Predictive Maintenance Optimization Framework for Pavement Management

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Abstract –

The preservation of highway infrastructure is essential for maintaining its capacity, safety, and efficiency for commerce and defense. Pavements are among the most important elements of highway systems that deteriorate over time. Hence, the goal of pavement asset management is to seek efficient investments where the methods applied will aid in identifying the most appropriate allocation of the resources available to the highway agencies. In the absence of unlimited resources, such decisions will always result in trade-offs in which funding certain assets will be needed at the expense of the other. Decision-makers need data-driven information regarding trade-offs to avoid the reactive solutions that are far from optimum and may be counter-productive over the long run. This paper proposes using a multi-objective predictive maintenance optimization framework using a non-dominated sorting multi-objective evolutionary algorithm (MOEA), for the optimum upkeep of pavements. The algorithm aims to find a spread of Pareto-optimal solutions by concurrently minimizing the life cycle cost and maximizing the level of service (LOS). A case study was developed to compare the model's effectiveness based on the maintenance data from the asset management plan of the California department of transportation. The results from the study will help develop promising techniques for the application of various multi-objective optimization systems and thus pave the way for efficient decision-making tools for the maintenance of highway infrastructure projects.

Keywords –

Asset Management; Life Cycle Cost; Level of Service; Multi-objective Optimization

1 Introduction

Pavement systems constitute one of the most valuable assets in all transportation agencies worldwide. Huge investments are made annually to preserve, expand, and operate these facilities, which are invaluable for the movement of people, services, and goods. Driving on roads that need repair costs 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 the form of lower vehicular upkeep and maintenance costs, time savings, lower fuel consumption, safety, minimized bridge upkeep costs, and lower emissions as a consequence of enhanced traffic flow [1].

Pavement maintenance is essential for extending the service life of deteriorating highway assets. The deterioration of the pavement surface due to aging and extensive use is the main threat to the level of service provided by the highway system networks. Thus, transportation agencies endeavor to renew, repair, and maintain the transportation systems already in place [2]. With the advancement of technology, highway officials and maintenance managers have the opportunity to analyze both the short- and long-term consequences of the maintenance strategies. Utilizing the maintenance strategies to extend the service life of highway systems reduces the frequency of infrastructure replacement and life cycle costs [3].

The funding allocated for maintenance, repair, and rehabilitation 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 the 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 [4]. To achieve the best results at both individual and overall system levels, an optimal scheme for fund allocation to individual assets needs to be identified. This necessitates the simultaneous optimization of more than one objective while satisfying all of the necessary constraints [5].

Asset management encourages considering the trade-offs between deferred maintenance and sustaining current pavement conditions and between short-term fixes and long-term solutions [6]. A well-developed model will enable maintenance managers to consider the impact of selecting one maintenance policy over another. Interventions applied too soon may add little incremental benefit. On the other hand, interventions applied too late may likely be ineffective [7]. It is hypothesized that there is a certain optimal level of performance in between these two extremes of profligacy and parsimony at which the intervention would yield maximum cost-effectiveness [8].

The main objectives of the study are to (1) develop a maintenance optimization framework using a non-dominated multi-objective evolutionary algorithm, non-dominated sorting genetic algorithm II (NSGA-II) and (2) develop an optimization framework that not only minimizes the cost over the lifespan of the highway assets but also maximizes the performance.

2 Literature Review

Asset Management. Highway asset management aims to secure and expand physical highway asset items belonging to transport facilities and sustain a certain level of service for its users. Researchers have proposed several optimization techniques to achieve optimal fund allocation for highway asset maintenance over the last two decades. [9] used an empirical index to combine seven project-level objectives using priority weights. [10] solved the single-objective budget allocation problem using priority weights of several assets based on the prevailing conditions. [11] developed a multi-asset optimization of roadway asset maintenance.

Multi-objective Optimization. Multi-objective optimization (MOO) algorithms are used for handling trade-offs among various objectives. Every multi-objective problem is unique and 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 [12]. Advanced methodologies based on a MOO formulation treat all the performance measures as additional merit objective functions that are not restrictive. As a result, the performance-based maintenance management methodologies lead to a group of non-dominated solutions, each of which represents a unique, optimized trade-off between a large set of alternative solutions.

In the past decade, a number of earnest attempts have been made to carry out the MOO for the purpose of asset management. [13] developed a cross-asset trade-off analysis based on multiple criteria for long-term highway investment. [14] developed a MOO method for bridge-management investment decision analysis using utility theory.

Life Cycle Cost Analysis (LCCA). LCCA arranges for a framework to specify the projected total incremental cost of constructing, using, developing, and retiring a specific infrastructure project. The six phases in a product's life are: need recognition, design development, production, distribution, use, and disposal [15]. LCCA enables the pavement engineers to conduct a comprehensive assessment of long-term costs, and ideally, agency highway funding can be allocated more optimally. LCCA is applied in road construction to explore the possibility of more efficient investment. LCCA evaluates not only the initial construction cost of the pavement but also all the associated maintenance costs during its service life. Therefore, pavement engineers can choose the pavement type and design with the lowest cost in the long run [16].

Previously, [17] proposed best value award algorithms over low-bid initial costs to choose the pavements. [18] evaluated LCCA practices in the Michigan DOT.

Level of service (LOS). The LOS concept was first proposed in the Highway Capacity Manual (HCM) of version 1965 [19] and then defined by the six levels in relation to a number of traffic conditions in the HCM of version 1985 [20]. 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 differentiate between LOS A, LOS B, and LOS C and so on [21]. 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.

[22] 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. [23] determined motorists' views on what aspects of freeway travel are important to them and identified: travel time, density/maneuverability, road safety, and travel information were the most important factors.

3 Method

The primary objective of the proposed model is to minimize the maintenance cost throughout the life cycle of the pavement (LCC) and maximize the level of service (LOS) of the infrastructure. The decision variables are the type of maintenance strategies as shown in Table 2, and the optimization problem has two objectives of LCC and LOS. With this, we established a multi-objective optimization model that will be further discussed in the next section. Since the study targets optimizing two objectives simultaneously, the research adopted a quantitative approach to investigate the benefits using a multi-objective optimization technique (MOO) for predictive maintenance. It must be acknowledged that the intent of the two objectives are incompatible with each other. Therefore, they 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 a best-suited way while focusing on delivering the best possible results.

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 allocation of maintenance resources. 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 specifying a sharing parameter that helps it find a diverse set of solutions and converge near the true Pareto-optimal set.

3.1 Genetic Algorithms for MOO

The Genetic Algorithms (GA's) are a type of heuristic algorithms that follow the survival of the fittest principle and are formulated loosely based on the Darwinian evolution. 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 creating new parent pools through the iterative process. The entire iteration process consists of copying, modifying, and exchanging parts of the genetic representation in a pattern similar to the natural genetic evolution.

The solutions generated in the parent pool are evaluated by means of the objective function. The fitness value of each solution is used to determine its potential contribution to 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 based on the number of iterations or the magnitude of improvement of the generated solution [24].

3.2 Concept of Pareto Solutions

In the evaluation of a pool of solutions in the 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 problems) which is composed of all the non-dominated solutions. This curve or surface is known as the Pareto frontier. Each set of Pareto-optimal solutions 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 one objective is better than the rest of the solutions is known as a non-dominated solution. This process of producing new solutions repeatedly continues until a set of globally non-dominated solutions is found. This globally non-dominated set of solutions is called Pareto optimal set and defines the Pareto optimal front [25].

3.3 Optimization Objectives

The desired MOO model comprises two objectives which form the optimization algorithm in the model development. The two objectives consist of minimizing (1) Life-Cycle Cost (LCC), and maximizing (2) Level of Service (LOS).

3.3.1 Life-Cycle Cost

The total expected costs during the lifetime of a highway, as adopted from [26] is given as:

$$Ct = Cet + Cpm + Cins + Cf \tag{1}$$

Where Cet is the initial cost of construction, Cpm is the expected cost of maintenance, Cins is the expected cost of inspections, and Cf is the 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:

$$C_{pm} = \sum_{i=1}^{40} \sum_{j=0}^{3} M_{ij} \tag{2}$$

Cpm = cost of predictive maintenance
i = number of years (from 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 [27] is:

$$PV = FV[\frac{1}{(1+r)^n}] \tag{3}$$

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

3.3.2 Level of Service

The level of service concept in the Highway Capacity Manual (HCM) is used as a qualitative measure representing freeway operational conditions. Many different quantifiable performance measures are currently included in the FHWA Highway Planning and Monitoring Systems (HPMS) database to determine the pavement level of service. In this study, Pavement Condition Rating (PCR) is used to quantify performance of 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. Several studies have approached the performance prediction of highways assets [28]. In this study the performance prediction equation for flexible pavement as adapted from [29] is presented by the equation:

$$PCR(t) = 90 - a[exp\ exp\ (Age^b)\ - 1]log[\frac{ESAL}{SNC^c}] \quad (4)$$

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.

$$SNC = \sum\ aihi + SNg \quad (5)$$

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)

3.4 Model Implementation

A graphical representation of the step-by-step procedure for the algorithm's functionality is shown in Figure 1.

3.4.1 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 PCR which is an ASTM standard for the pavement condition assessment. PCR values are allotted to a scale that ranges from 0 to 100. The PCR for a pavement section at any given time t is computed as follows:

$$PCR(t) = 90 - a[exp\ exp\ (Age^b)\ - 1]log[\frac{ESAL}{SNC^c}] \quad (6)$$

The PCR varies from 100 for a perfect pavement condition to 0 for a near failing condition. The optimization model 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: $PCRt$ ≥ α1   j = 1, 2, N

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

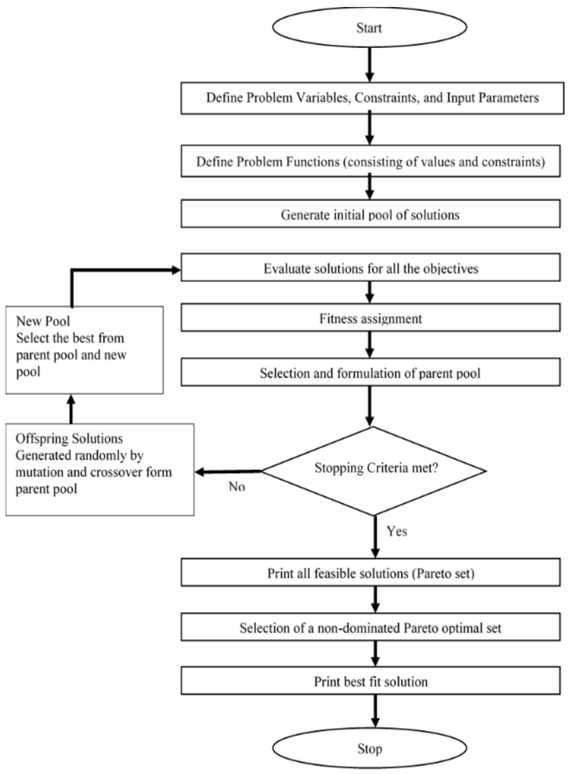

Figure 1. Genetic Algorithm Analysis for Multi-Objective Optimization.

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

4 Result and Discussion

4.1 Application of the model on a Case Study

The developed framework for determining optimal PM technique for the maximum LOS and minimum LCC is illustrated using a case study involving a section of the California Department of Transportation Asset Management Plan (TAMP). The data presented below is adapted from 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 1. Data depicting types of maintenance, schedule and cost in $/lane mile adopted from [30]

Treatment	Schedule (Years)	Cost ($/lane mile)	Present Value ($/lane mile)
Seal surface	4	6000	5129
Thin mill & overlay	8	152000	111065
Seal surface	12	6000	3748
Thin mill & overlay	16	152000	81154
Seal surface	20	6000	2738
Thin mill & overlay	24	152000	59298
Seal surface	28	6000	2001
Thin mill & overlay	32	170000	48460
Dig-out, crack seal, & seal surface	36	76000	18519
Medium overlay	40	325000	67690
Net Present Value $399,806			

Here, the three major types of maintenance activities are: 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, the cost involved with each kind of maintenance activity is defined in terms of cost $/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.

Table 2. Data for the case study adopted from [31]

Maintenance	Treatment	Gain 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 depicted in table 2 is applied to the GA NSGAII MOO algorithm. The maintenance activities, treatment type, and cost is obtained from California TAMP (2018). The algorithm was programmed to run 10,000 times. The minimum performance threshold of 40 PCR was selected. The results obtained after the accomplishment of the stopping criteria were imported into a matrix format, and all the feasible, non-dominated optimized solutions were printed. Moreover, to better illustrate the solutions, graphs are plotted for each solution, Table 3 and Figure 2 illustrate the various solutions and graphs.

Table 3. Depiction of the various solution sets (S1 to S16) 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

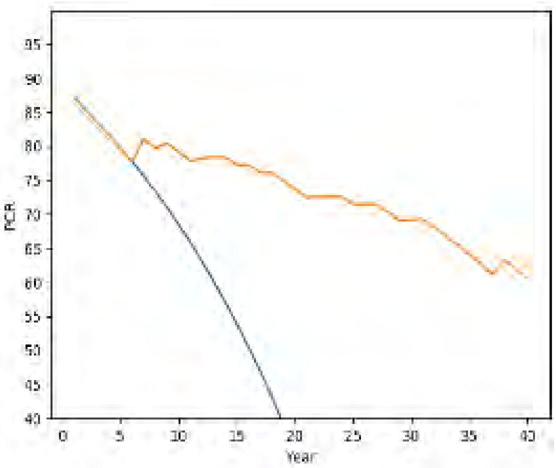

Figure 2. Graph for the S1 solution

Figure 2, gives the graphical representation of the solution 1 (S1) obtained from the algorithm. Similar plots could be made for solution S2 to S16. 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 detailed data for the gain in value of PCR for the pavement each year, from 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 Table 3. Depicted in Fig. 3 is a graphical representation of the Pareto set of solutions obtained.

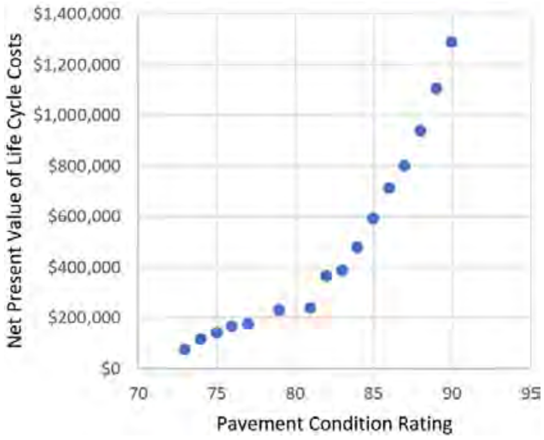

Figure 3. Pareto front obtained via the convergence of the two objectives.

The Pareto set of non-dominated feasible solutions for the two objectives contained 16 set of solutions. The Pareto front obtained covers a vast range of PCR values along with a 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 $73,196 to $1,287,603 in terms of present value for a total span of forty years.

A brief comparative summary for the results of the case study has been depicted below in table 4.

Table 4. Summary of the case study result

Metrics	Optimized Solution	Caltrans Report
Total Solutions	16	1
Time-frame	40	40
Constraint	1 (min PCR 40)	None
Objectives	2	1
Test run for algorithm	1000	N/A
Minimum cost (NPV)	$73196 with PCR of 73	$399806
Maximum cost (NPV)	$1287603 with PCR of 90	Unknown
Total 9/16 optimized solutions outperformed the Caltrans estimations in terms of $ cost		

4.2 Sensitivity Analysis

A sensitivity analysis is conducted by altering the values of benefits in the value of PCR for the various maintenance interventions. The range of the benefits in terms of PCR is associated with the different maintenance types. The types of distress, treatment, and the budget associated with the interventions are explained in table 1 and table 2 of section 4.1 in this research study. The range of the PCR that was taken is depicted in Table 5:

Table 5. Maintenance type (M1, M2, & M3) PCR ranges for sensitivity analysis adopted from [33]

M1 (PCR)	M2 (PCR)	M3 (PCR)
8	36	18
12	38	22
		25

The algorithm was run for 10,000 times at a minimum threshold of a PCR equal to 40 throughout for 40 years. The minimum PCR refers to a threshold defined by a decision maker and represents a level of service that is considered acceptable to a transportation agency. In future, the decision makers can set a different threshold value for the PCR and the model can provide an alternative set of optimized solutions. The results obtained were put into a .CSV file and a graph was plotted using Microsoft Excel 2016. The various combinations associated with the maintenance types and benefits in PCR have been depicted in the figure 4 below.

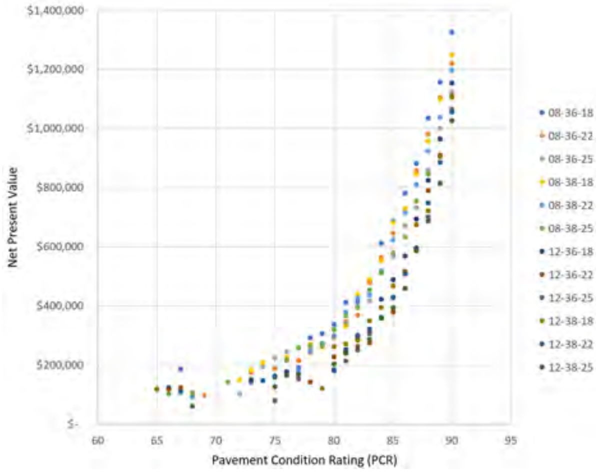

Figure 4. Sensitivity analysis of the Pareto front

It is observable that a wide range of Pareto optimal front is obtained with the various combinations of the benefits in PCR associated with the 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 benefits in the PCR. 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 Conclusion

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 data from California Department of Transportation Asset Management Plan. The real data was fit into the model and the program was run for 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. 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 to acquire a more holistic approach towards the predictive maintenance optimization problem. Moreover, the approach can be applied to more research cases in addition to California DOT data to test the model and its efficiency. Application of the optimization model to a more complex highway asset management scenario with the possibility of multiple intermediate maintenance actions will give a better result that will help in decision-making with greater confidence.

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