

A FRAMEWORK FOR DEVELOPING STOCHASTIC MULTI-OBJECTIVE PAVEMENT MANAGEMENT SYSTEMS

by

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ABSTRACT

Management of large transportation infrastructure, such as pavements, requires sound management tools to guide activities in an optimal fashion. Several pavement management systems (PMS) are in use by many transportation agencies. There are two types of management systems. There are those systems that are driven by optimization models and those that rely on expert (knowledge) systems. As transportation networks become larger and larger, it becomes imperative that some form of optimization modeling is needed. The majority of such optimization models are of the type where a single objective is optimized. In reality however, transportation officials are faced with multiple objectives or criteria that need to be traded off each other before a final decision is reached. In this paper, the author proposes a framework for developing a stochastic, multi-objective PMS. The paper discusses the multi-objective framework and highlights the departure from its predecessor; stochastic single-objective PMS. The paper shows that this proposed approach would result in several non-dominated (Pareto-optimal) policies. These are PMS policies whose attributes make them competitive. The advantage of this approach is to allow decision makers to have an important leverage in the final choice of PMS policy. The paper also outlines added advantages to this approach. These include possibility of generating dual equivalence (e.g., distress-based and roughness-based) policies that have similar network consequences. This feature is shown to have potentials for developing maintenance trigger levels in both scales. The feature could also enable agencies to develop distress-roughness equivalence tables where equivalent distress/roughness levels that would trigger same treatment actions may be developed.

1. INTRODUCTION

Planning and managing activities for a large network of transportation infrastructure is a daunting task. Many projects and interests compete for the limited resources allocated to a transportation agency and infrastructure management is only one of such competing interests. How much resources to allocate to transportation infrastructure and how to get the best value for the allocated resources have received high priority by top management officials of these agencies. The decision makers who have to make these types of choices often do so based on a number of criteria. Such criteria include limited budget for capital and recurrent expenditure, the need to keep the transportation network open at an acceptable level of service, etc. In this paper the author develops a framework that can be used by decision makers to make such multi-criteria or multi-objective choices in the management of transportation infrastructure. Specifically, this paper focuses on the management of highway pavements, also referred to here as Pavement Management System (PMS). The pavement management communities, such as the Organization for Economic Co-operation and

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Development - OECD [1], usually identify two major administrative levels of PMS namely, network-level PMS and project-level PMS. Analysis techniques and data requirements differ between these two levels.

The paper first defines the two administrative levels of PMS, and then discusses existing stochastic or probabilistic, single-objective network-level PMS models. The author then develops a framework for building stochastic, multi-objective network-level PMS models. Finally, the paper discusses practical issues of applying the multi-objective framework. This discussion also includes practical aspects and policy implications of applying such multi-objective decision support systems.

1.1 Network-Level PMS

Network-level¹ PMS is a set of planning tools and techniques that take into consideration pavement condition and repair work that need to be done to all highway segments being managed by a transportation agency. At this level the main objectives are to establish network-level repair policies, budget requirements, repair priorities and schedules. *The AASHTO Guidelines for Pavement Management Systems* [2] identifies specific products required to meet the objectives of a network-level PMS as:

- Information concerning the condition or health of the pavement network.
- Establishment of maintenance, rehabilitation and reconstruction policies.
- Estimation of budget requirements.
- Determination of network priorities.

The results of network-level PMS are of great interest to state-level transportation officials, budget directors, and managers of transportation agencies. Data requirement for network-level PMS often includes overall indices of pavement distress, roughness, safety, or structural adequacy.

1.2 Project-Level PMS

Project-level (also known as tactical-level) PMS determines optimal techniques for repairing specific segments of highway pavement or projects. This level of management involves assessing causes of pavement deterioration, determining potential solutions, assessing effectiveness of alternative repair techniques, and selecting solution and design parameters. Detailed site-specific data on pavement condition, materials, etc., are required at this level of decision-making.

In a typical “top down” PMS, network-level decision-making is done first, followed by project-level decision-making. In this case, the detailed project-level decision-making is essentially guided by the network-level (long-term) strategies, observes budget restrictions and network priorities. In such a system, long-term network preservation and performance take precedence over the life-cycle-cost of preserving individual projects.

2. SINGLE-OBJECTIVE VERSUS MULTI-OBJECTIVE NETWORK-LEVEL PMS

2.1 Single-Objective PMS

Optimization-based network-level PMS models try to optimize some objective while observing a number of constraints or resource restrictions. The models are of the form:

¹ The term network-level PMS in this case includes techniques that are referred elsewhere as strategic-level as well as program-level PMS.

Minimize (Maximize) Z

Subject to:

Constraint 1

Constraint 2

.

.

.

Constraint n

In this case, Z is a single objective to be optimized, such as *agency-cost*, *user-cost*, or *network condition*. The constraints often depict resource limitations of the agency, externally determined threshold conditions of a network, etc. Such problems are usually combinatorial in nature since the decision variables are often discrete. Many standard texts such as that by Papadimitriou and Steiglitz [3] give extensive discussion of combinatorial optimization problems. There are other forms of near-optimal techniques of optimizing combinatorial problems, such as genetic algorithms - discussed elsewhere [4, 5], that do not necessarily take the above form. However, the majority of network-level optimization models are of this type.

Single-objective optimization techniques are adequate if the decision maker is satisfied with optimizing only one objective. However, often there are more than one objective that need to be optimized. These competing multiple objectives may have significantly different impact on the resulting solutions. For example, an agency may wish to find suitable maintenance strategies that minimize its own cost (*agency-cost*) while also minimizing the traveling public's or tax-payers' cost (*user-cost*). In this example, any strategy that minimizes *user-cost* would require that pavements be maintained at a high level of service, which in turn will increase agency cost significantly. A compromise has often been to either optimize one objective and include the competing objectives as constraints, or optimize the sum of the competing objectives. There are shortcomings with both of these techniques:

2.1.1 Including competing objectives in the constraints.

The technique involves optimizing one objective, say minimize *user-cost*, and make other objectives as constraints, for example making the *agency-cost* a budget constraint. The technique pre-supposes that one already knows the optimal or desired levels of the objectives being put in the constraints. Since the optimal levels of competing objectives may vary from agency to agency, this technique may result in unsatisfactory results.

2.1.2 Adding all competing objectives into a single objective.

This technique creates a single composite objective from the set of competing objectives (e.g., $total-cost = user-cost + agency-cost$). One problem with this technique is that it assumes that all competing objectives can be expressed in a single unit. For example, if the objectives are *agency-cost*, *drivers/passengers comfort*, and *average pavement distress level*, one needs to quantify and convert all three objectives into a single unit for this techniques to work.

Another consequence of optimizing a single composite objective (e.g., $user-cost + agency-cost$) is that if there is no budget restriction, the optimal maintenance strategy requires that the *marginal user-cost* equals *marginal agency-cost*. This means that highly trafficked roads will need to be maintained at higher standards than low traffic roads. In many developed

communities where highway traffic volume is high, transportation agencies have criticized this method as being too favorable to car users at the expense of non-car users (e.g., transit users, or non-users of highway modes); both groups being taxpayers and hence also being the payers of the agency cost.

2.2 Multi-Objective PMS

The way to tackle competing objectives optimization problems is not to pitch objectives against each other *a priori*, but to develop solution strategies that include all possible combinations of the competing objectives. Different decision makers may then choose differently from the set of resulting alternative solutions (maintenance strategies or policies) based on their respective criteria. A typical multi-objective problem setup looks as follows:

$$\begin{aligned}
 & \text{Optimize } \mathbf{Z}_1, \mathbf{Z}_2, \dots, \mathbf{Z}_m \\
 & \text{Subject to:} \\
 & \quad \text{Constraint 1} \\
 & \quad \text{Constraint 2} \\
 & \quad \vdots \\
 & \quad \text{Constraint } n
 \end{aligned}$$

Solution techniques involve methods of generating all possible *non-dominated* or *Pareto-optimal* solutions to the problem. Solution X is said to be *Pareto-optimal* or *non-dominated* if no other feasible solution is at least as good as X with respect to every objective and strictly better than X with respect to at least one objective. This means a decision maker is not entirely better off changing from one solution to the other if the two solutions are non-dominated. A line (or a hyper-plane) connecting all non-dominated solutions is known as the efficient frontier. Figure 1 shows an example of non-dominated solutions, dominated solutions, and an efficient frontier presented in a two-dimensional objectives space. Solutions such as S_1 and S_2 are non-dominated since none of them has both objectives better than those of the other. However, it is clear that solution S_3 is dominated by (inferior to) both S_1 and S_2 . All Pareto-optimal solutions (all solutions on the efficient frontier) are potential alternatives for the decision maker. Different decision makers may choose different Pareto-optimal solution based on their specific criteria or utility function. Multi-objective decision analysis and techniques of generating non-dominated (Pareto-optimal) solutions and efficient frontiers are documented in many standard textbooks, such as that by Goicoechea et al. [6]

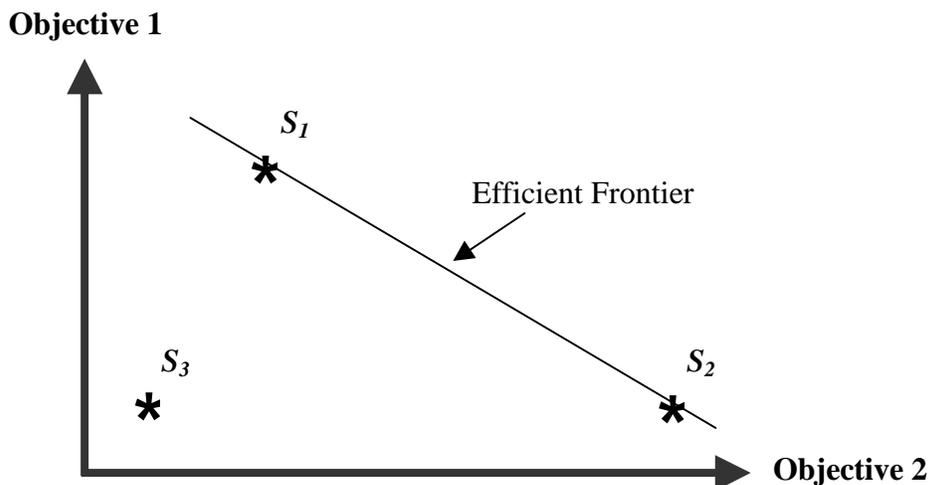


Figure 1. Efficient Frontier (Non-dominated or Pareto-optimal Solutions):
Assuming more is better.

3. STOCHASTIC, SINGLE-OBJECTIVE NETWORK-LEVEL PMS

Single-objective stochastic decision support systems or PMSs have been developed and discussed by many authors including Mbwana and Turnquist [7], Mbwana [8] and Kulkarni, Golabi, and Way [9]. The theory of stochastic (Markov or semi-Markov) decision processes is discussed in standard texts such as Derman [10]. First, let us discuss the nature of a single-objective PMS model that uses stochastic pavement deterioration processes. Later the author will develop a framework for instituting a stochastic, multi-objective PMS models.

A stochastic single-objective network-level PMS model is a dynamic model where the pavement deterioration process is stochastic (semi-Markovian) in nature. This is a more appealing method of modeling pavement deterioration since there are many factors, ranging from weather condition, to traffic flow levels, to material characteristics, that make the process of pavement deterioration probabilistic in nature. The deterioration process is therefore, represented by transition probabilities. In general terms a transition probability, P_{ij} , represents the probability that a pavement section will deteriorate from condition (e.g., distress or roughness level) i to condition j in one year. Table 1 shows an example of such probabilities, grouped in a matrix. The matrix in table 1 is one of the pavement distress deterioration models that were developed for New York State highway system [11]. Based on such a transition matrix, an average distress deterioration curve such as that shown in Figure 2 can be derived.

Table 1. One-Year Markov Transition Probability Matrix for a Flexible Pavement:
(Low trafficked asphalt concrete road after 2.5-3" overlay & preventive maintenance)

0.1421	0.6130	0.2448	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.5612	0.3825	0.0563	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.6695	0.2886	0.0418	0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.7556	0.1770	0.0673	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.9146	0.0416	0.0437	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000	0.9474	0.0332	0.0194	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.9500	0.0288	0.0212	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.9500	0.0261	0.0239
0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.5000	0.5000
0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000

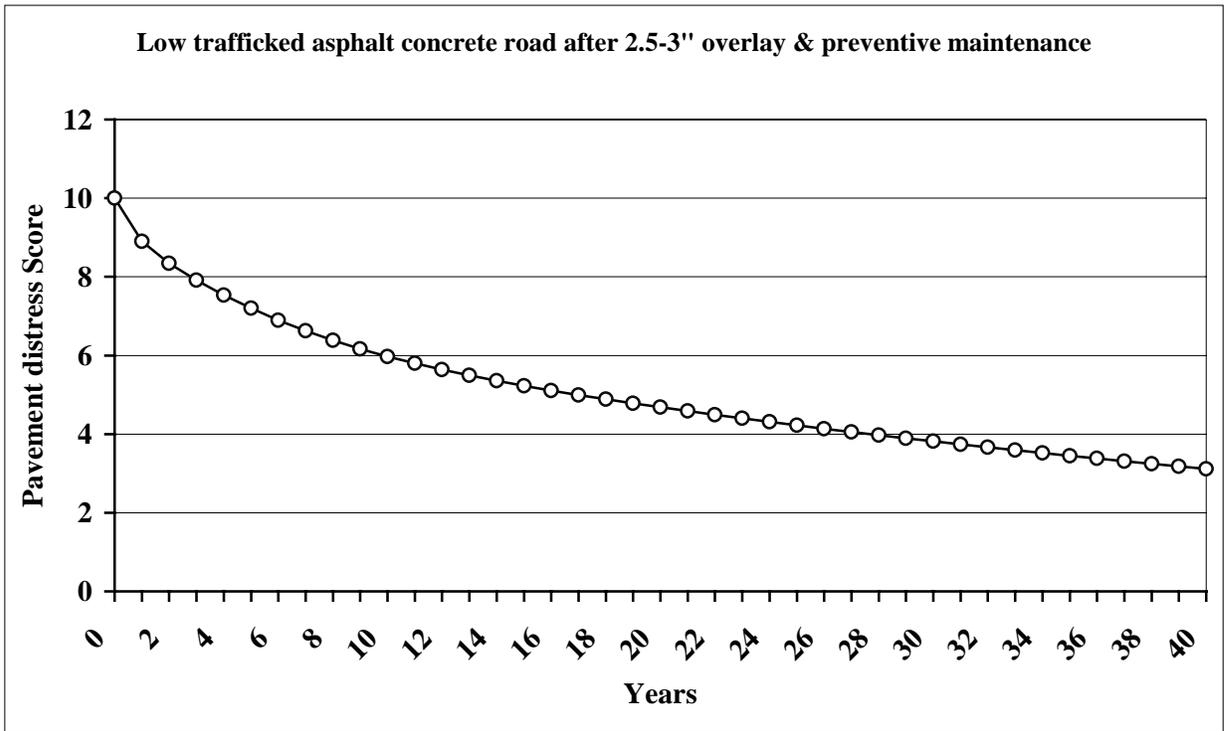


Figure 2: Average Performance Curve for a Flexible Pavement in New York State

Figure 3 gives a rough idea of the distress scale (pavement surface rating – PSR, ranging from 1 to 10) used in New York State and its qualitative rating. Historical data from this distress scale were used to develop the stochastic deterioration model. Detailed discussions of how to estimate such transition probabilities from historical data are presented in Mbwana [8] and Mbwana/Meyburg [11].

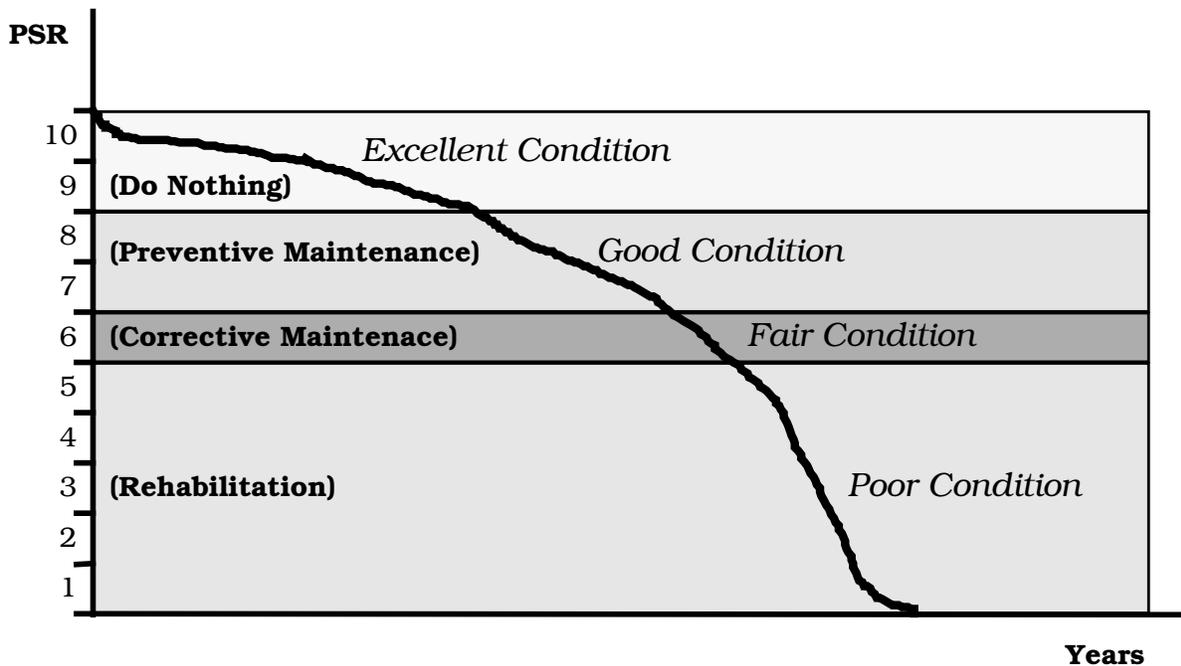


Figure 3. New York State Pavement Surface Distress Scale.

The following is an example of a single-objective, network-level (or long-term) stochastic PMS model. This is a distress-based model that minimizes *agency-cost* (single-objective) subject to a number of constraints. In this model the pavement condition modeled by the dynamic (time-variant) stochastic process is distress

Single-Objective, Distress-Based PMS Model

Minimize (agency cost) $\sum_t \sum_c \sum_i \sum_a X_{tcia} AC_{cia}$1
Subject to:	
Conservation of highway network size $\sum_i \sum_a X_{tcia} = X_{tc} \quad \forall t, c$2
Dynamic changes in pavement distress conditions (semi-Markov process) $\sum_a X_{tcja} = \sum_i \sum_a X_{tcia} P_{tciaj}^{(d)} \quad \forall t, c, j$3
Annual (long-term) total budget allocation $\sum_t \sum_c \sum_i \sum_a X_{tcia} AC_{cia} \leq B$4
Network distress condition specifications $\sum_t \sum_c \sum_a X_{tcia} \leq \delta_i \quad \text{if } i \text{ is unacceptable}$5
$\sum_t \sum_c \sum_a X_{tcja} \geq \omega_j \quad \text{if } j \text{ is unacceptable}$6
Non-negativity $X_{tcia} \geq 0 \quad \forall t, c, i, a$7

where:

- B = Total annual budget allocation.
- X_{tcia} = Number of lane-miles of pavement category c and traffic category t that will be in distress level i and get repair action a .
- X_{tc} = Number of lane-miles of pavement category c carrying traffic category t .
- AC_{cia} = Agency cost of applying repair action a on one lane-mile of pavement category c that is in distress level i .
- $P_{tciaj}^{(d)}$ = Probability that a pavement of category c and traffic category t will change from distress level i to distress level j in one year if repair action a is applied.
- δ_i = Maximum number of lane-miles in unacceptable distress level i .
- ω_j = Minimum number of lane-miles of roads in acceptable distress level j .

The optimal solution X_{tcia} from this model will generate long-term distress-based policies D_{tcia} where:

Optimal maintenance policy $D_{tcia} = \frac{X_{tcia}}{\sum_b X_{tcib}} 100$ 8

This policy states that, in the long run D_{tcia} percent of road segments of category c , carrying traffic level t will be in distress level i and repair action a will be applied. Another way of

looking at these policies is that, whenever road segments of category c , carrying traffic level t are in distress level i apply repair action a D_{icia} percent of the time. Please note that since the transition probabilities are modeling pavement deterioration in distress units, the resulting policies are distress-based. This means the optimal maintenance policies will use pavement distress levels as trigger values for repair actions.

For the sake of comparison, let us look at a roughness-based PMS model. The single objective used in this case is *user-cost*. Since roughness (rather than distress) is a better determinant of *user-cost*, it is preferable to use pavement distress as the dynamic process that drives the model. Therefore, the pavement deterioration matrix, P , is in roughness scale.

Single-Objective, Roughness-Based PMS Model

$$\text{Minimize } \sum_t \sum_c \sum_l \sum_a Y_{tcla} \left[\sum_m UC_{tcm} P_{tclam}^{(r)} \right] \dots\dots\dots 9$$

Subject to:

Conservation of highway network size

$$\sum_l \sum_a Y_{tcla} = Y_{tc} \quad \forall t, c \dots\dots\dots 10$$

Dynamic changes in pavement roughness conditions (semi-Markov process)

$$\sum_a Y_{tcma} = \sum_l \sum_a Y_{tcla} P_{tclam}^{(r)} \quad \forall t, c, m \dots\dots\dots 11$$

Annual (long-term) total budget allocation

$$\sum_t \sum_c \sum_l \sum_a Y_{tcla} AC_{cla} \leq B \dots\dots\dots 12$$

Network roughness condition specifications

$$\sum_t \sum_c \sum_a Y_{tcla} \leq \delta_l \quad \text{if } l \text{ is unacceptable} \dots\dots\dots 13$$

$$\sum_t \sum_c \sum_a Y_{tcma} \geq \omega_m \quad \text{if } m \text{ is acceptable} \dots\dots\dots 14$$

Non-negativity

$$Y_{tcla} \geq 0 \quad \forall t, c, l, a \dots\dots\dots 15$$

where:

- B = Total annual budget allocation.
- Y_{tcla} = Number of lane-miles of pavement category c and traffic category t that are in roughness level l and get repair action a .
- Y_{tc} = Number of lane-miles of pavement category c carrying traffic category t .
- AC_{cla} = Agency cost of applying repair action a on one lane-mile of pavement category c that is in roughness level l .
- UC_{tcl} = User (vehicle operating) cost per lane-mile on a pavement of category c and roughness level l that carries traffic category t .
- $P_{tclam}^{(r)}$ = Probability that a section of pavement category c and carrying traffic level t will change from roughness level l to roughness level m in one year if repair action a is applied.

- δ_l = Maximum number of lane-miles in unacceptable roughness level l .
- ω_m = Minimum number of roads in acceptable roughness level m .

The optimal solution Y_{tcla} from this model will generate long-term roughness-based policies R_{tcla} where:

$$\text{Optimal maintenance policy } R_{tcla} = \frac{Y_{tcla}}{\sum_b Y_{tclb}} 100 \dots\dots\dots 16$$

The roughness-based policy R_{tcla} has similar interpretations as the distress-based policy D_{tcia} . The only difference is that the former is used pavement roughness levels to trigger repair actions while the latter used pavement distress levels to trigger actions.

As discussed earlier, if one wishes to find pavement maintenance policies that minimize both objectives (i.e., *agency-cost* and *user-cost*) the best way would be to develop a multi-objective model that will generate an efficient frontier of non-dominated policies. These non-dominated policies can then be viewed as alternative policies from which different decision makers may choose differently, based on their respective criteria. Later, the paper discusses a technique by which the decision makers can rationally choose from a set of non-dominated policies generated by the multi-objective PMS.

4. STOCHASTIC, MULTI-OBJECTIVE NETWORK-LEVEL PMS

This section presents a framework for developing a stochastic multi-objective PMS model. To illustrate this framework, an example formulation is used in which two objectives (*agency-cost* and *user-cost*) are to be minimized. It is assumed (as it is indeed the case) that pavement roughness and traffic volume will be the major determinants of *user-cost* while pavement surface distress and repair type will be the determinants of *agency-cost*. Since there is no clear relationship between pavement distress and pavement roughness, the model will include deterioration models for both conditions as two separate stochastic processes. Even though distress and roughness will be presented as separate processes, it should be noted that these processes are being driven by the same set of decision factors, namely the repair actions applied. The two objectives will be denoted as O_1 (*agency-cost*) and O_2 (*user-cost*), respectively.

Network-Level Multi-Objective PMS Model

$$\text{Minimize } O_1, O_2 \dots\dots\dots 17$$

Subject to:

Objective number 1: agency cost (a function of pavement distress & repair action)

$$O_1 = \sum_t \sum_c \sum_i \sum_a X_{tcia} AC_{cia} \dots\dots\dots 18$$

Objective number 2: user cost (a function of pavement roughness & traffic volume)

$$O_2 = \sum_t \sum_c \sum_l \sum_a Y_{tcla} \left[\sum_m UC_{tclm} P_{tclam}^{(r)} \right] \dots\dots\dots 19$$

Conservation of highway network size

$\sum_i \sum_a X_{tcia} = X_{tc} \quad \forall t, c$20
Conservation of highway network size (link distress and roughness variables)	
$\sum_l \sum_a Y_{tcla} = X_{tc} \quad \forall t, c$21
Dynamic changes in pavement distress conditions (semi-Markov process)	
$\sum_a X_{tcja} = \sum_i \sum_a X_{tcia} P_{tciaj}^{(d)} \quad \forall t, c, j$22
Dynamic changes in pavement roughness conditions (semi-Markov process)	
$\sum_a Y_{tcma} = \sum_l \sum_a Y_{tcla} P_{tclam}^{(r)} \quad \forall t, c, m$23
Annual (long-term) total budget allocation	
$\sum_t \sum_c \sum_i \sum_a X_{tcia} AC_{cia} \leq B$24
Network distress condition specifications (optional)	
$\sum_t \sum_c \sum_a X_{tcia} \leq \delta_i \quad \text{if } i \text{ is unacceptable}$25
$\sum_t \sum_c \sum_a X_{tcja} \geq \omega_j \quad \text{if } j \text{ is unacceptable}$26
Network roughness condition specifications (optional)	
$\sum_t \sum_c \sum_a Y_{tcla} \leq \delta_l \quad \text{if } l \text{ is acceptable}$27
$\sum_t \sum_c \sum_a Y_{tcma} \geq \omega_m \quad \text{if } m \text{ is acceptable}$28
Non-negativity	
$X_{tcia} \geq 0 \quad \forall t, c, i, a$29
$Y_{tcla} \geq 0 \quad \forall t, c, l, a$30

where:

- X_{tcia} = Number of lane-miles of pavement category c and traffic category t that are in distress level i and get repair action a .
- Y_{tcla} = Number of lane-miles of pavement category c and traffic category t that are in roughness level l and get repair action a .
- X_{tc} = Number of lane-miles of pavement category c carrying traffic category t .
- AC_{cia} = Agency cost of applying treatment a on one lane-mile of pavement category c that is in distress level i .
- UC_{tcl} = User (vehicle operating) cost per lane-mile on a pavement of category c and roughness level l that is carrying traffic category t that is in.
- $P_{tciaj}^{(d)}$ = Probability that a pavement of category c and traffic category t will change from distress level i to distress level j in one year if repair action a is applied.
- $P_{tclam}^{(r)}$ = Probability that a section of pavement category c and traffic level t will change from roughness level l to roughness level m in one year if repair action a is applied.
- δ_i = Maximum number of lane-miles in unacceptable distress level i .
- ω_j = Minimum number of roads in acceptable distress level j .

- δ_l = Maximum number of lane-miles in unacceptable roughness level l .
- ω_m = Minimum number of roads in acceptable roughness level m .

Given the above multi-objective network-level PMS model one can generate a number of non-dominated (Pareto-optimal) solutions that form the efficient frontier. Techniques such as the *weighting method* or the *constraint method*, which are outlined in several multi-objective analysis texts, like that by Goicoechea et al. [6], can be used to accomplish this task. The main focus of this paper however, is not to discuss the generation of the efficient frontier, but rather to explore the implications of:

- a dual policy (distress-based, D_{tcl} , and roughness-based, R_{tcl}) existence for each non-dominated solution to the above problem, and
- rational choice by decision makers from various non-dominated policies resulting from the non-dominated solutions generated by the above PMS model.

To illustrate these two points, Figure 4 shows a typical set of non-dominated solutions and an efficient frontier that may be generated by the above PMS model. The figure shows four non-dominated solutions, S_1, S_2, S_3, S_4 that cover the entire range of objectives O_1 (*agency-cost*) and O_2 (*user-cost*). Any point along the efficient frontier can be a potential non-dominated solution. Solution S_1 , for instance, is synonymous to an aggressive pavement repair policy that maintains pavement surfaces to a high quality (hence low *user-cost*) but requires a lot of agency resources (hence high *agency-cost*). Solution S_4 , on the other hand, represents a scenario where the agency simply does the minimum of repair (resulting in low *agency-cost*, maybe due to severe budget constraints) resulting in poor state of pavement condition that leads to high *user-cost*. Solutions S_3 and S_2 would generate policies that result in less and less *user-cost* but at increasing rate of *agency-cost*, respectively. This is a typical situation facing a decision maker in a multi-objective PMS framework. Before discussing how to choose rationally from a set of non-dominated solutions, let us first discuss the implications of a dual-policy existence for each given non-dominated solution.

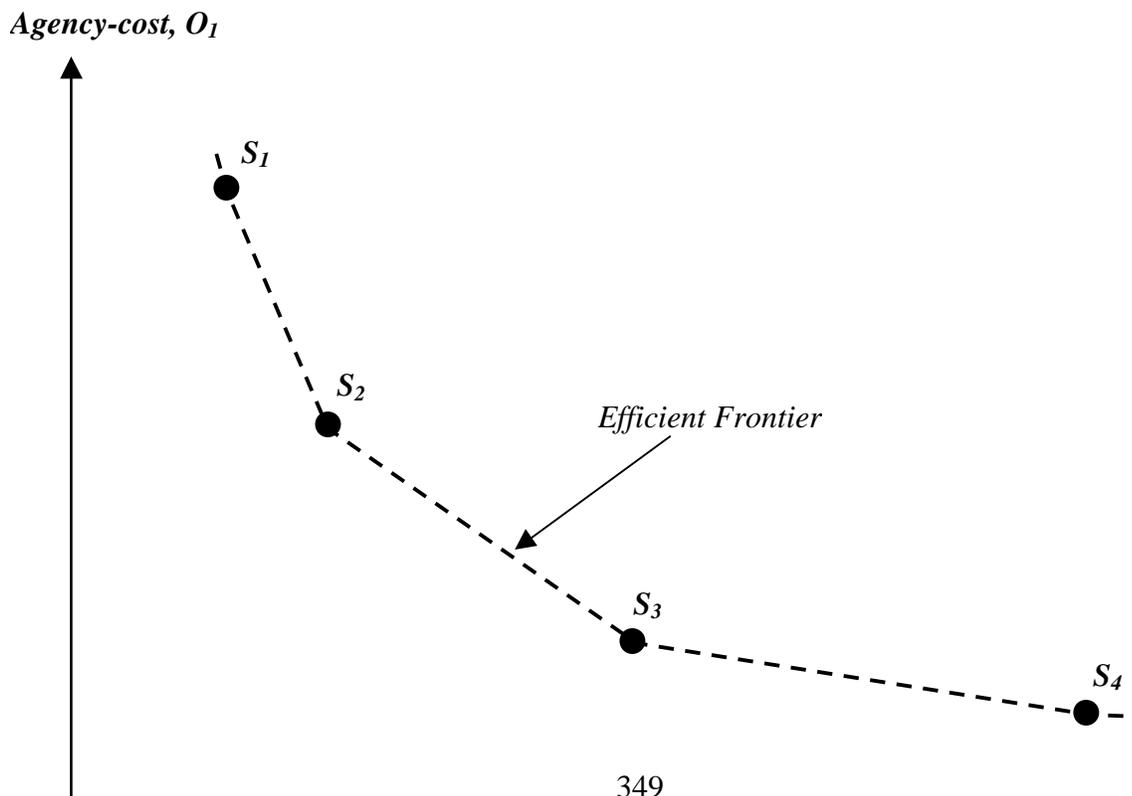


Figure 4. An Illustrative Example of an Efficient Frontier and Four Non-Dominated Solutions

4.1 Existence of Dual-Policies

For each non-dominated solution from the PMS model, there will be a set values of X_{tcia} and Y_{tcla} . These values can be used to generate either a distress-based repair policy, as shown in Equation 8 and repeated below,

$$\text{i.e., } D_{tcia} = \frac{X_{tcia}}{\sum_b X_{tci b}} 100$$

or a roughness-based repair policy as shown in Equation 16 and repeated below.

$$\text{i.e., } R_{tcla} = \frac{Y_{tcla}}{\sum_b Y_{tcl b}} 100$$

Each one of these policies can be used to guide network-level programming of pavement maintenance activities. One advantage of having such dual policies is that they gives analysts and decision makers the flexibility of developing either distress-based or roughness-based pavement repair trigger values. Therefore, for agencies that consider minimization of user cost as an important objective, roughness-based policies would be more appropriate to use. The reason for this is that such policies are likely to portray greater sensitivity to those factors that contribute to user-cost. For example, solution S_1 in Figure 4 will generate roughness-based policies, R_{tcla} , that would be sensitive to traffic volume and would recommend aggressive repair work on high traffic volume roads in order to minimize roughness, and less aggressive repair work on low volume roads. This policy sensitivity may not be as apparent on distress-based policy, D_{tcia} , even though both policies, if applied, will achieve the same network level goal. It is anticipated that, as more research data is gathered on this approach, it will be apparent that some non-dominated solutions will favor the use of one policy type than the other. For example, if a decision maker chooses a solution closer to S_1 then it is likely that roughness-based policies will be more favorable and more intuitive than distress-based policies. On the other hand the closer to S_4 the decision maker's choice is, the more intuitive the distress-based policies will be.

Dual policies that have similar consequences create an added advantage in this case. The related policies can be helpful in developing distress-roughness correspondence table. Several researchers have tried to develop meaningful relationships between distress and roughness measures of pavement quality without much success. This method has a chance of enabling agencies to develop distress-roughness correspondence matrices. The correspondence matrix will not necessarily lead to closed form relationships. However, it will have information regarding which distress level would trigger the same response as a given roughness level. An important aspect of this observation that is currently being researched is whether the distress-roughness correspondence tables will differ depending on the chosen alternative along the efficient frontier.

The last advantage of these dual policies is that transportation agencies will be able to establish optimal network conditions and priorities for different parts of the network in both roughness terms as well as distress terms.

The main disadvantage of this method is that it is data intensive. It requires deterioration models (transition probabilities) to be developed for both distress and roughness measures of pavement quality. It is recommended that the application of this method be a long-term goal of transportation agencies. With time, such agencies would be able to accumulate historical data on distress and roughness from which models can be built.

4.2 Choosing Between Several Non-Dominated Policies (Analytic Hierarchy Process-AHP)

When one has to select an alternative from a set of several non-dominated alternatives based on multiple objectives or criteria, it is often hard to make such choice rationally. For example, if one has to choose a job from say, three offers, there may be several criteria to consider such as starting salary, distance of work site from family, benefit packages attached to each offer, etc. While one offer may have attractive starting salary, it may have less attractive benefit package compared to another offer.

This example is similar to a situation presented in Figure 4. In this example, four (or even more) non-dominated solutions (each of which will result to a different repair policy) that were generated by the multi-objective PMS, are shown on the figure. A decision maker needs to choose between these alternatives policies based on a number of criteria such as *user-cost*, *agency-cost* and their resulting impacts on network conditions. The author recommends the use of standard multi-criteria ranking techniques to enable the decision maker to choose from a set of non-dominated solutions. Thomas Saaty's Analytic Hierarchy Process – AHP [12] provides a powerful tool for this purpose. The technique involves conducting pair-wise comparisons of alternatives as well as objectives or criteria in order to determine decision maker's priorities. The result of this process is a rational ranking of alternatives in the order their respective utilities to the decision maker. This process has been used successfully in many situations involving multi-criteria decision-making.

5. CONCLUSIONS AND RECOMMENDATIONS

The multi-objective PMS framework presented in this paper is intended to enhance existing single-objective systems. The framework ties standard engineering management techniques to highway pavement management and demonstrates the advantages of applying a multi-objective analysis to PMS. The main advantage of a multi-objective PMS is that it allows decision makers in transportation agencies to have control in the policies being generated by PMS models. Specifically, it allows these officials to have an input on the weights attached to various criteria used to generate management policies.

As a bonus to the benefits of a multi-objective approach to PMS, the paper also shows that there could be added benefits to this approach. An example was presented where it was shown that multi-objective PMS could generate dual policies that have similar network consequences. For example, it is possible to have distress-based maintenance policies with corresponding roughness-based policies. If implemented successfully, this feature has the ability do specify simultaneous maintenance trigger values in both distress and roughness scales. This type of result could also be used to create distress-roughness correspondence tables where equivalent distress scales that would trigger similar actions as a given roughness scale may be specified. The distress-roughness equivalence scale would vary from agency to agency depending on the distress measures used. Assuming that the International Roughness Index (IRI) is used as a standard measure of roughness, this method could also be used to

compare distress scales of various agencies. The implications of dual (or multiple) policies generated by this technique could be an interesting area for further research work.

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