OPTIMIZATION OF PAVEMENT PRESERVATION STRATEGY CONSIDERING COST AND ENVIRONMENTAL IMPACTS

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ABSTRACT OF THE DISSERTATION

Optimization of Pavement Preservation Strategy Considering Cost and Environmental Impacts

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Road maintenance is crucial for the purpose of retarding deterioration of pavement, which is a complex and continuous process due to the interaction of heavy traffic, environmental condition, and material aging. The combination of increased traffic and lack of appropriate maintenance causes a higher rate of degeneration in the roads. Transportation agencies need to develop a system for disseminating limited funds and decide the timing to conduct maintenance and repairs. In order to establish a cost-effective budget and achieve the optimum utilization of available resources, the agency needs to decide which maintenance treatment to use and where and when to apply it.

The primary objective of this dissertation is to develop network-level pavement preservation decisions considering multiple objectives of cost and environmental impacts. This research will produce multi-objective optimization models designed to provide highway agencies with means of making road maintenance decisions among different concerns. Therefore, this study developed regression models of CO_2 emissions for four vehicle types to quantify the environmental impact at the use stage.

The simulated constraint boundary method (SCBM) was used as a tool to find Pareto optimal solutions for the pavement multi-objective optimization problem of minimizing agency costs and minimizing CO_2 emissions by minimizing average network IRI value. This method is based on solving one objective and converting the other objective to constraint, so the decision makers need to decide first which objective should be considered as the primary objective (the objective that deserves the most attention among the competing objectives). The results show that the crack seal is still the most dominant preservation treatments compared to thin overlay although it has less effect on the reduction of IRI than the thin overlay treatment. So, the objective of minimizing agency cost controls the optimization results although the minimization of CO_2 emissions was considered in the optimization process.

Another method that was used in this research to achieve both objectives of minimizing agency costs and emissions is the Weighted Sum method. Weighted sum method is based on converting the two objectives into one single objective by adding both objectives together after multiplying each objective by a weighting factor. The value of weighting factor should be considerable relative to other weighting factors and comparative to its corresponding objective function. The results for the distribution of pavement preservation treatments show that less costly preservation treatments were selected for the most segments of the network when the priority of optimization was given to the objective of minimization agency cost. The treatments that have higher effectiveness on pavement condition were selected for the most segments of the network when the objective of minimization CO_2 emission is the main objective compared to the other objective.

DEDICATION

*To my dear husband and best friend, **Abbas Jasim**, for your patience, love, and making everything possible.*

Israa Al-Saadi

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Israa Al-Saadi

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CHAPTER 1 INTRODUCTION

1.1 BACKGROUND

Economy, society, and environment are three significant elements of sustainability. Recently, environmental sustainability becomes more recognized due to the concern of climate change and human health. Although pavement management system is used to maintain the acceptable condition of pavements and keep pavements smooth and safe, it is desired to investigate the tradeoff between cost and environmental effects of pavement investments.

Many sustainable practices have been implemented for pavements through improved or innovative design such as long-lasting pavement and porous pavement, utilization of recycled material and industry by-products, such as recycled asphalt and concrete materials. Permeable pavements have been designed to decrease the need for storm-water reservation tanks and develop the quality of storm-water runoff, while long-lasting used to increase sustainability through long service lives, minimum maintenance and repair, and reduced traffic disruptions. Recycled asphalt pavement (RAP) is becoming commonly recycled materials in flexible pavements to reduce construction costs and the use of non-renewable resources. Likewise, the increasing use of high percentages of additional cementitious materials in rigid pavements cannot only recycle waste material but also produces significant greenhouse gas (GHG) emissions. In the recent years, the use of warm mix asphalt (WMA) has been encouraged because of its energy and environmental benefits.

On the other hand, road maintenance is crucial for the purpose of retarding deterioration of pavement, which is a complex and continuous process due to the interaction of heavy traffic, environmental condition, and material aging. The pavement deteriorates gradually and becomes uneven and potholed. The combination of increased traffic and lack of appropriate maintenance causes a higher rate of degeneration in the roads. Transportation agencies need to develop a system for disseminating limited funds and decide the timing to conduct maintenance and repairs. In order to establish a cost-effective budget and achieve the optimum utilization of available resources, the agency needs to decide which maintenance treatment to use and where and when to apply it. In addition, rolling resistance due to tire-pavement interaction and pavement surface condition causes direct effects on vehicle operation costs, fuel consumption, and greenhouse gas (GHG) emissions particularly. In 2008, the road transport produced thirty-three percent of the GHG emissions in the U.S. The economic and environmental impacts of different pavement maintenance and preservation activities are important for the selection of pavement repair. These issues need to be taken into account to formulate a sustainable strategy for pavement maintenance.

1.2 PROBLEM STATEMENT

Recently, transportation agencies started to increase focus on preservation and address the deterioration of the nation's highways. Compared to rehabilitation, pavement preservation (or preventive maintenance) treatments mainly focus on surface refreshment to alleviate functional distresses of pavement and retard pavement deterioration. At the construction stage of pavement maintenance and repair, there are significant differences in energy consumption and GHG emissions among various treatments mainly due to different raw material components and manufacturing processes. At the usage stage of pavement after treatments, fuel consumptions and vehicle emission vary significantly depending on tire rolling resistance that is affected by pavement surface roughness, macro-texture, and deflection. Therefore; it is needed to develop an efficient approach to quantify environmental impacts of pavement preservation during its whole life cycle including the usage stage.

Most of the previous studies focused on the environmental impact of pavements at material and construction phases while neglected their impacts at usage phase. This is mainly due to the lack of a model that can quantify the relationship between vehicle emission and pavement surface characteristics for different vehicle types and operation statuses. It is not sure if the current available models will produce the consistent results. For example, several studies tried to quantify the energy consumptions and emissions of pavement at usage stage through running Motor Vehicle Emission Simulator (MOVES) with different input parameters. By changing and updating input values in MOVES, exporting and importing files consumes much time in addition to execution time. For this reason, it is important to develop an emission rate function with respect to different parameters through running MOVES and regression analysis.

Some existing studies have been carried out about multi-objective optimization models for the purpose of optimizing pavement maintenance in the time horizon. Nevertheless, one of the notable gaps in the existing literature is that few studies had the goal of considering cost and environmental impacts for the optimum application of different pavement preservation treatments at the network level. This becomes more critical for the situation that there is an annual budget set separately for pavement preservation. In addition, there is a lack of existing research focusing on the integration of the development of the multi-objective model and the post-optimization decision making. The Pareto optimal concept, an approach that is ideal for generating nondominant solutions, need be used to get solutions for multi-objective problems.

1.3 RESEARCH OBJECTIVES AND SCOPE

The primary objective of this dissertation is to develop network-level pavement preservation decisions considering multiple objectives of cost and environmental impacts. During last few years, most of the research focused on the environmental impact of pavement at material and construction stages but neglected the use stage. For this reason, this work will cover the use stage to quantify the impact of pavement preservation on energy consumption and CO_2 emissions. This research will produce multi-objective optimization models designed to provide highway agencies with means of making road maintenance decisions among different concerns.

To achieve this objective, the following research tasks are conducted:

1. Develop emission rate functions with respect to vehicle speed and pavement surface characteristics through running MOVES and regression analysis;
2. Quantity life-cycle energy and emission of pavement preservation treatments with different application strategies;
3. Develop network-level optimization on pavement preservation strategy considering multiple objectives of cost and environmental impacts.

1.4 DISSERTATION OUTLINE

This dissertation is divided into seven chapters. The first chapter introduces the problem statement, objective, and methodology of the dissertation. The second chapter summarizes an extensive literature review, which will describe the previous studies conducted on existing pavement preservation techniques and optimization methods.

In chapter three, emission rate functions were developed with respect to vehicle speed and pavement surface characteristics through running MOVES and regression analysis.

Chapter four focused on quantifying environmental impact of three pavement preservation treatments, chip seal, crack seal, and thin overlay, with different application strategies and scenarios at construction and use stage using life-cycle assessment (LCA) approach.

Chapter five focused on developing pavement preservation strategy at the network level considering multi-objective optimization of minimizing agency costs and minimizing environmental impacts in terms of CO_2 emissions by using SCBM method.

Chapter six aimed to find the optimal timing of pavement preservation strategy at the network level considering multi-objective optimization of minimizing agency costs and minimizing CO_2 emissions by using Weighted Sum method.

Finally, Chapter 7 summarizes the key findings and conclusions of the dissertation and provides recommendations for future research to further explore the potential of applying multi-objective optimization techniques in pavement preservation.

CHAPTER 2 LITERATURE REVIEW

2.1 PAVEMENT MANAGEMENT SYSTEM

2.1.1 Pavement Management Activities

Hass and Hutchinson (1970) first put forward the PMS concept in 1970 in their seminal work “A Management System for Highway Pavement." The PMS framework, according to the American Association of State Highway and Transportation Officials (Guide, 2002), is a cohesive and formal method of organizing all pavement management activities effectively. There are a set of key elements that must comprise an effective PMS to facilitate decision-making activities on different levels of management, namely surveys focused on the condition and serviceability of roads, a database of all information relating to pavements, an analysis scheme, decision criteria and implementation processes.

There are three primary categories of pavement management activities in terms of intensity and the structural changes involved. These three types are Maintenance, Rehabilitation, and Reconstruction (MR&R). The FHWA (2005) divide pavement management activities into four groups on the basis of their objectives, namely corrective maintenance, pavement preservation, major rehabilitation, and reconstruction. Furthermore, pavement preservation activities can be sub-divided into routine maintenance, preventative maintenance, and minor rehabilitation.

Corrective maintenance (CM) refers to the activities that are taken to overcome any defects or deficiencies that may endanger the safe and efficient function of the facility and compromise the integrity of the pavement in the future (FHWA, 2005). These activities are typically reactive in nature and are undertaken to maintain all pavements to a minimum standard in light of unexpected damage or events. CM is also performed to enhance the structural capacity of the facility on a local level and can include the repair of potholes or the patching of small areas of pavement damage.

Pavement preservation (PP) is defined as the long-term activities taken on a network level to improve the functionality of pavements based on a cohesive and cost-intensive range of strategies that enhance safety, satisfy the needs of motorists and extend the lifespan of pavements. Thus, pavement preservation refers to all activities that are performed to ensure that roadways are maintained to a specific standard. The main purpose of such activities is to improve performance, reduce costs, minimize user delays and extend pavement life and can include minor, routine or preventative maintenance. However, pavement perseveration does not include construction, reconstruction or the enhancement of the structural capacity of pavements.

Routine maintenance (RM) is defined as activities that are scheduled and undertaken periodically to ensure the long-term performance of the highway system and to respond efficiently to specific conditions or events to maintain an adequate level of user service (FHWA, 2005). These activities are performed on a regular basis and can include crack filling, ditch cleaning, line striping, and mowing. All of these activities are non-pavement related except crack filling.

Preventative maintenance (PM) is defined as a cost-effective strategy designed to maintain existing roadway systems in a way that hinders future damage, maintains or enhances functionality without enhancing structural capacity to any large extent and ensures that the facility continues to meet minimum requirements (FHWA, 2005). Such activities include surface treatments, like cape sealing, scrub sealing, chip sealing, fog sealing or crack sealing.

Pavement rehabilitation is defined as structural improvement activities that increase the load carrying capacity of pavements or extends their lifecycle. Such activities include structural overlays and restoration works. Non-structural improvements, such as the overlay of 1.5 inches of asphalt are referred to as minor rehabilitation works. On the other hand, major rehabilitation works include structural enhancements that increase the lifecycle of existing pavements and enhance its load carrying capacity, such as the overlay of 3 or 4 inches of asphalt.

Pavement reconstruction refers to the complete replacement of an existing pavement network through the application of the same or an extended pavement structure (FHWA, 2005). The end result in this case is a completely new pavement structure, which is essentially the same as new construction.

According to Zaniewski and Mamlouk (1996), crack filling and sealing can be regarded as preventative maintenance activities as their function is to prevent further damage, hinder progressive deterioration, and lower routine maintenance or service requirements. It is common for researchers to define activities as corrective or preventative in terms of how long the treatment takes as opposed to the treatment itself as a specific type of treatment can be used in both corrective and preventative maintenance activities. For instance, crack sealing activities on a highly functioning pavement may be regarded as preventative whereas crack sealing on a defective or deteriorating pavement may be regarded as corrective as the aim is to seal the surface and alleviate mild-moderate distress. Nonetheless, this ambiguity can cause issues for agencies attempting to deploy an effective pavement management system as similar treatments are used for routine, corrective and preventative maintenance activities.

2.1.2 Consideration of Pavement Preventive Maintenance in PMS

Preventative maintenance as a key element in the pavement preservation process has become a more popular strategy for highway agencies as it helps to maintain existing roadways and prevent the need for more cost-intensive rehabilitation works. This approach also improves the user quality, reduces user costs and ensures a higher level of user satisfaction. In the past, agencies prioritized routine, and corrective maintenance works as opposed to minor rehabilitative work or preventative maintenance. These activities are generally performed when signs of damage or threshold values are detected, and major rehabilitative work is often neglected as a result.

The efficacy of various kinds of Pavement Preventive Maintenance (PPM) has been modeled by some scholars (Hicks et al. 1997), and some have sought to determine the ideal time for PPM treatments to be performed (Mamlouk & Zaniewski, 2001). These studies indicate that treatments applied at the most optimal time effectively reduce costs as they delay the need to perform major rehabilitative works for several years and increase the cost-effectiveness of the whole network over the course of its lifecycle. Further studies indicate that every dollar spent on effective preventative activities can lead to savings of up to $6 over the course of the lifecycle (Robert & Jim, 2003; Jackson 2001). These studies indicate the value of effective pavement preservation.

In 2001, a survey performed by the Foundation for Pavement Preservation (FP^2) discovered that 10 of every 34 highway agencies surveyed have yet to implement a formal PPM system while 5 of every 23 agencies that have already deployed a PPM system feel that the program is inadequate. The findings also indicate that the majority of agencies believe that PPM can reduce costs and ensure better quality pavement conditions. However, the system has yet to be deployed on a nationwide level. Further still, when PPM is implemented, it often performs ineffectively.

A range of challenges must be overcome by decision makers when establishing a PPM program, particularly in terms of PPM treatments. A survey performed in 2005 by the National Center for Pavement Preservation (NCPP) and the FHWA revealed that 66% of state transportation departments had implemented PPMs into their cohesive network strategies that cover both reconstruction projects and rehabilitation works. In addition, 59 % of agencies have autonomous preservation systems and pavement management systems in place (Peshkin and Hoerner, 2005). However, few take PPM treatments and MR&R activities into account or focus only on reconstruction activities or PPM. As a result, it is often difficult to persuade agencies to abandon the “worst first” approach as some of these models recommend performing preventative maintenance on roads that are already in relatively good condition despite other pavements requiring rehabilitation works Due to insufficient funding, all of these treatments cannot be performed simultaneously, which indicates the need to assess all different kinds of treatment collectively, in light of available funding to determine best practice. In effect, an integrated optimization model is required that takes all treatment types into account and considers all potential sources of finance that could be used to facilitate the implementation of a PMS.

The absence of a cohesive practical planning guide is another issue despite that several studies were conducted for prioritization models and optimized planning strategies. The main issue with these models is that they apply very basic solutions for rather complex mathematical problems or conduct a cost-benefit timing strategy for only one treatment type at a time. Thus, agencies lack confidence in the real world application of these models as they are unable to take network issues into account or generate a completely optimal planning program.

There is a lack of knowledge regarding the efficacy of different treatment options, preventative treatments in particular. According to Wu and Groeger (2010), a lack of knowledge regarding the impact of pavement preservation activities in the US means that the system is hard to apply in practice despite being theoretically sound. The widespread lack of pavement preservation programs may be attributable to the absence of fundamental knowledge and information regarding treatment performance. For instance, as several treatment options for high load roadways are regarded as inadequate, such as chip seals, information related to the performance of this treatment on roads of varying traffic loads is inaccurate. Also, federal funding for preventive maintenance has only been available for 20 years to evaluate the effectiveness of the treatments and to collect the information about in-service performance and effectiveness. Furthermore, different tools and standards are applied in different states to measure the performance and condition of roads. Thus, nationwide standards are required to provide more insight into the performance of preventative maintenance activities and to facilitate more effective decision-making activities. Lastly, effectiveness analysis from a long-term perspective is compromised by the absence of a cohesive long-term monitoring strategy for the nation’s roadways.

2.1.3 The effectiveness of Pavement Preservation on Pavement Performance

Eltahan et al. (1999) studied the performance of the LTPP SPS-3 test sections in the southern region. The performance of the treatment sections was compared with control sections on the basis of three existing conditions: good, fair, and poor. The study concluded that if the existing pavement is in a fair condition, the treatments make the most significant difference. For thin overlay, the average benefit compared with no treatment is 4.8 years, whereas it is 3.5 years for slurry seal and 5.7 years for crack seal. The study also concluded that chip seal outperformed all the other treatments.

Chen et al. (2003) conducted a study in the Texas DOT reviewed fourteen LTPP test sites. In terms of the overall performance, chip seal was ranked first, followed by thin overlay, and slurry seal, which is tied with crack seal. The most comprehensive study on the LTPP SPS-3 experiment was conducted under the National Cooperative Highway Research Program's (NCHRP) Project 20-50 (03/04), which analyzed data from all the SPS-3 sites. The study found that the thin overlay treatment was the only one of the four treatments to have a significant initial effect on rutting, and crack seals did not demonstrate any initial or long-term effect with respect to the international roughness index (IRI), rutting, or cracking (Hall et al. 2002).

Lu and Tolliver (2012) designed an optimization model to minimize total agency costs and minimize pavement network average roughness based on the Pareto optimal concept to solve all types of constraints. In their study, Lu and Tolliver evaluated the short-term effectiveness of the IRI change, using Long-Term Pavement Performance (LTPP) data. They found that the short-term pavement treatment effectiveness in terms of IRI followed a polynomial relationship with the pre-treatment condition. The main conclusion of that study is that they observed average reductions of IRI equal to 1.44, 0.27, and 0.72 m/km for mill overlay, crack sealing, and chip seal, respectively. In addition to Lu and Tolliver's (2012) study, Wang et al. (2012) completed a study on preservation treatments using LTPP roughness data from multiple experiment sites.

With many treatment types, Hot Mix Asphalt (HMA) overlay had the highest performance time, followed by micro-surfacing with chip seal, slurry seal, crack filling, and crack sealing. Furthermore, thin overlay was the most expensive treatment, followed by micro-surfacing and chip seal tied with slurry seal. Wang et al. (2012) used statistical tests, such as a paired t-test, to compare the LTPP control sections with the treatment section roughness. They found that all treatments used in their study caused a significant roughness reduction. They also ordered the effectiveness of the treatments based on roughness reduction. HMA overlay had the most significant effect on roughness reduction, followed by chip seal, crack seal, and slurry seal. Finally, comparing the average difference of International Roughness Index (ΔIRI) between the control section and the treatment sections, crack seal, slurry seal, and overlay were found to be 0.124, 0.083, and 0.407 with a standard deviation of 0.269, 0.04, and 0.618, respectively.

After extensive studies, Carvalho et al. (2011) presented the effects of several design parameters on pavement responses and performance using rigid and flexible pavements. Weighted distress was utilized in that study as a performance indicator, which represents the total normalized area under the distress-time curve. The main results of Carvalho et al.'s (2011) study showed that thin overlay performed better than other treatments in terms of with a Weighted Distress-IRI. The Weighted Distress-IRI of thin overlay and slurry seal equals 4.80 ft/mile (0.91 m/km) and 7.66 ft/mile (1.45 m/km), respectively. Additionally, slurry seal treatment showed the worst performance over an eight-year period.

2.2 PAVEMENT PERFORMANCE MODELING

2.2.1 Pavement Performance Models

The most important element in a pavement management plan is the prediction of the future performance and conditions of roads. Effective PPMs incorporate pavement forecasting models that have a direct influence over the actions of decision makers. In fact, PMSs are now increasingly reliant on the anticipation of pavement conditions in the future. As such, dependable prediction models have become invaluable.

Such prediction tools are commonly applied to forecast future changes to the performance or condition of pavements along with a range of explanatory variables. These models are referred to as mechanistic, mechanistic-empirical or empirical (AASHTO, 2001). A general review of the different types of models as presented by the AASHTO Pavement Management Guide (AASHTO, 2001) is presented in Table 2.1. Predictions made by mechanistic models are based on the evaluation of the degradation process as performance is regarded as a function of a set of parameters that are identified using mechanical means. The most common parameters are loading factors and climatic history. On the other hand, empirical models seek to find a connection between the performance of pavements and other types of field data that influence pavement performance and can be directly observed. Mechanistic-empirical models operate on the basis of a mechanistic model focusing on the materials response as calibrated with recorded field data (ARA, 2004). As the available data is LTTP in-service data, this section will offer an overview of empirical pavement deterioration models to determine varying deterioration behaviors under varying conditions. This review will also explore the explanatory variables used by previous authors and will discuss how these influence rehabilitation and maintenance work.

Table 2.1 Performance Prediction Models Summary (After AASHTO 2001)

Model	Description	Strengths	Weaknesses
Mechanistic	Performance as a function of a number of parameters which is mechanically determined	Predict future changes in mechanistic response of the pavement such as strain, stress as a function of some factors that would cause changes in those responses	Each currently used measure of condition is affected by different factors, some of which cannot be described in purely mechanistic terms
Empirical Regression Analysis	Statistical method using historical data to develop relationship between performance indicator and explanatory variables	Better practical value because of the infinite complexity of the underlying Phenomena	Limited to the conditions of segments data used to develop the model Unknown factors may affect the precision of the model
Empirical Fuzzy sets	Instead of assuming crisp data it uses fuzzy set	It handles uncertainties and randomness well	Modeling fuzziness is difficult because of complex interactions among factors
Empirical Artificial Neural Network	ANN mimic the actions of human brain to sort out patterns and learn from trial and error, discerning and extracting the relationship that underlie the data	Capability of learning from past examples Produce correct responses when presented with partially incorrect or incomplete data	Demanding a large amount of good quality data Difficult to explain the relationship to link the data Difficult to understand how input data influence the output data through learning

Mechanistic-Empirical Models	Using mechanistic analysis to predict the pavement response and empirical analysis to relate the responses to observed condition	Reduce the amount of data needed results based on mechanics are not limited by the range over which the tests were conducted	Still need a relative huge amount of data
Probabilistic Markov models	Use transition matrices describe the probability that a pavement in a known condition state at a known time will change to some other condition state in the next time period	Stochastic process models represents actual pavement performance process	Demanding large amount of transition matrixes fixed time interval
Probabilistic Survivor curves	Markov process with random time intervals	Reducing the size of the problem using random time intervals	Demanding adequate data to develop the probability distributions of time intervals between consecutive stages
Probabilistic Bayesian	Combining observed data with expert experience using Bayesian statistical approaches	Using field data or expert opinion to adjust model	Requiring expert opinion and Previous experiences.

Previous studies most commonly employ empirical regression models as they are more applicable in practice due to the inherent complexity of the processes under investigation (AASHTO, 2001). These models offer insights into the future performance of pavements under certain conditions and also address the relationship that exists between performance indicators and influencing variables. The examination of this relationship is crucial in this case in demonstrating how performance indicators are affected by influencing variables.

An empirical pavement performance prediction model can be either deterministic or probabilistic (Gendreau & Soriano, 1998). The former offers an absolute measure of how a pavement is likely to perform in the future and is a commonly used method due to its inherent simplicity and insights into how pavements will likely deteriorate with the passing of time. Probabilistic models, on the contrary, offer a measurement distribution of the future performance of pavements and offer a range of potential future conditions using a stochastic process. The majority of scholars show a preference for the deterministic model as it is much easier and quicker to apply.

A limited number of explanatory variables are used by most deterioration models in this review, namely traffic loading, pavement age and climatic conditions (Hein & Watt, 2005; Isa et al. 2005). The use of a small number of variables is largely attributable to the complexity in understanding how certain factors, including initial structure quality and environmental information, affect the long-term damage of pavements. Traffic loading, age, and climatic conditions are often treated as exogenous factors (AASHTO, 2001; Gendreau & Soriano, 1998) as well soil and construction factors in some cases (Gendreau & Soriano, 1998).

2.2.2 Previous Studies on Pavement Performance Models

Focusing on traffic loading and age, Hein and Watt (2005) put forward a pavement performance prediction model while Ozbay and Laub (2001) formulated a simple IRI prediction model using structural number, analysis age, pavement age, initial IRI value and the age of cumulative ESAL during analysis. On the other hand, Gibby and Kitamura (1992) determined what factors had the most impact on pavement condition, the namely prior condition of pavements, date of last rehabilitation activity, soil profile of roadway drainage, surface thickness, functional classification, and jurisdiction. According to Paterson and Attoh-Okine (1992), the roughness progression of flexible pavement is formulated on the basis of environmental variables, age, strength and traffic loading. In the event that all distress parameters become available, the model should also incorporate cracking, patching and rutting.

The roughness progression in an AC pavement is largely influenced by environmental variables (Perera & Kohn, 2001). In this case, the researchers indicate that the impact of such variables may be undetectable if the pavement has been developed by taking site conditions such as traffic and climate into account. The authors discussed also concur that pavement deterioration is significantly affected by climate and age factors. However, none of these studies have examined the impact of different treatment options on pavement performance, and the majority of these studies do not incorporate valid maintenance and rehabilitation data as it is difficult to source. Thus, a limited number of models consider how deterioration is affected by maintenance (Ramaswamy & Ben-Akiva, 1990).

It is widely acknowledged that pavement performance is strongly influenced by maintenance and rehabilitation works. However, it has also been argued that these factors are considered as endogenous variables (Prozzi & Mandanat, 2004; Ramaswamy & Ben-Akiva, 1990) as their inclusion as explanatory variables in the models would lead to endogeneity bias (Madanat et al. 1995). According to Ramaswamy and Ben-Akiva (1990), the parameter estimates of key explanatory variables are counterintuitive due to endogeneity and multicollinearity bias. Typically, roads subject to larger traffic loads exhibit signs of damage more quickly. Such roads are usually maintained more effectively and are generally in relatively good condition. Thus, by including traffic and maintenance in the model, it would be natural to surmise that roads with high traffic loads are in a better state of repair. Knowledge of these scenarios can facilitate the avoidance of endogeneity bias and multicollinearity as both are taken directly into consideration.

Lytton (1987), along with several others, acknowledges the need for more cohesive models that take exogenous interventions into consideration while also integrating them with the impacts of maintenance works. Several studies have attempted to achieve this by taking maintenance and rehabilitation effects into consideration while simultaneously preventing endogeneity and multicollinearity bias. The condition of pavements is significantly affected by maintenance and rehabilitation activities, which is why it is advised to exclude both factors as exogenous explanatory variables (Ramaswamy & Ben-Akiva, 1990).

A model has been formulated by Fwa and Sinha (1986b) that combines general pavement performance and average routine maintenance expenses. The implementation of this model provides insights into the impact of routine maintenance on pavement performance based on the measurement of how much is spent on the activity. This model provides knowledge on how routine maintenance affects pavement condition but fails to determine specific causes of distress to pavements or the most suitable kinds of maintenance or rehabilitation options.

A model presented by Ramaswamy and Ben-Akiva (1990) can address how exogenous factors affect the deterioration of pavements at the same time as maintenance activities undertaken to remediate the damage. Maintenance and pavement condition are mutually dependent and also dependent on exogenous factors. The authors used maintenance as the exogenous variable when comparing the outcome of a single regression equation to the outcome of a simultaneous equation, the latter of which is estimated at the same time using a series of maintenance equations. The findings indicate that considerable improvements were achieved by acquiring all the expected signs for significant parameters. Thus, this particular model seems to be more reliable and applicable in estimating the deterioration of pavements considering the impact of maintenance works. This study highlighted the complexity in considering both maintenance and deterioration collectively and is limited by the fact that while the simultaneous equation estimator eliminates the endogeneity bias, the fit of the model becomes less accurate as a result (R^2 values is 0.28). In addition, as the model operates on the assumption that both factors are mutually dependent, it can be hard to accurately predict future conditions in light of numerous M&R policies. Thus, the model is not as beneficial in facilitating more effective M&R decision-making.

The independent estimation of maintenance effectiveness and pavement performance models is an alternative method. A serial performance model was devised by Al-Mansour and Sinha (1994) comprising five maintenance categories and two classes of highways. Pavement age and mean annual ESALs are the exogenous factors with the region as the dummy variable for modeling the impact of climatic conditions. The results of maintenance affect pavement performance models tend to be consistent with anticipated findings. However, the maintenance effectiveness indices can rise in line with pavement age.

To explore different maintenance and rehabilitation works, a model was devised by Madanat and Mishalani (1998) using the grouping approach. According to Chu and Durango-Cohen (2008), these models offer approximations of how pavement performance can be enhanced by different maintenance and rehabilitative works as a function of cumulative exogenous factors. That being said, it is more difficult to unite separate maintenance and deterioration models in order to predict future performance in light of various M&R policies, primarily because performance models and maintenance effectiveness models deal with continuous deterioration and incremental condition changes respectively. It is hard to apply these models to facilitate decision-making in relation to M&R as all performance models for different maintenance activities are distinct as they have been formulated using the maintenance grouping approach. In effect, the model considers pavements that have been subject to a specific kind of maintenance treatment in a similar way but fails to consider the impact of the timing of the maintenance work. Decision makers want information regarding the optimal timing of specific treatments and the different outcomes of different treatment options. However, these models cannot offer information of this nature.

Several scholars state that advanced yet easily applied models are required to facilitate the delineation of M&R policies that take endogeneity bias into account as well as the impacts of maintenance and rehabilitation.

A performance model was formulated by Gao and Zhang (2010) that has the capacity to determine which observations were most likely influenced by maintenance interventions. However, this model failed to describe how the data identified could be used to formulate the performance model. In addition, the model is unable to distinguish between different levels of maintenance.

Using a combination of experimental and in-service field observations, Prozzi and Madanat (2004) presented a model using ASSHO road test experimental data initially before approximating the parameters once more through the application of joint estimation in conjunction with the field data set. Endogeneity bias can be avoided by using experimental data that has been carefully designed. However, Prozzi and Madanat (2004) failed to include seasonal effects and maintenance works, although they do claim that such data, if available, can be included in the model. This model demonstrates the value in applying joint estimation to enhance the accuracy of forecasts, reduce variance in estimations and prevent parameter bias. However, the model is limited by the fact that field data and experimental data is necessary for areas that experience similar weather conditions and maintenance activity level in the event that such information cannot be sourced.

A rather simple system for modeling the direct analysis of pre-treatment and post-treatment performance curves as well as treatment performance changes was developed by Haider and Dwaikat (2010). Treatment performance changes moderate the relationship between pre- and post-treatment performance curves. The authors examine the impacts of different treatment timings and cross-analyze the performance of pavements before and after treatment at different timing intervals. This approach distinguishes between pavement performance and maintenance effect models and also determines how to unify the effects with the performance model. However, this model is limited by the fact that it needs historical data relating to pre-treatment conditions in order to generate the post-performance curves and a variety of post-treatment datasets to generate a variety of post-treatment performance curves. The determination of the impacts of different treatment timings also necessitates the use of excessive post-treatment datasets, many of which may be difficult or too expensive to source.

2.3 MULTI-OBJECTIVE DECISION MAKINGS IN PMS

2.3.1 Pavement Management Decision Makings

The sections of pavement that require treatment are identified using decision support analysis tools. These tools also indicate what kind of treatment is needed and how much it will cost. Examples of such tools include ranking approaches and optimization techniques as presented in the AASHTO Pavement Management Guide (2001).

The ranking is a rather basic technique, and the results can be easily interpreted. Nonetheless, the ranking method is limited by its inability to incorporate varying constraints and does not typically generate the most optimal results. Optimization models are generally more effective at incorporating multiple constraints and resolving several issues at the same time. Theoretically speaking, optimization models are advantageous for PMSs in terms of operation research. However, in practice, these models have been heavily criticized for being overly complicated with results that cannot be easily interpreted. The optimal solution generated also requires modification in most cases taking into account political, social, economic or environmental factors that affect decision-making with regard to project selection (AASHTO, 2001). In order to obtain more equitable pavement management decisions, several highway agencies have implemented optimization models. Some others have implemented ranking methods due to a lack of expertise in the use of optimization models, insufficient data, or the absence of administrative support.

Optimization models used to perform network-level analysis can be either macroscopic or microscopic-based on how they are developed. It is possible to make model formulations and the determination of solutions easier by incorporating a range of various pavement classes as a proportion of the pavements used in macroscopic models, thus limiting the number of variables included. Nonetheless, decision variables pertaining to individual sections of pavement are incorporated into microscopic models, meaning that there is an excess of decision variables which causes the optimization process to become overly complex (Abaza, 2007).

A mathematical model that is used to determine the most appropriate pavement preservation or reconstruction treatments in terms of efficacy and cost-effectiveness is referred to as a maintenance optimization model. These models are often used in pavement management programs and are classified as either single objective or multi-objective.

According to Mbwana (2000), single objective optimization models generally have a number of different aims, namely to reduce costs, enhance the efficacy of treatments and enhance the condition or lifespan of the pavement. The costs incurred by the user and agency collectively throughout the lifetime of the facility are referred to as agency costs and are measured as a function of preservation activities. The costs incurred by users include accident costs, travel delays and vehicle operation in normal and work zone operations (Walls & Smith, 1998). These costs are measured as a function of pavement performance and the preservation activities performed (ARA, 2004). By seeking only to lower costs, the roughness of the pavement may increase. On the other hand, by seeking only to enhance pavement condition, the costs may increase.

In some cases, decision-makers may be satisfied to achieve only a single objective. Nonetheless, in most cases, the agency will seek to find an optimal solution that satisfies multiple objectives at the same time. There is a range of measures that can be taken to unify objectives that appear to be contradictory (Mbwana, 2000; Abaza, 2007; Lu 2011). Firstly, one objective can be optimized while applying the other objectives as fixed boundary constraints. For instance, the condition of pavements could be enhanced while limiting the amount of funding that can be allocated towards the activity or costs could be reduced while ensuring that a minimum standard of facility quality is maintained. Secondly, all objectives can be combined to form a single cohesive objective. For instance, user costs and agency costs are treated as a single objective as opposed to two contradicting objectives (Mbwana, 2000). Thirdly, a direct multi-objective optimization can be undertaken that takes all objectives into account. For instance, solution measures that seek to reduce agency costs while also enhancing pavement quality can be identified (Wu & Flintsch, 2008).

There are, however, limitations to these different methods. The first method is limited by the fact that it assumes knowledge of the optimal levels of the constraints applied and the fixed boundaries limit the optimal levels of the objectives. The second method is limited by the fact that all objectives must be transformed into a single unit and it is quite hard to convert certain costs into a single objective along with pavement roughness. In addition, while agency and user costs may be successfully converted into a single unit, many argue that this method assumes that marginal user costs are the same as marginal agency costs when non-highway users are taken into account (Mbwana, 2000). It has also been argued that the relatively large scale of user costs causes them to take precedence of lower agency costs (Wu & Flintsch, 2009) and the attempt to unify two costs is essentially unfeasible. The third method is limited by how difficult it is for the model to generate an optimal solution, particularly when multiple contradictory objectives are incorporated. As such, authors who implement a true multi-objective optimization model in the literature reviewed do not attempt to unify all objectives with many focusing on direct agency costs and pavement condition while others focus on direct agency costs and partial user costs (Worm & Harten, 1996; Labi & Sinha, 2003b; Wu & Flintsch, 2009; Wu & Flintsch, 2008). Broadly speaking, such models are limited by the fact that objectives cannot be assessed accurately and objectively (Wu & Flintsch, 2008). The models are also quite hard to develop on account of the complex objectives and constraints applied.

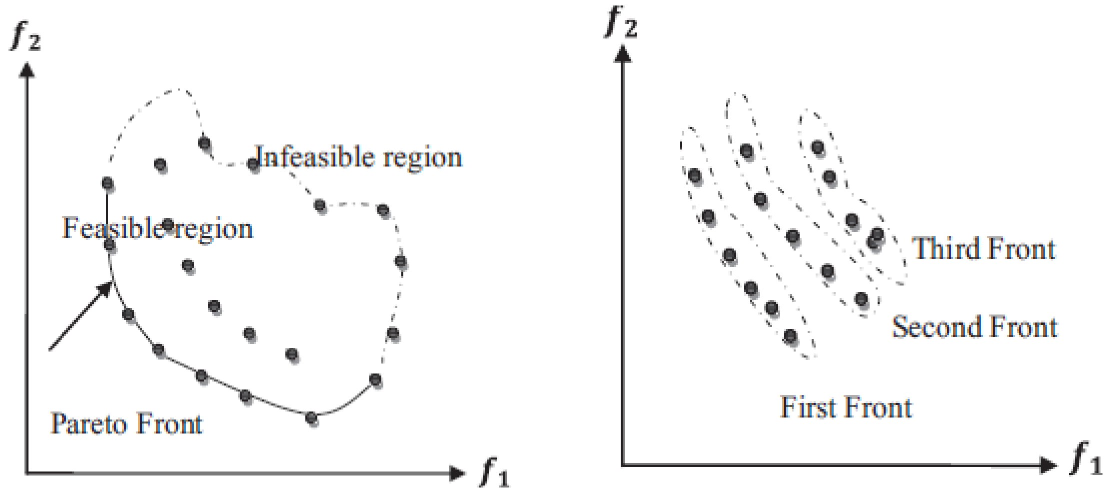
2.3.2 Multi-Objective Optimization Theories

The concept of optimization when dealing with single objectives is defined as the minimization or maximization of a specific objective. However, for problems that involve multiple objectives, an optimal solution can be hard to identify unless an improvement in one objective also leads to improvements in the others. In most cases, there is unlikely to be a single optimal solution for multiple objectives.

Highway maintenance agencies seek to reduce costs while also maintaining a low level of pavement roughness. However, these two objectives are directly contradictory as a reduction in costs will likely cause an increase in road roughness. In theory, an ideal solution would be to maintain roads with a low level of roughness at no cost. In practice, it is impossible to satisfy both objectives as there is no single optimal solution that successfully satisfies both criteria. Thus, the aim is to generate a range of solution options where pavement roughness and costs are applied as boundary conditions. In such cases, all proposed solutions will inevitably compromise one objective for the benefit of another. As such, the goal is to find a solution that is acceptable and balanced.

The range of solutions generated to resolve a multi-objective problem suffers from Pareto Efficiency or Pareto Optimality as there is no way to achieve improvements in one objective without compromising another.

Pareto optimality or Pareto efficiency is named after the Italian economist Vilfredo Pareto, who first introduced the concept in his studies (Pareto, 1906). Figure 1a illustrates the concept of Pareto optimality considering two objectives. The feasible region shown in Figure 1a represents all practical solutions for all objective functions in the system that satisfy all constraints. In the case of minimization function, the optimal solutions lie on the outermost lower-left edge of the feasible region. These sets of Pareto-optimal solutions are called the Pareto front. In multi-objective optimization, Pareto front sorting may be used to measure the fitness of a solution in a given iteration.



a. The concept of Pareto optimality b. Pareto-front sorting.

Figure 2.1 Concept of Pareto optimality and Pareto-front sorting (after El-Beltagy 2010)

Using Pareto-front sorting, the set of non-dominated solutions defining the Pareto front is identified and assigned a rank of one. These solutions are then set apart, and the remaining solutions are compared to identify a new set of non-dominated solutions with a rank of two. This process continues until the entire population is ranked, as shown in Figure 1b. A solution with a lower-numbered rank is assigned a higher fitness than a solution with a higher-numbered rank. Accordingly, for minimization problems, the fitness of each solution *i* is calculated by Equation 2.1 (El-Beltagy et al. 2010).

$$(\mathrm{Fitness})_{\mathrm{i}} = {}^{1}\!/_{(\mathrm{rank})_{\mathrm{i}}} \quad \ldots\ldots\ldots.(2.1)$$

Where, fitness and rank are the new fitness value and rank number, respectively, for solution *i*.

A balance between well-converged and well-distributed optimal solutions is the main goal of the multi-objective optimization process. The more diverse the solution, the better informed the decision maker is in the range of possible solutions. A multi-objective optimization is defined as the result vector of the decision variables that satisfy the constraints to give reasonable values to all objective functions.

The identification of a vector of decision variables that adhere to constraints and generate values for each objective function that are considered acceptable is referred to as multi-objective optimization. In mathematical terms, this is defined the vector X* = $[x_1^* \quad x_2^* \ldots \quad x_m^*]^T$ of *m* decision variables to optimize *n* objectives.

$$F(X) = [f_1(X), \quad f_2(X), \ldots \quad f_n(X)]^T \text{.........(2.2)}$$

subject to p inequality constraints

$f_i(X) \leq 0\,, \qquad i = 1, \ldots\ldots, p$

And q equality constraints

$h_j(X) = 0\,, \quad j = 1, \ldots\ldots, q$

Where, X = $[x_1^* \quad x_2^* \ldots \quad x_m^*]^T$ is the vector of *m* decision variables, and F(X) = $F(X) = [f_1(X), \quad f_2(X), \ldots \quad f_n(X)]^T$ is the vector of *n* objective functions, which must all be minimized.

Decision vector X* represents Pareto Optimality as it satisfies equality and inequality constraints in the feasible solution region *Ω*. Pareto Optimality is achieved only when or if $\forall_i \in \{1,2, \ldots, n\}, f_i(X^*) \leq f_i(X)$U $\exists$j $\in \{1,2, \ldots n\}, f_j(X^*) < f_j(X): X \in$ Ω.

In effect, X* achieves Pareto Optimality when there are no additional solutions that will dominate X * by benefiting all objectives at the same time. Typically, a multi-objective problem can be solved using a range of Pareto optimal solutions, also referred to as non-dominant solutions. All Pareto optimal vectors are contained in a Pareto set *P**.

A Pareto front $PF*$ is a set of vectors of objective functions that are generated by employing the decision variables vectors contained within the Pareto set. This is expressed as follows:

$$PF^* = \{ F(X) = (f_1(X), \quad f_2(X), \dots \quad f_n(X)) : X \in P^* \} \ldots\ldots (2.3)$$

To find a feasible solution for a multi-objective problem, it is necessary first to identify the Pareto set and its relevant Pareto front. A suitable solution can be selected from the Pareto set in light of personal preferences or other criteria.

2.3.3 Multi-Objective Optimization Solvers

The most common problem associated with multi-objective optimization is the fact that none of the feasible solutions generated offer optimal solutions that satisfy all objectives equally. While there are several methods of resolving multi-objective issues, they can be broadly classified as either the converted single objective approach or the Pareto non-dominant solutions approach (Messac 2003). The former aims to create a single objective function that reflects the needs of the decision maker with the solutions generated assumed to be optimal. The latter approach, on the other hand, generates Pareto optimal solutions and the decision maker then determines which is most suitable in light of their own preferences or requirements.

2.3.3.1 Goal Programming

Goal programming is perhaps the most widely applied first class solver approach, and this aims to assign a specific numeric goal to each objective and enables deviation in a negative or positive direction, or perhaps even both. Lower bound, upper bound and two-sided bounds are the three-goal types. This approach can also be classified on the basis of goal prioritization as non-preemptive goal programming and preemptive programming.

A priority hierarchy is needed for preemptive goal programming and is easy to apply when one goal is clearly more important than the rest. Thus, the most important goal is assigned first priority while the others are ranked in descending order of importance. Using this system, the aim is to find a solution that deviates the least from the highest priority goals.

On the other hand, using the non-preemptive approach, it is assumed that all goals are of equal importance and they are thus assigned equal priority. In such scenarios, the objective function is measured as the overall sum of how far these objectives deviate from their goals. Alternatively, the penalty-weighted sum of all deviations can be used. Using this approach, the aim is to identify a solution that limits the overall extent to which these objective functions deviate from their respective goals.

For multi-objective problems with conflicting goals, goal programming is a dependable, flexible and easy to use the method of finding an optimal solution. According to Wu and Flintsch (2008), this method’s main aim is to limit deviations, which distinguishes it from the relative scales of the original objective functions. However, goal programming is limited by the need for decision-makers to have prior knowledge of how to allocate and rationalize relative weights to each deviation and how to clearly determine which objectives should be given priority. The solution generated using this method is presumably optimal in terms of the decision maker’s personal requirements. This method is also limited by the fact that it directly compromises the goals of certain objectives and does not facilitate a trade-off between goals of varying priority levels using the preemptive method. Furthermore, goal programming is unable to generate Pareto optimal solutions every time. According to Marler and Arora (2004), goal programming generates Pareto optimal solutions in the event that all goals are unachievable while non-Pareto optimal solutions can be generated using the non-preemptive method.

2.3.3.2 Weighted Sum Method

Another kind of solver is to identify the Pareto optimal solutions for all contradictory objectives, an approach that is ideal as it can generate solutions that cause minimal conflict and does not necessitate previous experience in allocating weight (Pareto, 1906). The weighted sum method is one of the most common means of determining Pareto optimal solutions (Wu & Flintsch, 2009; Das & Dennis, 1996; Srinivas & Deb, 1994; Cohon, 2013). Using this method, the multiple objectives are weighted and converted into Z – a single objective function – which can be expressed as follows:

$$Z = \sum_{i=1}^{n} \omega_i f_i(x) \quad \ldots\ldots\ldots\ldots\ldots\ldots (2.4)$$

In the above equation, the fractional weight values in the range 0-1 are denoted by (ω_i).

Using this approach, the control of the weight vector for all possible weight situations along with an incremental step in ω_i facilitates the identification of Pareto optimal solutions as all weights are converted into a single unit. The weight of each respective objective can be modified to assign priority. This method is widely used in the literature as it is easy to apply and relatively intuitive (Wu & Flintsch, 2009). The weight assigned to each objective is determined on the basis of the size of each objective function. However, the weight values do not reflect the relative importance of each objective but the relative significance of relationships (Wu & Flintsch, 2009). For instance, while $\omega_1 > \omega_2$ implies that $f_1(x)$ is of greater importance than objective $f_2(x)$, but cannot assume that objective $f_1(x)$ is (ω_1/ω_2) times more important than objective $f_2(x)$. This reflects one of the limitations of the model as decision makers often find it hard to interpret the quantitative relationships between objectives and thus have difficulty choosing the ideal solution for their own requirements. For instance, the difference between $\omega_1 = 0.6$ & $\omega_1 = 0.4$ and $\omega_1 = 0.7$ & $\omega_1 = 0.3$ is hard to identify as each weight set implies that $f_2(x)$ is less important than $f_1(x)$ but does not offer any additional information. According to Wu and Flintsch (2009), the decision maker using the incremental weight step approach requires theoretical knowledge of their own preferences before choosing the most suitable Pareto optimal solution. In addition, the decision maker will struggle to select and interpret a weight factor as the weights do not offer any qualitative information.

The concern in which the objectives are converted into a single objective using different scales is an additional limitation of this method as the widely used weighted linear sum approach necessitates that all weighted objective functions are transformed into a single objective function. The user must then identify the Pareto optimal solution by minimizing or maximizing one of the objectives. The scales employed and the objective function units often vary. For instance, the user may seek to reduce agency costs and enhance the IRI values of pavement surface condition. Agency costs are typically calculated in dollars within a range of $1,000 to $100,000 or more. IRI values, on the other hand, are calculated in m/km on a scale of 0.5 to 3m/km. Thus, the scale for each objective is clearly different as well as the objective units and to combine the total of each is essentially unfeasible (Messac, 2003). Wu and Flintsch (2009) argue that while the user may attempt to convert the values using the same scale, the variation in objective units would still limit the applicability of the totals. Therefore, as variation in units prevents summation offering any meaningful data, weights are allocated to each objective. Nonetheless, these weights do not provide any insights into how each objective is related. Finally, in the event that the true Pareto frontier or the objective to be minimized is not globally concave, the weighted sum method is unlikely to generate any valid or meaningful solutions (Das & Dennis, 1997).

Alternatively, there are other ways of finding Pareto optimal solutions. For instance, the objectives can be converted into aggregate objective functions (AOF) where several objectives are combined into one. By developing AOF using the weights originally assigned to each objective where a Pareto optimal solution is generated for each set of weights, the normal boundary intersection method (NBI) (Das & Dennis, 1996), the normal constraint method (NC) (Messac 2003), and successive Pareto optimization method (SPO) can be used to resolve the multi-objective problem. These methods overcome at least one of the limitations associated with the weighted sum approach. More specifically, the NBI method has the ability to find Pareto solutions for a Pareto frontier that is non-convex while the NC method can generate solutions along the periphery or true Pareto front. NBI and NC can also generate a Pareto frontier than is distributed evenly as they resolve the issues associated with the relative scale of objectives. SPO, on the other hand, has the ability to systematically find solutions near the periphery. All of these approaches, the weighted sum method included, can be classified as AOF approaches as their function lies in creating a single objective by combining multiple objectives and experience in allocating weight to each objective is needed in order to select the most suitable Pareto optimal solution. Wu and Flintsch (2009) argue that these methods are all equally as effective and the choice of solution relies largely on the requirements of the decision maker, available data and software resources (Marler & Arora, 2004).

2.3.3.3 Genetic Algorithm

The use of a single-objective optimization engine to resolve multi-objective issues forms the basis of the multi-objective methods discussed thus far. These methods are often deployed using classical search engines in conjunction with a point-by-point rule. Thus, they must be implemented several times in order to generate Pareto optimal solutions as only one solution can be generated per iteration. Nonetheless, there are alternatives that can be used. For instance, in 1984, the genetic algorithm (GA) was put forward by Holland (1975) as an evolutionary algorithm that has been widely used for multi-objective problems from 1993 onwards. This method is a non-standardized optimization approach that is population-based and is perhaps the most widely used algorithm for finding direct Pareto-optimal solutions in a single iteration.

GA seeks to emulate the theory of natural selection as it is assumed that those who are fitter and healthier will naturally survive in a given environment and reproduce. Every person within a specific environment has a number of attributes that measure their level of suitability. The fittest of these people generally survive, and the subsequent generations inherit these attributes and increase their odds of survival as they inherit the best attributes from each parent. Thus, beneficial attributes are maintained in the environment while unfavorable ones are eliminated, thus ensuring the positive development of the population.

Every person has a string of genes or DNA that determines their unique characteristics. During reproduction, the DNA strings of two people combine to create a brand new string of DNA for the offspring that contains elements of each parent strand. Mutation occurs when a specific gene does replicate that of the parent exactly.

The following processes form the basis of the GA:

- Encoding – the string of DNA is defined, incorporating the variables and characteristics of decisions and, and the objectives are delineated.
- Initialization – an initial population of possible solutions is presented.
- Evaluation – the effectiveness or 'fitness' of each proposed solution is assessed in light of objectives and other constraints.
- Selection – two of the most favorable solutions are selected.
- Crossover – offspring of these two solutions are generated at different points on the DNA string to create two additional solutions.
- Mutation – Use mutation probability to mutate the DNA of the offspring solutions.
- Evaluation – Assess the feasibility of the new solutions in light of the objectives.
- Reiteration – Repeat the cycle again

A considerable number of cycles are usually performed using this method with a large number of populations to find the most suitable Pareto optimal solutions.

Population size, iteration number, crossover rate and mutation rate are the primary criteria applied when using GA.

There are several key differences between GA and other optimization methods (Liu & Hammad, 1997). For instance, GA does not generate a single solution but instead seeks to enhance the feasibility of a range of solutions based on random initialized populations, data derived from prior cycles and the objectives. Thus, GA can be modified with ease to generate Pareto optimal solutions. On the other hand, traditional optimization models generally focus on generating one solution at a time. Furthermore, GA facilitates the incorporation of a wide range of parameters as objective functions or decision variables, which means that the method can generate valid solutions irrespective of the specific decision variables or objectives. In effect, the method operates autonomously from the nature of objective functions and constraints (Liu & Hammad, 1997). Thus, GA is an ideal method when using a wide range of contradictory objectives or decision variables. GA also enhances the outcome of the solution identification process by incorporating non-fit characteristics and maintaining the most favorable as opposed to performing the search on the best-fit string alone. This method also enhances the process by enabling population variation on account of mutation, which is why GA would perform well as a global searching instrument.

According to Liu and Hammad (1997), the effectiveness of GA in assessing the feasibility of solutions to multi-objective problems is the main issue as the concept of fitness determines the assessment methods used by the model. Marler and Arora (2004) classify these methods as (1) vector evaluated genetic algorithm (VEGA); (2) ranking; (3) Pareto-set filter; (4) tournament selection; (5) niche techniques; (6) fitness sharing; and (7) additional techniques. That being said, none of these methods is inherently better than the others as the most suitable method will depend on the needs of the decision maker and any other relevant data (Marler & Arora, 2004). In terms of negative criticism regarding the GA model, several authors have argued that the quality of convergence to true Pareto-optimal solutions generating using this method varies according to population size and number of cycles while the model is also cost-intensive to run in terms of computational power (Marler & Arora, 2004; Harik, 1997). Also, there is no single generality that can be applied to perform GAs and the values of parameters are different in different circumstances. The management of constraints is an additional issue that could potentially compromise the quality of the convergence to Pareto optimal solutions.

In conclusion, no problem-solving operation or process that performs more efficiently than the others when attempting to resolve multi-objective optimization problems. The method used will depend on the needs of the decision makers (agencies), available data, software resources and the anticipated outcome. In this case, the author intends to develop a brand new simulated constraint boundary model that can generate Pareto optimal solutions. This new solver model will be formulated using Statistical Analysis Software (SAS) version 9.3.

2.4 ENVIRONMENTALLY PREFERABLE PAVEMENT MANAGEMENT SYSTEM

2.4.1 The relationship between Pavement Roughness and Fuel Consumption and Greenhouse Gas Emission

Studies have shown increased in vehicle operation costs on rough pavement due to the decrease in fuel economy. World Bank performed the main studies on the effect of pavement roughness on fuel economy on unpaved, gravel, or earthen roadway surfaces in developing countries in order to improve and revise the Highway Design and Maintenance (HDM) models that excessively applied (Bennett and Greenwood 2001; Chesher and Harrison 1987; Watanatada et al. 1987). These models were calibrated to U.S. roadway status since they were not developed on roughness data in the U.S. (Chatti and Zaabar, 2012)

De Weille (1966) used the data from previous literature in US to find a relationship between fuel consumption and pavement surface type. The researcher used three different pavements surfaces in his study; gravel, earthen, and smoother paved roadways. The researcher mentioned that the fuel consumption was 20% higher on gravel roads than paved roads and 40 % higher on an earthen road. Also, Missouri Department of Transportation (MoDOT) reported about 2.5% increase in fuel efficiency on new pavement comparative to the rough pavement before resurfacing (Amos, 2006).

Ross (1986) found a nonlinear relationship between fuel consumption and pavement roughness using five test sites with serviceability index (SI) ranged from 0.9 to 4.4. This study reported that about 3% increase in fuel consumption between the smoothest (SI = 4.4) and roughest (SI = 0.9). Another conclusion found in Ross study is that the increase in fuel consumption could be estimated with a linear function even the relationship was nonlinear such that 1.5% more fuel would be consumed on the pavement with an SI of 1.5.

Regardless of the lack of statistical calculations to determine the association between roadway roughness and fuel consumption, such an association is still proposed by various researchers. Sandberg (1990) determined that that up to a 12% increase in fuel consumption is seen when a surface alters from a smooth to rougher texture. Nevertheless, the impact on fuel consumption of pavement roughness is difficult to calculate with a discounting of additional variables, thus is difficult to support with quantitative data.

Hugo and Martin (2004) also emphasized that a 2% elevation in fuel consumption is an outcome of an alteration in IRI to 1.18 m/km (75 in/mi) from 1.08 m/km (68 in/mi). Regardless, Gillespie and McGhee (2007) noted that the age of a vehicle was not taken into consideration. Santero (2009) suggested that roughness would not appear to have such an impact on the calculated values for fuel consumption if vehicle age was accounted for.

On the other hand, there are many experimental and theoretical methodologies were used to investigate the effect of pavements stiffness, smoothness, and texture on rolling resistance and fuel consumptions. Surface texture and roughness generate vibrations in vehicle tires that cause an increase in fuel consumption.

For passenger cars, Beuving et al. (2004) reported that different pavement textures influence fuel consumption by approximately 10% and there is no difference in fuel consumption between asphalt and concrete road surfaces. Furthermore, surface roughness has a proven enormous influence on the fuel consumption and noise development. Taken these aspects into consideration the total truck and passenger car population might easily result in an advantage in fuel consumption for asphalt pavements.

In order to predict the total fuel consumption, Bester (1984) investigated the effect of pavement type and roughness on the rolling resistance of vehicles. Except for gravel pavement surfaces, the researcher found that the pavement type has an insignificant effect on fuel consumption and the roughness correlates strongly with rolling resistance.

Ardekani and Sumitsawan (2010) undertook research for the University of Texas, Arlington, replicating a city driving environment on both Portland Cement Concrete and Asphalt Concrete surfaces, to investigate the relationship between CO_2 emissions and fuel consumption. The assessment considered vehicle speed, acceleration, roadway grade, IRI and pavement type. The association between pavement materials and fuel consumption levels to more effectively design urban environments, in terms of longevity of surfaces and reducing expenditure, was the primary aim of the investigation, regardless of the assessment of IRI. Consequently, the association of CO_2 emissions and fuel consumption to IRI was not the focus of the research.

Kalemb et al. (2011) investigated the correlation between CO_2 emissions and the pavement roughness. CO_2 emissions quantities were computed using MOVES2010a, a vehicle emission modeling software program. They concluded that there is a slight increase in the mean speed value from roads in poor condition to roads in either fair or good condition, which causes a decrease in CO_2 emissions.

In term of GHG emissions and costs associated with roughness, the effects of roughness on fuel economy and costs has been quantified by several researchers

(Schuring 1988). The Schuring (1988) study is motivated by the tire industry's analysis of rolling resistance due to various tire formulations.

For non-fuel-based user costs, the challenge is to find user costs as a function of pavement roughness. The Paterson (1987) study is a standard reference, but the age of the study and the fact that the costs are estimates in Brazilian pesos makes application to California over twenty years later less than ideal. Barnes and Langworthy (2004) published a semi-meta-analysis on this issue ("semi-meta" as some data is original). The non-fuel-based user costs due to pavement roughness (maintenance/repair, tires, and depreciation) used in the case studies are based on their results.

Recently, two common models related to rolling resistance and fuel consumption were developed. One of these models was developed by Chatti and Zaabar (2012) for vehicle operating costs. The fuel consumption model was adjusted over several pavements using light, medium and heavy vehicles. The second model was developed for rolling resistance In Road Infrastructure Asset Management systems called (MIRIAM) (Hammarstom et al. (2012). The model was developed based on empirical results from coast-down measurements in Sweden, and includes impacts of pavement roughness, macrotexture, temperature, speed, horizontal curvature and the road grade. The model was developed for three vehicle types: car, heavy truck, and heavy truck with a trailer.

2.4.2 Life-Cycle Assessment of Pavement Maintenance and Preservation

The concept of life-cycle assessment is to evaluate the environmental effects associated with any given activity from the initial gathering of raw material from the earth until the point at which all residuals are returned to the earth. This concept often referred to as “cradle to grave” assessment, is not new. While the practice of conducting life-cycle studies has existed for more than 30 years, there has been few comprehensive studies to describe the procedure in a manner that would facilitate understanding of the entire process, the underlying data, and the inherent assumptions.

Life Cycle Assessment (LCA) is the most popular approach to assessing the effects of transportation on the environment. On pavement systems, the goal of LCA is to fully explain the direct and indirect processes that are associated with infrastructure decisions. This approach is therefore very useful in evaluating the environmental performance of pavements throughout their life cycle.

A major issue of usage phase revolves around the consequences of pavement and vehicle interaction on the environment. These consequences are influenced by pavement properties, including surface characteristics (roughness and texture) and structural deformation. Pavement LCAs typically insufficiently address the environmental impacts of the use phase because of time, data, and model constraints (Santero et al. 2011). The phases of pavement LCAs focus on construction, with evaluators using comparative analyses to justify the disregard of use phase effects and adopting simplified assumptions (such as the use of average speed) to develop rough estimates that do not fully account for the impacts of different pavement types (Hakkinen and Makela 1996; Treloar et al. 2004). In general, different degrees of pavement stiffness, roughness, and degradation result in varying energy consumption and emission levels. Taylor and Patten (2006) compared emissions from tandem drive tractors that pull semi-trailers on asphalt and concrete roadways and found that traveling at 100 km/h on concrete road surfaces produced fewer emissions.

Many studies have been done for life cycle assessment (LCA) of pavements. For example, Yanowitz et al. (2000) reviewed the in-use emissions from over-the-road heavy-duty diesel vehicles. Many techniques were used in their study measuring emissions, such as chassis dynamometer, tunnel studies, and remote sensing. They concluded that carbon monoxide (CO) and particulate matter (PM) emissions increased significantly with an increase in the inertial weight. The researchers also observed little change in emissions between different vehicle sizes, and nitrogen oxides (NO_x) remained the same. In this study, the energy was calculated using vehicles per pavement section, considering the traffic in each direction. They concluded that the energy and GHG emissions caused by traffic were greater than the energy and emissions during the construction phase. Additionally, the researchers found that the change in traffic intensity produced more GHG emissions.

Most studies have been directed to provide sustainability indicators for pavement systems using LCA. Different structural design and rehabilitation techniques were considered, including flexible and rigid pavement, overlay, reconstruction, and cold in-place recycling (Thenoux et al. 2006; Weiland and Muench 2010; Yu and Lu 2012). The surprising results showed that the Hot Mix Asphalt (HMA) consumed a high amount of energy as compared with the other preservation options, while the global warming impact is highest in the Portland cement concrete (PCC) option. On the other hand, the smallest effect on the environment from the viewpoint of energy consumption is also achieved by cold in-place recycling.

Many studies evaluated the cost-effectiveness of pavement preservation and their energy and environmental impacts. As known, Pavement preservation treatments considered as the most consuming amounts of energy and generate GHG emissions. Different pavement preservation techniques can produce different pavement surfaces with various amounts of emissions. Preservation type has a significant effect on the usage cost of vehicle operation. Therefore, efficient preservation techniques are preferred to estimate the environmental impacts of its whole life cycle.

Mallela and Sadasivam (2011) calculated emission vehicle costs as a function of vehicle miles traveled and unit costs ($/ton) by the emission type. They included Volatile Organic Compounds (VOC), carbon monoxide (CO), oxides of nitrogen (NOx), sulfur dioxide (SOx), and Carbon dioxide (CO_2) for calculating air pollutant emissions and GHG emission. They also estimated that emissions costs were a function of vehicle miles traveled (VMT) and unit costs (dollars per ton).

Wang et al. (2012) confirmed that during the usage phase of pavement, the savings in energy and GHG emissions increased as the tire rolling resistance decreased. In addition, they concluded that the rehabilitation of higher traffic volume pavement with a rough surface had more potential to reduce fuel consumption and GHG emission, while the construction quality and materials for a low traffic road played a significant role in payback time for energy use and emissions. In other words, rehabilitation of a rough pavement surface with high traffic volume causes a higher reduction in fuel consumption and GHG emissions if compared to pavement with low traffic volume. Furthermore, Wang et al. (2012) incorporated the effects of IRI by developing equations that relate IRI to the default parameters in MOVES to examine the effect of pavement roughness on energy consumption; however, these modified equations have yet to be applied for the use phase. In addition, their approach did not consider vehicle type responses to pavement degradation. Wang et al. (2012) proposed updating the rolling resistance coefficient (A) in MOVES using the ratio of the rolling resistance on existing pavement surface on the default rolling resistance on a smooth surface.

In 2014, Gangaram developed LCA model to quantify the impact of pavement preservation on energy consumption and GHG emissions. The Highway Development and Management Model (HDM-4) and the Motor Vehicle Emission Simulator (MOVES) were used in this study. HDM-4 was used to measure the effect of tire rolling resistance on pavement surface characteristics, and MOVES was used to get the vehicle energy consumption and GHG emissions. Gangaram stated that “the thin overlay had the highest energy consumption and emissions among four preservation treatments during the construction stage, but at the same time resulted in the greatest reduction of energy and emission at usage stage.” In addition, the reductions in GHG emissions at the usage stage are much higher than the GHG emission produced in the construction stage for all preservation treatments.

2.4.3 Multi-Decision Making in PMS considering Cost and Environmental Impact

The impact of pavement maintenance on rolling resistance and vehicle operating costs from a lifecycle perspective should be considered in PMS. For example, the minimal maintenance cost alternative for rehabilitating a pavement may be to apply minor maintenance at a defined number of intervals. However, a more extensive rehabilitation may reduce the rate of deterioration of pavement distresses and the rate of increase in surface roughness, which leads to a reduction in the fuel consumption, total vehicle operating costs, and vehicle emissions.

Several studies have attempted to integrate pavement management operations with LCA to reduce environmental impacts. Zhang et al. (2010) developed a life-cycle optimization (LCO) model to calculate an optimal preservation planning for a pavement overlay system and to reduce the greenhouse gas (GHG) emissions, total life-cycle energy consumption, and costs within an analysis period. Zhang et al. (2010) used dynamic programming optimization techniques to minimize the environmental impacts in the pavement life cycle for project level case studies and a very small local road network, respectively and used relatively simple emission models by optimizing the M&R frequency and intensity through multicriteria decision analysis. The LCO model has applied both concrete and hot mix asphalt overlay system. For the concrete, the LCO results showed that the optimal preservation strategies would reduce the total life-cycle energy consumption, GHG emissions and costs by 5–30%, 4–40%, and 0.4–12% respectively.

Giustozzi et al. (2012) presented a multi-criteria approach for evaluating preventive maintenance activities that included costs, performance, and environmental impact measures during the analysis. Several maintenance strategies were evaluated based on the measures, and a method for comparing all strategies by rescaling each measure was developed. The first step in their analysis was to define the strategies, as well as the associated life-cycle cost for each strategy. Then the performance was calculated as the area under the curve defining the condition as a function of time. Finally, the energy consumption and emissions related to each strategy were calculated for the materials and construction phase of the LCA. The measures were all scaled between zero and one, with one representing the worst case and zero representing the worst case value, and the rescaled values were weighted and summed to calculate a single index.

At the network level, sustainable pavement management practices include designing maintenance strategies and selecting projects considering impacts related to the triple bottom line of sustainability. This may include modifying the objectives of a network level analysis to consider multiple criteria beyond cost and condition. The resulting multi-objective decision problem of the network level pavement management was converted to a single objective problem by treating some of the objectives as the constraints (Wu and Flintsch 2009). In this way, an agency seeks to maximize or minimize one particular objective (e.g., minimizing the cost divided by the performance of the pavement condition) subject to constraints that arise from the original objectives (e.g., budgetary constraints or constraints defining a minimum allowable pavement condition).

At the project and network levels of pavement management, Bryce (2014) presented in his dissertation many papers about the impact of decision making on the environmental impact of pavement. Bryce et al. (2014) revealed that the required energy consumption from maintenance can be offset by improving road conditions that resulted in the reduced rolling resistance. However, for a given network condition this adjustment of reduced energy consumption also included the increased costs. Based on their results, it is not necessary that the lowest energy consumption values place along the line defined by reducing the cost divided by the pavement condition.

On pavement resurfacing problems, Lidicker et al. (2013) extended the continuous-time to solve the multi-criteria problem based on two main objectives;

minimum cost and emission. Two case studies in California with two different traffic volumes (high and light) were used in their study. The researchers concluded that minimum achievable roughness and traffic loadings had a significant role to increases or decrease total GHG emissions. For the same smoother rehabilitated pavement, the low traffic volume produced lower emission than heavy traffic. Heavy traffic sections forced more frequent overlays, while the smoother pavement created more emissions.

To improve the pavement maintenance schedule optimizations, Yu et al. (2013) developed a methodology to incorporate the environmental damage cost (EDC) in the cost evaluation systems. In general, The researchers combined life cycle assessment (LCA) to life-cycle cost analysis (LCCA) model to optimize the pavement maintenance plans using EDC. Three overlay systems were used a case study which is hot mix asphalt (HMA) overlay, Portland cement concrete (PCC) overlay, and crack, seat, and overlay (CSOL). The optimized maintenance plans a reduction between 9–13 % energy/GHGs and 6–10% regarding holistic costs compared to the before optimization plans.

On concrete bridge infrastructure, Kendall et al. (2008) developed an integrated life-cycle assessment and life-cycle cost analysis model (LCA-LCCA) to enhance the sustainability. Two different bridge decks were used in their study: a conventional mechanical steel expansion joint design and an Engineered Cementitious Composite (ECC) link slab design. When these bridge decks were evaluated over the entire life cycle, the study concluded that the slab design resulted in lower life-cycle costs and reduced environmental impacts. Due to traffic delay caused by construction, costs to the funding agency include less than 3% and 0.5 % of total costs and environmental costs, respectively. Also, an integrated model; LCA-LCCA; was applied to other road infrastructure applications including pavement overlays.

Gosse et al. (2013) proposed an expanded PMS framework to include greenhouse gas (GHG) emissions by utilizing a multiobjective genetic algorithm (GA). In this study, the model suggested different maintenance plans that produce higher network pavement performance with lower costs and GHG emissions. Also, this study found that the optimized management strategy could achieve the same network pavement performance with 60% and 50% of the cost and GHG emissions respectively.

CHAPTER 3 EMISSION MODELS DEVELOPED WITH MOTOR VEHICLE EMISSION SIMULATOR (MOVES)

3.1 OVERVIEW OF MOTOR VEHICLE EMISSION SIMULATOR (MOVES)

Motor vehicle emissions are a crucial factor in estimations of air pollution, which is a critical concern for planners, engineers, and policymakers. Many tools, such as the U.S. Environmental Protection Agency's (EPA), Motor Vehicle Emission Simulator (MOVES), the California Air Resources Board's Emission Factors (EMFAC) model, and the Comprehensive Modal Emissions Model (CMEM), have been developed to calculate and measure pollutant emissions from motor vehicles (EPA 2012).

HC, CO, CO_2, NO_x, CH_4, N_2O, PM_{10}, and $PM_{2.5}$ are a conventional vehicle and pavement outputs that adversely affect human life. Taking these emissions into account is very useful in estimating the discharge of different kinds of harmful pollutants on the basis of vehicular volumes and environmental conditions (Ozguven et al. 2013). Since 2010, two officially approved mobile source emission models have been typically used in transportation conformity: the MOVES and EMFAC models developed by the EPA and California Air Resources Board, respectively. Many studies focused on comparing these models to estimate emission levels accurately. Examples include the research conducted by Chamberlin et al. (2011) and Bai et al. (2009). The authors indicated that the new features of MOVES make it a superior tool for emission modeling and analysis.

MOVES is Motor Vehicle Emission Simulator that is used to calculate emissions from all on-road vehicles that travel over various types of roads (EPA 2012). MOVES was developed in 2010 and updated in late 2012. The EPA replaced previous emissions model for on-road mobile sources, namely, the MOBILE model with MOVES. MOVES more accurately estimates the impacts of changes in operational traffic than do older MOBILE models, as determined by comprehensive analyses of the differences between MOVES and the latest version of MOBILE. These studies revealed that apart from the distinct advantage of the new interface provided by MOVES, more accurate database development and increased availability of default data are presented by the model. Compared with MOBILE, MOVES is more sensitive to speeds and estimates higher levels of emissions, except for CO. It also includes an analysis of emissions from idle vehicles feature that adds a more active and influential factor to the model.

The MOVES interface presents different geographical scales, such as national, county, state, and multi-state levels, but a user must provide all necessary geographical information, including grade, vehicle type and speed, road type, fuel type, and time frame. There are many calculations steps for predicting energy consumption and emission by using the input and the default information present in the MOVES model. Two of the important steps are the importing and exporting of files from MOVES. These data include information about vehicle specific power (VSP), rolling resistance coefficient, vehicle age distribution, vehicles miles traveled (VMT), and vehicle age distribution. MOVES files also contain various types of information that are related to different parameters, such as speed, grade, roughness, texture depth, traffic volume, and engine running status. The model simultaneously analyzes these parameters to derive emission level output.

Vehicle Specific Power (VSP), which distinguishes between running modes, is one of the important factors in calculating engine running status. It is indirectly related to energy consumption and traffic emissions (EPA 2012). The VSP indicated in MOVES represents the engine running status for emission calculation, as presented in Equation 3.1. This equation is defined as the engine power per unit mass of a vehicle and reflects a vehicle's power demand for operation over various conditions and speeds. VSP also includes some important components for calculating vehicle speed second by second for different emission types. Equation 3.1 is expressed as follows:

$$VSP = \frac{A}{M} \times v + \frac{B}{M} \times v^2 + \frac{C}{M} v^3 + (a(1 + \varepsilon_i) + g \times grade) \times v \ldots\ldots\ldots (3.1)$$

Model coefficients *A*, *B*, and *C* refer to rolling resistance components, higher order rolling resistance and mechanical rotating friction, and air drag, respectively, with the coefficients expressed in units of kW·s/m, kW·s^2/m^2, and kW·s^3/m^3, respectively; M is the vehicle mass; and v denotes the instantaneous speed. Coefficients a and ε_i are the vehicle acceleration and mass factor terms. *A*, *B*, and *C* are not input data but are stored in the MOVES model database. They are unique to each vehicle type and can be modified by users. Modifying these coefficients for different levels of roughness enables the consideration of roadway surface conditions in simulations.

The default values of *A*, *B*, and *C* are derived from the track load horsepower indicated in the Mobile Source Observation Database (MSOD) (U.S. EPA 2010a). The default value of the rolling resistance coefficient (*A*) is obtained from vehicle dynamometer tests, in which vehicles run on a smooth surface, usually steel (EPA 2010b). For this reason, the influence of pavement surface characteristics on vehicle operation is disregarded by the default VSP model in MOVES. Furthermore, *A*-value cannot be used directly in MOVES without adjustments.

3.2 CONSIDERATION OF ROAD SURFACE CHARACTERISTICS IN MOVES

Pavement life cycle assessment at the use stage mainly focuses on fuel consumption and consequently, pollutant emissions due to the effect of tire rolling resistance on vehicle operations. The rolling resistance is the vehicle energy loss associated with the tire-pavement interaction, which is affected by tire properties, pavement surface deflection, and surface characteristics at a different wavelength (roughness and surface texture) (Descornet, 1990).

To calculate the VSP terms, two types of models were used in this work with different terms. The first model was based on Wang et al. (2012) study, which considered the effect of rolling resistance coefficient (A) in MOVES and speed on emission. The other model was based on Ghosh et al. (2015) study using rolling resistance coefficient (A), air drag coefficient term (C), and speed.

3.2.1 Model 1: Updating Rolling Resistance Coefficient (A)

Wang et al. (2012) incorporated the effects of IRI by developing equations that relate IRI to the default parameters in MOVES to examine the effect of pavement roughness on energy consumption; however, these modified equations have yet to be applied for the use phase. In addition, their approach did not consider vehicle type responses to pavement degradation. Wang et al. (2012) proposed updating the rolling resistance coefficient (A) in MOVES using the ratio of the rolling resistance on existing pavement surface on the default rolling resistance on a smooth surface. The relationship is presented in Equation 3.2 below. In Wang et al.'s procedure, the rolling resistance at the tire-pavement interface was calculated based on the Highway Development and

Management Tool (HDM-4). The HDM-4 presented by World Bank included a model to quantify the vehicle operating cost for road management and planning (Bennett and Greenwood, 2003). The rolling resistance forces are functions of different parameters, such as pavement conditions, tire parameters, and vehicle characteristics. Equation 3.3 shows the effects of pavement surface roughness, macro-texture, and deflection on tire rolling. Two steps are required to estimate emissions. Equations 3.2, 3.3, and 3.4 by the HDM-4 model were used to calculate rolling resistance as the first step, and then the MOVES model was used to calculate the fuel consumption and emissions as the second step. The MOVES default values of rolling resistance coefficient (A) and the parameters (α_0, α_1, α_2, and α_3) in the HDM-4 model are listed in Table 3.1.

$$A_{updated} = A_{default} * (CR_{2pavement}/CR_{2dynamometer}) \ldots\ldots \quad (3.2)$$

$$(F_{rolling})_{HDM-4} = CR_{\,2}.\,FCLIM \times (b_{11}\,.\,N_w + CR_1 \times (b_{12}\,M + b_{13}\,.\,v^2))\ldots\ldots \quad (3.3)$$

$$CR_2 = Kcr_2\,.\,(\alpha_0 + \alpha_1\,.\,MPD + \alpha_2\,.\,IRI + \alpha_3\,.\,DEF) \ldots\ldots \quad (3.4)$$

Where,

$A_{updated}$ = updated rolling resistance coefficient used in the calculation,

$A_{default}$ = default rolling resistance coefficient in MOVES,

$CR_{2pavement}$ = rolling resistance on real pavement surface,

$CR_{2dynamometer}$ = rolling resistance on a smooth surface (both IRI and MPD vlaues are zero),

$(F_{rolling})_{HDM-4}$ = rolling resistance from HDM-4 software;

CR_1 = rolling resistance tire factor;

CR_2 = rolling resistance surface factor;

M = mass of the vehicles;

N_w = number of wheels; and

v = speed

b_{11}, b_{12}, and b_{13} = coefficients related to tire type and other technologies;

Kcr_2 = a calibration factor

FCLIM = climatic factor related to the percentage of driving snow and rain;

α_0, α_1, α_2, and α_3 = coefficients for pavement surface characteristics from HDM-4 model;

MPD = mean profile depth in mm,

IRI = international roughness index in m/km, and

DEF = pavement surface deflection in mm (using Benkelman Beam).

The MOVES model is equipped with a built-in database that is used as default data based on some inputs in the first step to calculate emissions. The MOVES model default data need to be combined with the other input data of the project to get emission outputs.

Some default data result from dynamometer tests of vehicles. A dynamometer test is conducted by running the vehicle on a smooth steel surface (Wang et al., 2011). Based on this test, both IRI and MPD values are zero because a steel surface is much smoother than the actual pavement while the passenger car DEF is also zero. Thus, the contribution of pavement surface characteristics to vehicle operation is considered by updating the rolling resistance coefficient (A) in MOVES. Wang et al. (2012) established a relationship between $A_{updated}$ and $A_{default}$, which is mentioned in Equation 3.2.

IRI must be updated for different preservation cases for the selected pavement section in the CR_2 pavement Equation 3.4. The updated value has to be used in MOVES to “Generic/sourceusetypephysics” file to predict the emissions. The deflection value was set to zero for passenger cars and 0.3556 mm for the other two vehicle types (passenger truck and single unit short-haul truck).

The whole process of predicting emissions using MOVES and HDM-4 starts with using the HDM-4 model to calculate the value of $A_{updated}$. In the HDM-4 model, the rolling resistance values can be calculated depending on the equations that are functions of IRI, MPD, and DEF for each vehicle type. These updated values were used as input values in MOVES (EPA, 2010b). By selecting the values of link traffic volume, link speed, link length, source type fractions, and $A_{updated}$, energy consumption and CO_2 emissions were calculated by setting updated values into MOVES for execution. Table 3.1 shows the default HDM-4 model parameters and A-default in MOVES. Finally, all this information including traffic information and roughness data for different preservation treatments was used by MOVES to calculate the vehicle fuel consumption and GHG emissions.

Table 3.1 Parameters for CR2 model in HDM-4 Model and A-default in MOVES

Vehicle	A-default	Vehicle weight (kg)	a_0	a_1	a_2	a_3
Passenger Car	0.1565	<=2500	0.5	0.02	0.1	0
Passenger Truck	0.2211	>2500	0.57	0.04	0.04	1.34
Single Unit Short Haul Truck	0.6122	>2500	0.57	0.04	0.04	1.34

3.2.2 Model 2: Updating Rolling Resistance Coefficient (A) and Air Drag Term (c)

Ghosh et al. (2015) developed the vehicle specific power (VSP) equation as a function of IRI based on the rolling term (A) and air drag term (C) to examine the effect of pavement roughness on energy consumption. The previous model used by Wang et al. (2012) recommended that MOVES default coefficient values correspond to the scenario in which IRI = 0 because the sources from which MOVES obtained values for the coefficients were computed using a dynamometer test on a steel or similarly smooth surface. This means the coefficients were not affected by pavement conditions. However, the results from this method do not seem to match MOVES default values, suggesting that the HDM-4 provided coefficients that are different from the default case. To resolve this issue, each suggested parameter value was examined in Ghosh et al. (2015) study.

The VSP in terms of engine power per unit of vehicle mass that MOVES uses to calculate the energy consumption and emission is shown in Equation 3.5 as a representative for the engine running status.

$$\mathrm{VSP} = \frac{\mathrm{A}}{\mathrm{M}} \times \mathrm{V} + \frac{\mathrm{B}}{\mathrm{M}} \times V^2 + \frac{\mathrm{C}}{\mathrm{M}} V^3 + (\mathrm{a}(1 + \varepsilon_{\mathrm{i}}) + \mathrm{g} \times \mathrm{grade}) \times \mathrm{V} \ldots\ldots\ldots (3.5)$$

Where,

A is the coefficient of rolling resistance component in *MOVES*;

B is the coefficient of higher order rolling resistance factors and mechanical rotating friction losses in *MOVES*;

C is the coefficient of air drag term in *MOVES*;

M is the mass of vehicles in kg;

V is the vehicle speed in m/s;

grade is the gradient, which is vertical rise divided by slope length;

g is the acceleration of gravity in m^2/s;

a is vehicle acceleration in m^2/s; and

ε_i is the "mass factor," which is the equivalent translational mass of the rotating components (wheels, gears, shafts, etc.) of the powertrain;

The connection between MOVES and HDM-4 has been established by considering three main resistances—rolling, aerodynamic, and inertia and gradient—that VSP must overcome as shown in Equations 3.6 (Wang et al., 2012).

VSP = Rolling resistance + Air resistance + Inertial and Gradient resistance….. (3.6)

$$= F_{rolling} \times \frac{V}{M} + F_{aerodynamic} \times \frac{V}{M} + F_{inerttial\ and\ gradient} \times \frac{V}{M} \ldots\ldots \quad (3.6a)$$

$$= C_R g \times V + \frac{1}{2} \times \frac{\rho_a C_D A_{front}}{M} (V + V_w)^2 \times V + (a(1 + \varepsilon_i) + g \times grade) \times V \ldots \quad (3.6b)$$

Where,

$F_{rolling}$ is the rolling resistance in Newtons;

$F_{aerodynamic}$ is the aerodynamic resistance in Newtons;

$F_{inertial\ and\ gradient}$ is the inertial resistance (if in acceleration) and gradient resistance (if on hill) in Newtons;

V_w is the speed of headwind into the vehicle in m/s;

C_R is the rolling resistance coefficient;

ρ_a is the ambient air density (1.207 kg/m^3, at 20°C);

A_{front} is the front area of the vehicle in m^2; and

C_D is the aerodynamic drag coefficient;

According to HDM-4 such as Zaabar and Chatti Report, the rolling resistance term ($F_{rolling}$) is the only factor that is a function of IRI as shown in Equations 3.7 and 3.8. The other resistances in VSP-aerodynamic resistance ($F_{aerodynamic}$) and inertia and gradient resistance ($F_{inertia\ and\ gradient}$)-are independent of roadway surface roughness.

$$F_{rolling} = CR_2.FCLIM\left(b_{11}N_w + CR_1(b_{12}M + b_{13}V^2)\right) \text{ ……………..….(3.7)}$$

$$CR_2 = K_{cr2}(a_0 + a_1 \times Tdsp + a_2 \times IRI + a_3 \times DEF) \text{ ……………..… (3.8)}$$

Where,

CR_2 is the factor of surface characteristics influenced by IRI;

CR_1 is a function of tire type, 1.3 for cross-ply bias, 1.0 for radial, and 0.9 for low profile tires;

$FCLIM$ is the climate factor related to the percentage of driving done in snow and rain;

N_w is the total number of wheels;

b_{11}, b_{12}, and b_{13} are the coefficients related to tire type and technologies;

K_{cr2} is a calibration factor;

Tdsp is the texture depth from the sand patch method in mm, which can be calculated from MPD as: Tdsp = 1.02*MPD + 0.28 for asphalt pavement; for concrete pavement, MTD is used to represent Tdsp directly;

IRI is the International Roughness Index in m/km;

DEF is the Benkelman Beam rebound deflection in mm, a measure of pavement elastic deflection; and

a_0, a_1, a_2, and a_3 are coefficients for different surface characteristics.

By equating Equations 3.5 and 3.6a,

$$\frac{A}{M} \times V + \frac{B}{M} \times V^2 + \frac{C}{M} V^3 + (a(1+\varepsilon_i) + g \times grade) \times v = F_{rolling} \times \frac{V}{M} + F_{aerodynamic} \times \frac{V}{M} + F_{inerttial\ and\ gradient} \times \frac{V}{M}$$

$$\frac{A}{M} \times V + \frac{B}{M} \times V^2 + \frac{C}{M} \times V^3 + (a(1+\varepsilon_i) + g \times \text{grade}) \times V$$
$$= CR_2 \times FCLIM\big(b_{11}N_w + CR_1(b_{12}M + b_{13}V^2)\big) \times \frac{V}{M} + \frac{1}{2} \times \frac{\rho_a C_D A_{front}(V+V_w)^2}{M} \times V$$
$$+ F_{\text{inertial and gradient}} \times \frac{V}{M}$$

$$\frac{V}{M}(A + BV + CV^2 + (a(1+\varepsilon_i) + g \times \text{grade})M)$$
$$= \frac{V}{M}\Big(CR_2 \times FCLIM\big(b_{11}N_w + CR_1(b_{12}M + b_{13}V^2)\big) + \frac{1}{2}\rho_a C_D A_{front}(V+V_w)^2$$
$$+ F_{\text{inertial and gradient}}\Big)$$

$$A + BV + CV^2 = CR_2 \times FCLIM(B_{11}N_w + CR_1 b_{12}M + CR_1 b_{13}V^2) + \frac{1}{2}\rho_a C_D A_{front}(V+V_w)^2$$
$$A + BV + CV^2 = CR_2 \times FCLIM \times b_{11} \times N_w + CR_2 \times FCLIM \times CR_1 \times b_{12} \times M + CR_2 \times FCLIM \times CR_1$$
$$\times b_{13} \times V^2 + \frac{1}{2}\rho_a C_D A_{front}(V+V_w)^2$$

$$A + BV + CV^2 = CR_2 \times FCLIM(b_{11} \times N_w + CR_1 \times b_{12} \times M) + CR_2 \times FCLIM \times CR_1 \times b_{13} \times V^2$$
$$+ \frac{1}{2}\rho_a C_D A_{front}(V+V_w)^2$$

Then,

$$A = CR_2 \times k_A \quad \text{...(3.9)}$$

$$C = CR_2 \times k_c + b_c \quad \text{..................................(3.10)}$$

Where, k_A and k_c represent the effect from rolling resistance, and b_c is that from aerodynamic resistance as shown in Equations 3.11 through 3.13

$$k_A = FCLIM\ (b_{11}N_w + CR_1\ b_{12}\ M) \quad \text{........................(3.11)}$$

$$k_c = FCLIM\ CR_1\ b_{13} \quad \text{..............................(3.12)}$$

$$b_c = \frac{1}{2}\rho_a C_D A_{front} \quad \text{.................................(3.13)}$$

Theoretically, it is feasible to compute MOVES model coefficients A and C using the Equations 3.8 through 3.13.

3.3 PAVEMENT FACTORS AFFECTING VEHICLE EMISSION

To exemplify the proposed methodology and to show the importance of considering the two models parameters when calculating Carbon Dioxide emissions (CO_2), a sensitivity analysis was conducted for one-lane mile segment with speed limit of 65 mph. In this study, it was assumed that the AADTT is 1500 ESALs and the analysis period is 20 years (2015-2035).

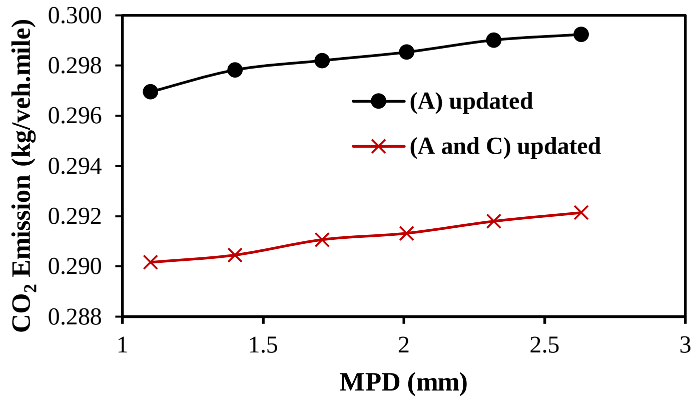
To evaluate the effect of different surface characteristics parameters on the emission, both models results will be compared with MOVES real results. Range of values was selected for MPD, IRI, DEF, and speed as input data for the three vehicle types as shown in Table 3.2.

As mentioned in Table 3.2, three types of vehicles are considered in this study; passenger car (PC) and passenger truck (PT) with gasoline fuel, and single unit short-haul truck (SUSHT) with diesel fuel. Also, the road type that was considered is a restricted urban road with one lane-mile preservation treatments (one mile by 12 ft). By changing one factor in Table 3.2 while keeping the others constant, different values of CO_2 emissions were obtained for three vehicle types using MOVES as shown in Figures 3.1 through 3.4.

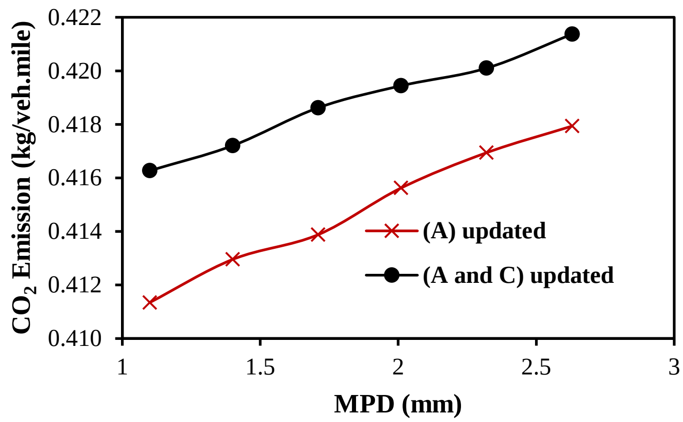
Table 3.2 Variables used in sensitivity analysis

Variables	Range	Default value
MPD (mm)	1.1-2.63	1.4
IRI (m/Km)	0.8-3.2	2
DEF (mm)	0.2032-0.5080	0.356
Speed (mph)	5-65	65
Type of vehicles	3	Passenger car (21), Passenger truck (31), and Single unit short-haul truck (52)

Pavement texture in mean profile depth (MPD) has a significant effect on rolling resistance due to vehicle vibration that causes an excess fuel consumption (Sandberg, 2011). In this study, a range of MPD values (1.1, 1.4, 1.71, 2.01, 2.32, and 2.63 mm) was selected to perform a sensitivity analysis of emissions in MOVES using model 1 and 2 while other factors (IRI, DEF, and speed) were kept constant, as shown in Figure 3.1. Figure 3.1 shows that the CO_2 emissions increase when MPD was increased for passenger cars, passenger trucks, and single unit short-haul truck.



(a)



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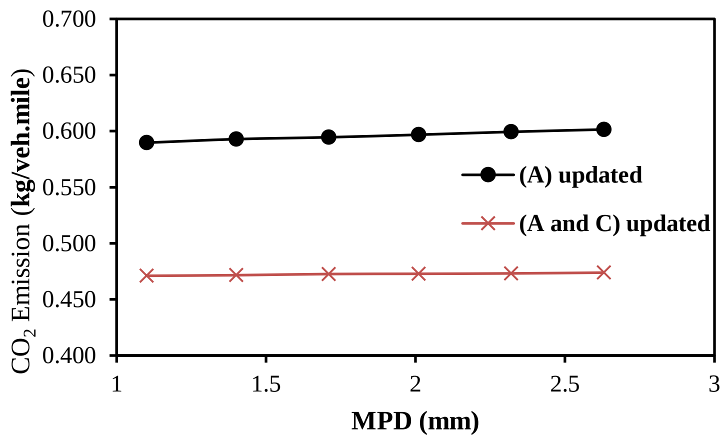
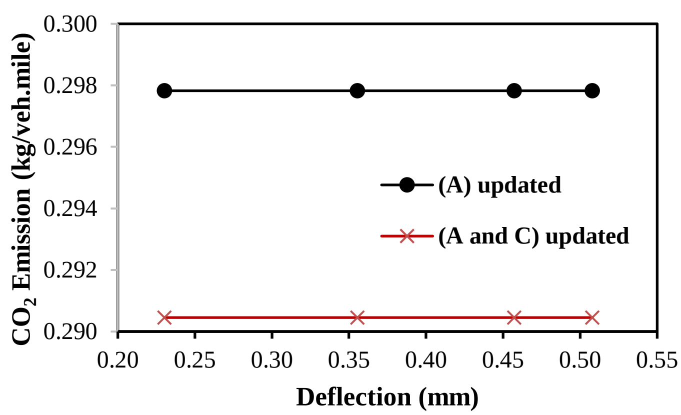


(c)

Figure 3.1 Effect of MPD on Carbon Dioxide emissions (CO_2) emission with (a) Passenger Car (21); (b) Passenger Truck (31); (c) Single Unit Short Haul Truck (52)

Neglecting the traffic load effect, flexible pavement offers higher surface deflection (DEF) than rigid pavement which requires more energy to keep the vehicle movement because of the tire rolling resistance (Lenz, 2011). A sensitivity analysis of CO_2 emissions in MOVES was performed by selecting range values of DEF (0.2032, 0.356, 0.4572, and 0.508 mm) and keeping other factors (IRI, MPD, and speed) constant, as shown in Figure 3.2. Using models 1 and 2, Figure 3.2 shows that the CO_2 emissions increase when the pavement deflection was increased for passenger truck and passenger single unit short-haul truck, while the CO_2 emission remains constant with the increase of deflection values for passenger cars because the value of a_3 in CR_2 is zero (Equation 3.8).



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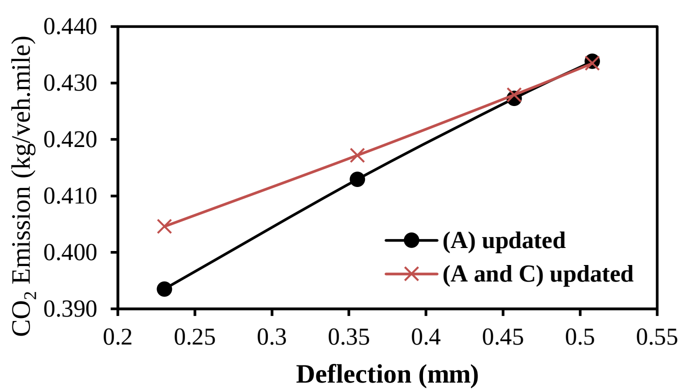

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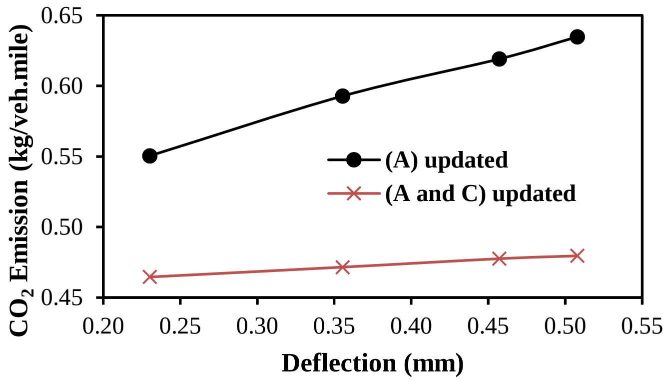
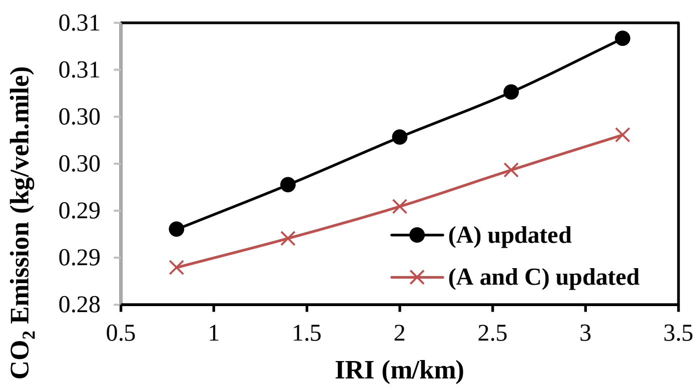


(c)

Figure 3.2 Effect of deflection on Carbon Dioxide emissions (CO_2) emission with (a) Passenger Car (21); (b) Passenger Truck (31); (c) Single Unit Short Haul Truck (52)

In most state agencies, International Roughness Index (IRI) is used to quantify the pavement roughness. Therefore, IRI plays an important role on vehicle rolling resistance. Figure 3.3 shows the sensitivity analysis of CO_2 emissions with IRI for the three vehicle types. The MPD, DEF, and speed were kept constant, while the IRI values range were 0.8, 1.4, 2.0, 2.6, and 3.2 m/km. The Figure shows that the CO_2 emissions increase when the IRI values were increased for passenger cars, passenger trucks, and single unit short-haul truck due to the energy dissipation in tire and vehicle suspension system.



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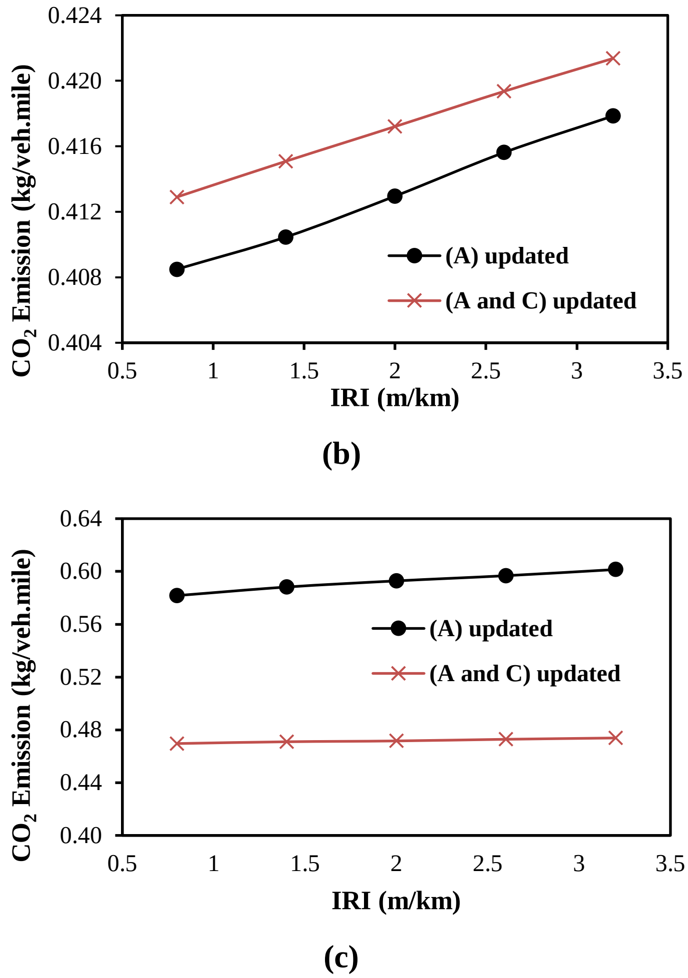
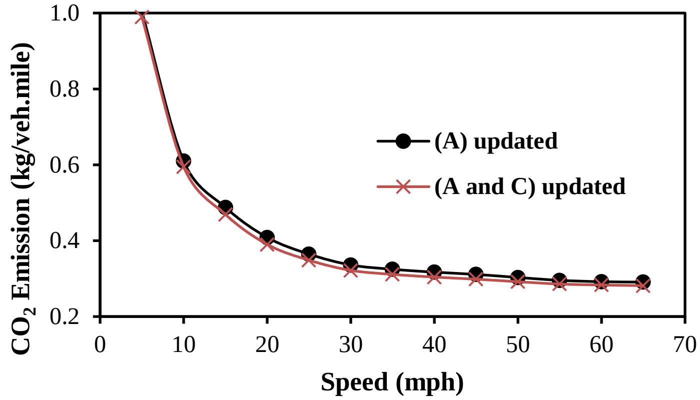


Figure 3.3 Effect of IRI on Carbon Dioxide emissions (CO_2) emission with (a) Passenger Car (21); (b) Passenger Truck (31); (c) Single Unit Short Haul Truck (52)

IRI, MPD, and DEF are all pavement related factors that affect emissions and energy consumptions. In order to study the speed factor which is related to the vehicle, a sensitivity analysis of CO_2 emissions with vehicle speed for the three vehicle types was conducted as shown in Figure 3.4. The IRI, DEF, and MPD were kept constant, while the speed was changed from 5 to 65 mph by an increment of 5 mph. In Figures 3.4, the CO_2 emissions decrease when the speed was increased for the three vehicle types.



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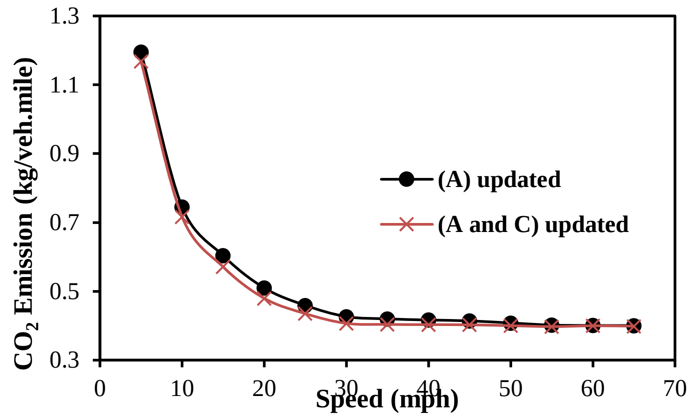

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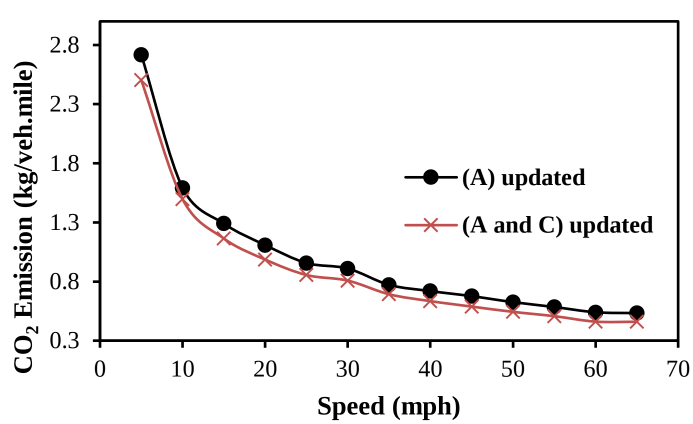


(c)

Figure 3.4 Effect of speed on Carbon Dioxide emissions (CO_2) emission with (a) Passenger Car (21); (b) Passenger Truck (31); (c) Single Unit Short Haul Truck (52)

3.4 DEVELOPMENT OF REGRESSION MODELS

To simplify the calculation process and make the run faster in the optimization process later, 450 and 6300 MOVES runs were used to develop regression models for predicting total energy consumptions (TEC) and Carbon Dioxide emissions (CO_2) for four vehicle types for model 1 and 2 respectively. In general, 15 values of speeds (0-75 mph), 30 values of A (0.1-3) and 14 values of C (0.0003-0.005) were used to develop regression equations to predict the emission and energy consumption.

Table 3.3 Variables used in regression model development

Variables	Range	Default value
Speed (mph)	0-75	40, 65
Type of vehicles	4	Passenger car (21), passenger truck (31), single unit short-haul truck (52), and combination long-haul truck (62)
A-value (rolling term) in MOVES	0.1- 3	PC = 0.1565 PT = 0.2211 SUSHT = 0.6122 CLHT = 1.5522
C- Value (Drag term) in MOVES	0.0003-0.005	PC = 0.0005 PT = 0.0007 SUSHT = 0.0016 CLHT = 0.0039
Section length (lane-mile)	1	
AADTT (ESALs)	1500	
Fuel type	Gasoline (PC & PT) Diesel (SUSHT & CLHT)	

Regression statistics using ANOVA was used to find a relationship between CO_2 emission and total energy consumption as a Y-value variable with two different X-values, speed, and A-value for four vehicle types as shown in Table 3.4. Also, Table 3.5 shows a relationship between CO_2 emission and total energy consumption as a Y-value variable with three different X-values, speed, A-value, and C-value for the four types of vehicles.

Table 3.4 CO_2 emission and total energy consumption (TEC) relationship with speed and A-Value for different vehicles

	Vehicle Type	Equation	R^2
CO_2 emission (Kg/Veh-mile)	Passenger Car	$CO_{2emission\_21} = 1.1437 + 0.17797\,A - 0.05298\,V + 0.001111\,V^2 - 0.000008\,V^3$	0.906
	Passenger Truck	$CO_{2emission\_31} = 1.2831 + 0.18961\,A - 0.0632\,V + 0.001369\,V^2 - 0.000009\,V^3$	0.924
	Single Unit Short-Haul Truck	$CO_{2emission\_52} = 2.8587 + 0.16305\,A - 0.14508\,V + 0.002818\,V^2 - 0.000018\,V^3$	0.933
	Combination Long Haul-Truck	$CO_{2emission\_62} = 4.5053 + 0.2177\,A - 0.17907\,V + 0.003223\,V^2 - 0.000018\,V^3$	0.924
Total Energy Consumption (MJ/Veh-mile)	Passenger Car	$TEC_{\_21} = 15.914 + 2.4763\,A - 0.7371\,V + 0.015453\,V^2 - 0.000106\,V^3$	0.906
	Passenger Truck	$TEC_{\_31} = 17.853 + 2.6383\,A - 0.8794\,V + 0.019046\,V^2 - 0.000131\,V^3$	0.924
	Single Unit Short-Haul Truck	$TEC_{\_52} = 38.809 + 2.213\,A - 1.9695\,V + 0.03826\,V^2 - 0.00024\,V^3$	0.933
	Combination Long Haul-Truck	$TEC_{\_62} = 61.163 + 2.955\,A - 2.431\,V + 0.04376\,V^2 - 0.000249\,V^3$	0.924

Where A=Rolling term and V=Speed (mph)

Table 3.5 CO_2 Emission and total energy consumption relationship with speed, A-value, and C-value for different vehicles

	Vehicle Type	Equation	R^2
CO_2 emission (Kg/Veh-mile)	Passenger Car	$CO_{2emission\_21} = 1.1582 + 0.12377\,A + 61.61\,C - 6502\,C^2 - 0.049636\,V + 0.001061\,V^2 - 0.000008\,V^3$	0.844
	Passenger Truck	$CO_{2emission\_31} = 1.25761 + 0.13829\,A + 83.1\,C - 8796\,C^2 - 0.060537\,V + 0.001358\,V^2 - 0.00001\,V^3$	0.855
	Single Unit Short-Haul Truck	$CO_{2emission\_52} = 2.6886 + 0.16013\,A + 69.67\,C + 2634\,C^2 - 0.14533\,V + 0.002869\,V^2 - 0.000018\,V^3$	0.903
	Combination Long Haul Truck	$CO_{2emission\_62} = 4.3724 + 0.19071\,A + 73.93\,C + 4730\,C^2 - 0.18485\,V + 0.003304\,V^2 - 0.00002\,V^3$	0.926
Total Energy Consumption (MJ/Veh-mile)	Passenger Car	$TEC_{\_21} = 16.116 + 1.7223\,A + 857.3\,C - 90470\,C^2 - 0.69067\,V + 0.014764\,V^2 - 0.000105\,V^3$	0.844
	Passenger Truck	$TEC_{\_31} = 17.4993 + 1.9242\,A + 1156.2\,C - 122398\,C^2 - 0.84235\,V + 0.018897\,V^2 - 0.000135\,V^3$	0.855
	Single Unit Short-Haul Truck	$TEC_{\_52} = 36.499 + 2.1739\,A + 945.8\,C + 35757\,C^2 - 1.973\,V + 0.03895\,V^2 - 0.000244\,V^3$	0.903
	Combination Long Haul Truck	$TEC_{\_62} = 59.359 + 2.589\,A + 1004\,C + 64218\,C^2 - 2.5095\,V + 0.044857\,V^2 - 0.000266\,V^3$	0.926

Where A=Rolling term, C=Air drag term and V=Speed (mph)

A review of the statistical literature (Neter et al., 1990; Snee 1977) suggests the following methods for validating a regression model:

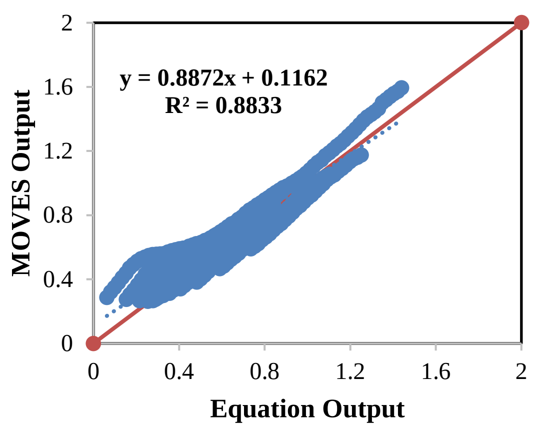
1. Check on model predictions and coefficients
2. Collection of new data
3. Comparison with previously developed models
4. Data splitting
5. Predicted residual error sum of squares (PRESS)

The literature suggests that all available methods of validation could be used. However, it is not possible to use all the methods of validation. Therefore, the applicability of each method in terms of the validation of the developed models will be discussed, and the most appropriate methods of validation will be selected.

The first method (check on model predictions and coefficients) attempts to make sure that the selected model agrees with the physical theory. This essentially has been already checked during the development process. The second method (collection of new data) suggests that a new dataset should be collected. Unfortunately, the collection of the new data is not possible due to time constraints. The third method (comparison with previously developed models) compares the results of a newly developed model with a previously developed model or with a theoretical model. The fourth method (data splitting) has recommended that one may not consider data splitting unless $N > 2P+25$, where N is the sample size and P is a number of estimated parameters. The last method (prediction sum of squares) is a form of data splitting, and it is not feasible because of the available large sample size.

Based on the details mentioned above and to minimize the error of mean for the accuracy requirements, a scatter plot graphs the actual MOVES outputs data against the values predicted by the model 1 and 2. The scatter plot displays the predicted values along the X-axis and shows the actual values along the Y-axis. It also shows a line that illustrates the perfect prediction, where the predicted value exactly matches the actual value. The distance of a point from this ideal 45-degree angle line indicates how well or how poorly the prediction performed. In addition, the adjusted R^2 of the line shows the degree of correlation between the two results.

Figures 3.5, 3.6, 3.7, and 3.8 show the relationships of the CO_2 emissions and TEC for MOVES outputs with CO_2 emissions and TEC from model 1 for the four vehicle types of 21, 31, 52 and 62, respectively. In Figures 3.5, 3.6, 3.7, and 3.8, the values of R^2 for CO_2 emissions are 0.883, 0.880, 0.930 and 0.923, respectively, and for TEC are 0.907, 0.925, 0.934 and 0.925, respectively.



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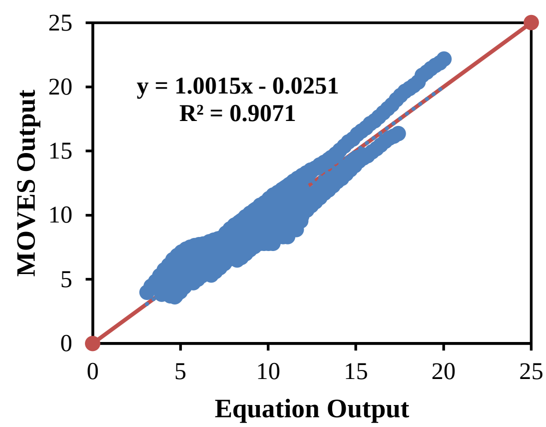
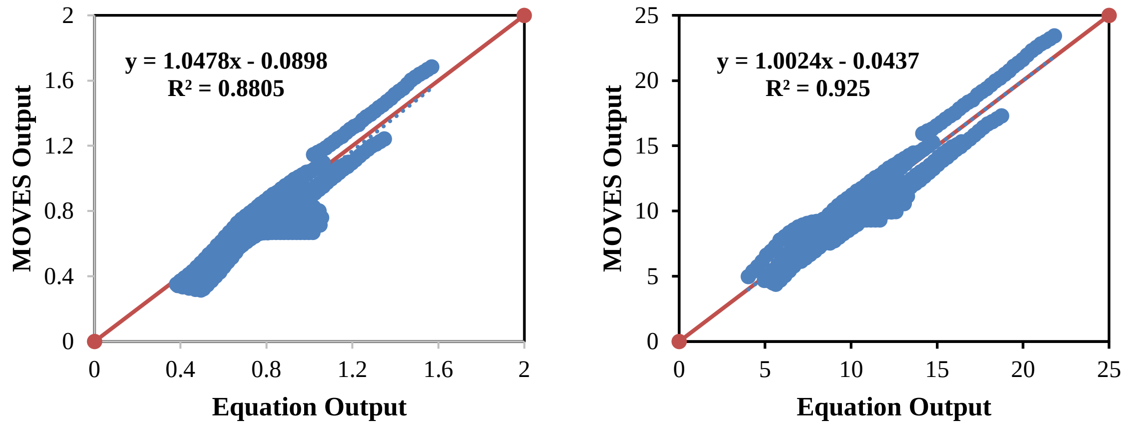


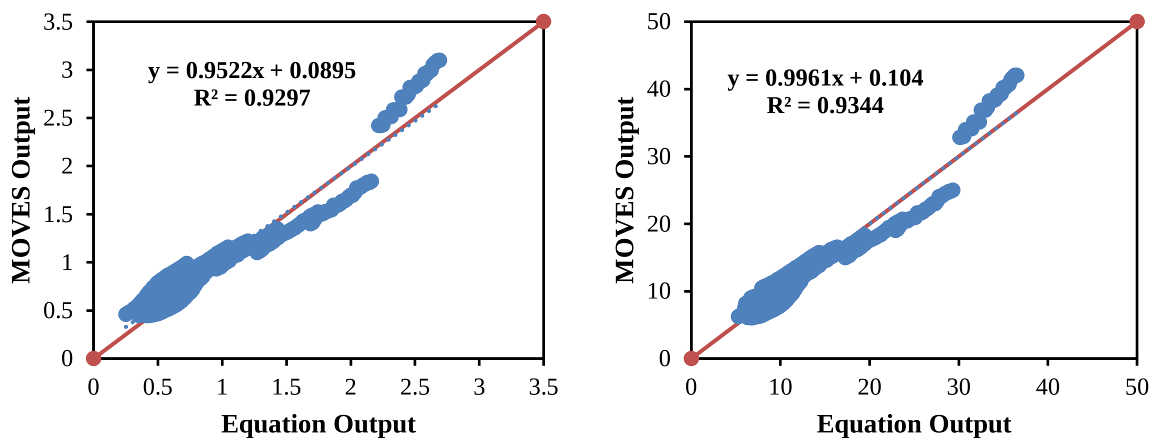
(b)

Figure 3.5 Passenger cars predicted vs. actual values of (a) CO_2 emission (b) TEC



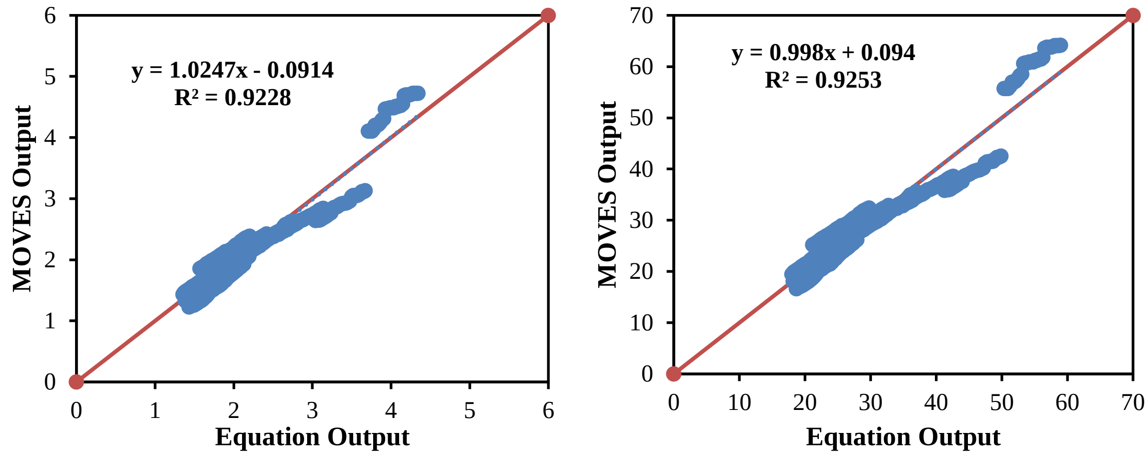
(a) **(b)**

Figure 3.6 Passenger trucks predicted vs. actual values of (a) CO_2 emission (b) TEC



(a) **(b)**

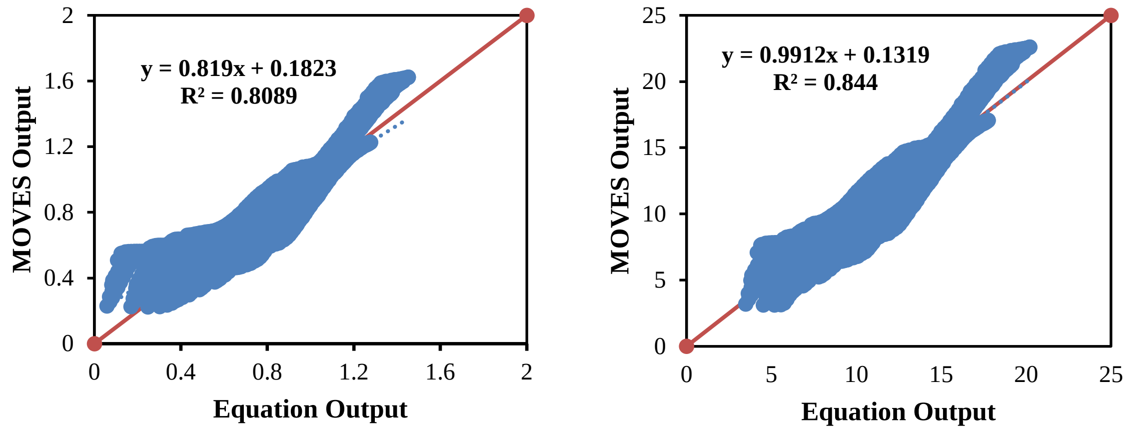
Figure 3.7 Single unit short-haul truck predicted vs. actual values of (a) CO_2 emission (b) TEC



(a) **(b)**

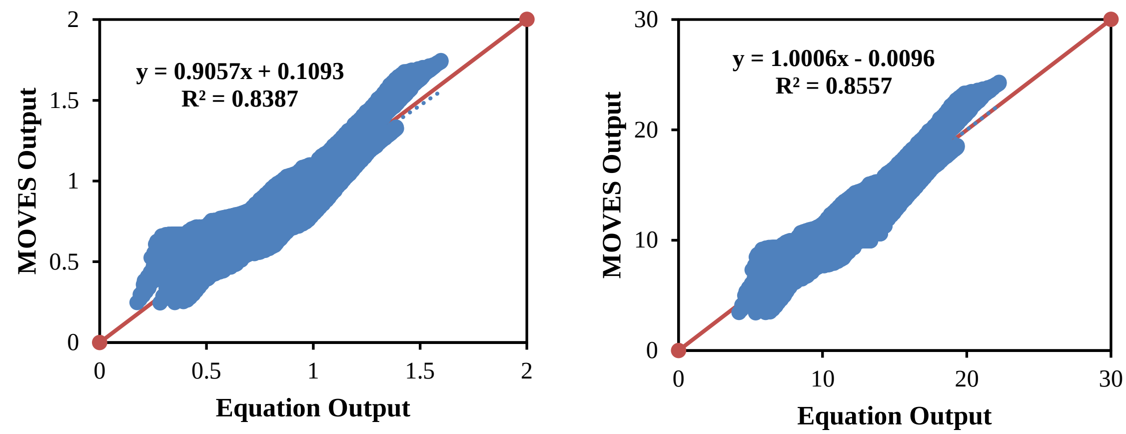
Figure 3.8 Combination long haul-truck predicted vs. actual values of (a) CO_2 emission (b) TEC

Figures 3.9, 3.10, 3.11 and 3.12 show the relationships of the CO_2 emissions and TEC for MOVES outputs with CO_2 emissions and TEC from model 2 for the four vehicle types of 21, 31, 52 and 62, respectively. In Figures 3.9, 3.10, 3.11 and 3.12, the values of R^2 for CO_2 emissions are 0.809, 0.839, 0.904 and 0.924, respectively. In Figures 3.9 through 3.12, the R^2 values for TEC are 0.844, 0.856, 0.904 and 0.926 for passenger cars, passenger truck, single short-haul truck and combination long-haul truck, respectively.



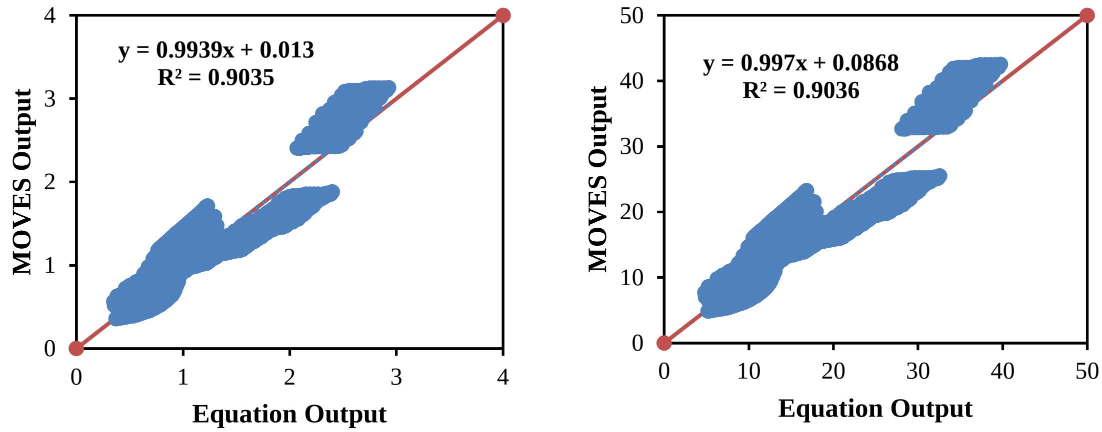
(a) **(b)**

Figure 3.9 Passenger cars predicted vs. actual values of (a) CO_2 emission (b) TEC



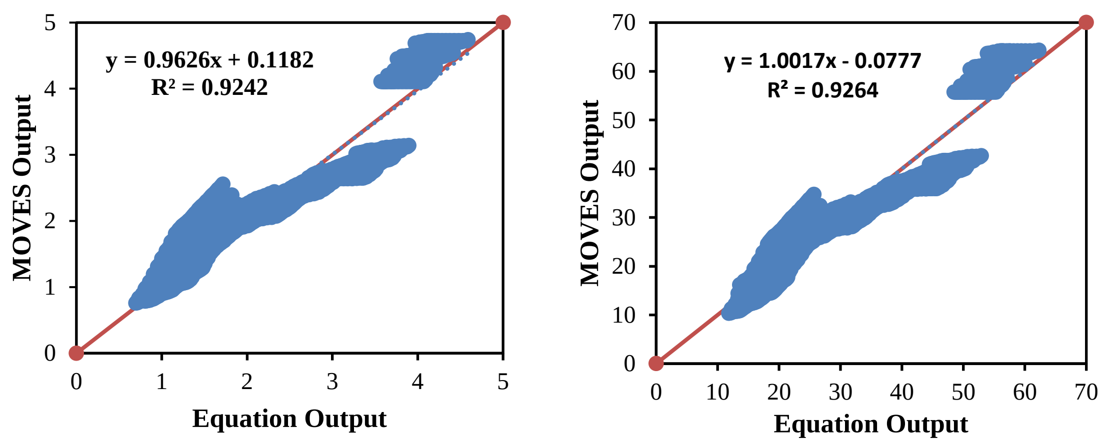
(a) **(b)**

Figure 3.10 Passenger trucks predicted vs. actual values of (a) CO_2 emission (b)



(a) (b)

Figure 3.11 Single unit short-haul truck predicted vs. actual values of (a) CO_2 emission (b) TEC



(a) (b)

Figure 3.12 Combination long-haul truck predicted vs. actual values of (a) CO_2 emission (b) TEC

3.5 SUMMARY

To calculate the VSP terms, two models were evaluated in this work with different terms. The first model was based on Wang et al. (2012) study, which considered the effect of rolling resistance coefficient (A) in MOVES and speed on emission; the other model was based on Ghosh et al. (2015) study using rolling resistance coefficient (A), air drag coefficient term (C), and speed.

Based on the current output of these two models and sensitivity analysis, model 2 was selected because it contains more efficient coefficients than model 1. In general, model 2 uses HDM-4 to develop equations for vehicles specific power (VSP) as a function of IRI. Model 2 outputs revised MOVES coefficients A and C, which enables MOVES simulation to consider the effect of road roughness on energy consumption and CO_2 emissions. In the next Chapters, energy consumption and CO_2 emissions will be quantified using Model 2 only.

CHAPTER 4 QUANTIFYING ENVIRONMENTAL IMPACT OF ASPHALT PAVEMENT PRESERVATION AT CONSTRUCTION AND USE STAGE

4.1 INTRODUCTION

The issue of transportation and the environment is conflicting in nature since transportation carries essential socioeconomic benefits, but at the same time transportation is impacting environmental systems. In recent decades, the growth of freight mobility has expanded the role of transportation as a main source of emission of pollutants and their multiple impacts on the environment (Rodrigue and Comtois, 2013). In addition, Cross et al. (2011) mentioned that transportation takes the second place after electricity in generating of greenhouse gas emissions. They indicated that transportation causes about one-third of all U.S. end-use sector carbon dioxide (CO_2) emissions.

Construction, rehabilitation, and maintenance of highway pavements require obtaining, processing, transporting, manufacturing, and placement of large amounts of construction materials. A sustainable pavement comes with the combination of durability, cost-effectiveness, eco-efficiency, and longevity. Recently, transportation agencies start to increase focus on preservation to prevent deterioration of the nation’s highways. Compared to rehabilitation, preventive maintenance treatments mainly focus on surface refreshment to alleviate functional indicators of pavement deterioration, such as friction, minor cracking or oxidation of asphalt pavements, rather than repair structural deterioration. Therefore, preventive maintenance can retard pavement failures and reduce the need for corrective maintenance or rehabilitation and eventually prolong pavement service life.

The economic impacts of different pavement maintenance and preservation activities are important for the selection of pavement repair alternative. A lot of studies have been conducted to evaluate the cost-effectiveness of pavement preservation using life-cycle cost analysis (LCCA) (Pittenger et al. 2011; Wang et al. 2013). However, few studies have been conducted to evaluate and select appropriate pavement preservation treatments considering its environmental impacts.

Life-cycle Assessment (LCA) is a technique for assessing potential environmental burdens and impacts throughout a product's life from raw material acquisition through production, use, and disposal (ISO 2006). LCA is an appropriate tool for assessing the environmental impacts and helps to identify which impacts are the most significant across the life-cycle. As such, the LCA should be based on an understanding of all pavement-related processes, including material extraction and processing, construction, operation, preservation, rehabilitation, and disposal that go into all phases of the life-cycle of pavement.

A number of studies have been conducted to provide sustainability indicators for pavement systems using LCA. In these studies, different structural design and rehabilitation techniques were considered including asphalt or concrete, overlay, reconstruction, and cold in-place recycling (Thenoux et al. 2006; Weiland and Muench 2010; Yu and Lu 2012; Chong and Wang 2017). Chehovits and Galehouse (2010) focused on the construction stage only by calculating and comparing energy usage and GHG emissions for construction, rehabilitation, and preservation of asphalt pavements.

Recently, studies have shown that Greenhouse Gas (GHG) emission at use stage is affected by pavement surface characteristics (roughness and texture) and pavement deflection resulted from tire-pavement interaction (Chatti and Zaabar 2012; Akbarian et al. 2012; Hammarstrom et al. 2012). The role of use stage is more critical in the pavement life-cycle assessment for highway sections with high traffic volumes (Huang et al. 2009; Zhang et al. 2010; Wang et al. 2012; Trupia et al. 2017).

Pavement preservation treatments consume massive amounts of nonrenewable resources and generate GHG emissions at construction stage. At use stage of pavement after treatments, fuel consumptions and vehicle emission vary significantly depending on tire rolling resistance that is affected by pavement surface roughness, macro-texture, and deflection. Therefore, a systematic approach is needed to evaluate the environmental impacts of pavement preservation at its whole life-cycle.

4.2 LIFE-CYCLE ASSESSMENT FRAMEWORK

The formal structure of LCA was framed by International Standards Organization (ISO) with three basic stages: goal definition, inventory analysis, and impact assessment (ISO 2006). The goal is to define the questions that are to be answered, such as identifying the environmental impact of each material/process and find an alternative approach to reduce the impact. Inventory analysis is analyzing an inventory flow for a product or process from cradle stage to end stage. Impact assessment is to assess the influences on specific environmental categories and rank relative seriousness of the influences.

The LCA framework used in this study is shown in Figure 4.1, respectively, for construction and use stages. Material production stage includes each step in the materials manufacturing process, from the extraction of raw materials to their changeover into a pavement input material. It also includes any necessary transportation that occurs between facilities. The construction stage is all the processes used in the placement of pavement materials at the project location. It includes onsite construction equipment and transportation.

The use stage follows the construction stage in which the pavement is used for traffic. A comprehensive LCA of pavement should include traffic delay, rolling resistance, concrete carbonation, pavement albedo, lighting, leachate, and end of life allocation (Santero et al. 2011). However, there are still many areas in the use stage where supporting data are incomplete that may cause great uncertainty if considering the whole pavement LCA framework. This study only considers the effects of traffic parameters and pavement surface conditions on vehicle emission in the use stage because there are models available to quantify these effects. Since pavement preservation treatments are usually conducted at nights, the traffic interruption caused by construction can be minimized. Therefore, traffic delay due to work zone is considered negligible for pavement preservation.

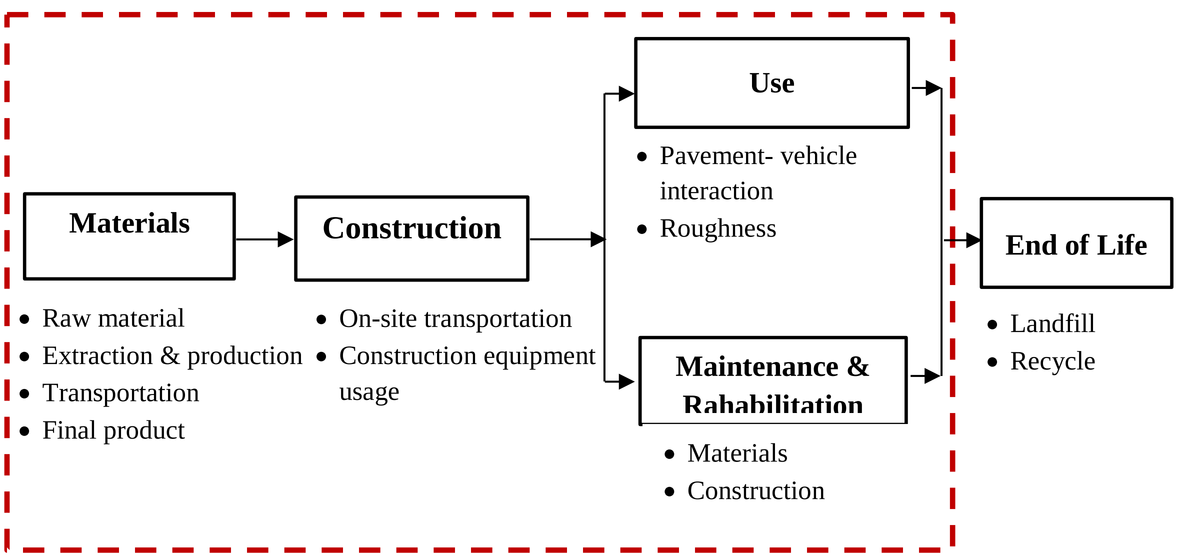


Figure 4.1 LCA framework of pavement preservation at construction and use stages

4.3 EMISSION OF PRESERVATION TREATMENTS AT CONSTRUCTION STAGE

4.3.1 Types of Pavement Preservation

Thin overlay is a popular preservation approach to improve pavement surface condition, protect pavement structure, reduce the pavement deterioration rate, correct surface deficiencies, reduce permeability, and improve the ride quality of the pavement. The hot-mix asphalt (HMA) overlay is usually applied with a thickness range of 0.5-2 inches. Thin overlays are generally used with a relatively high cost with greater performance exception compared to other preservation treatments.

Chip seal is a surface treatment in which pavement surface is sprayed with asphalt emulsion and then immediately covered with aggregate and compacted by the roller. Chip seals are used primarily to seal pavement with non-load-associated cracks and to improve surface friction. They are commonly used as a wearing course on low volume roads. In chip seal, the adhesion of emulsion and aggregate is crucial, and aggregates should be completely dry and clean to prevent the adhesion failure. Failure of chip seal occurs mainly because of two reasons: stripping and bleeding.

Crack seal is one of the most common preservation treatments because it is cost-effective and can be easily applied. It extends the service life of pavement through reducing the amount of moisture that can infiltrate pavement structure and prevent incompressible materials into existing cracks. One of the most important steps for the crack seal is to prepare (clean) the cracks and then filling it with crack sealant. The crack sealant is usually rubberized asphalt or polymer modified asphalt with a small amount of filler.

Although the material designs of preservation treatments may vary slightly depending on local experience, assumptions were made in this study based on typical practice. The thickness of thin overlay is 1.5 inch, and the proportion of asphalt and aggregate is 5% and 95% respectively. The chip seal has an application rate of 1.632 kg/m^2 and 15 kg/m^2 for emulsion and aggregate, respectively. The crack seal has an application rate of 0.37 kg/m^2 for pavement surface with a crack density of 0.37 m/m^2 (Peshkin et al. 2004; Caltrans 2003).

4.3.2 Effectiveness of Pavement Preservation on Pavement Performance

Eltahan et al. (1999) studied the performance of the LTPP SPS-3 test sections in the southern region. The performance of the treatment sections was compared with control sections on the basis of three existing conditions: good, fair, and poor. The study concluded that if the existing pavement is in a fair condition, the treatments make the most significant difference. For thin overlay, the average benefit compared with no treatment is 4.8 years, whereas it is 3.5 years for slurry seal and 5.7 years for crack seal. The study also concluded that chip seal outperformed all the other treatments.

Chen et al. (2003) conducted a study in the Texas DOT reviewed fourteen LTPP test sites. In terms of the overall performance, chip seal was ranked first, followed by thin overlay, and slurry seal, which is tied with crack seal. The most comprehensive study on the LTPP SPS-3 experiment was conducted under the National Cooperative Highway Research Program’s (NCHRP) Project 20-50 (03/04), which analyzed data from all the SPS-3 sites. The study found that the thin overlay treatment was the only one of the four treatments to have a significant initial effect on rutting, and crack seals did not demonstrate any initial or long-term effect with respect to the international roughness index (IRI), rutting, or cracking (Hall et al. 2002).

With many treatment types, Hot Mix Asphalt (HMA) overlay had the highest performance time, followed by micro-surfacing with chip seal, slurry seal, crack filling, and crack sealing. Furthermore, thin overlay was the most expensive treatment, followed by micro-surfacing and chip seal tied with slurry seal. Wang et al. (2012) used statistical tests, such as a paired t-test, to compare the LTPP control sections with the treatment section roughness. They found that all treatments used in their study caused a significant roughness reduction. They also ordered the effectiveness of the treatments based on roughness reduction. HMA overlay had the most significant effect on roughness reduction, followed by chip seal, crack seal, and slurry seal. Finally, comparing the average difference of International Roughness Index (ΔIRI) between the control section and the treatment sections, crack seal, slurry seal, and overlay were found to be 0.124, 0.083, and 0.407 with a standard deviation of 0.269, 0.04, and 0.618, respectively.

After extensive studies, Carvalho et al. (2011) presented the effects of several design parameters on pavement responses and performance using rigid and flexible pavements. A weighted distress was utilized in that study as a performance indicator, which represents the total normalized area under the distress-time curve. The main results of Carvalho et al.'s (2011) study showed that thin overlay performed better than other treatments in terms of Weighted Distress-IRI. The Weighted Distress-IRI of thin overlay and slurry seal equals 4.80 ft/mile (0.91 m/km) and 7.66 ft/mile (1.45 m/km), respectively. Additionally, slurry seal treatment showed the worst performance over an eight-year period.

4.3.3 Life-Cycle Inventory Data

In order to quantify energy consumption and emission of preservation treatments, the first need is to determine the material components and manufacturing processes for each treatment. Life inventory data of raw materials, manufacturing, transport, and placement were reviewed from published reports by a number of researchers, mainly including the Portland Cement Association (Marceau et al. 2007), the Swedish Environmental Research Institute (Stripple 2001), the ATHENA Sustainable Material Institute (ATHENA 2006), the University of BATH at UK (Hammond and Jone 2008), and Swiss Centre for Life Cycle Inventories (2011). Although multiple data sources are available for life-cycle inventory data of typical construction materials, discrepancies may exist due to different local conditions, technologies, and system boundaries.

Table 4.1 lists the inventory data for energy and emission, respectively for construction materials and processes used in three preservation treatments considered in this study. The fuel and electricity that are used in plant operations and transportation of raw materials cause direct energy consumption and emissions, while energy and emissions related to the production of fuels and electricity are considered as indirect energy usage and emissions (upstream) (Harvey et al. 2016). However, the energy and emission data listed in Table 4.1 include upstream processes. The emission rates of CO_2 and CH_4 are presented in Table 4.1. The other types of pollutant emissions were found negligible in the analysis. Life inventory of asphalt products was mainly obtained from the data published by European bitumen industry (Eurobitume 2012) that covers extraction of crude oil, manufacturing of asphalt product, storage, and construction of refinery facility. A report published by Swedish Environmental Research Institute (IVL)

(Stripple 2001) was mainly used to obtain energy consumption and emission data for aggregate production, manufacturing of HMA, transportation, and machinery used in construction.

For the production of asphalt products, the energy sources are diesel oil, electricity, fuel used for producing electricity (biomass fuel, peat, coal, uranium), and natural gas. The emissions are computed starting from oil extraction and passing through the process of transportation, processing, refining, and storage. Energy consumption for aggregate production includes quarrying, hauling, crushing, and screening. Manufacturing of HMA includes handling, storing, drying, and mixing.

As for the laying down process of the material (in-place works), the mechanical performance of the most common machines and standard construction procedure have been considered. For example, HMA thin overlay is constructed by using an asphalt paver and roller compaction. For chip seal, asphalt emulsion is spread over pavement surface, and then aggregate is laid. Crack seal includes both sawing and sealing work using diesel driven equipment.

For transportation of materials to the construction site, it is assumed to be done by a distribution truck with 100% full front haul and an empty backhaul. Air emissions are strictly dependent on fuel consumptions used by construction equipment and transport vehicles.

Table 4.1 Life Inventory Data Related to Preservation Treatments (Sources: IVL and Eurobitume)

Product/Process	Energy	CO_2	CH4
Asphalt	3.08E+09 J/ton	1.76E+02 kg/ton	6.00E-01 kg/ton
Aggregate	3.20E+07 J/ton	1.42E+00 kg/ton	3.82E-06 kg/ton
Asphalt emulsion	3.09E+09 J/ton	2.04E+02 kg/ton	6.40E-01 kg/ton
Polymer modified crack sealant	5.94E+09 J/ton	2.96E+02 kg/ton	1.09E+00 kg/ton
Production of hot-mix asphalt	3.69E+08 J/ton	2.23E+01 kg/ton	5.04E-06 kg/ton
Transportation	9.00E+05 J/ton-km	6.70E-02 kg/ton-km	4.23E-08 kg/ton-km
Laying of thin overlay (paving + compaction)	1.3E+06 J/m^2	9.60E-02 kg/m^2	6.06E-08 kg/m^2
Laying of chip seal (spraying + roll)	6.00E+05 J/m^2	4.70E-02 kg/m^2	2.67E-08 kg/m^2
Crack sealing (crack density of 0.37 m/m^2)	2.60E+05 J/m^2	1.90E-02 kg/m^2	1.18E-08 kg/m^2

4.3.4 CO_2 Emission of Preservation Treatments at Construction Stage

At construction stage, energy consumptions and pollutant emissions of preservation treatments are calculated, respectively, for production of raw material, manufacturing of treatment material to be used on pavement, transportation of material to the site, and placement of the material. Table 4.2 shows the calculated pollutant emissions at construction stage for one lane-mile of pavement surface area, respectively, for thin overlay, chip seal and crack seal.

The results indicate that there are significant differences in energy consumptions among various preservation treatments mainly due to different raw material components and manufacturing processes. Thin HMA overlay is similar to traditional pavement construction including plant production, laying down loose asphalt material, and compacting to an acceptable density. Application of chip seal requires a spray of asphalt emulsion and aggregate followed by rolling on aggregate; while crack seal only requires sawing of crack faces and pouring of crack sealant. Overall, thin HMA overlay requires the greatest energy consumption because the operation of asphalt plant is required to produce the HMA and a large amount of raw material is needed. As expected, crack seal requires the least amount of energy because the small amount of material is consumed in the entire process.

Table 4.2 Pollutant Emissions of Preservation Treatments (per lane-mile)

Emission	Raw material	Manufacture	Transport (20 mile)	Placement	Total
			Thin overlay		
CO_2 (kg)	5.27E+03	1.16E+04	1.12E+03	5.65E+02	1.86E+04
CH_4 (kg)	1.56E+01	2.61E-03	7.05E-04	3.57E-04	15.60E+00
			Chip seal		
CO_2 (kg)	2.16E+03	-	2.09E+02	2.77E+02	2.65E+03
CH_4 (kg)	6.40E+00	-	1.32E-04	1.57E-04	6.40E+00
			Crack seal		
CO_2 (kg)	2.96E+02	-	2.16E+00	1.12E+02	4.10E+02
CH_4 (kg)	1.09E+00	-	1.36E-06	6.95E-05	1.09E+00

4.4 VEHICLE EMISSION AT PAVEMENT USE STAGE

4.4.1 Vehicle Specific Power Model in MOVES

Pavement life cycle assessment at the use stage mainly focuses on fuel consumption and consequently, pollutant emissions due to the effect of tire rolling resistance on vehicle operations. The rolling resistance is the vehicle energy loss associated with tire-pavement interaction, which is affected by tire properties, pavement surface deflection, and surface characteristics at a different wavelength (roughness and surface texture) (Descornet, 1990).

Vehicle Specific Power (VSP), which distinguishes between running modes, is one of the important factors in calculating engine running status. It is indirectly related to energy consumption and traffic emissions (EPA 2012). The VSP indicated in MOVES represents the engine running status for emission calculation, as shown in Equation 4.1. This equation is defined as the engine power per unit mass of a vehicle and reflects a vehicle's power demand for operation over various conditions and speeds.

$$VSP = \frac{A}{M} \times v + \frac{B}{M} \times v^2 + \frac{C}{M} v^3 + (a(1 + \varepsilon_i) + g \times grade) \times v \qquad (4.1)$$

Where, *A*, *B*, and *C* refer to rolling resistance components, namely higher-order rolling resistance and mechanical rotating friction, and air drag, respectively; *M* is the vehicle mass; *v* denotes the instantaneous speed; a and ε_i are the vehicle acceleration and mass factor terms.

The model coefficients *A*, *B*, and *C* are not input data but are stored in the MOVES model database. They are unique to each vehicle type and can be modified by users. Modifying these coefficients for different levels of roughness enables the consideration of roadway surface conditions in simulations. The default values of *A*, *B*, and *C* are derived from the track load horsepower indicated in the Mobile Source Observation Database (MSOD) (EPA 2010a). The default value of rolling resistance coefficient (*A*) is obtained from vehicle dynamometer tests, in which vehicles run on a smooth steel surface (EPA 2010b). For this reason, the influence of pavement surface characteristics on vehicle operation is disregarded by the default VSP model in MOVES.

4.4.2 Updating Rolling Resistance Coefficient

The rolling resistance at the tire-pavement interface has been calculated based on the Highway Development and Management Tool (HDM-4). The HDM-4 presented by World Bank included a model to quantify the vehicle operating cost for road management and planning (Bennett and Greenwood, 2003). The rolling resistance forces are functions of different parameters, such as pavement conditions, tire parameters, and vehicle characteristics. Equations 4.2 and 4.3 shows the effects of pavement surface roughness, macro-texture, and deflection on tire rolling.

$$(F_{rolling})_{HDM-4} = CR_2 \,.\, FCLIM \times (b_{11} \,.\, N_w + CR1 \times (b_{12}\, M + b_{13} \,.\, v^2)) \qquad (4.2)$$

$$CR_2 = Kcr_{2.}\,(a_0 + a_1{\times}MPD + a_2{\times}IRI + a_3{\times}DEF) \qquad (4.3)$$

Where, $A_{updated}$ is updated rolling resistance coefficient used in the calculation; $A_{default}$ is default rolling resistance coefficient in MOVES; $CR_{2pavement}$ is rolling resistance on real pavement surface; $CR_{2dynamometer}$ is rolling resistance on a smooth surface (both IRI and MPD values are zero); $(F_{rolling})_{HDM-4}$ is rolling resistance from HDM-4 software version 2.05; CR_1 is rolling resistance tire factor; CR_2 is rolling resistance surface factor; M is mass of the vehicles; N_w is number of wheels; v is speed; b_{11}, b_{12}, and b_{13} are coefficients related to tire type and other technologies; Kcr_2 is calibration factor; FCLIM is climatic factor related to the percentage of driving snow and rain; a_0, a_1, a_2, and a_3 are coefficients for pavement surface characteristics from HDM-4 model; MPD is mean profile depth in mm; IRI is international roughness index in m/km; and DEF ispavement surface deflection in mm (using Benkelman Beam).

Wang et al. (2012) proposed updating the rolling resistance coefficient (A) in MOVES using the ratio of the rolling resistance on pavement surface on the default rolling resistance on a smooth surface. However, the results from this method do not seem to match default values in MOVES as IRI equal to zero. To resolve this issue, each parameter in the VSP model should be examined. Ghosh et al. (2015) developed the vehicle specific power (VSP) equation as a function of IRI based on rolling term (A) and air drag term (C) to examine the effect of pavement roughness on energy consumption. The connection between MOVES and HDM-4 has been established by considering three main resistances - rolling, aerodynamic, and inertia and gradient, as shown in Equation 4.4.

$$\begin{aligned} \text{VSP} &= \text{Rolling resistance} + \text{Air resistance} + \text{Inertial and Gradient resistance} \\ &= \mathrm{F_{rolling}} \times \frac{v}{\mathrm{M}} + \mathrm{F_{aerodynamic}} \times \frac{v}{\mathrm{M}} + \mathrm{F_{inerttial\ and\ gradient}} \times \frac{\mathrm{v}}{\mathrm{M}} \\ &= \mathrm{CR_2} \times \mathrm{FCLIM}\big(\mathrm{b_{11}N_w} + \mathrm{CR_1}(\mathrm{b_{12}M} + \mathrm{b_{13}}v^2)\big) \times \frac{\mathrm{V}}{\mathrm{M}} + \frac{1}{2} \times \frac{\mathrm{\rho_a C_D A_{front}}v^2}{\mathrm{M}} \times \mathrm{V} \\ &\quad + \mathrm{F_{inertial\ and\ gradient}} \times \frac{v}{\mathrm{M}} \end{aligned} \tag{4.4}$$

Where, $F_{rolling}$ is the rolling resistance in Newtons; $F_{aerodynamic}$ is the aerodynamic resistance in Newtons; $F_{inertial\ and\ gradient}$ is the inertial resistance (if in acceleration) and gradient resistance (if on hill) in Newtons; ρ_a is the ambient air density (1.207 kg/m^3, at 20°C); A_{front} is the front area of the vehicle in m^2; and C_D is the aerodynamic drag coefficient;

According to HDM-4, the rolling resistance term ($F_{rolling}$) is the only factor that is a function of IRI. The other resistances in VSP are aerodynamic resistance ($F_{aerodynamic}$) and inertia and gradient resistance ($F_{inertia\ and\ gradient}$), which are independent of roadway surface characteristics.

By equating Equations 4.1 and 4.4, Equations 4.5 and 4.6 can be obtained as follows:

$$A = CR_2 \times k_A \tag{4.5}$$

$$C = CR_2 \times k_c + b_c \tag{4.6}$$

Where, k_A and k_c represent the effect from rolling resistance (Equations 4.7 and 4.8); and b_c is that from aerodynamic resistance (Equation 4.9).

$$k_A = FCLIM\ (b_{11} N_w + CR_1\ b_{12}\ M) \tag{4.7}$$

$$k_c = FCLIM\ CR_1\ b_{13} \tag{4.8}$$

$$b_c = \frac{1}{2} \rho_a C_D A_{front} \tag{4.9}$$

In this study, the model parameters for tire rolling resistance used are based on the calibrated HDM-4 parameters based on U.S. conditions (Chatti and Zaabar 2012). The pre- and post-treatment IRI values were considered as time-dependent functions that vary between pavement sections with different preservation treatments. The deflection value was set to be constant at 0.356 mm that is a typical value for thick flexible pavements (Nasimifar et al. 2016). This is because the main function of pavement preservation is to restore pavement serviceability and it will not increase pavement structure capacity. The MPD value was set to be 2 mm for the pavement section with chip seal, but 1.4 mm for control pavement section and the pavement sections with crack seal and thin overlay (McGhee and Flintsch 2003; Adams and Kim 2014). Both macro-texture depth and deflection are assumed constant within the analysis period.

4.4.3 IRI Jumps and Development Functions for Different Treatments

Pavement performance data collected at long-term pavement performance (LTPP) program specific pavement studies 3 (SPS-3) were used to develop IRI models before and after preservation treatments. The SPS-3 includes the performance of four maintenance treatment alternatives (thin overlay, chip seal, crack seal, and slurry seal) under three design factors which include climate (precipitation and temperature), pavement structure (subgrade type and existing pavement condition) and traffic loading. The IRI changes due to preservation treatments include the immediate IRI jump at the timing of preservation treatments and the pre-treatment and post-treatment IRI development functions, respectively (Labi et al. 2007).

It is expected that IRI drops to some extent after treatment application. The application timing of preservation treatment affects the jump between post-treatment and pre-treatment IRI. For example, when the IRI is low, the preservation treatment may not change the existing IRI much. Using LTPP data, Lu and Tolliver (2012) found that after preservation treatment, the short-term jump of IRI followed a polynomial relationship with the pre-pretreatment IRI ($IRI_{existing}$), as denoted in Equation 4.10. Table 4.3 represents the performance jump IRI equations with α, β and γ values for each treatment type that are used in this study. They focused in their study only on three design factors of SPS-3 data which include precipitation, temperature, and existing pavement condition. The average reductions in IRI for thin overlay, chip seal, and crack seal were calculated to be 1.44 m/km, 0.72 m/km, and 0.27 m/km, respectively.

$$IRI_{jump} = \alpha \times IRI_{existing}^3 + \beta \times IRI_{existing} + \gamma \tag{4.10}$$

Where, IRI_{jump} is the difference between immediate before and immediate after treatment; $IRI_{existing}$ is the IRI value immediate before treatment; and $\alpha, \beta,$ and γ are the estimated parameters for each treatment type .

The results indicate that maximum IRI jumps exist at the specific pre-treatment condition for crack seal and chip seal. As the pre-treatment IRI value moves away from the specific IRI values, the treatment becomes less effective. This trend is consistent with the expectation and past research that identified the ceiling for treatment effectiveness (Markow 1991). However, for thin asphalt overlay, the pavement with the higher pre-treatment IRI value has more significant IRI jump after treatment.

Table 4.3 IRI jumps after preservation treatments (after Lu and Tolliver 2012)

Treatment	R^2	Polynomial regression function (IRI_{jump})	
Thin overlay	0.88	$-0.008IRI_{existing}^3 + 0.971IRI_{existing} - 0.726$	(4.11)
Chip seal	0.52	$-0.081IRI_{existing}^3 + 1.606IRI_{existing} - 1.637$	(4.12)
Crack seal	0.83	$-0.052IRI_{existing}^3 + 0.774IRI_{existing} - 0.749$	(4.13)

The most previous studies examined the development of IRI as an exponential function of pavement age (Haider and Dwaikat, 2010). It is rational that the traffic should have a certain influence on the IRI deterioration rate. Previous studies have recommended considering AADTT into a different form of the IRI deterioration function (Huang and Dong 2009; Ong et al., 2010). Wang and Wang (2017) proposed an exponential model to describe the development of IRI as a function of initial pavement condition and traffic. In other words, different treatments with different traffic volume can directly affect the overall IRI deterioration rate over time. Based on LTPP database, Wang and Wang (2017) determined the initial IRI (IRI_o) and the deterioration rate of IRI (R) through nonlinear regression of IRI data with pavement age. Their analysis found that the average IRI deterioration rates (in m/km per year) were 0.0327, 0.0345, 0.0353, and 0.0289 for the pavement section with chip seal, crack seal, do-nothing, and thin overlay respectively. The researchers analyzed the effect of traffic on the deterioration rates for each site to get the two model coefficients a and b, as denoted in Equation 4.14 for each treatment type. Table 4.4 represents the IRI development equations with a and b values for each treatment type that are used in this study.

$$\mathrm{IRI(t)} = \mathrm{IRI_0} . \mathrm{e}^{\mathrm{R.t}} = \mathrm{IRI_0} \mathrm{e}^{(\mathrm{a+b*AADTT).t}} \tag{4.14}$$

Where, IRI_0 is the initial value of IRI (t=0); R is pavement deterioration rate with time; a is the treatment effect on IRI deterioration rate; b is the traffic effect on IRI deterioration rate, AADTT is average annual daily truck traffic in ESALs, and t is pavement age in year.

Table 4.4 IRI development equations for preservation treatments (after Wang and Wang 2017)

Treatment	R^2	IRI Development	
Control section	0.48	$\mathrm{IRI(t)} = \mathrm{IRI_0}\ \mathrm{e}^{(2.22\times10^{-2}+2.83\times10^{-5}\times \mathrm{AADTT})t}$	(4.15)
Chip seal	0.63	$\mathrm{IRI(t)} = \mathrm{IRI_0}\ \mathrm{e}^{(2.08\times10^{-2}+2.71\times10^{-5}\times \mathrm{AADTT})t}$	(4.16)
Crack seal	0.68	$\mathrm{IRI(t)} = \mathrm{IRI_0}\ \mathrm{e}^{(2.21\times10^{-2}+2.76\times10^{-5}\times \mathrm{AADTT})t}$	(4.17)
Thin overlay	0.71	$\mathrm{IRI(t)} = \mathrm{IRI_0}\ \mathrm{e}^{(1.66\times10^{-2}+2.55\times10^{-5}\times \mathrm{AADTT})t}$	(4.18)

4.5 LIFE-CYCLE IMPACT OF PAVEMENT PRESERVATION ON EMISSION

The life-cycle impact of pavement preservation on emission was analyzed for different treatments as compared to the control pavement section (do-nothing scenario). At the current stage of analysis, it is assumed that only one preservation treatment is applied before IRI reaches the terminal value. Since the pavement section with preservation treatment reaches the terminal IRI value at a later time, the IRI at control pavement section is kept unchanged after reaching the terminal IRI value in order to have the same analysis period between control section and treatment sections. The initial and terminal IRI values were set to be 1 m/km and 2.714 m/km for the reference case, respectively. It is assumed that average annual daily traffic (AADT) is 15,000 and the percentages of passenger car, passenger truck, and combination long-haul truck in the traffic stream are 45%, 45%, and 10%, respectively. Assuming that combination truck has a truck factor of 1.0, the AADTT in ESALs will be 1500 for the reference case. The analysis was conducted for one lane-mile asphalt pavement segment with a speed limit of 65 mph.

Figure 4.2 shows examples of development curves of IRI for control section and the pavement section with chip seal applied. The line curve represents IRI values at each year for control section. The dotted curve represents the IRI values after chip seal treatment considering both short-term and long-term effectiveness. After capturing the post-treatment IRI values, both rolling term (A) and air drag term (C) were updated using the procedure described above to calculate the emission for each vehicle type.

The life-cycle benefit of pavement preservation on emission is defined by the reduction of emission at the use stage due to pavement preservation subtracted by the emission caused by construction of preservation treatment. It is expected that the application timings of preservation treatments have significant effects on emission at the use stage and therefore the life-cycle impact of pavement preservation.

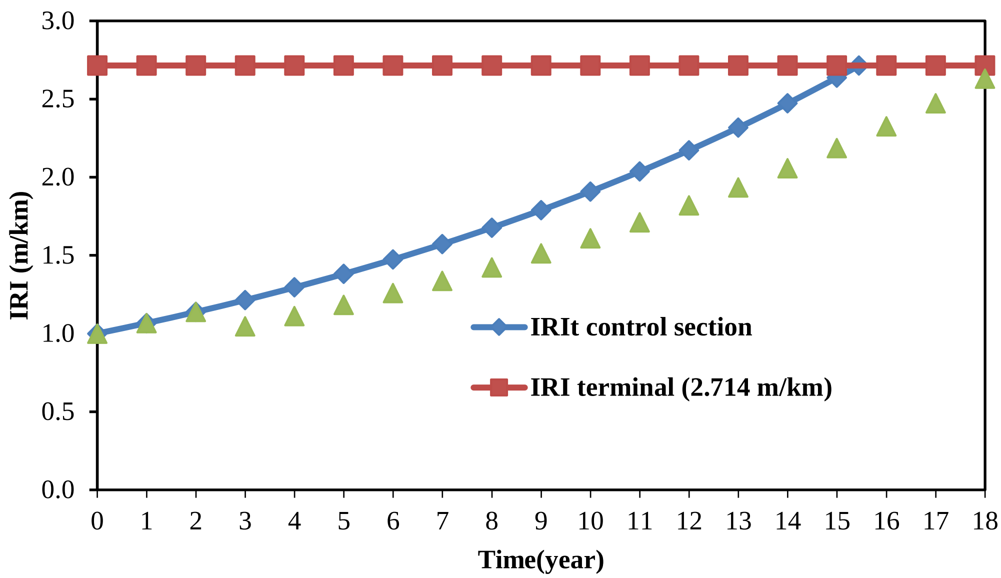


Figure 4.2 Example of IRI development curves before and after chip seal preservation treatment

Figure 4.3 shows the effect of application timing on CO_2 emission in the pavement life-cycle for three types of preservation treatments, respectively. The results show that the CO_2 emission at use stage is two to three orders greater than the one at construction stage. In general, the emission reductions increase until reaching peak values and then decreases when the application time of treatment changes over the years. This implies that the optimal timing of preservation treatment exists to achieve the maximum life-cycle benefit of preservation on CO_2 emission. For example, the maximum reductions in CO_2 emissions were observed at the year of 9, 8 and 7 for chip seal, crack seal, and thin overlay, respectively.

It is obvious that thin overlay treatment has the highest reduction of CO_2 emission due to the fact that pavement surface after thin overlay has the lowest roughness value at the use stage as compared to the other two treatments, although thin overlay generates the highest emission at the construction stage. On the other hand, crack seal has the lowest reduction of CO_2 emission due to the small changes in the short-term and long-term development of IRI values.

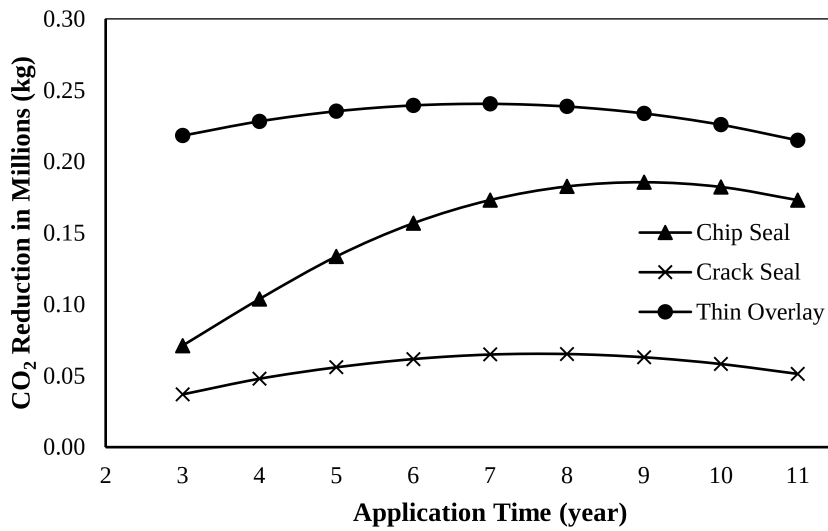
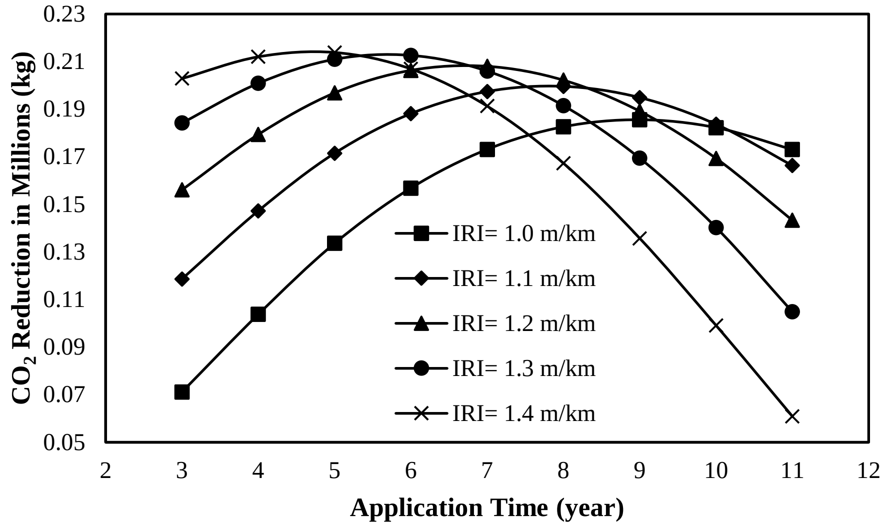
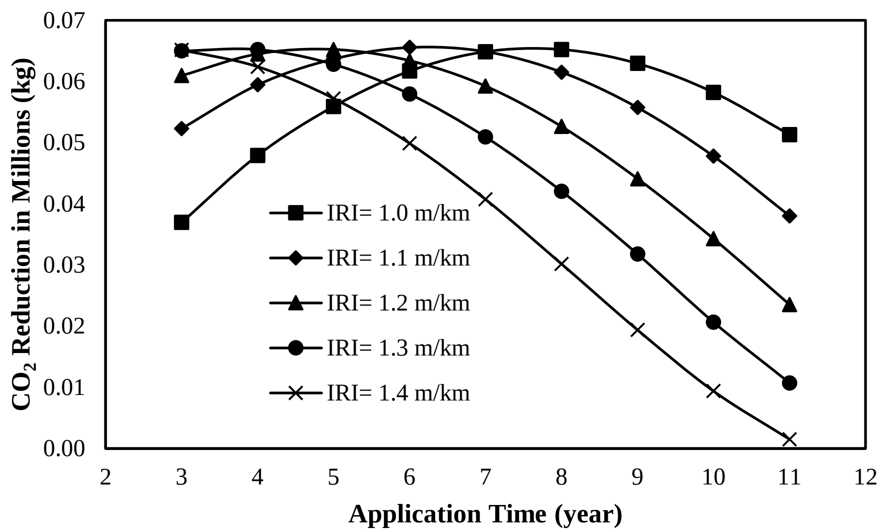


Figure 4.3 Effect of application time on CO_2 reduction in the pavement life-cycle for different preservation treatments (AADTT=1500 ESALs, Initial IRI=1.0 m/km)

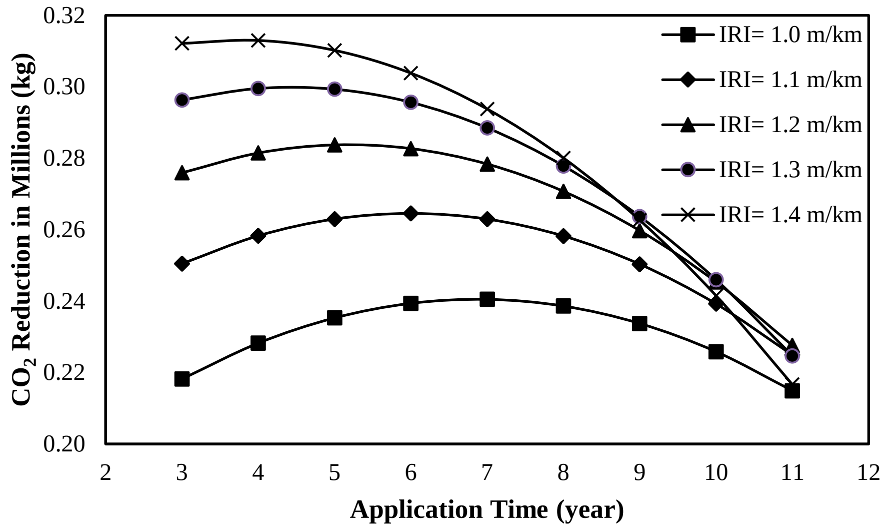
Figure 4.4 shows the reductions of CO_2 emission at different initial IRI values (1.0, 1.1, 1.2, 1.3, and 1.4 m/km). In general, the optimum timing of treatment application becomes earlier when the initial IRI value increases. This is due to the fact that the pavement with the higher value of initial IRI (poor condition) needs to be treated earlier in order to reduce CO_2 emission at the use stage. On the other hand, the maximum reductions of CO_2 emission due to preservation treatments increase as the initial IRI increases for chip seal and thin overlay, while the maximum reduction of CO_2 emission has negligible variations with the initial IRI values for crack seal.



(a)



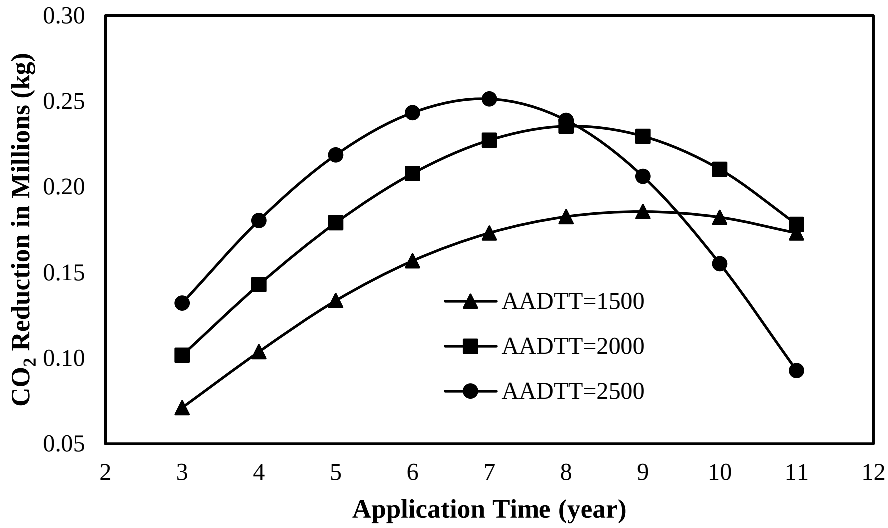
(b)



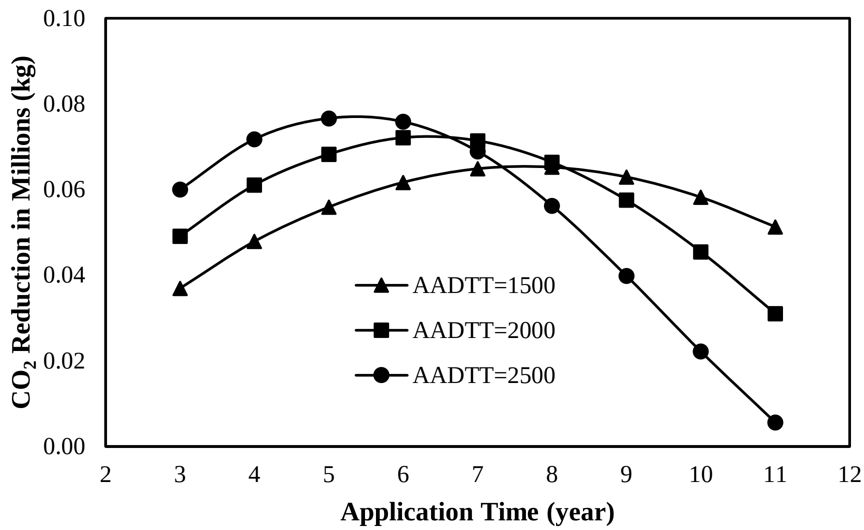
(c)

Figure 4.4 Effect of different initial IRI on application time and CO_2 reductions in the use and construction stages using (a) chip seal (b) crack seal (c) thin overlay (AADTT-1500 ESALs)

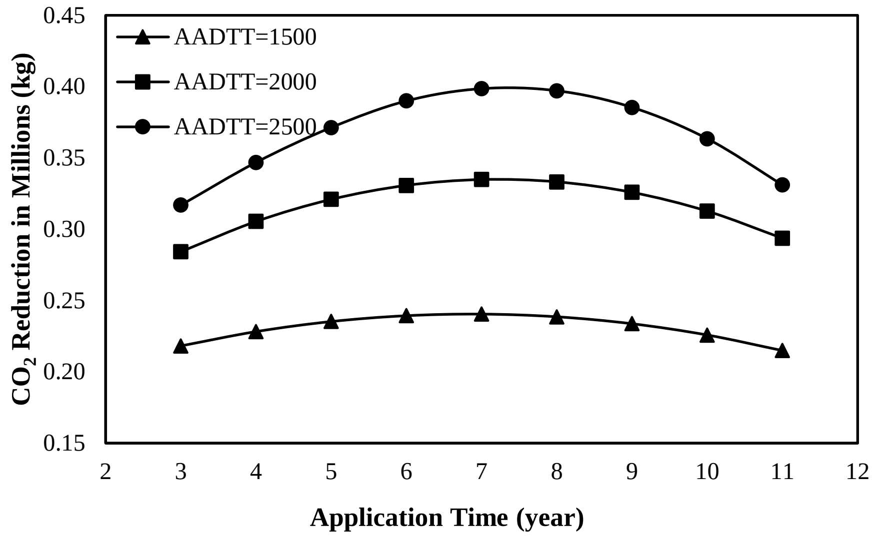
Figure 4.5 shows the reductions in CO_2 emission at three different AADTT levels (1500, 2000, and 2500 ESALs). The results show that the optimum timing of treatment application becomes earlier for chip seal and crack seal when the traffic volume increases; while the optimum timing of treatment keeps relatively constant for thin overlay when the traffic volume changes. On the other hand, the maximum reductions of CO_2 emission increase generally as traffic volume increases. This is due to the fact that the higher traffic volume results in the higher impact of CO_2 emission at the use stage regardless of the timing of treatment application. In general, the results here indicate that the environmental benefits of pavement preservation at the use stage of pavement should not be neglected.


0.30
0.25
0.20
0.15
0.10
0.05
2
3
4
5
6
7
8
9
10
11
12
CO_2 Reduction in Millions (kg)
Application Time (year)
AADTT=1500
AADTT=2000
AADTT=2500

(a)


0.10
0.08
0.06
0.04
0.02
0.00
2
3
4
5
6
7
8
9
10
11
12
CO_2 Reduction in Millions (kg)
Application Time (year)
AADTT=1500
AADTT=2000
AADTT=2500

(b)



(c)

Figure 4.5 Effect of different AADTT values on application time and CO_2 reductions in the use and construction stages using (a) chip seal (b) crack seal (c) thin overlay (Initial IRI=1.0 m/km)

4.6 SUMMARY

In this chapter, only carbon dioxide (CO_2) emissions are quantified for both construction and use stages. Preservation treatments considered in this study include thin asphalt overlay, chip seal, and crack seal. The entire process of each treatment, including raw material, manufacturing, transport, and placement, were considered as appropriate for quantification of CO_2 emission at construction stage. The pre- and post-treatment IRI models were developed using the data obtained from the Long-Term Pavement Performance (LTPP) program Specific Pavement Studies (SPS-3). The effect of pavement surface characteristics on vehicle fuel consumption at use stage was investigated using the Highway Development and Management Tool (HDM-4) and the Motor Vehicle Emission Simulator (MOVES) version 2014a considering different vehicle types, speeds, and surface characteristics. The environmental impact of pavement preservation treatments was evaluated through the life-cycle reduction of CO_2 emission considering different application timings of treatments in the pavement life.

CHAPTER 5 MULTI-OBJECTIVE OPTIMIZATION OF PAVEMENT PRESERVATION STRATEGY CONSIDERING AGENCY COST AND ENVIRONMENTAL IMPACT

5.1 INTRODUCTION

Highway maintenance agencies seek to reduce agency costs while also maintaining a low level of pavement roughness. However, these two objectives are directly contradictory as a reduction in cost will likely cause an increase in road roughness. In theory, an ideal solution would be to maintain roads with a low level of roughness at no cost. In practice, it is impossible to satisfy both objectives as there is no single optimal solution that successfully satisfies both criteria.

The most common multi-objective problem in pavement management can be assumed to have two performance measures or objectives. In this particular problem, both objectives are in linear forms so that the problem can be considered as a linear multi-objective optimization problem. When decision makers consider additional objectives that can be in non-linear form, the problem will be considered as a nonlinear, multi-objective optimization problem. For example, the decision makers may want to maintain highway network with evenly distributed smoothness, the other objective, which can be a measure of standard deviation of the pavement network roughness index, will be added to the objectives. The objective will be in a nonlinear format of the decision variable. In such a case, the problem will be viewed as a non-linear, multi-objective optimization problem.

For pavement management system, a mathematical model that is used to determine the most appropriate pavement preservation or reconstruction treatments regarding efficacy and cost-effectiveness is referred to as a maintenance optimization model. These models are often used in pavement management programs and are classified as either single objective or multi-objective.

The general form of single-objective optimization model is to minimize (maximize) X subjected to (constraint 1, constraint 2, constraint n). X is the single objective to be optimized. For instance, most of the agencies try to minimize agency costs, or user costs, or maximize pavement condition. The constraints usually include budget limitation of the agency, pavement threshold condition, etc.

Multi-objective optimization is needed if the decision makers look for achieving two or more objectives together. For example, transportation agencies try to find an adequate maintenance strategy to minimize agency cost and at the same time user cost. The minimization of user costs requires keeping pavement in good condition with a high level of service, which leads to increase in agency cost. In other words, these two competing objectives (agency cost and user cost) are contradictory. There is a range of measures that can be taken to unify objectives that appear to be contradictory (Mbwana 2001; Abaza 2007).

According to Mbwana (2001), single objective optimization models generally have number of different aims, namely to reduce costs, enhance the efficacy of treatments and enhance the condition or lifespan of the pavement. The costs incurred by the agency collectively throughout the lifespan of the facility are referred to as agency costs and are measured as a function of preservation activities. The costs incurred by users include accident costs, travel delays and vehicle operation in normal and work zone operations (Walls & Smith, 1998). These costs are measured as a function of pavement performance and the preservation activities performed (ARA, 2004). By seeking only to lower costs, the roughness of the pavement may increase. On the other hand, by seeking only to enhance pavement condition, the costs may increase.

In some cases, decision-makers may be satisfied to achieve only a single objective. Nonetheless, in most cases, the agency will seek to find an optimal solution that satisfies multiple objectives at the same time. There are some common techniques that can be taken to unify objectives that appear to be contradictory (Mbwana, 2001; Abaza, 2007). One method to achieve multiple-objectives is to optimize one objective while imposing competing objectives to serve as constraints in the optimization formulation (Grivas et al. 1993; Chen et al. 1996; Liu and Wang 1996; Li et al. 1998; Shivakoti and Soleymani 2006). This approach exhibits some limitations such as selection of the objective that deserves the most attention among the competing objectives and selection of the proper range values for those objectives that are not included in the objective function but instead set as constraints. These limitations may lead to suboptimal solutions concerning those derived directly from multi-objective considerations (Fwa et al. 2000; Wang et al. 2003; Yoo 2004). The prior knowledge is needed about the required level of the objectives that are converted to constraints. Therefore, it may lead to unacceptable results since the required level of competing objectives may differ depending on different assumptions.

In the second method which is called weighted sum method, all objectives can be combined to form a single cohesive objective. For instance, user costs and agency costs are treated as a single objective as opposed to two contradicting objectives (Mbwana, 2001). This method is limited by the fact that all objectives must be transformed into a single unit and it is quite hard to convert certain costs into a single objective along with pavement roughness. In addition, while agency and user costs may be successfully converted into a single unit, many argue that this method assumes that marginal user costs are the same as marginal agency costs when non-highway users are taken into account (Mbwana, 2001). It has also been argued that the relatively large scale of user costs cause them to take precedence of lower agency costs (Wu & Flintsch, 2009) and the attempt to unify two costs is essentially unfeasible.

The third method is a direct multi-objective optimization that takes all objectives into account. This method is limited by the ability of model solving to generate an optimal solution, particularly when multiple contradictory objectives are incorporated. Broadly speaking, such models are limited by the fact that objectives cannot be assessed accurately and objectively (Wu & Flintsch, 2009). The models are also quite hard to develop considering the complex objectives and constraints applied. As such, most previous studies that derived the multi-objective optimization model in the literature do not attempt to unify all objectives on agency costs, pavement condition, and user costs (Worm & Harten, 1996; Labi & Sinha, 2003; Wu & Flintsch, 2009).

Although existing studies have been conducted using single and multi-objective optimization models for pavement maintenance, one of the notable gaps is that few studies focused pavement preservation that intends to extend pavement life and improve pavement smoothness. It is expected that the application of pavement preservation would directly benefit the saving of vehicle operating cost and fuel consumption. Few studies have considered both agency cost and environmental impacts in the optimum selection of different pavement preservation treatments at the network level.

The concept of optimization when dealing with single objective is defined as the minimization or maximization of a specific objective. However, for problems that involve multiple objectives, an optimal solution can be hard to identify unless an improvement in one objective also leads to improvements in the others. In most cases, there is unlikely to be a single optimal solution for multiple objectives. Also, there is a lack of existing research focusing on the integration of the development of the multi-objective model and the post-optimization decision making. The Pareto optimal concept, an approach that is ideal for generating nondominant solutions, need be used to get solutions for multi-objective problems.

During last few years, many studies recommend single objective optimization for simplicity, while other studies suggest multi-objective optimization for accuracy. Thus, this paper was elaborated on the mathematical statements of the problem by providing a detailed on single and multi-objective optimization formulation. For multi-objective optimization, the aim is to generate a range of solution options where pavement roughness and costs are applied as boundary conditions. In such cases, all proposed solutions will inevitably compromise one objective for the benefit of another. As such, the goal is to find a solution that is acceptable and balanced.

5.2 PAVEMENT PRESERVATION TREATMENTS

5.2.1 Cost of Pavement Preservation Treatments

In this study, three typical preservation treatments were considered, including crack seal, chip seal, and thin overlay. Crack seal is conducted by filling cracks with a crack sealant that is usually rubberized asphalt or polymer modified asphalt. It extends the service life of pavement through preventing moisture infiltration and incompressible materials in existing cracks. Chip seal is a surface treatment in which pavement surface is sprayed with asphalt emulsion and then immediately covered with aggregate and compacted by the roller. Chip seals are used primarily to seal pavement with non-load-associated cracks and to improve surface friction. The thin overlay is usually applied with using a thin layer (0.5-2 inches) of hot-mix asphalt (HMA). It can improve pavement surface condition, reduce permeability, and improve the ride quality of pavement.

The agency costs of different preservation treatments were selected from a previous study that summarized the costs from different state agencies (Wang et al. 2013), as shown in Table 5.1.

Table 5.1 Agency Costs of Preservation Treatments (After Wang et al. 2013)

Preservation Treatment	Crack seal	Chip Seal	Thin overlay
Agency cost ($/lane-mile)	2,000	10,000	30,000

5.2.2 Pavement IRI Before and After Preservation Treatments

The benefits of pavement preservation treatments on pavement smoothness are expressed using the short-term and long-term change of International Roughness Index (IRI). The short-term change is the reduction of IRI right after preservation treatment; while the long-term change is the change of development curve of IRI over time due to the application of preservation treatment. In the authors' previous work, the IRI data in the Long-Term Pavement Performance (LTPP) database was used to develop the IRI models before and after preservation treatment. The short-term and long-term change of IRI models are shown in Tables 5.2 and 5.3, respectively (Lu and Tolliver 2013; Wang and Wang 2017).

Table 5.2 Performance jump in IRI after preservation treatments

Treatment	**Polynomial regression function**	**R^2**
Thin overlay	$\mathbf{IRI\ jump} = -0.008 IRI_{existing}^{3} + 0.971 IRI_{existing} - 0.726$	0.88
Chip seal	$\mathbf{IRI\ jump} = -0.081 IRI_{existing}^{3} + 1.606 IRI_{existing} - 1.637$	0.52
Crack seal	$\mathbf{IRI\ jump} = -0.052 IRI_{existing}^{3} + 0.774 IRI_{existing} - 0.749$	0.83

Table 5.3 IRI development equations for each treatment type

Treatment	**IRI Development**	**R^2**
Control section	$\mathbf{IRI(t) = IRI_0\ e^{(2.22\times10^{-2}+2.83\times10^{-5}\times AADTT)t}}$	0.48
Chip seal	$\mathbf{IRI(t) = IRI_0\ e^{(2.08\times10^{-2}+2.71\times10^{-5}\times AADTT)t}}$	0.63
Crack seal	$\mathbf{IRI(t) = IRI_0\ e^{(2.21\times10^{-2}+2.76\times10^{-5}\times AADTT)t}}$	0.68
Thin overlay	$\mathbf{IRI(t) = IRI_0\ e^{(1.66\times10^{-2}+2.55\times10^{-5}\times AADTT)t}}$	0.71

5.2.3 CO_2 Emission from Vehicles

Although empirical models exist between pavement surface roughness and vehicle fuel consumption and CO_2 emission, they were developed using specific datasets and thus cannot cover general scenarios with different pavement conditions and vehicle types (Hammarstrom et al., 2012).

In this study, the effect of pavement smoothness on CO_2 emission of vehicles was calculated using the Motor Vehicle Emission Simulator (MOVES). In the MOVES, Vehicle Specific Power (VSP) functions are used to calculate the energy consumption and traffic emissions considering the effects of rolling resistance, vehicle mass, speed, road grade, and vehicle operation status, as shown in Equation 5.1. However, the influence of pavement smoothness is disregarded by the default VSP model in MOVES. Ghosh et al. (2015) developed an approach to consider the effect of pavement surface condition on rolling resistance by adjusting the values of the rolling term (A) and air drag term (C) in the VSP model based on IRI values, which was used in this study to consider the effect of pavement roughness on vehicle emission.

$$VSP = \frac{A}{M} \times v + \frac{B}{M} \times v^2 + \frac{C}{M} v^3 + (a(1 + \varepsilon_i) + g \times grade) \times v \tag{5.1}$$

Where, A, B, and C refer to rolling resistance components, namely higher-order rolling resistance and mechanical rotating friction, and air drag, respectively; M is the vehicle mass; v denotes the instantaneous speed; and a and ε_i are the vehicle acceleration and mass factor terms.

To simplify the calculation process and avoid running large number of cases using MOVES in the optimization process, totally 7140 runs with MOVES were used to develop regression models for predicting CO_2 emission. The variables considered in the analysis include vehicle types, speed, rolling resistance (expressed by A and C values due to different IRI values). Table 5.4 shows the developed regression models with R-square values. In general, the high R-square values indicate that the regression models can be used for prediction of CO_2 emission with acceptable accuracy.

Table 5.4 Regression Models for CO_2 Emission

Vehicle Type	Equation for CO_2 Emission (kg/veh-mile)	R^2
Passenger Car	$\mathbf{CO_{2emission\_21} = 1.1582 + 0.12377\,A + 61.61\,C - 6502\,C^2 - 0.049636\,\mathit{V} + 0.001061\,V^2 - 0.000008\,V^3}$	0.844
Passenger Truck	$\mathbf{CO_{2emission\_31} = 1.25761 + 0.13829\,A + 83.1\,C - 8796\,C^2 - 0.060537\,V + 0.001358\,V^2 - 0.00001\,V^3}$	0.855
Single Unit Short-Haul Truck	$\mathbf{CO_{2emission\_52} = 2.6886 + 0.16013\,A + 69.67\,C + 2634\,C^2 - 0.14533\,V + 0.002869\,V^2 - 0.000018\,V^3}$	0.903
Combination Long Haul Truck	$\mathbf{CO_{2emission\_62} = 4.3724 + 0.19071\,A + 73.93\,C + 4730\,C^2 - 0.18485\,V + 0.003304\,V^2 - 0.00002\,V^3}$	0.926

Where, A=Rolling term, C=Air drag term and V=Speed (mph)

5.3 OPTIMIZATION MODEL FORMULATION

5.3.1 Optimization Objectives and Constraints

The two main objectives considered here are the minimization of agency costs and the minimization of network CO_2 emissions. Due to the variation of IRI values at different pavement segments, the minimization of average IRI in the pavement network is used for the approximate estimation of CO_2 emissions. For single optimization, only one objective was considered each time. For multi-objective optimization, minimization of agency cost was used as study objective and minimization of average roughness was considered as constraint.

All the objectives should be subject to constraints. The constraints depend on agency policy, which typically include performance requirement and available budget. In this study, the total budget ceiling amount and the unacceptable level of roughness for each road segment are formulated as constraints. It was assumed that only one treatment can be applied at each roadway segment.

The multi-objective optimization problem can be expressed mathematically, as shown in Equations 5.2-5.6.

$$\boldsymbol{min}\sum_{i=1}^{n}\sum_{j=1}^{m} C_{ij} \times \boldsymbol{X_{ij}} \tag{5.2}$$

$$\mathbf{min}\left(\mathbf{1}/\sum_{i=1}^{n}\boldsymbol{d_i}\right)\times\sum_{i=1}^{n}\left(\boldsymbol{d_i}\times\sum_{j=1}^{m}\boldsymbol{IRI_{ij}^{1}}\times\boldsymbol{X_{ij}}\right) \tag{5.3}$$

subjected to: $\sum_{j=1}^{m}\boldsymbol{IRI_{ij}^{1}}\times\boldsymbol{x_{ij}}\leq\boldsymbol{IRI_{ui}}\ \forall\ \boldsymbol{i}\in\{\mathbf{1},\mathbf{2},\dots,\boldsymbol{n}\}$ (5.4)

$$\sum_{i=1}^{n}\sum_{j=1}^{m}\boldsymbol{C_{ij}}\times\boldsymbol{x_{ij}}\ \leq\boldsymbol{B} \tag{5.5}$$

$$\sum_{j=1}^{m} \boldsymbol{x_{ij}} = \mathbf{1} \ \forall\ \boldsymbol{i} \ \in \ \{\mathbf{1}, \mathbf{2}, \ldots., \boldsymbol{n}\} \tag{5.6}$$

Where,

C_{ij} = cost of treatment j applied for pavement segment i;

d_i= distance weight parameter to pavement segement i (lane mile of the segment i);

IRI_{ij}^{1} = IRI value 1 year later for treatment j applied to pavement segment i;

IRI_{ui} = unacceptable IRI level for pavement segments i;

B = annual budget level for the pavement network;

n = the total number of pavement segments in the network ;

m = the total number of pavement treatment options;

$$x_{ij} = \begin{cases} 1 & \text{if treatment j selected to pavement segment i} \\ 0 & \text{if treatment j not selected to pavement segemnt i} \end{cases}.$$

To simplify the problem and include all variables, some assumptions were used in this study. A roadway network consisting of 30 road segments with different initial IRI values was considered. A base case scenario was first built, and sensitivity analysis was conducted to investigate the effect of various factors. For the base case, 15 segments are assumed in good condition with IRI values ranging from 1.0 to 1.5 m/km, and the other 15 segments are assumed in fair condition with IRI values ranging from 1.5 to 2.5 m/km. The annual network budget level was set at $750,000. The unacceptable level of IRI was set at 2.5 m/km for all segments. The analysis period was one year assuming the treatment was conducted at the beginning of the year, which simulates the situation where an annual budget is set separately for pavement preservation. It was also assumed that average annual daily traffic (AADT) was 15,000 which was the same for all segments.

The percentages of passenger car, passenger truck, single unit short-haul truck, and combination long-haul truck in the traffic stream were 45%, 45%, 5%, and 5%, respectively. Assuming that single unit truck and combination truck had the same truck factor of 1.0, the average annual daily truck traffic (AADTT) in ESALs would be 1,500 for the base case. The distance for each segment was assumed the same (one lane-mile), and the speed limit was 65 mph.

5.3.2 Simulated Constraint Boundary Model

The Simulated Constraint Boundary Model (SCBM) was used in this study to solve the multi-objective optimization problem (Mbwana, 2001; Abaza, 2007; Lu & Tolliver, 2013). This technique often assumes a known optimal level for the bounded or converted objective by providing a fixed boundary (Mbwana, 2001). In this study, the multi-objective problem (minimizing agency cost and average network roughness) was converted into single objective problem by converting the objective of minimizing pavement network average roughness (Equation 5.3) to the bounded constraint (Equation 5.7) which is mathematically expressed as follows:

$$\min\left(1/\sum_{i=1}^{n} d_i\right) \times \sum_{i=1}^{n}\left(d_i \times \sum_{j=1}^{m} IRI_{ij}^{1} \times X_{ij}\right) \leq IRI_{average} \tag{5.7}$$

Where $IRI_{average}$ = predefined network average roughness.

The simulated constraint boundary model seeks the Pareto optimal solutions by fine changing $IRI_{average}$. Then, the corresponding network average CO_2 emission for each predefined $IRI_{average}$ value was calculated using the developed regression models of CO_2 emission in Table 5.4. For each calculated average CO_2 emission value, one potential Pareto optimal solution can be obtained. The evenly distributed potential Pareto optimal solutions are obtained by indirectly fine changing average CO_2 emission value.

The SCBM does not require decision makers' prior knowledge about the optimal level of the converted or bounded objective. In other words, the approach does not require the boundaries for the converted objective. Moreover, the method is independent on the scales of objectives. There is no need to transform different units of objectives to dimensionless units or the monetary units. The objectives can be in different units and scales that can be handled directly. Finally, the technique can also provide decision makers with evenly distributed Pareto optimal solutions if the steps of the boundary change are fine enough. The multi-objective problem was solved using the PROC OPTMODEL module of SAS/OR software version 9.4.

5.3.3 Generation of Pareto Optimal Solutions

The range of solutions generated to resolve multi-objective problem suffers from Pareto efficiency or Pareto optimality as there is no way to achieve improvements in one objective without compromising another. It is not difficult to perform one run to simulate all possible boundaries for the objective with a fine changing step in SCBM. One potential Pareto solution is obtained with each boundary. Thus, with simulating fine changed boundary values for the objective, the Pareto optimal solutions can be found for the multi-objective problem.

In this study, the SCBM seeks the Pareto optimal solutions by fine changing the network average IRI value which leads to the change of CO_2 emission in the road network. The network average IRI for the base case is set between 0.7 to 2.5 m/km with the changing interval of 0.001 m/km. For each fixed average IRI value (average CO_2 emission), one potential Pareto optimal solution was obtained.

After finding the complete Pareto optimal solutions, the next step is selecting the final solution among many Pareto solutions (Zeleny 1982). Marler and Arora (2004) summarized some existing methods for selecting the final solution among Pareto optimal solutions. One of the most important methods is Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). The selected point is as close as possible to the positive ideal solution, utopia point. The positive ideal solution can be understood as the solution that is composed of the best or most desirable solution for the objective functions. This method was selected in this study to demonstrate the final decision-making procedure after obtaining the Pareto solutions.

The ideal solution will achieve zero CO_2 emissions with zero agency cost which is impossible. The more realistic utopia point should be the least CO_2 emission value and the least total agency cost that can be achieved without violating constraints. So, the realistic utopia point for the base case is ($2,000, 68,400,000 kg).

In order to apply the TOPSIS, the closest point on Pareto frontier to the utopia point should be chosen. For the optimization problem with two objectives, the distance between the utopia point and the points on Pareto frontier was calculated using Equation 5.8.

$$D_i = \sqrt{[f_{i1}(X) - f_1^*]^2 + [f_{i2}(X) - f_2^*]^2} \tag{5.8}$$

Where,

Di = distance between the *i*th Pareto solution and utopia point;

f_{i1}(X)= first objective value corresponding to the *i*th Pareto solution;

f_{i2}(X)= second objective value corresponding to the *i*th Pareto solution;

f^*_1 = the ideal utopia point value for first objective; and

f^*_2 = the ideal utopia point value for second objective.

Note that the scales of objectives will affect the calculated distances. If the scales of objectives are very close, the distances are comparable using Equation 5.8. If the scales of objectives are different, the objective with the greater scale will dominate the other. In other words, the results will favor the objective with the greater scale. In this case, the calculated distance will be dominated by CO_2 emissions and almost independent on agency costs.

Therefore, the normalized Pareto optimal point is used to avoid such bias due to scale effect. One way is to normalize the data into a common scale (0–1). The method can be expressed as shown in Equation 5.9.

$$f_i^{norm} = \frac{f_i - f_{min}}{f_{max} - f_{min}} \tag{5.9}$$

Where:

f_i^{norm} = normalized objective value corresponding to the *i*th Pareto solution;

f_i = objective value corresponding to the *i*th Pareto solution;

f_{max} = maximum objective value corresponding to the *i*th Pareto solution;

f_{min} = minimum objective value corresponding to the *i*th Pareto solution.

In this study, Equation 5.9 was used to normalize the Pareto optimal points and utopia point. For the base case, the (f_{min}, f_{max}) values are ($2,000, $750,000) for agency cost and (68,496,900 kg, 69,150,000) for CO_2 emission, respectively. After normalizing the Pareto optimal points for the two objectives (f_{i1}^{norm}, f_{i2}^{norm}), the distance between the utopia point and the ith points on Pareto frontier was calculated using Equation 5.8. Then, the final solution was obtained according to the minimum distance.

5.4 RESULTS AND DISCUSSION

5.4.1 Comparison of Single and Multi-Objective Optimization Results

Both single-objective and multi-objective optimization problems were solved. Table 5.5 shows the optimization results corresponding to the minimization of either agency costs or CO_2 emission or both. As expected, the single objective of minimizing agency cost keeps the road segments in poor condition that leads to the highest amount of CO_2 emission. On the other hand, the agency cost increases to the budget constraint ($750,000) for the single objective of minimizing CO_2 emissions. In addition, the single objective of minimizing agency cost has the highest value of cost-effectiveness in emission reduction compared to do do-nothing because this objective has the lowest value of agency cost and the highest value of emission compared to other objectives.

Table 5.5 Single objective optimization results

Scenario	**Agency Cost ($)**	**CO_2 Emission (kg)**	**Cost-effectiveness in emission reduction (kg/$)**
Do nothing	0	68,839,612	/
Minimize agency cost	2,000	68,834,648	2.482
Minimize CO_2 emission	750,000	68,496,682	0.457
Minimize agency cost and CO_2 emission	136,000	68,687,382	1.119

Figure 5.1 presents the minimum distance between Pareto frontier and utopia point for multi-objective optimization. For multi-objective optimization of both agency costs and CO_2 emission, the final solution (point A) has the minimum distance between Pareto solutions and the realistic utopia point which is ($136,000, 68,687,382 kg). The result falls into the middle part of the Pareto frontier that matches the expectation because selecting the mid-point on the frontier curve will improve both objectives, while selecting any point at the end sections on the curve will be incorrect for one objective

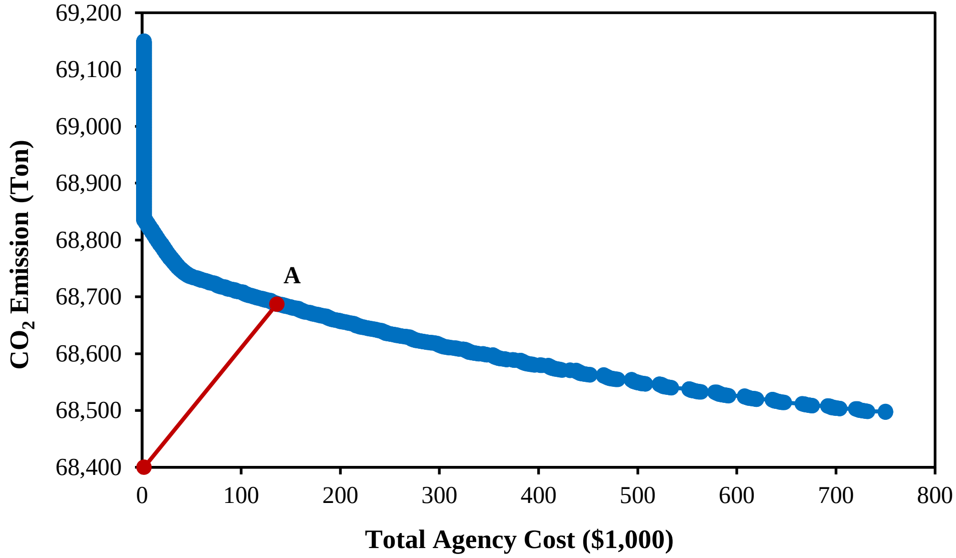


Figure 5.1 Final solution from Pareto frontier for multi-objective optimization

Figure 5.2 shows the comparison of treatment selection strategies between single-objective and multi-objective optimization solutions. It is obvious that do-nothing treatment is dominant for single objective of minimizing agency cost; while thin overlay is dominant in the case of minimizing emission because it causes the higher IRI reduction as compared to the other two treatments (crack seal and chip seal). To achieve the minimization of both agency cost and emission, crack seal was selected for most sections and thin overlay was selected for the remaining sections, which is the balance of treatment cost and effectiveness.

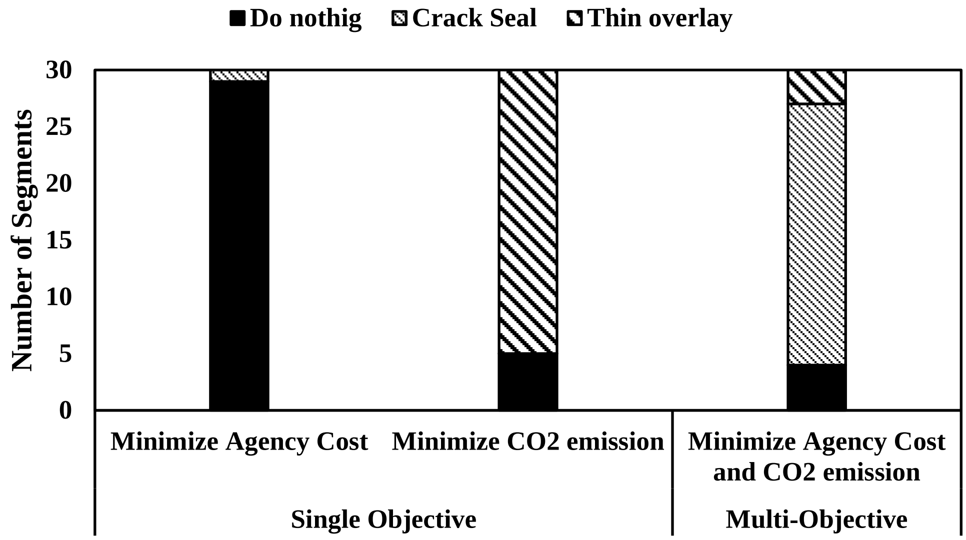
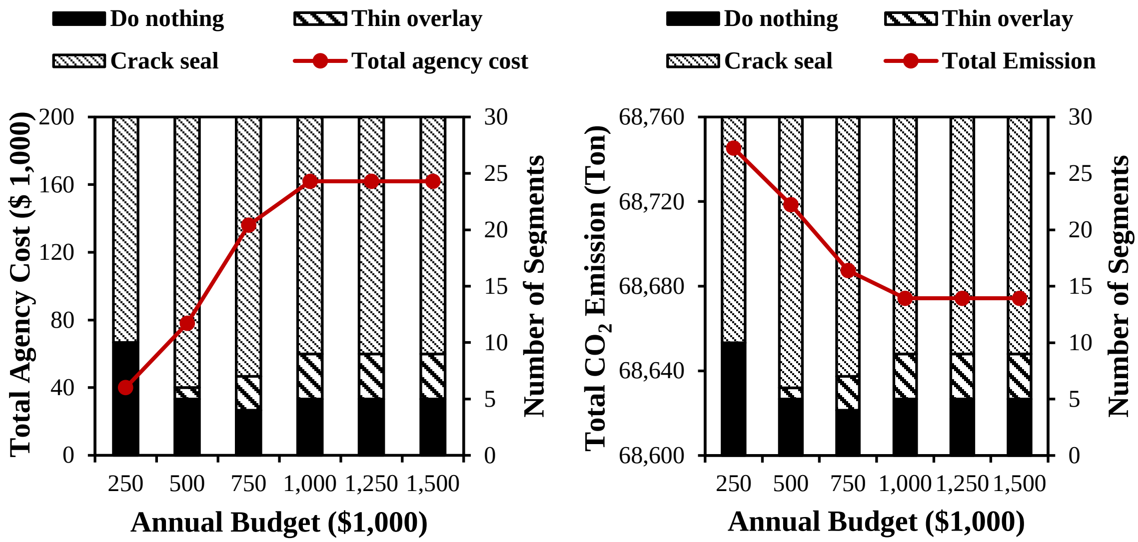


Figure 5.2 Comparison of treatment selection strategies between single objective and multi-objective optimization solutions

To study the effect of annual budget on multi-objective optimization results, the analysis was repeated for varying budget levels ranging from $250,000 to $1,500,000. Figure 5.3 shows the selection of preservation treatments in road network with the results of agency cost and CO_2 emission at different network budget levels. The results show that when the annual budget increases, the agency cost increases until reached a constant value, while the CO_2 emission decreases to a constant value. The number of segments treated with do-nothing decreases and the number of segments treated with thin overlay increases until that the annual budget reaches $1,000,000. This indicates that the multi-objective optimization results are not affected by the network budget after it reaches a certain level, which is due to the balance between two contradictory objectives.



(a) (b)

Figure 5.3 Effect of annual budget on multi-objective optimization with (a) agency cost; and (b) CO_2 emission

5.4.2 Effect of Pavement Condition on Optimization Results

The effect of changing the number of segments in GOOD condition (IRI = 1.0-1.5 m/km) and FAIR condition (IRI = 1.5 – 2.5 m/km) on the optimization results for both single and multi-objective optimization were investigated. Three different types of pavement conditions were assumed in this study, which are LS (5 segments under good condition and 25 segments under fair condition), ES (15 segments under good condition and 15 segments under fair condition), and HS (25 segments under good condition and 5 segments under fair condition).

Figure 5.4 shows the treatments distribution between segments as the pavement condition was changed from LS to HS for the two single objectives. In general for the two single objectives, the number of segments that are treated with do nothing increases when the pavement condition was improved from LS to HS. When the pavement condition was improved, this means the IRI values decrease and no need to any treatment action or maintenance repair to keep the agency cost and CO_2 emissions at the minimum value.

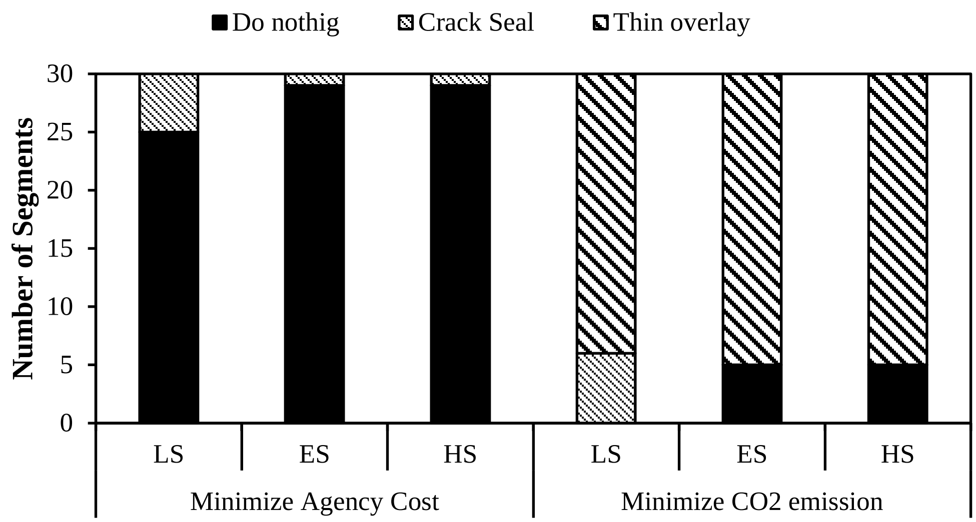
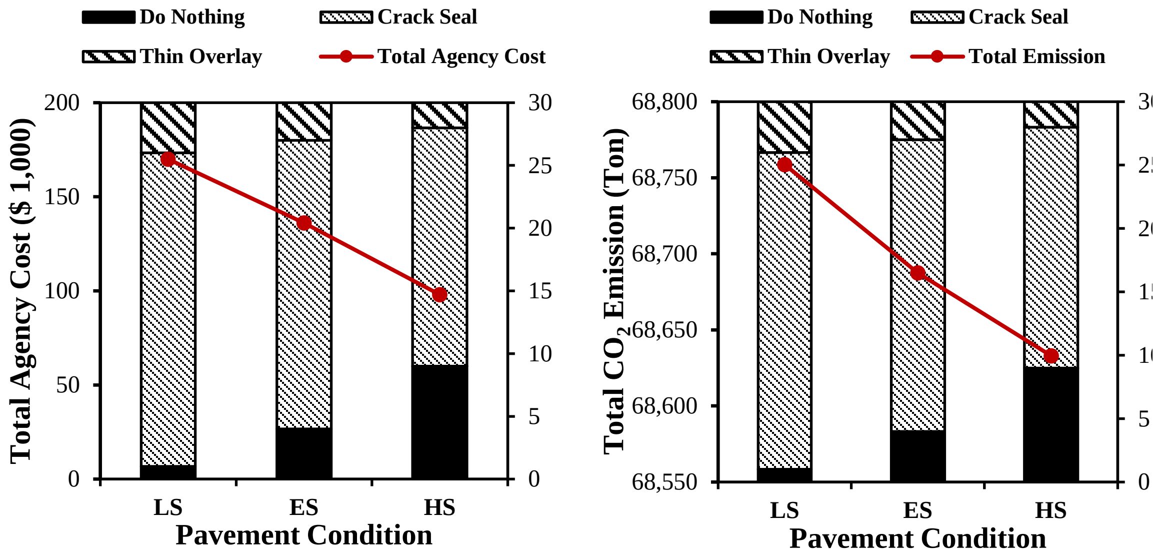


Figure 5.4 Effect of pavement condition on treatment selection for single-objective optimization

Figure 5.5 shows the selection of preservation treatments in a road network with the results of agency cost and CO_2 emission at different pavement conditions. The results show that both agency cost and CO_2 emission decrease when the initial pavement condition is improved. The number of segments that are treated with thin overlay and crack seal decreases when the initial pavement condition is improved.



(a) (b)

Figure 5.5 Effect of pavement condition on multi-objective optimization with (a) agency cost (b) CO_2 emission

5.4.3 Effect of Truck Percentage on Optimization Results

In order to study the effect of truck percentage on the optimization of pavement preservation strategy, the study assumed three different values of truck percentage which are 10%, 20%, and 30% of traffic stream with AADT of 15,000. By assuming the truck factor is 1.0, the calculated AADTT were 1,500, 3,000, and 4,500 ESALs for the truck percentage of 10%, 20%, and 30%, respectively.

Figure 5.6 shows the treatments distribution between segments as the truck percentage was increased for single objective optimization. When the truck percentage was increased, the number of segments treated with do nothing decreases and the number of segments treated with crack seal increases in the case of minimizing agency cost. For the single objective of minimizing CO_2 emissions with 10% truck, 25 segments were selected to be treated with thin overlay which causes a total agency cost of $750,000 (maximum annual network budget). Therefore, the number of segments treated with do nothing decreases and the number of segments treated with crack seal instead of thin overlay increases when the truck percentage was increased from 10% to 30% since crack seal has the lowest agency cost value.

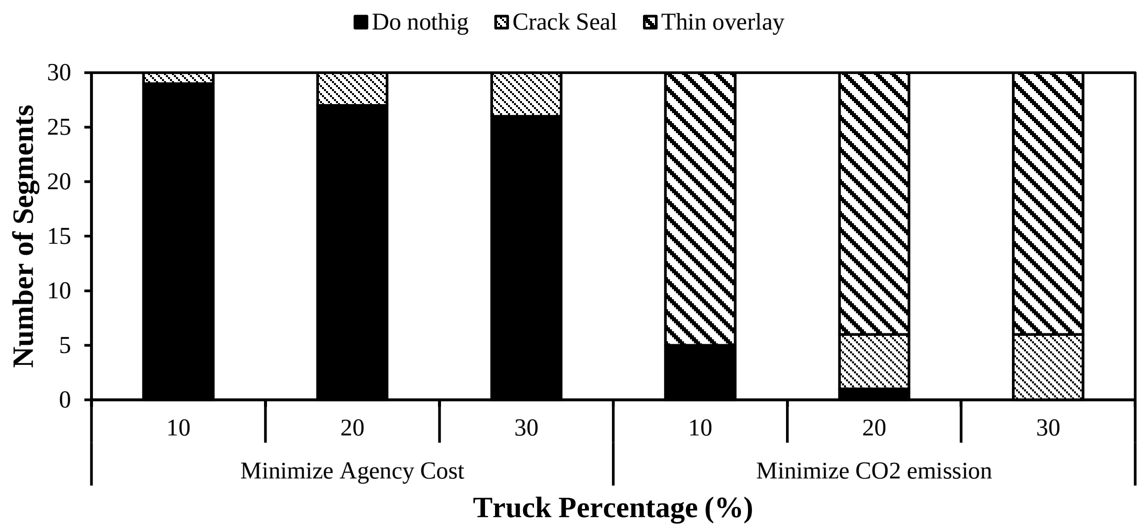
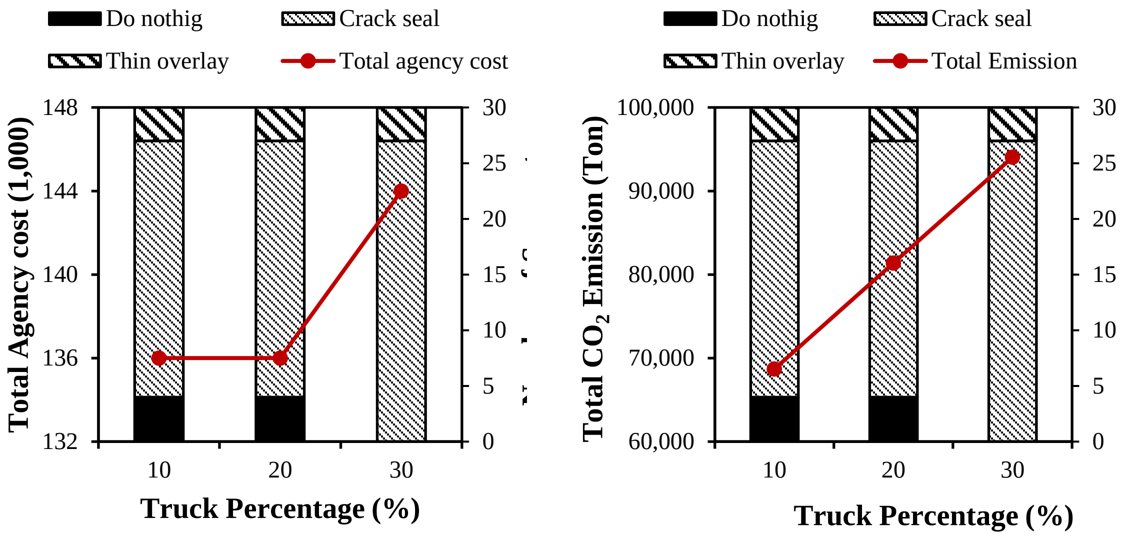


Figure 5.6 Effect of truck percentage on treatments distribution for the two single objectives optimization.

Figure 5.7 shows the selection of preservation treatments in a road network with the results of agency cost and CO_2 emission at different truck percentages. The results show that both the agency cost and CO_2 emission increase when the truck percentage increased. In addition, the number of segments that are treated with crack seal increases when the truck percentage increased because the network with higher truck percentage has higher deterioration rate (higher values of IRI) which needs to crack seal preservation treatment to minimize the agency cost and CO_2 emission at the same time.



(a) **(b)**

Figure 5.7 Effect of truck percentage on multi-objective optimization with (a) agency cost; and (b) CO_2 emission

5.4.4 Effect of Unacceptable IRI Level on Optimization Results

In this study, the unacceptable level of IRI **(**$IRI_{uaacceptable}$) was considered as a constraint in the optimization process that is equal to 2.5 m/km for the base case. Three different unacceptable levels of IRI (1.5, 2.0, and 2.5 m/km) were selected to investigate their effects on optimization results.

Figure 5.8 shows the treatment distribution between segments as the $IRI_{unacceptable}$ level was increased for single objective optimization. When the $IRI_{unacceptable}$ was decreased to 1.5 m/km (the IRI of each segment should be less than 1.5 m/km) for minimizing agency cost, the number of segments treated with do nothing decreases and the number of segments treated with chip seal increases since the chip seal treatment has higher reduction of IRI compared to crack seal. On the other hand, the number of segments that are treated with thin overlay and chip seal increases when the $IRI_{unacceptable}$ level was decreased to 1.5 m/km for the case of minimizing CO_2 emissions.

Figure 5.9 shows the selection of preservation treatments in a road network with the results of agency cost and CO_2 emission at different unacceptable levels of IRI. The results show that the agency cost decreases when the unacceptable level of IRI increases from 1.5 to 2.5 m/km. This is because keeping the IRI value for each segment at the higher threshold causes the fewer number of segments that need be treated with thin overlay. Accordingly, this causes the greater emission values when the unacceptable level of IRI increases.

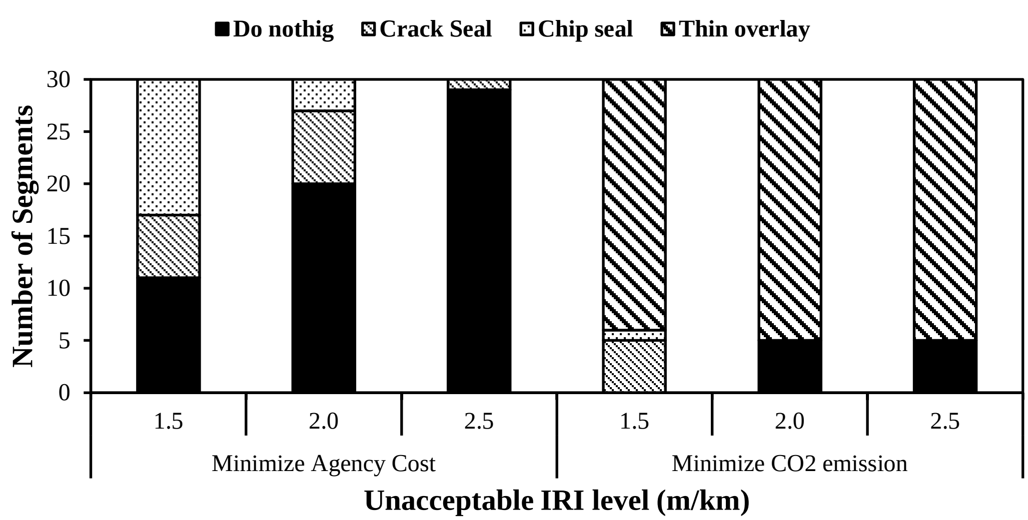
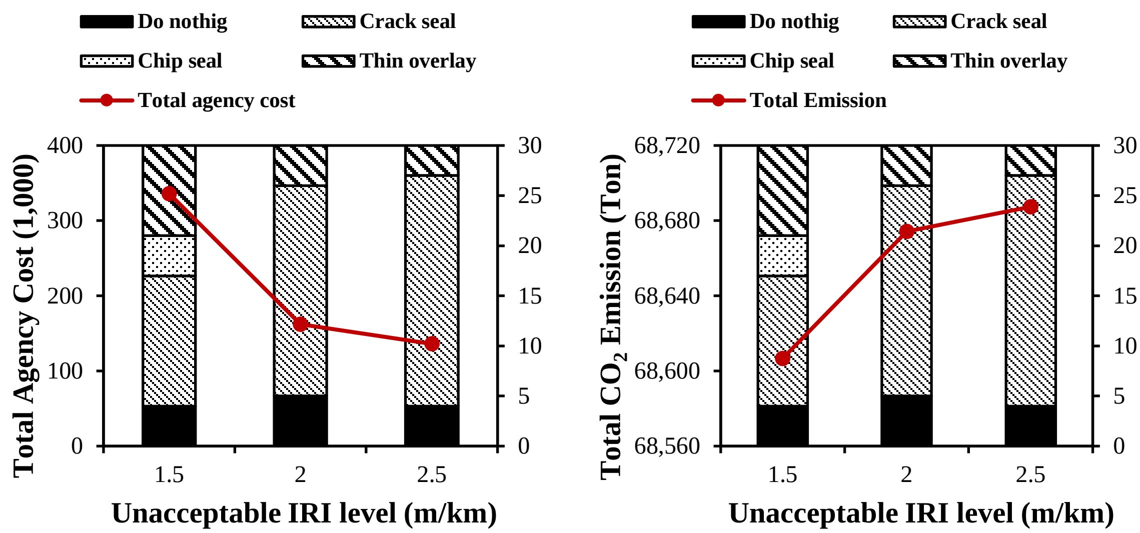


Figure 5.8 Effect of unacceptable IRI level on treatments distribution for the two single objectives optimization.



(a) **(b)**

Figure 5.9 Effect of unacceptable IRI level on multi-objective optimization (a) agency cost (b) CO_2 emission

5.4.5 Effect of Analysis Period

The analysis period for base case in this study is one year with the assumption that the preservation treatment is applied at the beginning of year one. So, the analysis period is another factor that should be considered in the sensitivity to find its effect on optimization results. However, three different analysis periods of 1, 3, and 5 years are considered in this study with the assumption that the preservation treatment is still applied at the beginning of year one.

Figure 5.10 shows the treatment distribution between segments as the analysis period was increased from 1 to 3 years for single objective optimization. When the analysis period was increased for minimizing agency cost, the number of segments treated with do nothing decreases and the number of segments treated with crack seal increases since the crack seal has the lowest value of agency cost. For minimizing CO_2 emission, thin overlay is still the dominant preservation treatment for about 24 segments of the network since it causes a higher reduction on IRI compared to other treatments when the analysis period was increased from 1 to 5 years.

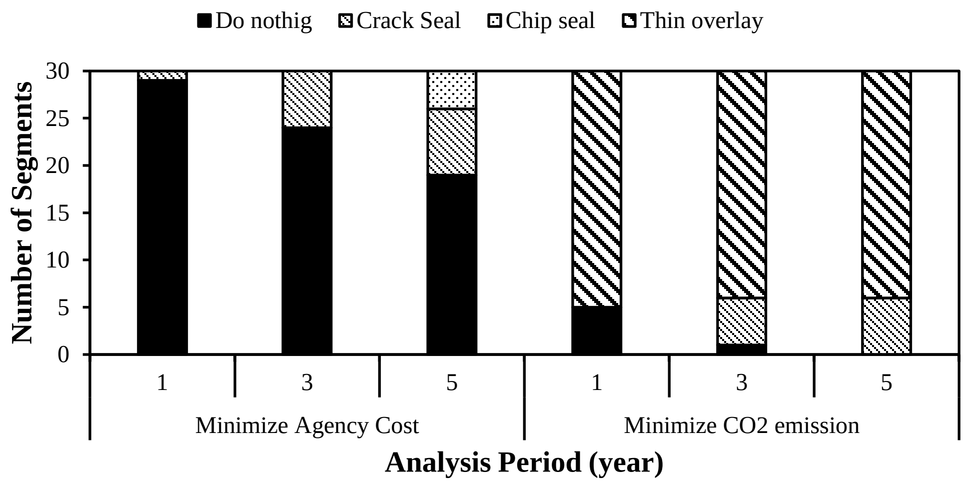
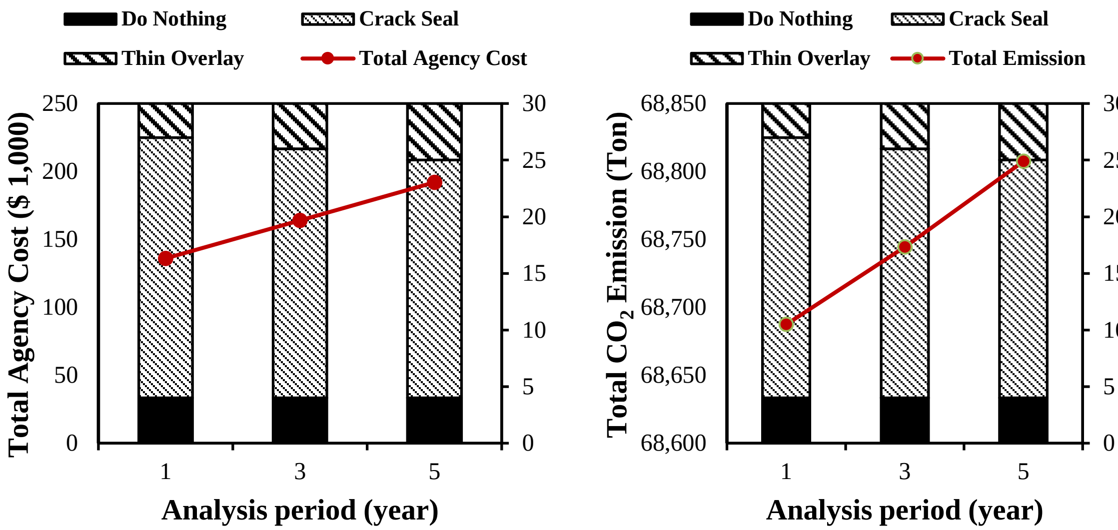


Figure 5.10 Effect of analysis period on treatments distribution for the two single objectives optimization.

For multi-objective optimization of minimizing agency cost and CO_2 emission, Figure 5.11 shows the treatment selection strategy at different analysis periods. The results show that both agency cost and CO_2 emission increase when the analysis period increases. However, the selection strategy does not have significant changes as the analysis period increases. Although the number of segment for thin overlay increases slightly, crack seal is still selected for most segments in the network.



(a) **(b)**

Figure 5.11 Effect of analysis period on multi-objective optimization (a) agency cost (b) CO_2 emission

5.5 SUMMARY

This chapter aims to develop pavement preservation strategy at the network level considering multi-objective optimization of minimizing agency costs and minimizing network average CO_2 emissions by minimizing pavement network average roughness.

The multi-objective optimization problem is solved using Simulated Constraint Boundary Model (SCBM) method which is based on solving one objective (agency cost) and converting the other objective (average network roughness) to constraint. Also, the annual network budget and unacceptable level of roughness are considered as constraints in the optimization. The multi-objective optimization results on pavement preservation strategy were compared to the results obtained from single-objective optimization of minimizing either agency costs or CO_2 emissions. The single and multi-objective problems were solved using the PROC OPTMODEL module of SAS/OR software version 9.4. A base case study was built to perform the optimization process, and sensitivity analyses were performed to study the effect of other factors on the pavement preservation strategy.

CHAPTER 6 WEIGHTED SUM METHOD FOR MULTI-OBJECTIVE OPTIMIZATION OF PAVEMENT PRESERVATION STRATEGY

6.1 INTRODUCTION OF WEIGHT SUM METHOD

Design optimization is to seek the best design that minimizes or maximizes the objective function by changing design variables while satisfying design constraints. During design optimization, one often needs to consider several design criteria or objective functions simultaneously. When more than one design objective is associated, the design problem becomes multi-objective, in which case the usual design optimization for a scalar objective function cannot be used.

To generate the set of Pareto optimal solution, many optimization methods can be used such as the standard constraint method (Messac et al. 2003), genetic algorithms (Holland 1975), the multiobjective simplex method (Cohon 1978), and the weighting sum method (Zadeh 1963). The selection of a specific method depends on the type of information provided, users' preferences, the availability of software, and the solution requirements (Marler and Arora 2004).

Stadler (1979 and 1984) applied the notion of Pareto optimality to the fields of engineering and science in the 1970s. The most widely-used method for multiobjective optimization is the weighted sum method (Wu & Flintsch, 2009; Das & Dennis, 1996; Srinivas & Deb, 1994; Cohon, 2013). The method transforms multiple objectives into an aggregated objective function. This method combines multiple objectives into a single objective by multiplying each objective by a weighting factor. Using this method, the multiple objectives are weighted and converted into Z– a single objective function – which can be expressed as follows:

$$Z = \sum_{i=1}^{n} \omega_i f_i(x) \tag{1}$$

Where, ω_i is the fractional weight value in the range 0-1 for objective *i*; $f_i(x)$ is the objective function *i*; and *n* is the number of objective functions.

Obviously, setting relative weights for individual objectives becomes a primary issue in applying this method. As the weight vector for the multiple objectives often depends highly on the magnitude of each objective function, it is desirable to normalize those objectives to achieve roughly the same scale of magnitude. This study used the weighting sum method as it is an approach sufficient for Pareto optimality and simple to implement.

Using this approach, the control of the weight vector for all possible weight situations along with an incremental step in ω_i facilitates the identification of Pareto optimal solutions as all weights are converted into a single unit. The weight of each respective objective can be modified to assign priority. This method is widely used in the literature as it is easy to apply and relatively intuitive (Wu & Flintsch, 2009). The weight assigned to each objective is determined on the basis of the size of each objective function. However, the weight values do not reflect the relative importance of each objective but the relative significance of relationships between objectives (Wu & Flintsch, 2009). For instance, while $\omega_1 > \omega_2$ implies that $f_1(x)$ is of greater importance than objective $f_2(x)$, but cannot assume that objective $f_1(x)$ is (ω_1/ω_2) times more important than objective $f_2(x)$. This reflects one of the limitations of the model as decision makers often find it hard to interpret the quantitative relationships between objectives and thus have difficulty choosing the ideal solution for their own requirements. For instance, the difference between ω_1 = 0.6 & ω_2= 0.4 and ω_1 = 0.7 & ω_2 = 0.3 is hard to identify as each weight set implies that $f_2(x)$ is less important than $f_1(x)$ but does not offer any additional information. According to Wu and Flintsch (2009), the decision maker using the incremental weight step approach requires theoretical knowledge of their own preferences before choosing the most suitable Pareto optimal solution. In addition, the decision maker will struggle to select and interpret a weight factor as the weights do not offer any qualitative information.

The concern in which the objectives are converted into a single objective using different scales is an additional limitation of weighting sum method. The scales employed and the objective function units often vary. For instance, the user may seek to reduce agency costs and enhance the IRI values of pavement surface condition. Agency costs are typically calculated in dollars within a range of $1,000 to $100,000 or more. IRI values, on the other hand, are calculated in m/km on a scale of 0.5 to 3m/km. Thus, the scale for each objective is clearly different as well as the objective units and to combine the total of each is essentially unfeasible (Messac et al. 2003). Wu and Flintsch (2009) argue that while the user may attempt to convert the values using the same scale, the variation in objective units would still limit the applicability of the totals. Therefore, as variation in units prevents summation offering any meaningful data, weights are allocated to each objective. Nonetheless, these weights do not provide any insights into how each objective is related.

6.2 PAVEMENT PERFORMANCE BACKGROUND

Pavement preservation has been widely applied to pavements in order to repair minor distressed, retard failures and prolong the serviceable lifespan of the pavement. The effectiveness of pavement preservation treatments can be measured in terms of friction and life extension. There has been much research into the effectiveness of pavement preservation.

Research has been varied and includes a cost effective analysis of thin surface maintenance treatments such as chip seal, crack seal, thin overlay and microsurfacing (Morian, 2011), and assessment of the effectiveness of preservation treatments on surface friction such as the long-term discrepancy analysis of surface friction conducted by Wang and Wang in 2013. Three methods to measure the short-term effectiveness of pavement preservation have been identified and examined as Performance Jump, Deterioration Rate Reduction and Deterioration Reduction Level (Labi et al., 2003).

A recent life-cycle cost analysis of different pavement preservation treatments examined the cost of the lifespan analysis analytical technology to determine the association between overall performance index and pavement life extension. The results were displayed using second-order polynomial regression methods (Wang et al., 2013). Earlier research created a decision tree to select various functional pavement classes based on the costs and results of different preservation treatments (Wei and Tighe, 2004). Peshkin et al. (2004) show that NCHRP report 523 examined pavement performance and cost data to conclude the optimal timing for pavements to be treated in order to enhance preservation, and presented the outcome using MS Excel-based software called OPTime. Agency costs, user delay costs and benefit-cost ratios are all taken into consideration to decide the ideal time for treatments. Haider and Dwaikat (2010) progressed a number of statistical methods to evaluate the best time for a variety of maintenance treatments, founded on different evaluation criteria.

Dong and Huang (2012), Lu and Tolliver (2012) and Wang and Wang (2012) all conducted research into preservation treatments and concluded that treatments could offer significant advantages in the reduction of International Roughness Index (IRI). It was found that thin overlay, poor rehabilitation condition and high traffic levels can increase the corrosion of newly applied overlay (Dong et al. 2012). This research was conducted by examining the effectiveness and cost-effectiveness of various asphalt restorations against the long-term pavement performance (LTPP) database. In other research, the life extension of thin overlay was measured against the effectiveness and cost of preventive treatments for flexible pavements (Wang and Mastin, 2012). Results showed that the increase in life extension of thin overlay was 5.4 years, crack sealing was 1.7 years, and ship sealing was 1.9 years.

The improvements of pavement condition and the reduction of deterioration as a result of treatment are short-term measures of effectiveness (Labi at al., 2007). The treatment service life and the area bounded by pavement performance curve are long-term measures of effectiveness in preservation treatments (Dong and Huang, 2012). By examining the characteristics of the studied of pavement performance both under the influence of preservation treatments, and with no treatment, the value of treatments in the long- and the short-term can be evaluated.

Haider and Baladi (2010) studied the increase of IRI as an exponential function of pavement age, however, they did not include the traffic volume. Huang and Dong (2009) and Ong et al. (2010) recognized the importance of the traffic volume on the deterioration rate of IRI and citied its significance when conducting research. Labi et al. (2007) reported that the long-term value of pavement preservation treatments is influenced by factors including traffic, age and pavement type while short-term effectiveness is largely influenced by pre-treatment condition.

6.3 OPTIMIZATION MODEL FORMULATION

6.3.1 Optimization Objectives and Constraints

This study focused on two main objectives which are the minimization of agency costs and CO_2 emissions at the network level. All the objectives should be subjected to constraints. The constraints depend on agency policy, which typically include performance requirement and available budget. In this study, the annual network budget ceiling amount and the unacceptable level of roughness for each road segment are formulated as constraints. It was also assumed that only one treatment can be applied at each roadway segment. On the basis of these assumptions, the optimization models are formulated as follows:

minimize $$Z_1 = \sum_{k=1}^{t} \sum_{j=1}^{n} \sum_{i=1}^{m} X_{ijk} \times C_i \times l_j \quad (6.1)$$

minimize $$Z_2 = \sum_{k=1}^{t} \sum_{j=1}^{n} E_{kj} \quad (6.2)$$

Subject to:

$$R_k^j = R_{k-1}^j \left[1 - \sum_{i=1}^{m} X_{ijk}\right] + \sum_{i=1}^{m} X_{ijk} \left[a_i + b_i \times AADTT_j\right] \quad \forall\ k, j \tag{6.3}$$

$$IRI_{ijk}^{jump} = \alpha_i \times IRI_{k-1}^{j^3} + \beta_i \times IRI_{k-1}^{j} + \gamma_i \qquad \forall\ k, i, j \tag{6.4}$$

$$IRI_k^j = e^{R_k^j}\left[IRI_{k-1}^j - \sum_{i=1}^{m} X_{ijk} \times IRI_{ijk}^{jump}\right] \ \forall\, k, j \tag{6.5}$$

$$\sum_{i=1}^{m} X_{ijk} \leq 1 \ \ \forall\, k, j \tag{6.6}$$

$$\sum_{j=1}^{n} \sum_{i=1}^{m} X_{ijk} \times C_j \times l_j \leq B_k \ \forall\ k \tag{6.7}$$

$$IRI_k^j \leq IRI_{threshold} \ \ \forall\ \ k, j \tag{6.8}$$

$$X_{ijk} = \{0,1\} \ \ \forall\ k, i, j \tag{6.9}$$

Where;

Z_1 = total network cost of treatment i applied for pavement segment j in planning horizon k;

Z_2 = total network CO_2 emission from vehicles driving on segment j in planning horizon k;

n = total number of pavement segments in the network;

m = total number of pavement treatment options;

k = total number of years in planning horizon;

E_{kj}= CO_2 emission from vehicles driving on pavement segment j in planning horizon k which is a function of $A, C, and\ v$ (Table 3.5);

C_i = cost of treatment *i* ($/veh.mile);

l_j = length of segment *j* (miles);

R_k^j =deterioration rate of segment *j* in year *k*;

IRI_{ijk}^{jump} = jump value of IRI of segment *j* caused by the treatment *i* in year *k*;

IRI_k^j = international roughness index of segment *j* in year *k*;

a_i, b_i = two model coefficients for treatment *i* (Equation 4.14 and Table 4.4);

$AADTT_j$ = annual average daily truck traffic for segment *j* (ESALs);

$\alpha_i, \beta_i, and\ \gamma_i$ = three model coefficients for treatment *i* (Equation 4.10 and Table 4.3);

B_k = annual budget level for the pavement network in year *k*;

$IRI_{threshold}$ = unacceptable IRI level that IRI of each segment *j* in yaer *k* cannot exceed;

$$X_{ijk} = \begin{cases} 1 & \text{if treatment i selected to pavement segment j} \\ 0 & \text{if treatment i not selected to pavement segemnt j} \end{cases};$$

6.3.2 Case Study

To simplify the problem and include all variables, some assumptions were used in this study. A roadway network consisting of 30 road segments with different initial IRI values was considered to be treated with three preservation treatments: chip seal, crack seal, and thin overlay. For the base case, 15 segments are assumed in good condition with IRI values ranging from 1.0 to 1.5 m/km, and the other 15 segments are assumed in fair condition with IRI values ranging from 1.5 to 2.5 m/km. The annual network budget level was set at \$750,000. The unacceptable level of IRI was set at 2.5 m/km for all segments.

The analysis period was 20 years assuming the treatment was conducted at the beginning of the year. It was also assumed that average annual daily traffic (AADT) was 15,000 which was the same for all segments. The percentages of passenger car, passenger truck, single unit short-haul truck, and combination long-haul truck in the traffic stream were 45%, 45%, 5%, and 5%, respectively. Assuming that single unit truck and combination truck had the same truck factor of 1.0, the average annual daily truck traffic (AADTT) in ESALs would be 1,500. The distance for each segment was assumed the same (one lane-mile), and the speed limit was 40 mph.

6.3.3 Model Transformation

Weighted sum is the method that was used in this study to solve the multi-objective optimization problem which includes the minimization of both agency cost and emission. This method sums the two objective values into a single objective measure after multiplying each objective by a weighting factor. Since the two objectives have different scales, the first step is to normalize each objective by using Equation (6.10):

$$Z_i^{norm} = \frac{Z_i - \min(Z_i)}{\max(Z_i) - \min(Z_i)} \tag{6.10}$$

Where, the values of $\max(Z_i)$ *and* $\min(Z_i)$ can be estimated or calculated by solving each objective individually.

The second step is converting the two objectives into single objective after normalization step, as shown in Equation (6.11):

$$\min_{X \in \hat{X}} Z_1(X) \; and \; \min_{X \in \hat{X}} Z_2(X) \;\; \rightarrow \;\; \min_{X \in \hat{X}} Z(X) = \; [w_1 Z_1^{norm} + \; w_2 Z_2^{norm}] \qquad (6.11)$$

Where, $\hat{X}$ is the feasible solution set; and $w_1 and\ w_2$ is the two weighting factors between the two objectives $Z_1\ and\ Z_2$, respectively; $w_{1,}\ w_2 > 0; and\ w_1 + \ w_2 = 1$. By changing $w_1 and\ w_2$ values, range of non-dominated solutions of Pareto Frontier can be obtained.

6.4 RESULTS AND DISCUSSION

6.4.1 Generation of Pareto Optimal Solutions

The converted optimization model in this study was solved by using the commercial software, AIMMS (Advanced Integrated Multidimensional Modeling Software) version 4.43. This software was put in as an integrated collection of a modeling language, a graphical user interface, and numerical solvers. AIMMS is one of the most developed expansion environments for building optimization-based decision support uses and advanced design frameworks.

Different combinations of weighting (w_1 and w_2) factors lead to different solutions. The different combinations of the two weighting factors reflect the differences in decision makers' value systems for judging the relative importance between the two objectives, "minimization of total agency cost, Z_1" and "minimization of total CO_2 emission, Z_2." Figure 6.1 shows the frontier curve made by the non-dominated solutions of Z_1 and Z_2 while changing the weighting ratio between the two excessive situations of minimizing both agency costs and CO_2 emissions.

Figure 6.1 shows that an increase in agency cost leads to a decrease in the CO_2 emission, while CO_2 emissions increase when the agency costs is decreased. So, any loss in one objective is included with a progression in the other objective, and it is difficult to get the best values of both objectives at the same time. Therefore, it is the decision maker's responsibility to decide the point (Pareto optimal solution) on the frontier curve that caused a large improvement in one objective at a small loss in the other. It is obvious in Figure 6.1 that selecting the mid-point on the frontier curve will improve both objectives, while selecting any point at the end sections on the curve will be incorrect for one objective.

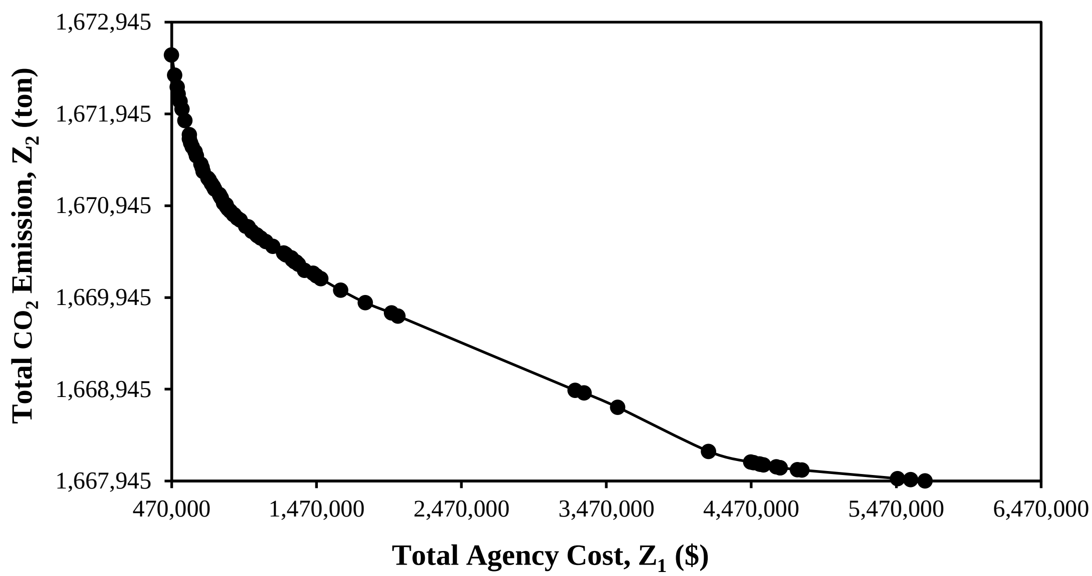


Figure 6.1 Pareto frontier of non-dominated solutions for multi-objective optimization

6.4.2 Effect of Annual Network Budget on Optimization Results

In order to study the effect of annual network budget constraint on the feasible solutions of objectives Z_1 and Z_2, a sensitivity analysis was performed in this study. Weight combinations of $w_1/w_2 = 0.75/0.25$ and $w_1/w_2 = 0.25/0.75$ were selected for the sensitivity analysis of objectives Z_1 and Z_2 as shown in Figures 6.2 and 6.3, respectively. In general, Figures 6.2 and 6.3 show that the agency cost increases and the CO_2 emission decreases when the annual budget was increased from $250,000 to $1,500,000. Since the weighting factor w_1 of minimizing agency cost objective, Z_1 in Figure 6.2 is higher than its value in Figure 6.3, the values of agency cost in Figure 6.2 is about 10 times less than their values in Figure 6.3. This is because considering a higher weighting factor for one objective makes the optimization process gives priority to that objective.

In addition, since the objective Z_1 has the priority of the minimization in Figure 6.2, the increase in agency cost value becomes insensitive to the budget increase after $750,000 once a feasible solution was reached. In Figure (6.3), the decrease in CO_2 emission becomes insensitive after an annual budget of $1,000,000 since the emission objective Z_2 has the priority.

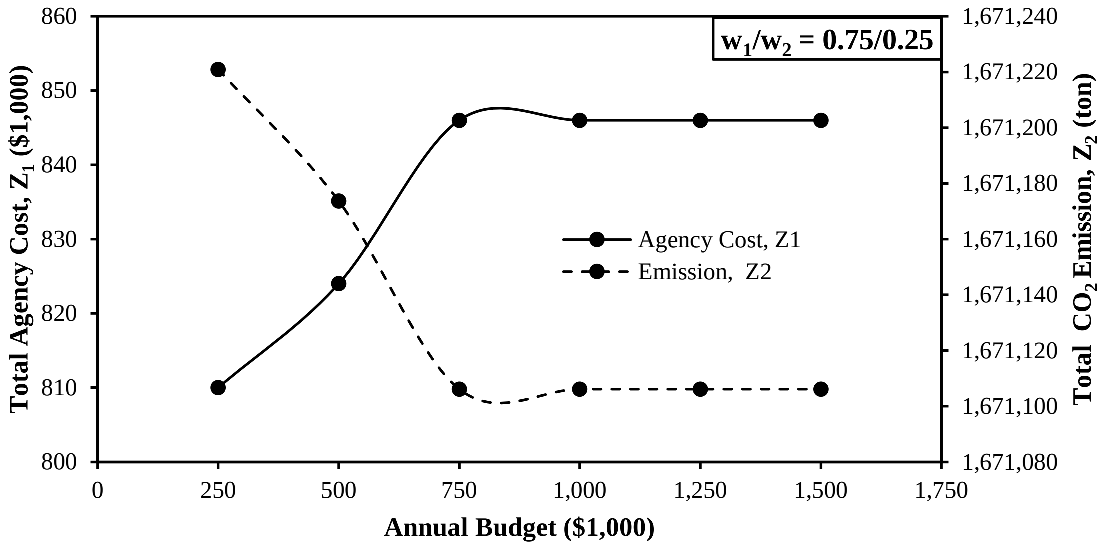


Figure 6.2 Effect of annual budget on two objectives for w_1/w_2=0.75/0.25

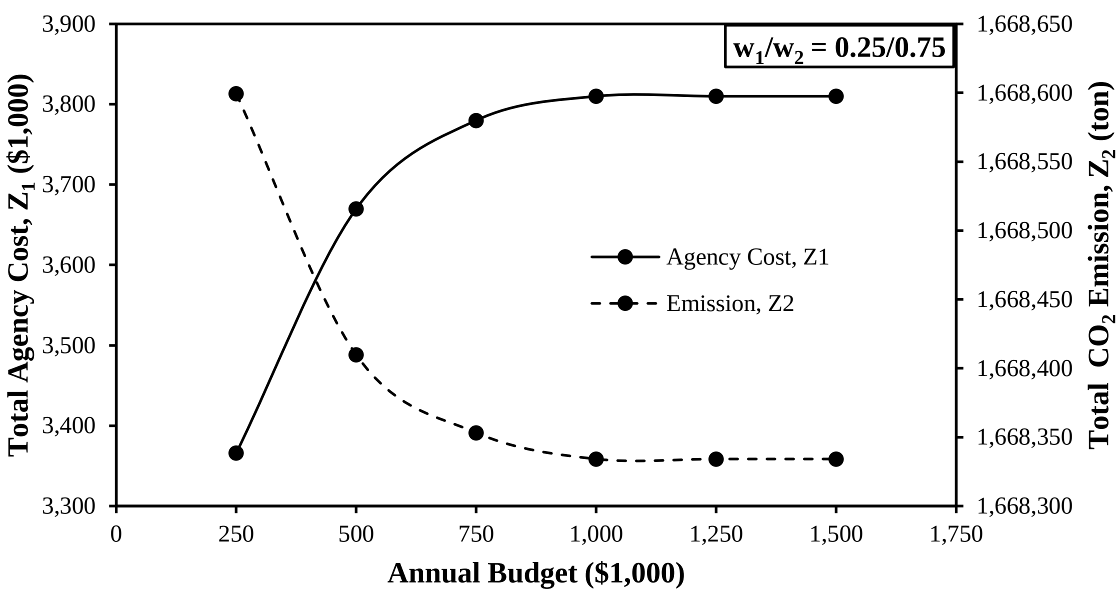


Figure 6.3 Effect of annual budget on two objectives for w_1/w_2=0.25/0.75

Table 6.1 and 6.2 show the distribution of preservation treatments (chip seal, crack seal, and thin overlay) at same weighting factors ratio of w_1/w_2 = 0.25/0.75 for two annual budget levels of \$250,000 and \$750,000, respectively. In Table 6.1, the number of chip seal, crack seal, and thin overlay preservation treatments that were selected for the network segments are 20, 23, and 104, respectively at network annual budget level of \$250,000. When the network annual budget level was increased to \$500,000 as shown in Table 6.2, the number of chip seal and crack seal preservation treatments decrease to 15 and 5 respectively and thin overlay increases to 117 in order to achieve the two objectives of minimizing agency costs and minimizing CO_2 emissions.

Tables 6.3 and 6.4 show the distribution of preservation treatments (chip seal, crack seal, and thin overlay) at same annual budget constraint of \$750,000 for weighting factors ratio of w_1/w_2 = 0.75/0.25 and w_1/w_2 = 0.25/0.75, respectively. When a large weight factor of w_1=0.75 was given to the agency cost objective Z_1 in Table 6.3, the optimization process looks for treatment types that have less cost without violation of constraints and at the same time keeps the network in good condition to minimize the total emission. Therefore, the most selected types of treatments in Table 6.3 is crack seal since it has the lowest value of agency cost. On the other hand, the optimization process gives the priority to the minimization of CO_2 emission objective Z_2 when a large weight factor of w_2=0.75 was selected to Z_2 objective as shown in Table 6.4. It is obvious in Table 6.4 that thin overlay is the dominant preservation treatment for the most segments in the network since it has the highest effectiveness on pavement condition which achieves the objective Z_2 of minimizing network CO_2 emission.

Table 6.1 Optimal Decision Variables of w_1/w_2 = 0.25/0.75 at annual budget of $250,000

Year / Segment	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	Sum
1			$\color{red}{\checkmark}$	$\color{green}{\checkmark}$					$\color{green}{\checkmark}$						$\color{green}{\checkmark}$						4
2			$\color{red}{\checkmark}$	$\color{green}{\checkmark}$							$\color{green}{\checkmark}$				$\color{green}{\checkmark}$						4
3			$\color{red}{\checkmark}$	$\color{red}{\checkmark}$	$\color{green}{\checkmark}$				$\color{green}{\checkmark}$						$\color{green}{\checkmark}$						5
4			$\color{green}{\checkmark}$					$\color{green}{\checkmark}$				$\color{green}{\checkmark}$				$\color{green}{\checkmark}$					4
5		$\color{green}{\checkmark}$						$\color{green}{\checkmark}$							$\color{green}{\checkmark}$						3
6	$\color{red}{\checkmark}$	$\color{red}{\checkmark}$	$\color{red}{\checkmark}$	$\color{red}{\checkmark}$	$\color{green}{\checkmark}$				$\color{green}{\checkmark}$					$\color{green}{\checkmark}$							7
7	$\color{green}{\checkmark}$					$\color{green}{\checkmark}$					$\color{green}{\checkmark}$						$\color{green}{\checkmark}$				4
8	$\color{red}{\checkmark}$	$\color{red}{\checkmark}$	$\color{green}{\checkmark}$						$\color{green}{\checkmark}$							$\color{green}{\checkmark}$					5
9	$\color{red}{\checkmark}$	$\color{green}{\checkmark}$					$\color{green}{\checkmark}$				$\color{green}{\checkmark}$						$\color{green}{\checkmark}$				5
10	$\color{green}{\checkmark}$					$\color{green}{\checkmark}$							$\color{green}{\checkmark}$			$\color{green}{\checkmark}$					4
11	$\color{red}{\checkmark}$	$\color{green}{\checkmark}$						$\color{green}{\checkmark}$					$\color{green}{\checkmark}$					$\color{green}{\checkmark}$			5
12	✓		$\color{green}{\checkmark}$							$\color{green}{\checkmark}$							$\color{green}{\checkmark}$				4
13	✓		$\color{green}{\checkmark}$				$\color{green}{\checkmark}$					$\color{green}{\checkmark}$				$\color{green}{\checkmark}$					5
14	✓			$\color{green}{\checkmark}$				$\color{green}{\checkmark}$						$\color{green}{\checkmark}$							4
15	✓		$\color{red}{\checkmark}$	$\color{green}{\checkmark}$						$\color{green}{\checkmark}$							$\color{green}{\checkmark}$				5
16	$\color{red}{\checkmark}$	$\color{green}{\checkmark}$						$\color{green}{\checkmark}$						$\color{green}{\checkmark}$							4
17	✓		$\color{red}{\checkmark}$	$\color{green}{\checkmark}$			$\color{green}{\checkmark}$					$\color{green}{\checkmark}$					$\color{green}{\checkmark}$				6
18	✓		$\color{red}{\checkmark}$	$\color{red}{\checkmark}$	$\color{green}{\checkmark}$					$\color{green}{\checkmark}$				$\color{green}{\checkmark}$							6
19	✓	$\color{green}{\checkmark}$						$\color{green}{\checkmark}$						$\color{green}{\checkmark}$							4
20	✓		$\color{red}{\checkmark}$	$\color{green}{\checkmark}$						$\color{green}{\checkmark}$						$\color{green}{\checkmark}$					5
21	✓		$\color{green}{\checkmark}$				$\color{green}{\checkmark}$				$\color{green}{\checkmark}$				$\color{green}{\checkmark}$						5
22	✓		$\color{green}{\checkmark}$					$\color{green}{\checkmark}$				$\color{green}{\checkmark}$				$\color{green}{\checkmark}$					5
23	✓	$\color{green}{\checkmark}$						$\color{green}{\checkmark}$				$\color{green}{\checkmark}$				$\color{green}{\checkmark}$					5
24	✓		✓			$\color{green}{\checkmark}$					$\color{green}{\checkmark}$						$\color{green}{\checkmark}$				5
25	✓	$\color{green}{\checkmark}$					$\color{green}{\checkmark}$						$\color{green}{\checkmark}$								4
26	✓	$\color{red}{\checkmark}$	$\color{red}{\checkmark}$	$\color{green}{\checkmark}$			$\color{green}{\checkmark}$						$\color{green}{\checkmark}$					$\color{green}{\checkmark}$			7
27	✓	$\color{red}{\checkmark}$	$\color{red}{\checkmark}$	$\color{green}{\checkmark}$			$\color{green}{\checkmark}$				$\color{green}{\checkmark}$						$\color{green}{\checkmark}$				7
28	✓	$\color{green}{\checkmark}$					$\color{green}{\checkmark}$			$\color{green}{\checkmark}$					$\color{green}{\checkmark}$						5
29	✓		✓		$\color{green}{\checkmark}$							$\color{green}{\checkmark}$				$\color{green}{\checkmark}$					5
30	✓	$\color{red}{\checkmark}$	$\color{green}{\checkmark}$						$\color{green}{\checkmark}$		$\color{green}{\checkmark}$						$\color{green}{\checkmark}$				6

Note: ✓ = chip seal; $\color{red}{\checkmark}$ = crack seal; and $\color{green}{\checkmark}$ = thin overlay

Table 6.2 Optimal Decision Variables of $w_1/w_2 = 0.25/0.75$ at annual budget of $500,000

Segment \ Year	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	Sum
1	✓					✓			✓						✓						4
2	✓					✓					✓				✓						4
3	✓				✓				✓						✓						4
4		✓	✓					✓				✓				✓					5
5	✓	✓						✓							✓						4
6	✓	✓			✓				✓					✓							5
7	✓					✓					✓						✓				4
8	✓		✓						✓							✓					4
9	✓	✓					✓				✓						✓				5
10	✓					✓							✓				✓				4
11	✓	✓						✓					✓				✓				5
12	✓		✓							✓							✓				4
13	✓						✓					✓					✓				4
14	✓	✓						✓						✓							4
15	✓	✓						✓		✓							✓				5
16	✓	✓						✓						✓							4
17	✓	✓					✓					✓					✓				5
18	✓				✓					✓				✓							4
19	✓	✓						✓						✓							4
20	✓	✓				✓				✓						✓					5
21	✓		✓				✓				✓				✓						5
22	✓	✓	✓					✓				✓					✓				6
23	✓	✓						✓				✓					✓				5
24	✓					✓					✓						✓				4
25	✓	✓					✓						✓				✓				5
26	✓			✓			✓						✓				✓				5
27	✓	✓				✓					✓						✓				5
28	✓	✓					✓			✓					✓						5
29	✓	✓			✓							✓					✓				5
30	✓		✓						✓		✓						✓				5

Note: ✓= chip seal; ✓= crack seal; and ✓= thin overlay

Table 6.3 Optimal Decision Variables of w_1/w_2 = 0.75/0.25 at annual budget of $750,000

Segment \ Year	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	Sum
1				✓	✓		✓	✓	✓		✓		✓	✓	✓		✓	✓			11
2				✓	✓	✓		✓	✓		✓	✓		✓	✓		✓	✓			11
3				✓		✓	✓	✓		✓		✓	✓		✓		✓	✓			10
4				✓	✓	✓		✓	✓		✓	✓		✓	✓	✓		✓			11
5			✓	✓		✓	✓	✓		✓	✓		✓		✓	✓		✓			11
6		✓		✓		✓	✓	✓		✓	✓		✓		✓	✓		✓			11
7		✓	✓		✓		✓	✓		✓	✓		✓	✓	✓		✓	✓			12
8	✓		✓	✓	✓		✓	✓		✓	✓	✓		✓	✓		✓	✓			13
9	✓	✓		✓	✓		✓	✓		✓	✓		✓	✓	✓		✓	✓			13
10	✓	✓	✓	✓		✓	✓		✓	✓	✓		✓	✓		✓	✓	✓			14
11	✓	✓	✓	✓		✓	✓	✓		✓		✓	✓	✓		✓		✓			13
12	✓	✓	✓		✓	✓		✓		✓	✓		✓		✓	✓		✓			12
13	✓	✓	✓		✓	✓		✓		✓	✓		✓		✓	✓		✓			12
14	✓	✓	✓	✓		✓		✓	✓	✓		✓	✓		✓	✓		✓			13
15	✔				✓	✓		✓		✓	✓		✓		✓	✓		✓			10
16	✔				✓	✓		✓		✓	✓		✓	✓		✓	✓	✓			11
17	✔				✓	✓				✔				✓	✓	✓		✓			8
18	✓	✓	✓	✓	✓		✓	✓	✓		✓		✓	✓	✓		✓	✓			14
19	✔				✓	✓				✔				✓	✓	✓		✓			8
20	✔			✓	✓		✓	✓		✓	✓	✓		✓	✓		✓	✓			12
21	✓	✓	✔			✓	✓		✓	✓		✓	✓		✓	✓		✓			12
22	✔			✓	✓		✓	✓		✓	✓		✓	✓	✓		✓	✓			12
23	✔			✓	✓	✓		✓		✓	✓		✓		✓	✓		✓			11
24	✔		✓		✓	✓		✓		✓	✓		✓		✓	✓		✓			11
25	✓	✔			✓	✓		✓	✓		✓	✓	✓		✓	✓		✓			12
26	✓	✔			✓	✓		✓	✓		✓	✓	✓		✓	✓		✓			12
27	✓	✔			✓	✓		✓	✓		✓	✓		✓	✓		✓	✓			12
28	✓	✔			✓	✓		✓	✓		✓	✓		✓	✓		✓	✓			12
29	✔	✔				✓	✓		✓	✓		✓		✓	✓		✓	✓			11
30	✔	✔			✓	✓		✓	✓		✓	✓	✓		✓	✓		✓			12

Note: ✔= chip seal; and ✓= crack seal

Table 6.4 Optimal Decision Variables of w_1/w_2 = 0.25/0.75 at annual budget of $750,000

Segment \ Year	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	Sum
1	✓					✓			✓						✓						4
2	✓					✓					✓						✓				4
3	✓				✓			✓							✓						4
4	✓				✓						✓				✓						4
5	✓							✓					✓				✓				4
6	✓			✓				✓						✓							4
7	✓				✓							✓					✓				4
8	✓					✓					✓				✓						4
9	✓						✓				✓						✓				4
10	✓			✓				✓						✓							4
11	✓	✓						✓					✓			✓					5
12	✓					✓				✓					✓						4
13	✓	✓					✓						✓				✓				5
14	✓	✓				✓				✓					✓						5
15	✓	✓				✓				✓					✓						5
16	✓	✓						✓					✓			✓					5
17	✓	✓					✓				✓						✓				5
18	✓	✓						✓				✓					✓				5
19	✓	✓					✓				✓				✓						5
20	✓		✓					✓							✓						4
21	✓		✓					✓				✓					✓				5
22	✓	✓					✓					✓				✓					5
23	✓			✓							✓						✓				4
24	✓				✓			✓					✓				✓				5
25	✓	✓						✓						✓							4
26	✓				✓		✓						✓				✓				5
27	✓	✓				✓					✓						✓				5
28	✓	✓					✓				✓						✓				5
29	✓		✓							✓					✓						4
30	✓			✓						✓							✓				4

Note: ✓= chip seal; and ✓= thin overlay

6.4.3 Effect of Including Construction Stage Emissions on Optimization Results

In order to study the effect of including the emission of construction stage for each type of preservation treatment (Table 4.2) on the optimization results, the objective Z_2 of minimizing CO_2 emissions in Equation 6.2 was modified in AIMMS software to include the emission of construction stage for each preservation treatment in addition to the emission of the use stage. Table 6.5 and Table 6.6 show the distribution of preservation treatments at annual budget constraint of $750,000 for weighting factors ratio of w_1/w_2 = 0.75/0.25 and w_1/w_2 = 0.25/0.75, respectively.

In general, the number of segments treated with chip seal and crack seal decrease as shown in Table 6.5 compared to Table 6.3 to minimize both the agency cost and CO_2 emissions since the crack seal has the lowest value of both agency cost and CO_2 emission at construction stage. On the other hand, the dominant preservation treatment in Table 6.6 is crack seal compared to Table 6.4 which was thin overlay because thin overlay has the highest value of emission at the construction stage.

Table 6.5 Optimal Decision Variables of w_1/w_2 = 0.75/0.25 at annual budget of $750,000 including construction stage emissions

Segment \ Year	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	Sum
1					✓	✓		✓		✓		✓		✓		✓	✓				8
2				✓			✓		✓	✓			✓	✓		✓	✓				8
3					✓		✓		✓		✓	✓		✓	✓		✓				8
4					✓		✓		✓		✓	✓		✓	✓		✓				8
5				✓	✓			✓	✓		✓	✓		✓		✓		✓			9
6			✓		✓		✓		✓	✓		✓	✓			✓	✓				9
7			✓		✓	✓		✓		✓		✓		✓		✓	✓				9
8		✓		✓		✓	✓		✓	✓			✓	✓		✓	✓				10
9	✓	✓		✓		✓	✓			✓	✓		✓		✓		✓				10
10	✓		✓		✓		✓		✓		✓		✓		✓		✓				9
11	✓		✓	✓		✓	✓			✓	✓	✓			✓	✓					10
12	✓		✓	✓		✓			✓	✓	✓		✓		✓		✓				10
13	✓	✓		✓		✓			✓	✓	✓		✓		✓		✓				10
14	✓	✓	✓		✓		✓			✓	✓		✓		✓		✓				10
15	✓	✓	✓	✓			✓	✓			✓		✓	✓		✓	✓				11
16	✓	✓	✓	✓		✓		✓		✓	✓		✓	✓			✓				11
17	✓	✓	✓	✓		✓	✓			✓	✓	✓			✓	✓					11
18	✓	✓	✓		✓		✓		✓		✓	✓			✓	✓		✓			11
19	✓	✓	✓		✓	✓			✓		✓	✓			✓	✓		✓			11
20	✓				✓		✓		✓	✓		✓	✓			✓	✓				9
21	✓	✓	✓	✓		✓		✓	✓		✓	✓			✓	✓					11
22	✓	✓	✓	✓	✓		✓			✓	✓		✓		✓		✓				11
23	✓	✓	✓	✓	✓		✓			✓	✓		✓		✓		✓				11
24	✓			✓		✓		✓	✓		✓	✓			✓	✓					9
25	✓	✓	✓	✓	✓	✓			✓	✓		✓	✓			✓	✓				12
26	✓	✓	✓	✓		✓			✓	✓		✓	✓			✓	✓				11
27	✓	✓	✓	✓	✓		✓	✓		✓		✓		✓		✓		✓			12
28	✓	✓	✓	✓		✓	✓			✓	✓	✓			✓	✓					11
29	✓	✓	✓	✓	✓		✓			✓	✓		✓		✓		✓				11
30	✓	✓		✓	✓			✓		✓		✓	✓		✓	✓					10

Note: ✓= chip seal; and ✓= crack seal

Table 6.6 Optimal Decision Variables of w_1/w_2 = 0.25/0.75 at annual budget of $750,000 including construction stage emissions

Segment \ Year	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	Sum
1			✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		17
2			✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		17
3		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		18
4		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		18
5		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		18
6	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		19
7	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		19
8	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		19
9	✓	✓	✓	✓	✓	✓	✓	✓							✓						9
10	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		18
11	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		18
12	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		18
13	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		18
14	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		18
15	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		18
16	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		18
17	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		18
18	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		18
19	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		18
20	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		18
21	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		18
22	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		19
23	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		19
24	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		19
25	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		19
26	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		19
27	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		19
28	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		19
29	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		19
30	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		18

Note: ✓= chip seal; ✓= crack seal; and ✓= thin overlay

6.5 SUMMARY

This Chapter aims to find the optimal timing of pavement preservation strategy at the network level considering multi-objective optimization of minimizing agency costs and minimizing CO_2 emissions. The multi-objective optimization problem was solved using Weighted Sum method which is based on converting the two objectives (agency cost and emission) into one single objective by adding both objectives together after multiplying each objective by a weighting factor. AIMMS software version 4.43 was used to solve and optimize the converted objective model. A case study was built to perform the optimization process, and a sensitivity analysis was conducted to study the effect of annual network budget constraint on the optimization of two objectives and pavement preservation strategy.

CHAPTER 7 FINDINGS, CONCLUSIONS AND RECOMMENDATIONS

7.1 FINDINGS

The major findings that represent different stages of the research undertaken include the following:

7.1.1 Development of Emission Models

1. Two regression models were developed for predicting total energy consumption (TEC) and Carbon Dioxide Emissions (CO_2) for four vehicle types. Model 1 considered the effect of rolling resistance coefficient (A) and speed on emission and energy consumption, and model 2 considered the effect of rolling resistance coefficient (A), air drag coefficient term (C), and speed on emission and energy consumption. Model 2 was used in the analyses of this research since it contains more effective coefficients than model 1.

7.1.2 Effect of Pavement Preservation on Life-Cycle Energy and Emission

1. At construction stage, there are significant differences in energy and emissions among various preservation treatments mainly due to different raw material components and manufacturing processes. Compared to chip seal and crack seal, thin overlay has the greatest CO_2 emissions because large amount of raw material and operation of asphalt plant are needed.
2. The IRI development trends after preservation treatment are affected by pre-treatment IRI and traffic loading. Quantitative relationships were developed to

determine the short-term IRI jump and long-term IRI models for different preservation treatments using LTPP SPS-3 data.

3. Pavement preservation brings environmental benefit in reduction of CO_2 emission due to the improved pavement surface condition despite the emission generated at construction stage. Thin overlay produces the highest life-cycle reduction in CO_2 emission due to the significant IRI jump after treatment; while crack seal has the lowest reduction of CO_2 emission.
4. The application timing of preservation treatment has significant effects on emission at use stage, and there is an optimal timing of preservation treatment to achieve the maximum life-cycle benefit of preservation. The optimal timing of treatment becomes earlier as traffic volume or the initial IRI value increases.

7.1.3 Multi-objective optimization

A. Simulated Constraint Boundary Model (SCBM)

1. For the single objective optimization of minimizing agency costs, most of the segments in the network are selected to be treated with crack seal since it has the lowest agency costs compared to chip seal and thin overlay treatments.
2. For the single objective optimization of minimizing CO_2 emissions, the thin overlay is the dominant preservation treatment for most of the segments because it causes the lowest IRI value after adding treatment (higher IRI jump) as compared to the other treatments.
3. For multi-objective optimization of minimizing both agency costs and emissions, the distribution of preservation treatments between segments is a combination of

the results for the two single objectives. The crack seal is still the most dominant preservation treatments compared to thin overlay although it has less effect on the reduction of IRI than the thin overlay treatment. So, the objective of minimizing agency cost controls the optimization results although the minimization of CO_2 emissions was considered in the optimization process.

4. The SCBM is a useful technique for solving the multi-objective optimization problems, but the decision makers need to decide first which objective should be considered as the primary objective (the objective that deserves the most attention among the competing objectives).

B. Weighted Sum Method

1. The weighted sum method provides an essential and easy way to use for multi-objective optimization. The value of weighting factor should be considerable relative to other weighting factors and comparative to its corresponding objective function when setting weighting factors for articulation preferences between objectives.
2. Sensitivity analysis results of annual budget constraint indicate that the minimization of network CO_2 emission is achieved with the increase of budget, while the objective of minimization total agency cost ultimately is insensitive to budget increase. When the annual budget was increased for the same weighting factor, the number of segments treated with chip seal and crack seal decrease and the number of segments treated with thin overlay increases.

3. The results for the distribution of pavement preservation treatments appeared that less costly preservation treatments were selected for the most segments of the network when the priority of optimization was given to the objective of minimization agency cost. The treatments that have higher effectiveness on pavement condition were selected for the most segments of the network when the objective of minimization CO_2 emission is the primary objective compared to the other objective.

7.2 CONCLUSIONS

Preserving network-level road pavements typically involves decisions about how, where, and when to maintain and rehabilitate to keep the pavement conditions at a reasonable level using the limited budget. This research used SCBM and weighted sum methods procedure to solve multi-objective network-level pavement maintenance programming problems. The conclusions can be drawn as follows based on the summary and main findings:

1. SCBM method is independent on the scales of objectives, and there is no need to transform different units of objectives to dimensionless units. The objectives can be in different units and scales that can be handled directly. On the other hand, this method requires the selection of the objective that deserves the most attention among the competing objectives and selection of the proper range values for those objectives that are not included in the objective function but instead set as constraints.

2. Although the weighted sum method is limited by the fact that all objectives must be transformed into a single unit, this method provides an essential and easy way to use for multi-objective optimization.
3. Finding the Pareto-optimal frontier is just the first step in the complete pavement maintenance scheduling decision-making process, however, the decision makers need to subsequently pick up the best compromise solution from the Pareto-optimal frontier between selected objectives and constraints. Given the selected best solution, the proportion of each road segment that needs a certain maintenance treatment can be accordingly determined.

7.3 RECOMMENDATIONS

The following recommendations are made based on the results gained in this research:

1. The effect of climate and road grade need to be considered in the developed regression models of CO_2 emissions by updating these factors in MOVES.
2. Since this study focused on the environmental impact of pavement preservation treatment at use stage, other phases of LCA need to be included for future work.
3. It is necessary to consider the work zone effect and traffic delay into life-cycle assessment model since the work zone has two major effects on road users; reduction in operating speed and increase in travel time; that result in a higher environmental impact.
4. The minimization of agency costs and emissions are the only two objectives considered in this study. The minimization of user costs (vehicle operating costs)

is another objective that should be included in the future work since this cost is affected directly by pavement surface characteristics.

5. This study focused on solving multi-objective optimization problems using SCBM and Weighted Sum methods. Genetic Algorithm method is an effective tool to solve multi-objective optimization problems that should be used in future work.

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