PREDICTIVE MAINTENANCE OPTIMIZATION FRAMEWORK FOR PAVEMENT MANAGEMENT

by

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ABSTRACT

AMIT KUMAR. A Predictive maintenance Optimization approach for highway asset management. (Under the direction of DR. OMIDREZA SHOGHLI)

The development of a progressive modern highway system is essential for the enhancement of the road capacity, safety, efficiency, commerce, and national defences of a country. These highway systems consist of various integrated individual asset components that undergo constant deterioration during their usage. The difficulty with maintaining these infrastructure systems is, the various asset components have a different service life and erode with a different rate during the lifespan of the system. This research study proposes the use of a multi-objective predictive maintenance optimization system using a non-dominated sorting-based multi-objective evolutionary algorithm (MOEA), for the optimum upkeep of a highway infrastructure project. The model has been applied on a pavement system in this study, but the framework can be effectively applied on other multi-asset infrastructure systems as well. The algorithm aims to find a spread of Pareto-optimal solutions by concurrently optimizing two objectives consisting of minimizing the life cycle cost (LCC), and maximizing the level of service (LOS) throughout the life-cycle. A case study was developed to compare the effectiveness of the model, based on the maintenance data from the asset management plan of the California department of transportation published in October 2017.

It is acknowledged in this research study that the two objectives have a conflicting nature of various degrees and thus the research suggests a set of solutions for different ranges rather than a single value solution. The approach proposed in this research study will also analyze the role of a robust multi-objective optimization (MOO) system for

highway maintenance through application to a deteriorating highway project. The results from the study will be helpful in developing promising techniques for the application of various multi-objective optimization (MOO) systems and thus pave the way for efficient decision-making tools for the maintenance of highway infrastructure projects.

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LIST OF ABBREVIATIONS

AASHTO	American Association of State Highway and Transport Officials
AM	Asset Management
ASCE	American Society of Civil Engineers
ASTM	American Society for Testing and Materials
BMS	Bridge Management System
CMS	Congestion Management System
DOD	Department of Defense
DOT	Department of Transportation
EA	Evolutionary Algorithm
FHWA	Federal Highway Administration
FV	Future Value
GA	Genetic Algorithm
GAO	General Accounting Office
GASB	Government Accounting Standards Board
HCM	Highway Capacity Manual
HPMS	Highway Planning and Monitoring Systems
IESTA	Intermodal Surface Transportation Efficiency Act
IRI	International Roughness Index
LCC	Life Cycle Cost
LCCA	Life Cycle Cost Analysis
LOS	Level of Service
LP	Linear Programming

MINLP	Mixed Integer Nonlinear Programming
MOEA	Multi-Objective Evolutionary Algorithm
MOGA	Multi-Objective Genetic Algorithm
MOO	Multi-Objective-Optimization
MOPOP	Multi-Objective Probabilistic Optimization Process
MPEC	Mathematical Programs with Equilibrium Constraints
MR&R	Maintenance, Repair, and Rehabilitation
NHRCP	National Cooperative Highway Research Program
NHS	National Highway System
NSGA-II	Non Dominated Sorting Genetic Algorithm-II
PAES	Pareto Archived Evolution Strategy
PCI	Pavement Condition Index
PCR	Pavement Condition Rating
PM	Predictive Maintenance
PMS	Pavement Management System
PQI	Pavement Quality Index
PSI	Pavement Serviceability Index
PSR	Pavement Serviceability Rating
PV	Present Value
QCQP	Quadratically Constrained Quadratic Programming
QP	Quadratic Programming
SDP	Semi-Definite Programming
SHM	Structural Health Monitoring

SIP	Semi-Infinite Programming
SMS	Safety Management System
SOCP	Second Order Cone Programming
SPEA	Strength Pareto Evolutionary Algorithm
TRB	Transportation Research Board
TSP	Travelling Salesman Problem

CHAPTER 1: INTRODUCTION

Highway systems and facilities constitute one of the most valuable assets in all level of government agencies throughout the world. Huge investments are made on an annual basis for the preservation, expansion, and operation of these facilities, which are invaluable for the movement of people, services, and goods. The U.S. roads carried people and goods over 3.2 trillion miles in the year 2016. According to the American Infrastructure Report Card 2017, 21% of the United States highways had poor pavement condition in 2015. Driving on roads that are in need of repair cost U.S. motorists $ 120.5 billion in extra motor vehicle repairs and operating costs. The Federal Highway Administration (FHWA) estimates that each dollar spent on the road, bridge, and highway upgrade returns $ 5.20 in form of lower vehicular upkeep and maintenance costs, time savings, lower fuel consumption, safety, minimised bridge upkeep costs and lower emissions as a consequence of enhanced traffic flow (ASCE, 2017).

Highway maintenance is essential for extending the service life of deteriorating highway assets. The pavement structure along with the roadside appurtenances, such as guardrails, signs, and luminaries form a major portion of highway features whose upkeep and timely maintenance is very critical to maximize the life-cycle of the highway. Their life-expectancy is largely reduced by poor maintenance (Jha & Abdullah, 2006). The effectiveness and efficiency of the service life depend upon the accuracy of assessing and predicting the structural performance (Mohanty, Verma, & Ray, 2009). The complexity associated with maximizing the service life of an infrastructure system is mostly because of the uncertainties involved with the prediction and determination of the processes involved. It is possible to improve the productivity and usefulness of service life management if appropriate amount of data can be collected over a period of time and the uncertainties involved with the interpretation can be minimized (S. Kim & Frangopol, 2017).

With the construction of the nation's interstate highway system almost complete, the attention of the Transportation Officials (AASHTO), the FHWA, the American Association of State Highway, and the State Department of Transportation (DOT) has moved on from investing money into the construction of new lane-miles to maintaining the lane-miles that are already in service. The deterioration of the pavement surface due to ageing and extensive use is the main threat to the level of service provided by the highway system networks. Thus, highway agencies across the United States are on an endeavour to renew, repair, and maintain the transportation systems that are already in place. With the advancement of the improved computer technology, highway officials and maintenance managers have the opportunity to analyse both the short and long term consequences of the numerous maintenance strategies (de la Garza & Krueger, 2007; Jesus, Akyildiz, Bish, & Krueger, 2011). Comprehensive asset management is the ultimate goal of highway officials, incorporating engineering principles and economic guidelines in order to operate, maintain, and preserve transportation assets cost-effectively. Engineers have always been aware that it is far less expensive to maintain highway and its asset items than it is to reconstruct or rehabilitate a highway that is in poor condition. Utilizing the maintenance strategies to extend the service life of highway systems reduces the frequency of infrastructure replacement and life cycle cost (Chasey, 1997).

In the present era of growing travel demand and higher public expectations, highway agencies face the challenge of maintaining the condition or service levels of their highway infrastructure in an environment of inadequate funding (US, 1999). The funding allocated for maintenance, repair, and rehabilitation (MR&R) is always limited. Therefore, it is necessary to prioritize and select the options that are best aligned with the asset managing organization's objectives, which, in case of infrastructure, should also reflect the needs of society. The criteria used in this process are often unclear, conflicting and sometimes subjective, including the type of maintenance intervention, risk and reliability, overall network performance, life cycle costs, desired level of service, budgetary concerns and construction and social costs (Šelih, Kne, Srdić, & Žura, 2008). In highway asset maintenance management, the objectives required to be achieved for each individual asset system and the overall highway asset system are often multiple and are sometimes mutually incompatible. To achieve best results at both the individual system and the overall system levels when a given overall budget is available, an optimal scheme for fund allocation to individual asset needs to be identified. This necessitates the simultaneous optimization of more than one objective while satisfying all of the necessary constraints (T. Fwa & Farhan, 2012).

Asset management encourages maintenance managers to consider the trade-offs between deferred maintenance and sustaining current pavement conditions, and between short-term fixes and long term solutions (Dornan, 2001). A well-developed simulation model will enable highway maintenance managers to wisely consider the impact of selecting one maintenance policy over another. Highway maintenance managers should be able to consider the available maintenance budget and target goals for the overall condition of their highway network in order to determine the best maintenance policy (de la Garza & Krueger, 2007).

Interventions applied too soon (i.e. when the asset item is in good condition) may add little incremental benefit and may cause waste of funds. On the other hand, interventions applied too late (i.e. when the asset item is in advanced state of deterioration) may likely be ineffective (Labi & Sinha, 2005; Peshkin & Hoerner, 2005). It is hypothesized that in between these two extremes of profligacy and parsimony, there is a certain optimal level of performance at which the intervention would yield maximum cost effectiveness. This problem is a classic example of optimal control application in engineering. Optimal control is the management of the operations of a system such that a certain optimally performance criterion is achieved (Khurshid, Irfan, & Labi, 2010).

To enhance the ability to diagnose existing and potential problems in the pavement network and to evaluate and prioritize alternative strategies, most state transportation agencies have developed various management systems. Some of these include pavement management systems (PMS), bridge management systems (BMS), congestion management systems (CMS), and safety management systems (SMS). The primary purpose of these systems is to track and address the condition of the various components of the highway network and to assist in establishing cost-effective strategies to sustain an acceptable condition for such facilities (Z. Li & Sinha, 2004).

In the wake of the recommendation by the Federal Highway Administration (FHWA), which encourages the several transportation agencies all across the United States of America (USA) to apply the concepts of asset management in their investment decision making, this research study first carries out a review of relevant literature on the subject of highway asset items, relevant concepts, and terminology. Then the research study goes on to present a methodology and its framework for multicriteria decision making in highway asset management. Examples of analogous concepts include optimization of the allocated budget within and across the various asset program areas and quantifying the consequences of decision making in terms of monetary value or performance measures. (Bai, Labi, & Sinha, 2011)

It must be acknowledged that several types of asset items have their own unique sets of performance measures. Hence, adaptation of multiple performance criteria in the process of decision making is required to capture the performance of each and every project in the candidate pool, which is in alignment with the multi-objective optimization (MOO) (Bai et al., 2011). An exemplary pavement management program for a highway road network would be the one that has maintained all the pavement sections and other asset items at a sufficiently high level of service (LOS) and structural conditions, but need only reasonably low funding and use of resources like money, manpower, materials, and machinery. Furthermore, the pavement management program must not generate any serious undesirable impacts on the environment, safe traffic operations, social, and community activities (T. Fwa, Chan, & Hoque, 2000). However, in the complex process of decision making for highways, it is often needed to examine the consequences of various optimal solutions under various performance and funding scenarios, therefore, establishing a reasonable balance between the various performance objectives under the limitation of insufficient budget is required, which is known as trade-off analysis, one of the prime principles of asset management (Bai et al., 2011).

CHAPTER 2: RESEARCH OBJECTIVE

The condition of the civil infrastructure systems around the world is deteriorating because of several degrading agents that includes aging, stress from the environment, natural hazards, (e.g. storms, earthquakes, and landslides) and artificial hazards (e.g. fire, floods, and explosion blasts). As a consequence of this deterioration, improving the safety and condition of these aging civil infrastructure systems is a key concern worldwide (Dan M Frangopol, Dong, & Sabatino, 2017). The use of optimization techniques for the management and upkeep of highway assets has earned increasing attention in the last few decades because of tight budgets, swelling demands, and stricter accountability in transportation investments and guidelines (Wu, Flintsch, Ferreira, & Picado-Santos, 2012).

Optimization-based tools such as Bridge Management Systems (BMS) and Pavement Management Systems (PMS) use the basic framework of linear and nonlinear programming to include single-objective optimization analysis. However, generally in the real world, decision making that is concerned with asset preservation and renewal often includes many objectives that show the various goals of the organization and the need to assess the possible alternatives in accordance with several criteria. The traditional methods through single-objective optimization often tend to choose a single most important objective while ignoring the less critical associated objectives in the calculation of the optimization. As a result, single objective optimization techniques leave the following questions unanswered:

1) Justification of the selected objective as the one that is considered as most pivotal over other contending objectives.

2) Determination of range of the objectives that are taken as constraints and are not included in the objective function.

Limitations imposed by unanswered questions such as these lead to an inaccurate optimal solution as compared to the results derived directly from multi-objective optimization techniques (T. Fwa et al., 2000).

This study proposes an approach to obtain a Multi-Objective Optimization (MOO) approach for pavement maintenance management. Two objectives are proposed for Multi-Objective Optimization (MOO) system planning: O1= minimizing the life cycle cost (LCC), O2= maximizing the level of service (LOS) is proposed. The assumptions and uncertainties affiliated with the calculation of the two objectives will be considered and stated in the formulations. Moreover, the effects of the maintenance actions on the service life and cost of the pavement infrastructure system will be integrated into the formulation of the total service life extension and the life cycle cost. The study will also carry out a sensitivity analysis to address the maintenance planning techniques considering multiple objective optimization processes and compare the findings.

A number of optimal solutions are generated from the data, based upon the data available and the constraints of the two objectives. The solution will clearly provide the details about the number of times the various maintenance activities will be performed on the asset item along with the monitory value associated with the objective. Details about the starting time of each maintenance activity and the number of times each maintenance activity is to be implemented can also be calculated based on data obtained from the findings. Thereupon, an organized list of alternatives consisting of the most suitable solutions could be established based upon the requirements of the prevailing scenario. The study will also help to estimate the benefits associated with each alternative solution. The consequential and superfluous activities could be identified, thus helping the organization to choose from a pool of solutions based upon the weights of the essential objectives and choose a well-balanced decision suitable for the pavement maintenance activity. The approach suggested in this research study accounts for the interdependencies and clashes amongst the two objectives under consideration.

The main objective of this research study is to propose a multi-objective optimization system (MOO) for pavement infrastructure management and to highlight the advantages of multi-objective optimization techniques. Research objectives of this study are:

- Developing a maintenance optimization framework using a non-dominated sorting-based multi-objective evolutionary algorithm (MOEA), called non-dominated sorting genetic algorithm II (NSGA-II).
- Developing an optimization framework that not only minimizes the cost over the life-span of the highway assets but also maximizes the performance.

The research study considers two major objectives namely: life-cycle cost (LCC) and level of service (LOS) while trying to incorporate them into a generalized framework for multi-criteria optimization for the life-cycle management of an infrastructure system.

CHAPTER 3: LITERATURE REVIEW

3.1 ASSET MANAGEMENT

"Asset management is a systematic process of maintaining, upgrading, and operating physical assets cost-effectively. It combines engineering with sound business practices and economic theory, and it provides a tool to facilitate a more organized, logical approach to decision-making. Thus, asset management provides a framework for handling both short-and long-range planning" (US, 1999).

3.1.1 INTRODUCTION/BACKGROUND

Highway asset management arrangements are designed to secure and expand physical highway asset items belonging to transport facilities and sustain a certain level of service for its users. These transport infrastructures are almost exclusively managed and engineered by environmental and civil engineers. In recent years, there has been a growing concern over the approach and efficiency of the management techniques that are employed to ensure the proper upkeep and functionality of these infrastructures. Poor performance related to congestion, safety, and condition has led the agencies to adopt highway asset management programs that consists transportation system installations, roadside improvements, management of state facilities, major or new construction, pavement and bridge preservation, safety improvements, system expansion, and other different activities such as corridor studies, and multimodal maintenance (Z. Li & Sinha, 2004; Moon, Aktan, Furuta, & Dogaki, 2009).

It is imperative that the goal of asset management is to seek more efficient investments where the methods applied will aid in identifying the most appropriate allocation of the monetary funds available to the highway agencies. In the absence of unlimited resources, such decisions will always result in making trade-offs in which funding certain assets will be needed at the expense of the other. Asset management focuses towards providing relevant information regarding trade-offs to managers and decision-makers so that they can avoid the reactive solutions that are far from optimum and may in fact be counter-productive over the long run.

To well identify the trade-offs related with investment decisions, the decision makers need a clear understanding of the following two components: (1) the definition of the objectives of the infrastructure owner, and the metrics correlated with these objectives, and (2) the ability to monitor and forecast the identified metrics to support the identification of trade-offs. In addition, the cost component of the primary objective must also be accounted for, which will require the ability to identify and extrapolate costs of the various asset items and its components throughout the life-cycle of the infrastructure in various scenarios. Accomplishing these fundamental prerequisites will need well-organized leveraging of various other powerful concepts such as structural health monitoring (SHM), performance based engineering, and life-cycle cost (LCC) analysis (Moon et al., 2009).

3.1.2 HISTORY

The significance of the application of 'sound management principles' in making decisions pertaining to civil infrastructure development projects, operations, and expenditures related to maintenance, have been long advocated by many agencies since the early 1990's. The 1991 Intermodal Surface Transportation Efficiency Act (IESTA) in the

United States required the various states to utilize bridge, congestion, safety, pavement, intermodal, and public transportation management systems (Moon et al., 2009). As per P. D. Thompson (2014), the requirement for applying Asset Management (AM) principles to public infrastructures was highlighted as early as 1997 by the US General Accounting Office (GAO) and the Government Accounting Standards Board (GASB), which established a set of accounting requirements in 1999. The Federal Highway Administration (FHWA) established the office of asset management (AM) in 1999, and the National Cooperative Highway Research Program (NCHRP) published a process-oriented guide in 2002. (Moon et al., 2009; Scheinberg, 1997; US, 1999).

3.1.3 PREVIOUS WORKS

Highway researchers have proposed several different optimization techniques to achieve optimal fund allocation for highway asset maintenance over the last two decades. Some of these are: Small and Swisher (2000), who made use of an empirical index to combine seven objectives at project level using priority weights. Sadek, Kvasnak, and Segale (2003) solved the single-objective budget allocation problem using priority weights of several assets based on the prevailing conditions. W. T. Chan, Fwa, and Tan (2003) solved the budget allocation problem using empirical aggregated performance indices by extending the problem to dual management levels. Z. Zhang, Aki, and Hudson (2002) proposed a multi-asset, network level budget allocation solution using shortfall analysis and Markowitz theory while, Amekudzi, Crichton, Robert, and Comeau (2001) proposed a multi-asset budget allocation solution by applying priority indices, considering only a single objective and single management level. Z. Li and Sinha (2004) and Falls, Haas, and Tighe (2006) respectively made use of utility function as pavement and bridge performance measures to allocate budgets based on single objective. Mrawira and Amador (2009) solved a multi-asset, single-objective problem using empirical asset condition indices.

3.1.4 FUTURE SUGGESTIONS

In the past studies, researchers have focused mainly on time-based warrants (asset age) and relatively less focus has been applied on performance-based warrants. The time based warrants have many limitations for asset intervention timing as this approach implicitly assumes little or no variation in LOS trends over time. In other words, interventions based on time intervals (e.g. apply treatment X for every 5 years) inherently fail to account for the performance-time relationship and may not truly represent the actual asset performance. In the future, the researchers need to come up with solutions that address the complete dual-level optimization problems involving multiple-asset systems each with its own set of multiple objectives (T. Fwa & Farhan, 2012; Khurshid et al., 2010).

Table 1: Summary of asset management applications in transport infrastructure.

Techniques	Reference	Highway	Bridge	Other
Pavement asset management system (PAMS) + LCCA	(H. Zhang, Keoleian, & Lepech, 2012)			✓
Asset management system + Risk appraisal	(Meyer, Amekudzi, & O'Har, 2010)			✓
Pareto-optimization + Cross asset trade off algorithm	(T. Fwa & Farhan, 2012)	✓		
Cost effectiveness analysis	(Khurshid et al., 2010)			✓
Multi-objective analysis	(H. Zhang et al., 2012)	✓		
NSGA-II	(Bai et al., 2011)			✓
Spatially integrated small-format aerial photography (SFAP)	(Chen, Hauser, Boyle, & Natarajan, 2015)		✓	
Multi-source bridge content distribution system	(Cooper & Munro, 2012)		✓	
Multi-criteria-decision-making-method (MCDM)	(Kabir, Sadiq, & Tesfamariam, 2014)			✓

3.2 MULTIOBJECTIVE OPTIMIZATION

A multi-objective optimization (MOO) algorithm is used for handling trade-offs among various objectives. Every multi-objective problem is unique in nature and there is no black box approach to implement multi-objective genetic algorithms in all problems. A multi-objective approach has the ability to incorporate various user preferences. It can thus prove to be an effective and versatile tool for decision making and can be used by highway agencies while allowing quick evaluation of several competing alternatives, and performing a trade-off analysis (Jha & Maji, 2007).

3.2.1 INTRODUCTION/BACKGROUND

Satisfactory lifetime performance of civil infrastructure is of critical importance to sustained economic growth and social development of modern society. In particular, the highway transportation system is considered to be one of the society's critical foundations. A well-developed civil infrastructure system can significantly upsurge a nation's competitiveness in the global market and enhance resilience to adversarial conditions such as natural vulnerabilities (e.g. Earthquakes, hurricanes, cyclones, and floods). In addition to developing more advanced maintenance technologies, infrastructure managers urgently need methodologies to cost-effectively allocate limited budgets for maintaining and managing aging and deteriorating civil infrastructure over the specified time period. Their goal with these methodologies is optimally balancing lifetime structure performance and whole-life maintenance cost (M. Liu, 2007). Stringent budgets, strict accountability, and ever increasing demands in the transportation industry have led the policy-makers and investors to look for an innovative approach such as using optimization for managing highway assets. In the last few decades, many engineering management systems have included optimization based tools for various asset classes such as pavement management systems (PMS) and bridge management systems (BMS) (Wu et al., 2012). Most performance indicators are expected to change over time, and the goal of maintenance strategy is to plan interventions that improve or maintain the performance at acceptable levels. Hence, the main ingredients of a maintenance optimization method are the chosen performance indicators, their predictive models, the selected types of maintenance, the optimization problem formulation, and the solution technique (Okasha & Frangopol, 2009). Recent studies have been formulated and solved Multi-Objective Optimizations (MOO's) problems where performance or quality is treated as an objective to be improved (Shoghli & de la Garza, 2017; Kasaeian, Afshar & Shoghli, 2007). Other research studies also reported a model where performance or level of service was selected as one the major objectives of their problem. It had also been the focus of (Dan M Frangopol & Liu, 2007; Neves, Frangopol, & Cruz, 2006; Neves, Frangopol, & Petcherdchoo, 2006). Multi-Objective Optimization (MOO) techniques can be categorized into preference-based methods (in which decision makers' preferences are incorporated in the optimization process) and non-preference based methods (in which decision makers' preferences are not considered) (Miettinen, 1999).

In real-world problems with multiple performance measures, decisions that exclude the preferences of decision makers have proven to not be practical (Branke, Branke, Deb, Miettinen, & Slowiński, 2008). Thus, non-preference based methods are seldom applied in practice. Of the preference based methods, there are three basic techniques (Hwang & Masud, 2012): (1) Priority preference articulation- this technique transforms the multi-objective optimization problem into a single objective problem before the optimization, by incorporating decision makers preferences. (2) Progressive preference articulation- in this technique, the decision makers' preferences and optimization process are intertwined, and preference information is automatically generated when the optimization is carried out. (3) Posteriori preference articulation- a set of efficient candidate solution is first determined and then a decision is made on the choice of the best solution. Advanced methodologies based on a MOO formulation treat all the performance measures as additional merit objective functions that are not restrictive in nature and the actual performance levels are at the discretion of civil infrastructure of managers. As a result, the performance-based maintenance management methodologies lead to a group of non-dominated solutions, each of which represents a unique optimized tradeoff between a large set of alternative solutions that help the civil infrastructure managers' active decision-making. These solutions help by selecting a maintenance technique with the most desirable balance between the conflicting infrastructure performance objectives such as LCC, reliability, safety etc.

3.2.2 HISTORY

Initially almost all the pavement maintenance programming tools were based on single-objective optimization function, which aggregates a variety of judgement criteria using the weighted sum method. Consequently, an optimal or near-optimal solution is required as the final result (Yang, Kang, Schonfeld, & Jha, 2014). The optimization techniques employed included linear programming (Lytton, 1985), dynamic programming (Feighan, Shahin, & Sinha, 1987; N. Li, Xie, & Haas, 1995), integer programming (Tien Fang Fwa, Sinha, & Riverson, 1988), optimal control theory (Markow, Brademeyer, Sherwood, & Kenis, 1987), nonlinear programming, and heuristic methods (OECD, 1987). In these single objective analysis, those requirements that were not selected as the objective function were imposed as constraints in the formulation. That could be viewed as an interference of the optimization process by artificially setting limits on selected problem parameters. As a result, the solutions obtained from those single-objective analysis were suboptimal with respect to the ones derived from multi-objective considerations (T. Fwa et al., 2000). Research advancements made in the area of optimizing construction resource utilization led to a number of optimization models that were developed using improved variety of methods, including linear programming, integer programming, dynamic programming, ant colony optimization, and genetic algorithm (GA) (Shoghli & de la Garza, 2016; El-Rayes & Kandil, 2005). The development of GA-based formulation for multi-objective optimization of pavement asset management activities are a robust search techniques formulated on the mechanics of natural selection and natural genetics (Holland, 1975). These techniques are employed to generate and identify better solutions until convergence is reached. The selection of good solutions is based on the so-called Pareto-based fitness evaluation procedure by comparing the relative strength of the generated solutions with respect to each of the adopted objectives. The application of the algorithm could be on a two- three- or multiple objective optimization problem.

3.2.3 PREVIOUS WORKS

In the past decade, a number of earnest attempts have been made to carry out the MOO for the purpose of asset management. Sinha, Muthusubramanyam, and Ravindran (1981) adopted goal programming to achieve optimum allocation of federal and state funds for highway system improvement and maintenance Z. Li and Sinha (2004), developed a method for multicriteria decision making in highway asset management, using a priority preference articulation method with the help of multi-attribute utility functions (Keeney &

Raiffa, 1993). Similarly, Gharaibeh, Chiu, and Gurian (2006) also applied the multi-attribute utility method to allocate funds across transportation assets and investigated the performance impacts of hypothetical changes in the distribution of funds. (Mrawira & Amador, 2009) developed a cross-asset trade-off analysis on the basis of multiple criteria for long-term highway investment. T. Fwa et al. (2000) conducted a multi-objective-optimization study for pavement-maintenance planning and programming using Genetic Algorithm (GA). Patidar, Labi, Sinha, and Thompson (2007) developed a MOO method for bridge-management investment decision analysis using utility theory. Wu and Flintsch (2009) applied the weighted-sum technique to generate Pareto solutions and adopted the normalized Euclidian to identify the best solution.

3.2.4 FUTURE SUGGESTIONS

The previous studies in the past have made significant contributions to the development of analytical procedures for decision making through MOO. However, additional techniques are needed to effectively provide relevant outputs of MOO data in the context, language, and format desired by the decision makers (Bai et al., 2011). Additionally, maintenance officials need to use MOO to fix the sources of uncertainty associated with the deterioration process of civil infrastructure and make sensible decisions on preserving failing structures (M. Liu, 2007). Depending on the objective of the optimization process, the managers should consider all the possible objectives simultaneously using the MOO approach so that the decision makers select the most well-balanced solution among the multiple trade-off solutions. In general, the methods used to solve the MOO problem needs to be categorized into preference-based and Pareto front-based approach which could be represented by the weighted sum method and evolution algorithm respectively (S. Kim & Frangopol, 2017; Saxena, Duro, Tiwari, Deb, & Zhang, 2013; Verel, Liefooghe, Jourdan, & Dhaenens, 2011). Furthermore, a synergistic combination of complementary systems can help in the development of hands-on and effective decision-making tools that can take the advantages of the individual techniques without facing drawbacks. A favorable organizational culture and willingness to adopt best practices are very important for achieving the full benefits of MOO. It is important to remove, the reservations some practitioners may have about MOO. This can be achieved by proper training and education which will help pave way for a wide variety of application of these methods in conventional infrastructure management (Wu et al., 2012).

Table 2: Summary of multi-objective optimization applications in transport infrastructure adopted from Wu et al. (2012).

Techniques	Reference	High-way	Bridge	Other assets
Priori Articulation of Preferences				
Weighting sum method	(MAKING, 1995)	✓		
	(Dissanayake, Lu, Chu, & Turner, 1999)	✓		
	(F. Wang, Zhang, & Machemehl, 2003)	✓		
	(Sadek et al., 2003)			✓
	(Xiong & Shi, 2004)		✓	
Goal Programming	(Sinha et al., 1981)	✓		
	(Ravirala & Grivas, 1995)	✓	✓	
	(Ravirala, Grivas, Madan, & Schultz, 1996)		✓	
Multiattribute utility theory	(Pesti, Khattak, Kannan, & McCoy, 2003)		✓	
	(Z. Li & Sinha, 2004)	✓		
	(Gabriel, Ordóñez, & Faria, 2006)			✓
	(P. Thompson, Sinha, Labi, & Patidar, 2008)		✓	
AHP	(Ramadhan, Al-Abdul Wahhab, & Duffuaa, 1999)	✓		

Techniques	Reference	High-way	Bridge	Other assets
	(Cafiso, Di Graziano, Kerali, & Odoki, 2002)	✓		
	(Z. Li & Sinha, 2009)		✓	
Genetic algorithm	(W. T. Chan et al., 2003)	✓		
Fuzzy logic	(Sandra, Rao, Raju, & Sarkar, 2007)	✓		
Grey relation + Goal programming	(Hsieh & Liu, 1997)			✓
Fuzzy set + Weighting sum method	(Tonon & Bernardini, 1999)			✓
Goal Programming + AHP	(Wu, Flintsch, & Chowdhury, 2008)	✓		
Posterior Articulation of Preferences				
Weighting sum method	(Gabriel et al., 2006)			✓
ε – constraint method	(M. A. Chowdhury, Garber, & Li, 2000)			
	(M. Chowdhury & Tan, 2005)		✓	
ε – constraint method + Compromise programming	(Lounis & Vanier, 1998)		✓	
Genetic Algorithm	(C. Liu, Hammad, & Itoh, 1997)		✓	
	(Pilson, Hudson, & Anderson, 1999)		✓	
	(Zheng, Ng, & Kumaraswamy, 2005)			✓
	(El-Rayes & Kandil, 2005)	✓		
	(M. Liu & Frangopol, 2005)		✓	
	(Neves, Frangopol, & Petcherdchoo, 2006)		✓	
	(K. Wang, Nguyen, & Zaniewski, 2007)	✓		
	(Morcous, 2007)			
ε – constraint method + Genetic algorithm	(Miyamoto, Kawamura, & Nakamura, 2000)		✓	
Compromise programming + Genetic algorithm	(T. Fwa et al., 2000)	✓	✓	
Optical Image Brightness analysis+A* type algorithm	(Myr, 2015)	✓		
Optimization algorithm	(P. Zhang et al., 2015)			✓
	(Torres-Machi, Pellicer, Yepes, & Chamorro, 2017)			✓
	(Saad, El-Sattar, & Marei, 2018)			✓

3.3 LIFE CYCLE COST

The general goal of life-cycle cost (LCC) analysis of civil infrastructures is to produce a cost-effective engineering solution that addresses in monetary terms various sources of expenses including design, construction, operation, inspection, maintenance, repair, and damage/failure consequences during a designated life horizon (Kita, 2000).

3.3.1 INTRODUCTION/BACKGROUND

Life Cycle Cost (LCC) analysis arranges for a framework to specify the projected total incremental cost of constructing, using, developing and retiring a specific infrastructure project. Life cycle engineering has emerged as an effective approach to addressing these issues in today's competitive global market. The nation spends at least $ 5000000000 per year for highway bridge design, construction, replacement, and rehabilitation. Given this huge investment along with an increasing scarcity of resources, it is essential that the funds be used as efficiently as possible. Effective maintenance/inspection can extend the life expectancy of a system while reducing the possibility of costly failures in future (Dan M Frangopol, Lin, & Estes, 1997). Over 70% of the total LCC of a product is committed at the early design stage, designers are in a position to substantially reduce the LCC of the products they design by giving due consideration to LCC implications of their design decisions. The ability of an organization to compete effectively in the global market is greatly dependent upon the cost, services, and the quality of its products (Asiedu & Gu, 1998). The life cycle of a product starts with the acknowledgement of demand and spread out through the design, production, services, consumer, usage and finally, disposal. The six phases in a product's life are: need recognition, design development, production, distribution, use, and disposal (Alting, 1993).

Life cycle cost analysis (LCCA) is becoming an essential practice among transportation agencies if the sustainability of its infrastructure systems is to be realized (Ozbay, Jawad, Parker, & Hussain, 2004). LCCA has become a common practice in road construction at the state level during the past decade in the United States. It enables the pavement engineers to conduct a comprehensive assessment of long-term costs, and ideally agency highway funding can be allocated more optimally (A. Chan, Keoleian, & Gabler, 2008). LCCA is a key component of the infrastructure management process, and is used extensively to support network and project level decisions. LCCA is a technique that is built on the well-established codes of economic analysis to assess the long term economic efficiency amongst several competing alternative investment options (Ferreira, 2013). The LCC analysis is of particular usefulness for infrastructure managers to make rational decisions in order to allocate limited financial resources for maintaining functionality of aging infrastructure systems that exhibit significant deterioration in serviceability (condition) and/or safety (load-carrying capacity) state (Dan M Frangopol & Liu, 2004). It incorporates initial and discounted future agency, user, and other relevant costs over the lifetime of alternative investments. It attempts to identify the best value (the lowest long-term cost that satisfies the performance objective being sought) for investment expenditures (Walls & Smith, 1998). Highway agencies are facing the challenges of aging highways, deteriorating networks, and inadequate pavement preservation budgets (H. Zhang et al., 2012). Highway infrastructure represents a significant part of the public assets, and through its lifetime, is exposed to various deterioration processes leading to the depreciation of its value. It is therefore of vital importance to manage these assets aiming to reduce the loss of their value with time to a minimum (Lamptey, Labi, & Li, 2008). With more than one- third of major roads in the United States in poor or mediocre conditions, the American Association of State Highway and Transportation Officials (AASHTO) advises that annual capital outlay spending should be increased by 42% and 94% respectively to maintain and improve the physical conditions of the roads (ASCE). The failure to provide adequate funding to improve the substandard road conditions will lead to serious roadway safety and operational concerns and affect the national economy. In this regard, the LCCA is applied in road construction to explore the possibility for more efficient investment. LCCA not only evaluates the initial construction cost of the pavement, but also all the associated maintenance costs during its service life. Therefore, pavement engineers are able to choose the pavement type and design with the lowest cost in the long run (A. Chan et al., 2008). Life cycle cost analysis (LCCA) can be one of the most important asset management tools for road infrastructure, the value of which exceeds $ 2 trillion nationally. The optimal lifetime inspection/repair strategy is obtained by minimizing the expected total LCC while satisfying the constraints on the allowable level of structural lifetime reliability in service. The expected total LCC includes the initial cost and the cost of preventive maintenance, inspection, repair, and failure (Dan M Frangopol et al., 1997). Budget tightening, escalating costs for public maintenance, and increased populace censure of government-related expenditures have caused all segments of our socioeconomic system to tune into the importance of effective management of resources and assets. Furthermore, an asset base of more than 1trillion (i.e. the value of the transportation system in the United States as estimated by the FHWA in 1999) is under the influence of many natural and man-made dynamics, which are uncontrollable, uncertain, or both. Therefore, decision making and effective asset management must be based on informed and conversant support. One of the most renowned techniques in the transportation domain for providing such informed support-when applied properly- is LCCA (Ozbay et al., 2004).

3.3.2 HISTORY

The concept of highway engineering economics was introduced as early as the end of the 19th century, when Gillespie issued his Manual of the Principles and Practices of Road Making in 1847. Gillespie then characterized the most cost effective project as one which has the highest rate of return to cost of construction maintenance (Peterson, 1985). However, this concept was not used in the highway projects until the 1950's (Ozbay et al., 2004). The LCC concept was initially applied by the US Department of Defense (DOD). The works of the engineering economist Winfrey in the 1960's and AASHTO's Redbook (1960) ushered in the concept of LCCA to the transportation domain (Wilde, Waalkes, & Harrison, 1999; Winfrey, 1969). The concept of LCCA in road construction was first discussed by AASHTO "Red Book" in the 1960s (Wilde et al., 1999), but it did not appear in federal legislation until the Intermodal Surface Transportation Efficiency Act (ISTEA) of 1991. With the realization of the effects of considering LCC in the evaluation of transportation projects, extensive research began. It focused on issues such as data gathering and integration but, mostly the research aimed at quantifying the user cost and vehicle-operating cost by conducting large-scale field experiments, such as the road test experiment initiated by the World Bank in Brazil in the 1960's and developing empirical models of those costs (Peterson, 1985). IESTA mandated the consideration of "the use of LCC in the design and engineering of bridges, tunnels, or pavement." The National Highway System Designation Act of 1995 further imposed a new requirement making

LCCA compulsory for National Highway System (NHS) projects costing more than $ 25 million (A. Chan et al., 2008). LCC must still be considered as a part of FHWA's value engineering process for NHS projects costing more than $ 25 million. In 2000, within Federal Highway Administration (FHWA), LCCA came under the charge of the Office of Asset Management (US, 1999). One of its recent products (late 2002) is the development of an LCCA instructional software package for pavement-FHWA Probabilistic LCCA. In the domain of bridges, National Cooperative Highway Research Program (NHRCP) initiated Project 12-43 in 1996. The resulting Report 483 presents a comprehensive methodology for carrying out bridge LCCA and using the accompanying software that automates the methodology (Hawk, 2003).

3.3.3 PREVIOUS WORKS

Life-cycle cost (LCC) is considered an important tool by several authors for the design and maintenance of infrastructures, such as bridges, highways, pavements, etc. Peterson (1985) explains how LCCA can be used by pavement designers and maintenance engineers to select a pavement structure that is least expensive over time. Gransberg and Molenaar (2004) stated that minimizing the pavement LCC will enhance the sustainability of the nation's highways by delivering pavements that last longer and reduce user impact costs. They proposed best value award algorithms over low-bid initial costs to choose the pavements. A. Chan et al. (2008) evaluated LCCA practices in the Michigan DOT and analyzed its accuracy in projecting the actual costs over the pavement service life. Salem, AbouRizk, and Ariaratnam (2003) presented an approach for estimating LCC and evaluating infrastructure rehabilitation and construction alternatives, derived from probability theory and simulation application. Z. Li and Madanu (2009) presented an uncertainty-based methodology for highway project-level LCCA that handles certainly, risk and uncertainty inherited with the input factors for the computation. Thoft-Christensen (2009) stated that in the life cycle of an infrastructure, user costs are usually greater than maintenance, rehabilitation or replacement costs of the infrastructure, and furthermore, stated that in most of the cases of bridge structures, user costs completely dominate the total costs. Tien F Fwa and Sinha (1991) concluded that there is a need to consider pavement performance in LCCA. Abaza (2004) presented a deterministic performance prediction model for the use in the rehabilitation and management of flexible pavements using the serviceability concept adopted by the American Association of State Highway and Transportation Officials (AASHTO) for use in the design of flexible pavements. Ozbay et al. (2004) proved that there is a gap between the state of the practice and the art of LCCA to practical case studies that could be useful for Highway agencies. Santos and Ferreira (2013) presented a new LCCA system based on an optimization model considering pavement performance, called OPTIPAV to help pavement designers to choose the best pavement structure for a road or a highway.

3.3.4 FUTURE SUGGESTIONS

The analysis period of LCCA model depends on the nature of the project. For new construction events, the analysis period is 26-30 years, which is the expected service life of the new pavement with scheduled maintenance; for rehabilitation events, the period used is 20-21 years (A. Chan et al., 2008). It is somewhat different from FHWA recommendations, which suggests a>35-year analysis period to include at least one major rehabilitation event for each alternative being considered (Administrataion). The Portuguese manual of pavement structures states the importance of making a LCCA for a period of no less than 40 years, called project analysis period, in order to compare different pavement solutions in terms of global costs for the final choice of the pavement structure for national road or highway. It also suggests that the construction costs, maintenance costs throughout the project analysis period, user costs and the pavement residual value at the end of the project analysis period must be considered in the LCCA (Ferreira, 2013; JAE, 1995).

Table 3: Summary of LCC application in transport infrastructure.

Techniques	Reference	Highway	Bridge	Other
Structure Health Monitoring + Performance-Prediction	(Dan M. Frangopol & Soliman, 2016)			✓
OPTIPAV	(Santos & Ferreira, 2013)			✓
Dynamic Optimization Technique	(H. Zhang, Keoleian, Lepech, & Kendall, 2010)			✓
Stochastic LCCA Model	(Pittenger, Gransberg, Zaman, & Riemer, 2012)	✓		
Context-sensitive process-based approach	(Cass & Mukherjee, 2011)			✓
Network-Level-Pavement Asset Management System (PAMS) + Geographic Information System (GIS)	(H. Zhang et al., 2012)	✓		
Qualitative Technique	(Lee, Edil, Tinjum, & Benson, 2010)	✓		
Risk based approach	(Padgett, Dennemann, & Ghosh, 2010)		✓	
Analytical Modelling	(Cusson, Lounis, & Daigle, 2010)		✓	
Probabilistic assessment + Performance Index	(Alipour, Shafei, & Shinozuka, 2010)		✓	

3.4 LEVEL OF SERVICE

The current highway capacity manual (HCM) defines Level of Service (LOS) as, "a qualitative measure describing operational conditions within a traffic stream, generally in terms of such service measures as speed and travel time, freedom to maneuver, traffic interruptions, and comfort and convenience" (Board, 2000).

3.4.1 INTRODUCTION/BACKGROUND

The level of service (LOS) concept was first proposed in the HCM of version 1965 (Manual, 1965), and then defined by the six levels in relation to a number of traffic conditions in the HCM of version 1985 (Manual, 1985). The current concept of LOS is applied in a six level scale (levels of service A-F) that are distinguished in the current HCM by traffic density-the sole criterion used to distinguish between LOS A, LOS B, LOS C and so on (Choocharukul et al., 2004). These measures of LOS used there such as traffic density and traffic flow rate are not the LOS itself, but merely characteristics of traffic conditions which have rather a strong relationship to the LOS of the traffic, and do not necessarily show the quality of service perceived by the drivers (Kita, 2000).

Increased use of road vehicles in the last 30 years induced extremely high occupation of roads and especially urban highways (Gregurić, Buntić, Ivanjko, & Mandžuka, 2013). Levels of traffic congestion are currently measured by the widely accepted concept of LOS (Hubbard, Bullock, & Mannering, 2009), The implementation of this concept to determine specific LOS categorization of freeway facilities is primarily based on the judgement of transportation professionals (Board, 2000). The proximity of this professional judgement corresponding to the road-user perception of levels of traffic congestion is an open question, since, the currently used measures of LOS to evaluate the traffic condition of road sections are not necessarily linked to the driver's perceived LOS (Kita, 2000). However, it is an important question to be answered because these perceptions can affect the planning, design, and operational aspects of transportation projects as well as the allocation of limited financial resources amongst competing transportation projects (Choocharukul et al., 2004).

Recently, the American Society of Civil Engineers (ASCE) released its "2005 Report Card for America's Infrastructure", in which the nation's roads received a near failing grade of "D" which shows a worsening trend, since the grade in 2001 was D+. Amongst the recommendations, the ASCE encouraged the use of life-cycle cost analysis principles to evaluate the total costs of projects" (de la Garza & Krueger, 2007). Agencies have limited budgets and wish to deliver the highest levels of service with the minimum costs possible. Highway users, in turn, wish to experience the lowest possible vehicle operating costs while using the highway network. The intended purpose of a highway network is to maintain basic mobility in terms of travel time, ensure specified LOS for traffic congestion and safety, and minimize adverse impacts to the environment (Z. Li & Sinha, 2004).

3.4.2 HISTORY

The first edition of the Highway Capacity Manual (HCM), published in 1950 presented a series of empirical procedures for the estimation of the traffic-carrying capabilities of a variety of traffic facilities. Although this manual did not specifically mentioned the word "level of service", it actually provided a first attempt at a service quality description by prescribing three levels of capacity: basic capacity, possible capacity, and practical capacity. Capacity was described in terms of maximum hourly volume that could be maintained without causing a serious deterioration in the quality of traffic flow (Roess & Prassas, 2014).

The concept of LOS was formally introduced in the 1965 HCM as follows: “Level of service is a qualitative measure of the effect of a number of factors, which include speed and travel time, traffic interruptions, freedom to maneuver, safety, driving comfort and convenience, and operating cost (Manual, 1965).

The 1965 HCM defines six LOS, with latter designations A-F. LOS A designates the best quality of service and refers to virtually free flow in traffic pattern in which the operation of an individual vehicle is not significantly affected by the presence of other vehicles. While LOS F designates the worst quality of flow and refers to conditions in which stop-and-go travel, long delays and queued traffic exist. The LOS was defined in terms of two parameters, operating speed and volume-to-capacity ratio (v/c). The two were expressed as independent controls on LOS, and highway operations had to meet both the speed and v/c criteria to achieve a given level.

HCM 85 introduced some new measures specific to different types of facilities, e.g., density for basic freeway segments and flow rate for ramp junctions. HCM 85 described the characteristics of traffic conditions under operation included travel speed, traffic flow rate, and traffic density for various types of roads. There were subsequent versions of the HCM introduced in the years 2000 and 2010 respectively, which addressed the ever changing critical policy determination issues regarding the concept of LOS.

It must be noted that these measures of LOS used there such as traffic density and traffic flow rate are not the LOS itself, but merely characteristics of traffic conditions which have a rather strong relationship to the LOS of the traffic, and do not necessarily show the quality of service perceived by drivers. More recent capacity analysis procedures, however have tended to incorporate a wider range of measures of effectiveness into its procedures. Of greater importance, however is the fact that interpretation of LOS is becoming more complex and is not always the same as, or even similar to the LOS defined in the 1965 HCM (Kita, 2000; Roess, 1984)

3.4.3 PREVIOUS WORKS

In the United States, Laetz (1990) noted, through direct measurement and public-opinion polls, that perceptions of traffic congestion substantially influence what constitutes an acceptable LOS (Choocharukul et al., 2004). Pfefer (1999) provided a framework to develop tools to reflect road user perception on service quality by defining the quality of service as a function of five performance measures- mobility, perception, of the lack of safety, environment, comfort and convenience, and road user direct cost. Hall, Wakefield, and Al-Kaisy (2001) determined motorists' views on what aspects of freeway travel are important to them and identified: travel time, density/maneuverability, road safety, and travel information. Travel time was identified to be the most important aspect in the focus groups (Choocharukul et al., 2004).

3.4.4 FUTURE SUGGESTIONS

In recent years, several alternatives have been suggested for improving the scaling and determination of LOS. For example, the studies of Brilon (2000), Maitra, Sikdar, and Dhingra (1999), Baumgaertner (1996), and Cameron (1996) all provided some insight into the limitations of the current LOS measure. Amongst all the approaches suggested by these studies, expanding the six current LOS designations to nine or more in an attempt to better describe traffic was a common theme (Choocharukul et al., 2004).

Another common theme in the past research has been the issue of understanding the role that road user preferences should play in LOS determination. For example, Matsui and Fujita (1994) worked on driver's perception on speed at which they would classify the road as being congested. Mizokami (1996) developed a model to distinguish delay and non-delay as perceived by drivers, Kita (2000) investigated merging behavior at an on-ramp section of an expressway, and Nakamura, Suzuki, and Ryu (2000) found the flow rate most strongly affects the degree of driver's satisfaction and perceived LOS. Other significant Parameters included the number of lane changes, the elapsed time while following other cars, and driving experience (Choocharukul et al., 2004).

Table 4: Summary of LOS application in transport infrastructure.

Techniques	Reference	Highway	Bridge	Other Assets
Priority Index	(Rashidi, Samali, & Sharafi, 2016)		✓	
Pavement preservation using PaLATE software	(S. Chan, Lane, Kazmierowski, & Lee, 2011)	✓		
Pedestrian and Bicycle LOS	(Asadi-Shekari, Moeinaddini, & Zaly Shah, 2013)			✓
Sensitivity analysis	(Qiao, Flintsch, Dawson, & Parry, 2013)	✓		
System dynamic modelling approach	(Egilmez & Tatari, 2012)	✓		
SHM using Wireless sensor network	(Hu, Wang, & Ji, 2013)	✓	✓	
Ramp Metering	(Gregurić et al., 2013)	✓		
Sensitivity Testing + Multimodal LOS	(Carter et al., 2013)	✓		
Simple Multi-Attribute Rating Technique (SMART)	(Rashidi & Lemass, 2011)		✓	
Linear Programming	(Jesus et al., 2011)			✓

CHAPTER 4: METHOD

4.1 IMPORTANT CONCEPTS RELATED TO OPTIMIZATION

4.1.1 TYPES OF OPTIMIZATION PROBLEMS

The primary purpose of the proposed multi-objective optimization (MOO) system is to minimize the maintenance cost and maximize the service life and performance of the infrastructure. Several optimization techniques have been used in the past for managing such infrastructure assets. The integration of the MOO technique for a highway infrastructure management project not only helps in minimizing the LCC of a highway asset, but also to maximize the performance or other objectives (Wu et al., 2012).

Table 5 depicts some of the most widely used optimization mechanisms used for a number of problem types:

Table 5: Types of optimization adopted form Tuy (1995) and Harker and Pang (1990).

Serial No	Optimization Type	Serial No	Optimization Type
1	Bound Constrained Optimization	15	Nonlinear Programming
2	Combinatorial Optimization	16	Nonlinear Equations
3	Complementary Problems	17	Nonlinear Least-Squares Problems
4	Constrained Optimization	18	Optimization Under Uncertainty
5	Continuous Optimization	19	Quadratically Constrained Quadratic Programming (QCQP)
6	Derivative-Free Optimization	20	Quadratic Programming (QP)
7	Discrete Optimization	21	Semi-definite Programming (SDP)
8	Global Optimization	22	Semi-infinite Programming (SIP)
9	Integer Linear Programming	23	Stochastic Linear Programming
10	Linear Programming (LP)	24	Second Order Cone Programming (SOCP)

11	Mixed Integer Nonlinear Programming (MINLP)	25	Stochastic Programming
12	Mathematical Programs with Equilibrium Constraints (MPEC)	26	Travelling Salesman Problem (TSP)
13	Multi-Objective Optimization	27	Unconstrained Optimization
14	Non-differentiable Optimization		

4.1.2 STEPS IN OPTIMIZATION PROBLEM

4.1.2.1 CONSTRUCTING THE MODEL

This is the first step in the entire optimization process. A well-constructed model is helpful in identifying the various objectives, variables, and the constraints of the complication. Furthermore, a model is also pivotal in expressing the process in mathematical formulation (I. Y. Kim & de Weck, 2005).

- Objective: An objective is a measurement of the system's performance in a quantifiable manner. An objective could be intended to be maximised or minimised for a particular set of problem, depending upon the needs.
- Constraints/Limits: These are the set of functions that define how the variables interact with each other that are a part of an objective.
- Variables: These are the unknowns that are part of the system that we want to find values for.

4.1.2.2 DETERMINATION OF THE TYPE OF ALGORITHM

In this step, the optimization technique that is best suited for the problem type is determined from the pool of available optimization types (Onwunalu & Durlofsky, 2010).

4.1.2.3 SELECTION OF THE ALGORITHM

In this step, an algorithm is selected that is found to be appropriate for the optimization problem that needs to be solved. Multi-objective problems can be optimized either by classical optimization techniques or by evolutionary algorithm such as a genetic algorithm (GA) (Maji & Jha, 2009).

- Classical Optimization: These optimization techniques are capable of delivering a solution for specific type of optimization problem for which they are designed (Dolan & Moré, 2002).

- Genetic Algorithm (GA): It helps to formulate various models for optimization and evaluate their solutions. These systems takes input form the user, process the data with the help of the algorithm, and deliver the output. These modelling systems are generally built around the modelling language (Olaechea, Stewart, Czarnecki, & Rayside, 2012).

4.1.3 GENETIC ALGORITHMS FOR MOO

The Genetic algorithms (GAs) are a type of heuristic algorithms that follow survival-of-the-fittest principle and are formulated loosely based on the principle of Darwinian evolution. Since their formal appearance in the 1960's these GAs have been successfully applied to a wide range of problems because of their ease of implementation and robust performance (Dan M Frangopol & Liu, 2007). The problem-solving process of the GAs begin with the identification of the problems and the generic coding of the selected parameters. The search procedure of GAs involves generating an initial pool of feasible solutions that is generated randomly to form a parent solution pool, this is followed by obtaining new solutions and forming new parent pools through the iterative process. The entire process of iteration consists of copying, modifying, and exchanging parts of the genetic representation in a pattern that is similar to the natural genetic evolution.

GA's are different from the traditional optimization methods in a few significant aspects. Firstly, the GAs work by manipulating a pool of feasible solutions rather than working with a single solution, which enables GAs to detect and explore characteristics simultaneously in several search directions. Secondly, GAs employ probabilistic transition rules to generate new solutions from the existing pool of solutions, which enables perturbations to move out of the local optima. Third, GAs produce a better set of solutions in every step by directly comparing the objective function values of the solutions that are generated.

The solutions generated in the parent pool are evaluated by the means of objective function. The fitness value of each solution is used to determine its probable contribution in the generation of new solutions known as offspring. The next parent pool is formed by selection of the fittest offspring based on their fitness. The process is allowed to continue and repeat itself until the pre-determined stopping criterion is met on the basis of number of iterations, or the magnitude of improvement of the generated solution (T. Fwa et al., 2000; Holland, 1975).

4.1.4 CONCEPT OF PARETO SOLUTIONS

In the evaluation of a pool of solution in multi-objective genetic algorithm (MOGA), is a 2-D curve (for two-objective optimization) or a 3-D surface (for three or more multi-objective problem) which is composed of all the non-dominated solutions. This curve or surface is known as Pareto frontier. Each set of Pareto-optimal solution represents a trade-off among different objectives. The Genetic Algorithm optimization process looks to produce new solutions that can give an improved frontier that dominates the existing frontier. A solution, in which a value of at least on objective is better than the rest of the solutions, is known as non-dominated solution. This process of producing new solutions continues reputedly until, a set of globally non-dominated solution is found. This globally non-dominated set of solutions is called Pareto optimal set and defines the Pareto optimal front (T. Fwa et al., 2000; Yang et al., 2014).

4.2 OVERVIEW

The research adopted a quantitative approach to investigate the benefits of using a multi-objective optimization technique (MOO) for predictive maintenance. The desired MOO model comprises of two objectives which form the optimization algorithm in the model development. The two objectives consists of (1) Life-Cycle Cost (LCC), and (2) Level of Service (LOS). Both of the two objectives are incorporated into the MOO algorithm to generate a set of Pareto optimal solutions that are consistent with the performance goals and resource constraints in the best-suited way while focusing on delivering the best possible results.

The method can also be used to evaluate the trade-offs between the two objectives to find out the set of best optimal combination of pavement maintenance interventions. However, it must be acknowledged that the intent of the two objectives are incompatible with each other. Therefore, a set of Pareto solutions is identified. A suitable solution pertains to the Pareto set in which the performance of one objective cannot be improved without compromising the efficiency of at least one other.

The formulation of the mathematical solution involved three major steps: (1) Identification of a major asset classes in the highway system. For example- bridge, drainage, pavement, traffic barriers, hazard markers etc. (2) Identification of the types of maintenance activities involved with the asset item. For example- surface treatment, thin/thick overlay, fixing potholes etc. (3) Mathematical formulation of the objectives and constraint.

Given the limitations identified in the various sections, a heuristic non-dominated sorting-based multi-objective EA (MOEA), called non-dominated sorting genetic algorithm II (NSGA-II) is deployed. It considers a sustainable assessment of predictive maintenance alternatives and aims to improve the current allocation of maintenance resources for the highway project. NSGA-II has a fast non-dominated sorting approach with $O(MN^2)$ computational complexity (where M is the number of objectives and N is the population size). Additionally, NSGA-II has a non-elitism approach and does not require the need for specifying a sharing parameter, as might be the case with other MOEA's. These characteristics help NSGA-II to outperform the other contemporary MOEA's like Pareto-archived evolution strategy (PAES) and Strength-Pareto EA (SPEA) in terms of finding a diverse set of solutions and in converging near the true Pareto-optimal set.

4.2.1 LIFE-CYCLE COST

It is one of the most pivotal performance measures in the evaluation of a highway infrastructure project. It is possible to allocate the resources properly while minimising the total cost and maintaining a desired level of structural safety. The total expected cost during the lifetime of a highway, as adopted form Dan M Frangopol and Liu (2004) is given as:

$$Ct = Cet + Cpm + Cins + Cf$$

Where, Cet is the initial cost of construction, Cpm is the expected cost of maintenance, C_{ins} is the expected cost of inspections, and C_f is expected failure cost. Assuming the occurrence of the hazard (e.g. flood, earthquake). In the formulation of this research-study,

Cet is taken as 0 as the research concentrates on maintenance, not on construction. Additionally, $Cins$ and Cf are also excluded to simplify the problem as they are constants. Cost of predictive maintenance is calculated as:

$$C_{pm} = \sum_{i=1}^{40} \sum_{j=0}^{3} M_{ij}$$

Cpm = cost of predictive maintenance

i = number of years (form 1 to 40), j = maintenance types 0, 1, 2, and 3.

M = cost of maintenance associated with maintenance activity for each year.

The total cost is calculated in terms of Present Value (PV), the formula for which as adopted from Beaves (1993) is:

$$PV = FV[\frac{1}{(1+r)^n}]$$

Where, PV = present value, FV = future value, r = discount rate =3%, n = n^{th} year.

4.2.3 LEVEL OF SERVICE

The level of service concept in the Highway Capacity Manual (HCM) is used as a qualitative measure representing freeway operational conditions over the past several decades. The LOS has been categorized into six different categories (from LOS A to LOS F) to represent the traffic flow conditions of a highway. However, the current HCM procedure of using traffic density as the only criterion for determining LOS on freeways has been challenged in the light of recent studies that show road-user perceptions and other measurable traffic-stream characteristics needs to be incorporated into the concept, such as travel time, road safety, maneuverability and comfort. (Choocharukul et al., 2004).

Many different quantifiable performance measures are included currently in the FHWA Highway Planning and Monitoring Systems (HPMS) database to determine the pavement condition. Some of these are International roughness index (IRI), Pavement Serviceability Rating (PSR), Pavement Serviceability Index (PSI), Pavement Quality Index (PQI), and Pavement Condition Index (PCI). For the purpose of this research, Present Condition Rating (PCR) is used to quantify performance measure for the pavement. The PCR is a composite index (marked on a scale of 0 to 100) derived from monitoring data-pavement roughness and distress rating. The performance prediction equation for flexible pavement as adopted from George, Rajagopal, and Lim (1989) is presented by the equation:

$$PCR(t) = 90 - a[\exp(Age^{b}) - 1]\log[\frac{ESAL}{SNC^{c}}]$$

Where, a = 0.6349; b = 0.4203; c = 2.7062

$PCR(t)$ = pavement condition rating at time t (in years). $ESAL$ = traffic volume and weight, which are expressed in terms of yearly equivalent single-axle loads. SNC = Strength and condition of pavement structure represented by modified structural number.

$$SNC = \sum aihi + SNg$$

Where, ai = material layer coefficients, hi = layer thickness (in.), SNg = subgrade contribution, and = 3.51 log CBR – 0.85 $(Log\ CBR)^2$ – 1.43

$$R^2 = 0.75$$

CBR= California bearing ratio of subgrade (percent) (George et al., 1989).

4.3 GENERAL FRAMEWORK FOR SOLVING MOO PROBLEM

Establishing a robust framework is essential step towards developing an algorithm for a MOO problem. These frameworks provide and insight into the logic and reasoning involved behind the subsequent steps of an optimization problem. A graphical representation has been made to display the step-by-step procedure for the functionality of the algorithm in Figure 1.0, which also depicts a generic framework for a MOO problem.

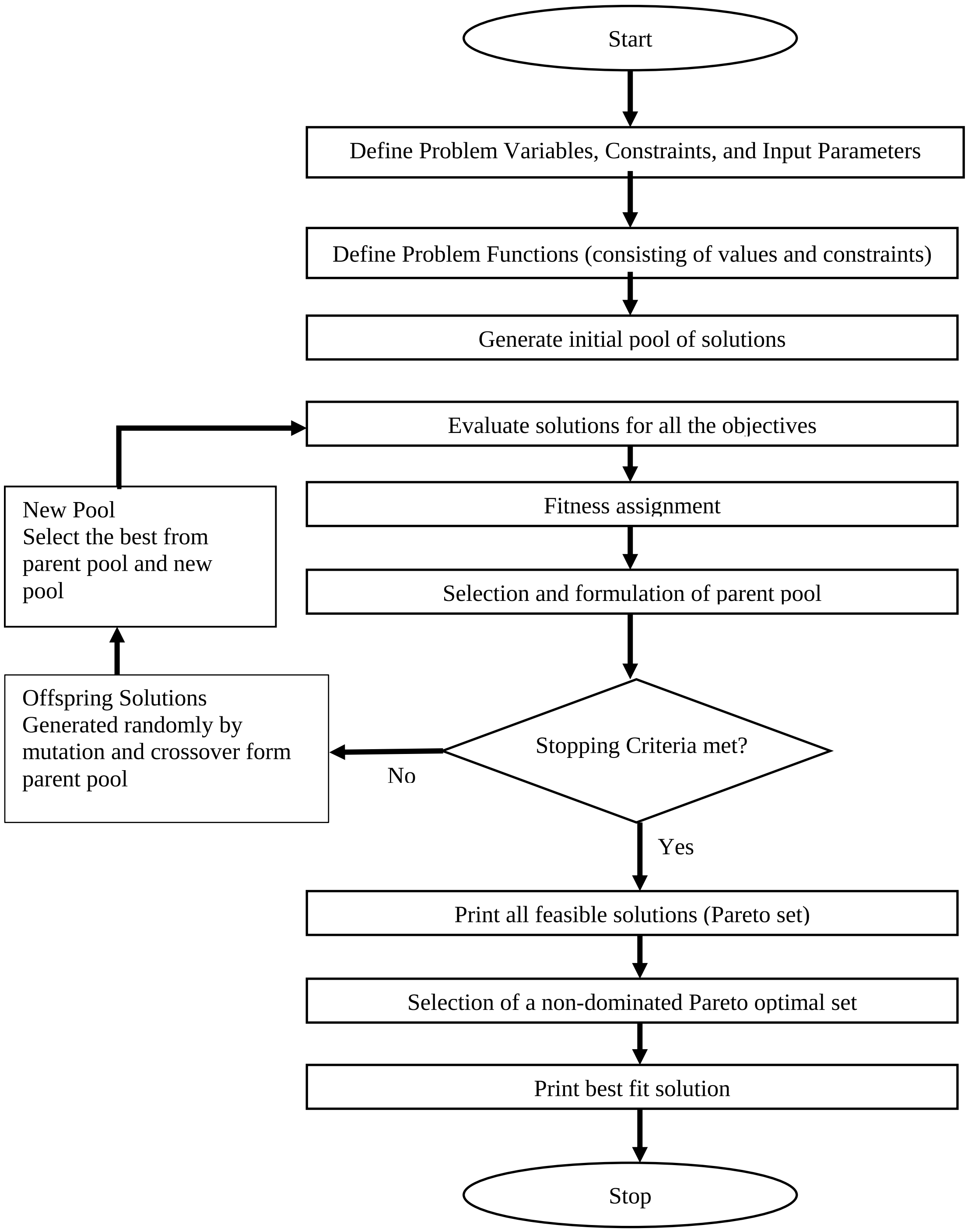

Figure 1: Genetic Algorithm Analysis for Multi-Objective Optimization adopted from Chikezie, Olowosulu, and Abejide (2013)

4.4 MATHEMATICAL FORMULATION OF THE MODEL

In this formulation, the pavement condition is considered as a representative of LOS for the highway, which is depicted in terms of pavement condition rating (PCR). Pavement condition rating is an ASTM standard for the pavement condition assessment. PCR values are allotted to a scale that ranges from 0 to 100. The rating on the scale for a pavement depends upon the type of the distress, density, and severity. The PCR of any pavement section at any given time t is computed by using the following equation:

$$PCR(t) = 90 - a[\exp(Age^{b}) - 1]\log[\frac{ESAL}{SNC^{c}}]$$

The formula has been discussed in detail in the above section of 4.2.3. The PCR value varies from 100 for a perfect pavement condition to 0 for the near failing condition. The model formulation for the predictive maintenance optimization approach is established for the pavement management system (PMS) with two objectives, namely, maximization of the average pavement PCR and minimization of the life-cycle cost of the pavement maintenance. The formulation also has a constraint that the PCR of the pavement sections should not fall below a predefined level, which is set at 40 for this research study. Therefore, the optimization model for this maintenance approach can be represented mathematically as the following equations:

Objective functions:

1. Maximize the average PCR over the design life of the pavement: Maximize $\sum_{t=1}^{N} PCRt\ /N$
2. Minimize the maintenance cost

   Minimize $\sum_{j=1}^{N} Cj$

Subjected to: $PCRt \geq \alpha 1$ j = 1, 2, N

Where, N = total number of years = 40; Cj = maintenance cost for pavement section j; $PCRt$ signifies the pavement condition rating of the pavement section at time t; and α1 is the minimum pavement condition threshold for the pavement section (set at 40). The maintenance model is prepared for a span of 40 years.

Solution to the objective functions mentioned above will provide a family of Pareto optimal solutions. Each solution in the Pareto family gives the optimal maintenance program and the resultant amount of maintenance cost for corresponding values of average PCR.

4.5 EXAMPLE PROBLEM

The model conceptualized above is tested on a sample problem with assumed values for a flexible pavement type as follows:

Table 6: Highway infrastructure facility for example problem

Infrastructure asset	**Type**	**Quantity**
Pavement	Flexible	Lane per mile

Table 7: Pavement maintenance actions and costs for the example problem

Maintenance type	Distress Type	Maintenance Action	Gain in PCR	$ Cost (in million)
M0	-	Do nothing	0	0
M1	Block Cracking	Routine Maintenance	4	3
M2	Depression	Minor Maintenance	7	6
M3	Pot holes	Major Maintenance	20	28

Where, maintenance action comprises of the activities that must be implemented to fix the pavement according to the distress type. Here, maintenance action for M1, M2, and M3 can be slurry seal, crack seal, and resurfacing respectively.

PROBLEM PARAMETERS AND INPUT DATA

A one mile single-lane section is considered for easy illustration of the example formulation. Only three types of distresses are assumed to occur in the pavement at the selected highway section: Block-cracking, depression, and pot-holes. Table 6 and Table 7 describe the asset characteristics and the maintenance cost data. The following four possible maintenance options are considered for each pavement section for the various distress types: (1) Do nothing, (2) Routine maintenance, (3) Minor maintenance, and (4) Major maintenance.

ANALYSIS AND RESULTS

Firstly, the procedure outlined in Figure 1 is applied to the component system. MOO technique is employed to solve the example problem. In this research study, a fast and elitist Multi-objective Genetic Algorithm: NSGA II has been deployed. NSGA II is a non-dominated sorting-based multi-objective evolutionary algorithm (MOEA) with computational complexity of $O(MN)^2$ degree. Simulation results on difficult test results in the past have shown that the proposed NSGAII, is able to find much better spread of solutions and better convergence near the true Pareto-optimal front as compared to other elitist MOEAs that pay special attention towards creating a diverse Pareto-optimal front (Deb, Pratap, Agarwal, & Meyarivan, 2002). The solution space available for the algorithm follows a progression of type e^x. Where, e is the number of maintenance options available for each year (i.e. four) and x is the total duration for the maintenance activities (here, it is 40). So, the total number of solution space that is available is of the magnitude 4^{40}= 1,208,925,819,614,629,174,706,176.

Table 8: Depiction of the various sets of solution for 40 years of maintenance

	SOLUTIONS																		
Year	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**	**S10**	**S11**	**S12**	**S13**	**S14**	**S15**	**S16**	**S17**	**S18**	**S19**
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	7	0	0	0	7	7	7	7	7	7	20	20	20	20	20	20	20	20	20
7	0	4	7	7	7	4	20	7	7	7	20	7	20	20	0	20	20	7	20
8	4	7	4	4	4	7	4	7	7	20	20	20	4	20	20	20	20	20	20
9	4	4	4	7	7	7	7	4	4	7	7	7	20	7	20	20	0	20	20
10	4	7	7	0	7	7	4	4	20	20	7	20	20	20	20	20	20	20	20
11	4	7	7	4	7	0	7	7	7	7	20	4	7	20	20	7	4	20	20
12	4	0	0	7	0	0	7	4	20	0	7	7	20	20	20	7	20	4	20
13	0	0	0	7	4	7	7	7	20	20	4	4	7	7	7	4	20	20	4
14	0	7	7	4	0	7	4	4	7	7	7	7	7	20	20	20	20	7	20
15	4	0	7	7	4	7	7	7	7	7	7	20	20	7	20	20	20	7	0
16	4	4	0	7	7	7	7	4	7	0	7	4	7	7	20	20	20	7	20
17	4	0	4	7	7	4	7	7	0	7	0	4	4	0	0	20	20	20	20
18	0	0	0	4	0	7	4	20	4	7	4	7	4	7	4	7	20	20	7
19	0	7	7	0	0	0	0	7	7	4	7	7	7	4	0	7	7	7	7
20	4	7	7	7	7	7	0	4	4	7	7	7	7	4	0	4	20	20	4
21	0	0	4	7	4	4	7	4	7	0	4	0	7	7	7	4	7	20	4
22	7	4	7	7	0	4	0	0	0	7	0	4	7	7	7	20	7	20	20
23	7	0	7	4	7	7	7	7	0	7	4	20	4	4	4	7	7	20	7
24	0	4	7	0	4	4	4	4	0	0	4	4	4	4	7	4	0	4	20
25	7	7	0	0	7	0	7	7	0	4	0	0	0	4	7	4	0	7	7
26	4	0	0	0	4	7	0	7	0	0	7	0	0	7	7	4	7	0	20
27	7	7	0	4	0	7	0	7	4	7	7	4	0	7	7	0	20	0	20
28	7	4	4	7	7	7	4	7	4	4	0	4	7	4	4	0	0	0	20
29	4	7	0	4	7	7	4	4	4	4	0	4	4	7	4	0	7	4	20
30	0	7	0	0	7	0	0	0	0	7	4	0	4	0	0	0	7	20	20
31	0	0	0	0	4	4	4	0	4	0	7	0	0	4	7	7	0	4	7
32	4	0	0	0	4	0	4	4	0	0	0	7	4	4	7	4	7	20	20
33	0	0	4	0	0	4	4	4	0	0	0	7	0	0	4	20	4	20	7
34	0	0	4	0	0	0	0	0	0	0	0	7	4	0	0	7	0	7	7
35	4	4	4	0	0	0	4	4	4	4	4	7	4	0	4	0	7	20	4
36	4	4	0	4	4	0	0	0	0	7	0	0	0	0	4	4	0	4	0
37	0	0	0	0	0	0	0	0	0	0	4	4	0	0	0	0	0	20	0
38	4	0	4	4	4	4	0	0	0	0	0	0	0	0	4	0	4	4	0
39	0	0	4	0	0	4	0	0	0	0	4	0	0	4	0	0	7	0	4
40	0	0	0	4	0	0	0	0	0	0	0	0	0	7	0	4	4	4	4
PCR	68	69	70	71	72	73	74	75	76	77	78	79	80	81	82	83	84	85	86
NPV	44	47	51	56	62	68	82	84	108	119	140	151	172	195	218	242	275	306	331

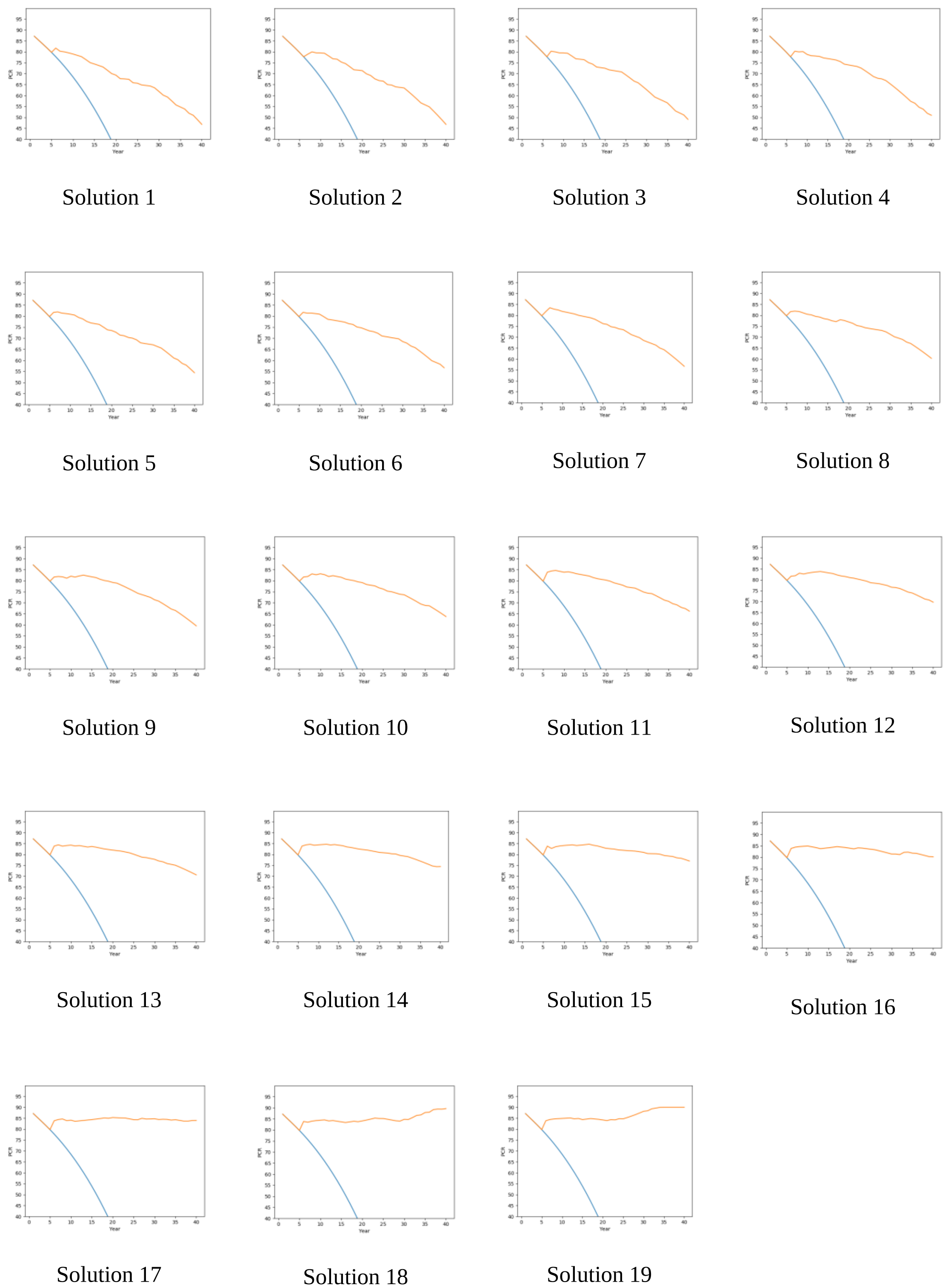

Figure 2 : Graphs for the various sets of solutions for 40 years of maintenance

The table number 8 as depicted above, gives the description of the total 19 solutions obtained from the algorithm. Each set of the solution has unique information about the distinct maintenance activities carried out each year for a time span of 40 years. The constraint being that at no point of time, the average PCR value must drop below 40. Every set of solution gives a detailed data for the gain in value of PCR for the pavement every year, form this data the total number of maintenance activities carried out for forty years can also be found out. The cost is calculated on the basis of net present value (NPV) and depicted as millions USD.

Fig. 3 gives a graphical representation of the Pareto set of solutions obtained.

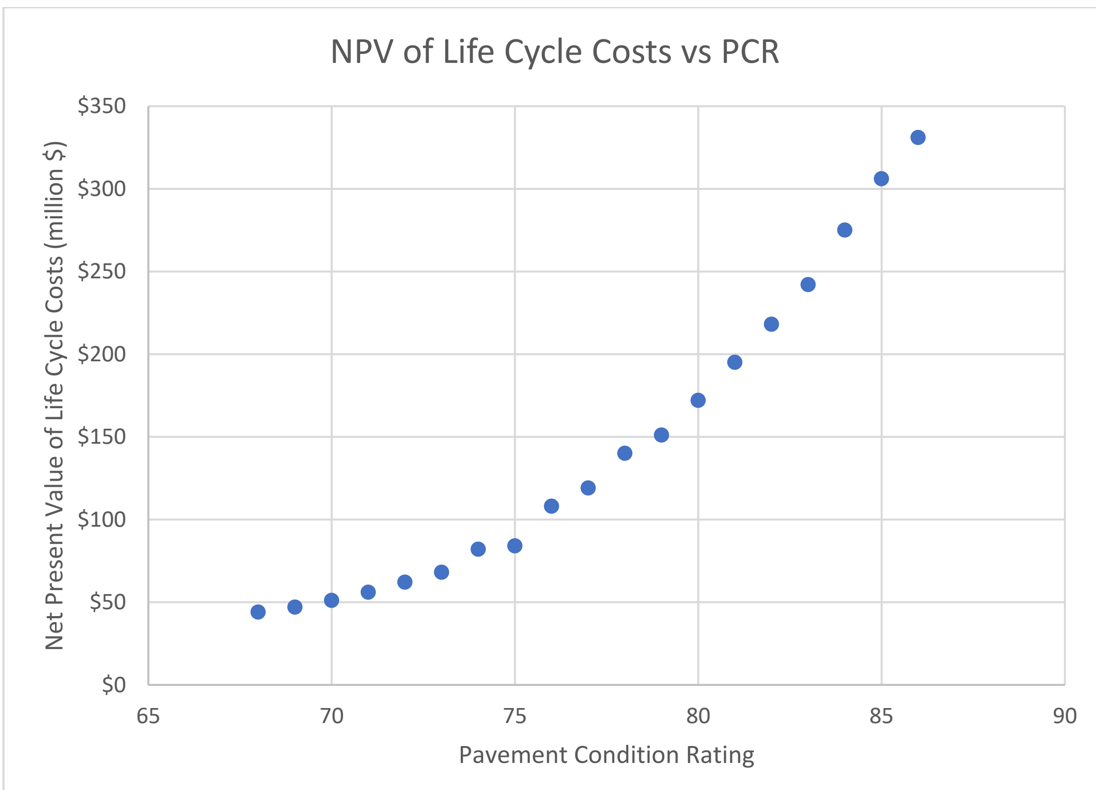

Figure 3: Depiction of the Pareto-optimal convergence for the two objectives.

An initial test run of 10,000 was performed for the genetic-algorithm analysis. The performance threshold value of 40 was selected so that the average PCR value must not drop below that for the maintenance duration of 40 years. (This is a constraint). With the initial test, a Pareto set of non-dominated feasible solutions was obtained. The solution set contains 19 optimized solutions for the given range of design life. It can be seen that the Pareto frontier of Figure 3 covers a wide range of PCR form 65 (more than the minimum PCI threshold set at 40) to 86. This plot shows the minimum budget required to meet the maintenance needs for the proper upkeep of pavement above the minimum threshold. The minimum budget needed for the PMS is 44 million $ per lane per mile, which will give an average PCR rating of 68 for 40 years. These figures show the budget vs the PCR rating that is needed for the asset item to meet its basic maintenance needs. (i.e., to meet the minimum condition thresholds). The result also indicates the upper-end budget to be in the order of $ 331 million which will maintain an average PCR of 86 throughout the life-span of 40 years. Hence, the total management budget cost per mile for the pavement must lie between $ 44 million to $ 331 million in terms of PV which will keep the average PCR value of the pavement in-between 68 to 85 respectively.

The decision to deploy one particular solution over the rest of 18 available optimized solutions spread across the Pareto front will depend upon the wisdom of the decision makers. It is imperative that one solution cannot be chosen over the other without compromising some benefits in terms of either of the objective functions. Thus, a certain trade-off has to be made based on the constraints that the owners might have with respect to the availability of the funds, resources, manpower, or machinery.

CHAPTER 5: RESULT AND DISCUSSION

5.1 CASE STUDY

The developed framework for determining optimal PM technique for the maximum LOS and minimum LCC is herein illustrated using a case study involving a section of the California Department of Transportation Asset Management Plan (TAMP). The data presented below is adopted from the table 4-2 of the California Transportation Asset Management Plan- Fiscal Years 2017/18-2026/27, published in January 2018. The table below depicts a typical example of life cycle treatments (for a 40 year design) for pavements of class I in average climate conditions.

Table 9: Data depicting types of maintenance, schedule and cost in $/lane mile adopted from (TAMP, 2018)

Treatment	Schedule (in Years)	Cost ($/lane mile)	Present Value ($ lane mile)
Seal Surface	4	6,000.00	5,129.00
Thin Mill & Overlay	8	152,000.00	111,065.00
Seal Surface	12	6,000.00	3,748.00
Thin Mill & Overlay	16	152,000.00	81,154.00
Seal Surface	20	6,000.00	2,738.00
Thin Mill & Overlay	24	152,000.00	59,298.00
Seal Surface	28	6,000.00	2,001.00
Thin Mill & Overlay	32	170,000.00	48,460.00
Dig-out, Crack Seal, & Seal Surface	36	76,000.00	18,519.00
Medium Overlay	40	325,000.00	67,694.00
		Net Present Value	$399,806.00

Here, we can see that three major types of maintenance activities are taking place: 1) seal surface, 2) thin mill & overlay, and 3) dig-out, crack seal, and seal surface. The schedule of the type of maintenance activity to be performed is pre-determined on certain interval of years. Furthermore, there is a definite value of cost involved with each kind of maintenance activity, which is defined in terms of cost $ per lane mile. The total net present value for the entire 40 years of design life of the pavement system sums up to $ 399,806 per lane mile. Little information is available on the effects of the maintenance activities or the condition of the pavement prior to or after the treatment is applied.

Table 10: Data for the case study adopted from Rajagopal and George (1991)

Maintenance	Treatment	Gain/Jump in PCR	Budget
M0	None	0	0
M1	Seal surface	10	6000
M2	Thin mill & overlay	35	152000
M3	Dig-out, crack seal, & seal surface	20	76000

The data present here in table 10 is applied to the GA NSGAII MOO algorithm. The maintenance activities, treatment type, and the cost are obtained from California TAMP (2018), as depicted above in table 9. The values of gain/jump in PCR with the various maintenance activities are adopted from Rajagopal and George (1991). The algorithm was programmed to run 10,000 times. The minimum performance threshold value of 40 was also selected for average PCR. The results obtained after the accomplishment of the stopping criteria was imported into a matrix format in a Microsoft Excel Comma Separated Values File (a .csv file) and all the feasible, non-dominated optimized solutions were printed. Moreover, to better illustrate the solutions in terms of benefits with respect to both the objectives, graphs are plotted for each solution and the files are stored in the form of Portable Networks Graphics format (.png) in a separate folder. The various solutions and graphs are illustrated in table 11 and figure 4 below.

Table 11: Depiction of the various solution sets for 40 years of maintenance.

Year	SOLUTIONS															
	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	S15	S16
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	35	35	35	10	35	10	10	20	35	10	10	10	0	0	0
7	10	10	10	35	20	10	10	10	20	10	10	10	10	10	10	10
8	0	20	10	10	10	35	10	10	10	10	10	10	10	10	10	10
9	10	20	20	10	10	10	10	0	10	0	20	20	35	0	0	0
10	0	20	10	35	10	35	0	10	10	35	0	0	10	0	0	0
11	0	35	20	20	35	10	10	10	10	10	35	10	10	0	0	0
12	10	35	35	10	35	35	10	0	10	10	10	0	10	10	10	10
13	10	10	10	20	10	10	10	10	10	10	0	10	0	10	10	20
14	10	10	35	20	10	10	10	10	10	10	10	10	10	10	10	10
15	0	35	10	35	10	0	10	0	10	10	10	10	10	0	0	0
16	10	10	35	20	20	10	10	10	10	10	10	10	20	10	10	10
17	0	10	20	10	20	10	10	10	35	10	10	0	0	0	0	0
18	10	35	0	10	20	10	10	20	35	10	0	10	10	0	0	10
19	0	10	35	10	10	20	10	20	20	10	10	0	10	0	10	0
20	0	10	10	35	0	10	10	10	10	10	10	0	35	20	0	0
21	0	35	20	10	10	10	20	0	20	10	10	10	0	10	10	10
22	10	35	10	10	10	10	10	10	10	10	10	0	10	10	10	10
23	10	35	35	10	10	10	0	0	20	10	10	10	10	10	10	10
24	10	10	10	20	10	10	10	10	10	10	10	10	10	10	20	20
25	0	0	35	20	10	20	10	10	35	20	10	10	10	0	0	10
26	10	20	20	10	10	10	0	10	10	10	20	0	10	0	10	10
27	10	10	20	10	20	35	0	10	10	10	0	0	10	0	10	10
28	0	35	0	10	10	35	10	0	20	35	0	0	10	0	0	0
29	0	35	20	10	0	0	20	0	20	10	35	0	35	0	0	10
30	10	10	10	0	10	10	10	0	10	0	10	0	0	10	10	10
31	10	10	35	35	10	10	10	0	20	10	10	10	10	20	0	0
32	0	20	10	10	0	10	0	20	0	10	10	10	0	0	10	0
33	0	20	10	10	20	20	20	10	10	20	0	0	0	0	10	10
34	0	10	20	0	10	0	10	0	10	0	10	10	0	10	10	10
35	0	35	10	0	0	20	35	10	35	20	10	10	10	0	10	10
36	0	10	10	10	10	0	10	0	0	10	20	35	10	0	0	0
37	0	0	10	10	0	10	10	20	0	10	10	0	10	0	0	0
38	20	0	10	10	0	0	10	0	0	10	0	10	0	0	0	0
39	0	20	10	0	35	10	0	20	0	0	0	10	10	10	35	20
40	0	0	0	0	10	0	10	0	0	0	10	10	10	0	0	0
PCR	73	90	89	88	85	87	81	79	86	84	82	77	83	74	75	76
NPV	7	129	110	94	59	80	24	23	71	48	36	17	39	12	14	17

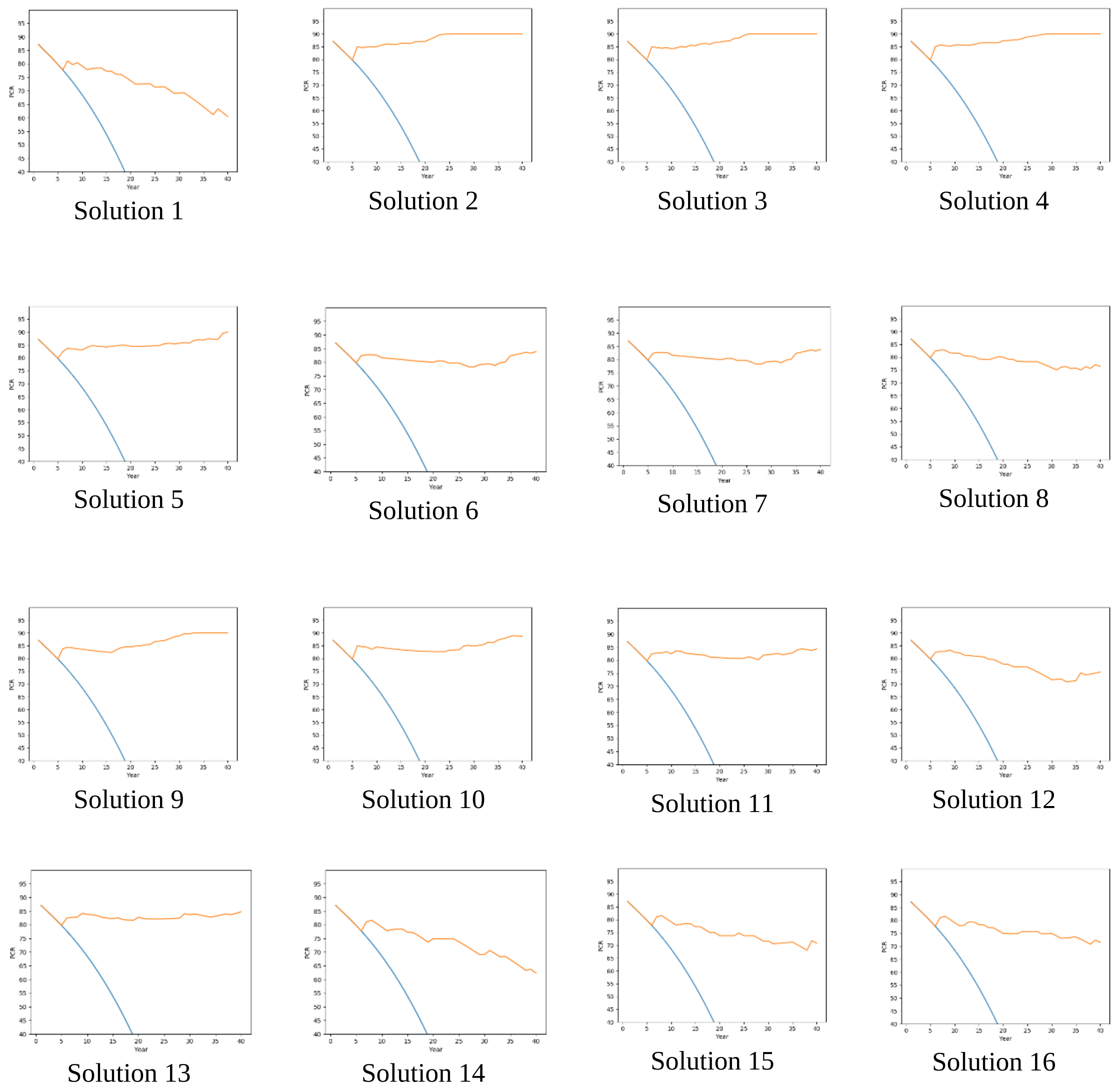

Figure 4: Graphs for the various sets of solution for 40 years of maintenance

The figure 4 as depicted above, gives the description of the total 16 solutions obtained from the algorithm. Each set of the solution gives information about the maintenance activity carried out for a time span of 40 years, under the constraint that at no point of time, the average PCR value dropped below 40. Every set of solution gives a detailed data for the gain in value of PCR for the pavement each year, form this data the type of maintenance activity carried out each year can also be found out. The cost is calculated on the basis of net present value (NPV) and depicted (rounded off) to the nearest 10,000 $ value at the bottom of the table 11.

Fig. 5 gives a graphical representation of the Pareto set of solutions obtained.

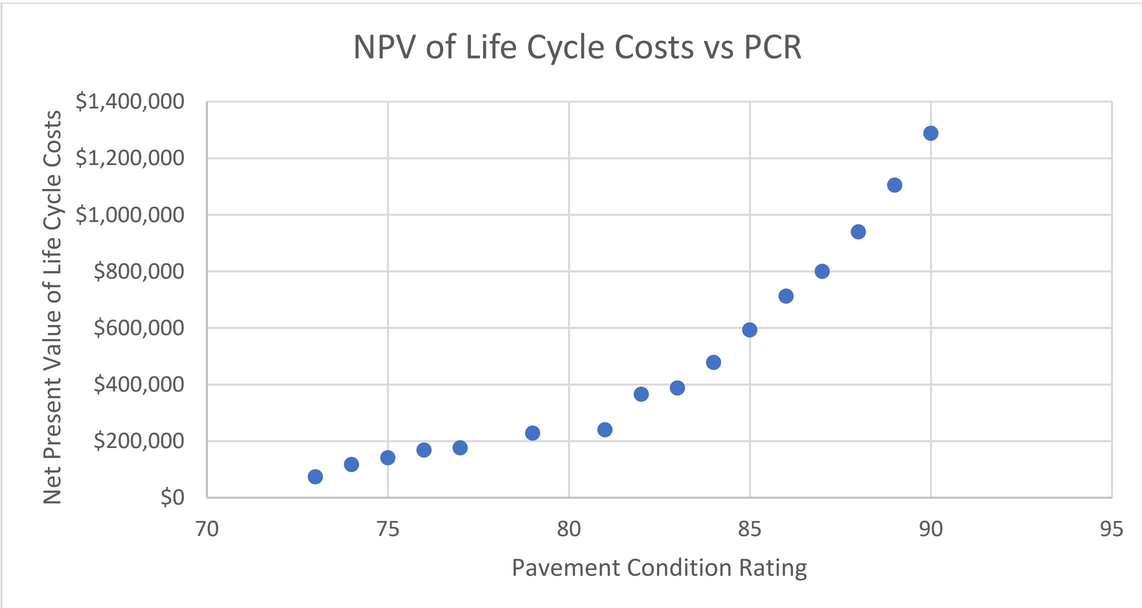

Figure 5: Pareto front obtained via the convergence of the two objectives.

The Pareto set of non-dominated feasible solutions for the two objectives contained 16 set of solutions. The Pareto frontier that is obtained covers a vast range of PCR values along with a wide range of costs associated with them. The range of PCR varies from 73 (lowest) to an excellent value of 90 (i.e. the highest). Subsequently, the costs associated with the various sets of maintenance solutions range from 73196 $ to 1287603 $ in terms of present value for a total span of forty years.

In conclusion, we can see that the solutions obtained from the MOO is far superior to the conventional maintenance technique used by the California DOT. The Pareto-front gives a wide range of solutions with several options to trade-off between the two objectives.

5.2 RESULTS

The effect of using MOEA NSGA-II for optimizing the two objectives, LCC and LOS in terms of total cost of maintenance and average PCR value was investigated by using the MOO. The results suggest that the MOEA NSGA-II is capable of tracking the overall pavement performance as well as the maintenance costs much more efficiently as compared to the conventional maintenance techniques.

The algorithm is tested for its effectiveness with the help of a case study in section 5.1. It involves a section of pavement in California Department of Transportation Asset Management Plan. The real data was fit into the model and the program was being run for a 10000 times to test for solutions that can be compared with the data from the Caltrans report. Based on the constraints and limitations, 16 feasible, non-dominated, optimized solutions were generated on the Pareto-front. The Pareto-front covers a large range of PCR values ranging from 73 to 90 and costs ranging from $ 73,196 to $ 1,287,603 respectively. Overall, 9 solutions are obtained across the Pareto front that outperformed the Caltrans estimation for LCC on the basis of cost alone. Moreover, the PCR value in the optimization model has a lower limit constraint for average PCR at 40, while there is no data available on the level of service for the pavement condition in the Caltrans data.

In conclusion, the solutions obtained from the MOO are far superior in comparison with the conventional time based maintenance warrants used by the California DOT. The Pareto-front gives a wide range of flexibility with the option of trade-offs between the two objectives. A brief comparative summary for the results of the case study has been depicted below in table 12.

Table 12: Summary of the case study result

Metrics	Optimized Solution	Caltrans Report
Total Solutions	16	1
Time-frame (design-life)	40	40
Constraint	1 (min PCR 40)	None
Objectives	2	1
Test run for algorithm	10000	N/A
Minimum cost obtained (NPV)	$ 73196 with PCR of 73	$ 399,806
Maximum cost obtained (NPV)	$ 1287603 with PCR of 90	Unknown
Total 9/16 optimized solutions outperformed the Caltrans estimations in terms of cost		

5.3 HOW MANY TIMES TO RUN THE ALGORITHM?

The more number of times we run the algorithm, the better convergence we get of the Pareto front towards optimal solution. However, after a definite number of iterations, the benefits in terms of convergence tends to be marginal and not much progress is made in terms of convergence towards the optimal Pareto front. To illustrate this, the above mentioned values in Table 10 have been optimized with Objective 1 as minimizing total cost, and Objective 2 to maximize average PCR over the span of 40 years. The iterations for 1000, 2000, 3000, 4000, 5000, 6000, 7000, 8000, 9000 and 10,000 runs have been plotted in the figure 6.

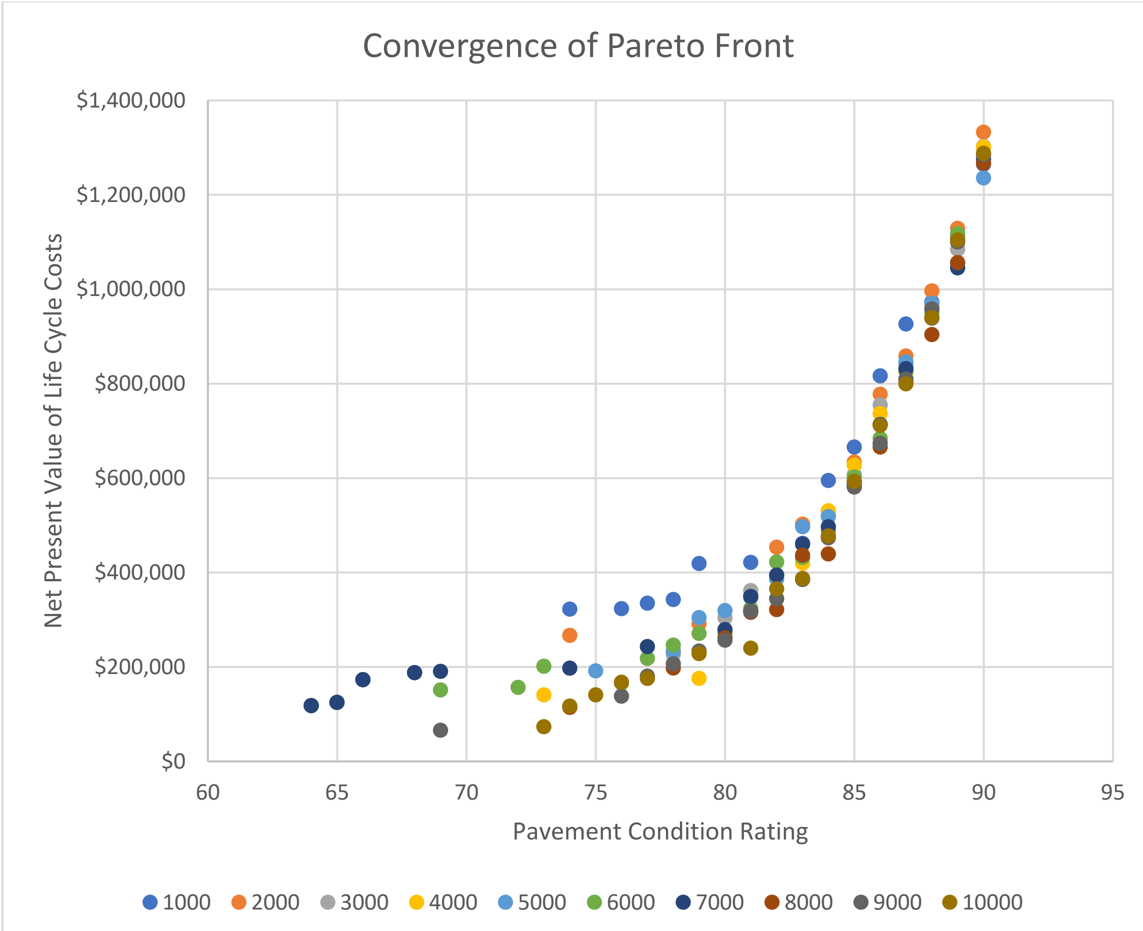

Figure 6: Pareto-optimal convergence for 1, 2, 3, 4, 5, 6, 7, 8, 9, and 10K runs of algorithm

From the above graph, it is inferred that the more number of times the algorithm runs, better convergence of Pareto front is obtained towards the optimal solution. But after a limit, the convergence is minimal. So, it is not desirable to run the algorithm several thousand times after a limit. In conclusion, the stopping criteria for the algorithm must be either a pre-determined benchmark in terms of performance measure with respect to both the objectives, or the number of times an algorithm is allowed to run beyond which the benefits in terms of convergence towards Pareto optimal front becomes minimal. In this research study, the optimum run is assumed to be 10000 runs, because around that the convergence of the Pareto front starts to become minimal.

5.4 SENSITIVITY ANALYSIS

A sensitivity analysis for the model is conducted by altering the values of benefits/jump in the value of PCR for the various maintenance interventions. The range of the benefits in terms of PCR associated with the different maintenance types is adopted from George et al. (1989). The types of distress, treatment, and the budget associated with the interventions are explained elaborately in Table 9 and Table 10 of section 5.1 of chapter 5 in this research study. The range of the PCR that were taken is depicted in table 13 below:

Table 13: Values of PCR ranges considered for the sensitivity analysis adopted from George et al. (1989).

	Maintenance 1	Maintenance 2	Maintenance 3
	8	36	18
PCR	12	38	22
			25

The algorithm had been programmed to run for 10,000 times and minimum average PCR of 40 was put for the maintenance interventions throughout for 40 years. The results obtained for the various values of the PCR and the NPV associated with them were put into a .CSV file and a graph was plotted using Microsoft Excel 2016. The various combinations associated with the maintenance types and the jump in the value of PCR associated with them have been depicted in the legend section of the figure 7 below:

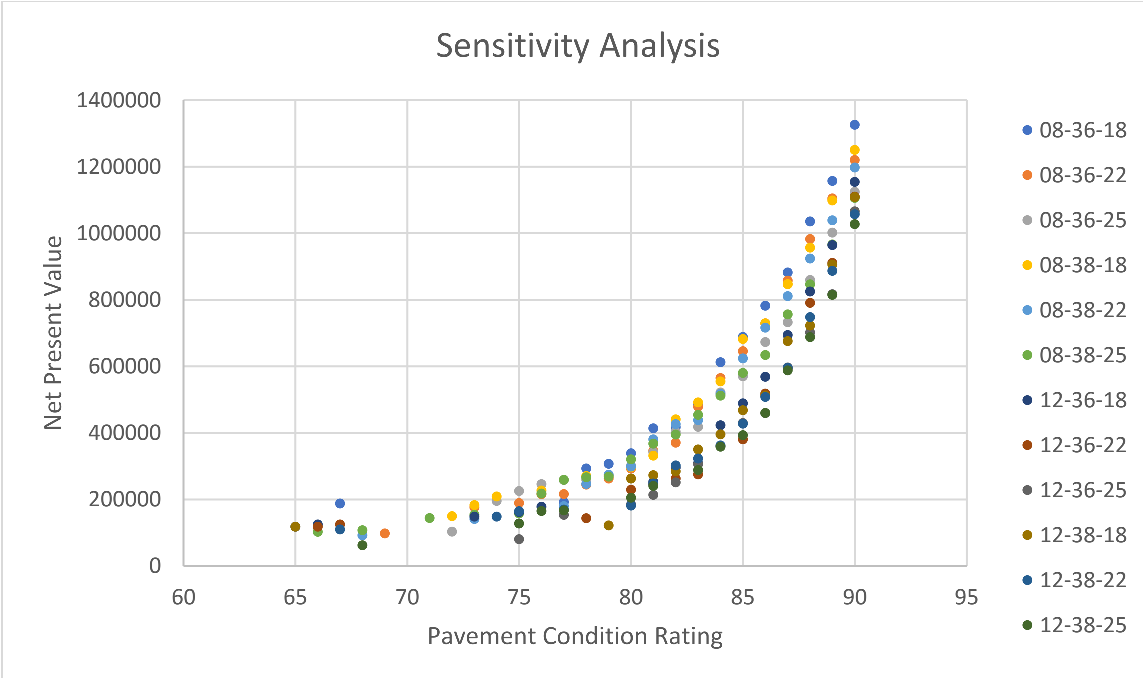

Figure 7: Pareto front convergence of the two objectives for sensitivity analysis

It can be observed that a wide range of Pareto optimal front was obtained with the various combinations of the jump in PCR associated with different maintenance types. Through the analysis, it was obvious that a trend followed, that gave better convergence of the Pareto-front with increase in the values of the jump in the PCR associated with the various maintenance types. The minimum value of PCR observed is 63 while the maximum value soared at 90. The minimum cost in terms of NPV was observed to be $ 80,447 while the maximum value NPV was documented as $ 1325882.

5.5 LIMITATIONS

The MOO model is proven to be effective and the total cost of the predictive maintenance can be determined with the help of the MOO model to make optimal decisions regarding life cycle cost and level of service. Accurate judgements can be made with this model to maintain, monitor, repair, and replace components of a pavement infrastructure project. However, certain assumptions were made in order to simplify the formulation of the optimization approach:

- The optimization model is limited in its approach in the sense that it considers only PCR value as a performance measure in the formulation of LOS. As the concept of LOS keeps expanding and improving, the model can take measures to incorporate more concepts into its formulation of the LOS like, including the user's perception into the formulation of the model.
- The optimization model is also constrained by not taking into account, the inspection cost and the failure cost into the LCC formulation.
- The objective functions are defined in terms of time only in the formulation of this research study. Whereas, in a real scenario, those objectives can also be dependent on other variables as well.
- The performance evaluation of the optimization approach for the highway asset management system in this research study is based only on two objectives, i.e. LCC and LOS. However, in a real scenario, the performance measure can be dependent on several other objectives such as environmental impact, sustainability, resiliency, etc.

5.6 FUTURE DIRECTIONS

Several extensions of this research study can be worked upon in the future. Some of the most significant ones include:

- The predictive maintenance optimization approach is applied on a two-objective system in this research study. However the approach is applicable to multi-objective analysis with any specified number of objectives.
- The pavement is the only asset item that is being considered in this research study and its formulation whereas in the future, more asset items can be incorporated in the algorithm system to acquire a more holistic approach towards the predictive maintenance optimization problem.
- Application of the optimization model to a more complex highway asset management scenario with the possibility of multiple intermediate maintenance actions.
- Incorporating errors related to the uncertainty in maintenance inspection, testing, data collection, calibration, and validation of the highway asset management.
- The data for the pavement maintenance has been derived from a single state only, it would be interesting to compile the data, derive, and compare the results from several DOT's across various states to see the potential variations in the solution.

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