *et al.*, 2011; Strutu, Stamatescu, and Popescu, 2013). In particular the potential of using the output of smartphone sensors in determining IRI for pavement was studied (Douangphachanh and Oneyama, 2013, 2014; Du, Liu, Wu, and Jiang, 2014; Hanson *et al.*, 2014; Islam, Buttlar, Aldunate, and Vavrik, 2014). IRI has become an international standard for road roughness since its beginning (Hanson *et al.*, 2014; Tighe, 2013). In Canada, IRI was the most widely used pavement performance index by provincial, federal, and territorial agencies in Canada, with 85% of the 14 agencies surveyed reported using it (Tighe, 2013).

4.2 Objective

The main objective of this paper is to develop a Pavement Management System (PMS) for an on-street bicycle network in an urban context. The bike network of *Plateau-Mont-Royal* was used to assess the condition and available implementation of interventions, with goals to developing investment plans. The paper also discusses the advantages of adopting PMS to bicycle lanes as well as the limitation and drawbacks of low-cost data collection approaches. Finally, the study concludes with the potential future work in this research area.

4.3 Methodology

The size of bicycle network in the City of *Montréal* is approximately 748 km, of which 214 km and 181 km are on-street bicycle lanes, and roads shared by cars and bicycles, respectively (*Vélo Québec*, 2015). the City of *Montréal* is ranked 2nd across Canada after Calgary's network, 1032 km (*Vélo Québec*, 2015). *Plateau-Mont-Royal* region itself has 46.3km of bicycle lanes, of which 40.6km are on shared roads which makes it the densest borough for bicycle lanes in the City of *Montréal* (*Vélo Québec,* 2015). Furthermore, *Plateau-Mont-Royal* has the highest bicycle mode share (percentage of trips made by travelers using a particular type of transportation); 10.8% versus 2.5% across the Island of *Montréal* (Vélo Québec, 2015). For these reasons, *Plateau-Mont-Royal* was selected as a case study in this paper. The performance curves were developed based on a dataset that contains road condition in terms of International Roughness Index (IRI) for two years, 2010 and 2015. This dataset was provided by City of *Montréal*. The condition of on-street bicycle lanes was evaluated during the year 2017, and an optimization algorithm was used to identify the required budget and achievable condition levels for 40 years.

4.3.1 Performance Curves

The following steps are followed to accomplish the main objective: first, to create performance curves for *Montréal*'s road network based on data collected in 2010 and 2015. Second, to collect pavement roughness data for *Plateau-Mont Royal* borough for 2017. Third to prepare a decision support system based on an optimization framework to forecast budget allocation for different interventions over a period of 40 years.

Performance curves were developed for road segments with low volume of vehicles, since on-street bicycle lanes are impacted by minimal loads. It is expected that the environmental freeze-thaw cycle is the dominating criterion in the deterioration process of bicycle lanes where the environment is expected to be the main factor. Low-traffic-volume was set for Equivalent Single Axle Load (ESAL) values below 3,739,185; the 33rd percentile threshold within the whole island.

Road segments were categorized into four homogeneous groups of similar characteristics those have an effect on the performance model such as pavement structure, as-built quality, environmental exposure, traffic loading, and maintenance practice. This step is helpful in developing performance models for network-level long-term planning (Amador-Jiménez and Mrawira, 2009; Butt, Shahin, Feighan, and Carpenter, 1987; Pedigo, Hudson, and Roberts, 1981). This resulted in four homogeneous groups: arterial roads made of flexible pavement, local roads made of flexible pavement, arterial roads made of rigid pavement, and local roads made of rigid pavement, all of them have low traffic volumes. Table 4.1 presents a summary of the groups along with average IRI and ESALs values for each group.

Table 4.2 Summary of database, low-traffic-volume roads

Pavement Type	**Flexible Pavement**		**Rigid Pavement**	
Road Classification	Arterial	Local	Arterial	Local
Average ESALs	2,078,553	1,983,417	1,986,362	2,457,579
Average IRI 2010	3.66	4.33	3.92	4.84
Average IRI 2015	4.72	5.37	4.98	5.87
Number of segments	541	2066	1933	1045

The performance curves for these homogeneous groups were developed using the approach proposed by (Amador-Jiménez and Mrawira, 2009); by which a pavement performance model can be formulated using as little as two time-series data for a large cross-sectional sample (whole network of roads) on condition and traffic data. Figure 4.1 shows the developed performance curves for homogeneous groups. As noticed in Figure 4.1, the four homogeneous groups have similar behaviour in terms of deterioration, thus, an overall performance curve was considered for all groups with a best-fitted linear equation.

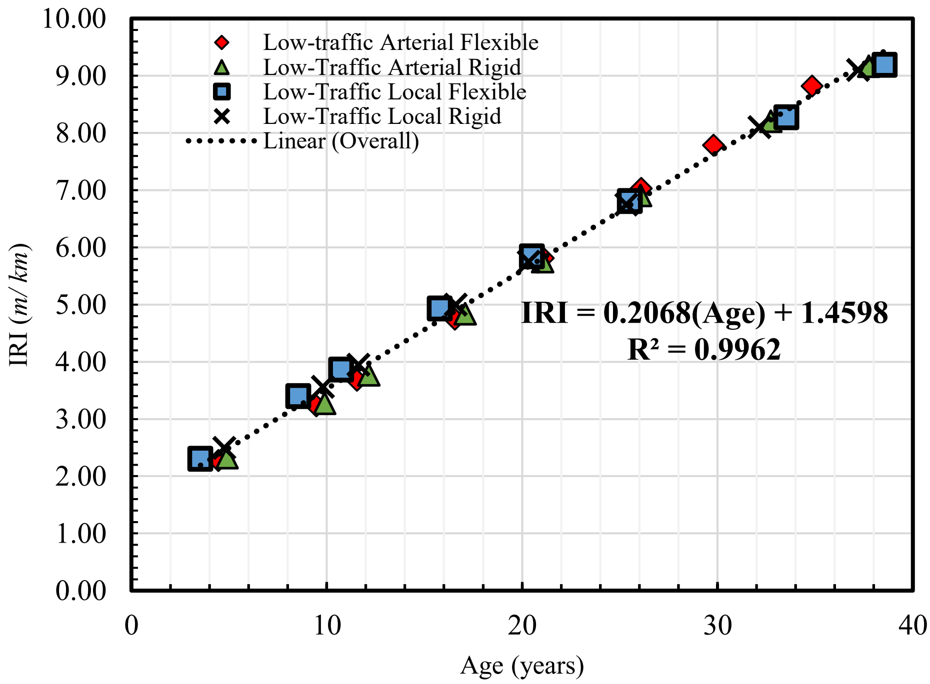


Figure 4.1 Performance curves developed for homogeneous groups

4.3.2 Data Collection Using Smartphone

Data was collected using the Android-based application, *ANDROSENSOR* (https://play.google.com/store/apps/details?id=com.fivasim.androsensorandhl=en), using two separate smartphones on January 21st 2017 and January 28th, 2017, between 10:00AM-3:00PM in order to validate observed values. Values of acceleration and speed were logged every 0.25 seconds. The type of smartphone might have an impact on the data collection process. However, this does not significantly affect the data collected for long-term planning purposes at a network-level scale. For instance, the highest percent of difference between the estimated IRI values using smartphones and those measured by Class 1 profiler was 5.4% (Hanson *et al.*, 2014). In the second session, data collection was done every 0.02 seconds, which represented 50 data points collected per second. Both of these data collection files are presented in Figure 4.2.

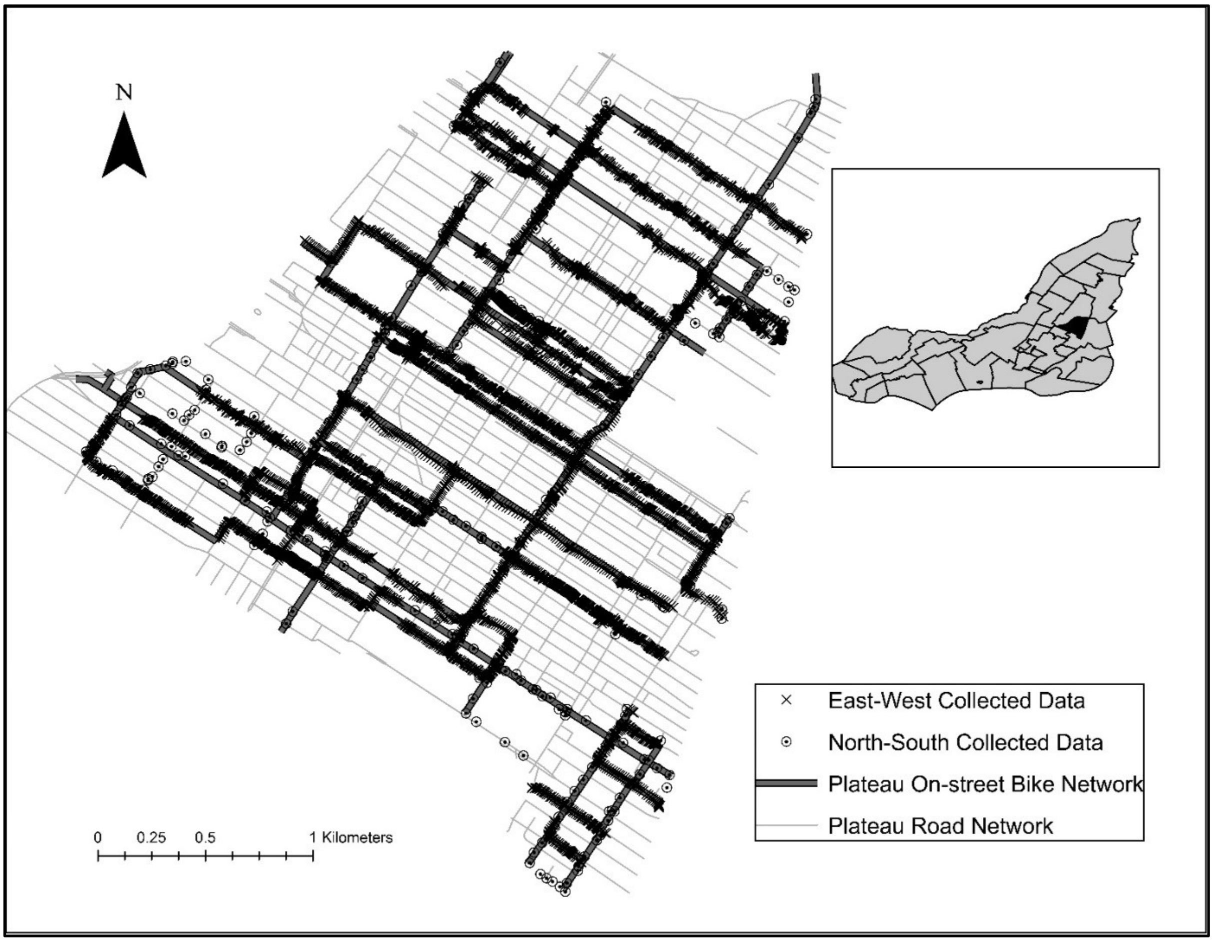


Figure 4.2 Collected data in the Plateau-Mont-Royal

For both surveys, data was collected using the same automobile and the same driver to minimize the effect of the damping system in the vehicle, and to some extent, the driver's behaviour. The smartphones were left to rest on the floor of the vehicle in two different locations. The latter was assumed not to cause discrepancies in the data since it was concluded that smartphone applications, the type of the device, and the location of the smartphone inside the vehicle have insignificant impact on the observed vertical accelerations (Al-Dabbagh, 2014). Variability in the speed of the vehicle is a factor that could affect data collected, because the car reacts differently at high speeds versus low speeds and the driver generally drives at a speed suitable to the road surface condition (the driver will slow down to avoid violent movements which cause discomfort and vehicle damage on the poor-condition road). Thus, data collection initiated well before the initial and final locations of each road segment to remove the effect of acceleration and deceleration. In addition observed vertical accelerations were normalized by speed (1/s) and speed was kept constant as previously suggested (Al-Dabbagh, 2014). Extreme values caused by the presence of speed bumps were eliminated from the data collected. One of the difficulties found was the fact that on-street bicycle lanes take a portion of the road on which it is difficult to drive on.

4.3.3 Estimating Roughness Index (RI)

Several studies have verified that Z-axis acceleration obtained from smartphones can be used as an effective and reliable signal estimation of road surface condition (Amador-Jimenez and Matout, 2014; Hanson, Cameron, and Hildebrand, 2014; Li and Goldberg, 2018). Based on the recorded data by *ANDROSENSOR*, Root Mean Square (RMS) was used to capture variation on cyclical responses of sinusoidal form. The following equations were generated based on (Al-Dabbagh, 2014, Amador-Jiménez and Matout, 2014; Li and Goldberg, 2018), and were used to estimate Roughness Index (RI):

Standard deviation of the vertical component of acceleration (σ_z):

$$\sigma_z = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(a_{zi} - \bar{a})^2} \qquad [4.1]$$

Speed-normalized standard deviation of the vertical component of acceleration:

$$\frac{\sigma_z}{v_{yi}} = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(a_{zi} - \bar{a})^2}}{v_{yi}} \qquad [4.2]$$

Roughness Index:

$$(RI) = \frac{\sigma_z}{v_{yi}} \times 100 \qquad [4.3]$$

where a_{zi} is the vertical component of acceleration, $\bar{a}$ is the mean, *N* is the total number of recorded values, v_{yi} is the vehicle's speed.

Values of RI for the roads that contain on-street bicycle lanes or shared roads (bicycles and automobiles) were extracted from the City of *Montréal*'s geo-database. The data points were imported from a Geo-referenced map of the *Plateau-Mont-Royal* region using *ArcGIS 10.3*.

Table 4.2 presents the operational window of each treatment, lower and upper ranges for each applicable treatment along with the service life extension, values were provided by practitioners and local engineers in *Montréal*.

Table 4.3 Service life, cost and operational window for each treatment

Treatment	Treatment service life (Years)	Treatment cost (US$/m^2)	Operational Window
Micro-surfacing	4	6.74	RI ≤ 2.49
Mill and Overlay	8	25	RI ≤ 3.53
Reconstruction	Brand New	42	RI > 3.54

Dynamic binary programming was applied to achieve the optimal pavement roughness condition (Amin and Amador-Jiménez, 2015). This is done by minimizing $\overline{RI}$ while subjected to a given budget (Equations 4.4 and 4.5). The identification of the sequence of interventions through time is further detailed by Equation 4.6. This identification relies on a time transfer function that connects all periods of time.

$$\text{Min } \sum_{t=1}^{T}\sum_{i=1}^{a} L_i RI_{t,i} \qquad [4.4]$$

$$\text{Subject to: } \sum_{t=1}^{T}\sum_{i=1}^{a}\sum_{j=1}^{k} C_{t,j} x_{t,i,j} L_i \le B_t \qquad [4.5]$$

$$\text{where } \quad RI_{tij} = x_{tij}\,(RI_{(t-1)ij} - E_{ij}) + (1-x_{tij})\,(RI_{(t-1)ij} + D_{it}) \qquad [4.6]$$

$$x_{t,i,j} \in [0,1]$$

where x_{tij} is 1 if treatment j is applied on road segment i at year t, zero otherwise; RI_{ti} is condition Index for road segment i at year t; RI_{tij} is condition index of road segment i at year t for intervention j; $RI_{(t-1)ij}$ is condition Index of road segment i at year (t-1) for intervention j; C_{tj} is cost ($) of intervention j at year t; L_i is length of road (km) for road segment i; E_{ij} is improvement in terms of RI reduction on road segment i from intervention j, D_{it} is deterioration on road segment i at time t, B_t is the budget at year t.

The above optimization problem was solved over a 40-year period of time using a Commercial package: *Remsoft*. The solution was expressed in terms of the application of the most cost-effective intervention at the most suitable period of time to each road segment within the inventory.

4.4 Analysis and Results

Bicycle-lanes' condition (minimize RI) was maximized with an annual budget of $200,000 over a 40 year-period. The average RI obtained for each year due to treatment actions is illustrated in Figure 4.3. The RI value decreased over the first 15 years until reaching a minimum value representing a very good average surface condition for the bicycle-lanes network. Figure 4.4 shows details of the treatment expenditure per year. During the first 11 years, reconstruction is the dominant choice, however, for the remaining 29 years, mill and overlay and micro-surfacing are the appropriate solutions to sustain the good condition on the bicycle network (Figure 4.4). Figure 4.5 illustrates the percentage of road segments according to their surface condition. The percentage of segments with poor surface condition is decreasing over the first 11 years. After 13th year, all segments in the network become at good condition; this phase can be described as stable and sustainable.

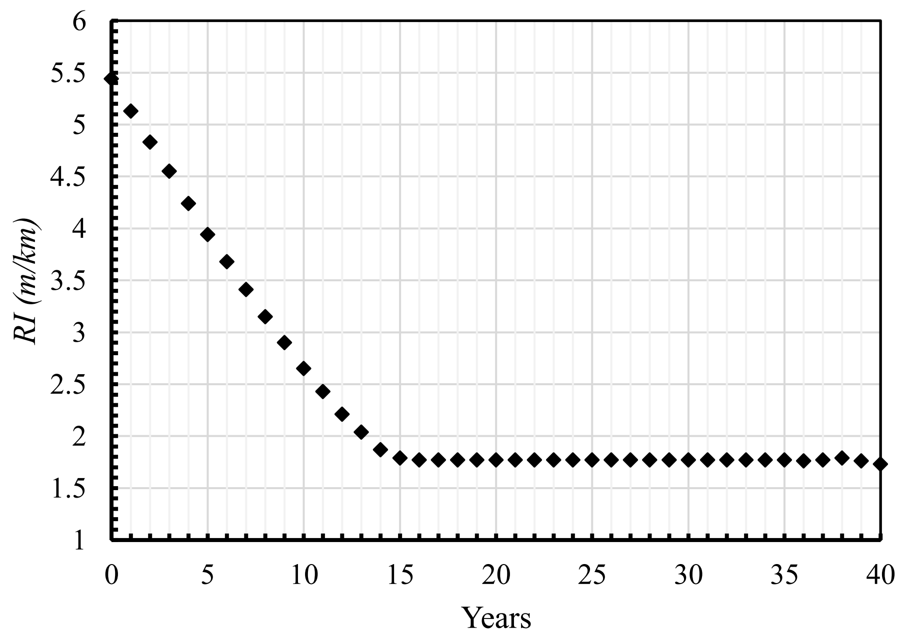


Figure 4.3 Average RI of on-street bicycle lanes

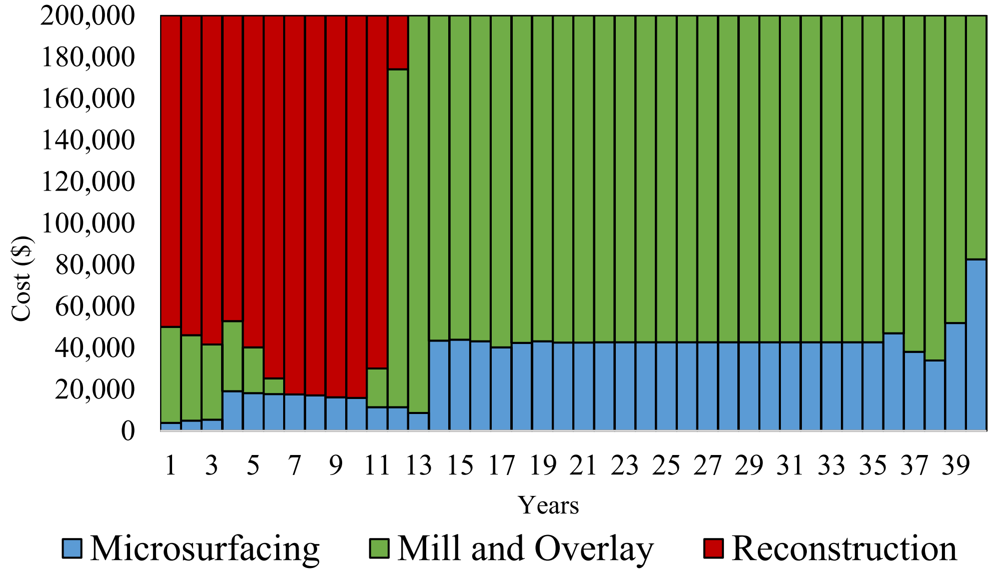


Figure 4.4 Expenditure according to applied treatment actions

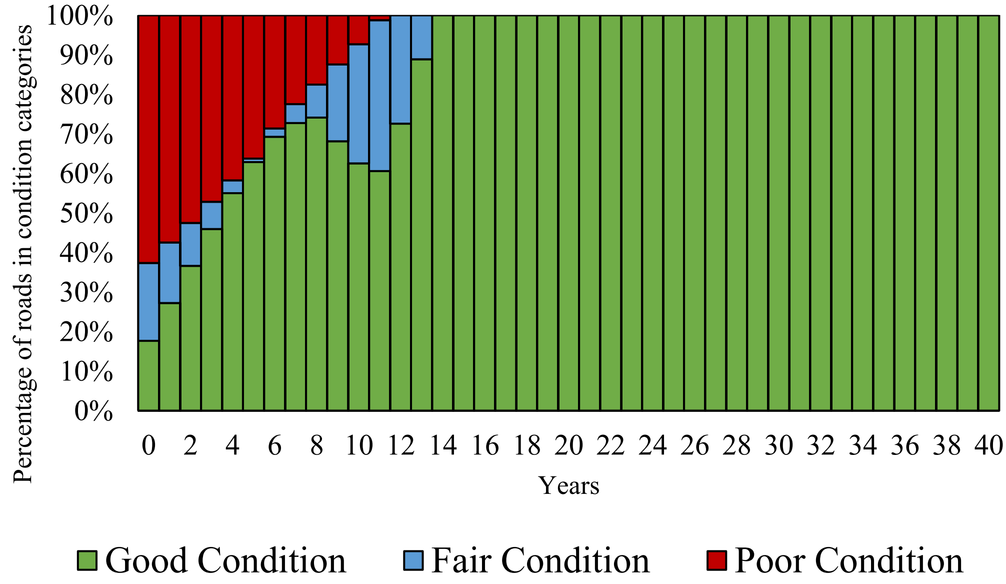


Figure 4.5 Surface condition of on-street bicycle lanes

4.5 Discussion and Future Work

This study proposed a procedure to apply the techniques of PMS to bicycle networks by adapting and extending the work by Amin and Amador (2015). *Plateau-Mont-Royal* region was considered as the case study. Furthermore, it considered the costs associated with utilizing different treatment interventions in the *Plateau-Mont-Royal* borough. However, this PMS has several limitations which are discussed in details including the shortcomings of conventional PMS techniques, such that future PMS will be enhanced.

First, an error can arise in the data collection process. Speed has a significant effect on the collected of data. During our data collection process, the speed of the car ranged from 10 km/hr to 60 km/hr. The variation in speed affects how the car reacts to the pavement condition. Bicycles usually occupy a small portion of the lane, so this differs slightly from the pavement that is being totally occupied by the car.

The PMS for this case study used historical data to forecast future performance in pavement condition. Accordingly, there is some deterioration uncertainty associated with the PMS approach. Also, the operational windows of treatments were subjectively developed.

Another consideration is that only one indicator was used in defining the operational window (RI); other indicators, such as rutting, roughness, segregation, transverse cracks, ravelling and wheel path bleeding, were not taken into account. The PMS for this case study found the optimal path to take advantage of cost-effectiveness of individual treatments. However, it still did not address socio-economic criteria such as safety, congestion, mobility, pollution, or social costs. Even more, indicators related to the convenience of the bicycle network, such as safety, lighting, proximity to public transportation, protection, etc. should be incorporated in future research. Therefore, there is a need for PMS to be "extended, by incorporating dynamic states of land use, regional economy, travel modelling, and socio-economic criteria" (M. S. R. Amin, 2015). Policy makers need to consider socio-economic benefits of communities when allocating budget in M&R planning (M. S. R. Amin, 2015). Environmental conditions should become the main factor behind the development of deterioration models and the role of ESAL values must be removed whereas possible.

Finally, this study did not consider a life cycle cost analysis or unforeseen costs associated with specific treatments; rather, it focused on the costs of the treatment interventions themselves. Nevertheless, a life cycle cost analysis is needed to better understand the best treatment option. For instance, specific preservation strategies may be affected by existing pavement lane width. Furthermore, if overlay is proposed as a first treatment option, costs associated with pre-treating distress repair prior to overlay should be considered.

4.6 Conclusion

Pavement management systems can be applied to bicycle lanes given the set of tools that allow to keep the pavement at a predetermined level of service while applying certain budget limitations. This case study adopted the concepts of pavement management systems.

Historical data of pavement condition (IRI) for low-volume roads in *Montréal* was used to develop performance curves transferable to bicycle networks along with a dataset of current surface condition that were collected using a smartphone. This resulted in developing an optimal long-term plan over a span of 40 years. This allows selecting the most cost-effective treatment alternative among several Maintenance and Repair actions and contributes in establishing long-term strategies, and maximize the operational efficiency. The results of this study show that an annual budget of around $200,000 is appropriate to improve the surface condition of on-street bicycle lanes in the study area up to a good level and then to sustain that level of the segments in the network. This annual amount is allocated for 43.89 km of bike lanes. As a quick approximation, it costs $4557 per km, which sums up to $3.41 million as an annual operating budget to cover the whole bicycle network in Montreal. This amount represents 2.47% of the annual operating budget for road repairs allocated by the City of Montreal allocated in 2016 (City of Montreal, 2016). This procedure, that adopts the principles of PMS can be a powerful tool that helps practitioners, planners, policy makers and government agencies to set the optimal annual operating budget to achieve their strategic objectives.

Chapter 5: Towards Convenient Bikeway Networks: Incorporating Bicycling demand into Road Management Systems

Abstract

Several cities around the world have announced strategies to extend and/or upgrade their bikeway networks in response to the rapid increase of bicycle users. However, there is a disconnection between these strategies and management systems, often used for the scheduling of maintenance and rehabilitation of roads. Such systems fail to sustain bicycle pathways in optimal condition, and most importantly, to consider bicycling demand as the driving element to budget for improvements. In turn, more convenient, and safer bicycling facilities can encourage more individuals to shift their daily commuting habits to bicycling. This study incorporates bicycling demand into road management systems to produce strategic plans for the maintenance and improvement of the bicycle networks. Furthermore, this study employs the capabilities of smartphones in representing bicycling demand via GPS trajectories of bicycles. Goal optimization was applied to schedule interventions and improvements. Two scenarios were investigated with different annual budgets. The results show that the first scenario allows upgrading all bicycle lanes to protected paths more rapidly while accomplishing good levels of condition of pavements. The second scenario is not able to prevent the deterioration of pavement segments.

5.1 Introduction

Bicycling is increasingly being promoted as a sustainable mode of transportation in several cities around the world due to health benefits, reduced air and noise pollution, savings in energy consumption, and to reduce congestion on transportation infrastructure in urban regions (Deenihan and Caulfield, 2014; Mueller *et al.*, 2015; Pérez *et al.*, 2017; Rojas-Rueda, de Nazelle, Teixidó, and Nieuwenhuijsen, 2013). Policy makers therefore are adopting strategies to encourage sustainable modes of transportation in cities (transit, bicycling and walking), and discourage the use of the automobiles. Several cities around the world announced their strategies to extend and/or upgrade their bikeway networks such as Amsterdam (The City of Amsterdam, 2012), Melbourne (The City of Melbourne, 2016), Copenhagen (The City of Copenhagen, 2011), San Diego (The City of San Diego, 2013), Seattle (Seattle Department of Transportation, 2017), and Wellington

(City Council of Wellington, 2015). Regional and municipal governments have been taking initiatives to encourage bicycling (Pucher, Dill, and Handy, 2010). A significant correlation was found between pavement quality and the share of residents bicycling to work (Parkin, Wardman, and Page, 2007). Nevertheless, pavement condition is used as a key variable in determining the Bicycle Level of Service (BLOS), which is based on cyclists' perceptions of the roadway environment. Pavement condition for BLOS analysis is a general classification of the pavement surface, three categories are used: desirable, typical, and undesirable pavement condition (FDOT, 2013, 2014). This study extended the traditional management system of road infrastructure to incorporate bicycling demand, therefore, to promote bicycling in cities by providing more compatible, convenient, smooth, and safe bicycle facilities.

5.2 Literature Review

5.2.1 Bicycling Travel Demand

The objective of travel demand forecasting is to predict changes in travel behaviour and transportation conditions, as a result of proposed transportation projects, policies, and future changes in socioeconomic characteristics of the users and land use patterns. For non-motorized (bicycling and walking) users the objective is generally to predict the change in volumes or characteristics of bicycling, walking, or vehicle-trips as a result of facility improvements or policy changes which are designed to make bicycling or walking more attractive (FHWA, 1999).

Generally, available methods to estimate demand are grouped into five broad categories: aggregate behavioural studies, comparison studies, sketch pan methods, discrete choice models, and regional travel models. An overview of these methods, typical applications, their capabilities and limitations can be found in FHWA (1999).

Traditional methods for estimating bicycle volumes can be categorized as multi-step travel demand models or as direct demand models (Porter, Suhrbier, and Schwartz, 1999). Multi-step models attempt to forecast a detailed combination of travel choices across large transportation networks. The common four-step model is a sophisticated procedure to estimate four aspects of travel behaviour: trip generation, trip distribution, mode choice, and route choice (McDaniel, Lowry, and Dixon, 2014). The trip generation step tries to estimate the number of trips originating from a specific analysis zone for a particular purpose and time of day. The trip distribution is a prediction of the destination for each generated trip. The mode choice attempts to predict the mode of travel that will be used to make the trip. Finally, the route choice step aims at predicting the network segments that will be used to reach the destination. Several studies investigated, developed and applied various approaches for each step: trip generation (Barnes and Krizek, 2005; Cui, Mishra, and Welch, 2014; Franco, Campos, and Monteiro, 2014; Stinson, Porter, Proussaloglou, Calix, and Chu, 2014), trip distribution (Eash, 1999), mode choice (An and Chen, 2007; Broach and Dill, 2016; Eash, 1999; Kuhnimhof, Chlond, and Huang, 2010; Stinson *et al.*, 2014), and route choice. Route choice studies used either stated preference surveys (Monsere, McNeil, and Dill, 2012; Segadilha and Sanches, 2014b; Sener, Eluru, and Bhat, 2009; Stinson and Bhat, 2003), or revealed preference surveys (Howard and Burns, 2001; Kang and Fricker, 2013). The latest are often based on GPS-collected data (Broach, Dill, and Gliebe, 2012; Casello and Usyukov, 2014; Chen, Shen, and Childress, 2018; Heesch and Langdon, 2016; Guensler, and Ogle, 2005; Muresan, and Fu, 2017; Menghini, Carrasco, Schüssler, and Axhausen, 2010; Segadilha and Sanches, 2014a; Ton, Cats, Duives, and Hoogendoorn, 2017; Zacharias and Zhang, 2016).

Direct demand models simply avoid the behavioural aspect of travel by predicting the volume on a particular bicycle facility as a function of the attributes of the facility. Several studies proposed and applied direct demand models in estimating bicycle volume (Fagnant and Kockelman, 2016; Griswold, Medury, and Schneider, 2011; Hankey *et al.*, 2012; Hankey and Lindsey, 2016; Tabeshian and Kattan, 2014). Although direct demand models are advantageous since they simplify the complexities of travel behavior, but this feature makes it more difficult to gain a comprehensive understanding of travel patterns. In contrast, multi-step demand models are capable of providing rich understanding of travel behavior: for example they can predict every expected turn movement through an intersection rather than just predicting the total number at the intersection. However, this ability of multi-step demand models rely significantly on the availability of detailed information about the entire network and the interaction between origins and destinations (McDaniel *et al.*, 2014).

Recent practices in regional demand modeling of non-motorized travel in the United States were reviewed (Liu, Evans, and Rossi, 2012). Three structural approaches in the regional modeling framework were discussed: pre-trip distribution, pre-mode choice, and mode choice. In addition, non-motorized travel modeling may be carried out via route choice-trip assignment in which a pre-mode choice or mode choice travel model application is required. The study recommended agencies to use the mode choice approach with the route choice-trip assignment option in modeling non-motorized travel to evaluate proposed bicycle facilities. However, this requires intensive data that usually do not exist in the database, and some sensitivities to urban design variables may not be representative (Liu *et al.*, 2012).

5.2.2 Bicycling Rates and Bicycling Facilities

Recently, the number of studies investigating the impact of various types of bicycling facilities on bicycling rates in cities has been increased significantly. Several studies found a positive relationship between bicycling rates and the presence of bike lanes (Buehler and Pucher, 2012; Dill and Carr, 2003; Goodno, McNeil, Parks, and Dock, 2013). Approximately 1% increase in bicycling rates is found to be associated with each additional linear mile of bike lanes per square mile land area (Dill and Carr, 2003). Buehler and Pucher (2012) studied the influence of bike paths and lanes on commuting using bicycle based on a dataset contains the length of bike lanes and paths in 2008 collected from 90 large cities in US. The findings show that 10% greater supply of bicycle lanes is associated with a 3.1% greater number of bike commuters per 10,000 population. Similarly, a 10% greater supply of bike paths is associated with a 2.5% higher level of bike commuting. Furthermore, three revealed-preference studies from Copenhagen, Washington, DC, and five US cities found an increase in bicycling levels after the installation of cycle tracks (Goodno *et al.*, 2013; Monsere *et al.*, 2014; Snizek, Nielsen, and Skov-Petersen, 2013). Goodno *et al.* (2013) concluded that the bicycle volume roughly quadrupled after the installation of a two-way cycle track, well above the average in the city, and the BLOS was also improved.

Monsere *et al.* (2014) studied the effect of installing cycle tracks (protected bicycle lanes) in five cities: Austin, TX; Chicago, IL; Portland, OR; San Francisco, CA; and Washington, D.C in terms of use, perception benefits and impacts, using video, surveys of intercepted bicyclists (n=1,111) and nearby residents (n=2,283), and count data. City database containing counts before and after installation of protected bicycle lanes, along with counts extracted from video observation, were used to analyze change in ridership. They observed a measured increase in ridership ranging from 21% to 171% on all facilities. The increases were greater than overall increases in bicycle commuting in each city. Some of the increase in ridership at each facility likely came from new riders (i.e. riders who, in the absent of the protected bike lane, would have travelled using a different mode or would not have taken the trip) and some from riders diverted from other nearby streets (i.e. riders who were attracted to the route because of the facility, but would have chosen to ride a bicycle for that trip regardless). The study also conducted a stated-preference survey which showed that 10% of the riders shifted from other modes, and 24% switched from other bicycle routes. An increase in the frequency of biking on the installed protected lanes was reported by over a quarter of respondents. A strong support for building protected bicycle lanes at other locations was also reported by 75% of the residents. Approximately 67% of surveyed residents expressed their intention to ride a bicycle if motorized traffic and bicycles were physically separated by a barrier.

Parker, Gustat, and Rice (2011) studied the impact of the installation of the first on-street bicycle lane (3.1 mile dedicated bike lane) in New Orleans, LA during the spring of 2008. The results show an increase in the mean number of cyclists observed per day from 90.0 to 142.5 (58.33%). Parker *et al.* (2013) similarly studied the impact of installing 1-mile dedicated bike lane on S. Carrollton Avenue in New Orleans, LA in 2010. This study examined the impact through direct observation of one street with a new bike lane and two adjacent streets without bike lanes, before and after the installation. The study found an increase in the average daily number of cyclists after the installation of the bike lane from 79.2 to 257.1 (224.62%), but a reduction on the two adjacent streets from 54.4 to 36.4 (-33.09%). The study concluded that more people rode in the overall neighborhood after the lanes were striped; however, the increase in cyclists was greatest on the street with the new bike lane. The decrease in cyclists on the side streets suggests that few of those cyclists may have started using the dedicated bike lane.

In Montreal, Lusk *et al.* (2011) studied six cycle tracks (two-way protected bicycle lanes on one side of the street), and compared each cycle track with one or two reference streets without bicycle facilities that were considered alternative bicycling routes. The study found that the cycle tracks were much highly used, 2.5 times (250 % increase in ridership), compared with reference streets, and the risk injury was lower in the cycle tracks.

5.2.3 Pavement Management System

The Pavement Management System (PMS) is a set of tools or approaches that assist decision makers in identifying optimum strategies for providing and maintaining pavements in a serviceable condition over a given period of time (Haas, Hudson, and Zaniewski, 1994). Although the expenditure for sustaining and rehabilitating deteriorating pavement to provide a network at serviceable level is unavoidable, overall cost can be minimized through timely, appropriate, and effective Maintenance and Rehabilitation (M&R) strategies. PMS is an effective way to address the growing concern of managing high expectation from the road users, while considering budgetary limitations. Government agencies and municipalities use PMS as a planning tool in identifying cost-effective strategies for maintaining a pavement network at the desired level of service and determining the required level of funding. The PMS is composed of three essential components: a comprehensive database, pavement performance prediction (PPP) models, and a set of prioritization tools and optimization methods to assist in establishing cost-effective strategies for the evaluation and maintenance of roadway pavement.

An effective PMS requires a comprehensive and periodically updated database. Generally, besides traffic volume, traffic load, and environmental conditions, two types of data are collected for a PMS: inventory and condition. Inventory data describe physical elements of the roadway network that do not experience a noticeable change over time such as pavement surface type, pavement structure (number and thickness of layers), functional classification, number of lanes, lane width, segment length, segment width, and type and width of shoulder. Condition data describe the functional condition (e.g. roughness and skid resistance) and structural condition (e.g. surface distresses and load capacity) of pavement over time. A record of historical maintenance treatments, effectiveness of treatments, and associated cost information are also necessary. Technically, the type of required data for PMS depends on agency goals and PMS software that is being used. Several agencies use Geographic Information System (GIS) to store location-referenced spatial data to connect multiple data items to specific links or nodes of a roadway network (Kulkarni and Miller, 2003).

PPP models aims at predicting future pavement conditions under specified traffic loading and environmental conditions (Kulkarni and Miller, 2003). The current PPP models use either deterministic or probabilistic methods to characterize pavement performance (Mills, Attoh-Okine, and McNeil, 2012). Reliable PPP models are necessary for identifying the least-cost rehabilitation strategies that maintain desired levels of pavement performance (Kulkarni and Miller, 2003).

The optimization component involves using various methods to identify optimal pavement rehabilitation policies. The purpose is to maximize benefits given budgetary and other applicable policy constraints or to minimize the overall cost subject to meeting predefined performance levels and agency goals. Before the development of formal optimization techniques, agencies relied on simple priority ranking approaches. In the 1980s, few optimization models were developed for project-level decision making (Kulkarni and Miller, 2003). The first network-level optimization model was proposed in the PMS developed for the Arizona Department of Transportation (Kulkarni, 1984). Recently, several optimization methods have been applied in the PMS such as linear optimization (Amador-Jiménez and Mrawira, 2009), dynamic optimization (Farhan and Fwa, 2012), and genetic algorithm (Moreira, Fwa, Oliveira, and Costa, 2017).

5.3 Methodology

This study introduces an integrated approach in which bicycling demand is incorporated into a PMS. The approach, first, identifies the optimal set of M&R actions over a long-term planning horizon that achieves and sustains an acceptable level of service in terms of pavement condition at the network-level, second, upgrade the bikeway network to increase bicycling rates and promote bicycling as a sustainable mode of transportation. Figure 5.1 illustrates the procedure followed in this study. The first step involves developing a PPP model based on a historical dataset of pavement condition. In the second step, paths that are frequently traversed by cyclists were identified. It should be noted that bicycling demand was represented by bicycle counts estimated based on GPS cyclist trip data. The third step involves a decision-making framework of selecting M&R activities considering estimated bicycle counts.

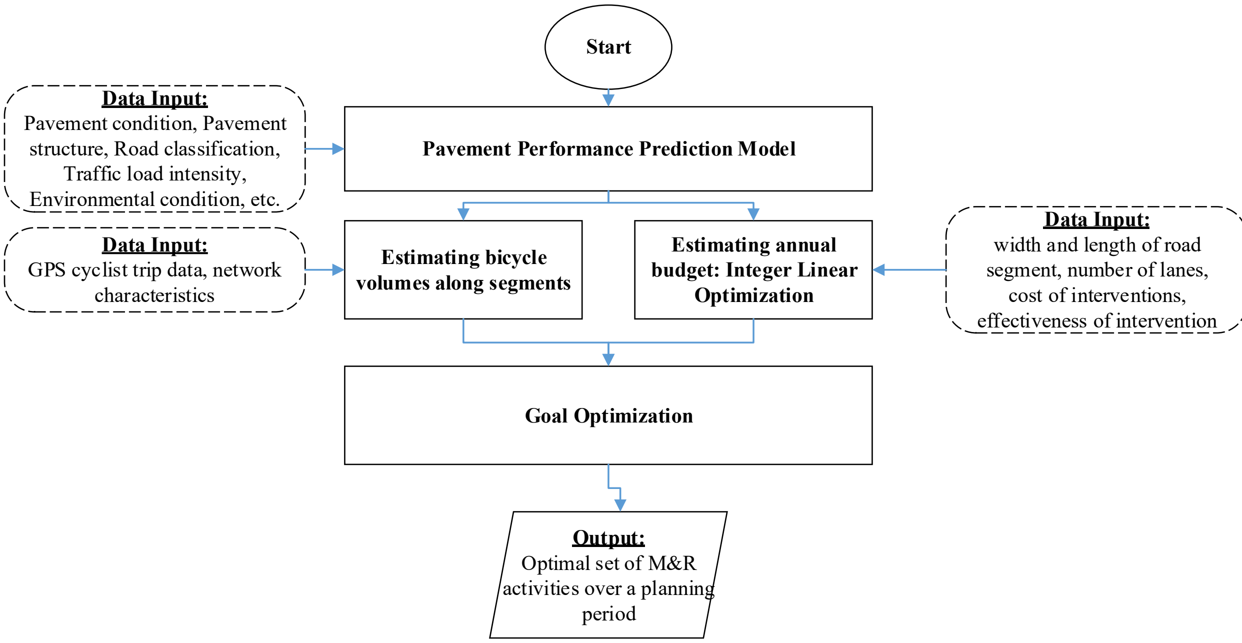


Figure 5.1 The procedure followed in this work

5.3.1 Smartphone GPS Travel Survey

This study uses GPS cyclist trip data collected by the *MTL Trajet* smartphone application. *MTL Trajet* dataset files are accessible on the official website of the City of Montreal (http://donnees.ville.montreal.qc.ca/dataset/mtl-trajet). This study uses data collected from cyclists between September 9th, 2016 and December 1st, 2016. Cyclists start this application at the beginning of their trips, and it provides second-by-second positional information, in terms of latitudes and longitudes, and timestamps (depending on the smartphone and the quality of the GPS signal). The total number of recorded bicycle trips is 3955. The collected trip data allow analyzing the movements of cyclists and identifying the traversed routes. This provides cost-effective approach to collect revealed data over an extended spatial area. However, smartphone GPS receivers have system errors. These errors could be significant in the presence of tall buildings and tunnels. For most GPS-enabled smartphones, the average horizontal error is around 20 meters, but can range from 5 to 35 meters (Paek, Kim, and Govindan, 2010). It is therefore necessary to pre-process the GPS traces by filtering the outliers.

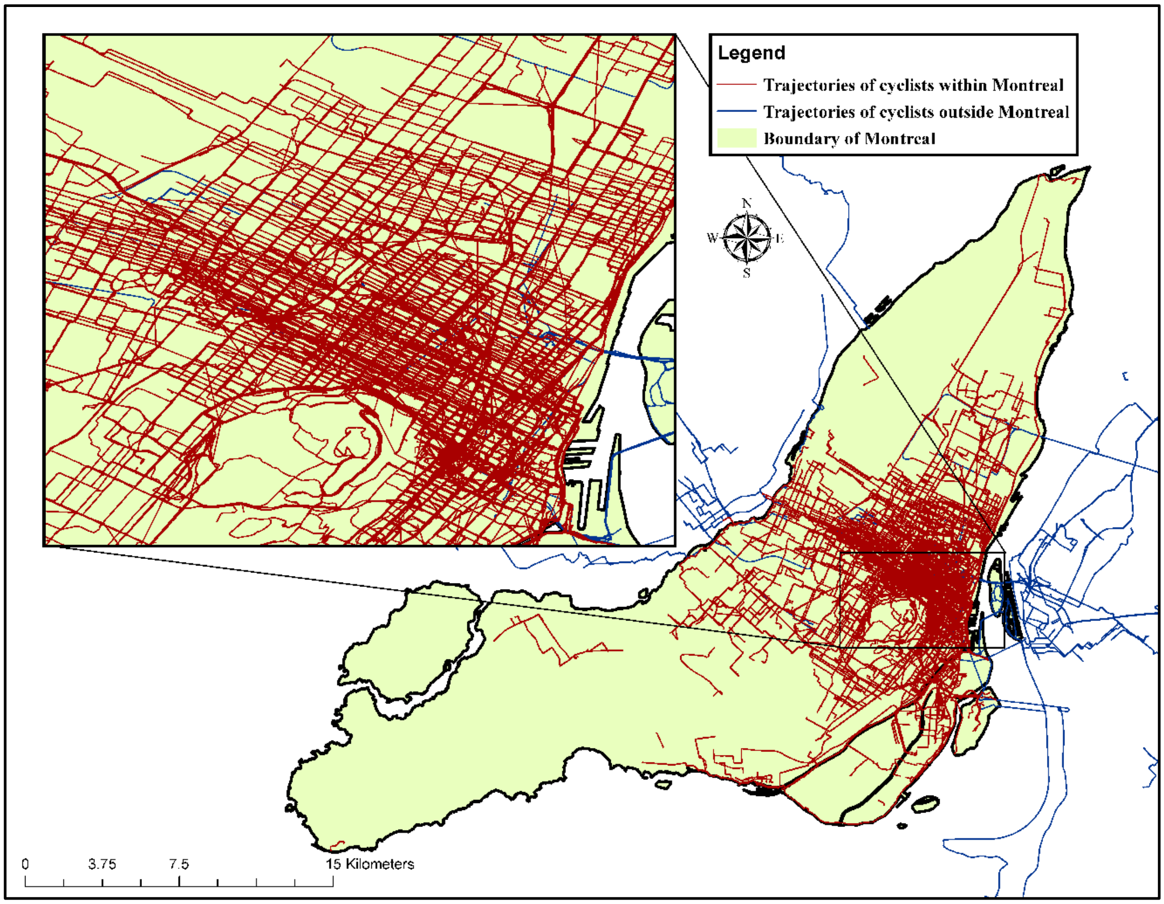


Figure 5.2 GPS trajectories extracted from *MTL Trajet* survey

The GPS observations were filtered based on average speed, duration and location of the trip, and consequentially, some trips were dropped as follows:

- **Average trip speed**

Based on the average speed for each entire trip, the entire trips having an average more than 30 km/h were classified as non-bike trips and excluded from the analysis. These trips are more likely were done by motorized vehicle while the application was running and recording (Zangenehpour, Miranda-Moreno, and Saunier, 2015). Similarly, trips with an average speed less than 1 km/h were excluded from the analysis since it is very likely that the application was left collecting the data for hours after the trip ended and the cyclist reached the intended destination (Strauss and Miranda-Moreno, 2017a).

- **Minimum trip duration**

Since the purpose is to estimate bicycle counts, trips with duration less than 1 min were excluded from the analysis as they are too short for our interests.

- **The location of the trip**

The trips that were not recorded entirely within the island of Montreal were excluded from the analysis as they fall outside the scope of our interest.

5.3.2 Assignment of GPS Traces

Since the reconstruction process of trips from GPS traces (i.e. trajectories) requires complex algorithms to accurately assign the traces to the associated network segments, simplified approach was used in this study to assign GPS traces/trajectories and estimate bicycle counts along each link in the network. This was accomplished via *ArcGIS* software by the following steps:

1. Integrate road and bicycle links.
2. Create a buffer area around the links in the entire network to enclose the GPS traces of cyclists. This allows to attach each cyclist trace to the nearest segment. The enclosing of GPS traces within this buffer area minimizes the error due to the fact that some GPS traces were irregular and projected far away from the network segments. This issue is caused when GPS signals are hindered by tall buildings, trees and tunnels as well as the accuracy degree of the smartphones' GPS system. The buffer area was chosen to be 25 m around the network segments, this was enough to enclose the most GPS traces.
3. Determine the central point of each segment and create a circular buffer area with a radius of 25 m around the central point. This circular buffer area serves to catch the crossing lines (GPS traces) as shown in Figure 5.3. The number of intersecting lines (GPS traces) to each circular buffer area represents the bicycle count on this segment.

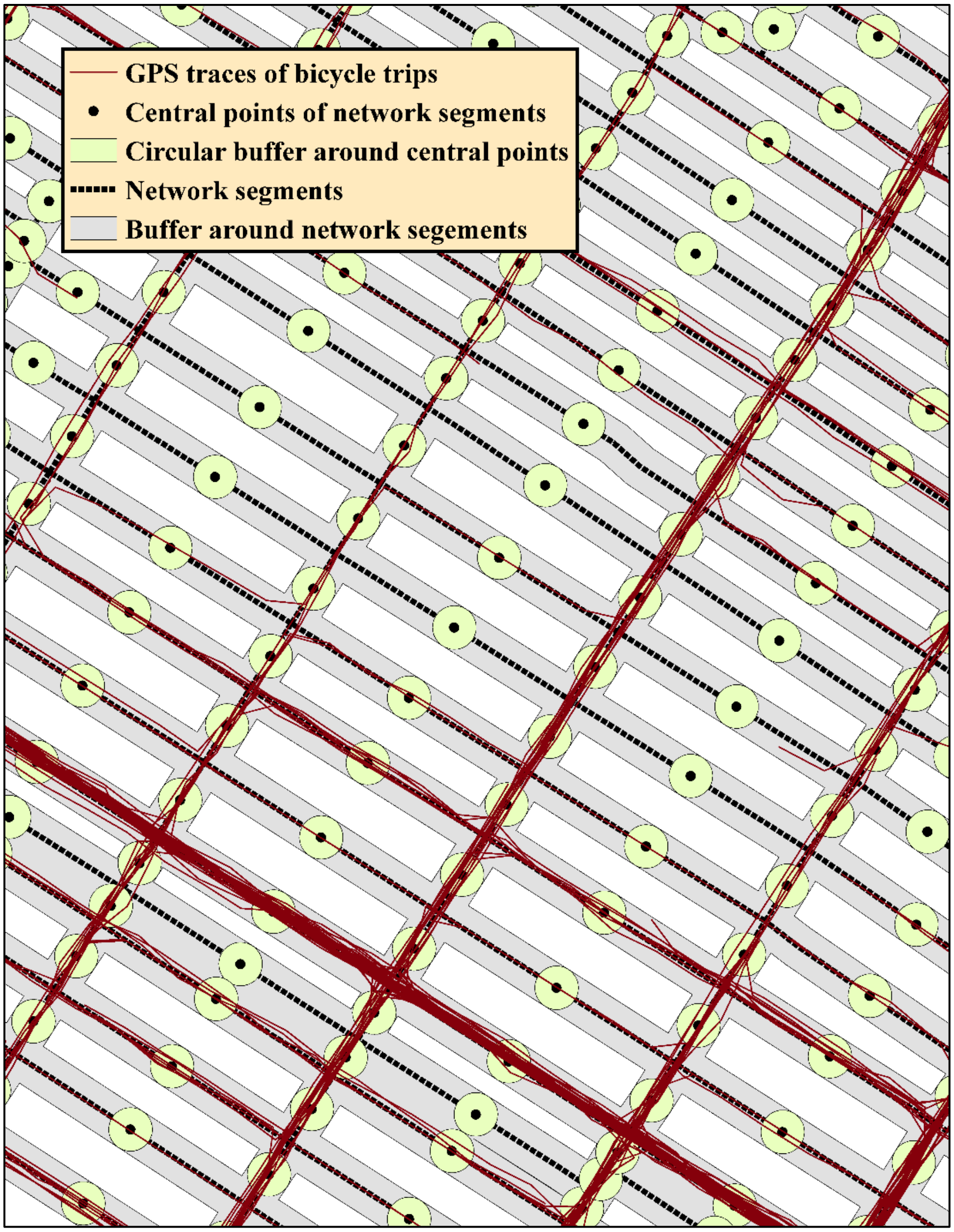


Figure 5.3 Snapping of GPS traces to network segments

5.3.3 Pavement Performance Prediction Model

Several casual factors could affect the deterioration process of pavement including traffic loading, pavement structure such as number and thickness of layers, material types, soil strength, or environmental exposure conditions. For simplicity, traffic loading was used as the primary causal factor in the performance model. Traffic loading can be expressed in term of the accumulated amount of Equivalent Single-Axle load (ESALs) on pavement sections. In this study, the International Roughness Index (IRI) was used as the indicator of pavement surface condition. A dataset containing pavement surface condition (i.e. IRI) of road segments in Montreal for 2010 and 2015 was used to develop the performance model. The development of the performance model was based on a procedure proposed by Amador-Jiménez and Mrawira (2009, 2011). The procedure suggested separating the pavement sections into homogeneous groups of similar characteristics such as pavement structure, environmental conditions, and traffic loading. This helps enhance the reliability of the performance model developed for network-level long-term planning. In the absence of road absolute age data, the surface condition of pavement (i.e. IRI) in 2010 was used to separate the pavement sections into homogeneous groups. They were broken into three levels: good, fair, and poor; while traffic load intensity was divided into three levels: high, medium and low. This resulted in establishing nine groups of pavements, corresponding to each pair of traffic-apparent age level as shown in Table 5.1. The apparent age represents the age that is associated with the existing condition of a pavement, considering the treatments that were received.

According to the criteria mentioned in Table 5.1, most roads in Montreal have poor pavement surface condition in 2015 as shown in Figure 5.4. Since there are three levels of traffic load intensity; high, medium, and low, three PPP models were developed corresponding to each level. Figure 5.5 shows the deterioration process of pavement as in terms of traffic loading and apparent age. Since the three groups have similar behavior, one performance curve was used to represent the overall behavior of all groups.

Table 5.1 Summary of pavement groups mean condition, 2010–2015

Group	IRI 2010 rang (m/km)	Condition class	ESAL/year (10^4)	Mean 2010 IRI (m/km)	Mean 2015 IRI (m/km)
1	≤ 2.5	Good	>953	2.13	3.13
2	2.5-4	Fair	>953	3.30	4.31
3	> 4	Poor	>953	5.62	6.54
4	≤ 2.5	Good	389-953	2.12	3.24
5	2.5-4	Fair	389-953	3.24	4.28
6	> 4	Poor	389-953	5.60	6.60
7	≤ 2.5	Good	<389	2.12	3.21
8	2.5-4	Fair	<389	3.26	4.31
9	> 4	Poor	<389	5.57	6.60

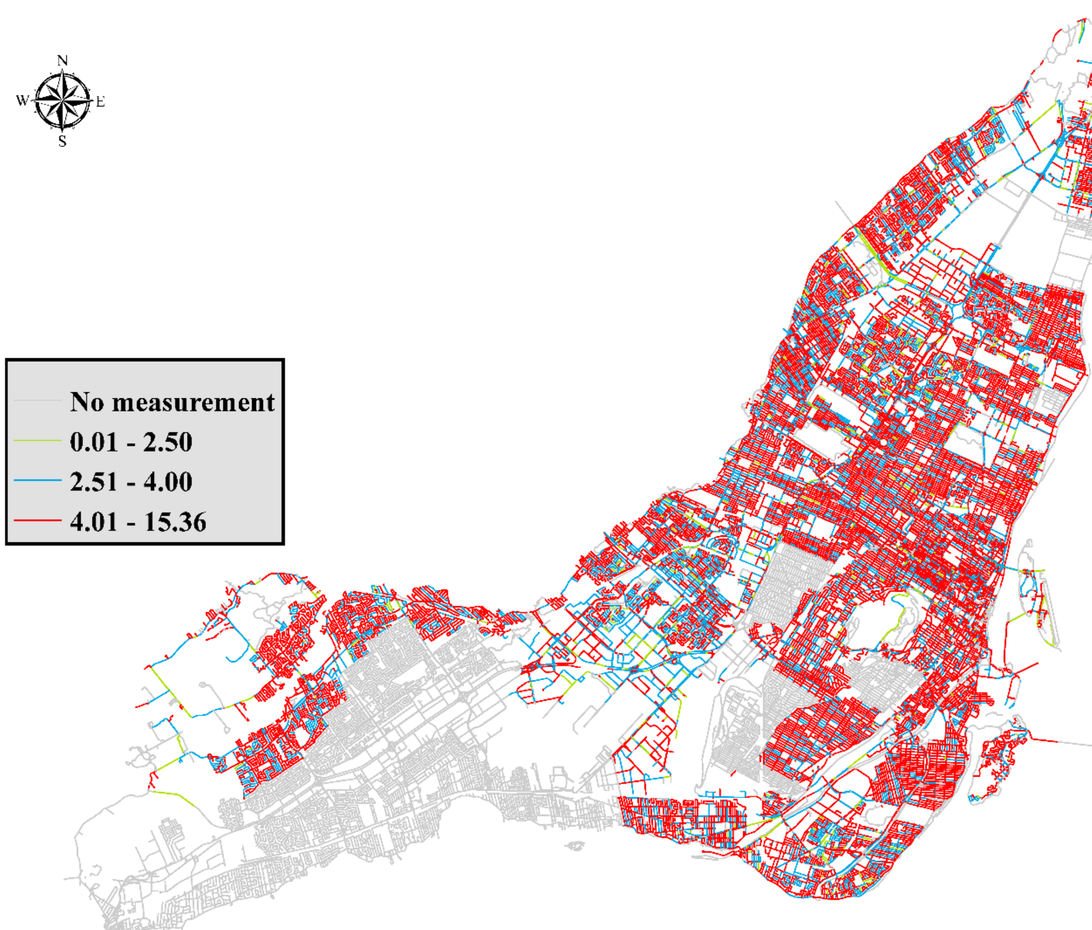


Figure 5.4 Pavement surface condition 2015-Montreal

5.3.4 Optimal Allocation of Budget

Once M&R actions have been evaluated, pavement managers need to optimize the allocation of the available budget. Pavement management systems mainly rely on mathematical programming and near-optimization methods (Torres-Machí, Chamorro, Videla, Pellicer, and Yepes, 2014). The scheduling of M&R activities to achieve an acceptable level of service at the network-level has been addressed (Amador-Jiménez and Afghari, 2013; Amin and Amador-Jiménez, 2015; Faghih-Imani and Amador-Jimenez, 2013; Haas, and Huot, 1998). In this study, goal programming which is a branch of multi-objective optimization based on integer linear programming (ILP) is proposed to achieve a cost-effective allocation of the available budget.

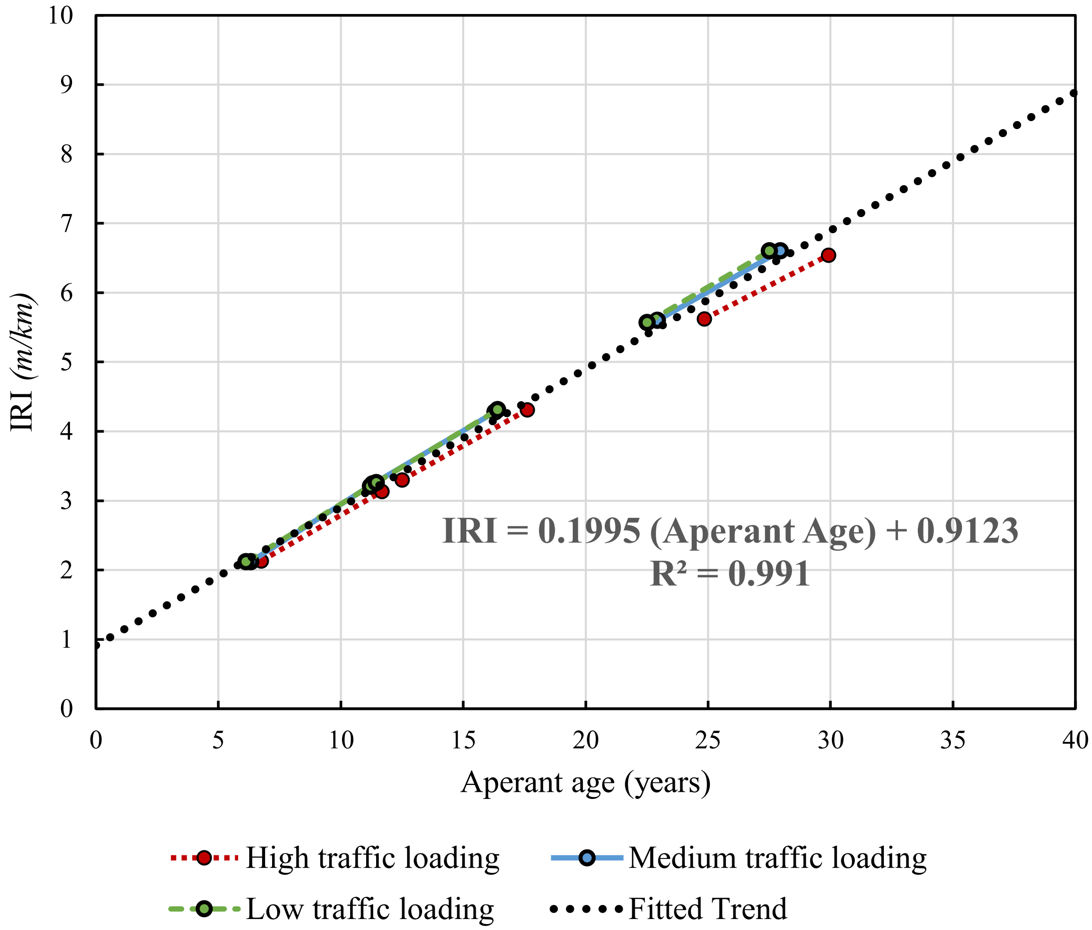


Figure 5.5 Pavement performance prediction model

A typical application of the optimization process seeks maximizing the aggregated network pavement condition subject to a given budget per a planning period (B_t). Other traditional constraints include the limitation that every pavement can receive no more than one treatment per year, and, in some circumstances, the preclusion of treating pavements within a certain period after they have received a special intervention. The main objective of this study is to incorporate the bicycling travel demand into a strategic planning of M&R projects at the network-level. The first step was to determine the minimum budget required to prevent the aggregated network pavement condition from declining. It is worth mentioning that the bicycle demand was not considered in this step. The mathematical formulation to estimate the minimum required budget relies on ILP method, and can be synthesized by Equations 5.1, 5.2, and 5.3:

minimize

$$Z = \sum_{i=1}^{N} \sum_{j=1}^{K} C_{t,j} x_{tij} \, L_i \qquad \text{for values of } t \qquad [5.1]$$

subject to

$$\sum_{i=1}^{N} L_i IRI_{it} \leq \sum_{i=1}^{N} L_i IRI_{it-1} \qquad \text{for values of } t \qquad [5.2]$$

where $IRI_{tij} = x_{tij} \, (IRI_{(t-1)ij} - E_{ij}) + (1 - x_{tij}) \, (IRI_{(t-1)ij} + D_{it})$ [5.3]

$x_{tij} \in [0,1]$

where

Z= total aggregated cost at the network-level;

x_{tij} = 1 if treatment j is applied on road segment i at year t, 0 otherwise;

IRI_{it} = the pavement condition index for road segment i at year t;

$IRI_{i(t-1)}$ = the pavement condition index for road segment i at year (t-1);

IRI_{tij} = the pavement condition index of road segment i at year t for intervention j;

$IRI_{(t-1)ij}$ = the pavement condition index of road segment i at year (t-1) for intervention j;

C_{tj} = the cost (CAD$) of intervention j at year t;

L_i = the length (km) of road segment i;

E_{ij} = the improvement in terms of IRI reduction on road segment i from intervention j;

D_{it} = the deterioration on road segment i at time t;

B_t = the budget at year t;

N = the total number of road segments;

T = the total number of time periods; and

K = the total number of applicable treatments.

This formulation relied on the forward dynamic links of Equation 5.3 which support a decision tree containing all possible paths of pavement condition across time, after hypothetically receiving available treatments (Amador-Jiménez and Afghari, 2013; Amin and Amador-Jiménez, 2015; Faghih-Imani and Amador-Jimenez, 2013). This tree is based upon a transfer function used to estimate pavement condition (IRI_{ti}) as a combination based on the decision variable (x_{tij}) and the effectiveness (E_{ij}) or deterioration (D_{it}) of the specific road segment on time t (Equation 5.3).

After estimating the required budget, the allocation of budget was done using goal programming. The objective is to achieve and sustain an acceptable level of network mean pavement condition (i.e. IRI) while encouraging cyclists to ride more frequently and non-cyclists to consider bicycling in making their trips. To promote bicycling as a sustainable mode of transportation, and increase its rates across the city, this study proposes including an upgrade alternative of roads either having dedicated lanes for bicycles or having no bicycling facilities to protected bicycle paths (i.e. cycle tracks). The optimal strategic programming of M&R actions for pavements in the network considering bicycle count on each road segment V_i is done using goal programming approach, which seeks maximizing both the network aggregate pavement condition and bicycling rates. The formulation of the optimization model is presented as follows:

objective functions:

$$f_1 = \sum_{i=1}^{N} IRI_{ti} \leq \sum_{i=1}^{N} IRI_{(t-1)i} \qquad \text{for all values of } t \qquad [5.4]$$

$$f_2 = \sum_{i=1}^{N} V_{ti} \geq \sum_{i=1}^{N} V_{(t-1)i} \qquad \text{for all values of } t \qquad [5.5]$$

$$f_3 = \sum_{i=1}^{N} \sum_{j=1}^{K} C_{t,j} x_{tij} L_i \leq B_t \qquad \text{for all values of } t \qquad [5.6]$$

where

$$IRI_{tij} = x_{tij} \left(IRI_{(t-1)ij} - E_{ij}\right) + (1-x_{tij}) \left(IRI_{(t-1)ij} + D_{it}\right) \qquad [5.7]$$

$$V_{tij} = x_{tij} \left(P_{ij} V_{(t-1)ij}\right) + (1-x_{tij})\left(V_{(t-1)ij}\right) \qquad [5.8]$$

P_{ij} = the potential increase in bicycling rates on road segment i from intervention j; while the remaining variables are as defined earlier.

5.4 Analysis and Results

5.4.1 Bicycle Counts from GPS trajectories

The bikeway network in Montreal is composed of 233 km of bicycle lanes, 69 km of cycle tracks, 294 km of off-street paths and 187 km of streets that are shared with motorized traffic, as shown in Figure 5.6. The assignment of GPS traces of cyclists was done by following the procedure described in section 5.3.2. After the filtration process, 1778 GPS traces from the total of 3955 were assigned to network segments. The results show bicycle counts ranging from no bicycle count on some links to 181. As expected, high bicycle counts were observed in downtown area. Figure 5.7 shows the distribution of estimated bicycle counts over the entire network.

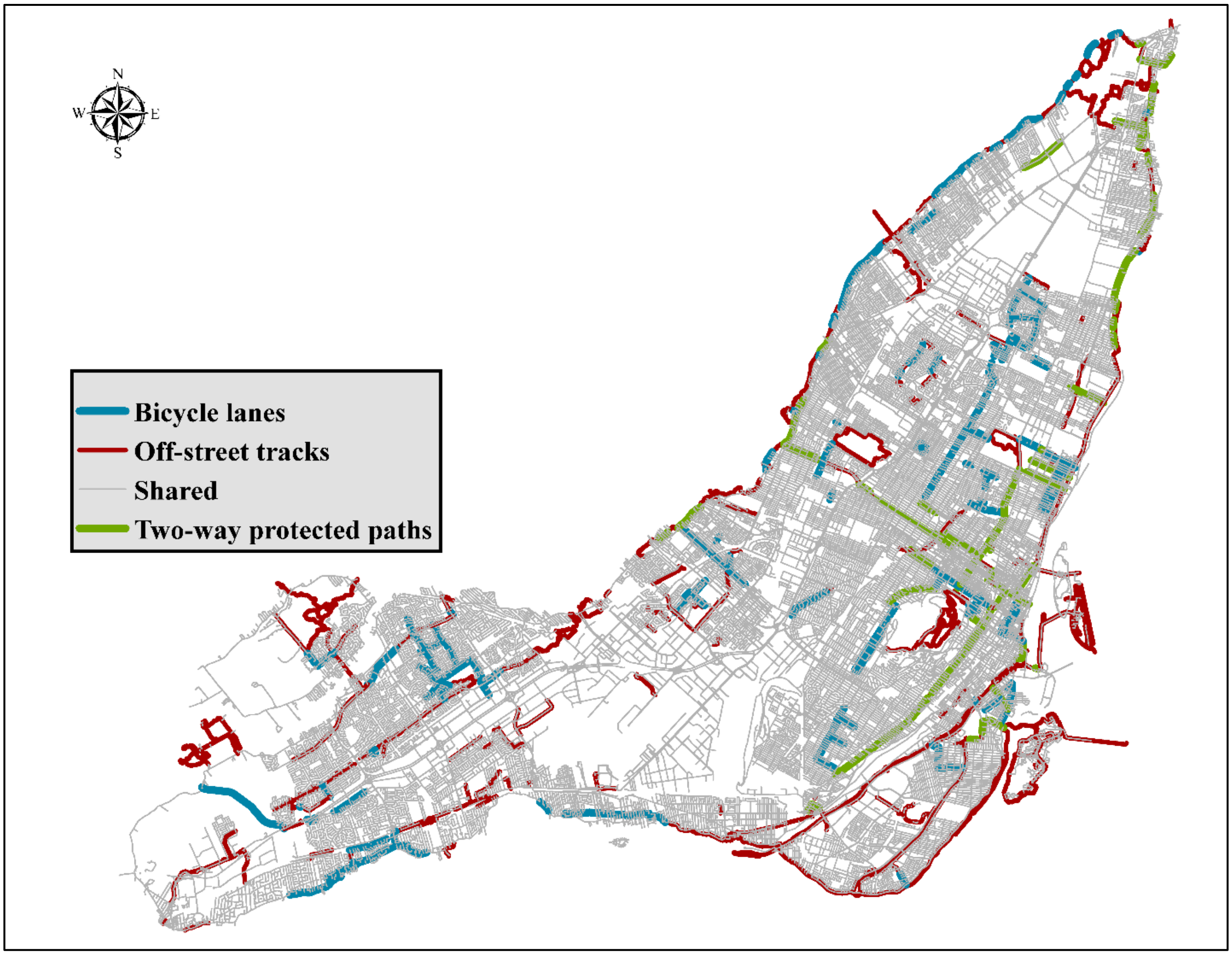


Figure 5.6 Bikeway network- Montreal

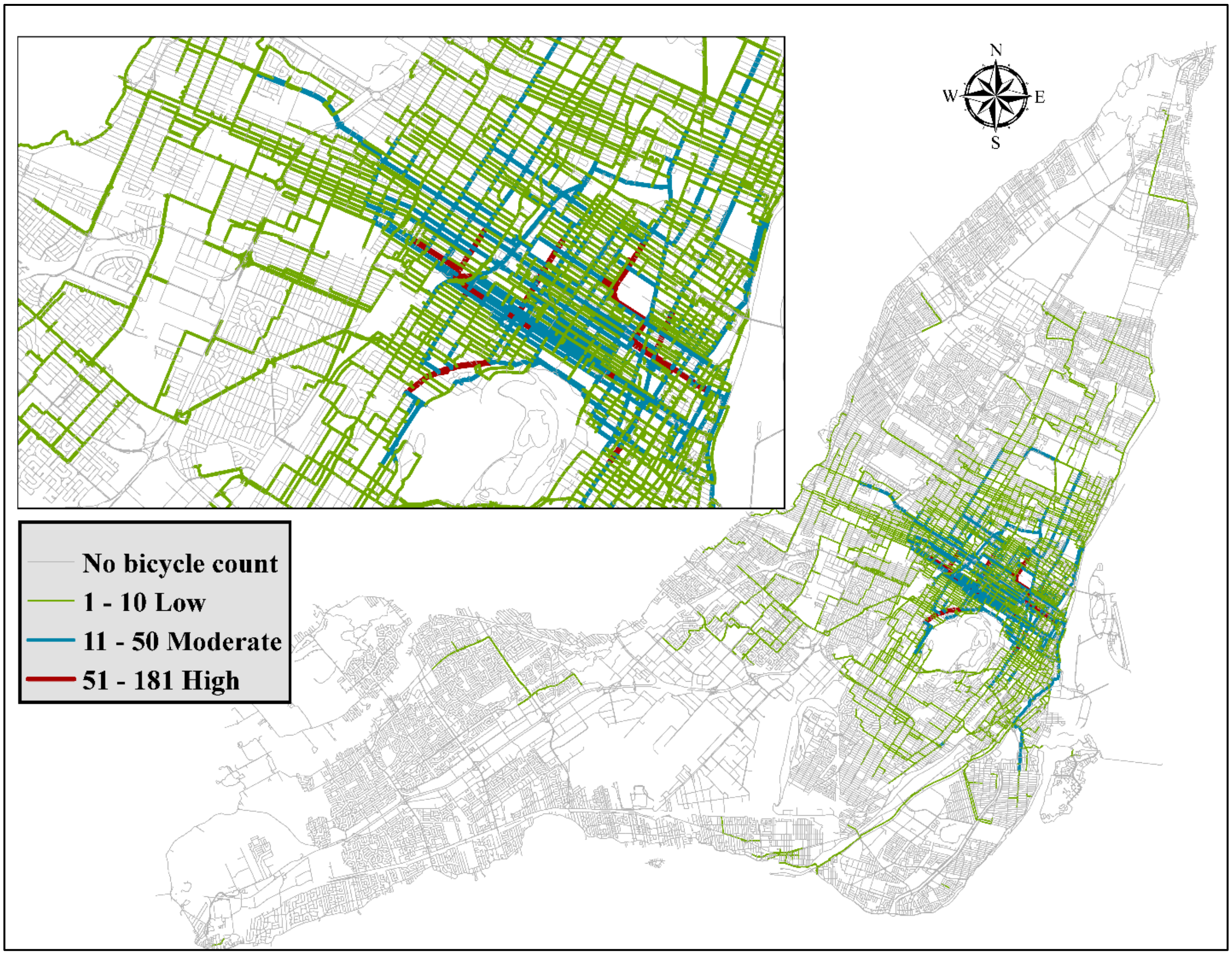


Figure 5.7 Bicycle counts-*MTL Trajet*

5.4.2 Budget Allocation

Table 5.2 presents the criteria used in identifying the type of intervention that is applicable to every segment at different points of time and which considers multiple periods of time. The criteria includes cost, effectiveness and range of applicability. Costs of interventions were roughly estimated based on local practices and include material, labour, and transportation. The timing of the intervention is modelled as a binary decision variable (Equations 5.1 through 5.8). The optimization algorithm identifies the optimal set of interventions for the whole network during the analysis period (40 years in this study) within a complex structure with time dependencies that link the consequences of decisions through time. Both optimization models were solved with *Remsoft*® *Spatial Planning System 4.0*; which has the capability of modelling linear binary programming, including goal and weighted objective formulations for long-term planning as a standard linear programming, generating matrices and solving the problem with commercial solvers (e.g., *MOSEK*, *LPABO*).

This study qualitatively grouped pavement condition in terms of IRI into three groups: good (IRI ≤ 2.5), fair (2.5 < IRI ≤ 4.00), and poor (IRI > 4.00). The applicability of upgrading depends on two thresholds; pavement condition and predefined bicycle volume V_o. The pavement condition threshold was selected to be the same as the reconstruction intervention. For the second threshold, the 33th percentile of the bicycle counts was selected in this study.

It is worth to mention that the Annual Average Daily Bicycle (AADB) volume is typically estimated using daily, hourly, and monthly adjustment factors as well as short-and- long term counts (El Esawey, 2016). Recently, a regression model was proposed to estimate AADB volumes along segments and intersections in the entire network based on short-term, long-term, and GPS data (Strauss, Miranda-Moreno, and Morency, 2015). The potential increase in bicycling rate is usually estimated based on stated preference surveys, revealed surveys, or before-and-after studies. The last approach is able to provide more accurate insights than other ones: an average of previous studies suggest that AADB could increase as much as 400%, with other studies identifying a 224% and a 171%, however a potential increase of 150% was used in this study to remain on a more conservative side.

In the case of protected bicycle paths (those fully separated from the road with a median), “Reconstruction” and “Mill and Overlay” interventions were applied over the width of the path and not the road. Whereas, the total width of the road was considered in the application of the interventions for the remaining facilities. It is worth mentioning that: all roads in the network were assumed to have two lanes, 3.6 m each, and only bicycle lanes (those with sufficient space to enable a separate bike-lane through pavement markings) were considered as candidates for upgrading to protected bicycle paths. Although the bicycle volumes might have an impact on the deterioration of pavement, the minimum recommended thickness by AASHTO is 7.5 cm (AASHTO, 1993)

The aggregation of individual annual interventions found at the solution of Equations 5.1, 5.2, and 5.3 returns the minimum annual budget to achieve and sustain acceptable pavement condition at the network-level, therefore, the required budget was found to be CAD$320 million on average per year as show in Figure 5.8. Figure 5.9 shows the expected mean pavement condition for each year during the panning period based on the previously mentioned scenario. However, the City of Montreal announced CAD$138 million as an annual budget for repairing roads in the city (Ville de Montreal, 2016). Two scenarios considering both budget amounts were investigated in this study.

Table 5.2 Cost effectiveness, cost and operational window of interventions

Intervention	Cost effectiveness		Cost (CAD$/lane-km)	Operational window
	Improvement in pavement condition	Potential increase in bicycling rate		
Reconstruction	As new	-	600,000	IRI > 4.0
Major rehabilitation (mill and overlay)	Extension of 10 years	-	175,000	2.5 < IRI ≤ 4.0
Preventive treatment (Micro-surfacing)	Extension of 5 years	-	80,000	IRI ≤ 2.5
Upgrade to a protected bicycle path	As new	150%	600,000	IRI > 4.0 and $V_i > V_o$ only bike lanes with sufficient space

Figure 5.10 shows that overall pavement condition will deteriorate during the analysis period under an annual budget of CAD$138 Million, with or without upgrading bike lanes to protected bike paths. After 40 years, the mean aggregate IRI of the network is estimated to be 7.93 m/km. The distributions of expenditures according to applied interventions for a budgetary constraint of CAD$138 million is illustrated in Figure 5.11. Only a small portion of the overall budget is required during the first four years to upgrade all bicycle lanes to protected bike paths. Signifying that bike lanes could be easily improved without affecting overall road network condition. The deterioration trend of both scenarios with CAD138 Million is almost identical, however, an increase from 30% to 46% is noticed in the percentage of roads that are in good or fair condition as shown in Figure 5.12.

On the other hand, a budget of CAD$320 (Figure 5.10) is the minimum to accomplish continuous improvement in the overall pavement condition during the 40 year analysis period. The expected mean IRI in the 40th year is 3.9 m/km, which overall indicates a fair condition of roads in the city. Nevertheless, the percentage of roads that are not in poor condition is estimated as 78% as shown in Figure 5.14. The distributions of expenditures according to applied interventions under budgetary constraints of CAD$320 million is illustrated in Figure 5.13. The budget will invested in upgrading all bicycle lanes to protected bicycle paths in the first year according to CAD320-miilion-budget scenario. While the upgrading processes will take place during the first four years in the other scenario. Reconstruction projects are more uniformly distributed over the planning period under an annual budget of CAD$320 million, while the pattern is more irregular under an annual budget of CAD$138 million.

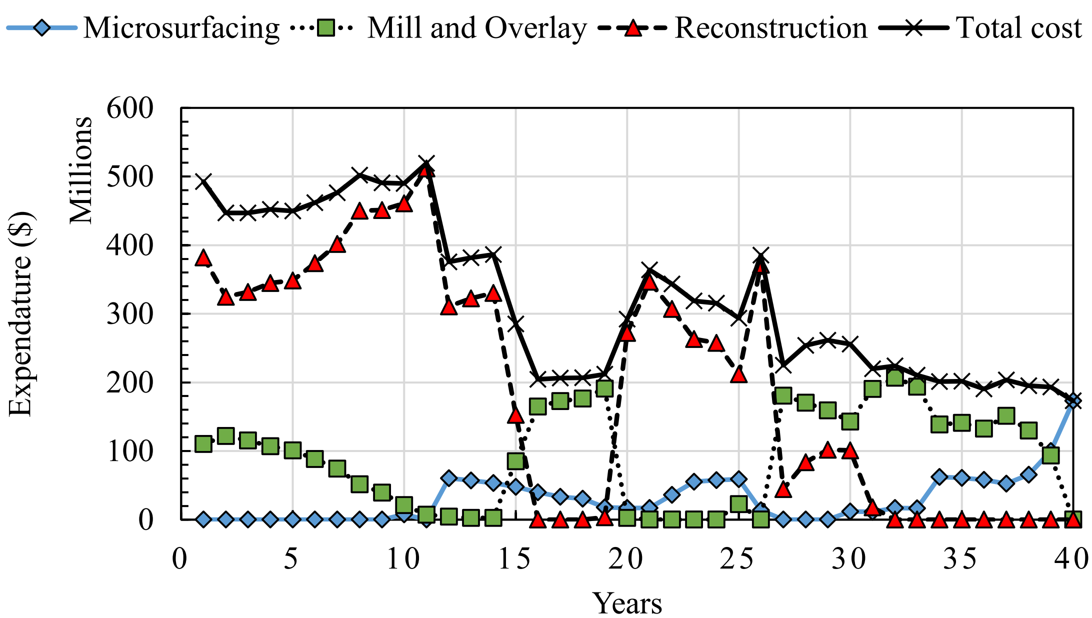


Figure 5.8 Annual expenditures for each intervention

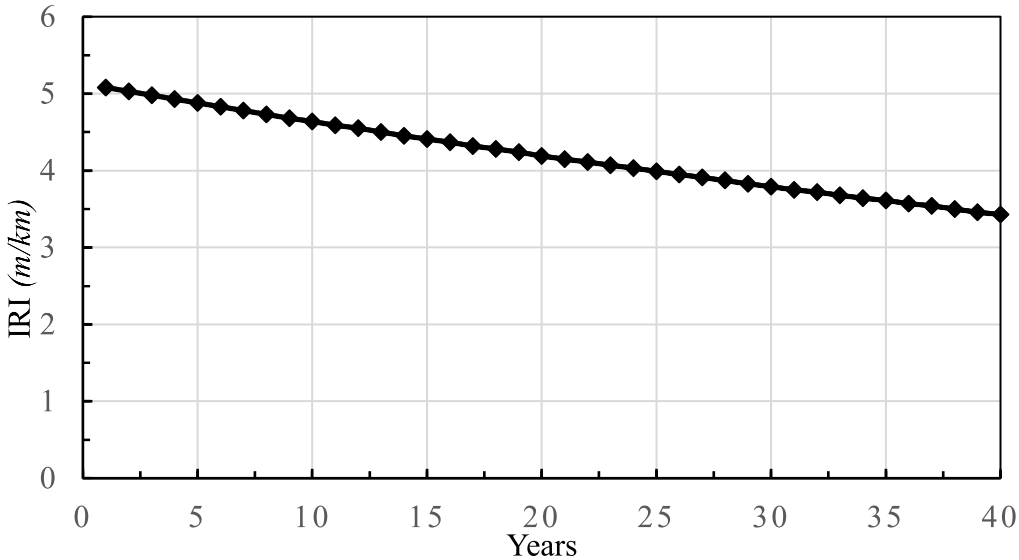


Figure 5.9 Overall pavement condition

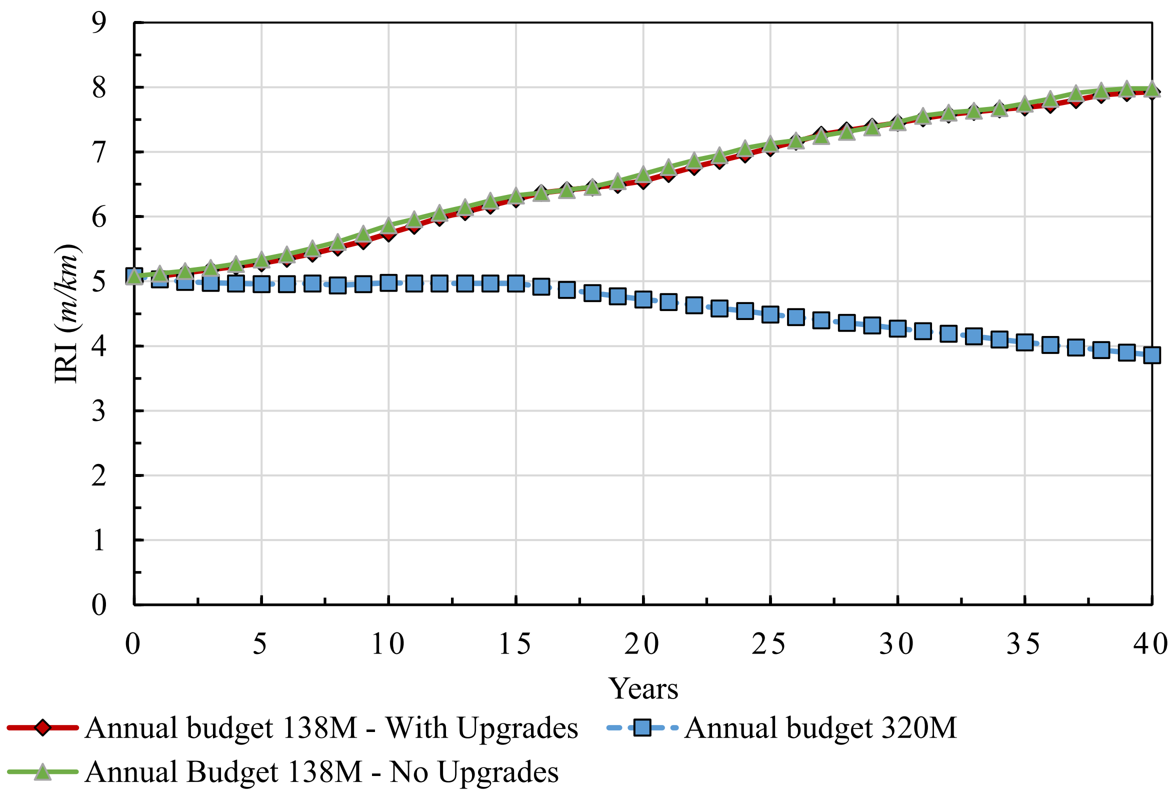


Figure 5.10 Overall pavement condition for both scenarios

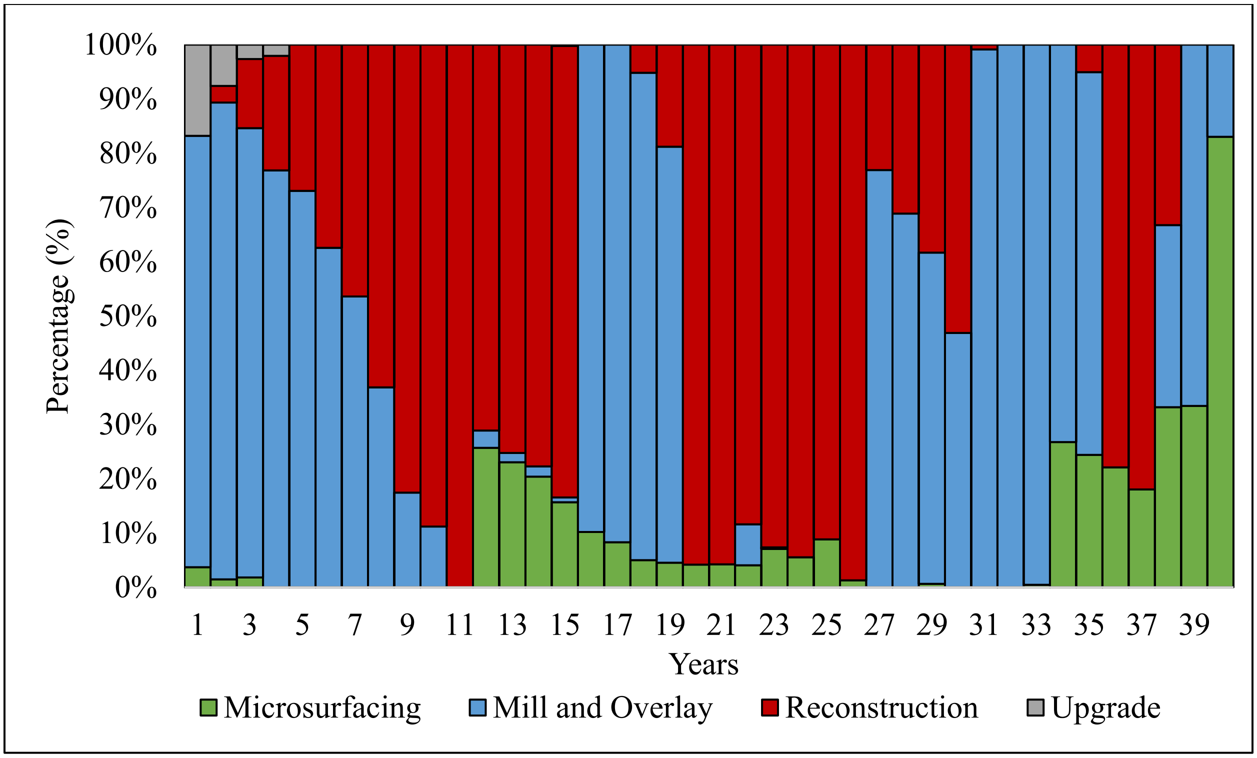


Figure 5.11 Expenditures according to applied interventions; annual budget of CAD$138 million

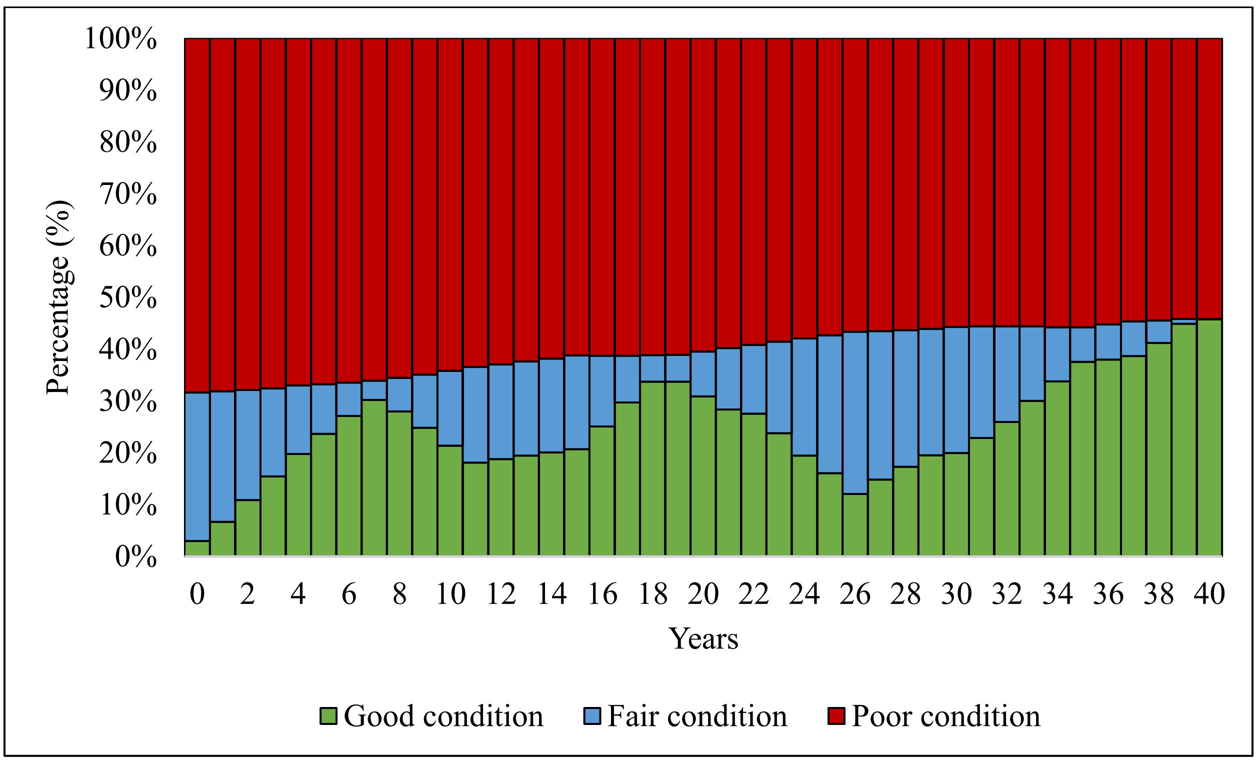


Figure 5.12 Pavement condition; annual budget of CAD$138 million

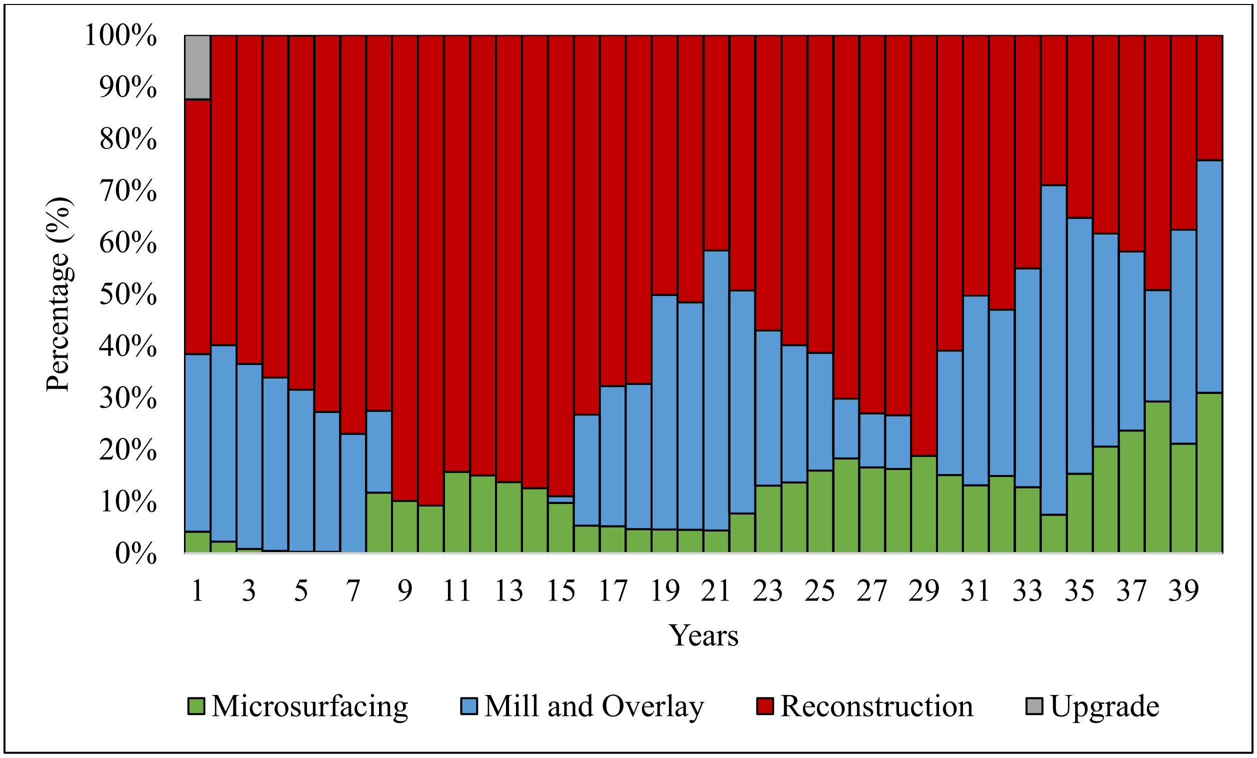


Figure 5.13 Expenditures according to applied interventions; annual budget of CAD$320 million

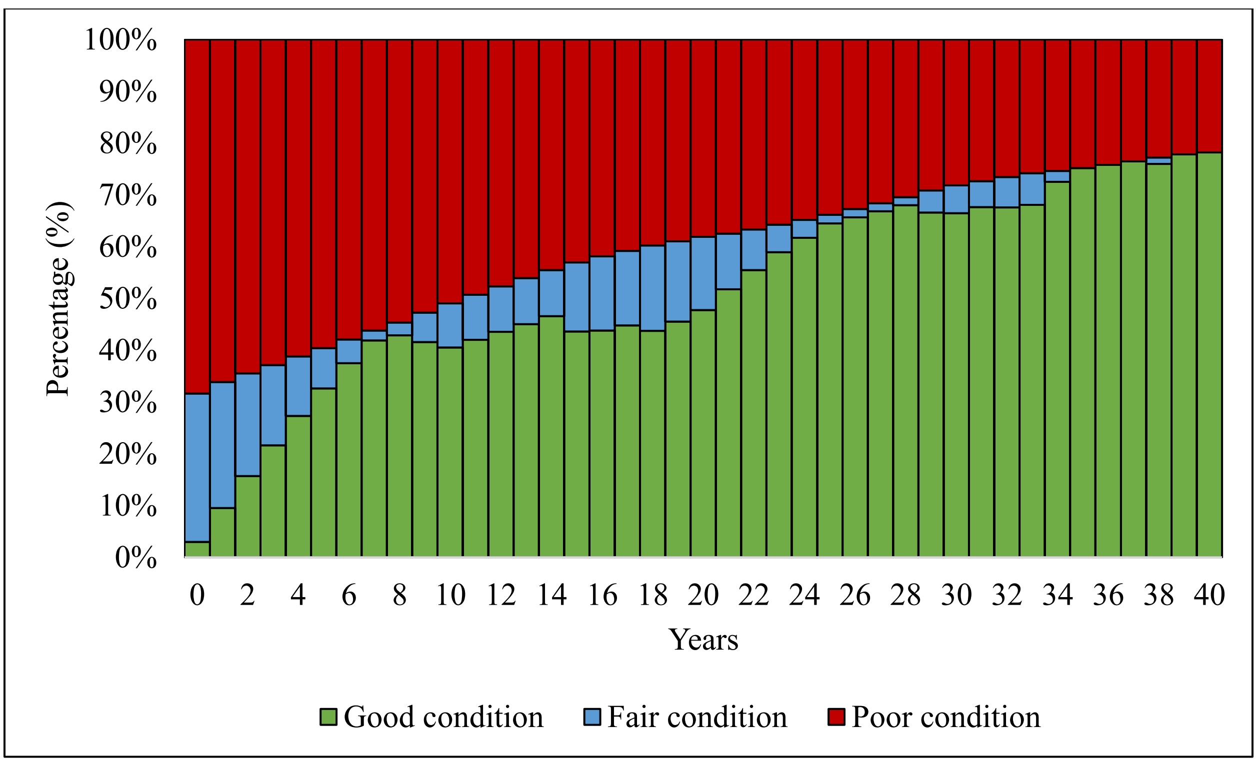


Figure 5.14 Pavement condition; annual budget of CAD$320 million

5.5 Conclusions

The scheduling process of M&R projects is usually based on pavement performance indicators (e.g. PCI, IRI, etc.) as well as other associated costs (e.g. vehicle operating costs) and environmental impact such as greenhouse gas emissions produced by M&R actions. This study proposes an approach to incorporate bicycling demand into long-term planning of M&R activities of pavements at the network-level. This is in line with strategies that have been adopted by several cities around the world to encourage bicycling among individuals through a wide variety of bicycling interventions. Goal optimization was applied to address the conflicting objectives in the scheduling of interventions; reconstruction, major rehabilitation, preventive treatments, and upgrading. Furthermore, this work employed the capabilities of smartphones in representing bicycling demand through a sample of bicycle volumes over the entire road network. The bicycle counts on network segments were estimated based on GPS traces of cyclists across the city. In this work we investigated two scenarios with different annual budgetary constraints; CAD$320 million and CAD$138 million respectively. The results show that the first scenario allows upgrading all bicycle lanes to protected paths in the first year of the planning period. In the second scenario, the upgrading process is being executed over the first four years. The first scenario led to achieving an acceptable overall pavement surface condition. However, the condition of pavement segments continued deteriorating until reaching poor condition due to the lack of sufficient financial resources in the second scenario.

The main benefit of using GPS data is the large spatial coverage it provides through a sample of cyclists collected over the entire road network. This spatial coverage is crucial to establish more realistic urban infrastructure planning models. For instance, GPS trip data help in planning new bicycling infrastructure by identifying the network segments that are highly traversed by cyclists. Nonetheless, the collected sample of bicycle volumes can be extrapolated to AADB by means of regression models based on short- and long- terms counts. Among the limitations, first, this study did not consider the practical issues of upgrading bicycle lanes to protected paths as well as the potential impact on vehicular traffic conditions. Second, further investigation is needed to define the criterion in terms of bicycle volume to trigger the upgrading intervention instead of using the 33th percentile value of bicycle counts in this study.

The proposed decision-making model in this study can be extended to include other factors such as vehicular traffic flows, environmental impact, vehicle operating costs, and social characteristics of urban neighbourhoods. Finally, this study attempts to propose an integrated decision-making model that assists government agencies, municipalities, policy makers, urban planners, and engineers in establishing more efficient strategies to promote bicycling in cities.

Chapter 6: Conclusions and Recommendations

6.1 Conclusions

This research has presented an extension to traditional performance-based optimization for strategic management of road infrastructure to incorporate bicycling demand in cities. The main objective is to propose a decision-making model that assists policy makers in establishing strategies that supports sustainability in cities and encourage bicycling among individuals. The model presented in this research can be extended to include vehicular traffic; vehicle operating cost induced by surface roughness; environmental impact from maintenance and rehabilitation actions; and social characteristics of urban neighbourhoods.

The first goal of this thesis was to introduce an approach to develop an initial pavement management system for on-street bicycle facilities. This approach adopted the concepts of traditional pavement management system. Historical data of pavement surface condition in terms of IRI for roads with low traffic load intensity were used to develop pavement performance prediction models that are transferable to bicycle facilities. Moreover, the proposed approach demonstrates the utilization of smartphone capabilities in collecting pavement surface condition data via built-in accelerometers that are able to capture the surface vertical irregularities. Smartphones can provide, in absent of surface data collected through standardized methods, a practical solution to collect data and provide indicators about the current pavement surface condition. The coordination of maintenance and rehabilitation projects was accomplished through the application of linear optimization software *Remsoft® Spatial Planning System 4.0*; which allows selecting the most cost-effective set among various treatment alternatives. A case study of a portion of the roads in *Plateau-Mont-Royal* region in Montreal was used to demonstrate the proposed approach. *Plateau-Mont-Royal* region was selected since it has around 44 km of bicycle lanes. A long-term plan, over a span of 40 years, was established to achieve and sustain an acceptable overall pavement surface condition, and maximize the operational efficiency. The results show that an annual budget of around $200,000 is sufficient to improve the surface condition of bicycle lanes in the study area up to a good level and then to sustain that level.

The second objective of this research aimed at extending the mathematical formulation of traditional management system of road infrastructure to incorporate bicycling demand. The presented approach, first, identifies the optimal set of M&R actions over a long-term planning horizon that achieves and sustains an acceptable level of service in terms of pavement surface condition at the network-level, second, upgrade the bikeway network to increase bicycling rates and promote bicycling as a sustainable mode of transportation. Goal optimization was applied to maximize mean pavement surface condition (i.e. minimize average IRI of all segments), and maximize bicycling rates over the entire network. The bicycling facilities were classified into cycle tracks (i.e. protected bicycle paths), bicycle lanes, off-street facilities, and those shared with motorized traffic. Based on previous studies, providing more cycle tracks has a significant positive influence on bicycling rates. For instance, the physical separation of cyclists from motorized traffic results in improved safety conditions. Consequently, the set of interventions investigated in this study included reconstruction, major rehabilitation, preventive treatment, and upgrading to physically separated bicycle paths (cycle tracks). Furthermore, this work employed the capabilities of smartphones in representing bicycling demand through a sample of bicycle volumes over the entire road network. The bicycle counts on network segments were estimated based on GPS traces of cyclists across the city. The results show that an annual budget of CAD$320 million is required to achieve and sustain an acceptable overall pavement surface condition, while all bicycle lanes are being upgraded to cycle tracks in the first year. Whereas, an annual budget of CAD$138 million is not sufficient to keep the pavement condition in the network at serviceable levels, though bicycle lanes will be upgraded during the first four years.

6.2 Future Work

In terms of modeling, accurate costing, intervention effectiveness and pavement performance are crucial for the trade-off between condition, intervention and potential impact on bicycling demand. In this research some of such values were approximated (intervention unit cost), others incorporated from common practices (treatment applicability) and some assumed (potential impact on demand) in the agreement with the purposes of this academic work. In addition, the development of specific PPP models for physically separated bicycle pathways (e.g. cycle tracks) is recommended since these pathways do not carry vehicular traffic.

In this research, a potential increase of 150% in bicycle ridership was assumed; however, microsimulation of bicycling traffic should be conducted to investigate the impact of various designations of bicycle infrastructure on safety levels. Once new facility is added or an existing facility is improved, bicycle traffic in the network is expected to be affected and more bicycle riders are expected to be attracted, depending on how attractive the facility is.

Further, to enhance our understanding of behavioural aspects of cyclists, impedance factors should be estimated via the development of route choice models with a consideration to different designations of bicycling facilities and various configurations of bicycle pathways in terms of separation from other road users. In this context, GPS trip data provide a rich source to develop such more realistic models that are able to capture and predict patterns of demand, route preferences, and other behavioural factors.

Before and after studies should be conducted after the implementation of protective measures to evaluate the effectiveness and more accurately determine the impact on bicycling demand.

Nonetheless, first mile and last mile initiatives such as heated cabins; showers; and bike parking at bus stops, rail and transit stations, particularly sheltered or guarded, can be provided to encourage the modal shift towards bicycling in cities. Most bike parking in cities is in unsheltered bike racks on sidewalks, so there is a need to providing sheltered parking, at least covered with a roof. Guarded parking can also be provided to prevent theft, both in special facilities such as bike stations and in outdoor parking guarded by attendants.

The incorporation of such initiatives as well as safety measures and pathway related improvements into management systems help in developing a more comprehensive decision making– behavioural framework.

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