DEVELOPMENT OF A MULTI-DIMENSIONAL LIFE CYCLE ANALYSIS FRAMEWORK TOWARDS SUSTAINABLE PAVEMENT MANAGEMENT ON PROJECT AND NETWORK LEVELS

RUIJUN CAO

PhD

The Hong Kong Polytechnic University

2020

The Hong Kong Polytechnic University

The Department of Civil and Environmental Engineering

Development of A Multi-Dimensional Life Cycle Analysis Framework towards Sustainable Pavement Management on Project and Network Levels

Ruijun Cao

A thesis submitted in partial fulfillment of the requirements for

the degree of Doctor of Philosophy

Dec 2019

CERTIFICATE OF ORIGINALITY

I hereby declare that this thesis is my own work and that, to the best of my knowledge and belief, it reproduces no material previously published or written, nor material that has been accepted for the award of any other degree or diploma, except where due acknowledgment has been made in the text.

(Signed)

Ruijun Cao (Name of student)

ABSTRACT

Pavements act as an essential component of civil infrastructure for supporting transportation, economic development, and improvement of life quality. With ever-increasing road mileages and emerging functional requirements, simple procedures and cumulative but unmethodical personnel experience that worked previously are no longer able to manage the continuous expansion of pavement networks. In addition, conventional approaches to maintaining huge pavement network in satisfactory condition inevitably result in considerable budget and environmental burdens. This exacerbates tensions between the multi-dimensional pillars of sustainability (environment, society, and economics) which decision-makers must balance. Consequently, it is a critical part for developing an effective and efficient pavement management system.

The research in this dissertation proposes a methodological decision-support framework for sustainable pavement management and implements it in several emerging green pavement technologies (e.g. in-place recycling, rubberized asphalt, warm mix asphalt, and low-noise porous asphalt pavement). The entire framework comprises two general decision levels, namely project level and network level. Although the two decision levels differ in their system boundaries, they share the same ultimate principles oriented towards the selection of optimal alternatives among competitors. The sustainability targets identified through this study are destined to not merely achieve the best pavement utility, but also to minimize the influences on ecology that result from each decision made. To realize sustainable pavement management on two decision-making levels, several sustainable evaluation, integration, and optimization techniques have been developed and interconnected in the framework.

At the project level, after the life-cycle pavement-related sustainability indicators (e.g. environmental impact, cost and performance) have been identified and evaluated, the integration method to support final identification of alternatives was firstly realized by developing the single-dimensional integration (i.e., cost-benefit integration), and further improved by applying the concept of eco-efficiency as the multi-dimensional integration (i.e., eco-efficiency integration). Uncertainty analysis was subsequently incorporated in the evaluation procedures to increase assessment reliability and avoid the likelihood of misunderstanding. The usability and capability of the above-mentioned methods were verified by practical comparisons of competitive pavement rehabilitation techniques and asphalt materials.

At the network level, decisions are required to consider both the degree of consumption and functional improvement as they relate to the adoptable projects, and the pavement function deterioration rates varying by time and space. As two critical components for network-level decision-making, the long-term performance prediction model and the multi-objective optimization model have been investigated and developed by two machine learning techniques (i.e., artificial neural network and support vector machine) and a multi-objective optimization algorithm (i.e., genetic algorithm). This research employed pavement acoustic performance as the functional performance to test the feasibility and applicability of the proposed modelling methods and provide complementary reference for decision-makers as well.

The analysis outcomes at both the project and network levels could contribute to finding approaches to facilitate improvements in sustainable pavement management decision-making in three ways. First, multi-disciplinary cooperation in quantitative evaluation, sustainable integration, uncertainty analysis, and multi-objective planning increases the approach capability and versatility in addressing complicated problems. Second, the innovative applications in the emerging pavement technologies could contribute as a quantitative and informative reference for agencies, pave a more sustainable and efficient way to improve current decision-making tools, and lay a rational basis for future resource allocation and policy planning. Finally, the successful implementation of the proposed decision-making framework in pavement infrastructure management in this study indicates its potentials for application to other types of civil infrastructure.

LIST OF PUBLICATIONS

Journal Papers (Published)

Cao, R, Leng, Z, Yu, H, et al., 2019. Comparative life cycle assessment of warm mix technologies in asphalt rubber pavements with uncertainty analysis [J]. Resources, Conservation and Recycling, 147: 137-144.

Cao, R, Leng, Z, Hsu, S. C., 2019. Comparative eco-efficiency analysis on asphalt pavement rehabilitation alternatives: Hot in-place recycling and milling-and-filling [J]. Journal of cleaner production, 210: 1385-1395.

Leng, Z., Al-Qadi, I. L., & **Cao, R**., 2017. Life-Cycle Economic and Environmental Assessment of Warm Stone Mastic Asphalt [J]. Transportmetrica A: Transport Science, 1-14.

Chen, J., Su, M., **Cao, R.**, Hsu, S., & Lu, J., 2015. A Self Organizing Map Optimization based Image Recognition and Processing Model for Bridge Crack Inspection [J]. Automation in Construction, 73: 58-66.

Journal Papers (In preparation)

Cao, R, Leng, Z, Hsu, S. C., Modelling of the Pavement Acoustic Longevity in Hong Kong through Data Mining Techniques. Transportation Research Part D: Transport and Environment. (Under review)

Cao, R, Leng, Z, Hsu, S. C., Multi-Objective Optimization for Sustaining Low-Noise Pavement Network System. (Final stage)

Cao, R, Leng, Z, Hsu, S. C., A Review of Applications of Data Mining Techniques in Pavement Management. (Final stage)

Conference Papers (Published)

Cao, R., Leng, Z., & Hsu, S., Yu, H, Wang, Y., 2017. Integrated Sustainability Assessment of Asphalt Rubber Pavement Based on Life Cycle Analysis [C]. Proceedings of the Pavement Life Cycle Assessment Symposium, 199-209, Champaign, Illinois, USA, 12-13 April 2017.

Cao, R., Leng, Z., & Hsu, S., 2016. Eco-Efficiency Analysis on Asphalt Pavement Rehabilitation Alternatives: Hot In-Place Recycling (HIPR) and Milling and Filling (M&F) [C]. Proceedings of the 2016 International Conference on Transportation Infrastructure and Materials, 1: 56-63. Xi'an, China, 16-18 July 2016.

ACKNOWLEDGMENTS

Throughout the writing of this dissertation I have received a great deal of support and assistance.

I would first like to express the deepest gratitude to my chief supervisor Dr. Zhen Leng for his patience, motivation, and immense knowledge and for the continuous support of my Ph.D. study and related research. His guidance helped me in all the time of research and writing of this thesis.

I would like to express my sincere thanks to my co-supervisors, Dr. Shu-Chien Hsu and Prof. Jinguang Teng, for their insightful comments and encouragement, but also for the hard question which incented me to widen my research from various perspective.

I am sincerely thankful to the financial support from Research Institute for Sustainable Urban Development at the Hong Kong Polytechnic University.

I gratefully acknowledge the support and contributions of the co-authors in the publications arising from this study.

My genuine appreciation also goes to the data supports from the Freetech Road Recycling Technology Limited, Dr. Huayang Yu, and Dr. Wing-Tat Hung.

I would like to express the sincere thanks to my colleagues for sharing their professional knowledge and experience.

Last but not the least, I would like to thank my family, my parents and my

husband, for supporting me spiritually throughout writing this thesis.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ACRONYMS

AASHTO	American Association of State Highway and Transportation Officials
ANN	Artificial Neural Networks
AP	Acidification Potential
APWA	American Public Works Association
AR	Asphalt Rubber
ARS	Warm Asphalt Rubber Mixture with Surfactant Additive
ARSMA10	10mm Asphalt Rubber Stone Matrix Asphalt
ARW	Warm Asphalt Rubber Mixture with Organic Wax Additive
ARZ	Warm Asphalt Rubber Mixture with Zeolite Additive
C&SD	Census and Statistics Department
Caltrans	State of California Department of Transportation
CBI	Cost-Benefit Integration
CEG	China Energy Group
CLCD	Chinese Life Cycle Database
CPX	Close Proximity
CRM	Cumber Rubber Modifier
DM	Data Mining
DQI	Data Quality Indicator
EDC	Environmental Damage Costs
EEI	Eco-Efficiency Integration
EIO	Economic Input-Output
ELO	End-of-Life
ELT	End-of-Life Tire
FHWA	Federal Highway Administration
GA	Genetic Algorithm
GIS	Geographic Information System
GHG	Greenhouse Gas
GSA	Global Sensitiviy Analysis
GWP	Global Warming Potential
HDM-4	Highway Development and Management Software
HIPR	Hot In-Place Recycling
HKHyD	Hong Kong Highways Department
HKSAR	Hong Kong Special Administrative Region
HMA	Hot Mix Asphalt

IEC	International Electrotechnical Commission
INDOT	Indiana Department of Transportation
IRI	International Roughness Index
IRF	International Road Federation
ISO	International Organization for Standardization
IUCN	International Union for Conservation of Nature
LCA	Life Cycle Assessment
LCCA	Life Cycle Cost Analysis
LCI	Life Cycle Inventory
LCIA	Life Cycle Impact Assessment
LEGCO	Legislative Council
LNRS	Low-Noise Road Surface
M&F	Milling-and-Filling
M&R	Maintenance and Rehabilitation
MAD	Mean Absolute Deviation
MEPDG	Mechanistic Empirical Pavement Design Guide
MLP	Multilayer Perception
MOO	Multi-Objectives Optimization
NCHRP	National Cooperative Highway Research Program
NCSA	National Crushed Stone Association
NPV	Net Present Value
NSGA-II	A Fast and Elitist Multi-Objective Genetic Algorithm
ODP	Ozone Depletion Potential
OECD	Organization for Economic Cooperation and Development
PDF	Probability Density Function
PMFC	Open-Graded Polymer Modified Friction Course
PMS	Pavement Management System
PMSMA10	10mm Polymer Modified Stone Matrix Asphalt
POPC	Photochemical Ozone Creation Potential
R^2	Coefficient of Determination
RAP	Reclaimed Asphalt Pavement
RAP	Rubber Asphalt Association
RD	Rut Depth
RMSE	Root Mean Square Error
SCDER	Sacramento County Department of Environmental Review
SVM	Support Vector Machine
UCPRC	University of California Pavement Research Center
UDC	User Delay Cost

VOC	Vehicle Operating Cost
WAR	Warm Asphalt Rubber
WC	Dense-Graded Wearing Course
WMA	Warm Mix Asphalt

CHAPTER 1 INTRODUCTION

1.1 Research Background

Pavements act as an essential component of civil infrastructure, supporting over nine trillion ton-km of freight and fifteen trillion km of passenger transportation around the globe annually (IRF, 2010). It also plays a significant role in economic development and improving quality of life. Figure 1-1 (Meijer et al., 2018) illustrates the world distribution of road mileages that have reached more than 21 million km in total. This signifies that high-density road networks are always accompanied by densely populated and more affluent areas. With the ever-increasing road mileages and emerging functional requirements of the road infrastructure, conventional approaches to maintaining huge pavement networks in satisfactory condition inevitably result in considerable budget and environmental burdens (IRF, 2010; Wang & Gangaram, 2014; Zhou et al., 2012).

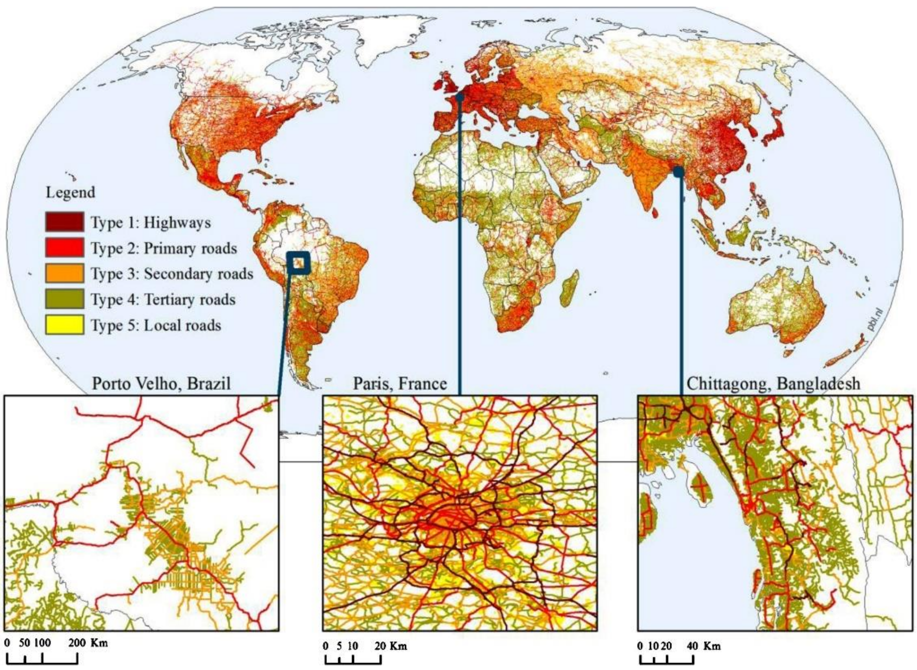


Figure 1-1 Global distribution of road mileages

China (142,500 km) and the United States (108,394 km) are the World's Top two countries in the length of expressways (IRF, 2019b). In 2016, global transportation infrastructure investment and maintenance spending was over \$940 billion, where China and the United States accounted for 63.8% and 10.7% of this spending, respectively (IRF, 2019a). According to the data from the Asia Sustainable and Alternative Energy Program (2009), greenhouse gas (GHG) emissions from transport sector accounted for 12.5% to 13% of global total emissions, about 72% of which was attributed to road construction, maintenance, and usage activities. In China, 50 million tons of rocks were consumed for annual highway maintenance, which resulted in approximately 1.1 million tons of carbon dioxide emissions annually (Zhou et al., 2012). In the United States, maintenance and rehabilitation (M&R) of existing pavement and construction of new pavement for the highway system are estimated to consume about 320 to 780 million metric tons of raw materials annually (Holtz & Eighmy, 2000).

Sustainability has gained fast-growing attention and awareness since the twenty-first century. Brundtland Report (Brundtland, 1987) defined sustainability as that "meets the needs of the present without compromising the ability of future generations to meet their own needs", which reveals the essential contradiction between the ecological disruption due to economic growth and the inevitable requirements for such growth to get rid of poverty. The core thinking of sustainability has been broadly accepted as a trade-off in three 'pillars': environment, economics and society (Adams, 2006). The International Union for Conservation of Nature programme 2005-2008 (IUCN, 2004) illustrated the relationship among the three sustainability dimensions using interlocked circles (Figure 1-2). Although the imbalanced situations of the three dimensions have been identified since 2004, the trade-off requirement in management among all three pillars is never out of date as the accelerated urbanization process.

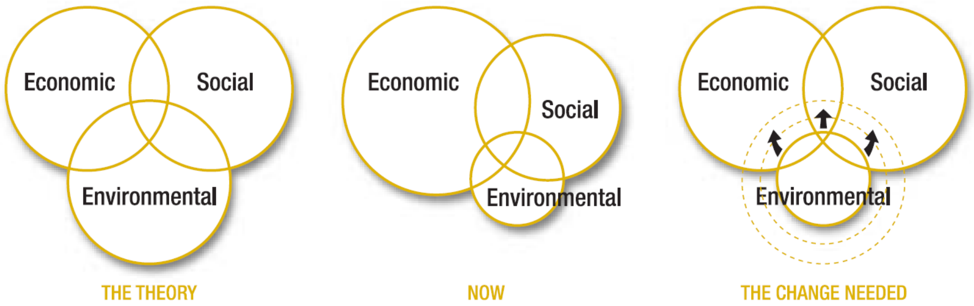


Figure 1-2 The three pillars of sustainability and the need to correct in future

Given the great challenges posed by the construction and maintenance of the ever-increasing number of pavement networks while also aiming for sustainable development, various sustainability enhancing solutions associated with pavement engineering have been developed (Ali et al., 2013; Kristjánsdóttir et al., 2007; Leng et al., 2017b; Lodico & Donavan, 2018; Yu et al., 2018b), such as in-place recycling rehabilitation techniques, reuse of recycled materials (e.g., reclaimed asphalt pavements and crumb rubber from end-of-life tyre), and development of low-construction-temperature, low-noise, and high-permeability pavement designs (e.g., porous asphalt pavement and warm mix asphalt). Despite the aforementioned efforts, a decision support system that could both systematically quantify and effectively balance the conflicting sustainability goals remains needed by pavement administrative agencies.

To be more specific, the major challenge involved in managing pavements in conformance with sustainability is the tension between the constant demands of maintaining pavement function to meet society's transport needs and the unavoidable adverse effects on nature from such fundamental requirements. Consequently, a sustainable pavement management system needs to provide conscientious strategies in sustainability evaluation, integration and optimization for final decision-making. The evaluation would start from determining the time horizon and space scope first, as the implementation of sustainable development is not only for nature, but also for pavement service.

For the time horizon, pavement life cycle has been widely used by administrative agencies in the management process (Santero et al., 2011b). The associated life-cycle approaches include life cycle cost analysis (LCCA) and life cycle assessment (LCA), which evaluate the economic and environmental impacts, respectively, have been established as part of several professional guidance and international standards (FHWA, 2014; Harvey et al., 2016; ISO, 2006a, 2006b; Walls & Smith, 1998).

For the space scope, selection of pavement scale would determine the management decision-making levels, which can be generally categorized into project and network levels (AASHTO, 1985). The project level handles the lower-level (bottom-up) decisions for specific pavement projects, such as pavement material selection, maintenance treatment comparison, and construction technique determination, while the network level considers the pavement network as a whole and deals with higher-level (top-down) decisions about network-wide planning, policy and budget.

The ultimate decision made at project level heavily relies on the approach integrating multi-dimensional sustainability indicators. However, the network level complicates the decision-making process and requires more powerful techniques to realize multi-objective optimization. Either integration or optimization would conclusively affect the implementation and achievement of sustainable development principles in pavement management. Although the two decision levels differ in space boundary and complexity, their ultimate principles that are oriented towards optimal selection of sustainable alternative schemes among competitors remain the same.

1.2 Research Aim and Objectives

Although sustainable development principles have been broadly recognized, the outcomes of the implementations vary by different decision-making levels and methods in terms of interrelation and multi-dimensionality. Due to the dynamic interaction among the three sustainable pillars, the problem cannot be addressed by just improving single dimension, which emphasizes the significance in applying integration technology to conduct trade-off.

In addition, the capacities of decision-support techniques required for different decision-making levels have their own particular focuses. The purpose for a pavement project can be summarized as improvement of specific function or performance. The improvement level could often be affected by material types and construction behavior. Thus, the decisions related to pavement project mainly deal with the improvement. For a pavement network, when doing nothing, the network would deteriorate. The deterioration rate would depend on the traffic condition, climate condition, material types and construction behavior. Therefore, the improvement intervention by project is required in order to maintain an acceptable service function. Therefore, the network-level decisions need to concern both improvement and deterioration. Based on the above, compared to relatively simpler bottom-up integrations for project-level management, the higher complexity of network-level management requires more capable tools to conduct top-down planning.

Therefore, the overall aim of this research is to establish more systematic sustainable decision-making frameworks for both project-level and network-level pavement management, along with innovative case studies. This aim is achieved by following the objectives that serve both management levels.

For project-level decision-making:

(1) To establish a *single-dimensional integration* framework with multi-dimensional sustainability indicators and verify its usability and capability through case study.

(2) To establish a *multi-dimensional integration* framework with multi-dimensional sustainability indicators and verify its usability and capability by case study.

(3) To incorporate *uncertainty analysis* into the evaluation procedure and verify its usability and capability by case study.

For network-level decision-making:

(4) To establish an empirical pavement functional *performance longevity model* and verify its usability and capability with real data.

(5) To establish a sustainable *multi-objective optimization framework* and verify its usability and capability by case study.

1.3 Research Significance

The outcomes of this research are expected to contribute to the improvement of sustainable pavement management in terms of both theorey and practical application. First, the established methodology framework that can effectively evaluate sustainability and optimally support decision-making at both project and network levels would help pavement management decision-makers to find ways to facilitate sustainability improvements. Second, incorporation of multi-disciplinary knowledge in the framework, such as pavement engineering, environmental science, statistics, and computer science, would considerably enhance the capability and efficiency of the decision-making procedures. Third, the novel applications in this research would not merely verify the feasibility of the proposed framework, but also serve as quantitative references for pavement administrators for corresponding decision-making. Finally, the findings of this research have several policy implications for pavement management.

1.4 Thesis Outline

The thesis is comprised of eight chapters. The organization of the thesis is illustrated in Figure 1-3. The methods applied for project-level and network-level decision-making are not competing relationship and could work together to solve the practical pavement management problems.

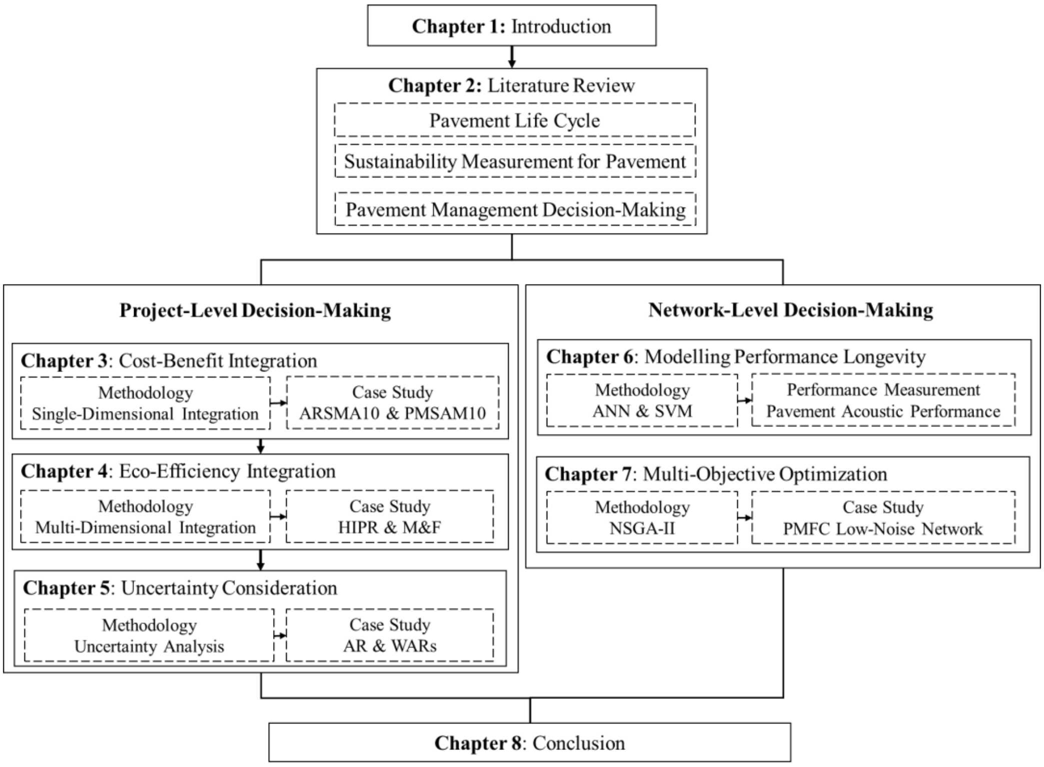


Figure 1-3 Organization of chapters in this thesis

Chapter 1: Introduction. This chapter introduces the general background with problem statements, research objectives, expected contributions, and thesis outline.

Chapter 2: Literature Review. Both the methodology and application parts in this dissertation involve a range of research fields. This chapter starts with an introduction to the pavement life cycle, which assists in identifying potential critical issues that could influence the sustainability of pavement. Then sustainability measurements are explored and discussed according to pavement performance, cost, and environmental perspectives. Finally, project-level and network-level management with attention to associated decision-support tools and criteria are presented.

Chapter 3: Cost-Benefit Integration. This chapter employs the cost-benefit approach to develop a single-dimensional integration framework that evaluates sustainability during a pavement life cycle considering environmental, economic, and social impacts, followed by a monetized integration of these multi-dimensional indicators. Meanwhile, the usability of the proposed methodology framework is embodied in the comparison of two flexible pavement designs, namely 10mm Asphalt Rubber Stone Matrix Asphalt (ARSMA10) and 10mm Polymer Modified Stone Matrix Asphalt (PMSMA10).

Chapter 4: Eco-Efficiency Integration. As a solution to address the monetary transformation limitations of the Cost-Benefit Integration in Chapter 3, this chapter presents an eco-efficiency integration framework that synthesizes the different sustainability indicators in multi-dimensional ways. With this framework, two pavement rehabilitation techniques, namely milling-and-filling (M&F) and hot in-place recycling (HIPR), are systematically evaluated and compared in terms of environmental impacts, economic performance, and life extension capacity by identifying the trade-off eco-efficiency position.

Chapter 5: Uncertainty Consideration. To improve the result reliability and generalization, this chapter introduces uncertainty analysis into the evaluation procedure by considering the propagation of various uncertainties (probability distribution), which substantially improves the reliability and objectivity of the methodology by providing more information for decision-makers. Based on this, the energy-saving role of three different warm mix additives (zeolite, organic wax, and surfactant) in the asphalt rubber (AR) pavement is further explored.

Chapter 6: Modeling Performance Longevity. When taking the decision to the higher network level, the primary concern is the degradation of the specific function as pavement ages. This chapter takes emerging pavement acoustic performance as the major consideration, and to model the long-term performance by utilizing two well-established machine learning algorithms, namely artificial neural network (ANN) and support vector machine (SVM). The models are intended to serve as the essential component to support the final decision-making by combining with intervention information and multi-objective optimization module. In addition, the longevity of pavement acoustic performance is originally modelled and explored as one of the pavement functional performance by using local tyre-pavement noise data.

Chapter 7: Multi-Objective Optimization. Based on the performance longevity model developed in Chapter 7, This chapter proceeds with establishing a multi-objective optimization (MOO) model for maintaining a low-noise pavement network. In accordance with multi-dimensional sustainability goals, the trade-off is made between maximizing the low-noise function demand and the minimizing the investments and environmental impacts due to such demand. The solutions are specifically searched by applying a heuristic optimization algorithm, namely the non-dominated sorting genetic algorithm II (NSGA-II). The selection of optimal strategies associated with conflicting objectives would be based on the posteriori articulation of preferences of local decision-makers that varies by different societal situations, budget restrictions and policy requirements.

Chapter 8: Conclusions and Recommendations. This chapter summarizes the major research findings, contributions, and limitations, as well as provides recommendations for future work.

CHAPTER 2 LITERATURE REVIEW

2.1 Overview

In this chapter, the findings from the empirical literature are reviewed, which serves to increase the understanding of the current research status, identify the research gaps that need to fill in, and lay the foundations for the subsequent studies. The summary starts from the introduction of the pavement life cycle, which provides the basic knowledge to identify the potential sustainability issues related to pavement. Then, the sustainability measurements associated with pavement in three aspects are explored and discussed. Finally, in relation to different decision-support tools and criteria, the review of decision-making in both project- and network-level management is subsequently presented. Based on the thorough understanding of the existing literature, this study can be further proposed and developed.

2.2 Pavement Life Cycle

Pavement life cycle is a “cradle to grave” process that has been increasingly researched and applied by either administrative agencies or academic scholars for more effective and efficient pavement management (Chong, 2015; Labi & Sinha, 2005). For a well-designed pavement, its life cycle is generally divided into material production, construction (e.g., new construction, preservation, maintenance, and rehabilitation), use, and end-of-life stages (Harvey et al., 2016; Wang et al., 2012a). Figure 2-1 (Wang et al., 2012a) elaborates the typical components and activities of each stage. **Material production** stage refers to all the procedures to acquire and process the required materials for pavement, such as the stone mining, crude oil extraction, asphalt refinery, and material mixing. **Construction** stage includes all the activities and equipment employed to provide and sustain the pavement. **Use** stage refers to the pavement in-service period that is often involved with the interaction between vehicles and environment. **End-of-life** stage includes all the processes to deal with the pavement that has reached its service life, such as landfill, reused, and recycled activities.

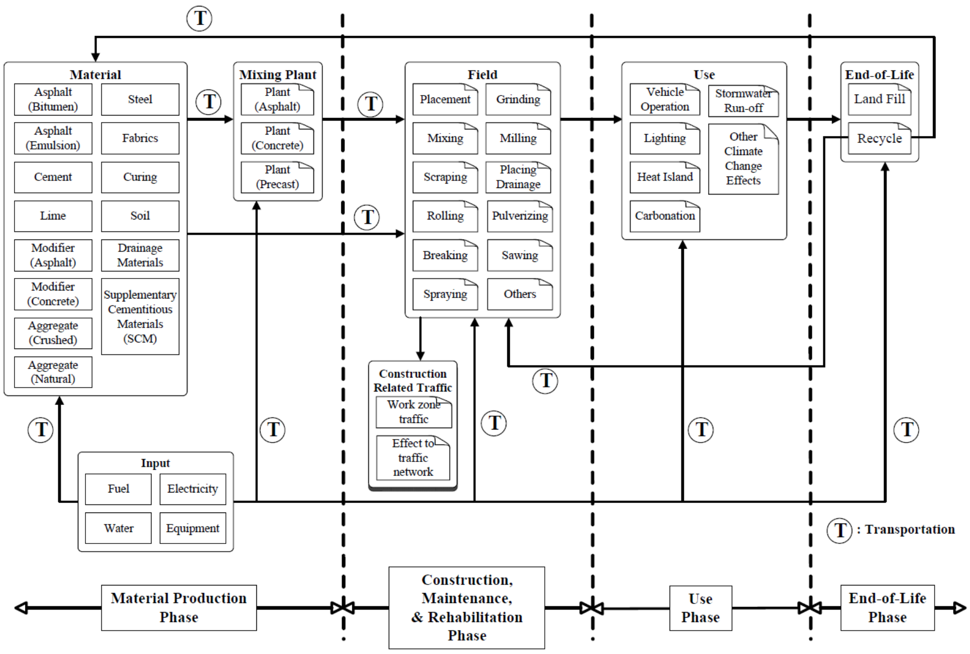


Figure 2-1 Pavement life cycle stages

Wide participation of multitudinous processes in pavement life cycle stages signifies the individual potential to affect the whole. To be more specific, from the additive of asphalt mixture to the selection of maintenance and rehabilitation (M&R) treatments, the decisions related to any process may influence the entire pavement life cycle. For instance, addition of cumber rubber modifier (CRM) to asphalt could improve the rutting and cracking resistance of pavement (Lee et al., 2008; Oliveira et al., 2013), which therefore extends the pavement service life and quality. Besides, studies have also shown that timely and appropriate M&R interventions could not only shortly improve the pavement condition but also influence the future deterioration rate (Dong & Huang, 2012; Labi & Sinha, 2003; Labi & Sinha, 2005).

2.3 Sustainability Measurement for Pavement

Sustainability measurement is the initial step for any sustainable decision-making associated with pavement management. As the concept of sustainability requires multi-dimensional (social, economic, and environmental) achievements, the three major measurements for pavement corresponding to each dimension are described in the following sections.

2.3.1 Performance Assessment

The social role of a pavement is to provide smooth, safe, comfortable, and efficient drive of vehicles. Therefore, number of pavement characteristics are favorable, such as skid resistance, rolling resistance, rutting resistance, low-noise generation, durability, and drainage etc. (Sandberg, 2008). The realization of specific functions could be tackled with engineering specifications and standards. Pavement performance assessment is to evaluate the performance of the intended pavement functions, which is also connected with specific attributions, such as material property, construction behavior and distress measurement (Harvey et al., 2016).

The performances linked to the abovementioned three attributions have been considered and evaluated in a wide range of studies. To be more precise, for the attribution of material property, the researches endeavored in developing the combination complexity and diversity of the pavement material, such as the styrene butadiene styrene (SBS) polymer modifier (Airey, 2004), crumb rubber modifier (Lee et al., 2008), warm mix agent (Kristjánsdóttir et al., 2007), rejuvenator of reclaimed asphalt pavement (RAP) (Zaumanis et al., 2014), and porous asphalt pavement (Sandberg, 2008), were all intended to strengthen the inherent properties and create new characteristics that directly linked to the improvement of either pavement service quality or durability. In addition, construction behavior is the second attribution connected with pavement performance. It mainly includes construction techniques and timings, which result in various effectiveness in performance change. The quantification of changing effectiveness should not merely consider the short change of the pavement performance after completion (Labi & Sinha, 2003), but also involve the effect in future deterioration rate and service life (Dong & Huang, 2012; Labi & Sinha, 2005). Thirdly, distress measurement is the most direct link with pavement performance, including cracking, rutting, and mega-texture roughness (AASHTO, 2008). Different pavement distress forms reflect the performance in varying aspects. Among multifarious pavement distress indicators, the international roughness index (IRI) is prevalent applied as the performance indicator in pavement management decision-making (Dong & Huang, 2012; Labi & Sinha, 2005; Yu et al., 2015), while the pavement condition index (PCI) (AASHTO, 1993) with more comprehensive distress description and higher computation requirement has drawn much attentions as well (Elhadidy et al., 2015).

Long-term retention of the measured performance data could serve for trend analysis and help administrative agencies to preview the patterns that can be applied to prevent problems in the future. There are various tools to obtain long-term performance patterns, such as regression techniques (Kim & Kim, 2006; Pan et al., 2011), Markov process (Butt et al., 1987; Elhadidy et al., 2015), calibration of existing deterioration model (Hall et al., 2011; Li et al., 2009a), and Pavement Mechanistic-Empirical Design (ME-PDG) software (AASHTO, 2008; Noshadravan et al., 2013). The former three techniques require adequate long-term performance data to support the computation, while the later one only needs pavement design, material property, traffic loading, and climate information.

2.3.2 Life Cycle Cost Analysis

In addition to ensuring the qualified pavement performance, the long-term cost performance is another major consideration for agencies in planning and budgeting investment. Therefore, the guidance of life cycle cost analysis (LCCA) for pavement was established by the Federal Highway Administration (FHWA) to systematically estimate the impacts in the economic dimension (Walls & Smith, 1998). As the name implies, LCCA contains all the cost items occurred during the lifetime of the pavement system, which is classified into agency costs and user costs. Agency costs typically include initial construction costs, construction administration and supervision, and associated future M&R costs. For ex-post evaluation, the agency cost can be obtained through the executed contracts. For ex-ante evaluation, the entire accounting of the current price for each item by specialized tools or experts is required, such as the RealCost software developed by FHWA (2011). User costs focus more on the user delay costs (UDC) and vehicle operating costs (VOC), which are severely affected by the current and future characteristics traffic operations, such as traffic demand, volume and composition. As illustration in equation 2-1, the net present value (NPV) that discounts all future costs with real discount rates is applied as the indicator to show the conclusive economic efficiency.

$$\mathrm{NPV} = \mathrm{ICC} + \mathrm{UCC} + \sum_{t=1}^{N} (MC_t + UMC_t) \left[\frac{1}{(1+r)^{n_t}}\right] \tag{2-1}$$

where, ICC = initial construction costs;

UCC = user costs due to initial construction;

MC = future maintenance (incl. presentation, rehabilitation & reconstruction) costs;

UMC = user costs due to future maintenance (incl. presentation, rehabilitation & reconstruction);

N = analysis periods;

r = discount rate;

n_t = year of expenditure.

The original intention of LCCA is to evaluate the entire economic efficiency and identify the most valuable investment option among the competitive alternatives. A number of good practices have been made beyond that. Wilde et al. (1999) integrated various LCCA models, programmes, and spreadsheets to establish a more comprehensive assessment framework for Portland cement concrete pavements with incorporating the pavement performance models. Abaza (2002) applied the concept of "life-cycle disutility" to connect the life cycle cost and performance to figure out the optimum plan with minimum disutility value. Lamptey et al. (2005) enhanced the conventional LCCA methodology in treatment types, strategies, costs and effectiveness to determine the optimal mix of pavement design and preservation strategy for the Indiana Department of Transportation (INDOT). Labi & Sinha (2005) further investigated the effects of preventive treatment timing and types on the cost-effectiveness through the life cycle evaluation. Santos & Ferreira (2013) applied the LCCA-based optimization model to evaluate the pavement structure designs in serviceability and found that the pavement structures recommended by the Portuguese manual were not always the optimum solutions.

Although previous LCCA-based procedures could systematically estimate the cost during pavement life cycle, the potential benefits brought by the more expensive investment options have not been fully considered (Harvey et al., 2016), which signified the need to set up more systematic evaluation.

2.3.3 Life Cycle Assessment

As increasing awareness of environment, the life cycle assessment (LCA) began to be applied in the pavement management decision-making. LCA is a method that provides systematic procedures to quantify the environmental impacts of a product, system, or process with evaluating all the input and output environmental burdens during the life cycle. The general processes for LCA have been well-defined in the International Organization for Standardization (ISO, 2006a, 2006b), which includes four major processes: goal & scope definition, life cycle inventory (LCI) analysis, life cycle impact assessment (LCIA), and interpretation (Figure 2-2).

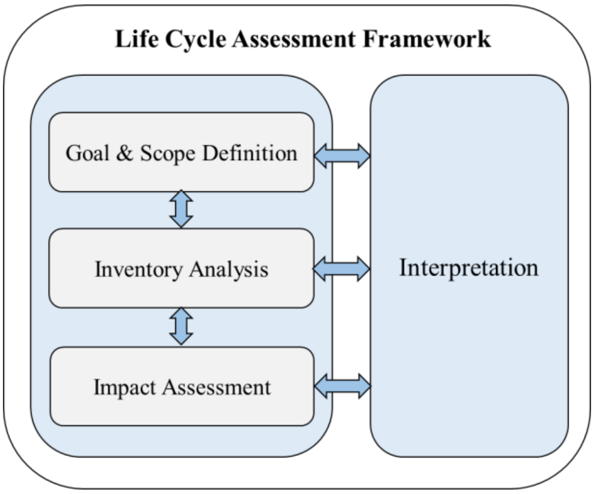


Figure 2-2 Life cycle assessment framework

Among them, the LCI analysis is the most appreciated phase for providing the methodology in estimating the input resource consumption and output emissions during the life cycle (Rebitzer et al., 2004). Many pavement LCA studies only conduct LCI analysis without further transferring the inventory data to various potential impacts through indicators, as LCI could control the full LCA implementation based on the ISO guidelines as an independent study (Santero et al., 2011b). In general, there are three approaches to conduct LCI in LCA: process-based method, economic input-output (EIO) method, and hybrid method, which are different in the data source, flow unit, level of detail, and covered life cycle stage (Rebitzer et al., 2004). In pavement field, process-based approach is more favored (Santero et al., 2011b), as collecting the environment-related data in industry wide is more challenging than obtaining the process-unit data.

The application of LCA in pavement has started since 1990s (Berthiaume & Bouchard, 1999; Häkkinen & Mäkelä, 1996; Horvath & Hendrickson, 1998). The theme of the early application revolved round the environmental impact comparison between rigid and flexible pavement (Athena, 2006; Nisbet et al., 2001; Stripple, 2001; White et al., 2010; Zapata & Gambatese, 2005). Along with the emergency of the new pavement technologies, the applications in topic diversity have been extended, such as comparation of warm mix technologies (Rodríguez-Alloza et al., 2015; Tatari et al., 2012; Vidal et al., 2013), evaluation of asphalt rubber with recycled end-of-life tyre (Bartolozzi et al., 2014; Farina et al., 2017), and investigation of the environmental benefit of in-place recycling techniques (Santos et al., 2014; Turk et al., 2016). By following the broad ISO standard, a pavement-specific LCA framework has been established by the FHWA (2014) with elaborating the precise materials and processes related to the environmental impacts of pavement life cycle, which further certifies the transformation of LCA from an environmental evaluation approach to a decision-making tool.

Although the extensive applications have attested its value in identifying and improving the environmental impacts, the pavement LCA is still an evolving field. The environmental impacts from the usage of pavement have been neglected by most of the pavement LCA studies (Santero et al., 2011a), which could be prominent and go far beyond the impacts of other stages especially for the roads with high-volume traffic (Araújo et al., 2014; Wang et al., 2012b). In addition, the LCA results are sensitive to many uncertainties, such as system boundary, data appropriateness, region, transportation distance and pavement performance model (Tatari et al., 2012; Wang et al., 2012b). Although incorporation of uncertainty analysis into LCA has been suggested by many literature (Huijbregts, 1998a, 1998b; Noshadravan et al., 2013; Weidema et al., 2013; Yu et al., 2018a), very limited studies could be found for pavements.

2.4 Pavement Management Decision-Making

After thorough review about sustainability assessments associated with pavement issues, the implementations of pavement management concepts would be systematically reviewed as follows. Since 1960s, pavement management has been developed and updated to an integrated technology in order to meet the increasing demands of pavement functions (Haas & Hudson, 1978). Table 2-1 lists the evolution of pavement management concepts in chronological order.

The highlighted differences of the various above-mentioned interpretations of pavement management reasonably formed the current understanding of pavement management system (PMS). Generally, most of the official definitions in pavement management agreed on the three major involved components: data inventory development, criterion establishment, analysis scheme (Haas et al., 1994), which concerns multi-disciplinary knowledge and has been parallelly investigated by a number of studies all over the world (Amin, 2015). For decision criteria, previous studies have been attaching the primary importance to economic performance. However, as a further improvement by this study, the multi-dimensional sustainability criteria would be considered. Besides, the required data and analysis scheme are varied by the management structure. The structure of pavement management is generally categorized into project level and network level (Horton, 1990;

Lamptey et al., 2005; Mbwana, 2001; Smith et al., 2001; Zhang, 2009), which is extensively reviewed and discussed in the two subsequent sections.

Table 2-1 Evolution of pavement management concept

Reference	Definition Description
Haas & Hudson (1978)	Systematically integrates the activities including identification of data requirements; determination of current and future needs; development of rehabilitation and maintenance programs; and implementation.
Hudson et al. (1979)	A set of tools or methods that assist decision-makers in finding optimum strategies for providing and maintaining pavements in a serviceable condition over a given period of time.
AASHTO (1985)	The effective and efficient directing of various activities involved in providing and sustaining pavements in a condition acceptable to the travelling public at the least life cycle cost.
AASHTO (1986)	Encompasses all the activities involved in the planning, design, construction, maintenance, and rehabilitation of the pavement portion of a public works program.
OECD (1987)	A system of decision support tools for the entire range of activities involved in providing and maintaining pavements.
APWA (1993)	A systematic method for routinely collecting, storing, and retrieving the kind of decision-making information needed to make maximum use of limited maintenance (and construction) dollars.
Ouertani et al. (2008)	An approach that incorporates the economic assessment of trade-offs between competing alternatives at both network and project levels.

2.4.1 Project-Level Management

The project-level management is a bottom-up approach that deals with the lower level decision in selecting the optimal design for new construction, reconstruction and rehabilitation of a specific pavement segment (Horton, 1990), such as determination of pavement structure (Athena, 2006; Häkkinen & Mäkelä, 1996; Nisbet et al., 2001), comparison of mixture type (Farina et al., 2017; Rodríguez-Alloza et al., 2015; Vidal et al., 2013), and arrangement of construction or rehabilitation activities (Huang et al., 2009; Yu & Lu, 2012; Zhang et al., 2010). Furthermore, the effects introduced by the corresponding selections would be propagated and accumulated along the pavement life cycle (Lamptey et al., 2005; Santero, 2009). Thus, various evaluation tools with life cycle consideration have been included in a large number of studies in order to provide more comprehensive project-level decisions.

As reviewed previously, LCCA was the most frequently employed technique for pavement project options. Markow (1990) initially applied LCCA to testify the economic benefit of routine prevention of pavement with indicating its importance in improving the maintenance inspection, materials, equipment, and quality control. The up-to-date studies showed the improvement in LCCA methodology as well as its gradual popularization. Rister and Graves (2002) reviewed three computer programs in relation to quantifying road user cost of LCCA and compared the tools with field measured data to further elaborate the computation process of various parameters. Jung et al. (2002) utilized LCCA to compare the economic impacts of asphalt rubber (AR) pavement and conventional hot mix asphalt (HMA) pavement and claimed that AR pavement performed more cost-effectively. Gransberg and Molenaar (2004) developed a best-value award procurement algorithm based on LCCA method for highway pavement projects. Ferreira and Santos (2012) proposed a life cycle cost analysis system named OPTIPAV to serve for the Portuguese flexible pavement structure design and found that the capacity of optimum pavement structure always remains unchanged or declined with the increase of applied discount rate. Babashamsi et al. (2016) extensively reviewed the international applications of LCCA to further confirm its essential role in practice.

Since the dramatic increase in environmental consumption and emissions due to the pavement-related activities has been widely recognized, LCA method started to be applied by many recent studies to provide more sustainable decision direction. The initial purpose of LCA is to quantify and evaluate environmental performance and consequently identify the improving opportunities. Loijos et al. (2013) comprehensively quantified the life cycle GHG emissions for the concrete pavement in the United States and signified its large contributions in the total national GHG emission. In addition, the most frequent utilization of LCA is intended to make comparisons, which is often related to the adoption of typical green techniques, such as recycled material, warm mix asphalt (WMA), and in-place recycling. Huang et al. (2009) applied LCA on the real case in London Heathrow Airport to quantify and compare the CO_2 emissions of the pavement materials where nature aggregates were replaced with waste glass, incinerator bottom ash and reclaimed asphalt pavement (RAP). Giustozzi et al. (2012) studied the life cycle carbon footprint of the airfield pavement reconstruction by comparing the rehabilitation alternatives between using only virgin materials and using 85% of recycled materials. Hassan (2010) found that the use of WMA could provide 15% reduction on the environmental impacts of HMA though comparative estimation by LCA. Rodríguez-Alloza et al. (2015) applied hybrid input-output LCA to investigate relative environmental benefits of WMA with Fischer-Tropsch wax and found WMA could save 18% energy and reduce 20% GHG emissions. Santos et al. (2014) compared the life cycle environmental performance of full depth patch, mill and replace and cold in-place recycling (CIPR) maintenance methods and showed the environmental advantage of CIPR. In generally, all the above-mentioned comparative studies indicated the superior environmental performance by applying the green techniques. However, some studies concluded that there was significant variability in evaluating environmental performance when considering the different impact categories (Tatari et al., 2012; Vidal et al., 2013). Furthermore, in order to enhance the result generalization, several studies incorporated the sensitivity analysis into the LCA framework. Thenoux et al.

(2007) considered the energy consumption of three different pavement rehabilitation alternatives under different ESALs and material haulage distances. Turk et al. (2016) compared the conventional pavement reconstruction with the CIRP with additional sensitivity analysis on the material delivery distances. Huang et al. (2012) conducted the sensitivity analysis of the LCA allocation methods and the results showed a high variation. Bloom et al. (2017) compared the prior planned data and post construction data in the LCA calculation for evaluating the environmental impacts of the recycling-based and virgin-material-based rehabilitation techniques and specified the importance of data quality. Noshadravan et al. (2013) employed more comprehensive uncertainty analysis with combining the data quality and data variance in the comparative LCA of asphalt pavement and Portland concrete pavement.

Nevertheless, in practical decision-making, the sustainable objectives in multi-dimensions are conflicting and always required to be balanced (Zhang, 2009). Several studies established multi-objective optimization framework to trade off the multi-objectives. The typical application is to determine the optimal maintenance and rehabilitation (M&R) strategies during the pavement life cycle. Chikezie et al. (2013) proposed a bi-objective optimization model to arrange the maintenance treatments in 20-year period with maximized pavement serviceability index (PSI) and minimized maintenance cost. Zhang et al. (2010) and Santos et al. (2017b) further integrated the LCA and LCCA methods to determine the optimal M&R interval at the minimized life-cycle GHG emissions and life-cycle cost. Santos et al. (2017b) extended the single life-cycle cost objective to the user cost and agency cost objectives respectively in optimization. User cost included user delay costs and extra vehicle operating cost, which contributes to solving the trade-off between pavement maintenance activities and traffic delays that might result. For the same research aim, Yu et al. (2015) conducted a tri-objective optimization with maximizing pavement performance, minimizing life cycle cost, and minimizing environmental impacts. Yet these studies still have some limitations. The final optimal strategies are heavily relied on the prediction accuracy of pavement performance model and were varied due to the different performance indicators.

Furthermore, the implementation of project-level management typically involves specific technical consideration and detailed information associated with each alternative selection (Haas et al., 1994), such as the specific material property, potential change in pavement-vehicle interaction, and effect on the deterioration rate. For the purpose of accurately connecting the specific selection to the potential effects in technical view, various studies and models have been engaged in addressing the requirements. Fwa & Sinha (1991) quantified the relationship between pavement performance and the cost for each life-cycle stage to emphasize the significance of performance incorporation. Jung et al. (2002) developed an IRI prediction model of AR and HMA pavement based on fitting the 11-year measured data to an exponential function in order to evaluate the user costs due to the pavement degradation. Wu et al. (2010) investigated the life extension of 20 types of pavement preservation based on the field tests to assist to find optimum preservation strategies. Dong and Huang (2012) further developed an empirical model of maintenance effectiveness based on the long-term performance (LTPP) database. Noshadravan et al. (2013) incorporated the MEPDG predictive model and calibrated HMM-4 models to transfer the pavement roughness change into the extra fuel consumption of vehicles. Similarly, Santos et al. (2014) and Wang et al. (2012b) combined the vehicle emissions model MOVES with the calibrated HDM-4 rolling resistance model to quantify the additional fuel consumption and consequent environmental impacts resulting due to the pavement deterioration. Yang et al. (2015) developed a progression model of international roughness index

(IRI) in the LCA to compute the GHG emissions and energy consumption of vehicles.

In general, the project-level management for pavement is featured with life-cycle time horizon, relatively simpler models, fewer data requirements, less data integration, and more independent of calibration.

2.4.2 Network-Level Management

The network-level management is a top-down approach that handles the pavement network as an integral and concerns high-level decision associated with the network-wide planning, policy and budget (Smith et al., 2001). At this level, the pavement segment priority, maintenance alternatives, time horizon, budget allocation and environmental implication are determined. To be more preciously, the network-level decisions generally deal with the questions about which section, what treatment, and when under the given criteria.

Running a pavement network system requires the cooperation of manpower and material resources and the collaboration of hardware and software. As the information about current and future pavement condition is the primary requirement for identifying the priorities to receive treatments for pavement segments, collecting condition data is the fundamental preparation for either developing empirical models or calibrating mechanical models. There is a large-scale range of survey equipment and techniques for condition measurement for road network under given specifications (Bennett et al., 2006; Pierce et al., 2013). In addition, the development of the image recognition technologies, such as filtering approach (Salman et al., 2013; Wang, 2013), neural network (Chen et al., 2001; Xu et al., 2008), and support vector machine (Li et al., 2009b; Lin & Liu, 2010), provides opportunities to improve the efficiency and accuracy of surface condition detection. Under the corresponding assistants, the collection methods have been transferred from the conventional visual and manual approaches to the more automatic and intelligent fashion.

Once the qualified data have been well-prepared, the pavement performance prediction models are established as the basis of management system. Reliability of the performance prediction heavily relies on the modeling methods, as well as the selected performance indicators. According to the previously used prediction techniques and considered indicators, the performance models for network-level management could be generally categorized as probabilistic models, structure performance models, functional performance models (Lytton, 1987). Some selected example studies are summarized in Table 2-2, which lists the applied modeling techniques in relation to each model category above.

Table 2-2 Summary of pavement performance prediction models

Model Type	Technique	Reference	Performance Indicator
Proabilistic Models	Markov process	Butt et al. (1994)	PCI[(a)]
		Mbwana and Turnquist (1996)	PSR[(b)]
		Li et al. (1997)	PCI
		Medury and Madanat (2013)	Nework Capacity
		Abaza (2014)	PDR[(c)]
		Elhadidy et al. (2015)	PCI
Structure Performance Model	Mechanistic-empirical method	Ali and Tayabji (1998)	Fatige cracking
		Von et al. (2007)	Cracking, rutting
		Li et al. (2009)	Cracking, rutting, IRI[(d)]
		Hall et al. (2011)	Cracking, rutting,
		Jorge and Ferreira (2012)	Cracking, rutting, disintegration, IRI
		Moghadas Nejad et al. (2013)	Rutting
	Artificial neural network	Attoh-Okine (1994)	IRI
		Attoh-Okine (1999)	Cracking, rutting, IRI
		Mazari and Rodriguez (2016)	IRI
	Regression analysis	Kim and Kim (2006)	Rutting
		Luo (2013)	PCR[(e)]
Functional Performance Model	Mechanistic-empirical method	Jung et al. (1975)	RCI[(f)]
		Abaza (2004)	PSI[(g)]
		Jorge and Ferreira (2012)	PSI
		Pereira and Pais (2018)	Skid resistance
	Artificial neural network	Roberts and Attoh - Okine (1998)	PSR
		Bianchini and Bandini (2010)	PSI
		Freitas et al. (2015)	Noise reduction
	Regression analysis	Pan et al. (2011)	PSI
		Lee et al. (2015)	Crash severity level

Notes: PCI[(a)]: pavement condition index; PSR[(b)]: pavement surface rating; PDR[(c)]: pavement distress rating; IRI[(d)]: international roughness index; PCR[(e)]: pavement condition rating; RCI[(f)]: riding comfort index; PSI[(g)]: pavement serviceability index;

The different models showed the preference option of performance indicators for different model types. Markov process is typical probabilistic model that presented the probability of the condition transition of a pavement ‘family’ to another within a specified time horizon based on the specific assumptions (Butt et al., 1987). Through this method, both pavement condition index and functional index could be modeled. The structure performance models primarily predict the distress (e.g., rutting, cracking, IRI) and condition index in the components of pavement, while the functional performance models are intended to predict the index that reflects the pavement function level in supporting the comfort and safety of mobility, such as serviceability index, skid resistance, noise reduction, and safety index. Either mechanistic-empirical or empirical (e.g., artificial neural network and regression analysis) methods could be applied to develop the latter two deterministic models. The mechanistic-empirical models could be established through either self-development (Jung et al., 1975) or calibration of the existing models (Hall et al., 2011), which confines to modeling distress-related indicators. However, for the empirical models, the selection of performance indicators is more flexible as enough data and sufficient computational power have been given. Besides, it is worth to be noticed that there is no purely mechanistic pavement performance model in current literature.

As another significant part in the pavement management scheme, the optimization-based tools have played a conclusive role in controlling the decision-making by following the corresponding criteria. Optimization is to formulate the objective into an evaluation function and then apply a search algorithm to find the solution that can minimize or maximize the objective function (Burke & Kendall, 2014). In the context of sustainable development, the three-pillar criteria in social, environmental, and economic have been clearly identified (IUCN, 2004), which requires to consider multiple and conflicting sustainability objectives in the optimization process for pavement management decision-making. The multi-objective optimization problem is generally defined as the following expressions:

$$\text{Minimize } F(x) = [F_1(x), F_2(x), \dots, F_k(x)] \tag{2-2}$$
$$\text{subject to } g_i(x) \leq 0, \quad i = 1,2,\dots,m$$

where, $F(x)$ = set of objective functions;

k = the number of objective function;

$g(x)$ = set of constriants;

m = the number of contraints.

Compared with single-objective, multi-objective optimization has higher complexity in the searching space and convergence requirements, which has more than one cardinality of the optimal set, called Pareto optimality (Deb, 2014). The definition is described as: "A point $x^* \in X$, is Pareto optimal if there does not exist another point, $x \in X$, such that $F(x) \leq F(x^*)$, and $F_I(x) \leq F_I(x^*)$ for at lease one function" (Marler & Arora, 2004). In order to search the Pareto Optimality efficiently, various approaches have been proposed, which are generally classified into the methods with priori and posteriori articulation of decision-maker's preferences (Marler & Arora, 2004). Both methods have been extensively applied in developing multi-objective optimization for pavement management. Wu et al. (2012) reviewed the various applications of multi-objective optimization (MOO) techniques in road asset management and concluded their theoretical advantages and complexity in mathematical formulation. Based on that, Table 2-3 updated the summary of MOO applications with additional studies and methods by identifying the considered objectives in decision-making.

Table 2-3 Summary of MOO applications in pavement management

	Technique	Reference	Objectives
Priori Articulation of Preferences	Weighted sum method	Dissanayake et al. (1999)	(1). Nighttime visability; (2). Congestion; (3). Freeway driving; (4). Maneuvering curves; (5). Deficiencies in driving knowlwdge; (6). Location of traffic signs; (7). Gap acceptance
		Wang et al. (2003)	(1). Min. Cost; (2). Max. M&R effectiveness
		Wu and Flintsch (2009)	(1). Min. Cost; (2). Max. Network condition
		Torres-Machí et al. (2015)	(1). Min. Cost; (2). Max. Treatment effectiveness; (3). Min. CO_2 emissions
	Multi-attribute utility theory	Davis and Campbell (1995)	(1). Max. Safety; (2). Min. Cost; (3). Max. Convenience
		Li and Sinha (2004)	(1). System preservation; (2). Agency cost; (3). User cost; (4). Mobility; (5).Safety
		Gao et al. (2012)	(1). Min. Cost; (2). Max. Proportion of road network in “very good” condition statte
		Bryce et al. (2014)	(1). Min. Cost; (2). Max. Condition; (3). Min. Energy
	Goal programming	Sinha et al. (1981)	(1). Max. System condition; (2). Max. Service level; (3). Max. System safety; (4). Min. Energy consumption
		Ravirala and Grivas (1995)	(1). Min. Capital investment; (2). Max. Condition improvement
		Wu et al. (2008)	(1). Min. Cost; (2). Max. Total system age gain
		Anastasopoulos et al. (2016)	(1). Min. Cost; (2). Max. Service life; (3). Min. Accident rates
Posteriori Articulation of Preferences	ε-constraint method	Chowdhury et al. (2000)	(1). Min. Probability of crash; (2). Probability of injury level; (3). Min. disutility loss
	Genetic algorithm	Fwa et al. (2000)	(1). Min. Cost; (2). Max. Network condition
		Herabat and Tangphaisankun (2005)	(1). Min. Vehicle operating cost; (2). Min. Average IRI
		El-Rayes and Kandil (2005)	(1). Min. Project time; (2). Max. Project cost; (3). Max. Project quality
		Deshpande et al. (2010)	(1). Min. Cost; (2). Max. Pavement reliability
		Bai et al. (2012)	(1). Min. Average IRI; (2). Max. Bridge condition index; (3). Max. Remaining service life; (4). Min. Crash rate; (5). Max. Travel

			speed
		Chikezie et al. (2013)	(1). Min. Cost; (2). Max. Network performance
		Gosse et al. (2013)	(1). Min. Cost; (2). Max. Segement condition; (3). Min. Annual GHG emissions
		Meneses and Ferreira (2013)	(1). Min. Agency cost; (2). Min. User cost
	Heuristic greedy algorithm	Torres-Machi et al. (2017)	(1). Min. Cost; (2). Max. Maintennace effectiveness; (3). Min. GHG emission
	Particle swarm algorithm	Chou and Le (2011)	(1). Min. Cost; (2). Max. Performance reliability

Among the various applied approaches, the weighted sum method was most widely used due to its simple procedure, which combines multiple objective functions into a single objective function by assigning user-defined weighting factors (Meneses & Ferreira, 2013). The further application of multi-attribute utility theory could both capture the preferences of decision-maker and alleviate the subjectivity in setting objective weight (Wu et al., 2012). Goal programming is another popular priori articulation of preferences method in minimizing the sum of underachievements and overachievements of objectives with or without setting goal's priorities (Marler & Arora, 2004). In the absence of information from decision-makers, heuristic-based searching algorithms were applied, such as genetic algorithm, particle swarm algorithm, and heuristic greedy algorithm. Among them, the genetic algorithm has attracted great interest as its capability in solving non-linear optimization problems, and its capability continued to be enhanced along with the evolutionary in the simplicity and efficiency of algorithms (Konak et al., 2006). The ε-constraint method was rarely used due to its limitation in the constraint setting (Wu et al., 2012). It was agreed that no single approach is superior to others, and the method selection would largely depend on the information completeness, solution requirements, and user preference (Meneses & Ferreira, 2013; Wu et al., 2012). In relation to the estimated objectives, the cost and pavement structure performance were basically considered by extensive studies which seldom involved environmental impact indicators and functional performance.

Beyond that, the volume, variaty and geometric characteristics of network-level data suggested the employment of geographic information system (GIS) to store, integrate, and analysis in a visualised manner (Golabi & Pereira, 2003). GIS platform could graphically identify the pavement segments with corresponding pavement conditions, traffic information, and auxiliary data and allows engineers and administrators to query, examine, manage, and plan on a visual basis (Zhang, 2009). A number of applications have been made by both researchers and agencies to strengthen the pavement management system (Bham et al., 2001; Medina et al., 1999; Parida et al., 2005; Zhang, 2009; Zhou et al., 2009).

In general, compared with project-level approach, the characters of the network-level management are identified as the network topology with more sophisticated models, larger data requirement, higher integration and optimization capability.

2.5 Summary

This chapter provides a thorough review of literature related to the critical issues in pavement sustainability measurements, project-level and network-level management decision-making. The three measurements are both independent in different dimensions and correlated with one another to constitute the entirety of sustainability. The approaches to pavement management are inclined to either project-level dealing from bottom up or network-level allocating from top down. Both the two management structures have their specific objectives, requirements, and analytical capabilities.

Therefore, toward sustainable development, a pavement management decision-making always needs new attempts to improve both systematisms of multi-dimensional integration methods and exert the potential applications of various decision-support methods in emerging pavement functions.

CHAPTER 3 COST-BENEFIT INTEGRATION

3.1 Introduction

Although the environmental impact variables in a pavement life cycle are complicated, various efforts have been undertaken to minimize environmental burdens from pavement project activities. For example, many recycled materials, such as waste tyre rubber, are now being used in pavement construction to conserve raw material resources without compromising pavement performance. Asphalt rubber (AR), which is composed of raw asphalt and at least of 15% of waste tire rubber as modifier, is one good example of using waste materials in pavement. However, AR has received different popularities in different areas around the world, because on one hand it provides various benefits, such as recycling waste tires, enhancing pavement performance, and reducing tire-road noise (Lo Presti, 2013; RAP, 1999; SCDER, 1999), while on the other hand, it requires higher construction temperature and cost.

As previously reviewed, life cycle assessment (LCA) provides a systematic procedure to quantify the environmental performance of products throughout their life cycles. Pavement LCA studies have been documented in many literature since 1996 (Häkkinen & Mäkelä, 1996). Although recent researches have combined LCA with other analytical methods to achieve more extensive results, the research focus and result still differs in various studies. Besides, noise, on which AR pavement can provide significant benefit, is often regarded as one of the social-economic impacts and has not been included and defined in the staple life cycle inventories (LCI). Therefore, multi-dimensional sustainable criteria require the more effective and comprehensive integration method for decision-making. Cost-Benefit integration (CBI) is an efficient method to quantify and synthesize the sustainable impacts from different dimensions into single monetary values.

This chapter compared the Asphalt Rubber Stone Matrix Asphalt with 10 mm maximized aggregate size (ARSMA10) and Polymer Modified Stone Matrix Asphalt with 10 mm maximized aggregate size (PMSMA10), which is presented as a case study to originally achieve the more comprehensive sustainability evaluation and integration of pavement mixture designs by CBI method. This chapter is organized into five sections. After introduction of background, the methodology section identifies the detailed CBI procedures along with the required inventory analysis. Then, case study section lists the detailed design information for evaluation. The fourth section illustrates and discusses the results corresponding to the processes in methodology. Ultimately, the summary section concludes the major findings of this chapter.

3.2 Methodology

This study applies the cost-benefit concept to integrate the multi-dimensional sustainability indicators into single-dimensional monetary value. The methodology involves miscellaneous tools and techniques, such as MEPDG software, life cycle analysis (LCA), life cycle costing analysis (LCCA), monetary transformation and cost-benefit integration. For the two compared pavement materials, i.e., ARSMA10 and PMSMA10, all calculations were conducted under the same traffic, structure design and climate condition. The method can be further divided into five steps:

1) Determine the maintenance plans for the two comparison materials according to the performance modeling results of the MEPDG;
2) Perform LCA to acquire the environmental impacts;

3) Conduct the LCCA to quantify the life-cycle agency cost;
4) Convert the GHG emission and noise reduction to corresponding monetary value; and
5) Integrate the overall cost and benefit based on the evaluation results of the former four steps.

3.2.1 Goal and Scope Definition

The goal of this study is to evaluate the life cycle environmental, economic and social impacts of two pavement materials (ARSMA10 and PMSMA10) through cost-benefit integration and compare the overall sustainability of the two mixtures based on their estimated performance in the life cycle view. The functional unit of this study is the square meter (m^2) of 40 mm wearing course throughout the 56-year analysis period. The system boundary determination will have significant influence on the results when considering the environmental impacts. In this study, four life-cycle stages were considered, including: material production, construction, usage and end-of-life (EOL). The examining processes of ARSMA10 in each stage are illustrated in Figure 3-1.

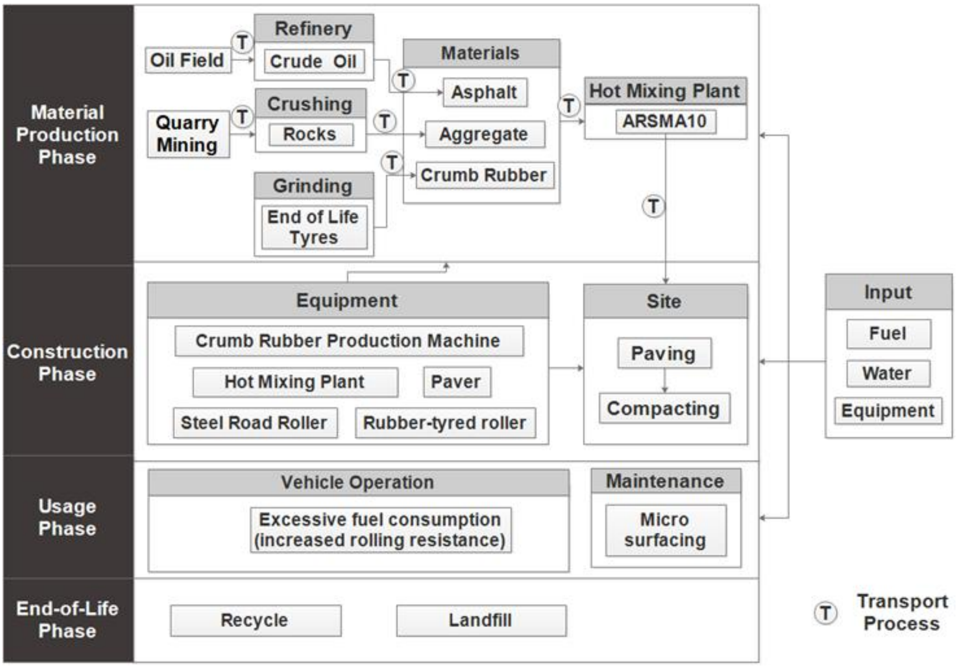


Figure 3-1 Life cycle phase and system boundary of ARSMA10

Three things are noticeable for the system boundary. Firstly, the processes of the two asphalt mixtures are almost identical except for the difference in the material production phase, where ARSMA10 includes an additional process of producing crumb rubber modifier from EOL tires. Secondly, the pavement distress performance is predicted by the MEPDG software based on the material property data from several lab tests. Thirdly, the only variable in this comparison study is the asphalt mixture and other parameters (i.e., traffic loading, climate, construction and maintenance methods) were fixed and assumed as invariable.

3.2.2 Maintenance Strategy Determination

The MEPDG methodology was adopted in order to predict pavement performance based on the traffic loading, material properties, and environmental data. The responses were utilized to predict incremental damage over designed lifetime (Baus & Stires, 2010). The MEPDG software applied in this study was AASHTOWare Pavement ME Design (Version 2.2), and its design methodology is documented in the Mechanistic-Empirical Pavement Design Guide, Manual of Practice, Interim Edition(AASHTO, 2008). There were two objectives of employing MEPDG: to make sure the pavement designs of the two materials can meet the performance criterion, and to predict the distress developing pattern of pavement material.

Despite that both the polymer modified asphalt mixture and asphalt rubber mixture are new material technology and have not been calibrated well with the empirical part of the mechanistic-empirical models, the employment of MEPDG software still enabled to provide general information for comparison purposes. In addition, successful utilization of the prediction results would help to tell what kind of field data required, which could provide a direction for future data collection, otherwise the study would be hampered by lacking field data. Also, in order to get the results closer to Hong Kong's scenario, the Hong Kong climate condition (e.g., wind speed, air temperature, and precipitation) and traffic condition were used as one of the input data.

To predict the accumulated deterioration of the two materials, the laboratory measured material properties were used as the input variables. Specifically, the property input of ARSMA10 and PMSMA10 included unit weight, effective binder content, dynamic modulus of mixture, and Superpave performance grade of asphalt. The international roughness index (IRI) and rutting depth (RD) were selected as the distress measurement indicators in this study. The first index represents a standardized pavement unevenness (Sayers et al., 1986), while the second one refers to the accumulated pavement deformation (Simpson, 2003). Based on these two indicators, an effective pavement maintenance strategy was developed accordingly.

Previous studies have shown that preventive maintenance may prevent a pavement from requiring corrective maintenance and can be six to ten times more cost-effective than a "do nothing" maintenance strategy (Johnson, 2000). Hence, preventive maintenance strategy was selected in this study.

Furthermore, among various candidates for the preventive maintenance treatments, micro-surfacing was selected in this study, considering that it is documented to be appropriate for most of the common distress types, such as roughness, rutting, cracking and raveling (Wilde et al., 2014). The maintenance frequency of pavements with the two asphalt mixtures was determined based on the accumulated deterioration predicted by the MEPDG software. Although the maintenance scenario that only considered the preventive maintenance may not be very practical, it could provide the general information for the comparison purpose. In addition, when the maintenance scenario involves rehabilitation or reconstruction treatment, the difference of the corresponding impacts between the two materials would get larger.

3.2.3 Life Cycle Inventory Analysis

Life cycle inventory (LCI) analysis is the most essential stage of LCA method (ISO, 2006a, 2006b). This stage is dedicated to present the major unit processes and relative calculation procedures within the considered life-cycle stage.

The environmental impacts considered in the assessment included GHG emissions and energy consumption, as the effects of both two impacts on climate change and non-renewable resource shortage are of long-term and global importance. Although there are others impact types, like eco-toxicity and human health, their influence degree would be largely affected by the population density, population composition, and climate condition, which would introduce the variables that hard to be controlled.

The material production phase included the extraction and initial processing of aggregates, asphalt, and other supplementary materials such as crumb rubber (Wang et al., 2012b). The unit processes considered in this study included asphalt refinery, aggregate production, and mixture hot mixing. For ARSMA10, rubber powder production was also considered. The data with respect to the energy consumption factor and GHG emission factor of aggregate were obtained from the Chinese Life Cycle Database (CLCD, 2010), and the relative factors of polymer modified asphalt were provided by the European Bitumen Association (Eurobitume, 2011). Besides, the process of manufacturing asphalt rubber included crumb rubber production and asphalt rubber production. The data for energy consumption and GHG emissions were calculated according to the survey results of Zhu et al. (2014). Reference inventory data of material production phase employed in this study are summarized in Table 3-1.

The construction phase consisted of two parts: transportation of material and on-site construction. Thirty-tonne diesel truck was employed to transport raw materials and hot mixtures, and the corresponding energy consumption and emissions were calculated according to the database CLCD (2010). The construction schedule and equipment activities of ARSMA10 were formulated following the Asphalt Rubber Design and Construction Guidelines (Hicks, 2002), by only considering the paving and compacting. Furthermore, construction activities of PMSAM10 and ARSMA10 were assumed to be the same. The emission factors of the paving and compacting processes of the two materials were calculated according to the power of machines and production efficiency (Zhu et al., 2014).

The usage phase primarily focused on the roughness effect on the additional fuel consumption and GHG emissions. The relationship between pavement smoothness and extra fuel consumption of vehicles has been studied in various literature. It was reported that from 60 to 123.4 inch/mile (0.95 to 1.95 m/km), a 63.4 inch/mile (1 m/km) incremental change of IRI would increase the energy consumption by 3.7% for passenger cars, 1.2% for small trucks, 1.3% for medium trucks, and 0.9% for large trucks (Yang et al., 2015). According to Kalembo et al. (2012), the GHG emissions can increase 35,010 kg annually for the traffic volume of 1,000 vehicles per hour when the IRI changes from the good (<95 inch/mile) to poor condition (>150 inch/mile). In this study, the IRI changes of ARSMA10 and PMSAM10 were predicted by MEPDG software, so the calculation of the GHG emissions and energy consumption in the functional unit should be consistent with the AADT, growth rate and the vehicle distribution used in the MEPDG. Furthermore, pavement maintenance work is necessary during the operation of the pavement system, and the corresponding emissions and energy required were also counted into the usage phase in this study.

When a pavement reaches its service life, it can remain in place serving as support for a new pavement structure or be removed. By adopting a "cut-off" allocation method, no environmental impacts were assigned to the EOL phase in this study.

Table 3-1 GHG emission and energy consumption of pavement life cycle inventory

<table>
<tr><th colspan="3" rowspan="2">Life Cycle Inventory</th><th colspan="2">Mixture Type</th><th>Data Reference</th></tr>
<tr><th>ARSMA10</th><th>PMSMA10</th><td rowspan="18">CLCD (2010); Eurobitume (2011); Zhu et al. (2014)</td></tr>
<tr><td rowspan="4">Material Production</td><td rowspan="2">Asphalt</td><td>Energy consumption[a]</td><td>189.33</td><td>311.20</td></tr>
<tr><td>Emissions[b]</td><td>21.42</td><td>18.57</td></tr>
<tr><td rowspan="2">Aggregate</td><td>Energy consumption</td><td>29.99</td><td>29.99</td></tr>
<tr><td>Emissions</td><td>2.29</td><td>2.99</td></tr>
<tr><td colspan="2" rowspan="2">Transportation of Raw Materials (50km)</td><td>Energy consumption</td><td colspan="2">40.20</td></tr>
<tr><td>Emissions</td><td colspan="2">3.74</td></tr>
<tr><td colspan="2" rowspan="2">Asphalt Mixture Hot Mixing</td><td>Energy consumption</td><td>353.50</td><td>336.67</td></tr>
<tr><td>Emissions</td><td>29.67</td><td>28.26</td></tr>
<tr><td colspan="2" rowspan="2">Transportation of Hot Mixture (20km)</td><td>Energy consumption</td><td colspan="2">16.08</td></tr>
<tr><td>Emissions</td><td colspan="2">1.50</td></tr>
<tr><td rowspan="4">Pavement Construction</td><td rowspan="2">Paving</td><td>Energy consumption</td><td colspan="2">15.86</td></tr>
<tr><td>Emissions</td><td colspan="2">1.18</td></tr>
<tr><td rowspan="2">Compaction</td><td>Energy consumption</td><td colspan="2">18.60</td></tr>
<tr><td>Emissions</td><td colspan="2">1.38</td></tr>
<tr><td rowspan="6">Pavement Usage</td><td rowspan="2">Preservation</td><td>Energy consumption</td><td colspan="2">6.50</td><td rowspan="2">Chehovits and Galehouse (2010)</td></tr>
<tr><td>Emissions</td><td colspan="2">0.30</td></tr>
<tr><td rowspan="4">Additional energy consumption and GHG emissions caused by IRI changes</td><td rowspan="3">Energy consumption[c]</td><td>Passenger car</td><td>0.15</td><td rowspan="3">Yang et al. (2015); Kang et al. (2014)</td></tr>
<tr><td>Single-unit truck</td><td>0.12</td></tr>
<tr><td>Combination truck</td><td>0.25</td></tr>
<tr><td>GHG Emissions[d]</td><td colspan="2">0.004</td><td>Kalembo et al. (2012)</td></tr>
</table>

Note: [a] Unit = MJ/t; [b] Unit = CO_2-e kg/t; [c] Unit = MJ/vehicle mile, under the condition that per 63.4 inch/mile (1m/km) increase of IRI; [d] Unit = CO_2-e kg/vehicle hour, under the conditions that IRI increases from good condition (<95 inch/mile) to poor condition (>150 inch/mile).

3.2.4 Cost-Benefit Integration

The report by the World Conservation Union (2004) suggests that the three dimensions of sustainability: environmental, social and economic, are the mainstream sustainability thinking, which needs to be balanced and better integrated. In this study, all three dimensions were considered and expressed as the cost and benefit. The economic impacts were represented by the life cycle agency cost; the environmental impacts computed from LCA were converted to the environmental damage cost; and the social impacts of pavement materials mainly focused on the noise impact to people, which were presented as the noise reduction benefits. After the monetary process, the final step was to integrate the multi-dimensional impacts into a single-dimensional value so as to the more accessible comparison.

The evaluated agency costs during life cycle consisted of the material cost, construction cost and maintenance cost, which were investigated according to the data from Asphalt Rubber Usage Guide (Caltrans, 2003), Rubber Asphalt Industrialization Feasibility Report in Guangdong Province (Guangzhou Municipal Industries Ltd., 2011), and Handbook on Asphalt Pavement Maintenance (Johnson, 2000).

Environmental Damage Costs (EDC) are the costs for unit of air pollutants that people need to pay to offset the effects on environment. A statistical analysis was conducted by Yu et al. (2013) to find the mean values (50 \$/t in 2010) of the EDC for CO_2 among the wide range from 5 \$/t to 1667 \$/t.

The value of noise was calculated as the unit marginal cost per person exposed to a specified noise level (European Commission, 2014), which are provided in the Handbook on Estimation of External Costs in the Transport Sector (Maibach et al., 2008). The noise reduction benefit of asphalt mixtures is the difference between the noise costs of ARSMA10 and PMSAM10. According to various global rubberized asphalt studies, the average noise reduction of asphalt rubber would be 2-3 dB and the noise of asphalt rubber overlay is measured and documented as 73.7 dB. Consequently, 3 dB was selected as the noise reduction when employing ARSMA10 in this evaluation, and 200 persons were assumed to be directly exposed to the highway every year. The details of the life cycle costs are listed in Table 3-2.

Table 3-2 Summary of monetary transformation

Life Cycle Cost[(a)]		ARSMA10	PMSMA10	Data Reference
Construction Cost[(b)]	Material ($/t)	87	68	Caltrans (2003)
	Equipment ($/m^2)	0.17		Guangzhou Municipal Industries Ltd. (2011)
	Fuel($/m^2)	1.37		
	Labor($/m^2)	0.07		
	Management($/m^2)	0.04		
Maintenance Cost[(c)] ($/m^2)		3.92		Johnson (2000)
Environmental Damage Costs[(d)] ($/t)		63.27		Yu et al. (2013)
Noise Costs ($/person year)		510.86 (>73dB)	593.97 (>76dB)	Maibach et al. (2008), RAP (1999), SCDER (1999)

Notes: [(a)] The costs have been converted to the present value (PV) according to the cost in the reference, and 4% was selected as the discount rate.
[(b)] The thickness of pavement is 40mm
[(c)] The maintenance refers to the pavement preservation treatment, micro-surfacing.
[(d)] The air pollutant item considered is the mass of CO_2 in the whole life cycle.

3.3 Case Study

This study is designed to compare the two flexible pavement materials, namely, ARSMA10 and PMSMA10. In order to estimate the effect of addition with recycled waste tyre rubber into asphalt mixture on the pavement life cycle sustainability, the structural design of the pavement with two materials kept consistent. Table 3-3 summarizes the overall pavement design information, which was assumed according to the common practice in Hong Kong.

Table 3-3 Summary of pavement design information

General Information		
Pavement type	Flexible Pavement	
Design life (years)	20	
Layer Thickness (mm)	40	
Length (m)	1000	
Lane width (m)	3.5	
Number of Lanes	4	
Discount Rate	4%	
Traffic Information		
AADT	10000	
Growth Rate	3%	
Growth Function	Linear	
Vehicle Distribution	37.3%	Passenger car
	23.2%	Single-unit, short-haul truck
	37.2%	Single-unit, long-haul truck
	1.8%	Combination short-haul truck
	0.5%	Combination long-haul truck,
Operation Speed (km/h)	90	
Climate Information *		
Climate Station	Hongkong, HK (99998)	
Mean annual Wind speed (kph)	9.31	
Mean annual Air temperature (deg C)	23.41	
Mean annual sun radiation	80.91%	
Mean annual precipitation (mm)	100.8	
Annual depth to water table (m)	6	

Note: *The climate data is time-related and dynamic, the values of climate information in the table were calculated based on the hourly climate data from Jan/2000 - Jan/2010 to reflect the average level.

3.4 Results and Discussion

3.4.1 Maintenance Strategy

The results of the accumulated change of IRI and RD in 20-year design life predicted by the MEPDG software are illustrated in Figure 3-2. It is evident that the IRI values for the two materials stay within the permissible range of MEPDG during the design life.

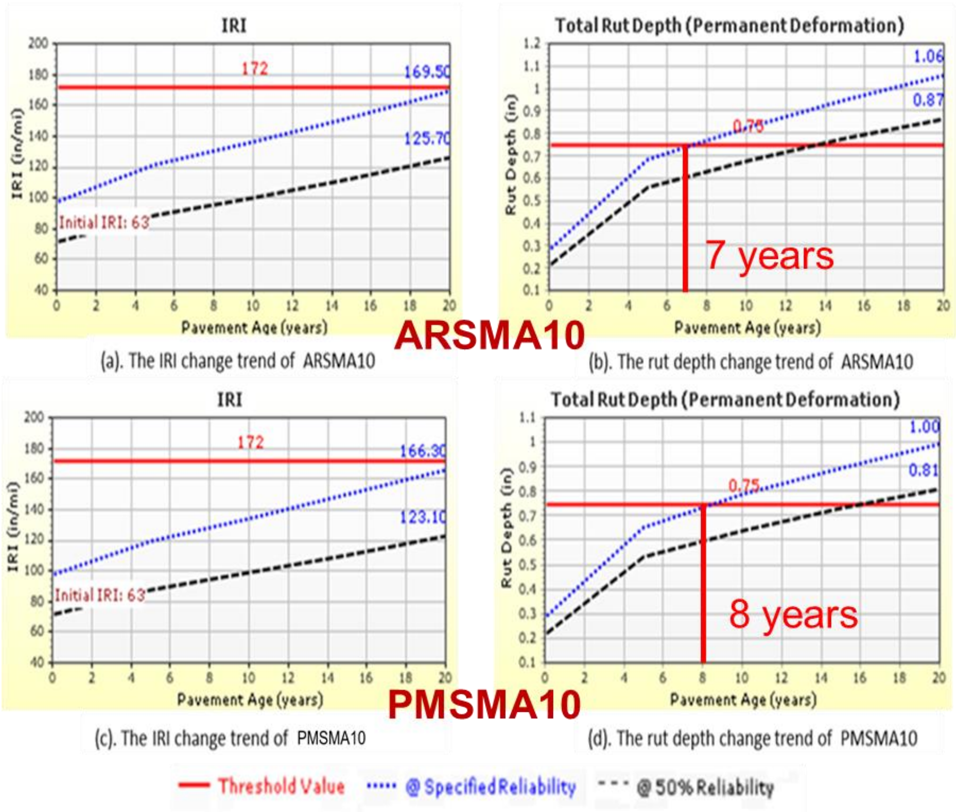


Figure 3-2 Performances of the two materials predicted by the MEPDG software

For ARSMA10, when it reaches approximately seven years, the predicted rut depth exceeds the threshold value, while for PMSMA10, it takes eight years. This indicates that the rutting resistance of selected polymer modified asphalt mixture is preferable to that of the asphalt rubber mixture in this study. Maintenance strategies were then determined according to the estimated development of rutting depth. The analysis period (56 years) is calculated as the least common multiple (LCM) of maintenance intervals (7 & 8 years) for the two materials based on the rut depth prediction. As depicted in Figure 3-3, in the 56-year analysis period, the preservative maintenance (micro-surfacing) would be conducted every eight years for PMSMA10, and every seven years for ARSMA10.

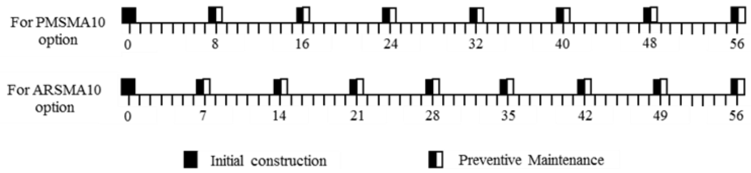


Figure 3-3 Maintenance plans for the two pavement material designs

3.4.2 Environmental Performance

The breakdowns of GHG emissions and energy consumption for the four major phases of the life cycle of the two mixtures are illustrated in Figure 3-4 and Figure 3-5, respectively. In the 56-year analysis period, the dominant contributions were presented by the extra impacts caused by the pavement IRI change. In general, PMSMA10 has better environmental performance than ARSMA10 with regarding to both emissions and energy consumption.

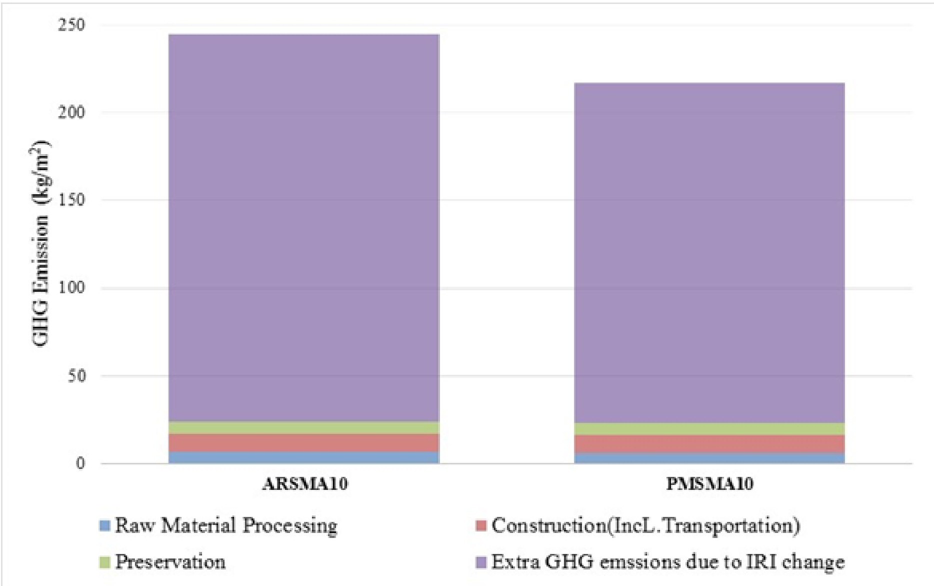


Figure 3-4 GHG emissions breakdown of the two pavement materials

As shown in Figure 3-4, the percent distribution of the extra GHG emissions due to roughness change in the usage phase is especially overwhelming, approximately 242 and 214 kg/m^2 for the two mixes, respectively, since the sum of emissions in the other life-cycle phases of ARSMA10 and PMSAM10

(3.37 and 3.35 kg/m^2) are almost negligible in comparison.

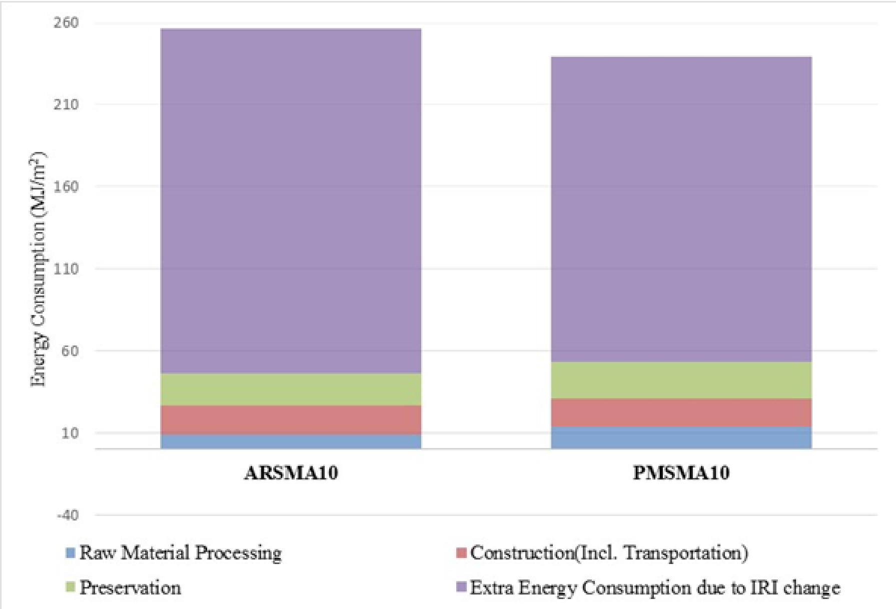


Figure 3-5 Energy consumption breakdown of the two pavement materials

As the illustration in Figure 3-5, when the impact of IRI in the usage phase is ignored, the energy consumption by the function unit of ARSMA10 (46.5 MJ/m^2) is less than that of PMSMA10 (53.5 MJ/m^2). Because of the better serviceability performance of PMSAM10 predicted by MEPDG, the extra energy consumed by vehicles on ARSMA10 pavement (209.8 MJ/m^2) is estimated to be more than that by vehicles on PMSMA10 (185.7 MJ/m^2), which leads to more overall life-cycle energy consumption of ARSMA10.

3.4.3 Sustainability Performance

When the environmental impact is considered as the only evaluation indicator, PMSAM10 is estimated to perform better because of its lower EDC (13.5 \$/m^2). In addition, the investment cost of ARSMA10 (17.2 \$/m^2) is slightly higher than that of PMSMA10 (16.2 \$/m^2), as the asphalt rubber material had a higher price than the polymer modified asphalt.

Nevertheless, when assuming that the ARSMA10 can contribute 3 dB noise reduction from 76 dB noise of PMSMA10, the noise reduction benefit (29.1 $/m^2) of ARSAM10 in the 56-year analysis period is estimated to be able to offset the other cost expenditure (32.7 $/m^2) in economic and environmental dimensions.

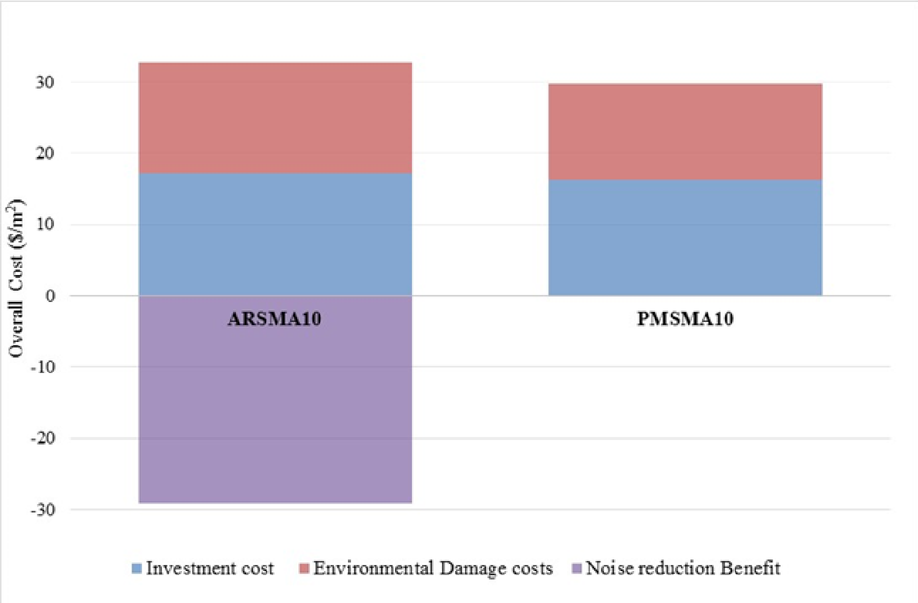


Figure 3-6 Overall cost breakdown of the two pavement materials

3.5 Summary

In this chapter, comparative sustainability assessment and integration were conducted on two asphalt mixtures: ARSMA10 and PMSAM10, by converting their corresponding economic, environmental and social impacts to the monetary values with the cost-benefit concept. The following points summarize the main findings of this study:

- In the 56-year analysis period, the dominating contributing factor for environmental impact is the extra GHG emissions and energy consumption of vehicles due to the pavement roughness change. Overall, PMSMA10 has better environmental performance than ARSMA10, in terms of both emissions and energy.

- When the noise impact is not taken into account, the overall long-term performance of PMSMA10 is better with lower agency investment cost and environmental damage cost.

- The long-term accumulated noise impact is considerable assuming that ARSMA10 is able to decrease the noise by 4%, which can almost offset its higher agency investment cost and environmental damage cost.

Based on the findings of this study, further research is recommended on the cost and benefit analysis of installing noise barrier to PMSMA10 pavement to achieve the same amount of noise reduction as the ARSMA10 pavement. It is also worth to mention that the land saving due to the recycling of End-of-life tyre in ARSMA10 was not considered in this study, which is the factor that has potential to further improve the environmental performance of ARMSA10.

Furthermore, this research was confined to specific standard, condition, and guidance: the cost benefit calculation process was adopted from European standards; Pavement material design and performance prediction was conducted based on Hong Kong traffic and climate condition; and the data from the regions in United States (U.S.) and China was accessed as reference. To fully explore the research limitations, the potential effects from this multi-standard employment would be discussed through comparing the energy structure and regional characteristics of Hong Kong with other regions (e.g. China, U.S., and Europe).

For the LCA part, when assuming the same decisions in selecting construction equipment and techniques, the GHG emissions would be greatly affected the energy type and distribution. According to Hong Kong Energy Statistics (C&SD, 2015), Hong Kong derives its energy supplies almost entirely from external sources. Energy is either imported directly or produced through some intermediate transformation processes using imported fuel input. In the contrary, both China and U.S. can self-supply to satisfy the domestic energy demands (CEG, 2014; Ratner & Glover, 2014). In this sense, when the energy demands are same, the energy costs and environmental impacts in Hong Kong would be evidently larger than the other two regions.

Besides, the cost-benefit transformation of non-monetary sustainability indicators may create deviation due to the influences of various regional features. For monetization of noise reduction, the cost factors are investigated as willing-to-pay (WTP) for reducing annoyance based on stated preference studies and quantifiable costs of health effects in Europe. It is hard to say that the WTP in Hong Kong would be higher than Europe. Nonetheless, the regional uniqueness of Hong Kong (e.g. hot climate, topography, dense population, high-rise buildings and intensive bus traffic) is most likely to create more serious noise impacts.

In general, the variables brought by the different standard, condition, and guidance would indeed cause some effects on the overall impacts, however, from the perspective of comparison, simultaneous increase or decrease would not greatly affect the relative results from the two comparative objects. In addition, this chapter investigated and compared the ARSMA10 and PMSMA10 as a case study, sensitivity analysis is recommended in the future study to take into consideration of the effects of uncertainties in various variables, such as the material composition and performance, time period, system boundaries, transportation distance, and treatment of refinery allocation.

CHAPTER 4 ECO-EFFICIENCY INTEGRATION

4.1 Introduction

Cost-benefit concept could effectively integrate the multi-dimensional sustainability performance through monetizing all related impacts. However, some challenges have been recognized when applying this cost-benefit transformation (Harvey et al., 2016), such as the potential for double counting the overlapped part of the impacts, the accuracy in expressing the irreversible impacts, and the variation resulting from monetary value identification. Therefore, in this chapter, a multi-dimensional integration method, named Eco-efficiency integration (EEI) is further proposed to address the above-mentioned concerns.

EEI is an emerging sustainability evaluation tool for pavement project alternatives by quantifying and integrating the cost-effective and environmental-friendly performance during life-cycle phases (i.e., raw material extraction, construction, transportation, and end-of-life). This rising sustainability decision-support tool could be regarded as an extension of life cycle assessment (LCA) by combining the environmental impact with economic performance (Saling et al., 2002). In this chapter, the primary objective is to build a pavement eco-efficiency integration framework through incorporating LCA and life cycle cost analysis (LCCA), which provides the methodology for systematically evaluating life-cycle environmental and cost performances.

As previously reviewed, timely maintenance and rehabilitation (M&R) of existing asphalt pavements with appropriate technologies is of crucial importance not only in terms of economics but also environmental impacts.

As a conventional rehabilitation technique, milling-and-filling (M&F) technique has been prevalently applied on various the asphalt pavement distresses, which is carried out by employing the handheld breakers and cold milling machines to break and remove distressed pavement materials and replacing the virgin bituminous materials to recreate a smooth road surface (FHWA, 2015). It is recorded that M&F can extend the service life of existing roadways by approximately 15 to 18 years (LEGCO, 2012). However, a noteworthy disadvantage of the conventional M&F technique is the inefficiency caused by the process of hauling away the milled materials and the greater demand in the virgin materials. As a consequence, various recycling techniques for pavement rehabilitation have been developed to improve the efficiency of road maintenance and maximize the material utilization in the burgeoning pavement network (Giustozzi et al., 2012; Santos et al., 2014). Among these recycled techniques, hot in-place recycling (HIPR), has gained growing interests among pavement engineers and researchers. As an alternative to M&F, HIPR is carried out through remixing the heated existing pavement material with added virgin asphalt materials and rejuvenator. Compared to M&F, HIPR has the advantage of eliminating the trucking and handling of the reclaimed asphalt pavement (RAP) by completing the whole process on site. It is documented that HIPR can restore the pavement surface to its original condition and prolong the average service life of roadway from 8 to 12 years (Ali et al., 2013; Caltrans, 2008).

However, very few literatures quantifying and comparing the sustainability performance of HIPR with other rehabilitation techniques. The effects of corresponding life extensions, as the one of the most significant performance evaluations of a rehabilitation technique, have been missed in previous studies as well. Therefore, the two prevalent resurfacing techniques, namely M&F and HIPR, were evaluated not only for illustrating the EEI framework as a case study but also for the purpose of comparing and serving as the more comprehensive reference for decision-makers. Furthermore, the trade-off point among environmental impact, economic performance and life extension due to maintenance was explored based on the sensitivity analysis of functional performance of alternatives.

The organization of this chapter is presented into five sections. After a brief introduction, the system scope and functional unit were identified and defined in the methodology section with elaborating the concepts, equations and impact categories. The case study that evaluated the sustainability of HIPR and M&F with a sensitivity analysis of rehabilitated life extensions is the third section. The next section presents and discusses the comparison results including the normalized environmental impacts, normalized economic performances and the overall eco-efficiencies of the two resurfacing alternatives for different service life scenarios of HIPR. Finally, the major findings of this study are summarized.

4.2 Methodology

The eco-efficiency concept was originally developed by the German chemicals company BASF and used to identify the best alternative in competing products, processes or services. In pavement field, this method has not been fully excavated for decision-support purpose. The ecological impact and economic performance were evaluated by calculating "the ratio of economic creation to ecological destruction from the perspective of the end consumer" (Bengtsson, 2004; Saling et al., 2002). In addition to addressing the monetized challenges from the single-dimensional CBI method, another strength in applying eco-efficiency is that the relative portfolio position plotted enables easy visual comparison and communication. The evaluation categories could involve both the environmental impacts as well as cost on account of the combination of LCA (Harvey et al., 2016; ISO, 2006a, 2006b) and LCCA (Walls & Smith, 1998).

Figure 4-1 illustrates the general EEI procedure applied which firstly defines the goal and scope. The LCA and LCCA are jointly employed to evaluate the relative environmental and economic impacts of the two rehabilitation alternatives. Then, eco-efficiency integration is conducted on the basis of normalization, weighting and portfolio position calculation.

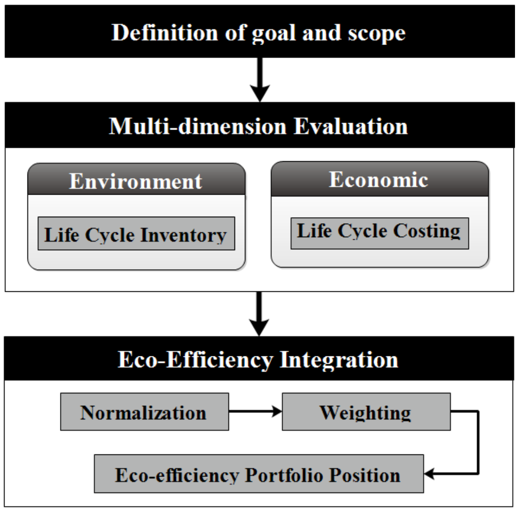


Figure 4-1 The general framework of Eco-Efficiency Integration

4.2.1 Goal and Scope Definition

The functional unit was determined as 1 m^2 of the rehabilitated pavement. Considering that there are multiple scenarios of life extensions in this study, the project analysis period was selected as the least common multiple (LCM) of the life extensions of HIPR and M&F techniques.

The life cycle of a pavement is generally divided into the following five stages: materials extraction and production, construction, usage, M&R and end-of-life (EOL) phase. The impacts of the usage phase resulted from the tyre/road interaction were often considered as the additional fuel consumption and emissions of vehicles due to the pavement roughness change. These additional impacts were highly dependent on the intensity of traffic loads, the performance characteristics of materials, and local weather conditions (Gransberg et al., 2014). Although it was reported that these additional environmental impacts accounted for the greatest proportion (80-90%) in the entire pavement life cycle (Santos et al., 2014), when the two rehabilitation alternatives were compared under the same material, climate and traffic conditions, there would be no expectation on much differences of the usage phase impacts between them. Instead, the pavement performance improvement (life extensions) determined by the rehabilitation techniques would be considered as a sensitivity indicator in this study. Therefore, the defined system boundary covered raw material production, transportation, construction, and EOL phase. Meanwhile, the energy and raw materials (i.e., crude oil, coal, rock) as the input would be distributed to each phase of life cycle boundary.

The detailed processes considered in each life cycle stage have been illustrated in Figure 4-2. Material production phase focused on the extraction of aggregates and asphalt and processing of hot mixture. Its unit processes considered in this study involve asphalt refinery, aggregate production, and mixture hot mixing; The transportation phase referred to the hauling processes of required materials to mixing plant, construction site. For the M&F method, it included the additional distance to haul the milled pavement material to the disposal site. The dominating environmental impacts arose in the transportation phase were due to the emissions released by the hauling vehicles. For the construction phase, the most noticeable difference between the two alternative resurfacing techniques is the in-place recycling process of RAP for HIPR; When the service life of a pavement has been reached, it could serve as the new pavement supporting structure or be removed. A “cut-off” allocation method was suggested to be adopted (Santos et al., 2014), which signified that no ecological impact was allocated to the end-of-life phase. Consequently, the environmental burdens resulting from the four aforementioned life cycle phases could be primarily quantified and categorized as raw material consumption, fuel consumption and emissions released by either on-road or non-road equipment.

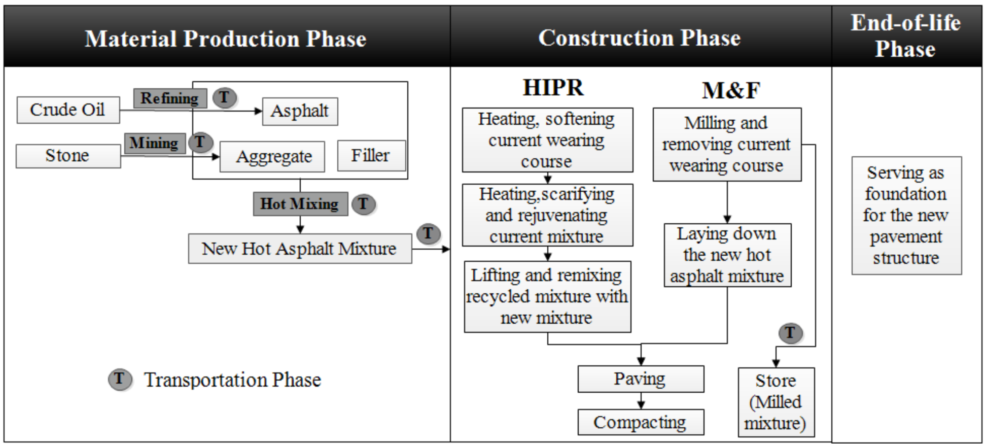


Figure 4-2 The system boundary involved in the HIPR and M&F techniques

4.2.2 Evaluation Category

(1) Environmental Impacts

In this study, the impacts in environmental dimension are determined based on five major categories: raw material consumption, energy consumption, emissions, toxicity potential, and risk potential.

Energy consumption is the consumption of primary energy over the entire life cycle phase, such as nature gas, crude oil and coal. Beyond that, energy production that also consumes resources will influence the category of "raw material consumption".

In the raw material consumption category, the mass of the required raw materials due to relevant processes should be firstly determined. Then, the quantitative material was weighted based on their individual reserve status (Saling et al., 2002). The weighting factors shown in Table 4-1 are inversely proportional to the sizes of the reserves.

Table 4-1 Weighting factors and years of reserve for some common nature resources

Raw Materials	Years of reserves	Factor
Coal	160	6.3
Oil	42	24
Gas	63	16
Rockstone	1000	1
Sand	500	2
Limestone	500	2

Emissions to air are evaluated depending on their weighted contributions to four impact potentials: Global Warming Potential (GWP), Ozone Depletion Potential (ODP), Photochemical Ozone Creation Potential (POCP), and Acidification Potential (AP). The factors applied to calculate the four potential categories are listed in Table 4-2 (Saling et al., 2002).

Table 4-2 Arithmetic values for impact potentials in the case of emissions to air

Air emission	GWP	ODP	POCP	AP
CO_2	1.0	-	-	-
SO_2	-	-	-	1.0
NO_x	-	-	-	0.7
CH_4	11	-	0.007	-

Toxicity considered by EEI is primarily human toxicity. To determine toxicity potential, the evaluation followed the guideline of the German Chemicals Act (Saling et al., 2002). The hazard symbols are specified numerical factors based on the classification-relevant values such as half lethal dose (LD50) values.

Risk potential is defined by Bengtsson (2004) as the product of the severity of consequences and the probability of occurrence. The possible hazards refer to any accident or misuse that might cause damage to environment and human health (Bengtsson, 2004). Due to the data limitation, this study presumed the same toxicity potential and risk potential levels for the two alternative techniques.

(2) Economic Performance

The economic performance was measured by the costs in the EEI framework, which includes any costs that arise when a product is produced, used and disposed (Saling et al., 2002), which was determined as life cycle cost. It implies an accounting for the present values (PV) of costs generated throughout the entire life cycle of a product or process (Kicherer et al., 2007). After normalization, the rescaled LCC value is integrated with the overall environmental impacts to generate an eco-efficiency portfolio position in one coordinate system.

4.2.3 Integration Procedure

The EEI method combines the ecological parameters and ultimately plots the results as an individual position in a coordinate system with providing only comparative information instead of absolute values (Kicherer et al., 2007; Saling et al., 2002). It implies that the conclusive eco-efficient level reflects the relative status among the multiple competitive alternatives.

The integration procedure involves two major steps: data processing (i.e., normalization and weighting) and data visualization. Normalization serves to compress the environmental and cost data. More specifically, the least favorable alternative is set to be the value of 1 on its corresponding impact category and the rest of alternatives are awarded the values from 0 to 1 depending on their relative performance. The overall weighting scheme (Figure 4-3) employed in this study is a combination of "relevance weighting factor" and "societal weighting factor" investigated and derived by Saling et al. (2002). The "Relevance" weighting factors signify the importance or contribution of the individual ecology category impact to the total impact of corresponding category of the investigated field. The "societal" weighting factors reflect social view of the corresponding ecologic category, and was jointly decided by management consultants Roland Berger and BASF via survey, public opinion polling, expert interview, etc.

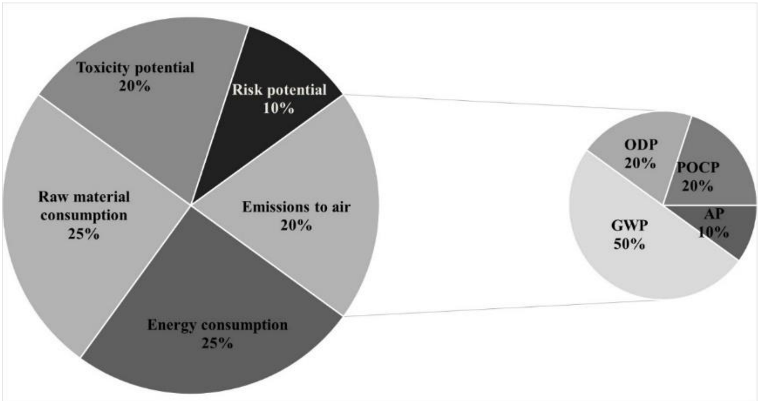


Figure 4-3 Overall weighting scheme in EEI

Data visualization is realized through the calculation of the eco-efficiency portfolio position. The Environmental Impact (EI) and the Normalization Factor for the Costs (NFC) are used to calculate the portfolio point in accordance with the following equations (Kicherer et al., 2007).

$$\mathrm{PP}_{\mathrm{E},\alpha} = \frac{EI_\alpha}{(\Sigma \mathrm{EI})/\mathrm{j}} \tag{4-1}$$

$$\mathrm{PP}_{\mathrm{C},\alpha} = \frac{NF_{C,\alpha}}{(\Sigma NF_C)/\mathrm{j}} \tag{4-2}$$

where $\mathrm{PP}_{\mathrm{E},\alpha}$= Environmental impact portfolio position for product α;

$\mathrm{PP}_{\mathrm{C},\alpha}$ = Cost impact portfolio position for product α;

EIa = Environmental impact of product α;

$NF_{C,\alpha}$= Normalization factor for the costs of product system α;

j = Number of products under consideration.

The overall numerical calculation procedure of the EEI method is summarized in Figure 4-4. In the eco-efficiency portfolio plot, the most satisfactory alternatives are located in the top-right corner while the least favorable selections are distributed in the bottom-left side.

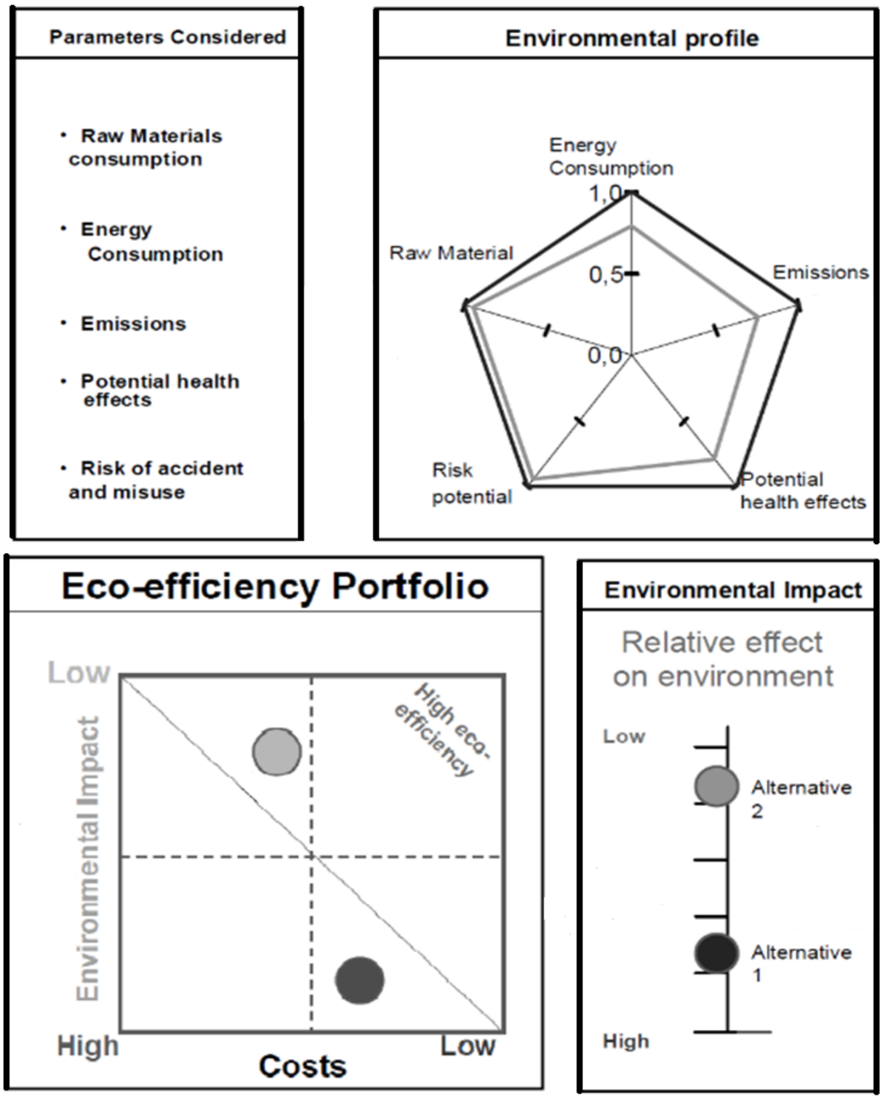


Figure 4-4 Integration procedure of EEI

4.3 Case Study

4.3.1 Case Information

The case investigated in this study is a project that rehabilitated the Yingbin Avenue located in Shaanxi Province of China (Figure 4-5), which is a two-way six-lane road section connecting the Wen Lin road and the Xianyang International Airport. The total length and area for rehabilitation are 3.8 km and 87,400 m2, respectively. According to the project report, the HIPR construction scheme employed half range closure construction by adding 20mm new asphalt mixture to renew the original top layer of pavement from AC-10 to AC-13. Existing road dimensions were used to calculate the volume of the pavement materials. During the construction phase, the traffic of other lanes is kept as usual, since only the operation lane of the construction is closed. In the premise of completing on schedule, the smooth flow and safety of pedestrian and traffic should be ensured.

Figure 4-5 Geographic information of road

Correspondingly, the construction scheme of the M&F is modeled based on the same pavement and traffic conditions according to three Chinese Standards (Ministry of Transportation, 2004, 2006, 2007): Specifications for

Design of Highway Asphalt Pavement (JTG-D50-2006), Technical specification for highway asphalt pavement construction (JTG-F40-2004) and Budgetary Norm of Highway Project (JTG/T B06-02-2007). In other words, the HIPR case is a real case, while the M&F case is a mock case for the same project for comparison purpose. Table 4-3 summarized the basic information of the two cases.

Table 4-3 Summary of general information

	HIPR	M&F
Construction Scheme	Wearing course: AC-10 30mm Base course: AC-25 50mm →	Wearing course: AC-13 40mm Base course: AC-25 50mm
	Adding 20 mm new asphalt mixture	Milling 30 mm old mixture Filling 40 mm new mixture
	Half Range Closure	Half Range Closure
Reference	Construction Report from the Freetech Technology Ltd.	JTG-D50-2006 JTG-F40-2004 JTG/T B06-02-2007
Service life	11-15 years (Assumption)	15 years (Assumption)

4.3.2 Data Collection and Processing

(1) Environmental Impact Data

Before merging into the eco-efficiency impact categories, the background LCA data source was decomposed into the process-based level of the entire life cycle. The corresponding estimation and computation tools employed in each life cycle phase are listed in Table 4-4.

Table 4-4 Environmental computation tools for each phase

Life Cycle Phase	Software	Developer
Material production phase	Simapro 7.0	PRe Consultants
Transportation phase	MOVES 2014a	US EPA
Construction phase	NONROAD	US EPA
End-of-life phase	"Cut-off" allocation method	

To be specific, Simapro 7.0 was applied to estimate the GHGs, energy and consumed raw material in the material production phase. MOVES 2014a was employed to evaluate the GHGs from vehicles during the transportation processes (Figure 4-6), which involved hauling raw materials to the plant (40 km), hauling manufactured materials to the construction site (0.5 km), and hauling milled asphalt mixture to the scrap yard (15 km).

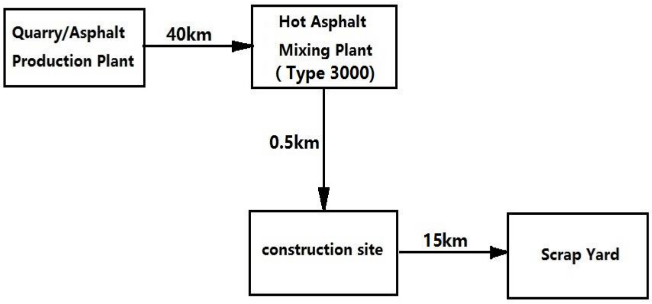


Figure 4-6 Transportation diagram

For the construction phase, the priority should be first given to clarify the specific construction schedule and equipment activities of the corresponding rehabilitation alternatives (Appendix 1). The duration of construction and maintenance activities were estimated according to the project report and Chinese Specifications for Design of Highway Asphalt Pavement (JTG-D50-2006). Then, NONROAD software was used to calculate emissions based on the provided emission factors for various ranges of horsepower of different construction equipment. Finally, in accordance with the previously defined system boundary and “Cut-off” allocation method, there would be no environmental impacts in the end-of-life phase.

(2) Cost Data

The life-cycle cost is the sum of agency and user costs over all the life cycle phases. Analogously, the cost figures related to the project is in the same system boundaries as that of LCA, while focusing on its monetary impacts

(Rebitzer, 2002). Due to data availability, the agency costs in this study only included the costs of main construction processes of the two rehabilitation methods and energy consumption costs. Besides, under the same condition, the results are relative normalized values, which can eliminate some error caused by the absolute values. For user costs, the traffic delay costs were estimated according to a FHWA's LCCA software, which was under the assumption that the Average Annual Daily Traffic (AADT) was about 15,000 and the speed limit was reduced from 90 km/h to a work zone speed of 60 km/h. Table 4-5 listed the breakdown of the item price for the cost evaluation. The data was collected from the real Chinese projects, which may bring some limitations in result generalization due to regional factors. However, in the consideration of comparison, the results could provide the general information by identifying the relative better alternative.

Table 4-5 Price list

Treatment	Type	Item	Unit	Price (CNY)
HIPR	Material	Petroleum Asphalt	t	122.536
		Mineral filler	t	128.404
		Crush rocks (<15mm)	m3	723.22
		Crush rocks (2-10mm)	m3	261.18
		Rejuvenate agent	kg	11
	Construction	Hot mixing Asphalt concrete（Incl. human, material and machinery）	1000m3	634,685
		HM16 Heater	machine-team	13,921.88
		RM6800 Hot-in-place recycling machine	machine-team	25,794.17
		EM6500 Lifting and remixing machine	machine-team	30,214.07
		Paver (<4.5m)	machine-team	680.97
		Steel Road Roller (<12t)	machine-team	610.79
		rubber-tyred roller(20-25t)	machine-team	760.27
	Fuel	Diesel	kg	5.3
		Liquefied petroleum gas	kg	3.2
		Electricity	kwh	0.75
	Transportation	Dump truck (20t) (New HMA)	1000 m3	5,148 (<1 km)
M&F	Material	Petroleum Asphalt	t	122.536
		Mineral filler	t	128.404
		Crush rocks(<15mm)	m3	723.22
		Crush rocks(2-10mm)	m3	261.18
	Construction	Hot mixing Asphalt concrete（Incl. human, material and machinery）	1000 m3	634,685
		W2100 Milling machine	1000 m2	3,970
		Paving machine (<4.5m)	machine-team	680.97
		Steel Road Roller (<12t)	machine-team	610.79
		Rubber-tyred roller (20-25t)	machine-team	760.27

	Fuel	Diesel	kg	5.3
		Electricity	kwh	0.75
	Transportation	Dump truck (20t) (New HMA)	1000 m3	5,148(<1 km)
		Dump truck (20t) (Milled HMA)	1000 m3	11,053 (20 km)

4.3.3 Sensitivity Analysis of Life Extension

The environmental impacts and economic costs are not only directly resulted from the material consumption and fuel combustion of on-road and non-road vehicles, but also indirectly associated with the frequency of maintenance and rehabilitation activities and effectiveness of maintenance techniques. The life extension ability is often regarded as one of the parameters to evaluate the long-term maintenance effectiveness (Mamlouk & Dosa, 2014), Consequently, a sensitivity analysis was conducted in this study to explore the eco-efficiency performance of the two alternatives under different treatment service life scenarios.

As illustrated in Figure 4-7, the five different scenarios (Scenario A to E) were created to show the life extension situations. The lives extended by HIPR treatment were decreased progressively from fifteen years by one year for each scenario. The environmental impacts and cost performance were computed accumulatively based on the lowest common multiple of the two alternatives' service lives.

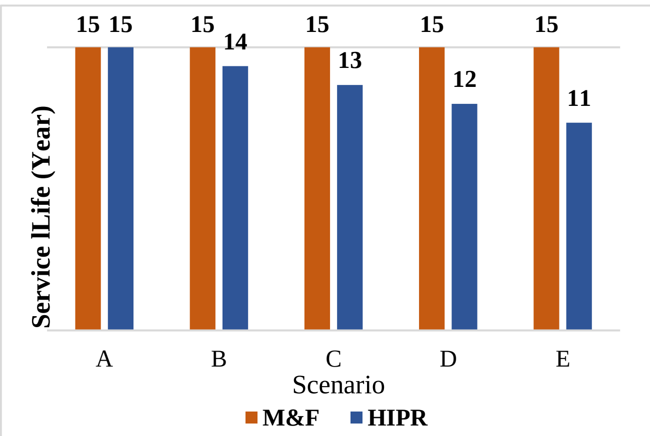


Figure 4-7 The five analysis scenarios

Three hypotheses were made during the sensitivity analysis process:

1). Whenever the road service reaches its end, the same rehabilitation techniques would be applied continuously;

2). The impacts brought by the life extension variable only considered as the environmental and cost burdens due to the repeated maintenance times of the corresponding rehabilitation techniques in the analysis period;

3). When comparing, the baseline life extension is set to be 15 years with the descending durability of hot in-place recycling are from 15 to 11 years.

4.4 Results and Discussion

4.4.1 Eco-efficiency Performances under the Same Life Extension

The normalized results of environmental impacts and cost performance of the two rehabilitation alternatives were illustrated in Table 4-6, under the equal consideration of life extension for the two rehabilitation techniques.

It can be obtained that HIPR reduced 28% air emission and saved 48% raw material than conventional M&F, while M&F saved 7% energy than HIPR mainly due to the additional heating energy required by HIPR in the construction phase. The toxicity potential and risk potential were set to be the same for both techniques, resulting in the equivalent normalized value of 1 for both. In the monetary aspect, 29% agency cost was saved by HIPR compared with M&F, since M&F requires higher raw material and transportation cost. The user costs for both were almost same for the same road closure method and traffic flow assumption, the slight difference was resulted from the construction period difference. The overall results in Table 4-6 implied that HIPR can reduce approximately 16% environmental impacts and save 5% costs than those of M&F.

Table 4-6 Normalized numerical results under the same service life

<table>
<tr><th colspan="2">Normalized results</th><th colspan="3">HIPR</th><th colspan="3">M&F</th></tr>
<tr><td rowspan="8">Environmental Impacts</td><td rowspan="4">Emissions (20%)</td><td rowspan="4">0.72</td><td>GWP (50%)</td><td>0.51</td><td rowspan="4">1</td><td>GWP (50%)</td><td>1</td></tr>
<tr><td>ODP (20%)</td><td>1</td><td>ODP (20%)</td><td>1</td></tr>
<tr><td>POCP (20%)</td><td>0.5</td><td>POCP (20%)</td><td>1</td></tr>
<tr><td>AP (10%)</td><td>1</td><td>AP (10%)</td><td>0.16</td></tr>
<tr><td>Energy consumption (25%)</td><td colspan="3">1</td><td colspan="3">0.93</td></tr>
<tr><td>Raw material consumption (25%)</td><td colspan="3">0.52</td><td colspan="3">1</td></tr>
<tr><td>Toxicity potential (20%)</td><td colspan="3">1</td><td colspan="3">1</td></tr>
<tr><td>Risk potential (10%)</td><td colspan="3">1</td><td colspan="3">1</td></tr>
<tr><td colspan="2">Overall environmental impact</td><td colspan="3">0.82</td><td colspan="3">0.98</td></tr>
<tr><td rowspan="2">Cost Performance</td><td>Agency cost (50%)</td><td colspan="3">0.71</td><td colspan="3">1</td></tr>
<tr><td>User cost (50%)</td><td colspan="3">1</td><td colspan="3">0.99</td></tr>
<tr><td colspan="2">Total Cost performance</td><td colspan="3">0.95</td><td colspan="3">1</td></tr>
<tr><td colspan="2">PP_E</td><td colspan="3">0.91</td><td colspan="3">1.09</td></tr>
<tr><td colspan="2">PP_C</td><td colspan="3">0.97</td><td colspan="3">1.03</td></tr>
</table>

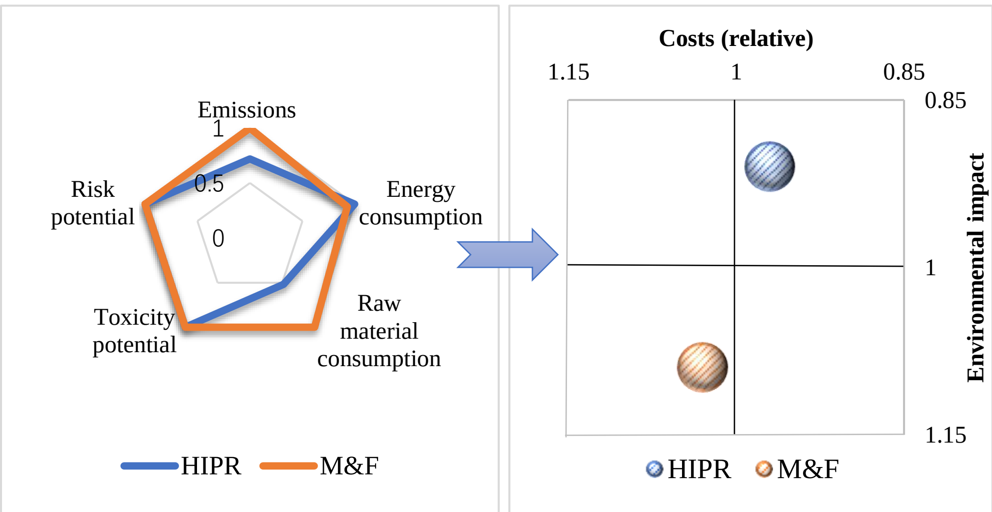


Figure 4-8 Graphical results under the same service life

As illustration in Figure 4-8, the environmental results were visualized into a spider diagram to reflect relative impacts of HIPR and M&F techniques in each subcategory. Beyond that, the ultimate eco-efficiency portfolio was plotted in a coordinate system according to the value of PP_E and PP_C. It is clear to signify that HIPR located in the upper right corner and was more eco-efficient than M&F when the life extensions of the two were same. This result conformed to the conclusions of existing studies (Louhghalam et al., 2017; Noshadravan et al., 2013; Wang et al., 2012b) about ecological benefits of the cold in-place recycling due to its lower trucking demands and material saving, and additionally provided the quantified comparative data of hot in-place recycling and milling-and-filling as supplement.

4.4.2 Eco-efficiency Performances under Different Service Lives

When the HIPR and M&F have the same durability extension, the HIPR has already performed better in the both overall ecology and cost aspects. If the HIPR had the longer life extension (i.e., durability extension of M&F lower than that of HIPR), to reach the same life cycle analysis period, the frequency to conduct M&F would be higher than HIPR, which leads to the obviously same conclusion with the scenario under the same durability. Furthermore, the ability of HIPR to extend service life documented in the previous literatures was ranged from 3 to 12 years (Ali et al., 2013; Anderson et al., 2016; Caltrans, 2008; Wu et al., 2010), which was less likely to achieve the same intervention effects as M&F: 6 to 18 years (Anderson et al., 2016; LEGCO, 2012; Speight, 2015; Wu et al., 2010). Therefore, based on the above-mentioned literatures, we first selected 15 years as a compromised durability of M&F with subtracting 3 margin years from the maximum, and then employed the descending durability from 15 years of HIPR to find the trade-off point between life extension and eco-efficiency.

Figure 4-9 presents the relative environmental performances and their variation tendencies of two M&R alternatives under different life extension of HIPR. It can be observed that the colors of Scenarios A to E are changed from dark to light for both alternatives. This implied that with the service life reduction of HIPR, the environmental impacts of M&F are diminishing (shrinking trend), while those of HIPR become more serious (expanding trend).

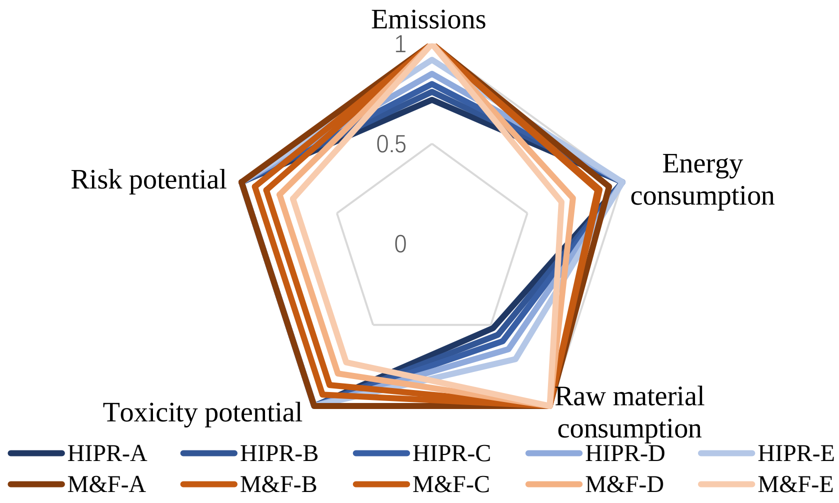


Figure 4-9 Environmental performance under the different service life

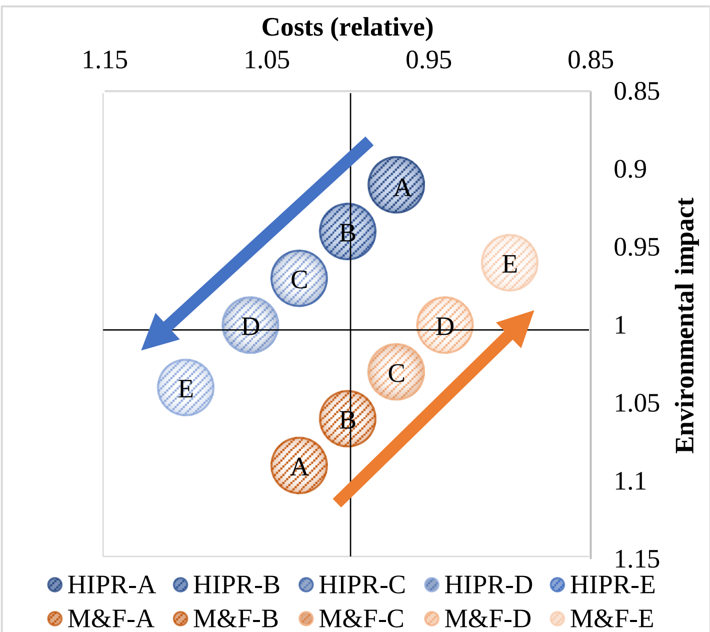


Figure 4-10 Eco-efficient performance under the different service life

As illustrated in Figure 4-10, along with the decreasing life extension of HIPR, the eco-efficiency positions of HIPR move from the higher efficiency to the lower direction. On the contrary, the trajectory of M&F moves towards the opposite direction correspondingly. More precisely, HIPR shows its strength in both environmental and cost performance when it has the same treatment effectiveness (i.e., life extension) with M&F (Scenario A). After one-year reduction in the service life of HIPR (Scenario B), the cost performances of both become the same, but the HIPR is still more favorable due to its persistently better environmental performance compared to M&F. In the circumstance of Scenario C, the cost performance of M&F wins the more satisfactions, while the HIPR is still more environmental-friendly. When the service-life ratio of HIPR and M&F is 12/15, the environmental impacts of two alternatives get to be equivalent, while M&F remains more cost efficient When there is a four-year gap between them, M&F starts to show its advantages in both environmental and monetary aspects.

A previous investigation (Anderson et al., 2016) about long-term performance of hot in-place recycling project also reflected the importance of the life extension in the life cycle cost: the shorter life of the HIPR (9 years) results in an annual per lane mile cost that is $3,700 higher than the HMA mill and fill (15 years). Beyond that, according to the report of FHWA (Wu et al., 2010), based on the survey of 3 practical projects, HIPR could extend pavement service life ranging from 3 to 8 years, while M&F could extend pavement service life ranges from 6 to 17 years according to the summary of 9 related projects. Combining this with the analysis results of this study, even both the techniques could reach the above maximum life extensions, HIPR still lose its ecological benefits in the long-term perspective, even though hot-in place recycling has been promoted to be cost effective and low carbon emissions for years (Watson, 2011). Thus, it can be seen that in addition to involving different abilities in life extension into the eco-efficiency consideration of M&R techniques, the different system boundaries and analysis periods may further lead to the inconsistent results with previous studies.

4.5 Summary

This chapter proposed an eco-efficiency integration framework for pavement M&R alternatives with sensitivity analysis of maintenance effectiveness. To further verify the usability of the framework, two prevalent rehabilitation alternatives, namely HIPR (real project) and M&F (mock case), was systematically evaluated and compared as case study in relation to eco-efficiency and maintenance effectiveness.

Under the situation with the same life extension ability, the environmental impacts and economic performance of HIPR technique and conventional M&F approach have been quantified and visualized. For the rehabilitation cases presented in this study, HIPR is more favorable in terms of its eco-efficiency location, because it is plotted in the upper right corner, while M&F is positioned in the opposite corner. More preciously, HIPR could reduce approximately 16% environmental impacts and save 5% costs than those of M&F.

However, it should be noted that the results are quite sensitive to the treatment effectiveness of rehabilitation techniques. Therefore, the life extension, as one of effective parameters, was involved into this study. The sensitivity analysis concluded that the decreasing life extension of HIPR witnessed its eco-efficiency reduction compared with M&F technique. When the life extension ratio of the two alternatives was up to 12/15 (HIPR/M&F), the M&F started to show it advantages. In the five different scenarios, the "worst case" (scenario E) would suggest that when maintenance effectiveness ratio of HIPR/M&F reduced to a threshold (11/15), both environmental and cost benefits of HIPR will lose. This signifies the importance of guaranteeing the construction quality and effectiveness of rehabilitation techniques.

Even though the eco-efficiency analysis method showed its high potential and good visuality as an effective and more systematic sustainability assessment tool for comparing asphalt pavement rehabilitation alternatives, there are two unavoidable limitations in this study. First, because of the data limitation, the value assignment of the life extensions of the two rehabilitation techniques are considered on the basis of the investigations by previous technical documents or literatures (Ali et al., 2013; Anderson et al., 2016; Caltrans, 2008; LEGCO, 2012; Speight, 2015; Wu et al., 2010). In the view of statistics, there is always a probability distribution of life extension for specific treatments. The extension year applied in this case just offered a reasonable entry to find the potential trade-off point between the eco-efficiency and life extension of corresponding treatment. For future studies, the application of more accurate life extension prediction models, either empirical or mechanistic-empirical models, were recommended.

Second, the data uncertainty due to the regional or geographic factors as an inherent attribute of life cycle assessment, to some extent, might affect the quantified results of the life cycle assessment impacts. According to the investigation by Santero et al. (2011b) in 15 LCA studies from 1996 to 2010, the energy consumption of cement production could range from 4.6 to 7.3 MJ/kg, and the energy consumption range of asphalt production is 0.7-6.0 MJ/kg. The uncertainties could be discussed in two data types in the life cycle assessment system: foreground data and background data (EC, 2010). The foreground data (case data) including the scope definition, processes of life-cycle phase, pavement design information, material type, equipment model and productivity, etc., were all come from the real Chinese project report or Chinese specification standards. The foreground uncertainties are primarily due to the different choices. The background data connected with the foreground data through various professional LCA data sources (Table 4-4), which is the significantly part affected by the regional uncertainty factor. These factors involved crude source distribution, refinery allocation and the national energy structure etc. Therefore, it is hard to estimate the result generalization by simply subjective judgment. In order to obtain more general and applicable results, a recommendation to filled in this gap in the future pavement life cycle evaluation is to apply the uncertainty analysis, such as Monte Carlo simulation (Huijbregts, 1998a, 1998b) and pedigree matrix approach (Weidema et al., 2013).

In general, the eco-efficiency integration framework and case study results in this chapter could support as reference to the agencies or decision-makers to identify the advantages and disadvantages of the two rehabilitation techniques (HIPR and M&F) under the gradually decreasing life extension of HIPR. The concluded trade-off point between the eco-efficiency and life extension parameter could help to find ways to facilitate improvements.

CHAPTER 5 UNCERTAINTY ANALYSIS

5.1 Introduction

As one of major limitations of the LCA-based studies, the conclusions were generally drawn from single or multiple case studies. It may lead to inconsistent findings due to different assumptions and uncertainty factors, such as system boundary, data appropriateness, region, transportation distance and pavement performance model (Tatari et al., 2012; Wang et al., 2012a). Although the uncertainty analysis in LCA has been suggested by many literatures (Huijbregts, 1998a, 1998b; Noshadravan et al., 2013; Weidema et al., 2013; Yu et al., 2016a), very limited studies could be found on considering these uncertainties in the pavement life cycle. Therefore, the major objective of this chapter is to include the uncertainty consideration into the evaluation framework to decrease the likelihood of misunderstanding or negative effect on external interest. In this context, the incorporation of uncertainty was originality implemented in comparing the life-cycle energy consumption of warm asphalt rubber (WAR) pavements built with three typical warm additives: organic wax, surfactant additive, and zeolite, as the research on identifying the long-term energy-saving role of WMA technologies in Asphalt rubber (AR) pavement is still very limited.

AR pavement, which is incorporated with more than 15% of waste tire rubber by weight of asphalt binder, has received growing attention in the past years because of its various advantages, such as potential energy recovery from end-of-life tires, excellent durability and lower tire-road noise (Rodríguez-Alloza et al., 2015). The environmental benefits of AR mixture because of using waste material have been studied and reported by many researchers (Bartolozzi et al., 2014; Farina et al., 2017; Wang et al., 2012a). However, the construction temperature of AR mixture would be 86 - 122 °F (30 - 50 °C) higher than conventional hot mix asphalt (Yu et al., 2017), which results in more energy consumption and emission during the construction process. As a solution, warm mix asphalt (WMA) technologies can be applied to reduce the construction temperature of AR mixture with the assistance of various WMA additives (Kristjánsdóttir et al., 2007). These additives can be generally classified into three categories based on their working mechanisms (D'Angelo, 2008; Rubio et al., 2012; Yu et al., 2016b): organic additives (e.g., organic wax), chemical additives (e.g., surfactant additive) and foaming additives (e.g., zeolite). Several field trials and life cycle assessment (LCA) studies have been conducted to evaluate the environmental effects of WMA technologies (Hassan, 2010; Hicks et al., 2010; Hurley et al., 2009; Kristjánsdóttir et al., 2007; Rodríguez-Alloza et al., 2015; Tatari et al., 2012; Vidal et al., 2013). Some of them indicated an evident energy saving and environmental impact reduction by using WMA (Harvey et al., 2016; Hicks et al., 2010; Hurley et al., 2009; Kristjánsdóttir et al., 2007; Rodríguez-Alloza et al., 2015), while the other evaluation studies (Tatari et al., 2012; Vidal et al., 2013) found that there was significant variability among different WMA technologies, and the reduction in the impacts of WMA resulting from the lower mixing temperature was offset by the greater impacts of the materials used.

This chapter is composed of five major sections. The first section briefly introduces the background, research gap, and chapter outline. The second section focuses on the methodology development. More specifically, along with the LCA of the four comparative mixtures, the uncertainty was quantified by either basic uncertainty or additional uncertainty. The basic uncertainty expressed the variation potentially due to the measurement error, activity specific variations, temporal variations, use of assumption, lacking verification, sample incompleteness etc. (Weidema et al., 2013). The additional uncertainty referred to the uncertainty introduced by the data quality and appropriateness. The Monte Carlo simulation was performed based on the characterized distributions and propagated the uncertainties into the life cycle energy consumption of the selected warm AR mixtures. Then, the third section present the detailed information of the case study in mixture design, performance prediction, and involved uncertainties. After the discussion, the major findings are summarized finally. By incorporating uncertainty analysis, more comprehensive information could be provided for decision-making compared with the conventional deterministic assessment results.

5.2 Methodology

Three major processes were involved in the methodology part, including the definition of the system boundary and life cycle inventory (LCI) data collection, incorporation of the uncertainty factors and corresponding probability distributions into LCA, and integration of the uncertainties with the LCA through Monte Carlo simulation.

5.2.1 Life Cycle Assessment

LCA is a systematic environmental impact evaluation tool for a product, technique or service in its defined lifetimes. A pavement life cycle analysis framework involving the cradle-to-grave stages of pavement, has been established by the Federal Highway Administration (FHWA) (Harvey et al., 2016). The LCA in this study followed the FHWA guideline in accordance with ISO 14040 and 14044 (ISO, 2006a, 2006b).

A comparative attributional LCA incorporated with uncertainty analysis is used to identify the superior probabilities of the four rubber asphalt pavement mixtures based on the estimated input uncertainty factors under the equitable functional unit (FU), system boundary, and allocation rule. The functional unit is defined in accordance to the functional outputs of the life cycle system. In this study, the considered FU was 1 km-lane pavement area with 20-year analysis period. The system boundary considered five main stages as shown in Figure 5-1: (1) material extraction and production stage, (2) transportation stage, (3) construction stage, (4) usage stage, and (5) end-of-life (EOL) stage.

The material extraction and production stage quantified the energy consumption in the asphalt refinery, aggregate mining and crushing, crumb rubber recycled from end-of-life tires (ELTs), the production of WMA additives, and plant mixing process. The transportation stage computed the energy consumption related to the processes to transport materials: transport of asphalt binder from refinery site to the mixing plant, transport of aggregates from local quarry to the mixing plant, transport of ELTs from initial collection site to the crumb rubber processing site, transport of crumb rubber powder to the mixing plant, and transport of asphalt mixtures from mixing plant to construction site. The construction stage calculated the energy burdens from the construction activities, including laying mixture, paving, compacting, sweeping, and lighting, assuming the same compaction efforts between AR and WAR mixtures. The usage stage quantified the extra energy consumption associated with the vehicle operation due to the pavement deterioration. At the end-of-life stage, the typical scenarios may include full-depth reclamation, recycled materials, and landfilling (Harvey et al., 2016). In this study, it was assumed that the EOL pavement surface would be completely reclaimed on site as part of new pavement surface material and serve for the next life cycle system. Thus, no environmental impact would be assigned to the EOL stage. The energy burden associated with recycling ELTs was ascribed to crumb rubber production, and no virgin material would be associated with the crumb rubber creation. The fate of co-product was also excluded in the evaluation. For the asphalt refinery in the system (multi-output situations), though the physical-based (mass) allocation rule was the basically applied in the data sources, the refining crude oil is a complex process and hard to be properly allocated.

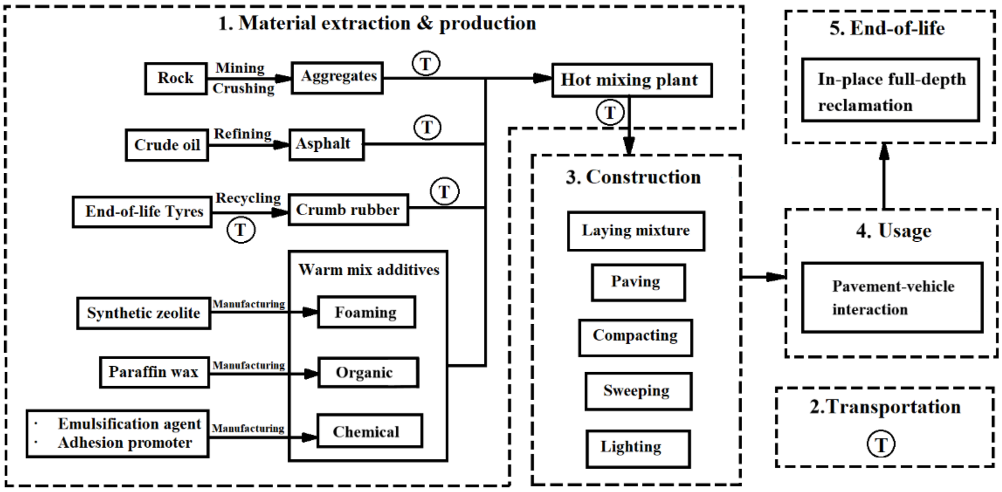


Figure 5-1 System boundary for warm mix asphalt rubber pavement

Therefore, to characterize the uncertainty in the LCI data sources, the life cycle inventory analysis would follow the above-defined system boundary together with the available primary data from various sources (Appendix 2). A range of energy consumption in the asphalt binder, crumb rubber and aggregate production, transportation and construction equipment, and corresponding transportation distances were extracted and collected from the relative studies and databases. As different types of energy/fuel consumption (e.g., crude oil, diesel, gasoline, natural gas, and electricity etc.) was calculated in different energy units, the total energy consumption is converted and integrated into a uniform unit (megajoule) based on the corresponding energy contents (Weidema et al., 2013).

Among the three evaluated WMA additives, the water contained in the zeolite would be released during the asphalt mixture mixing process to create a foamed asphalt and improve the mixture workability (Yu et al., 2016b); the organic wax additive could reduce the viscosity of asphalt binder at the asphalt mixture construction temperature (Leng et al., 2017b); and the surfactant warm mix additive employs the chemistry packages including the emulsification agents and adhesion promoters to enhance the mixture workability (Yu et al., 2017). The environmental burden in manufacturing the WMA additives was often ignored by the previous studies due to the limited available information provided by the manufactures. In this study, the LCI data of synthetic zeolites from the study by Fawer et al. (1998) were used for the evaluation for zeolite production, and the evaluation of organic wax production employed the LCI data of paraffin wax from the study by Tufvesson and Börjesson (2008). Considering the detailed components of surfactant additive varied, the LCI data of asphalt emulsion and polymer modified additive (Wang & Gangaram, 2014) were used to calculate the environmental burden to produce surfactant additive. Since this substitution may introduce unreliability in the results, a high data quality variance was considered in the later uncertainty analysis.

For the mixing plant evaluation, a linear relationship ranged from 480 to 1100 BTU/°F/ton (Prowell et al., 2014; West et al., 2014) between the mixing temperature and energy consumption was employed. This thermodynamic model was calibrated by real data with regarding to aggregate moisture content, casing losses and mix and stack temperatures (Prowell et al., 2014; Rodríguez-Alloza et al., 2015; West et al., 2014).

In the pavement usage stage, the pavement roughness acts as a major function, which is closely linked to the fuel efficiency of vehicles (Chatti & Zaabar, 2012; Harvey et al., 2014). Therefore, the corresponding impact was considered as the extra energy consumption by vehicles due to the pavement deterioration. International roughness index (IRI) was employed to characterize the pavement roughness level. Since the parallel LCAs of the four mixtures were supposed to serve in the planning stage, the prediction of IRI trend over time was achieved by using the pavement performance prediction model. Despite many tools and models have been applied with regarding to the pavement roughness prediction (Bryce et al., 2014; Santos et al., 2017a), the Mechanistic Empirical Pavement Design Guide (MEPDG) software (AASHTO, 2008; NCHRP, 2004) was employed in this work, as it could provide the prescribed level of IRI prediction reliability with an underlying probabilistic model. The uncertainty in IRI evolution was propagated through the quantification of extra fuel consumption in the pavement-vehicle interaction model. The effects of the uncertainties would vary depending on the pavement materials and their deviations in the time-related roughness curve. Figure 5-2 (AASHTO, 2008) illustrates the uncertainty characterization by the IRI prediction curves at different reliability levels, where the upper limit reliability (1-α) curve and the lower limit reliability α curve constitute the pavement IRI uncertainty band.

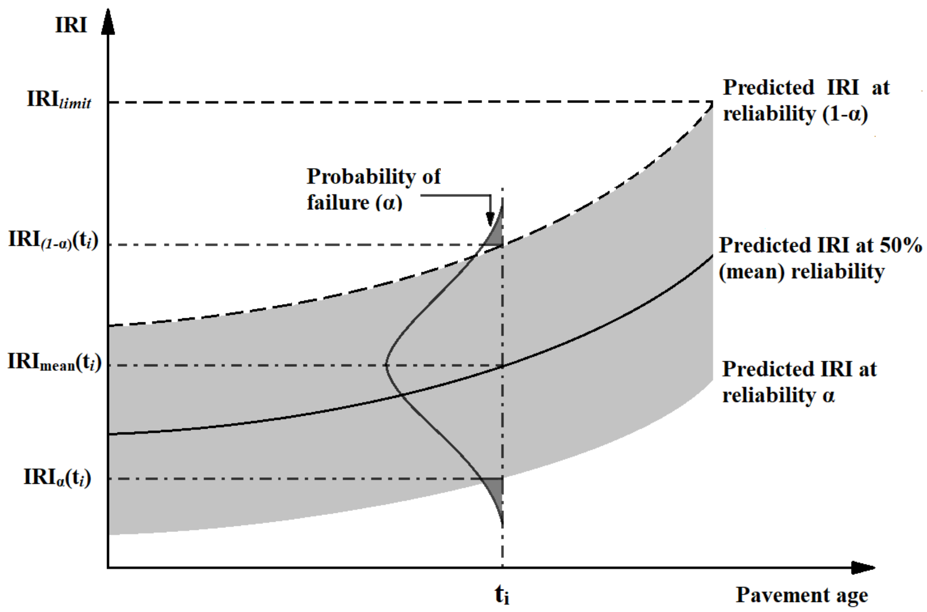


Figure 5-2 Schema of MEPDG IRI prediction over pavement age at 50% (mean), α and (1-α) reliability levels

The extra fuel consumption was then translated from the increasing IRI via a mechanistic model developed as part of the Highway Development and Management software (HDM-4) with the parameters calibrated by Zaabar and Chatti (2010), Akbarian and Ulm (2012), and Jiao and Bienvenu (2015).

The uncertainty in the IRI evolution associated with the extra vehicle fuel consumption was propagated by the Monte Carlo simulation, employing the IRI evolution curves in different reliability levels under the MEPDG prediction.

5.2.2 Uncertainty Analysis

Uncertainty is a statistical term defined by ISO 3534-1 (ISO, 2006c) to cover any distribution of data within a population, caused by either random variation or bias (Weidema et al., 2013). The classification of uncertainties was varied in different uncertainty typology researches (Heijungs & Huijbregts, 2004; Weidema et al., 2013), which may occur in any life-cycle step or stage. In this study, two types of uncertainties were estimated: basic uncertainty and additional uncertainty.

The basic uncertainty can be ideally modeled by a probability distribution and incorporated into the LCA framework by the Monte Carlo simulation method. The choice of distribution has limited influence on the overall uncertainty of system, since the aggregation of a large number of independent variables each with their distribution will always approach a result with normal distribution, which is called "central limit theorem". In this study, the lognormal distribution defined as the "probability distribution where the nature logarithm of the observed values that are normally distributed" (Weidema et al., 2013), was characterized by the variances of underlying normal distributions that describe the collected LCI input sample data. There are three reasons to employ it. First, many real-life effects are multiplicative rather than additive. Second, most parameters for real life populations are always positive. Thirdly, the standard deviation of the underlying normal distribution is scale independent.

For the additional uncertainty, the pedigree matrix approach established by

Weidema and Wesnaes (1996) was used to quantify the data quality indicators (DQIs), which was incorporated to the underlying lognormal distribution derived from the above-mentioned basic uncertainty. The five independent indicators of pedigree matrix include “reliability”, “completeness”, “temporal correlation”, “geographical correlation”, “further technological correlation”, and each of them are classified into five levels with a pedigree score (Weidema et al., 2013). The pedigree scores were then transferred to the statistical variances of underlying normal distribution. The relationship of the scores and variances was specified by Weidema et al. (2013a), with the higher scores reflecting the higher variance and lower data quality. In this study, the data quality of the collected LCI sample data was quantified with regarding to the five independent quality variances. Considering the covariance equals zero for their independent relationships, when the variance of the underlying normal distribution of basic uncertainties was donated as σ_b^2, the variance of the overall variance σ_t^2 with the five additional uncertainties σ_i^2 can be calculated using the following equation:

$$\sigma_t^2 = \sigma_b^2 + \sum_{i=1}^{5} \sigma_i^2 \quad (5\text{-}1)$$

5.2.3 Monte Carlo Simulation

Figure 5-3 summarizes the Monte Carlo simulation procedures in this study. After the LCA input uncertainty factors had been characterized by quantifying either basic or additional variances, the simulation was performed to propagate the uncertainty factors into the life cycle energy consumption estimation. Based on this purpose, numerical values of all the uncertainty factors were randomly sampled with following their characterized distributions. For each sampled set, the inputs were delivered into the predefined LCA system to compute the corresponding energy consumption of single life stages and whole life cycle. Then, the energy consumption samples were obtained by applying n repetitions of the above computation process. Finally, the probability distributions of these samples can be estimated.

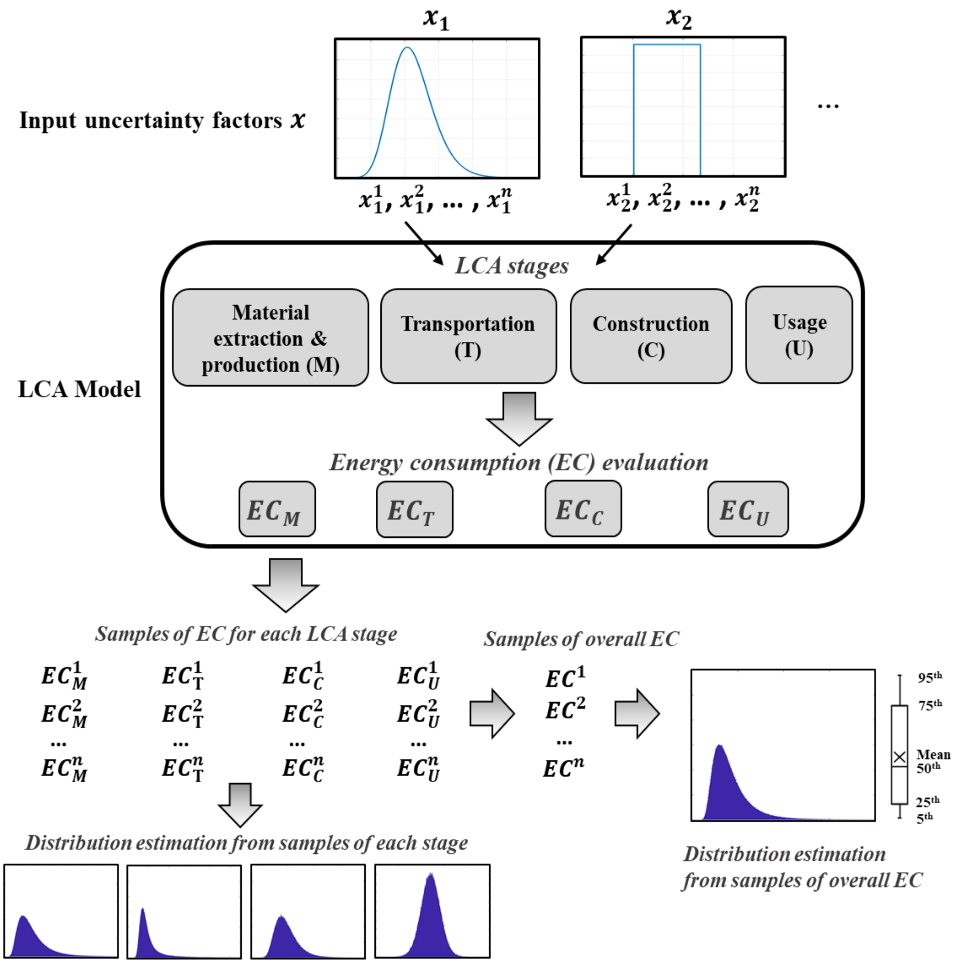


Figure 5-3 LCA Monte Carlo Simulation Schematic Diagram

The simulation results present the probability distribution of the life cycle energy consumption of the alternative mixtures. The comparative indicator, defined as the rate of the life-cycle energy consumption of the two compared mixtures, was used to describe the relative differences in the view of statistics. At each Monte Carlo iteration, the comparative indicators were calculated and stored. For the four AR mixtures in this study, a matrix consisting of corresponding comparative indicators (Table 5-1) was generated and analyzed, which intend to signify the superiority likelihood that one alternative than the other one. For instance, the term $P(E_B/E_A<1)$ represents the probability of the events that the life-cycle energy consumption of mixture B was less than that of mixture A involving all computing iterations, and vice versa. Then, a decision regarding to the energy-saving superiority of mixture A over mixture B can be made accordingly.

Table 5-1 Comparative indicator matrix of the four designed pavement materials

Mixture	A	B	C	D
A	-	$P(E_A/E_B<1)$	$P(E_A/E_C<1)$	$P(E_A/E_D<1)$
B	$P(E_B/E_A<1)$	-	$P(E_B/E_C<1)$	$P(E_B/E_D<1)$
C	$P(E_C/E_A<1)$	$P(E_C/E_B<1)$	-	$P(E_C/E_D<1)$
D	$P(E_D/E_A<1)$	$P(E_D/E_B<1)$	$P(E_D/E_C<1)$	-

5.3 Case Study

The four mixtures evaluated in the case study are the asphalt rubber mixture without WMA additive (AR), the warm AR mixture with surfactant additive (ARS), the warm AR mixture with organic wax additive (ARW), and the warm AR mixture with zeolite additive (ARZ), which represent control mixture and the mixtures with three common warm additives – chemical, organic, and foaming additives, respectively. Table 5-2 summarizes the formula of the four estimated wearing course mixtures, including the percentage of crumb rubber modifier (CRM), the type and dosages of warm technologies, the binder content, and the unit weight of each mixture.

Table 5-2 Summary of AR and WAR mix formula

Mixture	CRM content[(a)]	Warm Additives	Additive Content[(a)]	Binder Content[(b)]	Unit Weight[(c)]
AR	18	N/A	N/A	6.7	2320
ARS	18	Surfactant	5	6.7	2298
ARW	18	Wax	3	6.7	2315
ARZ	18	Zeolite	5	6.7	2352

Note: (a) Unit: wt% of AR; (b) Unit: wt% of mix; (c) Unit: kg/m^3

The essential input for the MEPDG model included structures of pavement, material properties, traffic information and climate information. The structure and material information from a series of rheological and mechanical experiments (Yu, 2017) were used as the input parameters, including binder complex modulus, dynamic modulus, stage angle, mixture gradation, and air void. The climate condition including the temperature, wind speed, humidity, and cloud amount were collected from the Hong Kong Weather Observatory. For the traffic loading condition, the 9,355 annual average daily traffic with 70% for car and 30% for truck was employed based on the recorded maximum traffic volume by the Hong Kong Highway Department (HyD). The MEPDG software modeled their IRIs at 50% reliability and 90% reliability (Figure 5-4), where the initial IRIs of the four mixtures were assumed to be 1m/km. The prediction results showed an acceptable smoothness within the 20-year design life.

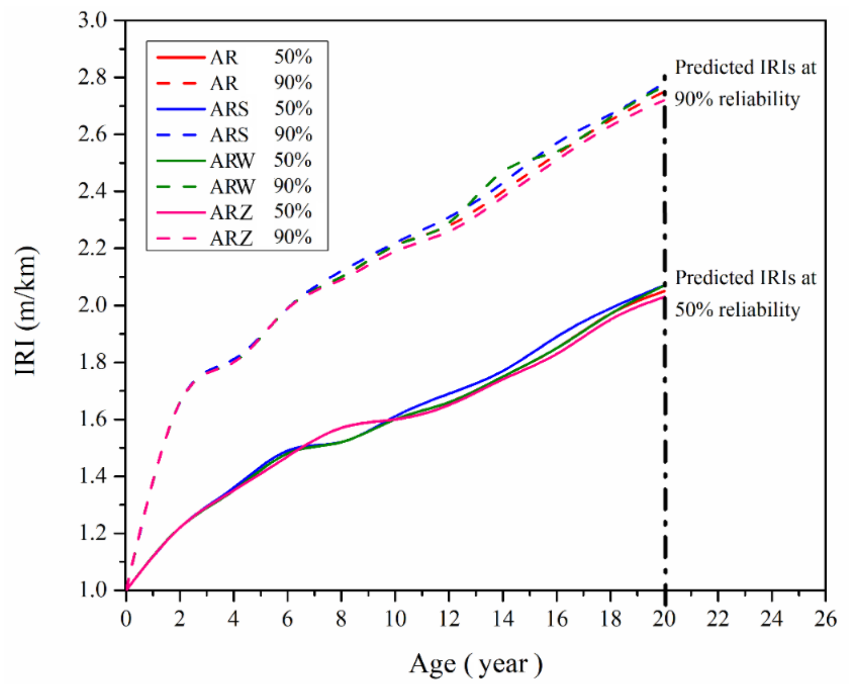


Figure 5-4 The MEPDG IRI prediction curves of the four mixtures in 20-year design life

Based on the above-mentioned methods and collected LCI sample data, the uncertainty factors were classified into four categories: energy consumption in material production, mixing temperature reduction and corresponding energy saving, transportation distance, and energy consumption of construction equipment. Table 5-2 summarized the computed uncertainty formula parameters (e.g., mean: μ and standard deviation: σ) for the involved uncertainty factors based on the addition variance (DQI) and basic variance of inventory data presented in the Appendix 2.

Table 5-3 Summary of uncertainty factors

Uncertainty Factors		Uncertainty type	Parameters (formula)*
Material production energy consumption (MJ/kg)	Aggregate	Lognormal	μ = -2.7489, σ = 0.8526
	Asphalt	Lognormal	μ = 1.0383, σ = 1.2487
	Crumb rubber	Lognormal	μ = 0.5288, σ= 0.6751
	AR mixture	Lognormal	μ = 0.5938, σ = 0.6625
	Surfactant additive	Lognormal	μ = 1.3536, σ = 0.4583
	Organic wax	Lognormal	μ = 4.6151, σ = 0.2159
	Zeolite	Lognormal	μ = 3.2753, σ = 0.2126
Mixing process	Unit mixing energy saving (MJ/°F/ton)	Uniform	lower=0.51, upper=1.15
	Surfactant temperature reduction (°F)	Uniform	lower = 100, upper = 130
	Organic wax temperature reduction (°F)	Uniform	lower = 32, upper = 97
Transportation distance (km)	Transport crumb rubber powder	Lognormal	μ = 4.1349, σ= 1.2461
	Transport asphalt	Lognormal	μ = 4.7536, σ = 0.6682
	Transport aggregates	Lognormal	μ = 3.0784, σ = 1.5764
	Transport asphalt mixture	Lognormal	μ = 3.9666, σ = 0.3626
Energy consumption of construction equipment (L/h)	Road sweeper	Lognormal	μ = 3.2943, σ = 0.1436
	Paving machine	Lognormal	μ = 3.1532, σ =0.5014
	Steel roller	Lognormal	μ = 2.8364, σ = 0.4713
	Pneumatic roller	Lognormal	μ = 2.7526, σ = 0.4459
	Generator	Lognormal	μ = 3.9485, σ = 0.1217

Note: * μ and σ were the parameters of corresponding underlying normal distribution.

5.4 Results and Discussion

The comparation in this study was carried out under the equivalent functional unit, system boundary, allocation methods, data type identification, performance considerations and energy evaluating methods as stated in the LCA method section. The effects provided by the data variations and data quality were estimated and integrated into the LCA calculation processes through the Monte Carlo simulation. After 1 million operations of the Monte Carlo simulations, the statistics distributions of energy consumption for the comparative material sets were formulated. The comparative matrix that reflects the superior probability was also computed.

5.4.1 Monte Carlo Simulation Results

The breakdowns of the energy consumption in MJ/km-lane associated with the life cycle stages of the compared pavement mixtures are shown in Figure 5. The 5th, 25th, 50th (median), 75th, 95th percentiles and the mean of the data are indicated in the box-plots. The blue colors varying from dark to light in the plots distinguish the AR, ARS, ARW, and ARZ mixtures in turn.

In Figure 5-5, from the view of energy consumption contribution level, the order-of-magnitudes of the energy consumption values were varied in different stages. The construction stage contributes the minimum energy consumption, while the usage stage consumption accounts for the dominant portion. Considering such huge disparity in energy consumption (4-5 magnitudes) between the usage stage consumption and the other stages, the accuracy of the MEPDG prediction results plays foundational role in evaluating the energy consumption of different pavements in their life cycles.

Visible differences could be observed in the plotted results of material production stage. The main contribution for these differences was due to their varied energy saving potentials and different energy demands in producing additives. While for the usage stage, it is hard to catch the differences directly in the box-plots due to the close proximities in the predicted effects of WMA technologies on the pavement roughness. Nonetheless, these slight differences are still worth to be noted because their large orders of magnitude. Even the difference is 0.0001, after multiplying it by 10^9, the final amount is still large enough to easily affect the overall life-cycle energy consumption results. Such significant impact of the pavement-vehicle interaction in the usage stage has also been in line with the conclusions of the previous studies (Louhghalam et al., 2017; Noshadravan et al., 2013; Wang et al., 2012a).

The corresponding sensitivity analysis of the predicted IRI value on the final fuel consumption showed that every 0.1 m/km deviation of the predicted IRI values would lead to 7.6 ml/vehicle-km difference of fuel consumption for heavy trucks and 1.6 ml/vehicle-km difference for passenger cars. This deviation would be considerably amplified by traffic volume and percentage of heavy truck. Therefore, the accuracy of the IRI prediction would be the critical consideration in the future evaluation and improvement of the pavement life cycle performance, especially for the roads with great traffic volume and high percentage of heavy truck.

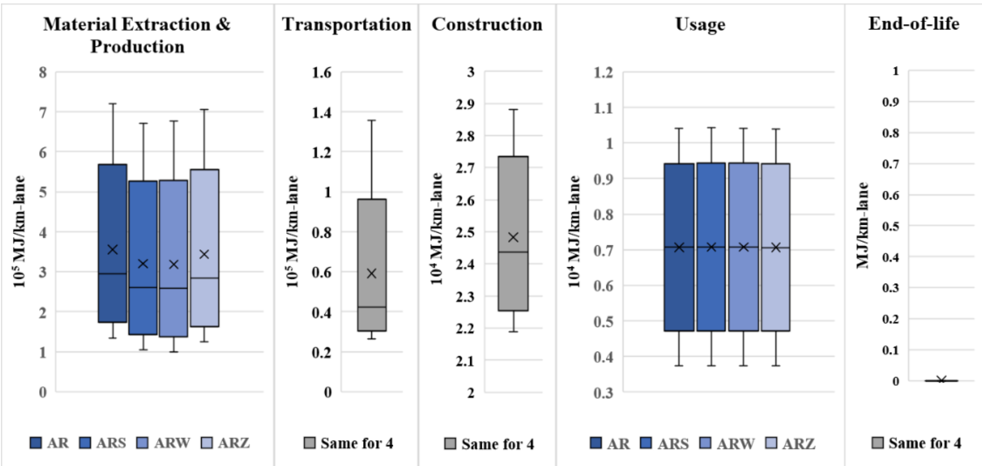


Figure 5-5 Estimated contributions of energy consumption breakdown

Although the system boundaries without usage stage was also the most frequent consideration by the previous pavement LCA studies (Hassan, 2010;

Tatari et al., 2012; Vidal et al., 2013), it can be seen from the results of this study that compared with the contribution of the usage stage, the total energy consumption in other stages can be almost negligible. Therefore, the overall life-cycle energy consumption both with and without usage stage were determined as presented in Figure 5-6. The significant differences among the four mixtures could be observed for the overall energy consumption without usage stage. When the system boundary includes the pavement-vehicle interaction, the differences of life cycle energy consumption among the compared mixtures have largely melted away, which is attributed to their close roughness performances predicted by the MEPDG software. Based on the existing input data, very limited effects of WMA technologies on the pavement roughness change were identified. Thus, the dominant energy consumption in the usage stage offset the conspicuous variability in the material production stage.

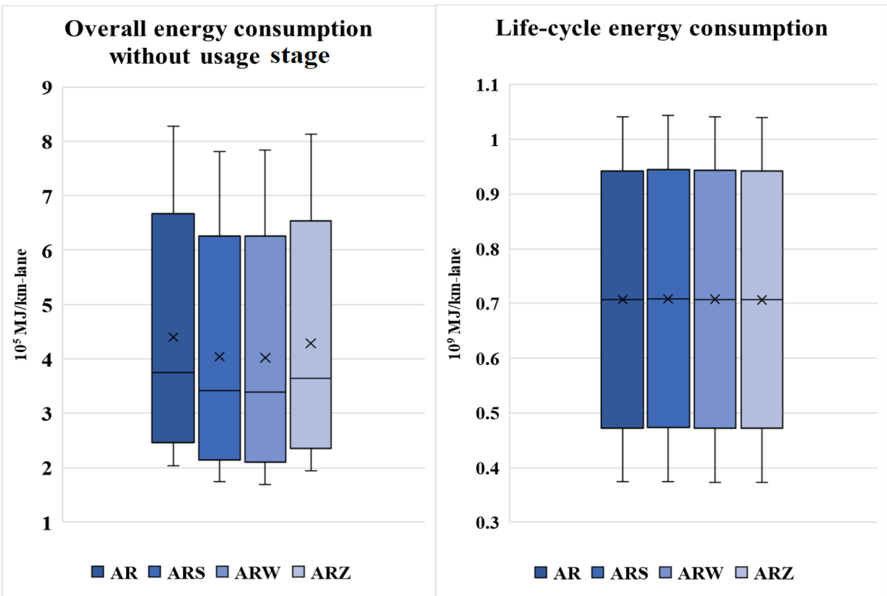


Figure 5-6 Estimated life-cycle energy consumption with and without usage stage

5.4.2 Comparative Matrix

In order to prevent the best-case representation of LCA commissioning party and worst-case representation of the compared alternatives in the comparison study, the corresponding comparative indicators were also calculated and stored to compute the overall comparative matrix for the four mixtures. Table 5-4 presents the comparative indicators (probabilities) for the overall energy consumption with and without considering usage stage.

Without considering the pavement-vehicle interaction in the usage stage, all the three warm AR mixtures provide the probabilities with lower energy consumption compared with the conventional AR mixture. Among different warm AR mixtures, ARW has the best performance for its highest estimated probability of the events with lower energy consumption. However, it is worth noting that the energy consumption in production of surfactant warm mix additive has the potential to be underestimated, because the detailed components of the corresponding commercial products are confidential and only asphalt emulsion and polymer modifiers were assumed as the substitutes. Under this circumstance, ARS mixture has higher likelihood to have lower energy consumption than ARZ mixture, which is also consistent with the conclusion drawn by Tatari et al. (2012). When the extra IRI-induced energy consumption in the usage stage is considered, the energy-saving advantages of the WMA technologies becomes negligible in the life cycle point of view, which also signifies the importance of both the effect of pavement roughness and the roughness prediction accuracy.

Table 5-4 Comparative matrix

Without usage stage					**With usage stage**				
	AR	**ARS**	**ARW**	**ARZ**		**AR**	**ARS**	**ARW**	**ARZ**
AR	-	0.44	0.43	0.48	**AR**	-	0.5008	0.4995	0.5001
ARS	0.56	-	0.49	0.54	**ARS**	0.4993	-	0.4986	0.4981
ARW	0.57	0.51	-	0.55	**ARW**	0.5005	0.5014	-	0.5001
ARZ	0.52	0.46	0.45	-	**ARZ**	0.4999	0.5019	0.4999	-

5.5 Summary

This chapter evaluated the energy-saving performances of three WMA technologies (zeolite, organic wax, and surfactant) in AR pavements through LCA incorporated with uncertainty consideration. The probability distribution of energy consumption for each life cycle stage was characterized, which followed the comparative matrix to illustrate effects of the different WMA technologies on energy saving.

Among all the life cycle stages, the use stage contributed dominant energy consumption, which almost covered up the energy-saving advantages of the three WMA technologies in the material production stage. This indicates the significance in ensuring the long-term pavement performance for any application of warm mix technologies. The results with and without considering the usage stage showed clear differences for the four considered AR mixtures, which signifies the great influence provided by the life cycle system boundary definition on the LCA results.

Among the three warm mix technologies, ARW mixture stayed in the greater probabilities in reducing the energy consumption compared with other mixtures for the life cycle whether involved usage stage or not. Whereas, the energy-saving probabilities of ARZ and ARS mixtures tended to be less than the probabilities of traditional AR mixture after the usage stage was considered. The consideration of probability in the comparative LCA study could decrease the likelihood of misunderstanding or negative effect on external interest.

In addition to the energy-saving performance, more environmental impact categories were recommended to be considered in the future study. As the ranking was also influenced by the involved impact categories. For example, it was found that ARS mixture showed an increase in the production emissions and relied highly on limited non-renewable resources, while ARZ was less sustainable in terms of renewable ecological resources consumption (Hurley et al., 2009; Tatari et al., 2012). Furthermore, the maintenance scenario in this study is "do-nothing" in the 20-year design life, compared with the routine maintenance schedule. This scenario may bring more serious pavement deterioration situation and the IRI-induced energy consumption might be overestimated to some extent. The maintenance stage was also suggested to be included in future studies.

In general, the more comprehensive results of this study could improve the reference quality for decision-making. Besides, the breakdown of the estimated energy consumption in each life cycle stage could also help to identify the issues that have potentials to enhance the pavement sustainability.

CHAPTER 6 MODELING PERFORMANCE LONGEVITY

6.1 Introduction

In the previous chapter, the life cycle results showed the huge disparity in environmental impacts between the use stage and the other stages, which verified the significance of pavement long-term performance as well as the prediction accuracy in project-level decision-making. In addition, for network-level planning, pavement performance prediction model is also an indispensable component in the analysis scheme. As reviewed in Chapter 2, compared with mechanistic-empirical approaches, empirical methods could provide more flexible options in predicting either pavement condition performance or functional performance.

As a new vision in empirical methods, data mining (DM) is a robust technique that can be utilized to obtain data-driven knowledge and retrieve patterns or models from the complex correlations between the variables by applying specific algorithms (Domingos, 2012). Among the many DM algorithms and methods, artificial neural networks (ANN) and support vector machine (SVM) are most commonly applied in solving the nonlinear regression problems (Lagat et al., 2018; Naguib & Darwish, 2012; Tinoco et al., 2011). In pavement research field, DM techniques have been successfully applied in various modeling, such as predicting the energy consumption due to tyre-pavement interaction (Araújo et al., 2019), forecasting energy consumption in hot mix asphalt (HMA) production (Androjić & Dolaček-Alduk, 2018), modeling tyre-pavement noise (Freitas et al., 2015), predicting rolling resistance in clay loam soil (Taghavifar et al., 2013), previsSing the performance of stabilized aggregate bases subjected to wet-dry cycles (Maalouf et al., 2012), and predicting HMA stiffness (Gopalakrishnan & Kim, 2011).

As an increasingly significant pavement functional performance, traffic noise emission has grown to be a pervasive problem, especially in the metropolitan cities with large-scale traffic network and high population density. The tyre-pavement noise has been proven to be one of the major noise contribution sources when the vehicle speed is greater than 48 km/h (30 mph) (Lodico & Donavan, 2018), as the vehicle propulsion noise is being controlled by the vehicle design process. Although noise barrier is an effective method to reduce traffic noise, due to the limited land space and large number of high-rise building in Hong Kong, it could be less effective for covering a considerable part of the road width. Instead, low noise road surface (LNRS), which reduces tyre-pavement noise at the source, could be an optimal solution (Sandberg, 2008). The generation of tyre-pavement noise is a complex process with various contributing factors, such as tyre radial vibrations, air pumping, stick-slip, and stick-snap (Lodico & Donavan, 2018). Many studies (Beckenbauer et al., 2008; Chen et al., 2018; Ding & Wang, 2017; Freitas et al., 2015; Klein et al., 2008; Rochat & Donavan, 2018; Sandberg & Ejsmont, 2002) have been conducted to build tyre-pavement noise prediction models based on pavement surface characteristics and pavement materials properties. Although these tyre-pavement noise models have good modeling performance, the acoustic durability as one of the primary concerns for noise abatement has been largely ignored. Several studies have attempted applying traditional statistical method to model the acoustical durability as the constant linear trends (Blokland et al., 2016; Rasmussen et al., 2007). However, the correlation coefficients from 0.01 to 1 showed high model instability owing to the insufficient data analysis techniques.

This chapter illustrated and compared the two long-term performance prediction approaches, namely ANN and SVM, in modeling the pavement acoustic longevity based on the long-term tyre-road noise data collected from 270 asphalt pavement sections in Hong Kong. Meanwhile, the global sensitiviy analysis (GSA) was conducted to explore the dual effects of pavement age and vehicle speed on the acoustic performance. Four steps were bound to reach the target. First, the research scope was identified based on the dependent and independent variables selection. Second, the long-term acoustic performance data were collected by an at-source-measurement method, namely close proximity (CPX). Third, the obtained data were applied for training the longevity model by the ANN and SVM algorithms, and three metrics were used to evaluate and compare the model performance. Finally, a two-dimensional sensitivity analysis (2D-SA) was conducted to visualize and interpret the relative importance of age and vehicle speed variables and reveal the inter-relationships among the variables in the two models.

6.2 Methodology

6.2.1 Model Variable Selection

Tyre-pavement noise is generated by the superimposed interaction mechanisms. Vehicle travel speed is one of the significant impact factors (Freitas et al., 2015; Sandberg, 2008). From the perspective of pavement, the intrinsic properties to influence the noise generation and propagation include pavement layer stiffness, surface texture and pavement layer acoustic absorption (Ding & Wang, 2017). Nevertheless, these properties are fundamentally affected by the interaction among the pavement surface thickness, binder content, aggregate size, and air void content (Roberts et al., 1996). Therefore, when the target variable is tyre-pavement noise, age of surface (age – t), vehicle's travel speed (speed – V), and surface design features (maximum aggregate size – Amax, layer thickness – Th, target air void – Av., mix binder content – Pb), were selected as the independent variables and recorded in each tyre-pavement noise measurement in this study.

Table 6-1 Summary of surface designs

Surface material	Surface image	Maximum aggregate size (mm)	Binder content (%)	Target air void content (%)	Reference	Thickness (mm)
WC		10	6.0	3.8	HKHyD (2018a)	20
		20	5.0	4.4	HKHyD (2018a)	40, 45
FC		10	4.5	20.0	HKHyD (2018b)	30
PMFC		10	5.5	20.8	HKHyD (2018a)	30, 50
		20	4.5	21.3	Sandberg (2008)	30, 50
SMA		10	6.0	4.5	HKHyD (2018a)	45, 50
		20	6.3	4.4	HKHyD (2018a)	45, 50
PMSMA		10	6.0	4.5	HKHyD (2018a)	30
		6	6.5	7.4	HKHyD (2018a)	25, 30, 50

The pavement surfaces monitored in this study covered five major flexible pavement surface types in Hong Kong, including dense-graded wearing course (WC), gap-graded stone mastic asphalt (SMA), open-graded friction course (FC), open-graded polymer modified friction course (PMFC), and gap-graded polymer modified stone mastic asphalt (PMSMA). The porous PMFC applied as the typical LNRS has covered a considerable length of high-speed expressways in Hong Kong. Table 6-1 summarizes the 16 design schemes involved in the five aforementioned pavement surfaces.

6.2.2 Acoustic Performance Measurement

Although the influence levels of traffic noise could be affected by the distance from the receptor to the noise source and the propagation path, the application of low-noise pavement reduces traffic noise levels at the source of tire-road interface. The CPX method was applied to collect the pavement acoustic performance data, which is an at-the-source method for measuring the tyre-pavement noise in isolation of other sources and allowing the acoustics performance of the pavements over time to be compared. Following the standard method specified by ISO 11819-2 (ISO, 2017), it provides an opportunity to obtain reliable large volume of data for developing statistical pavement acoustic longevity model.

The certified CPX trailer with complete measurement system (Hung et al., 2008; Mak, 2014) was employed to collect long-term data in the urban areas of Hong Kong. The system was equipped with four Type 1 microphones (IEC, 2013), a third-octave band filter software (IEC, 2014), a Class 1 sound level calibrators (IEC, 2017), a microwave speed sensor, a tyre load measurement equipment, and an inflation pressure measurement equipment. The acoustical enclosure with sound absorption material inside was towed by a 5.5-ton light goods vehicle to conduct surveys on the road segments. Inside the acoustical enclosure, the standard reference test tyre (SRTT) specified by ASTM standard and four mandatory microphones were placed as depicted as in Figure 6-1. Four microphones were fixed at 100mm (± 20mm) above the pavement level and 200mm (± 20mm) from the tyre sidewall, and two microphones were distributed on the two sides of the tyre. The “front” microphones (M1) were mounted at an angle of 45º ± 5º to the rolling direction, and the “rear” microphones (M2) were mounted at an angle of 135º ± 5º to the rolling direction.

In this study, all the CPX measurements were carried out in at-least 200-m road section for at least four runs with the same starting/stopping spots. The sound level recording, editing and analysis from National Instruments (NI) were used for tyre-pavement noise data collection and analysis. The noise is quantified as the "close-proximity sound index for passenger cars and light traffic" (CPXP) according to ISO 11819-2 (ISO, 2017). This index represents the sound pressure level (SPL) in A-frequency and FAST time weighted under the condition of passenger car tyre (Goubert et al., 2014).

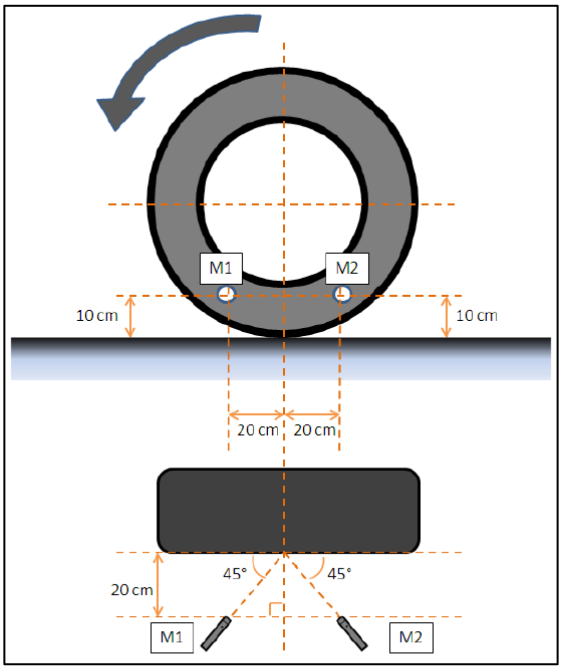


Figure 6-1 Microphones positions in CPX measurement (Mak, 2014)

6.2.3 Modelling and Evaluation

As tyre-pavement noise is generated by superimposed interaction mechanisms, allowed nonlinearities and no prior knowledge required about natural relationships among data (Stulp & Sigaud, 2015) are the primary reasons that enable the Support Vector Machine (SVM) and Artificial Neural Network (ANN) methods to be suitable for defining new models from the data collected by the CPX method. As a baseline comparison, the Multiple

Linear Regression (MLR) was performed as well. The models were generated by using Matlab R2018b (https://www.mathworks.com/) and the corresponding code scripts are listed in Appendix 3 and 4.

6.2.3.1 Artificial Neural Network

ANN is a computational technique that simulates the human nervous system structure (Kenig et al., 2001). This technique has been proved to be robust in modelling complex nonlinearity, which is particularly helpful for the problems without analytical formulation (Freitas et al., 2015). The ANN used in the present work was implemented by a fully connected multilayer perception (MLP) (Figure 6-2), with 6 nodes in input layer, 10 nodes in one hidden layer, one node in output layer, bias connections (b), and hyperbolic tangent sigmoid (tansig) activation functions.

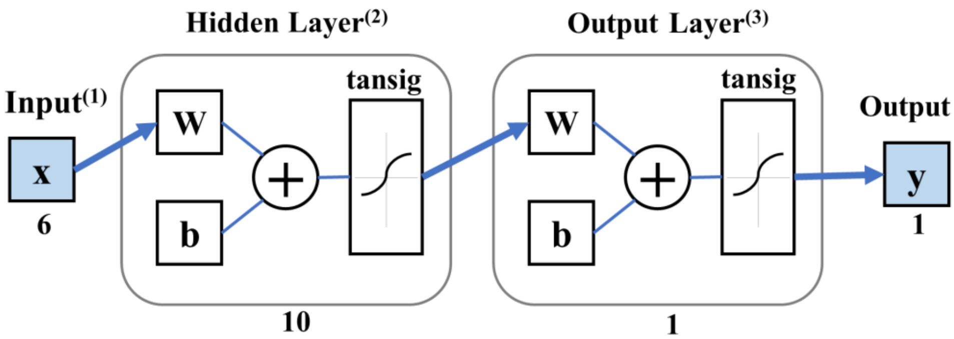


Figure 6-2 Scheme of the multilayer perceptron applied

Equation 6-1 denotes the general model of MLP applied in this study (Hastie et al., 2017).

$$\hat{y} = b_O^{(3)} + \sum_{j=1}^{H}\left(\sum_{i=1}^{I} x_{i,j} \cdot W_{i,j}^{(1,2)} + b_j^{(2)}\right) \cdot W_{j,O}^{(2,3)} \tag{6-1}$$

where $I, H,$ and O refer to the number of nodes in the input layer (1), hidden layer (2), and output layer (3), respectively (in this study: $I = 6$, $H = 10$,

$O = 1$); $W_{i,j}^{(1,2)}$ represents the weight of the connection from node i in layer 1 to the node j in layer 2; and b corresponds to the bias units.

To find the optimum solution, the backpropagation Lenvenberg-Marquardt algorithm was employed to minimize the sum-of-square error function. The weights of the network were randomly initialized. The errors computed at the output were allocated backwards through the network. Then the initial weights could be corrected based on the gradient of the error function. The training automatically stopped at the trade-off point of generalization and improving, which was identified when the computed mean square error (MSE) of the validation dataset has continuously increased in 6 runs.

6.2.3.2 Support Vector Machine

SVM is a machine learning technique that can be employed for both classification and regression problems. Its nonparametric advantage could avoid the need to specify the basic functions in priority. The universal approximation capability of SVM was realized through various kernel functions (Peng & Bai, 2018). The kernel functions transform the data into a higher dimensional feature space to make it possible to find the best hyperplane to make linear separation (Figure 6-3).

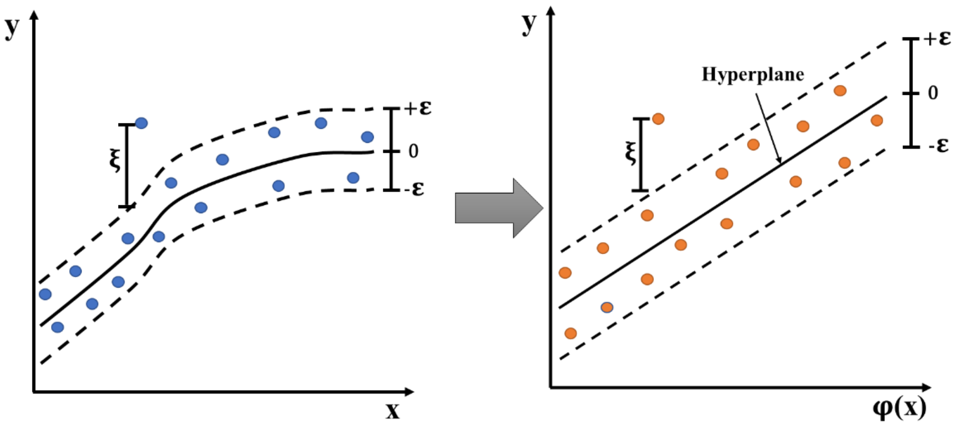


Figure 6-3 Scheme of transformation and epsilon (ε) band with slack variables (ξ)

As illustration in Figure 6-3, the input x is first mapped on to a higher dimensional feature space through a nonlinear transformation φ, then the linear model was established in the transformed feature space. Regression was implemented through minimizing the epsilon (ε) intensive loss function that ignored the errors locating within the ε band (Vapnik et al., 1997). The deviation of training samples outside ε-intensive band was also minimized by introducing the slack variables ξ. Using this method, the optimization problem can be transformed into the dual problem, and the optimal solution function in the transformed predictor space is given by the following equation:

$$f(x) = \sum_{i=1}^{I}(a_i - a_i^*)k(x_i, x) + b \quad (6\text{-}2)$$

where I is the number of Support Vectors; b is the 'bias' term, which could be dropped when the data was preprocessed to be zero mean; α_i and α_i^* are the Lagrange multipliers should satisfy the constraints $0 \leq \alpha_i, \alpha_i^* \leq \mathrm{C}$, and C is called box constraint, a positive numeric value that controls the penalty imposed on observations that lie outside the ε band and helps to prevent overfitting; and $k(x_i, x)$ is a nonlinear kernel function. In this study, the Gaussian kernel as shown below was applied:

$$k(x_i, x) = e^{(-\gamma \times \|x_i - x\|^2}, \gamma > 0 \quad (6\text{-}3)$$

The γ is the kernel scale parameter. Considering its potential impact on the SVM performance, a heuristic procedure with subsampling was employed to select γ.

The sequential minimal optimization (SMO) algorithm was applied to solve the SVM training. The meta-parameters were treated by the default input. The box constraint parameter C was set as $iqr(Y)/1.349$, where $iqr(Y)$ is the interquartile range of the target variable Y. The ε tolerance was set as $iqr(Y)/13.49$, which is an estimate of a tenth of the standard deviation using the interquartile range of Y. The 5-fold cross validation was performed in order to evaluate the effectiveness of the SVMs with the selected meta-parameters, which is training 5 SVMs with different subsets of the entire dataset.

6.2.3.3 Evaluation Metric

The main goal of this study is to train a model that minimizes the error measurement between observed and predicted values. Thus, three common metrics were calculated in order to evaluate the model performance (Tinoco et al., 2011): the coefficient of determination (R^2), the root mean square error (RMSE), and the mean absolute deviation (MAD), as shown in the equations below.

$$\mathrm{MAD} = \frac{\sum_{i=1}^{n}|y_i - \hat{y}_i|}{n} \tag{6-4}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \tag{6-5}$$

$$R^2 = 1 - \mathrm{FVU} = 1 - \frac{SSE}{SST} = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \tag{6-6}$$

where n is the number of data; y_i represents the observe value; $\hat{y}_i$ corresponds to the predicted value; $\bar{y}_i$ is the mean of the observe data; FVU is the fraction of variance unexplained; SSE is the error sum of squares; and SST is the total sum of squares.

6.2.4 Global Sensitivity Analysis

To increase the interpretability of the “black box” of the ANN and SVM models, the Global Sensitivity Analysis (GSA) algorithm was applied as it could capture the relative importance of parameters in influencing the acoustic level and the interaction between input parameters (Kewley et al., 2000). This method uses F features varying with L levels simultaneously. The number of simultaneous sensitivity variables can range from 1 (1D-SA) to M dimensionality (MD-SA) (Cortez & Embrechts, 2013). In this study, the sensitivity of pavement age and speed variables was computed in pair (M=2) to explore the interaction of them, as the other design variables could be determined at the beginning. The sensitivity was measured by the gradient (S_g). For the L-level input variable x_a, the gradient is expressed as following equation (Cortez & Embrechts, 2013).

$$S_{g,a} = \sum_{i=2}^{L} \frac{\left|\hat{y}_{a_i} - \hat{y}_{a_{i-1}}\right|}{L-1} \tag{6-7}$$

The relative importance of a variable (age, speed) was measured using the global range of the output responses. Let $\left\{\hat{y}_{(A_i,V_i)}: i \in \{1, \cdots, L\}\right\}$ denote the sensitivity responses related with L×L changes of input pair (x_A, x_V). Let S_{g,A_i} and S_{g,V_i} represent the gradient computed based on $\hat{y}_{A_i}$ and $\hat{y}_{V_i}$. The higher the gradient value, the more interrelated is the input. Therefore, the relative importance R_a of input variable x_a could be given by the following equation (Cortez & Embrechts, 2013).

$$R_a = \frac{S_{g,a}}{\sum_{m=1}^{M} S_{g,m}} \times 100\% \tag{6-8}$$

In this study, the importance values are denoted by the M×L matrix R = (R_A, R_V) (M = 2), where R_A represents the relative importance vector of the age variables, and R_V represents the relative importance vector of the speed variables.

6.3 Data Characterization

In this study, the noise dataset with 270 records from 2010 to 2017 in Hong

Kong was used as input. All the involved pavement segments associated with their CPX noise levels are highlighted in the Hong Kong road network geographic information system (GIS) map, as shown in Figure 6-4. The corresponding descriptive statistics (average, maximum, minimum, standard deviation, and skewness) of the analyzed variables are presented in Table 6-2.

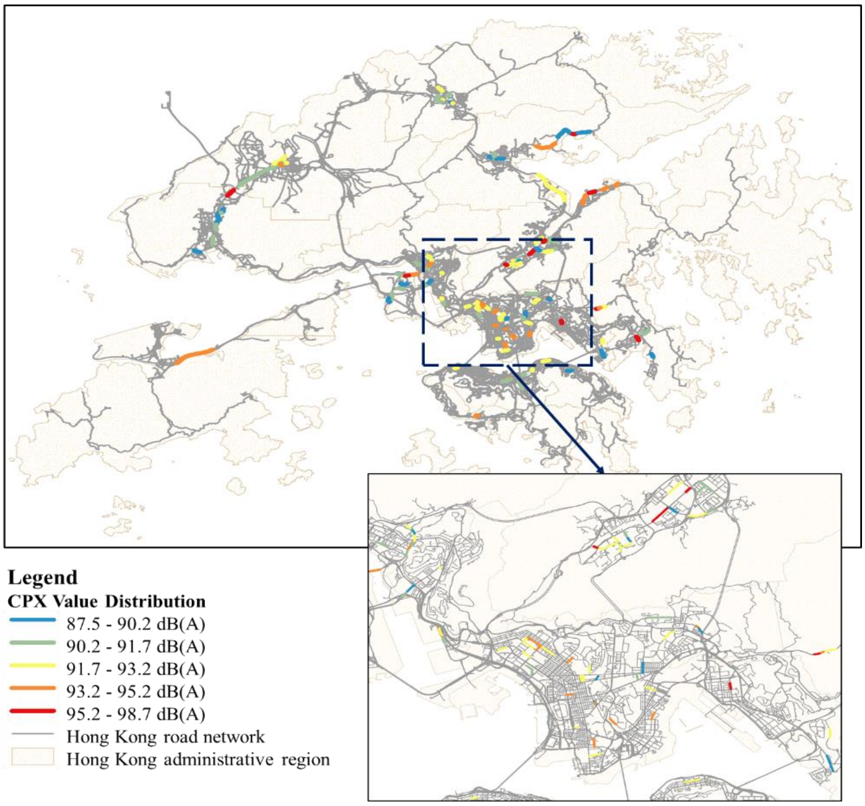


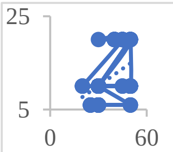
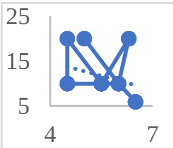
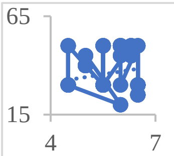
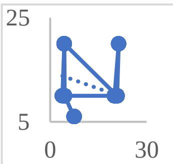
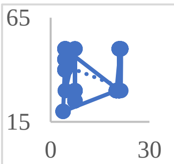
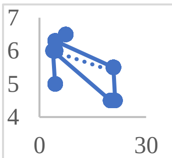
Figure 6-4 Hong Kong GIS map of CPX level distribution

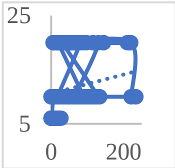
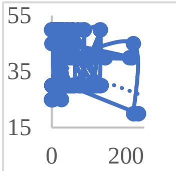
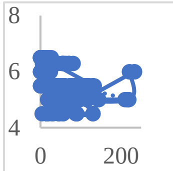
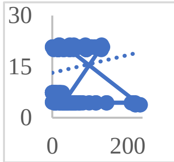
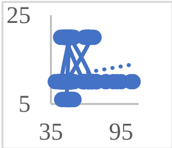
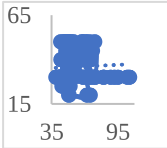
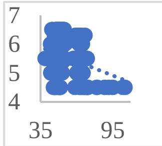
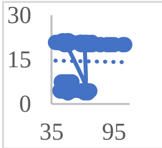
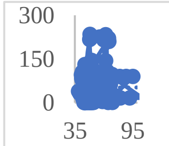
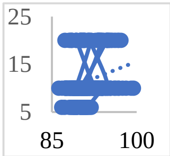
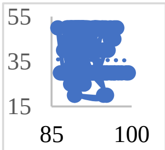
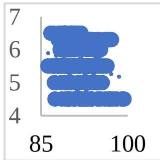
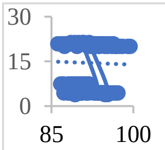
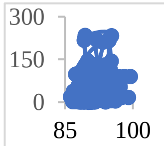
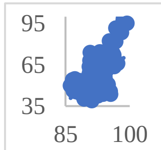
Table 6-2 Descriptive statistics of quantitative variables

Statistic	Amax (mm)	Th (mm)	Pb (%)	Av. (%)	t (month)	V (km/h)	CPXP (dB)
Av.	11.49	35.76	5.60	14.52	51.56	52.67	91.21
Max.	20.00	50.00	6.50	21.30	234.00	105.30	99.40
Min.	6.00	20.00	4.50	3.80	0.03	38.80	86.20
Std.	4.34	8.87	0.54	7.67	49.13	9.91	2.46
Skew	1.22	0.71	-0.14	-0.44	1.37	2.41	0.66

Table 6-3 summarizes the correlation matrix between all variables examined in this study. On the right side of the figure, the correlation coefficients were indicated, and on the left side the corresponding graphs were plotted. The correlation coefficient shows the degree of the two variables that are related to each other. The positive correlation value indicates the response Y increases as the variable X increases, and vice versa. A coefficient of 0 indicates no correlation. According to Table 3, a relatively strong correlation (0.5848) between V and CPXP could be observed as expected, while the remining variables show relatively weak correlations. Therefore, all variables were used in training models in the following sections. Before training through the ANN and SVM, the data variables were standardized to zero mean and one standard deviation. Then, the inverse transformation (Hastie et al., 2017) was post-processed before analyzing the predictions.

Table 6-3 Correlation matrix between all variables used in this study

	Amax (mm)	Th (mm)	Pb (%)	Av. (%)	Age (month)	V (km/h)	CPXP (dB)
Amax (mm)	1	0.4970	0.2589	0.3828	0.1993	0.1055	0.2641
Th (mm)		1	0.1716	0.5234	0.2676	0.0338	-0.0090
Pb (%)			1	0.5095	0.3245	0.3010	-0.2666
Av. (%)				1	0.1667	0.0100	-0.0226

Age (month)					1	0.0026	0.2706
V (km/h)						1	0.5848
CPXP (dB)							1

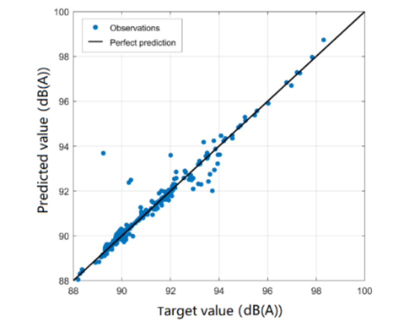
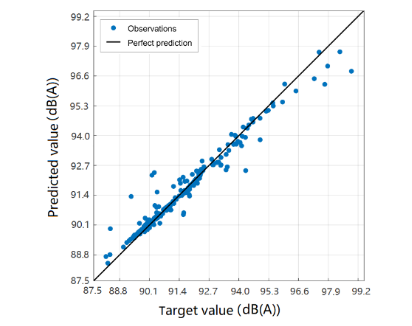
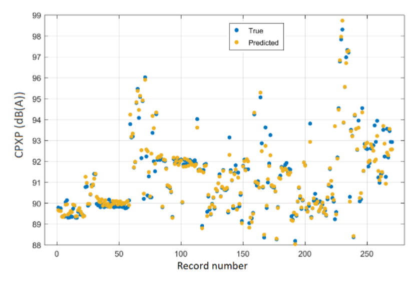
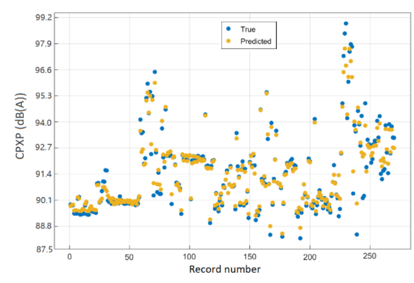
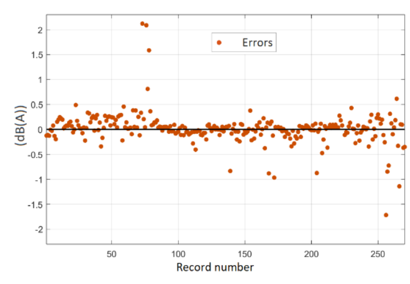
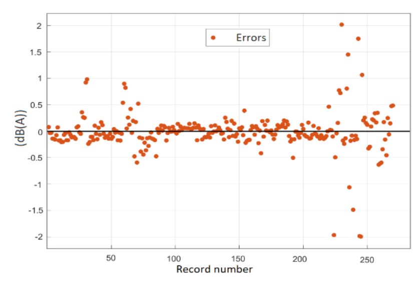
6.4 Results and Discussion

6.4.1 Model Performance Evaluation

In this study, the Hong Kong pavement acoustic degradation was modelled though ANN and SVM techniques according to the measured CPX data. As a baseline comparison, the training results of MLR method showed relatively poor performance (MAD=0.7648, RMSE=0.9780, R^2=0.7012), which was therefore excluded in the subsequent discussion. The performances of the ANN and SVM models were evaluated and compared by the model metrics in Table 6-4. High-quality regression (R^2>0.9) was achieved by both the ANN (0.9431) and SVM (0.9617) models, as the higher R^2 value means the higher fraction of the variance explained by the model function. The SVM model showed lower RMSE (0.3760), while the ANN model provided lower MAD value (0.1874). MAD measures the average magnitude of the prediction errors without considering directions. Although RMSE also measures the average magnitude of errors, its quadratic scoring rule squares the errors before they are averaged, which highlights the undesired large errors. Therefore, the prediction of the SVM model was closer to the data feed into for the lower RMSE value, while the prediction performance of the ANN model was generally satisfactory because of the lower MAD value. The relatively better results in the performance evaluation of the SVM model could be traced to its theoretical advantages over ANN (Tinoco et al., 2011), as the model always converges to the optimal solutions rather than the local minimum in the learning phase.

Table 6-4 Training performance metrics and plots of the ANN and SVM

	ANN	**SVM**
MAD	**0.1874**	0.2039
RMSE	0.4187	**0.3760**
R^2	0.9431	**0.9617**

Regression plot		
Predicted vs. True plot		
Errors plot		

6.4.2 Case Interpretation

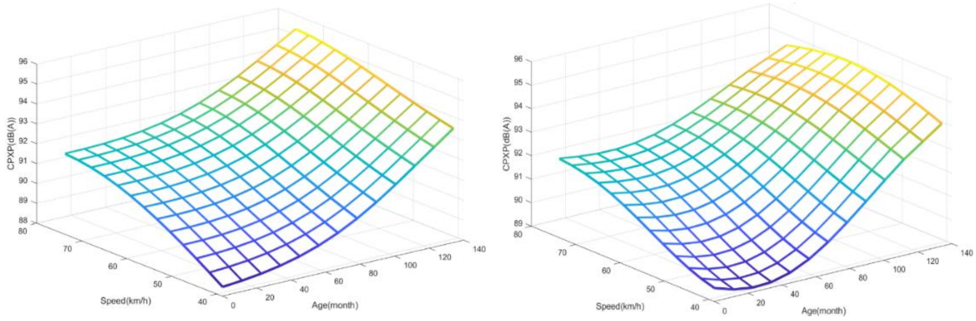
Although the error metrics could evaluate the performance of the regression models, the estimation on the superiority of a model should not be determined on performance metrics only. Besides, these measurements could not identify the deep fundamental connection or mechanisms among pavement acoustic level and input variables. Therefore, to examine the two data-driven models, the predicted acoustic trends along vehicle speed and pavement age were visualized and compared with the general mechanisms in previous literature. In this work, the case employed to interpret the two machine learning models is the PMFC pavement surface with 10 mm maximum aggregate size and 30 mm thickness (PMFC10/30) (Sandberg, 2008), as it was the major mitigation measure and widely used in reducing the tyre-pavement noise in Hong Kong (HKHyD, 2016). After the acoustic performance along the pavement age and vehicle speed has been predicted and visualized, the relative importance of vehicle speed and pavement age variables could reveal the inter-relationships.

6.4.2.1 Prediction Visualization

For PMFC10/30, both techniques could provide the nonlinear acoustic prediction trends along pavement age and vehicle speed (Figure 6-5). Although the SVM model showed better training performance metrics, the predicted trend by the ANN model was more aligned with the general aging mechanisms of porous road surface (Männel & Altreuther, 2016) compared with the more complex responses in the SVM model.

In the ANN prediction pattern (Figure 6-5-a), the changing trend could be mapped to the general aging mechanism of porous road surface which interprets each aging period (Männel & Altreuther, 2016). In Figure 4a, the noise level consolidates in the initial period (40-70 months) for all speed level. This tendency conformed to the initial metastable equilibrium between clogging and self-cleaning of the open pores in the road surface. Once reaching the “acoustic lifetime”, the noise level would increase rapidly due to the accumulated clogging of the pores and the initial aggregate loss. This increase followed the initial equilibrium period and could be found in the prediction pattern. The increase rates and durability varied depending on the vehicle speed. Finally, the increase rate would slow down, when the noise level reached a limit. The metastable equilibrium periods in the lower speed levels (< 50km/h) were shorter than that in the higher speed level (> 50km/h). The fast clogging on the low speed roads is partly due to the relative unsatisfied drainage on the low speed road in Hong Kong (Sandberg, 2008) : the water with dirt pollutant flow from the pedestrian areas of low speed road will accelerate the spread out and clogging of the PMFC carriageway rather than directly draining away.

In the SVM prediction pattern (Figure 6-5-b), although the prediction trend showed more complex behaviour with the depression rather than simply going up along variables, the metastable equilibrium periods (40-70 months) and the following pore clogging period were still generally identifiable. Since the model trained highly depended on the training data, the lower RMSE of the SVM model showed higher accuracy to translate the rules of the input data. The variance in the collected data would be consequently reflected in the prediction rule to some extent. The records in other pavement acoustic ageing investigations (Bendtsen et al., 2010; Blokland et al., 2016; Sandberg, 2008) also showed some depression in the largely growing trend.



(a). ANN prediction (b) SVM prediction

Figure 6-5 The predicted acoustic performance of PMFC10/30

6.4.2.2 Sensitivity Analysis

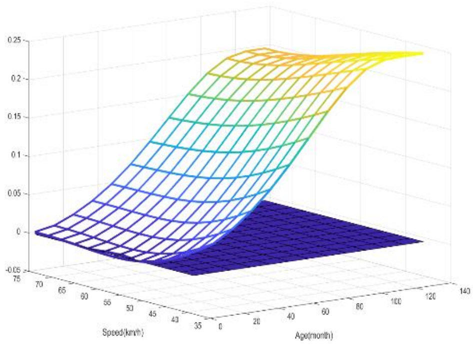
The 2D-SA on age and speed variables was performed to increase the model interpretability. The acoustic gradients along the age and speed directions of the ANN and SVM models were plotted in Figure 6-6, and the relative importance change of age and speed variables is illustrated in Figure 6-6.

For the gradient in the age dimension (Figure 6-6-a and 6-6-c), the acoustic gradient could be identified as the acoustic deterioration rate. Many studies simplified the pavement acoustic deterioration as the constant linear increase within a certain analysis period (Bendtsen et al., 2010; Blokland et al., 2016;

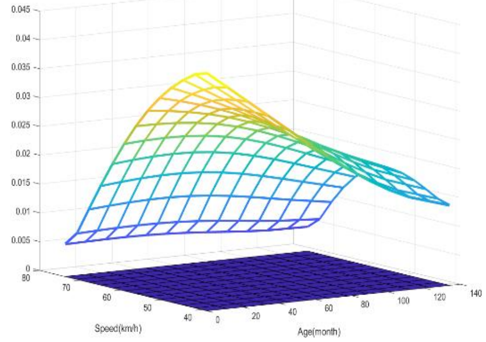
Sandberg, 2008), with a rate ranging from 0 to 1 dB(A)/year. Based on the models obtained from the ANN and SVM techniques, the predicted acoustic aging rate of PMFC10/30 surface could vary from -0.1 to 0.28 dB(A)/month depending on the different aging periods and vehicle speed levels.

The initial metastable equilibrium state of the acoustic deterioration consolidated at 0 – 0.05 dB(A)/month for the ANN model and -0.1 – 0.02 dB(A)/month for the SVM model. The later increasing clogging of pores resulted in the noticeably rise from 0.05 to 0.23 dB(A)/month for ANN model and from 0.02 to 0.25 dB(A)/month for the SVM model. Both the ANN and SVM models can identify the upper limits where the acoustic deterioration rate started to level off and even decline. Moreover, the predicted acoustic deterioration rate at high-speed level is relatively lower than that on the low-speed road, which also testified the view of Sandberg (2008) that the acoustic service life of PMFC on the high-speed roads is longer than low-speed roads.

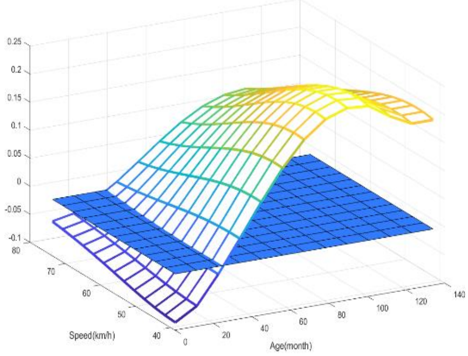
The significance of speed influence in the tyre-pavement noise has been explored by many studies (Hanson et al., 2004). From Figure 6-6-b and 6-6-d, it can be observed that the noise increasing rates obtained by the two models follow the same pattern, which is accelerating first until attaining the turning speed (55 km/h) and slowing down afterwards. This predicted turning speed in this study conformed with the national average value (50km/h) from the FHWA's Traffic Noise Model (Hanson et al., 2004).



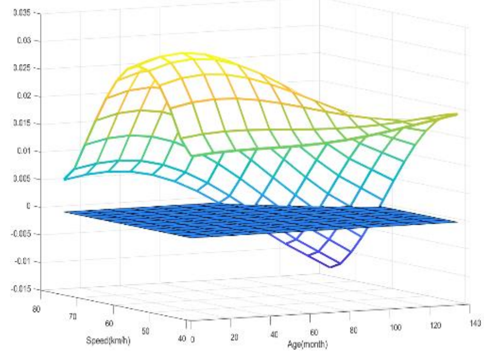
(a) ANN model: gradient along age dimension



(b) ANN model: gradient along speed dimension



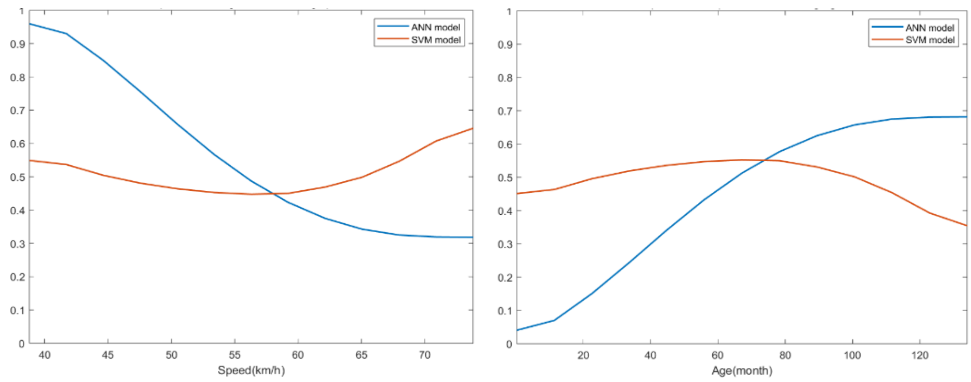
(c) SVM model: gradient along age dimension



(d) SVM model: gradient along speed dimension

Figure 6-6 Acoustic gradient along the age and speed directions of the ANN and SVM models

The relative importance in Figure 6-7 revealed the non-constant interactions between the pavement age and vehicle speed variables in controlling the output acoustic level. For the ANN model, the blue trendline showed a decreasing importance of the age variable when the vehicle speed increased, and an increasing importance of the vehicle speed when the pavement ages. It is worth mentioning that, when the vehicle speed is low enough (< 37km/h), the pavement age is the major control variable as its relative importance is 95%. Meanwhile, a more complicated interaction was provided by the SVM model by introducing the turning points. As the speed increased, the relative importance of the age variable started to ascend after it bottomed out (45%). Correspondingly, along with the increase of pavement age, the relative importance of speed variable showed an opposite trend that begined to decline after peaking at 55%. Compared with the monotonic increasing or decreasing in the ANN model, the variable relative importance in the SVM model fluctuated at generally equivalent importance with the growth in both speed and age dimensions. This higher flexibility of the SVM technique enables the lower interpretability and makes it hard to fully understand the internal behavior (Tinoco et al., 2011), although the SVM model showed excellent performance in training accuracy.



(a) Relative importance of age variable along speed direction

(b) Relative importance of speed variable along age direction

Figure 6-7 Relative importance of age and speed variables for ANN and SVM model

6.5 Summary

In this chapter, two data mining techniques, ANN and SVM, were first employed to model the asphalt pavement acoustic longevity with the data collected in Hong Kong, as the function of the surface thickness, binder content, maximum aggregate size, air void content, and age of the pavement, as well as the vehicle speed. Then, the models were implemented to the PMFC material as a case study, which allowed to verify the applicability of the empirical models in consideration of the acoustic aging mechanism of the porous road surface. The model performance metrics provided preliminary insight of the roles of ANN and SVM in the data-driven modelling. The 2D-

SA of pavement age and vehicle speed variables revealed their inter-relationships in the models.

It was found that both the SVM and ANN models could successfully model the acoustic longevity of five selected asphalt pavement surfaces in Hong Kong with acceptable model performance metrics (R^2, MAD, RMSE). The acoustic changing rates varied in a range rather than keeping a constant value, depending on pavement ageing periods and vehicle speed levels. Both empirical models could serve for the purpose of decision-making in developing pavement system management strategies.

The comparison of ANN and SVM techniques was conducted in two aspects, model performance and model interpretability. For the model performance, SVM model showed better performance in term of regression coefficient (R^2) and higher accuracy in responding to the target value of the input data variables (RMSE). For the model interpretability, although the SVM model had better training performance metrics, the predicted acoustic trend of the ANN model was more aligned with the acoustic deterioration mechanism. Sensitivity considerations of the pavement age and vehicle speed variables further revealed their different control capacities and non-constant relationships in the two models. The comparation in either pavement age and vehicle speed suggested the significance in incorporating the implementation verification and interpretability instead of looking at the model performance metrics only.

It is worth noting that the empirical models developed in this study were based on the long-term CPX tyre-road noise data collected in Hong Kong. Therefore, the findings of this study are confined to Hong Kong's climate and pavement design specification, and light vehicle condition. In future study, more CPX data from different countries in the world are advised to be used to further improve the capability of the models developed in this study and draw more generally applicable conclusions.

CHAPTER 7 MULTI-OBJECTIVE OPTIMIZATION

7.1 Introduction

Running a pavement network system poses a challenge for decision-makers in not only the selection and prioritization of individual pavement segment, but also the trade-off determination of time horizon and intervention timing. To promote sustainable development, the objectives that could target the sustainable strategies need to be initially settled. On the other side, these objectives considered in real life may conflict with each other that cannot be achieved simultaneously, such as concurrently minimizing maintenance cost and maximizing pavement system condition. To solve this, a reasonable solution set for the multi-objective optimization (MOO) problem would be searched, and each solution is non-dominated by others (Censor, 1977). A final trade-off and compromising decision could be made among the non-dominated solution set by decision-makers according to the corresponding social situation, budget restriction and policy requirement.

Besides, optimization techniques could also considerably determine the efficiency and effectiveness in arranging the intervention scheduling associated with the achieved degrees of the multiple objectives. As reviewed in Chapter 2, many planning techniques have been successfully applied to solve the conflicting MOO problems in pavement network-level management, such as weighted sum method (Torres-Machí et al., 2015; Wu & Flintsch, 2009), goal programming (Anastasopoulos et al., 2016; Ravirala & Grivas, 1995), and genetic algorithm (GA) (Chikezie et al., 2013; Elhadidy et al., 2015; Fwa et al., 2000). Among them, the genetic algorithm as an unconventional heuristic method has gained great interest due to its robust problem-solving capability for a complex optimization problem (Wu et al., 2012). As an improved extension of GA, a fast and elitist multi-objective genetic algorithm (NSGA-II) was implemented in this study with lower computational complexity, faster non-dominated sorting speed, and higher diversity of solutions (Deb, 2002).

As described in the previous chapter, the increased urbanization induced pavements to realize more functions beyond fundamentally carrying traffic loads. Low noise is one of a significant function to mitigate the urban traffic noise. Porous pavements have been identified as the typical low-noise pavement due to its air-pumping reduction and additional sound attenuation attributes (Lodico & Donavan, 2018). To meet the specification requirement of acoustic function, the construction and maintenance of porous pavement cost substantially more compared with the conventional dense asphalt pavement (Sandberg, 2008). Regarding the cost effectiveness of the function realization, the acoustic durability consequently becomes the major concern of low-noise porous pavement. As the previous pavement management systems (PMS) chiefly considered the basic mobility function and condition maintenance (Elhadidy et al., 2015; Wu et al., 2012; Yu et al., 2015), strategies for sustaining auxiliary function like low-noise function were rarely studied. It is increasingly significant as the growing demands in the transportation development especially when the pavement surface act as the only noise mitigation measure.

Therefore, the primary objective of this chapter is to establish a MOO decision-making framework for sustaining acoustic function of porous pavement network. Finding effective strategies that could balance the interactions of acoustic deterioration and improvement in a sustainable way is the essential achievement of the framework (Amador-Jimenez, 2016). Prior to this, both acoustic-specific deterioration and improvement models need to be identified in order to define the decision-making system. For the improvement, many acoustic-specific intervention options to maintain the acoustic function have been put forward, such as cleaning of porous structure, renewal, and winter salting (Morgan et al., 2007). The options were varied in the application condition, improved effectiveness, cost, and environmental impact in both long and short terms (Muirhead, 2014). For acoustic deterioration, the durability largely depends on retaining the porous structure open and keeping the surface detritus free (Morgan et al., 2007). A non-linear pattern with different growth rate periods was observed (Maennel & Altreuther, 2016), which means even the same intervention activity may still bring various improvement benefits depending on the timing and currently acoustic deterioration state of the porous surface.

This chapter presents a MOO model to develop optimal intervention strategies that could sustain the noise reduction function of the porous pavement surface network in 5-year planning period. Three objectives are expected to be satisfied in the decision-making process: (1) maximizing the average noise reduction per segment per year; (2) minimizing the maintenance costs; and (3) minimizing the greenhouse gas (GHG) emissions due to the maintenance activities. Once the acoustic-specific deterioration and intervention options have been identified based on corresponding field data and literature, the NSGA-II algorithm was employed to search the Pareto optimal solutions associated with three proposed objectives. The specific MOO model of pavement low-noise sustainability proposed in this paper could serve as the complementary module of the entire pavement management system, and the output strategies from the case study in Hong Kong could provide more informative reference for decision-makers

7.2 Methodology

To maintain the low-noise level of the network, the management system considers the acoustic deterioration and corresponding intervention improvement as one. Equation 7-1 combines the two possible patterns in an inter-dependent way, which is the core of the decision-making system that attempts to optimally balance in this study. As expression, pavement acoustic performance would experience deterioration annually if no intervention applied, otherwise improvement.

$$N_{i,(t+1)} = \left(1 - x_{i,t,j}\right)\left(N_{i,t} - D_{i,t}\right) + x_{i,t,j}\left(N_{i,t} + I_{t,j}\right) \tag{7-1}$$

where, $x_{i,t,j}$ is a binary decision variable that takes on the value of one whenever on year t segment j receives treatment i (otherwise zero); $D_{i,t}$ is the acoustic deterioration of segment i at year t; $I_{t,j}$ is the acoustic improvement of intervention j at year t; $N_{i,t}$ is noise level of segment i at year t; $N_{i,(t+1)}$ is the noise level of segment i next year either improves or deteriorates.

7.2.1 Pavement Acoustic Deterioration

The acoustic performance of porous pavement surface is influenced by the material acoustic impedance and surface texture (Maennel & Altreuther, 2016). Corresponding to the two influence factors, clogging of the open pores and aggregate loss are the two foremost acoustic deterioration reasons. The acoustic deterioration of porous surface followed a nonlinear trend being dependent upon the different degrees of clogging and aggregate loss. As illustration in Figure 7-1 (Maennel & Altreuther, 2016), the surface acoustic life was generally divided into three periods. After the slight initial increase period, the noise level consolidates in a “metastable equilibrium” period due to self-cleaning effect (Maennel & Altreuther, 2016). During this period, the open pores are self-cleaned by the rolling pressure of fast traffic in wet conditions. After 3 to 4 years' equilibrium (Nilsson et al., 2010), the voids in the porous surface gradually becomes compacted by traffic and clogged by accumulated dirt and detritus from both surface and vehicle tyres until the acoustic benefit is totally degraded (Morgan et al., 2007). Besides, increasing aggregate loss over time is another concern of porous pavement acoustic aging associated with surface texture change.

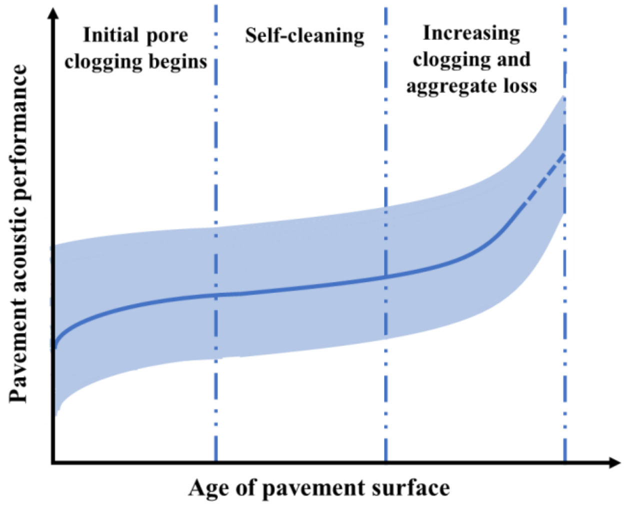


Figure 7-1 Scheme of the porous asphalt pavement acoustic deterioration

7.2.2 Pavement Acoustic Improvement

To recover the low-noise function and durability of porous pavement surface, the specific improvement interventions need to be identified. In this study, cleaning of pores and resurfacing were the two major intervention options. Cleaning of porous structure is primarily targeted for tackling the clogging problem, which is accomplished through spraying high-pressure water/air by the cleaning machine in slow moving speed. The collected mass of dirt could range from 6 to 350 g/m^2 depending on the different clogging states, cleaning techniques and moving speed (Morgan et al., 2007; Nilsson et al., 2010). When the surface aggregates loss extensively and cleaning of pores hardly improves noise-reduction function, resurfacing of the top layer (30mm) could enable the initial noise level acquisition (87 to 89 dB) immediately after replacement (Nilsson et al., 2010).

It is worth to be noted that the acoustic improvement brought by the interventions could benefit in all years of planning time horizon, not just the unique year when the intervention performed. To fully consider the improvement benefit of the interventions, the average noise reduction for per segment in each year due to the interventions compared with the do-nothing scenario were used to evaluate the sustainability of low-noise function.

7.2.3 Multi-Objective Optimization Model

Once the decision-making system has been identified and formulated, the multi-objective optimization (MOO) method was applied as the decision-making tool to find the optimal maintenance strategies.

7.2.3.1 Pareto Front

Compared with single objective, multi-objective optimization (MOO) often involves conflicting objectives, which means that a solution may be the best for one objective but not the best or even the worst for the others. Thus, the solutions that cannot improve any objective without weakening any other objective, constitute a non-dominated solution set (Censor, 1977). Figure 7-2 illustrated the Pareto optimality associated with two-objective minimization. Under this circumstance, among all the feasible solution points (dominated and non-dominated), the optimal solutions lie on the lower-left edge of the feasible region. This set of non-dominated solutions are generally called Pareto front (Elhadidy et al., 2015).

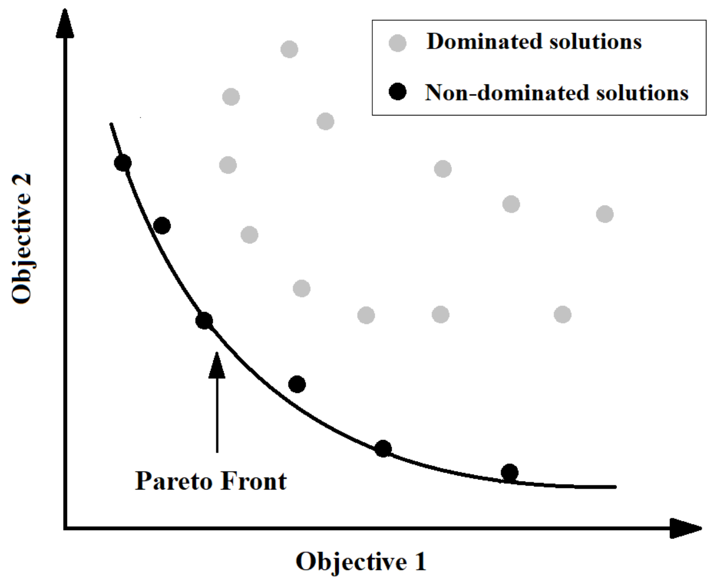


Figure 7-2 Pareto optimality

7.2.3.2 Solving Algorithm

In the absence of information from decision-makers, the heuristic-based searching algorithm with posteriori articulation of preferences was required. To solve the multi-objective problem, the non-dominated sorting genetic algorithm II (NSGA-II) was employed. It is an extension of genetic algorithms with lower computational complexity, faster non-dominated sorting speed, and higher diversity of solutions (Deb, 2002).

Figure 7-3 (Deb, 2002) illustrated the general NSGA-II procedure. The N random population of input variables P_t was initially formed. The population Q_t is the offspring of P_t that was created by basic genetic operators (selection, mutation and crossover) in size N. Population R_t (size = 2N) is composed by population P_t and population Q_t. Then, the whole population R_t was evaluated by the objective (fitness) functions through the non-dominant procedures. Then all the populations in R_t are sorted based on the descending order of nondomination. This is the elitism operation. The solutions in F_1 are the best non-dominant solutions in the entire population R_t, and the subsequent population classifications (e.g., F_2 and F_3) are in the same fashion. Based on the ranking, the best N population was chosen to form the new parent population P_{t+1} by rejecting the other half of the population, which would continually create new offspring population Q_{t+1} in size N for the next generation. This process would be continued until no more classification sets could be accommodated in the new parent population P_{t+1}. During this process, the crowed-comparison operator was employed as the selection criterion to recognize the enough number of fronts that have N population in P_{t+1}. The operator was determined as the crowding distance. The crowding distance of the specific solution in its front is the perimeter of the cuboid formed by the vertices that are the nearest neighbors. Therefore, the solution with smaller crowding distances signified its higher proximity extent with other solutions. When the two solutions belong to the same front, the solution with greater crowding distances is preferred. This operation could ensure the diversity of the solutions in their Pareto front. Finally, the NSGA-II algorithm would stop until the optimal Pareto front that had the solutions located in the less crowded area with better nondomination ranking was searched (Deb, 2002).

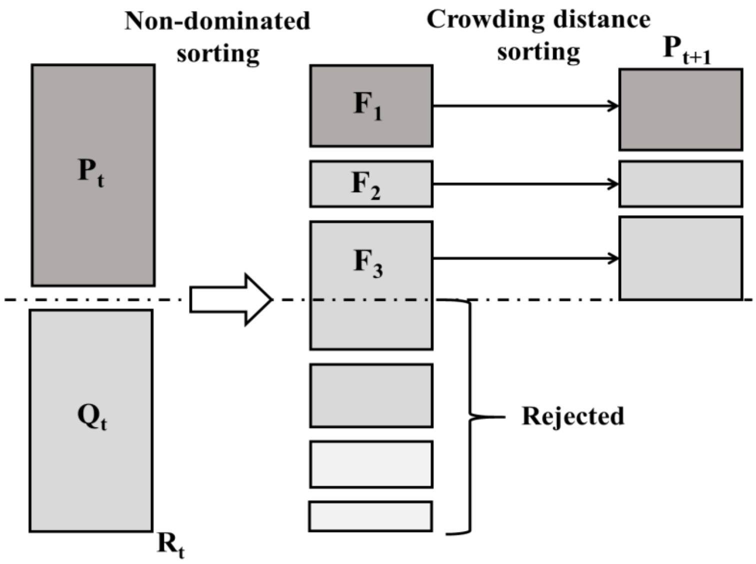


Figure 7-3 NSGA-II procedure

7.2.3.3 Solution Representation

The applied genetic algorithm required a chromosome structure to represent the solution variables, which is made of a string of decision variables. As illustration in Figure 7-4, the solution chromosome consists of a string of n×T decision variables, where n is equal to the number of pavement segments and T represents the planning time horizon (year). The values of each chromosome element varied from 1 to 3 to denote the decisions corresponding to the intervention options (1 = Do-nothing, 2 = Cleaning, 3 = Resurfacing). The decision variables contained the strategies that specified the selection of the intervention options for each segment in all planning years.

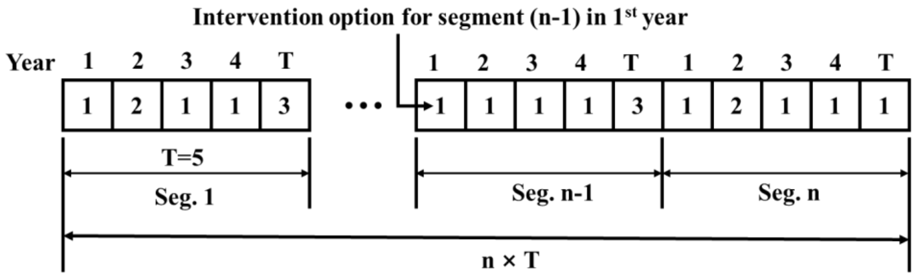


Figure 7-4 Solution representation

7.2.3.4 Objective Function Formulation

In this study, in order to balance the acoustic deterioration and cost of improvement interventions in a sustainable way, three objectives are considered: (1) maximizing the average noise reduction per segment each planning year (Eq. 7-2); (2) minimizing the total maintenance costs in all planning years (Eq. 7-3); and (3) minimizing the GHG emissions due to the maintenance activities (Eq. 7-4), which are formulated as following equations:

$$\text{Max. Average Noise Reduction} = \frac{\sum_{i=1}^{n}\sum_{t=1}^{T}(N_{i,t+1,worst} - N_{i,t+1,X})}{T\times n} \tag{7-2}$$

where, T is the planning time horizon (year); n is the number of pavement segments; $N_{i,t+1,worst}$ is the next-year noise level of segment i under the worst scenario that the intervention options for all are “Do-nothing”; $N_{i,t+1,opt}$ is the next-year noise level of segment i under the intervention option X.

$$\text{Min. Cost} = \sum_{i=1}^{n}\sum_{t=1}^{T} A_i \times C_{i,j,t} \times (1+\gamma)^t \tag{7-3}$$

where, A_i is the area of segment i; $C_{i,j,t}$ is the cost of intervention treatment j on the segment i at year t; γ is the discount rate.

$$\text{Min. GHG Emission} = \sum_{i=1}^{n}\sum_{t=1}^{T} A_i \times E_{i,j,t} \tag{7-4}$$

where, $E_{i,j,t}$ is the GHG emission of intervention treatment j on the segment i at year t.

7.3 Case Study

The polymer modified friction course10 mm maximum aggregate size and 30 mm thickness (PMFC10/30) as the typical porous road surface has been widely applied as major noise mitigation measure in Hong Kong since 2002 (Sandberg, 2008). Maintaining the low-noise function of PMFC surface in a sustainable way has become equally important as creating new porous surface. A small-scale PMFC10/30 surface network was selected as a case study to implement the proposed multi-objective optimization model. Table 7-1 listed the road inventory including the road name, length, age, number segments divided for each road, and the A-frequency and FAST time weighted noise level tested by the close proximity method (ISO, 2017). Every 500 meters was separated as a segment with corresponding surface age and noise level.

Table 7-1 Road inventory definition

Road Name	Length (m)	Age (year)	Number of Segments	Noise Level (dB(A))
Castle Peak Rd.	14,500	9 - 11	29	89.9 - 91.1
Chiu Shun Rd.	2,000	11	4	90.6
Chui Tin St.	1,000	11	2	90.5
Chuk Yuen Rd.	2,500	3	5	90.3
Long Ping Rd.	2,000	11	4	92.0
Ngan Shing St.	1,000	1	2	90.6
Pak Wo Rd.	3,000	5	6	91.7
Sha Tin Wai Rd.	500	5	1	90.9
Siu Lek Yuen Rd.	1,000	1	2	90.8
Wang Tat Rd.	2,500	1	5	91.0

As illustration in Chapter 6, the acoustic deterioration model utilized in this study was obtained through the Artificial Neural Network method. The measurement of acoustic durability of PMFC surfaces has been conducted in Hong Kong, which has shown a clear acoustic drop-off over their lifetime (Sandberg, 2008). The model was evaluated to have the acceptable performance in the coefficient of determination (R^2=0.94), root mean square error (RMSE=0.42) and mean absolute deviation (MAD=0.19). Based on the prediction results, the annually acoustic deterioration degree of PMFC10/30 under the vehicle speed of 50 km/h was illustrated in Figure 7-5. The predicted nonlinear trend was also consistent with the porous pavement acoustic aging mechanism (Maennel & Altreuther, 2016) with initial self-cleaning equilibrium period (initial 3 years) and subsequent clogging periods (after 3 years).

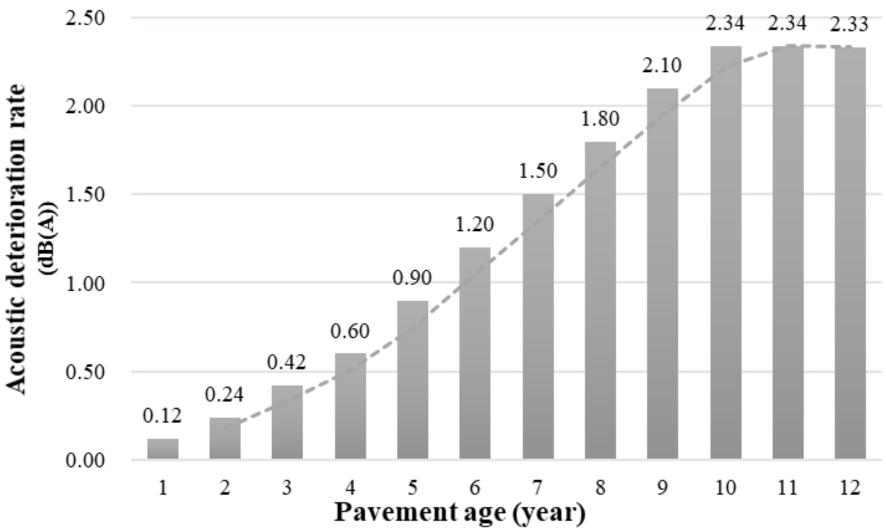


Figure 7-5 The predicted annually acoustic deterioration rate of PMFC10/30

The specific low-noise intervention options considered in this study were do-nothing, cleaning of pore, and resurfacing. Table 2 listed the details in relation to the unit cost, GHG emissions and intervention effectiveness of each option, which is integrated from different data source specified as follows. The selection of do-nothing option signified the undergoing acoustic deterioration of segment in corresponding rate. For the cleaning intervention, the relevant effectiveness could reduce the noise level by 1.3 dB(A) compared to the non-clean structure based on the test of Nilsson et al. (2010). Meanwhile, it was expected that self-cleaning effect was sufficient to keep the porous structure open. As a result, no cleaning intervention was performed during the first three years of the new PMFC surface. The GHG emissions due to the cleaning were mainly considered the cleaning machine operation emissions (Grigoratos et al., 2019) and the emissions of the collected dirt landfill (Lee et al., 2017). The unit cleaning cost (Nielsen et al., 2005) was updated to the 2017 value based on 4% discount rate. For the resurfacing intervention, the initial noise level of PMFC was reset to be 89 dB(A) associated with age (1 year) in this study. The resurfaced PMFC road would experience the self-cleaning and clogging periods as new surface. The GHG emission (Torres-

Machi et al., 2017) and updated 2017 unit cost value (Zhang et al., 2013) of resurfacing intervention were also summarized in Table 7-2 accordingly.

Table 7-2 Summary of intervention information

ID	Intervention	Cost (US$/m^2)	GHG emission (g CO_2e/m^2)	Timing	Improvement (dB(A))
1	Do-nothing	0	0	Anytime	Deterioration
2	Cleaning	13.69	86	Age>3	1.3
3	Resurfacing	42.23	6750	Anytime	Reset to 89

7.4 Results and Discussion

After operation of the proposed multi-objective optimization model, the Pareto optimal solution (non-dominated solution) set for the case study has been searched. Figure 7-6 plots the Pareto front in the three-objective space. Each point denotes an optimal solution with the specific decision variables. The color of each solution represents the average noise reduction per segment per year based on the corresponding decision variables. The value of average noise reduction is obtained by comparing the optimized strategies with the worst scenario, which means the zero average noise reduction equals to the do-nothing strategy for all 5 years. The maximized noise reduction could reach 3.14 dB(A) per segment per year through the optimized strategies. This would be equivalent to the effect that cutting traffic volume by 50%, which is extremely difficult to accomplish in other ways (Sandberg, 2008). Nevertheless, sustaining such an improvement signifies the huge cost consumption and GHG emissions. Therefore, more appropriate maintenance strategies need to be identified based on the trade-off evaluation among all the Pareto optimal solutions.

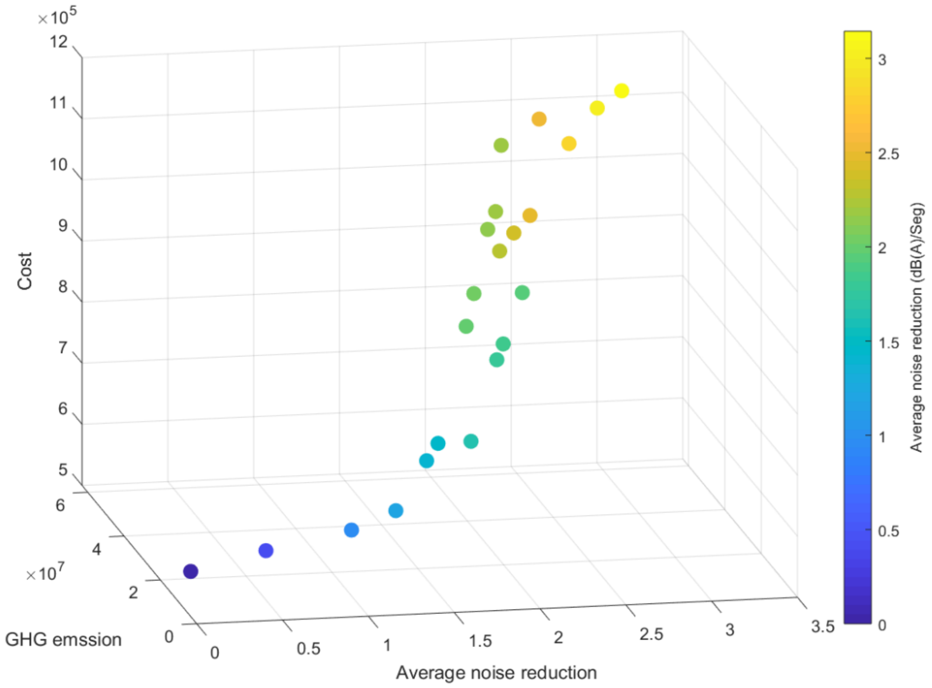


Figure 7-6 Pareto optimal solutions in objective space

The final compromised solution always depends on the decision maker with considering the relevant policy and budget. On the premise of this, ten different intervention strategies of the non-dominant Pareto front were compared. Table 7-3 illustrates the detailed strategies for the 60 segments and 5-year time horizon decision system, each intervention strategy included 300 integer decision variables ranging from 1 to 3 (1 = Do-nothing, 2 = Cleaning, 3 = Resurfacing) as described in the solution representation section.

The corresponding objective values realized by the above solutions were summarized in Table 7-4. The quantitative interaction of the three objectives could be observed based on the solutions shown in table. Solution 4 and 5 are two extreme strategies that had maximum (3.14 dB(A)) and minimum (0.94 dB(A)) average noise reduction respectively. Based on these results, there are opportunities to sustaining the noise-reduction function of the PMFC surface network in 0.94 to 3.14 dB(A) per segment per year. However, this additional 2.2 dB(A) noise reduction would enable 3-time and 60-time increase in the maintenance cost and GHG emissions. Although there is positive relationship between the objectives of cost and GHG emissions, the increase of GHG emissions is obviously more sensitive to the noise reduction objective. As the decisions need to be supported by posteriori articulation of preferences, the best-compromised strategy could be finally identified by decision maker based on the significance and constraint consideration of objectives accordingly. For instance, with permission of budget and policy, the road sections that are located in some special areas with schools or high-density residents may require lower noise influence. The noise reduction could be assigned higher user-defined weighting factors. While the road sections that are far from city or in rural areas would not have such high weighting requirement on acoustic performance.

Table 7-3 Optimal maintenance strategies

Segment	1					2					3					4					…	59					60				
Solution \ Year	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	…	1	2	3	4	5	1	2	3	4	5
1	1	1	1	1	1	2	1	1	2	1	1	1	2	1	1	1	2	1	1	1		2	1	1	1	1	1	1	1	1	2
2	1	1	1	1	1	1	2	1	1	1	1	1	2	1	1	1	1	1	1	1		2	1	1	1	1	1	1	1	1	2
3	1	1	1	1	1	1	1	2	1	1	1	1	2	1	1	1	1	1	1	1		2	1	1	1	1	1	1	1	1	1
4	**1**	**1**	**1**	**1**	**2**	**1**	**1**	**1**	**2**	**1**	**1**	**1**	**2**	**1**	**1**	**1**	**1**	**1**	**1**	**3**		**2**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**2**
5	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**2**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**2**	**1**	**1**	**1**	…	**2**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
6	1	1	2	1	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1	1		2	1	1	1	1	1	1	1	1	2
7	1	1	1	1	2	1	2	1	1	1	1	1	2	1	1	1	1	1	1	1		1	1	1	1	2	2	1	1	1	1
8	1	1	1	1	1	1	1	1	2	1	1	1	1	1	3	1	2	1	1	1		2	1	1	1	1	1	1	1	1	1
9	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	2	1	1	1		2	1	1	1	1	1	1	1	1	1
10	1	2	1	1	1	1	1	1	1	1	1	1	2	1	2	1	3	1	1	1		2	1	1	1	1	1	1	1	1	2

Table 7-4 Pareto optimal objectives

Solution	Objectives		
	Average noise reduction (dB(A)/Seg/Year)	GHG emission (g $CO_2e/m^2 \times 10^6$)	Cost (US$$\times 10^5$)
1	1.96	3.91	6.80
2	1.84	2.86	4.96
3	1.38	1.96	3.38
4	**3.14**	**61.77**	**8.70**
5	**0.94**	**1.35**	**2.32**
6	1.20	1.51	2.61
7	1.64	2.11	3.66
8	2.54	49.36	6.89
9	2.48	48.60	5.59
10	2.98	61.47	8.15

7.5 Summary

This chapter proposes a multi-objective decision support system for sustaining the low-noise function of porous pavement network specifically. Both time horizon and network scale were involved in the system. A fast and elitist multi-objective genetic algorithm (NSGA-II) is applied to search the Pareto front solution sets, which could provide the decisions about the selections of segments, interventions, and conduct timings. The proposed low-noise sustainability model is implemented in a three-objective optimization case by maximizing the average noise reduction, minimizing the costs and GHG emissions due to the interventions. Field pavement acoustic data obtained based on the CPX test according to the process standardized by the ISO. The costs, GHG emissions and improvement effectiveness of the corresponding interventions were integrated based on various data sources. The major findings could be summarized in the model capability and output strategies two aspects.

The implementation of the case study in Hong Kong showed the capability of the proposed MOO model in supporting the three-objectives decision-making system to sustain the low-noise function for porous pavement system. It could serve as the complement of the traditional PMS system that only considered the mobility condition. In the long-term perspective, the potential significance and effectiveness of maintaining pavement acoustic performance could become greater, as the development of quieter power units of vehicles (Sandberg, 2008).

The output strategies from the case study identified the optimal intervention actions on the appropriate pavement segments at right timings. The maximized average noise reduction is always accompanied with the maximum costs and GHG emissions due to interventions. The compromise is bound by the decision-maker according to the specific budget and policy priorities. Compared with converting the multi-objective into one, the searched Pareto optimal solution set provided more informative reference and selections for decision-maker.

CHAPTER 8 CONCLUSIONS AND RECOMMENDATIONS

8.1 Findings and Conclusions

This dissertation presents a methodological decision-making framework for sustainable pavement management accompanied by original case implementations. The framework is comprised of two pavement management levels, namely project level and network level. Although they differ in the system boundary and analysis approach, they share the same ultimate aims that are oriented towards the selection of optimally sustainable design or planning alternatives among competitors. Based on the findings of this thesis, the following major conclusions can be drawn.

(1) Developing and applying decision-making methods to support sustainable pavement management requires the collaboration among different disciplines.

Sustainability is a broad concept covering economic, environmental and social dimensions. Using appropriate assessment tools for precise evaluation of the impacts in each dimension is the initial step for sustainable management decision-making, which requires specialized knowledge and skills in the fields of environmental science, economics, and pavement engineering. Then, integration is the conclusive process to connect the evaluations in each dimension and realize the decision-making upon the required levels and objectives. The decision objectives in this research serve for improving sustainability of pavement infrastructure at either project or network level. However, the achievement degrees of these objectives would be vitally affected by selection and implementation of the integration methods that have different applicability and specifications.

For the project-level decision-making, CBI and EEI are the two relatively simple and efficient schemes for integrating the multiple objectives, however, result generalization is the major limitation. Collaboration with uncertainty analysis through applying statistics could exactly enhance the reliability of integration techniques and improve the decision value. For the network-level decision-making, integration process requires more sophisticated and powerful techniques to realize more complicated decision-making. In addition to the knowledge of pavement engineering, the realization of data inventory management, long-term performance modeling and multi-objective optimization requires incorporation of many advanced computer science techniques, such as geographic information system, machine learning and heuristic optimization algorithm.

(2) The proposed methodological framework in this research has capability to effectively support sustainable decision-making at different pavement management levels.

The capabilities of proposed method modules in the framework have been verified and identified through their applications on different case studies. At the project level, applications of CBI and EEI show their potentials to identify the most sustainable asphalt mixture designs and pavement M&R treatment among alternatives. In addition, incorporation of uncertainty analysis in the life cycle evaluation process can widen applicability of methodology and increase generalization of results. At the network level, validation of the developed ANN and SVM models with the real low-noise (PMFC) pavement data in Hong Kong not only verify the capability of applied techniques and developed models, but also identify the significance of considering model interpretability instead of merely looking at the model performance metrics. Then, implementation of NSGA-II algorithm in practical pavement network management showed its capability in supporting multi-objective decision-making.

(3) Taking into consideration the multi-dimension and long-term significances can improve the completeness and appropriateness of decision-making framework.

The comparison results of PMSMA10 and ARSMA10 reveals the significant effects that are engendered by the consideration of impact dimensions of sustainability in bottom-up decision-making. Besides, in developing top-down planning strategies, the considered impact dimensions can affect the complexity and effectiveness of the trade-off algorithms. In addition, the comparative evaluations of HIPR and M&F and energy-saving assessement of WMA technologies highlightes the great influence yielded by long-term consideration as a component for completeness and appropriateness of an decision-making framework.

(4) The proposed methods can provide quantitative reference and identify enhanced approaches to improve sustainability of pavement infrastructure.

In pursuit of the research aim, the proposed methods were eventually applied in sustainable pavement management decision-making by providing quantitative reference and enhanced approaches. In this research, the specific improvement suggestions vary by different management levels and are on case-by-case basis. At project level, a quantitative trade-off point of the multi-objective integration was identified, such as the 4% noise decrease of ARSMA10 and 12/15 life extension ratio of HIPR and M&F. While for network level, a optimal solution set was searched, which included several trade-off points under the required objectives. The final compromise can be made by decision-maker according to the budget and policy priorities.

8.2 Research Contributions

8.2.1 Theoretical Contributions

This dissertation established a theoretical framework for effectively evaluating sustainability and optimally supporting decision-making at both project and network levels. Based on the previously established assessment tools for either environmental or economic aspects, the framework creatively connects and integrates various methods and tools covering engineering, environmental science, statistics, computer science, and management science to meet the objectives of this research. Each presented methodology has its own contributions, which are described in corresponding chapters and summarized as follows.

In Chapter 3, the proposed cost-benefit integration initially combines the sustainability indicators of all three dimensions through the monetization that additionally included potential benefit rather than solely considering cost as in previous studies. Subsequently, in order to address the challenges and underlying bias brought by this monetary transformation, Chapter 4 presents the eco-efficiency approach to multidirectionally integrate sustainable indicators without compromising each other. Then, as described in Chapter 5, the incorporation of uncertainty analysis effectively compensates for the inherent insufficiency of the previous evaluation tools in result specificity, and decreases the likelihood of misunderstanding or negative effect on external interest. For the consolidation of higher-level decision-making, the proposed approach as discussed in Chapter 6 incorporates global sensitivity analysis into machine learning techniques, which contributes to not merely developing and comparing different pavement performance models, but also in identifying the deep connection between the training performance and model interpretability. Ultimately, by following the evolution of the multi-objective optimization algorithm, the employment of the more efficient and capable genetic algorithms presented in Chapter 7 creates more possibilities in solving the complicated nonlinear problem and provided more sensible strategies in pavement management.

In general, the theoretical contributions of this research pave a more sustainable and efficient path to improving current decision-making tools for pavement management on both project and network levels. In addition, multi-disciplinary synthesis and applications in this research increase the approach capability and versatility in addressing problems related to various issues in different areas.

8.2.2 Application Contributions

The methodological contributions provided by this research are also instantiated in specific applications, which not only prove the feasibility of the method, but also provide preliminary insights on the sustainable value of corresponding decision made. The applications in this research involved two-level decision-making associated with several emerging sustainable pavement technologies, which include bottom-up evaluations for selection of the most sustainable material designs, M&R treatments, and material additives among competing alternatives, and top-down planning for sustainable maintenance strategy optimization.

On the project level, the implementation results could provide a quantitative and qualitative reference to agencies or decision-makers for identifying the best alternatives and determining ways to facilitate improvements in pavement sustainability. On the network level, the original application on maintaining the low-noise function could serve as a complement of the traditional PMS that only considered the pavement condition. From a long-term perspective, the potential significance and effectiveness of maintaining pavement acoustic performance could become greater with the development of quieter vehicle power units. Furthermore, beyond pavement infrastructure, the proposed methods in this research also have great potential to be applied to other types of civil infrastructure.

8.2.3 Policy Implications

The policy implications of this research touch on updating pavement management criteria and improving management techniques. First, the findings of this research suggest the necessity of shifting management criteria from principally economic-based ones to more sustainable and comprehensive considerations. This shift entails the adoption of systematic sustainability evaluation and planning tools in order for agencies to make more optimal decisions. Second, as hardware and software tools continue to become more sophisticated, management approaches could also be further honed towards a more automatic and intelligent direction. Third, multi-disciplinary approaches enable the development of more effective and efficient decision-support methods.

8.3 Limitations

This study has several limitations, which fall in the arenas of parameter, model, and data limitations, described as follows.

(1) Parameter limitations

The methodologies of this research involve various parameters, including monetary conversion factors in CBI methods, weighting factors in the EEI method, the coefficients of the HDM-4 pavement-vehicle interaction model, training parameters of ANN and SVM algorithms, and searching parameters of NSGA-II algorithm. The corresponding parameter selections were based on the investigation, calibration, default values or values used by previous studies. The selection of parameter values may bring variances in results. Therefore, the outcomes were contingent upon the setting of the specific parameters in this research.

(2) Model limitations

Mechanistic-empirical and empirical models are the two major model types applied in this research. Both categories have their own limitations. The application of mechanistic-empirical models (i.e., MEPDG and HDM-4 models) was limited to the calibration of the data in other studies, which may not fit employed data well. For the self-developed empirical models (i.e., ANN and SVM models) in this study, they were constrained by the specific data used to train and obtain the models.

(3) Data limitations

Data plays a central role in the management decision-making, which vary by different regions, measuring systems, climate conditions, and traffic conditions. Therefore, the findings of this research are limited by the corresponding data availability, volume, and quality.

8.4 Recommendations for Future Work

The methodologies and models in this research are recommended to be strengthened or extended in the following directions.

(1) System boundary extension

The system boundary considered in future studies is suggested to be extended in either life-cycle stage or impact category, which could contribute to sufficiently capturing the wider impacts of alternatives for either pavement project or network throughout the entire life cycle and improving decision-making processes.

(2) Method comparison

Research could be further extended through horizontal comparison of alternative methodologies, such as through comparing EIO-LCA and process-based LCA, evaluating various pavement-vehicle interaction models, considering different data mining techniques, and examining different optimization algorithms.

(3) Model improvement

Future research could overcome model limitations in the present study in various ways. For eco-efficiency integration models, conducting local public survey in capturing the social views will help to eliminate the variances brought by region, state of the economy, and culture in the weighting scheme. For mechanistic-empirical models, calibration with local data will likely improve model fitness. For empirical models, more data from different countries are recommended to be used to further improve the models and draw more generally applicable conclusions.

(4) Application extension

On the project level, other emerging sustainable pavement technologies such as the addition of waste plastic, replacement of aggregates with waste glass, and cold mix technology, could be incorporated and evaluated. On the network level, integration of more functional performance rather than condition performance, such as permeability, skid resistance, and rolling resistance performance, into the PMS for more up-to-date and comprehensive decision-making would be valuable. Moreover, broader applications to either pavement infrastructure or other long-lived civil infrastructure would likely enhance the research potential and capability of the proposed methods.

REFERENCES

AASHTO. (1985). *Guidelines on Pavement Management*. Retrieved from American Association of State Highway and Transportation Officials, Washington D.C.

AASHTO. (1986). *Guide for Design of Pavement Structures*. Retrieved from American Association of State Highway and Transportation Officials, Washington D.C.

AASHTO. (1993). *AASHTO Guide for Design of Pavements Structures*. Retrieved from American Association of State Highway and Transportation Officials, Washington, D.C.

AASHTO. (2008). *Mechanistic-Empirical Pavement Design Guide, Interim Edition-A Manual of Practice*. Retrieved from American Association of State Highway and Transportation Officials.

Abaza, K. A. (2002). Optimum flexible pavement life-cycle analysis model. *Journal of Transportation Engineering, 128*(6), 542-549. doi:10.1061/(ASCE)0733-947X(2002)128:6(542)

Abaza, K. A. (2004). Deterministic Performance Prediction Model for Rehabilitation and Management of Flexible Pavement. *International Journal of Pavement Engineering, 5*(2), 111-121. doi:10.1080/10298430412331286977

Abaza, K. A. (2014). Back-calculation of transition probabilities for Markovian-based pavement performance prediction models. *International Journal of Pavement Engineering, 17*(3), 253-264. doi:10.1080/10298436.2014.993185

Adams, W. M. (2006). *The Future of Sustainability: Re-thinking Environment and Development in the Twenty-first Century*. Retrieved from The World Conservation Union.

Airey, G. D. (2004). Styrene butadiene styrene polymer modification of road bitumens. *Journal of Materials Science, 39*, 951– 959.

Akbarian, M., & Ulm, F.-J. (2012). *Model Based Pavement-Vehicle Interaction Simulation for Life Cycle Assessment of Pavements*. Retrieved from Cambridge, MA, USA.

Ali, H., et al. (2013). Performance of hot in-place recycled Superpave mixtures in Florida. *Construction and Building Materials, 49*, 618-626. doi:10.1016/j.conbuildmat.2013.08.043

Ali, H. A., & Tayabji, S. D. (1998). Evaluation of mechanistic-empirical performance prediction models for flexible pavements. *Transportation Research Record, 1629*(1), 169-180.

Amador-Jimenez, L. (2016). Civil Infrastructure Management. In *Civil Engineering Systems Analysis*: CRC Press.

Amin, M. S. R. (2015). *Pavement Management Systems: Integration of Transportation Modeling, Land Use, Economy and Indicators of Development.* (Doctor of Philosophy), Concordia University, Montreal, Quebec, Canada.

Anastasopoulos, P. C., et al. (2016). Safety-oriented pavement performance thresholds: Accounting for unobserved heterogeneity in a multi-objective optimization and goal programming approach. *Analytic Methods in Accident Research, 12*, 35-47. doi:10.1016/j.amar.2016.10.001

Anderson, K. W., et al. (2016). *Long-term performance of a hot in-place recycling project final report*. Retrieved from Washington (State). Dept. of Transportation.

Androjić, I., & Dolaček-Alduk, Z. (2018). Artificial neural network model for forecasting energy consumption in hot mix asphalt (HMA) production. *Construction and Building Materials, 170*, 424-432. doi:10.1016/j.conbuildmat.2018.03.086

Araújo, J. P. C., et al. (2014). The importance of the use phase on the LCA of environmentally friendly solutions for asphalt road pavements. *Transportation Research Part D: Transport and Environment, 32*, 97-110. doi:10.1016/j.trd.2014.07.006

Araújo, J. P. C., et al. (2019). Estimation of energy consumption on the tire-pavement interaction for asphalt mixtures with different surface properties using data mining techniques. *Transportation Research Part D: Transport and Environment, 67*, 421-432. doi:10.1016/j.trd.2018.12.022

Asia Sustainable and Alternative Energy Program. (2009). *Greenhouse gas emission mitigation in road construction and rehabilitation.*

Athena. (2006). *A Life Cycle Perspective on Concrete and Asphalt Roadways: Embodied Primary Energy and Global Warming Potential*.

Attoh-Okine, N. O. (1994). "Predicting roughness progression in flexible pavements using artificial neural networks. *Transportation Research Board Conference Proceedings., 1*(1).

Attoh-Okine, N. O. (1999). Analysis of learning rate and momentum term in backpropagation neural network algorithm trained to predict pavement performance. *Advances in Engineering Software, 30*, 391-302.

Babashamsi, P., et al. (2016). Evaluation of pavement life cycle cost analysis: Review and analysis. *International Journal of Pavement Research and Technology, 9*(4), 241-254. doi:10.1016/j.ijprt.2016.08.004

Bai, Q., et al. (2012). Trade-Off Analysis for Multiobjective Optimization in Transportation Asset Management by Generating Pareto Frontiers Using Extreme Points Nondominated Sorting Genetic Algorithm II. *Journal of Transportation Engineering, 138*(6), 798-808. doi:10.1061/(asce)te.1943-5436.0000369

Bartolozzi, I., et al. (2012). *The environmental impact assessment of asphalt rubber: life cycle assessment*. Paper presented at the 5th Asphalt RubberRoads of the Future International Conference, Munich, Germany.

Bartolozzi, I., et al. (2014). Life Cycle Thinking in Sustainable Supply Chains: the Case of Rubberized Asphalt Pavement. *Environmental engineering and management journal*.

Baus, R. L., & Stires, N. R. (2010). *MEPDG Implementation*. Retrieved from

University of South Carolina.

Beckenbauer, T., et al. (2008). Tyre/road noise predicition: A comparison between the SPERoN and HyRoNE models - Part 1. *The Journal of the Acoustical Society of America, 123*(5), 3388.

Bendtsen, H., et al. (2010). *Acoustic Aging of Asphalt Pavements: A Californian/Danish Comparison*.

Bengtsson, S. (2004). *The BASF Eco-Efficiency Analysis method*. Retrieved from Akzo Nobel Surface Chemistry: Product Stewardship & Sustainability.

Bennett, C. R., et al. (2006). *Data Collection Technologies for Road Management*. Retrieved from the World Bank, Washington, DC.

Berthiaume, R., & Bouchard, C. (1999). Exergy analysis of the environmental impact of paving material manufacture. *Trans. Can. Soc. Mech. Eng., 23*(1B), 187–196.

Bham, G. H., et al. (2001). *Developemtn of GIS-based Illinois highway pavement management system.* . Paper presented at the ESRI User Conference, San Diego, California.

Bianchini, A., & Bandini, P. (2010). Prediction of Pavement Performance through Neuro-Fuzzy Reasoning. *Computer-Aided Civil and Infrastructure Engineering, 25*(1), 39-54. doi:10.1111/j.1467-8667.2009.00615.x

Blokland, G. v., et al. (2016). Modeling of Aging of Low-noise Road Surfaces. In J. M. Torrenti & F. L. Torre (Eds.), *Materials and Infrastructures 1, 5A* (pp. 287-299).

Bloom, E., et al. (2017). Life Cycle Assessment of Highway Reconstruction: A Case Study. *Transportation Research Board*.

Brundtland, G. H. (1987). *Our common future: Report of the 1987 World Commission on Environment and Development*. Retrieved from United Nations, Oslo, 1-59.

Bryce, J. M., et al. (2014). A multi criteria decision analysis technique for including environmental impacts in sustainable infrastructure management business practices. *Transportation Research Part D: Transport and Environment, 32*, 435-445. doi:10.1016/j.trd.2014.08.019

Burke, E. K., & Kendall, G. (2014). *Search Methodologies: Introductory Tutorials in Optimization and Decision Support Techniques* (Second Edition ed.): Springer, Boston, MA.

Butt, A. A. (2014). *Life cycle Assessment of Asphalt Roads: Decision Support at the Project Level.* (Doctoral), KTH Royal Institute of Technology, Stockholm, Sweden. (TRITA-TSC-PHD 14-006)

Butt, A. A., et al. (1987). Pavement Performance Prediction Model Using the Markov Process *Transportation Research Record: Journal of the Transportation Research Board*(1123), 12-19.

Butt, A. A., et al. (1994). *Application of Markov Process to Pavement Management Systems at Network Level*. Paper presented at the 3rd International Conference on Managing Pavements.

C&SD. (2015). *Hong Kong Energy Statistics: 2015 Annual Report*.

Caltrans. (2003). *Asphalt Rubber Usage Guide*. Retrieved from State of California Department of Transportation.

Caltrans. (2008). Chapter 13 – In-Place Recycling. In *Flexible pavement Preservation* (2nd ed., Vol. 1).

CEG. (2014). *Key China Energy Statistics 2014*. Retrieved from China Energy Group

Censor, Y. (1977). Pareto Optimality in Multiobjective Problems. *Applied Mathematics and Optimization, 4*, 41-59.

Chatti, K., & Zaabar, I. (2012). *Estimating the Effects of Pavement Condition on Vehicle Operating Costs*. Wshington, D.C.: the National Academies Press.

Chehovits, J., & Galehouse, L. (2010). *Energy usage and greenhouse gas emissions of pavement preservation processes for asphalt concrete pavements*. Paper presented at the First International Conference on Pavement Preservation, Newport Beach, CA.

Chen, D., et al. (2018). Prediction of tire-pavement noise of porous asphalt mixture based on mixture surface texture level and distributions. *Construction and Building Materials, 173*, 801-810. doi:10.1016/j.conbuildmat.2018.04.062

Chen, H. D., et al. (2001). Novel Approach to Pavement Cracking Detection Based on Neural Network. *Transportation Research Record: Journal of the Transportation Research Board, 1764*(1).

Chikezie, C. U., et al. (2013). Multiobjective optimization for pavement maintenance and rehabilitation programming using genetic algorithms. *Archives of Applied Science Research, 5*(4), 76-83.

Chong, D. (2015). *Life Cycle Optimization of Flexible Pavement Design and Management Based on the Principles of Sustainability.* The Hong Kong Polytechnic University, The Hong Kong Polytechnic University.

Chou, J.-S., & Le, T.-S. (2011). Reliability-based performance simulation for optimized pavement maintenance. *Reliability Engineering & System Safety, 96*(10), 1402-1410. doi:10.1016/j.ress.2011.05.005

Chowdhury, M. A., et al. (2000). Multiobjective Methodology for Highway Safety Resource Allocation. *Journal of Infrastructure Systems, 6*(4), 138-144.

CLCD. (2010). Chinese Life Cycle Database, Sichuan University & IKE.

Cortez, P., & Embrechts, M. J. (2013). Using sensitivity analysis and visualization techniques to open black box data mining models. *Information Sciences, 225*, 1-17. doi:10.1016/j.ins.2012.10.039

D'Angelo, J., et al. (2008). *Warm-Mix Asphalt: European Practice* Retrieved from Federal Highway Administration.

Davis, C. F., & Campbell, G. M. (1995). Selection of Pavement Markings Using Multicriteria Decision Making. *Transportation Research Record: Journal of the Transportation Research Board, 1509*.

Deb, K. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Transaction on Evolutionary Computation, 6*(2), 182-197.

Deb, K. (2014). Multi-objective optimization In *Search methodologies* (pp. 403-449): Springer, Boston, MA.

Deshpande, V. P., et al. (2010). Reliability-Based Optimization Models for Scheduling Pavement Rehabilitation. *Computer-Aided Civil and Infrastructure Engineering, 25*(4), 227-237. doi:10.1111/j.1467-8667.2009.00636.

Ding, Y., & Wang, H. (2017). FEM-BEM analysis of tyre-pavement noise on porous asphalt surfaces with different textures. *International Journal of Pavement Engineering*, 1-8. doi:10.1080/10298436.2017.1388507

Dissanayake, S., et al. (1999). Use of Multicriteria Decision Making to Identify the Critical Highway Safety Needs of Special Population Groups. *Transportation Research Record: Journal of the Transportation Research Board, 1693*.

Domingos, P. (2012). A few useful things to know about machine learning. *Communications of the ACM, 55*(10). doi:10.1145/2347736.2347755

Dong, Q., & Huang, B. (2012). Evaluation of Effectiveness and Cost-Effectiveness of Asphalt Pavement Rehabilitations Utilizing LTPP Data. *Journal of Transportation Engineering, 138*(6), 681-689. doi:10.1061/(asce)te.1943-5436.0000378

EC. (2010). *ILCD Handbook: General Guide for Life Cycle Assessment - Detailed Guidance*. Retrieved from European Commission, Joint Research Centre, Institute for Environment and Sustainability, Luxembourg.

Ecoinvent Database. (2007). Swiss Centre for Life Cycle Inventories, Zürich and Dübendorf, Switzerland. In.

El-Rayes, K., & Kandil, A. (2005). Time-Cost-Quality Trade-Off Analysis for Highway Construction. *Journal of Construction Engineering and Management, 131*(4), 477-486.

Elhadidy, A. A., et al. (2015). Optimum analysis of pavement maintenance using multi-objective genetic algorithms. *HBRC Journal, 11*(1), 107-113. doi:10.1016/j.hbrcj.2014.02.008

Eurobitume. (2011). *Life Cycle Inventory: Bitumen*. Retrieved from European Bitumen Association, Brussels, Belgium.

European Commission. (2014). *Guide to Cost-benefit Analysis of Investment Projects: Economic appraisal tool for Cohesion Policy 2014-2020.* . Retrieved from European Commission, Brussels, Belgium.

Farina, A., et al. (2014). *Life Cycle Assessment of Road Pavements Contanining Crumb Rubber from End-of-Life Tires*. Paper presented at the International Symposium on Pavement LCA 2014, Davis, California, USA, 14-16 October, 2014.

Farina, A., et al. (2017). Life cycle assessment applied to bituminous mixtures containing recycled materials: Crumb rubber and reclaimed asphalt pavement. *Resources, Conservation and Recycling, 117*, 204-212. doi:10.1016/j.resconrec.2016.10.015

Fawer, M., et al. (1998). Life Cycle Inventory for the Production of Zeolite A for Detergents. *The International Journal of Life Cycle Assessment, 3*(2), 71-74.

Ferreira, A., & Santos, J. (2012). LCCA System for Pavement Management:

Sensitivity Analysis to the Discount Rate. *Procedia - Social and Behavioral Sciences, 53*, 1172-1181. doi:10.1016/j.sbspro.2012.09.966

FHWA. (2011). RealCost (version 2.5): Life-cycle cost analysis software product [software] http://www.fhwa.dot.gov/infrastructure/asstmgmt/lccasoft.cfm.

FHWA. (2014). *Tech Breif: Life Cycle Assessment of Pavements*. Retrieved from Federal Highway Administration.

FHWA. (2015). *Chapter 9. Hot In-Place Recycling (Construction Methods and Equipment)*. Retrieved from Federal Highway Administration.

Freitas, E., et al. (2015). Modelling Tyre-Road Noise with Data Mining Techniques. *Archives of Acoustics, 40*(4), 547-560. doi:10.1515/aoa-2015-0054

Fwa, T. F., et al. (2000). Multiobjective Optimization for Pavement Maintenance Programming. *Journal of Transportation Engineering, 126*(5), 367-374.

Fwa, T. F., & Sinha, K. C. (1991). Pavement Performance and Life-Cycle Cost Analysis. *Journal of Transportation Engineering, 117*(1), 33-46.

Gao, L., et al. (2012). Network-Level Road Pavement Maintenance and Rehabilitation Scheduling for Optimal Performance Improvement and Budget Utilization. *Computer-Aided Civil and Infrastructure Engineering, 27*(4), 278-287. doi:10.1111/j.1467-8667.2011.00733.

Giustozzi, F., et al. (2012). Recycled airport pavements for achieving environmental sustainability: An Italian case study. *Resources, Conservation and Recycling, 68*, 67-75. doi:10.1016/j.resconrec.2012.08.013

Golabi, K., & Pereira, P. (2003). Innovative pavement management and planning system for road network of Portugal. *Journal of Infrastructure Systems, 9*(2), 75-80.

Gopalakrishnan, K., & Kim, S. (2011). Support Vector Machines Approach to HMA Stiffness Prediction. *Journal of Engineering Mechanics, 137*(2), 138-146. doi:10.1061/共 ASCE 兲 EM.1943-7889.0000214

Gosse, C. A., et al. (2013). Environmentally Preferable Pavement Management Systems. *Journal of Infrastructure Systems, 19*(3), 315-325. doi:10.1061/(asce)is.1943-555x.0000118

Goubert, L., et al. (2014). *Assessing the acoustic properties of audio-tactile road markings*. Paper presented at the INTER-NOISE and NOISE-CON Congress and Conference Proceedings.

Gransberg, D. D., & Molenaar, K. R. (2004). Life-Cycle Cost Award Algorithms for Design/Build Highway Pavement Projects. *Journal of Infrastructure Systems, 10*(4), 167-175. doi:10.1061/(asce)1076-0342(2004)10:4(167)

Gransberg, D. D., et al. (2014). Sustainable pavement preservation and maintenance practices. In K. Gopalakrishnan, W. & J. Harvey (Eds.), *Climate Change, Energy, Sustainability and Pavements* (pp. 393-418). Berlin Heidelberg: Springer-Verlag.

Grigoratos, T., et al. (2019). Real world emissions performance of heavy-duty Euro VI diesel vehicles. *Atmospheric Environment, 201*, 348-359. doi:10.1016/j.atmosenv.2018.12.042

Guangzhou Municipal Industries Ltd. (2011). *Rubber asphalt industrialization*

feasibility report in Guang-dong Province.
Haas, R., & Hudson, W. R. (1978). *Pavement management systems.* . McGraw-Hill, New York, N.Y..
Haas, R., et al. (1994). *Modern pavement management*. Malabar, FL: Krieger Publishing Company.
Häkkinen, T., & Mäkelä, K. (1996). *Environmental adaptation of concrete; environmental impact of concrete and asphalt pavements*. Retrieved from Espoo, Finland.
Hall, K. D., et al. (2011). Calibration of the Mechanistic–Empirical Pavement Design Guidefor Flexible Pavement Design in Arkansas. *Transportation Research Record, 2226*(1), 135-141.
Hanson, D. I., et al. (2004). *Tire-pavement noise study*. Retrieved from National Center for Asphalt Technology.
Harvey, J., et al. (2014). Application of LCA Results to Network-Level Highway Pavement Management. In *Climate Change, Energy, Sustainability and Pavements* (pp. 41-73).
Harvey, J. T., et al. (2016). *Pavement Life-Cycle Assessment Framework* Retrieved from Federal Highway Administration.
Hassan, M. (2010). Evaluation of the Environmental and Economic Impacts of Warm-Mix Asphalt Using Life-Cycle Assessment. *International Journal of Construction Education and Research, 6*(3), 238-250. doi:10.1080/15578771.2010.507619.
Hastie, T., et al. (2017). *The elements of statistical learning: data mining, inference, and prediction* (Second Editon ed.): Springer.
Heijungs, R., & Huijbregts, M. A. J. (2004). *A Review of Approaches to Treat Uncertainty in LCA.* Paper presented at the 9th International Congress on Environmental Modelling and Software.
Herabat, P., & Tangphaisankun, A. (2005). Multi-Objective Optimization Model using Constraint-Based Genetic Algorithms for Thailand Pavement Management. *Journal of the Eastern Asia Society for Transportation Studies, 6*, 1137 - 1152.
Hicks, R. G. (2002). *Asphalt Rubber Design and Construction Guidelines*. Retrieved from Corvallis, Oregon.
Hicks, R. G., et al. (2010). Assessment of Use of Warm Mix Technologies for Use with Asphalt Rubber Applications - Technical Memo.
HKHyD. (2016). *Guidance notes on low noise road surface*. Retrieved from Hong Kong Highways Department, Hong Kong.
HKHyD. (2018a). Index of Provisionally Approved Mix Designs: Hong Kong Asphalt (Green) Limited.
HKHyD. (2018b). Index of Provisionally Approved Mix Designs: K. Wah Asphalt Limited.
Holtz, K., & Eighmy, T. (2000). Scanning European Advances in The Use of Recycled Materials in Highway Construction. *Public Roads, 64*(1), 34-40.
Horton, S. (1990). *Project level pavement management system development*.

Retrieved from Federal Highway Administration
Horvath, A., & Hendrickson, C. (1998). Comparison ofenvironmental implications ofasphalt and steel-reinforced concrete pavements. *Transportation Research Record Journal of the Transportation Research Board, 1626*(1), 105-113.
Huang, Y., et al. (2009). Development of a life cycle assessment tool for construction and maintenance of asphalt pavements. *Journal of Cleaner Production, 17*(2), 283-296. doi:10.1016/j.jclepro.2008.06.005
Huang, Y., et al. (2012). Sensitivity analysis of methodological choices in road pavement LCA. *The International Journal of Life Cycle Assessment, 18*(1), 93-101. doi:10.1007/s11367-012-0450-7
Hudson, W. R., et al. (1979). *Pavement Management System Development*. Retrieved from National Cooperative Highway Research Program, Washington, DC.:
Huijbregts, M. A. J. (1998a). Part I: A General Framework for the Analysis of Uncertainty. *The International Journal of Life Cycle Assessment, 3*(5), 273 - 280
Huijbregts, M. A. J. (1998b). Part II: Dealing with parameter uncertainty and uncertainty due to choices in life cycle assessment. *The International Journal of Life Cycle Assessment, 3*(6), 343-351.
Hung, W. T., et al. (2008). *Certification of a CPX Trailer for measuring tyre/road noise in Hong Kong*. Paper presented at the Proceedings of Inter-noise 2008: 37th International Congress and Exposition on Noise Control Engineering, 26-29 October, Shanghai, China.
Hurley, G. C., et al. (2009). *Ohio field trial of warm mix asphalt technologies - Construction Summary*.
IEC. (2013). International Electrotechnical Commission 61672-1:2013 Electroacoustics - Sound level meters - Part 1: Specifications. In.
IEC. (2014). International Electrotechnical Commission 61260: 2014 Electroacoustics - Octave-band and fractional-octave-band filters. In.
IEC. (2017). International Electrotechnical Commission 60942:2017 Electroacoustics - Sound calibrators. In.
IRF. (2010). *World Road Statistics 2010*. Retrieved from Geneva, Switzerland: International Road Federation.
IRF. (2019a). *Transportation Infrastructure Investment and Maintenance Spending*. Retrieved from OECD in 05 Jul 2019.
IRF. (2019b). *World Road Statistics 2019*. Retrieved from Geneva, Switzerland: International Road Federation.
ISO. (2006a). ISO 14040: environmental management - life cycle assessment - principles and framework. In. Geneva.
ISO. (2006b). ISO 14044: environmental management - life cycle assessment - Requirements and guidelines. In. Geneva.
ISO. (2017). International Organization for Standardization 11819-2: Acoustics - Measurement of the influence of road surfaces on traffic noise - Part 2: The close-proximity method. In. Geneva.
IUCN. (2004). *The IUCN Programme 2005-2008: Many Voices, One Earth*.

Retrieved from IUCN – The World Conservation Union.
Jiao, X., & Bienvenu, M. (2015). Field Measurement and Calibration of HDM-4 Fuel Consumption Model on Interstate Highway in Florida. *International Journal of Transportation Science and Technology, 4*(1), 29-46. doi:10.1260/2046-0430.4.1.29
Johnson, A. (2000). *Best Practice Handbook on Asphalt Pavement Maintenance*. Retrieved from University of Minnesota.
Johnson, C. (1993). *Pavement (Maintenance) Management Systems*. Retrieved from American Public Works Association (APWA).
Jorge, D., & Ferreira, A. (2012). Road network pavement maintenance optimisation using the HDM-4 pavement performance prediction models. *International Journal of Pavement Engineering, 13*(1), 39-51. doi:10.1080/10298436.2011.563851
Jung, F. W., et al. (1975). *A performance prediction subsystem—flexible pavements*. Retrieved from Ontario Ministry of Transportation and Communications, Downsview, Ont., Research Report 200.
Jung, J.-S., et al. (2002). *Life Cycle Cost Analysis: Conventional Versus Asphalt-Rubber Pavements*. Retrieved from Rubber Pavements Association.
Kalembo, C., et al. (2012). *Evaluation of the impact of pavement roughness on vehicle gas emissions in Baltimore County*. Paper presented at the Transportation Research Board Annual Meeting.
Kang, S., et al. (2014). Life-cycle greenhouse gases and energy consumption for the material and construction phases of pavement with traffic delay. *Transportation Research Record: Journal of Transportation Research Record*(2428), 24-27.
Kenig, S., et al. (2001). Control of properties in injection molding by neural networks. *Engineering Applications of Artificial Intelligence, 14*(6), 819-823.
Kewley, R. H., et al. (2000). Data strip mining for the virtual design of pharmaceuticals with neural networks. *IEEE Transactions on Neural Networks, 11*(3), 668 - 679. doi:10.1109/72.846738
Kicherer, A., et al. (2007). Eco-efficiency. *The International Journal of Life Cycle Assessment, 12*(7).
Kim, S. H., & Kim, N. (2006). Development of performance prediction models in flexible pavement using regression analysis method. *KSCE Journal of Civil Engineering, 10*(2), 91-96.
Klein, P., et al. (2008). Tyre/road noise prediction: A comparison between the SPERoN and HyRoNE models - Part 2. *The Journal of the Acoustical Society of America, 123*(5), 3389-3389. doi:10.1121/1.2934049
Konak, A., et al. (2006). Multi-objective optimization using genetic algorithms: A tutorial. *Reliability Engineering & System Safety, 91*(9), 992-1007. doi:10.1016/j.ress.2005.11.018
Kristjánsdóttir, Ó., et al. (2007). Assessing Potential for Warm-Mix Asphalt Technology Adoption. *Transportation Research Record: Journal of the Transportation Research Board, 2040*, 91-99. doi:10.3141/2040-10

Labi, S., & Sinha, K. C. (2003). Measures of short-term effectiveness of highway pavement maintenance. *Journal of Transportation Engineering, 129*(6), 673-683.

Labi, S., & Sinha, K. C. (2005). Life-Cycle Evaluation of Flexible Pavement Preventive Maintenance. *Journal of Transportation Engineering, 131*(10), 744-751. doi:10.1061/ASCE0733-947X2005131:10744

Lagat, A. K., et al. (2018). Support Vector Regression and Artificial Neural Network Approaches: Case of Economic Growth in East Africa Community. *American Journal of Theoretical and Applied Statistics, 7*(2), 67-79. doi:10.11648/j.ajtas.20180702.13

Lamptey, G., et al. (2005). *Life cycle cost analysis for INDOT pavement design procedures.* Retrieved from Joint Transportation Research Program, Indiana Department of Transportation and Purdue University, West Lafayette, Indiana.

Lee, J., et al. (2015). Effects of Pavement Surface Conditions on Traffic Crash Severity. *Journal of Transportation Engineering, 141*(10). doi:10.1061/(asce)te.1943-5436.0000785

Lee, S.-J., et al. (2008). The effect of crumb rubber modifier (CRM) on the performance properties of rubberized binders in HMA pavements. *Construction and Building Materials, 22*(7), 1368-1376. doi:10.1016/j.conbuildmat.2007.04.010

Lee, U., et al. (2017). Evaluation of landfill gas emissions from municipal solid waste landfills for the life-cycle analysis of waste-to-energy pathways. *Journal of Cleaner Production, 166*, 335-342. doi:10.1016/j.jclepro.2017.08.016

LEGCO. (2012). *Trial use of Thermal Patcher for Small Scale Resurfacing of Bituminous Pavement*. Retrieved from Legislative Council Panel on Transport: CB(1)1157/11-12(04)

Leng, Z., et al. (2017a). Life-cycle economic and environmental assessment of warm stone mastic asphalt. *Transportmetrica A: Transport Science*, 1-14. doi:10.1080/23249935.2017.1390707

Leng, Z., et al. (2017b). Optimizing the mixing procedure of warm asphalt rubber with wax-based additives through mechanism investigation and performance characterization. *Construction and Building Materials, 144*, 291-299. doi:10.1016/j.conbuildmat.2017.03.208

Li, J., et al. (2009a). Calibration of flexible pavement in mechanistic–empirical pavement design guide for Washington state. *Transportation Research Record, 2095*(1), 73-83.

Li, N., et al. (1997). Development of a new asphalt pavement performance prediction mode. *Canadian Journal of Civil Engineering, 24*(4), 547-559.

Li, N., et al. (2009). *Automation Recognition of Pavement Surface Distress Based on Support Vector Machine*. Paper presented at the 2009 Second International Conference on Intelligent Networks and Intelligent Systems.

Li, Z., & Sinha, K. C. (2004). *A Methodology for Multicriteria Decision-Making in*

Highway Asset Management. Paper presented at the 83rd Transportation Research Board of the National Academies, , Washington, D.C.

Lin, J., & Liu, Y. (2010). *Potholes Detection Based on SVM in the Pavement Distress Image*. Paper presented at the 2010 Ninth International Symposium on Distributed Computing and Applications to Business, Engineering and Science.

Lo Presti, D. (2013). Recycled Tyre Rubber Modified Bitumens for road asphalt mixtures: A literature review. *Construction and Building Materials, 49*, 863-881.

Lodico, D., & Donavan, P. (2018). *Quieter Pavement: Acoustic Measurement and Performance*. Retrieved from California Department of Transportation.

Loijos, A., et al. (2013). Life cycle climate impacts of the US concrete pavement network. *Resources, Conservation and Recycling, 72*, 76-83. doi:10.1016/j.resconrec.2012.12.014

Louhghalam, A., et al. (2017). Carbon management of infrastructure performance: Integrated big data analytics and pavement-vehicle-interactions. *Journal of Cleaner Production, 142*, 956-964. doi:10.1016/j.jclepro.2016.06.198

Luo, Z. (2013). Pavement performance modelling with an auto-regression approach. *International Journal of Pavement Engineering, 14*(1), 85-94. doi:10.1080/10298436.2011.617442

Lytton, R. L. (1987). *Concepts of Pavement Performance Prediction And Modeling*. Paper presented at the 2nd North American Conference on Managing Pavements. Vol. 2.

Maalouf, M., et al. (2012). Support vector regression to predict the performance of stabilized aggregate bases subject to wet-dry cycles. *International Journal for Numerical and Analytical Methods in Geomechanics, 36*(6), 675-696. doi:10.1002/nag.1023

Maennel, M., & Altreuther, B. (2016). *Ageing of low noise road surfaces*. Paper presented at the 45th International Congress and Exposition on Noise Control Engineering INTER-NOISE 2016, Hamburg, Germany.

Maibach, M., et al. (2008). *Handbook on estimation of external costs in the transport sector: Internalisation Measures and Policies for All External Cost of Transport (IMPACT).* . Retrieved from CE Delft.

Mak, K. L. (2014). *Statistical modelling of tyre-road noise for urban driving conditions.* (Doctor of Philosophy), the Hong Kong Polytechnic University, the Hong Kong Polytechnic University.

Mamlouk, M. S., & Dosa, M. (2014). Verification of effectiveness of chip seal as a pavement preventive maintenance treatment using LTPP data. *International Journal of Pavement Engineering, 15*(1), 879–888.

Männel, M., & Altreuther, B. (2016). *Aging of low noise road surface*. Paper presented at the INTER-NOISE and NOISE-CON Congress and Conference Proceedings.

Markow, M. J. (1990). Life-cycle cost evaluations of the effects of pavement maintenance. *Transportation Research Record,, 1276*.

Marler, R. T., & Arora, J. S. (2004). Survey of multi-objective optimization methods for engineering. *Structural and Multidisciplinary Optimization, 26*(6), 369-395. doi:10.1007/s00158-003-0368-6

Mazari, M., & Rodriguez, D. D. (2016). Prediction of pavement roughness using a hybrid gene expression programming-neural network technique. *Journal of Traffic and Transportation Engineering (English Edition), 3*(5), 448-455. doi:10.1016/j.jtte.2016.09.007

Mbwana, J. R. (2001). *A framework for developing stochastic multi-objective pavement management system*. Retrieved from Technology Transfer in Road Transportation in Africa, Arusha, Tanzania.

Mbwana, J. R., & Turnquist, M. A. (1996). Optimization Modeling for Enhanced Network-Level Pavement Management System. *Transportation Research Record: Journal of the Transportation Research Board*. doi:10.1177/0361198196152400109

Medina, A., et al. (1999). Geographic information systems-based pavement management system. *Transportation Research Record, 1652*, 151-157.

Medury, A., & Madanat, S. (2013). Incorporating network considerations into pavement management systems: A case for approximate dynamic programming. *Transportation Research Part C: Emerging Technologies, 33*, 134-150. doi:10.1016/j.trc.2013.03.003

Meijer, J. R., et al. (2018). Global patterns of current and future road infrastructure. *Environmental Research Letters, 13*(6). doi:10.1088/1748-9326/aabd42

Meneses, S., & Ferreira, A. (2013). Pavement maintenance programming considering two objectives: maintenance costs and user costs. *International Journal of Pavement Engineering, 14*(2), 206-221. doi:10.1080/10298436.2012.727994

Ministry of Transportation. (2004). Technical specification for highway asphalt pavement construction (JTG-F40-2004). In: Beijing: China Communication Press. (in Chinese).

Ministry of Transportation. (2006). Specifications for Design of Highway Asphalt Pavement (JTG-D50-2006). In: Beijing: China Communication Press. (in Chinese).

Ministry of Transportation. (2007). Budgetary Norm of Highway Project (JTG/T B06-02-2007). In: Beijing: China Communication Press. (in Chinese).

Moghadas Nejad, F., et al. (2013). Rutting performance prediction of warm mix asphalt containing reclaimed asphalt pavements. *Road Materials and Pavement Design, 15*(1), 207-219. doi:10.1080/14680629.2013.868820

Morgan, P. A., et al. (2007). *The feasibility of using twin-layer porous asphalt surfaces on England's strategic road network*. Retrieved from Transport Research Laboratory.

Muirhead, M. (2014). *Cost/benefit analysis an Life Cycle Costing of noise mitigation measures and methodology for implementation into pavement management systems*. Retrieved from Conference of European Directors of Roads (CEDR): Noise.

Naguib, I. A., & Darwish, H. W. (2012). Support vector regression and artificial neural network models for stability indicating analysis of mebeverine hydrochloride and sulpiride mixtures in pharmaceutical preparation: a comparative study. *Spectrochim Acta A Mol Biomol Spectrosc, 86*, 515-526. doi:10.1016/j.saa.2011.11.003

NCHRP (2004). *Guide for Mechanistic-Empirical Design of New and Rehabilitated Pavement Structures*. Retrieved from National Cooperative Highway Research Program, Washington DC

NCSA (1977). *Flexible pavement cost estimating guide: Inflation/energy effects worksheets, spec data.* Retrieved from National Crushed Stone Association, Alexandria, VA.

Nielsen, C. B., et al. (2005). *Noise reducing pavement in Japan*. Retrieved from Road Directorate, Danish Road Institute, Denmark

Nilsson, R., et al. (2010). *Effective Cleaning of Low-Noise Pavements* Paper presented at the INTER-NOISE 2010, Lisbon, Portugal.

Nisbet, M. A., et al. (2001). *Environmental life cycle inventory of Portland cement concrete and asphalt concrete pavements*. Retrieved from Portland Cement Association.

Noshadravan, A., et al. (2013). Comparative pavement life cycle assessment with parameter uncertainty. *Transportation Research Part D: Transport and Environment, 25*, 131-138. doi:10.1016/j.trd.2013.10.002

OECD. (1987). *Pavement management systems : report / prepared by an OECD scientific expert group*. Retrieved from OECD Publications and Information Centre.

Oliveira, J. R. M., et al. (2013). Use of a warm mix asphalt additive to reduce the production temperatures and to improve the performance of asphalt rubber mixtures. *Journal of Cleaner Production, 41*, 15-22. doi:10.1016/j.jclepro.2012.09.047

Ouertani, M. Z., et al. (2008). Towards an approach to select an asset information management strategy. *International Journal of Computer Science and Applications, 5*(3b), 25 – 44.

Pan, N. F., et al. (2011). Pavement performance prediction through fuzzy regression. *Expert Systems with Applications, 38*(8), 10010-10017. doi:10.1016/j.eswa.2011.02.007

Parida, M., et al. (2005). Enhancing pavement management systems using GIS. *Proceedings of the Institution of Civil Engineers-Transport, 158*(2).

Peng, H., & Bai, X. (2018). Improving orbit prediction accuracy through supervised machine learning. *Advances in Space Research, 61*(10), 2628-2646. doi:10.1016/j.asr.2018.03.001

Pereira, P., & Pais, J. (2018). *Skid Resistance and Texture of Compacted Asphalt Mixes Evaluated from the IFI in Laboratory Preparation*.

Pierce, L. M., et al. (2013). *Practical Guide for Quality Management of Pavement Condition Data Collection*. Retrieved from Federal Highway Administration.

Prowell, B., et al. (2014). *Effects of WMA on Plant Energy and Emissions and Worker Exposures to Respirable Fumes, NCHRP09-47A_FR-VolumeII*.

RAP (1999). *Noise Reduction with Asphalt-Rubber*. Retrieved from Rubber Asphalt Association.

Rasmussen, R., et al. (2007). *The Little Book of Quieter Pavements*. Retrieved from

Ratner, M., & Glover, C. (2014). *US Energy: Overview and Key Statistics*. Retrieved from Washington: Congressional Research Service

Ravirala, V., & Grivas, D. A. (1995). Goal-Programming Methodology for Integrating Pavement and Bridge Programs. *Journal of Transportation Engineering, 121*(4), 345-351.

Rebitzer, G. (2002). Integrating Life Cycle Costing and Life Cycle Assessment. In S. Seuring (Ed.), *Cost Management in supply chains* (pp. 127–146). Physica, Heidelberg.

Rebitzer, G., et al. (2004). Life cycle assessment part 1: framework, goal and scope definition, inventory analysis, and applications. *Environ Int, 30*(5), 701-720. doi:10.1016/j.envint.2003.11.005

Rister, B. W., & Graves, C. (2002). *The Cost of Construction Delays and Traffic Control for Life-Cycle Cost Analysis of Pavement*. Retrieved from Kentucky Transportation Center.

Roberts, C. A., & Attoh-Okine, N. O. (1998). A comparative analysis of two artificial neural networks using pavement performance prediction. *Computer-Aided Civil and Infrastructure Engineering, 13*(5), 339-348.

Roberts, F. L., et al. (1996). *Hot mix asphalt materials, mixture design and construction*.

Rochat, J. L., & Donavan, P. R. (2018). Investigations of Effects of Porous Pavement on Traffic Noise and Traffic Noise Prediction. *Transportation Research Record: Journal of the Transportation Research Board, 2362*(1), 42-48. doi:10.3141/2362-06

Rodríguez-Alloza, A. M., et al. (2015). Hybrid input–output life cycle assessment of warm mix asphalt mixtures. *Journal of Cleaner Production, 90*, 171-182. doi:10.1016/j.jclepro.2014.11.035

Rubio, M. C., et al. (2012). Warm mix asphalt: an overview. *Journal of Cleaner Production, 24*, 76-84. doi:10.1016/j.jclepro.2011.11.053

Saling, P., et al. (2002). Eco-efficiency analysis by BASF: the method. *The International Journal of Life Cycle Assessment, 7*(4), 203-218.

Salman, M., et al. (2013). *Pavement Crack Detection Using the Gabor Filter*. Paper presented at the 16th International IEEE Annual Conference on Intelligent Transportation Systems (ITSC 2013), Hague, Netherlands.

Sandberg, U. (2008). *Review and evaluation of low-noise road surfaces in Hong Kong*. Retrieved from Hong Kong.

Sandberg, U., & Ejsmont, J. A. (2002). *Tyre/Road Noise Reference Book*. Informex, SE-59040 Kisa, Sweden (www.informex.info).

Santero, N. J. (2009). *Pavements and the Environment: A Life-Cycle Assessment Approach.* (PhD), University of California, Berkeley.

Santero, N. J., et al. (2011a). Life-cycle assessment of pavements Part II: Filling the research gaps. *Resources, Conservation and Recycling, 55*(9-10), 810-818. doi:10.1016/j.resconrec.2011.03.009

Santero, N. J., et al. (2011b). Life-cycle assessment of pavements. Part I: Critical review. *Resources, Conservation and Recycling, 55*(9-10), 801-809. doi:10.1016/j.resconrec.2011.03.010

Santos, J., et al. (2014). A life cycle assessment of in-place recycling and conventional pavement construction and maintenance practices. *Structure and Infrastructure Engineering, 11*(9), 1199-1217.

Santos, J., & Ferreira, A. (2013). Life-cycle cost analysis system for pavement management at project level. *International Journal of Pavement Engineering, 14*(1), 71-84. doi:10.1080/10298436.2011.618535

Santos, J., et al. (2017a). A multi-objective optimization-based pavement management decision-support system for enhancing pavement sustainability. *Journal of Cleaner Production, 164*, 1380-1393. doi:10.1016/j.jclepro.2017.07.027

Santos, J., et al. (2017b). Environmental and economic assessment of pavement construction and management practices for enhancing pavement sustainability. *Resources, Conservation and Recycling, 116*, 15-31. doi:10.1016/j.resconrec.2016.08.025

SCDER. (1999). *Report on Status of Rubberized Asphalt Traffic Noise Reduction*. Retrieved from Sacramento County Department of Environmental Review.

Sinha, K. C., et al. (1981). Optimization Approach for Allocation of Funds for Maintenance and Preservation of the Existing Highway System. *Transportation Research Record: Journal of the Transportation Research Board, 826*.

Smith, R. E., et al. (2001). *Integration of network- and project-level performance models for TxDOT PMIS*. Retrieved from Texas Department of Transportation

Speight, J. G. (2015). *Asphalt Materials Science and Technology*. Retrieved from Butterworth-Heinemann.

Stammer, R. E., & Stodolsky, F. (1995). *Assessment of the energy impacts of improving highway-infrastructure materials*. Retrieved from Argonne, Illinois.

Stripple, H. (2001). *Life Cycle Assessment of Road: A Pilot Study for Inventory Analysis*.

Stulp, F., & Sigaud, O. (2015). Many regression algorithms, one unified model: A review. *Neural Netw, 69*, 60-79. doi:10.1016/j.neunet.2015.05.005

Taghavifar, H., et al. (2013). Artificial Neural Network estimation of wheel rolling resistance in clay loam soil. *Applied Soft Computing, 13*(8), 3544-3551. doi:10.1016/j.asoc.2013.03.017

Tatari, O., et al. (2012). Comparative sustainability assessment of warm-mix asphalts: A thermodynamic based hybrid life cycle analysis. *Resources, Conservation and Recycling, 58*, 18-24. doi:10.1016/j.resconrec.2011.07.005

Thenoux, G., et al. (2007). Energy consumption comparison for different asphalt pavements rehabilitation techniques used in Chile. *Resources, Conservation and Recycling, 49*(4), 325-339. doi:10.1016/j.resconrec.2006.02.005

Tinoco, J., et al. (2011). Application of data mining techniques in the estimation of the uniaxial compressive strength of jet grouting columns over time. *Construction and Building Materials, 25*(3), 1257-1262. doi:10.1016/j.conbuildmat.2010.09.027

Torres-Machí, C., et al. (2015). Sustainable Pavement Management - Integrating Economic, Technical, and Environmental Aspects in Decision Making. *Transportation Research Record: Journal of the Transportation Research Board, 2523*(1), 56-63. doi:10.3141/2523-07

Torres-Machi, C., et al. (2017). Towards a sustainable optimization of pavement maintenance programs under budgetary restrictions. *Journal of Cleaner Production, 148*, 90-102. doi:10.1016/j.jclepro.2017.01.100

Tufvesson, L. M., & Börjesson, P. (2008). Wax production from renewable feedstock using biocatalysts instead of fossil feedstock and conventional methods. *The International Journal of Life Cycle Assessment, 13*(4), 328-338. doi:10.1007/s11367-008-0004-1

Turk, J., et al. (2016). Environmental comparison of two alternative road pavement rehabilitation techniques: cold-in-place-recycling versus traditional reconstruction. *Journal of Cleaner Production*(121), 45-55.

U.S. Life Cycle Inventory Database. (2012). National Renewable Energy Laboratory. Accessed November 19, 2012: https://www.lcacommons.gov/nrel/search.

Vapnik, V., et al. (1997). *Support vector method for function approximation, regression estimation, and signal processing*. Paper presented at the Advances in Neural Information Processing Systems 9, Cambridge, MA, USA.

Vidal, R., et al. (2013). Life cycle assessment of hot mix asphalt and zeolite-based warm mix asphalt with reclaimed asphalt pavement. *Resources, Conservation and Recycling, 74*, 101-114. doi:10.1016/j.resconrec.2013.02.018

Von, Q., et al. (2007). *Mechanistic-Empirical Pavement Design Guide Flexible Pavement Performance Prediction Models for Montana--Volume I Executive Research Summary*. Retrieved from National Transportation Library.

Walls, J., & Smith, M. R. (1998). *Life-cycle cost analysis in pavement design*. Retrieved from Federal Highway Administration.

Wang, F., et al. (2003). *Decision making problem for managing pavement maintenance and rehabilitation projects*. Paper presented at the 82nd Transportation Research Board of the National Academies, Washington, DC.

Wang, H., & Gangaram, R. (2014). *Life Cycle Assessment of Asphalt Pavement Maintenance*. Retrieved from Center for Advanced Infrastructure & Transportation Rutgers, The State University of New Jersey.

Wang, K. C. P. (2013). *Matched Filtering Algorithm for Pavement Cracking Detection*. Paper presented at the Annual Meeting of the Transportation

Research Board.

Wang, T., et al. (2012a). *UCPRC Life Cycle Assessment Methodology and Initial Case Studies for Energy Consumption and GHG Emissions for Pavement Preservation Treatments with Different Rolling Resistance*. Retrieved from University of California Pavement Research Center UC Davis, UC Berkeley.

Wang, T., et al. (2012b). Life cycle energy consumption and GHG emission from pavement rehabilitation with different rolling resistance. *Journal of Cleaner Production, 33*, 86-96. doi:10.1016/j.jclepro.2012.05.001

Watson, D. (2011). *Hot In-Place Recycling: Literature Reivew*. Retrieved from Florida Dept. of Transportation.

Weidema, B. P., et al. (2013). *Overview and Methodology - Data Quaility Guideline for the ecoinvent Database version 3*. Retrieved from Swiss Centre for Life Cycle Inventories.

Weidema, B. P., & Wesnaes, M. S. (1996). Data quality management for life cycle inventories—an example of using data quality indicators. *Journal of Cleaner Production, 4*(3-4), 167-174.

West, R., et al. (2014). *Engineering Properties and Field Performance of Warm Mix Asphalt Technologies*.

White, P., et al. (2010). Modeling climate change impacts of pavement production and construction. *Resources, Conservation and Recycling, 54*(11), 776-782. doi:10.1016/j.resconrec.2009.12.007

Wilde, W. J., et al. (1999). *Life Cycle Cost Analysis of Portland Cement Concrete Pavements*. Retrieved from University of Texas at Austin. Center for Transportation Research.

Wu, Z., et al. (2012). Framework for Multiobjective Optimization of Physical Highway Assets Investments. *Journal of Transportation Engineering, 138*(12), 1411-1421. doi:10.1061/(asce)te.1943-5436.0000458

Wu, Z., & Flintsch, G. W. (2009). Pavement preservation optimization considering multiple objectives and budget variability. *Journal of Transportation Engineering, 135*(5), 305-315.

Wu, Z., et al. (2008). Hybrid Multiobjective Optimization Model for Regional Pavement-Preservation Resource Allocation. *Transportation Research Record: Journal of the Transportation Research Board, 2084*(1), 28-37. doi:10.3141/2084-04

Wu, Z., et al. (2010). *Performance Evaluation of Various Rehabilitation and Preservation Treatments.* . Retrieved from Federal Highway Administration

Xu, G., et al. (2008). *Automatic Recognition of Pavement Surface Crack Based on BP Neural Network*. Paper presented at the 2008 International Conference on Computer and Electrical Engineering.

Yang, R., et al. (2015). Environmental and economic analyses of recycled asphalt concrete mixtures based on material production and potential performance. *Resources, Conservation and Recycling*(104), 141-151.

Yu, B., et al. (2015). Multi-objective optimization for asphalt pavement maintenance plans at project level: Integrating performance, cost and environment.

Transportation Research Part D: Transport and Environment, 41, 64-74. doi:10.1016/j.trd.2015.09.016
Yu, B., et al. (2016a). Data quality and uncertainty assessment methodology for pavement LCA. *International Journal of Pavement Engineering, 19*(6), 519-525. doi:10.1080/10298436.2016.1176166
Yu, B., & Lu, Q. (2012). Life cycle assessment of pavement: Methodology and case study. *Transportation Research Part D: Transport and Environment, 17*(5), 380-388. doi:10.1016/j.trd.2012.03.004
Yu, B., et al. (2013). An improved pavement maintenance optimization methodology: Integrating LCA and LCCA. *Transportation Research Part A: Policy and Practice, 55*, 1-11.
Yu, B., et al. (2018a). Estimation and uncertainty analysis of energy consumption and CO2 emission of asphalt pavement maintenance. *Journal of Cleaner Production, 189*, 326-333. doi:10.1016/j.jclepro.2018.04.068
Yu, H. (2017). *Application of warm asphalt rubber as a sustainable paving material: component interaction mechanism investigation and performance characterization.* (PhD), the Hong Kong Polytechnic University.
Yu, H., et al. (2018b). Workability and mechanical property characterization of asphalt rubber mixtures modified with various warm mix asphalt additives. *Construction and Building Materials, 175*, 392-401. doi:10.1016/j.conbuildmat.2018.04.218
Yu, H., et al. (2016b). Rheological and chemical characteristics of rubberized binders with non-foaming warm mix additives. *Construction and Building Materials, 111*, 671-678. doi:10.1016/j.conbuildmat.2016.02.066
Yu, H., et al. (2017). Optimization of preparation procedure of liquid warm mix additive modified asphalt rubber. *Journal of Cleaner Production, 141*, 336-345. doi:10.1016/j.jclepro.2016.09.043
Zaabar, I., & Chatti, K. (2010). Calibration of HDM-4 Models for Estimating the Effect of Pavement Roughness on Fuel Consumption for U. S. Conditions. *Transportation Research Record: Journal of the Transportation Research Board, 2155*, 105-116. doi:10.3141/2155-12
Zapata, P., & Gambatese, J. A. (2005). Energy Consumption of Asphalt and Reinforced Concrete Pavement Materials and Construction. *Journal of Infrastructure Systems, 11*(1), 9-20. doi:10.1061/(ASCE)1076-0342(2005)11:1(9)
Zaumanis, M., et al. (2014). Influence of six rejuvenators on the performance properties of Reclaimed Asphalt Pavement (RAP) binder and 100% recycled asphalt mixtures. *Construction and Building Materials, 71*, 538-550. doi:10.1016/j.conbuildmat.2014.08.073
Zhang, H. (2009). *Sustainable Pavement Asset Management Based on Life Cycle Models and Optimization Methods.* (Doctor of Philosophy), University of Michigan, (CSS09-14)
Zhang, H., et al. (2013). Network-Level Pavement Asset Management System Integrated with Life-Cycle Analysis and Life-Cycle Optimization. *Journal*

of Infrastructure Systems, 19(1), 99-107. doi:10.1061/(asce)is.1943-555x.0000093

Zhang, H., et al. (2010). Life-Cycle Optimization of Pavement Overlay Systems. *Journal of Infrastructure Systems, 16*(4), 310-322. doi:10.1061/共 ASCE 兲 IS.1943-555X.0000042

Zhou, G., et al. (2009). Integration of GIS and data mining technology to enhance the pavement management decision making. *Journal of Transportation Engineering, 136*(4), 332-341.

Zhou, K., et al. (2012). The Carbon Emission Quantification of the Low Carbon Road Maintenance Technology in China. *Applied Mechanics and Materials, 260-261*, 833-840. doi:10.4028/www.scientific.net/AMM.260-261.833

Zhu, H., et al. (2014). *Life cycle assessment on different types of Asphalt Rubber in China*. Paper presented at the International Symposium on Pavement LCA.

APPENDICES

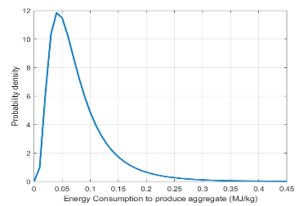
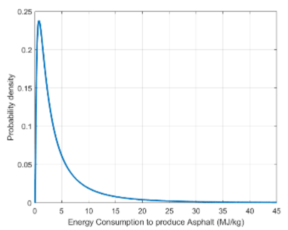
APPENDIX 1 Construction Equipment Information of HIPR and M&F Techniques

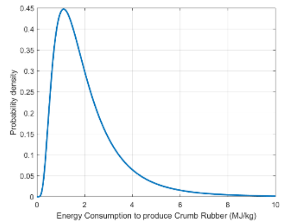
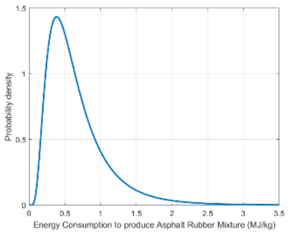
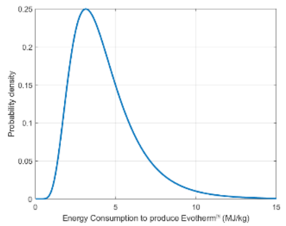
HIPR Equipment Information						
Equipment Model		Function	Productivity for Single Lane (km/h)	Fuel Economy		
				LPG*	Diesel	Electricity
Hot Mixing Plant	Type 3000 asphalt mixing plant	Mixing hot asphalt and aggregates	220 t/h	N/A	7 kg/t	650 kwh
Construction Equipment	HM16 Heater	Heating and softening pavement	1.75 km/machine-team	751.5 kg/ machine-team	85.7 kg/machine-team	N/A
	RM6800 Hot-in-place recycling machine	Heating, scarifying and rejuvenating, and leveling the pavement	1.75 km/machine-team	727.6 kg/ machine-team	113.5 kg/ machine-team	N/A
	EM6500 Lifting and remixing machine	Adding new asphalt mix, lifting and Remixing new and recycled asphalt	1.75 km/machine-team	882.2 kg/ machine-team	128.7 kg/ machine-team	N/A
	Paver (<4.5m)	Paving	0.18 km/h	N/A	33.6 kg/h	N/A
	YZ16 Steel Road Roller (10t)	Compacting	Initial compaction (Twice): 2km/h Final compaction (Twice): 3km/h	N/A	13.2 kg/h	N/A
	SSR260 rubber-tyred roller (25t)		Second compaction (4 times): 5km/h	N/A	22 kg/h	N/A
Transportation Equipment	Dump truck (20t)	Carrying Hot Asphalt mixture from plant to construction site (0.5km)	Full load:40km/h Empty load:60km/h	N/A	Full load: 40.4 kg/100km Empty load: 19.3 kg/100km	N/A

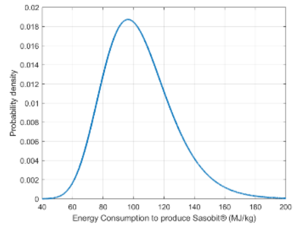
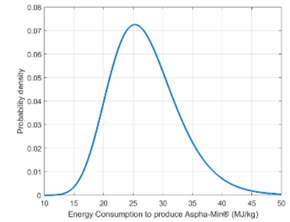
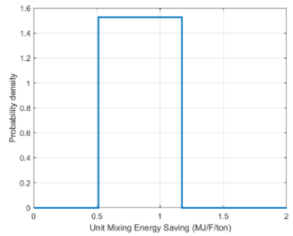
M&F Equipment Information						
Equipment Model		**Function**	**Productivity for Single Lane (km/h)**	**Fuel Economy**		
				LPG	Diesel	Electricity
Hot Mixing Plant	Type 3000 asphalt mixing plant	Mixing hot asphalt and aggregates	220 t/h	N/A	7 kg/t	650 kwh
Construction Equipment	W2100 Milling machine	Pavement Milling	5km/h	N/A	61.4 kg/h	N/A
	Paver (<4.5m)	Paving	0.18km/h	N/A	33.6 kg/h	N/A
	YZ16 Steel Road Roller (10t)	Compacting	Initial compaction (Twice): 2km/h Final compaction (Twice): 3km/h	N/A	13.2 kg/h	N/A
	SSR260 rubber-tyred roller (25t)		Second compaction (4 times): 5km/h	N/A	22 kg/h	N/A
Transportation Equipment	Dump truck (20t)	Transporting new asphalt mixture from plant to construction site (0.5km)	Full load:40km/h Empty load:60km/h	N/A	Full load: 40.4 kg/100km Empty load: 19.3 kg/100km	N/A
	Dump truck (20t)	Carrying old asphalt mixture waste to scrap yard （15km)	Full load:40km/h Empty load:60km/h	N/A	Full load: 40.4 kg/100km Empty load: 19.3 kg/100km	N/A

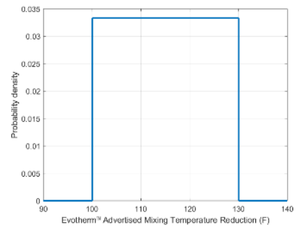
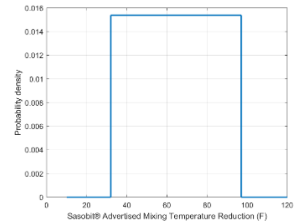
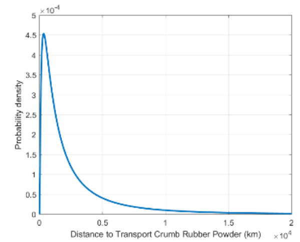
Note: *LPG refers liquefied petroleum gas

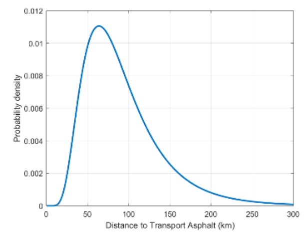
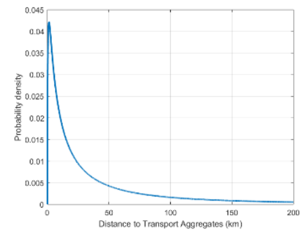
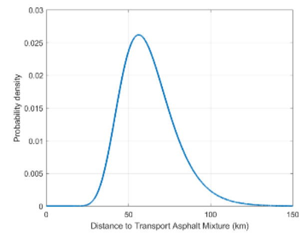
APPENDIX 2 Supplementary Information for Summary of Uncertainty Factors

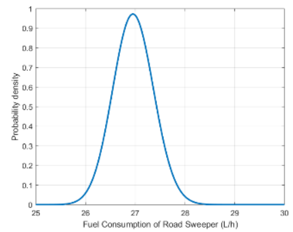
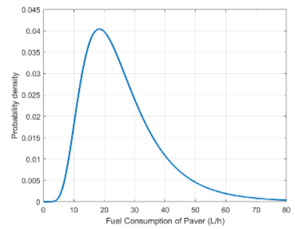
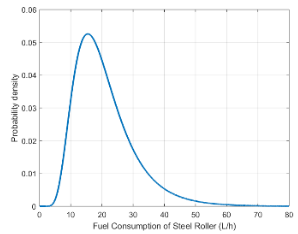
Inventory		Data source	Pedigree scores[a]	DQI[b]	Basic variance	PDF
Material production energy consumption[c] (MJ/kg)						
Aggregate	0.0296	Farina et al. (2017)	[3,4,1,5,2]	0.0066	0.4172	
	0.0866	Stripple (2001)	[2,3,5,5,2]	0.0438		
	0.0936	Athena (2006)	[2,3,4,4,2]	0.0104		
	0.1990	Ecoinvent Database (2007)	[3,3,4,5,2]	0.0132		
	0.0957	U.S. Life Cycle Inventory Database (2012)	[3,2,4,4,2]	0.0107		
	0.0530	NCSA (1977)	[2,4,5,5,2]	0.0452		
	0.0222	Berthiaume and Bouchard (1999)	[3,4,5,5,2]	0.0526		
	0.0740	Stammer and Stodolsky (1995)	[3,4,5,5,2]	0.0526		
	0.0760	Häkkinen and Mäkelä (1996)	[3,4,5,5,2]	0.0526		
	0.0382	Butt (2014)	[4,4,2,4,2]	0.0114		
Asphalt	3.7783	Farina et al. (2017)	[3,4,1,5,2]	0.0066	1.3241	
	2.8900	Stripple (2001)	[2,3,5,5,2]	0.0438		
	5.3200	Athena (2006)	[2,3,4,4,2]	0.0104		
	9.0000	Ecoinvent Database (2007)	[3,3,4,5,2]	0.0132		
	10.5000	U.S. Life Cycle Inventory Database (2012)	[3,2,4,4,2]	0.0113		
	0.6300	Stammer and Stodolsky (1995)	[3,4,5,5,2]	0.0466		
	0.4200	NCSA (1977)	[2,4,5,5,2]	0.0452		
	6.0000	Häkkinen and Mäkelä (1996)	[3,4,5,5,2]	0.0466		

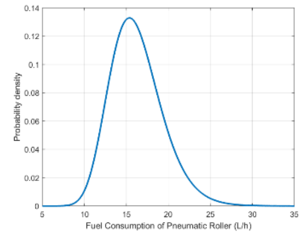
	1.3120	Butt (2014)	[4,4,2,4,2]	0.0114		
Crumb rubber	0.9360	Bartolozzi et al. (2014)	[2,4,2,5,2]	0.0054	0.4199	
	1.4196	Farina et al. (2017)	[3,4,1,5,2]	0.0066		
	4.2700	Wang et al. (2012b)	[4,2,3,4,2]	0.0167		
	1.4616	Bartolozzi et al. (2012)	[2,4,3,5,2]	0.0072		
AR mixture	0.3180	Bartolozzi et al. (2014)	[2,4,2,5,2]	0.0054	0.3655	
	0.8641	Farina et al. (2017)	[3,4,1,5,2]	0.0066		
	0.4040	Stripple (2001)	[2,3,5,5,2]	0.0438		
	0.3750	Athena (2006)	[2,3,4,4,2]	0.0104		
	1.2624	Bartolozzi et al. (2012)	[2,4,3,5,2]	0.0072		
Surfactant additive	3.8715	Wang and Gangaram (2014)	[5,5,5,5,5]	0.2100	-	

Organic wax	101.0000	Tufvesson and Börjesson (2008)	[3,4,5,5,2]	0.0466	-	
Zeolite	26.4500	Fawer et al. (1998)	[2,4,5,5,2]	0.0452	-	
Mixing process						
Unit energy Saving	0.51 - 1.16 (MJ/°F/ton)	Prowell et al. (2014) Rodríguez-Alloza et al. (2015)	-	-	-	

Surfactant temperature reduction	100 - 130 (°F)	Kristjánsdóttir et al. (2007)	-	-	-	
Organic wax temperature reduction	32 - 97 (°F)	Kristjánsdóttir et al. (2007)	-	-	-	
Transportation distance (km)						
Transport crumb rubber powder	150	Bartolozzi et al. (2014)	[2,4,2,5,2]	0.0054	1.5223	
	100	Farina et al. (2017)	[4,2,1,5,2]	0.0107		
	10	Bartolozzi et al. (2012)	[2,4,3,5,2]	0.0072		
	100	Bartolozzi et al. (2012)	[2,4,3,5,2]	0.0072		
Transport asphalt	100	Farina et al. (2017)	[4,2,1,5,2]	0.0107	0.3987	
	100	Butt (2014)	[4,4,2,4,2]	0.0114		
	280	Vidal et al. (2013)	[4,2,3,4,2]	0.0113		
	50	Bartolozzi et al. (2012)	[2,4,3,5,2]	0.0072		

	150	Bartolozzi et al. (2012)	[2,4,3,5,2]	0.0072		
Transport aggregates	2	Bartolozzi et al. (2014)	[2,4,2,5,2]	0.0054	2.4304	
	5	Butt (2014)	[4,4,2,4,2]	0.0114		
	60	Farina et al. (2017)	[4,2,1,5,2]	0.0107		
	30	Bartolozzi et al. (2012)	[2,4,2,5,2]	0.0072		
	80	Bartolozzi et al. (2012)	[2,4,2,5,2]	0.0072		
	73	Vidal et al. (2013)	[4,4,2,5,2]	0.0128		
Transport asphalt mixture	50	Farina et al. (2014)	[4,2,2,5,2]	0.0109	0.0874	
	60	Farina et al. (2017)	[4,2,1,5,2]	0.0107		
	72	Wang et al. (2012b)	[4,2,3,4,2]	0.0113		
	36.00	Leng et al. (2017a)	[4,4,1,4,2]	0.0112		
Energy consumption of construction equipment (L/h)						
Road sweeper	26.67	Bartolozzi et al. (2012)	[2,4,2,5,2]	0.0072	0.0002	

	25.25	Zapata and Gambatese (2005)	[3,3,4,5,2]	0.0132		
Paving machine	30.00	Farina et al. (2017)	[2,4,3,5,2]	0.0072	0.1093	
	15.10	Zapata and Gambatese (2005)	[3,3,4,5,2]	0.0132		
	18.10	Bartolozzi et al. (2012)	[2,4,2,5,2]	0.0072		
	20.00	Stripple (2001)	[2,4,5,5,2]	0.0452		
	22.00	Stripple (2001)	[2,4,5,5,2]	0.0452		
	26.62	Vidal et al. (2013)	[4,4,2,5,2]	0.0128		
	40.13	Wang et al. (2012a)	[4,2,3,4,2]	0.0113		
Steel roller	30.67	Wang et al. (2012a)	[4,2,3,4,3]	0.0187	0.1102	
	12.00	Stripple (2001)	[2,4,5,5,3]	0.0526		
	18.00	Stripple (2001)	[2,4,5,5,3]	0.0526		
	17.00	Zapata and Gambatese (2005)	[3,3,4,5,2]	0.0132		
	17.00	Farina et al. (2017)	[2,4,3,5,3]	0.0128		
	12.85	Bartolozzi et al. (2012)	[2,4,2,5,3]	0.0146		
Pneumatic roller	18.55	Wang et al. (2012a)	[4,2,3,4,3]	0.0187	0.0343	
	12.00	Stripple (2001)	[2,4,5,5,3]	0.0526		
	18.00	Stripple (2001)	[2,4,5,5,3]	0.0526		
	17.00	Zapata and Gambatese (2005)	[3,3,4,5,2]	0.0132		

	17.00	Farina et al. (2017)	[2,4,3,5,3]	0.0128		
	12.85	Bartolozzi et al. (2012)	[2,4,2,5,3]	0.0146		

Note: [(a)]The set of five pedigree scores represents ["reliability", "completeness", "temporal correlation", "geographical correlation", "further technological correlation"].

[(b)]The additional variance was estimated as data quality indicator (DQI), which denotes the appropriateness that the data could be applied in this study.

[(c)]The energy data extraction and integration process was based on the corresponding density and energy contents presented in Weidema et al. (2013a).

APPENDIX 3 MATLAB Scripts for ANN Regression Model

```
function [Y,Xf,Af] = myNeuralNetworkFunction(X,~,~)
%MYNEURALNETWORKFUNCTION neural network simulation function.
%
% Auto-generated by MATLAB, 19-Nov-2018 20:29:12.
%
% [Y] = myNeuralNetworkFunction(X,~,~) takes these arguments:
%
%   X = 1xTS cell, 1 inputs over TS timesteps
%   Each X{1,ts} = 6xQ matrix, input #1 at timestep ts.
%
% and returns:
%   Y = 1xTS cell of 1 outputs over TS timesteps.
%   Each Y{1,ts} = 1xQ matrix, output #1 at timestep ts.
%
% where Q is number of samples (or series) and TS is the number of timesteps.

%#ok<*RPMT0>

% ===== NEURAL NETWORK CONSTANTS =====
% Input 1
x1_step1.xoffset = [-1.26733852209231;-1.77647115294255;-2.05820386749596;-
1.39846787288022;-1.04878374676157;-1.40020070355975];
x1_step1.gain =
[0.619554422142857;0.5914068924;0.536426003;0.876454257485714;0.41999369047313
8;0.297932384962406];
x1_step1.ymin = -1;

% Layer 1
b1 = [-2.0437321253884461747;-1.4625444290636213651;2.5115682710096343122;-
1.0259061952360277736;1.4643619065684763125;0.1254414778185445889;-
1.1524039284351048629;-0.8587088240117612958 4;0.7709687918975602904 9;-
1.846559594221269362 5];
IW1_1 = [-0.5765527837745725303 6 -0.99522628055196882269
1.3266393498802304673 -1.4059403244464225846 -0.25952233228914345364
0.49113671616006726595;1.6358018702034580194 -1.1237978449744314702 -
1.4500425392922957624 0.83217069983985214598 -0.52508980840545360635
0.59401532790855071653;-0.86603456084442509422 1.6113363471942279137
0.70622112527768199364 -1.2720828052421682131 0.48587996774009128975 -
0.22600543779006496137;-0.43258293854286272717 1.9385698064495786586
1.0999823201204923517 -0.35073495608598637 13 0.61235541325556142045
1.2397371664072613928;-0.45613304151783889973 0.63112440151625681661 -
0.57691226289632091 54 -1.5844544573508700935 -0.97315692462409419949
```

```
2.3963129505200124747;-2.1924388138039523355 -1.1018275545698115181
0.15624294130045951468 0.59325231413806434055 -1.6032335016336671796
0.48699319705293098171;-2.1820401039043959557 2.2920969211432504764
0.11094251359004252133 1.1623897040092279198 -1.2542713390737283419 -
1.7244863383862971684;-0.51571509130746995275 0.61663896198335199639 -
0.51584674077808301274 0.73557772328437254217 -1.4047079387088035052
0.63403288492552800637;0.76335009963231470476 0.71017618611669430795
1.7468803886543873283 -2.7459280010056148491 -1.424668488933795496
0.23532171787321171097;-0.54594035219641001699 -0.65674575271915958119 -
1.5146291154696009951 1.8070469680096130638 1.4044811001210695256
0.092310322339517386636];

% Layer 2
b2 = -1.1699703439799975513;
LW2_1 = [-0.025441729180876029165 1.3050297527361420791 1.098801823704265157
0.82350826189092884988 0.85641159761786234128 0.97010877811750240163 -
0.62796401163966641956 -1.5970302839991499244 -1.8615142525919463612 -
1.3419825117377075507];

% Output 1
y1_step1.ymin = -1;
y1_step1.gain = 0.440388065181691;
y1_step1.xoffset = -1.526417595605;

% ===== SIMULATION ========
% Format Input Arguments
isCellX = iscell(X);
if ~isCellX
    X = {X};
end

% Dimensions
TS = size(X,2); % timesteps
if ~isempty(X)
    Q = size(X{1},2); % samples/series
else
    Q = 0;
end

% Allocate Outputs
Y = cell(1,TS);

% Time loop
for ts=1:TS
```

```
    % Input 1
    Xp1 = mapminmax_apply(X{1,ts},x1_step1);

    % Layer 1
    a1 = tansig_apply(repmat(b1,1,Q) + IW1_1*Xp1);

    % Layer 2
    a2 = repmat(b2,1,Q) + LW2_1*a1;

    % Output 1
    Y{1,ts} = mapminmax_reverse(a2,y1_step1);
end

% Final Delay States
Xf = cell(1,0);
Af = cell(2,0);

% Format Output Arguments
if ~isCellX
    Y = cell2mat(Y);
end
end

% ===== MODULE FUNCTIONS ========
% Map Minimum and Maximum Input Processing Function
function y = mapminmax_apply(x,settings)
y = bsxfun(@minus,x,settings.xoffset);
y = bsxfun(@times,y,settings.gain);
y = bsxfun(@plus,y,settings.ymin);
end

% Sigmoid Symmetric Transfer Function
function a = tansig_apply(n,~)
a = 2 ./ (1 + exp(-2*n)) - 1;
end

% Map Minimum and Maximum Output Reverse-Processing Function
function x = mapminmax_reverse(y,settings)
x = bsxfun(@minus,y,settings.ymin);
x = bsxfun(@rdivide,x,settings.gain);
x = bsxfun(@plus,x,settings.xoffset);
end
```

APPENDIX 4 MATLAB Scripts for SVM Regression Model

```
function [trainedModel, validationRMSE] = trainRegressionModel(trainingData)
% [trainedModel, validationRMSE] = trainRegressionModel(trainingData)
% returns a trained regression model and its RMSE. This code recreates the model trained
% in Regression Learner app. Use the generated code to automate training the same model
% with new data, or to learn how to programmatically train models.
%   Input:
%   trainingData: a matrix with the same number of columns and data type
% as imported into the app.
%   Output:
%       trainedModel: a struct containing the trained regression model. The
%         struct contains various fields with information about the trained
%         model.
%
%       trainedModel.predictFcn: a function to make predictions on new data.
%
%       validationRMSE: a double containing the RMSE. In the app, the
%         History list displays the RMSE for each model.
%
% Use the code to train the model with new data. To retrain your model, call the function
% from the command line with your original data or new data as the input argument
% trainingData.
%
% For example, to retrain a regression model trained with the original data
% set T, enter:
%     [trainedModel, validationRMSE] = trainRegressionModel(T)
%
% To make predictions with the returned 'trainedModel' on new data T2, use
%     yfit = trainedModel.predictFcn(T2)
%
% T2 must be a matrix containing only the predictor columns used for
% training. For details, enter:
%     trainedModel.HowToPredict

% ===== EXTRACT PREDICTORS AND RESPONSE ========
% This code processes the data into the right shape for training the model.
% Convert input to table
inputTable = array2table(trainingData, 'VariableNames', {'column_1', 'column_2',
'column_3', 'column_4', 'column_5', 'column_6', 'column_7'});

predictorNames = {'column_1', 'column_2', 'column_3', 'column_4', 'column_5',
'column_6'};
predictors = inputTable(:, predictorNames);
```

```
response = inputTable.column_7;
isCategoricalPredictor = [false, false, false, false, false, false];

% ===== TRAIN A REGRESSION MODEL ========
% This code specifies all the model options and trains the model.
responseScale = iqr(response);
if ~isfinite(responseScale) || responseScale == 0.0
    responseScale = 1.0;
end
boxConstraint = responseScale/1.349;
epsilon = responseScale/13.49;
regressionSVM = fitrsvm(...
    predictors, ...
    response, ...
    'KernelFunction', 'gaussian', ...
    'PolynomialOrder', [], ...
    'KernelScale', 2.4, ...
    'BoxConstraint', boxConstraint, ...
    'Epsilon', epsilon, ...
    'Standardize', true);

% Create the result struct with predict function
predictorExtractionFcn = @(x) array2table(x, 'VariableNames', predictorNames);
svmPredictFcn = @(x) predict(regressionSVM, x);
trainedModel.predictFcn = @(x) svmPredictFcn(predictorExtractionFcn(x));

% Add additional fields to the result struct
trainedModel.RegressionSVM = regressionSVM;
trainedModel.About = 'This struct is a trained model exported from Regression Learner
R2018b.';
trainedModel.HowToPredict = sprintf('To make predictions on a new predictor column
matrix, X, use: \n    yfit = c.predictFcn(X) \nreplacing "c" with the name of the variable that
is this struct, e.g. "trainedModel". \n \nX must contain exactly 6 columns because this
model was trained using 6 predictors. \nX must contain only predictor columns in exactly
the same order and format as your training \ndata. Do not include the response column or
any columns you did not import into the app. \n \nFor more information, see <a
href="matlab:helpview(fullfile(docroot, "stats", "stats.map"),
"appregression_exportmodeltoworkspace")">How to predict using an exported
model</a>.');

% Extract predictors and response
% This code processes the data into the right shape for training the model.
% Convert input to table
inputTable = array2table(trainingData, 'VariableNames', {'column_1', 'column_2',
```

```
'column_3', 'column_4', 'column_5', 'column_6', 'column_7'});

predictorNames = {'column_1', 'column_2', 'column_3', 'column_4', 'column_5',
'column_6'};
predictors = inputTable(:, predictorNames);
response = inputTable.column_7;
isCategoricalPredictor = [false, false, false, false, false, false];

% Perform cross-validation
KFolds = 5;
cvp = cvpartition(size(response, 1), 'KFold', KFolds);
% Initialize the predictions to the proper sizes
validationPredictions = response;
for fold = 1:KFolds
    trainingPredictors = predictors(cvp.training(fold), :);
    trainingResponse = response(cvp.training(fold), :);
    foldIsCategoricalPredictor = isCategoricalPredictor;

    % Train a regression model
    % This code specifies all the model options and trains the model.
    responseScale = iqr(trainingResponse);
    if ~isfinite(responseScale) || responseScale == 0.0
        responseScale = 1.0;
    end
    boxConstraint = responseScale/1.349;
    epsilon = responseScale/13.49;
    regressionSVM = fitrsvm(...
        trainingPredictors, ...
        trainingResponse, ...
        'KernelFunction', 'gaussian', ...
        'PolynomialOrder', [], ...
        'KernelScale', 2.4, ...
        'BoxConstraint', boxConstraint, ...
        'Epsilon', epsilon, ...
        'Standardize', true);

    % Create the result struct with predict function
    svmPredictFcn = @(x) predict(regressionSVM, x);
    validationPredictFcn = @(x) svmPredictFcn(x);

    % Add additional fields to the result struct

    % Compute validation predictions
    validationPredictors = predictors(cvp.test(fold), :);
```

```
    foldPredictions = validationPredictFcn(validationPredictors);

    % Store predictions in the original order
    validationPredictions(cvp.test(fold), :) = foldPredictions;
end

% Compute validation RMSE
isNotMissing = ~isnan(validationPredictions) & ~isnan(response);
validationRMSE = sqrt(nansum(( validationPredictions - response ).^2) /
numel(response(isNotMissing) ));
```

APPENDIX 5 MATLAB Scripts for MOO operation

```
% ===== THREE OBJECTIVE FUNCTIONS ========
function f1 = NoiseReductionBenefit(Choice)
Choice_worst = ones (1,50*60);          % The worst case (Do-nothing)
[Seg_N_con_worst,~] = DecisionChoice(Choice_worst);     % The worst situation
[Seg_N_con,~] = DecisionChoice(Choice);                 % Optimized situation
f1 = sum(sum(Seg_N_con_worst-Seg_N_con))/(5*60);

function f2 = GHG_Emission(Choice)
GHG_treatment = [0 86 6750]*500*3.5;
GHG_optimized = zeros(5,60);
%GHG emission due to different choices
for i=1:1:60
  for t=1:1:5
    switch round(Choice(i*t))
        case 1 % Do-nothing
        GHG_optimized(t,i) = GHG_treatment(1);

        case 2 % Cleaning
        GHG_optimized(t,i)=GHG_treatment(2);

        case 3 % Resurfacing
        GHG_optimized(t,i)=GHG_treatment(3);
    end
  end
end
f2 = sum(sum(GHG_optimized));

function f3 = Cost_Consumption(Choice)
C_treatment = [0 13.69 42.23;0 14.2376 43.92; 0 14.807104 45.6768; 0 15.39938816
47.503872; 0 16.01536369 49.40402688]*500*3.5;
C_optimized = zeros(5,60);
% Cost due to different choices
for i=1:1:60
  for t=1:1:5
    switch round(Choice(i*t))
        case 1 % Do-nothing
        C_optimized(t,i) = C_treatment(t,1);

        case 2 % Cleaning
        C_optimized(t,i) = C_treatment(t,2);

        case 3 % Resurfacing
        C_optimized(t,i) = C_treatment(t,3);
```

```
    end
  end
end
f3 = sum(sum(C_optimized));


% ===== MOO COMPUTATION========
fitnessfcn =
@(Choice)[NoiseReductionBenefit(Choice),GHG_Emission(Choice),Cost_Consumption(C
hoice)];
nvars = 300;
lb=zeros(1,300)+0.5;
ub=zeros(1,300)+3.4;
options = optimoptions('gamultiobj','ParetoFraction',0.35);
[s,fval] = gamultiobj(fitnessfcn,nvars,[],[],[],[],lb,ub,options);    % Objective function value
means solutions
f1 = fval(:,1);
f2 = fval(:,2);
f3 = fval(:,3);
solution = round(s);
% Plot pareto front
c=-f1;
h=80;
scatter3(-f1,f2,f3,h ,c,'filled')
xlabel('Average noise reduction')
ylabel('GHG emssion')
zlabel('Cost')
grid on
cb=colorbar;
set(get(cb,'label'),'string','Average noise reduction (dB(A)/Seg)');
% title('Pareto Points in Objective Space')
```