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MULTI-OBJECTIVE OPTIMIZATION OF MAINTENANCE, REPAIR AND REHABILITATION SCHEDULE CONSIDERING GREENHOUSE GAS EMISSIONS

A Thesis in

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ABSTRACT

Pavement maintenance, repair, and rehabilitation (MRR) planning is a complex decision-making process, which traditionally focuses on maximizing pavement condition or minimizing agency costs. However, objectives such as minimizing road user costs and greenhouse gas emissions are often overlooked. Additionally, lane closures in construction work zones can significantly impact traffic flow and emissions throughout the network. To address these challenges, this thesis aimed to optimize the MRR schedule of a network by minimizing agency costs, user costs, and emission costs while considering the impact of work zones on travel delay and detours in a dynamic traffic environment. The study employed a bi-level optimization framework, using the population-based incremental learning (PBIL) algorithm to generate MRR schedules while considering constraints on the number of activities. The Link Transmission Model (LTM) was utilized to simulate the effects of MRR actions on specific links, accounting for traffic flow dynamics. Different scenarios were simulated on an urban network. The results demonstrated that optimizing schedules with emissions led to the lowest overall costs, despite slightly higher user costs. The approach resulted in significant savings in agency expenses and emissions while simultaneously maintaining pavement conditions. The optimized scenarios outperformed a prescribed scenario where MRR actions were implemented based only on pavement conditions. Furthermore, a Pareto front revealed the trade-off between emissions and user-agency costs. More expense on the agency and user end results in lower emissions that eventually lead to diminishing returns of emission reduction after a certain point. The proposed methodology can be applied to the MRR planning of larger networks, providing valuable insights for agencies in improving overall network performance and sustainability.

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CHAPTER 1: INTRODUCTION

A well-functioning highway infrastructure network is crucial for the economic development and overall progress of a country. Maintained roadways play a vital role in facilitating the efficient movement of goods, services, and people, thereby enhancing trade, commerce, and socioeconomic growth. Unfortunately, roadway pavements are subject to constant deterioration due to various factors such as vehicle movements, weather conditions, and material quality. This deterioration not only affects the quality of the ride but also results in increased tire wear, vehicle damage, and higher fuel consumption costs for motorists. Consequently, it places financial burdens on individual vehicle owners and negatively impacts the overall economy due to increased operating costs. To mitigate these issues and uphold the functionality of transportation infrastructure, it becomes imperative to plan and execute maintenance, repair, and rehabilitation (MRR) activities in a timely manner. Neglecting to prioritize MRR activities can have severe consequences. Failing to perform regular maintenance and timely repairs can enable further degradation of road conditions, leading to the formation of potholes, cracks, and uneven surfaces that pose hazards to road users. Additionally, negligence in timely MRR activities contributes to shortening the lifespan of roadways and necessitating costly repair or reconstruction projects in the long run. Therefore, a strategic and proactive approach to MRR is essential to ensure the longevity and safety of the transportation infrastructure.

MRR activities require considerable capital investment, and limited MRR funds have become one of the important challenges faced by highway agencies in various countries. The US has been underfunding its roadway maintenance for years, resulting in a backlog of $786 billion of road and bridge capital needs. In 2017, federal, state, and local governments spent just $177 billion on roads and bridges, with an increasing focus on operations and maintenance needs (ASCE Infrastructure Report card, 2021). With a limited budget, agencies must prioritize which sections of the road network require maintenance, repair, or rehabilitation. This prioritization is typically based on factors such as traffic volume, pavement condition, and safety considerations. However, prioritizing high-traffic areas may mean that less-trafficked areas are neglected, which can lead to further deterioration and higher repair costs in the future. Therefore, effective planning and allocation of MRR funds are crucial for ensuring the long-term sustainability and safety of the road network.

Traditionally, state highway agencies (SHAs) have primarily focused on maintaining the condition of their pavement networks and minimizing costs associated with keeping the network functioning at an acceptable level for users. However, there has been limited consideration given to the impact of these maintenance and repair (MRR) decisions on greenhouse gas (GHG) emissions. This is significant because the transportation sector is a major contributor to anthropogenic GHG emissions in the United States, accounting for 29% of the total emissions in 2021 (USEPA, 2021). Incorporating GHG emissions into the MRR planning process is challenging as an MRR schedule can impact GHG emissions in many ways. The condition of pavement plays a significant role in influencing vehicular emissions. When roads are rough and deteriorated due to inadequate maintenance, vehicles experience increased rolling resistance, leading to higher fuel consumption, faster vehicle depreciation and increased emissions (Lee & Madanat, 2017; Zhou et al., 2022). During maintenance and repair activities, congestion and detours can have a substantial impact on emissions. Moreover, the emissions directly associated with MRR activities themselves can vary depending on the specific methods employed and equipment used. Frequent pavement maintenance activities may cause negative environmental impacts due to emission of carbon oxides, nitrogen oxides, and sulfides, which are crucial components of global warming, acidification, and photochemical pollution (Chen & Zheng, 2021a).

In addition, the effects of additional congestion, rerouting, or queue spillbacks due to work zone impacts the overall costs of an MRR schedule. Therefore, the spatial and temporal planning of MRR activities is crucial to ensure the optimal condition of the pavement, as the decision of implementing MRR action in one segment might impact the whole network.

Study objective

This thesis aims to explore the integration of GHG emissions in the optimization of MRR activities for pavements while considering the impact of traffic dynamics, specifically on urban traffic networks.

Detailed objectives:

- Review existing literature on methods of MRR activity planning.
- Propose a method to optimize MRR activity schedules incorporating user costs, agency costs and GHG emissions using heuristics.
- Simulate the MRR schedules on an urban network while accounting for traffic dynamics to understand how work zones impact different cost components.

Chapter organization

The remainder of this thesis consists of four chapters. Chapter 2 reviews existing literature on costs considered in the MRR planning process and methods of optimizing MRR activity schedules.

Chapter 3 introduces the proposed method and the case study. Chapter 4 discusses the application of the proposed method and analyzes the results. Finally, Chapter 5 concludes the findings, limitations and presents future research directions.

CHAPTER 2: LITERATURE REVIEW

This chapter first explores existing literature pertaining to understanding the state of the pavements, how they deteriorate, what actions can be taken to improve that condition, and the different costs associated with the improvement activities. As these costs may be interdependent, methods of optimizing multi-objectives are then reviewed. Finally, a research gap is identified that this thesis addresses. While pavement management is a vast branch of literature, the scope of this chapter is specifically centered around pavement maintenance schedules and its optimization, providing a focused analysis and discussion.

Pavement condition indices

To plan a maintenance schedule, it is important to understand the condition of pavements. Measuring pavement conditions is an important tool for infrastructure asset management to assess the state of the pavement and the resulting measurements can help determine the necessary actions. If pavement conditions are not assessed regularly and timely maintenance actions are not taken, it can lead to worsening pavement conditions and require more costly repairs in the future. Different indices exist that are used to indicate the condition of a pavement. Present Serviceability Rating (PSR) is a subjective rating of the pavement condition assigned by experts or stakeholders based on the smoothness and rideability of the pavement (J. Bryce et al., 2019; Mubaraki & Sallam, 2021). The Present Serviceability Index (PSI) is a numerical rating of the pavement condition based on a mathematical model that relates PSR to measured surface distresses such as cracking, patching and rutting (Mubaraki & Sallam, 2021; Piryonesi & El-Diraby, 2021). Pavement Condition Index (PCI) is another composite index that evaluates the pavement condition based on the type, extent and severity of surface distresses. It also ranges from 0 to 100, with higher values indicating better condition (Sahin et al., 2014). There are many agency-specific condition measuring indices that have been used in different regions. For example, Texas Department of Transportation (TxDOT) uses the Pavement Management Information System (PMIS) Condition Score which is a composite index that combines different pavement distresses and their severities into a single number that represents the overall pavement condition. It ranges from 0 to 100, with higher values indicating better condition (France-Mensah et al., 2018).

International Roughness Index (IRI) is one of the most used measures of road roughness worldwide It is calculated using a quarter-car vehicle math model, which simulates the vertical movement of a car wheel and its suspension system when it travels along a road profile. The model produces an output that represents the accumulated vertical displacement of the car body over a certain distance. This output is then divided by the profile length to get the IRI value, which has units of slope (such as m/km or in/mi). A higher IRI means a rougher road surface and vice versa (Sayers, 1995; Šroubek et al., 2022). IRI has been widely used in studies to optimize maintenance activities and improve pavement condition. (J. Bryce et al., 2019; Lee & Madanat, 2017; Santos et al., 2015). In this thesis, IRI has also been chosen over other indices as the measure of pavement condition as it is a better indicator of serviceability or rideability and large availability of data.

Pavement deterioration models

Pavement is subjected to continuous wear and tear due to vehicular traffic, weather conditions, and other factors. Over time, this wear and tear can lead to the deterioration of pavements, which can manifest in various forms such as cracking, rutting, and potholes. To plan MRR actions, understanding how pavements deteriorate over time and what actions can be taken to remedy the deterioration is necessary. There exists a large branch of literature that explores different pavement deterioration models, however, the scope of this thesis is not the prediction of future pavement states or conditions. Rather, this section is limited to reviewing deterioration models used in prior studies on MRR planning.

Pavement deterioration models are used to simulate how pavements degrade over time and to predict the future condition of pavements under different scenarios. These models take into account a range of factors that can affect pavement performance, such as traffic loads, environmental conditions, pavement design, and maintenance practices. (Onayev & Swei, 2021) summarized the different approaches and estimation techniques that have been developed for discrete and continuous measures of pavement deterioration. The authors mentioned two types of probabilistic models for discrete infrastructure condition measures: state-based and time-based models. State-based models predict the probability that a facility will undergo a change in condition-state at a given time (i.e., Markov chains), while time-based models (i.e., maximum likelihood) predict the probability distribution of time during which a given facility changes its state (Hong & Prozzi, 2010; Yang et al., 2005). Three types of continuous models are generally used for pavement deterioration: empirical, mechanistic, and mechanistic-empirical. Empirical models use statistical methods and historical data to establish empirical relationships between pavement performance and influencing factors such as traffic, climate, age, and structural design. On the other hand, mechanistic models use principles of mechanics and material properties to simulate how pavements respond to various loads and predict their performance based on stress, strain, and deflection of pavement layers. To combine the statistical rigor of empirical methods with the theoretical foundation of mechanistic models, researchers have developed mechanistic empirical models. These models integrate both mechanistic and empirical approaches to provide a more comprehensive understanding of pavement deterioration (Shtayat et al., 2022). Each type of model has its own advantages and disadvantages depending on the data availability, accuracy, and complexity.

To predict the state of pavements throughout the planning horizon, prior studies on MRR schedule optimization have used linear models (Santos et al., 2018a); exponential models ((Dalla Rosa et al., 2017; Paterson, 1987; Sahin et al., 2014; Tsunokawa, 1994)); or continuous complex deterioration models that combine exponential and polynomial functions (Lee & Madanat, 2017).These models consider factors such as pavement age, climate, subgrade, treatment type, pavement type, traffic loading, functional system, initial pavement conditions, etc.

Although the exponential function is effective for modeling pavement deterioration when the pavement is in a poor condition, it is not suitable for accurately representing the deterioration process when the pavement is in good condition. This is because the Markovian property, which assumes that the future state depends only on the current state and not on the past, does not hold true in the case of pavement deterioration. In good condition, the pavement does not deteriorate further, and general exponential functions fail to capture this aspect. To tackle this problem, (Ouyang & Madanat, 2004) proposed a modified exponential deterioration model that accounts for pavement design, traffic loading, and environmental condition parameters to determine the deterioration rate. The proposed model has demonstrated its ability to capture the deterioration process in both poor and good pavement conditions and therefore, has been used in this thesis.

MRR options and their improvement criteria

Pavement deterioration is a natural phenomenon, and timely maintenance is crucial to slow down this process and keep the pavement in good condition. The intensity of the maintenance action plays a vital role in improving the pavement condition. This section reviews studies that have proposed various pavement improvement criteria based on maintenance actions.

There are several treatment options available to agencies, including patching, crack and joint sealing, micro-surfacing, milling, and resurfacing, seal coating, pavement overlays, etc. (Shoghli et al., 2016). Studies that seek to optimize the planning of these activities on a project or network scale, tend to categorize these actions into fewer treatment categories for simplification. For example, (France-Mensah & O'Brien, 2019; Sahin et al., 2014) grouped the MRR actions into four categories: preventive maintenance (PM), light rehabilitation (LR), medium rehabilitation (MR), and heavy rehabilitation (HR), based on the thickness of overlays and types of treatments used. Similarly, (J. M. Bryce et al., 2014) assumed preventive maintenance (PM), corrective maintenance (CM), restorative maintenance (RM) and reconstruction (RC) as treatment categories in their research. The authors assigned specific improvement values to each category of MRR action and assumed the condition of a pavement is improved by that value if any MRR action in that category is undertaken. The impact of these actions on road conditions varies based on the intensity of the interventions. Minimal MRR actions yield limited improvements, while more intensive interventions result in substantial enhancements to road quality and performance. On the other hand, (Lee & Madanat, 2017) defined three different pavement improvement models for routine maintenance, rehabilitation, and reconstruction activities based on the previous condition and time between the previous action. Overall, different studies have assumed different improvement strategies based on the categories of MRR techniques used for pavement maintenance and rehabilitation. A similar methodology for treatment categories has been used in this thesis.

Description of cost

Agency and user costs

When planning for maintenance, repair, and rehabilitation (MRR) activities, agencies and decision-makers need to consider the costs associated with different inputs. These costs can be broadly categorized into two types: agency costs and user costs.

The concept of agency costs is a fundamental aspect of transportation infrastructure management. These costs refer to the expenses incurred by the agency responsible for managing the transportation infrastructure, which could be a government agency or a private company. The costs include both the direct costs of construction and maintenance activities as well as the indirect costs of managing these activities. The direct costs of MRR activities include materials, labor, equipment, and other related expenses. For example, the cost of resurfacing a road includes the cost of asphalt, labor to lay the asphalt, and the cost of any equipment used for the resurfacing process. The estimation of these costs is typically based on several factors, such as the anticipated number of MRR activities required during a given period, the expected cost per activity, and the prevailing market rates for materials, labor, and equipment. Additionally, the costs may vary depending on the locality and the intensity of the MRR work. For example, the cost of resurfacing a road in a heavily trafficked urban area may be higher than that of a rural road with less traffic. Some studies have focused solely on the application cost of maintenance, rehabilitation, and reconstruction (MRR) activities such as crack sealing, micro-surfacing, overlaying, and milling as the agency cost (J. M. Bryce et al., 2014; Moreira et al., 2017; Shoghli et al., 2016) while other studies have included additional agency costs such as material production and extraction, as well as the cost of the construction phase(Santos et al., 2018a).

User costs, on the other hand, refer to the costs that users incur as a result of vehicle operation on roadways as well as excess travel time costs due to congestion. In the MRR planning process, studies have considered various components for user costs in their objectives, e.g., only fuel consumption (Moreira et al., 2017); tire wear, vehicle maintenance and repair, vehicle depreciation along with fuel consumption costs (Islam & Buttlar, 2012; Santos et al., 2015) energy consumption (Ziyadi et al., 2018) etc.

Moreover, the presence of work zones results in lane closures which translates to reduced roadway capacity. This may cause a bottleneck which leads to excess travel time. Some studies have considered the impact of work zone travel delay on users while optimizing MRR schedule. However, these studies are limited to constant delay considerations (Santos et al 2017., Mensah Obrien 2019) or use the Bureau of Public Roads (BPR) function (Zhou et al., 2022) which is a static travel time function that relates the travel time on a link to the volume of traffic on that link. A static model does not take into account the dynamic nature of traffic and how work zones contribute to congestion or queue spill back. In addition, they fail to account for detours that lead to increased vehicle operating costs due to additional distances traveled. Two studies, (Avetisyan et al., 2014) and (Lu et al., 2018) conducted detailed analyses of the impact of work zones on greenhouse gas (GHG) emissions using micro-simulation software. However, the scope of these studies was not the optimization of MRR activities.

Emission costs

The transportation sector is responsible for significant emissions of greenhouse gases (GHGs) that contribute to climate change. These emissions can be divided into two categories: those resulting from MRR activities and those resulting from vehicle operations. Both need to be accounted for when estimating the cost of implementing an MRR plan.

The maintenance and operation of transportation infrastructure has a significant environmental cost in the form of GHG emissions. MRR activities involve the use of construction materials that contribute to GHG emissions throughout their production, transportation, and application during construction, and more intense MRR activities tend to lead to higher emissions due to increased quantity of construction materials and more extended periods of construction equipment activities (Ozcan-Deniz & Zhu, 2017; Wang et al., 2012). (Lee and Madanat., 2017) developed models to calculate emissions from three categories of maintenance actions based on the thickness of the treatment.

Emissions from vehicle operations are impacted by factors such as vehicle size, engine capacity, and speed, and are further exacerbated by congestion and poor pavement conditions. To estimate the emissions resulting from vehicle operations, researchers have proposed various models. The Motor Vehicle Emission Simulator (MOVES) is an advanced emissions modeling tool developed by the Environmental Protection Agency (EPA) that estimates air pollution emissions for various vehicles and equipment, including on road vehicles like cars, trucks, and buses, as well as nonroad equipment such as bulldozers and lawnmowers (US EPA, 2021). MOVES estimates emissions for criteria air pollutants, greenhouse gases, and air toxics, making it a comprehensive tool for analyzing and mitigating air pollution. Furthermore, pavement condition also directly impacts vehicular emissions, as vehicles travelling on rough roads have larger emissions (Lidicker et al., 2013; Liu et al., 2010)

The increase in travel time resulting from slower speeds in work zones also leads to increased fuel consumption and GHG emissions (Liu et al., 2010). (Lee & Madanat., 2017) assumed that less intensive maintenance and repair actions take place at night, therefore, no excess emissions are recorded on the user end. However, for more intensive actions, the authors considered that the excess vehicular emissions from congestion due to work zones is approximately 20% of the total construction emissions. Areas with higher traffic volumes are expected to face greater traffic disruptions resulting in more emissions. A study by (France-Mensah & O’Brien, 2019) assumed an average marginal increase in GHG emissions due to traffic disruptions per AADT.

This thesis aims to enhance the assessment of costs and environmental consequences associated with pavement maintenance by incorporating the impact of work zones on cost and emissions.

Multi-objective optimization and solution methods

Optimally planning an MRR schedule requires the consideration of multiple conflicting objectives and their associated costs. Multi-objective optimization (MOO) is an approach to solve problems that try to optimize two or more conflicting objectives. This section reviews literature on MOO and its application in MRR scheduling.

MOO allows decision-makers to identify a set of optimal solutions that represent the tradeoffs among the objectives and choose the most suitable one according to their preferences and constraints (Santos et al., 2018a; Wu et al., 2012). (Chen & Zheng, 2021b) conducted a critical review discussing the importance of using MOO methods in pavement maintenance and management decision-making.

MOO techniques can be applied in pavement MRR planning at both project level and network level. At project level, MRR activities are carried out based on the condition of individual pavement segments to maintain their serviceability and prolong their life. The objective of project-level MOO is to optimize the maintenance activities, considering multiple objectives such as pavement quality, service life, life-cycle cost and environmental impact (Chen & Zheng, 2021c). By doing so, project-level MOO can help practitioners make informed decisions and provide a transparent decision support tool.

On the other hand, network-level MRR work evaluates the overall condition of the road network, including the pavement segments, to develop a comprehensive maintenance plan. Network-level MOO takes into account multiple objectives, such as the cost of maintenance, the condition of the pavement, and the reliability and functionality of the road network, to achieve an optimal solution. Network-level MOO can help agencies allocate limited resources more efficiently and effectively, leading to improved system reliability and functionality, and ultimately help achieve the agency goals and objectives (Rejani et al., 2022). Nevertheless, decisions made at one level have influence on decisions and results made at other level (Gao et al., 2012; Wu et al., 2012).

Solving MOO problems in transportation systems is both challenging and complex. MOO problems involve multiple conflicting objectives that need to be optimized simultaneously, making them difficult to solve using traditional methods, therefore, requiring the use of specialized algorithms and techniques such as, evolutionary algorithms, bottom-up solution, ant colony, and mathematical programming methods (Santos et al., 2018b) These methods search for the optimal solutions in a search space by evaluating the objective functions at different points and iteratively refining the search based on the results.

Genetic algorithm (GA) - an evolutionary algorithm, is a widely used method for multi-objective optimization, which involves generating a population of candidate solutions and using selection, recombination, and mutation operators to create new solutions. These new solutions are then evaluated and selected for further iterations in order to find the optimal solution. In (Santos et al., 2018a)), a multi-objective optimization algorithm was used to find optimal pavement management alternatives that minimize life cycle costs and environmental impacts. Multiple bi-objective optimization analyses were conducted using a genetic algorithm to consider agency costs, user costs, and greenhouse gas emissions. Similarly, in (Torres-Machi et al., 2017a), a decision support system (DSS) was developed for pavement management to identify optimal sustainable maintenance and rehabilitation strategies. Multiple bi-objective optimization analyses based on a genetic algorithm were used to obtain non-dominated solutions that improve environmental and economic aspects of pavement sustainability. (Moreira et al., 2017; Santos et al., 2018a; Zhao et al., 2019)also developed genetic algorithm-based optimization model to minimize total costs (road user, agency costs, emission cost).

Some studies have modified genetic algorithms for multi-objective optimization by integrating them with different techniques. (Yu et al., 2015) proposed a multi-objective optimization algorithm to minimize life-cycle costs while maximizing user and agency benefits. The authors integrated a niched Pareto genetic algorithm with a population-based constraints handling approach to obtain a diverse population of Pareto solutions spread along the Pareto frontier. (Denysiuk et al., 2017) proposed a two-stage approach for scheduling maintenance activities with multi-objective optimization using multi-objective evolutionary algorithms (MOEAs) in each stage to find optimal strategies for each pavement section and then for the whole network. The optimization problem considers objective functions and constraints related to pavement quality and maintenance costs.

The process of solving a multi-objective optimization problem using the bottom-up approach involves breaking down the problem into smaller sub-problems, which can be optimized individually. Each sub-problem represents a different objective, and the optimization algorithm is used to find the best solutions for each of them. The solutions from each sub-problem are then combined to generate a set of candidate solutions that trade off the different objectives. The process is iterative, with the candidate solutions refined and improved until a satisfactory set of solutions is obtained. This approach can be effective in solving complex multi-objective problems, where traditional optimization methods may struggle to find a global optimal solution. (Lee & Madanat., 2017) developed a bottom-up solution algorithm that uses Lagrangian relaxation and dynamic programming to optimize a randomized policy for minimizing greenhouse gas emissions in pavement maintenance and rehabilitation while considering multiple budget constraints.

Ant colony optimization (ACO) is a population-based metaheuristic inspired by the foraging behavior of ants. In ACO, artificial ants search for good solutions to an optimization problem by depositing pheromones on the ground to mark favorable paths. The pheromone trails evaporate over time, leading the ants to explore other paths, and the probability of selecting a particular path is proportional to the amount of pheromone deposited on it. The process is repeated for several iterations until a satisfactory solution is found . (Terzi & Serin, 2014) used ACO to find the optimal solution to schedule and budget the maintenance activities in highway networks. Multi-colony ant colony optimization (MCOACO) is an extension of the basic ACO algorithm that involves the use of multiple colonies of ants working in parallel to search for solutions. Each colony of ants operates independently and explores different regions of the search space. (Shoghli et al., 2016) proposed a multi-objective approach to optimize maintenance techniques for multiple roadway assets considering maintenance time, cost and environmental impacts using MCOACO algorithm.

The branch-and-cut method is an exact algorithm that combines the branch-and-bound algorithm with cutting planes and is commonly used to solve mixed-integer linear programming (MILP) problems. The basic idea behind the method is to iteratively partition the search space into smaller and smaller regions using a branching strategy, and then solve linear programming relaxations of the problem in each region. (France-Mensah & O'Brien, 2019) used the branch-and-cut method, to solve their integer-linear optimization model to minimize GHG emissions as well as roadway user costs while maximizing pavement conditions.

Modeling traffic dynamics

User cost in previous studies has typically been a function of traffic volumes on roadways at equilibrium, however, the dynamic nature of traffic in the presence of a work zone has not been considered. Average Annual Daily Traffic (AADT) has been used to determine operation cost (France-Mensah & O'Brien, 2019) and fuel consumption (Moreira et al., 2017) in previous work. (Zhou et al., 2022) used the BPR function to conduct a static analysis of travel delay on the user end. However, the presence of MRR activities on a highway can result in the temporary closure of lanes or capacity reduction as well as forced lane changes, which can create a bottleneck effect. This bottleneck can cause congestion and lead to increased delays, additional vehicle miles traveled due to detours and higher fuel consumption for motorists, particularly during peak travel periods. (Weng & Meng, 2013) conducted a comprehensive review of the approaches used to estimate work zone capacity and traffic delay. Their review categorized the existing approaches for work zone capacity estimation into parametric (e.g., multi-regression approach), non-parametric (e.g., decision tree approach, neural-fuzzy logic approach), and simulation approaches (e.g., VISSIL, CORSIM) . Non-parametric approaches perform better in terms of estimation accuracy, but when there are strong linear relationships between work zone capacity and influencing factors, parametric approaches can outperform non-parametric approaches. The authors suggested that a hybrid method combining non-parametric and simulation approaches for work zone capacity estimation and the use of agent-based traffic simulation for traffic delay estimation could improve computational efficiency and accuracy in future studies.

The Link Transmission Model (LTM) is a numerical method for solving dynamic network loading problems in traffic networks (Yperman et al., 2005). It is based on first-order kinematic wave theory and offers a more efficient alternative to the Cell Transmission Model (CTM) (Daganzo, 1994). The LTM requires calculations only at network nodes, resulting in a computational complexity that is significantly lower than that of the CTM. The model calculates dynamic link travel times based on time-varying traffic demand and split proportions at each junction. Traffic evolution is represented by the cumulative number of vehicles passing each link over time. The LTM divides simulation time into intervals and uses a two-step process to determine sending and receiving flows for each link and transfer vehicles between links while updating cumulative vehicle numbers. The LTM has been widely used to solve various transportation infrastructure problems (Bayrak et al., 2021a; Bayrak & Guler, 2020; Chakraborty et al., 2018).

Bi-level optimization

Multi-objective optimization of MRR activities is a challenging problem due to the dynamic interaction between the roadway users and the planning of MRR activities, which imposes spatial and temporal modifications to a transportation network. These modifications, such as lane closures, detours, and other restrictions, cause vehicles to reroute and incur delays, resulting in additional vehicle miles traveled and excess travel time, which add to the user costs and emission costs of implementing that MRR schedule. The complexity of this problem increases significantly as the number of variables or the size of the network increases, making it an NP-hard optimization problem. Therefore, determining an optimum solution is difficult, and heuristics are typically used instead. Consequently, there is a need for more efficient and accurate optimization methods that can account for the complex dynamic interactions between MRR activities and roadway users.

When an accurate mathematical formulation is unavailable for scheduling problems, bi-level optimization methods that rely on heuristics are commonly used. These methods involve the generation of candidate schedules in the upper level to implement a treatment, and the evaluation of the value of the objective function using analytical methods or agent-based simulations in the lower level. Heuristics such as Genetic Algorithms (GAs) are very efficient and are known to converge toward near-optimal results. Many researchers have used genetic algorithm in their research in pavement maintenance (Moreira et al., 2017; Santos et al., 2018a; Torres-Machi et al., 2017b; Zhao et al., 2019). GAs perform a guided search across a large solution space to evaluate a handful of combinations, converging toward the fittest solutions through natural selection, mimicking Darwinian evolution theory (Mirjalili, 2019). Bi-level optimization methods have previously been employed to optimize work zone time and maintenance work scheduling in several studies. (Denysiuk et al., 2017; Li & Fan, 2021; Zhou et al., 2022)

One limitation of the traditional genetic algorithm is its inability to consider the interdependence of solutions, which may lead to suboptimal solutions (Goldberg., 1989a, 1989b). Spatial or temporal dependence can arise due to the stochastic nature of vehicle routing and the impacts of treatment implementation at one location at a particular point in time in a network on decision-making throughout the network. To address this, researchers have developed messy genetic algorithms or distribution algorithms. For instance,(Shummet & Baluja, 1994) introduced Population Based Incremental Learning (PBIL), an optimization algorithm that utilizes a probability vector instead of individual solutions, outperforming standard genetic algorithms in various problem domains while presenting its own set of advantages and disadvantages. (Bayrak et al., 2021b) used a PBIL algorithm to optimize the implementation schedule of bus lanes to reduce project costs and traffic delays from construction work zones, while (Bayrak & Gayah, 2021) used PBIL, Bayesian Optimization Algorithm (BOA), and a hybrid PBIL-BOA to identify the optimal location of left turn restrictions in a network. (Ahmed, 2023)utilized PBIL within a bi-level optimization framework to identify the best locations for adaptive traffic signal controls in a real network.

Research gap

While several studies have examined the multiple objectives of agencies, users, and emissions in a pavement maintenance system, none have addressed the dynamic nature of traffic due to work zones in a network when calculating the user costs and emissions. Since work zones have a significant impact on both user costs and emissions, it is necessary to consider these effects when optimizing the MRR schedule.

Therefore, we propose a bi-level optimization framework using the Population Based Incremental Learning (PBIL) algorithm and the Link Transmission Model (LTM) that seeks to minimize agency, user and emission costs while taking into account the dynamic nature of traffic resulting from work zones in the network.

CHAPTER 3: METHODOLOGY

This chapter describes the formulation of the multi-objective optimization problem followed by the proposed bi-level optimization framework to determine the optimal schedule of MRR actions.

The following diagram illustrates the research approach for this thesis. The approach starts with a multi-objective optimization process where three objectives are considered. Then, a bi-level optimization framework is introduced where the upper level uses the population-based incremental learning (PBIL) algorithm to generate a set of MRR schedule and the lower level uses a link transmission model to simulate the traffic flow in a network. Finally, the approach is applied in a network to obtain the optimized schedule and associated agency cost, user cost, and emission. The obtained results are discussed to draw insights from this research approach.

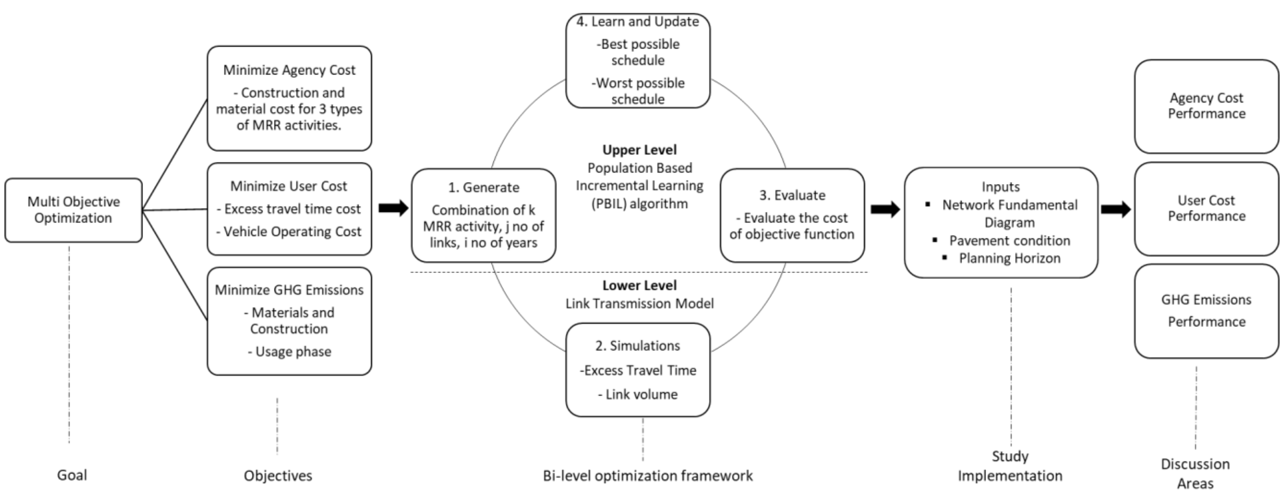


Figure 1. Overall research approach

Problem Formulation

The objective function is formulated as a multi-objective optimization (MOO) and includes three components: the agency cost, $\mathcal{AC}$ - defined as the cost incurred by the transportation agency for performing MRR activities in the network; the user cost, $\mathcal{UC}$ – defined as the excess travel time from work zone congestion and excess vehicle operating costs as a function of pavement conditions; and the emission cost, $\mathcal{EC}$ – defined as the greenhouse gas (GHG) emissions from MRR activities and the excess vehicular emission due to work zone congestion and rerouting on the user end. Therefore, the MOO problem can be defined as:

$$\min \mathcal{AC} = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K} \mathrm{AC_{jk}} \times x_{ijk} \tag{1}$$

$$\min \mathcal{UC} = \sum_{i=1}^{I}\sum_{j=1}^{J} \mathrm{UC_{ij}} \tag{2}$$

$$\min \mathcal{EC} = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K} EC_{jk}^{agency} \times x_{ijk} + EC_{ij}^{user} \tag{3}$$

where, $\mathrm{AC_{ijk}}$ denotes the agency costs in year i, link j for MRR treatment k, UC_{ij} denotes the user cost components in year i, link j; EC_{ijk}^{agency} denotes the GHG emissions from agency actions in Ton-CO_2 in year i, link j for MRR treatment k; EC_{ij}^{user} denotes the GHG emissions from users in Ton-CO_2 in year i, link j; x_{ijk} is a binary decision variable indicating whether MRR action k has been performed on link j in year i; I denotes the total number of years in the planning horizon; J denotes the total number of links in a network; and K denotes the complete set of MRR treatment options available.

The solution of a MOO is often represented by a set of Pareto points that indicate the optimal trade-off between the considered objectives. A Pareto-optimal solution cannot be improved in one objective without sacrificing quality in another. In the field of highway asset management, various methods have been employed to address the MOO problem, such as weighting sum, goal programming, compromising programming, ε-constraint, dominance-based approaches, multi-attribute utility theory, analytic hierarchy process (AHP), and evolutionary algorithms (Wu et al.,2012). Here the problem is defined as a minimization of total costs, $\mathcal{TC}$ which is a sum of agency, user, and emission costs (4). Hence, a preference-based MOO procedure that assigns weights to the different objectives to improve computational efficiency of the algorithm is adopted to solve the given problem. Specifically, weights, $w1$ and $w2$ are assigned to the combined agency and user costs, and emission costs, respectively, see Equation 4. By varying the weights, a Pareto frontier analysis is conducted between emission and combined user and agency costs to understand the tradeoffs.

$$\min \mathcal{TC} = w1(\mathcal{AC} + \mathcal{UC}) + w2(\mathcal{EC}) \tag{4}$$

The dynamic interaction between roadway users and the implementation of MRR activities affects the overall costs hence, the formulated MOO problem does not have an exact solution. Moreover, the number of potential MRR schedules is very large and grows exponentially with the duration of the planning horizon, size of the network or number of MRR categories. Determining the globally optimum solution of the problem is computationally extensive. Therefore, a bi-level optimization framework is employed.

Bi-level optimization

The bi-level optimization method used in this study is a two-step approach to finding the optimal schedule for MRR activities on the roadway network. In this methodology, the upper level (UL) determines the optimal combination of MRR schedule to minimize total cost, while the lower level (LL) evaluates the objective function. The bi-level approach is necessary since network delay and vehicle miles travelled for different combinations of MRR activity schedules needs to be computed to determine the user and emission costs, which is a computationally costly calculation.

Upper Level

In the upper level, the Population-Based Incremental Learning (PBIL) algorithm is used to evaluate the objective function and optimize the MRR schedule. PBIL algorithm is an optimization algorithm that combines elements of genetic algorithms and learning processes that can be used to identify a near optimal maintenance schedule that minimizes agency, user and emission costs in a network.

Step 1: Initiate

In the initialization step of the PBIL algorithm for MRR scheduling, the algorithm's parameters are set up. The first parameter defined is the generation size $\mathcal{G}$, which specifies the number of iterations that the algorithm will perform. Each iteration is called a generation. The population size $\mathcal{P}$ is the number of MRR schedules generated in each generation. The population size determines the diversity of the solutions explored by the algorithm.

MRR scheduling involves planning for a fixed planning horizon, considering a network where agencies can undertake a range of MRR actions. Each candidate, n is defined by the year (i), link (j) and the type of MRR action (k) taken. Therefore, the candidate size $\mathcal{C}$ contains all possible candidate combinations in a schedule. For a planning horizon of I number of years, J number of links and K number of possible MRR actions, the candidate size $\mathcal{C}$ is $I \times J \times K$ which represents the size of the search space that the algorithm will explore. The probability vector P is a one-dimensional vector of size $\mathcal{C}$. Each element $\mathrm{p}_{n(i,j,k)}^{g}$ in the probability vector P represents the probability of choosing candidate $n(i,j,k)$ in each population of generation, g.

For example, if we have 2 years, 3 links, and 4 MRR actions, the candidate size $\mathcal{C}$ would be 2 x 3 x 4 = 24, representing the 24 possible candidates. The initial probability vector for generation 0, p^{0} , would be a one-dimensional vector of length 24, where each element $\mathrm{p}_{n(i,j,k)}^{0}$ would represent the probability of choosing a specific candidate $n(i,j,k)$ in the first generation.

Step 2: Generate population

The second step of the PBIL algorithm for MRR scheduling involves generating a population of potential MRR schedules to be tested. Each element in this population is an MRR schedule which is a one-dimensional vector of size $\mathcal{C}$ that contains binary indicator, x_{ijk} representing whether the corresponding candidate, $n(i,j,k)$ is chosen or not. This is generated randomly using the associated probability vector for that generation. Specifically, a number between 0 and 1 is generated randomly for each candidate, $n(i,j,k)$. If this number is less than $\mathrm{p}_{n(i,j,k)}^{g}$, the associated probability of candidate action $n(i,j,k)$ in generation g, then the candidate is considered in the schedule, i.e., $x_{ijk} = 1$. Otherwise, $x_{ijk} = 0$. This is repeated for all elements for the number of schedules in the population.

PBIL is an unconstrained optimization algorithm that randomly samples the solution space and generates MRR schedules. However, the solution space contains a list of all possible combinations of MRR actions and not all can be accommodated into a feasible sequence. For example, it is not realistic to perform multiple MRR actions on a link in a given year. It is also possible that the algorithm generates a particular schedule where all the links in a network undergo repair activities which would be not feasible from an operations and budgetary standpoint. By imposing constraints, the MRR schedules are narrowed down to a feasible and realistic set of activities that can be performed on the road network.

- Only one activity per link per year: The PBIL can suggest all possible combinations of activities on each link for each year. However, to make the schedule realistic, only one activity can be chosen for each link in a given year. This is implemented by searching across each schedule to find links that contain multiple activities in a year. To ensure exploration, across solutions, 1 activity is chosen while the excess are dropped randomly.

$$\begin{aligned} &while \ \textstyle\sum_{k=1}^{K} x_{ijk} > 1: \ \forall \text{ i, j, k} \\ &\quad rand(x_{ijk}) = 0 \end{aligned} \tag{5}$$

- No consecutive activities on the same link: The PBIL can also suggest consecutive activities on the same link, which is not realistic. To prevent this, if repair activities are performed on a particular link in multiple consecutive years, only one action is chosen while the excess are randomly removed from the schedule. This constraint ensures that the links are maintained properly over time and prevents over-maintenance.

$$\begin{aligned} &while \ \textstyle\sum_{i}^{i+1} \sum_{k=1}^{K} x_{ijk} > 1: \ \forall \text{ i, j, k} \\ &\qquad rand(x_{ijk}) = 0 \end{aligned} \tag{6}$$

- Budget constraint: Every agency has budgetary constraints, which means that only a certain number of links can be maintained each year. To incorporate this into the PBIL algorithm, a constraint on the maximum number of activities that can be performed each year, N_{max} is set. If the number of MRR activities in a year exceed N_{max}, the excess activities with the lowest probabilities in the probability vector of that generation are removed. This constraint exploits better solutions and ensures that the MRR schedule is feasible from a financial perspective and prevents overspending.

$$while \ \sum_{j=1}^{J} \sum_{k=1}^{K} x_{ijk} > N_{max} \ ; \forall \text{ i, j, k} \\ x_{ijk} = 0; \quad s.t. \ \mathrm{p}_{n(i,j,k)}^{g} = \min (P^{g}) \tag{7}$$

Step 3: Evaluation

In the third step of multi-objective optimization, each MRR schedule generated in the previous step is evaluated based on the objective function that considers agency, user, and emission costs using the lower level model. This evaluation is done by simulating yearly link closures due to work zones in the network corresponding to each MRR schedule. The link transmission model is used to simulate the network with reduced capacities on links that have been selected for maintenance. If a schedule with a planning horizon of 5 years is generated, the LTM will simulate the network 5 times, with updated link capacities to reflect the work zones each year.

The simulation calculates the travel time and distance travelled by vehicles and then aggregates these values to calculate the total agency, user, and emission costs associated with the potential MRR schedule. The schedules are then ranked based on their total cost, and the best and worst solutions are identified. These solutions will be used in the next step to update the probability vector of the next generation.

Step 4: Learn, Mutate and Update

Step 4 involves updating the probability vector via positive and negative learning, as well as mutation operations. Positive learning updates the probability vector of the next generation to favor the candidates in the best solution, whereas Negative learning moves away from the inferior candidates.

$$\wp_n^{g+1} = \wp_n^g \times (1 - LR^+) + \left(B^g \times LR^+\right);\ \forall i, \tag{8}$$

$$\wp_n^{g+1} = \wp_n^g \times (1 - LR^-) - \left(W^g \times LR^-\right);\ \forall i \tag{9}$$

where B^g and W^g are the best and worst MRR schedules identified in generation g respectively; LR^+ is the positive learning rate; and LR^- is the negative learning rate.

Mutation is also applied, which allows greater exploration of the solution space by randomly mutating the probabilities of certain candidates by a mutation rate, Δ_m.

$$\wp_n^{g+1} = \wp_n^g \times (1 - \Delta_m) + \Delta_m;\ where, \mathrm{M}_n^g = 1 \tag{10}$$

where M^g is the Mutation vector of size $\mathcal{C}$ containing indicator variables. This is randomly generated using a mutation probability of m.

Step 5: Check the termination criteria

There are two common termination criteria for the PBIL algorithm: convergence ratio and maximum number of generations. The convergence ratio is checked to see if the ratio between the total cost of the previous generation and the current generation is less than a defined threshold, indicating that the algorithm has converged. The other termination criterion is usually based on the maximum number of generations defined at the initialization step. In this study, the second criterion is used. If the current generation number has reached the defined generation size, $\mathcal{G}$, the algorithm stops iterating and outputs the MRR schedule with the lowest total cost as the best solution. However, if the maximum number of generations has not yet been reached, the algorithm proceeds to the next generation repeating step 2.

Lower Level

At the lower level, three components of cost are calculated: 1) Agency cost, 2) user cost, 3) emissions costs as described below.

Agency cost

In this thesis three categories of MRR activities have been considered. The cost estimates used in this study were derived from the Pavement Comparative Analysis Technical report (FHWA, 2015), which relies on industry recommendations and current data obtained from the National Center on Asphalt Technology and State asphalt pavement association representatives regarding the costs of asphalt overlay construction. The total cost for milling and overlay, which includes the costs of milling, tack, overlay placement, and traffic control, was estimated to be approximately $8.00 per square yard for a 1.5-inch-thick overlay, and between $11 and $12 per square yard for a 2-inch or 2.5-inch-thick overlay. The cost for milling is $1.65 per square yard. An additional milling course has been taken into account for the extensive repair option. The description of the MRR cost is as following:

- Preventive Maintenance – This activity involves adding a 1 to 1.5-inch overlay to the existing pavement surface to prevent further deterioration.
- Corrective Maintenance/Rehabilitation – This activity involves a 3-inch overlay with milling, which means removing the top layer of the pavement surface to repair underlying issues.

- Major Rehabilitation/Partial-Depth Reconstruction – This activity involves a 4.5-inch overlay with milling, which is a more extensive repair than the previous activities. This activity involves removing a greater depth of pavement to repair underlying structural issues.

Table 1. Description of MRR actions

MRR activity type, $(\boldsymbol{k})$	Treatment Description	Agency cost $/lane-mile (2015)	Agency Cost $/lane-mile (2022), $\boldsymbol{C_k}$
Do Nothing (0)	No MRR actions	0	0
Preventive Maintenance (1)	1 to 1.5-in overlay	$56,320	$68,527
Corrective Maintenance/Rehabilitation (2)	3-in overlay with milling	$91,520	$111,357
Major Rehabilitation/Partial-Depth Reconstruction (3)	4.5-in overlay with milling	$124256	$151,188

The 2015-unit costs for MRR activities were adjusted for inflation to 2022 using the Producer Price Index by FRED economic data(U.S. Bureau of Labor Statistics, Producer Price Index, n.d.). Therefore, agency costs in (1) can be calculated as:

$$AC_{jk} = C_k \times ll_j \tag{11}$$

Where, C_k is the cost of undertaking MRR activity k; and ll_j is the length of the link.

User Costs

The improvement in pavement condition after an overlay can have a significant impact on user costs. The user costs that have been considered for this project include:

- Excess travel time (Δt),
- Excess fuel consumption (Δf),

- Excess tire wear (Δtw),
- Excess vehicle repair and maintenance (Δrm), and
- Excess depreciation cost (Δdc).

Excess travel time is assumed to occur due to congestion (i.e., lower travel speeds on roadways) during MRR activities. Excess tire wear, vehicle repair and maintenance and depreciation cost are assumed to occur mainly due to IRI of pavements being higher than an assumed baseline for a newly paved road, IRI_{base}, which is assumed to be 63 inches/mile in this thesis. The excess fuel consumption is assumed to be due to both congestion (lower travel speeds) and higher IRI of pavements.

The excess travel time of the network has been calculated by considering two scenarios: one where some road segments are closed due to MRR work and the other where all road segments are open with no closures. The difference in travel time between these two scenarios is considered as excess travel time which is calculated as:

$$\Delta t = \alpha_1 \times (\mathrm{TTT}_{MRR} - \mathrm{TTT}_{\mathrm{base}}) \qquad (12)$$

where, TTT_{MRR} is the total travel time of the network when MRR activities take place; $\mathrm{TTT}_{\mathrm{base}}$ is the total travel time of the base network without any link closures; α_1 is the cost of incurred delay per hour which is taken as \$28.70/hr (Santos et al., 2018a).

Fuel consumption can also be affected by work zones and road conditions. When vehicles are forced to slow down, stop or rerouted due to construction or other factors, they may consume more fuel than they would otherwise. In addition, driving on rough roads can cause a vehicle to use more fuel than it would on a smoother surface. Rolling resistance force refers to the force required to keep a vehicle moving at a constant speed on a road surface. When a vehicle travels on a rough road surface, the rolling resistance force increases, which means more energy is required to keep the vehicle moving at the same speed. This increased energy requirement translates to higher fuel consumption, which ultimately leads to higher energy costs. Therefore, the excess fuel consumption on link j can be calculated as the difference between the fuel consumption when the MRR activity takes place and a baseline fuel consumption when there are no MRR activities on that link:

$$\Delta f = f_{mrr} - f_{base} \tag{13}$$

$$f = \alpha_2 \times (0.0286 \times [(1.209 + 0.000481 \times IRI_j \times v_j + 0.0394 \times MPD_j + 0.000667 \times v_j^2 + 0.0000807 \times ADC_j \times v_j^2 - 0.00611 \times RF_j + 0.000297 \times RF_j^2)\ 1.163] \times v_j^{0.056}) \times V_j \times ll_j \tag{14}$$

Where, f is fuel consumption due to rolling resistance; IRI_j is pavement roughness, v_j is the average vehicle speed; MPD_j is the pavement's macrotexture represented by the parameter mean profile depth ; ADC_j is the road curvature; RF_j is the road slope; and V_j is the vehicular volume. MPD, ADC and RF are assumed to be zero in our model. The fuel price (α_2) is assumed to be \$3.78/gal.

Vehicle repair and maintenance cost is influenced by road roughness. As a vehicle travels on a rougher road, it will experience more wear and tear, which can result in higher maintenance and repair costs over time. (Zaniewski J.P., 1982). developed a method to estimate an adjustment factor to find the repair and maintenance cost as a function of pavement condition. Later (Islam & Buttlar, 2012) fitted an equation to calculate the adjustment factor of vehicle repair and maintenance (R&M) cost. Therefore, the excess repair and maintenance cost, Δrm on link j can be calculated using:

$$\Delta rm = \alpha_3 \times ((5 \times 10-5 \times \mathrm{IRI}_j^2 + 0.0049 \times \mathrm{IRI}_j + 0.6239) - 1) \times \mathrm{V}_j \times ll_j \qquad (15)$$

where, α_3 is the R&M cost / vehicle / mile which is taken as 6.98 cents/vehicle-mile (Buttler and Islam, 2012).

Tire wear and depreciation cost are all related to the physical condition of the road. The amount of tire wear can be affected by various factors, including pavement roughness and the type of aggregate used in the pavement. Studies have shown that there is a definite increasing trend in tire wear with increasing pavement roughness. (Haugodegard T., 1994) Vehicle depreciation refers to the decrease in value of a vehicle over time due to usage, wear and tear, and obsolescence. Several factors can impact depreciation costs, such as mileage driven, age of the vehicle, and road conditions (Islam & Buttlar, 2012). This can also lead to a decrease in the resale value of the vehicle due to the increased depreciation caused by the rough road conditions. (Zaniewski J.P., 1982) conducted a study on tire wear and depreciation cost using surveys and vehicle registration data. Based on the findings he proposed adjustment factors that were based on a PSI of 3.5 as a reference point, which was later converted to IRI values by (HALL and CORREA, 2016).

Table 2 MFs for cost for passenger cars and pickup truck based on IRI (Zaniewski et al., 1982)

PSI	IRI (in./mi)	MFs for Tire wear Cost	MFs for Depreciation Cost
4.5	40	0.76	0.98
4.0	63	0.86	0.99
3.5	84	1.00	1.00
3.0	123	1.16	1.02
2.5	180	1.37	1.04
2.0	320	1.64	1.06

1.5	610	1.97	1.09

Based on the data, the following equations have been fitted to calculate tire wear cost and depreciation cost of vehicles on link j as a function of IRI.

$$\Delta tw = \alpha_4 \times ((0.4888\ln(\mathrm{IRI}_j) - 1.1724) - 1) \times \mathrm{V}_j \times ll_j \tag{16}$$

$$\Delta dc = \alpha_5 \times ((0.0443\ln(\mathrm{IRI}_j) + 0.8062) - 1) \times \mathrm{V}_j \times ll_j \tag{17}$$

Where, α_4 is tire wear cost (1.1 cents/vehicle-mile) & α_5 is depreciation cost (7.53 cents/vehicle-mile) according to (Islam & Buttlar, 2012)

The equation of user cost becomes:

$$\mathrm{UC}_j = \Delta t + \Delta f + \Delta rm + \Delta tw + \Delta dc \tag{18}$$

Emission costs

Two types of emission costs are considered: 1) Emissions generated during the MRR construction activity, and 2) User emissions.

The MRR activity emissions are associated with the emissions generated during the construction work. These emissions can be significant and is important to consider in the optimization of the maintenance schedule as they play a role in the overall environmental impact of the network. Motivated by (France-Mensah & O'Brien, 2019; Lee & Madanat, 2017), the emissions from MRR activity, k is calculated as:

$$E_k^{MRR} = n \times d_k . e \tag{19}$$

Where, n is the number of lanes, d_k is the applied overlay thickness, e is emission constant. Using (9), assuming one lane will be closed down due to a work zone, corresponding emissions of each undertaken MRR category are reported in **Error! Reference source not found.**.

Table 3. Estimated emissions of MRR activities

MRR activity category	**Emissions (kg CO2/lane-mile)** E_k^{MRR}
Do Nothing	0
Preventive Maintenance	13801.7
Corrective Maintenance/Rehabilitation	27603.5
Major Rehabilitation/Partial-Depth Reconstruction	41405.2

The total emissions from implementing a specific schedule of MRR activities in a network can be calculated as:

$$EC_{jk}^{agency} = \beta \times E_k^{MRR} \times ll_j \tag{20}$$

where, E_k^{MRR} is the emission from activity k from table 3; β is the monetary conversion rate (\$185/$Ton - CO_2$) from emission.

The user emission is a measure of the amount of carbon dioxide (CO_2) emitted by vehicles as they travel on the network. The calculation of user emission is based on the fuel consumption equation, which takes into account the speed of the vehicles and the distance they travel on the network. The fuel consumption equation is converted into emission by using emission factors for cars and trucks as reported in a previous study (Lee & Madanat, 2017). Since the fuel consumption equation captures the effects of congestion, delay and rerouting, the user emission also takes into account the emissions that result from these factors.

$$EC_j^{user} = \beta \times \Delta f \times \gamma \tag{21}$$

where, EC_j^{agency} is the emission from users on link j; γ is emission factors to convert truck(3.1 kg CO_2 /L) and car (2.7 kg CO_2/L) fuel consumption into emission;

The simulation is run for 1 hour and the k factor is assumed to be 11%. The k factor represents the ratio of the design hour to the Average Daily Traffic (ADT). All the costs obtained from the 1-hour simulation have been scaled up to a daily basis and then to a yearly basis for conversion.

Other inputs into the cost calculations

To calculate the costs, the change in IRI due to deterioration and maintenance activities, along with the link volumes and travel speeds during MRR construction activities need to be determined.

Change in IRI

The pavement deterioration model from (Ouyang & Madanat, 2004) has been used in this study. This is an exponential model which is a simplification over the original deterioration model proposed by (Paterson et al., 1990). This simplification allows the deterioration rates to remain almost constant during short periods. The model is expressed as:

$$s_{i+1,j} = \left(s_{i,j} + \sigma *\right). \exp\,(\rho) \tag{22}$$

where $s_{i,j}$ denotes the pavement condition on link j in year i; the constant ρ and parameters $\sigma *$ are used in (15) to determine the rate of pavement deterioration, which is influenced by various factors such as pavement design, traffic loading, and environmental conditions. The value of $\sigma *$ ranges from 1.2 to 9 depending on the slow or fast deterioration rate of the pavement.

Assumptions were also made on how the pavement condition would improve with the maintenance activities. The International Roughness Index (IRI) for a brand-new pavement depends on the quality of construction and the type of pavement material and it usually ranges from 52 to 66 inches/mile (FHWA-HIF-16-032, 2016). In the absence of maintenance or rehabilitation actions, the IRI of the pavement will deteriorate over time from the initial condition. An overlay does not restore the initial roughness of the pavement, and the IRI cannot go back to its initial condition. Hence, a lower bound of 80 inches/mile is assumed for the IRI improvement after an overlay. If preventive maintenance is carried out, it is assumed that the pavement condition will improve by 5% of its previous roughness. If corrective maintenance is applied, the pavement condition will improve by 60% of its previous IRI. For major rehabilitation, the IRI will be set back to the lower bound of IRI.

Evaluation of link volumes and travel time: Link Transmission Model

The Link Transmission Model (LTM) is used to calculate the excess travel time and vehicle mile travelled in the network. The LTM is a traffic simulation model that is based on the kinematic wave theory. It simulates the movement of vehicles on a network. The LTM is capable of capturing the impacts of queue spillbacks because it takes into account the capacity constraints of links and nodes. The network is represented as a series of links and nodes, where links represent road segments and nodes represent intersections or origins/destinations of car trips. The LTM uses three functions - sending flow, receiving flow, and transition flow - to propagate vehicles. The concept of LTM is similar to cell transmission model (CTM), however vehicles travel along links rather than cell here.

The sending flow from link p, $S_p(t)$ is defined as the number of vehicles that can exit a link if the link is connected to a node with infinite capacity at its downstream end which is calculated as:

$$S_p(t) = min\{N(x_p^0, t + \Delta t - ll_p/vf_p) - N(x_p^L, t), Q_{max,p}\Delta t\} \quad (23)$$

where $N(x_p^0, t)$ and $N(x_p^L, t)$ denote the cumulative counts of vehicles at the upstream and downstream ends of link p at time t respectively; vf_p is the free flow speed on link p; $Q_{max,p}$ is the capacity of link p; and Δt is the duration of the timestep.

The receiving flow to link q, $R_q(t)$ is the highest number of vehicles that can enter a link within each time step, assuming an unlimited supply of cars. This flow is constrained by the link's capacity and the traffic conditions downstream from the link and can be calculated as:

$$R_q(t) = min\{N(x_q^L, t + \Delta t - ll_q/w_q) + K_{jam,q} \times ll_q - N(x_q^0, t), Q_{max}\Delta t\} \quad (24)$$

where w_q is the backward wave speed on link q; and $K_{jam,q}$ is the jam density on link q.

The transition flow between links, $G_{pq}(t)$ determines the number of vehicles that leave a link p and enter link q at time t, taking into account the actual demand by using turning fractions and scaling these by the actual number of cars that can leave the sending link and the space available in the receiving link.

$$G_{pq}(t) = TF_{pq}\, min\{min\,(\frac{S_p R_q}{\sum_\alpha TF_{\alpha q} S_\alpha}, S_p)\};\ \alpha \in p \quad (25)$$

where TF_{pq} is the turning fraction of vehicles from link p to q.

The calculated transition flows are used to update the upstream $N\left(x_q^o, t+\Delta t\right)$ and downstream $N\left(x_p^L, t+\Delta t\right)$ cumulative vehicle counts on each links p and q respectively as follows:

$$N\left(x_q^o, t+\Delta t\right) = N\left(x_q^o, t\right) \sum_p G_{pq} \tag{26}$$

$$N\left(x_p^L, t+\Delta t\right) = N\left(x_p^L, t\right) \sum_q G_{pq} \tag{27}$$

Travel time is a crucial factor when it comes to making routing decisions. Trave time by car is determined by adding up the average travel times for each road segment along the shortest path taken during the previous cycle. To assign cars to specific routes, a logit model is used at each time step and intersection. The logit model helps determine the probability of cars choosing a particular route based on travel time. Specifically, cars are distributed to routes that have the same travel distance as the route with the shortest travel time according to (X). A detailed description on the route assignment is provided in (Bayrak, 2020).

$$P_r = \frac{\exp\left(a \times TT_r\right)}{\sum_R \exp\left(a \times TT_r\right)} \tag{28}$$

Where, r is a route from a vehicle's current position to its destination; R is the set of all possible routes from a vehicle's current position to its destination; TT_r is the travel time of route r; and a is a sensitivity coefficient.

The total travel time by the vehicles in the network is calculated based on the upstream and downstream count. The input-output diagram for each link in the network can be obtained using cumulative count curves. These curves represent the cumulative number of vehicles that have arrived at and departed from a link over time. By taking the difference between the arrival and departure curves, we can obtain the number of vehicles that have entered or exited a link during a given time interval. The travel time on link j can be calculated by taking the area between the arrival curve $A_j(t)$ and departure curve $D_j(t)$ using (21). To obtain the total travel time for a network, the travel time for all the links in the network are summed up.

$$TTT_j = (A_j(t) - D_j(t)) * \Delta t \tag{29}$$

Two different scenarios have been simulated to evaluate the impact of maintenance, repair, and rehabilitation (MRR) activities on the travel time of a network. The first scenario involves performing MRR activities on some of the links, resulting in a reduced capacity of the links. The links that are under maintenance are assumed to be reduced to half of their capacity, and the vehicles are rerouted based on the shortest path algorithm. The total travel time of the network is then calculated for this scenario. The second scenario is a base scenario where all links in the network are open, no MRR activities are assumed to be taking place. To compare the impact of MRR activities on the network, the excess travel time is calculated by taking the difference between the total travel time of the MRR scenario and the base scenario using (22). The excess travel time represents the additional travel time that is incurred due to the reduced capacities on links with MRR activities. This excess travel time is considered as a parameter to quantify the impact of MRR activities on the network.

$$\Delta t = TTT_j^{MRR} - TTT_j^{base} \tag{30}$$

Volume on each link j , V_j is calculated based on the downstream counts on link j at the end of the simulation.

$$V_j = N(x_j^L, \mathrm{T}) \tag{31}$$

Case study

This section describes a case study to test the proposed method for the identification of an optimal MRR schedule. The method is applied to a 2×2 network followed by a 5×5 network. The inputs to the simulation are described along with scenarios that were implemented to understand how the objective costs vary.

2×2 Network

The proposed methodology for network maintenance and rehabilitation planning was tested on a 2×2 homogenous grid network. This network consists of 16 main links, with each link being 200 meters long with two lanes in each direction. The network also contains four entering links for vehicles and four exiting links. An illustration of the network is shown in Figure 2. Note that at the middle nodes it is assumed that there is no signal control. The links are assumed to be bi-directional and have a speed limit of 50 km/h. The capacity of each link is assumed to be 1200 veh/hr/lane, and the jam density is 135 veh/km/lane. Each intersection, e.g., at the corners of the network, is signalized with a green phase of 30 seconds and a red phase of 30 seconds. The planning horizon for the network is assumed to be five years, during which at most four links can be repaired each year. It is assumed that, when a maintenance action takes place, one lane of the road segment will be closed, and the capacity of the segment will be reduced by half.

The International Roughness Index (IRI) of the road segments is assumed to be uniformly distributed between 200 inch/mile to 600 inches/mile. If no maintenance, repair, and rehabilitation action is taken, the pavement will deteriorate according to the pavement deterioration model (22).

If an MRR action is taken, the IRI of the segment will improve according to the improvement criteria discussed.

The IRI is usually measured assuming a speed of 80 km/h, which represents standard testing conditions. For this work, it is assumed that the speed limit is 50 km/h, which is substantially lower than 80 km/h. Vehicles are less sensitive to road roughness at reduced speeds, since they have more time to adapt and absorb the impacts caused by irregularities. Drivers can adjust their behavior, accordingly, making slight steering corrections or further reducing their speed to minimize discomfort. Thus, it is assumed that on the urban network considered, the IRI of the roadway does not change the travel speed or traffic flow in this work.

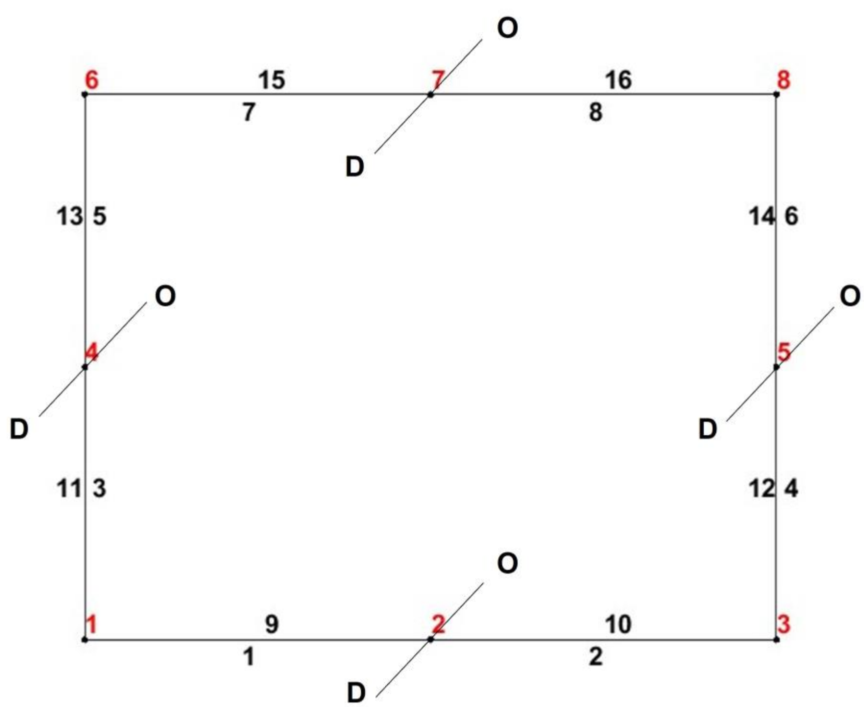


Figure 2. Visual representation of 2 × 2 network

To evaluate each candidate, the traffic is simulated year-wise using the LTM. Since the planning horizon is assumed to be 5 years, the LTM is run five times to simulate the network performance over each of the five years for each candidate. The simulation includes a time-varying demand, comprising of a 15-minute warm-up period,45 minutes of peak demand and then a cool down period for as long as the network becomes empty. A total of 3,648 vehicles enter the network over a 60 minutes followed by a cooldown period when the demand is set to zero, and the simulation continues until the network is empty. The excess travel time, which is the time vehicles spend traveling beyond what they would like in perfect conditions with no link closures, is calculated at the end of each simulation.

5×5 Network

The thesis aims to apply the proposed optimization method to a real urban network in Philadelphia (Figure 3). The chosen network is a 5×5 homogenous grid network that includes 160 main links and 40 entering and 40 exiting links for vehicles that can be visualized from Figure 4 . The length of each link is 70 meters, and the speed limit is 25 mph. However, the average speed of vehicles in the network is slightly higher than the imposed speed limit, which is why it is considered to be 30 mph. As previously discussed, we have assumed that the variation in IRI will not have a major impact on the flow and speed of the network under the premise of a lower speed limit. The actual demand and IRI values of the road segments in the 5×5 network in Philadelphia have been extracted from the PennDOT Roadway Management System dataset. A total of 6794 vehicles enters in the network during the simulation period. Some of the lanes in the network are one directional, but for simplicity in calculation, all the lanes are assumed to be bi-directional with two lanes in each direction. The fundamental diagrams used in the simulation are assumed to be similar to the ones used in the 2×2 network. The planning horizon is considered to be 5 year and a value of $N_{max} = 10$ is assumed meaning at most 10 road segments can be repaired each year.

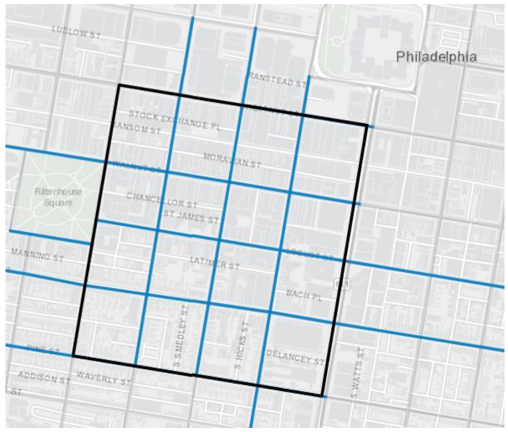


Figure 3. Map of actual 5×5 network of Philadelphia, PA

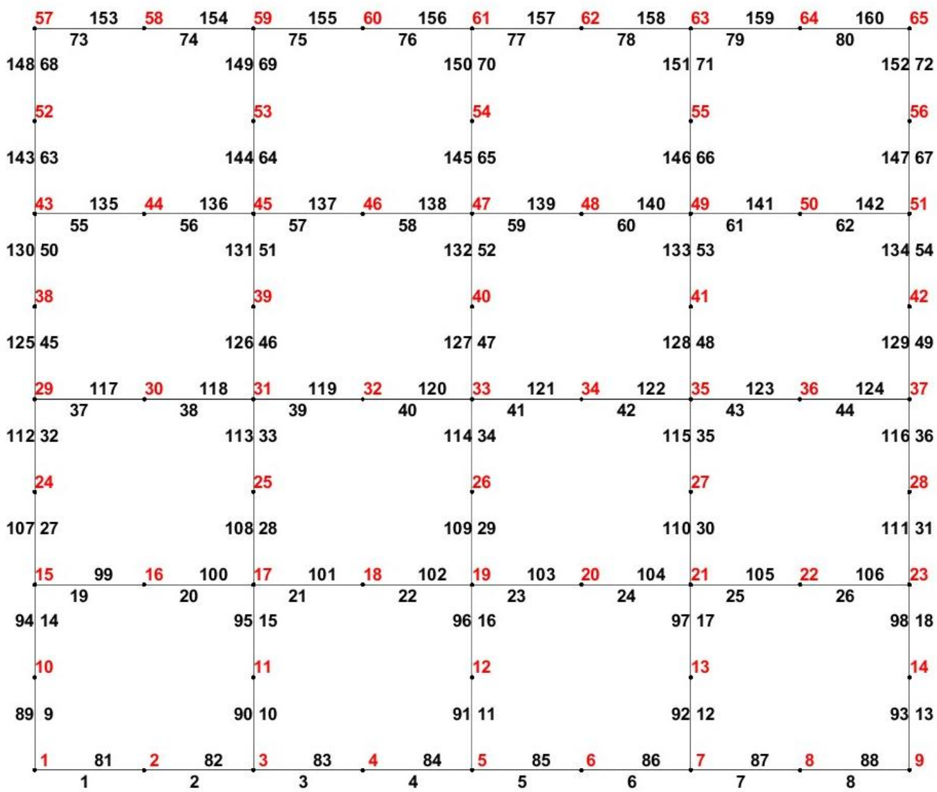


Figure 4. Visual representation of the 5×5 network in LTM

Scenario setup

For both networks, 2 scenarios are simulated to understand the impact of considering emissions in the MOO problem. Scenario 1 considers an objective function without emission costs by setting $w2 = 0$ in (4) and optimizes the MRR schedule by minimizing only agency and user costs. On the other hand, in the second scenario, the MRR schedule is optimized considering all three objectives: minimizing agency cost, user cost, and emission cost ($w1 = 1, w2 = 1$).

However, it is difficult to quantify the exact monetary value of emissions, which makes it challenging to directly compare the emission cost with the agency and user cost. To identify the tradeoffs between emission cost and user/agency cost, a Pareto frontier analysis was conducted by varying the weight of emission, $w1$ with combined user and agency cost, $w2$ in (4). The Pareto-optimal frontier was constructed by varying $w2$ between 0.1 to 0.9.

$$w1 = 1 - w2; \quad s.t.\ w1 + w1 = 1 \tag{32}$$

By varying the weightage factor of emissions, the relative importance of emissions on the overall cost can be analyzed, and a suitable balance between the different objectives can be identified. For example, if the emission cost is low, then the focus can be on minimizing user and agency cost, while if the emission cost is high, then more emphasis may be placed on reducing emissions even if it results in slightly higher user or agency cost.

Finally, the effectiveness of the proposed method is evaluated by comparing the best schedule output of the PBIL algorithm with a deterministic schedule. The prescribed scenario is developed where 10 links with the highest IRI will undergo MRR actions every year of which, three links with the highest IRI will receive extensive MRR (activity 3); the next three worst links will receive repair action 2; and the next four links will receive repair action 1. The emission cost, user cost, and agency cost corresponding to this schedule will be compared to the PBIL outputs.

CHAPTER 4: RESULTS

This section analyzes the results of the simulations and compares the findings of the different scenarios.

2×2 Network

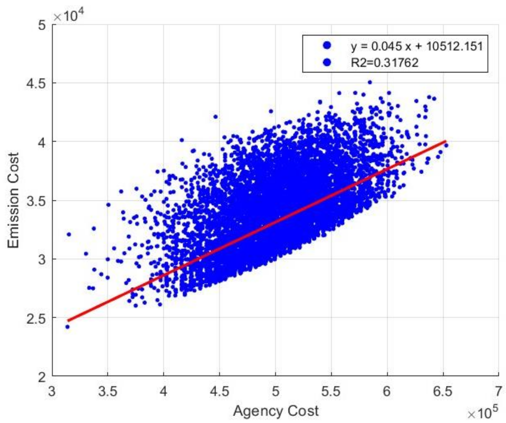
Relationship between objectives

The PBIL algorithm used in this study involved a generation size of 100 and a population size of 100, meaning that 10,000 MRR schedules of the 2×2 network were simulated in total. To visualize the relationship between different objectives, the resulting costs of each objective were plotted against each other for each simulation. Specifically, the plots show the relationship between emission cost and agency cost, emission cost and user cost, and user cost and agency cost. Each dot on the plot represents a single solution generated by the PBIL algorithm.

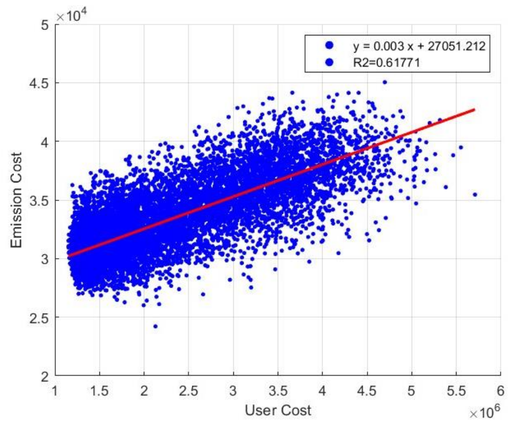
First, the scatter plot of emission cost vs agency cost Figure 5a shows that as the agency cost increases, the emission cost also tends to increase. This indicates that there is a trade-off between the agency's cost of maintaining the pavement and the environmental impact of the maintenance activities. Higher agency costs may mean that more resources are being allocated towards maintaining the pavement, which may result in more maintenance activities being carried out, leading to a higher emission cost.

Next, the scatter plot Figure 5b also shows a similar increasing trend. As the user cost increases, the emission cost tends to increase as well. Higher user costs may mean that the road condition is poorer, resulting in more fuel consumption and vehicle operating cost, leading to a higher emission cost.

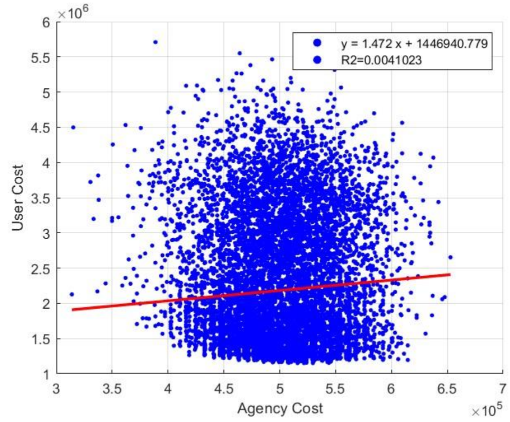
Finally, the scatter plot of Figure 5c shows almost no correlation between user and agency cost. Agency cost represents the cost of MRR actions, while user cost includes the cost of excess travel time, fuel consumption, repair and maintenance, tire wear, and depreciation, all of which are affected by the condition of the road. When more MRR activities are done on the network, the road condition improves, which decreases the vehicle operating cost, and therefore reduces the repair and maintenance, tire wear, and depreciation costs. However, MRR activities may also require road closures, resulting in detours and longer travel times for vehicles, which increases the excess travel time cost, fuel consumption cost, and user cost overall. So, it is important to strike a balance between agency cost and user cost when optimizing the MRR schedule.



(a)



(b)



(c)

Figure 5. Scatter plots of different objectives in with-emission scenario on the 2×2 network: (a) Emission cost vs Agency Cost; (b) Emission cost vs User Cost; (c) User cost vs Agency Cost.

However, note that these trends may not fully reflect the true relationship between the different objectives. Initially, the algorithm performs a random search across the solution space, meaning that solutions are randomly generated and evaluated without any prior knowledge of the problem. As a result, the initial solutions generated by the algorithm are likely to be inferior in terms of their performance compared to later iterations. However, as the algorithm proceeds, it begins to learn from the solutions generated in each iteration. This learning process allows the algorithm to gradually improve its performance over time, generating better solutions with each iteration. Nonetheless, by generating a large number of solutions and analyzing their performance across multiple objectives, the PBIL algorithm provides a useful framework for exploring the tradeoffs between different objectives and identifying promising solutions that balance these competing priorities.

Comparison of best schedule of with- and without-emission scenarios:

In this section, we compare the best schedules generated by the PBIL for two scenarios where the objective of the first scenario is to minimize user and agency costs, while the second scenario minimizes the cost of emissions in addition to the user and agency costs.

Figure 6 and Figure 7 shows the best schedule of MRR activities obtained by the proposed methodology. In the with emission scenario, the algorithm selected a total of 16 maintenance actions, including 13 major rehabilitation activities, 1 corrective maintenance activities, and 2 preventive maintenance actions, over a planning horizon of 5 years. The major rehabilitation activities are typically more time-consuming and expensive but have a significant impact on pavement condition, while corrective and preventive maintenance activities are less expensive and less time-consuming but have a smaller impact on pavement condition. The algorithm optimized the maintenance schedule to minimize both user and agency costs, as well as the emissions generated from the maintenance activities.

On the other hand, the without-emission scenario Figure 7 focused solely on minimizing user and agency costs. This resulted in the selection of a larger number of maintenance actions, including more preventive and corrective maintenance activities. The algorithm selected a total of 19 maintenance actions, including 10 major rehabilitation activities, 5 preventive maintenance actions, and 4 corrective maintenance activities. It chose more MRR activities, to improve the road condition, without considering its emission cost.

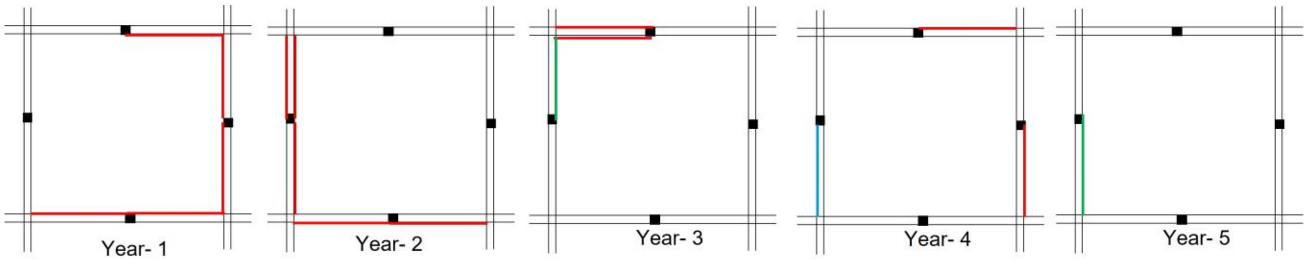


Figure 6 with-emission scenario optimal MRR schedule.

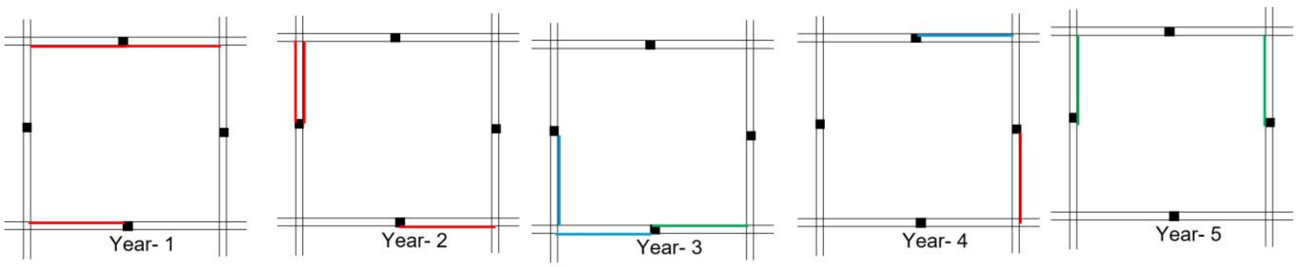


Figure 7. without-emission scenario optimal MRR schedule.

Comparison of objective costs

Figure 8 compares the costs and emissions for the two scenarios. Under the without-emission scenario, the total agency cost is around $25,000 higher than the with-emission scenario. The total user cost is also around $50,000 higher under the without-emission scenario. Finally, the total emissions generated under the without-emission scenario are around 4,000 kg higher than the with-emission scenario.

The bar chart shows that the with-emission scenario achieves better results in all three categories, even though it involves fewer MRR activities overall as seen from **Error! Reference source not found.**. This is because the with-emission scenario selects more intense MRR actions that improve the overall pavement condition more effectively, reducing user costs. Additionally, the scenario is also able to reduce agency costs and emissions by selecting fewer MRR activities compared to the without-emission scenario. It also highlights the relative magnitudes of the different categories. For example, it shows that the user cost is a much larger contributor to the overall cost than the agency cost, while emissions are comparatively smaller.

Overall, Figure 8 demonstrates that the with-emission scenario achieves better results in all three categories despite involving fewer MRR activities than the without-emission scenario.

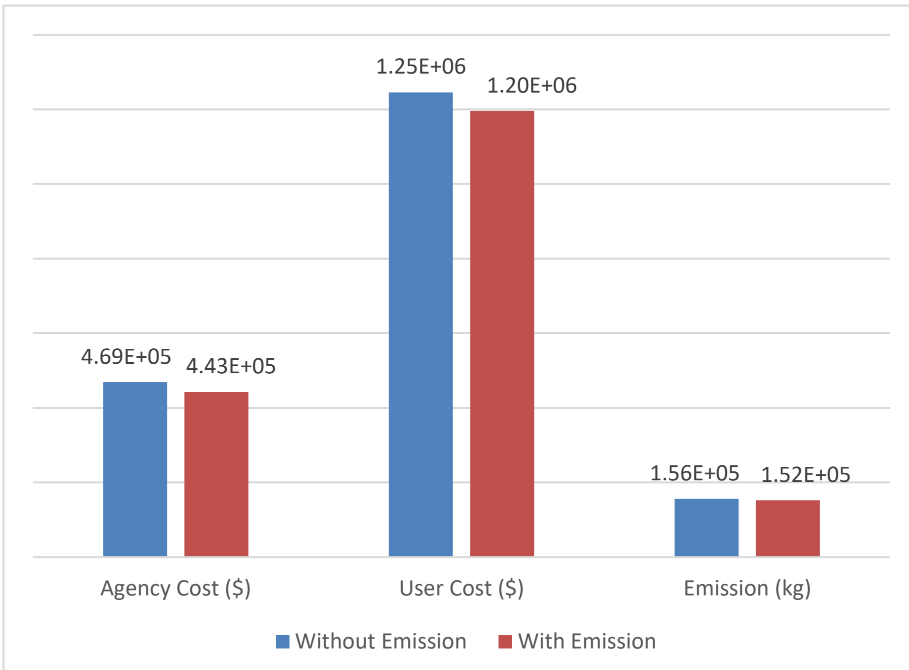


Figure 8. Comparison of the objective costs for without-emission and with-emission scenarios.

Road improvement over the years:

Figure 9 shows the pavement condition, measured in International Roughness Index (IRI), for three different scenarios over the planning horizon: "Do Nothing," "With-Emission," and "Without-Emission."

The "Do Nothing" scenario shows that from an initial IRI of 443 in/mile the network gradually deteriorates over time, reaching an IRI of 505 in/mile in year 5. This indicates that if no action is taken to maintain or rehabilitate the pavement, it will progressively become rougher and more expensive for users. In contrast, both the with-emission and without-emission scenarios undertake timely MRR activities that improve the pavement conditions in the network over time as seen from the red and green curves respectively.

The with-emission scenario is more efficient as it reduces the IRI of the network slightly more than the without-emission schedule thus, the pavement condition improves more rapidly, reaching an IRI of around 124 in/mile in year 5, while the without-emission scenario has a final network IRI of about 130 in/mile. This suggests that considering emissions in the objective function can be more effective at improving pavement condition than the without-emission scenario.

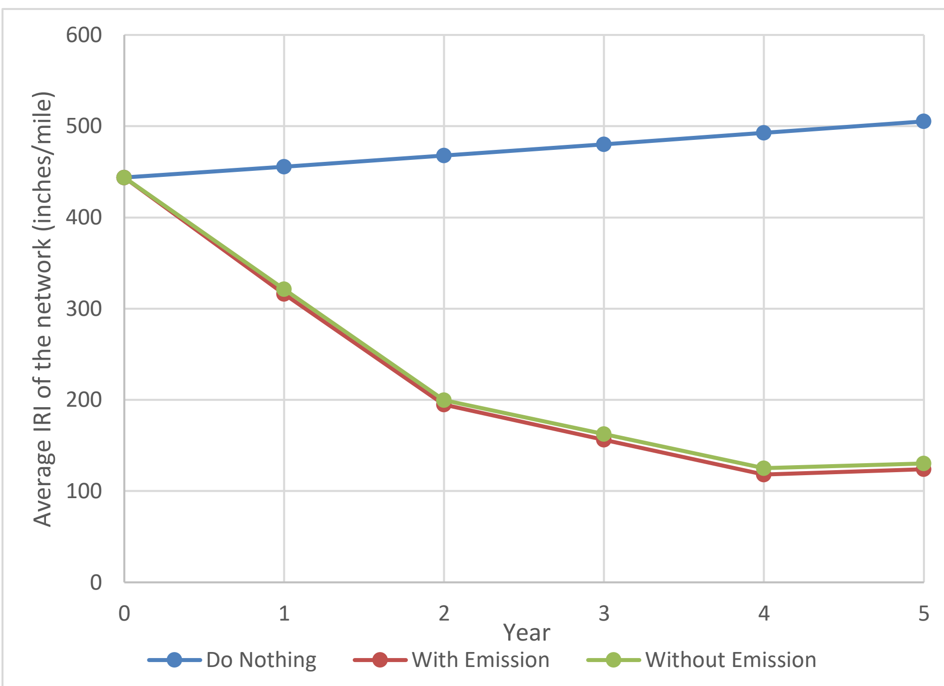


Figure 9. Average network IRI over five years.

Pareto frontier

A Pareto frontier analysis was conducted to assess tradeoffs between emissions and total user and agency costs. The analysis produced a set of non-dominated solutions, which represented the best options for balancing these conflicting objectives. To identify the Pareto-optimal frontier, weightage factors varied between 0.1 and 0.9, where the sum of weights equal to 1. For example, if the weightage factor for emissions was set to 0.8, the weightage factor for combined user-agency cost would be 0.2, and the optimization problem would prioritize minimizing the cost of emissions while searching for an optimal solution.

Figure 10 reveals a relationship between the weightage given to emissions and the resulting level of emissions reduction. Moving from left to right along the Pareto frontier, there is a decrease in emissions but an increase in total user and agency costs. This highlights the trade-off between minimizing emissions and costs on the user and agency end. Figure 10 shows that beyond a certain expenditure in agency and user cost (point A), the slope of the curve changes significantly. From the plot, it is evident that the marginal decrease in emissions diminishes after this threshold despite increasing user and agency costs. This suggests that there may be an optimal balance between emissions reduction and cost minimization that needs to be carefully considered in decision-making processes.

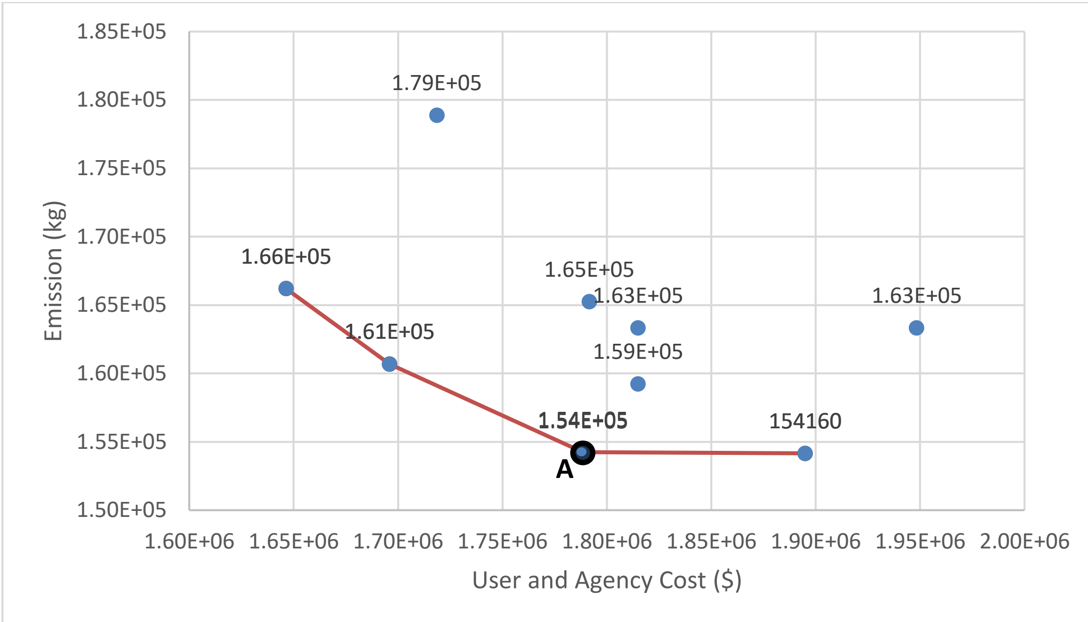
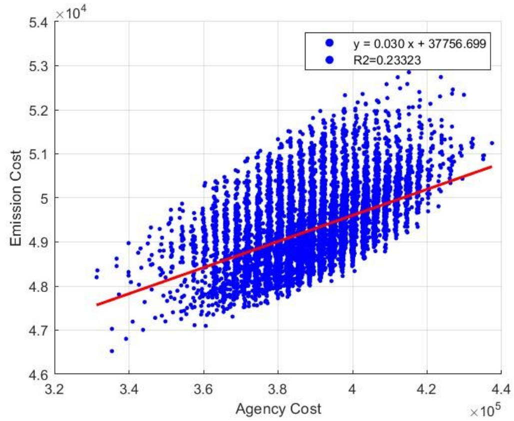


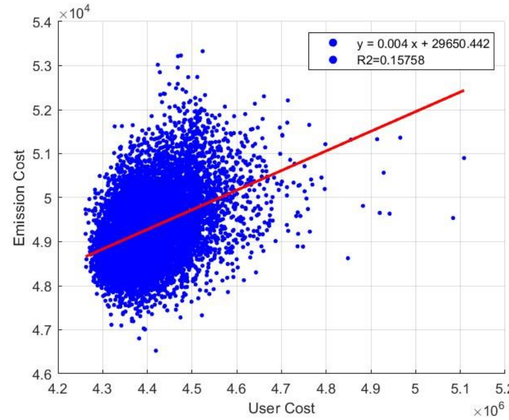
Figure 10. Pareto frontier by for Emission and Costs for the 2×2 network.

5×5 Network

The 5×5 network was simulated for 100 generations and 100 populations using the PBIL. The scatter plots in Figure 11 show the relationship among different pairs of objectives for the 10,000 evaluated schedules. While Figure 11a-b show similar trends to those observed in the 2×2 network (Figure 5a-b), from Figure 11c, it can be seen that as agency costs increase, the user costs decrease. This is because as agencies spend more money for the improvement of pavements, user vehicle operating costs decrease. Implementing capacity reduction on $N_{max} = 5$ links out of 16 on the 2×2 network led to increased excess travel times and fuel consumption for the users which outweighed the vehicle operating cost savings from better pavements. However, $N_{max} = 10$ was imposed out of 160 links on the 5×5 network meaning a smaller percentage of links had reduced capacities. This suggests that an overall reduction in user costs can be achieved by striking a balance in the number of MRR activities and ensuring proper network capacity.



(a)



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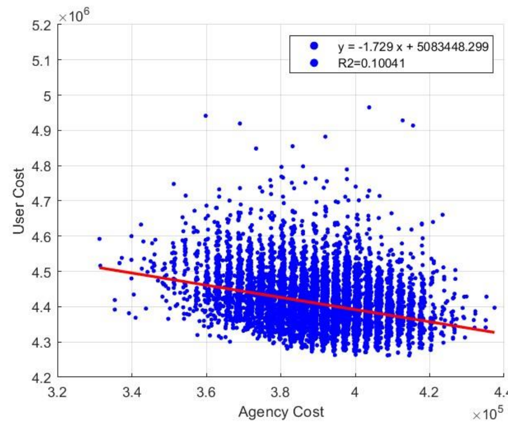


(c)

Figure 11. Scatter plots of different objectives in with-emission scenario on 5×5 network: (a) Emission cost vs Agency Cost; (b) Emission cost vs User Cost; (c) User cost vs Agency Cost.

Schedules for different scenarios

The MRR schedules for three different scenarios was considered: 1) a prescribed scenario, 2) the optimized scenario without considering emission costs in the objective function, and 3) the optimized scenario including emission costs in the objective function.

The Prescribed scenario followed a predetermined schedule where the 10 worst links in the network were repaired each year over the planning horizon. This schedule included performing major rehab on 3 links, corrective maintenance on 3 links, and preventive maintenance on 4 links. In total, 50 links were repaired based on their condition. The focus of this scenario was to address the most deteriorated links in the network and improve their condition. The schedule is shown in Figure 12.

The Without-emission scenario was obtained through an algorithm that aimed to minimize both user and agency costs over the planning horizon. The algorithm generated an optimal schedule that involved 23 major rehab/partial reconstruction actions, 10 corrective maintenance actions, and 17 preventive maintenance actions. The objective was to optimize the repair and maintenance activities while not considering the emission aspect. Figure 13 illustrates the schedule.

On the other hand, the With-emission scenario provided the best schedule that considered the minimization of agency and user costs as well as the emission cost. The algorithm produced a schedule consisting of 20 major rehab/partial reconstruction actions, 13 corrective maintenance actions, and 17 preventive maintenance actions. This scenario aimed to strike a balance between reducing costs for the agency and users while also minimizing emissions from the maintenance and repair activities. The schedule is depicted in Figure 14.

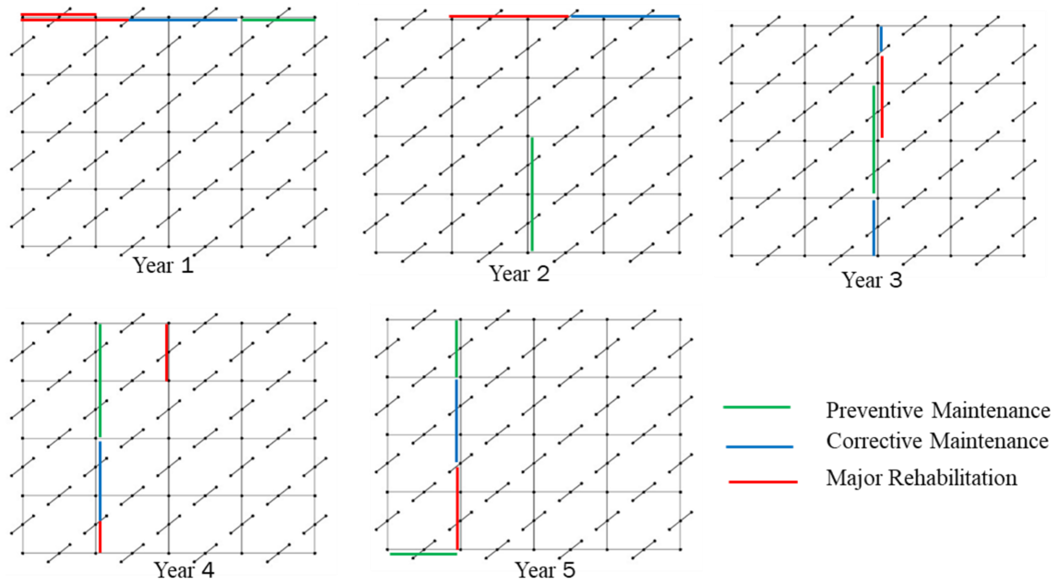


Figure 12. Prescribed schedule for 5×5 network.

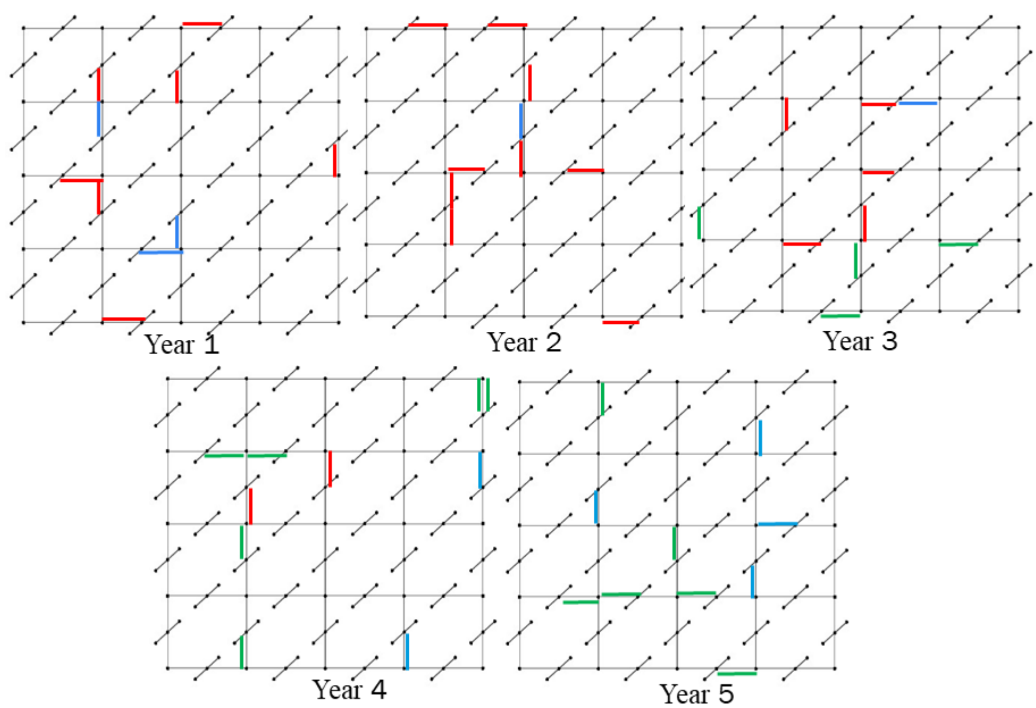


Figure 13. Without-emission schedule for the 5×5 network.

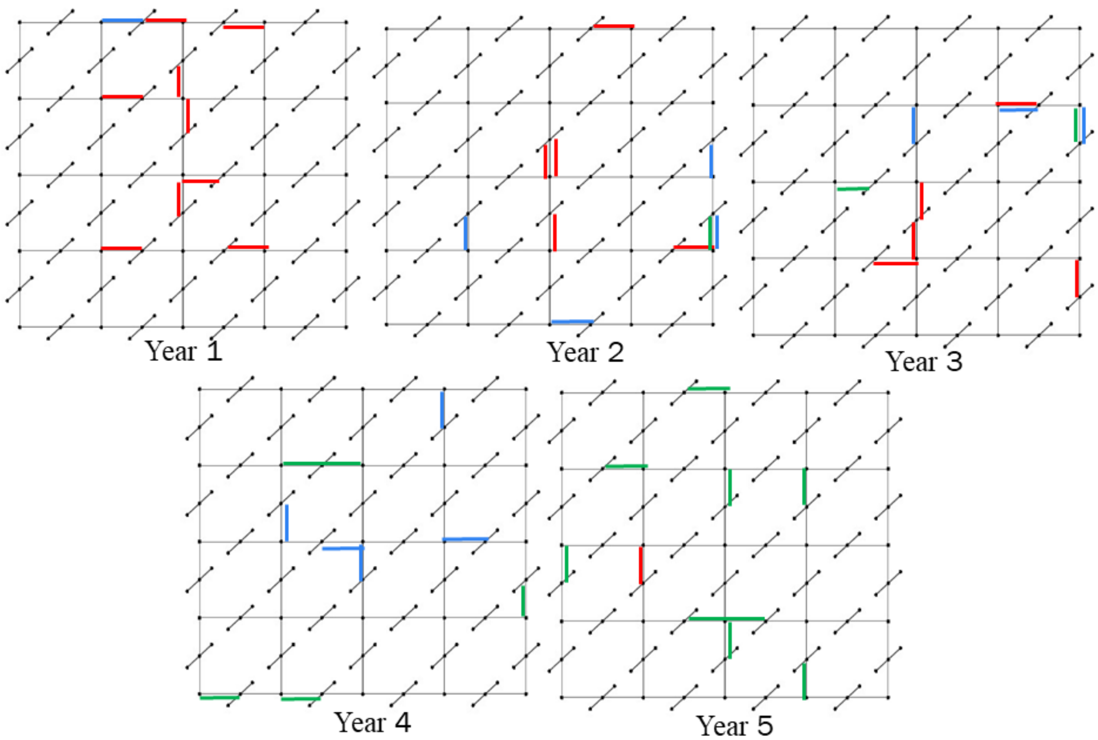


Figure 14. With-emission schedule for 5×5 network.

Comparison of objective costs

Figure 15 compares the total cost, agency cost, user cost and emissions from implementing MRR schedules using the prescribed scenario, without-emission scenario and with-emission scenario.

The prescribed scenario has the highest total cost, approximately $1.8 million more than the other policies. Comparing the with-emission and without-emission policies, the with-emission scenario achieves a slightly lower total cost. This suggests that it achieved a more favorable equilibrium between minimizing agency and user costs, while simultaneously addressing the objective of reducing emissions.

The prescribed schedule has the lowest agency cost among the three scenarios. It can be better explained by Figure 16; the prescribed scenario involves fewer major and corrective maintenance actions compared to the other policies. Intense maintenance activities are typically more expensive, and by incorporating less of them, the prescribed scenario achieves lower agency costs, whereas the with- and without-emission scenarios contain more intense actions.

In the case of the prescribed scenario, it has almost 30% higher user cost compared to the other policies. This can be attributed to the fact that the prescribed scenario undertakes fewer intense MRR actions on the network. By taking fewer and possibly less effective maintenance actions, the road condition may not have been improved significantly, leading to a higher user cost. Additionally, the prescribed scenario selected the worst links to be repaired, resulting in consecutive link closures and potential congestion. This congestion can lead to longer travel times and increased fuel consumption, further contributing to the higher user cost. When MRR actions are not strategically chosen, it can lead to disruptions in the road network, increased travel times, detours, congestion, and overall inconvenience for users, which is reflected very well in the predetermined schedule. On the other hand, both the with-emission and without-emission scenarios consider user costs in their objective functions. The with-emission scenario results in a slightly higher user cost compared to the without-emission scenario. This difference can be attributed to the fact that the with-emission scenario optimizes the maintenance schedule to minimize not only user costs but also emission costs. In the process of reducing emissions, the with-emission scenario may have made trade-offs that result in slightly higher user costs compared to the without-emission scenario.

All the scenarios have similar emission levels. Prescribed scenario has the highest emission whereas the with-emission scenario achieves the lowest emissions. The without-emission scenario does not explicitly consider emission reduction as an objective. As a result, it has higher emissions than with emission scenario. This suggests that the with-emission scenario has successfully optimized the maintenance schedule to reduce emissions while considering the trade-offs with agency and user costs.

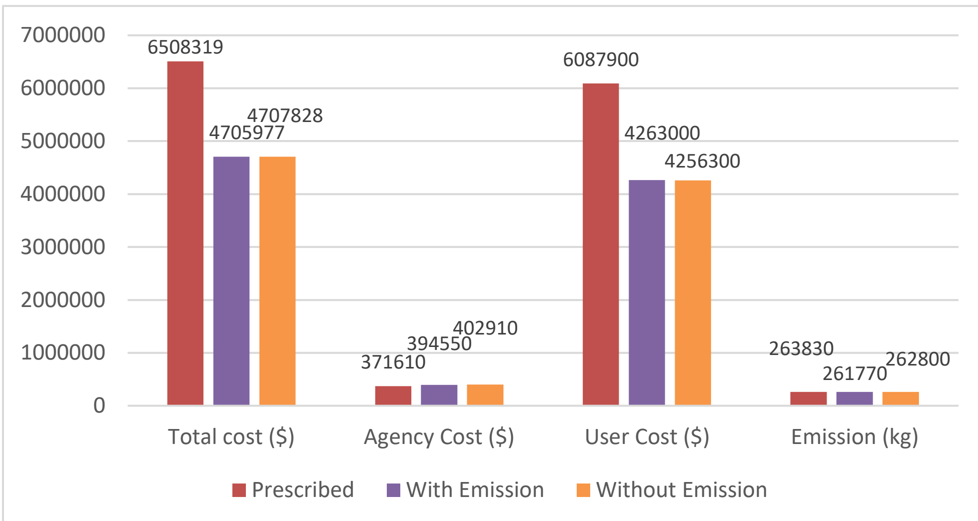


Figure 15. Comparison of costs for Prescribed, with and without-emission scenarios.

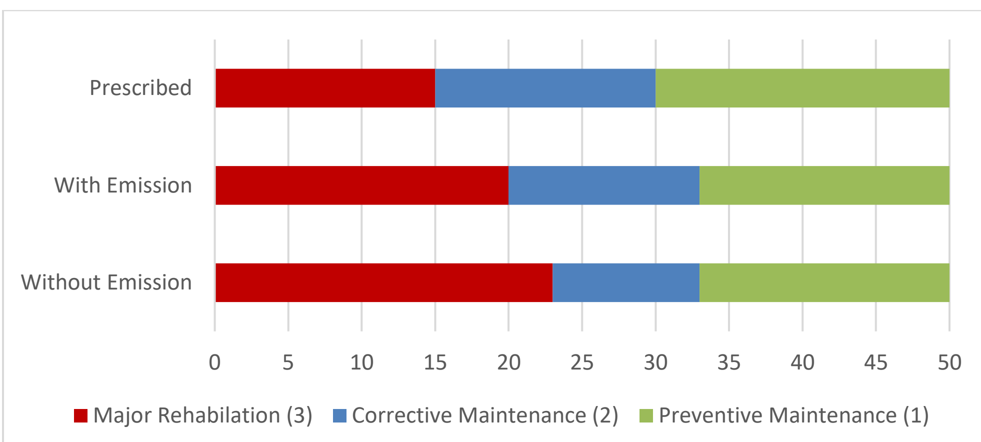


Figure 16. Number of MRR actions in each category by each scenario.

Road improvement over the years

Figure 17 shows the average IRI of the network for the 5×5 network for do-nothing and the three scenarios discussed. In the Do-Nothing condition, where no actions are taken to improve the pavements, the average IRI condition of the network steadily deteriorates over the years.

In the Prescribed scenario, the same sequence of actions is taken every year, resulting in a consistent improvement in the pavement condition. The average IRI of the network improves gradually from 418 inches/mile to 386 inches/mile over the planning horizon. This indicates that the prescribed actions taken each year effectively slow down the deterioration of the network and lead to a better pavement condition over time.

Comparing the without-emission and with-emission scenarios, it is observed that both scenarios result in more improvements than the prescribed scenario at the beginning. During the 5-year planning horizon, the algorithm suggests a strategy where the intensity of maintenance actions is reduced in the 4th and 5th years for both scenarios. This decision is driven by the observation that the benefits achieved in terms of cost savings in agency, user, and emission aspects gradually decrease during this period. The relatively short planning horizon contributes to this reduction in savings, leading to a strategic adjustment in the maintenance intensity during the later years.

The algorithm chose to implement more intensive actions in the best schedule generated from the without-emission scenario resulting in slightly better pavement conditions throughout the planning horizon compared to the with-emission scenario. Therefore, this scenario achieves a lower user vehicle operating cost which adds up over the planning horizon. However, the average

IRI of the network for the without and with-emission scenario ends up almost the same at 391 inches/mile and at 396 inches/mile respectively. Despite the VOC savings from improved pavement conditions in the without-emission scenario, performing more intense actions resulted in higher costs due to delay and additional distance traveled, that offsets its benefits. In fact, the user cost saving from implementing the without-emission scenario is only 0.2% over its counterpart. Whereas the with-emission scenario achieves a saving of 2.1% and 0.4% in terms of agency costs and emissions. This suggests that, despite implementing fewer intensive actions, the with-emission scenario is more efficient.

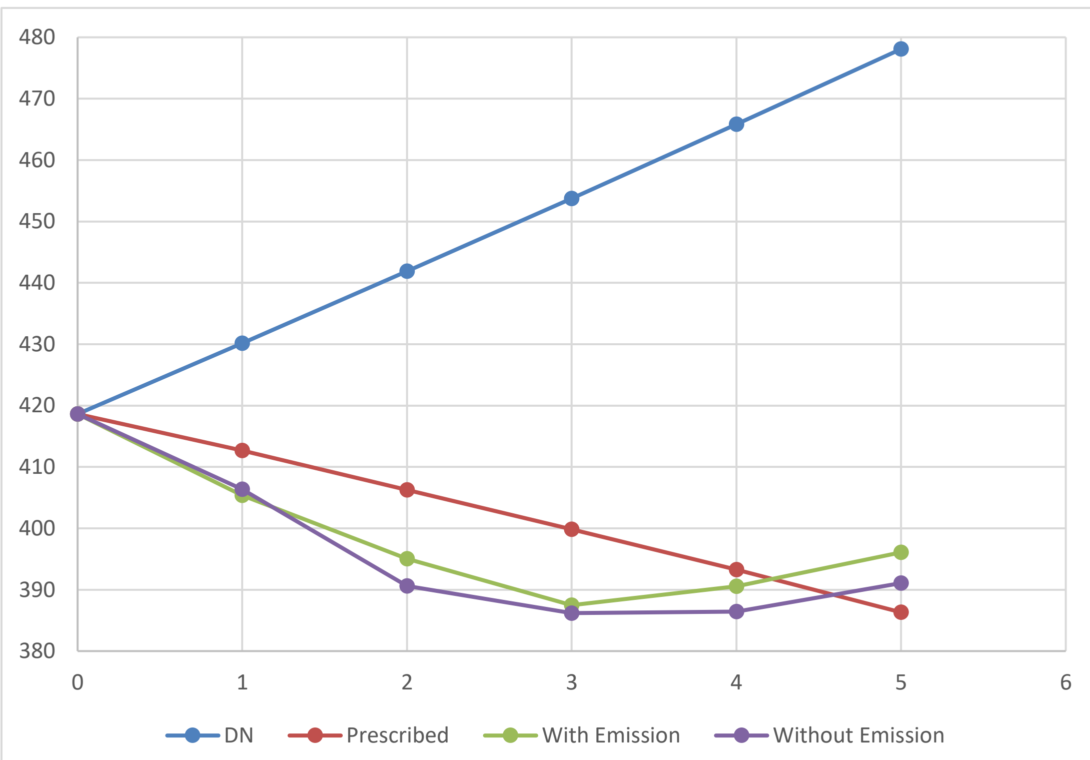


Figure 17. Road improvement over five years for 5×5 network.

Pareto Frontier

A Pareto frontier was obtained following the same methodology of 2×2 network. A similar tradeoff is also seen for the 5×5 network. From Figure 18 it can be observed that as the user and agency costs increase, the emission decreases. Beyond a certain threshold point, A, of user and agency cost in Figure 18, the reduction in emissions is not proportional to the incurred costs.

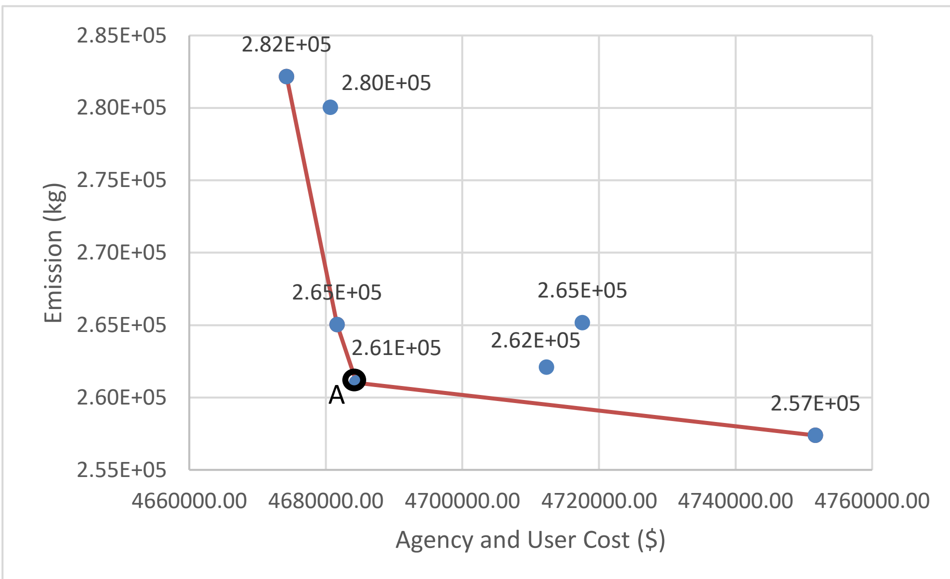
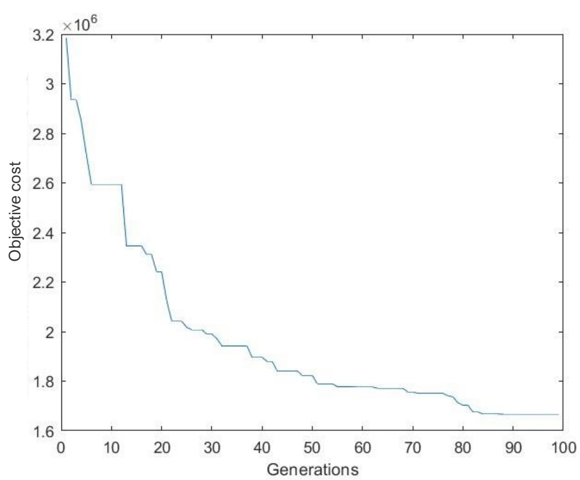


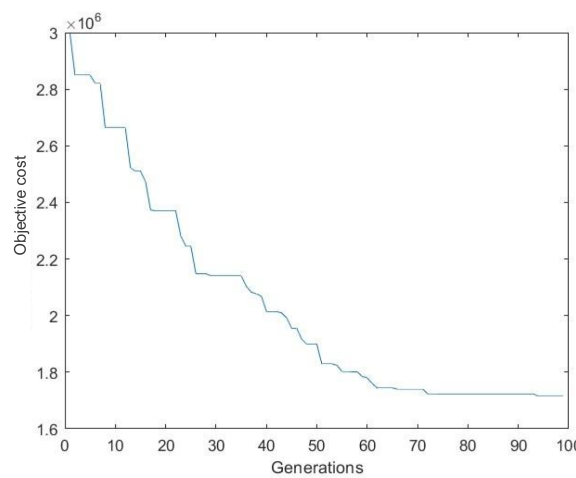
Figure 18 Pareto frontier for Emission and Costs for the 5×5 network.

Algorithm Performance

The PBIL algorithm evaluates a population of MRR schedules in every generation and updates the probability to reflect on the best solutions. Therefore, with increasing generations, better solutions are obtained until a termination criterion is reached. The performance of the algorithm has been evaluated by convergence graphs in Figure 19. The graph shows the progression of the minimum total cost values as the algorithm iteratively searched for better solutions. A properly converged graph indicates that the algorithm has successfully reached a stable and near-optimal solution. Both the 2×2 and the 5×5 networks were simulated for the with- and without-emission policies using a population size of 100 for 100 generations. From the results, it is evident that, initially, the algorithm efficiently explores the solution space and rapidly reduces the total cost values, indicating its ability to quickly identify good solutions. As the algorithm progresses, the changes in the total cost values diminish, implying that it has effectively exploited promising regions of the search space and reached solutions with lower costs. Towards the end of the execution, the convergence graphs display a clear trend towards convergence, with minimum total cost values stabilizing and exhibiting minimal fluctuations. This behavior signifies that the PBIL algorithm has effectively explored the solution space and found a near-optimal solution that satisfies the termination criterion. However, the 5×5 network has a very large solution space. Therefore, it is possible that better solutions could be obtained by evaluating a larger number of schedules through the adjustment of PBIL parameters i.e., increasing the population size and the number of generations.



(a)



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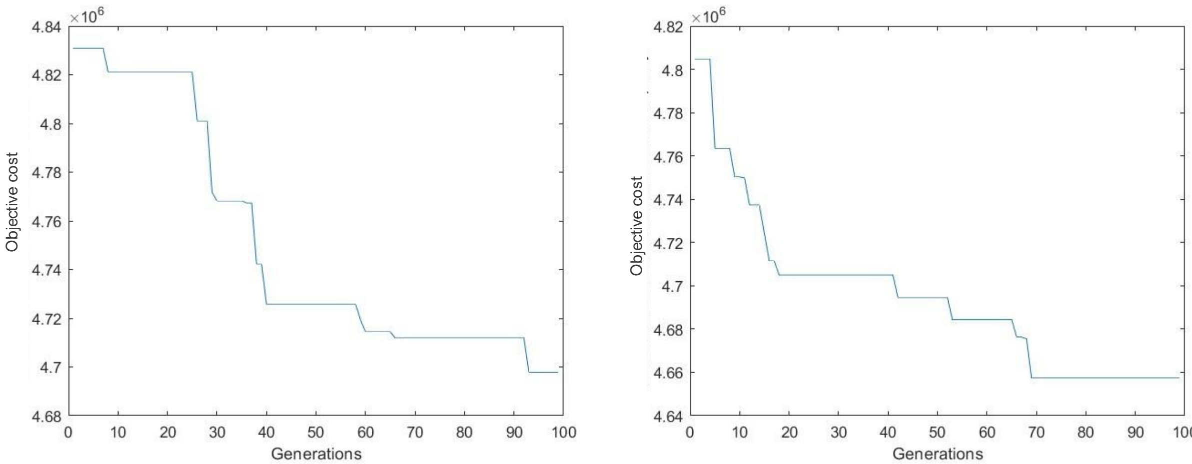

(c) (d)

Figure 19. Algorithm convergence graphs: (a) 2×2 network – with emission; (b) 2×2 network – without emission; (c) 5×5 network – with emission; (d) 5×5 network – without emission

CHAPTER 5: CONCLUSIONS

The aim of this thesis was to determine an optimal maintenance, repair, and rehabilitation (MRR) schedule by minimizing agency costs, user costs, and emission costs. A contribution of this work is the incorporation of the excess costs and emissions from travel delay and detours due to work zones in a dynamic traffic environment. An exponential pavement deterioration function was used to model the deterioration of pavement conditions. Three categories of MRR activities were defined along with their improvement criteria. To solve the multi-objective optimization (MOO) problem, a bi-level optimization approach was employed. At the upper level, a set of MRR schedules was generated using the population based incremental learning (PBIL) algorithm while incorporating constraints on the number of MRR activities. The lower level utilized the Link Transmission Model (LTM) to simulate the impact of MRR actions on specific links, accounting for traffic flow dynamics and queue formation behavior as per the kinematic wave theory. Accounting for traffic dynamics provided a more accurate approximation of user costs. Through multiple generations of simulation, learning and update, the framework generated a near-optimal schedule from a large solution space using heuristics. The proposed methodology was applied to a network and tested under different policies: a deterministic prescribed scenario, optimization with-emission scenario and, optimization without-emission scenario. The prescribed scenario was deterministically formulated to perform MRR actions on a fixed number of links with the highest IRI. The two optimization policies differ in the formulation of their objective functions as the former aims to minimize the costs of emission in addition to user and agency costs while the latter only minimizes the user and agency costs.

The results revealed that the optimized schedule with emissions yielded the lowest overall costs compared to the other scenarios. Despite resulting in slightly higher user costs, the with-emission scenario demonstrated significant cost savings in terms of agency expenses and emissions by efficiently choosing fewer MRR actions while keeping the pavement conditions similar to the without-emission scenario. From the prescribed scenario, it could be inferred that simply selecting road segments based on poor condition may not be the best approach for MRR planning as it resulted in the highest overall costs and the worst average network condition. A Pareto frontier further revealed that there exists a trade-off between emissions and user-agency costs. Reduction in emissions results in an increase in costs on the user and agency end. However, as costs increase, the marginal reduction in emissions diminishes, highlighting the diminishing returns of emission reduction efforts.

There are limitations to this thesis that need to be addressed. Due to the random nature of the PBIL algorithm, which relies on heuristics, it may not identify the best possible schedule. Moreover, there is a chance that the algorithm may converge toward a local optimum. However, it provides a reasonable estimation within the vast solution space making it computationally efficient. Another limitation is that the simulation only considered passenger cars, while real traffic comprises a mix of vehicle types that have different operating costs and emissions. Future work should incorporate mixed traffic scenarios to enhance the model's applicability. Another interesting direction may be the incorporation of informed decision-making within the PBIL. The algorithm initiates assuming equal probabilities on activities, whereas assigning probabilities based on pavement conditions could better guide the algorithm's candidate selection process and improve the algorithm's efficiency.

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